APPLICATION OF ANN AND GA FOR TRANSFORMER WINDING/ INSULATION FAULTS

By

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FINAL PROJECT REPORT

Submitted to the Department of Electrical & Electronics Engineering
in Partial Fulfillment of the Requirements
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CERTIFICATION OF APPROVAL

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Approved:

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June 2007

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Khairun Nisa' binti Nashruladin

ABSTRACT

This report 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. While, heuristic method of Genetic Algorithm is used to locate the optimal values to enhance the accuracy of fault detection. The dissolved gas in oil analysis is chosen to diagnosis the transformer faults in this project as the method is known to be an early fault detection method and enables to carry out during online operation of the transformer. Besides, the condition of the transformer could be monitored continuously by time to time. The project outcome is analyzed using Neural Network and Genetic Algorithm MATLAB Toolbox. Comparison between the real fault and predicted fault is made as to observe the accuracy rate of the system. As transformer faults detection concentrated more in conventional method such the stability of the voltage and current of the transformer. Therefore, hopefully the transformer winding and insulation faults could be studied from new point of view and method.

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LIST OF ABBREVIATIONS

ANN: Artificial Neural Network

GA: Genetic Algorithm

DGA: Dissolved Gas Analysis

CHAPTER 1
INTRODUCTION

This project is concentrating on the studies of transformer winding and insulation faults detection using the Artificial Intelligence system. The transformer faults are analyzed using the Dissolved Gas Analysis (DGA) and predicted using Artificial Neural Network (ANN) and Genetic Algorithm (GA) methods.

Transformer is a vital equipment especially in the power distribution system as well as the industrial field area. Due to its function, maintaining the transformer performance is important as to avoid any fault incident which could affect the power system operation. Even though the transformers have been provided with the protection devices and maintenance routine schedule, the early faults detection could prevent any premature breakdown besides improving the system reliability.

Therefore, the studies on transformer faults helps in predicting the fault behaviors and the outcome of this project studies could be used to prevent and evaluate the same fault from reoccurring in the system. In order to achieve that objective, the dissolved gas analysis (DGA) in transformer insulation oil is applied as this method enable an online inspection without having to isolate the transformer and the condition of oil could be monitored time to time.

The transformer winding/insulation fault detection had being determined and analyzed in different methods and approaches. From the research, the previous project on transformer faults detection, most of the methods being applied are the Expert system [6] and also Fuzzy set concept method [7]. On the other hand, there were projects dealing with Neural Network method and analysis which used the wavelet and Multilayer perceptron methods [8] and also a combination analysis using

Genetic Algorithm and Neural Network [4]. In this project, the transformer faults are analyzed by using Neural Network and Genetic Algorithm.

1.1 Problem Statement

1.1.1 Problem Identification

Either in power system or industry field area, any power disturbance or failure will cost a lot of money as every shut down will delay the production. Therefore, continuous maintenance is being done in order to assure that all devices work in proper manner. But, this procedure is just a real time checking as only current condition of the transformer able to observe while ongoing hidden faults which occurred could not be detected until the transformer protection devices detect any failures.

The Dissolved Gas Analysis is the best monitoring tool which helps to analyze the transformer faults. The analysis from the transformer insulation oils could explain the real condition of the transformer and predict the fault that are going to take place in a few months or years ahead. By the DGA analysis, any failure could be cured before the transformer condition becomes worst. This project report is based on the Dissolved Gas Analysis for the study on transformer faults.

1.1.2 Significant of the project

The aim of this project is to determine and diagnose the transformer faults using the dissolved gas analysis in oil along with prediction by Artificial Neural Network and Genetic Algorithm.

The transformer faults are being diagnosed using dissolved gas analysis in oil technique which is quite new and unfamiliar technique. Therefore, hopefully the basic understanding of dissolved gas analysis could enhance the author's knowledge in transformer. Similar to the artificial neural network and Genetic algorithm where the fault prediction diagnosed by dissolved gas analysis could be learned and predicted by these systems.

Even though there is a lot of research paper on dissolved gas analysis using intelligent systems yet there is few research papers appeared in Malaysia. Hence, it is hoped that this project could be one of successful projects in analyzing transformer faults using intelligent systems.

1.2 Objectives of study

- To study the transformer winding/insulation faults using Dissolved Gas Analysis method.
- To learn the Artificial Neural Network and Genetic Algorithm and design fault detection studies and analysis using both systems.
- Ability to study the transformer winding/ insulation faults detection using both Artificial Neural Network and Genetic Algorithm (MATLAB Toolbox Learning).

1.3 Scope of the study

In dissolved gas analysis, the hydrocarbon gases concentration where hydrogen, methane, ethane, ethylene, acetylene, carbon dioxide and carbon monoxide existed in the insulation oil after a few years in operation are monitored. The concentration of these gases leads to the specific fault. These fault gases generate corona or partial discharge, thermal heating and arcing faults. There are a few methods of fault interpretation. In order to diagnose the faults, the author concentrated on the Roger's Ratio and Key Gas methods as to test the system using both conventional and modern techniques that are widely being used in transformer insulation oil testing.

As for artificial neural network, the relationship between the fault gases and fault related is learned and trained in order to produce the fault accordingly to the fault interpretation method. Five hydrocarbon gases (hydrogen, methane, ethane, ethylene and acetylene) are input as the ANN training data as the diagnosis is concentrated only dissolved gas analysis in oil. Therefore, the carbon dioxides and carbon monoxide is ignored in this research.

In genetic algorithm, the system analyzed is the Roger's ratio fault diagnosis where the ratio of the hydrocarbon gases performance is optimized to enhance the accuracy of the prediction method. The most optimized system will be the base of the fault prediction for the dissolved gas analysis.

CHAPTER 2
LITERATURE REVIEW

2.1 Dissolved Gas Analysis [1]

Dissolved Gas Analysis (DGA) is an online method of transformer oil testing. The process starts from oil sampling to gas identification where the dissolved gas in the oil will be extracted and identified. The advantage of the dissolved gas analysis is that the process could be done during online. So, there is no need transformer shut down and the transformer itself is not disturbed.

From the immersed oil, the hydrocarbons gases extracted are hydrogen, methane, ethane, ethylene, acetylene, carbon dioxide and carbon monoxide. These gases prompt to produce specific faults when the amount of gas being produced exceeding their limit of existence in the transformer oil. This is due to different gases being generated in the oil did produce different energy which possibly produces different faults. Therefore, severity causes by the gases are different. The faults due to these gases are partial discharge, overheating, arcing and also cellulose. The fault severity varies from arcing (most severe), overheating (moderate), and partial discharge (least severe).

The difficulty in analyzing the Dissolved Gas Analysis is to identify the line between normal and abnormal data as to assure fault do occur in the system. There are quite a few methods of interpretation used by DGA to detect fault. The important aspect of fault analysis is collecting the data that been generated and correctly diagnosing the fault that is generating the gases that have been detected. The common methods used are Dörnenburg's ratio method, Roger's ratio, IEC's ratio and Key gas method. These methods have their own ratio limit of the hydrocarbon gases for each of the faults [1]:

2.1.1 Roger's Ratio

The Roger's ratio method is used by The Central Generating Board (CEGB) in which the magnitude of four ratios of hydrocarbon gases are used to generate a four digit code as shown in Table 1. These codes are related to the diagnostic interpretation in Table 2.

Table 1 CEGB Fault Gas Ratios

C.E.G.B FAULT GAS RATIOS[4]		
RATIO	RANGE	CODE
CH_4/H_2	≤ 0.1	5
	$> 0.1 < 1$	0
	$\geq 1 < 3$	1
	≥ 3	2
C_2H_6/CH_4	< 1	0
	≥ 1	1
C_2H_4/C_2H_6	< 1	0
	$\geq 1 < 3$	1
	≥ 3	2
C_2H_2/C_2H_4	< 0.5	0
	$\geq 0.5 < 3$	1
	≥ 3	2

Table 2 CEGB Diagnostics

C. E. G. B. DIAGNOSTICS				
CODE				DIAGNOSIS
CH_4/H_2	C_2H_6/CH_4	C_2H_4/C_2H_6	C_2H_2/C_2H_4	
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)
$CO2 / CO > 11$				Higher than normal temperature in insulation

2.1.2 IEC's Ratio

This method is an IEC Standard based on the 1978 review by the IEEE: "Guide for Interpretation of the Analysis of Gases in Transformer and Other Oil-filled Equipment in Service". The gas ratio is determined and assigned by individual limits as shown in Table 3 and 4 [6]:

Table 3 IEC Ratio Codes

IEC GAS RATIO		
RATIO	RANGE	CODE
CH_4/H_2	≤ 0.1	0
	$> 0.1 < 1$	1
	$\geq 1 < 3$	1
	≥ 3	2
C_2H_4/C_2H_6	≤ 0.1	0
	$> 0.1 < 1$	1
	$\geq 1 < 3$	1
	≥ 3	2
C_2H_2/C_2H_4	≤ 0.1	0
	$> 0.1 < 1$	1
	$\geq 1 < 3$	1
	≥ 3	2

Table 4 Fault Classification based on IEC Ratio Codes

IEC DIAGNOSTICS			
CODE			DIAGNOSIS FAULT TYPES
C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	
0	0	0	No fault
0	1	0	Partial discharges of low energy density
1	1	0	Partial discharges of high energy density
1,2	0	1,2	Discharge of low energy
1	0	2	Discharge of high energy
0	0	1	Thermal fault of low temperature,< 150°C
0	2	0	Thermal fault of low temperature,150°C – 300°C

0	2	1	Thermal fault of mediumtemperature,300°C- 700°C
0	2	2	Thermal fault of medium temperature,>700°C

2.1.3 Key Gas [2]

A particular fault is identified based on the relationship between key gases and fault types:

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

The Key gas method Guideline by California State University-Sacramento Guideline in Table 5:

Table 5 Key Gas Guideline

GAS	NORMAL (PPM)	ABNORMAL (PPM)	INTERPRETATION
H2	<150	>1000	Arcing, corona
CH4	<25	>80	Sparking
C2H6	<10	>35	Local overheating
C2H4	<20	>100	Severe overheating
C2H2	<15	>70	Arcing
CO	<500	>1000	Severe overloading
CO2	<10000	>15000	Severe overloading

2.2 Artificial Neural Network

Artificial Neural Network (ANN) is known as intelligent system where the network architecture and system duplicate human biological nervous systems patterns. The system is good in recognizing a certain set of pattern and making simple rules for complex problems besides having an excellent training capability.

The ANN structure consists of huge interconnection neurons which are known as processing elements where they co-operate in solving a respective problem given appropriate input data. The respective output produced is analyzed through the training mode where the process of analyzing the input data that is to deliver the target output.

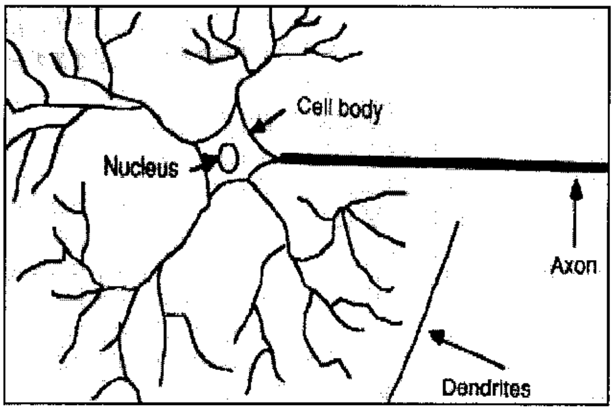

Figure 1 The components of neuron

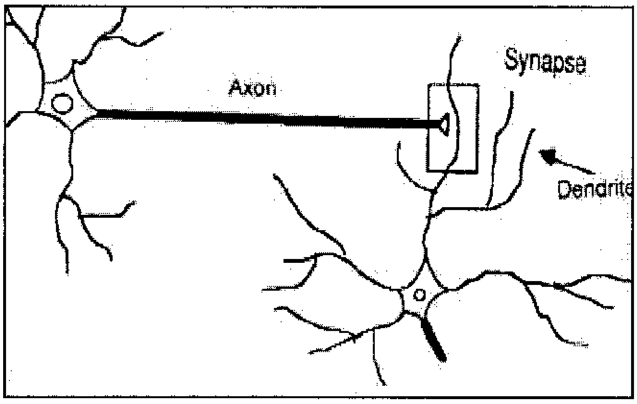

Figure 2 The synapse

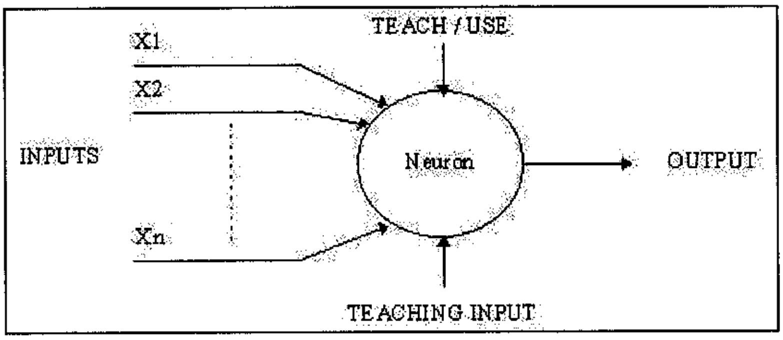

Figure 3 A simple neuron diagram

In ANN analyzing process, mathematical or computational model to process the input data is required. Generally, in normal applications, the ANN system required an input, output, network architecture and weighted connection of nodes which are known as the hidden layer. This system would represent the relationship between the input and output of the network where the process of relating the input and output is performed by the hidden layer of the network.

The input data which is fed into the network via connection will be multiplied by the weighted value (synaptic efficiency) of the network before adding up to form a weighted sum of inputs. Each of neurons is provided with single threshold value. Subtraction of weighted sum and threshold value compose an activation signal of the neuron. This activation signal passed through the activation function (called transfer function) to generate output of the neurons as shown in Figure 2:

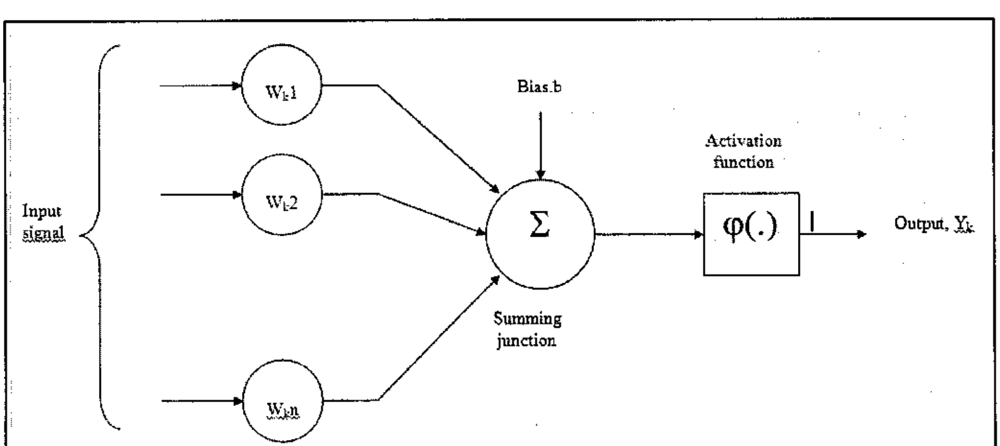

Figure 4 The nonlinear model of neuron

Depending on the network, the output would remain as an output or being an input to the next hidden layer of the network depending on the design structure.

The advantages of ANN are that the system allows a non-linear data modeling tools which is applicable in modeling a complex relationship between input and output to find the data patterns. On the other hand, with its adjustable structure, using the same data, estimation, prediction and simulation using a new input data is allowable.

2.2.1 Back-Propagation structure

Back propagation is one of Artificial Neural Network structures. This type of structure provides training network for multilayer feed-forward network. In ANN, data training is an important step as it helps in getting the most accurate target output. Back propagation allows automatically or self learning network where all weighted and biases values will be adjusted in each training level and train the input data until it reaches the desire output.

Besides, this type of training network tends to produce accurate output even though the network is inserted with unknown input data. Therefore, it is called a supervised learning network and was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks where the network weights are moved along the negative of the gradient of the performance function [3].

Three available transfer functions to generate the function output are:

1. Log-sigmoid – output range between 0 and 1
2. Tan-sigmoid – output range between -1 and 1
3. Purelin – linear output range between 0 and 1

Back propagation algorithm:

1. Forward activation: $y_i = f_i(\Sigma\, w_{ij}\, y_j)$

2. Calculating output error: $E=1/2\ \Sigma(t_o-y_o)^2$

where;

y_j= output of first layer

w_{ij}= weight of the network

t_o= target output

y_o= simulation output

The input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by the designer. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs [3].

2.3 Genetic Algorithm

Mechanism based on the Darwin Theory, principle of natural evolution. It produces result of emulation which also known as numerical implementation of the evolution principle. This principle observed in the nature that appearing in the population of living beings. The evolutionary process the initial target forward in order reaches the probably and nearest better solution. Therefore, Genetic Algorithm (GA) is capable in providing different potential solution for a given problem for the designer to choose and also useful for identifying the alternatives solution simultaneously.

Genetic Algorithm basically is being applied to solve a various optimization problems [4]. The following points are to be noted:

- process one problem in a coded form and not in problem parameters.

- perform in a certain population of initial prediction where the system is not perform alone or with single starting point
- apply a probabilistic method
- optimization process is controlled by suitable defined goal function

Therefore, GA is under a particular class of evolutionary algorithm that uses and borrowed the techniques motivated by evolutionary biology such as inheritance, mutation, selection and recombination [4]:

- **Population** : defined as a set of individuals of selected number
- **Individual**: a representative of the prospective problem solutions given in a coded form
- **Chromosome:** defined as the sequences of genes or vectors
- **Gene**: defined as a single element of the "genotype" which is a set of individual chromosome in particular of the chromosome
- **Phenotype**: a set of values corresponding to given genotype or known as the decoded structure

A genetic algorithm starts off with an initial population of randomly generated chromosomes. During successive iterations, called generations, the initial chromosomes advance towards stronger chromosomes by reproduction among members of the previous generation. New generations are created by three genetic operators: selection, crossover and mutation. Selection of the best chromosomes makes sure that only the best chromosomes can crossover or mutates by rating the individual chromosomes by their adaptation or associated fitness to present solution.

CHAPTER 3
METHODOLOGY

3.1 Artificial Neural Network

3.1.1 Procedure Identification for Neural Network

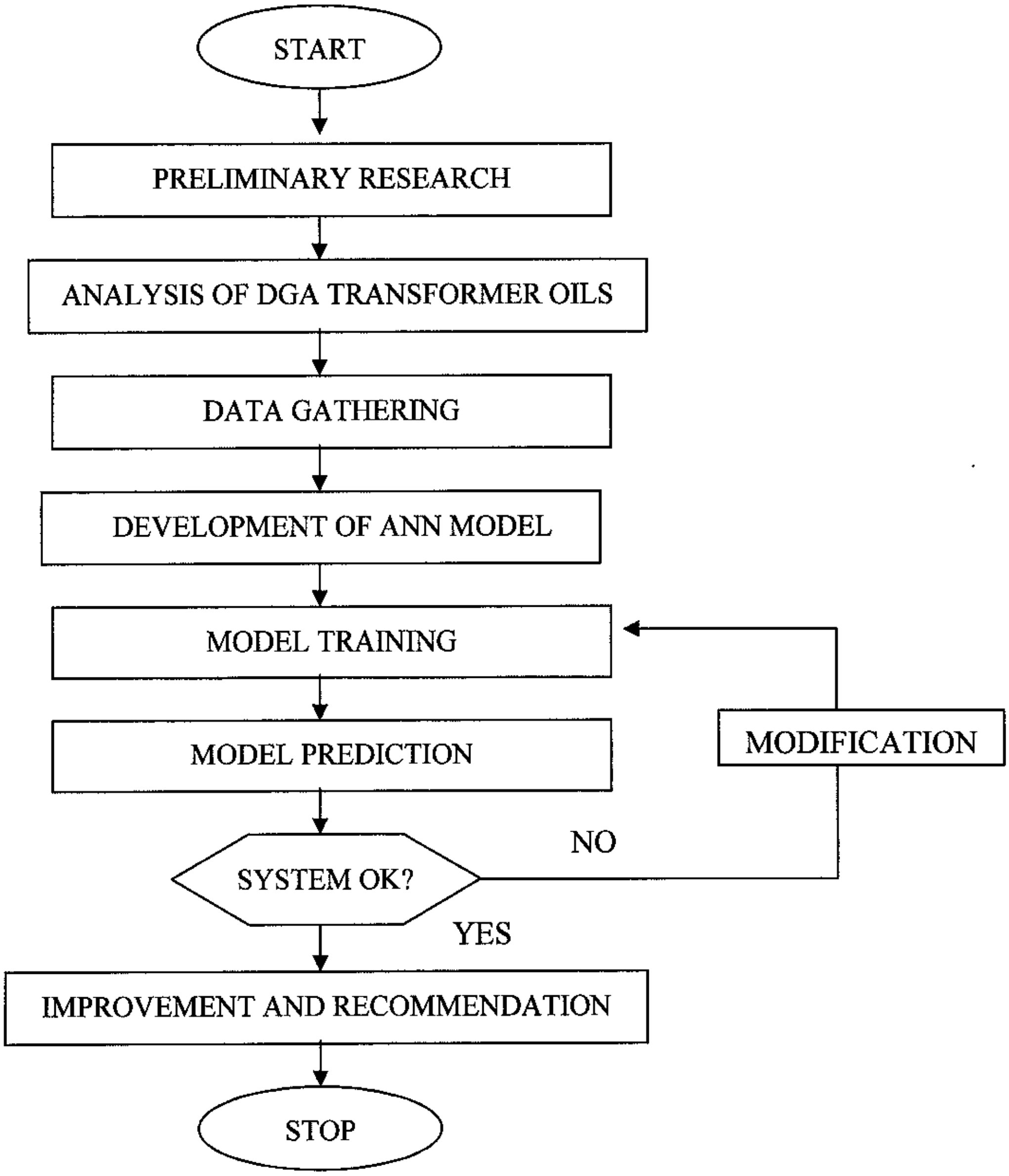

Figure 5 Flow chart of project methodology

3.1.2 Model Development [3]

In this project, the simulation is performed using Neural Network MATLAB Toolbox. Before applying the neural network coding, the basic coding on the Roger's ratio and key gas method needs to create in order to produce data and target value for each sample of the DGA data. This basic coding will produce the fault ratio data, *p*, expected target, *t*, and data normalization, *pnorm*, which later will be needed in the Back propagation network.

Five input data are inserted into the design Neural Network. For the Key Gas method, four outputs will be observed that are normal, corona, overheating and arcing. Data trimming method is applied to the fault data and the fault data is normalized. Hence, the normalized data is compatible with the target data over a range between 0 and 1. By then, the process in the Neural Network will be more appropriate.

Normalization equation;

$$f_{norm} = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}}$$

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 Levernberg-Marquardt training with feed-forward structure is designed with *tan- sigmoid* transfer function in the first layer and *log-sigmoid* at the output layer as the target is required to fall in range of 0 to 1. The hidden layer is trained using 50 neurons while 4 neurons at the output layer. The optimal value of neurons used in the hidden layer is obtained by trial and error technique because it depends on the complexity of the system itself.

The initialization of the Back propagation network training:

```
net=newff((minmax(ptr)),[30 R],{'tansig','logsig'},'trainlm','learnwh');
net.layers{1}.initFcn='initwb';
net.inputWeights{1,1}.initFcn='rands';
net.biases{1,1}.initFcn='rands';
net.biases{2,1}.initFcn='rands';
net.trainParam.epochs= 500;
net.trainParam.show= 5;
net.trainParam.goal= 1e-5;
net.trainParam.lr=0.01;
net.trainParam.max_fail=5;
net.trainParam.mem_reduc=1;
net.performFcn='mse';
```

3.1.3 Model training

In training mode, the neural network is trained by 52 training data and 10 test data collected from the research paper on the Dissolved gas analysis [10]. The data is trained in the network so that the network could learn the characteristics of the data and produce the desired output.

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

The network was validated by different number of training and validation data using the 30 training data to the network. The effectiveness of validation is tested using 3 sets of data:

Set 1: 90% training data, 10% validation data

Set 2: 80% training data, 20% validation data ↓ smaller the network error

Set 3: 70% training data, 30 %validation data

```
[net,tr]=train(net,ptr,ttr,[],[],v,t);
a=sim(net,ptr)
train_error=mse(a-ttr)
e=mae(a-ttr)
atest=sim(net,t.P)
test_error=mse(atest-t.T)
```

3.1.4 Test data from Petronas Fertilizer (Kedah) Sdn Bhd

Test data reference used to test the network. Therefore, real data from industry is necessary to test the performance of network. Different test data is collected from Petronas Fertilizer (KEDAH) Sdn Bhd (PFK) in order to test the structure and ability of the network to produce accurate resulst. Besides, the data gained from PFK is provided with details of fault analysis that helped in checking the result produce by the neural network structure.

3.2 Genetic Algorithm

3.2.1 Procedure Identification for Genetic Algorithm

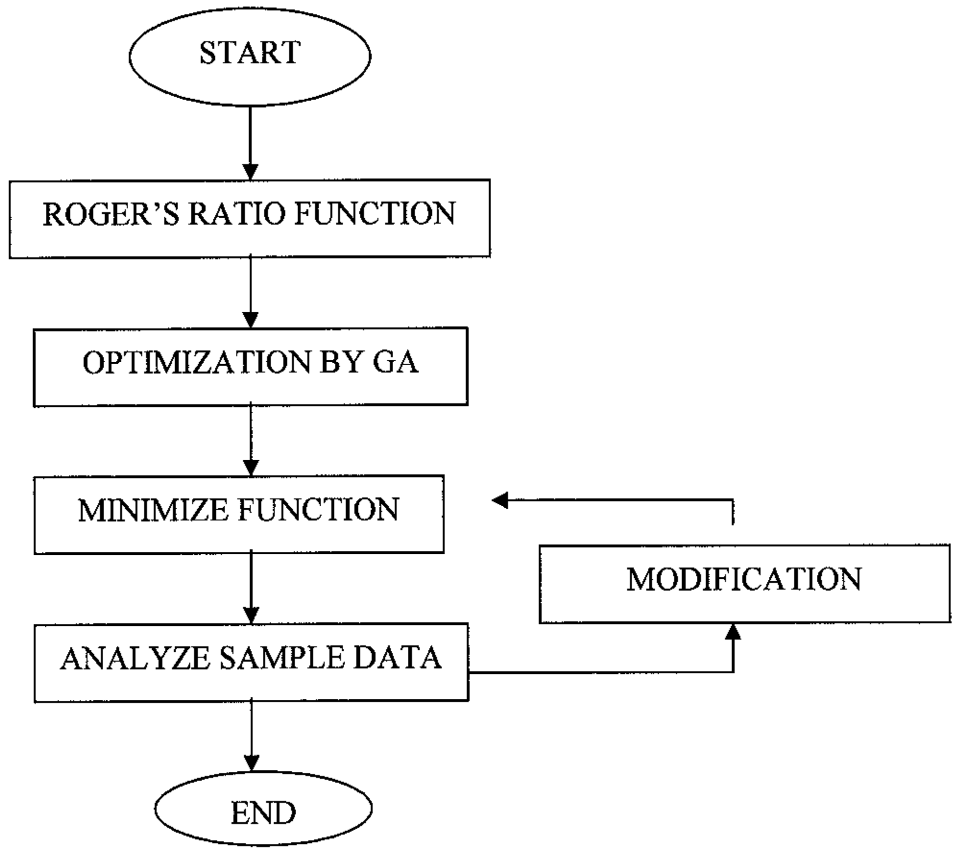

Figure 6 Flow chart for GA

3.2.2 Coding Fitness Function

For genetic algorithm, the simulation is simulated using the genetic algorithm toolbox. In order to optimize the dissolved gas analysis, suitable fitness function is formed and coded based on the Roger's Ratio method of interpretation. Hence, there are four fitness functions to be optimized which save in m-file:

- Ratio of methane and hydrogen

$$y1 = \frac{x2}{x1} \qquad \text{where ;} \qquad x2 = \text{methane}\ ,\ x1 = \text{hydrogen}$$

- Ratio of ethane and methane

$$y2 = \frac{x5}{x2} \qquad \text{where ;} \qquad x5 = \text{ethane},\ x2 = \text{methane}$$

- Ratio of ethylene and ethane

$$y3 = \frac{x4}{x5} \qquad \text{where ;} \qquad x4 = \text{ethylene},\ x5 = \text{ethane}$$

- Ratio of acetylene and ethylene

$$y4 = \frac{x3}{x4} \qquad \text{where ;} \qquad x3 = \text{acetylene},\ x4 = \text{ethylene}$$

3.2.3 Parameter Setting [13]

Currently, the default setting in the genetic algorithm toolbox is been used to simulate the fitness function. The parameter setting required is:

- Number of variables

The variables of each function will be two as the fitness function created was a ratio of two hydrocarbon gases.

- Population size

The functions are tested with different number of population sizes starting from population size equal to 20 up to 140. The reason of varies the population size is to observe the most optimal output so that the population of the minimize output could be set.

- Mutation probability

The mutation probability is set to the default rate of 0.05.

- Crossover probability

The crossover probability is set to the default rate of 0.8.

- Lower bound and Upper bound

Each of the hydrocarbon gases is constraint within specific range of lower and upper value. This is to ensure that the ratio functions are optimized within the desired range. The lower and upper bound of each gas is referred to the key gas guideline in Table 5.

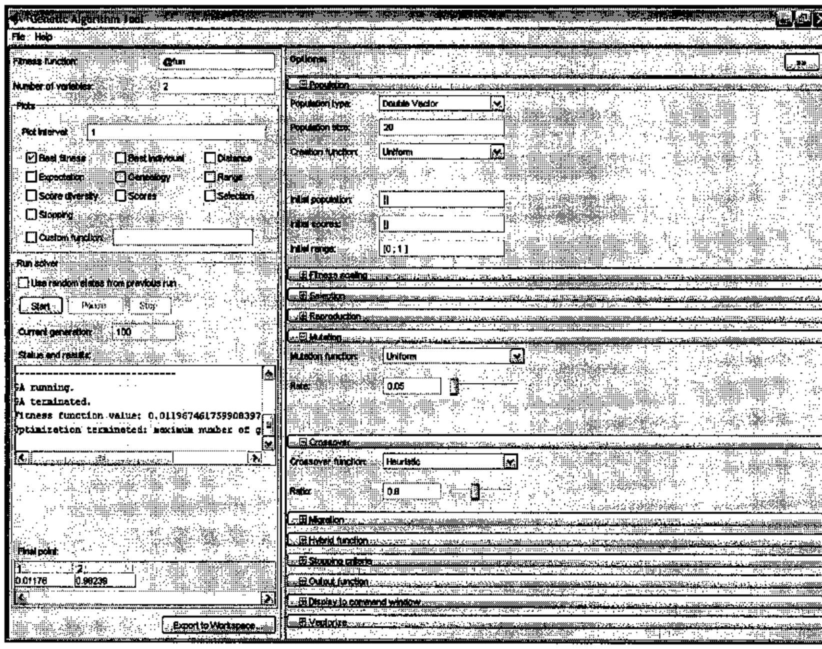

Figure 7 The parameter setting in Genetic Algorithm Toolbox

3.2.4 Output observation

Each of the ratio functions will have different optimal population size as each of the ratios is set with different range of lower and upper bound value. Therefore, with fixed number of population size, the objective function of each gas ratio is minimized by varying the number of generation started from 50 until 1000.

This is to observe the most optimal output with various numbers of generations. It helps is determined the point at where the output function starts to decrease and become constant.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Artificial Neural Network

4.1.1 Simulation Results

The simulation results based on the Key Gas method is over a range between 0 and 1 as the neural network is trained to produce target output between these values. Below is the test data output using **20** percent of validation data and **80** percent of training data. The test data is applied to the network as to test the network performance when being introduced with unseen data. The simulation error which is gained by the difference of the target and simulation values is **0.1543.**

Table 6 Validation percentage for the network training (The chosen percentage: Training data – 80%, Validation data – 20%)

Set	No. of neurons	MAE	MSE	Training Performance
1	5	0.2557	0.2416	0.139645
	10	0.3262	0.2183	0.082115
	15	0.3262	0.2651	0.055416
	20	0.5989	0.5978	0.446343
	25	0.2878	0.2509	0.020814
	30	**0.2436**	**0.2158**	**0.012126**
	35	0.4924	0.4395	0.121586
	40	0.2546	0.2368	0.115913
2	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

Set	No. of neurons	MAE	MSE	Training Performance
3	5	0.3052	0.2224	0.103628
	10	0.2914	0.2074	0.091625
	15	0.324	0.3039	0.161291
	20	0.2849	0.2458	0.012048
	25	0.256	0.2478	0.162722
	30	**0.2749**	**0.2183**	**0.021204**
	35	0.2584	0.2502	0.121506
	40	0.235	0.2175	0.112571

By comparison, set 2 validation data was chosen for the network training as it produced the least error compared to set 1 and set 3 validation data and have compatible training performance.

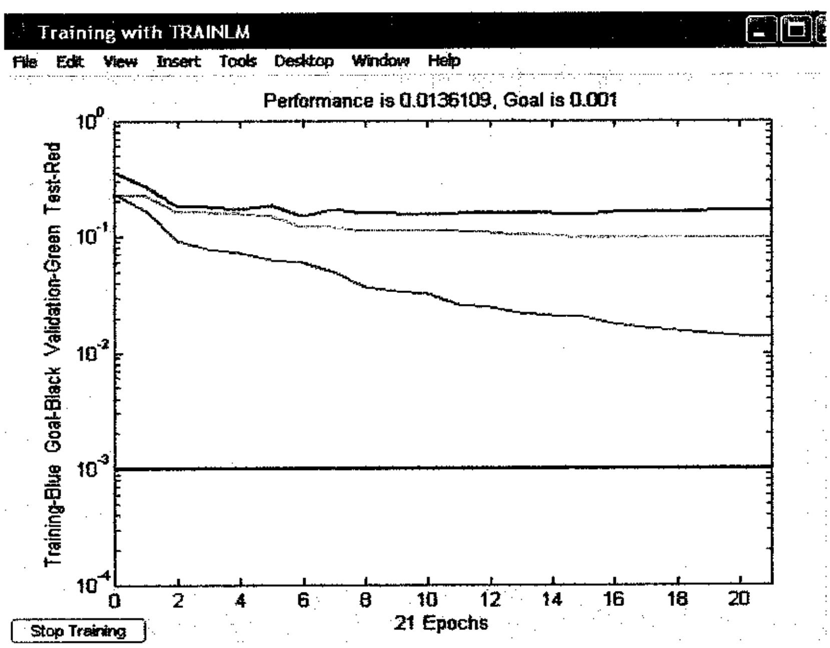

Figure 8 The performance of the training network with number of neuron= 30

From the Figure 8, it shown that the characteristic of the performance of validation data (green) and test data (red) are quite similar. It observed that the training network did perform well as the training stopped when validation stopped as the error of the network started to increase.

Table 7 Test data from research paper [10]

No	H2	CH4	C2H2	C2H4	C2H6
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

Table 8 Predicted faults of the test data from the simulation

No	Actual	Normal	Corona	Overheating	Arcing	ANN Diagnosis
1	Arcing	0	0	0	1	Arcing
2	Arcing	0	0	0	1	Arcing
3	Overheating	0	0	0	0	None
4	Corona	0	1	1	0	Corona & Overheating
5	Normal	0	0	1	0	Overheating
6	Arcing	0	0	0	1	Arcing
7	Overheating	0	0	1	0	Overheating
8	Corona	0	0	1	0	Overheating
9	Normal	1	0	0	0	Normal
10	Arcing	0	0	0	1	Arcing

Table 7 showed that 7 of the tested data simulation result prediction are correct while another 3 of the simulation failed to produce the correct prediction. Overall, based on the simulation results, it is presented that the back-propagation ANN approach is exceptional for transformer faults analysis even with limited and unrecognized sample data. Therefore, an improvement on network training is a must in order to detect transformer winding and insulation faults using DGA with high efficiency.

4.2 Genetic Algorithm

4.2.1 Simulation Results

Genetic Algorithm for minimization of Roger's Gas ratio 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 population size as shown in the tables below. Each of the minimized values produced for every population size is compared as to choose the most optimal value for each ratio.

Table 9 Optimal output ratio of methane and hydrogen at pop_size=80

No of population size, pop_size	Function value, fval
20	0.025457079
40	0.025024049
60	0.025114786
80	**0.02500754**
100	0.025001099
120	0.025009045
140	0.025457079

Table 10 Optimal output ratio of ethane and methane at pop_size=140

No of population size, pop_size	Function value, fval
20	0.714605952
40	0.714390728
60	0.714512201
80	0.714318545
100	0.714358432
120	0.714308611
140	**0.714286601**

Table 11 Optimal output ratio of ethylene and ethane at pop_size=60

No of population size, pop_size	Function value, fval
20	0.100117
40	0.100339
60	**0.100001**
80	0.100005
100	0.100029
120	0.100002
140	0.100007

Table 12 Optimal output ratio of acetylene and ethylene at pop_size=100

No of population size, pop_size	Function value, fval
20	0.285826
40	0.285745
60	0.285752
80	0.285739
100	**0.285715**
120	0.285714
140	0.285715
160	0.285826

Based on Table 8, 9, 10, 11 the Roger's Gas ratio function is now minimized using optimal population size obtained with varies number of generations. Hence, the minimized output could be observed to assess whether the condition of hydrocarbon ratio fall under no fault or fault condition based on the Roger's Gas Ratio Diagnostic in Table 2. The minimized gas ratio results with varies number of generations could be observed in Figure 9, 10, 11 and 12.

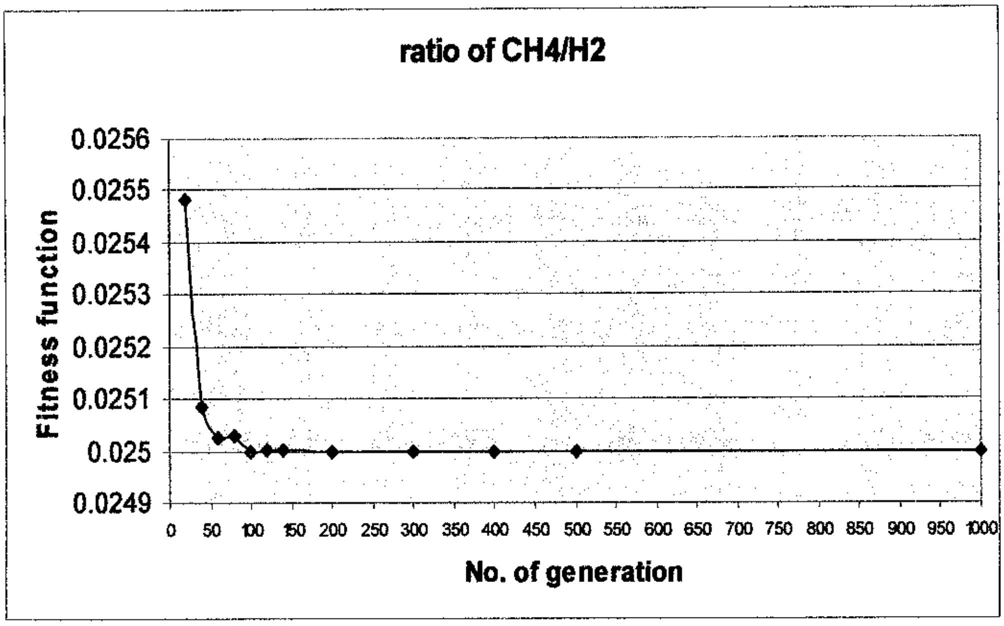

Figure 9 Graph represent the minimized gas ratio of methane and hydrogen for variation number of generation where the function become constant at 100 with optimal pop-size= 80.

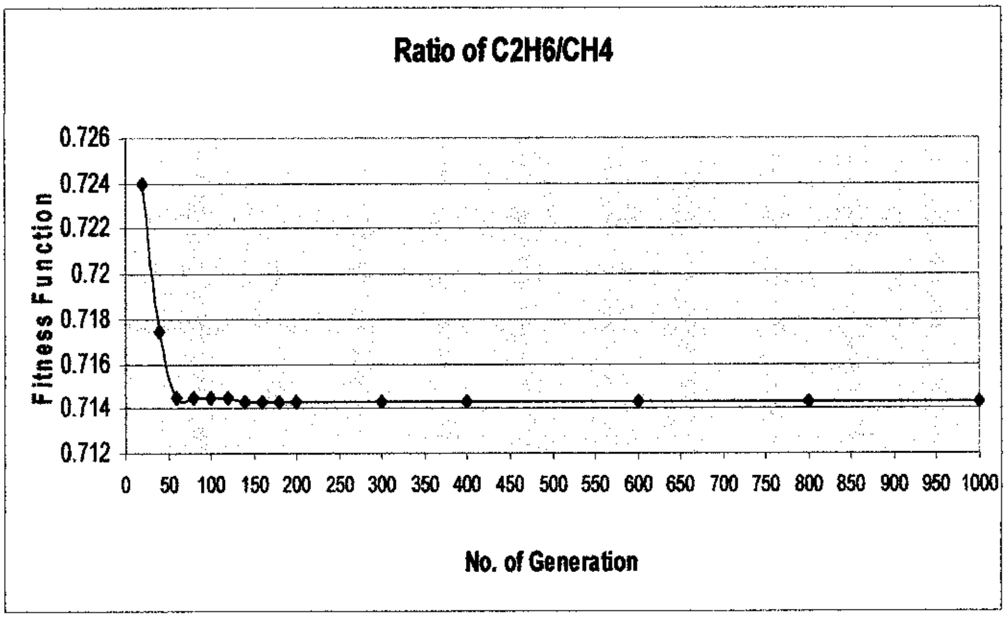

Figure 10 Graph represent the minimized gas ratio of ethane and methane for variation number of generation where the function become constant at 150 with optimal pop-size= 140.

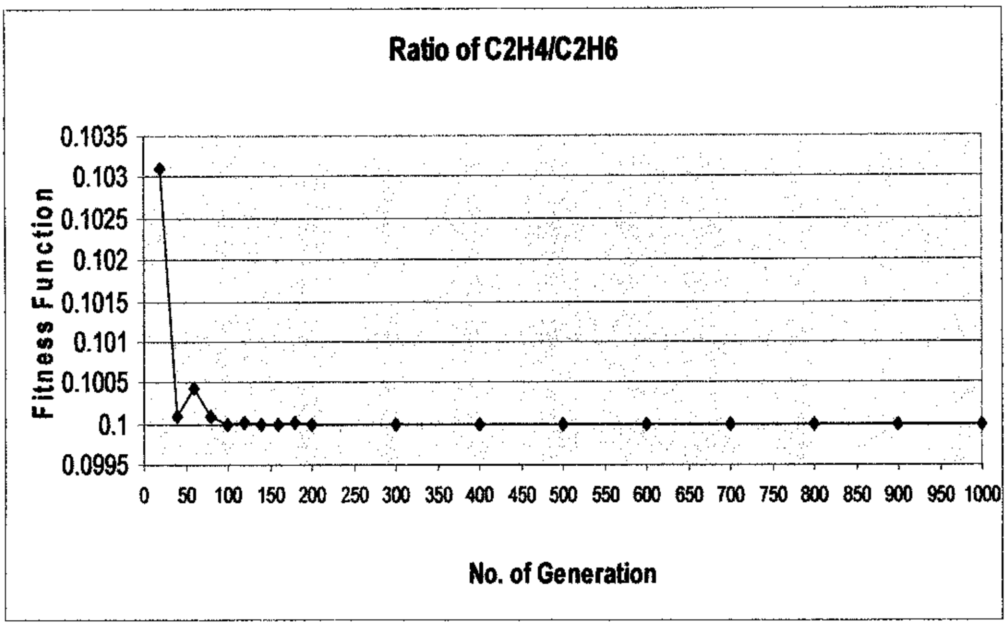

Figure 11 Graph represent the minimized gas ratio of ethane and methane for variation number of generation where the function become constant at 100 with optimal pop-size= 60.

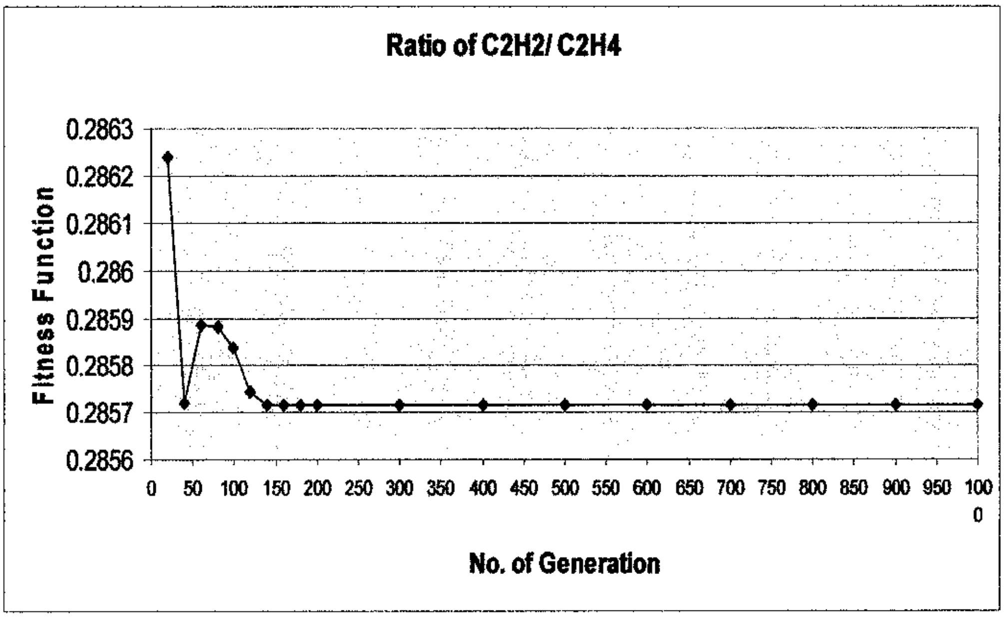

Figure 12 Graph represent the minimized gas ratio of acetylene and ethylene for variation number of generation where the function become constant at 150 with optimal pop-size= 100.

4.2.2 Testing Results

Table 13 The minimized function of the four ratios

	$CH_4 \backslash H_2$	$C_2H_6 \backslash CH_4$	$C_2H_4 \backslash C_2H_6$	$C_2H_2 \backslash C_2H_4$
FVAL	0.025000	0.714285	0.100000	0.285714
CODE	5	0	0	0

Table 14 The comparison of the actual ratio output with the minimized function ratio of the four gas ratio

NO		$CH_4 \backslash H_2$	$C_2H_6 \backslash CH_4$	$C_2H_4 \backslash C_2H_6$	$C_2H_2 \backslash C_2H_4$	FAULT
1	RATIO	0.895833	0.069767	25	1.08	ARCING
	CODE	0	0	2	1	
	FVAL	Exceed	Below	Exceed	Exceed	
2	RATIO	0.769230	0.4	3.25	0	Not available
	CODE	0	0	2	0	
	FVAL	Exceed	Below	Exceed	Below	

If any of the gas ratios exceeded the minimized function gained from the optimization technique, it is assumed that the gas ratio faced the possibilities to experience faults. This is because each of the gas ratios had been assigned with appropriate lower and upper bound values during the optimization process where the limitation for the system was set between normal and abnormal value of each gases.

In sample 1, it indicates that arcing is the fault experienced by the transformer based on the Roger's Gas Ratio. For the first ratio of methane and hydrogen, the ratio value was exceeded the minimized function value gained from the optimization. But, the ratio is still under good condition as the ratio was between the normal ranges according to the Roger's Gas Ratio table.

CHAPTER 5
CONCLUSION

From the current progress, it is shown that Artificial Neural Network (ANN) is capable in predicting transformer faults as its capability in producing relevant outputs of the simulation are proved. While the Genetic Algorithm did performed in enhancing one's system through optimization so that the system is performing in optimum mode and generates the best results.

Continuous learning of the system could enhance the capability of the Artificial Neural Network and Genetic Algorithm in producing the best and optimum fault detection method for dissolved gas analysis

CHAPTER 6
RECOMMENDATION

From the author's observation, Artificial Neural Network can give an outstanding accurate fault prediction. While for Genetic Algorithm, in order to achieve an optimized value, an appropriate objective function needs to be determined and chosen correctly. Therefore, continuous learning on the system could enhance the capability in detecting and predicting the transformer winding and insulation faults using Dissolved Gas Analysis. In order to achieve these objectives, it is recommended as follows:

6.1.1 Acquire more data

The ANN training did require a lot of data as to achieve high accuracy in understanding the characteristics of the data itself. In this project, the author collected the training data from various research papers. Therefore, it is observed that the data is not sufficient enough in detecting the transformer faults.

6.1.2 Comparison with other Artificial Intelligence systems

The transformer faults detection is predicted and analyzed with different intelligence systems. If the system created by the author could be compared with other intelligence systems such as Fuzzy Logic or Expect system, the accuracy of the designed system could be determined and the system itself could be upgraded.

6.1.3 Fitness function of genetic algorithm

In this project, it is quite difficult to find the objective function for GA to optimize as the DGA fault interpretation method is analyzed the sample data statistically. Therefore, a suitable function needs to be created in order to optimize using GA.

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[13] Genetic Algorithm and Direct Search Toolbox 2 User's Guide

APPENDICES

APPENDIX A

MATLAB CODING

ARTIFICIAL NEURAL NETWORK

```
%%%%%using key gases method%%%%%%%
%%%%%%based on california state university-sacramento guideline%%%%%
%%hydrogen(h2)>1000=corona,arcing
%methane(CH4)>80=sparking
%ethane(C2H6)>35=local overheating
%ethylene(C2H4)>100=severe overheating
%acetylene(C2H2)>70=arcing

%fault=[normal corona overheating arcing]
%x=[H2 CH4 C2H2 C2H4 C2H6 CO CO2];

clc;
x=xlsread('dga.xls');
x=floor(x);
x
[R Q]=size(x);
k=[1:1:R];
f1(k,1)=x(k,1)& x(k,2)&x(k,3)& x(k,4)&x(k,5);
f2(k,1)=x(k,1);
f3(k,1)=x(k,5)& x(k,4)& x(k,2);
f4(k,1)=x(k,3);

%%%TARGET DATA%%%%5
for k=1:R;
if (x(k,1)<1000)&(x(k,2)<80)&(x(k,3)<70)&(x(k,4)<100)&(x(k,5)<35)
   f1(k,1)=1;
else
   f1(k,1)=0;
end
if (x(k,1)>=1000)%&(x(k,2)>=80)
   f2(k,1)=1;
else
   f2(k,1)=0;
end
end
n=[f1];
m=[f2];
for k=1:R;
if (x(k,5)>=35)|(x(k,4)>=100)|(x(k,2)>=80)
   f3(k,1)=1;
else
   f3(k,1)=0;
end
```

```
if (x(k,3)>=70)%|(x(k,1)>=1000)
   f4(k,1)=1;
else
   f4(k,1)=0;
end
end
k=[f3];
l=[f4];
t=[n m k l]

%%%%NORMALIZE INPUT DATA%%%%%
for i=[1:1:R];
   %for j=[1:1:7]
   xmax(i,:)=max(x(i,:));
   xmin(i,:)=min(x(i,:));
   %end
end
xmax
xmin
for i=[1:1:R]
  for j= [1:1:5]
  pnorm(i,j)= (x(i,j)-xmin(i))./(xmax(i)-xmin(i));
  end
end
pnorm

%%%%%%%NEURAL NETWORK CODING%%%%%
%%%%%%validation%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%5
clc;
which keygas1
which keygastestdata


pnorm;
t;
ptest=dtest;
test;
ptest=ptest'
ttest=test'
p=pnorm'
tp=t'
[R,Q]=size(p);
Q;
%30%validation data
```

```
%iival=[4:1:4 8:1:8 12:1:12 16:1:18 20:1:20 24:1:25 28:1:28 32:1:32 36:1:36 40:1:40
44:1:44 48:1:48 52:1:52];
%iitr=[1:1:3 5:1:7 9:1:11 13:1:15 19:1:19 21:1:23 26:1:27 29:1:33 37:1:39 41:1:43
45:1:47 49:1:51];
%10
%iival=[4:1:4 16:1:16 28:1:28];
%iitr=[1:1:3 5:1:15 17:1:27 29:1:52];

%20
iival=[4:1:4 10:1:10 12:1:12 16:1:16 20:1:20 28:1:28 30:30 35:1:35 40:1:40 50:1:50];
iitr=[1:1:3 5:1:9 11:1:11 13:1:15 17:1:19 21:1:27 29:1:34 36:1:39 41:1:49 51:1:52];


%iitst=[24:1:30];
p(:,iival)
p(:,iitr)
%p(:,iitst)

%t(:,iitr)
%t(:,iitst)
v.P=p(:,iival);
ptr=p(:,iitr);
t.P=ptest;
v.T=tp(:,iival);
ttr=tp(:,iitr);
t.T=ttest;
%tstS=
%trS=

%[trS,cvS,tstS]=dividevec(pnorm,0.1,0.1)


%%%%%%ANN network%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[R,Q]=size(tp);
rand('seed',491218382)
```

```
net=newff((minmax(ptr)),[25 R],{'tansig','logsig'},'trainlm','learnwh');
%a1=sim(net,p)

net.layers{1}.initFcn='initwb';
net.inputWeights{1,1}.initFcn='rands';
net.biases{1,1}.initFcn='rands';
net.biases{2,1}.initFcn='rands';
net.trainParam.epochs= 500;
net.trainParam.show= 5;
net.trainParam.goal= 1e-5;
net.trainParam.lr=0.01;
net.trainParam.max_fail=5;
net.trainParam.mem_reduc=1;
net.performFcn='mse';
net=init(net);

[net,tr]=train(net,ptr,ttr,[],[],v,t);
%[net,tr]=train(net,p,tp);
a=sim(net,ptr)
%a=sim(net,ptr)
train_error=mse(a-ttr)
e=mae(a-ttr)
error=sum(sum(abs(a-ttr)))/R
MAPE=(1/R)*sum((abs(a-ttr))/sum(abs(ttr)))*100
atest=sim(net,t.P)
figure(3)
plot(tr.epoch,tr.perf,tr.epoch,tr.vperf,tr.epoch,tr.tperf)
legend('tr','val','test',-1);
ylabel('mse');xlabel('epoch')
```

GENETIC ALGORITHM (using GA toolbox)

Basic coding:

```
%%%ch4/h2(ratio1)
%[ch4 h2]
%LB=[100 25];
%UB=[1000 80];
%function y =funkn(x);
%y= x(2)./ x(1);

%%c2h6/ch4(ratio2)
%LB=[10 25];
%UB=[35 80];
%function y =funkn(x);
%y= x(1)./ x(2);

%%c2h4/c2h6(ratio3)
%[c2h4 c2h6]
%LB=[20 10];
%UB=[100 35];
%function y =name(x);
%y= x(1)./ x(2);

%%c2h2/c2h4(ratio4)-ok
%[c2h2 c2h4]
%LB=[15 20];
%UB=[70 100];

%function y =fun(x);
%y= x(1)./ x(2);
```

APPENDIX B
ANN TRAINING DATA

Training data is taken from three research paper [2], [9], [11]:

H2	CH4	C2H2	C2H4	C2H6
280	1500	140	1200	150
130	98	65	56	7
17000	110000	16000	89000	84000
300	240	140	160	14
48	610	0	10	29
1565	93	0	47	34
320	1370	9	1980	417
1400	3000	4	3500	560
1000	720	360	450	31
0	1	0.1	0.1	0
200	700	250	740	1
300	490	180	360	95
56	61	75	32	31
33	26	6	5.3	0.2
176	205.9	47.7	75.7	68.7
70.4	69.5	28.9	241.2	10.4
162	35	5.6	30	44
345	112.25	27.5	51.5	58.75
181	262	210	528	0
172.9	334.1	172.9	812.5	37.7
2587.2	7.882	4.704	1.4	0
1678	652.9	80.7	1005.9	419.1
206	198.9	74	612.7	15.1
180	175	75	50	4
34.45	21.92	3.19	44.96	19.62
51.2	37.6	5.1	52.8	51.6
106	24	4	28	37
180.85	0.574	0.234	0.188	0
27	90	42	63	0.2
138.8	52.2	6.77	62.8	9.55
14.7	3.7	0.2	2.7	10.5
345	112.3	58.8	51.5	27.5
181	262	0	28	41
173	334	37.7	812.5	172
127	107	224	154	11
60	40	70	110	6.9
220	340	14	480	42
170	320	3.2	520	53
27	90	0.2	63	42
565	53	0	47	34
56	286	7	928	96
200	48	131	117	14
78	161	10	353	86

32.4	5.5	13.2	12.6	1.4
980	73	0	12	58
160	130	0	96	33
650	53	0	20	34
95	110	0	50	160
300	490	95	360	180
200	700	1	740	250
625	130	0	2	47
56	61	31	32	75

APPENDIX C

GA SIMULATION RESULTS

Table 15 Optimal output ratio of methane and hydrogen at pop_size=80 where the function value starts to be constant at 100 and above

Generation	fval
20	0.025483225
40	0.025085766
60	0.025026853
80	0.025029467
100	0.025000016
120	0.025000452
140	0.025002132
200	0.025000004
300	0.025000000
400	0.025000000
500	0.025000000
600	0.025000000
700	0.025000000
800	0.025000000
900	0.025000000
1000	0.025000000

Table 16 Optimal output ratio of ethane and methane at pop_size=140 where the function value starts to be constant at 140 and above

No of Generation	Function value
20	0.724000221

40	0.717464256
60	0.714442883
80	0.714442883
100	0.714442883
120	0.714442883
140	0.714285714
160	0.714285714
180	0.714285714
200	0.714285714
300	0.714285714
400	0.714285714
500	0.714285714
600	0.714285714
700	0.714285714
800	0.714285714
900	0.714285714
1000	0.714285714

Table 17 Optimal output ratio of ethylene and ethane at pop_size=60 where the function value starts to be constant at 200 and above

Generation	fval
20	0.103114
40	0.100077
60	0.100443
80	0.100087
100	0.100002
120	0.100008
140	0.100001
160	0.100003
180	0.100007
200	0.100000
300	0.100000

400	0.100000
500	0.100000
600	0.100000
700	0.100000
800	0.100000
900	0.100000
1000	0.100000
20	0.103114
40	0.100077

Table 18 Optimal output ratio of ethane and methane at pop_size=100 where the function value starts to be constant at 160 and above

Generation	fval
20	0.28624
40	0.28572
60	0.285889
80	0.285886
100	0.285839
120	0.285742
140	0.285717
160	0.285715
180	0.285714
200	0.285716
300	0.285714
400	0.285714
500	0.285714
600	0.285714
700	0.285714
800	0.285714
900	0.285714
1000	0.285714