APPLICATION OF ANN TO PREDICT INCIPIENT FAULTS IN POWER TRANSFORMER BASED ON DGA METHOD

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Abstract— **This paper Artificial Neural Networks (ANN) are used to predict incipient faults in power transformers oil. The prediction is performed through the Dissolved Gas Analysis (DGA) method. The function of this method is for detect and diagnose the different types of incipient faults that occur in power transformers. By interpretation of dissolved gasses in oil insulation of power transformers, this method was applied the Artificial Neural Networks (ANN) to classify the different faults by using the DGA method. In DGA method, the Roger's Ratio and International Electrotechnical Commission (IEC) Ratio were applied into ANN to see the performance of ANN's network. For assessment, two set databases are employed: Roger's ratio and IEC ratio. The data bases are collected from Tenaga Nasional Berhad (TNB) data. The results show these methods were used to predicting the fault more than 90% of accuracy in best cases.**

Keywords- DGA method, ANN-EP, incipient fault, power transformer.

I. INTRODUCTION

The main objective of this project is to observe the To observe the artificial neural network (ANN) whether is suitable for diagnosis the incipient fault in power transformer or not. Other objectives are to observe about the dissolved gas-in-oil analysis (DGA) method and to observe about the characteristics of incipient fault that occur in the power transformer.

Power transformer is important in transmission and distribution of electrical power system in a country. The oil mineral insulator shows the performance of power transformer either it in well condition or not. The life of transformers depend on the life of its insulation [1]. Failure of power transformer may cause long interruptions in power supply and required expensive repair or replace a new one. The incipient fault in power transformer depending the gasses that appeared in the oil insulation in the power transformers and it must detected before the fault become worst and in the end it cause the power transformer break down or damage. This incipient fault should be detected as early as possible to prevent the power transformer from further deterioration [2].

Dissolved gas-in-oil analysis (DGA) is the most important test for identified the condition of a power transformer and it can identify incipient fault in oil insulation [3] [4]. The Dissolved gas ratios concentrations are processed using predefined criteria. These dissolved gasses contains mainly hydrogen (H_2), methane (CH_4), ethane (C_2H_6) , ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO) and carbon dioxide (CO_2) [5] [6].

The fast development of artificial intelligence (AI) method to detect the incipient fault in power transformer will increase the efficient performance of detection. The Artificial neural networks (ANN) are widely used for power transformer fault diagnosis because of their superior learning, generalization capabilities and fault-tolerate capabilities in practical applications [3] [7] [8].

II. DGA INTERPRETATION METHOD

The mineral oil of the power transformer function as cooler for transformer and as an insulator. The oil mineral will show the power transformer performances either it well or not. When the mineral oil exposed to high thermal and electrical distresses, it decomposes and it will cause the mineral oil to generate the unknown gasses bubble out from the oil mineral. These unknown gasses are take for analysis for identified the incipient fault. This fault can cause another fault in certain pattern and amounts depending on characteristics of the fault in future [9].

Dissolved gas-in-oil analysis (DGA) is a common used and reliable technique for diagnoses the incipient fault in the mineral oil of the power transformers. This method can predicts several of fault and it addressed in this paper [9].

TABLE I. GAS RATIO CODES [9]

Fault type	Code
Thermal fault at low temperature	TF
Overheating and sparking	OH
Arching	ARC
Partial Discharge and Corona	PD
Normal	Normal

There are many methods in dissolved gasses analysis (DGA). The ratio is the most popular used by researcher. This paper studied two type of ratio method: Roger's Ratio and IEC Ratio. Each method shown the several type of fault and this is tabulate in Table II .

TABLE II. GAS RATIO CODES [9]

Method	TF	OH	ARC	PD	NORMAL
Roger	Slight overheating < 150°C Slight overheating 150 - 200°C Slight overheating 200 - 300°C	General conductor overheating Winding circulating currents Core and tank circulating currents, overheated joints	Flashover, no power follow through Arc, with power follow through Continuous sparking to floating potential	Partial discharge Partial discharge with tracking (note CO)	Normal
IEC	Thermal fault < 150°C Thermal fault 150 - 300°C	Thermal fault 300 - 700°C Thermal fault > 700°C	Discharge of low energy Discharge of high energy	PDs of low energy density PDs of high energy density	Normal

A. *Roger's Ratio*

Roger ratio method used four gas ratios: CH_4 / H_2, C_2H_2 / C_2H_4, C_2H_4 / C_2H_6 and C_aH_6 / CH_4. Diagnose of incipient fault is accomplished via simple coding scheme based on ranges of ratios as tabulated in Table III and IV [9].

TABLE III. GAS RATIO CODES [10]

Gas Ratio	Ratio Code	Range	Ratio Fault Codes
CH_4 / H_2	i	$x \le 0.1$ $0.1 < x < 1$ $1 \ge x < 3$ $x \ge 3$	5 0 1 2
C_aH_6 / CH_4	j	$x < 1$ $x \ge 1$	0 1
C_2H_4 / C_2H_6	k	$x < 1$ $1 \le x < 3$ $x \ge 3$	0 1 2
C_2H_2 / C_2H_4	l	$x < 0.5$ $0.5 \le x < 3$ $x \ge 3$	0 1 2

TABLE IV. CLASSIFICATION OF INCIPIENT FAULT BASED ON ROGER'S RATIO CODES [10]

Ratio Fault Code				Diagnosis	Fault Code
i	j	k	l		
0	0	0	0	Normal	NORMAL
5	0	0	0	Partial discharge	PD_1
5	0	0	1,2	Partial discharge with tracking (note CO)	PD_2
1,2	0	0	0	Slight overheating < 150°C	TF_1
1,2	1	0	0	Slight overheating 150 - 200°C	TF_2
0	1	0	0	Slight overheating 200 - 300°C	TF_3
0	0	1	0	General conductor overheating	OH_1
1	0	1	0	Winding circulating currents	OH_2
1	0	2	0	Core and tank circulating currents, overheated joints	OH_3
0	0	0	1	Flashover, no power follow through	ARC_1
0	0	1,2	1,2	Arc, with power follow through	ARC_2
0	0	2	2	Continuous sparking to floating potential	ARC_3

B. *IEC Ratio*

The IEC is originally taken from the Rogers' method except the ratio of C_2H_6/CH_4. This is since C_2H_6/CH_4 only indicated a limited temperature range of decomposition. the By using IEC uses three gas ratio, C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. Each ratio is classification to a code of 0, 1 or 2. The total possible combination (fault types) can be found is 27 combination, IEC define only 11 combinations leading to non-decision diagnosis, when falling within the invalid group of 16 remaining combinations[1] [6] [11].

TABLE V. GAS RATIO CODES [9]

Gas Ratio	Ratio Code	Range	Ratio Fault Codes
CH_4 / H_2	i	$x \le 0.1$ $0.1 < x < 1$ $1 \ge x < 3$ $x \ge 3$	5 0 1 2
C_2H_4 / C_2H_6	k	$x < 1$ $1 \le x < 3$ $x \ge 3$	0 1 2
C_2H_2 / C_2H_4	l	$x < 0.5$ $0.5 \le x < 3$ $x \ge 3$	0 1 2

TABLE VI. CLASSIFICATION OF INCIPIENT FAULT BASED ON IEC RATIO CODES [9]

Ratio Fault Code			Diagnosis	Fault Code
i	k	l		
0	1	0	Thermal fault < 150°C	TF_1
2	0	0	Thermal fault 150 - 300°C	TF_2
2	1	0	Thermal fault 300 - 700°C	OH_1
2	2	0	Thermal fault > 700°C	OH_2
0	1-2	1-2	Discharge of low energy	ARC_1
0	2	1	Discharge of high energy	ARC_2
1	0	0	PDs of low energy density	PD_1
1	0	1	PDs of high energy density	PD_2
0	0	0	Normal	NORMAL

III. ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is a subject area that has recently appear in the field of artificial intelligent (AI) [12]. ANN system is based on the function of biological neural network. Basically, system of ANN is a structure that receives an input, process the data, and provides an output. In this paper, the ANN has pattern classifiers function where the input that from the gases detected in the input and the output can be known based on the gas ratio [13].

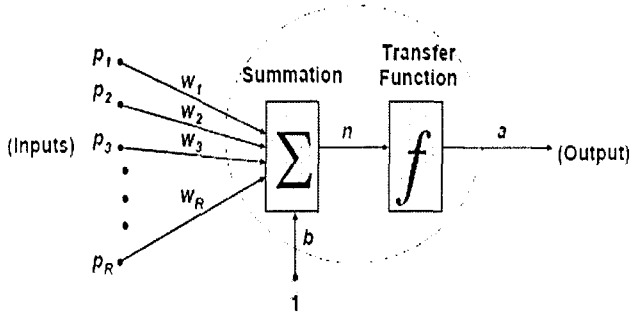

Figure 1. A Simple Articifial Neural Networks

In this ANN, the function of hidden layer is to increase the expressiveness of the network. The hidden layer is necessary to capture non-linear dependencies between the data features and the variable output to be predicted [14]. By trying various numbers of hidden layers neurons the performance of the ANN's network will be optimized. Each input data is multiplied by a weight and the results are added together producing the combined value to fed into a function before it transfer to the output layer [12].

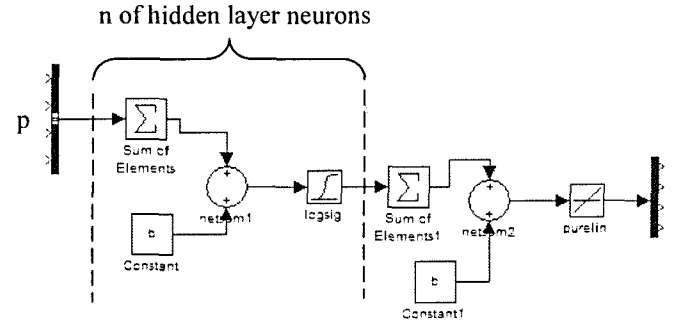

Figure 2. A double layer with single hidden layer

IV. METHODOLOGY

A. Fault Data Analysis

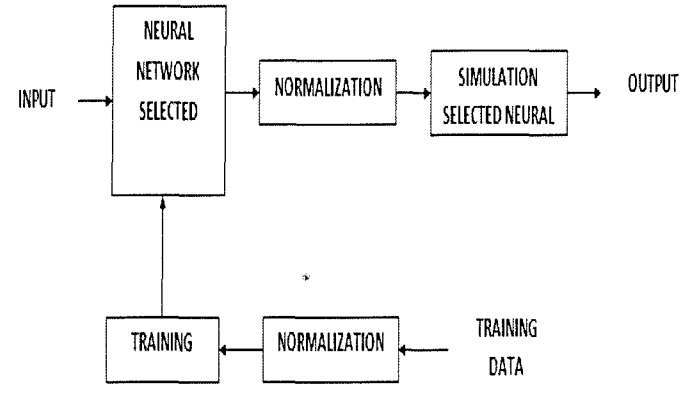

Figure 3. The flowchart for overall process in ANN

Figure 1 shows that the overall of the process of the training, test and apply the best network for simulate the actual data for indicate the incipient fault in the power transformer.

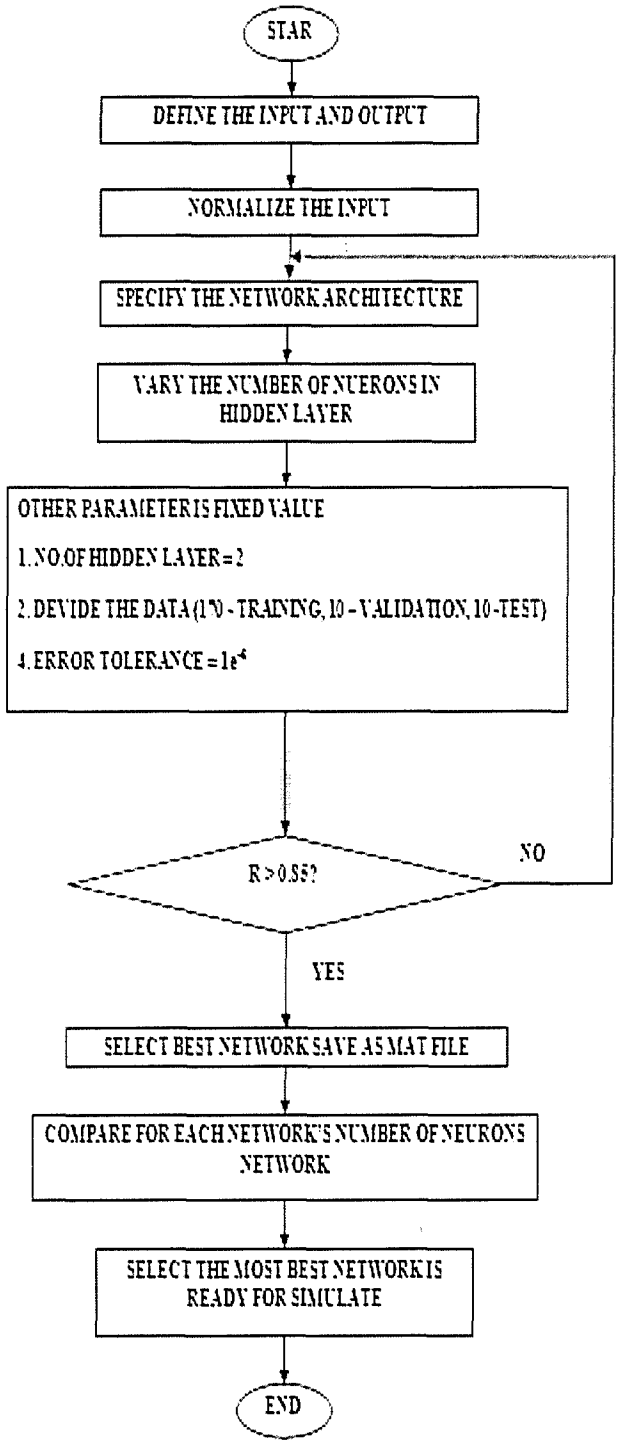

Figure 4. The flowchart for training, validation and testing the ANN

Figure 2 shows that the flowchart of ANN. For the Roger's Ratio Method, there are four input and four output represent for four ratio (i, j, k and l). For the IEC RatioMethod, there are three input and three output represent the three ratio (i, k and l).

the flowchart is repeat by varying the number of nuerons in hidden layer. The best network performance of each neurons is filled in table to compare. From the best network, the most best network's performance had been selected to performed.

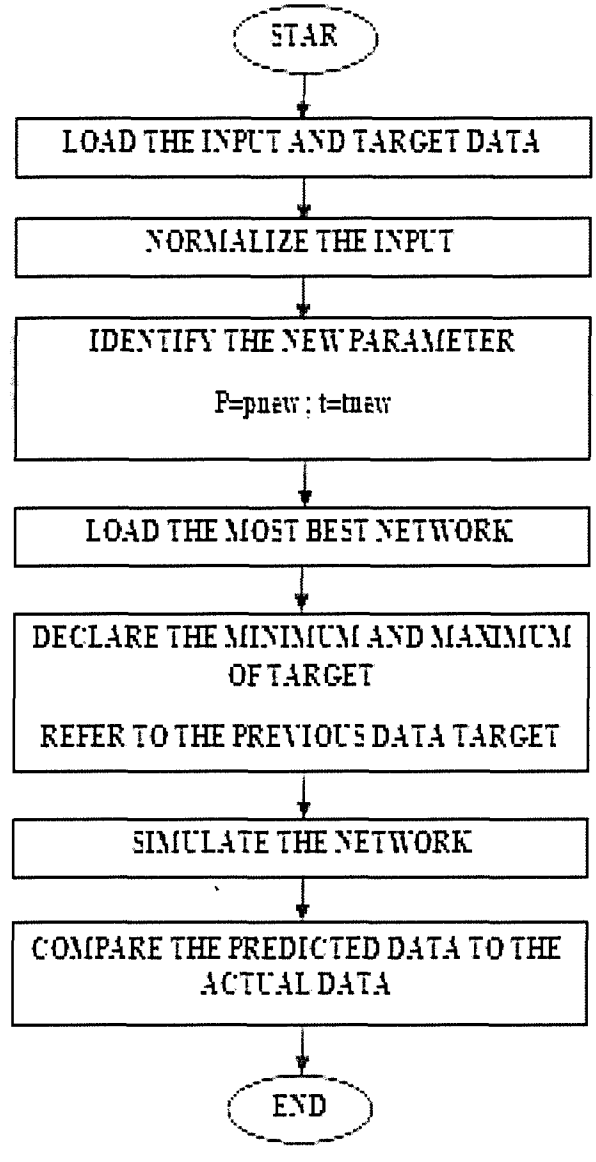

Figure 5. The flowchart of simulate the best network of ANN to another data

Figure 3 is about the flowchart the most best network's performance is performed to another data for makesure the network is applicable to diagnosis the incipient fault in power transformer for Roger's Ratio Method and IEC Method.

V. RESULT AND DISCUSSION

A. Test Data

The investigation use two databases and there are dataset Roger and dataset IEC and both content 200 oil samples of various data from fault cases and another 10 oil samples for test the next performance of the ANN, respectively. Each sample consist hydrogen (H_2), methane (CH_4), ethane (C_2H_6) , ethylene (C_2H_4) and acetylene (C_2H_2) gas concentration value and its respective fault classes. The fault type had assigned to sample by the Tenaga Nasional Bhd. (TNB). In order to evaluate the performance of ANN, 200 oil samples were used for training the ANN and 10 oil samples were used for test ANN. The 10 oil samples were tabulated in Table VII.

TABLE VII. DGA SAMPLE

Sample data No.	H_2	CH_2	C_2H_2	C_2H_4	C_2H_6
1	150	100	50	10	5
2	100	95	57	13	10
3	150	90	55	15	15
4	500	55	41	29	50
5	550	56	39	31	55
6	150	95	41	80	80
7	250	71	55	150	180
8	200	74	50	100	185
9	150	77	33	135	190
10	65	150	23	90	100

The sample of each gasses had been applied using ANN for both methods: Roger's Ratio and IEC Ratio. Table VIII and Table IX show the result accuracy of both methods with different number of hidden layer neurons.

By changing the number of hidden layer neurons to change from 3 to 20 layers neurons for 200 samples to see the performance of the ANN. Performance of ANN had been determined by increasing the hidden layer neurons with same parameter in the initial network. The best result show when the Regression near to 1.

Table VIII shows for all regression network's performance for training, validation and testing. By comparing all networks, it show that the best performance of networks is when the number of neurons in hidden layer is 20 for Roger's Ratio Method. It is because the different between regression of training, validation and testing is not too significant and all regression is more than 0.99. It shows the network's performance is ready to simulate for diagnosis the real incipient fault in power transformer.

Table IX shows for all regression network's performance for training, validation and testing. By comparing all networks, it show that the best performance of networks is when the number of neurons in hidden layer is 20 for IEC Ratio Method. It is because the different between regression of training, validation and testing is not too significant and all regression is more than 0.99. Hence, it shows the network's performance is ready to simulate for diagnosis the real incipient fault in power transformer.

TABLE VIII. FAULT CLASSIFICATION REGRESSION OF THE ANN METHOD VERSUS NUMBER OF HIDDEN LAYER NEURONS APLLIED TO THE ROGER RATIO CODES

Neurons	Training	Validation	Test
3	0.95720	0.93223	0.92068
5	0.96107	0.95513	0.95460
7	0.97576	0.97817	0.97666
9	0.99362	0.95341	0.92288
11	0.99058	0.96113	0.95577
13	0.98915	0.98424	0.97461
15	0.99379	0.97820	0.97382
17	0.98082	0.97244	0.94913
20	0.99949	0.99919	0.99892

TABLE IX. FAULT CLASSIFICATION REGRESSION OF THE ANN METHOD VERSUS NUMBER OF HIDDEN LAYER NEURONS APLLIED TO THE IEC RATIO CODES

Neurons	Training	Validation	Test
3	0.93151	0.94752	0.93499
5	0.93319	0.91854	0.94308
7	0.96675	0.95798	0.96612
9	0.97443	0.97525	0.95150
11	0.97384	0.93453	0.95735
13	0.99609	0.98576	0.98049
15	0.99391	0.98553	0.97559
17	0.97742	0.95611	0.96904
20	0.99593	0.99154	0.99413

The result of ANN for both Roger's ratio and IEC ratio are approximately same. IEC ratio result is more accurate that the Roger's ratio. The performance of ANN's network drop after apply another 10 oil samples for test the network of the ANN and shown in Table X.

TABLE X. FAULT CLASSIFICATION REGRESSION OF THE ANN METHOD FOR 20 OF HIDDEN LAYER NEURONS FOR ROGER'S RATIO AND IEC RATIO

Method	Test
Roger's Ratio	0.90453
IEC Ratio	0.86603

Table X shows that the ANN's performance for Roger's Ratio is more accurate than the ANN's performance for IEC's Ratio. The problem while dealing the ANN is the result of network performance not usually good for the first trial. The repetition of training is needed to find the best performance of the ANN for both methods for each number of hidden layer.

TABLE XI. THE ACTUAL OUTPUT AND PREDICTED OUTPUT FOR ROGER'S RATIO METHOD

Sample Data	Actual output						Predicted output					
	Roger's Ratio Code				Actual Fault Code	Diagnosis	Roger's Ratio Code				Actual Fault Code	Diagnosis
No.	i	j	k	l			i	j	k	l		
1	0	0	1	2	ARC_2	Arc, with power follow through	0	0	1	2	ARC_2	Arc, with power follow through
2	0	0	1	2	ARC_2	Arc, with power follow through	0	0	1	2	ARC_2	Arc, with power follow through
3	0	0	1	2	ARC_2	Arc, with power follow through	0	0	1	2	ARC_2	Arc, with power follow through
4	0	0	0	1	ARC_1	Flashover, no power follow through	0	0	0	0	NORMAL*	Normal condition
5	0	0	0	1	ARC_1	Flashover, no power follow through	0	0	0	1	ARC_1	Flashover, no power follow through
6	0	0	1	1	ARC_2	Arc, with power follow through	0	0	1	1	ARC_2	Arc, with power follow through
7	0	1	0	0	TF_3	Slight overheating 200 - 300°C	0	1	0	0	TF_3	Slight overheating 200 - 300°C
8	0	1	0	0	'TF_3	Slight overheating 200 - 300°C	0	1	0	0	TF_3	Slight overheating 200 - 300°C
9	0	1	0	0	TF_3	Slight overheating 200 - 300°C	0	1	0	0	TF_3	Slight overheating 200 - 300°C
10	1	0	0	0	TF_1	Slight overheating < 150°C	1	0	0	0	TF_1	Slight overheating < 150°C

Table XI shows the different between the actual output and the predicted output. This show that only the data in number four is different from the actual output. The data of number four should show there is flashover, no power follow through (ARC_1) but the network of Roger's Ratio give the data output as normal condition (NORMAL).

Table XII shows the different between the actual output and the predicted output. This show that the data in number five and number ten are different from the actual output. From the result, it show that the Roger's Ratio Method is more accuracy and efficient than IEC Ratio Method.

TABLE XII. THE ACTUAL OUTPUT AND PREDICTED OUTPUT FOR IEC RATIO METHOD

Sample Data	Actual output					Predicted output					
	IEC Ratio Code			Actual Fault Code	Diagnosis	IEC Ratio Code			Actual Fault Code	Diagnosis
No.	i	k	l			i	k	l		
1	0	1	2	ARC_1	Discharge of low energy	0	1	2	ARC_1	Discharge of low energy
2	0	1	2	ARC_1	Discharge of low energy	0	1	2	ARC_1	Discharge of low energy
3	0	1	2	ARC_1	Discharge of low energy	0	1	2	ARC_1	Discharge of low energy
4	0	0	0	NORMAL	Normal condition	0	0	0	NORMAL	Normal condition
5	0	0	0	NORMAL	Normal condition	1	0	0	PD_1*	PDs of low energy density
6	0	1	1	ARC_1	Discharge of low energy	0	1	1	ARC_1	Discharge of low energy
7	0	0	0	NORMAL	Normal condition	0	0	0	NORMAL	Normal condition
8	0	0	0	NORMAL	Normal condition	0	0	0	NORMAL	Normal condition
9	0	0	0	NORMAL	Normal condition	0	0	0	NORMAL	Normal condition
10	1	0	0	PD_1	PDs of low energy density	2	0	0	TF_2*	Thermal fault 150 - 300°C

VI. CONCLUSION

In this paper, ANN are used by using DGA ratio: Roger's Ratio and IEC Ratio to classify the incipient fault that occur in the power transformers. Due to the unequal samples of each fault classes, the training of network is not processed well and cause the test not fit well. Both methods can be used in ANN for the interpretation of fault types from DGA data. To optimize the ANN's network performance, the repetition of training is needed. Otherwise it will cause the ANN's network during testing become reduced and some time the results are different from the predicted output or actual output.

In conclusion, Roger's Ratio Method is more suitable in ANN as DGA method applied to it for diagnosis the incipient fault in power transformer. From the result, it show that the objectives of project are achieved and the ANN is suitable to use for diagnosis the incipient fault.

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