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Comparative Study of DGA Based Fault Diagnosis using ANN and Fuzzy Systems

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Abstract

Dissolved Gas Analysis (DGA) method for fault detection has been implemented using Artificial Neural Networks (ANN), Fuzzy Logic (FL) and Adaptive Neuro Fuzzy Inference System (ANFIS). Incipient faults can be detected using DGA which provides reasonably good results. We have tried to improve this method in order to surpass its limitations. Comparative analysis using the mentioned methods have been done on IEC 599 standard, Rogers Ratio Method and Doernenburg's method. Using Fault databases, the training has been done to improve the diagnostic capabilities. The obtained results clearly show the superiority of ANFIS on ANN and FL. Being a combination of both, its degree of accuracy in prediction and ease of use, provides a promising alternative in replacing the conventional methods.

Keywords: Adaptive Neuro Fuzzy Inference Systems, Artificial Neural Networks, Dissolved Gas Analysis, Fuzzy Logic

1. Introduction

One of the most important and expensive parts of the power system are Oil Immersed Transformers. Hence its timely maintenance is crucial for the proper functioning of the power grids. Therefore, to detect the insipient faults and conduct fault diagnosis, DGA has been used extensively[1]. The insulation materials experience various of stresses which leads to the production of different gases which are dissolved in the oil. Different faults produce different concentrations of certain gases. Thereby, using this knowledge we can perform chromatography to get the dissolved gas concentrations in ppm.

The gases that are produced include CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2 and H_2[2]. Based on the DGA there are various methods used to obtain the nature of the fault. The common methods include IEC 599 method, Rogers Ratio Method, Duval Triangle, Doernenburg's Method[3]. The above-mentioned methods use gas ratios to determine the fault type and diagnosis. These method's detection abilities are purely based on the expertise of the analyst as there is no mathematical formulation used. Apart from this each method has a certain limitation of its own. They provide erroneous results sometimes and can't determine the type of fault[4].

In order to overcome these limitations and increase the accuracy, researchers have taken the help of prediction and estimation tools. These methods include Artificial Neural Networks (ANN), Fuzzy Logic (FL), Fuzzy Neural Systems, Support Vector Machines (SVM), etc. These methods help in better classification and diagnosis of the fault[5]. The fuzzy logic theory though is fast at computation but has limited learning capability. Neural networks have the ability of parallel processing and self-learning but has the local minima problem. To overcome these limitations a better system comprising of both the abilities has been used. The Adaptive Neuro Fuzzy Inference System (ANFIS) uses the basics of fuzzy logic and integrates it in a neural network framework. This helps in better prediction abilities[6].

In this paper a comparative study has been done on DGA based fault diagnosis techniques, and it has been observed that ANFIS provides a better and accurate result compared to the results given by Neural Network and Fuzzy logic method. A fault database of 50 transformers has been used which has been divided into Training,

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Testing and Validation sets. The obtained accuracy is very good and ANFIS methods has been seen to be superior.

2. Dissolved Gas Analysis

2.1 International Electrotechnical Commision (IEC) Standard for DGA

IEC standard determines the faults based on ratios of 5 gases namely H_2, CH_4, C_2H_4, C_2H_6 and C_2H_2. Three gas ratios ($X1=C_2H_2/C_2H_4$, $X2=CH_4/H_2$, $X3=C_2H_4/C_2H_6$) are used. These are assigned a coded value and based on the code the nature of the fault is predicted. Total of 9 types of different faults can be known using this method.

Table 1. Fault codes for IEC faults

Sl.No	Type of Fault	Code		
		X1	X2	X3
1	No Fault (F0)	0	0	0
2	Partial Discharge with low energy density (F1)	0	1	0
3	Partial Discharge with high energy density (F2)	1	1	1
4	Discharge (arc) with low energy (F3)	½	0	½
5	Discharge (arc) with high energy (F4)	1	0	2
6	Thermal faults of temperatures < 150°C (F5)	0	0	1
7	Thermal faults of temperatures between 150°C and 300°C (F6)	0	2	0
8	Thermal faults of temperatures between 300°C and 700°C (F7)	0	2	1
9	Thermal faults of temperatures > 700°C (F8)	0	2	2

2.2 Rogers Ratio Method

Rogers Ratio method uses five gases for fault determination. Three gas ratios are computed using the gases as $X1=CH_4/H_2$, $X2=C_2H_4/C_2H_6$ and $X3=C_2H_2/C_2H_4$. Sometimes this method gives ratios which wouldn't fit any fault type, thereby needing other methods to do so (Table 2).

Table 2. Rogers ratio method fault codes.

Sl.No	Type of Fault	X1	X2	X3
1	No Fault (F0)	$0.1<X1<1$	$X2<1$	$X3<0.1$
2	Partial Discharge with low energy density (F1)	$X1<0.1$	$X2<1$	$X3<0.1$
3	Discharge (arc) with high energy (F2)	$0.1\leq X1\leq 1$	$X2>3$	$0.1\leq X3\leq 3$
4	Low temperature thermal (F3)	$0.1<X1<1$	$1\leq X2\leq 3$	$X3<0.1$
5	Thermal faults of temperatures < 700°C (F4)	$X1>1$	$1\leq X2\leq 3$	$X3<0.1$
6	Thermal faults of temperatures > 700°C (F5)	$X1>1$	$X2>3$	$X3<0.1$

2.3 Doernenburg's Method

Doernenburg's method uses fives gases to compute four ratios as $X1=CH_4/H_2$, $X2=C_2H_2/C_2H_4$, $X3=C_2H_2/CH_4$ and $X4=C_2H_6/C_2H_2$. Based on the individual gas concentrations, it is firstly determined if a fault situation is present. Once this is ascertained, the type of fault is determined using the mentioned gas ratios. This methods validity for fault diagnosis is solely based on the fact that one of the gas concentrations crossed the minimum limit (Table 3).

Table 3. Doernenburg's method fault codes.

Sl.No	Type of Fault	X1	X2	X3	X4
1	No Fault (F0)	[Conc.(H_2 or CH_4 or C_2H_2 or C_2H_4)>2L1 and Conc.(C_2H_6 and CO)<L1] or [Conc.(H_2 or CH_4 or C_2H_2 or C_2H_4)<2L1]			
2	Thermal Decomposition(F1)	X1>1	X2<0.75	X3<0.3	X4>0.4
3	Partial Discharge (Low Density) (F2)	X1<0.1	X2=no sig.	X3<0.3	X4>0.4
4	Arcing (High Density PD) (F3)	0.1<X1<1	X2>0.75	X3>0.3	X4<0.4

3. Prediction Techniques Applied on DGA

3.1 Artificial Neural Networks (ANN)

Neural networks are a series of algorithms that are able to recognize underlying set of relationships of a particular data, thereby mimicking the way we humans think. It generally consists of three basic layers namely Input layer, Hidden layer and the output layer as shown in Figure 1. In each layer we provide an activation function which controls the amplitude of the output. Each layer is interconnected and have assigned weights to it.

The network first undergoes a forward propagation to give a trained output which is then compared with the target output to give an error. This error is minimised using back propagation until error becomes less than a specified set limit.

3.2 Fuzzy Logic (FL)

Fuzzy Systems rather than using stringent mathematical models it uses a logical system to provide an input-output mapping using a set of linguistic rules. These rules are determined by the understanding obtained by the user. It is a three step process for evaluation. The steps are Fuzzification, Fuzzy Inference and Defuzzification.

In fuzzification we assign a degree of membership (gauss, triangular, trapezoidal, etc.) to a crisp value. In fuzzy inference we make conclusions based on the assigned if-then rules. In defuzzification, using a suitable defuzzification method the reconversion of outputs corresponding to the rules back to a crisp value is done.

3.3 Artificial Neuro Fuzzy Inference System (ANFIS)

ANFIS can be interpreted as a hybrid learning rule-based system. It has both the benefits of ANN and Fuzzy logic and uses this for better computation. Similar to ANN it has layers and connecting weights. The nodes present in the layers can be adaptive or fixed depending on the requirement.

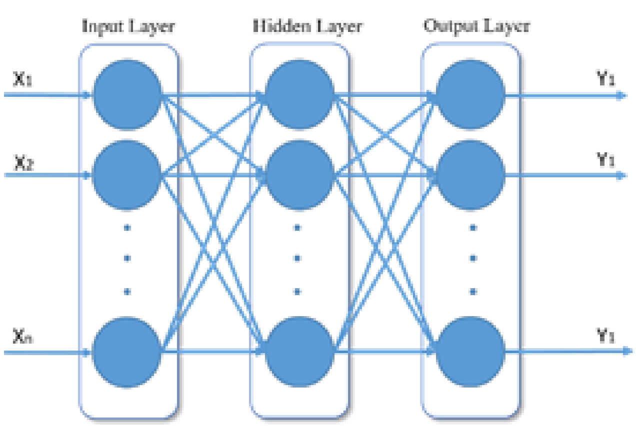

Figure 1. Artificial neural network architecture.

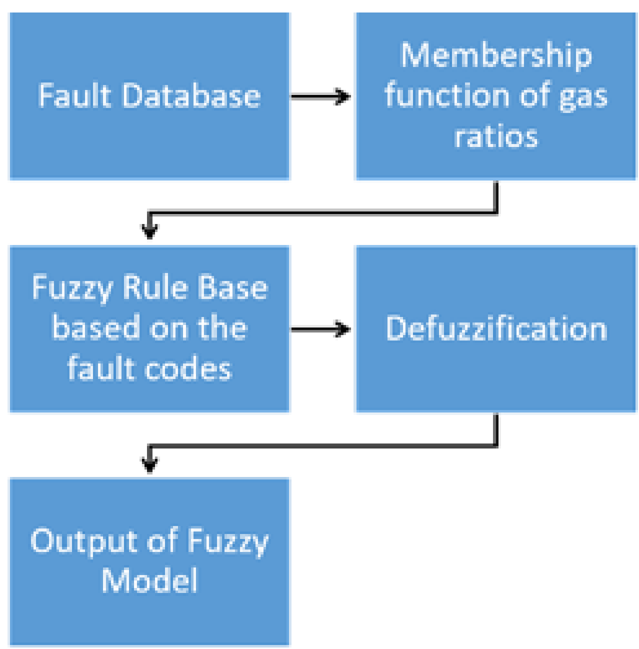

Figure 2. Fuzzy logic model.

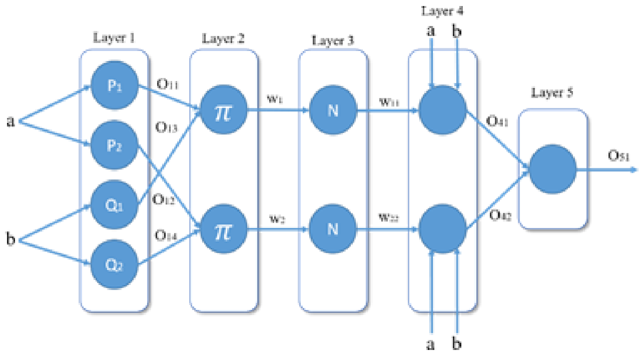

Figure 3. ANFIS Architecture.

The ANFIS network as shown in Fig 3 comprises of five layers. Layer 1 comprises of nodes P1, P2, P3 and P4. Each of these nodes represent a fuzzy set and their outputs give the belongingness of these sets to the inputs which can be given as:

$O_{11} = \mu_{P1}(a)$ (1)

$O_{12} = \mu_{P2}(a)$ (2)

$O_{13} = \mu_{Q1}(b)$ (3)

$O_{14} = \mu_{Q2}(b)$ (4)

The layer 2 consists of fixed nodes which performs the product functioning of the incoming signals. The layer 2 output can be given as:

$$w1 = \mu_{P1}(a) + \mu_{Q1}(b) \quad (5)$$

$$w2 = \mu_{P2}(a) + \mu_{Q2}(b) \quad (6)$$

The nodes of layer 3 perform the normalization using the functions given as:

$$w11 = \frac{w1}{w1+w2} \quad (7)$$

$$w22 = \frac{w2}{w1+w2} \quad (8)$$

Layer 4 consists of adaptive nodes whose output depends on consequent parameters of the nodes. The output of this layer can be given as:

$$O_{41} = w11 * f1 \quad (9)$$

$$O_{42} = w22 * f2 \quad (10)$$

f1 and f2 are functions given by Sugeno System of fuzzy logic.

The final output is given after performing a summation function in layer 5 and it is given as:

$$O_{51} = \frac{w1f1+w2f2}{w1+w2} \quad (11)$$

4. Simulation and Results

A fault dataset comprising of 50 transformers is used for the analysis purposes. The data has been divided into 3 sets for training, testing and validation. The training is done using data of 30 transformers, testing and validation is done using data of 10 transformers respectively. MATLAB R2019b has been used for the coding and simulations. Using these methods, the shortcomings of the conventional diagnosis are improved and a high degree of accuracy has been reached.

4.1 ANN based DGA

A three-layer structure has been used with the gas ratios as inputs and predicting the fault type as the output. The efficiency achieved by this method is 52% for IEC Standard, 60% for Roger's Ratio method and 91.4% for Doernenburg's method.

The output of the network is given in Table 4. and it can be seen that for some of the faults the prediction was not what was expected.

Table 4. Diagnosis result of artificial neural networks.

Fault case No.	Fault type as per Std.			Predicted Fault by ANN		
	IEC	Rogers Ratio	Doernenburg	IEC	Rogers Ratio	Doernenburg
1	F1	F1	F1	F1	F1	F1
2	F7	F3	F2	F7	F3	F2
3	F6	F4	F3	F5	F4	F3
4	F8	F5	ND	F8	F6	F2
5	F5	ND	F3	F4	F3	F1

Table 5. Diagnosis result of fuzzy logic model.

Fault case No.	Fault type as per Std.			Predicted Fault by Fuzzy Logic		
	IEC	Rogers Ratio	Doernenburg's	IEC	Rogers Ratio	Doernenburg's
1	F7	F4	F2	F7	F4	F2
2	F4	F2	F1	F4	F2	F1
3	F7	F3	ND	F6	F3	F2
4	F6	F0	F3	F6	F0	F3
5	F3	F5	ND	F3	F4	F1

Table 6. Diagnosis result of ANFIS models.

Method	Fault Type	Predicted Fault by ANFIS	
		Output Values	Fault Type
IEC	F7	[0.0332, 0.00110, 0.00445, 0.00441, 0.0023, 0.01035, 0.10715, 0.84727, 0.00020]	F7
	F1	[0.0098, 0.90366, -0.0498, -0.0024, - 0.0007, -0.0292, 0.0031, -3.63E-05, -1.44E- 06]	F1
	ND	[-0.0773, -0.0104, -0.0207, -0.0227, - 0.0142, 0.0119, 1.2854, -0.1229, -0.0004]	F6
Rogers Ratio	F4	[-0.0026, 0.0536, -0.0002, -0.0427, 1.0546, 0.0009]	F4
	F5	[0.0079, -0.0128, -0.0014, 0.7442, 0.1878, 0.0257]	F4
	F0	[0.9222, -0.0023, -0.0008, 0.2018, 0.0912, - 0.0002]	F0
Doernenburg's	F2	[0.08603, 0.89368, 0.01505]	F2
	F1	[0.9174, 0.0777, -0.0057]	F1
	ND	[0.0932, 0.8827, 0.0175]	F2

4.2 Fuzzy Logic based DGA

Fuzzy logic system is designed for the fault diagnosis. The gas ratios are taken as inputs. Each input is assigned a crisp value based on the codes from Table 1. To fuzzify these crisp values various types of membership functions have been used and tested to get the best solution. The codes are then used to create a set of if-then rule base for diagnosis of different fault types.

Membership functions are assigned to the output one for each type of fault. This method is followed for each type of DGA analysis technique and corresponding results are obtained. The accuracy of prediction obtained is 91.3% for IEC Standard, 86.67% for Rogers Ratio method and 95% for Doernenburg's method.

4.3 ANFIS based DGA

In this model we have used the gas ratios as the input to the system and have predicted the fault type. ANFIS models have been developed corresponding to each fault type. Training is done for each fault type separately. Dataset have been modified in such a way to provide a dataset of a particular fault type being to be high (set = 1) while rest are set to low (set = 0). The training is continued for a sufficient number of iterations until the training error is below a set ε.

This type of datasets is generated for all three DGA methods and models have been trained. The outputs obtained by using this have reached an accuracy of 95% for IEC Standard, 90% for Rogers Ratio method and 98% for Doernenburg's method. Also, ANFIS models are able to make some predictions on data which the conventional methods couldn't determine.

5. Conclusion

In this paper we have conducted a comparative study on the performance of three soft computing techniques namely Artificial Neural Networks (ANN), Fuzzy Logic

(FL) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) for fault diagnosis using DGA data. The intent was to improve on the existing conventional methods of incipient fault detection. It was observed that all the three models perform satisfactorily in predicting the nature of the fault with a good level of accuracy. Even though the training dataset was small the methods performed well.

The ANFIS model is found to be the best suitable method with accuracy reaching up to 98%. It outperforms the other two methods and comes out to be a suitable alternative to replace the conventional methods. Thereby the objective of comparing and using a better method for fault diagnosis which could surpass the existing conventional methods is achieved.

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