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Short Communication

Obtaining a high Accurate Fault Classification of Power Transformer based on Dissolved Gas Analysis using ANFIS

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Abstract

Power Transformers are a vital link in a power system. Well-being of power transformer is very much important to the reliable operation of the power system. Dissolved Gas Analysis (DGA) is one for the effective tool for monitoring the condition of the transformer. To interpret the DGA result multiple techniques are available.IEC codes are developed to diagnose transformer faults. But there are cases of errors and misleading judgment due to borderline and multiple faults. Methods were developed to solve this problem by using fuzzy membership functions to map the IEC codes and heuristic experience to adjust the fuzzy rule. This paper proposes a neuro-fuzzy method to perform self learning and auto rule adjustment for producing best rules.

Keywords: Dissolved gas analysis, fault diagnosis, fuzzy inference system, gas concentration.

Introduction

Power transformer plays an important role in power system. Hence for the reliable operation of power supply system the health of transformers must be properly maintained. Power transformer is subject to various thermal, electrical and mechanical stresses. These stresses can cause incipient faults, deterioration or even failure of power transformer. To prevent this timely fault detection via a suitable standard technique is must. Dissolved Gas Analysis (DGA) is an important tool for online monitoring of transformers of transformers[1-3]. Different standards are available such as the IEC 599 ratio codes, Rogers's ratio and Triangle ratio[1-3]. These ratio methods are efficient and simple to use.

There are certain limitations of the ratio methods. In case of more than one fault present, only the dominating faults are represented in these rules. Due this some of the faults are left unrecognized. Another shortcoming is due to the structure of the IEC codes used. Known as the gas ratios these codes are quantized to define the crisp boundaries. Practically mostly these figures are fuzzy. Thus these codes could lead to errors. To find out the solution of this difficulty some of artificial neural network (ANN) methods were employed[1-4]. In these ANN based methods the key gas methods were not used which is very important for the correct fault diagnosis. Finally a fuzzy DGA method was developed which uses both IEC 60599 and the key Gas concentration[5].

Material and Methods

IEC 60599 DGA Codes: During faults in the transformer due to electrical and thermal stresses, oil and paper decomposition occurs evolving gases that will decrease the heat dissipation capability and the dielectric strength of the oil. These released gases get dissolved in the oil, which are known as dissolved gases.

Different fault are associated and are reflected by the different concentration of the gases in oil. IEC 50699 uses 3 gas ratios C_2H_2/C_2H_4 (acetylene upon ethylene) , CH_4/H_2 (methane upon hydrogen) and C_2H_4/C_2H_6 (ethylene upon ethane). Each ratio is quantized to a classification code 0, 1 or 2. Thus there must be total 27 combinations but IEC 50699 defines only 11 combinations leading to non-decision diagnosis.

Table-1
IEC gas ratios

	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
<0.1	0	1	0
0.1-0.25	1	1	0
0.25-1	1	0	0
1-3	1	2	1
>3	2	2	2

The IEC codes are extended into the expert rules using experiences in the field by filling in the gaps created by IEC. The new knowledge base is given in the tables 1 and whose main advantage is elimination of the non-decision problem with all the 27 combinations included. It shows the IEC codes for different gas concentration ratios.

Fuzzy Diagnosis System: The fuzzy logic analysis involves three successive process namely: fuzzification, fuzzy inference and deuzzification. Fuzzification converts a crisp gas ratio into a fuzzy input membership. A chosen fuzzy inference system (FIS) is responsible for obtaining conclusions from the knowledge based fuzzy rules set of if – then linguistic statements. Defuzzification then converts the output values back into the crisp values.

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Input of the System: The input for our fuzzy diagnosis system are three gas ratios C_2H_2/C_2H_4 (acetylene upon ethylene), CH_4/H_2 (methane upon hydrogen) and C_2H_4/C_2H_6 (ethylene upon ethane). The values of these ratios i.e Code 0, Code 1 or code 2 are each represented by a trapezoidal membership function. These inputs are given to a sugeno model for obtaining the output.

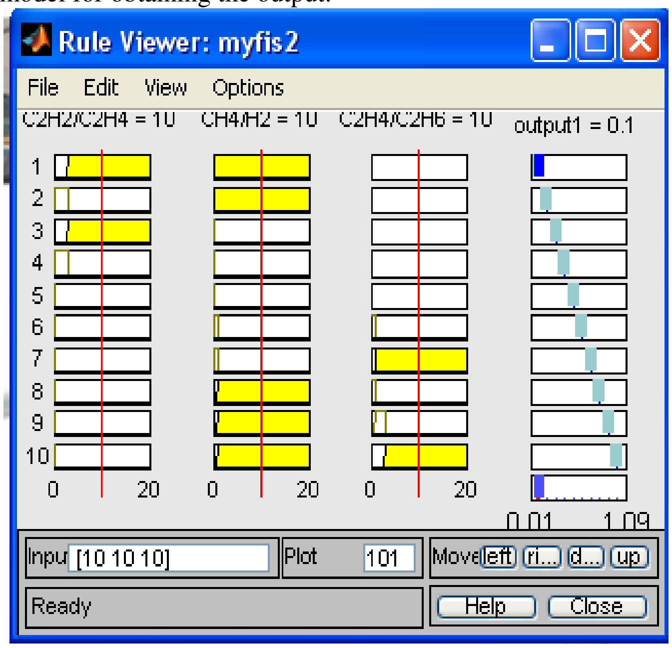

Figure-1
Fuzzy (sugeno) analysis of the fuzzy rules

Fuzzy Rules Base: The three gas ratios constitutes the fuzzy inputs. The if-then statements is used to make decision on the fuzzy inputs derieved from the three gas ratios. The fault s are described in the given table 2. For example if C_2H_2/C_2H_4 is 0, CH_4/H_2 is 2 and C_2H_4/C_2H_6 is also 0 then the fault type corresponding to this combination of the ratios is OH_T2 i.e thermal fault (overheating)150<T<300. Such ten fuzzy rules are created in the matlab environment.

Fuzzy Inference System (FIS): The fuzzy inference system can be of two types mamdani ant the sugeno type. Here the fuzzy inference system used is of the sugeno type.It obtains its output from judging all the written fuzzy rules by finding the membership for the fault types as shown by the fuzzy rules.Depending upon the concentrations of the different gas elements of the DGA, the) , ratios for C_2H_2/C_2H_4 (acetylene upon ethylene), CH_4/H_2 (methane upon hydrogen C_2H_4/C_2H_6 (ethylene upon ethane) are found out. Depending on this value a code is assigned to each ratio, which can be 0, 1 or 2. The figure 1 shows the analysis of the 10 fuzzy rules graphically.

Thus fuzzy logic can be effectively used to obtain the output of the system. As the age of transformer increases there is a continuous change in the relationship between the gas ratios and the fault type. Hence the fuzzy logic fault diagnosis can cause error in the decision. Thus artificial neural networks can be engaged for self learning. This paper proposes fault diagnosis of the transformer based on the DGA employing ANFIS (Adaptive Neuro-fuzzy inference system. It is an small attempt to make the diagnosis intelligent by self learning[5-6].

Table-2
Table of the details about the fault

Fault type	Fault Description	C_2H_2 /C_2H_4	CH_4 /H_2	C_2H_4 /C_2H_6
HEDA_4	High Energy Discharge Arcing	2	0 or 2	X
HEDA_3		1	0 or 2	X
HEDA_2	Low Energy Discharge	2	1	X
HEDA_1		1	1	X
LED	Partial Discharge	0	1	X
Normal	Normal Aging condition	0	0	0
OH_T1	Low temp overheating	0	0	1 or 2
OH_T2	Thermal Fault T1	0	2	0
OH_T3	Thermal Fault T2	0	2	1
OH_T4	Thermal Fault T3	0	2	2

Adaptive Neuro-Fuzzy Inference System (ANFIS): For implementing the current system ANFIS is coded in matlab environment.

Following given is the ANFIS model information: Number of nodes-78, Number of linear parameters-27, Number of Non-Linear Parameters-27, Total number of Parameters-54, Numbers of training data pairs-10, Number of checking data pairs-94, Number of fuzzy rules-27.

Results and Discussion

The ANFIS has been trained and tested for 94 different transformer DGA data. The results obtained are also comparable. Out of 94 different data, the proposed system is able to classify almost all the faults. Only four combinations are left undetected. The results are clearly visible from the figure 4. The average error is 0.21. Here the anfis –window is shown. Here different colors (blue and red) dots are shown. These are actually the outputs of our system. The blue color dots represent the actual values while the red dot represent output calculated from existing membership functions. Firstly the system was trained with the available known data set and then it is tested for real transformer data. The classification rate is nearly 90% for the same.

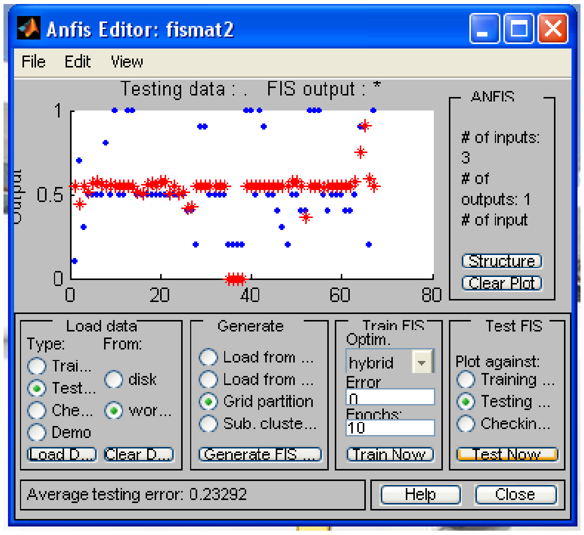

Figure-2
Anfis Results

Conclusion

The anfis has been trained and tested for 94 different transformer DGA data. The results obtained are also comparable. Out of 94 different data, the proposed system is able to classify almost all the faults. Only four combinations are left undetected. The results are clearly visible from the figure 2. The average error is 0.23. Here the anfis –window is shown. Here different colors (blue and red) dots are shown. These are actually the outputs of our system. The blue color dots represent the actual values while the red dot represent output calculated from existing membership functions. Firstly the system was trained with the available known data set and then it is tested for real transformer data. The classification rate is nearly 90% for the same.

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