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FAULT DIAGNOSIS OF POWER TRANSFORMER USING NEURO-FUZZY MODEL

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ABSTRACT

In this study, we have presented Neuro-Fuzzy model for fault diagnosis of power transformer based on dissolved gas analysis (DGA). DGA is a very efficient tool for monitoring transformers in-service behavior to avoid catastrophic failures, costly outages and losses of production. Determination of the fault type with few key gases is a convenience for on-line gas-in-oil monitoring systems, used for detecting incipient faults. Three key gases Methane (CH_4), Ethylene (C_2H_4) and Acetylene (C_2H_2) were chosen for this study. Neuro-Fuzzy is a reliable classification technique based on fuzzy and Artificial Neural Networks (ANN). Total accumulated amount of these gases were calculated and 100 percents (%) of each gas used as inputs of Neuro-Fuzzy. The output is one of the fault types PD, D1, D2, T1, T2, and T3. Classification accuracy has reached up to 76.0 %.

Keywords: Fault Diagnosis, ANFIS, Dissolved gas in oil analysis, Classification, Power transformer, Neuro-Fuzzy

I. INTRODUCTION

The basic function of power distribution system is to supply customers with electric energy as economically as possible and with an acceptable degree of reliability and quality. System reliability depends on components' reliability. The condition of components and the environment directly affects system condition resulting in equipment failures. Power transformers are essential devices in a transmission and distribution system. As a major apparatus in a power system, the power transformer is vital to system operation. Failure of a power transformer may cause a break in power supply and loss of profits. Failure of these transformers is very costly to both the electrical companies and customers. Therefore, it is of great importance to detect incipient failures in power transformers as early as possible, so that we can switch them safely and improve the reliability of power systems. [1-4]

To prevent the failures and to maintain transformers in good operating condition is a very important issue for utilities. Traditionally, routine preventative maintenance programs combined with regular testing were used. With deregulation, it has become increasingly necessary to reduce maintenance costs and equipment inventories. This has led to reductions in routine maintenance. The need to reduce costs has also resulted in reductions in spare transformer capacity and increases in average loading. [5]

Neuro-Fuzzy were studied worldwide recently for pattern recognition such as fault diagnosis. In addition, ANFIS has also been successfully applied to a number of real-world problems such as handwritten characters recognition,

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face detection, and medical diagnosis. The approach is systematic and properly motivated by statistical learning theory [6].

In this study, fault diagnosis in power transformers using Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented. Three DGA criteria commonly used in industry was trained and tested with ANFIS classifier. The results of this study are useful in development of a reliable transformer automated diagnostic system. We determined best model choosing and reached 76.0 % diagnostic success.

2. MATERIAL AND METHOD

2.1. Dissolved Gas in Oil Analysis

Dissolved gas analysis (DGA) is a very efficient tool for monitoring transformers in-service behavior to avoid catastrophic failures, costly outages and losses of production. Like a blood test or a scanner examination of the human body it can warn about an impendent problem, give an early diagnosis and increase the chances of finding the appropriate cure. The operating principle is based on the slight albeit harmless deterioration of the insulation that accompanies incipient faults, in the form of arcs or sparks resulting from dielectric breakdown of week or overstressed parts of the insulation, or hot spots due to abnormally high current densities in conductors. Whatever the cause, these stresses will result in the chemical breakdown of some of the oil or cellulose molecules constituting the dielectric insulation. The main degradation products are gases, which entirely or partially dissolve in the oil where they are easily detected at the ppm level by DGA analysis. [7]

The most significant fault gases produced by the decomposition of oil are hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane (C_2 H_6). The decomposition of paper in addition to the preceding gases produces carbon monoxide (CO) and carbon dioxide (CO_2). In analysis of the equipment condition, CO is considered a fault gas. C_3 and C_4 hydrocarbons are also formed, but experience has shown that a satisfactory diagnosis can be made without taking into account these gases.

A number of methods are in use for the interpretation of the dissolved gas analysis. A qualitative and quantitative interpretation has a generally accepted list of gases and associated conditions are found [8]. The techniques include the conventional Key Gas Method, Ratio Methods, Graphical representation techniques and recently artificial intelligent methods. Key gas method uses characteristic "Key gases" to identify particular fault types. The suggested relationship between key gases and fault types is summarized as:

H_2----Corona
O_2 & N_2----Non-fault related gases
CO & CO_2----Cellulose insulation breakdown
CH_4 & $C2H_6$----Low temperature oil breakdown
C_2H_4----High temperature oil breakdown
C_2H_2----Arcing

Rogers, Dornenberg and IEC [9] are the most commonly used ratio methods. They employ the relationships between gas contents. The key gas ppm values are used in these methods to generate the ratios between them. The ranges of the ratio are assigned to different codes which determine the fault types. Coding is based on experience and is always under modification. Ratio methods are limited in discerning problems when more than one type of fault occurs simultaneously [3].

2.2. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS system as a combination of ANN and Fuzzy Inference System (FIS) [10] are used to determine the parameters of FIS. ANFIS as shown in figure 1, which implements a Takagi Sugeno Kang (TSK) fuzzy inference system (figure 1) in which the conclusion of a fuzzy rule is constituted weighted linear combination of the inputs.

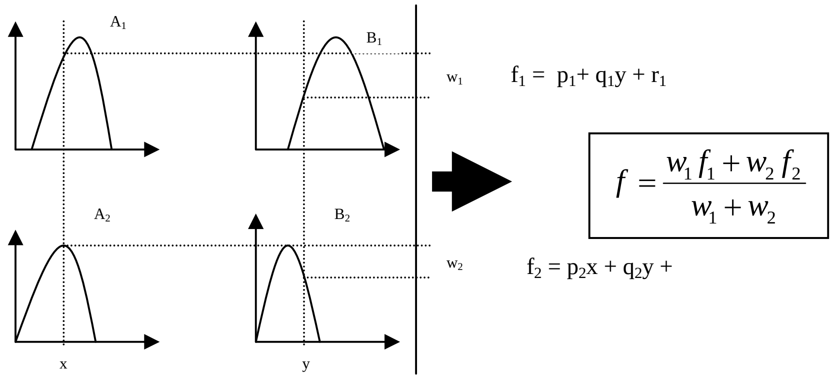


Figure 1. TSK type fuzzy inference system.

2.2.1. Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [11]. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if–then rules based on a first order Sugeno model are considered [11-14].

Rule 1: If (x is A_1) and (y is B1) then ($f_1 = p_1 + q_1 y + r_1$), (1)
Rule 2: If (x is A_2) and (y is B2) then ($f_2 = p_2 x + q_2 y + r_2$). (2)

where x and y are the inputs, Ai and Bi are the fuzzy sets, fi are the outputs within the fuzzy region specified by the fuzzy rule, pi; qi and ri are the design parameters that are determined during the training process.
The ANFIS architecture to implement these two rules is shown in Figure 2, in
which a circle indicates a fixed node, whereas a square indicates an adaptive node.
In the layer 1 , All the nodes are adaptive nodes.
The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by

$O_i^1 = \mu_{Ai}$ (x), i= 1, 2, or (3)

O_i^1 i = μ_{Bi-2} (y), i= 3, 4, (4)

where μ_{Ai} (x), μ_{Bi-2} (y) can adopt any fuzzy membership function. If the bell shaped membership function is used, $\mu_{A_i}(x)$ is

$$\mu_{A_i(x)} = \frac{1}{1 + |(x - c_i)/a_i|^{2b_i}}, \tag{5}$$

In the layer 2, the nodes are fixed nodes. They are labeled with M, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1, 2 \tag{6}$$

which are the so-called firing strengths of the rules.

In the layer 3, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer.
The outputs of this layer can be represented as

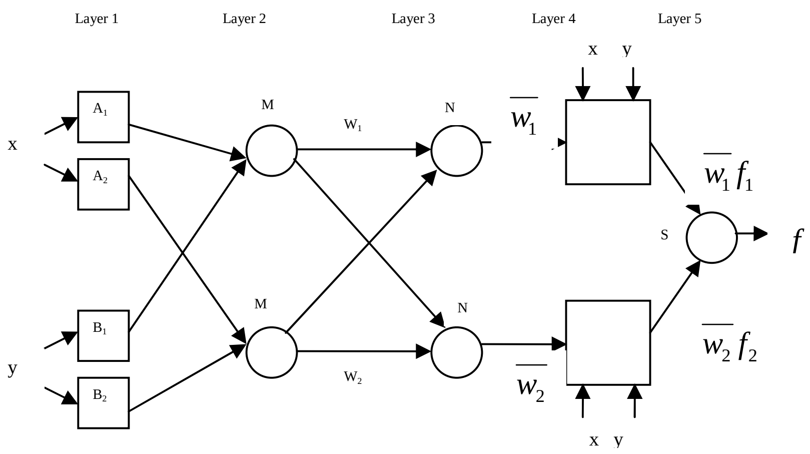


Figure 2. ANFIS architecture.

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1, 2 \quad (7)$$

which are the so-called normalized firing strengths.

In the layer 4, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order Sugeno model. Thus, the outputs of this layer are given by

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), i = 1, 2 \quad (8)$$

In the layer 5, there is only one single fixed node labeled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{(\sum_{i=1}^{2} w_i f_i)}{w_1 + w_2}. \quad (9)$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters {ai, bi, ci}, which are related to the input membership functions. These parameters are the so-called premise parameters.

In the fourth layer, there are also three modifiable parameters {pi, qi, ri}, pertaining to the first order Sugeno model. These parameters are called consequent parameters [13-14].

2.2.2. Hybrid learning algorithm of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i; b_i; c_i\}$ and $\{p_i; q_i; r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2. \quad (10)$$

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2. \qquad (11)$$

$$f = \overline{w}_1 (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2). \qquad (12)$$

$$f = (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2 . \qquad (13)$$

which is linear consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem [15-18]. The hybrid algorithm is composed of forward pass and backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed [16-18].

Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [19-20].

3. RESULTS

3.1. ANFIS Training and Model Selection

The training fault transformer with DGA set contained 150 examples. 38 of 150 examples achieved from Turkish national grid and rest of them taken from [21].

Shape of the membership functions of the antecedents we have used triangular function as

$$\mu_{Ai}(x) = \prod_{j=1}^{n} \max\left(0, 1 - \frac{|x_j - c_j^i|}{b_j^i}\right). \qquad (14)$$

where the matrix centers(i,j) represent the value of c_j^i and the matrix bases(i.,j) represent the value of b_j^i.

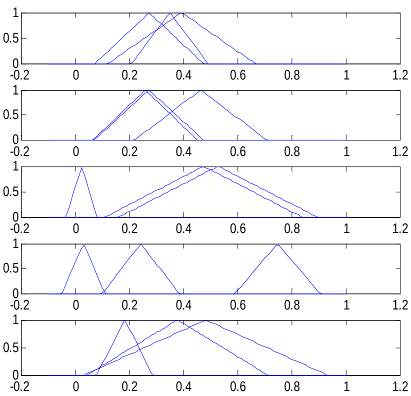
Parametric form of the consequent model it can be constant $y^i = p_i$ or linear

$$y_i = \sum_{j=1}^{n} p_{ij} x_j + p_{i0} \qquad (15)$$

we have used constant form in this work [19-20].

Our system has 3 inputs and 1 output, we used 15 rules (figure 3) and obtained 15x3 centers matrix, 15x3 bases matrix and 15x1 parametric matrix.

The aim of this study is to determine the fault type of failed power transformers with a few key gases using ANFIS. Determination of the fault type with few key gases is a convenience for on-line gas-in-oil monitoring systems, used for detecting incipient faults. Three key gases Methane (CH_4), Ethylene (C_2H_4) and Acetylene (C_2H_2) were chosen for this study. Total accumulated amount of these gases were calculated and 100 percents (%) of each gas used as inputs of Anfıs.



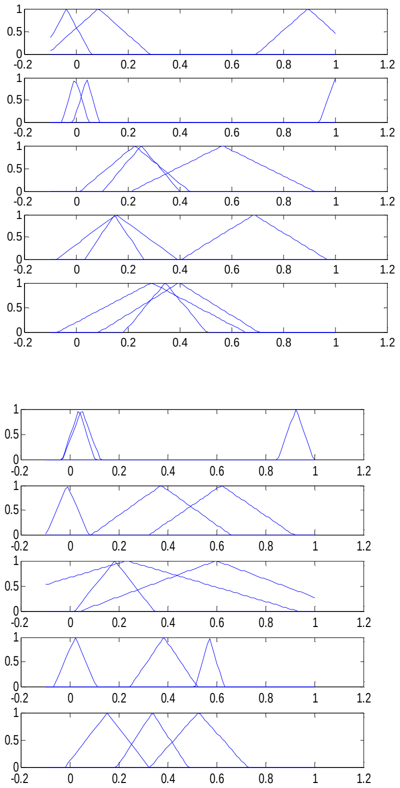


Figure 3. Triangular membership functions with 15 rules.

The output is one of the fault types are PD, D1, D2, T1, T2, T3. After evaluate 15 rules modeled our Neuro- Fuzzy system After 20 rules we modeled our system, and using our 50 test data sets than we got 76.0 % succeed (figure 4).

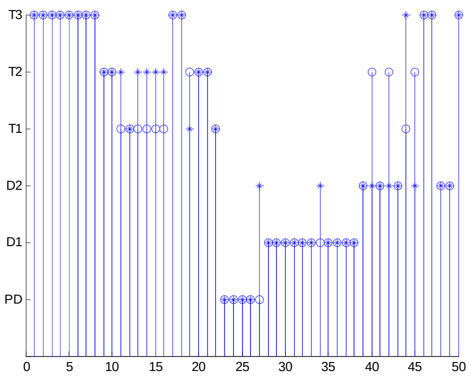


Figure 4. Evaluate of 50 patterns using ANFIS approach. “o” symbols are our testing outputs and stars “*” are our predicts.

4. CONCLUSION

ANFIS is powerful for the classification problems. Aim of this study is to determine the fault type of failed power transformers with a few key gases using ANFIS. Determination of the fault type with few key gases is convenience for on-line gas-in-oil monitoring systems, used for detecting incipient faults. Since dissolved gas analysis (DGA) is a very efficient tool for monitoring transformers failures. We determine best choosing kernel function and parameters of ANFIS for this problem. We obtained 76.0 % classification accuracy.

Table 1 : Centers parameters

0,39056	0,3473	0,27094
0,46098	0,26956	0,25644
0,021289	0,47169	0,52528
0,028268	0,23993	0,74492
0,47959	0,18054	0,37501
-0,03954	0,083646	0,89259
0,037651	-0,00594	1,0001
0,24845	0,22342	0,56304
0,68418	0,14547	0,15327
0,2885	0,34201	0,39455
0,045453	0,034002	0,92089
-0,01279	0,37024	0,61713
0,23016	0,18064	0,59482
0,019461	0,56807	0,38184
0,52327	0,3349	0,14987

Tablo 3. Linear p parameters

-3,5	-2,4	0,08	0,42	0,21	-8,7	-3,9	-3,9	-2,5	-1,6	-2,5	-3,3	0.20	-3.0

Table 2 : Bases Parameters

0,54203	0,28256	0,39874
0,48468	0,40055	0,38288
0,1129	0,72686	0,73255
0,15936	0,28242	0,31079
0,89666	0,20612	0,66685
0,18895	0,39654	0,39654
0,1	0,10244	0,12774
0,29665	0,41969	0,7041
0,55885	0,22663	0,46434
0,72075	0,31666	0,61263
0,15129	0,13214	0,14605
0,17506	0,56692	0,58765
1,395	0,32361	1,107
0,17396	0,11703	0,27275
0,39648	0,29036	0,33959

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