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An Approach to Neuro-Fuzzy Monitoring of Power Transformers

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***Abstract*— The article proposes a model of an adaptive network-based fuzzy inference system for power transformer monitoring based on the analysis of dissolved gases in transformer oil. The determination of the type and nature of the developing defect is carried out using the method of gas concentration ratios. The neuro-fuzzy system was tested on the results of dissolved gases analysis of power transformers operated at power plants. The proposed model of the neuro-fuzzy system with good accuracy allows you to determine the nature of the fault in the transformer. The proposed model of a neuro-fuzzy system can be used to build a continuous online monitoring system for power transformers.**

***Keywords*— power transformer; dissolved gas analysis; monitoring; gas ratio; adaptive neuro-fuzzy systems**

I. INTRODUCTION

The power transformer is a key element of the power system [1]. The failure of a power transformer can lead to catastrophic consequences with direct and indirect costs to the industrial, commercial, and residential sectors. Therefore, assessing the condition of the transformer is extremely important for the reliable operation of the power system. The use of monitoring tools and diagnostic methods makes it possible to increase the service life of transformers due to the timely detection or prevention of emerging defects in the power plant [2].

According to industry standards, the average life of a power transformer is about 40 years [3], [4]. After this time, the probability of catastrophic failure increases significantly. Internal defects of a transformer are divided into electrical and thermal. Electrical defects include partial discharges in oil, electric arcs, sparking resulting from deterioration of insulation. The most common thermal defects are heating of transformer oil and paper-oil insulation, aging, and moistening of oil and solid insulation [5], [6].

There are some electrical and chemical diagnostic methods currently in use for power transformers. According to separate studies, up to 70% of common defects in power transformers can be detected using dissolved gas analysis (DGA) [7]. DGA also makes it possible to build systems for the online monitoring of power transformers [1], [8].

An analysis of the quality of transformer oil allows one to determine increased electrical conductivity and the presence of moisture, which indicates a deterioration in insulation properties. A power factor or oil dissipation factor test can be used to determine dielectric loss and insulation integrity. Oil viscosity plays an important role in the heat transfer process in transformers. As the temperature rises, the viscosity of the pure oil decreases, which leads to a decrease in the insulating properties [9].

Despite the popularity of the DGA application, the problem of interpreting the results obtained remains unsolved. Comparing the results of different interpretation methods on the same sample can lead to a contradiction, and there is no clear way to prioritize any result [1]. Thus, the accuracy of the key gas method largely depends on the number of key gases. Roger's relationship method has a high accuracy of the result, but it allows diagnosing a limited number of types of defects. The Duval triangle method has a relatively good consistency and accuracy of results when accounting for cases that cannot be diagnosed by other methods, but requires careful study and analysis of gases [10].

A promising approach to improving the accuracy of interpreting the results of DGA is the use of various intelligent methods, including fuzzy logic, neural networks, genetic algorithms. Recently, these methods have been successfully used to solve various engineering problems [4], [11] - [16].

This paper proposes an approach to the use of a neural network based on a fuzzy inference system for interpreting the results of DGA by the method of gas concentration ratios following IEC 60599 [3].

II. USE OF GASES RATIO TO CALCULATE DEFECTS OF POWER TRANSFORMERS

The gases ratio method uses the concentrations hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene C_2H_4 и ethane C_2H_6 to identify and classify transformer faults. This method uses the ratios C_2H_2/C_2H_4, CH_4/H_2 и C_2H_4/C_2H_6 [3].

The kind of damage developing in the transformer is determined by the ratio of the following gases: H_2, CH_4, C_2H_2, C_2H_4 и C_2H_6 [3].

In this case, it is recommended to use such DGA results in which the concentration of at least one gas was 1.5 times greater than the limit value [3].

The condition for predicting "discharge":

$$C_2H_2/C_2H_4 \geq 0.1 \text{ and } CH_4/H_2 \leq 0.5 \quad (1)$$

The condition for predicting "overheating":

$$C_2H_2/C_2H_4 < 0.1 \text{ and } CH_4/H_2 > 0.5 \quad (2)$$

If the CO concentration is <0.05%, then "oil overheating" is predicted, and if the CO concentration is> 0.05% - "solid insulation overheating".

The conditions for predicting "overheating" and "discharge":

$$C_2H_2/C_2H_4 \geq 0.1 \text{ and } CH_4/H_2 > 0.5 \quad (3)$$

or

$$C2H_2/C_2H_4 < 0.1 \text{ and } CH_4/H_2 \leq 0.5. \quad (4)$$

According to the basic gas ratio method, the classification of various electrical and thermal faults is shown in Table 1 [3]. In some cases, design ratios may not match any of the classes shown in Table 1.

TABLE I. – BASIC GAS RATIOS

№	Gas ratio			Fault type
	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	
0	< 0.1	0.1-1	≤ 1	No fault
1	< 0.1	< 0.1	≤ 1	Partial discharges with low energy density
2	0.1-3	< 0.1	< 1	Partial discharges with high energy density
3	> 0.1	0.1-1	1-3	Discharges of low energy
4	0.1-3	0.1-1	≥ 3	Discharges of high energy
5	< 0.1	0.1-1	1-3	Thermal fault (< 150 °C)
6	< 0.1	≥ 1	< 1	Thermal fault (150-300 °C)
7	< 0.1	≥ 1	1-3	Thermal fault (300-700 °C)
8	< 0.1	≥ 1	≥ 3	Thermal fault (> 700 °C)

To further clarify the nature of the defects, the CO_2/CO ratio is additionally used. If the solid insulation is not affected by the damage, then

$$5 < CO_2/CO \leq 13 \quad (5)$$

If the damage affects solid insulation, then

$$CO_2/CO < 5 \quad \text{or} \quad CO_2/CO > 13 \quad (6)$$

It is necessary to consider that CO_2 and CO are produced in the transformer oil at normal operating temperatures as a result of the natural aging of the insulation.

Also, the CO_2 content in oil depends on the life of the transformer and the way the oil is protected from oxidation.

III. STRUCTURE OF THE NEURO-FUZZY MODEL

The transformer health assessment model is a rule-based mathematical fuzzy model. Interpretation of power transformer degradation can be best analyzed using a fuzzy logic approach [17]. Fuzzy logic is based on a soft computational method, in which verbal (linguistic) terms are usually used as variables. Verbal terms are easy to understand and easier to understand than formulas. In this case, rules of the "IF-THEN" type are used, which are also known as implications [18]. The purpose of the model is to simplify the assessment of the condition of the transformer and improve its performance. To simplify and achieve result accuracy, the basic model is subdivided into small models by fuzzifying all parameters.

In this work, the adaptive network-based fuzzy inference system (ANFIS) technology was used [19, 23]. The structure of the proposed ANFIS is shown in Fig. 1.

The layers of ANFIS-network perform the following functions.

Layer 1 is Inputs. For the object under study, 4 input parameters are considered. The network inputs are supplied with normalized signals characterizing the ratios of the measured gas concentrations.

Layer 2 is represented by radial basis neurons and models membership functions.

Layer 3 is a layer of AND-neurons that model a logical AND as

$$w_i = \mu^{T1}(x_1) \cdot \mu^{T2}(x_2) \cdot \mu^{T3}(x_3) \quad (7)$$

Layer 4 generates the value of the output variable as

$$y(x_1, x_2, x_3, x_4) = \omega_i \cdot y_i = \omega_i (c_{i1} \cdot x_1 + c_{i2} \cdot x_2 + c_{i3} \cdot x_3 + c_{i4} \cdot x_4) \quad (8)$$

Layer 5 operates finding the mean, i.e. it converts the results of fuzzy inference to a definite number using the formula:

$$y = \frac{w_1 \cdot y_1 + w_2 \cdot y_2 + w_3 \cdot y_3}{w_1 + w_2 + w_3} \quad (9)$$

Then the nearest whole is found.

At the output of the network, an integer numerical value is formed. This value corresponds to the type of fault and the presence of damage to the solid insulation of the transformer according to Table 1.

The following weights are assigned to the graph arcs: "1" (arcs between the first and second layers); functions of membership of the input to a fuzzy term (arcs between the second and third layers); rule weights (arcs between the third and fourth layers); "1" (arcs between the fourth and fifth layers) [20].

The relating of each exact value to one of the terms of the linguistic variable is determined employing membership functions. The most preferred forms of the membership function are triangular and trapezoidal since fuzzy inference is greatly simplified when using piecewise linear membership functions [21]. In this work, triangular membership functions were used.

The Sugeno algorithm [22] was used as the fuzzy inference algorithm.

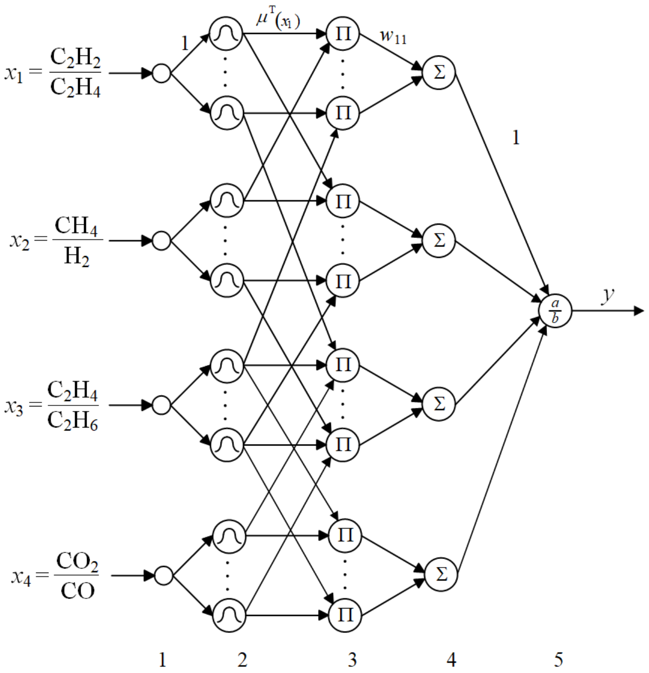

Fig. 1. The structure of the proposed ANFIS

IV. Results and Discussion

For ANFIS training 729 samples were formed. For modeling of ANFIS MATLAB was used.

The method "backpropagation" was used as a parameter setting method. The number of training cycles is 3000. The result of system modeling in the form of a graph of the network error, depending on the number of training cycles, is shown in Fig. 2.

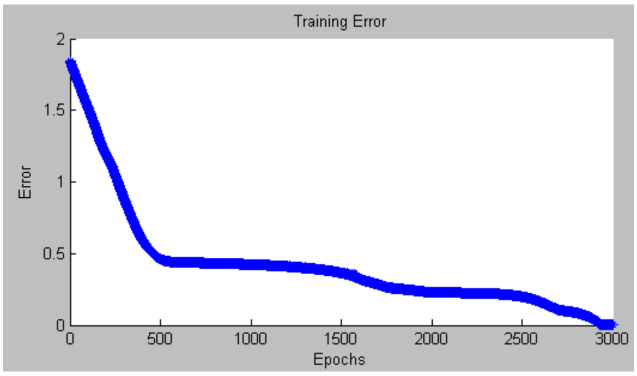

Fig. 2. Relationship of the learning error on the number of learning cycles

The results of ANFIS testing after training are presented in Table 2. This table presents the DGA data for power transformers operated at the power stations. Also, Table 2 shows the result of the interpretation of the DGA data obtained using ANFIS, and the actual results transformers diagnosis after their removal from service.

The test results (Table 2) showed that the generated ANFIS after training quite correctly allows us to determine the nature of the fault of the transformer. Incomplete information about the type of malfunction is observed in cases 5, 13, and 14 (Table 2). The incompleteness of information in case 5 is due to the properties of ANFIS learning. The incompleteness of information in cases 13 and 14 is explained by the lack of initial information on the content of CO_2 and CO gases in the transformer oil.

Thus, the use of a simple mathematical model that takes into account the real technical features of the transformer gives much better results than using a complex and more accurate mathematical model.

An actual opportunity to take into account all the variety of modifications of defect-free and defective transformer models is the transition from the use of stationary mathematical models to the use of adaptive models. In these models which the influence coefficients and integral coefficients are continuously corrected as operational information about the state of the transformer obtainments.

To implement ANFIS it is possible to use the FlexTool for MATLAB for generating microcontroller code. The software kernel supplied with FlexTool for MATLAB is compatible with controllers such as 8096VN, 8096-90, 90196 KR, 90196MC, 80196NT / NQ, etc.

Thus, the proposed ANFIS model can be easy integrated into continuous online monitoring systems, which is more reliable and affordable. This is largely due to the advent of inexpensive online or portable gas analyzers. Online monitoring based on DGA makes it possible to increase the power of individual transformers and bring them closer to temperature limits.

V. Conclusion

This article presents a neuro-fuzzy approach to monitoring power transformers based on dissolved gas analysis (DGA) analysis. An ANFIS structure is proposed that calculates the type of failure based on the input gas values. The model structure consists of 5 layers. Normalized signals are supplied to the input layer of the network, corresponding to the measured gas ratios. ANFIS testing was carried out according to the DGA data of power transformers operated at power plants. The proposed ANFIS model with good accuracy allows you to determine the nature of the fault in the transformer. ANFIS model can be easily integrated into continuous online monitoring systems.

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TABLE II. – VALIDATION OF THE PROPOSED ANFIS-MODEL

№	DGA data, % vol							ANFIS result	Actual result	Results comparison
	CH_4	C_2H_4	C_2H_2	C_2H_6	H_2	CO_2	CO			
1	0.0045	0.005	0	0.002	0.008	0.17	0.02	No fault	No fault	Correct
2	0.017	0.05	0.003	0.0048	0.0075	0.16	0.02	No fault	No fault	Correct
3	0.016	0.048	0.003	0.0047	0.01	0.15	0.02	No fault	No fault	Correct
4	0.018	0.051	0.0035	0.0053	0.01	0.15	0.02	Thermal fault (> 700 °C); No solid insulation failure	Burnout of copper winding tap	Correct
5	0.021	0.027	0.134	0.006	0.20	0.45	0.04	Partial discharges with high energy density; -	Break of the switch conductor	Correct*
6	0.0024	0.015	0.040	0.0006	0.016	0.162	0.05	Partial discharges with high energy density; Solid insulation failure	Breakdown of coil insulation	Correct
7	0.084	0.02	0	0.011	0.004	0.48	0.05	Thermal fault (> 700 °C); No solid insulation failure	Severe burning of selector contacts	Correct
8	0.09	0.167	0.008	0.03	0.01	0.24	0.019	Thermal fault (300-700 °C); No solid insulation failure	Closing of the pressing ring of the MV winding to the pressing ring of the LV winding through the fallen sleeve of the jack	Correct
9	0.18	0.3	0	0.043	0.03	0.19	0.016	Thermal fault (300-700 °C); No solid insulation failure	Short-circuit detected - touching the lower console with a spike	Correct
10	0.036	0.152	0	0.039	0.011	0.45	0.04	Thermal fault (300-700 °C); No solid insulation failure.	Burnout switch contacts	Correct
11	0.019	0.024	0.013	0.0023	0.097	0.27	0.064	Discharges of high energy; Solid insulation failure	Burnout of the stud insulation, touching the console tightening studs, burnout of the stud metal	Correct
12	0.021	0.027	0.134	0.0006	0.20	0.45	0.04	Discharges of high energy; No solid insulation failure	Burnout of movable and fixed contacts of the OLTCs.	Correct
13	0.02	0.049	0.0013	0.009	0.053	-	-	Partial discharges with high energy density; -	Break of the switch conductor	Correct*
14	0.025	0.030	0.024	0.007	0.27	-	-	Discharges of high energy; -	Detected discharge traces and burnout of the magnetic circuit	Correct*

* - No information about solid insulation failure.

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