Prediction of Fault in Distribution Transformer Using Adaptive Neural-Fuzzy Interference System

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Abstract— This presents a new method for simultaneous diagnosis of fault in distribution transformer. It uses an adaptive neuro-fuzzy inference system (ANFIS), based on Dissolved Gas Analysis (DGA). The ANFIS is first "trained" in accordance with IEC 599, so that it acquires some fault determination ability. The CO2/CO ratios are then considered additional input data, enabling simultaneous diagnosis of the type and location of the fault. Diagnosis techniques based on the Dissolved Gas Analysis (DGA) have been developed to detect incipient faults in distribution transformers. The quantity of the dissolved gas depends fundamentally on the types of faults occurring within distribution transformers. By considering these characteristics, Dissolved Gas Analysis (DGA) methods make it possible to detect the abnormality of the transformers. This can be done by comparing the Dissolved Gas Analysis (DGA) of the transformer under surveillance with the standard one. This idea provides the use of adaptive neural fuzzy technique in order to better predict oil conditions of a transformer. The proposed method can forecast the possible faults which can be occurred in the transformer. This idea can be used for maintenance purpose in the technology where distributed transformer plays a significant role such as when the energy is to be distributed in a large region.

Key words: Dissolved Gas Analysis (DGA), Adaptive Neuro Fuzzy Interference System (ANFIS)

I. INTRODUCTION

Electrical, mechanical, and thermal stresses can degrade the quality of the insulation in power transformers, causing faults. Several methods are used for fault diagnosis in transformers, e.g., dissolved gas analysis (DGA), measurement of breakdown voltage, and tan δ, pollution, sludge, and interfacial tension tests. Of these, DGA is the most frequently used.

Thermal and electrical stresses result in fracture of the insulating materials and the release of several gases. Analysis of these gases may provide information on the type of fault. Various standards have been suggested for the identification of transformer faults based on the ratio of dissolved gases in the transformer oil, e.g., International Electro technical Commission (IEC) standards, and these standards has been quoted in many papers. However, they are incomplete in the sense that, in some cases, the fault cannot be diagnosed or located accurately. Intelligent algorithms, e.g., wavelet networks, neuro-fuzzy networks, fuzzy logic, and artificial neural networks (ANN), have been used to improve the reliability of the diagnosis. In these algorithms, the type of fault is diagnosed first, and the fault is then located using the ratio of the concentrations of CO2 and CO dissolved in the transformer oil. The algorithms are not entirely satisfactory. The wavelet network has high efficiency but low convergence, the fuzzy logic method has a limited number of inputs and, in some cases, it is very difficult to derive the logic rules, and the ANN need reliable training patterns to improve their fault diagnosis performance.

A. Dissolved Gas Analysis

In normal operation, i.e., with no fault present, transformer oil contains gases such as H2, CH4, C2H4, C2H2, O2, and N2. When a fault is present, the concentrations of some of these gases increase, depending on the fault type and its location. The gases can be divided into three groups:

- Hydrogen and hydrocarbons: H2, C2H4, CH4, C2H2.
- Carbon oxides: CO2 and CO, and
- Non fault gases: O2 and N2.

Gas Ratio	Value	Code
$X = C_2H_2/C_2H_4$	$X<0.1$	0
	$0.1 \le X \le 3$	1
	$X > 3$	2
$Y = CH_4/H_2$	$Y < 0.1$	0
	$0.1 \le Y \le 1$	1
	$Y > 1$	2
$Z = C_2H_4/C_2H_6$	$Z < 1$	0
	$1 \le Z \le 3$	1
	$Z > 3$	2

Table 1: International Electro technical Commission Codes [3].

The accepted correlation between faults and dissolved gas concentrations is as follows:

- H_2 and C_2H_2: Increased concentrations of H_2 and C_2H_2 are almost always a sign of arcing faults. Temperatures in excess of 500°C are required for the generation of C_2H_2.
- C_2H_6, C_2H_4, CH_4, C_3H_8/C_3H_6 (propane/propylene) and H_2: Increased concentrations of C_2H_4, in combination with any one of C_2H_6, CH_4, and C_3H_8/C_3H_6, indicate thermal decomposition of the oil. These gases are generated at temperatures lower than 250°C.
- H_2 and CH_4: These are generated if partial discharge (or corona) takes place in the transformer oil.
- CO_2 and CO: Generation of both gases indicates thermal aging or partial discharge (corona) in the cellulosic insulation
- H_2 and O_2: The presence of both gases in the transformer oil, together with the absence of any hydrocarbon gas, indicates the presence of water in the transformer oil.

The Three Conventional Standards dissolved gas analysis has following standards. The concentrations of H_2, CH_4, C_2H_4, C_2H_6, and C_2H_2 in the transformer oil can be used to diagnose faults in the transformer. The concentration ratios between some of these gases are used in some standards. Details on the three conventional standards are as follows:

- IEC Standard: A three-digit code (X, Y, and Z) is used to indicate the fault type. Each digit indicates a gas concentration ratio (X = C_2H_2/C_2H_4, Y = CH_4/H_2, and Z = C_2H_4/C_2H_6).
- Rogers Ratio Method: Three gas ratios are used, namely, CH_4/H_2, C_2H_4/C_2H_6, and C_2H_2/C_2H_4. Table 3 shows the fault diagnosis corresponding to various combinations of these ratios.
- Doernenburg Ratio Method: In this method, four gas ratios, namely, CH_4/H_2, C_2H_2/C_2H_4, C_2H_2/CH_4, and C_2H_6/C_2H_2, are used to diagnose the fault.

B. CO_2/CO Ratio

Faults in the paper insulation are generally considered more serious than faults in the insulating oil. The paper insulation is located in areas of high electric field, so its degradation may lead to short-circuiting or severe arcing. Consequently, fault detection by DGA or by some other method is of considerable interest. Degradation of cellulosic materials, e.g., paper insulation, produces CO_2 and CO and much smaller quantities of other gases. The CO_2/CO ratio is sometimes used as an indicator of cellulose decomposition. High-temperature degradation of cellulose tends to decrease the CO_2/CO ratio, but the rates of CO_2 and CO production depend largely on O_2 availability, moisture content, and temperature. However, if the CO_2/CO ratio is less than approximately 3 or greater than approximately 11, the possibility of a fault involving cellulose degradation should be considered.

Thermal stress leads to the formation of CO and CO_2 in the oil, with the concentrations varying with transformer type. In new transformers or those filled with fresh oil, the CO and CO_2 concentrations initially increase quickly, with high CO_2/CO ratios. These ratios decrease as the oil ages and reach a nearly steady value.

Key Gas	L1 (ppm)
Hydrogen (H_2)	100
Methane (CH_4)	120
Carbon Monoxide (CO)	350
Acetylene (C_2H_2)	1
Ethylene (C_2H_4)	50
Ethane (C_2H_6)	65

Table 2 Minimum Concentration Limits (L1) Used in the Doernenburg Method [7].

Under normal operating conditions, that steady value is approximately 7, with a standard deviation of approximately 4. Tests have shown that the CO2/CO ratios are sensitive to the oil temperature and are an early indicator of oil aging.

However, CO_2/CO >10 found in a group of aged (25- to 35-year-old) station transformers was interpreted as an indication of a thermal fault in the paper insulation. Such faults have a long-term aging effect on the paper and reduce transformer lifetime. During aging, micro particles, cellulose fibre particles, carbon particles, and other particles are produced, the micro particles constitute up to 94% of the total particle volume. A CO_2/CO ratio <3 is generally considered an indication of carbonization of cellulosic insulation.

C. Adaptive neuro fuzzy interference system

1) The ANFIS Network

Although the standards are useful and effective for diagnosis of some faults, they do not cover all the likely gas ratio ranges. Furthermore, additional data cannot be used. This is not true of ANFIS, which was introduced by Jang in 1993. It is a type of adaptive multilayer feed-forward network. It combines the calculation capability of ANN with the logic capability of Sugeno-type fuzzy systems. A hybrid learning rule is used to train the ANFIS system.

2) ANFIS Structure

The Adaptive Neuro Fuzzy Inference System network consists of a number of nodes connected by directional links. The nodes can be adaptive or fixed, the output of an adaptive node depends on the parameters forming its input, but the output of a fixed node depends only on the output of the previous layer. (A layer consists of all nodes that have the same inputs.)

The ANFIS consists of five layers, connecting n inputs to one output f. Thus the ANFIS structure for each fault of the IEC standard has three inputs (X1 = C_2H_2/C_2H_4, X2 = CH_4/H_2, X3 = C_2H_4/C_2H_6) and one output (O_i). The output O_i represents the output pattern for the i^{th} fault. It follows that nine ANFIS systems should be used to determine O0 through O8. For the sake of simplicity, only two inputs are shown in Figure 1.

No.	**Type of Fault**	**Gas Ratio**			
		CH_4/H_2	**C_2H_2/C_2H_4**	**C_2H_2/CH_4**	**C_2H_6/C_2H_2**
1	Partial Density(Low Density PD)	CH_4/H_2 < 0.1	———	C_2H_2/CH_4 < 0.3	0.4 < C_2H_6/C_2H_2
2	Arcing (High Intensity PD)	0.1 < CH_4/H_2 < 1	C_2H_2/C_2H_4 > 0.75	C_2H_2/CH_4 > 0.3	C_2H_6/C_2H_2 < 0.4
3	Thermal Decomposition	CH_4/H_2 > 1	C_2H_2/C_2H_4 < 0.75	C_2H_2/CH_4 < 3	C_2H_6/C_2H_2 > 0.4
4	No Fault	H_2 < 2L1(H_2) or CH_4 < 2L1(CH_4) or C_2H_2 < 2L1(C_2H_2) or C_2H_4 < 2L1(C_2H_4)			
4	No Fault	H_2 > 2L1(H_2), CH_4 > 2L1(CH_4), C_2H_2 > 2L1(C_2H_2), C_2H_4 > 2L1(C_2H_4) and [C_2H_6 < L1(C_2H_6) or CO < L1(CO)]			
5	Fault Not Identified	Otherwise			
[1]PD = partial discharge; L1 = minimum concentration limit.					

Table 3: Fault Diagnosis Using Doernenburg Codes [7].

II. METHODOLOGY

A. Improving Fault Diagnosis

To improve fault diagnosis using the standards, in this work the ANFIS system was trained using separate input data sets for each fault listed in each standard. The input data sets are the gas ratios required by a given standard, and the output is

1 if the input data match the standard for the specific fault being investigated and 0 otherwise. In this work, the fuzzy rules used in ANFIS, based on an extended range of input data, improved the fault diagnosis capability of the standard.

For methods in which the fault is not diagnosed and located simultaneously, the fault type is first determined using a standard, e.g., ANN or ANFIS, and the CO2/CO ratio is then used to determine the fault location (in the oil or cellulosic insulation).

B. Simultaneous Diagnosis of Fault Type and Location

Figure 3 shows a flowchart for simultaneous fault diagnosis and location. There are two main stages, namely, training and testing.

1) The Training Stage

The initial values of the parameters are specified. These parameters include the ANFIS parameters for each standard and gas chromatography data for different transformers. The latter allow the initial training data set to be calculated for each standard. The ANFIS network is then trained for each training data fault.

The input consists of four or five gas ratios, and the output is a binary number. Thus the training data for fault 1 of the IEC

Standard in Table 2 (in oil) are $C_2H_4/C_2H_6 < 1$, $CH_4/H_2 < 0.1$, $C_2H_2/C_2H_4 < 0.1$, $3 < CO_2/CO < 11$, and the corresponding output value (O1) is 1 [3] [4]. For the training of this fault, the output corresponding to other faults is zero. In this study, one extra output value was used so that the fault location was determined simultaneously with the fault type. At least 10 training input and output sets were used to train the network for each fault in each standard, and a separate network were trained for each fault.

Each step in the ANFIS training process is called an epoch. When the training process reaches its maximum iteration (i.e., epoch = epoch max), the training process is complete. The epoch max should be large enough to allow the training process to converge to such an extent that the difference between the ANFIS output and 0 or 1 (the error) is less than 0.001.

2) The Testing Stag

The performance of the ANFIS method is evaluated for each fault in the standards. When ANFIS is trained through multiple iterations, the error may increase between successive iterations if the training data are noisy or the quantity of training data is insufficient. To overcome this problem, the performance of the ANFIS network is examined by using another set of gas chromatography data, called test data. The DGA test data are separate from the DGA training data and are used to verify the fuzzy inference model.

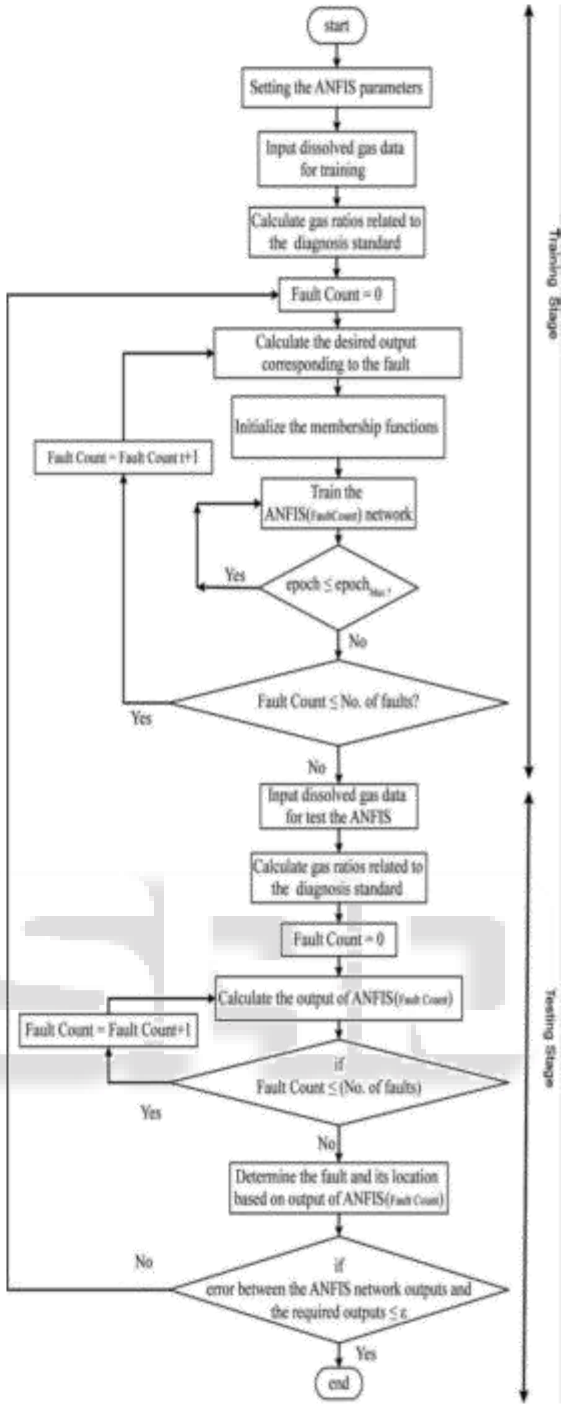

Fig. 3: The adaptive neuro-fuzzy inference system (ANFIS) flowchart based on dissolved gas analysis (DGA).

III. CONCLUSION

In this paper, we present an ANFIS algorithm based on classical standards for fault prediction in transformers. This study extends the diagnostic ability of the IEC, Rogers, and Doernenburg standards. A Sugeno training algorithm is used for the fuzzy inference systems. The ANFIS algorithm permits simultaneous diagnosis of fault type and fault location. It was applied to predict fault types in distribution transformers that the IEC, Rogers, and Doernenburg standards could not diagnose.

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