Power Transformer Interruption Analysis Based on Dissolved Gas Analysis (DGA) using Artificial Neural Network

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Abstract. The power transformer is an important component in the power system, as it is directly related to the reliability of the electric power system operation. Therefore, the diagnosis of disturbances in power transformers is important for device safety as well as electrical system stability. Dissolved Gas Analysis (DGA) is a disruptive diagnostic technique in power transformers that has been recognized effectively, because it provides knowledge of the state of the transformer based on the dissolved gas content in the transformer oil. The DGA test results can be represented by different methods such as Doernenburg ratio, Rogers ratio, IEC ratio, Duvals triangle, and key gases. The problem presented here is that two methods namely Doernenburg ratio and Rogers ratio, for the same data inputs give two different results from the error diagnosis to know the actual state of the transformer. In this paper, a combination method is proposed to solve the problem of conflict between Doernenburg ratio and Rogers ratio by utilizing multi-layer artificial neural network perceptron to localize and identify the error on the transformer and to select the most appropriate method.

1. Introduction
The power transformer is an important component in the electric power system [1], because it is directly related to the reliability of power system operation [2]. Therefore, the diagnosis of disturbances in power transformers is important for device safety as well as electrical system stability [3].

Dissolved Gas Analysis (DGA) is a disruptive diagnostic technique for power transformers that has been acknowledged effectively, because it provides knowledge of the transformer state based on dissolved gas content in transformer oil [4]. The DGA test results can be represented by different methods such as Doernenburg ratio, Rogers ratio, IEC ratio, Duvals triangle, and key gas [5].

However, the DGA method still has limitations mainly in the analysis and interpretation of dissolved gases which are not an exact science, but the subject of art for variability [6], and does not involve mathematical formulations and interpretations based on the method heuristics that vary so reliably [7]. To overcome these weaknesses, various computational models of artificial intelligence have been used such as artificial neural networks, expert systems, and fuzzy logic [8].

In a previous study using the neuro-fuzzy approach, it was concluded that most of the transformer faults could be attributed to the damage to its accessories. These accessories include bushing, load tap chargers, and cooling systems [9].

The problem presented here is that two methods namely the ratio of Doernenburg and Rogers ratios, for the same data inputs give two different results from the error diagnosis to know the actual state from
transformers [10]. In this paper, a combination method is proposed to solve the problem of conflict between the ratio of Doernenburg and Rogers ratios by utilizing multi-layer artificial neural network perceptron to localize and identify errors in the transformer and to select the most appropriate method.

2. Dissolved Gas Analysis
Transformer oil analysis is a useful and predictive maintenance to determine the health of the transformer. Along with the quality test of oil samples, the dissolved gas analysis (DGA) of the insulating oil is used to evaluate the health of the transformer. Details of electrical insulation materials and related components inside the transformer produce gas in the transformer. The resulting gas identity can be very useful information in the treatment program as well as the prevention of damage to the transformer [11].

There are several techniques for detecting dissolved gases in transformer oils and DGA has been recognized as the most informative method [4]. This method involves oil sampling and sample testing to measure the concentration of dissolved gases. Associations related to sampling standards, testing, and analysis of the results are ASTM D3613, ASTM D3612, and ANSI / IEEE C57.104.

The two main causes of gas formation in the transformer are electrical disturbance and thermal decomposition. All transformers produce gas to some extent at normal operating temperatures. The insulating oil for the transformer is a mixture of many different hydrocarbon molecules, and the decomposition process for these hydrocarbons in thermal or electrical failure produces complex chemical reactions involving breakdown of carbon-hydrogen and carbon-carbon bonds. During this process, active hydrogen atoms and hydrocarbon fragments are formed. These fragments may be combined with each other fragment to form gases such as: hydrogen (H2), methane (CH4), acetylene (C2H2), ethylene (C2H4), and ethane (C2H6). Furthermore, on insulation of cellulose / kraf paper in case of thermal decomposition or failure of electricity produces methane (CH4), hydrogen (H2), carbon monoxide (CO), and carbon dioxide (CO2). The gases listed above are generally referred to as key gases [11].

3. Artificial Neural Network (ANN)
Basically ANN is a machine designed to work in the same way as the human brain in performing certain tasks or functions of interest. Generally implemented by electronic components or simulation software on the computer. ANN generates computing power first through massively distributed parallel structures and the ability to learn and generalize. Generalization basically refers, when a reasonable output is generated for some input by ANN and input not found during the training process (Learning). Both capabilities of processing information for ANN allow to solve large-scale complex problems that are not currently trackable. MLP (Multi-layer perceptron) is used as one of the most widely used ANN structures for problem classification that has back propagation (BP) algorithm [10].

3.1. Multi-layer Perceptron (MLP) neural network
Multi-layer perceptron (MLP) basically consists of a finite number of consecutive layers or an organized network of layers, each of which has a limited number of processor units called neurons. Uniform groups of neurons with no connection to each other make the transformation vector. MLP is composed by an input layer, a number of hidden layers, and an output layer. In Figure 1 the network is fully connected using the sigmoid output function that has been considered because it is known that the number of these levels allows any decision-making area of any kind. In addition, MLP is the most popular method of ANN in pattern recognition [10].
MLP training often uses back-propagation algorithms consisting of forward pass and backward pass. Forward pass has a fixed value and equation (1) is a recurring thing used to get the output of all input layers. During the backward pass all values refer to the error correction equation.

\[ y_j^{(l)} = \Phi\left(v_j^{(l)}\right) = \Phi\left(\sum_{i=0}^{p} w_{ij}^{(l)} x_{ij}^{(l)}\right) \]  

(1)

Where:
- \( l \) = the layer number (\( l > 0 \)),
- \( y_j^{(l)} \) = the output of the \( j \)th neuron \( l \)th layer,
- \( v_j^{(l)} \) = the weighted sum of neuron’s input,
- \( x_{ij}^{(l)} \) = the \( i \)th input of the neuron,
- \( w_{ij}^{(l)} \) = the contribution weight of the \( i \)th input to the neuron,
- \( \Phi(…) \) = the activation function of the neuron.

The activation function is a fine non-linear function and can have various forms, such as the logistics function in equation (2) and the hyperbolic tangent function in equation (3).

\[ \Phi(v) = \frac{1}{1 + \exp(-av)} \]  

(2)

\[ \Phi(v) = a \tan h(bv) \]  

(3)

During the learning process (training), sample data must be represented to the network at random. Presents all the sample data to the network once called epoch. The number of epochs is usually required to train the network. The training ends when the quadratic error or system error is on average less than the predetermined value as the previous reference [3].

4. Fault Classification of Transformator by MLP ANN

4.1. Source of Training and Testing Date Collection

DGA method is implemented base on Multi-Layer Perceptron Neural Network with database, which consist of 37 samples actual gas taken from transformer Unit-2 in geothermal power plant Kamojang. The diagnostic outputs to the available proposed MLP ANN are: (1) no fault (NP), (2) partial discharge (PD), (3) discharge of low energy discharge (D1), (4) discharge of high energy discharge (D2), (5) thermal fault \( T<700°C \) (T1), (6) high temperature thermal fault \( T>700°C \) (T2).
4.2. Transformer Fault Diagnosis by Proposed MLP ANN Approach

The MLP ANN algorithm process is divided into two phases:

- Step 1: Training data generation: To simplifying the input variables for the MLP network.
- Step 2: Multi-Layer Perceptron Artificial Neural Network: The artificial neural network basically contains three processes that is training, validation and testing.

4.3. Implementation of Proposed MLP ANN Model

In this study, MLP ANN is used for fault identification of transformers on the MATLAB platform. While constructing MLP ANN, it is important to choose several essential parameters and a suitable transfer function for the correct classification. Selection of parameters and their corresponding values is shown in table 1.

| Name of parameters      | Value of parameters |
|-------------------------|---------------------|
| Neurons of input layer  | 4, 5, and 6         |
| The amounts of hidden layers | 1-2-3            |
| Neurons of hidden layer | 10                  |
| Neurons of output layer | 6                   |
| Transfer function       | Tangent sigmoid     |
| Epochs                  | 1000                |

In this process, the Doernenburg ratios, the Rogers ratios, and combined ratios are implemented using their corresponding input ratios. The tangent sigmoid function has been widely used in the past for solving complex problems. Structure of the MLP ANN consist of an input layer of which the number of neuron is equal to ratios used in the network, hidden layer (varied as one, two, and three) and an output layer for each output type.

5. Test Result and Discussions of MLP ANN Models

5.1. Rogers Ratios MLP ANN Model

The rogers ratios MLP ANN training model is developed using three inputs and all essential parameters is selected. Result obtained using this model at different hidden layers is shown in table 2.

| Number of hidden layer amounts | Output accuracy (%) |
|-------------------------------|---------------------|
| Single                        |                     |
| Two                           |                     |
| Three                         |                     |

5.2. Doernenburg Ratios MLP ANN Model

The four inputs, Doernenburg ratios MLP ANN training model is developed and all essential parameters is selected. Result obtained using this model at different hidden layers is shown in table 3.

| Number of hidden layer amounts | Output accuracy (%) |
|-------------------------------|---------------------|
| Single                        |                     |
| Two                           |                     |
| Three                         |                     |
5.3. Proposed Combined Ratios MLP ANN Model

To improve the performance of MLP ANN base DGA method, a proposed combined ratio of two methods that is Rogers and Doernenburg ratio used. Thus, the five ratios proposed combination models and essential parameters is selected. Result obtained using this model at different hidden layers is shown in Table 4.

Table 4. Percentage classification accuracy of MLP ANN combination ratios in proposed combined ratios MLP ANN model.

| Number of hidden layer amounts | Output accuracy (%) |
|-------------------------------|---------------------|
| Single                        |                     |
| Two                           |                     |
| Three                         |                     |

6. Conclusions

In this paper, for the purpose of incipient faults classification of power transformer, MLP ANN has been adopted. MLP ANN based DGA methods have been developed for the fault diagnosis on MATLAB platform. After comparing the performance of the proposed combined model of Rogers and Doernenbourg, it has been found that proposed combination ratio of MLP ANN model detects faults more accurately.

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