The Effectiveness of Neural Networks in Losses Prediction for Three-Phase Distribution Transformer

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Abstract— The objectives of this research were to develop and evaluate the effectiveness of neural networks in losses prediction for three-phase distribution transformer. The research procedures are (1) Data collection; (2) Model's creation; and (3) Training and testing of the Prediction Model. In this study, the value of effectiveness of losses prediction for three-phase distribution transformer (100 kVA 22000-400/230 V) was found using neural networks. The nodes in the hidden layer consisted of 3, 5 and 8 nodes with less variable and testing ranging from 1% - 100% at temperature of 30ºC for 10,000 sets. The 8,000 data sets were used to train, and the 2,000 data sets were used to test. The result of studying the effectiveness of losses prediction for three-phase distribution transformer found that the gradient values were equal to 31.1, 3.36 and 0.531. The mean squared error values were equal to 1.330, 3.610 and 0.966 respectively. Finally, the mean absolute percentage error values were equal to 0.1637, 0.798 and 1.437.

Keywords- Distribution Transformers, Losses Prediction, Neural Networks

I. INTRODUCTION

A Transformer is an electrical equipment used to change alternating current electricity. Also, it is an important tool for transmitting and distributing power supply. When a transformer is working, there is a waste called total losses, which consisted of core losses and copper losses. There are also many procedures and parameters relating to the design, which cause mistakes and consume time. In addition, the total losses involved in the material, temperature, resistant value, current, and voltage. These factors help evaluate the losses prediction, which is beneficial for designing a transformer according to the industrial standard (Tis no. 384-2543) or IEC 60076 Standard [1]

II. THE OBJECTIVE OF THE STUDY

1. Develop neural networks in losses prediction for three-phase distribution transformer.
2. Evaluate effectiveness neural networks in losses prediction for three-phase distribution transformer.

III. THEORY AND METHODOLOGY

In this study, the researcher used neural networks in losses prediction for three-phase distribution transformer. The detail of the study is presented as follows.

A. Losses Prediction for Transformer

Transformer efficiency can be improved by reducing electrical losses (P_T) which are composed of core loss (P_{Core}) and copper loss (P_{CU}) as following equation 1. [2]

$$P_T = P_{Core} + P_{CU} \tag{1}$$

1) Core losses

The core loss is defined as the power absorbed by the transformer when it is submitted to a voltage and frequency, being the circuit secondary in open that known as open circuit test. The open circuit test for 3-phase transformer is shown in Figure 1. The core loss (P_{Core}) is composed of hysteresis loss (P_H) and the eddy-current losses (P_E) as following equation 2. [3]

$$P_{Core} = P_H + P_E \tag{2}$$

The hysteresis loss is given by equation 3.

$$P_H = K_S \cdot B^{1.6} \cdot f \tag{3}$$

where K_S is the coefficient of core, B is the maximum flux density, and f is the frequency.

The eddy-current loss is given by equation 4.

$$P_E = K_e \cdot f^2 \cdot B^2 \cdot d^2 \cdot 10^{-3} \tag{4}$$

where K_e is a constant, d is the thickness of the laminated core, B is the maximum flux density, and f is the frequency.

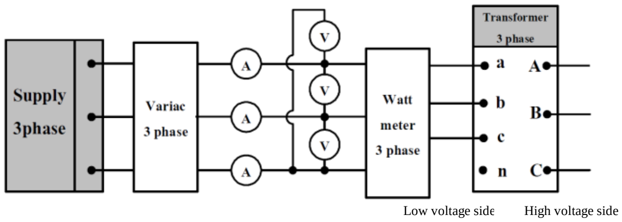

Figure 1. Open Circuit Test

2) Copper losses

Copper loss is the loss in a conductor depends upon its resistance and the square of the current it carries. The copper loss is defined as the power absorbed by the transformer when it is submitted to a much lower voltage than normal and frequency, being the circuit secondary in short which known as short-circuit test. [3]

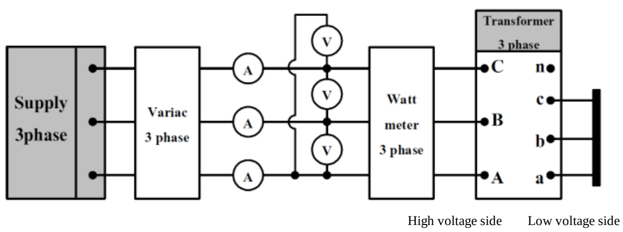

Figure 2. Short-circuit Test

Figure 2 shows a test to find the copper losses by short circuit test shown as following equation 5.

$$P_{CU} = 3\left(I_{HV}^2 \cdot R_{HV} + I_{LV}^2 \cdot R_{LV}\right) \quad (5)$$

Where R_{HV} is the winding resistance of the high- voltage coil, I_{HV} is the current of the high-voltage coil, R_{LV} is the winding resistance of the low-voltage coil, and I_{LV} is the current of the low-voltage coil.

Figure 3 and Figure 4 show the measuring of winding resistance by Wheatstone bridge with high accuracy. [4]

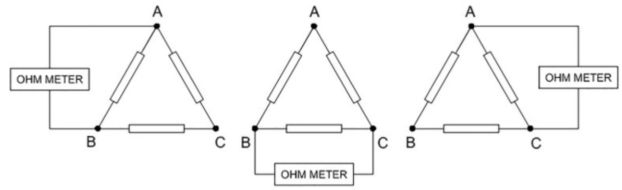

Figure 3. Measurement of winding resistance of the high-voltage coil (primary).

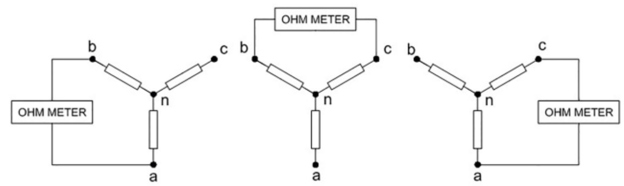

Figure 4. Measurement of winding resistance of the low-voltage coil (secondary).

The resistance of the coil in the high voltage side is shown as equation 6 and the low voltage side as equation 7.

$$R_{HV} = R/ph = \frac{3}{2}R_{WB(HV)} \quad (6)$$

$$R_{LV} = R/ph = \frac{3}{2}R_{WB(LV)} \quad (7)$$

Where R_{HV} is the resistance of the high voltage side (primary), R_{LV} is the resistance of the low voltage side (secondary), R_{WB} is the resistance measured by Wheatstone Bridge. [4]

Finding the required coil resistance, and coil temperature is shown in equation 8

$$R_r = R_a\left(\frac{235+\theta_r}{235+\theta_a}\right) \quad (8)$$

Where R_r is the require coil resistance at coil temperature (θ_r), R_a is the coil resistance at ambient temperature (θ_a).

B. NEURAL NETWORKS

Most neural network structures use some type of neuron. Many different kinds of neural networks exist, and programmers introduce experimental neural network structures all the time. Consequently, it is not possible to cover every neural network architecture. However, there are some commonalities among neural network implementations. An algorithm that is called a neural network will typically be composed of individual, interconnected units even though these units may or may not be called neurons. In fact, the name for a neural network processing unit varies among the literature sources. It could be called a node, neuron, or unit. A neural network does the same, as we can see in the following in Figure 3. [5]

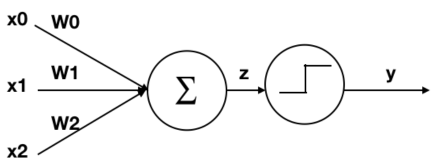

Figure 3 Neural Network Architecture

This is the mathematical model for a neural network architecture, represented as an explicit sum and as a matrix operation. The term $W^T x$ is the vectorized representation of the formula, where *W* is the weight matrix that is first transposed and is then multiplied by the vector of inputs, *x*.

To get a complete mathematical description, we should add a constant term, *b*, called the bias with the following equation 9. [6]

$$z = \sum_{i=1}^{n} W_i x_i + b = W^T x + b \tag{9}$$

C. Analysis Results

1) Mean Squared Error

The mean squared error (MSE) is a measure of the quality of an estimator. As it is derived from the square of Euclidean distance, it is always a positive value that decreases as the error approaches zero.

If a vector of *n* predictions is generated from a sample of *n* data points on all variables, and *Y* is the vector of observed values of the variable being predicted, with $\hat{Y}$ being the predicted values, then the within-sample MSE of the predictor is computed as equation 10. [7]

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{10}$$

2) Mean Absolute Percentage Error

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of prediction accuracy of a forecasting method in statistics. It usually expresses the accuracy as a ratio defined by equation 11. [8]

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{10}$$

where A_t is the actual value and F_t is the forecast value. Their difference is divided by the actual value A_t. The absolute value in this ratio is summed for every forecasted point in time and divided by the number of fitted points *n*.

IV. RESEARCH METHODOLOGY

Somsak Siriporananon, B.S. [4] determined losses prediction 5 input data, which consist of temperature (*T*), resistance of low voltage (R_{LV}), core loss (P_{Core}), low voltage current (I_{LV}), and magnetizing current (I_{Test}).

This research article uses only 4 input data, which consist of resistance of low voltage (R_{LV}), core loss (P_{Core}), low voltage current (I_{LV}), and magnetizing current (I_{Test}) as inputs to neural networks.

A. Data Collection

This research using data in three-phase distribution transformer, 100 kVA 22 kV-400/230 V were the data collected for 10,000 sets at the transformer manufacturer factory by setting the current flow from 1% to 100% at temperatures 30º C shown in Table I.

TABLE I. DATA COLLECTED FOR 10,000 SETS

No.	P_T (W)	I_{Test} (%)	I_{LV} (A)	P_{Core} (W)	RLV (mΩ)
1	240.3250387	1	1.443375673	240.2	10.55
2	240.700155	2	2.886751346	240.2	10.55
3	241.3253487	3	4.330127019	240.2	10.55
4	242.2006198	4	5.773502692	240.2	10.55
5	243.3259685	5	7.216878365	240.2	10.55
6	244.7013946	6	8.660254038	240.2	10.55
7	246.3268982	7	10.10362971	240.2	10.55
8	248.2024793	8	11.54700538	240.2	10.55
9	250.3281379	9	12.99038106	240.2	10.55
10	252.703874	10	14.43375673	240.2	10.55
9995	1377.947011	95	137.1206889	238.8	10.7011
9996	1402.055275	96	138.5640646	238.8	10.7011
9997	1426.415981	97	140.0074403	238.8	10.7011
9998	1451.02913	98	141.450816	238.8	10.7011
9999	1475.894721	99	142.8941916	238.8	10.7011
10000	1501.012755	100	144.3375673	238.8	10.7011

B. Create Model

Neural networks consist of 3 network layers, the input layer, hidden layer, and output layer. A hidden layer may have more than one layer as shown in Figure 4.

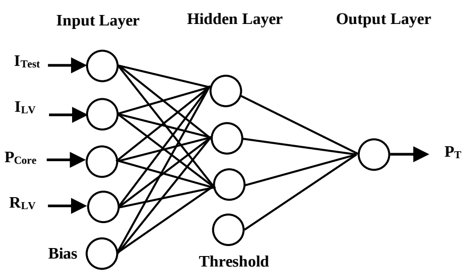

Figure 4 Model of Neural Network

C. Training and Testing of the Prediction Model

The data training process using neural networks identified the 5,600 sets of input data as shown in Table 1, and 1,200 sets of training targets. The training targets were divided into three sections. The first section was training, which accounted for 70% or 5,600 sets. The second section was validation, which accounted for 15% or 1,200 sets. The final section was testing, which accounted for 15% or 1,200 sets. After setting the sections, the next step was to set the network's structure. In this stage, number of hidden neurons was assigned as 3, 5, and 8. Then, the training called Levenberg-Marquardt Back Propagation (trainlm) was used. The average of Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) was used to assess the experiment.

V. RESULT

The experiment divided the input layer into 4 input counting from hidden layer to using feed-forward neural network. The Logsig in the hidden layer and feed-forward neural network, and the Linear in the output layer were set to have nodes in the hidden layer, which were 3, 5 and 8 nodes with the learning rate of 0.1, 80% of the training data sets, and 20% of the testing data sets. Furthermore, the target error value was set to 0.001. After the model's creation, the losses prediction current flows from 1% to 100%. Then, the model was evaluated its efficiency with the program. The result was shown in Table II.

TABLE II. THE RESULTS COMPARING THE EFFECTIVENESS OF NEURAL NETWORK IN LOSSES PREDICTION

Input Layer	Hidden Layer	Output Layer	Gradient	MSE	MAPE
4	3	1	31.1	1.330	0.163
4	5	1	3.36	3.610	0.798
4	8	1	0.591	0.966	1.437

The comparing results of the effectiveness of neural networks in losses prediction for three-phase distribution transformer were as follows. First, three nodes were in the hidden layer with the mean squared error equal to 1.330. Also, eight nodes were in the hidden layer with the mean squared error equal to 0.966, which was less than the prediction of five nodes in the hidden layer with the mean squared error equal to 3.6101.

The comparing results of the effectiveness of neural networks in losses prediction for three-phase distribution transformer were as follows. First, three nodes were in the hidden layer with the mean absolute percentage error equal to 0.163. In addition, five nodes were in the hidden layer with the mean absolute percentage error equal to 0.798, which was less than the prediction in eight nodes in the hidden layer with the mean absolute percentage error equal to 1.437.

VI. SUMMARIZE AND DISCUSSION

The results of the study are discussed as follows.

1) The losses prediction in this study chose only one variable, which was temperatures. In further study, other variables or factors affecting the losses prediction should be considered.

2) The program should be improved when the efficiency of the prediction decreases.

3) Since the model of prediction in this study might not be up-to-date and impractical in the future, the model should be updated and improved according to the modern world.

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