Analysis of Electrical Losses in Transformers using Artificial Neural Networks

N. Suttisinthong, and C. Pothisarn,

Abstract—**This paper proposes a technique to analysis electrical losses in distribution transformers 1-phase 30 kVA using of back-propagation neural networks (BPNN). Experimental data at various temperature of transformers obtained from manufacturer , are employed as an input pattern for BPNN while output pattern which corresponding to total losses in transformers. The total number of test set are 150 sets in order to verify the validity of the proposes technique. The results show that average accuracy obtained from the proposes technique gives satisfactory accuracy.**

***Index Terms*—Neural Networks, Transformer Loss, Power Transformer**

I. Introduction

DISTRIBUTION transformers is an important equipment of distribution system, for transfer electric energy by step up voltage or step down voltage in various for suitability with distribution system to users or industry. A resistance of copper in transformer winding which cause a power loss (even in a no-load condition) that effect to transformers. An important criteria for design transformers is guarantee the power losses within transformers are satisfactory. An analysis of total losses is relate with a copper loss, depend on parameters such as temperature, resistance, current, voltage, load and quality of copper. However, It's impossible to consider all factors that effect in transformers because the variation of load in power system. Considering total losses in transformer by using artificial neural networks (ANN) can calculate the electrical losses in transformers efficiency.

Recently, the application of ANN for transformer analysis is one of the most interested methods [1] – [11]. The advantages of trained ANN are fast assessment and high accuracy to solve the complicate problem. There are various classes of ANNs that suitable for solving difference problem. For solving the approximation problem, there are two classes of ANNs that suitable, Radial Basis Function (RBF) network and multi-layer feed-forward network. RBF's advantages are faster convergence and simple network structure coupled with easier control over network performance. However, RBF may require more training patterns to achieve a performance comparable to that of a multi-layer feed-forward network trained by back-propagation, when that happens to converge to a good solution [12]. In this paper, the multi-layer feed-forward neural network with back-propagation learning algorithm is used to calculate the total losses of transformer. Experimental data at various temperature of transformers obtained from manufacturer used to prepare training and testing pattern for neural networks.

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II. Electrical Loss

Electrical losses is a total losses in transformers, can a classify 2 types are copper loss and core loss.

A. Copper Losses

A short circuit test is a test for evaluate copper losses by a short circuit in low voltage side and distribute a voltage in high voltage side, copper losses calculation from (1).

$$P_{CU} = I_1^2 R_1 + I_2^2 R_2 \tag{1}$$

Where

P_{CU} : Copper losses (watt)

R_1: Resistance in primary side (Ω)

R_2: Resistance in Secondary side (Ω)

I_1 : Primary current (A)

I_2 : Secondary current (A)

A measurement resistance of copper made by the high accuracy bridge for a calculation copper losses and use to be temperature of copper test an increase temperature in transformer, resistance to reference temperature 75 °C for copper can calculate in equation (2).

$$R_r = R_a \frac{235+\theta_r}{235+\theta_a} \tag{2}$$

Where

R_a: Resistance of copper at temperature θ_a in steady state (Ω)

R_r: Resistance of copper at temperature θ_r in steady state (Ω)

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B. Core Losses

Open circuit test is a test for evaluate a core losses, It has an effect the hysteresis losses and eddy- current losses. Losses in core that a constant in every load conditon. Eddy current losses and hysteresis losses can calculate by equation (3) and (4) respectively

$$P_E = 2.22 f^2 B^2 d^2 \times 10^{-3} \tag{3}$$

$$P_H = K_S f \ B^{1.6} \tag{4}$$

Where

P_E: Eddy Current losses (watt)

f : frequency (Hz)

B : maximum flux density

d : laminate core density

P_H : Hysteresis losses (watt)

K_s: coefficient of steimmetz

f : frequency (Hz)

B : maximum flux density

Therefore, core losses to calculation by

$$P_{Core} = P_E + P_H \tag{5}$$

III. Decision Algorithm

In this paper, one hidden layers feed-forward neural network with Levenberg-Marquardt algorithm [13] is used to calculate the total losses of transformer. The input and output pattern for the ANN consist of 3 input variables and 1 output variable (the total losses of transformer), thus the number of neurons in input and output layers are 3 neurons and 1 neuron respectively. The number of neurons in the hidden layer of ANN was based on a sensitivity approach. Beginning with the minimum hidden neuron, the number is increased until maximum hidden neuron are found whilst checking occur at each step for the most appropriate structure for each group of training pattern (100 patterns for each temperature level). Each group of training patterns, there are the test current (Itest), temperature and copper losses used to trained ANN with tangent-sigmoid transfer function (6) in the hidden layers and linear transfer function (7) in the output layer. The output of ANN calculate by (8).

$$a(n) = \frac{1 - e^{-kn}}{1 + e^{-kn}} \tag{6}$$

$$a(n) = n \tag{7}$$

Where

k is a constant value.

$$\text{Output} = a^2\left\lfloor LW^{2,1} \times a^1\left(IW^{1,1} \times P + b^1\right) + b^2 \right\rfloor \tag{8}$$

Where

$IW^{1,1}$: Weights between input and the first hidden layer

$LW^{2,1}$: Weights between the first and the second hidden layers

b^1 : bias in the first hidden layer

b^2 : bias in the output layer

f^1 : activation function : tan-sigmoidf^2 : activation function : linear function

P = (P_1,P_2 … P_n) : input vector

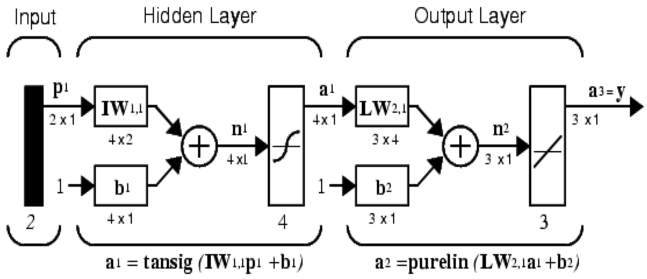

Fig. 1. Back-propagation neural networks structure

By an artificial neural networks make a calculate mean absolute percentage error : MAPE of test data which equation used calculate MAPE show in equation (9)

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\text{Real Result}_i - \text{Obtained Result}_i}{\text{Real Result}_i}\right] \times 100\% \tag{9}$$

Where

Real Result : real test value

Obtained Result : neural networks value

n : test data amount

Training of ANN used neural networks toolbox [13] of MATLAB. Figure 2. shows simulation of ANN for calculation the electrical losses in transformer. The input and output parameters of ANN are :

I_{test} : test value at current rated transformer 2-100%

T : temperature (◦C)

P_{CU} : copper losses (W)

P_t : total losses in transformer (W)

The number of training and testing data, the transformer test data in manufacturer at 35,,45 and 55 °C, are 100 and 50 sets respectively. The training process start with normalizing the training and testing data, random weight and bias and the beginning structure with 1 neuron in hidden layer then increase by 1 neuron until 15 neurons (to find the best structure), each structure is train for 20 cycles (each

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training cycle specify to adjust weight random and bias with 1000 iteration. Training process shows as flow chart in Figure 3.

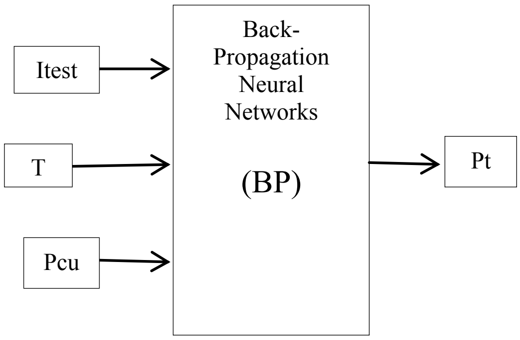

Fig. 2. Artificial neural networks simulation

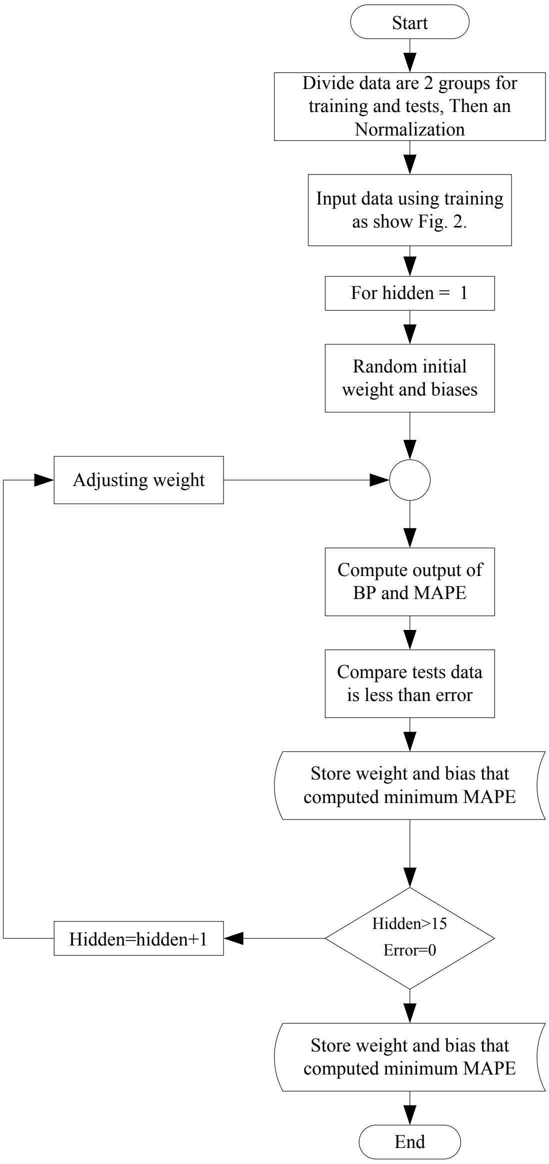

Fig. 3. Training Process.

IV. Experiment Results

After a training artificial neural networks for calculate electrical losses in transformer take artificial neural networks training to test with unseen test set 150 sets which change to temperature 35, 45 and 55°C respectively to be show in Fig. 4.

From Fig. 4 as show that when change to current rated (I_{test}) at temperature 35, 45 and 55 °C respectively. An electrical losses be similar to. From Fig. 5 as show that an error at 35 °C when change to copper losses as show that have an error less than 1 W. and when consider in Fig. 6 as show a percentage error when change to varied current rated. Regard with current rated in 2%-20% has an error more than varied current rated. However a percentage error to occur less than 1% which accept.

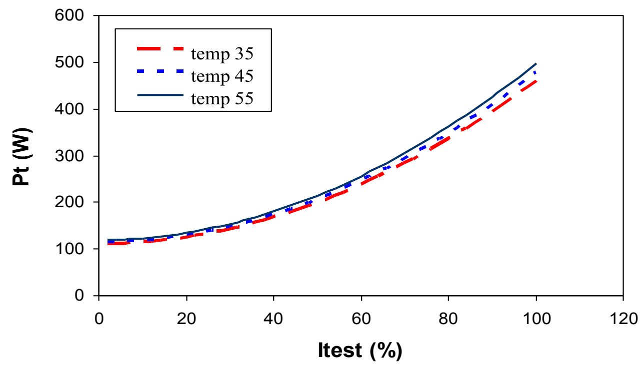

Fig. 4. Totol losses from artificial neural networks.

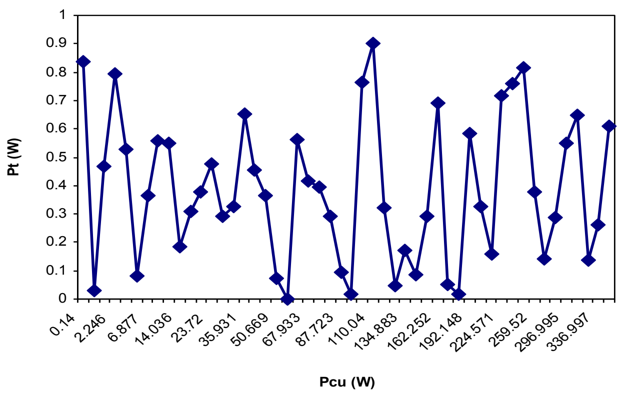

Fig. 5. Relationship between total losses in copper at 35°C.

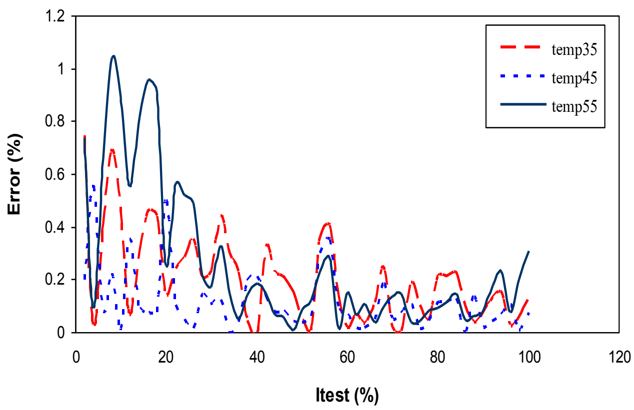

Fig. 6. Percentage error of test data 150 sets.

TABLE I. RESULTS OF LOSSES USING ARTIFICIAL NEURAL NETWORKS

Number of neurons in hidden layer	Times of training (Second)	MAPE Test (%)
1	19	0.1866
2	45	0.149
3	57	0.1341
4	67	0.1315
5	74	0.1321
6	81	0.1344
7	87	0.1317
8	91	0.1316
9	98	0.1386
10	110	0.1361
11	117	0.1373
12	128	0.1429
13	135	0.1404
14	142	0.1454
15	154	0.1412

V. CONCLUSION

This paper proposes an analysis electrical losses of distribution transformer single phase 30 kVA. Using back-propagation neural networks from an analysis used test data in manufacturer to training data 100 sets and test data 50 sets and test data using 150 sets at temperature 35 ,45 and 55 °C respectively as show in fig. 4-6. that accuracy be satisfiable by a maximum error is 1.2% received.

When a consider this paper, case studies as show that as well as effiency and high accuracy also artificial neural networks assist to analysis total losses in transformer together with applied this present with large transformer to development in the future.

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