Application of Artificial Neural Networks in Evaluation and Identification of Electrical Loss in Transformers According to the Energy Consumption

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Abstract: - The paper describes a novel neural model to estimate electrical loss in transformer according to the energy consumption (load curve). The network acts as identifier of structural features on electrical loss process, so that output parameters can be estimated and generalized from an input parameter set. The model was trained and assessed through experimental data taking into account core loss, copper loss, active power, reactive power, residential load factor, commercial load factor and time. The results obtained in the simulations have shown that the developed technique can be used as an alternative tool to make the analysis of electrical losses on distribution transformer more appropriate regarding to energy consumption. Thus, this research has led to an improvement on the planning of the electrical system.

Key-Words: - Transformer, losses identification, neural networks, energy consumption, load factor, load demand.

1 Introduction

The real necessity of reduction in electrical loss in the power system is associated with the growing demand for reliable and flexible power supply systems and the willingness for optimized network operation in both normal and emergency conditions, taking into account not only the hourly loading of transformer but also the kind of customers, have been the main motivation this paper.

Nowadays, the companies that produce distribution transformer are concerned mainly about electrical loss because it represents not only technical but also financial damages. In this context, the electrical loss constitute one of the most important parameters of transformer quality [1].

One critical requirement in designing transformers is to guarantee that the power dissipated in the transformer remains within an acceptable level. Power losses within transformers are generally classified in two types: core and copper losses.

It is essential to comment that the total loss in a transformer has been calculated by combination of core loss and cooper loss [2]. However, the cooper loss represents approximately 60% of the total loss in transformer.

Typically, electrical loss analysis related to the copper loss depend on the relationship among several parameters, such as temperature, current, tension, load and copper quality. These factors are taken into account during the transformer design stage. However, it is not possible to consider all these factors to model the thermal effect in transformers in the system due to the changing of load demand during part of the day, which depends on load features: residential, commercial or industrial.

Most of the methods used to determine transformer electrical loss are in general the ones proposed by standards organization. They have been based both on current graphs and table as well on former measurements [3]. Hence, this way is very difficult to establish the relationship among the parameters involved in the production process that expresses analytically the transformer electrical loss according to the energy consumption.

In this sense, it is crucial to estimate and to identify loss transformer by customers daily load patters.

Considering this problem, the mapping of electrical loss in transformers through Artificial Neural Networks (ANN) can be seen as an efficient tool to provide alternatives to the conventional methodologies, generating attractive results, mainly due to the intrinsic characteristics of the technique, such as the ability to automatically learn relationships between inputs and outputs independently of the size and complexity of the problem, generalization capacity and integration facility with other computational tools.

For this purpose, the present paper is organized as follows: In Section 2, it is presented the problem formulation. The Section 3 introduces some basic foundations of artificial neural networks. In Section 4, the neural approach used in the proposed methodology is presented. The Section 5 provides the simulation results obtained by the presented technique. Finally, the key issues raised in this paper and the conclusions drawn are presented in Section 6.

2 Problem Formulation

The rational use of energy demands a steadily following up on loss transformer in certain periods of the day to improve the performance of the electrical system. In this sense, it is essential to identify the behaviour related to the losses in transformers considering customers profile, too.

The development of this kind of study requires remarkable knowledge in the influence of some factors, such as copper loss, core loss, load factor, power factor, so on, to each kind of customer and a part of the day. These factors are described as follow:

2.1 Copper loss

Copper loss is equal to the sum of the squares of the currents multiplied by the resistances of the various windings. As the currents are fixed by the rating, it is evidently impossible to reduce their values in order to reduce the I^2R loss (Joule effect).

The only factors, therefore, which may be varied by designs in order to reduce the loss to a minimum are the resistances of the various windings. The resistances should be reduced to a minimum, and to do this it is evident that the total sections of the conductors should be as large as possible, and their total lengths as small as possible. While to increase the section of the conductors certainly reduces the resistance and consequently the I^2R loss, it also tends to increase the frame size, and therefore the loss in the magnetic circuit [3].

For single phase transformer the copper loss is given by:

$$W_j = R_1 I_1 + R_2 I_2 \tag{1}$$

where W_J is the copper loss (Watts), R_1 is a primary resistance, R_2 is secondary resistance, I_1 is a primary current and I_2 is a secondary current.

2.2 Core loss

The core loss or iron loss constitutes one of the main parameters for determining the transformer quality. Typically, this kind of loss has not suffered significant changes during a period of the day because it does not depend on the load system, its performance is strictly related to the quality of the material (iron) used in the project.

In this paper it was verified that core loss remains almost constant during most of time because the tension was varied slightly over a daily period.

2.3 Load Factor

The load factor has been used to verify if the electrical energy has been consumed rationally.

A high load factor (around 1) indicates that electrical charges were used rationally during a period. On the other hand, a low load factor indicates that there was a concentrated length of time.

Load factor is given by:

$$Fc = \frac{C}{D} \tag{2}$$

where Fc is the load factor, C is the consumption (kWh) and D is the demand (kW).

Improving the load factor demands some changing in the typical load, more specifically to commute certain loads that contribute to compose peaks to less concentrated of charge consumption.

2.4 Power Factor

Power factor indicates the efficiency degree of electrical system. It is important to mention that high values of power factor (around 1) show the efficient use of electrical energy while the low values stands out its bad performance, besides representing overload in the whole electrical system not only of customers but also of the utilities. Power factor is given by:

$$Fp = \frac{P}{S} \tag{3}$$

where P is the active power (kW) and S is the total power (kVA)

3 Foundations of Neural Networks

The ability of Artificial Neural Networks (ANN) in mapping functional relationships has become them an attractive approach that can be used in several types of problem [4]. This characteristic is particularly important when the relationship among the process variables is non-linear and/or not well defined, and thus difficult to model by conventional techniques.

An artificial neural network is a dynamic system that consists of highly interconnected and parallel non-linear processing elements that shows extreme efficiency in computation.

The main benefits of using ANN's on the electrical loss processes are the following: the ability of learning and therefore generalization; the facility of implementation in hardware; the capacity of mapping complex systems without necessity of knowing the eventual mathematical models associated with them.

In this paper, artificial neural networks of the type Multilayer Perceptron has been used to map the relationship among the electrical loss of the transformers in relation to the several variables that indicate the features to loss process.

A typical feedforward ANN is depicted in Figure 1, with *m* inputs and *p* outputs, and each circle representing a single neuron. The name feedforward implies that the flow is one way and there are not feedback paths between neurons. The output of each neuron from one layer is an input to each neuron of the next layer.

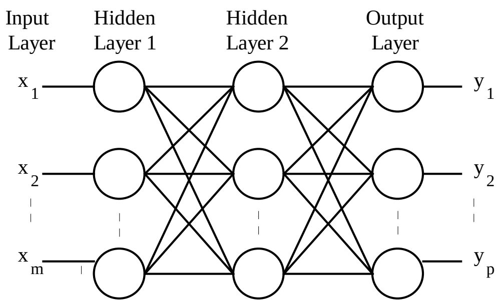

Fig. 1. Typical feedforward ANN

The initial layer where the inputs come into the ANN is called the input layer, and the last layer, i.e., where the outputs come out of the ANN, is denoted as the output layer. All other layers between them are called hidden layer.

Each neuron can be modeled as shown in Figure 2, with *n* being the number of inputs to the neuron. Associated with each of the *n* inputs x_i is some adjustable scalar weight, w_i (i=1,2,...,n), which multiplies that input. In addition, an adjustable bias value, *b*, can be added to the summed-scaled inputs.

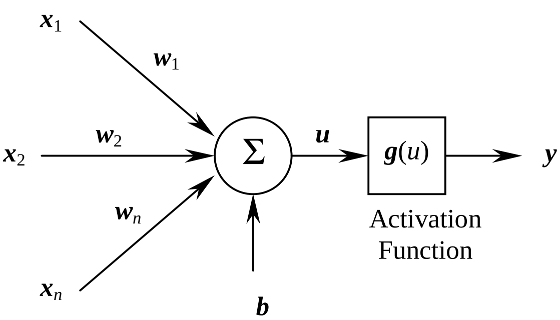

Fig. 2. Single artificial neuron

These combined inputs are then fed into an activation function, which produces the output *y* of the neuron, that is:

$$y = g(\sum_{i=1}^{n} w_i x_i + b) \tag{4}$$

where *g* is a sigmoid function defined by:

$$g(u)=(1+e^{-u})^{-1} \tag{5}$$

The training process of the neural network consists of the successive presentations of input-output data pairs. The basic structure having one hidden layer has been shown to be powerful enough to produce an arbitrary mapping among variables.

During the training, the data are propagated forward through the network, which adjusts its internal weights to minimize the function cost (weighted squared deviation between the true output and the output produced by the network) by using the back-propagation technique.

The detail of the derivation of the back-propagation algorithm is well known in literature and its steps can be found in [5].

A review of the main steps of the algorithm is presented here. The function to be minimized is the sum of the average squared error (E_{AV}) of the output vector,

$$E_{AV} = \frac{1}{N}\sum_{k=1}^{N} E(k) \tag{6}$$

where *N* is the number of training points and *E*(*k*) is the sum of squared errors at all nodes in the output layer, i.e.,

$$E(k) = \frac{1}{2}\sum_{j=1}^{p} (d_j(k) - y_j(k))^2 \tag{7}$$

For an optimum weight configuration, *E*(*k*) is minimized with respect to the synaptic weight *w*, so that for each data set,

$$\frac{\partial E(k)}{\partial w_{ji}^{l}} = 0 \tag{8}$$

where *w* is the weight connecting the neuron *j* of the *l*-layer to neuron *i* of the (*l* – 1)-layer.

Finally, the weights of the network are updated using the following relationship:

$$w_{ji}^{l}(k+1) = w_{ji}^{l}(k) - \eta \frac{\partial E(k)}{\partial w_{ji}(k)} \tag{9}$$

where η is a constant that determines the rate of learning of the back-propagation algorithm.

4 The Neural Approach

An Artificial Neural Network (ANN) of the type Multilayer Perceptrons is employed for the identification electrical loss of the transformer according to customers.

The variables that compose each input vector of the network are defined by those variables that indicate the loss of the transformer. These variables are identified as follows:

- T is the time (HR).
- F_R is the residential load factor.
- F_C is the commercial load factor.
- L_0 is the core loss (kW).
- L_C is the copper loss (kW).
- L_R is the reactive load (MVAR).

The output vector of the neural network has been composed by a unique variable, which represents the total loss (W) of the transformer. The neural architecture used to estimate the (W) of transformers is shown in Figure 3.

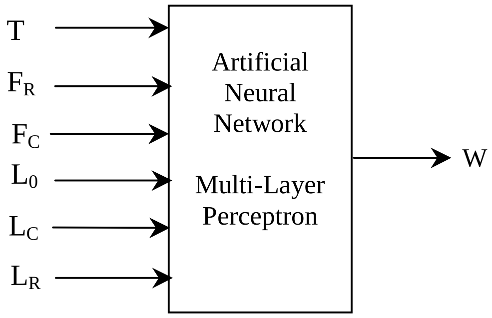

Fig. 3. General architecture of the ANN

The net training is made by the algorithm of Levenberg-Marquardt [6] with training data obtained from [7].

To evaluate the developed architecture, some preliminary tests were accomplished as following:

- Data set Training: 150
- ANN Topology:
- Architecture: Multilayer Perceptron
- Number of Hidden Layers: 1
- Number of Neurons of the hidden Layer: 5
- Mean Square Error: 1.520
- Mean Relative Error (test pattern): 1.5784

5 Results and Discussions

In this section, some preliminary simulations results and discussions are presented to illustrate the application of the neural network approach developed to solve electrical loss problems in transformers.

Figure 4 shows the behaviour of the losses system related to the three different values of commercial factor. These losses have been reflected by electrical losses.

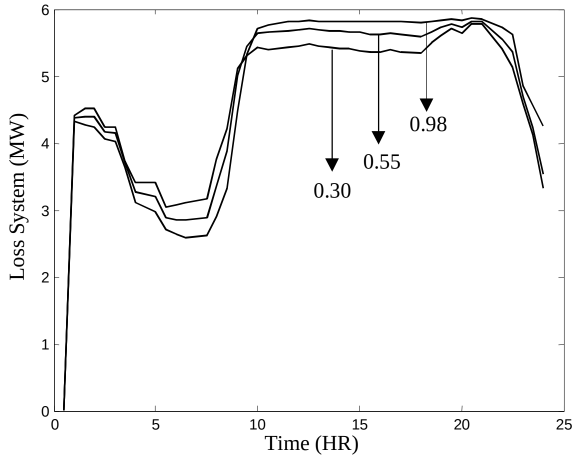

Fig. 4. Variation of commercial factor

Observing Figure 4 it is possible to notice that there is a higher concentration of losses (maximum losses) between 10 a.m. until at about 10 p.m.. However, it is also possible to verify that there is a variation of losses for each correspondent load factor. Then, the identification of best condition to achieve the least loss into the system, is made by changing the load factor once. It is difficult to have this kind of sensibility using the traditional tools or through of the load curve.

Figure 5 shows the behaviour of the loss system related to the three different values of residential factor.

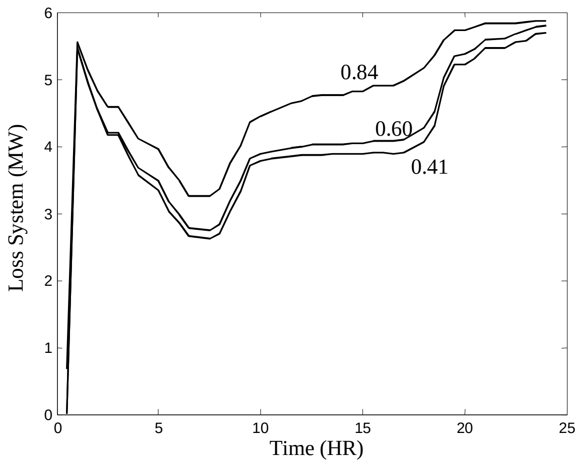

Fig. 5. Variation of residential factor

Observing Figure 5 it is possible to notice the behaviour of maximum losses during a shorted gap of time when it is compared to the commercial load. In this case the losses variation is quite significantly to small variation of the load commercial one what leads it towards to smaller losses.

Figure 6 shows the behaviour of the loss system related to the three different values of reactive load (0.8 MVAR, 1.6 MVAR and 2.6 MVAR).

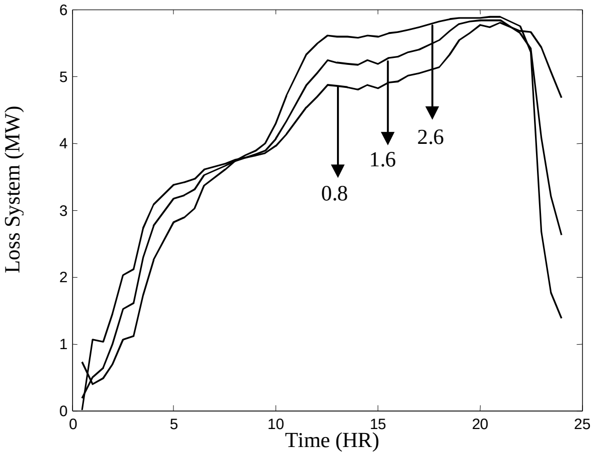

Fig. 6. Variation of reactive loss

Observing Figure 6, it allows to deduce that there is a direct relationship between the reactive load and system loss.

The almost nonlinear behavior verified on Figure 6 when compared with the other cases evidence that the loss system has been accumulative during the period studied.

Another remarkable aspect is that using neural approach it is possible identify the ratio where the loss system variation has been maximum during a period to different values of the reactive load.

This kind of situation would not be identified through traditional mathematical tools, proving that this process is very complex.

From Table 1, it is observed that the proposed neural approach provides results near to real values. The meaning relative error is acceptable.

Table 1 Relative error rate (%) of the system loss.

Measurements (MW)	ANN (MW)	Relative Error (%)
3.00	2.954	1.532
2.35	2.380	1.289
4.30	4.147	3.551
4.90	4.907	0.432
5.70	5.778	1.375

The achieved relative error rate under 1.57% demonstrates that ANN has succeeded in generalize the data that have not been supplied to the network.

All these results confirm that problems involving identification of the system loss in transformer considering the energy consumption can be effectively mapped by artificial neural networks.

6 Conclusions

In this paper, the artificial neural networks of the type Multilayer Perceptron has been used to map the relationship between the electrical loss in transformers in relation to the several variables that indicates the features to loss process and according to the energy consumption.

Artificial neural networks were considered within its context of identification of the systems loss process.

The training of the neural networks has been made using data obtained from [7]. After the training, the network was able to generalize novel inputs that were not simulated. This property allows to verify if the electrical energy has been consumed rationally.

The preliminary results obtained in the simulations show that the developed technique can be used as an alternative tool to become more appropriate to improvement on the planning of the electrical system.

Acknowledgement

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