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A Neural Network Based Method for Cost Estimation 63/20kV and 132/20kV Transformers

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ABSTRACT

Power transformers are one of the most important components in electrical network which has a vital role in electrification. Large numbers of transformers are required while expanding the electrification. In initial steps of evaluating project, having an estimated cost in short time can be beneficial. Around 15% of investment in transmission system goes towards transformer and since the major amount of transformers costs is related to its raw materials, cost estimating process can be an issue of crucial importance.

In this paper, a new method is presented to estimate transformers pricing. In order to this aim, a unique Multi-Layer Perceptron (MLP) neural network has been designed for two various types of 63/20kV and 132/20kV transformers in Iran. In the next stages the cost of the transformer is estimated, finding suitable coefficients for the weight of copper, iron, transformer oil (that are MLP neural network outputs) and a constant coefficient that is related to manpower cost and other components of transformer costs. The requirement training data for MPNN are the obtained from the transformers made by Iran-Transfo Company during last 4 years.

KEY WORDS: Artificial Neural Network (ANN), Back Propagation (BP), cost estimating, power system, transformer design.

INTRODUCTION

The transformers are one of the most important components of the power systems, which have a vital role in transmission and distribution of electrical power. The same way that continuous performance of transformers is necessary to retain the network reliability, forecasting its costs is also important for manufacturer and industrial companies. In initial steps of evaluating project, having an estimated cost of a short period is useful, but evaluating initial costs, by customary method is a time-consuming process. Progresses in design, manufacturing and costs estimating of transformer have been surveyed in various studies [1-6].

Designing a transformer is carried out to access all dimensions, based on the desired characteristics, available standards, and access to lower cost, lower weight, lower size and a better performance. Various methods have been studied and some techniques such as geometric programming [1], simulated annealing technique [2], genetic algorithm, finite element method [3], neural network [4], and some other new techniques [5-6] were performed to design a transformer. The major amount of transformer's costs is related to its raw materials. Thus, row materials play an extremely pivotal role in costs estimating process.

In recent years, neural network have quite often been used in the field of transformers design. Determining insulation aging [7], and the time left from life of transformers oil [8], estimation of transformers oil parameter [9], transformers protection [10], and core wire choice in order to reduce the cost [11] are few topics that has been carried out.

In this paper, a new method is introduced to estimate transformers costs by means of Artificial Neural Network (ANN) and based on data that were extracted from one transformer manufacturer (IRAN-TRANSFO Co.). In order to this, a unique Multi-Layer Perceptron (MLP) neural network has been designed for two various types of 63/20kV and 132/20kV transformers in Iran and the cost of the transformer is estimated finding suitable coefficients for the weight of copper, iron and transformer oil (that are MLP neural network outputs) and a constant coefficient that is related to manpower cost and other components of transformer costs. Then, artificial neural networks are revised, then the ANN configuration is applied and it has been trained using the data of IRAN-TRANSFO Co for estimating transformer costs. Finally, resulted outputs of trained neural network are presented which will prove the accuracy of price estimation and consumed material.

ARTIFICIAL NEURAL NETWORK (ANN)

ANN Structure

A neural network is determined by its architecture, training method, and exciting function. Architecture, determines the pattern of connections among neurons. Network training changes the values of weights and biases (network parameters) in each step in order to minimize the mean square of output error. Since feed-forward neural networks or Multi-Layer Perceptron (MLP) ANNs is used in engineering applications such as load forecasting, nonlinear control, system identification, and pattern recognition [12-13], thus in this paper, multi-layer perceptron network (with four

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inputs, three outputs and a hidden layer) with back-propagation training algorithm is used. Since, this method is based on error gradient method, differential function is used. Thus, differentiable functions like Sigmoid, hyperbolic tangent must be used and in this case nonlinear sigmoid transformation function is used. Fig. 1 shows the MLP network that is used in this study.

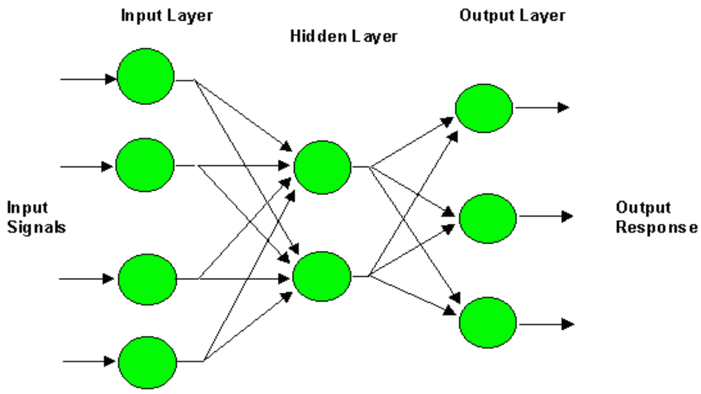

Fig. 1. Artificial Neural Network

Input and Output of ANN

The required data are the data which have been accumulated by IRAN-TRANSFO Co. in last four years, and are used for estimating the iron, copper, and oil weight of transformers and consequently transformer costs are estimated by the proposed method (in various installation height and temperature with different short-circuit impedance and volt per turn). The schematic of the presented method can be shown by Fig. 2.

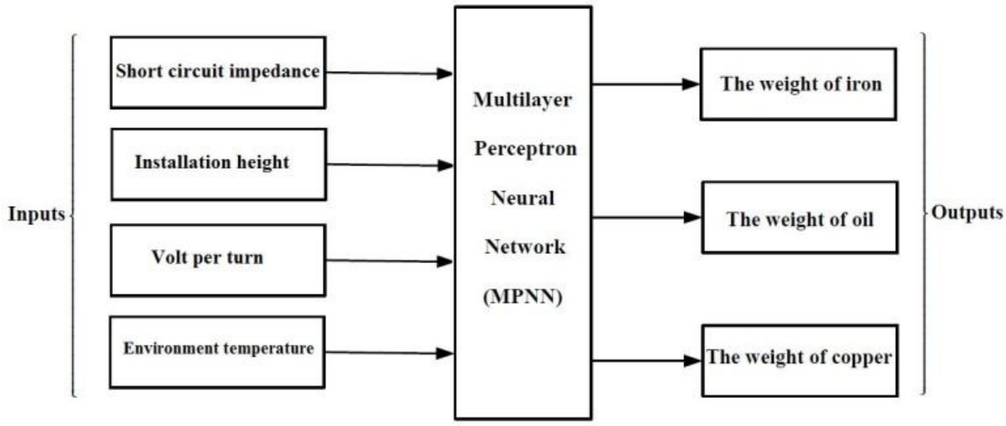

Fig. 2. Schematic of Inputs and Outputs

Training of ANN

In order to train a neural network we need data for training. The last four years transformer data obtained from IRAN-TRANSFO Co. is used. These data for the transformers 63/20kV and 132/20kV are shown in the Tables II, III and IV, V respectively.

An Artificial Neural Network MLP-Multi Layer Perceptron with back-propagation (BP) method can be used for reaching this goal. To determine weights and biases of neural network, a number of a different data are needed to learn the network. In table I structure of neural network and it training parameter are shown.

TABLE I
ARCHITECTURE OF ANN AND TRAINING PARAMETERS

Architecture of ANN The number of layers	3
The number of neuron on the layers	
Input	4
Hidden	2
Output	3
The initial weights and biases	Random
Activation functions	Sigmoid
Training parameters Learning rule	back-propagation
Learning rate	0.01
Momentum constant	1
Mean squared error	1e-4

BP FORMULATION FOR TRANSFORMER

With the help the artificial neural network of multi-layer perceptron with back propagation algorithm, a hidden layer is used for weight estimation of transformer's iron, oil, copper as shown in Fig. 1. Relation of multi layer perceptron, by back propagation algorithm is as following in equation (1)-(7):

1. Supremacy Path

$$a_o(k) = P(k) \tag{1}$$

$$\begin{gathered} a_{m+1}(k) = f_{m+1}(W_{m+1}(k)a_m(k) + b_{m+1}(k)) \\ m = 0,1,\ldots,M-1 \end{gathered} \tag{2}$$

$$a(k) = a_M(k) \tag{3}$$

2. Back Path

$$e(k) = t(k) - a(k) \tag{4}$$

$$S_M(k) = -2f'_M(n_M(k))e(k) \tag{5}$$

$$\begin{gathered} S_m(k) = f'_m(n_m(k))(W_{m+1}(k))^T S_{m+1}(k) \\ m = M-1, M-2,\ldots,2,1 \end{gathered} \tag{6}$$

3. Adjustment Parameters

$$\begin{cases} W_m(k+1) = W_m(k) - \alpha S_m(k)(a_{m-1}(k))^T \\ b_m(k+1) = b_m(k) - \alpha S_m(k) \end{cases} \tag{7}$$

$$m = 1,2,\ldots,M-1,M$$

Where, P is input vector, T is output vector, M is the number of network layers and S is vector of system's sensitivity. It can be concluded that M=3 and in hidden layer of sigmoid function is as the following equation (8):

$$sig(n) = \frac{1}{1+e^{-cn}} \tag{8}$$

Where, C's value was chosen to be 1, and motive sigmoid function was considered linear, in equation (9):

$$lin(n) = n \tag{9}$$

SIMULATION

For network learning, some input vectors (P) and some output vectors (t) are needed. Simulation is performed as in the following cases considering extracted data that is related to the two various types of 63/20kV and 132/20kV transformers from IRAN-TRANSFO Co..

CASE STUDY I: Transformer 63/20kV

Table II and III are present 25 input vector and 25 output vector that are used for network learning.

TABLE II
INPUTS FOR TRASFORMER 63/20 kV

Inputs	Short circuit impedance percent	Installation height	Volt per turn	Environment temperature
P_1	8	1000	87.719	50
P_2	10	1000	76.336	55
P_3	10	1000	84.034	50
P_4	10	1000	60.79	50
P_5	10	1000	68.027	45
P_6	12	1500	68.027	40
P_7	12	2200	54.795	40
P_8	12.5	1364	99.502	50
P_9	12.5	1500	54.201	40
P_{10}	12.5	1500	67.34	40
P_{11}	12.5	1500	76.923	50
P_{12}	12.5	1500	86.207	45
P_{13}	12.5	1500	106.952	45
P_{14}	12.5	1700	97.087	45
P_{15}	12.5	1900	49.948	39
P_{16}	13	2000	66.67	50
P_{17}	13.5	1000	79.94	47
P_{18}	13.5	1500	75.76	45
P_{19}	13.5	1500	75.785	40
P_{20}	13.5	1700	37.88	40
P_{21}	13.5	1700	47.17	55
P_{22}	13.5	1700	66.007	42
P_{23}	13.5	2000	46.62	50
P_{24}	13.7	1500	75.753	55
P_{25}	14	1000	121.212	45

TABLE III
OUTPUTS FOR TRANSFORMER 63/20 kV

Outputs	Weight of Iron	Weight of Oil	Weight of Copper
t_1	31200	13500	7700
t_2	25600	11500	7770
t_3	27000	11400	7094
t_4	22100	8500	7000
t_5	22700	9900	6894
t_6	24000	10600	8000
t_7	15100	7500	4124
t_8	38000	18000	11720
t_9	15250	7700	8667
t_{10}	22400	10300	6891
t_{11}	30160	13700	10000
t_{12}	30800	14520	9120
t_{13}	45470	19000	14850
t_{14}	33200	14100	9765
t_{15}	17450	8800	6600
t_{16}	25562	11820	9700
t_{17}	28750	11850	8950
t_{18}	27500	11100	9500
t_{19}	25600	10630	7387
t_{20}	9500	7250	2780
t_{21}	16700	8900	6300
t_{22}	27000	12250	8479
t_{23}	15550	8550	5199
t_{24}	25400	12300	7550
t_{25}	53100	25500	17450

After learning each network and converging of all weights and biases, each of weights and biases of proposed network layer will be as the following. The converging value of the network is considered to be $\alpha = 0.01$.

$$W_1 = \begin{bmatrix} 7.4733 & -0.2554 & 44.9077 & 26.0491 \\ 9.9807 & -4.3346 & 105.7249 & 36.3415 \\ 39.2733 & 4.7433 & 113.1023 & 47.4160 \\ 7.0358 & 0.6368 & 44.4176 & 25.6579 \end{bmatrix}$$

$$W_2 = \begin{bmatrix} 16.6983 & 16.8123 & 41.5289 & 16.5226 \\ 3.0072 & 22.3003 & 3.1627 & 2.9944 \end{bmatrix}$$

$$W_3 = \begin{bmatrix} 15.0497 & 25.7060 \\ 4.3241 & 12.3528 \\ 3.1704 & 8.7594 \end{bmatrix}$$

$$b_1 = \begin{bmatrix} -7.3453 \\ -16.2992 \\ -12.3578 \\ -7.2830 \end{bmatrix} \quad b_2 = \begin{bmatrix} -2.1148 \\ -4.4492 \end{bmatrix} \quad b_3 = \begin{bmatrix} 10.9421 \\ 6.9762 \\ 4.7545 \end{bmatrix}$$

The learning curve is shown in Fig. 3. In this figure mean squared error decreasing by increasing the number of repeats is illustrated.

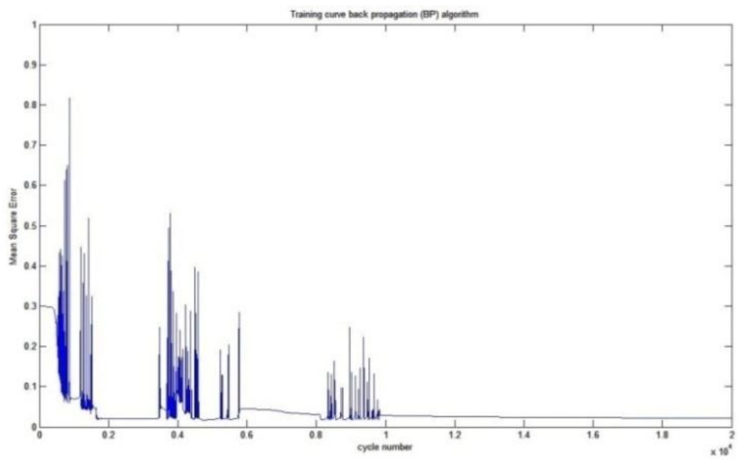

Fig. 3. Mean Square Error

CASE STUDY II: Transformer 132/20kV

In table IV and V, 20 input vector and 20 output vector that are used for network learning.

TABLE IV
INPUTS FOR TRASFORMER 132/20 kV

Inputs	Short circuit impedance percent	Installation height	Volt per turn	Environment temperature
P_1	11.5	1000	79.635	52
P_2	12	1000	106.383	50
P_3	12	1000	120.043	48
P_4	12	1000	130.36	48
P_5	12.5	1000	60.606	50
P_6	12.5	1000	87.858	48
P_7	12.5	1000	97.777	48
P_8	12.5	1350	88.106	40
P_9	12.5	1350	90.09	40
P_{10}	12.5	1500	44.15	45
P_{11}	12.5	1500	60.423	45
P_{12}	12.5	1500	98.039	45
P_{13}	12.5	1500	116.279	40
P_{14}	12.5	1700	90.909	45
P_{15}	12.5	1700	114.286	45
P_{16}	12.5	2000	91.05	40
P_{17}	13.5	1000	105.8	50
P_{18}	14	1000	80.829	48
P_{19}	16	1000	151.554	48
P_{20}	17	1000	168.394	48

TABLE V
OUTPUTS FOR TRANSFORMER 132/20 kV

Outputs	Weight of Iron	Weight of Oil	Weight of Copper
t_1	26700	14100	6900
t_2	43700	16700	10184
t_3	49200	22650	13120
t_4	54300	29000	13800
t_5	18500	11250	4700
t_6	32700	20700	8570
t_7	40000	22000	12000
t_8	27500	15480	6910
t_9	15400	15400	8877
t_{10}	13500	11500	2755
t_{11}	18000	11800	4567
t_{12}	34300	15950	8900
t_{13}	47350	22850	13000
t_{14}	28800	15500	6725
t_{15}	38750	16500	9750
t_{16}	29250	15500	6730
t_{17}	43000	20000	12200
t_{18}	33680	21050	9700
t_{19}	66330	31050	16500
t_{20}	80350	37500	22670

After learning each network and converging of all weights and biases, each of weights and biases of proposed network layer will be as the following. The converging value of network has been considered to be $\alpha = 0.01$.

$$W_1 = \begin{bmatrix} -2.7499 & 0.7275 & -20.3354 & -17.4651 \\ 4.8489 & -3.8294 & 44.5921 & 33.1134 \\ 2.2035 & 0.9106 & 28.6825 & 11.8429 \\ 0.0209 & 1.6786 & -25.5563 & -19.8255 \end{bmatrix}$$

$$W_2 = \begin{bmatrix} 4.9226 & -22.6422 & -8.9358 & 3.9326 \\ -6.3882 & 1.8057 & 6.9438 & -9.0265 \end{bmatrix}$$

$$W_3 = \begin{bmatrix} -29.6329 & 57.7119 \\ -8.2798 & 27.8681 \\ -7.7906 & 15.8360 \end{bmatrix}$$

$$b_1 = \begin{bmatrix} 0.4064 \\ -8.5438 \\ -6.5073 \\ 1.1257 \end{bmatrix} \quad b_2 = \begin{bmatrix} 0.2839 \\ -2.0211 \end{bmatrix} \quad b_3 = \begin{bmatrix} 42.7250 \\ 19.7424 \\ 11.3507 \end{bmatrix}$$

The learning curve is shown in Fig. 4. In this figure mean squared error decreasing by increasing the number of repeats is illustrated.

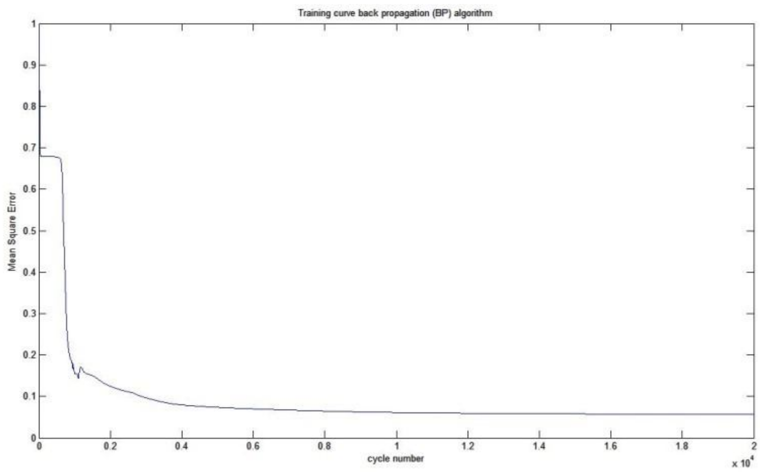

Fig. 4. Mean Square Error

TRANSFORMER DESIGN

A new method which is based on cost estimating is presented as following in equation (10).

$$f = c_1 w_i + c_2 w_o + c_3 w_c + c_4 \tag{10}$$

Where c_1, c_2, c_3 are the cost of iron, oil and copper of transformer per ton. And the value of w_i, w_o, w_c are obtained, applying properties of related transformer in neural network. The coefficient, c_4 is constant which is related to manpower cost and other components of transformer.

As an example if we need to estimate transformer cost with the following characteristics with help of employing neural network, the equations for manufacturing cost point of view are as follow:

Short circuit impedance percent	Installation height	Volt per turn	Environment temperature
12	1200	80	45

$$f = 23.845c_1 + 10.327c_2 + 6.756c_3 + c_4 \qquad for \qquad 63/20KV$$
$$f = 25.347c_1 + 12.183c_2 + 6.871c_3 + c_4 \qquad for \qquad 132/20KV$$

CONCLUSION

Power transformers are one of the most important components of the power systems. Around 15% of investment in transmission system goes towards transformer and since the major amount of transformers costs is related to its raw materials, so it has a high importance in costs estimating process.

In this paper a new method to estimate transformers pricing (by a cost function) is presented. In the cost function weight of iron, oil and copper play a crucial role and are suggested by the neural network according to the last four years of data from the transformers made by IRAN-TRANSFO Co.

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