Evaluation of Used and Repaired Power Transformers Using Neural Networks

Mohammad Farrokhi*, *Iran University of Science and Technology, Member, IEEE,*
Mansour Rafii**, *Power and Water Institute of Technology*

*farrokhi@iust.ac.ir **m_rafii@yahoo.com

Abstract-- **Power Transformers are one of the most expensive and the most utilized equipments in transmission and distribution power systems. The application of used and repaired power transformers by industrial consumers is common these days. To insure an acceptable and economic performance of power transformers, there is a need for evaluation and verification of these equipments. Such decision-makings always call for experts. It is shown that artificial neural networks yield satisfactory results in such cases. In this paper we present a new method based on neural networks with radial basis functions to evaluate and verify power transformers based on the data obtained from practical tests.**

***Index Terms*-- neural networks, power transformer evaluation, radial basis function.**

I. Introduction

MOST of the distribution transformers are overhauled or repaired after being damaged. Due to the cheaper price, some of the consumers have tendency to buy these transformers, but only experts can certify their usage. In fact, the rating of these transformers depends on the remaining of their lifetime and their reliability, which can't be formulated in an analytic form. Therefore, making a decision to accept or reject them calls for experience. To automate this kind of decision-making, we suggest the use of neural networks. Some authors have used neural networks for fault diagnosis of power transformers [1]-[4].

The main feature of neural networks is their ability to learn from samples and generalizing them, and also their ability to adapt themselves to the changes in the environment. In fact, neural networks are very suitable for problems in the real word. They can map from a set of patterns in the input space to a set of desired vales in the output space. In other words, neural networks try to emulate the learning activities of the human brain, but in a very simplified fashion. One of the most important applications of the neural networks is their use in decision-makings based on experience (just like human). One of the neural networks, which can perform this task, is the radial basis function (RBF) network. The main reason for the use of this network is the simplicity of its structure as well as the ease of training.

II. Radial Basis Function Network

In the simplest form, a radial basis function network consists of three layers; the input layer, which has source (input) nodes; the hidden layer, which has enough number of neurons; and the output layer, which defines the response of the network with regard to the applied inputs. The mapping from the input layer to the hidden layer is nonlinear, whereas the mapping from the hidden layer to the output layer is linear. The structure of the RBF network is shown in Fig 1.

In this network, the radial basis functions are Green functions with the following form:

$$\varphi_i(\mathbf{x}) = G(\|\mathbf{x}-\mathbf{t}_i\|) = \exp\left(-\|\mathbf{x}-\mathbf{t}_i\|^2\right), \quad i = 1,\dots,M \qquad (1)$$

where M is the number of neurons in the hidden layer, which can be less or equal to the number of training samples. The output of this network is an approximation of the desired output and is obtained as follows:

$$F^*(\mathbf{x}) = b + \sum_{i=1}^{M} w_i\, \varphi_i(\mathbf{x}) \qquad (2)$$

where w_i are the weights connecting the hidden neurons to the output layer. These weights and the center of the Green functions $\mathbf{t}_i$ will be obtained during the training of the network [5].

III. Formation and Training of The RBF Network

The first step for formation of the neural network is to define its structure. In order to determine the number of inputs to the neural network, important quantities in the evaluation of the transformers are identified and from them nine quantities, which can be obtained by relatively simple experiments, are chosen. These quantities are as follows:

Uk : Relative short-circuit voltage (in %)
Io : Relative no load current (in %)
Pcun: Nominal copper losses (in W)
Pcn : Nominal iron losses (in W)
$\tan\delta$: Oil insulation losses coefficient at 90 °C
εr : Oil relative permitivity
V_{br} : Oil breakdown voltage
P.I. : Polarization index [in MЂ (60 sec.)/ MЂ (15 sec.)]
I.R. : Insulation resistance (in GЂ)

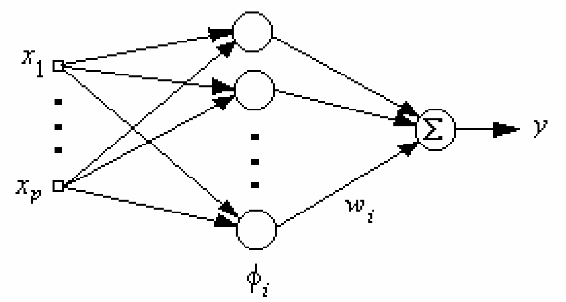

Fig. 1. Radial basis function network

There are other quantities effective in evaluation of power transformers, like oil acidity number and short-circuit enduring time under nominal voltage. But the chosen quantities have three characteristics: relative independence from each other, the ease of obtaining them, and the importance in evaluating of transformers. *Uk* and *P*cun are obtained from short-circuit test under nominal current; V_{br}, tanδ, and ε*r* are obtained from no load test under nominal voltage; and quantities P.I. and I.R. are obtained from meger test.

For this study, we have chosen the quantities of three phase transformers, with nominal values of 100KVA, 20KV/400V, as the inputs to the neural network. The inputs to the neural network are normalized before applying them. For this reason, all inputs are normalized from their peak-to-peak values (i.e. from [min, max]) to [hi, low] = [-1, +1] according to Eq. (3). The maximum and minimum values of the chosen quantities are acquired from experts and the standards, [6] and [7]. These values are shown in Table I.

$$S_i = \frac{\text{Hi}_i - \text{Low}_i}{\text{Max}_i - \text{Min}_i} \tag{3}$$

$$O_i = \frac{\text{Max}_i \times \text{Low}_i - \text{Min}_i \times \text{Hi}_i}{\text{Max}_i - \text{Min}_i} \tag{4}$$

$$X_i = S_i\, Y_i + O_i \tag{5}$$

In the above equations *i* is the number of the corresponding variable, S_i is the scaling factor, O_i is the offset value, Y_i is the i^{th} quantity in Table I, and X_i is the i^{th} input to the neural network.

For training of the RBF network we have used 20 input vectors, from which 10 vectors are from transformers with acceptable specifications (Table II) and the rests are from transformers with unacceptable specifications (Table III). These data are obtained from power transformer workshop in the Iranian Institute for Water and Electric Industry and also from experts. The desired output for acceptable transformers is $d = 1$, and for unacceptable transformers is $d = 0$.

IV. Testing the Neural Network and Analysis of the Results

In order to test the trained neural network, the response of the network to some input-output pairs, which the network has not seen before, is compared with the desired outputs.

TABLE I
THE MINIMUM AND THE MAXIMUM VALUE OF THE QUANTITIES FOR 100 KVA TRANSFORMERS APPLIED TO THE NEURAL NETWORKS

quantity	min.	max.
Uk [%]	3.6	4.4
Io [%]	1.82	3.38
*P*cun	1825	2457
*P*cn	291	388
tanδ	0	0.02
ε *r*	1	3
Vbr	30	70
P.I.	1.4	2
I.R.	0.4	60

Table IV shows these testing data along with the desired and the network outputs. The first five rows belong to the transformers, which have yield acceptable results, and therefore can be put into operation; hence the desired output for them is equal to one. The next five rows of data are for transformers with one or more quantities out of the acceptable range. Therefore, the general evaluation from them is negative and hence we expect the response of the network for these cases to be zero.

As Table IV shows, the output of the network for the first five transformers is close to one and for the last five transformers is close to zero. In the sixth row, the relative short-circuit voltage *Uk* and the nominal copper losses *P*cun are more than the maximum value, while in the seventh row the relative no load current *Io* and the nominal iron losses *P*cn are exceeding the maximum value. In the eighth row, the insulation resistance I.R. and the oil breakdown voltage V_{br} are less than the permitted value in table I, whereas the oil insulation losses coefficient tanδ and the polarization index P.I. in the ninth row are less than the minimum value. And finally in the tenth row, tanδ is too much above the maximum value. The above factors are the reason for the output of the network to be close to zero.

Comparing the desired outputs and the actual outputs of the neural network reveals that the response of the neural network, despite of very limited data, is reasonable and one can evaluate the performance of the transformers using these networks. Of course, the more we train the neural network with different cases, the better the response of the network for testing data will be.

V. Summary

In this paper we showed that neural networks are capable to evaluate the performance of power transformers. The simulation was performed on 100KVA, 20KV/400V, distribution transformers, but the presented method can be used to any power transformer. Since various transformers have different range of values for the quantities used for evaluation, we may need one properly trained neural network for every category of power transformers. The other method, which we suggest, could be the utilization of a hierarchical neural network, which consists of several sub-networks, each one for one category of power transformers. These issues will be addressed in the future papers.

TABLE II
DATA FOR 100 KVA, 20KV/400V, 3-PHASE TRANSFORMERS WITH ACCEPTABLE SPECIFICATIONS

No.	*Uk* [%]	*Io* [%]	*P* cun	*P* cn	tand	e *r*	*V*br	P.I.	I.R.
1	3.85	2.63	2100	310	0.007	1.23	58	1.39	40
2	3.95	2.61	2090	324	0.009	1.38	54	1.36	38
3	4	2.69	2311	364	0.006	1.12	56	1.4	37
4	3.91	2.71	2323	354	0.012	1.21	43	1.51	24
5	4.06	2.62	2278	322	0.018	1.83	41	1.73	17
6	4.15	2.59	2309	345	0.015	2.4	42	1.81	18
7	4.23	2.88	2111	338	0.007	1.3	50	1.35	40
8	4.3	2.65	2321	366	0.008	1.45	49	1.47	37
9	4.22	2.75	2256	353	0.013	2.11	44	1.66	28
10	4.4	2.76	2330	369	0.012	1.15	44	1.59	29

TABLE III
DATA FOR 100 KVA, 20KV/400V, 3-PHASE TRANSFORMERS WITH UNACCEPTABLE SPECIFICATIONS

No.	*Uk* [%]	*Io* [%]	*P* cun	*P* cn	tand	e *r*	*V*br	P.I.	I.R.
1	4.6	2.59	2483	312	0.003	2.2	48	1.82	0.1
2	4.22	2.93	2312	347	0.006	3.3	33	1.63	0.8
3	4.17	2.81	2250	355	0.004	1.8	27	1.25	0.02
4	4.18	2.75	2193	373	0.035	1.9	29	1.41	35
5	4.96	3.35	2085	399	0.008	3.2	39	0.15	30
6	4.05	2.73	2191	322	0.007	1.4	48	0.63	20
7	4.38	2.66	2707	345	0.006	1.8	49	1.58	28
8	3.92	3.47	2055	396	0.018	3.4	36	1.46	30
9	4.71	2.65	2518	324	0.007	2.1	45	2.1	31
10	4.28	2.71	2236	359	0.029	3.3	43	1.47	0.26

TABLE IV
COMPARISON BETWEEN THE DESIRED OUTPUT AND THE NETWORK OUTPUT FOR TESTING DATA

No.	*Uk* [%]	*Io* [%]	*P* cun	*P* cn	tand	e *r*	*V*br	P.I.	I.R.	desired output	network output
1	4	2.81	2160	337	0.0031	1	52	1.63	39	1	0.08815
2	4.11	2.66	2130	340	0.0027	2	50	1.49	48	1	0.7556
3	4.08	2.93	2210	325	0.003	1.7	47	1.6	35	1	0.924
4	4.14	2.72	2210	340	0.0029	2.2	48	1.46	20	1	0.7587
5	4.05	2.79	2150	338	0.0022	1.7	51	1.82	36	1	0.8345
6	4.43	2.66	2612	344	0.0022	3	31	1.33	23	0	-0.0268
7	4.25	3.91	2254	396	0.0043	1.2	38	1.61	42	0	0.209
8	4.05	2.73	2287	382	0.0041	2.7	28	1.41	0.01	0	0.0133
9	4.26	2.91	2264	356	0.0306	1.4	50	1.2	35	0	0.0001
10	4.08	2.83	2239	340	0.0473	1.5	46	1.94	44	0	0.0001

VI. Acknowledgement

The authors wish to thank Dr. Meshkot-tod-deenee and Mr. Ganjehee for their valuable suggestions and discussions and also for the data they provided us for this research.

VII. References

[1] L. Yongli , G. Fuhai, and H. Jiali, "An study on the fault identification of transformers using neural networks," in *Proc. 1998 Powercon*, pp. 1058 - 1063.
[2] T. Nagomi, Y. Yokoi, H. Ichiba, and Y. Atsumi, "Gas discrimination method for detecting transformer faults by neural network," in *Proc. 1994 International Conference on Neural Networks*, pp. 3800 -3805.
[3] Y. Zhang , X. Ding, Y. Liu, and P. J. Griffin, "An artificial neural approach to transformer fault diagnosis, " *IEEE Trans. On Power Delivery*, vol. 11, no. 4, Oct. 1998.
[4] X. Ding, , "A new method of processing the input data in BP network for power transformer diagnosis, " *Journal of Power System Technology*, vol. 22, no. 11, pp. 62 - 68, Nov. 1998.
[5] S. Haykin, *Neural Networks, A comprehensive Foundation*, New Jersey: Prentice Hall, 1999.
[6] *IEC Guid for Application of power transformers*, IEC Standard 606, 1982.
[7] *IEC Guid for Insulation level and dielectric tests*, IEC Standard 76, 1980.