VOLTAGE PROFILE OPTIMIZATION IN DISTRIBUTION SYSTEMS USING NEURAL NETWORKS

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ABSTRACT
In general, 5 to 13 percent of electric energy is lost as heat in distribution systems. There are several methods for reduction of losses in distribution systems. One of these methods is the reduction of current in distribution network branches and compensation of the reactive power of loads with capacitors. Then, the optimum value of the reactive powers, and hence the optimum value of the voltages, is achieved with tap changing on the transformers. In this paper, assuming that the compensators are installed, the optimization on the voltage profile of distribution networks is gained with changing the tap of the transformers using LVQ and RBF neural networks. We will show that this method is capable of bringing the change of the voltages in the 14-bus IEEE network to a range of [0.98, 1.02] with the minimum number of tap changing, hence decreasing the wear on mechanical parts. Also, since the proposed method is faster than the other methods (e.g. load flow and fuzzy logic), it would be easier to use it as an on-line scheme for distribution networks.

KEYWORDS
Distribution Networks, Voltage Profile Optimization, LVQ and RBF Neural Networks, Tap Changer

1. Introduction
Voltage profile adjustments in distribution networks, in the presence of loads with changing reactive power consumption, is an important and sometimes critical issue. The reactive power of all loads is subject to change continuously. These changes result in voltage variations (or adjustments of the voltage profiles) at the supplying point. These variations, in turn, affect the performance of all appliances connected to the supplying point and may lead to interferences between different loads. One of the methods to prevent this problem is a proper allocation of compensators. The other method is changing the tap of the transformers [5], [6], and [9]. In this paper we employ artificial neural networks to optimize the voltage profile, and hence reducing the losses of distribution networks, using tap changer of the transformers. In the rest of this paper, first we introduce the utilized neural networks, and then, assuming that the compensators are installed, the changes on the tap of the transformers for optimization of the voltage profile of 14-bus IEEE network (Fig. 1), using Learning Vector Quantization (LVQ) and Radial Basis Function (RBF) neural networks, are considered. At the end, the results of the proposed methods are compared with load flow and fuzzy logic methods.

2. Learning Vector Quantization Network
The LVQ method is in fact a supervised training scheme. In this method the Voronoi vectors are slowly shifted until the quality of decision making areas is improved. In this method, first, an input vector **x** is taken from the input space. If the sign of **x** and the sign of the Voronoi vector **w** are same, then the Voronoi vector **w** is shifted towards the input vector **x**, otherwise it is shifted away from it [3].

Let $\{\mathbf{w}_j \mid j = 1,\ldots, n\}$ be the set of Voronoi vectors and $\{\mathbf{x}_i \mid i = 1,\ldots, l\}$ the set of input vectors. Suppose that the number of input vectors is much bigger than the number of the Voronoi vectors. Assume the Voronoi vector $\mathbf{w}_c$ is the closest to the input vector $\mathbf{x}_i$, and $\mathbf{C}_{\mathbf{w}c}$ defines the class of Voronoi vectors for $\mathbf{w}_c$ and $\mathbf{C}_{\mathbf{x}i}$ determines the class of input vectors for $\mathbf{x}_i$. Then, the Voronoi vector $\mathbf{w}_c$ is adjusted as follows:

$$\begin{aligned}\mathbf{w}_c(n+1) &= \mathbf{w}_c(n) + \alpha_n[\mathbf{x}_i - \mathbf{w}_c(n)] \quad \text{if} \quad \mathbf{C}_{\mathbf{w}c} = \mathbf{C}_{\mathbf{x}i}\\ \mathbf{w}_c(n+1) &= \mathbf{w}_c(n) - \alpha_n[\mathbf{x}_i - \mathbf{w}_c(n)] \quad \text{if} \quad \mathbf{C}_{\mathbf{w}c} \neq \mathbf{C}_{\mathbf{x}i}\end{aligned} \tag{1}$$

3. Utilizing LVQ Neural Network in Voltage Profile Optimization Using Tap Changers
The input voltages, in this paper are the initial value of the voltages. Fig. 2 shows the block diagram of the optimization of the voltage profile using the LVQ network. As this block diagram shows, the overall LVQ network is composed of two sub-networks. The shown parameters in Fig. 1 are as follows:

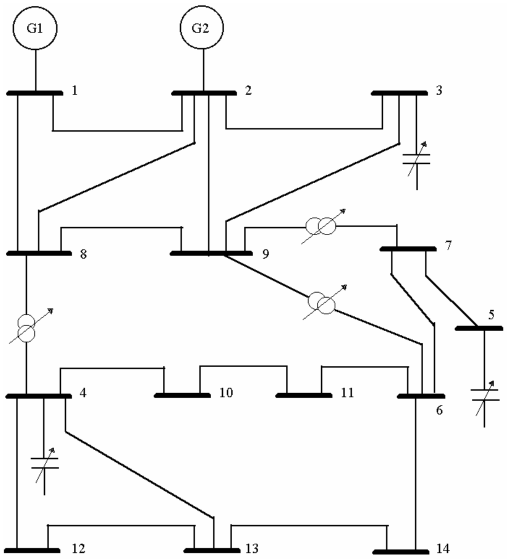

Fig. 1. The 14-bus IEEE distribution network

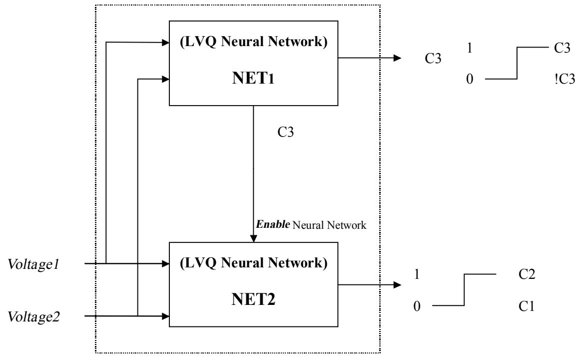

Fig. 2. Block diagram of the proposed LVQ network

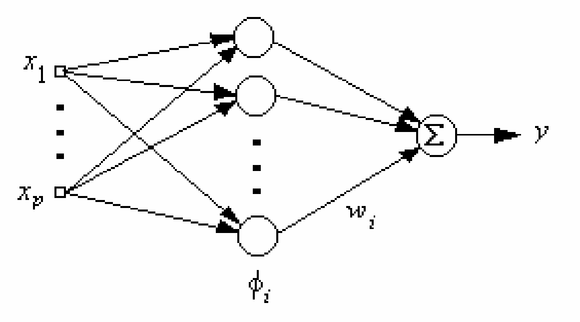

Fig. 3. Radial basis function network

Table 1. Line parameters of the IEEE 14 bus network

line no.	bus no.		line param. corresp. to p equiv. circuit (pu)		
	beg.	end	*R*	*X*	*B*
1	1	2	0.01938	0.05917	0.0528
2	1	8	0.05403	0.22304	0.0492
3	2	3	0.04699	0.19797	0.0438
4	2	9	0.05811	0.17632	0.0374
5	2	8	0.05695	0.17388	0.0340
6	3	9	0.06701	0.17103	0.0128
7	9	8	0.01335	0.04211	0.00
8	4	10	0.09498	0.1989	0.00
9	4	12	0.12291	0.25581	0.00
10	4	13	0.06615	0.13027	0.00
11	7	5	0.00	0.17615	0.00
12	7	6	0.00	0.11001	0.00
13	6	11	0.03181	0.0845	0.00
14	6	14	0.12711	0.27038	0.00
15	10	11	0.08205	0.19207	0.00
16	12	11	0.22092	0.19988	0.00
17	13	14	0.17093	0.34802	0.00
18	9	7	0.00	0.20912	0.00
19	9	6	0.00	0.55618	0.00
20	8	4	0.00	0.25202	0.00

Voltage 1: the voltage of the bus before the tap changer
Voltage 2: the voltage of the bus after the tap changer
C3 = 0: No need to change the voltages.
C3 = 1: There is need to change the voltages. Hence, the tap changer must be adjusted accordingly (increase or decrease of the tap changer). Therefore, NET2 is enabled to control the tap changer.
C1: To increase the tap changer
C2: To decrease the tap changer

NET1: Makes decision for change or no change of the tap changer.
NET2: Makes decision for increase or decrease of the tap changer.

The proposed network in Fig. 2 makes the minimum number of tap changing, which results in less wear on mechanical parts, and the most optimum voltages as compared to other methods. The flowchart algorithm for changing the tap of the transformers using the presented LVQ network in this paper is shown in Fig. 4. This algorithm has been performed on 14-bus IEEE network. To begin the algorithm, first the initial value of the buses must be entered. Then, the trained LVQ network makes a decision on whether to change taps or not, and brings the voltages to the range of [0.98 1.02]. The number of training epochs can be changed in order to give the proper amount of training to the network and hence reducing the range of the change of the voltages, assuming that the compensators are already installed in the proper locations in the distribution network.

The results of the simulations of the proposed LVQ network is compared to that of load flow method [8] and fuzzy logic method [10] in table 2. Figs. 5 and 6 show the voltages of the IEEE 14-bus system after the first training epoch and at the end of the training phase of the LVQ, respectively.

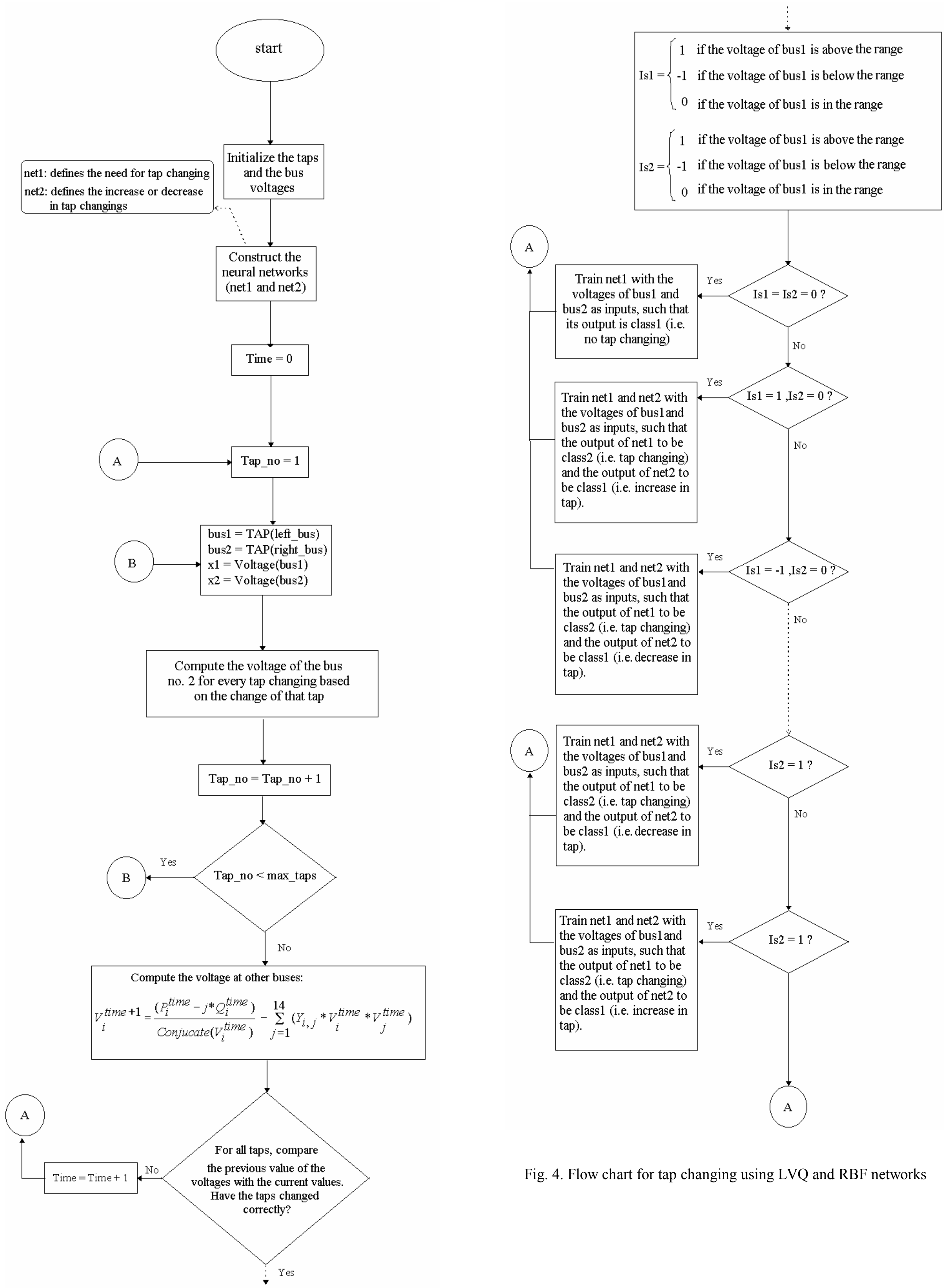

Fig. 4. Flow chart for tap changing using LVQ and RBF networks

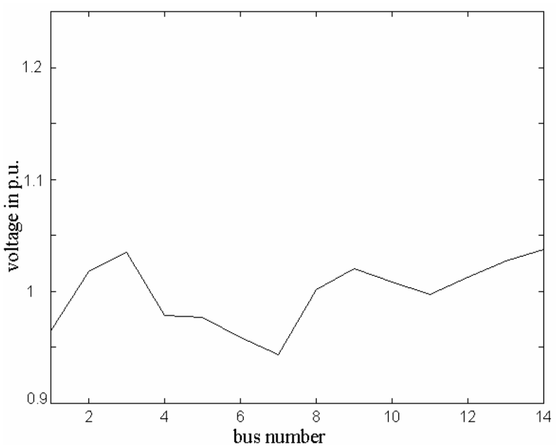

Fig. 5. Voltage profile of the 14-bus IEEE network after the first epoch of the training of the proposed LVQ network

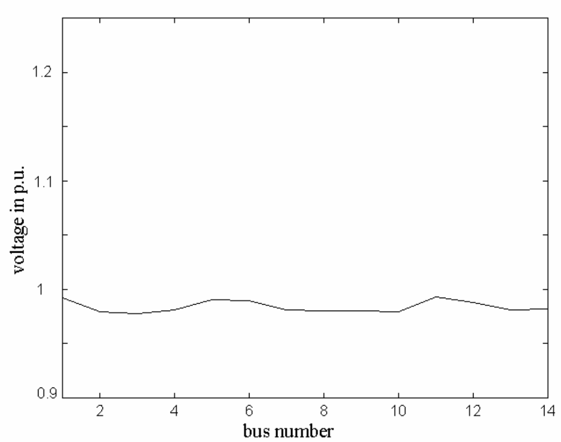

Fig. 6. Voltage profile of the 14-bus IEEE network at the end of the training of the LVQ network

4. Radial Basis Function Network

In the simplest form, an RBF network consists of three layers:

1- The input layer, which consists of source (or input) nodes.
2- The hidden layer, which has a different task than that of other neural networks and has enough number of neurons.
3- The output layer, which contains linear neurons and defines the response of the network with regard to the applied inputs.

Therefore, 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 an RBF network is shown in Fig. 3. In this network, the radial basis functions are Green functions with the following form:

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

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:

$$F^*(\mathbf{x}) = b + \sum_{i=1}^{M} w_i \, \varphi_i(\mathbf{x}) \qquad (3)$$

The weights in the output layer w_i and the center of the Green functions t_i are adjusted during the training of the network, using the gradient descent method [5].

5. Utilizing RBF Neural Network in Voltage Profile Optimization Using Tap Changers

This time, the algorithm in Fig. 4 is applied for RBF network. The results are shown in table 2. As this table shows, the RBF network can produce better results for optimization of the voltage profile of the distribution system than other methods.

The RBF network finds local nonlinear approximations for the nonlinear input-output mappings. Therefore, the rate of learning of the RBF network is faster than that of the LVQ network. Also, the RBF network is less sensitive to the order of the inputs applied to it. But, the number of hidden neurons in the RBF network might become very large. This is mainly because the hidden neurons of the RBF network find the Euclidean distance between the input vectors and the center of their Green function, while this is not the case in LVQ network.

6. Comparing the Neural Network Methods with Load Flow and Fuzzy Logic Schemes

The voltage profile optimization of the IEEE 14-bus system in Fig. 1 for the load flow and fuzzy logic methods are shown in Figs. 7 and 8, respectively. Also the results of the LVQ and RBF networks, which are proposed in this paper, are shown in Fig. 9 and Fig. 10, respectively. These four methods can be compared as follows:

1- The load flow method has complicated computations, while the training procedure in neural networks are relatively simpler and faster.
2- The required computation time in the load flow and the fuzzy logic method is more than that of the neural networks.
3- The load flow method does not yield good results for the IEEE 14-bus system. Although the results of the fuzzy logic method is satisfactory, but the required time for computations is more than that of the proposed neural networks.
4- The range of change of the voltage profile from neural networks is between 0.98 and 1.02, while this range is much wider for load flow and fuzzy logic methods.

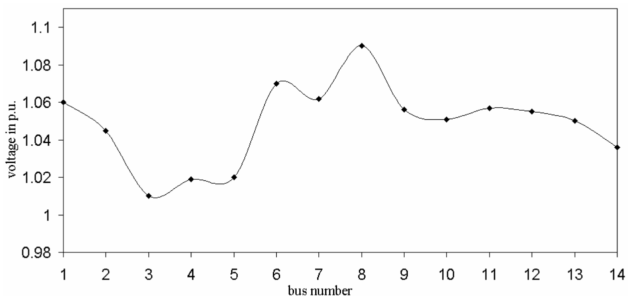

Fig. 7. Voltage profile of the 14-bus IEEE network using load flow method

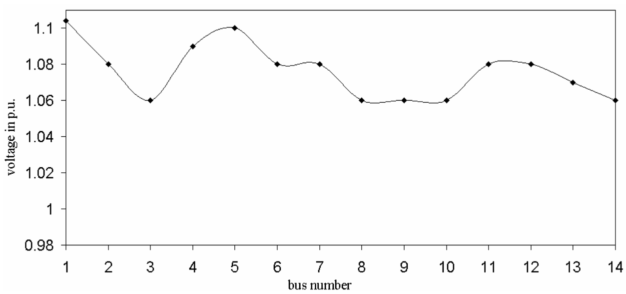

Fig. 8. Voltage profile of the 14-bus IEEE network using fuzzy logic

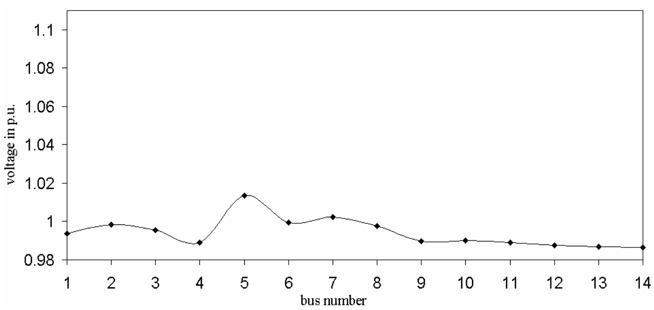

Fig. 9. Voltage profile of the 14-bus IEEE network using the proposed LVQ network

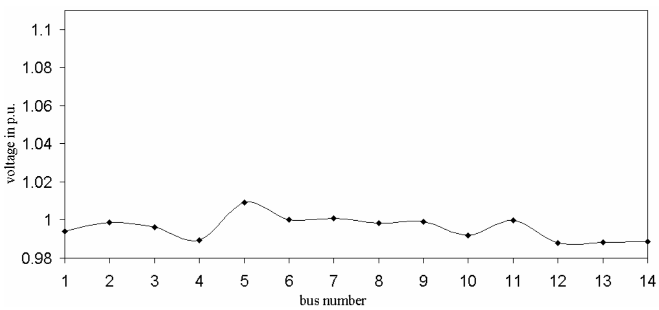

Fig. 10. Voltage profile of the 14-bus IEEE network using the proposed RBF network

TABLE 2

Comparison between neural networks and other methods

Bus number	Bus initial voltage	Load flow method	Fuzzy logic	LVQ network	RBF network	Error reduction*
1	0.987	1.060	1.104	0.9937	0.9940	10%
2	0.977	1.045	1.080	0.9985	0.9987	8%
3	0.969	1.010	1.060	0.9956	0.9963	7%
4	0.965	1.019	1.090	0.9890	0.9895	9%
5	0.984	1.020	1.100	1.0134	1.0001	8%
6	0.983	1.070	1.080	0.9995	1.0009	8%
7	0.965	1.062	1.080	1.0023	0.9982	7%
8	0.962	1.090	1.060	0.9976	0.9982	7%
9	0.963	1.056	1.060	0.9899	0.9990	8%
10	0.960	1.051	1.060	0.9901	0.9920	10%
11	0.987	1.057	1.080	0.9889	0.9999	7%
12	0.977	1.055	1.080	0.9875	0.9880	7%
13	0.971	1.050	1.070	0.9867	0.9882	9%
14	0.970	1.036	1.060	0.9866	0.9887	9%

*) In percent for the RBF network, relative to the LVQ network.

7. Conclusion

Based on the results shown in table I we can conclude that the proposed neural networks in this paper can give better results as compared to other existing methods. Moreover, the neural networks yield less number of tap changing, which results in less loss in power system and less wear on mechanical parts of the tap changers. Also the faster response of the neural networks makes them more appropriate for on-line applications. A comparison between the RBF and the LVQ network shows that the RBF network is the better network from the precision point of view.

8. Acknowledgement

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9. References

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