RBF Neural Network for Estimating Locational Marginal Prices in Deregulated Electricity Market

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Abstract. In the deregulated Power Market scenario, due to liberalized market structure and non-discriminatory open transmission access, the issue of congestion management and hence optimum use of transmission capacity, has become more crucial issue.. The pricing mechanism based on capacity allocation principle, to determine Locational Marginal Prices (LMP) can be proved to be substantial, about efficient utilization of transmission grid and available generation capacity. Regarding Congestion Management the Optimal pricing strategy breaks the Nodal pricing into two components; one is Locational Marginal Price (LMP) and second is Nodal Congestion Price (NCP). Both of these are significant for market participants as system security parameter. In the emerging deregulated environment, the Artificial Intelligent techniques like ANN provide instant and accurate LMPs, which boost up the motive of spot power market. This paper presents Radial Basis Function Neural Network (RBFNN) for estimating LMPs.
Since the test results are very accurate and awfully fast, these instant results can be directly floated to OASIS (open access same time information system) web site. The Market Participants willing to make transactions can access this information for any location of the market. The effectiveness of the proposed ANN has been established by comparing the testing results with those obtained with conventional Interior-Point OPF based method for a 6-bus test system having three generating units.

Keywords: Locational Marginal Price, Nodal Price, Congestion Management, Radial basis function (RBF) neural network.

Nomenclature

C_{S_i} Supply bid of unit i [\$ / MWh];
C_{D_j} Demand bid of unit j [\$ / MWh];
P_{S_i} Supply bid volume of unit i [MW];

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P_{D_j} Demand bid volume of unit j [MW];

$P_{S_{\max i}}$ Upper limit of power bid of unit i [MW];

$P_{S_{\min i}}$ Lower limit of power bid of unit i [MW];

$P_{D_{\max j}}$ Upper limit of demand bid of unit j [MW];

$P_{D_{\min j}}$ Lower limit of demand bid of unit j [MW];

Q_{G_i} Reactive power output of unit i [MVar];

$Q_{G_{\min i}}$ Upper limit of Reactive power at unit i [MVar];

$Q_{G_{\max i}}$ Lower limit of Reactive power at unit i [MVar];

V_i Voltage magnitude at unit i

I Set of indexes of generating units;

J Set of indexes of consumers

B Set of indexes of network buses;

N Set of indexes of transmission lines;

LMP_k Locational Marginal Prices at bus k;

P_i = real power load at i^{th} bus

Q_i = reactive power load at i^{th} bus

1 Introduction

With the advent of deregulation and policies of open access, allocation of scarce transmission resources has become a key factor for the efficient operation of electricity market. To ensure efficient use of transmission grid and generation resources by providing fast and correct economic signals, a spot price or nodal price theory has been developed [1]. To design a reasonable pricing structure of Power Systems and to provide an effective Congestion Management procedure nodal prices have been decomposed into a variety of parts corresponding to concerned factors such as generations, voltage limitations, transmission congestion and other constraints [2].

The optimal nodal prices [3] and [4] of electricity comprise of two components, one is price for cost of supplying next increment of electric power demand (based on Lagrangian Multiplier), at a specific node or bus, involving generation marginal cost and all power system equality constraints; other is price for congestion (i.e. shadow prices) considering inequality constraints only. The first component is called as Locational Marginal Price (LMP) and other is Nodal Congestion Price (NCP). A multi-objective optimal power flow approach to account for pricing system security through the use of voltage stability constraints is presented in [5]. In the deregulated electricity market, the market dispatch (unconstrained) stage is almost same for different market structures. These auction-based dispatches have no consideration for transmission situations and the resulting price is the Market Clearing Price (MCP). In economic terms, the market clearing price is the point of intersection of supply and demand bid curves. However LMP reflects the security constrained pricing. The various pricing mechanisms for Congestion Management are discussed in [6]. The method of Nodal Pricing (LMP and NCP) is adopted by PJM, ISO-NE and ISO-NY. Nodal prices are not necessarily capped by the marginal cost of the marginal units and can be higher than the most expensive unit running, and can be negative, in constrained out areas [7]. When there are no congestion in the market, then the LMPs are same at all buses and equal to the marginal cost to serve load in control area. Nodal Pricing of Electricity is highly volatile under constrained transmission condition. Sensitivities of LMPs are explored with respect to power demands in [8]. [9] presents an AC-OPF model for investigating marginal cost pricing for real and reactive power flow. An overview of various congestion management methodologies are presented in [10]. Rather than computing spot prices, the thrust area is forecasting spot prices and Day-Ahead load demand [11] using Artificial Intelligent techniques. [12] presents a method that forecasts next-day electricity prices, based on fuzzy logic and neural networks. The RBFNN is proposed in [13-15] for handling various problems in Power System operation and control.

This paper presents an RBFNN approach [13-15] for predicting LMPs in deregulated power market. Theoretically with enough RBF neurons, the RBFNN can realize zero error to all the training samples. Besides, the number of RBF neurons in the hidden layer can be determined during the parameter optimization process. The optimization process also speeds up the training process of neural network. These features make this ANN very attractive in practical use.

2 Methodology

2.1 The RBFNN Architecture

The architecture of the proposed RBF neural network consists of three layers, the input layer, hidden layer and output layers with the hidden layer composed of RBF neurons. The nodes within each layer are fully connected to the previous layer as shown in Fig. 1. The input variables are assigned to each node in the input layer and are forwarded to the hidden layer directly, without weights. The hidden nodes contain the radial basis functions and are analogous to the sigmoid function commonly used in feed-forward multi-layer perceptron model.

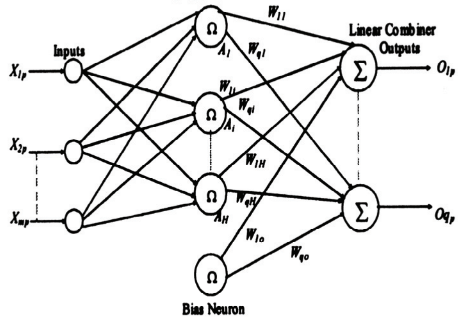

Fig. 1. Radial Basis Function NN Model

Most commonly used MLP models suffer from local minima and over fitting problems. The RBF neural networks have increasingly attracted interest for engineering applications due to their advantages over traditional MLP models, namely faster convergence, smaller extrapolation errors, optimized system complexity, minimized learning and recall times and higher reliability. They are highly promising for multivariable interpolation given irregularly positioned data points and provide good generalization ability with a minimum number of nodes to avoid unnecessarily lengthy calculations. The radial basis function is similar to the Gaussian density function, which is defined by a centre position and a width parameter. The width of the RBF unit controls the rate of decrease of function. The output of the i^{th} unit $a_i(Xp)$ in the hidden layer is given by:

$$a_i(X_p) = \exp\left(-\sum_{j=1}^{r}\left[x_{jp} - \overline{x}_{ji}\right]^2 / \sigma_i^2\right) \quad \textbf{(1)}$$

Where $\overline{x}_{ji}$ is the centre of i^{th} RBF unit for input variable j ,σ_i is width of i^{th} RBF unit and x_{jp} is the j^{th} variable of input pattern p. The connection between the hidden units and the output units are weighted sums as shown in Fig. 1. The output value o_{qp} of the q^{th} output node is given as:

$$o_{qp} = \sum_{i=1}^{H} w_{qi}\, a_i(X_p) + w_{qo} \quad \textbf{(2)}$$

Where w_{qi} is weight between i^{th} RBF unit and q^{th} output node and w_{qo} is biasing term at q^{th} output node.

The parameter of the RBF units is determined in three steps of the training process. First of all some form of clustering algorithm explores the unit centres. Then the widths are calculated by a nearest neighbor method. Finally weights connecting the RBF units and the output units are determined using multiple regression techniques. Euclidean distance based clustering technique has been employed in this paper to select the number of hidden (RBF) units and unit centres. The normalized input data are used for training of the RBF neural network. In this paper the dynamic version of RBFNN is used to make faster training. In this new RBFNN hidden nodes are altered until desired goal is reached.

2.2 Locational Marginal Pricing

The Locational Marginal Prices are the nodal prices, which are typically calculated as Lagrange multipliers associated with equality constraints, from the OPF solution [16]. For calculating these prices, the Pool Operator receives supplier bid and customer bid as bid plots. Fig. 2 shows bid plots for both supply as well as demand. Then Pool Operator determines the market clearing price (MCP) and a set of successful bidders on the basis of some auction mechanism. In the price assessment process, both optimal bidding strategy and auction mechanism play an important role. The intersection of supply and demand plots provides market clearing price and market clearing volume, as shown in Fig. 2 by G_m and H_m in \$/ MWh and in MW respectively. The supply bid plot shows the minimum price at which a generator is willing to produce a certain amount of power, while demand bid plot shows the maximum price, which is accepted by customers to buy a certain amount of power.

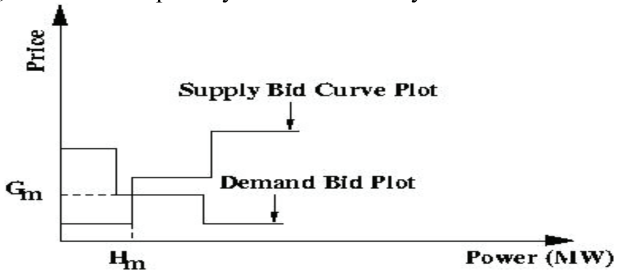

Fig. 2. Demand and Supply bid Plot

For the sake of simplicity it is assumed here that supply and demand bid is a single price not complete plot. In power market security pricing field, OPF-based approach is basically a non-linear constrained Optimization problem. One crucial outcome of this optimization procedure is Locational Marginal Prices. This outcome in pool-market operation is achieved through objective-function as maximization of social benefit *i.e.* maximizing the generator's income for their power production and simultaneously ensuring that consumers pay cheapest price for their power purchase. The OPF objective function is:

$$Min \quad G = \sum_{i \in I} C_{S_i} P_{S_i} - \sum_{j \in J} C_{D_j} P_{D_j} \tag{3}$$

subject to following equalities and inequalities constraints.

Power flow equations:

$$f(P_G, Q_G, V, \theta) = 0 \tag{4}$$

Power balance equations:

$$P_k = \sum_{i \in I} (P_{G_{io}} + P_{S_i}) - \sum_{j \in J} (P_{L_{jo}} + P_{D_j}) \tag{5}$$

$$Q_k = \sum_{i \in I} (Q_{G_{io}}) - \sum_{j \in J} (Q_{L_{jo}} + Q_{D_j}) \tan \phi_{D_j} \quad \text{where } \forall k \in B \tag{6}$$

Supply Bid Blocks:

$$P_{S_{\min_i}} \leq P_{S_i} \leq P_{S_{\max_i}} \quad \forall i \in I \tag{7}$$

Demand Bid Blocks:

$$P_{D_{\min j}} \leq P_{Dj} \leq P_{D_{\max j}} \quad \forall j \in J \tag{8}$$

Reactive Power Generation Limit:

$$Q_{G_{\min_i}} \leq Q_{G_i} \leq Q_{G_{\max_i}} \quad \forall i \in I \tag{9}$$

Voltage Security Limit:

$$V_{\min_k} \leq V_k \leq V_{\max_k} \quad \forall k \in B \tag{10}$$

Thermal Limit:

$$I_{mk}(\theta, V) \leq I_{mk_{\max}} \quad \forall (m,k) \in N \tag{11}$$

The Lagrange function of the optimization problem (3) – (11) can be written as,

$$\begin{aligned}
Min \quad \Im = {} & G - \lambda^T f(\delta, V, P_S, P_D, Q_G) \\
& - \mu^T_{PS_{\max}} \left(P_{S\max} - P_S - s_{Ps\max}\right) \\
& - \mu^T_{PS_{\min}} \left(P_S - s_{Ps\min}\right) \\
& - \mu^T_{PD_{\max}} \left(P_{D\max} - P_D - s_{PD\max}\right) \\
& - \mu^T_{PD_{\min}} \left(P_S - s_{PD\min}\right) \\
& - \mu^T_{\mathrm{Im}k_{\max}} \left(I_{\max} - I_{mk} - s_{Imk\max}\right) \\
& - \mu^T_{Ikm_{\max}} \left(I_{\max} - I_{km} - s_{Ikm\max}\right)
\end{aligned}$$

$$- \mu_{QG_{\max}}^{T} \left(Q_{G\max} - Q_{G} - s_{QG\max}\right)$$

$$- \mu_{QG\min}^{T} \left(Q_{G} - Q_{G\min} - s_{QG\min}\right)$$

$$- \mu_{V_{\max}}^{T} \left(V_{\max} - V - s_{V\max}\right)$$

$$- \mu_{s} \left(\sum_{i} \ln s_{i} \right) \tag{12}$$

where λ and μ are Lagrange multipliers with respect to equality and inequality constraints. Here *s* is a non negativity slack variable. The Lagrange multiplier λ *reflects* the locational marginal cost price at each node considering all equality constraints. The optimization of (12) is satisfied by the KKT optimality condition:

$$\nabla_{z} \Im_{\mu}(z) = 0 \tag{13}$$

Then by applying (13) in (12):

$$\partial \Im / \partial P_{S_i} = 0 = C_{S_i} - \lambda_{P_{S_i}} + \mu_{P_{S\max_i}} - \mu_{P_{S\min_i}} \tag{14}$$

$$\partial \Im / \partial P_{D_i} = 0 = -C_{D_i} + \lambda P_{D_i} + \lambda Q_{D_i} \tan(\phi_{D_i})$$

$$+ \mu P_{D_{\max_i}} - \mu P_{D_{\min_i}} \tag{15}$$

Thus the LMPs can be defined as,

$$LMP_{S_i} = \lambda_{P_{S_i}} = C_{S_i} + \mu_{P_{S\max_i}} - \mu_{P_{S\min_i}} \tag{16}$$

$$LMP_{D_i} = \lambda_{P_{D_i}} = C_{D_i} + \mu P_{D_{\max_i}} - \mu P_{D_{\min_i}}$$

$$- \lambda Q_{D_i} \tan(\phi_{D_i}) \tag{17}$$

Thus by this classical approach, the LMPs at both supply and demand node are determined for the 6-bus system [5]. Furthermore, it is established that system congestion do significantly affect market bids and associated costs, hence still there is a need for a precise model for taking in account security constraints. In this way LMPs are always better to take into consideration than MCPs. Equation (19) and (20) provide LMP_k i.e. LMPs at k^{th} node in the given system for both supply and demand bids.

3 Training Algorithm for RBFNN

Neural Network models are the trainable analytic tools that attempt to mimic the information-processing pattern in human brain. It has capabilities of learning generalization and fault tolerance, which make it suitable for on-line application environment among all other artificial intelligent techniques. The Radial Basis Function Neural Network (RBFNN) is proposed for providing LMPs at every node of the given 6-bus test system. The RBFNN can be designed in a fraction of time as compared with other design approaches for training standard feed-forward networks.

The solution algorithm for Locational Marginal Pricing using RBFN is given below.

(i) A large number of load patterns are generated randomly in wide range of load variation at each load bus.

(ii) For each load case Locational Marginal Price at different buses is computed by classical IPM-OPF method.

(iii) Real and Reactive loads at load buses i.e. bus no.4,5 and 6 are selected as input features for the RBF network.

(iv) For training of the RBF network, initialize all the connection weights between hidden nodes and output nodes.

(v) Compute the Gaussian function at the hidden node using equation (1) i.e.

$$a_i(X_p) = \exp\left(-\sum_{j=1}^{r}\left[x_{jp} - \overline{x}_{ji}\right]^2 / \sigma_i^2\right)$$

Where r is dimension of input vector.

(vi) For the given values of loads at bus no 4,5 and 6, calculate the output of the RBFNN, which is locational marginal prices at all the six buses using equation (2) i.e.

$$o_{qp} = \sum_{i=1}^{H} w_{qi}\, a_i(X_p) + w_{qo}$$

(vii) Calculate the Mean Squared Error e_p for the p^{th} input pattern using

$$e_p = \frac{1}{2} \cdot \frac{1}{NO} \sum_{q=1}^{NO} \left(t_{qp} - o_{qp}\right)^2 \tag{18}$$

Here t_{qp} is the target value at q^{th} neuron of output layer for p^{th} pattern and NO is the number of neurons in output layer.

(viii) Repeat steps (v) to (viii) for all the 240 training patterns comprising real and reactive power demand at bus no. 4, 5, 6 and locational marginal prices at all six buses.

(ix) Calculate the error function E_k using equation,

$$E_K = \sum_{p=1}^{p^{\max}} e_p = \frac{1}{2} \sum_{p=1}^{p^{\max}} \frac{1}{NO} \sum_{q=1}^{NO} \left(t_{qp} - o_{qp}\right)^2 \tag{19}$$

Where, $p^{\max}$ is the total number of training patterns which is 240 for this application of estimating locational marginal prices all the nodes/buses of the given system i.e. six-bus test system.

(x) Update the connection weights using equation

$$w_{qi}(K+1) = w_{qi}(K) + \Delta w_{qi}(K) \tag{20}$$

Where

$$\Delta w_{qi}(K) = \eta(K).\sum_{p=1}^{p^{\max}} \delta_{qp}.A_{pi} + \alpha.\Delta w_{qi}(K-1) \tag{21}$$

And
$$\delta_q = T_q - O_q \tag{22}$$

where, η (K) is learning rate or adaptive size at K^{th} iteration and δ_q is the error signal for unit q and $\propto$is momentum term and T_q , O_q are target and actual output respectively.

(xi) The procedure is continued till the error becomes negligible.

(xii) This trained RBFNN model is tested for previously unseen load patterns for estimating LMPs all the buses of the system.

4 Results and Discussion

Though the trained ANN has provided the accurate results (i.e. LMPs at each node) for all the 60 testing patterns, due to limited space, testing results for only 15 patterns are given in Table 1. This table also shows the percentage error as a performance index for proposed RBFNN. The actual and target output for all 60 load patterns are shown in Fig. 3.

From this figure it is clear that RBFNN has achieved the target within permissible accuracy limits (can be seen as overlapped display). It can be noted from Table 1, that the maximum percentage error for LMP_1, LMP2, LMP3, LMP_4, LMP_5 and LMP_6 are 0.267, 0.304, 0.328, 0.319, 0.315 and 0.340 respectively. For same ANN structure and same learning rate of 0.30 the performance of RBFNN is compared with a BPMLP model. The rms errors for RBFNN and a BPMLP model were obtained as 0.0867 pu and 0.1039 pu respectively, which clearly shows its superiority over other BPMLP models

It is evident from Fig. 3, that LMP at node-1 ranges from 9.0 – 9.85 \$/ MWh, LMP at node-2 ranges from 8.85 – 9.85 \$/ MWh, LMP at node-3 ranges from 9 – 10 \$/ MWh, LMP at node-4 ranges from 9.5 – 10.5 \$/ MWh, LMP at node-5 ranges from 9.6 – 10.4 \$/ MWh and LMP at node-6 ranges from 9.2 – 10.2 \$/ MWh. The different values. of LMPs at nodes show the presence of congestion in the system.

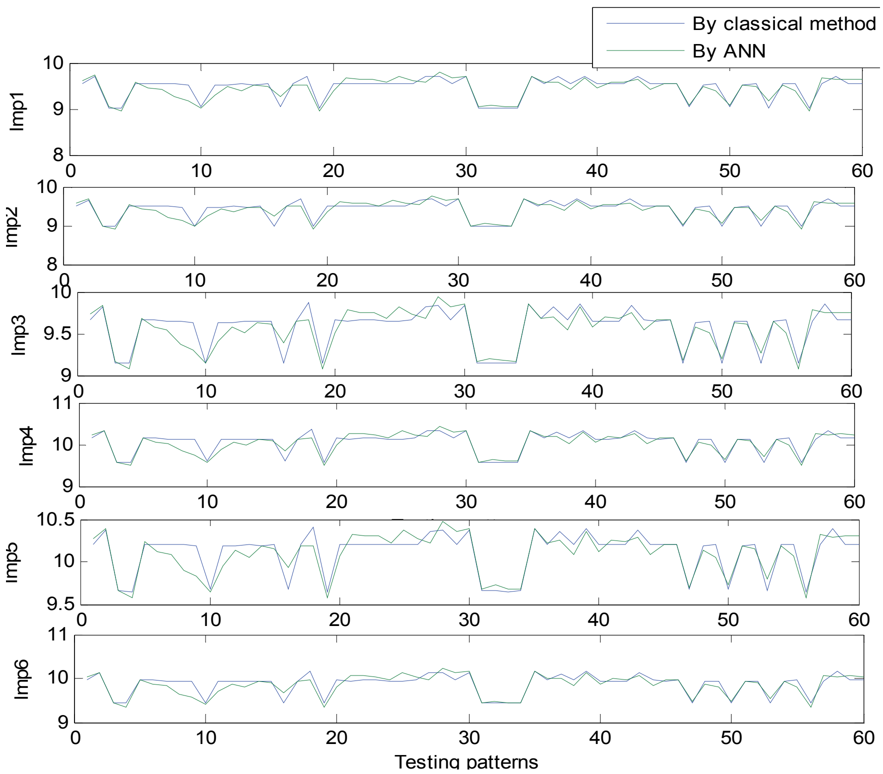

Fig. 3. Testing Performance of RBFNN for all 60 patterns.

5 Conclusion

A novel approach using radial basis function neural network is proposed, for estimating LMPs at both supply and demand nodes in the system. During testing phase the trained neural network furnished results within acceptable accuracy limits for previously unseen load patterns. The floating of this significant information of LMPs on OASIS website, would enable the Market Participants to peruse their transactions.

The MCPs do not have any hold on generation and transmission constraints. On the other hand LMPs are calculated as Lagrangian Multipliers (or dual variables) associated with OPF framework and are substantially affected by changes in demands, supply and transmission constraints that's why constitute essential information in an Electricity Market. The AI techniques are now admired specifically for spot pricing in budding deregulated power market and establishing economic signals among Market Participants.

Table 1. Testing Performance of Trained RBFNN for Locational Marginal Pricing

NP	TPD	TQD	METHOD	LMP1	LMP2	LMP3	LMP4	LMP5	LMP6
1	2.966	2.013	CLASSICAL	9.700	9.660	9.827	10.320	10.366	10.128
			BY ANN	9.726	9.677	9.842	10.335	10.394	10.140
			% Error	0.267	0.181	0.157	0.147	0.270	0.114
2	2.796	1.897	CLASSICAL	9.030	8.987	9.148	9.575	9.664	9.429
			BY ANN	9.033	8.993	9.158	9.576	9.667	9.442
			% Error	0.035	0.070	0.111	0.012	0.032	0.133
3	2.945	1.998	CLASSICAL	9.559	9.509	9.670	10.157	10.205	9.964
			BY ANN	9.574	9.524	9.686	10.169	10.233	9.979
			% Error	0.158	0.155	0.164	0.119	0.270	0.149
4	2.923	1.983	CLASSICAL	9.530	9.478	9.638	10.116	10.194	9.929
			BY ANN	9.529	9.476	9.637	10.115	10.188	9.928
			% Error	0.013	0.016	0.015	0.014	0.055	0.015
5	2.947	2.000	CLASSICAL	9.543	9.492	9.653	10.135	10.199	9.945
			BY ANN	9.531	9.484	9.646	10.126	10.189	9.939
			% Error	0.123	0.089	0.075	0.089	0.100	0.063
6	3.027	2.054	CLASSICAL	9.700	9.670	9.839	10.330	10.378	10.141
			BY ANN	9.706	9.678	9.847	10.339	10.386	10.150
			% Error	0.061	0.080	0.082	0.089	0.079	0.090
7	2.787	1.891	CLASSICAL	9.024	8.983	9.146	9.567	9.657	9.428
			BY ANN	9.039	8.999	9.165	9.583	9.673	9.449
			% Error	0.167	0.182	0.210	0.163	0.168	0.224
8	2.836	1.924	CLASSICAL	9.021	8.981	9.146	9.563	9.654	9.428
			BY ANN	9.043	9.000	9.161	9.590	9.679	9.441
			% Error	0.243	0.210	0.164	0.282	0.259	0.141
9	3.027	2.054	CLASSICAL	9.700	9.676	9.846	10.336	10.386	10.150
			BY ANN	9.706	9.678	9.847	10.339	10.386	10.150
			% Error	0.061	0.018	0.010	0.031	0.001	0.001
10	2.980	2.022	CLASSICAL	9.562	9.512	9.674	10.162	10.206	9.968
			BY ANN	9.574	9.527	9.689	10.173	10.225	9.984
			% Error	0.126	0.160	0.160	0.111	0.190	0.159
11	3.016	2.047	CLASSICAL	9.700	9.676	9.847	10.336	10.386	10.150
			BY ANN	9.680	9.647	9.815	10.303	10.353	10.115
			% Error	0.205	0.304	0.328	0.319	0.315	0.340
12	2.948	2.000	CLASSICAL	9.534	9.482	9.643	10.121	10.195	9.933
			BY ANN	9.551	9.501	9.663	10.145	10.205	9.956
			% Error	0.174	0.197	0.206	0.232	0.094	0.227
13	2.949	2.001	CLASSICAL	9.551	9.500	9.661	10.146	10.202	9.954
			BY ANN	9.551	9.501	9.663	10.145	10.205	9.956
			% Error	0.004	0.007	0.019	0.015	0.026	0.016
14	2.923	1.983	CLASSICAL	9.530	9.478	9.638	10.116	10.194	9.929
			BY ANN	9.529	9.476	9.637	10.115	10.188	9.928
			% Error	0.013	0.016	0.015	0.014	0.055	0.015
15	2.947	2.000	CLASSICAL	9.543	9.492	9.653	10.135	10.199	9.945
			BY ANN	9.531	9.484	9.646	10.126	10.189	9.939
			% Error	0.123	0.089	0.075	0.089	0.100	0.063

References

1. Schweppe, F.C., Caramanis, M.C., Tabors, R.D.: " Spot Pricing of Electricity", (Boston, MA:Kluwer Academic Publishers, 1988)
2. Chen, L., Suzuki, H., Wachi, T., Shimura, Y.: "Components of Nodal Prices for Electric Power Systems", IEEE Transactions on Power Systems, vol. 17, No. 1, February 2002, pp. 41-49.
3. Xie, K., Song, Y.H., Stonfam, J., Yu, E., Liu, G.: " Decomposition Model and Interior Point Methods for Optimal Spot Pricing of Electricity in Deregulated Environment," IEEE Transaction on Power Systems, vol. 15, no. 1, pp. 39-50, Feb. 2000.
4. Tanaka, Mokoto: Optimal Transmission Capacity under Nodal Pricing and Incentive Regulation for Transco, RIETI Discussion Paper Series 05-E-021, University of Tokyo, Japan, May 2005, pp. 1-19.
5. Milano, Federico: Pricing System Security in Electricity Market Models with Inclusion of Voltage Stability, Ph.D. thesis, University of Waterloo, Waterloo, ON, Canada, 2002.
6. Wu, Y.K.: " Comparison of Pricing Schemes of Several Deregulated Electricity Markets in the World,", IEEE/PES, Int. conf. on Security and Sustainable Development under Deregulation, August 14-18, 2005, PL2 - Panel Discussion, Power Market Design and Associated Issues , T&D-F1266, PL2-7, Dalian, China
7. Kirby, B.J., Van Dyke, J.W.: "Congestion Management Requirements, Methods and Performance Indices" Oak Ridge National Laboratory, South California, June 2002. Available at http:// www.osti.gov/bridge
8. Konejo, A.J., Castillo, E., Minguez, R., Milano, F.: "Locational Marginal Price Sensitivities" IEEE Transactions on Power Systems, vol. 20, No. 4, November 2005, pp. 2026-2032.
9. Rotoras, Recardo: "Transmission Pricing of Active and Reactive Power, Congestion Price and Supplement cost Allocation Method : A case of Philippines," Ph.D. Thesis, Available at www.asdu.ait.ac.th
10. Pandey, Seema N., Verma Shekhar, Srivastava., Laxmi: "Congestion Management In Restructured Power System Scenario : An Overview", Presented at International Conference on Challenges and Strategies for Sustainable Energy, Efficiency and Environment, held at UPTU, Lucknow, 10th – 11th June, 2006, pp. 410 – 421.
11. Hong, Ying-Yi., Lee, C.F.: "A Neuro-Fuzzy Price Forecasting Approach in Deregulated Electricity Markets," Electric Power System Research, Vol.73, Issue2, Feb2005, pp. 151-157.
12. Iyer, Vanaja, Fung, Chun Che, Gedeon, Tamas: "A Fuzzy-Neural Approach to Electricity Load and Price Forecasting in a Deregulated electricity Market,"TENCON 2003, Conference on Convergent Technologies for Asia Pacific region, Vol.4,15-17 Oct.2003, pp.1479-1482.
13. Bi, T.S., Ni, Y.X., Shen, C.M., Wu, F.F., Yang, Q.X.: "A Novel Radial Basis Function Neural Network for Fault Estimation in Transmission Networks", Proc. of 5th International Conference in Advances in Power System Control, Operation and Management, APSCOM 2000, Hong Kong, Oct. 2000.
14. Jain, T., Srivastava, L, and Singh, S.N.: "Fast voltage contingency screening using Radial Basis Function neural network", *IEEE Transactions on Power Systems*, Vol 18, No. 4, 2003, pp. 1359-1366.
15. Ram, D., Srivastava, L., Pandit, M., Sharma, J.: "Line Overloading Alleviation Using Radial Basis Function Neural Network," *Proceedings International Conference on Power Systems: "Challenges to Electric Utilities in the New Millennium"*, held in Kathmandu, Nepal, Nov. 3-5, 2004, 838-841.
16. Milano, F.: "PSAT - Matlab-based Power System Analysis Toolbox", available at http:// thundebox.uwaterloo.ca / ~fmilano, 2002.