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Spot Price Forecasting in a Restructured Electricity Market: An Artificial Neural Network Approach

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***Abstract:** In restructured electricity markets, market participants' mainly utilities, power producers, and traders are shown to increased risks due to spot price volatility. Accuracy of electricity price forecasting mainly affected by network congestions, use of renewable sources, system security, increasing loads due to appliance, weather dependency, market coupling, and global financial instability. Market participants use price forecasts to decide their bidding strategies to maximize their profits in the day-ahead market. Generating companies have to make decisions regarding unit commitment. Suppliers and consumers use price forecasts to optimize the proportion of forward market and bilateral contracts in their asset allocations. Facility owners use the long-term price trends to ensure recovery and profitability of their investments in generation, transmission, and distribution. This study demonstrates electricity spot price forecasting in day-ahead electricity market based on Artificial Neural Network (ANN) approach. Recently ANN techniques are emerged as the best technique and suitable for restructured power system problems. This study used Feed-Forward Neural Network (FFNN) and Radial Basis Neural Network to forecast electricity spot prices. The results are computed and compared for standard IEEE-57 Bus system. More accurate price forecasting is obtained using RB neural network based on several statistical errors.*

***IndexTerms:** Electricity Restructuring, Spot Price, Artificial Neural Network, Forecasting*

I. INTRODUCTION

In several decades, worldwide countries have spent substantial resources and efforts on implementing market-oriented restructuring in their electric power sectors. The desired objective under such regime is to achieve a more efficient power system facilitated by competition. A good and sustainable pricing scheme becomes a key issue in order to achieve efficient competition. In restructured electricity markets, market participants' mainly utilities, power producers, and traders are shown to increased risks due to spot price volatility. Accuracy of electricity price forecasting mainly affected by network congestions, use of renewable sources, system security, increasing loads due to appliance, weather dependency, market coupling, and global financial instability [1-2]. Market participants need to forecast short-term, mainly day-ahead, prices to maximize their profits in spot markets. These price forecasting facilitates market participants in terms of negotiations of bilateral contracts, hedge against risks of price volatility in spot markets, to ensure return on investment in electricity generation, transmission and distribution.

Today the electric power industry has entered in an increasingly competitive environment under which it becomes more realistic to improve economic efficiency and reliability with affected market forces [3]. Electricity Spot pricing in such an environment has now been emerged as an important mode of energy pricing [4]. Electricity spot prices reveal vital information to the market participants about their bidding and risk assessment strategies and Independent system operators about to perform market dispatch and market decisions through market clearing price under network congestion.

One of the applications of electricity spot pricing in deregulated regime is to accurately predict the electricity prices. Market participants need information about short-term price forecasting i.e. day-ahead to maximize their profits in spot markets, medium term price forecasting to negotiate bilateral contracts so that they can hedge against risks of price volatility in spot market. Generators and transmission owner needs long-term price trends to ensure investments recovery in the facility planning [5]. Also, forecasted prices provide system operators to predict possible exercises of market power and detect gaming behaviors leading to unreasonable prices.

In past decades, several hard computational techniques like time series models, auto regressive and auto regressive integrated moving average (ARIMA) models have been used to forecast electricity prices. Though these techniques are found accurate, but are limited to a large amount of historical information and the computational cost [6]. Recently generalized autoregressive conditional hetero-skedastic (GARCH) model [7-8] and the Wavelet-ARIMA technique have also been proposed. Apart from this, some soft computational techniques based on Artificial Intelligence approach also been proposed to improve the performance of price

forecasting. As these techniques do not require modeling the system; instead, they find an appropriate mapping between the several inputs and the output i.e. electricity price, usually learned from historical examples, thus being computationally more efficient [9].
Artificial Neural Networks (ANNs) techniques that have been widely used for short-term load forecasting are now developed for Electricity Spot price forecasting, market clearing price (MCP) and market clearing quantity forecasting due to its simple, flexible and more powerful tools [10]. The performance of price forecasting can be improve by providing adequate data for training, efficient selection of the input and output variables, an appropriate number of hidden units and enough computational resources i.e. transfer function, weights and bias available [11-12]. The advantages of ANNs of being able to approximate any nonlinear function and being able to solve problems where the input–output relationship is neither well defined nor easily computable, as ANNs are data-driven [13-14].
This study mainly used the family of ANN i.e. Feed-forward Neural Network and Radial Basis Neural Network to forecast electricity spot prices. The main contribution of our approach is to model first electricity spot prices for hybrid (AC-DC) system and forecast prices using several neural network techniques. The performance and accuracy of technique is measured through several statistical techniques.
The remainder of this paper is organized as follows: In Section 2 we give details of the electricity spot price modeling for hybrid system. In Section 3 we demonstrated importance of electricity price forecasting. In Section 4 we give modeling for FFNN and Radial Basis neural Networks and statistical parameters for performance evaluation. In Section 5 we provide electricity spot price forecasting results and statistical error comparison for standard IEEE-57 Bus system. In Section 6 we present the conclusions.

II. MODELLING ELECTRICITY SPOT PRICE

In restructured electricity market, electricity Spot price theory is introduced for efficient use of the transmission grid and generation resources and to provide correct economic signals [15-16]. It is a method to determine MCP for several locations on the transmission grid. The price at each location reflects cost of the energy and the cost of delivering it. The hybrid AC-DC OPF based spot pricing problem is modeled as follows.

A. AC System Equations- It is mathematically represented as

Minimize f (X, P, Q) for X (1)

Subject to S (X, P, Q) = 0 (2)

T (X, P, Q) $\leq$ 0 (3)

Where P, Q are for n bus system active and reactive power demands, X is control variables, S and T are equality and inequality constraints. f (X, P, Q) is short term operating fuel cost having cost characteristics represented by

$$f = \sum_{i=1}^{NG} a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad (4)$$

where, P_{Gi} is the real power output; a_i, b_i and c_i is the cost coefficient of the i^{th} generator, NG is the gen. buses.

Equality constraint has represented as-

$$P_G = P_D + P_{dc} + P_L \text{ and } Q_G = Q_D + Q_{dc} + Q_L \quad (5)$$

where D is demand, G is generation, ‘ dc ’is dc terminal and L is the transmission loss.

Inequality constraints is represented as-

T (X, P, Q) ≤ 0 (6)

which includes real and reactive power limits, Bus voltage limits, power flow limits represented as

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \ (i \in G_B) \text{ and } Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \ (i \in G_B) \quad (7)$$

$$|V_i^{min}| \leq |V_i| \leq |V_i^{max}| \ \text{(i= 1,……,}N_B\text{)} \ ; N_B \text{ is no. of buses.} \quad (8)$$

$$P_f^{min} \leq P_f \leq P_f^{max} \ \text{(f= 1,…, } Noele \text{) ; } Noele \text{ is No. of transmission lines.} \quad (9)$$

Then, operating conditions of a ac-dc system is described by the vector $X = [\delta, V, x_c, x_d]^t$ (10)

B. DC System Equations

Using the per unit (PU) system [17], the average value of the dc voltage of a converter connected to bus ‘i’ is

$$V_{di} = a_i V_i \cos\alpha_i - r_{ci} I_{di} \tag{11}$$

where, α_i is the gating delay angle; r_{ci} is the commutation resistance, and a_i is the transformer tap setting. For a lossless converter, the dc voltage written as

$$V_{di} = a_i V_i \cos\varphi_i \tag{12}$$

where, $\varphi_i = \delta_i - \xi_i$, and φ is the angle by which the fundamental line current lags the line-to-neutral source voltage. The real and reactive power flowing in or out of the dc network at terminal '*i*' may expressed as

$$P_{di} = V_i I_i \cos\varphi_i \quad \text{and} \quad Q_{di} = V_i I_i \sin\varphi_i \tag{13}$$

The operating condition of the dc system can describe by the vector $X_d = [V_d, I_d, a, \cos\alpha, \varphi]^t$ (14)

Here equations (1) – (3) are an OPF problem for the demand (P, Q). Newton method is used to get an optimal solution [19].

C. Electricity Spot Price

The real and reactive power prices at bus 'i' is the the Lagrangian function (or system cost) of equation defined as [18]

$$L(X,\lambda,\rho,P,Q) = f(X,P,Q) + \lambda S(X,P,Q) + \rho T(X,P,Q) \tag{15}$$

The optimal solution (X,λ,ρ) and for a set of given (P,Q), the spot price of real and reactive power for each bus is expressed as-

$$\pi_{p,i} = \frac{\partial L(X,\lambda,\rho,P,Q)}{\partial_{pi}} = \frac{\partial f}{\partial_{pi}} + \lambda\frac{\partial S}{\partial_{pi}} + \rho\frac{\partial T}{\partial_{pi}} \tag{16}$$

III. IMPORTANCE OF ELECTRICITY PRICE PREDICTION

Under restructuring environment and in various time horizons, the applications of price prediction or forecasting are different. In the short-term horizon, market participants use price forecasts to decide their bidding strategies to maximize their profits in the day-ahead or short-term forward market. Generating companies have to make decisions regarding unit commitment. They will only want their generators to be dispatched if it is profitable, and as these decisions are often required hours or days in advance, so they require price forecast in order to determine profitability.

For the medium-term horizon, suppliers and consumers use price forecasts to optimize the proportion of forward market and bilateral contracts in their asset allocations. Price forecasts are also references in the negotiation of bilateral contracts. Also scheduled maintenance of generating plants have to be decided based on price forecast to manage offline period that will have the least impact on profitability.

For the long-term time horizon, facility owners use the long-term price trends to ensure recovery and profitability of their investments in generation, transmission, and distribution.

Also often forecast and models of nodal prices serve various applications in the operation of electricity markets. Many industries use and pay for electricity as an important input in their operations, they also require forecasts of prices to determine their own profitability. In many markets around the world, users are able to purchase contracts for electricity at a fixed price over a specified time. The valuation of such financial derivatives require estimation of both the likely levels and volatility of nodal prices in order to determine fixed and fair price for the contract itself. Market or independent system operator needs accurate prediction of energy prices for market monitoring because the exercise of market power and gaming behaviour can increase the volatility of electricity prices [6].

IV. MODELLING ARTIFICIAL NEURAL NETWORK

This study used FFNN, and Radial Basis networks to forecast and compare day-ahead electricity nodal prices. The theoretical formulations are as follows

A. Feed Forward Neural Network with BP algorithm (FFNN)

The FFNN is shown in Figure 1 [20]. If the inputs of neuron j are the variables $x_1, x_2, \ldots, x_i, \ldots, x_N$, the output u_j of neuron j is obtained as

$$u_j = \varphi\left(\sum_{i=1}^{N} w_{ij} x_i + b_j\right) \tag{18}$$

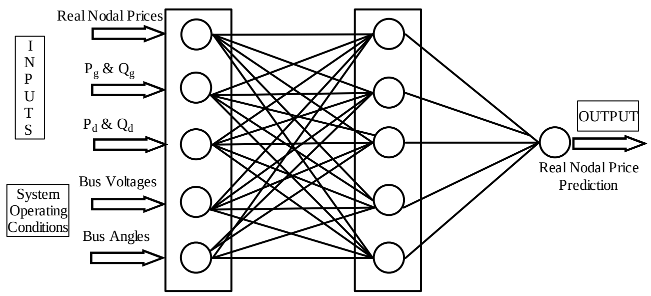

Fig. 1: FFNN model

The output u_j of neuron j is obtained as $u_j = \varphi\, hid\left(\sum_{i=1}^{N} w_{ij}^{hid}\ x_i + b_j^{hid}\right)$ (19)

The output y_k of neuron k (of the output layer) is obtained as $y_k = \varphi\, out\left(\sum_{j=1}^{M} w_{jk}^{out}\ u_j + b_k^{out}\right)$ (20)

The mean square error is represented as $E = \frac{1}{2}\sum_{k=1}^{Q}(y_k^d - y_k)^2$ (21)

The network outputs and the error are calculated again with the adapted weights and biases, and this training process is repeated at each epoch until a satisfied output y_k is obtained corresponding with minimum error. This is by adjusting the weights and biases of the BP algorithm to minimize the total mean square error and is computed as

$$\Delta w = w^{new} - w^{old} = -\eta \frac{\partial E}{\partial w} \quad \text{and} \quad \Delta b = b^{new} - b^{old} = -\eta \frac{\partial E}{\partial b} \qquad (22)$$

where η is the learning rate.

B. Radial Basis (RB) Network

This network can be used to approximate function. It creates a RBF neural network in an incremental way: at each step there is added a new hidden unit having as center an input vector from the training set. New hidden units are added until the goal specified by the user is reached.

The weights corresponding to the output units are computed as in the case of RBE.

Algorithm- It creates a two layer network.

The first layer has Radial basis transfer function neurons, and calculates its weighted inputs with Euclidean distance weight function, and its net input with Product net input function. The second layer has linear transfer function neurons, calculates its weighted input with the dot product weight function and its net inputs with sum net input function.

C. An Exact Radial Basis (RBE) Neural Network

It creates a radial basis function neural network which has as many hidden units as examples are in the training set. The centers are set to the input values in the training set.

The exact radial basis function takes matrices of input vectors P and target vectors T and a spread constant 'σ ' for the radial basis layer and returns a network with weights and biases such that the outputs are exactly T when the inputs are P. This function creates as many radial basis transfer function neurons as there are input vectors in P and sets the first-layer weights to P'. Thus, a layer of radial basis transfer function neurons is formed in which each neuron acts as a detector for a different input vector. If there are *Q* input vectors, then there will be *Q* neurons. Thus, exact radial basis creates a network with minimum error on training vectors. This makes the network function smoother and results in better generalization for new input vectors occurring between input vectors used in the design.

In order to predict electricity nodal prices for day-ahead electricity market, this study first computed AC-DC OPF based nodal prices for a real power system for peak demands (summer season) collected for several months. The resulted data electricity nodal prices, bus voltages, angles and available real and reactive demands are used as input to above neural networks.

D. Comparison Between FFNN and Radial Basis Neural Function Networks

1) RBF networks are local approximators, whereas FFNNs are global approximators.
2) RBF networks have a single hidden layer, whereas FFNN can have any number of hidden layers.
3) The output layer of a RBF network is always linear, whereas in FFNN it can be linear or nonlinear.
4) The activation function of the hidden layer in an RBF network computes Euclidean distance between the input signal vector and parameter vector of the network, whereas the activation function of FFNN computes inner product between input signal vector and pertinent synaptic weight vector.
5) RBF networks can overcome some of the limitations of FFNN because it can use a single hidden layer for modeling any nonlinear function. Therefore, it is able to train data faster than FFNN.
6) RBF networks have simpler architecture than FFNNs; it still maintains its powerful mapping capability. Due to the benefits of these characteristics, RBF network is an interesting alternative technique for classification problem.

E. Measurement and Performance evaluation of Electricity Price Forecasting

The most commonly used function is RMSE and it is calculated [22] by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Spot\Pr ice_{predicted} - Spot\Pr ice_{real})} \quad (23)$$

Mean Absolute Percentage error (MAPE) is given by

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|Spot\Pr ice_{predicted} - Spot\Pr ice_{real}|}{Spot\Pr ice_{real}} \quad (24)$$

The error variance (γ^2) is calculated by

$$\gamma^2 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|Spot\Pr ice_{predicted} - Spot\Pr ice_{real}|}{Spot\Pr ice_{real}} - MAPE\right)^2 \quad (25)$$

The Forecasted Mean Square error (FMSE) is computed by

$$FMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Spot\Pr ice_{real} - Spot\Pr ice_{predicted})^2} \quad (26)$$

Standard deviation is calculated as the square root of variance. It is given by

$$SD = \gamma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{|Spot\Pr ice_{predicted} - Spot\Pr ice_{real}|}{Spot\Pr ice_{real}} - MAPE\right)^2} \quad (27)$$

V. ELECTRICITY SPOT PRICE FORECASTING RESULT ANALYSIS AND STATISTICAL ERROR COMPARISON

The Simulation test system model is shown in the Figure 2. It has 7 generators, 57 buses, 17 transformers, and 80 transmission lines. A HVDC link is connected between bus 1 and bus 30. The ratings of the converter at these buses are 1.0 PU. The upper and lower bounds (real power) for generators G_1, G_2, G_3, G_6, G_8, G_9 and G_{12} and their fuel cost functions expressed as ($f_i = a_i P_{Gi}^2 + b_i P_{Gi} + c_i$) in ($/MWh). The upper and lower bounds (reactive power) for all generators are in the range of $-0.5 \le Q_{Gi} \le 0.5$.

The voltage values for all buses have bounded between 0.95 and 1.05. All of the values have indicated by PU. The AC-DC electricity spot pricing methodology is simulated for this system for daily hourly peak demands. The resulted bus voltages and real spot prices are computed with optimal power flow methodology.

To forecast the spot prices, the input variables assigned to neural network in terms of real and reactive power demands, resulted bus voltages, power angles, and real electricity nodal prices.

The parameters for various neural networks are selected and simulated in MATLAB to obtain the accurate price forecasting. Table 5.1 shows the ANN parameters setting in MatLab software.

Table 5.1: ANN parameters for electricity spot priceforecasting

Particular	Method/value	Particular	Method/value
For FFNN			
Neural network architecture		BP Learning and training	
Neural network	'Multiplayer perceptron algorithm (MLP)	Training method	'Trainlm' (Levenberg-Marquardt Back Propogation algorithm)
Number of input neurons	5	Learning method	'learngdm' (Gradient decent function)
No. of output neurons	1	Learning rate	0.5
No. of hidden layer	1	Momentum constant	0.3-0.8
No. of hidden Neurons	16	No. of iterations	100
Transfer Function	Tangent sigmoid, and linear transfer function	Data dividation method	Dividerand
Maximum Epoch	1000	Data used for training	60-70%
		Data used for validation	10-15%
		Data used for testing	20-30%
For RB and RBE			
Spread	0.5	Goal	0.001

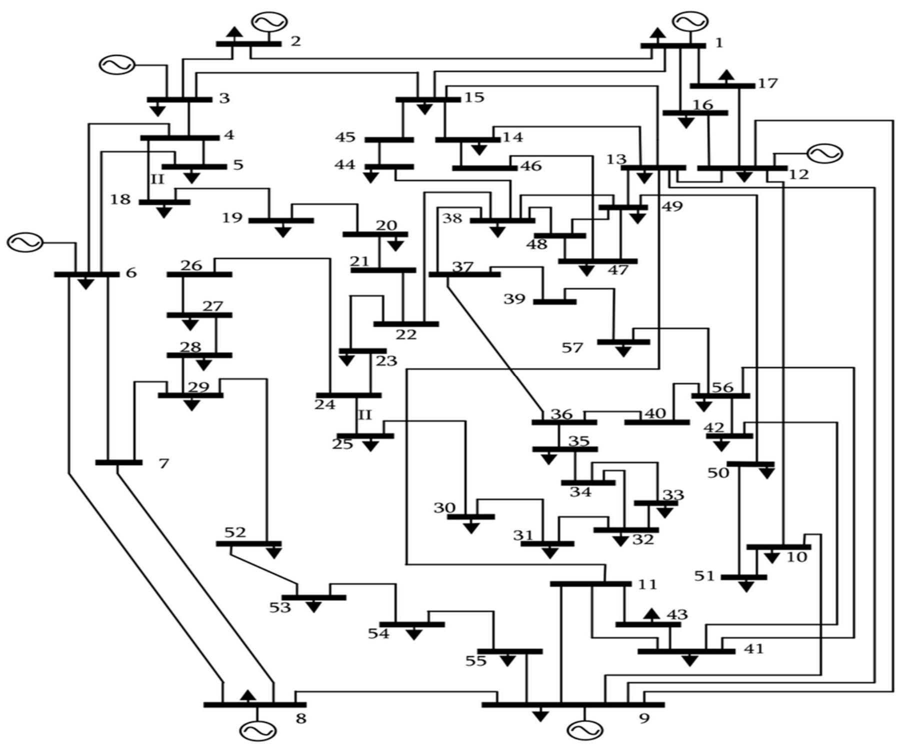

Figure 2: IEEE-57 Bus System

Several variations in load, generation and transmission capacity have been done and the obtained data is given to MATLAB to get the spot price. Spot Price and Errors using statistical tools for Feed Forward Neural Network (FFNN) and Radial Basis (RB) are calculated and compared as shown. Table 5.2 shows electricity spot price forecasting obtained by FFNN, RB and RBE neural networks.

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Table 5.2: Electricity Spot Price forecasting comparison

Bus No.	Electricity Spot Price ($/MWh)				Bus No.	Electricity Spot Price ($/MWh)			
	Real Price	FFNN	RB	RBE		Real Price	FFNN	RB	RBE
1	20.41	20.41	21.3903	21.987	30	23.77	23.8	21.9621	23.9627
2	20.57	20.56	23.8856	21.0928	31	24.51	24.51	21.4402	22.0347
3	21.1	20.95	21.243	23.4171	32	23.96	23.91	21.2901	23.3254
4	21.2	21.57	22.7184	20.1584	33	24.04	24	22.6458	21.4076
5	21.25	21.49	21.1079	23.2108	34	23.91	23.89	22.3584	22.3082
6	21.13	21.23	23.9626	20.8077	35	23.71	23.8	23.8856	21.679
7	20.81	21.61	22.2231	20.8077	36	23.42	23.45	23.8856	21.124
8	20.16	20.36	21.3903	23.3254	37	23.35	23.34	22.2201	20.9796
9	22.3	21.29	23.4291	22.3883	38	22.71	22.67	24.0317	22.0347
10	21.93	21.52	21.4532	22.8514	39	23.39	23.37	19.2973	24.5092
11	22.26	21.55	23.365	22.2481	40	23.46	23.26	22.4549	21.124
12	21.35	20.38	22.7208	23.9068	41	22.21	22.13	23.6924	22.953
13	22.01	21.73	21.0051	22.2481	42	23.21	23.24	21.3903	21.124
14	22.04	21.84	22.7208	22.0347	43	22.24	21.77	21.0018	20.8077
15	21.74	21.69	21.3865	23.2108	44	22.47	22.56	21.3865	21.679
16	21.28	21.22	21.6643	23.5632	45	21.67	21.78	21.3903	20.9796
17	20.98	21.09	23.4291	22.606	46	22.01	22.03	21.4532	23.7081
18	21.27	21.33	23.9466	21.2465	47	22.39	22.57	21.1079	20.762
19	22.3	22.71	22.4758	22.783	48	22.48	22.5	21.2901	24.0175
20	22.57	23.35	21.4532	22.7144	49	22.31	22.34	21.3865	23.4584
21	22.78	22.59	22.3584	23.4584	50	22.6	22.67	20.7625	22.7139
22	22.78	22.65	22.597	23.7081	51	21.88	21.55	23.6924	24.0175
23	22.81	22.65	21.1413	21.679	52	21.8	21.82	22.4549	22.8514
24	22.96	22.34	23.4291	22.783	53	22.09	22.19	22.4549	20.8077
25	23.22	22.99	21.6806	21.343	54	21.09	20.79	21.9621	21.0928
26	22.91	23.85	21.4974	21.2465	55	22.09	21.69	22.2231	21.49
27	21.96	22.23	22.2201	21.679	56	23.56	23.57	22.3584	20.8931
28	21.4	21.5	22.7208	21.343	57	23.82	24.06	21.6806	21.9872
29	20.97	20.94	21.2901	22.6679					

The performance of forecasting technique is validated by calculating errors using statistical tools and compared as shown in Table 5.3. The errors i.e. RMSE, MAPE, Variance, FMSE and Standard Deviation are computed and found optimum for Radial Basis neural network. More accurate price forecasting is obtained using RB neural network based on several statistical errors.

Table 5.3: Error comparison for FFNN and RB Neural Networks

Error Comparison of FFNN and RB Neural Network									
RMSE		MAPE		Variance		FMSE		Std. Deviation	
FFNN	RB	FFNN	RB	FFNN	RB	FFNN	RB	FFNN	RB
0.0000 + 0.1759i	0.0000 + 0.3519i	0.9992	0.8419	0.9787	0.6948	0.3427	0.3099	0.9893	0.8335

VI. CONCLUSION

This study demonstrates electricity spot price forecasting in day-ahead electricity market based on Artificial Neural Network (ANN) approach. ANN techniques are found more powerful technique for price forecasting suitable for restructured power system problems. This study presented mathematical formulation of optimum spot price calculation, forecasting techniques i.e. Feed-Forward Neural Network (FFNN) and Radial Basis Neural Network for use of electricity spot price forecasting for wholesale electricity market. The results are simulated and performance of each technique is compared for standard IEEE-57 Bus system. The RB showed reasonably smaller values for RMSE and MAPE as compared to other NNs for IEEE-57 Bus system. Spot Price forecasting obtained are accurate enough to be used by market participants to estimate the risk and have effective decision making in formulating bidding strategy.

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