

Electricity Nodal Price Prediction in a Day-Ahead Electricity Market

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Abstract— In developing countries, recent trend is to adopt High Voltage Direct Current (HVDC) transmission in the existing AC transmission system to gain its techno-economical benefits. In restructured electricity market, accurate prediction of day-ahead electricity nodal prices have become an important activity to address the system operations and price volatility in the marketplace and also to facilitate the market participants to estimate the risk and have better market oriented decision making. In the paper, Electricity nodal price prediction in a day-ahead electricity market using Artificial Neural Networks (ANNs) is presented. The numerical results are presented and compared for a real transmission system of India to demonstrate the rationality and feasibility of the proposed methodology.

Index Terms—AC-DC OPF, Electricity Nodal Pricing, Price Prediction, Artificial Neural Networks

I. INTRODUCTION

Electricity restructuring of vertical integrated power systems brings new requirements in operation and control management. One of the challenging issues is pricing electricity services. Recently, the electric power industry has entered in an increasingly competitive environment under which it becomes more realistic to improve economics and reliability of power systems by enlisting market forces. Nodal or locational marginal pricing (LMP) in this environment has now become an important mode of energy pricing [1]. LMPs reveal vital information to the market participants and to the system operators to perform favourably.

In order to address basic problems like ever increasing electricity demand, transmission congestion, infrastructure investment especially in transmission and distribution segment, few developing countries starts adopting High Voltage DC (HVDC) transmission in the existing AC system to gain techno-economic benefits of the investment and also to ensure consumer welfare. This trend has therefore needed to address in formulating nodal pricing scheme. Besides this, challenges involved

in restructured electricity market is to provide accurate nodal price information to market participants to decide their bidding strategies and risk management, to facilitate system operator to perform market dispatch and clearing decisions in network congestion etc.

Several hard computational techniques like time series models, auto regressive and auto regressive integrated moving average (ARIMA) models have been tried to predict electricity prices. Though these techniques are found accurate, but are limited to a large amount of historical information and the computational cost [2]. Apart from this, some soft computational techniques based on Artificial Intelligence approach also been proposed. 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.

Artificial Neural Networks (ANNs) techniques that have been widely used for short-term load prediction are now developed for electricity nodal price or LMP prediction due to its simple, flexible and more powerful tools. The performance of ANN based prediction is enhanced if there are enough data for training, an adequate selection of the input-output variables, an appropriate number of hidden units and enough computational resources available. 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.

In this paper, input variables i.e. historical real and reactive electricity demand, calculated power angle, bus voltages and real nodal prices using AC-DC OPF based nodal pricing methodology have been used to predict peak day-ahead price at various buses in a restructured electricity markets. NNs like FeedForward Neural Network (FFNN) with Backpropagation (BP) algorithm, and the generalized regression neural network (GRNN) are used to predict day-ahead nodal prices.

This paper is organized as follows: with the above introduction, section II discusses the importance of

electricity price prediction and applications in restructured electricity market; Section III take review of background study concerning electricity price prediction; Section IV and V presented AC-DC OPF based nodal pricing methodology and day-ahead price prediction by ANNs respectively; Section VI evaluates the numerical results for a real 400 kV Maharashtra State Electricity Transmission Company Limited, India. Finally, conclusions are drawn of this paper.

II. IMPORTANCE OF ELECTRICITY PRICE PREDICTION APPLICATION

The main objective of electricity restructuring in many developing countries is to attract investments capital, develop efficient wholesale electricity markets and competitions and serve demands at lower prices. In restructured electricity market, electricity price is no longer set by the monopoly utility company, rather it responds to the market and operating conditions. Offering the right amount of electricity at right time with right price has become the key for utilities and market participants. Under such competitive environment, the most vital identified applications of LMP or nodal pricing for utilities, market participants and system operators is to accurately predict or forecast the electricity prices.

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].

Price forecasting can also be used to predict market monitoring indexes and measurements. The market power indexes such as the Herfindahl–Hirschman Index (HHI) is used to measure the concentration of market shares, the Residual Supply Index (RSI) is used to identify pivotal suppliers, and the price-cost margin index, i.e., Lerner Index, is used to calculate the markup of prices over marginal costs are commonly used indices by market operator[5].

Electricity nodal prices are highly volatile due to congestions in transmission lines. Even though there always is a risk of volatility in almost every market, the degree of volatility is higher on electricity markets than other markets. As a result and the fact that electricity is a commodity that consumers need in their daily life to a great extent, need is to accurately predict electricity prices is of vital importance to both market participants and market operator in wholesale electricity markets.

III. PRESENT STUDY

A few literatures of electricity price prediction or forecasting have been reviewed as follows: [1] suggested Neural Networks (NNs) and fuzzy-c-means approach to forecast LMPs for bidding competition in deregulated electricity markets. The recurrent neural network and back-propagation algorithms are demonstrated for comparison. [3] gives a Wavelet Transformation (WT) based neural network model to forecast price. The historical price data is decomposed into wavelet domain constitutive sub series using WT and then combined with the other time domain variables to form the set of input variables to improve the forecasting accuracy. [4] suggested a two-stage hybrid methodology i.e. self-organized map (SOM) and support-vector machine (SVM) for forecasting short-term electricity price. A SOM applied in the first stage to cluster the input-data set into several subsets in an unsupervised manner. In the second stage, a group of SVMs is used to fit the training data of each subset in a supervised way to predict the next-day hourly electricity prices. [5] presented a fuzzy inference system (FIS), least-squares estimation (LSE) and the combination of both to select correlated data to improve the short-term forecasting performance in wholesale electricity markets. [6] developed Bayesian framework to analyze the uncertainties involved in a Market clearing price (MCP) prediction. [7] gives a methodology to predict next-day electricity prices by ARIMA model. [9] used NNs extended Kalman filter (EKF) to predict MCP and confidence interval (CI) in a deregulated power market. A modified U-D factorization method within the decoupled EKF framework is used to provide smaller CIs, faster convergence, provides more accurate predictions than the BP-Bayesian method. [10] presented WT and ARIMA techniques to forecast day-ahead electricity prices. The historical and ill-behaved price series is decomposed by WT. Then, these series are forecasted using ARIMA models. In turn, the ARIMA

forecasts allow through the inverse WT, reconstructing the future behavior of the price series. [12] introduced a panel model for hourly electricity prices in day-ahead markets. The result shows that hourly electricity prices exhibit hourly specific mean-reversion and that they oscillate around an hourly specific mean price level. [13] proposed two artificial neural network: the first to predict the day-ahead load and second to forecast the day ahead MCP. [14] presented a sensitivity analysis of similar days parameters to increase the accuracy of NNs and to forecast hourly electricity prices. The Mean Absolute Percentage Error (MAPE) obtained is smaller one and also accurate and efficient forecast.

This study first calculates accurately the nodal prices using AC-DC OPF based nodal pricing methodology. The resulted nodal prices, bus voltages, power angles and active and reactive demands information are used as input to various NNs to accurately predict the peak day-ahead nodal prices on a given system.

IV. AC-DC OPTIMAL POWER FLOW BASED ELECTRICITY NODAL PRICE FORMULATION

To induce efficient use of the transmission grid and generation resources by providing correct economic signals, a nodal price theory for the restructured electricity markets is developed [15]. It is a method to determine market-clearing prices for several locations on the transmission grid (node). The price at each node reflects cost of the energy and the cost of delivering it. The AC-DC OPF based electricity nodal pricing is formulated as follows

4.1: AC System Equations

Let $P = (p_1, \dots, p_n)$ and $Q = (q_1, \dots, q_n)$ for n bus system, where p_i and q_i be active and reactive power demands of bus- i respectively. The variables in power system operation to be $X = (x_1, \dots, x_m)$, i.e. real and imaginary bus voltages. Then the operational problem of a power system for given load (P, Q) can be formulated as OPF problem

$$\text{Minimize } f(X, P, Q) \quad \text{for } X \quad (1)$$

$$\text{Subject to } S(X, P, Q) = 0 \quad (2)$$

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

where $S(X) = (s_1(X, P, Q), \dots, s_{n_1}(X, P, Q))^T$ and $T(X) = (t_1(X, P, Q), \dots, t_{n_2}(X, P, Q))^T$ have n_1 and n_2 equations respectively, and are column vectors. Here A^T represents the transpose of vector A .

$f(X, P, Q)$ is a scalar, short term operating fuel cost. The generator cost function $f_i(P_{Gi})$ is considered to have 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 generation buses.

The constraints to be satisfied during optimization are

(A) Vector of equality constraint i.e. power flow balance and it is represented as

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

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

(B) The vector of inequality constraints includes upper and lower bounds of transmission lines, generation outputs, stability and security limits are gives as

The maximum and minimum real and reactive power outputs of the generating sources, bus voltage limits, power flow limits are given by

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \text{and} \quad Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad (6)$$

$$|V_i^{\min}| \leq |V_i| \leq |V_i^{\max}| \quad (i=1, \dots, N_B) \quad (7)$$

$$P_f^{\min} \leq P_f \leq P_f^{\max} \quad (f=1, \dots, Noele) \quad (8)$$

$Noele$ is number of transmission lines.

Then, operating conditions of a combined ac-dc electric power system may described by the vector

$$X = [\delta, V, x_c, x_d]^T \quad (9)$$

where, δ and V are the vectors of the phases and magnitude of the phasor bus voltages; x_c is the vector of control variables and x_d is the vector of dc variables.

4.2: DC System Equations

Using per unit (PU) system [16], the average value of the dc voltage of a converter connected to bus ' i ' is

$$V_{di} = a_i V_i \cos \alpha_i - r_{ci} I_{di} \quad (10)$$

where, α_i is the gating delay angle for rectifier operation or the extinction advance angle for inverter operation; r_{ci} is the commutation resistance, and a_i is the converter transformer tap setting. By assuming a lossless converter, the equation of the dc voltage written as

$$V_{di} = a_i V_i \cos \varphi_i \quad (11)$$

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

$$P_{di} = V_i I_i \cos \varphi_i \quad \text{or} \quad P_{di} = V_{di} I_{di}$$

$$Q_{di} = V_i I_i \sin \varphi_i \quad \text{or} \quad Q_{di} = V_i a_i I_i \sin \varphi_i \quad (12)$$

Equation (12) can substitute in the equation (5) to form part of the equality constraints. Based on these relationships, the operating condition of the dc system can describe by the vector

$$X_d = [V_d, I_d, a, \cos \alpha, \varphi]^T \quad (14)$$

The dc currents and voltages have related by the dc network equations. In ac case, references bus usually the bus of the voltage controlling dc terminal operating under constant voltage (or constant angle) control is specified for each separate dc system. Equations (1) to (3) are an OPF problem for the demand (P, Q) . In this study Newton's OPF method is used to optimize solution.

4.3: Electricity Nodal Price

The real and reactive power prices at bus ‘ i ’ is the Lagrangian multiplier value of the equality and inequality constraints and calculated by solving the first order condition of the Lagrangian, partial derivatives of the Lagrangian with respect to every variable concerned [17]. So the Lagrangian function (or system cost) of equation defined as

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

where, $\lambda = (\lambda_1, \dots, \lambda_n)$ is the vector of Lagrange multipliers of equality constraints; $\rho = (\rho_1, \dots, \rho_n)$ are the Lagrange multipliers of inequality constraints. Then at an optimal solution (X, λ, ρ) and for a set of given (P, Q) , the nodal price of real power for each bus is expressed below for $i = 1, \dots, n$.

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

Here $\pi_{p,i}$ is active and reactive nodal price at bus ‘ i ’, respectively. Equation (16) can be view as the system marginal cost created by an increment of real power load at bus i . The above formulation is programmed in MATLAB 7.5.

V. ARTIFICIAL NEURAL NETWORK MODEL

Artificial neural networks are an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. ANNs are highly interconnected processing units inspired in the human brain and its actual learning process. Interconnections between units have weights that multiply the values which go through them. Also, units normally have a fixed input called bias. Each of these units forms a weighted sum of its inputs, to which the bias is added. This sum is then passed through a transfer function. The prediction with neural networks involves two steps: training and learning. Training of neural networks is normally performed in a supervised manner. The success of training is greatly affected by proper selection of inputs. In the learning process, a neural network constructs an input–output mapping, adjusting the weights and biases at each iteration based on the minimization or optimization of some error measure between the output produced and the desired output. This process is repeated until an acceptable criterion for convergence is reached.

The objective of this study is to predict day-ahead AC-DC OPF based nodal prices for a real system using ANNs. The proposed model is shown in Figure 1.

Neural networks like Feed-Forward Neural Network (FFNN) with Back-Propagation (BP) algorithm, and Generalized Regression Neural Network (GRNN), models are used to predict day-ahead electricity nodal prices. The architecture and mathematical modelling of these neural networks are explained as follows.

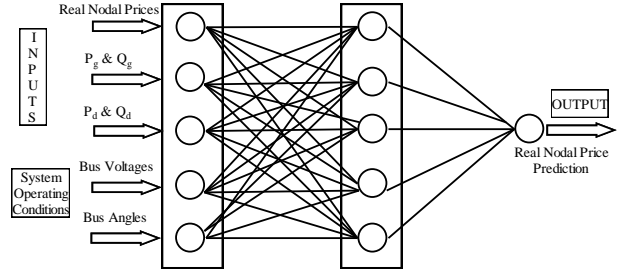


Figure 1: NN for electricity nodal price prediction

5.1: Feed-Forward neural network with Back-Propagation algorithm

A three layered feed forward neural network with BP training algorithm possesses the ability to classify mixed datasets and can be used effectively in obtaining the correct prediction. For generalization, the randomized data is fed to the network and is trained for different hidden layers. The number of processing elements in the hidden layer is varied. Input is passed layer through layer until the final output is calculated and it is compared with real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer. BP learning algorithm is the steepest descent algorithm that minimizes the sum of square errors. To accelerate the learning process, two parameters of the BP algorithm can be adjusted: the learning rate and momentum. Learning rate is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence. The momentum determines the proportion of change of past weights that should be used in calculation of the new weights. Feed-Forward neural network consists of an input, hidden and output layers as shown in Figure 2. Each neuron in a layer is connected to other neurons of the previous layer through adaptable synaptic weights w and biases b , shown in Figure 3.

If inputs of neuron j are the variables $(x_1, x_2, \dots, x_i, \dots, x_N)$, then output u_j of neuron j is obtained as

$$u_j = \varphi \left(\sum_{i=1}^N w_{ij} x_i + b_j \right) \quad (17)$$

where w_{ij} is the weight of connection between neuron j and i -th input; b_j is the bias of neuron j and φ is transfer (activation) function of neuron j .

Feed-Forward neural network is considered with N , M and Q neurons for the input, hidden and output layers, respectively. The input patterns of ANN represented by a vector of variables $x = (x_1, x_2, \dots, x_i, \dots, x_N)$, submitted to neural network by input layer are transferred to hidden layer.

Using the weight of connection between input and hidden layer and the bias of hidden layer, the output vector $u = (u_1, u_2, \dots, u_j, \dots, u_M)$ of the hidden layer is determined. Output u_j of neuron j is obtained as

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

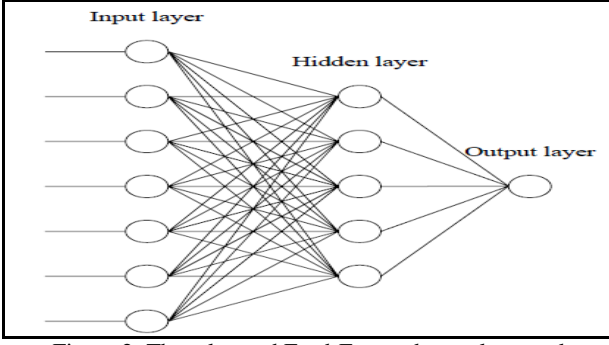


Figure 2: Three layered Feed-Forward neural network

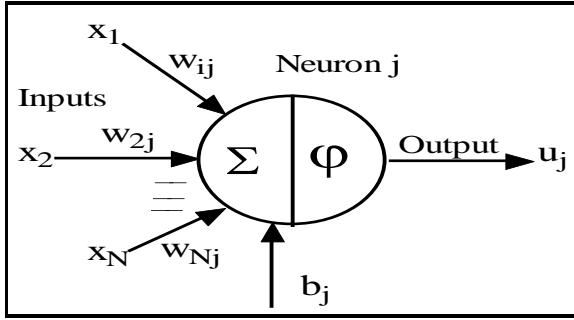


Figure 3: Information processing in a neural network

where w_{ij}^{hid} is the weight of connection between neuron j in hidden layer and the i -th neuron of input layer, b_j^{hid} represents the bias of neuron j and ϕ^{hid} is the activation function of hidden layer. Values of the vector u of hidden layer are transferred to output layer. Using weight of the connection between hidden and output layers and the bias of output layer, output vector $y = (y_1, y_2, \dots, y_k, \dots, y_Q)$ of the output layer is determined. Output y_k of neuron k (output layer) is obtained as

$$y_k = \phi out \left(\sum_{j=1}^M w_{jk}^{out} u_j + b_k^{out} \right) \quad (19)$$

where w_{jk}^{out} is weight of the connection between neuron k in output layer and the j -th neuron of hidden layer, b_k^{out} is the bias of neuron k and ϕ is the activation function of output layer. Output y_k is compared with the desired output (target value) y_k^d . Error E in output layer between y_k and y_k^d ($y_k^d - y_k$) is minimized using the mean square error at output layer (which is composed of Q output neurons), defined by

$$E = \frac{1}{2} \sum_{k=1}^Q (y_k^d - y_k)^2 \quad (20)$$

In the first step, the network outputs and the difference between actual (obtained) output and desired (target) output (i.e., the error) is calculated for the initialized weights and biases (arbitrary values). In the second stage, these weights in all links and biases in all neurons are adjusted to minimize the error by propagating the error backwards (BP algorithm). 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 BP algorithm to minimize the total mean square error and is computed as

$$\Delta w = w^{new} - w^{old} = -\eta \frac{\partial E}{\partial w} \quad \text{and} \quad \Delta b = b^{new} - b^{old} = -\eta \frac{\partial E}{\partial b} \quad (20)$$

where η is the learning rate. Equation (20) reflects the generic rule used by BP algorithm. Equations (21) and (22) illustrate this generic rule of adjusting the weights and biases. For output layer,

$$\Delta w_{jk}^{new} = \alpha \Delta w_{jk}^{old} + \eta \delta_k y_k \quad \text{and} \quad \Delta b_k^{new} = \alpha \Delta b_k^{old} + \eta \delta_k \quad (21)$$

where α is the momentum factor (a constant between 0 and 1) and $\delta_k = y_k^d - y_k$

For hidden layer,

$$\Delta w_{ij}^{new} = \alpha \Delta w_{ij}^{old} + \eta \delta_j y_j \quad \text{and} \quad \Delta b_j^{new} = \alpha \Delta b_j^{old} + \eta \delta_j \quad (22)$$

where $\delta_j = \sum_k^Q \delta_k w_{jk}$ and $\delta_k = y_k^d - y_k$

This study uses the Levenberg-Marquardt algorithm to train a three-layered Feed-forward neural network. This neural network is specially suited for implementing nonlinearities using sigmoid function for hidden layers and linear function for output layer.

5.2: Generalized Regression neural network (GRNN)

It is a normalized Radial Basis Function (RBF) network for which a hidden unit is centered at every training sample. The RBF units are characterised by the Gaussian kernels. The hidden layer to output layer weights are just the target values, so that output is simply a weighted average of the target values of training cases close to the given input case. The first layer is just like a RBF network with as many neurons as there are input/target vectors. Choosing the spread/smoothing parameters of the RBF determines the width of an area in the input space, to which each basic function responds. Figure 4 shows the general regression neural network architecture.

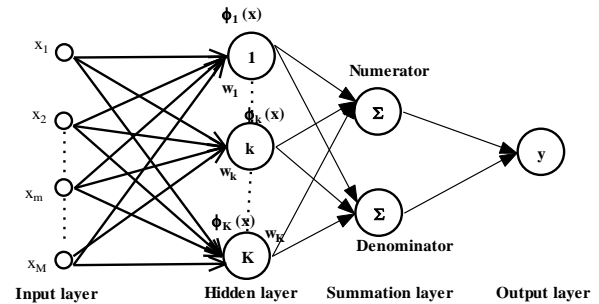


Figure 4: Generalized Regression neural network

If $f(x, y)$ be the joint continuous probability density function of a vector random variable x and a scalar random variable y and X be a particular measured value of the random variable x then the regression of y given X , is presented by the conditional expectation (E) of y on X

$$E[y/X] = \frac{\int_{-\infty}^{+\infty} yf(X, y) dy}{\int_{-\infty}^{+\infty} f(X, y) dy} \quad (23)$$

In practice, the probability density functions are usually unknown. So it is estimated from sample values of X_i and Y_i . The general form of estimator is

$$f_n(x) = \frac{1}{n\lambda} \sum_{i=1}^n \phi\left(\frac{x - x_i}{\sigma}\right) \quad (24)$$

Here, the kernel function estimator is used

$$\hat{f}(X, Y) = \frac{1}{(2\pi)^{\frac{(p+1)}{2}} \sigma^{p+1}} \frac{1}{n} \sum_{i=1}^n \exp\left[-\frac{(X - X^i)^T (X - X^i)}{2\sigma^2}\right] \exp\left[-\frac{(Y - Y^i)^2}{2\sigma^2}\right] \quad (25)$$

where p is the dimension of the vector variable x , n is the number of observations, σ is the width (spread) of the estimating kernel or smoothing factor, Y^i is the desired scalar output given the observed input X^i . Now defining the scalar function D_i^2

$$D_i^2 = (X - X^i)^T (X - X^i) \quad (26)$$

From equations (25) and (26), resulting kernel regression estimator can be presented by

$$\hat{Y}(X) = \frac{\sum_{i=1}^n Y^i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^n \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \quad (27)$$

The estimate $\hat{Y}(X)$ can be visualized as a weighted average of all the observed values, Y_i , where each observed value is weighted exponentially according to its Euclidean distance from X . The neural network is implemented as follows.

Let w_{ij} be the target output corresponding to input training vector X^i and j^{th} output, equation (24) can be expressed as follows

$$y_i = \frac{\sum_{j=1}^n w_{ij} h_j}{\sum_{j=1}^n h_j}; \quad \text{where } h_i = \exp\left(-\frac{D_i^2}{2\sigma^2}\right) \quad (28)$$

The topology of GRNN consists of four layers: input layer, hidden layer, summation layer and output layer. The function of input layer is simply to pass the input vector variables X to all the units in hidden layer. Hidden layer consists of the entire training sample X_1, \dots, X_m . When an unknown pattern X is presented, squared distance D_i^2 between unknown pattern and training

sample is calculated and passed through the kernel function. The summation layer has two units A and B.

Unit A computes the summation of $\exp\left(-\frac{D_i^2}{2\sigma^2}\right)$ multiplied by Y_i associated with X_i . B unit simply computes the summation $\exp\left(-\frac{D_i^2}{2\sigma^2}\right)$. Output unit divides A by B to provide the predication result.

5.3. Price Prediction by ANNs

In a competitive electricity market, the objective of price formulation is either to minimize the generation cost or maximize the consumer benefits. So prices is most optimally obtained at various nodes or location of the network depending on the availability of low cost generation, real and reactive demands and availability of sufficient transmission capacity or no network congestion. This study evaluated AC-DC OPF based nodal pricing methodology to obtained electricity prices at several nodes at hourly peak demands obtained for several days. The obtained data are nodal prices, power angles, and bus voltages and available real and reactive demands are used as input to above neural networks to predict the day-ahead prices. The neural network toolbox in MATLAB is selected and trained for various NNs with the ANN parameters as shown in Table 1.

Table 1: ANN parameters for best price prediction

Particulars	Method/Value	Particulars	Method/Value
For FFNN			
Neural Network Architecture		BP Learning and Training Method/Data	
Neural Network	‘MLP’	Training method	‘Trainlm’ (Levenberg-Marquardt BP)
No. of Input Neurons	4	Learning method	‘learnqdm’ (Gradient decent function)
No. of Output Neurons	1	Learning rate	0.5
No. of Hidden Layer	1	Momentum	0.3-0.8
		No. of iterations	100
No. of Hidden Neurons	16	Data dividation method	Dividerand
Transfer Function	‘Tangent sigmoid’, ‘Purelin’	Training data	60%
		Validation data	10%
		Data used for Testing	30%
For GRNN			
Spread	0.01		

The accuracy of price prediction is evaluated with root mean square error (RMSE) and mean absolute percentage error (MAPE) represented respectively, by

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Nodal \text{ price}_{pred} - Nodal \text{ price}_{Real})^2} \quad (29)$$

$$MAPE = \frac{100}{N} \sum_{i=1}^N \frac{|Nodal \text{ price}_{pred} - Nodal \text{ price}_{Real}|}{Nodal \text{ price}_{Real}} \quad (30)$$

where N is the number of sample nodal prices.

VI. PROBLEM SIMULATION: A REAL 400 kV MSETCL SYSTEM, INDIA

This study considered a real network of 400 kV Maharashtra State Electricity Transmission Company Limited (MSETCL), India shown in Figure 5.

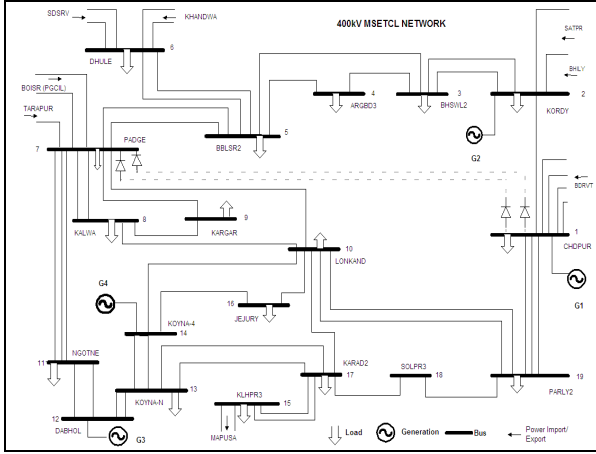


Figure 5: A 400 kV MSETCL system, India

It consists of 19 intra-state buses (i.e. Bus No. 1 to 19) and 8 inter-state buses. To fulfill power demand, Additional power is imported from inter-state generators namely BHILY, KHANDWA, SDSRV, BOISR, BDRVT, TARAPUR, and SATPR. The Real and Reactive demand variations are shown in Figure 6 and Figure 7 respectively. The voltages at all buses have bounded between 0.95 and 1.05 PU. A ± 500 kV HVDC link is connected between CHDPUR and PADGE. CHDPUR selected as a reference bus.

The AC-DC OPF based methodology is simulated for this real system. The resulted bus voltages variations and average real electricity nodal prices are shown in Figure 8 and Table 2 respectively.

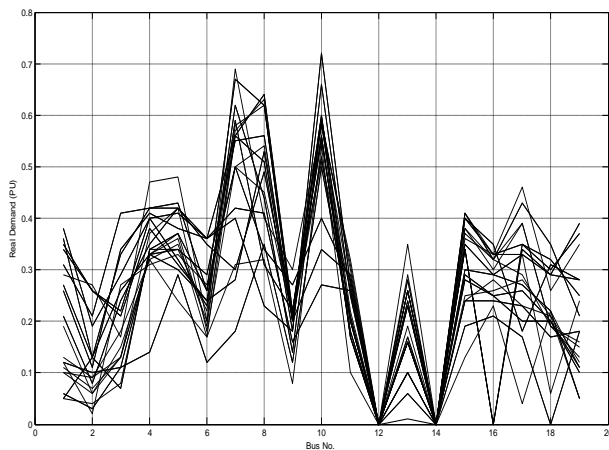


Figure 6: Real demand variation

To accurately predict the day-ahead electricity nodal prices, the input variables are assigned to various Neural Networks. The parameters for various neural networks as shown in Table 1 are selected and simulated in MATLAB to obtain the accurate price prediction. The comparison of average nodal price at various buses and predicted

nodal prices as obtained by proposed NNs is shown in Table 2.

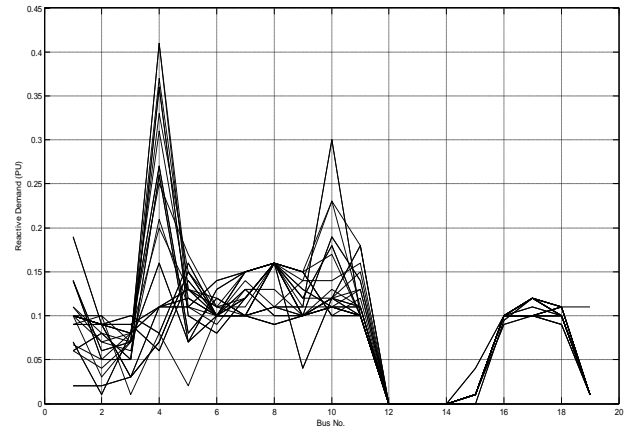


Figure 7: Reactive demand variation

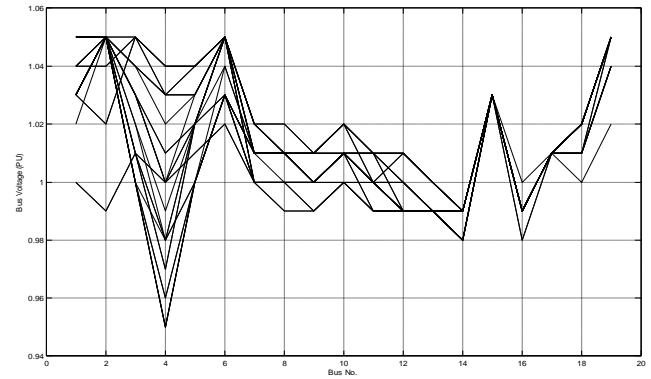


Figure 8: Bus Voltage Variation

Table2: Electricity nodal price and ANN prediction

Bus No.	Bus Name	Average Electricity Nodal Prices (₹/kWh)		
		Real	FFNN	GRNN
1	CHDPUR	1.79	1.78	1.81
2	KORDY	2.20	2.20	2.21
3	BHSLW2	2.42	2.43	2.42
4	ARGBD4	2.43	2.43	2.45
5	BBLSR2	2.62	2.63	2.60
6	DHULE	2.19	2.19	2.23
7	PADGE	2.47	2.48	2.46
8	KALWA	2.45	2.45	2.48
9	KARGAR	2.43	2.43	2.42
10	LONKAND	2.85	2.85	2.82
11	NGOTNE	2.36	2.37	2.37
12	DABHOL	2.84	2.84	2.83
13	KOYNA-N	2.81	2.82	2.84
14	KOYNA-4	2.60	2.60	2.61
15	KLHPR3	2.73	2.73	2.69
16	JEJURY	2.84	2.84	2.86
17	KARAD2	2.83	2.83	2.80
18	SOLPR3	2.48	2.49	2.47
19	PARLY2	2.40	2.39	2.36

The FFNN attended more accurate nodal price prediction as compared to GRNN. The performance of proposed NNs is evaluated by computing RMSE and MAPE. The

resulted values for various buses are shown in Figure 9 and Figure 10. Compared to GRNN, the RMSE and MAPE in FFNN is attended a reasonably smaller value at several buses gives more accurate nodal price prediction.

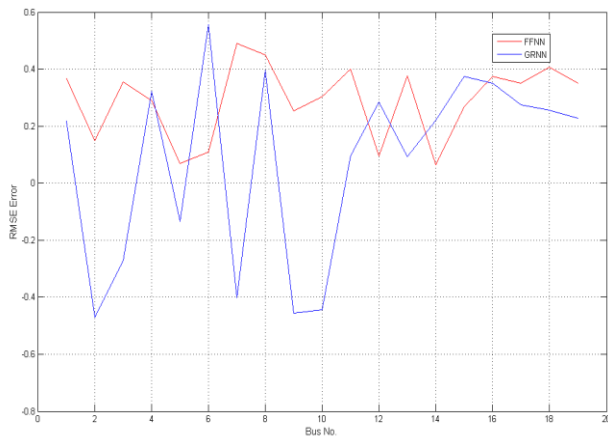


Figure 9: RMSE error comparison

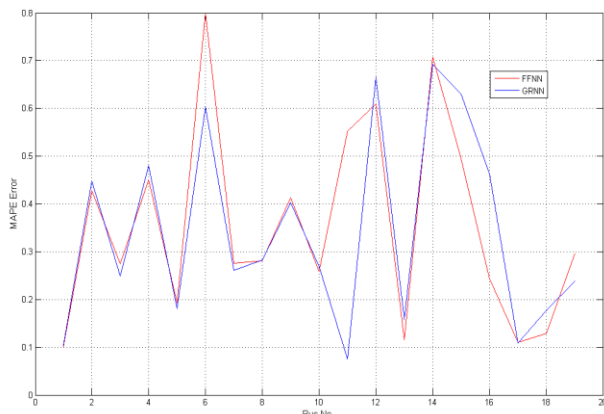


Figure 10: MAPE error comparison

CONCLUSIONS

In consideration with increase importance of accurate prediction of day-ahead electricity nodal prices in restructured electricity market, this paper presented an AC-DC OPF based day-ahead electricity nodal price prediction using artificial neural networks. The multilayer FFNN with a back-propagations algorithm attended reasonably smaller values for RMSE and MAPE as compared to other neural networks. The proposed scheme is more suitable to real power system as demonstrated in this paper. Price predictions obtained are accurate enough to be used by market participants to estimate the risk, formulating bidding strategy and other market oriented decision making. The proposed methodology is rational and more feasible for India and other similar developing countries to establish and maintain their wholesale electricity market.

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