SHORT TERM ELECTRICITY PRICE FORECAST USING WAVELET TRANSFORM INTEGRATED GENERALIZED NEURAL NETWORK

Nitin Singh[1], Ashutosk K Pandey[2], S. R. Mohanty[3]
[1, 2, 3] Department of Electrical Enggineering, MNNIT Allahabad, India
Email:[1]nitinsmnnit@gmail.com, [2]ashutosh10891@gmail.com, [3]srm@mnnit.ac.in

Abstract- In the present scenario when electricity has become a commodity which was capable of being traded by various market players, it becomes necessary that price forecasting of electricity should be accurate to maximize the profits of market players and competitive rates offered to the consumers. Various forecasting models exist in the history which can be broadly classified into statistical models, simulation models & soft computing based models. In the proposed work wavelet based generalized neural network (GNN) has been developed to forecast electricity price accurately in the deregulated market. Wavelet transform is used for decomposing the price into constitutive series Based on statistical features the behavior of price series and wavelet domain decomposed series has been studied.

Index terms- Electricity price forecasting, generalized neural network, wavelet transform, wavelet analysis.

I. INTRODUCTION

In the present deregulated markets there are different Market players or participants including generators, investors, traders, and load serving bodies that are engaged in the day to day activities of the market. Unlike the regulated market, in which the utilities are the one who has the power to set the electricity price, the deregulated market is a customer driven market and customers have the right to choose among different electricity suppliers. This implies that knowledge of the supply-demand balance ahead of time is extremely important for all market players and specifically for generating companies. In deregulated environment utilities work on profit maximization not on cost minimization, so electricity price must be predicted before real time operation. And, since the day the electricity market has changed the way it functions, the need to precisely predict future electricity prices has become a hot issue in the area.

Price forecasting plays a key role in the new electricity industry; in addition to helping independent generators in setting up optimal bidding patterns and also designing physical bilateral contracts, market prices strongly affect the decision on investing a new generation facilities in the long run. In general, different market players need to know future electricity prices as their profitability depends on them; whether it is the generating companies or the ISO, large industrial customers or investors, it is very critical to have this forecast.

Generally both hard and soft computing techniques could be used for this price forecasting. Hard computing techniques such as regression analysis need an exact model of the system. Although the result is very accurate here, but a lot of information is needed for prediction. The computational cost is also high in such methods. The soft computing based model using artificial neural network was also used for price forecasting but back propagation algorithm used for training has got limitations and to overcome the limitations the generalized neuron model has been developed, which is used for modelling [16], forecasting [15] and control applications [17].

II. FACTORS AFFECTING PRICE FORECASTING

Price forecasting techniques in power systems are relatively recent procedures. In the past, demand was predicted in centralized markets. Price forecasting has been at the centre of deep research for other commodity markets like stocks and agriculture. In recent years, electricity has been also considered like other commodity in various markets. But, electricity is having very distinct characteristics from other commodities. For example, electricity cannot be stored easily and economically, and transmission congestion may be an obstacle for a free exchange among control areas.

Thus, electricity price movements can exhibit a major volatility, and the application of forecasting methods which has used in other commodity markets, can give a large error in electricity price forecasting [1-10]. The major factors on which price depend are shown in fig. 1.

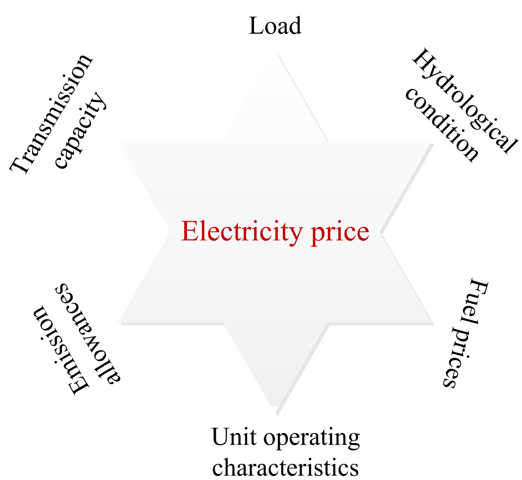

Fig.1. Factors Affecting Electricity Price

III. ARTIFICIAL NEURAL NETWORK

The classical artificial neural network trained using back-propagation algorithm has various drawbacks which are as follows [18]:

1. There is no method to decide the number of hidden neurons, for large and complex functions the required number of neurons in hidden layers is very large.
2. Slow learning, especially when used for training large networks.
3. Problem of local minima.
4. For complex functions a large number of unknowns to be determined in existing neural network. Because of this the requirement of the minimum number of input–output pairs increases.

The generalized neuron was developed to overcome the drawbacks of the classical artificial neural network.

IV. GENERALIZED NEURAL NETWORK

The generalized neuron consists of single higher order neuron as shown in fig. 2. The generalized neuron model uses two aggregation functions which are summation and product, the output of these aggregation functions has been passed through the two basis functions sigmoidal and gaussian functions respectively. Finally, the ouput of the basis function is aggregated to calculate the neuron output.

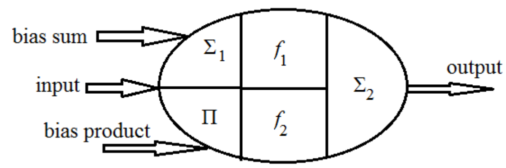

Fig. 2. Generalized Neuron Model

In many models weighted input x_i*w_i has been used in $\sum$ and π part. The model presented in this paper uses $(X+W)^2$ in $\sum$ part with sigmoidal activation function and weighted input is used in π part with Gaussian activation function [15].

The mathematical representation of the output of the neuron can be written as

$$O_i = O_\sum \times W_\sum + O_\pi \times (1-W_\sum) \quad (1)$$

The above mentioned neuron model is known as summation type compensatory neurons model, since the output of the sigmoidal and gaussian functions have been summed up.

V. GENERALIZED NEURON MODEL LEARNING ALGORITHM

The following steps are involved in the training of Generalized Neural Network

Step 1 The output of $\sum$-part of generalized neuron is

$$O_\Sigma = f_1 \left[(W_{\Sigma i} + X_i)^2 + X_{o\Sigma}\right] \quad (2)$$

Step 2 The output of π-part of generalized neuron is

$$O_\Pi = f_2 \left[(W_{\Pi i} \times X_i) + X_{O\Pi}\right] \quad (3)$$

Step 3 The output of Generalised Neuron can be written as

$$O_i = O_\sum \times W_\sum + O_\pi \times (1-W_\sum) \quad (4)$$

Step 4 After calculating the output of Generalized Neuron in the forward pass, it is compared with the desired output to find the error

$$E = Y_i - O_i \quad (5)$$

which is then minimized by updating the weights for the sigma and pi part of the neuron, where Y_i is desired output and O_i is the actual output of GNN. Sum squared error function is used for calculating the error

$$\text{Sum square error} = \tfrac{1}{2}\sum E_i^2 \quad (6)$$

Step 5 Reversed pass for modifying the connection strength. Now weights are adjusted with respect to error.

Total weight W is updated as

$$\Delta W = \eta\times(D\text{-}O)\times\{O(\Sigma) - O(\Pi)\} + \alpha W(j\text{-}1) \quad (7)$$

weights for the first part of Σ are updated as

$$W_{\Sigma i}(j) = W_{\Sigma i}(j\text{-}1) + \Delta W_{\Sigma i} \quad (8)$$

$$\Delta W_{\Sigma i} = \eta\times(D\text{-}O)\times W\times X_i + \alpha W_{\Sigma i}(j\text{-}1) \quad (9)$$

where i is the number of input, j is the number of iterations, α is momentum factor and η is learning rate.

weights for Π part are updated as

$$W_{\Pi i}(j) = W_{\Pi i}(j\text{-}1) + \Delta W_{\Pi i} \quad (10)$$

$$\Delta W_{\Sigma i} = \{(\eta\times(D\text{-}O)\times(1\text{-}W)\times P_{net})/W_{\Pi i}\} + \alpha W_{\Pi i}(j\text{-}1) \quad (11)$$

The input data given to the generalized neuron is normalized in the range of 0 to 1.

$$p_a = \left[(r_a - r_b)*\left(\frac{a-e}{b-e}\right)\right] + (r_b) \quad (12)$$

where r_a, r_b is chosen appropriately between 0 to 1, a = values of variables, e=minimum value in that set, b = maximum value in that set

VI. WAVELET TRANSFORM

Price signal is a non-stationary signal i.e. the signal has time varying frequency [11]. The Fourier transform tells whether a certain frequency component exists or not. This information is independent of where in time this component appears. Here it is needed that at what times these frequency components occur so FT can't be a proper tool to use. Wavelet transform is a proper tool to analyze non-stationary signal, the frequency response of WT varies in time. A good local representation can be produced with the help of Wavelet transform in both time and frequency domain because of that it has been utilized to solve problem of non-stationary price signal [12].

The CWT of x(t) with respect to a wavelet ψ(t) is defined as:

$$W(s,b) = \frac{1}{\sqrt{|s|}}\int \Psi^*(t)x(t)dt \quad (13)$$

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \quad (14)$$

where s and τ are real numbers known as scale or dilation parameter and time shift or translation parameter respectively and * denotes complex conjugation. Low frequencies (large scale) expands the signal and provide non-detailed part of the signal, whereas high frequencies (low scales) compress the signal and provide detailed part of the signal. The CWT is obtained by continuously scaling and translating the mother wavelet, adequate redundant part is generated. So, the mother wavelet can be scaled and translated using certain scales and positions known as discrete wavelet transforms (DWT). The DWT uses scale and position values based on power of two, called dyadic dilation and translations, which are obtained by discretized the scaling and translation parameters, denoted as

$$DWT_x(m,n) = 2^{-(m/2)}\sum_{t=0}^{T-1} x(t)\psi\left(\frac{t-n.2^m}{2^m}\right) \quad (15)$$

where T is the length of the signal $x(t)$. The scaling and translation parameters are functions of the integer variables m and n, where $s = 2^m$ and $\tau = n2^m$, t is the discrete time index

An algorithm for the implementation of the scheme using filters was developed by Mallat [13] which consists of two stages i.e. decomposition and reconstruction. In first stage, the raw signal is passed through two complementary filters and as a result of this two signals i.e approximation (low frequency part) and detailed (high frequency part) is obtained. Each of these signals has the same number of data points, and then these are down sampled by two, to get DWT coefficients.

This decomposition can be continued and successive approximations can be decomposed to many lower resolution components. In second stage, these components can be recollected back into the raw signal. Thus, wavelet decomposition involves filtering and down sampling, and the wavelet reconstruction involves up sampling and filtering. Seven-stage decomposition has been shown in fig. 3.

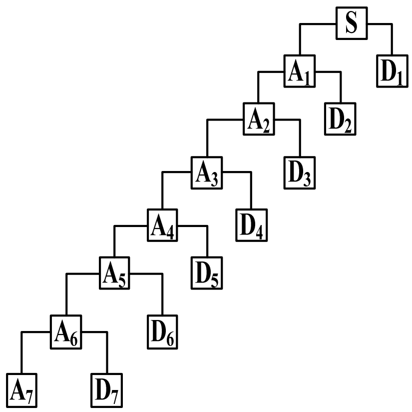

Fig 3. Seven Level Decomposition

VII. SELECTION OF WAVELET TRANSFORM

Price series shows volatility and contains some spikes which make it unsuitable for prediction. Wavelet transform is used to convert the ill-behaved price series into a set of constitutive series, while trying to convert the non-stationary time series into set of constitutive series for better prediction two question need to be answered 1) which mother wavelet to choose for transformation and 2) level of optimal decomposition. Out of the several mother wavelets present in the history daubechies series is best suited for the [19]. The level of smoothness increases with the increase in order, whereas the support intervals also increase so, there must be a careful selection of the order of the function.

The selection of decomposition level is also important as this will decide the better classification of data into low and high frequency components at the same time computational efficiency is reduced if higher levels of decomposition levels are considered. The approximate series (A_i) corresponds to the low frequency components which is essentially the price signal whereas detailed component (D_i) corresponds to the high frequency components of the price series which can be noise, spikes due to weather condition, network congestion etc. in the proposed work the comparison of the wavelet series for new south wales prise signal (NSW) is done for two orders of the function i.e. order 3 and 4 with seven level decomposition.

The transformed series should be close to the shape of original series while having the characteristics of the normal distribution. The different approximate and detailed series obtained are compared on the basis of skewness and kurtosis. A measure of the symmetry of the data around the data mean is known as skewness, its value is zero for an ideal normal curve. Kurtosis is a measure of how prone a distribution is to the outlier, the kurtosis of a normal distribution curve is three [14].

The skewness and kurtosis of the decomposed signal is calculated and shown in table 1 and table 2 for daubechies order 5 and 4 with decomposition level 7, fig.4 & 5 shows HNSWEP (Hourly New South Wales Electricity Price) price signal's approximate series from A1 to A7 and detailed series from D1 to D7 using db4 & db5 repectively.

After observing fig. 4 closely it becomes evident that A_1, A_2, A_3 and A_4 series are similar in shape to the original signal than the other approximation levels, where A_1 having statistically same characteristics as that of original series can be neglected for forecasting, while in fig. 5 only A_1, A_2 and A_3 are similar in shape to the original series. Low order wavelets are generally used for prediction, the same can also be observed from table 2 which shows skewness and kurtosis of the db4 function.

Table 3 helps in selecting the level of decomposition, it can be observed that approximate series A_1 to A_4 are close to the original series, making fourth level decomposition more suitable for the price signal.

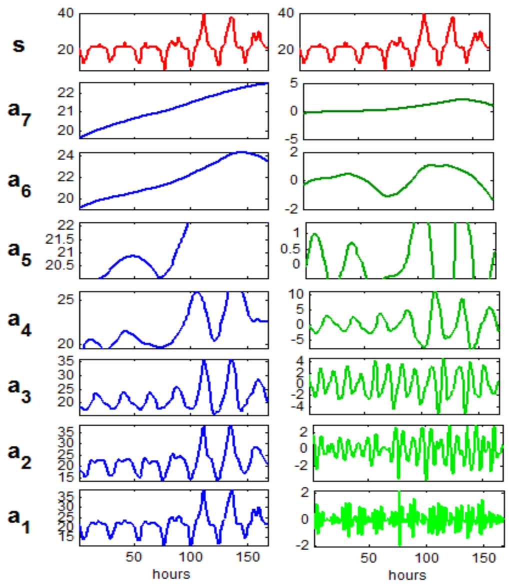

Fig 4. Decomposition of Price Series Using db4

Table 1 Skewness and kurtosis of db5 decomposed series

Time series	Skewness	Kurtosis	Time series	Skewness	Kurtosis
HNSWEP	0.7324	4.5895	HNSWEP	0.7324	4.5895
Approx A7	0.984	1.8232	Detail D7	0.4171	1.6777
Approx A6	0.6234	1.6047	Detail D6	-0.3443	2.2356
Approx A5	0.3269	1.5597	Detail D5	-0.4072	4.1198
Approx A4	0.9073	2.7613	Detail D4	0.2802	3.2924
Approx A3	1.3331	4.3621	Detail D3	-0.0134	2.1900
Approx A2	0.9861	4.4122	Detail D2	-0.1467	2.7594
Approx A1	0.7606	4.5905	Detail D1	0.1679	3.2087

Table 2 Skewness and kurtosis of db4 decomposed series

Time series	Skewness	Kurtosis	Time series	Skewness	kurtosis
HNSWEP	0.7324	4.5895	HNSWEP	0.7324	4.5895
Approx A7	-0.5160	2.0448	Detail D7	0.2248	1.4534
Approx A6	0.0503	1.5094	Detail D6	-0.0345	1.7131
Approx A5	0.4267	1.5907	Detail D5	0.0024	2.1529
Approx A4	0.2313	1.8531	Detail D4	0.3708	3.3474
Approx A3	1.1283	3.8205	Detail D3	0.1633	2.8303
Approx A2	0.7763	3.6088	Detail D2	-0.0914	3.4548
Approx A1	0.7335	4.4028	Detail D1	-0.1462	4.4489

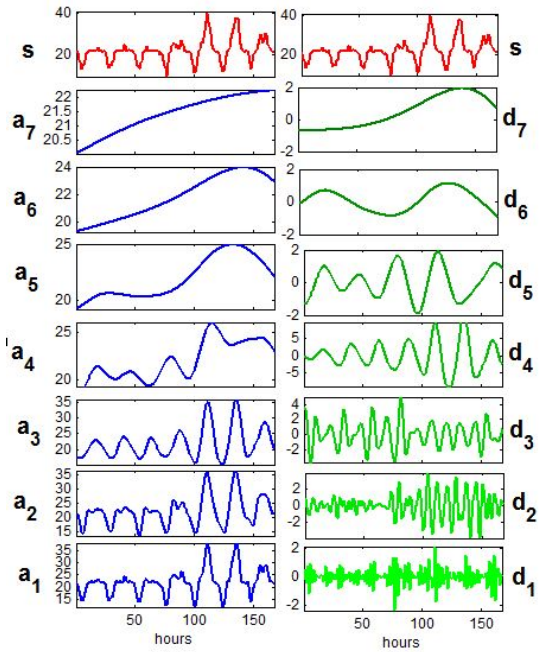

Fig 5. Decomposition of Price Series Using db5

Table 3 Statistical properties of db4 approximate series

Time series	Mean	Maximum	Minimum	Range	Standard Deviation
HNSWEP	22	39.9	9.91	29.99	5.247
Approx A7	21.41	22.24	20.03	2.21	0.6534
Approx A6	21.86	24.03	19.32	4.715	1.597
Approx A5	21.96	24.98	19.23	5.748	1.85
Approx A4	21.99	30.03	17.9	18.13	4.066
Approx A3	21.99	35.68	15.42	20.26	4.739
Approx A2	22	36.18	13.65	22.53	5.023
Approx A1	22	38.01	11.88	26.13	5.209

Now examining the corresponding detail series it can be observed that detail series D_5 to D_7 is essentially noise contained in the signal and does not contain any useful information about the signal while detailed series D_1 to D_4 contains useful data related to the signal.

Although, third decomposition level appears better in terms of statistical features of approximate part but due to ability of D4 to detect localized swings in price accurately, fourth decomposition level is better than third decomposition level and it is better positioned for price prediction. In the proposed work daubechies wavelet of order 4 i.e db4 with four decomposition level is used.

VIII. CASE STUDY

The electricity market of New South Wales (NSW) is considered for forecasting, the results obtained are shown in fig. 7 & fig. 8.

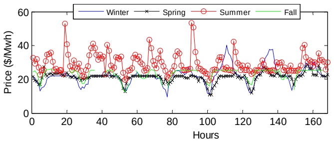

Fig.6 Average Weekly Price of Winter, Spring, Summer, Fall Seasons in NSW Market

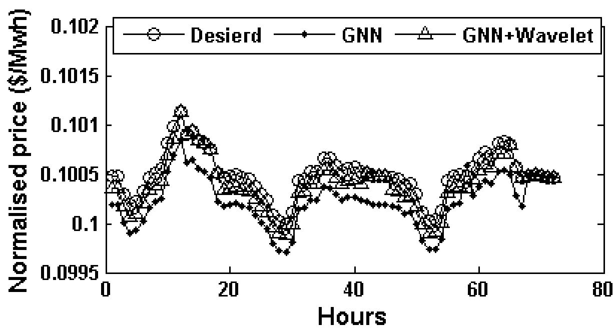

Fig.7 Seventy Two hours forecast of New South Wales Electricity Market

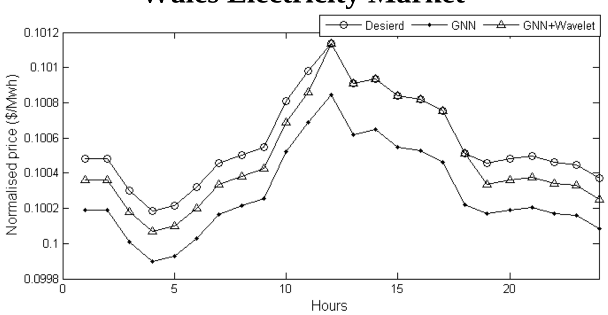

Fig.8 Twenty four hour forecast of New South Wales Electricity Market

Table 4 MAPE of weekday of New South Wales Electricity Market

Methods	ANN	GNN	GNN+ Wavelet
Winter	7.76	5.47	**3.74**
Spring	7.63	6.83	**4.26**
Summer	10.53	8.37	**7.72**
Fall	12.36	8.48	**6.86**

IX. CONCLUSION

In the proposed work the forecasting model for New South wales (NSW) market was suggested using generalized neuron model. The comparison of daubechies wavelet function is done on the basis of skewness and kurtosis and it was found that daubechies function of order 4 with four decomposition level is best suited for the NSW price signal. The decomposed series is given as input to the generalized neuron model for predicting the future prices and it has been found that generalized neuron model along with wavelet gives better result. The proposed model was compared with generalized neuron model alone and artificial neural network based model on the basis of MAPE (mean absolute percentage error) the results obtained are shown in table (4).

REFERENCES

[1] M. Shahidehpour, H. Yamin, and Z. Li, “Market operations in electric power systems," John Wiley and Sons, 2002
[2] E. Kreyszig, “Advanced Engineering Mathematics,” John Wiley and Sons, 1999.
[3] H. J. Zimmermann, "Fuzzy set theory and its application," Kluwer Academic Publishers, 1996.
[4] A. Faruqui, B. K. Eakin, "Pricing in competitive electricity markets," Kluwer Academic Publishers, 2000.
[5] M. Shahidehpour, M. Alomoush, “Restructured electrical power systems: operation, trading and volatility," New York: Marcel Dekker Publishers, 2001.
[6] M. Hutzler, “Electricity prices in a competitive environment: marginal cost pricing of generation servicesand financial status of electric utilities," DIANE publishing, 1998.
[7] A. Faruqui, B. K. Eakin, "Electricity pricing in transition," Kluwer Academic Publishers, 2002.
[8] M. D. Ilic, F. D. Galiana, L. H. Fink, “Power system restructuring: engineering and economics," Kluwer Academic Publishers, 1998.
[9] L. L. Lai, “Power system restructuring: trading, performance and information technology," John Wiley and Sons, 2001.
[10] C. Weber, “Uncertainty in the electric power industry: methods and models for decision support," Springer, 2005
[11] A. J. Conejo, J. Contreras, R. Espinola, and M. A. Plazas, “Forecasting electricity prices

for a day-ahead pool-based electric energy market," International Journal of Forecasting, vol. 21, no. 3, pp. 435-462, 2005

[12] Polikar,Robi."TheWaveletTutorial,"1996.http://person.hst.aau.dk/enk/ST8/wavelet_tutotial.pdf

[13] Mallat, Stephane G. "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 11, no. 7 (1989): 674–93

[14] Aggarwal, Sanjeev Kumar, Lalit Mohan Saini, and Ashwani Kumar. "Electricity Price Forecasting in Ontario Electricity Market Using Wavelet Transform in Artificial Neural Network Based Model." International Journal of Control, Automation, and Systems 6, no. 5 (2008): 639–50.

[15] D. K. Chaturvedi, M. Mohan, R. K. Singh, and P. K. Kalra. "Improved Generalized Neuron Model for Short-Term Load Forecasting" Soft Computing - A Fusion of Foundations, Methodologies and Applications 8, no. 5 (April 1, 2004)

[16] D. K. Chaturvedi, P. S. Satsangi, and Prem K. Kalra. "New neuron models for simulating rotating electrical machines and load forecasting problems." Electric Power Systems Research 52, vol no. 2 (1999) pp : 123-131.

[17] Chaturvedi, D. K., and O. P. Malik. "A Generalized Neuron Based Adaptive Power System Stabilizer for Multimachine Environment." Int. J. Soft Computing-A Fusion of Foundations, Methodologies and Applications 11.2 (2006): 149-155.

[18] Chaturvedi, D. K., O. P. Malik, and P. K. Kalra. "Experimental studies with a generalized neuron-based power system stabilizer." Power Systems, IEEE Transactions on 19, no. 3 (2004): 1445-1453.

[19] Agnaldo J. Rocha Reis, and Alexandre P. Alves Da Silva. "Feature extraction via multiresolution analysis for short-term load forecasting." Power Systems, IEEE Transactions on 20, no. 1 (2005) pp 189-198.