IMPLEMENTATION OF WAVENET TO EELCTRICITY PRICE FORECASTING

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ABSTRACT

competitive electricity markets, various long-term and short-term contracts based on spot price are implemented by independent market operator (IMO). An accurate forecasting technique for spot price facilitates the market participants to develop bidding strategies in order to maximize their benefit. Neural-Wavelet is a powerful method for forecasting problems under the condition of nonlinearity as well as uncertainty. In this paper, a new methodology based upon radial basis function (RBF) network is proposed to the forecasting spot price problem. To train the network, in order to apply historical information of the price behavior, some other effective parameters are used. Load level, fuel price, generation and transmission location as well as conditions are the effective parameters which are associated with general well known parameters. All these parameters are applied for learning process to an assumed neural wavelet network (NWN). Simulation results are presented in details in this paper, where these results indicate the effectiveness of the proposed forecasting tool as an accurate technique.

1. INTRODUCTION

In recent years, development of deregulated power market in many countries, moving towards a competitive environment become very important issue. The new conditions are of interest of all market participants such as producers (generators), consumers and retailers. Restructuring and deregulation of electricity industry is a movement with the aim of achieving reasonable prices to costumers through cost saving. Price would change according to the market conditions, marginal cost of generation and other factors in competitive markets, while spot price is an important issue for market participants. All factors that affect market player's operation conditions and costs such as electric power demands, weather conditions, fuel costs, transmission capacity, generation reserves. Although each of these factors has different effect but some of them are more important than the others, whereas they will be considered by different impacts on spot price. In the other hand various decisions in new environment may require better knowledge of future spot price of electricity to clear the real-time market. In other word, price forecasting is a essential task for producers, consumers and retailers that help them to determine their bidding strategy in order to maximizing their own benefit. Electricity balancing contracts can be affected by spot price as well. Therefore spot price forecasting is extremely needed to be considered by all market participants. One of the main issues in price forecasting is determining the most effective parameters and their importance in spot price. The other one is applying an efficient method for spot price forecasting. Some of the most important method that uses in price forecasting are time series (TS) based method such as auto regressive integrated moving average (ARIMA) [11], transfer function model and dynamic regression [1]. Also a support vector machine (SVC) based price forecasting is presented in [7]. In conventional method the model are base upon the relationship between price and factors influencing spot price. Since the relationship between spot price and factor influencing spot price is non-linear, it is very difficult to identify its non-linearity by using conventional methods. Neural Wavelet Networks (NWNs) are more suited to handle the non-linear relationship between the various input information. Therefore using NWNs, which have been recently implemented for load forecasting [14], is suggested for spot price forecasting in this paper. NWNs that are powerful and accurate tools for solve problem according to non-linear parameter and uncertainty are used for prediction issues in [12, 13, and 14]. In this paper a neural wavelet network (WaveNet) is applied to spot price forecasting under deregulated power markets. In the proposed NWN real data of effective factors on spot price is used, as an input patterns to train network and then another set of data – except of trained data –for test NWN is contributed. The structure and the design of the proposed model have been explained in the next sections. Results show that NWN has a good and accurate performance in price forecasting. Furthermore to have a high level of accuracy some other parameters can be introduced to NWN.

2. INTRODUCING FACTORS FOR PRICE FORECASTING

In deregulated power markets, fluctuation is a common behaviour of price that is because of many different economical as well as technical factors. Off course some of these factors are more effective on price variation. Historical data including power demand, weather conditions are the key factors in identifying the characters of market and load conditions. Some researches just used historical data of prices [6] or prices and demand [5] to forecasting spot price while other factors were not included. But by considering other parameter such as fuel costs, weather conditions and generation reserves the forecasted price would be more accurate. In this paper the following factors are used in order to investigate the influence of them on spot price.

2.1. ELECTRIC POWER DEMAND

One of the most important factors in spot price is system's total demand. As illustrated in figure (1), usually there is a certain and firm relationship between spot price and power demand. Some studies show that by system demand increasing, spot price is increases. It is also depending on the type of contracts that producer and consumer are dealing with. Especially in real-time, if electricity demand becomes more than electricity supply the spot price will be affect very much.

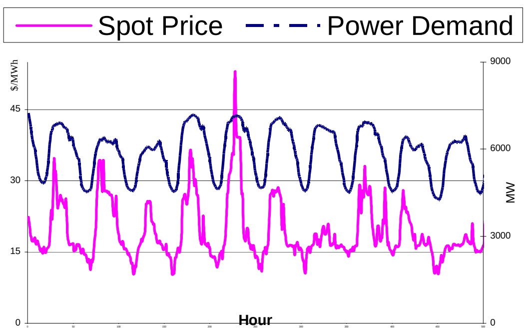

Figure 1: Hourly Spot Price & Hourly Demand

2.2 WHETHER CONDITIONS

Electricity demand certainly depended on weather conditions and especially daily temperature. In the other words weather fluctuation affect electricity demand and hence affecting spot price. If a rapid and large change happens in temperature it has very important impact on electricity prices. Therefore this fluctuation should be considered in price forecasting. Figure (2) illustrates the relationship between temperature and spot price. Another important factor of weather conditions that influences the demand and electricity spot price is humidity [2].

2.3 FUEL COSTS

Fuel costs is one of the main part of generation cost that its variation has a major impact on electricity spot price. Today usually power plants use fossil fuels such as: oil, gas and other derivatives, where their prices are very much changeable in world markets. Therefore considering these variations is very important in spot price forecasting issue. If crude oil price increases, generation electricity costs go up and electricity charges finally increase. The relationship between oil price and electricity spot price is shown in figure (3).

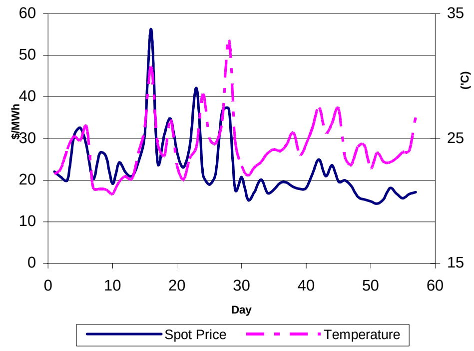

Figure 2: Electricity Spot Price and Temperature Variations

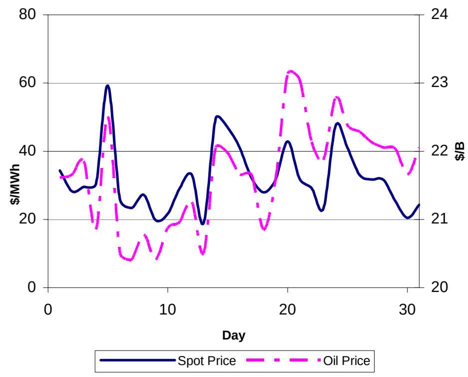

Figure 3: Electricity Spot Price and Oil Price Variations

2.4 AVAILABLE TRANSMISSION CAPACITY

Electric power is provided by generator that may be located far from location of consumers. It should be transmitted to consumers via transmission network facilities. If there is no limitation in transmission, generators can feed all their consumers regardless of their locations easily. But there is some physical constraint in transmission networks that is an obstruction for market participants to buy or sell electrical energy. These constraints cause sometimes congestion in transmission lines, where some of consumers can not receive their required energy easily. So this issue can affect important changes on spot price and may increase it. Therefore available transmission capacity is another important factor for spot price prediction.

2.5 GENERATION RESERVES

Having enough generation reserves is an important factor for electricity spot price, i.e. when demand increase suddenly if there is enough generation reserve capacity available as well as deliverable, consumers will be served. But if there is not sufficient generation reserves available, consumer would face with lack of received energy and therefore to make the balance between supply & demand electricity spot price increases. Therefore percentage of available generation reserves is included as an effective factor for spot price prediction in the proposed model.

3. NEURAL WAVELET NETWORKS

In price forecasting the main goal is to find feature electricity prices according to effective factors in spot price. Neural wavelet is a powerful method for this issue, because relationship between price variations and other parameters such as demand, weather conditions etc. is non-linear. It can be mentioned that finding such a model or function for this aim is a very complex as well as time consuming job. Conventional neural networks encounter difficulties when trying to predict under the condition of high nonlinearities and using the NWNs can provide better results [12, 13, and 14]. Usually the combination of wavelet theory and neural networks has lead to development of wavelet networks. Wavelet networks (t)are feed-forward neural networks using wavelets as activation function [13]. In the first approach of WaveNet methodology, signals are decomposed on some wavelet and the wavelet coefficients are furnished to RBF neural network and in second method wavelet theory and neural networks are combined into single method. In this paper the first approach is implemented.

NWNs don't require any standard model and if it is trained well, it can forecast price accurately. Furthermore, if NWN is trained with suitable data, it can give useful answer even for noisy input [1], that shows the powerfulness characteristic of it. Usually NWNs compose of three types of layers that each layer includes number of neurons. The first layer is input layer and the number of its neuron is equal to the number of each input pattern's data and output layer's neuron reflect output of NWN. It's should be mentioned that reduction of the input vector dimension in neural wavelet networks is possible, that shows the advantage of WaveNet in comparison with conventional neural networks. Reduction of the net input dimension provides simple hardware implementation of the network. Number of hidden layers and its neurons can be selected according to problem's condition. Output of each layer feeds the input of the next layer. In order to use a NWN, the main steps are:

Step (1): Designing the NWN topology, which consists of NWN structure and its training algorithm.

Step (2): Procuring suitable information to train NWN.

Step (3): Training process: in training process the data required in step (2) will be imposed to network and weights would be adjusted. This step would finish when NWN error meet proposed goal. The weights are updated after all patterns have been presented to the network.

Step (4): Testing NWN: when NWN trained, it should be give an acceptable output of new data that are in same format of training data.

3.1RBF NEURAL WAVELET NETWORK (RBFNWN):

Figure (4) shows the global structure of RBF neural wavelet network (RBFNWN), with comprises of three layers. The hidden layer possesses an array of neurons that the number of neurons can be varied depending on user's requirement. RBFNWN in compare with back propagation (BP) feed forward neural networks used in [2,5] for price forecasting, require less computing time for learning and has a more compact topology [10]. This fact also was tested for neural wavelet network based on RBF and BP and the similar result was obtained. It is also possible to reduce the dimension of the input vector without great difference in results.

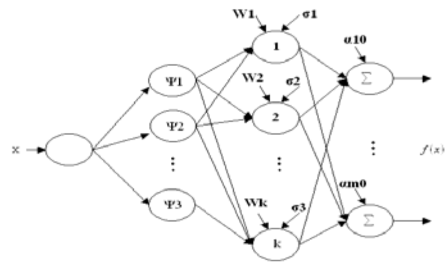

Figure 4: Structure of RBF Neural Wavelet Network

STRUCTURE OF RBFNWN

Figure (5) shows RBFNWN that is used for price forecasting in this paper. As mentioned before, the spot price always is a function of demand, weather conditions and generation reserves and transmission facilities. So as it is illustrated in Fig. (5) forecasted spot price for a sample day, the input pattern consists of following variables of the previous day.

- 1 node for daily average spot price ,1 node for daily average power demand
- 1 node for daily average temperature, 1 node for daily average humidity
- 1 node for daily average oil price, 1 node for generation reserves and 1 node for transmission capacity

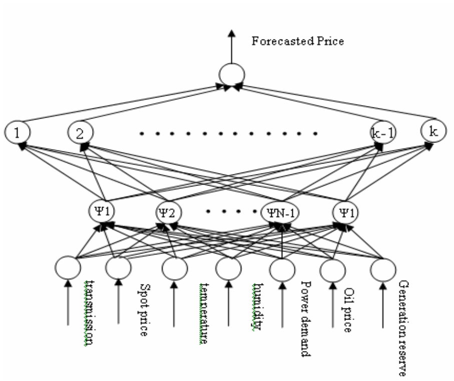

Figure 5: RBF Neural Wavelet Network for Price Forecasting

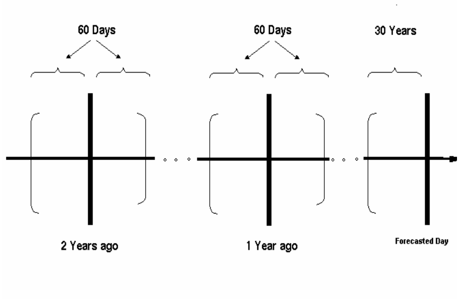

Figure 6 : Selected Day to Train ANN

The output consists of one neuron for a daily average forecasted spot price for next day. To train NWN we should collect same day's data and apply to NWN. In this paper for a particular day, it is assumed that same days are 30 days after the day before forecasted day and 30 days before forecasted day of the same year as well as for two previous years. Therefore to predict each day's hourly spot price 90 pattern from historical real data have been used.

4. CASE STUDY AND RESULTS ANALYSIS

In order to demonstrate the effectiveness of the proposed approach, NWN is tested with some actual data that didn't impose to NWN in training process. To measure the accuracy of the proposed forecasting approach the NWN's error for each hourly price was calculated according to (1)

$$error\,\% = \frac{\left|price_{Actual} - price_{Forecasted}\right|}{price_{Actual}} * 100 \quad (1)$$

The mean absolute percentage error (MAPE) is defined as (2) to determine the mean error of all the test results.

$$MAPE\ \% = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|price^{i}_{Actual} - price^{i}_{Forecasted}\right|}{price^{i}_{Actual}} * 100 \quad (2)$$

In so many papers for price forecasting the impact of generation and transmission reserve has not been included, but both are considered here to have more accuracy for price forecasting and to show the effect of these factors as well. Tow following case studies confirms the proposed technique as an accurate method.

- **Case A:** In this case generation and transmission reserve are ignored the and input layer of NWN decreases to 5 neurons, where the results are shown in figures (7,8) and table (1).
- **Case B:** In this case all factors that has been mentioned before are imposed to NWN and forecasted price are shown in Fig. (9,10) and table (2).

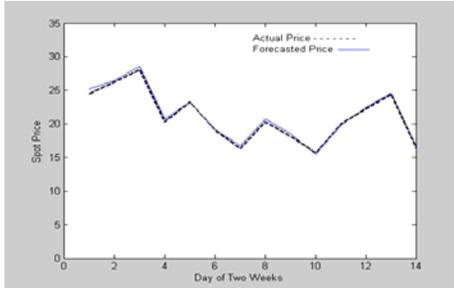

Figure 7: Forecasted Price for 2 Weeks (Case A)

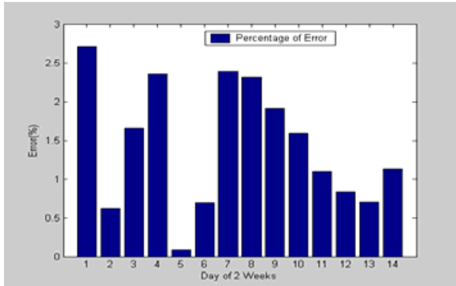

Figure 8:Absolute Error of Forecasted Price for 2 Weeks(%) (Case A)

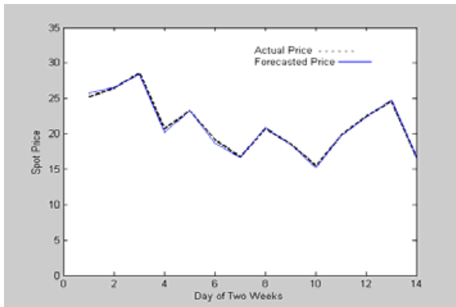

Figure 9: Forecasted Price for 2 Weeks (Case B)

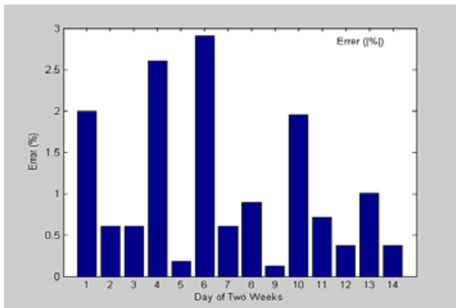

Figure 10:Absolute Error of Forecasted Price for 2 Weeks(%) (Case B)

Table 1: Results for 2 Weeks Prediction (Case A)

Day	Actual price	Forecasted price	Error	Errore(%)
1	25.215	24.5329	0.6821	2.7055
2	26.409	26.2466	0.1624	0.6152
3	28.590	28.1173	0.4727	1.6535
4	20.768	20.2784	0.4896	2.3575
5	23.262	23.2809	-0.0189	0.0815
6	19.202	19.0681	0.1339	0.6977
7	16.682	16.2828	0.3992	2.3930
8	20.771	20.2915	0.4795	2.3087
9	18.535	18.1821	0.3529	1.9044
10	15.493	15.7399	-0.2469	1.5937
11	19.802	20.0	-0.2174	1.0979
12	22.441	22.2526	0.1884	0.8396
13	24.591	24.4175	0.1735	0.7059
14	16.657	16.4692	0.1878	1.1276

Table 2: Results for 2 Weeks Prediction (Case B)

Day	Actual price	Forecasted price	Error	Errore(%)
1	25.215	25.7180	-0.503	1.9951
2	26.409	26.5700	-0.161	0.6098
3	28.590	28.4152	0.1748	0.6116
4	20.768	20.2279	0.5401	2.6010
5	23.262	23.3042	-0.0422	0.1818
6	19.202	18.6429	0.5591	2.9116
7	16.682	16.5802	0.1018	0.6105
8	20.771	20.9563	-0.1853	0.8924
9	18.535	18.5120	0.023	0.1244
10	15.493	15.1908	0.3022	1.9512
11	19.802	19.6609	.1411	0.7129
12	22.441	22.3576	0.0834	0.3719
13	24.591	24.8371	-0.2461	1.0008
14	16.657	16.7197 !	-0.0627	0.3767

5. CONCLUDING REMARKS

This paper proposes a Neural-Wavelet-based price forecasting approach for power markets. The implementation process and various design issues have been discussed. Necessary historical data are used to apply this technique for price prediction. This approach is very accurate and fast in order to apply the assumed data as they are available. It can be said that in comparison with neural network the proposed method has the advantage of decreasing the input dimension and more accuracy in the condition of nonlinearity and uncertainty. Forecasting error is less than 5% and forecasted price is acceptable for power market participants.The effectiveness of the implemented technique is shown through case studies.

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