Using Neural Networks to Forecast Price in Competitive Power Markets

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Abstract: Under competitive power markets, various long-term and short-term contracts based on spot price are used by producers and consumers. So an accurate forecasting for spot price allow market participants to develop bidding strategies in order to maximize their benefit. Artificial Neural Network is a powerful method in forecasting problem. In this paper we used Radial Basis Function (RBF) network to forecast spot price. To learn ANN, in addition to price history, we used some other effective inputs such as load level, fuel price, generation and transmission facilities situation. Results indicate that this forecasting method is accurate and useful.

Keywords: Spot Price Forecasting, Restructured Power Market, RBF Neural Network

1. INTRODUCTION

In recent years development of deregulated power markets in many countries has made moving from previous monopole structure to a more competitive one to be more attractive for market participants e.g. producers, consumers and retailers. Restructuring and deregulation of electrical industry aims to achieve lower price through cost saving. The price must be changed according to market conditions, marginal cost and other parameters of competitive market, figuring spot price heavily for market participants.

All factors affecting market players' operation and cost are effective on spot price such as electrical power demand, weather condition, fuel cost, transmission reserve, generation reserve, population and number of households and biological factors with their own importance respectively. In the other hand each decision making in the environment of a deregulated power market requires a good knowledge of future spot price of electricity. In other words price forecasting is an essential task for producers, consumers and retailers that help them to determine their bidding strategy in order to maximize the benefit and design month/yearly contracts properly, so it is extensively considered by market participants and electrical companies.

Main problems in price forecasting are determination of important parameters of spot price and finding an efficient forecasting method. Common forecasting methods are Time Series based method such as Auto Regressive Integrated Moving Average (ARIMA) [11], transfer function model [1] and dynamic regression [1]. Also a Support Vector Machine (SVC) based price forecasting is presented in [7]. Conventional methods are based on non-linear relationship between price and factors influencing spot price, and it is very difficult to identify its non-linearity. In contrast, Artificial Neural Networks (ANNs) are well suited to handle the non-linear relationship between various input information. Therefore using ANNs, that previously have been widely used for load forecasting [3,4,8] are suggested for spot pricing as accurate and powerful tools[2,5,6].

In this paper we use a Radial Based Function (RBF) Neural Network for spot price forecasting in deregulated power markets. In proposed ANN, we use real data of an effective factor e.g. an input pattern to train network and then we use alternate data to test ANN. To have a higher accuracy, one may add other inputs to ANN.

2. SELECTION OF PROPER FARCTORS

Fluctuation is a common behavior of price in deregulated power market and may have several economical and non-economical causes, with different importance. Historical data including power demand and weather conditions are the key factors in identification of market and load conditions. Not to ignore other measures such as fuel cost and reserve of generation may make forecasted price more accurate [5,6]. In this paper we use following factors to influence the spot price.

2.1 Electrical power demand

One of the most important factors in spot price is network's total demand, which as illustrated in Fig. 1, usually has a significant direct relationship with the price.

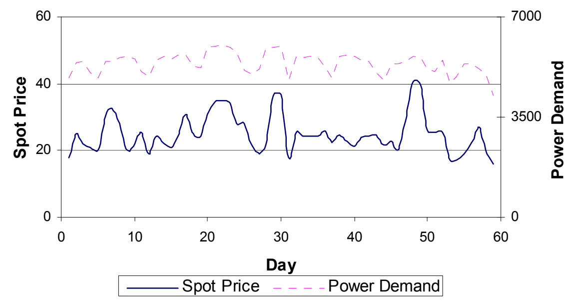

Figure1: Electricity spot price – Demand curve

Experience shows that a growth in network demand will increase spot price according to the type of existing contracts between parties, specially when demand is greater than generation.

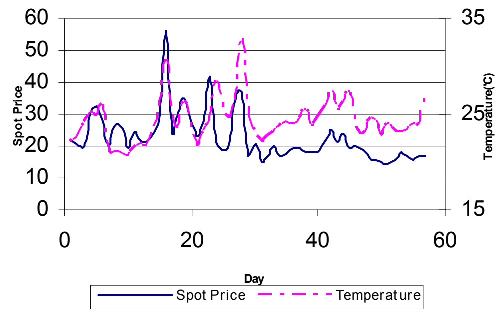

Figure2: Electricity spot price by Temperature

2.2 Weather condition

Electricity demand certainly depends on weather condition specially temperature. Sudden changes in temperature affect spot price heavily and must be considered in price forecasting. The relationship between temperature and spot price is illustrated in Fig. 2. The other important parameter in weather condition that influences electricity demand is humidity which in turn can impress spot price [2].

2.3 Fuel Cost

Fuel cost is one of the main parts of GENCO's cost that has a major effect on spot price. Today's common fuel of power plants e.g. oil and gas bear great price fluctuations in the world markets directly affecting electricity generation costs. The relationship between oil price and electricity spot price is shown in Fig. 3.

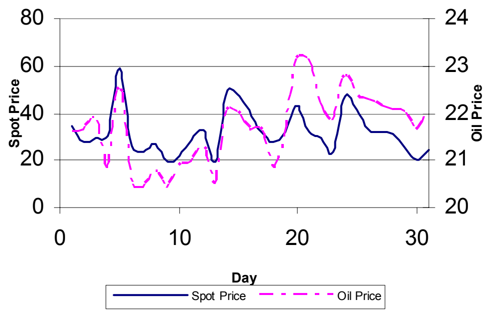

Figure3: Electricity spot price by oil Price

2.4 Available Transmission Capacity

Electricity provided by Generators far from consumers, is transmitted by transmission lines. If there was no constraint in transmission, generators could feed all of their generation to network and support each consumer irrespective to its location. Existing physical constraints obligate electricity trading. When there is a heavy growth in electricity demand, although GENCOs can provide required energy, but the existing congestion in transmission lines, may cause it not to be received by all consumers. This may increase electricity spot price showing that available transmission capacity is another measure impressing spot price.

2.5 Generation Reserve

When a sudden increment happens in electricity demand, generation reserve must be enough to refuse the consumer facing supplement deficiency and in turn raising price. This shows that reservation rate is counted an effective factor on electricity spot price.

3. NEURAL NETWORKS

The main goal in price forecasting is finding featured price according to effective factors in spot price. As the relationship between price variation and other related variables is non-linear, finding a model or function for this relationship is very complex and time consuming. ANNs do not require any standard model and if trained well, price can be forecasted accurately. Furthermore, if ANN is trained with suitable data, it can answer noisy inputs properly [10].

Usually ANN contains three layers, each including a number of neurons. First layer is input layer and the numbers of its neurons equals to the number of data patterns of each input. Neurons of output layer reflect output of ANN. In hidden layer choice number of its neurons is according to problem's condition. Output of each layer feeds the input of the next layer. Main steps in using an ANN are:

- Design the ANN topology, which consist determining ANN structure and its training algorithm.
- Collecting or producing suitable data to train ANN. Data should have same form and consistency of various conditions that ANN will face in future data.
- Training process, in which suitable data collected in step (2), would be presented to network and weights would be adjusted. This step finishes when ANN error meets proposed goal. The weights are updated after all patterns have been presented to network.
- Testing ANN: When ANN got trained, it must give acceptable output of new data. So in this step new data in the same form of training data are presented to ANN.

When output of test pattern and network's error locate in an acceptable range, ANN is completely useful.

3.1 RBF Neural Network (RBFNN)

Fig. 4 shows the general structure of RBF neural network, comprised three layers, the hidden layer possesses an array of neurons that number of neurons can be varied depending on user's requirement. RBFNN in comparison to Back Propagation (BPP) feed forward neural networks used in [2,5] for price forecasting, and require less computing time for learning and has a more compact topology [10].

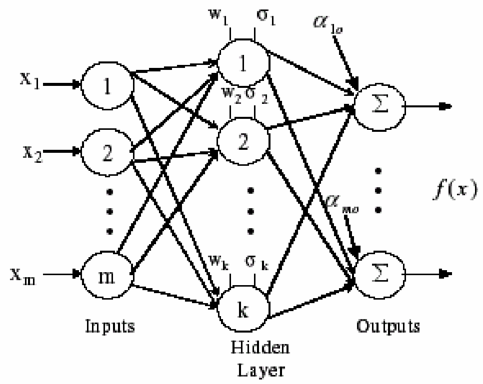

Figure 4: General Structure of RBF Neural Network

3.2 Structure of RBFNN

Fig. 5 shows RBFNN used for price forecasting. As mentioned above, the spot price always is a function of demand, weather conditions and reserve of generation and transmission.

In forecasted spot price for each day as shown in Fig. 5, the input pattern is consisted of following variables for the previous day.

1 node for daily average of spot price (mean daily spot price)
1 node for daily average of power demand
1 node for daily average of temperature
1 node for daily average of humidity
1 node for daily average of oil price
1 node for transmission reserve
1 node for generation reserve

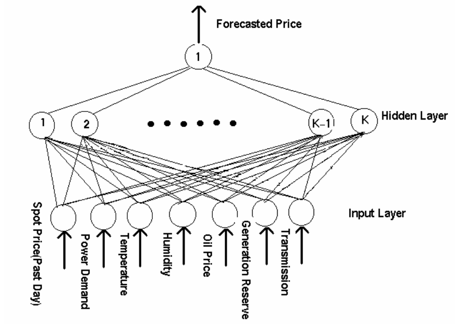

Figure 5: RBF Neural Network for Price Forecasting

Output is consisted of one neuron to give forecasted average spot price of the next day. To train ANN day's information should be collected and then presented to ANN. In this paper to forecast each day's hourly spot price we assume a data pattern collected from 150 points of real history including recent 30 days and 30 days before and 30 days after the same day of forecasting in latter 2 previous years.

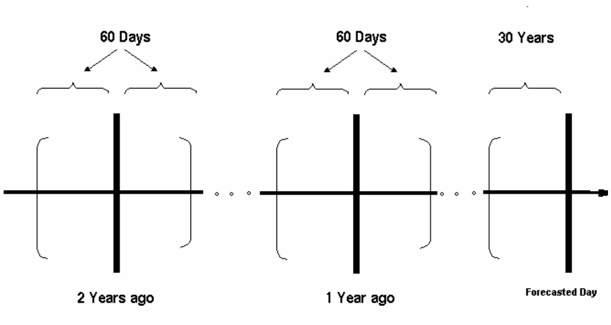

Figure 6: Selected days for training ANN

4. RESULTS

After ANN is trained, in order to demonstrate the effectiveness of proposed approach, ANN is tested with some actual data which were not presented to ANN in training process. The RBFNN is tested using both patterns within and outside the training set.

To measure the accurate of proposed forecasting approach the ANN's error for each daily average price was calculated according with (1)

$$error(\%) = \frac{|\mathrm{Price}_{\mathrm{Actual}} - \mathrm{Price}_{\mathrm{Forcasted}}|}{\mathrm{Price}_{\mathrm{Actual}}} \times (100) \qquad (1)$$

Mean Absolute Percentage Error (MAPE) is defined as equ. (2) to determine mean error of all test results.

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N} \frac{|\mathrm{Price}^{i}_{\mathrm{Actual}} - \mathrm{Price}^{i}_{\mathrm{Forcasted}}|}{\mathrm{Price}^{i}_{\mathrm{Actual}}} \times (100) \qquad (2)$$

In many of papers for price forecasting effect from generation and transmission reserve has been ignored, but we consider them to accurate price forecasting and to show affect of this factor we present two case of test:

Case A) In this case study we ignored the generation and transmission reserve and input layer of ANN decrease to 5 neurons and result are shown in Figures [6,7] and Table [1].

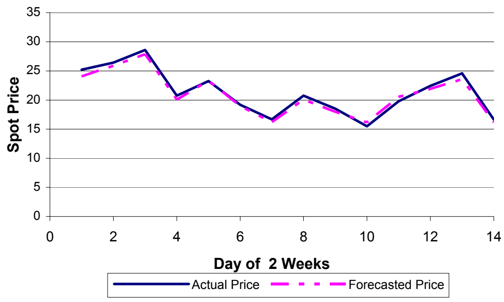

Figure6: Forecasted Price for 2 Weeks

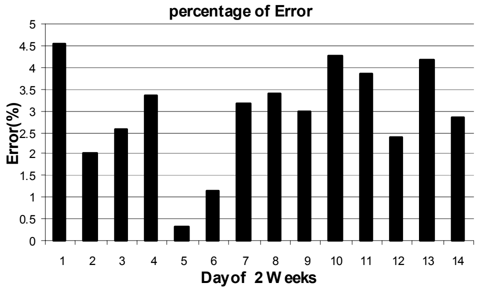

Figure7: Error of Forecasted Price for 2 Weeks(%)

Case B) In this case study all of factors that mentioned before has presented to ANN and forecasted price are shown in Figures [8,9] and Table [2] .

Table 1: Results for 2 Weeks

Day	Actual price	Forecasted price	Error	Errore (%)
1	25.215	24.066	1.148	4.556
2	26.409	25.875	0.534	2.024
3	28.590	27.85	0.737	2.579
4	20.768	20.069	0.699	3.366
5	23.262	23.332	-0.069	0.300
6	19.202	18.981	0.221	1.151
7	16.682	16.154	0.527	3.164
8	20.771	20.069	0.701	3.378
9	18.535	17.979	0.555	2.997
10	15.493	16.154	-0.661	4.266
11	19.802	20.567	-0.765	3.863
12	22.441	21.902	0.538	2.399
13	24.591	23.560	1.031	4.194
14	16.657	16.185	0.472	2.8361

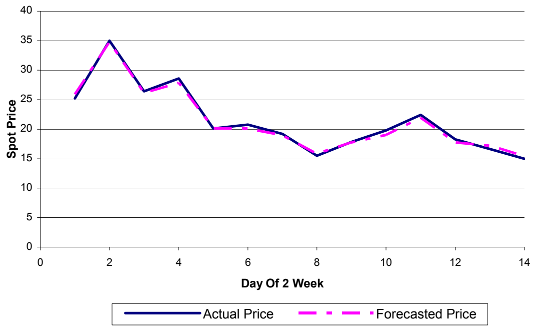

Figure8: Forecasted Price for 2 Weeks

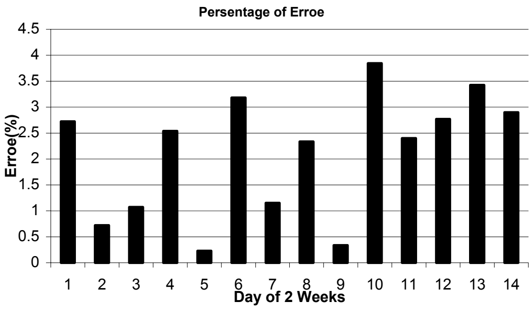

Figure9: Error of Forecasted Price for 2 Weeks(%)

Table 2: Results for 2 Weeks

Day	Actual price	Forecasted price	Error	Errore (%)
1	25.215	25.902	-0.687	2.725
2	35.101	34.849	0.251	0.719
3	26.409	26.126	0.283	1.072
4	28.590	27.864	0.725	2.538
5	20.114	20.160	-0.045	0.228
6	20.768	20.107	0.661	3.182
7	19.202	18.981	0.221	1.151
8	15.493	15.855	-0.361	2.335
9	17.831	17.77	0.059	0.336
10	19.802	19.041	0.761	3.844
11	22.441	21.902	0.538	2.399
12	18.277	17.771	0.506	2.770
13	16.657	17.228	-0.570	3.424
14	15.102	15.537	-0.434	2.899

Results of Case(A) and case(B) are compared in Table [3] and it illustrate that case (B) is more accurate.

Table 3: Comparison of the results for two cases

	CASE A	CASE B
MAPE (%)	2.9341	2.1162

5. CONCLUSIONS

This paper describes ANN-based Price Forecasting approach for power markets. The design process and various design issues have been discussed. Necessary historical data are used .This approach is very accurate and fast and used data are usual available. Error of result are less than 5% and forecasted price is useful for power market participants.

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