Market Clearing Price Forecasting in Deregulated Electricity Markets Using Adaptively Trained Neural Networks

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Abstract. The market clearing prices in deregulated electricity markets are volatile. Good market clearing price forecasting will help producers and consumers to prepare their corresponding bidding strategies so as to maximize their profits. Market clearing price prediction is a difficult task since bidding strategies used by market participants are complicated and various uncertainties interact in an intricate way. This paper proposes an adaptively trained neural network to forecast the 24 day-ahead market-clearing prices. The adaptive training mechanism includes a feedback process that allows the artificial neural network to learn from its mistakes and correct its output by adjusting its architecture as new data becomes available. The methodology is applied to the California power market and the results prove the efficiency and practicality of the proposed method.

1 Introduction

Deregulation has a great impact on the electric power industry nowadays. In a deregulated environment, electricity is supplied in a competitive market, and the pricing system plays an important role. In a pool-based electric energy market, producers submit to the market operator selling bids consisting of energy blocks and their corresponding minimum selling prices, and consumers submit to the market operator buying bids consisting of energy blocks and their corresponding maximum buying prices. In turn, the market operator runs an unconstrained dispatch algorithm without transmission and other security constraints, assuming the system as a single node interconnected to neighboring systems through single transmission lines. This dispatch defines the market-clearing price (MCP) as the cost of supplying one more megawatt beyond the point where supply and demand matches for each market period, typically one hour.

Producers and consumers rely on price forecast information to prepare their corresponding bidding strategies. A producer with low capability of altering MCPs (price-taker producer) needs day-ahead price forecasts to optimally self-schedule and to derive his bidding strategy in the pool. Retailers and large consumers need day-ahead MCPs for the same reasons as producers. However, MCPs in deregulated power markets are volatile. MCP prediction is a difficult task [1] since bidding strategies used by market participants are complicated and various uncertainties interact in an intricate way.

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Many attempts have been made to forecast day-ahead electricity prices. Reported techniques include ARIMA models [2], dynamic regression models [3], other time series techniques [4,5], wavelet transform models [6,7], heuristics [8], Bayesian techniques [9], and simulations and others [10-12].

Artificial neural network (ANN) method, because of its effectiveness and easy-to-implement, is very promising in fulfilling MCP forecasting task. ANNs have been applied to forecasting prices in the England-Wales pool [13], the Australian market [14], the PJM Interconnection [15] and the New England ISO [16].

This paper proposes an adaptively trained neural network to forecast the 24 day-ahead market-clearing prices. The adaptive training mechanism includes a feedback process that allows the ANN to learn from its mistakes and correct its output by adjusting its architecture as new data becomes available. The methodology is applied to the California power market.

The paper is organized as follows: Section 2 formulates the forecasting problem. Section 3 describes the proposed methodology for MCP forecasting and presents the persistence method with which the proposed method is compared based on the mean average percentage error on the test set. The application of the proposed methodology to the California power market and the obtained results are described in Section 4. Section 5 concludes the paper.

2 Problem Formulation

In a deregulated market environment, the unconstrained market-clearing price of an electricity pool is essentially calculated as follows:

- Generating companies submit bids to the electricity pool to supply a certain amount of electrical energy at a certain price for the period under consideration. These bids are ranked in order of increasing price. From this ranking, a curve showing the bid price as a function of the cumulative bid quantity is built. This curve is the supply curve of the market.
- The demand curve of the market is established based on the consumer offers that consist of quantity and price and ranking these offers in decreasing order of price. Since the demand for electricity is highly inelastic, this step is sometimes omitted and the demand is set at a value determined using a forecast of the load, i.e. in this case the demand curve is assumed to be a vertical line at the value of the load forecast.
- The intersection of the supply and demand curves represents the market-clearing price, i.e. the market equilibrium.

All the bids submitted at a price lower than or equal to the market-clearing price are accepted and generators are instructed to produce the amount of energy corresponding to their accepted bids. Similarly, all the offers submitted at a price greater than or equal to the market-clearing price are accepted and the consumers are informed of the amount of energy that they are allowed to draw from the system.

The market-clearing price represents the price of one additional megawatt-hour of energy. Generators are paid this MCP for every megawatt-hour that they produce, whereas consumers pay the MCP for every megawatt-hour that they consume, irrespective of the bids and offers that they submitted.

Producers and consumers rely on price forecast information to prepare their corresponding bidding strategies. A producer with low capability of altering MCPs (price-taker producer) needs day-ahead price forecasts to optimally self-schedule and to derive his bidding strategy in the pool [17,18].

Retailers and large consumers need day-ahead MCPs for the same reasons as producers. If a consumer is to buy on the spot market, it is essential that he predicts as accurately as possible the evolution of MCPs over the time horizon used to self-schedule [19].

Forecasting MCPs accurately is extremely complex because of the number of influential factors and the lack of information on some of these factors. Since the MCP derives from the market equilibrium, it is influenced by both load and generation factors [10,12]. On the load side, all the temporal, meteorological, economic and special factors that are used in load forecasting should also be taken into account when forecasting prices. The generation side is considerably more troublesome because some events occur at random (e.g., failures leading to withdrawal of capacity and price spikes) and others are not always publicly announced in advance (e.g., planned outages for maintenance). In addition, when the locational marginal price is needed, transmission congestion can have a sudden and hard to predict effect. Finally, when competition is less perfect, some generators have the ability to influence prices to suit their own objectives. From the above, it is concluded that MCPs are volatile and MCP prediction is a difficult task since bidding strategies used by market participants are complicated and various uncertainties interact in an intricate way.

The time framework to forecast the day-ahead MCPs in most markets is as follows. The 24 hourly MCPs for day d are required on day d-1, typically at hour h_b (around 10 am). On the other hand, data concerning results for day d-1 are available on day d-2 at hour h_c (around noon). Therefore, the actual forecasting of market prices for day d can take place between hour h_c of day d-2 and hour h_b of day d-1. Therefore, to forecast the 24 hourly prices for day d, price data up to hour 24 of day d-1 are considered known.

3 Forecasting Methodology

3.1 ANN Method

ANN is a computer information processing system that is capable of sufficiently representing any non-linear functions [20]. The techniques based on ANN are especially effective in the solution of high complexity problems for which a traditional mathematical model is difficult to build, where the nature of the input-output relationship is neither well defined nor easily computable.

The most popular ANN architecture is the three-layer feed-forward system trained with a back-propagation algorithm. The success of this approach dwells in the fact that it can learn the relationship between input and output, by training the network off-line using historical data derived from the system, with a supervised learning technique.

In case of MCP forecasting, there is no simple relationship among the parameters involved in the determination of the MCP. ANNs, due to their highly non-linear capabilities and universal approximation properties, are proposed in this paper for MCP forecasting. At the training stage, the proper ANN architecture (e.g., number and type of neurons and layers) is selected. An adaptive training mechanism allows the ANN to learn from its mistakes and correct its output by adjusting the parameters (weights) of its neurons. The adaptive training process enhances the performance of the proposed method as additional training data get to be available.

As input parameters to the ANN, three factors are considered: 1) historical MCP, 2) historical load and 3) forecasted load. Historical information refers to the previous day information, e.g. historical load information includes the 24 hourly actual (known) loads of the previous day. Similarly, forecasted load information includes the 24 hourly forecasted loads of the day-ahead, i.e., the day for which the MCP is to be forecasted. If all the above three factors are considered as inputs to the ANN, then the input layer has 72 neurons. The proposed training mechanism ensures that the optimum number of hidden neurons is selected. The output layer of the ANN has 24 neurons, each one corresponding to the MCP of one of the 24 hours of the day-ahead.

3.2 Persistence Method

In order to evaluate the performance of the ANN, its forecasts are compared with those of the persistence method. According to the persistence method, the forecasted price, Price(d,h), for the hour h of the day-ahead d is calculated as follows:

$$\mathrm{Price}(d,h) = \frac{\mathrm{Load}(d,h)}{\mathrm{Load}(d-1,h)} \cdot \mathrm{Price}(d-1,h) \tag{1}$$

where Load(d,h) is the forecasted load for the hour h of the day-ahead d, Load(d-1,h) is the actual load for the hour h of the previous day d-1 and Price(d-1,h) is the actual price for the hour h of the previous day d-1.

3.3 Performance Evaluation

To assess the prediction capacity of the ANN model and the persistence model, the mean average percentage error, MAPE, can be used:

$$\mathrm{MAPE} = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{\left|\mathrm{Actual\_Price}(i) - \mathrm{Forecast\_Price}(i)\right|}{\mathrm{Actual\_Price}(i)} \cdot 100\% \tag{2}$$

where N is the number of hours, Actual_Price(i) is the actual MCP for the hour i and Forecast_Price(i) is the forecasted MCP for the hour i calculated by the model under consideration (persistence or ANN).

However, the MAPE, as defined in (2), is not suitable for price forecasting, since it causes problems for zero MCPs. To overcome this problem, the following calculation for the MAPE is proposed and used throughout this paper:

$$\text{MAPE} = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{|\text{Actual\_Price(i)} - \text{Forecast\_Price(i)}|}{\text{Average\_Price}} \cdot 100\% \tag{3}$$

where Average_Price is calculated as follows:

$$\text{Average\_Price} = \frac{1}{N} \cdot \sum_{i=1}^{N} \text{Actual\_Price(i)} \tag{4}$$

To assess the prediction capacity of the ANN model and the persistence model, the MAPE is used, as defined in (3). The model with the lower MAPE on the test set is the most suitable for MCP forecasting.

3.4 Overview of the Proposed Methodology

The proposed methodology for MCP forecasting has three steps:

1. In the first step, the day-ahead load is predicted with the ANN method;
2. In the second step, the MCPs are forecasted with the persistence method;
3. In the third step, the MCPs are forecasted with the ANN method.

The first step is to predict the day-ahead load, since this information is needed by the persistence method and also it is expected to be an important input parameter for the ANN model to predict the day-ahead MCPs. This load forecasting is implemented with a multilayer feedforward neural network, which has 48 input neurons and 24 output neurons. The first 24 input neurons correspond to the 24 loads of the previous day (relatively to the day-ahead) and the rest 24 neurons correspond to the 24 loads of the same day (with the day-ahead) of the previous week.

The second step is to forecast MCPs with the persistence method by using (1) and to evaluate the performance of the persistence method by using the MAPE definition of (3).

The third step is to obtain the MCP forecast by using the ANN model. After many experiments, it was found that for the considered case study of Section 4, the best MCP forecasts are obtained by using 72 input neurons, out of which the 24 are for the 24 MCPs of the previous day, the next 24 neurons are for the previous day hourly loads and the rest 24 neurons correspond to the day-ahead hourly loads. The ANN has 24 output neurons, corresponding to day-ahead MCPs.

MATLAB Neural Network Toolbox [21] is used for implementing the above steps 1 and 3 (load and MCP forecasting with ANN).

Since the weights of the ANN are initialized randomly in MATLAB neural network toolbox, different executions of the ANN training and testing algorithm lead to different MAPE results. However, the objective is to train the ANN so as to provide the minimum MAPE for the test set. The proposed training mechanism automatically selects the neural network architecture with the minimum mean absolute percentage error on the test set for both the day-ahead load and MCP forecasting and this is achieved through the following steps:

1. Various ANN architectures are considered;
2. For each ANN architecture, the training and testing algorithm is executed 10 times and the trained ANN with the minimum MAPE on the test set is stored;

3. Among all the ANN architectures, the optimum architecture is the one with the minimum MAPE on the test set.

The structure of the ANN adapts itself as new data becomes available. This adaptation mechanism improves the ANN performance.

Fig. 1 presents the MCP forecasting methodology.

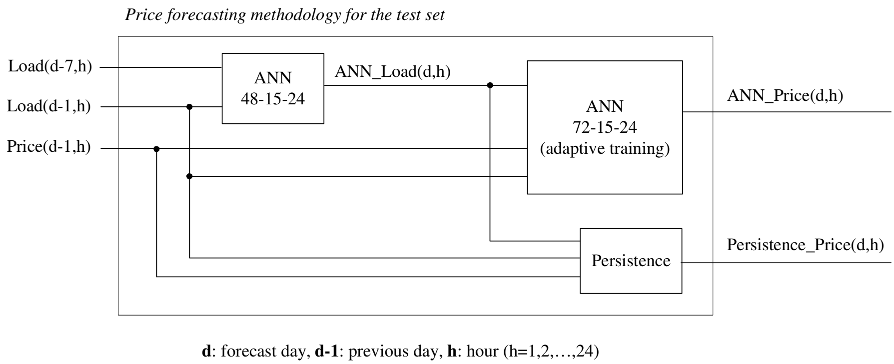

Fig. 1. MCP forecasting methodology

4 Case Studies

In this Section, the effectiveness of the proposed methodology is checked for the data of the California power market [22] for the year 1999. In the sequel, two case studies are analyzed in detail: in the first case study, the MCP data series are without price spikes, while in the second case study, the MCP data series include price spikes and as a consequence the MCP forecasting problem is more challenging.

4.1 Case 1: Without Price Spikes

In this section, the performance of the ANN model is compared with the performance of the persistence model for a time period without price spikes. The training period is from 1/3/1999 to 28/3/1999 and the testing period is from 29/3/1999 to 4/4/1999. As it can be seen from Fig. 2, the whole training and testing period has no price spikes. More specifically, the maximum MCP during that period is 35 $/MWh. On the other hand, the minimum MCP is 0 and this value justifies the necessity to define the MAPE from (3) instead of (2).

Table 1 presents the impact of input parameters on the forecasting performance for the test set. It is concluded from Table 1 that the minimum MAPE (optimum performance) for MCP forecasting is obtained when using historical MCP, historical load and forecasted load as inputs to the ANN, in line with the proposed forecasting framework of Fig. 1.

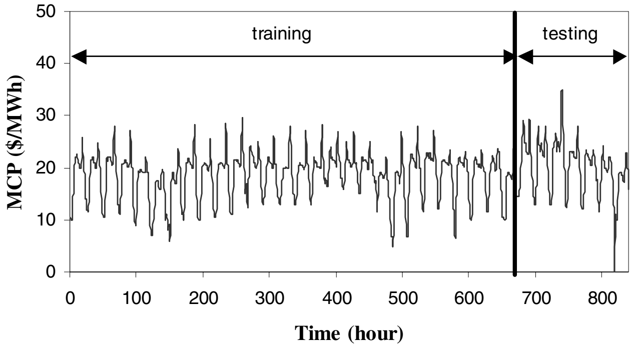

Fig. 2. Actual unconstrained MCP curve of California power market from 1/3/1999 to 4/4/1999

Table 1. Impact of input parameters on forecasting performance

Case	Inputs	MCP MAPE (%)	
		ANN	Persistence
1	Historical MCP	9.78	
2	Historical MCP, historical load	9.09	
3	Historical MCP, historical load, forecasted load	8.44	10.19

Table 2. Impact of quantity of training vectors on forecasting performance

Case	Training vectors		MCP MAPE (%)	
	Period	Quantity	ANN	Persistence
1	15/3-28/3	14	9.20	11.05
2	1/3-28/3	28	8.44	10.19
3	1/2-28/3	56	8.81	10.72
4	4/1-28/3	84	9.13	10.99

Table 2 presents the impact of the quantity of input vectors on the forecasting performance. It is concluded from Table 2 that the optimum performance for MCP forecasting is obtained when using 28 vectors that correspond to the 28 days before the week of the test set. That is why the training period has been selected to be from 1/3/1999 to 28/3/1999 (i.e. 28 days).

Having defined the appropriate input parameters (historical MCP, historical load, forecasted load) and the proper quantity of training vectors (28), in the sequel it is presented the way that the proposed methodology of Section 3.4 is applied in this particular case study.

According to the proposed methodology in Section 3.4, the first step is to predict the day-ahead load. After trial and error, it was found that the optimum forecasting results are obtained with an ANN having the architecture 48-15-24, i.e., 48 input neurons, 15 neurons in the hidden layer and 24 output neurons. For this ANN, the MAPE on the training set and the test set is 1.31% and 1.77%, respectively.

The second step is to forecast MCPs with the persistence method. The results show that the training MAPE is 6.92% and the testing MAPE is 10.19%.

The third step is to forecast MCPs with the ANN method. Table 3 shows the minimum testing MAPE for ANN architectures with different number of neurons in the hidden layer. Following the training mechanism of Section 3.4 and using the results of Table 3, it is concluded that the optimum ANN architecture is 72-15-24, since it provides a minimum testing MAPE of 8.44%, which is 17.17% better than the testing MAPE of the persistence method (10.19%). In Fig. 3, the MCP forecast of the optimum ANN versus the actual MCP is shown for the test set.

Table 3. Evaluation of alternative ANN architectures for MCP forecasting

Hidden neurons	Minimum MAPE (%)	Improvement versus persistence (%)
10	8.93	12.37
15	8.44	17.17
20	9.19	9.81
30	8.92	12.46
40	9.44	7.36

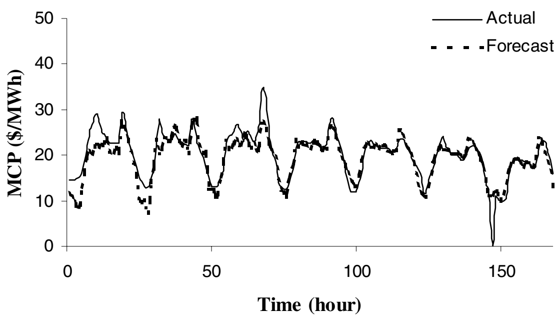

Fig. 3. MCP forecast versus actual MCP for the test set (from 29/3/1999 to 4/4/1999)

4.2 Case 2: With Price Spikes

In this section, the performance of the ANN model is compared with the performance of the persistence model for a time period with price spikes. The training period is from 16/6/1999 to 13/7/1999 and the testing period is from 14/7/1999 to 20/7/1999.

As it can be seen from Fig. 4, there are price spikes (e.g. prices over 80 $/MWh) in the period under consideration. More specifically, price spikes exist in 29/6, 30/6, 1/7, 12/7, 13/7, 14/7 and 15/7/1999. The appearance of price spikes makes the forecasting problem more difficult.

Table 4 presents the impact of the ANN adaptive training on the MCP forecasting performance for the test set using the MCP forecasting framework proposed in Fig. 1. It is concluded from Table 4 that the MCP MAPE obtained with the ANN is improved (reduced) as new data becomes available that is used for retraining the ANN. Moreover, the superiority of the proposed ANN method versus the persistence method is obvious.

Table 4. Impact of ANN adaptive training on ANN forecasting performance

	Training vectors		Testing vectors		MCP MAPE (%)	
Case	Period	Quantity	Period	Quantity	ANN	Persistence
1	14/6-11/7	28	14/7-20/7	7	22.63	35.28
2	15/6-12/7	28	14/7-20/7	7	18.45	30.12
3	16/6-13/7	28	14/7-20/7	7	15.87	27.33

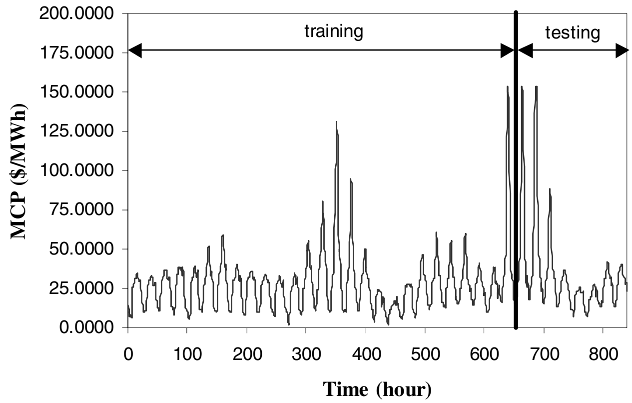

Fig. 4. Actual unconstrained MCP curve of California power market from 16/6 to 20/7/1999

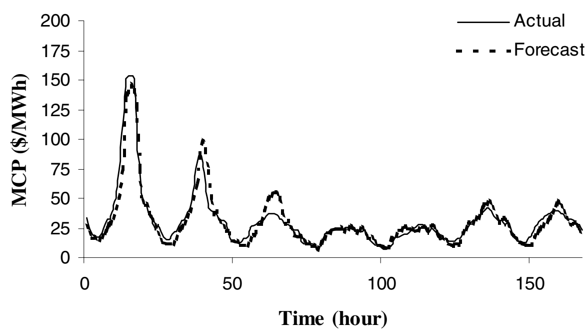

Fig. 5. MCP forecast versus actual MCP for the test set (from 14/7/1999 to 20/7/1999)

In Fig. 5, the MCP forecast of the optimum ANN (case 3 of Table 4) versus the actual MCP is shown for the test set.

5 Conclusions

The objective of this paper is to develop a simple and easy-to-use technique for the prediction of the hourly market clearing price in a deregulated electricity market environment using only the publicly available information. The proposed method uses two ANNs: the first ANN predicts the hourly load and the second ANN estimates the hourly market clearing price. The output of the first ANN together with the previous day load and the previous day market-clearing price are used as input to the second ANN.

An adaptive training mechanism is proposed, which includes a feedback process that allows the artificial neural network to learn from its mistakes and correct its output by adjusting its architecture as new data becomes available. The adaptively trained ANN provides the minimum MAPE for the test set, i.e. the optimum performance. The testing MAPE of the ANN is compared with the testing MAPE of a persistence method.

The methodology is applied to the California power market. Two case studies are analyzed: the first is without price spikes, while in the second case study there are price spikes in the MCP data series. In the first case study, the ANN testing MAPE is 8.44%, which is 17.17% better than the testing MAPE of the persistence method. In the second case study, the ANN testing MAPE is 15.87%, which is 41.93% better than the testing MAPE of the persistence method. These results prove the efficiency and practicality of the proposed method for forecasting the market-clearing price in deregulated electricity markets.

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