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Short-term electricity price forecasting in deregulated markets using artificial neural network

Shiva Shakiba, Mehdi Piltan, Seyed Farid Ghaderi, Mohsen Sadegh Amalnik
Department of Industrial Engineering
University of Tehran, Tehran, Iran

Abstract

In this paper, we have proposed an Artificial Neural Network (ANN) approach to forecast short-term hourly electricity prices. We considered three major factors impacting electricity price forecasting, including time factor, load factor and historical price factor. In order to obtain an accurate model, several combinations of input parameters have been considered. Accordingly three models have been defined. For accuracy measurement the MAPE (Mean Absolute Percentage Error) value is used. Model 1 with historical price and time factors as inputs is the best model which forecasts hourly electricity prices with high accuracy.

Keywords
Restructured power market, Artificial neural network, Price forecasting

1. Introduction

Since the beginning of deregulation in electricity markets around the world, electricity market changes into a competitive market. In such deregulated markets, market players need to be informed of future electricity prices to have fixed position; therefore electricity price forecasting has become one of the most important tasks. In Iran, restructuring and privatization in electricity network are in progress too. Government has planned to double the generation and transmission capacities up to year 2015. So we try to forecast hourly electricity prices in Iran's market in this paper.

Electricity has its distinct characteristics from other commodities. For example, electricity cannot be stored economically and transmission congestion may prevent free exchange among control areas. Thus, electricity price movement shows very great, actually, the greatest, volatility among all commodities [1].

A wide variety of models have been used for short-term electricity price forecasting. Aggarwal, Saini and Kumar [2] discuss the main methodologies used for electricity price forecasting, including stochastic time series, causal models and Artificial Intelligent (AI) based models. The quantitative analysis based on time horizon of prediction, input variables, output variables and other analysis were done in this paper. Diongue, Guegan and Vignal [3], investigate conditional mean and conditional variance forecasts using a dynamic model following a *k*-factor GIGARCH process in their research. From Pedregal's and Trapero's point of view, among all of the models, state space models are not yet fully exploited. So they propose a univariate dynamic harmonic regression model set up in a state space framework for forecasting prices in deregulated markets [4]. Also a research about short-term price forecasting in Iran electricity market was done by Bigdeli, Afshar and Amjadi which uses pay-as-bid payment mechanism [5].

Among the existing tools for price forecasting, new simulation techniques such as Artificial Intelligence (AI) have received a great deal of interest. Papers [1, 6-8], use an Artificial Neural Network (ANN) approach for short-term price forecasting.

The rest of this paper is organized as follows. In section 2, a description of the design and ANN architecture is given which includes ANN training and selection of input and output data for ANN. In section 3, simulation results are discussed and finally, conclusions are given in section 4.

2. Artificial neural network for price forecasting

The classical methods for forecasting include regression and state-space methods. The more modern methods include expert systems, evolutionary programming, fuzzy system, ANN and various combinations of these tools. ANN has gained more attention among the existing tools because of its clear model, easy implementation and good performance [1]. ANN is able to reproduce some functions of human behavior, i.e., learning and reproducing of trends.ANN is formed by a finite number of layers with different computing elements called neurons. The neurons are interconnected, building up a network [8].

For time series forecasting, especially when time series are complex and non-linear, ANN is a very suitable tool that has the possibility of relating inputs and outputs without knowing the internal relations. Since electricity price demonstrates non-linear behavior, it seems that ANN is a good choice for price forecasting. The most popular and successful model is feed-forward multilayer network [9]. A feed-forward network has a layered structure. Each layer consists of units which receive their input from units of a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. A multilayer feed-forward network is shown in Figure 1.

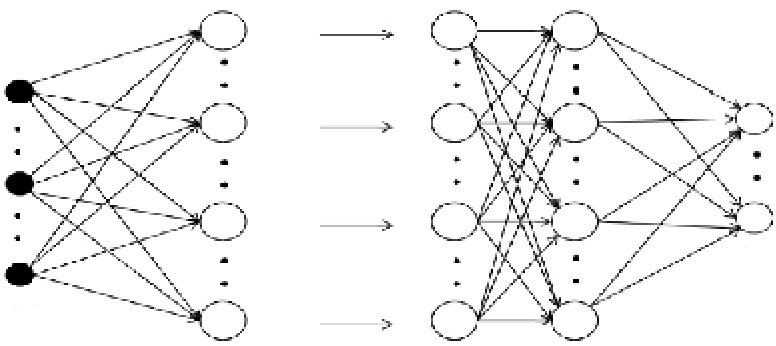

Figure 1: A multi layer feed forward network

It has been shown that only one layer of hidden units suffices to approximate any function with finitely many discontinuities to arbitrary precision, provided the activation functions of the hidden units are non-linear (The universal approximation theorem). In most applications, a feed-forward network with a single layer of hidden units is used with a sigmoid activation function for the units. Sigmoid activation function defines as follows:

$$F(s) = \frac{1}{1+e^{-s}} \tag{1}$$

ANN's forecasting procedure has two steps: training and simulation. In the training step, ANN finds the relationship between inputs and outputs according to the set of inputs and the corresponding outputs that we give to it. This set is called training set. In fact, in the learning process, a neural network constructs an input-output mapping, adjusting the weights and biases at each iteration based on the minimization of some error measure between the output produced and the desired output. The error minimization process is repeated until an acceptable criterion for convergence is reached [7].In simulation step, a testing set which includes new data that has never seen before by ANN is given to the network and the knowledge which the network acquires through the training step will be tested here.

The most common learning algorithm is the backpropagation algorithm, in which the input is passed layer through layer until the final output is calculated and it is compared to real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer [7].

2.1 ANN design, input preparation and sensitivity analysis

According to our aim in this paper, which is the simulation of the 24 hours electricity prices by ANN, our ANN should have 24 outputs.

Since irrelevant inputs may cause over fitting in ANN, we pay special attention to input selection in this paper. We consider the major factors impacting electricity price forecasting, including time factor, load factor and historical price factor. Because of different electricity consumption in different hours of day, we consider the input "hour of the day" with values between 1 and 24 and in order to distinguishing between labor and festive days, the input "day of the week" is considered which adopts values between 1 and 7, considering Saturday as the day number 1 and Friday as holiday.

After selecting the inputs of ANN, the most important step is the data pre-processing. Several mathematical operations are used in the pre-processing stage, which includes normalizing and ranking [6]. In this paper, we use normalizing for data pre-processing, which implies the transformation of the usual values of inputs and outputs into a new interval from 0 to 1.

As we know, historical prices and loads have a great impact on electricity price forecasting. Up to now, different sets of lagged prices have been proposed as input features for price forecasting in different markets, but there are no reasons to rationalize it [7]. In this paper, we use the correlation coefficient definition, for doing sensitivity analysis on historical electricity prices and loads to select lagged prices and loads.

The correlation coefficient, a concept from statistics, is a measure of how well trends in an especial value follow trends in past actual values. The correlation coefficient is a number between -1 and 1. If there is no relationship between an especial value and the past values, the correlation coefficient is 0 or very low. As the strength of the relationship between an especial value and past values increases, so does the correlation coefficient [7].

2.1.1 Sensitivity of the electricity prices to the previous hour's prices
For calculating the correlation coefficient of an hour's price with previous ones, we can select the prices of one week and find the correlation of an hour's price with 168 hours before. Results are shown in Figure 2. Results show that an hour's price has very high correlation with the following sets of the previous ones: $\{P_{h-24}, P_{h-48}, P_{h-72}, P_{h-96}, P_{h-120}, P_{h-144}, P_{h-168}\}$.

2.1.2 Sensitivity of the electricity prices to the loads
For calculating the correlation coefficient of an hour's price with loads, as mentioned in previous section, we select the loads of one week and find the correlation of an hour's price to the loads of 168 hours before. According to the results, we find that the price of each hour has a high correlation to the following sets of loads: $\{L_h, L_{h-24}, L_{h-48}, L_{h-71}, L_{h-72}, L_{h-96}, L_{h-120}, L_{h-144}\}$.

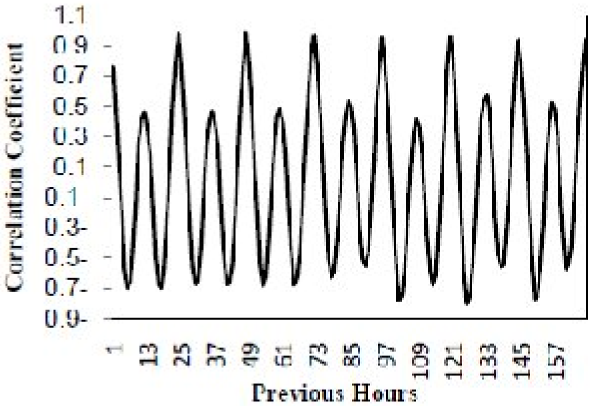

Figure 2: Correlation of an hour electricity price with previous ones

2.2 ANN training
As mentioned in the past section, training is the first step of forecasting with ANN. In this step, the architecture of ANN should be defined. Changes in the number of hidden layers, number of neurons in the hidden layer, and transfer function in the hidden layer and output layers will cause different architectures of the network. Combinations of these parameters should be examined to find the optimal architecture.

Although different types of network architectures can be used, we only use the multilayer perceptron with one hidden layer in this paper. For ANN training, backpropagation algorithm is used. In order to obtain an accurate model, several combinations of input parameters can be used. As shown in Table 1, we can present three models.

Table 1: Factors considered in different types of models

Factors	Model 1	Model 2	Model 3
Time	X	X	X
Historical price	X		X
Load		X	X

Time factor is fixed in each three model. In model 1, historical price factor; in model 2, load factor; and in model 3, both of the historical price and load factors are considered as input parameters. Available data for ANN's training and testing include the year 2007.

2.3 Accuracy measurement

To assess the prediction accuracy of the proposed models, the mean absolute percentage error (MAPE) is used. The MAPE value is computed as follow:

$$MAPE(\%)=\frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_{actual}-P_{forecasted}\right|}{P_{actual}}\times 100 \tag{2}$$

3. Simulation results

We select a three-layered feedforeward network for forecasting hourly prices. The transfer function of the hidden layer is hyperbolic tangent sigmoid and the transfer function of the output layer is purelinear. This configuration has been proven to be a universal mapping, provided that the hidden layer has enough neurons [7]. For this reason, different numbers of neurons in hidden layer have been examined.

The proposed neural network was trained and tested using the data derived from Iran's electricity market. Since the quantity of training vectors (training period) impacts on forecasting performance, we select the training period from 5/22 to 6/18 which varies from 2 to 4 weeks and in each of these periods, we obtain the MAPE for our models. The testing period is fixed from 8/4 to 8/17(336 hours). Each of three proposed models was run with selected architecture and results are presented in Table 2. Since the ANN results vary in each iteration (because of the randomness of the ANN weights), we repeat every ANN ten times and obtain the average errors which also are shown in Table 2.

As can be seen in Table 2, when the training period is 4 weeks, every three models have the best performance. The comparison between the actual prices and the forecasted ones of models 1-3 when the training period is 4 weeks are shown in Figures 3-5.

Table 2: Price forecasting errors

Number of Training weeks	Training Period	Testing MAPE(Average)		
		Model 1	Model 2	Model 3
2(336 hours)	5/22-6/4	2.2583	10.6883	4.2703
3(504 hours)	5/22-6/11	2.0197	9.3735	2.5496
4(672 hours)	5/22-6/18	1.8320	5.7765	2.5259

The average MAPE of models 1 to 3 when the training period is 4 weeks are 1.8320, 5.7765 and 2.5259. Accordingly model 1 is a very accurate model for hourly price forecasting. However, model 3 is also accurate.

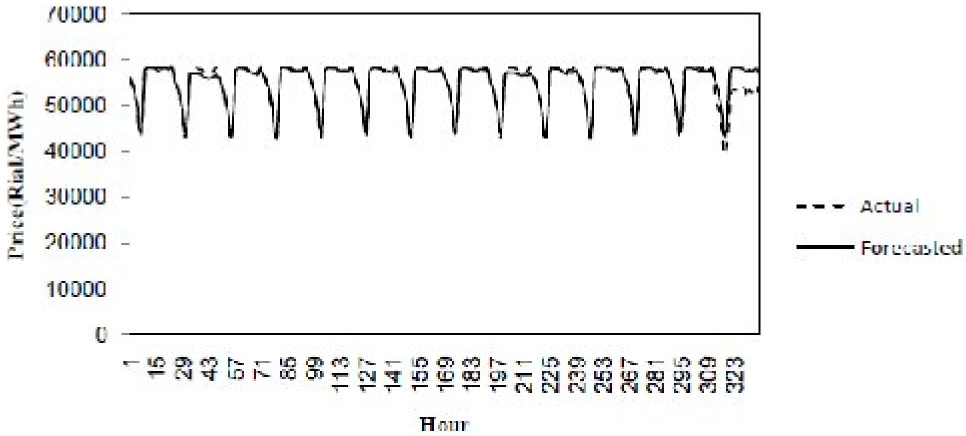

Figure 3: Actual and forecasted price curves of model 1 for 8/4 to 8/17 with 4 weeks training period

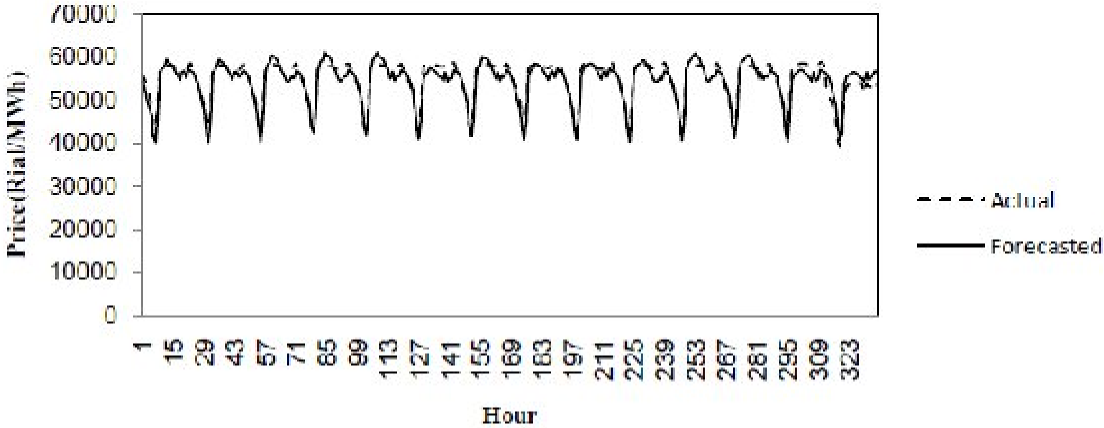

Figure 4: Actual and forecasted price curves of model 2 for 8/4 to 8/17 with 4 weeks training period

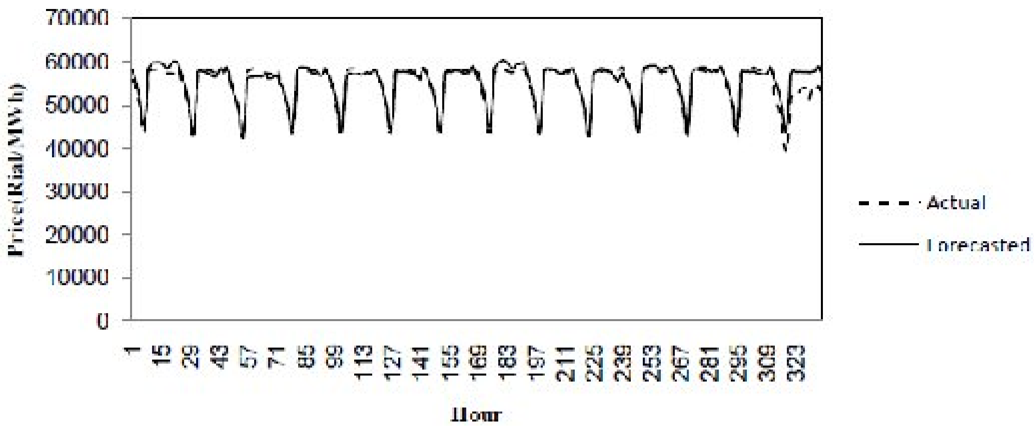

Figure 5: Actual and forecasted price curves of model 3 for 8/4 to 8/17 with 4 weeks training period

4. Conclusions

This paper presents a comprehensive model for hourly electricity price forecasting using artificial neural network (ANN) in Iran's electricity market. The factors impacting electricity price forecasting including time factor, load factor and historical price factor are considered. For selecting lagged prices and loads which impact on an hour's price, the correlation coefficient is used. Three models are defined and each model is implemented for four periods. Model 3 is a good forecaster but model 1 which uses time and historical price factors is better forecaster than two others which with increase in training period from 2 to 4 weeks, the average MAPE of this model decreases from 2.2583 to 1.8320. So the hourly electricity prices can be forecasted with model 1 with high accuracy.

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