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Price Forecasting Model for Turkish Day-Ahead Electricity Market Using Neural Network

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Abstract

Day-ahead electricity market (DAM) price forecasts are crucial parameters for market participants to create their next – day generation plan. Accurate price forecasts help participant companies to increase their profit by shifting generation to high price occurred hours. In this study we developed a forecast model for Turkish energy market because country's energy market mechanism hasn't got price forecast module and there is no available accurate price forecasts. Architecture of model is based on feed forward back propagation neural network approach. Four year period real market data are used in train and test phases. Results of this study show that forecasts of proposed model have acceptable accuracy and the performance of the model strongly depends on the market demand and generation capacities.

Key words: Energy market, price forecast, neural network

1. Introduction

Turkish energy market has transformed into a competitive environment for participants during the last decade. This competitive environment operates via the market mechanism. The mechanism has simple structure: Participants submit their bids to the market mechanism. These bids involve amount and price of generation or consumption sceneries for next day. Then software of the mechanism couples consumption and generation bids at optimum point. This optimum point gives market clearing price (MCP) and amount for coupled hour of next day. Software accepts consumption bid if price of bid is higher than or equal to MCP. Software accepts generation bid if price of bid is lower than or equal to MCP. This competitive environment motivates participants to shift their consumption bids to low MCP occurred hours and generation bids to high MCP occurred hours. These shifting processes obviously reduce costs and improves profits of participants. But participants should know MCPs of next day hours to shift operation sceneries. There is no price forecasting module in the software of market mechanism. For this reason price forecasting models are valuable for participant companies.

In literacy various methods are used to forecast future prices in competitive markets. Neural network based models for various markets are presented in [1-4]. Neuro-fuzzy approach is proposed in [5-7]. Also combination of neural network, wavelet transform, auto regressive

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moving averages etc. approaches are used in [8-11]. Some important methods in literacy are summarized in [12]. All proposed methods are tested in different market environments. So there is no general result of these approaches. Turkey is a developing country and there is an increase in energy consumption. This increase also affects energy market prices. On the other hand companies install new power plants to meet increased energy demand. These new power plants also reduce market prices. New installations and demand increase make price curves more complex and uncertain. For these reasons we proposed more compact and reduced-parameter model for price forecast. Model is based on feed forward back propagation neural network approach.

Aim of the study is to develop useful forecast model for market participants and test the performance of the model. Detailed explanation of proposed model and application is given in the next section. Results are summarized in Section 3 and discussed in Section 4. Also some conclusions are given in the last section.

2. Materials and Method

DAM electricity price is a function of variable and uncertain parameters. Some of them are; electricity demand, availability of renewable energy sources (wind, hydro, solar etc.), fuel prices, amount of bilateral contracts. Electricity demand has a strong relation with price. It is well known that price curve follows demand curve trajectory. Also renewable sources availability impacts prices. Renewable sources have uncertain and variable nature. Excess and deficient electrical energy generation from renewable energy sources causes decrease and increase in prices respectively. Fuel price is another important parameter. Because it impacts profit of generation companies. High fuel prices mean high cost for companies and this situation forces them to trade with high prices. Last parameter we mentioned is amount of bilateral contracts. These contracts limit the market capacity and obviously it influences price levels.

In this study we developed a price forecasting model for Turkish DAM. Including all mentioned parameters to price forecast model will increase the accuracy of forecasts. But accessing to these parameters is a hard process. Also some parameters like wind, hydro and solar available generation capacity are variable and uncertain so they are not useful for future forecasts but cyclic historical parameters are useful. Demand and price data are cyclic. Additionally Turkish DAM mechanism has demand forecast module and the accuracy of this module is very high so there is no need to use historical demand data. Consequently we decided to use two kinds of parameters as inputs of the forecast model. They are demand forecast and historical price parameters. This parameter reduction made model simple compact and more applicable. We used neural network approach to create the model. Detailed explanation of model and its application to the Turkish DAM is given in the next section.

2.1. Forecast Model and Application

Feed forward back propagation approach is used to create neural network based model. Model has single output and eleven inputs. Output is forecasted price value. Inputs are composed of two types of parameters as mentioned in previous section. Table 1 is the short description of model inputs. Topology of the model is given in Figure 1. Also Table 2 summarizes some details of model topology.

Table 1. Model inputs

No	Parameter	Inputs
1-2	Demand forecast change	Df(t)- Df(t-1)
3-5	Price (one day ago)	P(t-23), P(t-24), P(t-25)
6-8	Price (one week ago)	P(t-167) ,P(t-168), P(t-169)
9-11	Price (two week ago)	P(t-335) ,P(t-336), P(t-337)

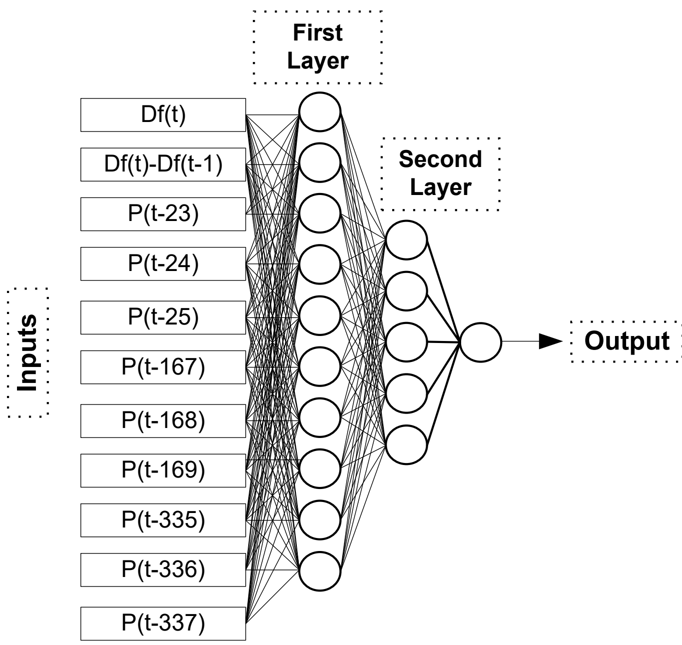

Figure 1. Neural network model

Table 2. Details of neural network model

Layer	Number of Neurons	Transfer Function
First	10	Hyperbolic tangent sigmoid
Second	5	Hyperbolic tangent sigmoid
Output	1	Linear

Real Turkish market data are used in application. Data set is composed of four years period (2012-2015) input parameters. Matlab software development environment is used to perform algorithms. Numerous test and train periods of model are investigated. Results of the application are given in the next section.

3. Results

Performance of the model is evaluated by using three indices. They are; root mean square error(RMSE), mean absolute error(MAE) and mean absolute percentage error(MAPE). Formulas of indices for test period T are given in equations (1-3) respectively. RMSE and MAE indices are normalised by dividing them into mean of price values of the test year.

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\left|(P_t^{actual} - P_t^{model})/P_t^{actual}\right| \tag{1}$$

$$NMAE = \frac{100}{T}.\left[\sum_{t=1}^{T}(\left|P_t^{actual} - P_t^{model}\right|)\right]/\frac{1}{T}\sum_{t=1}^{T}(P_t^{actual}) \tag{2}$$

$$NRMSE = 100\left[\sqrt{\frac{1}{T}\sum_{t=1}^{T}(P_t^{actual} - P_t^{model})^2}\right]/\frac{1}{T}\sum_{t=1}^{T}(P_t^{actual}) \tag{3}$$

In literacy, MAPE is widely used for performance evaluation. This index is not suitable for very small values because it gives very high values if prices are very low. For example, consider the mean of the test year price values is 100 TL, forecasted price of an hour is 15 TL and actual price is 10 TL, MAPE results %50. It is a very high index value because 5 TL error is only the %5 of mean value. Therefore three different indices are used to evaluate performance of the proposed model. Various training and testing periods are used to evaluate performance of the proposed model. Results of one year training and one year testing phases are given in Table 3. Results of one and two year training periods of the model are given in Table 4. Also Table 5 summarizes effect of training period on model's performance. Results shows that increase in period interval improves the accuracy of forecasts.

Table 3. Results of one year test and train periods

Train	Test	MAPE	NMAE	NRMSE	Mean Price
2012	2013	18.728	9.798	16.642	149.760
2013	2014	9.578	8.166	14.319	163.939
2014	2015	65.607	18.060	29.339	138.010

Table 4. Results of one and two year training periods

Train	Test	MAPE	NMAE	NRMSE
2013	2014	9.578	8.166	14.319
2012-2013	2014	9.440	7.970	14.169

Table 5. Results of one, two and three year training periods

Train	Test	MAPE	NMAE	NRMSE
2014	2015	66.883	18.666	30.498
2013-2014	2015	48.296	16.974	27.441
2012-2014	2015	47.355	16.032	25.784

Best result is achieved in test year 2014. Because prices are not changed in wide range during that year. Also fluctuation of price curve is smoother than the other test years. Figure 2 is a sample of best performance. Figure 3 is a histogram of error distribution of test year 2014.

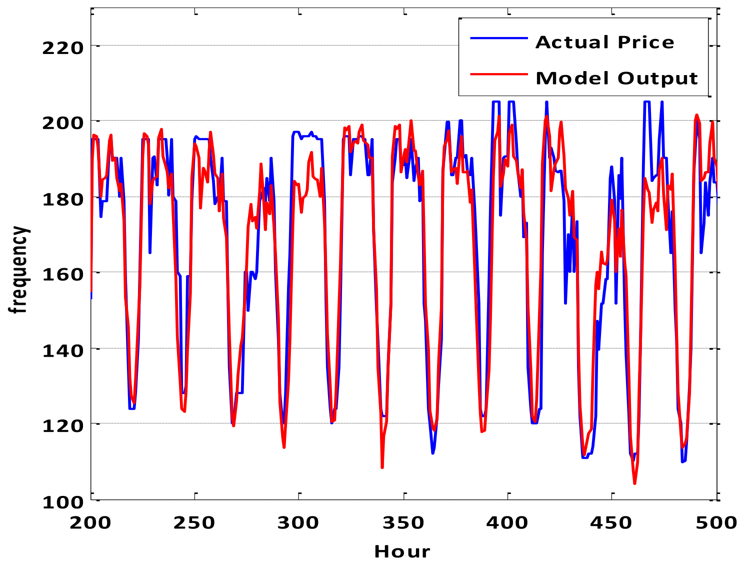

Figure 2. Sample actual and forecasted prices from test year 2014

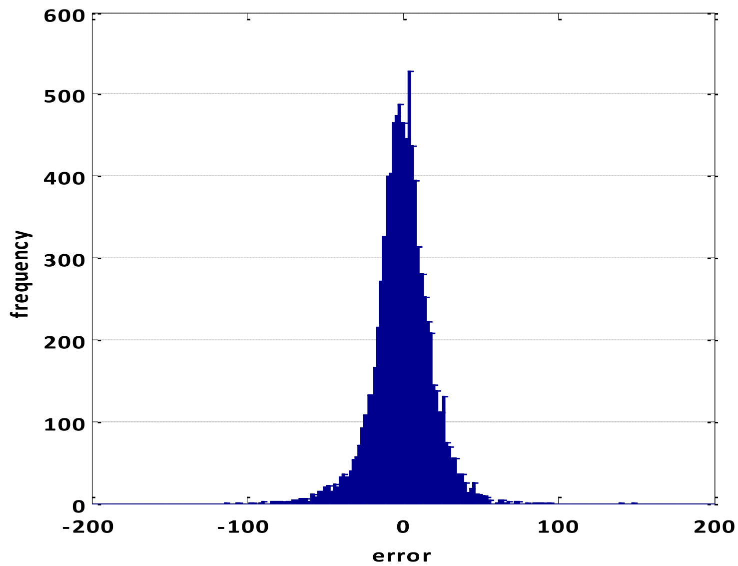

Figure 3. Forecast errors distribution of test year 2014

Worst result is achieved in test year 2015. Figure 4 is a sample of it. When compared with Figure 2, price curve fluctuates in wider range in Figure 4. Also price curve is more complex than in Figure 2. Error distribution of worst results is given in Figure 5. Market prices had minimum values in 2015 that have never been seen before. This situation is the result of increase in feed in tariff capacity and huge amount of new power plant installation. Because of these reasons, price curve of 2015 has more complex and uncertain nature than other years.

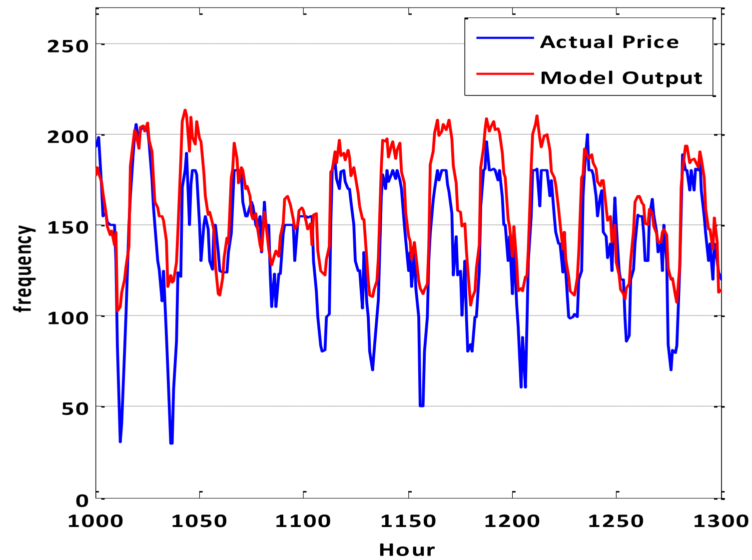

Figure 4. Sample actual and forecasted prices from test year 2015

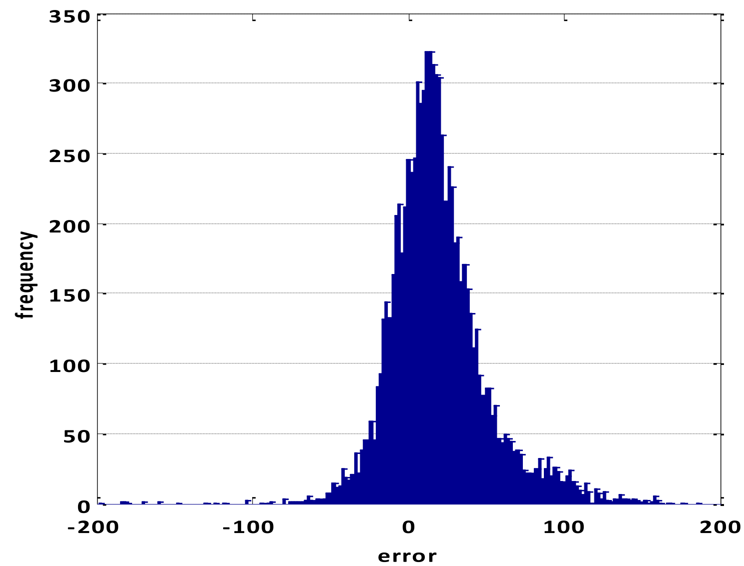

Figure 5. Forecast errors distribution of test year 2014

Results of the study shows that there is a strong relation between the performance of the forecast model and complexity level of the price curve. Also period of training data affects accuracy. Longer training period has higher accuracy results. Results show that forecast accuracy of proposed model is mostly enough for companies to use them to organise their bids.

4. Discussion

In literacy, lots of paper focused on performance of their forecast models in a specific period of price data. Results of this study show that there is a strong relation between performance of the model and the price curve complexity so it is not a proper approach to evaluate performance in specific period. From this point of view more performance evaluation indexes have to be considered in order to access proper results.

Conclusions

As a conclusion, forecasting models based on neural network approach will be useful for market participants. But it is not easy to say what the performance of model in future will be.

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