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Prediction of market-clearing price using neural networks based methods and boosting algorithms

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ABSTRACT

The development of Turkey's industry is contributing to a significant rise in electrical energy demand. Also, electricity is one of the critical elements in the household sectors. Therefore, the planning and managing of electrical energy is of great importance to support economic growth. In addition, effective prediction of market-clearing prices (MCP) is critical topic to meet the increasing energy demand and provide basis for decision making process. In this paper, MCP is predicted using artificial neural network (ANN), convolutional neural network (CNN), and also three boosting algorithms including extreme gradient boosting (XGBoost), categorical boosting (CatBoost), and adaptive boosting (AdaBoost). Various performance metrics are employed to evaluate the prediction performance of proposed methods. The results showed that proposed methods provide reasonable prediction results for energy sector. Hence, producers and consumers can use these methods to determine the bidding strategies and to maximize their profits.

1. Introduction

The world energy consumption is increasing exponentially in parallel with population growth, industrialization, and technological progress. Energy is taken into account as a prime agent in wealth creation and a significant influence in economic growth as well [1]. Especially, electric energy consumption has been one of the most significant indicators of economic and social growth.

The Turkish energy policy primarily focuses on the reliable and timely assurance of energy supply under economic and clean terms [1]. As a consequence of the rapid growth in Turkey's population, urbanization and industrialization especially prompted the need for electrical energy to rise regularly. Therefore, the electrical energy sector continues to expand and liberalize in Turkey [2].

Since electricity is an indispensable element of daily life, one of the goals of almost all countries is to provide consumers with continuous and reliable electrical system. This can only be possible with the correct planning and management of the electricity supply system that require effective modeling and prediction capability. Due to the unique characteristics of the electricity sector, it may be difficult to develop prediction models that are suitable for the different subsystems it carries. In literature, many prediction methods have been developed to evaluate the electricity. However, it is almost impossible to generalize and use them in demand prediction of any country. Hence, the development of methods that will include the unique characteristics of countries will provide more realistic prediction of electricity demand [3]. Most studies indicated that the key goal is to ensure sufficient electricity and fulfill potential needs. At this point, prediction is highly significant in the successful implementation of energy policies [4].

The worldwide electricity industry has undergone a change. The utilities owned by the government have been privatized. To be competitive in electricity market, policy makers and market managers need to research, evaluate and monitor the actions of market participants. At this point, strategic bidding problem should be solved to maximize profit. In the strategic bidding problem, MCP plays an important role because it defines which blocks will be

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nominated by the market clearing process [5]. It is also stated that the prices formed in the day-ahead electricity market are the reference prices for other markets. The reference price means that the prices formed in the day-ahead electricity market reflect the supply and demand balance of market in a very close time to the delivery time of the electricity. One of the markets where MCPs are considered as reference prices is the balancing power market [6].

MCP is one of the most significant power market indicators. In the energy market, prediction of MCP has a critical role for any decision making process. Effective MCP prediction not only has critical roles in planning and management of energy market, but also improves the profit in energy market.

Electric energy that is a form of energy is used at a high rate today because it is efficient and rapidly transmittable resource. Planning on supply-demand, transmission-distribution and pricing that occur with the use of electrical energy is of great importance [7]. Kilic [1] analyzed the major energy sources of Turkey and the significance of their use in the energy sector. Akbalık and Kavcıoğlu [2] reviewed and analyzed the energy sector considering the technological, environmental, and financial structure in Turkey. In addition, supply and demand of global energy were evaluated based on the energy types. The distribution of public and private sector in Turkey was also discussed.

In the energy sector, accurate prediction is important in terms of providing the energy supply. However, prediction can be difficult due to the presence of random factors. In literature, various methods are proposed to improve the prediction results in electricity market. Bilgili [8] predicted the net electricity consumption of Turkey by means of linear regression, nonlinear regression models, and the ANN. The results demonstrated that the performance of the ANN provided better results than other proposed methods. Marvuglia and Messineo [9] predicted the residential electricity consumption using an Elman network. In the study, several Elman networks were analyzed and the best network was determined according to the prediction error. Sensitivity analysis was applied to provide a better insight for inputs. Es et al. [10] evaluated the performance of the ANN and multiple linear regression models in the net energy demand prediction of Turkey. Başoğlu and Bulut [3] developed a new prediction method including the ANN and expert systems to predict the demand of short-term electricity in Turkey. Errors that may occur due to random elements of the ANN have been minimized with the help of an expert system. Expert system can take into account random elements and seasonal effects that occur in different forms at different times. The results demonstrated that prediction accuracy of proposed method was high. Kocadayı et al. [7] predicted the annual electricity consumption by means of the ANN. It was seen that the electricity consumption prediction results of the ANN model are very close to the real value. Nugaliyadde et al. [11] used the recurrent neural network and a long short term memory network to predict electricity consumption. The prediction results of proposed methods were compared with other prediction models to show the predictive ability of methods.

Tutun et al. [4] estimated future independent factors using predicted scenario approaches. Then, two new models with linear and quadratic behavior were applied for the prediction of net electricity consumption. Kaya et al. [12] presented the relationship between internet usage and electricity consumption for Turkey. In the paper, the number of internet users, gross domestic product (GDP), and annual percentage changes in electricity consumption were utilized. An autoregressive distributed lag model was employed. Accordingly, increasing the amount of internet users and growth in GDP has positive and statistically important impacts on the growth of electricity consumption in Turkey. Çamurdan and Ganiz [13] used publicly available data to create decision tree, linear regression and random forest models for electricity demand prediction. Li and Zhang [14] presented a novel optimized GM (1, 1) method to improve electricity consumption forecasts. Note that GM (m, n) represents a grey prediction model in which the differential equation order is m and variable number is n. In the model, data transformation was firstly applied for the original data sequence. Then, the background value was optimized by means of combination interpolation optimization. Finally, prediction model was created and evaluated. Two case studies were utilized to analyze the performance of the method. Sun et al. [15] proposed a monthly power consumption comprehensive prediction model. The model is capable of processing data for any type of seasonal variation factor. In addition, the change rate of seasonal component and trend component smoothness can be controlled. The actual monthly electricity consumption data was utilized to assess the efficiency of prediction model.

In the electricity market, long-term electricity purchases and sales are made through bilateral agreements. The electricity reference price that formed in the day-ahead market is important for market participants in determining the prices of bilateral agreements, making energy investments and determining energy trade risks. The day-ahead market provides a chance for market participants to eliminate the energy imbalances that may occur for the next day. The prices formed in the day-ahead market are accepted as the electricity reference price (MCP) due to their closeness to real time [16].

Producers and customers need information about price prediction to plan their bidding strategies. Producers with low ability to alter MCPs need day-ahead price prediction to make optimum self-scheduling and derive bidding strategy in the pool. For the same reasons as the producers, retailers, and large consumers need day-ahead MCPs. However, MCPs are volatile in deregulated power markets [17]. Therefore, various methods were developed to provide better strategy for producers and customers. Gao et al. [18] proposed the three-layer back propagation network to predict the MCP and market clearing quantity. Considering truncated historical prices and untreated spiking data, two methods were created. It was determined that the truncated method had better accuracy. Georgilakis [17] developed a methodology for the prediction of MCP in California power market considering three steps. Firstly, the ANN was employed to predict the day-ahead load. Secondly, the persistence method was utilized to predict the MCPs. Finally, the ANN was employed to predict the MCPs. Two case studies including without price spikes and with price spikes were applied. Singhal and Swarup [19] employed the ANN to predict the MCP for daily energy market. Pre-processing and post-processing were applied to improve the ANN performance. It was observed that proposed method gives good results for normal trend. On the other hand, performance of the model gradually degraded for days with price spikes. Şenocak and Kahveci [16] used the adaptive network based fuzzy inference systems (ANFIS) and the ANN to predict the MCP. It was determined that the prediction performance of the ANFIS was better than the ANN. Anamika and Kumar [20] used the ANN and the regression method to predict the MCP in deregulated electricity markets. It was determined that the regression model was better than the ANN method in MCP prediction of Indian electricity markets. Anamika and Kumar [21] applied the ANN on different groups to predict hourly MCPs in the Indian electricity exchange. To eliminate outliers or price spikes and normalize the rest, data was also preprocessed. Kabak and Tasdemir [22] used the ANN to create a Turkey's electricity day-ahead price prediction model that was utilized for supply and demand curves. It was determined that prediction error of model was lower if it was considered daily rather than hourly.

Yan and Chowdhury [23] proposed a model based on multiple support vector machine (SVM) containing a SVM classification module and a SVM regression module to predict hourly electricity MCP. Price patterns can also predicted by proposed model. Prabavathi and Gnanadass [5] used a mathematical model to solve the bidding function for suppliers and customers. In the paper, step bidding function was used to find the MCP. It was determined that MCP can be higher when demand is increased. Cheng et al. [24] proposed a novel grey prediction model to predict the mid-term electricity MCP. In the study, two improved GM (0, N) models whose parameters were determined by an improved particle swarm optimization were employed. In addition, a novel whitenization method was utilized to define the value of definite prediction. Tür [25] presented the analysis of the MCP and the system marginal price for consumers. Yanar and Akay [26] used the multilayer perceptron, recurrent neural network, CNN, and long short term memory to predict the MCP. From the literature it is apparently seen that a large number of studies are available. However, no single best prediction approach is available. Any method may not guarantee reasonable accuracy for all prediction situations. Therefore more improvement is required to increase the prediction accuracy. For the particular situations, it was also decided that each method has its own advantages. Further developments are required in the methods.

In this paper, MCP prediction is taken into account to cope with the challenges of electricity industry. Prediction models are created using XGBoost, CatBoost, AdaBoost, ANN, and CNN. Furthermore, the performances of the proposed methods are compared to evaluate the prediction results. Thus, a comparative analysis was provided on XGBoost, CatBoost, AdaBoost, ANN, and CNN to help academicians, economists, and statisticians selecting the best model for MCP prediction. It is seen that this line of study is highly contingent upon reliable prediction of MCP in Turkey. The contribution of this paper can be summarized as follows. Firstly, boosting algorithms including XGBoost, CatBoost, and AdaBoost are used to predict the MCP in Turkey. Secondly, ANN and CNN are employed for MCP prediction in Turkey. Thirdly, the performance of proposed methods is compared to evaluate the prediction.

2. Proposed Methods

In this paper, dataset covers the period from 01.07.2009 up to 01.03.2020. The dataset was downloaded from EPİAŞ (Market & Financial Settlement Center) [27]. Count (its value is 3897), mean (its value is 165.7), standard deviation (its value is 59.4), minimum (its value is 19.1), first quartile (its value is 130.3), second quartile (its value is 153.8), third quartile (its value is 180.2), and maximum (its value is 687) are evaluated as descriptive statistics of the MCP. Density plot and histogram of daily MCP dataset is also given in Figure 1 where the y-axis is in terms of density.

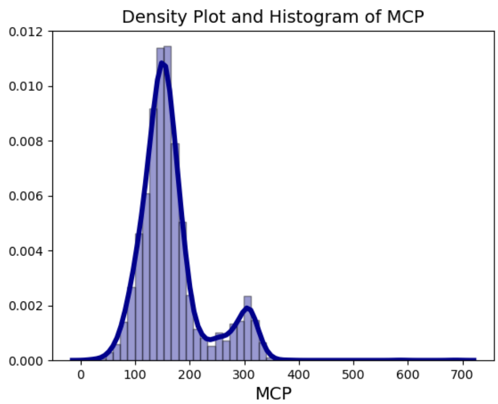

Figure 1. Density plot and histogram of daily MCP dataset

In this paper, boosting algorithms and neural network based methods are used to predict daily MCP. Note that the parameters of proposed methods are determined using trial and error method. In there, Mean Squared Error (MSE) was used as performance measurements to determine the parameters of proposed methods. Details about the proposed methods are given in following subsections. Note that processor is Intel (R)Core (TM) i7-8700CPU@3.70GH and Random-Access Memory (RAM) is 64 GB.

2.1 XGBoost

XGBoost can be described as a scalable end-to-end tree boosting system. It is used as an open-source package [28]. In XGBoost, weak classifiers are aggregated to create a powerful model. XGBoost can be represented as follows for a given dataset with n samples and m features ($D = \{(x_i, y_i)\}(|D| = n, x_i \in \mathbb{R}^m, y_i \in \mathbb{R})$).

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{1}$$

where $F = \{f(x) = w_{q(x)}\}(q: \mathbb{R}^m \to T, w \in \mathbb{R}^T)$ denotes the space of classification and regression trees (CART). $q(x)$ maps an input x to CART leaf node. The weight on the node represented as w and the total leave numbers in the tree is T. The XGBoost summarizes all weights provided from each CART and outputs a final score. Details about the XGBoost can be found in [29]. XGBoost utilizes a new regularization technique to control the overfitting that is the difference between XGBoost and other gradient boosting. Hence, XGBoost is faster and more robust during tuning of the method [30].

In XGBoost, the value of colsample_bytree (the subsample ratio of columns when constructing each tree) is 1. Maximum depth of a tree is determined as 3. In addition, reg_alpha (L2 regularization term on weights) and reg_lambda (L1 regularization term on weights) are specified as 1.3 and 1.1, respectively. min_child_weight (minimum sum of instance weight needed in a child) is 1. Finally, learning rate is assigned as 0.1. Note that dataset is divided into two separate parts as training (80%) and testing (20%).

2.2 CatBoost

CatBoost is a new gradient boosting decision tree algorithm. CatBoost can be used to overcome gradient bias. Multiple categorical features can be combined by CatBoost. A greedy way is utilized in CatBoost to integrate all categorical features and their combinations in the current tree. Random permutations of the training data are produced in CatBoost. To enhance the robustness of algorithm, multiple permutations can also be employed. CatBoost utilizes oblivious trees as base predictors [31-32]. CatBoost is an ensemble of symmetric decision trees that have less parameters, faster training and testing, and higher accuracy in their symmetry structure [33]. In this paper, the learning rate is taken as 1 and depth is 4 for proposed CatBoost algorithm.

2.3 AdaBoost

The application of AdaBoost can be briefly explained as follows. Its adaptation is that the sample weight of previous weak classifier is strengthened. To train the next new weak classifier, the updated sample of the weight is again used. Population is used to train the new weak classifier in training phase. New sample weights are generated. These procedures continue until a particular condition is satisfied such as maximum number of iterations. It can be said that multiple weak classifiers combined into a strong classifier in AdaBoost. The strong classifier is determined using following equation.

$$F(x) = \sum_{k=1}^{T} \alpha_k f_k(x) \tag{2}$$

The strong classifier is represented as $F(x)$ while the weak classifier is denoted as $f_k(x)$. The weak classifier weight is α_k and weak classifier number is T. Details about the AdaBoost can be found in [34]. The main advantages of AdaBoost are fast, simple, and easy to program [35]. In this study, the number of estimators, learning rate, and maximum depth are determined as 170, 1.518, and 3, respectively.

2.4 ANN

ANN includes the input layer and the output layer, and also hidden layer(s) which help(s) catch nonlinearity. ANN is constructed with the aim of processing the input information and transmitting the information via various connections. ANN has a powerful connection between the variables of input and output. Thus, ANN is able to model a dynamic non-linear relationship and to extract dependency of input-outputs. It is easy to propose the prediction model in the ANN. However, the performance of the ANN directly depends on the parameters.

In this paper, Adam is selected among available optimizers in Keras. Two hidden layers are used in the ANN. The number of neuron in first hidden layer is specified as 32 while the number of neuron in second hidden layer is specified as 64. The epoch number is utilized as 500. In addition, rectified linear activation function (ReLU) is used as the activation function. Note that dataset is divided into two separate parts as training (80%) and testing (20%).

2.5 CNN

The term "convolutional neural system" demonstrates that the system uses a mathematical linear operation named convolution. CNN included at least one convolutional layer and then followed by at least one fully connected layer as in a typical multi-layer ANN. Convolutional layer that defines the output of associated inputs is the main element in CNN. Fully connected layer seeks to build the predictions from the activations. In addition, sub-sampling layers between those two layers can exist [36]. Reducing the parameter numbers in the ANN is the most important feature of CNNs. Another significant feature of the CNN is to acquire abstract features as input propagates to deeper levels [37].

In this paper, settings of the common parameters of the CNN with the ANN are all the same. Thus, Adam is selected among available optimizers. Two hidden layers are used. The number of neuron in first hidden layer is specified as 32 while the number of neuron is specified as 64 in second hidden layer. The epoch number is utilized as 500. In addition, ReLU is used as the activation function. Note that dataset is divided into two separate parts as training (80%) and testing (20%).

3. Results and Discussion

Planning and management of the energy require effective modeling and prediction. The better prediction means more accurate investments and more satisfied customers. However, prediction is not an easy process in energy sector; it requires the consideration of very complex details. In this study, XGBoost, CatBoost, AdaBoost, ANN, and CNN are used to predict the MCP. The results of performance measures are given in Table 1.

Root-mean-square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and central processing unit (CPU) time are used to compare the proposed methods. Thus, RMSE, MSE, MAE, and CPU are used to determine which prediction method performed the best under different conditions. In literature, various performance measures are used to judge the prediction capability of the methods. Many researchers have also asserted that there are no universally applicable features for the accuracy measures. Thus, no measure is valid in all conditions and different measures treat different aspects of accuracy [38].

The results of this study demonstrated that AdaBoost required significantly less CPU time. The potential reason for AdaBoost algorithm gives less CPU time is that it has no parameters to tune. CatBoost gives the best value according to the MSE and MAE. CNN gives the best value according to the RMSE and MSE. It is also determined that the values of the RMSE, MSE, and MAE are relatively close in proposed methods. The MAE informs about the average size of prediction errors when negative signs are ignored. MSE and RMSE ensure a quadratic loss function and measure the uncertainty in prediction [39]. Note that the lower the values of the RMSE, MSE, and MAE, the closer the predicted values are to the actual values. The comparison between true values of MCP and the predictive values of each method is given in Figure 2.

In this study, the association strength based on Pearson's test is also calculated as given in Figure 3 for XGBoost, CatBoost, AdaBoost ANN, and CNN, respectively. When the coefficient of Pearson's correlation is equal to 1, it demonstrated that a linear relationship is available between the prediction result and the actual data. When the coefficient of Pearson's correlation is equal to 0, it demonstrated that no relationship is available. The coefficient of Pearson's correlation for ANN and CNN is higher than other methods. In addition, CatBoost has the lowest value when compared with XGBoost, AdaBoost ANN, and CNN.

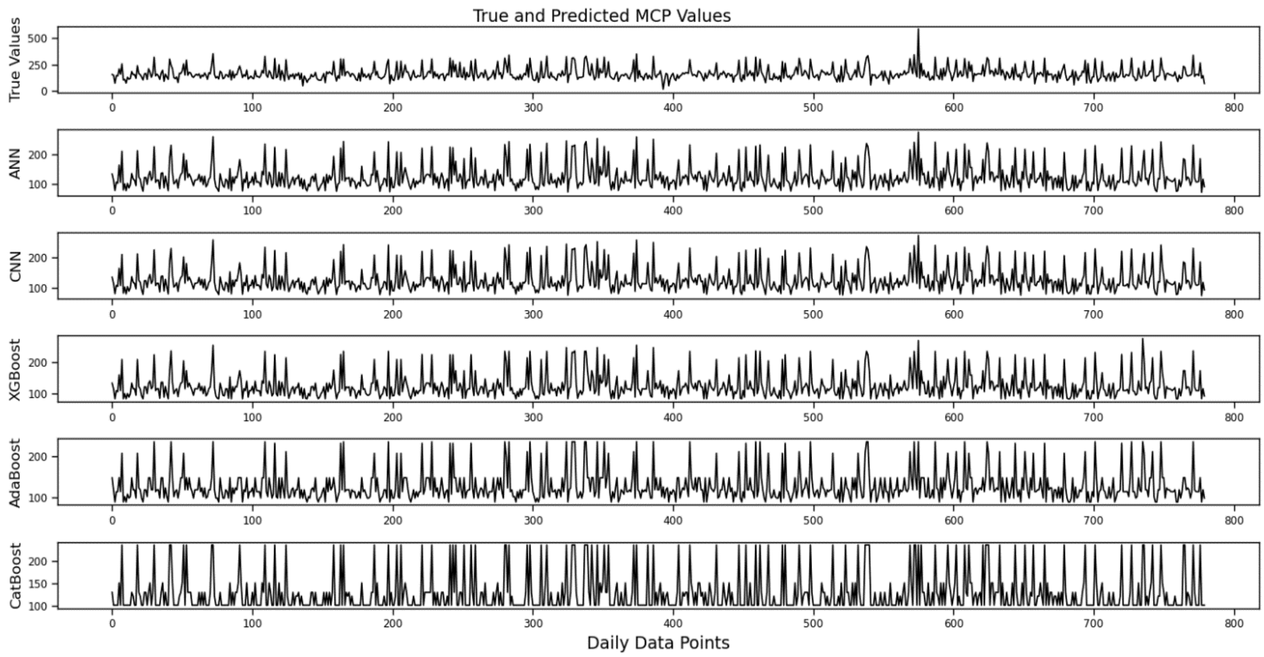

Figure 2. The true values of MCP and the prediction values of proposed methods

Table 1. The results of performance measures in proposed method

Methods	RMSE	MSE	MAE	CPU time (seconds)
XGBoost	0.0686	0.0047	0.0575	0.206
CatBoost	0.0671	0.0045	0.0558	0.441
AdaBoost	0.0690	0.0048	0.0559	0.035
ANN	0.0691	0.0049	0.0594	230.998
CNN	0.0664	0.0045	0.0568	243.925

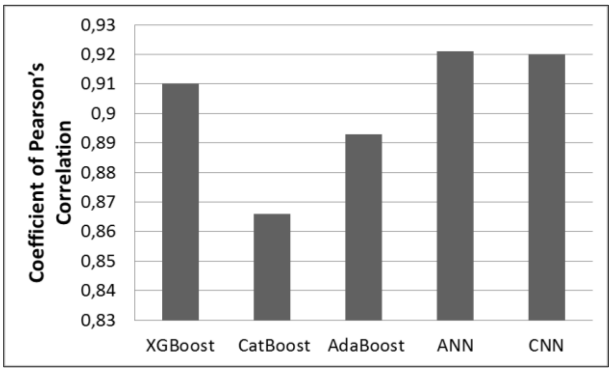

Figure 3. The coefficient of Pearson's correlation for proposed methods

4. Conclusion

Electricity is utilized in almost all kinds of human activity, such as industrial development, transportation, illumination, agriculture, residential, and heating. Electricity consumption is increasing every year. Therefore, prediction constitutes the significant part of the countries' energy policies. Due to the increasing population and industrialization, effective prediction is needed to meet the increasing energy demand. However, prediction in energy sector is a difficult task because of the uncertain and volatile nature. In this paper, MCP is predicted using XGBoost, CatBoost, AdaBoost, ANN, and CNN. Then, performances of proposed methods are compared to show the differences between methods. According to the results of CPU time, AdaBoost can be selected. It can be also said that the values of RMSE, MSE, and MAE are relatively close in proposed methods. However, the best value of MSE and MAE is provided by the CatBoost. CNN also provides the best value according to RMSE and MSE. Overall results of the study showed that all proposed methods can be successfully used to manage electricity usage and determine the bidding strategy. In future work, other optimization methods such as nondominated sorting genetic algorithm II can be employed when optimizing the parameters of methods in order to get better performance on prediction.

Declaration

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The author also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

A. Boru İpek developed the methodology, performed the analysis and wrote the manuscript.

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