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Research Article

Determining the Factors Affecting the Market Clearing Price by Using Multiple Linear Regression Method

Veli Rıza Kalfa, Ph.D. *

Lect., Honaz Vocational School, Pamukkale University, Denizli, Turkey, vrkalfa@pau.edu.tr

Burak Arslan

Pamukkale University, Denizli, Turkey, brkarslan20@gmail.com

İrfan Ertuğrul, Ph.D.

Prof., Department of Business Administration, Faculty of Economics and Administrative Sciences, Pamukkale University, Denizli, Turkey, iertugrul@pau.edu.tr

* Pamukkale Üniversitesi, Honaz Meslek Yüksekokulu, Afşinbey Mah. Türkcan Sok. No. 3, Honaz, Denizli, Türkiye

ABSTRACT

The aim of this study is to determine the factors affecting the market clearing price by the multiple linear regression method. In order to achieve this goal, hourly data for 2019 were obtained from the website of Energy Exchange Istanbul (EXIST). Due to the multiple linear regression analysis assumptions, only January and June data were included in the analysis. The analysis results show that the variables affecting the market clearing price are statistically determined as the amount of natural gas production, the amount of hydroelectric energy, the amount of energy produced in thermal power plants, and the amount of wind energy (only in January) at the significance level of 0.05. Methods with high specificity coefficient, low mean absolute percentage error (MAPE) and mean absolute deviation are known as the methods that adapt to the data better. In this study, artificial neural network method was used along with the multiple linear regression method in order to determine which prediction model fit the data better. Coefficient of determination (R2), mean absolute percentage error, and mean absolute deviation were used to compare the methods. In this study, it can be concluded that the artificial neural network method is a better predictive than the multiple linear regression method due to its high R2 and low MAPE and the mean absolute deviation values.

Keywords: Market Clearing Price, Multiple Linear Regression, Artificial Neural Networks

1. Introduction

The electricity industry in the world and in Turkey traditionally adopted a natural monopoly structure vertically integrated. Electricity generation plants, transmission lines and distribution systems were all of the same structure. Upon the regulation of the electrical energy sector, horizontally integrated structures have been adopted. Production, transmission, and distribution stages are separated, allowing individual companies to undertake these activities (Aydın, 2010: 62).

The reasons behind the desire to make changes in the electrical energy sector may show differences among countries. In most of the developing countries, electrical energy sector has such characteristics as low labour productivity, insufficient service quality, excessive system losses, the inability of the majority of the population to benefit from services, and insufficient prices to support new investments and to cover costs (World Bank, 1994: 25; Cengiz, 2006: 129).

When we look at the private electricity market, in the early years Turkey began to carry out a system where only the state controls domination. Electric operation process that started with the Turkish Electricity Authority (TEA) in 1970 has today incorporated Turkish Electricity Transmission Corporation (TEIAS), Electricity Generation Company (EGC), Energy Exchange Istanbul (EXIST), and private production and distribution companies upon the enforcement of laws considered as a reform in the electricity market (Çetintaş & Bicil, 2015: 10).

Energy Exchange Istanbul (EXIST), established on 18 March 2015 to ensure the reliable, transparent and independent formation of the market price as the most important requirement of energy markets, started its market operation activities as of September 1, 2015. EXIST takes priority in the planning, establishment, development, and operation of energy markets in an efficient, transparent and reliable way. EXIST aims to ensure the creation of reliable reference prices without discrimination and to become an energy market operator through market mergers where liquidity reaches the highest level with the increasing number of market participants, product variety and transaction volume (EXIST, 2016: 17- 20).

The day ahead market is an organized wholesale electricity market established and operated by EXIST for electrical energy purchase and sale transactions based on the settlement period to be delivered one day after. This market provides an environment for its participants to eliminate the energy imbalances that may occur for the next day, and the prices formed in the market are accepted as the Market Clearing Price (Şenocak and Kahveci, 2016: 664). In the day ahead market trading process, the market operator must notify the market operator about their offer notifications for the next day until 11:30. Optimization processes are completed until 13:00 and the market clearing price/amounts are determined for each hour of the relevant day and announced to the participants. The Balancing Power Market process is initiated by announcing the finalized prices as of 14:00 (Biçen, 2016: 435).

Estimating the Market Clearing Price (MCP) is very important for market participants. For this reason, trying to predict the market price through analysis has been the subject of research. Because the term electricity market was a new concept in the literature in the early times, especially studies as to the concept of the electricity market did not receive due emphasis in the Turkish market. However, considering the importance of the research subject and the research opportunities related to this subject, it is observed that interest in studies on market price prediction and analysis has increased recently. In particular, updating the market price data constantly makes it necessary to update the studies in this field as well.

2. Literature Review

Wang and Ramsey (1998) propose an artificial neural network-based approach to estimate the system marginal price (SMP), especially concerning weekends and public holidays. Results of the study show that the mean absolute percentage errors (MAPE) are 9.40% on Saturday, 8.93% on Sunday, and 12.19% on public holidays, respectively. The researchers probably attribute the lower MAPE value calculated for Sunday to the fact that the SMP curve on Sunday is less volatile compared to that of Saturday.

In their study, Contreras, Espinola, Nogales and Conejo (2003) aimed to estimate the electricity prices in Spain and California by the ARIMA method. For the Spanish electricity market, three weeks were chosen to predict and verify the performance of the ARIMA model. The week of April 3-9, 2000 was chosen for the California electricity market. Hourly data used to forecast this week was from January 1 to April 2, 2000. Average errors in the Spanish market were about 10% with and without the explanatory variables, while the average errors in the stable period of the California market were about 5%.

Amjady (2006) proposes an efficient method for short-term price prediction of electricity markets based on a new fuzzy neural network. This fuzzy neural network has an interlayer and feed-forward architecture with a new hypercubic training mechanism. The proposed method estimates hourly market clearing prices for the day ahead electricity markets. With the combination of fuzzy logic and an efficient learning algorithm, a suitable model is presented for the non-stationary behaviours and outliers of price series. The proposed method has been studied in the Spanish electricity market and shown that the method can provide more accurate results than other price prediction techniques such as ARIMA time series, wavelet-ARIMA, MLP, and RBF neural networks.

Akkas, Arikan and Çam (2018) tried to estimate the hourly price forecasts of the electricity market in Turkey using the Artificial Neural Networks method. In this prediction study, the model ensures itself by creating the input data that give the most successful results. To this end, past data were used. Levenberg Marquardt was used as the training algorithm in the method. The results were analysed using the market clearing prices of one day/two days/three days/a week ago, the load amounts of that day and the previous day, whether there is a working day or not, and natural gas/dam/lignite production amount data as input data in order to forecast hourly market clearing prices for the period of 1-28 February 2018, It has been concluded that the results obtained with a regression value of 93% during the training phase will prove that values close to real prices are obtained and that the method would be useful in guiding entrepreneurs operating in the energy sector.

Dikbaş (2019) estimated the Market Clearing Prices daily using artificial neural networks. Average absolute percentage error-success criteria was used as in comparing predicted prices and actual prices. The MAPE of the sample data section was found to be 14.13%. In the sample data set, the average daily MCP was 251.654 TL/ MWh, while the actual daily MCP average was found to be 244.020. The MAPE between the MCP and the network model estimation result between 01.01.2018-31.12.2018 was calculated as 15.26%.

In this study, while analysing the data, production values realized on an hourly basis for 2019, publicly shared on the website of EXIST, were used. The factors affecting the market price were analysed and the variables used in the study were compared using artificial neural network and multiple linear regression method. Again, the MCP data published by EXIST for 2019 was taken as a reference and the methods used were compared according to this price. The data were analysed and compared with the real market price. Variables were analysed with multiple regression analysis, and price estimation analysis was performed for statistically significant months. Also, the prediction performances of multiple regression and artificial neural networks were examined.

3. Methods

In this study, two methods were used to analyse the data. These methods include the multiple linear regression method and artificial neural networks method. One of the aims of this study is to determine the variables that have a statistically significant effect on the dependent variable, market demand price, using the multiple linear regression method. Another aim of the study is to calculate the tools (coefficient of certainty, average absolute percentage error, and mean absolute deviation) that enable us to measure the efficiency of estimation methods with the artificial neural networks method and to compare the results with the results found by the multiple linear regression method. The definitions of the variables used in the study are given below.

- MCP: Market Clearing Price (₺ / MWh)
- Natural Gas: Natural Gas Production Amount (MWh)
- Hydroelectric: Hydroelectric Energy Production Amount (MWh)
- Thermal: The Amount of Energy Produced in Thermal Power Plants (MWh)
- Wind: Wind Energy Production (MWh)
- Demand: The Amount of Demand for Energy

Error tests, which enable us to measure the efficiency of estimation methods, measure the difference between estimated demand and actual demand (Karahan, 2011, p.93). In this study, coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE) and mean absolute deviation values were used in comparison of artificial neural networks and multiple regression methods. It is possible to say that whichever estimation method has a high (R^2) value and a low mean absolute deviation value with MAPE, that model is a more successful prediction model. The mentioned equations are given below:

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|}{n} x100 \tag{1}$$

$$Adjusted\ R^2(\overline{R^2}) = 1-(1-R^2)\frac{n-1}{n-p-1} \tag{2}$$

Here;

- n: Number of observations
- y_i: Actual value
- $\hat{y}_i$: Predicted value
- p: The number of independent variables.

The mean absolute deviation is formulated as follows (Karahan, 2011: 93):

$$Mean\ Absolute\ = \frac{\sum_{i=1}^{n}|y_i-\hat{y}_i|}{n} \tag{3}$$

3.1 Sample

This study uses data published by EXIST in 2019 on the market clearing price, which constitutes the dependent variable of the study, and the data on the variables of natural gas production amount, hydroelectric energy production amount, the energy produced in thermal power plants, wind energy production amount, and amount of demand for energy produced. However, to apply the multiple linear regression method, some assumptions must be fulfilled. It is January and June data that provide these assumptions. For this reason, only the analyses made with the data of January and June are included in the study.

3.2 Data Collection Tools

Data sources are grouped as primary (original) and secondary (non-original) according to their physical proximity to the subject under investigation (Karasar, 2016: 175). The characteristic of a source being the primary data source is to be able to obtain the original data directly from that source. For example, the fact that a researcher obtains the opinions of the individuals participating in the research on the subject of the research through a specific data collection tool (questionnaire, etc.) provides the researcher with primary data. The secondary data source is a data source previously collected by other researchers or institutions for different purposes. Secondary data can be obtained from internal documents of companies, from research companies, from non-profit organizations, and from government institutions (Gürbüz and Şahin, 2017: 173-174). The data in this study has been obtained from the website of EXIST, which meets the secondary data requirement.

4. Application

4.1 Multiple Linear Regression Model

Multiple linear regression analysis is a statistical technique that can be used to analyse the relationship between a single dependent (criterion) variable and several independent (predictor) variables (Hair, Black, Babin and Anderson, 2010: 161). It is possible to list the usage purposes of multiple linear regression as follows (Güzeller, 2016: 89):

To estimate the value of the dependent variable by using the independent variables determined to have an effect on the dependent variable

To define the relationship between the independent variables and the dependent variable by determining which one or which of the independent variables are thought to have an effect on the dependent variable,

Explaining the relationship between the dependent and independent variables with the regression equation,

Determining how much the independent variables in the regression equation explains the change observed in the dependent variable,

Determining whether the independent variables in the regression equation explain the dependent variable in a meaningful way,

Determining the order of importance of the independent variables by considering the effect of the independent variables in the regression equation on the dependent variable.

It is possible to show the multiple linear regression model as in the following equation (Kiernan, 2004: 182):

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \ldots \ldots + \beta_k x_k + \varepsilon \quad (4)$$

In this model,

- y, random response variable,
- β_0, β_1, β_2 and β_k, parameters to be estimated based on sample data,
- x_1, x_2,..., x_k, Predictor variables are assumed to be constant and measured without error, and k denotes the number of predictor variables,
- ε, is the random error that allows each response to deviate from the mean y value, the errors are assumed to be independent, the mean is zero, and has a common variance (σ^2) and is normally distributed.

The assumptions of the multiple linear regression model can be listed as normal distribution, linearity, zero mean of error terms, constant variance, no autocorrelation, and no multiple connections between independent variables (Kalaycı, 2014: 258).

4.2 Artificial Neural Networks

Artificial neural networks are computer systems developed to automatically realize abilities such as generating new information, creating and discovering new information through learning, which are characteristics of the human brain, without any assistance. Artificial neural networks are computer systems that can learn about events by using examples realized by humans and determine how to react to events coming from the environment (Öztemel, 2006: 29).

Models known as artificial neural networks are inspired by the biological neural structure found in living organisms. However, the similarity with real neural networks is very weak. There are great contrasts between natural neural networks and artificial neural networks in terms of structure and capacity. Information about actual brain functions is very limited. However, there is enough information to sample real brain functions. It is impossible for any model to fully mimic the function of the human brain. Although this relationship is weak, artificial neural networks have a structure similar to the nervous system based on biological learning (Nabiyev, 2003: 575).

ANN architecture involves defining the number of layers, the number of neurons in each layer, and the interconnection scheme between neurons. Figure 1 shows the neural network architecture for a three-layer network with fully connected neurons from different layers. The selection of the number of layers is controlled by the training algorithm. Some training algorithms may require only one layer, while others may require a minimum of three layers. For example, the backpropagation algorithm requires an input layer, an output layer, and a hidden layer. The number of hidden layers is chosen depending on the complexity of the problem. The number of "neurons" in the input and output layers is specific to the problem. The connections between "neurons" are controlled by the training algorithm and the nature of the problem (Khare and Nagendra, 2006: 30).

The cell structure of artificial neural networks is shown in Figure 1 (Yıldıran and Kandemir, 2018: 98):

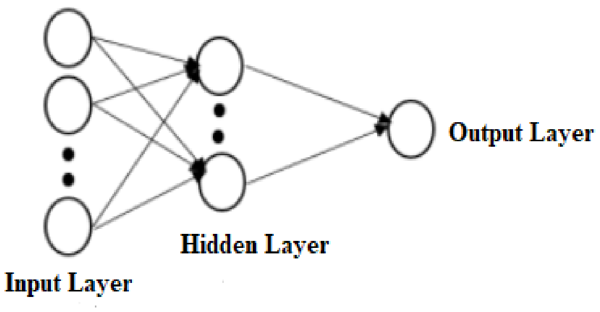

Figure 1. The cell structure of artificial neural networks

At a higher level, tasks performed using neural networks can be classified as tasks that require supervised or unsupervised learning. In supervised learning, a teacher can be used to indicate whether a system is working correctly or to indicate the desired response or to verify the acceptability of a system's responses, or to indicate the amount of error in system performance. This is the opposite of unsupervised learning where there are no teachers and learning must be based on guidance intuitively obtained by the system examining different sample data or environment. While a concrete example of supervised learning is provided with "classification" problems, "clustering" provides an example of unsupervised learning (Mehrotra, Mohan and Ranka, 1997: 24).

Artificial neural networks learn by training a specific problem directly on existing examples. Learning in artificial neural networks is the process of adjusting weights to fulfil the desired function. The training process consists of presenting input and output information to the neural network. By comparing the output value produced according to the network input information with the desired value, it obtains the information to be used in changing the weights. The training continues until the difference between the entered value and the desired value is smaller than the value predetermined as the error value. When the error value falls below the desired value, all the weights are fixed and the training process is terminated (Elmas, 2003; Çuhadar, Güngör and Göksu, 2009: 103).

After the training of the network is completed, the attempts to measure the performance of the network are called testing the network. To test the network, samples that the network did not see during learning are used. Using the link weights determined during training, the network produces outputs for those samples that it has not seen. The accuracy values of the outputs obtained provide information about the learning of the network. It is understood that the better the results, the better the educational performance (Öztemel, 2006: 55-56).

5. Analysis and Findings

The normality of variables is evaluated by statistical or graphic methods. The two components of normality are skewness and kurtosis. Skewness is related to the symmetry of the distribution; a skew variable is a variable whose mean is not in the centre of the distribution. Kurtosis is about the apex of a distribution. If there is a positive skew, there is a pile case on the left and the right tail is very long; there is a pile case on the right with negative skew and the left tail is very long. Kurtosis values above zero indicate a very peaked distribution with short, thick tails, and kurtosis values below zero indicate a very flat distribution. Non-normal kurtosis provides an underestimation of the variance of a variable (Tabachnick and Fidell, 2012: 79).

The coefficient of skewness can take values between -∞ and + ∞. However, if the skewness measure takes values between -3 and +3, it is considered normal (Kalaycı, 2014: 6). Looking at the data on a monthly basis for 2019, it is seen that the skewness and kurtosis coefficients of the variables for January and June take values between -3 and +3. Due to the fact that the variables of January and June meet the normal distribution condition and are therefore suitable for multiple regression analysis, the necessary analyses were applied to the data of January and June in this study.

5.1 Results for the Month of January

Before moving on to the multiple linear regression analysis for January, it was checked whether the data met other assumptions and also the correlation matrix was examined. When the correlation matrix including independent variables is examined, it is found that there is a high correlation between the demand quantity variable and the hydroelectric variable (0.837). In addition, it has been seen that the VIF value of the demand quantity variable is 18.005. If the variance increasing factor (VIF) that determines whether there is a multiple linear connection problem is equal to or greater than 10 (VIF ≥ 10), there is a multiple linear connection problem (Albayrak, 2005: 110). Due to the VIF value greater than 10 and the high correlation with the hydroelectric variable, the demand quantity variable was not included in the analysis. Table 1. displays multiple linear regression analysis results for January.

	β	Standard Error	Standard β	t	p
Constant	-273.986	19.077		-14.362	0.001
Natural Gas	0.003	0.001	0.072	2.370	0.018
Hydro	0.016	0.001	0.422	15.662	0.001
Thermal	0.028	0.002	0.418	13.091	0.001
Wind	-0.005	0.001	-0.081	-3.721	0.001
Model Information	R^2=0.663 F=363.401	Adjusted R^2=0.661 p=0.001		Durbin Watson=1.085	

* The R2 value calculated with artificial neural networks is 0.705.

Table 1. Multiple Linear Regression Coefficients Table

When the analysis results above are examined, it is seen that the multiple linear regression model is significant as a whole at the 0.01 significance level (p = 0.001 <0.01). All independent variables are statistically significant since the p values of the independent variables, which are thought to affect the dependent variable, are less than 0.05 significance level. Among these variables, the wind variable affects the dependent variable negatively. The R^2 value, which shows the rate of explanation of the dependent variable by the independent variable, takes values between 0 and 1 (including 0 and 1), and it is desired that the R^2 value be close to 1. R^2 for the month of January takes the value of 0.663 (66.3%). Durbin Watson statistic tests whether autocorrelation exists and takes a value between 0 and 4 (including 0 and 4). The Durbin Watson test value being around 1.5-2.5 indicates that there is no autocorrelation (Kalaycı, 2010: 267). Durbin Watson's value for January is 1.085. This value indicates the absence of autocorrelation.

Below is the multiple regression equation consisting of regression coefficients.

$$y = -273.986 + 0.003ngas + 0.016hydro + 0.028thermal - 0.005wind \qquad (5)$$

Using the multiple regression equation given above, MAPE values were calculated separately for each hour and each day. Table 2 includes MAPE values for some days of January.

Date	**MLR**	**ANN**
8 January 2019	16.43	8.96
17 January 2019	22.13	17.66
22 January 2019	14.59	7.82
25January 2019	24.02	15.02

Table 2. The value of MAPE

Table 3 also includes the average absolute deviation values for the month of January.

	MLR	**ANN**
Average Absolute Deviation	59.19	35.40

Table 3. Average Absolute Deviation

When we look at the R^2, MAPE and average absolute deviation values calculated for some days of January, it is seen that the R^2 value calculated with artificial neural networks (0.705) is higher than the R2 value calculated by multiple linear regression (0.663). However, if the MAPE and mean absolute deviation values are calculated with artificial neural networks, it is seen that it gives lower results than the multiple linear regression method. Based on these findings, it is possible to say that the artificial neural network method is a better estimation tool than the multiple linear regression method since it obtains high R2 and average absolute deviation values with low MAPE. Figure 2 shows the graphic created with the R package program for January.

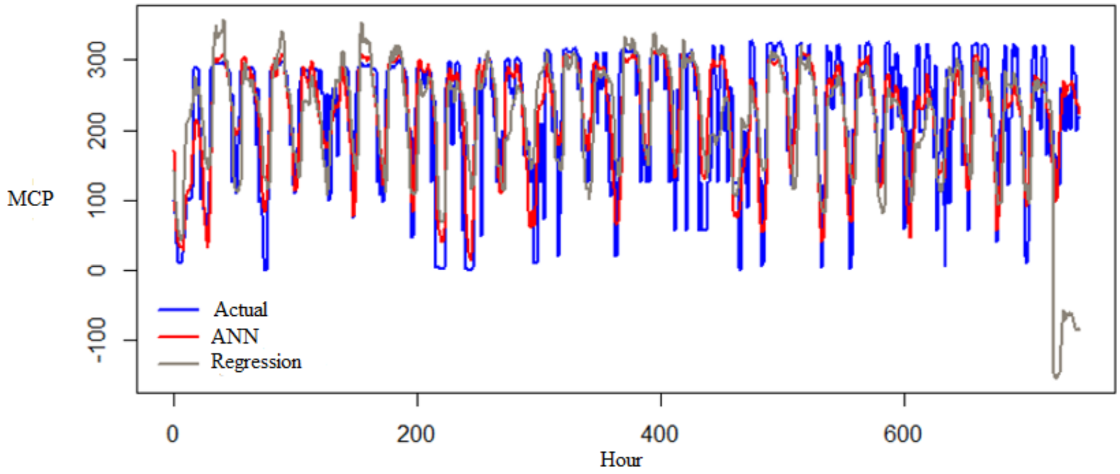

Figure 2. Actual MCP Values and Estimated MCP Values for January

When the graphic given above is examined, it is seen that the closest lines of the lines shown in blue colour belonging to the real MCP are the lines belonging to the artificial neural networks shown in red. This shows that the artificial neural network method is a better estimator.

5.2 Results for the Month of June

The studies for January were also carried out for June, the fulfilment of the assumptions was tested, similar results were encountered, and the demand quantity variable was excluded from the analysis because it did not provide the assumptions. Table 4 includes the results of multiple linear regression analysis.

	β	Standard Error	Standard β	t	p
Constant	-222.422	21.580		-10.307	0.001
Natural gas	0.014	0.002	0.306	8.530	0.001
Hydro	0.013	0.001	0.303	11.542	0.001
Thermal	0.020	0.001	0.508	13.396	0.001
Wind	0.004	0.002	0.044	1.752	0.080
Model Information	R^2=0.648 F= 328.58	Adjusted R^2= 0.648 p=0.001	Durbin Watson=0.639		

* The R2 value calculated with artificial neural networks is 0.744.

Table 4. Multiple Linear Regression Coefficients Table

Looking at the statistical values in Table 4, it is possible to say that the model is significant as a whole (p = 0.001 <0.01), and that the independent variables other than the wind variable create a positive significant difference on the dependent variable (due to the positive signs of the coefficients). Below is the multiple regression equation consisting of regression coefficients. Table 5 includes MAPE values for some days of June.

$$y = -222{,}422 + 0{,}014ngas + 0{,}013hydro + 0{,}020thermal \quad (6)$$

Date	MLR	ANN
7 June 2019	72.91	41.19
17 June 2019	37.72	27.03
21 June 2019	15.05	12.82
25 June 2019	18.70	11.86

Table 5. The Value of MAPE

Table 6 also shows the average absolute deviation values for June.

	MLR	ANN
Average Absolute Deviation	49.26	38.61

Table 6. Average Absolute Deviation

When the R^2 values for June are examined, it is seen that the R^2 value obtained by the multiple linear regression method (0.648) is lower than the R^2 value obtained by the artificial neural networks method (0.704). In addition, considering the MAPE and mean absolute deviation values of some days of June, it can be concluded that the predictions made with artificial neural networks give better results than the predictions made by multiple linear regression. Figure 3 shows the graphic created with the R package program for June.

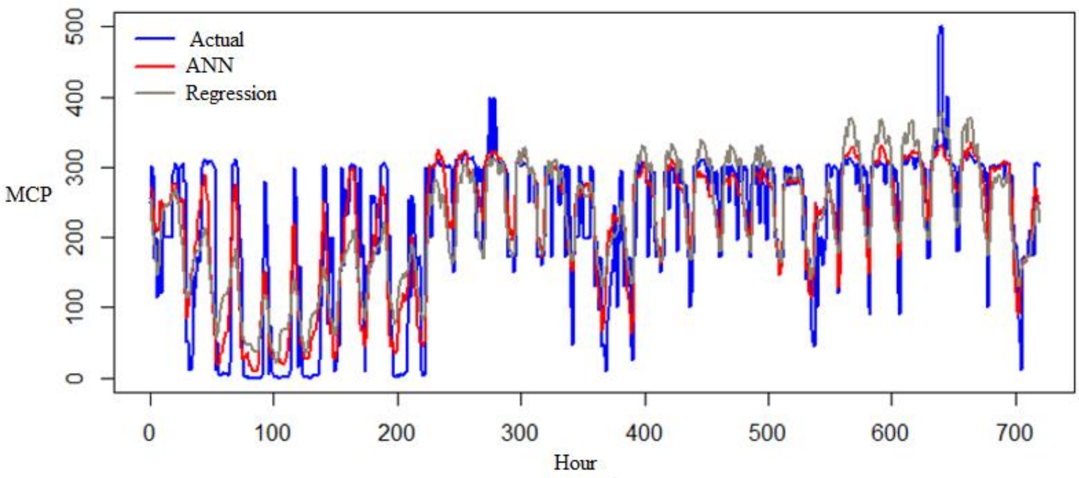

Figure 3. Actual MCP Values and Estimated MCP Values for June

When the graphic given in Figure 3 is examined, it can be seen that the closest lines of the lines shown in blue colour belonging to the Real MCP are the lines belonging to the artificial neural networks shown in red. This shows that the artificial neural network method is a better estimator.

6. Discussion, Conclusion and Suggestions

In this study, factors that influence the market-clearing price in the energy market in Turkey is examined. Hourly data for 2019 was obtained from EXIST's website. First of all, in the study, it was examined whether the assumptions required to perform multiple linear regression analysis were met. It was seen that the data for January and June provided the assumptions. As a result of the multiple linear regression analysis of January, it was concluded that the model as a whole was significant, R^2 values were higher than 0.50, and all independent variables that were thought to affect the dependent variable were found to be statistically significant at the 0.05 significance level. In June, similar results to January were encountered, only the wind independent variable was not found statistically significant at 0.05 significance level.

In the study, it was also found that the artificial neural networks method, for which R^2, MAPE and mean absolute deviation values were calculated separately for both estimation methods, gave better results than the multiple linear regression method. With the help of R package program, graphics of real and estimated values were drawn, and the results found with the analysis were verified. Takma, Atıl and Aksakal (2012) also obtained similar results as they stated that artificial neural networks have higher predictions than multiple linear regression analysis and yield results with less error. Similarly, Güngör and Çuhadar (2005) compared the estimation performances of an artificial neural network, multiple linear regression and multiple logarithmic regression models to be used in the estimation of German tourist demand for Antalya province and found that the artificial neural network model has lower deviation values and higher explanatory rates compared to regression models.

The main difference between artificial neural networks and statistical methods is that neural networks do not make any assumptions about statistical distribution or data properties (Ermiş, 2005: 126). For this reason, researchers are advised to prefer artificial neural networks instead of multiple linear regression when assumptions cannot be met.

When we look at the studies on the subject, we come across studies on the estimation of the market clearing price. Artificial neural networks are mostly used as a prediction method. In this study, not only the estimation process was made, but also the variables that had an effect on the market clearing price were determined. Furthermore, in the study, both the artificial neural networks method and also the multiple linear regression estimation methods were used, and the results obtained with both methods were compared. In addition, most of the studies in this field have been published in journals in the field of science. In this study, in addition to artificial neural networks, the multiple linear regression method, one of the most used estimation methods in Social Sciences, was used and different disciplines were integrated in a single study.

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