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Research Article/Araştırma Makalesi

The Effects of Electricity Generation from Solar and Wind Energy on the Day Ahead Market-Clearing Prices and Price Volatility: The Turkish Case[1]

Güneş ve Rüzgar Enerjisinden Elektrik Üretiminin Gün Öncesi Piyasa Takas Fiyatlarına ve Fiyat Volatilitesine Etkisi: Türkiye Örneği

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Abstract

Solar and wind generation are the primary tools to prevent climate change and high carbon emissions. Due to their intermittent generation characteristics, solar and wind power plants have a different impact on the market-clearing prices (mcp) formation compared to conventional generation sources. The paper investigates the effects of solar and wind generation on the day ahead mcp and mpc volatility in Turkey between the 2016 and 2022. To this end, several machine learning methods are used. The second-degree polynomial learner method generated the best-fitting model. We find that Dutch TTF increases mcp with a coefficient of 0.24. An increase in wind and solar generation reduces mcp. Solar generation is ineffective on mcp below a certain demand level. Wind generation reduces mcp with a 37.78 coefficient at low demand levels and a 6.55 coefficient at high demand levels. Solar generation has a price-reducing effect with 5.55 at high demand levels. Finally, Dutch TTF and wind generation increased volatility with coefficients of 0.04 and 0.69; solar generation reduced volatility with a coefficient of 0.83.

Jel Codes: *Q41, Q42, Q48*
Keywords: *Solar, Wind, Market-clearing Price, Wholesale Electricity Markets, Day Ahead Market*

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Öz

Güneş ve rüzgardan elektrik üretimi; iklim değişikliği ve yüksek karbon emisyonunu önlemenin önde gelen araçlarındandır. Güneş ve rüzgar santralleri kesintili elektrik üretim karakterlerinden dolayı piyasa takas fiyatı oluşumunda konvansiyonel üretim kaynaklarına göre farklı bir etkiye sahiptir. Bu makale, 2016 ve 2022 yılları arasında Türkiye'de güneş ve rüzgardan elektrik üretiminin gün öncesi piyasa fiyatı üzerindeki etkisini incelemektedir. Güneş ve rüzgardan elektrik üretim seviyesinin piyasa takas fiyat seviyesi ve oynaklığı üzerindeki etkisini analiz etmek için farklı makine öğrenmesi yöntemleri kullanılmıştır. En başarılı sonucu 2. derece polinom öğrenmesi yöntemi üretmiştir. Modellerin sonucu olarak, Hollanda TTF gaz fiyatının, piyasa takas fiyatını 0,24 katsayısı ile artırdığı bulunmuştur. Rüzgâr ve güneş enerjisi üretimindeki artışın, piyasa takas fiyatını düşürdüğü gözlemlenmiştir. Güneşten elektrik üretimi, belirli bir elektrik talep seviyesinin altında piyasa takas fiyatı üzerinde etkisizdir. Rüzgar üretimi, düşük talep seviyelerinde 37,78 katsayısı ve yüksek talep seviyelerinde 6,55 katsayısı ile piyasa takas fiyatını düşürmektedir. Güneşten elektrik üretimi yüksek talep seviyelerinde 5,55 ile fiyat düşürücü etkiye sahiptir. Son olarak, Hollanda TTF gaz fiyatı ve rüzgar üretimi, sırasıyla 0,04 ve 0,69 katsayılarıyla oynaklığı artırmaktadır; güneş enerjisi üretimi 0,83 katsayı ile oynaklığı azaltmaktadır.

Jel Kodları: *Q41, Q42, Q48*
Anahtar Kelimeler: *Güneş, Rüzgar, Piyasa Takas Fiyatı, Toptan Elektrik Piyasaları, Gün Öncesi Piyasası*

1. Introduction

In recent years, the increasing amounts of greenhouse gas emissions and their impact on climate have been the main issues for environmental sustainability. The countries have been launching or reinforcing the renewable energy suppport policies to attract investors to renewable energy resources (RES) since greenhouse gas emissions can be reduced by increasing the proportion of RES used to generate power (Hildman et al., 2013; Kyritsis et al., 2017). Turkey launched a competitive day-ahead market and started to promote investments in renewable energy in 2015. Currently, Turkey is one of the leading countries in Europe in renewable energy investments and has come to the fore among developing countries with its renewable energy incentive policies by rapidly increasing its installed renewable energy capacity over the last decade (Simsek & Simsek, 2013).

The incentive policies make RES investment more attractive than conventional electricity generation investments. However, renewable power plants affect market dynamics. First of all, the market-clearing prices (hereafter “mcp”) are affected by the penetration of renewable power plants into the market. On the one hand, Zeinalzadeh et al. (2018) and Mulder & Scholtens (2013) found that RES do not affect or adversely affect mcp in the European electricity markets. Schöniger & Morawetz (2022) examined the European energy markets from 2015 to 2019 in order to take the cost of RES into account and highlighted their conflicting effects on mcp. On the other hand, a great number of studies have provided evidence that renewable power plants reduce mcp, which is called the merit order effect (Cutler et al., 2011; Huisman & Kilic, 2013; Paraschiv et al., 2014; Chattopadhyay, 2014; Ballester & Furio 2015; Adom et al., 2018; Maekawa et al., 2018; Chen et al., 2019; Nieta & Contreras, 2020; Ocampo et al., 2021; Ma et al., 2022; He et al., 2022 among others) Therefore, there is no consensus on the effects of RES on mcp. Moreover, the effects of RES on mcp depend on the amount of their electricity production. Clo et al. (2015) found that the price effect of RES diminishes with an increase in RES production.

The advocators of merit order effect claim that it results from the fact that they generate electricity with low marginal cost (Edenhofer et al., 2013). This is because renewable power plants utilize free resources such as solar and wind, which is different from conventional power plants using coal and natural gas as inputs. However, for instance, under the guaranteed purchase agreements, one of the incentive mechanisms, the feed-in tariffs become greater than the marginal cost. The consumers, in turn, bear this price associated with renewable energy.

In addition to the effects on price, renewable power plants affect mcp volatility. For instance, for Portugal and Spain, Figueiredo & Silva (2019), for Spain, Ciarreta et al. (2020) and for Germany, Wozabal & Hirschmann (2016), Paraschiv et al. (2014), and Maciejowska (2020) found that electricity generation of renewable energy increases mcp volatility. Electricity generation from RES is intermittent since it depends on climate, seasons, certain hours in a day, etc. Therefore, their price bid in the wholesale electricity market, thus, mcp varies accordingly. The disadvantage of volatile prices in a market is that risk averse investors hesitate to invest in these markets because it creates uncertainty (Blazquez et al., 2018; Riesz & Milligan, 2019). Uncertainty grows as price volatility rises, resulting in a higher risk for them.

Hence, it is very crucial to understand how increasing electricity generation from renewable resources thanks to incentive mechanisms affects the market dynamics.

In this study, we investigate the effects of electricity generations from solar and wind energy on mcp and mcp volatility in the day-ahead electricity market. To this end, we apply the artificial intelligence methods using daily data from 1/1/2016 untill 07/31/2022. This study provides the first comprehensive empirical approach to this issue for the Turkish case.

Our study differs from the previous studies for several reasons. First, we investigate the effects of electricity generation from both solar and wind energy on mcp and mpc volatility. By doing so, we explore if their effects are different. Clo et al. (2015) took the Italian wholesale electricity markets as a case and found that wind generation has a higher impact on mcp than solar generation. Rintamaki et al. (2017) found that wind powers increase volatility in Germany whereas they decrease volatility in Denmark. Furthermore, they revealed that solar powers decrease volatility in Germany. Thus, different cases yield inconsistent results (Blazquez et al., 2018; Riesz & Milligan, 2019). Sirin & Yilmaz (2020) and Karatekin (2020) used quantile regression and simulation and found the merit order effect of RES for Turkey. However, they did not compare RES sources in terms of their merit order effects. We not only focus on the Turkish case but also compare the effects of different RES sources on the market dynamics. Morevover, we examine whether the size of the merit order effect depends on low and high demand periods for the Turkish case. Furthermore, we employ artificial intelligence methods instead of traditional approaches. There are a few studies on the Turkish wholesale electricity markets that focus on the day-ahead market where mcp is determined. However, most of the research aimed to predict mcp trends using various methods. For instance, Depren et al. (2022) compared time series econometric models (Ardl, Arma, Dols, Fmols, Markov, Ols) and machine learning methods (K-nn, Mars, Rf, Svm, Xgb) for Turkey between 2019 and 2021 and found that machine learning methods are superior to econometric ones. Oksuz & Ugurlu (2019) concluded that machine learning techniques outperform traditional approaches in the power market. Kabak & Tasdemir (2020) used artificial neural networks to find the best-fitting price forecasting model in Turkey in 2017. Ahmad & Chen (2020) used machine learning methods such as neural network to predict the energy prices. Different from them, we utilize machine learning methods not to determine mcp but to investigate the effects of RES penetration into the wholesale electricity market on mcp and mpc volatility.

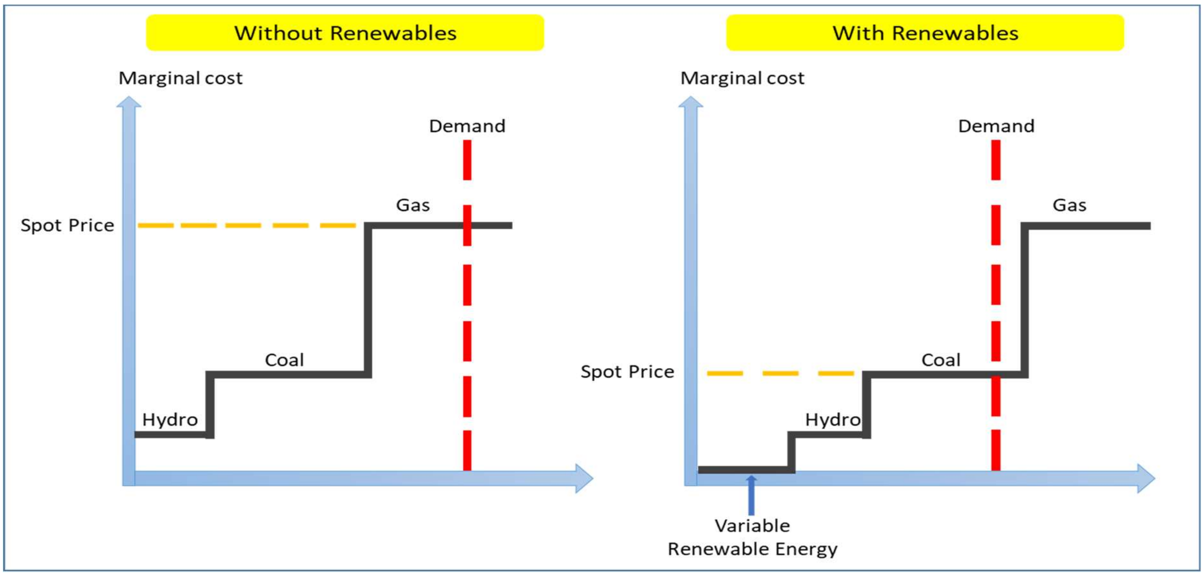
The remainder of the paper is structured as follows. Section 2 gives the structure of the wholesale electricity markets and reviews the literature on the merit-order effect and mcp volatility. Section 3 explains the Turkish wholesale electricity market. Section 4 presents data and the methodology. Section 5 gives the empirical results of the study. The robustness check is given in Section 6. Section 7 concludes.

2. The Structure of Wholesale Electricity Markets and Literature Review on the Merit Order Effect

In wholesale electricity markets, the intersection of aggregate supply and aggregate demand curves brings out mcp. The aggregate supply curve is made from the offers given by the electricity generators, and the aggregate demand curve is made from the consumers' purchase offers. Generators bid with a price including a profit margin. On the other hand, consumers enter a bid at the purchase price at which they can afford the electricity they want to buy. All generators and consumers trade at mcp formed at the intersection of aggregate supply and demand curves. The day-ahead market is where the equilibrium is established and mcp is determined.

The introduction of RES changes the supply-demand curve balance in the day-ahead market. The penetration of renewable energy power plants into the electricity market shifts the supply curve to the right. This is because they bid on the market with low production costs. This effect is called the merit order effect on mcp, which is shown in Figure 1. In the left graph of Figure 1, supply-demand equilibrium occurs in the intersection at the marginal cost of the electricity generation from natural gas. In the right graph, the demand curve stays where it was; generations from renewable energy enter the supply industry with negligible marginal cost, which shifts the supply curve to the right. Therefore, it decreases mcp.

Figure 1: Merit Order Effect: The Figure Shows the Shifting of The Electricity Supply Curve Due to Bids Coming from Renewable Energy Generations.

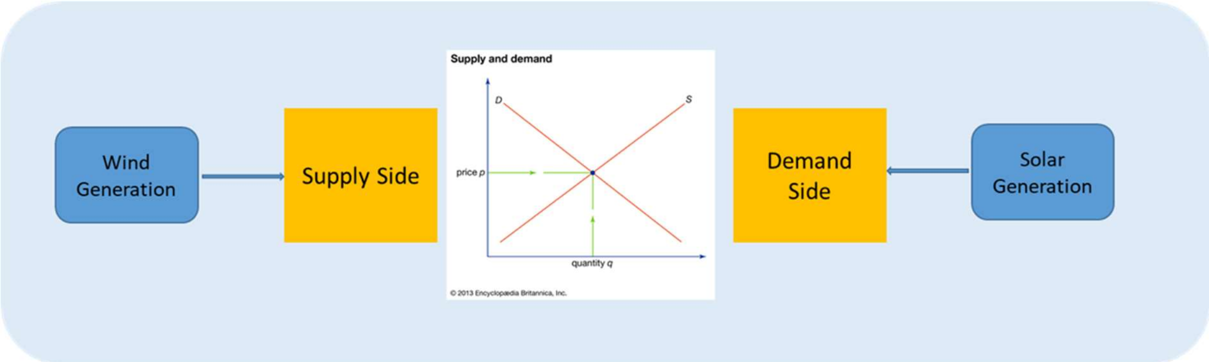


In the literature, a number of studies have investigated the merit order effect of the penetration of electricity generations from RES into the wholesale electricity market for different countries. For instance, Cutler et al. (2011) investigated the merit order effect of wind energy in Australian electricity market between 2008-2010 using descriptive statistics. They found evidence in favor of it. Huisman & Kilic (2013) used time series models to demonstrate the price-lowering effect of renewable energy sources and concentrated on Nord pool to assess the merit order effect of hydropower plants. Additionally, they asserted that the hydropower facilities' storage capacity boosts their merit order effect in the Nord pool wholesale market. Adom et al. (2018) estimated the impact of hydropower plants on mcp similar to Huisman & Kilic (2013). They emphasized the short and long-run merit order effect by using the ARDL model for the period between 1970-2013. Astaneh & Chen (2013) found the merit order effect of wind generation in Denmark and Norway using ARIMA modeling for the 2011-2012 period. Würzburg et al. (2013) used renewable energy generation except for hydroelectric generation in Germany and Austria and found that that the effect of renewable energy on mcp varies due to regional characteristics. Similar to Würzburg et al. (2013), Paraschiv et al. (2014) used wind and solar generations to investigate the effects of renewables on European Energy Exchange (EEX) day-ahead prices. They found a price-reducing impact of renewables by supply curve shifting property with zero marginal cost. Chattopadhyay (2014) studied the Indian national electricity market in 2017 and provided evidence about the merit order effect of RES by using simulation models. Similar to Chattopadhyay (2014), Perez & Garcia (2021) investigated the merit order effect of RES in the Colombian electricity market. They also modeled the interregional electricity transfers to fit the model to the electricity grid dynamics. Ballester & Furio (2015) focused on the behavior of mcp to increase renewable generation and found evidence about the merit order effect in Spain. Nieta & Contreras (2020) used Univariate Ordinary Least Squares and Mean Reversion to investigate the price-lowering impact of renewables on Spain's Iberian energy market between 2001 and 2013 and between 2015 and 2020. They emphasized the systematic impact of renewable generation on mcp. Ocampo et al. (2021), Chen et al. (2019), and Brown (2012) investigated the USA and used mathematical modeling to determine the merit order effect of RES by utilizing various generating scenarios. Prol & Schill (2020) and Bushnelland Novan (2018) found "the cannibalization effect of renewables" by studying California between 2013-2017 using Ordinary Least Squares. Woo et al. (2016) also focused on California between 2012-2015 in the day ahead market and real-time market by using regression analysis and found similar results to Prol & Schill (2020). Ma et al. (2022) and Maekawa et al. (2018) investigated Japan's electricity spot market to analyze the cross-regional effect of renewable penetration. They provided evidence about the merit order effect of RES by using descriptive statistics and regression models. In order to demonstrate the merit order effect of RES in China's electricity market, He et al. (2022) employed optimization for several scenarios.

The aforementioned studies provided evidence in favor of the merit order effect of RES, which is a price-reducing effect of RES in the wholesale electricity market.[4] This study uses the Turkish case in order to explore the merit order effect. A distinctive feature of the Turkish day-ahead market is that wind and solar generations bid differently than the other generations. While wind generation is immediately incorporated into the day-ahead market on the supply side, solar generation is integrated through the channels of retail companies (Figure 2). This brings about the question of whether electricity generation from RES causes similar merit order effects to each other under such mechanism for the Turkish case.

[4] On the other hand, Janda (2018) finds a negligible effect of solar energy on market-clearing price for Slovak wholesale electricity markets and the period 2011-2016 by using Ordinary Least Squares.

Figure 2: Wind and Solar Bids' Entrance in The Wholesale Electricity Market in Turkey. The Figure Shows That Wind Energy Enters to The Merit Order from Supply Side and Solar Energy Enters to The Merit Order from Demand Side.



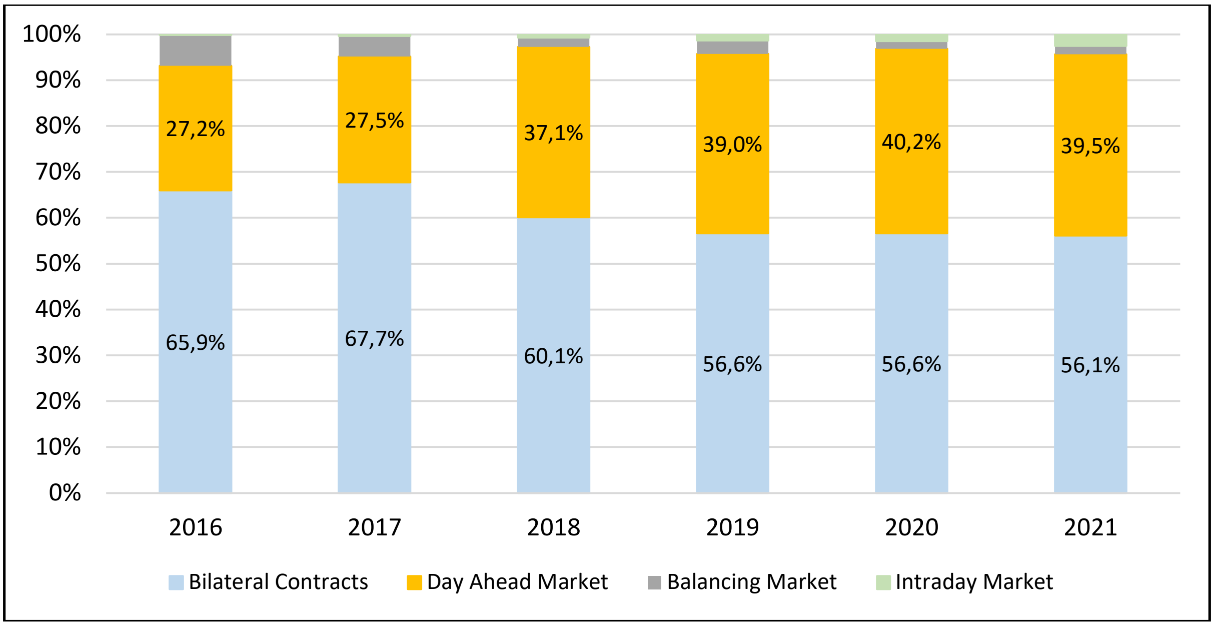
According to merit order effect, the penetration of electricity generation from RES reduces mcp. But the electricity generation from RES has also a disadvantage: It is intermittent. In other words, the electricity generation from RES is not continuous in the sense that it depends on climate conditions, thus, the season of the year and the time of the day, etc. For example, solar power plants cannot produce electricity during the night. Several studies have investigated the effects of the intermittency of RES and found that it causes volatility in the wholesale electricity market price. For instance, Ballester & Furio (2015) concluded that renewable energy production raises mcp volatility while lowering mcp level in Spain. In this vein, Wozabal & Hirschmann (2016), Paraschiv et al. (2014), and Maciejowska (2020) focused on Germany between 2010 and 2018 and emphasized the varying volatility effect of the renewables due to changing demand levels by measuring volatility with the same method as Ballester & Furio (2015). Ma et al. (2022) examined electricity markets in Japan and demonstrated that renewable generation causes a volatile mcp. Astaneh & Chen (2013) showed the volatility characteristic of wind generation by using ARIMA modeling and found that wind generation increases the volatility of mcp. According to Bushnell & Novan (2018), solar energy makes the California electricity market more volatile. In this study, we also investigate mcp volatility for the Turkish case and ask the question of whether it depends on renewable energy sources.

3. The Turkish Electricity Market

In the wholesale electricity market in Turkey, electricity trade occurs in four different sub-market structures: day-ahead market, bilateral contracts, intraday market, and balancing market. The day-ahead market is where the prices are determined by market participants' daily bids. The equilibrium price in this market is accepted as the reference point for all transactions in the Turkish electricity market from generation to retail. In a bilateral agreement, market participants have long-term contracts without bidding on the market, and the transactions do not affect wholesale market prices. The intraday market is used as a supplementary for the day-ahead market and buyers and sellers can adjust their order volumes in case. The balancing market is established as a separate session for each trading point and used to keep the system balanced at the last stage of the trade.

Figure 3 shows the sub-market shares of the trades in the wholesale electricity market in Turkey. As seen in Figure 3, the majority of electricity trade is done via bidding in the day-ahead market and signing bilateral agreements. Moreover, the day-ahead market volume, which was 27% in 2016, increased to 39% in 2021. A comparative increase in trade in day-ahead market over the bilateral contracts can be considered as an indicator for the liberalization of the electricity market in Turkey.

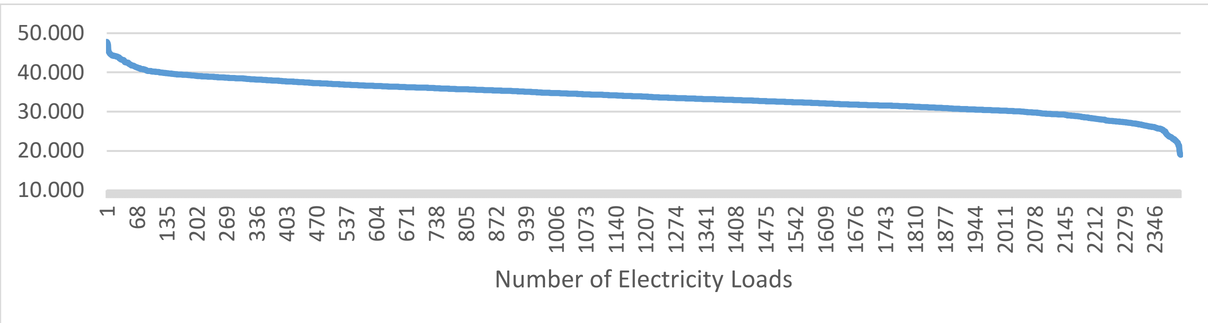
Figure 3: Share of The Trades in The Market (%): The figure includes share of the wholesale electricity markets. Day-ahead market share significantly increases in last five year and it reaches to 39.5%.



Source: https://seffaflik.epias.com.tr/transparency/

Figure 4 depicts the electricity load curve in Turkey. It is obtained by classifying daily average electricity loads from highest to lowest. The load below 28.000 MWh is called low demand period and above 40.000 MWh is called high demand period in Turkey.

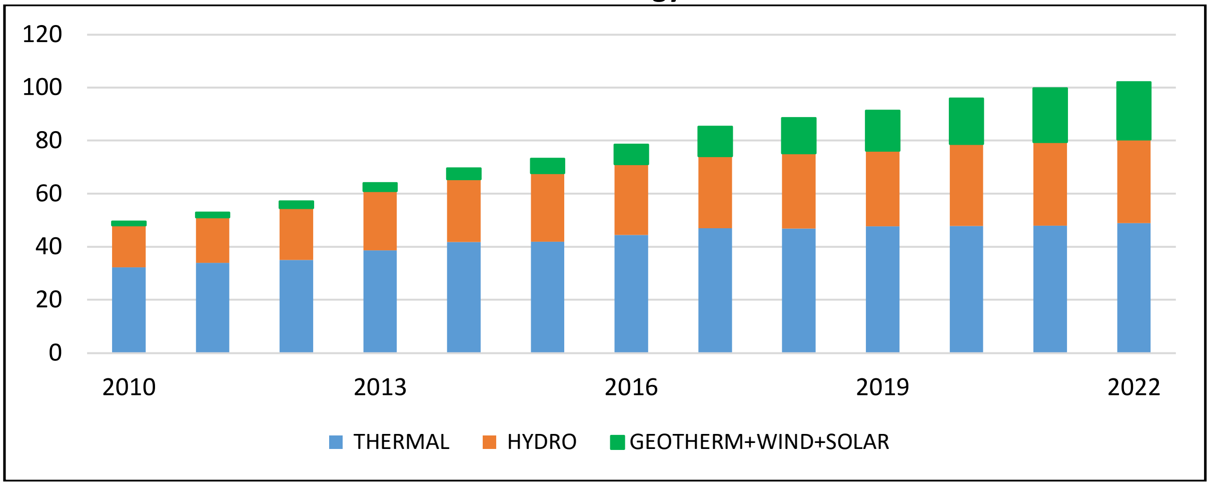
Figure 4: Electricity Load Curve in Turkey (MWh)



Source: https://seffaflik.epias.com.tr/transparency/

In Turkey, economic growth led to an increase in residential and industrial electricity use in the last ten years (Appendix 1). Along with the increasing demand for electricity, the electricity installed capacity in Turkey has doubled, which can be seen in Figure 5. The investments in hydropower, geothermal, solar, and wind plants have also increased up to 1.5 times.

Figure 5: Installed Capacity of Turkey (GW): The Figure shows the Turkish electricity installed capacity. Turkey showed an increase in recent years that consists of wind and solar energy.

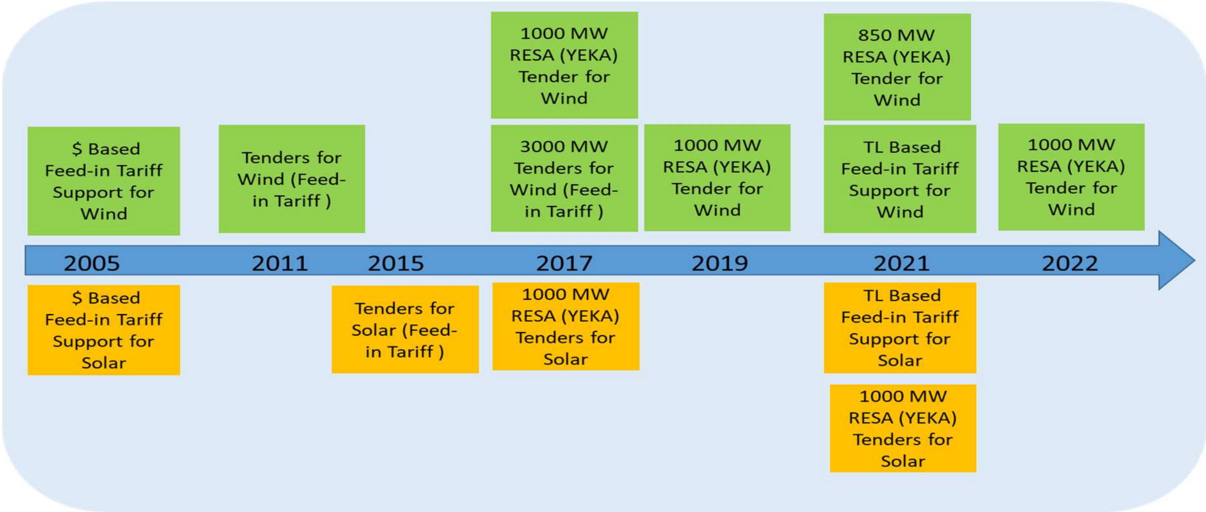


Source: http://emra.gov.tr/

The investments in renewable energy generators in Turkey began to be promoted in 2005 by Law no. 5346 on the Use of Renewable Energy Resources for the Purpose of Electricity Generation (YEK). This law was used to form the Renewable Energy Resources Support Mechanism (YEKDEM), which guaranteed the feed-in tariff for ten years after the establishment of the renewable energy power plant.[5] Then, in 2011, the first wind energy tender was launched. It was based on the contribution fee to be deducted from the YEKDEM Feed-in Tariffs. Afterward, in 2015 a 600 MW solar energy tender, then in 2017 a 3000 MW-capacity wind tender was placed. In 2006, the regulation on Renewable Energy Resource Areas (YEKA) was introduced. The first tender for a 1000 MW YEKA was in 2017. The wind power auction for a 1000 MW of capacity was then launched. The second wind tender was held in 2019. Following the new Renewable Energy Resources Support Mechanism that was developed in the middle of 2021, the first YEKA tender was for 1000 MW. Additionally, a ceiling price was set for the wind auction in 2021. Finally, a 1000 MW capacity first wind TL-based YEKA tender was launched in 2022. Figure 6 provides a visual representation of the RES incentive mechanisms in Turkey since 2005.

[5] A number of incentive mechanisms can be used to encourage investments in renewable energy generators in the countries. Feed-in tariffs are one of the policies instruments that are designed to provide the renewable energy generators with a fixed price at a guaranteed level of production. Feed-in-premium is another type of price-based policy instrument that pays eligible renewable energy generators a premium price, which is a payment over the wholesale price. Another incentive mechanism is contract for difference, which is a long-term agreement that guarantees price certainty during the lifetime of the contract.

Figure 6: Renewable Energy Support Scheme in Turkey: The Figure show the renewable energy supports in Turkey. Solar and Wind supports are shown from the beginning.



4. Data and Methodology

4.1. Data

In this paper, we used a model comprised of mcp ($/MWh) and mpc volatility as dependent variables and Dutch Natural Gas TTF price ($/MWh) (hereafter Dutch-ttf), wind generation (MWh), solar (Licensed+Unlicensed) generation (MWh), and electricity demand (MWh) as independent (explanatory) variables to investigate the effect of wind and solar generation on mpc and mpc volatility in the day-ahead market in Turkey. The data frequency is daily. The time span of data is 6 years from 1/1/2016 and 07/31/2022. Data is obtained from the market operator of the Turkish wholesale electricity markets (Exist).

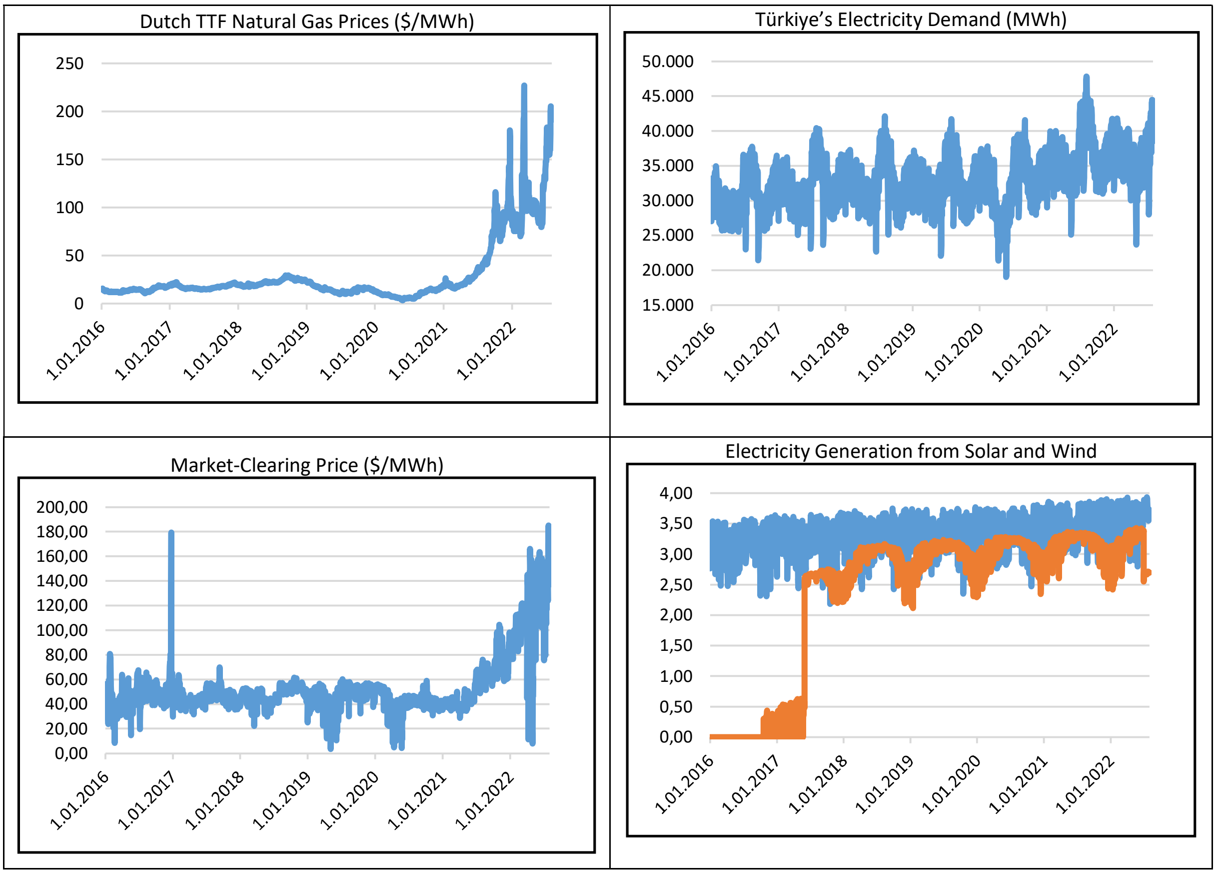
Figure 7 represents the graph of the variables. The graph of the Dutch-ttf price reveals its high volatility. Natural gas prices were stable until the beginning of 2021. With the emergence of the Covid-19 pandemic, which affected the supply chains, they started to climb. Even though the pandemic was left behind almost all over the world, in 2022 Russia invaded Ukraine, which led to a rise in the price of natural gas again. Russia is one of the largest gas suppliers, so it meets a significant part of the gas supply in Europe. The Russian invasion of Ukraine triggered the way to a great energy crisis in the world. With the Russia-Ukraine war's upsetting the natural gas markets, natural gas power plants, which have a high share in Turkey's electricity generation, became more effective on the electricity prices. This is why we used Dutch-ttf natural gas price among the factors affecting the price as an independent variable of the models.

Figure 7 also shows that Turkey's electricity demand has had a positive trend since 2016. The increase in electricity demand stems from economic growth, industrial development, and the rise in the number of residences. However, it decreased due to the Covid19 pandemic. The revival of the economy with the operation of the production lines towards the end of the pandemic caused the demand for electricity to increase again.

As seen in Figure 7, mcp was fluctuating around a certain level until the Covid-19 pandemic, apart from hitting the ceiling price with the intervention made in the market at the end of 2016. The deterioration of the supply-demand balance along with the pandemic and the decrease in the share of hydroelectric power plants in electricity generation led to high prices in 2021.

The last part of Figure 7 demonstrates that electricity generation from solar and wind power plants increased since 2016 thanks to the increasing renewable energy investments. Currently, the installed capacity of wind and solar energy separately exceeds 10 GW. The figure also reveals that the patterns of electricity generation from solar (orange line) and wind (blue line) energy are volatile, which suggests that they might have different effects on the electricity price.

Figure 7: Variables Between 2016 and 2022



In addition to other variables, we generated market volatility measures. The first measure is the variance of mcp in a day of 24 hours, named mcp volatility (Volvar). The second volatility measure is the difference between the maximum and minimum values of hourly prices in a day, named alternative mcp volatility (Vold). The second volatility measure was used to check the robustness of the volatility results. We used the logarithms of the dependent and independent variables. Table 1 presents the descriptive statistics of the dependent and independent variables.

Table 1: Descriptive Statistics of Variables

	Dutch TTF NG Price	Log of Electricity Demand	Log of Wind Generation	Log of Solar Generation
Mean	28.72	4.53	3.33	2.36
Standard Error	0.66	0.00	0.01	0.02
Median	17.25	4.53	3.37	2.95
Standard Deviation	32.60	0.05	0.29	1.21
Kurtosis	7.31	0.84	-0.08	-0.17
Skewness	2.67	-0.49	-0.51	-1.28
Range	223.69	0.40	1.75	3.43
Smallest	3.51	4.28	2.18	0.00
Biggest	227.20	4.68	3.93	3.43
Count	2404	2404	2404	2404
Confidence I. (95%)	1.30	0.00	0.01	0.05

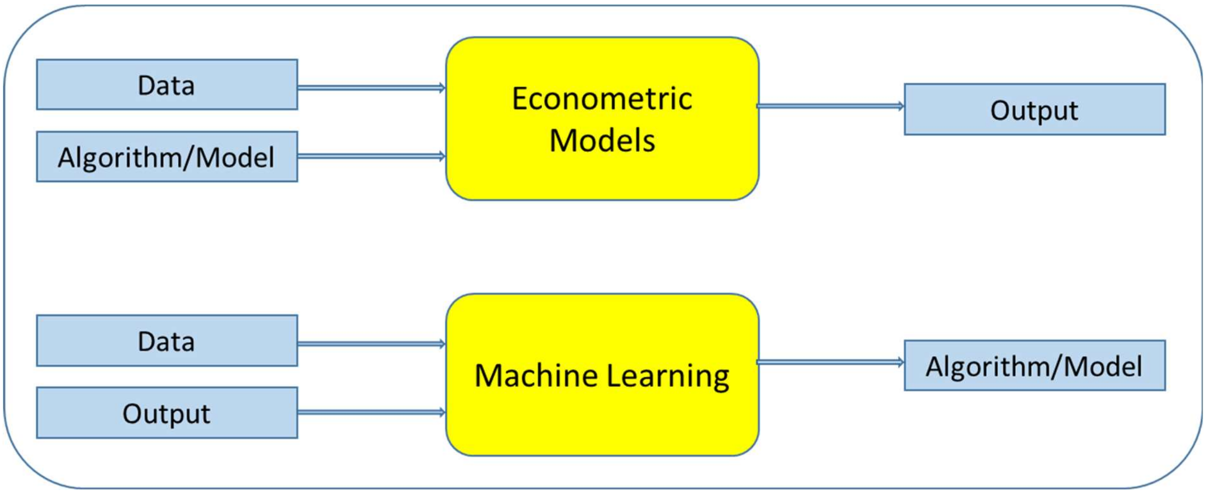
	Log of Supported Renewables Generation	Market-clearing Price	Market-Clearing Price Volatility$_{d}$	Market-Clearing Price Volatility$_{var}$
Mean	3.86	53.68	34.62	10.64
Standard Error	0.00	0.50	0.52	0.16
Median	3.88	47.45	29.06	9.09
Standard Deviation	0.16	24.27	25.74	8.05
Kurtosis	-0.14	6.36	47.19	43.79
Skewness	-0.41	2.40	4.26	4.17
Range	0.90	181.55	481.95	147.51
Smallest	3.33	3.63	0.13	0.01
Biggest	4.22	185.18	482.08	147.51
Count	2404	2404	2404	2404
Confidence I. (95%)	0.01	0.97	1.03	0.32

As can be deducted from Figure 7, the variables have high volatility. For example, the demand for electricity experienced sharp declines in the first period of the pandemic and quickly recovered in the following period. Mcp also exhibited high volatility due to similar reasons and some regulatory interventions. Another issue about the variables is that natural gas price affects not only mcp and its volatility but also the explanatory variables. To be clearer, an increase in the natural gas price level and volatility is expected to increase mcp level and volatility. Besides, the effect of natural gas on mcp depends on factors such as electricity generation from natural gas in the relevant period, the use of gas in natural gas storage, and the weight of Dutch-ttf in the contract where the natural gas is supplied. Furthermore, the volatility of natural gas prices is also expected to have an effect on electricity generation from wind and solar energy. Therefore, the variables are interrelated. The two other characteristics of variables are that the series of the variables are not normally distributed and that they constitute large data because of the high frequency of the series. These features of data make it difficult to work with traditional econometrics methods. The volatility of the variables, the dynamic inter-relationships among the variables, and the other issues about data can be handled using machine learning methodology.

4.2. Machine Learning Methodology

In this study, we employed machine learning methodology since it has several advantages. One of its advantages is that it can work without requiring a hypothetical model. Instead, machine learning algorithms rely on probabilistic methods. Figure 8 depicts the difference between econometric methods and machine learning methods in terms of their inputs and outputs. As can be seen in Figure 8, in econometric methods, data and model are the inputs and one gets output by using these inputs. However, in machine learning, data and the "output" for econometric models are inputs and the methodology yields the appropriate model even though the methodology is a "black box". In other words, "machine learning is a field of study that gives computers the ability to learn without being explicitly programmed (Arthur Samuel, 1959)". Second, machine learning responds to needs that econometric tools cannot meet, especially when it comes to large and big data. Third, machine learning methods are built on producing accurate predictions, where the main goal is to reach an unbiased and precise estimate (Ghoddusi et al., 2019) Fourth, machine learning methods can be used to explain nonlinear structures, interactions, and heterogeneity.

Figure 8: Comparison of Econometric Model and Machine Learning: In the Figure, Algorithm/Model and Output swap was shown in detail.



Several studies that compare machine learning methods with econometrics methods have provided evidence in favor of the former. Bolhuis & Rayner (2020) and Hall (2018) analyzed macroeconomic variables such as output gap, unemployment, and manufacturing between 1959 and 2019 to test the machine learning methods' accuracy. They found that the machine learning method outperforms time series models. Masini et al. (2021) studied stock exchange volatility between 2000 and 2020 in the U.S., the U.K., Germany, Hong Kong, and Japan by using ensemble learning, tree-based methods, and deep neural network. They focused on nonlinear machine learning models and demonstrated that these models are effective and efficient in economic forecasting by comparing their gains. Shobana & Umamaheswari (2021) compared econometric methods such as The Time Series Model, Exponential Smoothing Model, The Random Walk Model, ARIMA, and Auto-Regressive Model with machine learning algorithms by using economic survey data. They concluded the superiority of machine learning methods by using root mean square error, mean absolute error, and mean absolute percentage error metrics. Gabriel et al. (2019), Xuerong Li et al. (2019), and Aydin & Cavdar (2015) used similar methods to compare econometrics methods and machine learning methodology in the field of energy prices, crude oil prices, and banking.

In order to investigate the effects of electricity generation from solar and wind energy on mcp and mcp volatility, we separately used mcp and mcp volatility (denoted as "Volvar") as dependent variables in the models. We called these models as mcp models and volatility models, respectively. Mcp volatility is calculated by using variance equation:

$$Volvar = \sqrt{\frac{1}{24}\sum_{t=1}^{24}(P_t - P_a)^2}$$

P_t is the price of the hour in a day and P_a is the average price.

The independent variables are logarithm of electricity load (represented as "demand"), for electricity generation from wind energy ("wind"), electricity generation from solar energy ("solar"), generation from all supported renewable resources ("supren") including solar, wind, hydro, biomass, etc., and natural gas price in the Dutch-ttf hub ("Dutch ttf"). The first, second, and third lags of a variable, say x, are given as x(t-1), x(t-2), and x(t-3), respectively. We represent day as "d" and hour as "t".

There are several machine learning methods such as random forest learning, tree-ensemble learning, and polynomial learner.[6] In this study, we utilized several of them. We compared the results of these methods to find the best fit. To this end, we used goodness of fit (R^2), mean absolute error, and root mean square error criteria. Where y is the true value and $\hat{y}$ is the measured value, Mean Absolute Error (MAE) is represented by;

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

Root Mean Square Error (RMSE) is given as;

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}}$$

[6] The tree ensemble learners and random forests approach, a widely used method, combine the results of multiple trees to improve prediction accuracy and reduce variance at the expense of easy interpretability. They average the results of many deep trees growing in random subsamples of observations and subsets of variables (Basu & Ferreira, 2020).

The model with highest R^2 and the smallest MAE and RMSE is considered as the best fit. We also checked if Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) have small values. MSE is calculated as;

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2$$

MAPE is obtained as;

$$MAPE = \frac{100}{n}\sum_{j=1}^{n}\frac{y_j - \hat{y}_j}{y_j}$$

We found that according to the criteria given above for mcp models and volatility models the best fitting models were the polynomial learner models, which are given as;

$$Y = \beta_0 + \sum_{i=1}^{m}\beta_i \times \prod_{j=1}^{n} X_j^{a_{i,j}}$$

In the equation, βs are the coefficients of each variable and a denotes the degree of polynomial and the degree of the polinomial learner model such as first or second-degree polynomial learner model. Y and X represent the dependent and independent variables, respectively.

Before applying the machine learning algorithms, 10% of the data was separated using the randomly partitioning method. This method randomly parses a part of the data and this part is not used in the training part of the algorithm. This decomposed part was used to test the performance of the model when the model coefficients are estimated. Therefore, train-test ratios were 90/10. We used Knime 4.7.0 tool to apply the machine learning algorithms.

5. Empirical Results

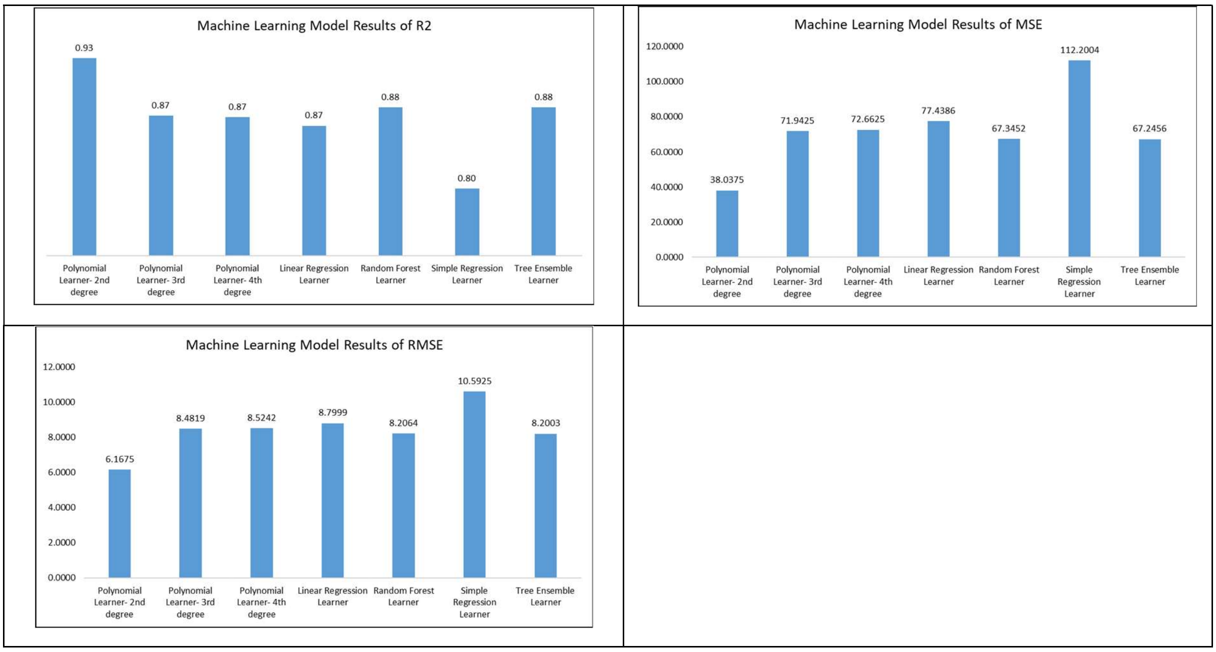
5.1. Estimation Results of Market-Clearing Price Models

First, we run the mcp models by using different machine learning methods such as second, third and fourth degrees of polynomial learner, random forest learner, linear regression learner, simple regression learner, and tree ensemble learner models. In these models, the dependent variable is mcp, and the independent variables are Dutch TTF gas hub price, electricity demand, and electricity generation from solar and wind. We also used the first lag of mcp as another independent variable, since the model without it has the serial correlation problem (Appendix 2). Table 2 and Figure 9 show R^2, MAE, RMSE that we calculated using the estimations. Table 2 also reports MSE and MAPE.

Table 2: Results of Different Machine Learning Methods

	Polynomial Learner-2nd degree	Polynomial Learner-3rd degree	Polynomial Learner-4th degree	Random Forest Learner
R^2	0.93	0.87	0.87	0.88
MAE	4.2992	4.9564	5.0016	4.2528
MSE	38.0375	71.9425	72.6625	67.3452
RMSE	6.1675	8.4819	8.5242	8.2064
MAPE	0.1068	0.1162	0.1170	0.1030
	Linear Regression Learner	**Simple Regression Learner**	**Tree Ensemble Learner**	
R^2	0.87	0.80	0.88	
MAE	5.0072	5.7924	4.3134	
MSE	77.4386	112.2004	67.2456	
RMSE	8.7999	10.5925	8.2003	
MAPE	0.1135	0.1489	0.1055	

Figure 9: Results of Machine Learning Methods for Price Level



As seen in Table 2 and Figure 9, 2nd degree polynomial learner model has the highest explanatory power (R^2) in all models. It also has the smallest Mean Square Error and Root Mean Square Error. Thus, we continued analyses with 2nd-degree polynomial learner model.

We applied the 2nd degree polynomial learner model to different variations of the mcp models. We treated the first model as the base scenario, which includes all critical variables. In the first model, we used the first lag of mcp, Dutch TTF, solar, wind, and demand as independent variables. In the second model, we excluded demand in order to explore the effect of solar and wind electricity generation in a more abstract way. In the second model, we used the first lag of mcp, Dutch TTF, solar, and wind are independent variables. In the third model, we tried to estimate mcp by omitting solar. The third model includes the first lag of mcp, Dutch TTF, and wind as independent variable. In the fourth model, solar is used instead of wind in the fourth model. Finally, the fifth model had the independent variables such as the first lag of mcp, Dutch TTF, and supren, which reflects generations from all renewable energy such as solar, wind, hydro, biomass, etc. that are supported. By incorporating supren into the model instead of solar and wind, we also aimed to explore the merit order effect of the generation from all kinds of RES.

Table 3 reports the estimation results of market clearing-price models. For all configurations, mcp are positively correlated with its first lag. Natural gas price increases mcp similar to lags of price. In Turkey, the natural gas cost reflects mcp. This might be due to the high share of natural gas in electricity generation. Contrary to Dutch-tff, electricity generation from wind and solar energy decreases mcp. Supren also decreases mcp (Model 5). Moreover, as seen in Table 3, the signs of the coefficients for the same variables in different models are the same and the coefficients are close to each other for each independent variable.

Table 3: 2nd Degree Polynomial learner Model Results for Market-Clearing Price

MCP – LEARNING(%90)	Model 1	Model 2	Model 3	Model 4	Model 5
mcp(t-1)	0.44*** (0.03)	0.65*** (0.04)	0.65*** (0.04)	0.60*** (0.04)	0.58*** (0.03)
Dutch-ttf	0.24*** (0.02)	0.24*** (0.01)	0.23*** (0.03)	0.20*** (0.02)	0.24*** (0.01)
demand	518.31** (155.51)				
wind	-40.72*** (10.46)	-37.78*** (11.27)	-35.07*** (10.62)		
solar	-1.22 (1.13)	-0.82 (0.92)		-1.23 (0.91)	
mcp(t-1)²	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Dutch-ttf²	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
demand²	50.08 (39.42)				
wind²	-7.42*** (1.61)	-6.55*** (1.73)	-6.10*** (1.63)		
solar²	-0.52* (0.27)	-5.15** (2.43)		-0.64** (0.31)	
supren					-99.32** (42.59)
supren²					-14.01** (5.57)
Intercept	-1353.07* (801.66)	-42.26** (18.33)	-37.97** (17.26)	13.48*** (1.21)	-161.51* (81.12)
R^2	0.90	0.93	0.90	0.82	0.88
Mean Absolute Error	4.4940	4.2992	4.9025	4.9845	4.4723
Mean Squared Error	43.3732	38.0375	80.2216	95.0200	62.2162
Root Mean Squared Error	6.5858	6.1675	8.9567	9.7478	7.8877
Mean Absolute Percentage Error	0.1038	0.1068	0.1453	0.1381	0.0994

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

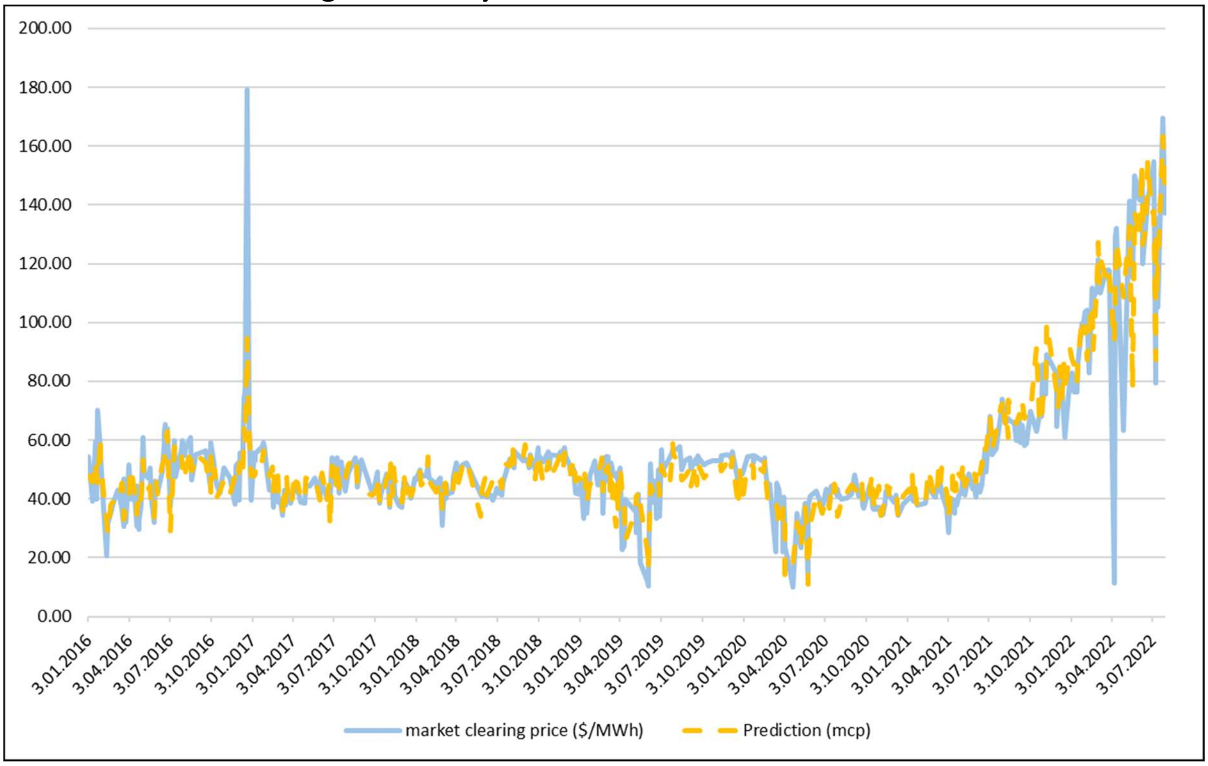
The second model has the highest R^2 of 0.93 and the smallest MSE and RMSE. It is represented as;

$$mcp_t = 0.65 \times mcp_{t-1} + 0.24 \times Dutch\ TTF_t - 37.78 \times lwind_t - 6.55 \times lwind_t^2 - 5.55 \times lsolar_t^2 - 42.26$$

As can be seen from the results, mcp depends on its first lag by the coefficient of 0.65. An increase in Dutch-ttf rises mcp with a coefficient of 0.24. Wind and solar generations reduce mcp. Wind generation has a reducing effect with -37.78 at low-demand periods and -6.55 at high-demand periods. Wind generation directly enters the merit order and has a price-reducing effect at low and high levels. Solar generation has a price-reducing effect with -5.55 only at high levels of demand. The difference between the merit order effect of solar and wind generations might be based on the distinctive feature of the Turkish wholesale electricity market. More clearly, the price bids on the day-ahead market of wind generations are on the supply side while the bids for solar generations are on the demand side. Thus, solar generations shift the electricity demand curve inwards while wind generations shift the supply curve outwards. The intersection of demand and supply curves might be at low-demand or high-demand periods. Therefore, mcp depends not only on the shifts of the demand and supply curves but also on whether it happens when it is a low or high demand period.

The graph of the model is demonstrated in Figure 10. There is a slight difference between mcp series and its estimation, especially during the ceiling price intervention and aftermath of the pandemic.

Figure 10: Polynomial Learner Forecast Results



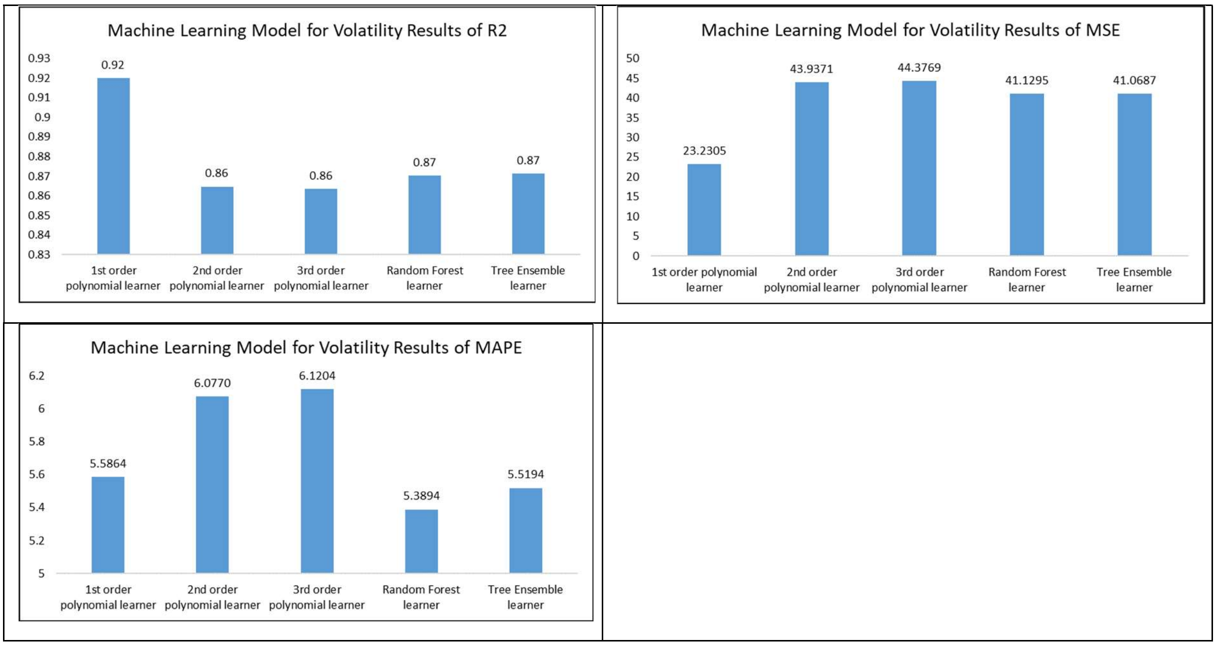
5.2. Estimation Results of Price Volatility Models

The estimation results of the volatility models using various machine learning methods are represented in Table 4 and Table 5. Similar to the analyses of the mcp models, first of all, we compared different machine learning methods such as polynomial learner, random forest learner, and tree ensemble learner in terms of goodness of fit (R^2), MAE, and RMSE, which are given by Table 4 and Figure 11 along with MSE and MAPE. As can be seen in them, 1st degree polynomial learner model gives the highest goodness of fit (R^2). Moreover, it has the smallest value of MAE and RMSE.

Table 4: Results of Different Machine Learner Methods for Volatility

	1st degree polynomial learner	2nd degree polynomial learner	3rd degree polynomial learner	Random Forest learner	Tree Ensemble learner
R^2	0.92	0.86	0.86	0.87	0.87
MAE	2.8950	3.3375	3.3680	2.8638	2.9046
MSE	23.2305	43.9371	44.3769	41.1295	41.0687
RMSE	4.8198	6.6285	6.6615	6.4132	6.4084
MAPE	5.5864	6.0770	6.1204	5.3894	5.5194

Figure 11: Results of Machine Learning Methods for Volatility



The first column of Table 5 represents the estimation results of 1st degree polynomial learner model. We used it as our base model and then we added 1st, 2nd, and 3rd lags of the Volvar (volatility measure) to obtain Model 2, Model 3, and Model 4, respectively, and apply 1st degree polynomial learner method to them. According to the criteria of the highest R^2 and the smallest MAE and RMSE, we concluded that the best-fitting model is Model 2.

As seen in Table 5, the estimation results of Model 2 reveal that volatility highly depends on its first lag. Model 1 has serially correlated error terms (see Appendix 3), thus, incorporating the first lag of volatility into the model also circumvented the issue of autocorrelation. Dutch-ttf and wind generation increase volatility with coefficients of 0.04 and 0.69, respectively; solar generation reduces volatility with a coefficient of 0.83.

Table 5: 1st Degree Polynomial learner Model Results for Volatility of Market-Clearing Price

Volatility of MCP – LEARNING(%90)	Model 1	Model 2	Model 3	Model 4
volvar(t-3)				0.06** (0.02)
volvar(t-2)			0.15*** (0.03)	0.11*** (0.03)
volvar(t-1)		0.63*** (0.02)	0.53*** (0.02)	0.53*** (0.02)
Dutch-ttf	0.12*** (0.00)	0.04*** (0.00)	0.04*** (0.00)	0.03*** (0.00)
wind	0.82** (0.55)	0.69** (0.13)	0.90** (0.17)	0.96** (0.23)
solar	-2.14*** (0.13)	-0.83*** (0.10)	-0.74*** (0.11)	-0.71*** (0.11)
Intercept	9.63*** (1.77)	2.44* (1.39)	1.20 (1.39)	0.78 (1.40)
R^2	0.56	0.92	0.90	0.90
Mean Absolute Error	4.5086	2.8950	2.8822	2.8795
Mean Squared Error	49.1718	23.2305	25.2245	24.8968
Root Mean Squared Error	7.0123	4.8198	5.0224	4.9897
Mean Absolute Percentage Error	14.6159	5.5864	4.9494	5.2315

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Model 2 is written as;

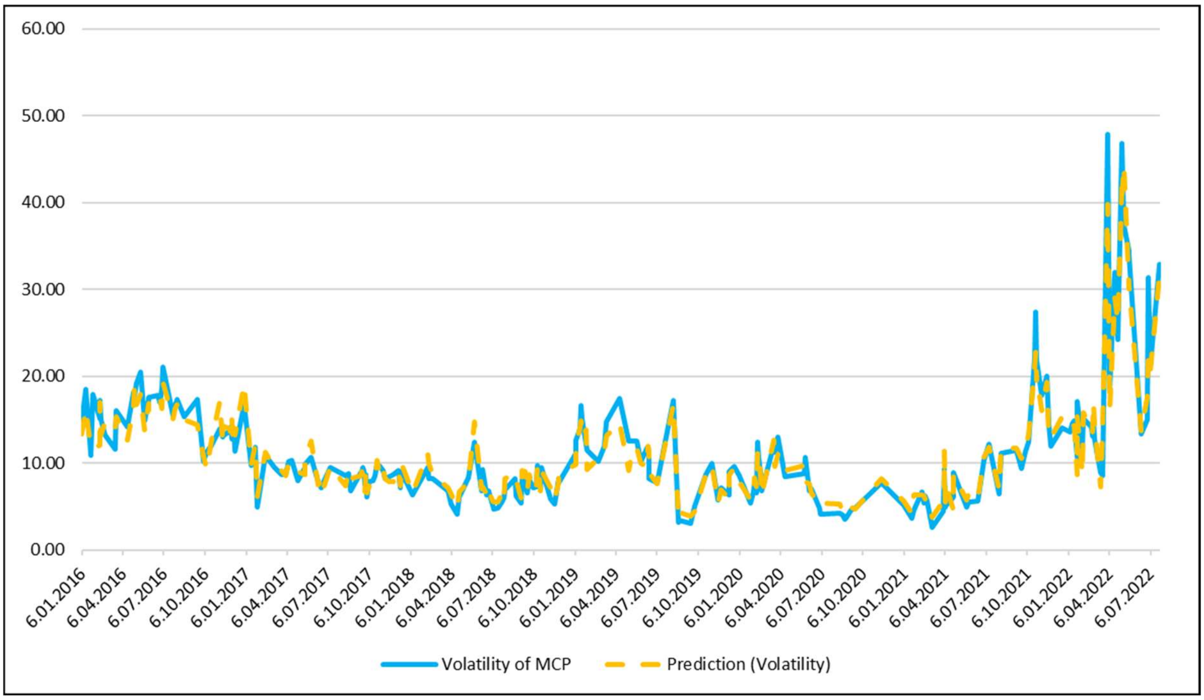
$$Volvar_t = 0.63 \times Volvar_{t-1} + 0.04 \times Dutch\_ttf_t + 0.69 \times wind_t - 0.83 \times solar_t + 2.44$$

The results suggest that wind generation increases volatility while solar generation decreases it. This finding is consistent with Rintamaki et al. (2017) for the German case. However, they also found that wind generation decreases volatility in Denmark. Another finding of our study is that solar generation has a higher coefficient (-0.83) compared to wind generation (0.69). Therefore, elasticity from solar and wind power of volatility is negative in total, which means that in increase in electricity generation from them might decrease volatility.

Solar energy generation depends on the day and the climate, but it is easier to predict the intraday pattern as the sun rises in the morning and descends in the afternoon and sets in the evening. However, wind generation is more irregular. Therefore, it is a fact that solar generation is more predictable than wind generation. This might be the reason why solar generation reduces electricity mcp volatility whereas wind generation increases it.

The graphical representation of the model is depicted in the Figure 12.

Figure 12: Volatility- Polynomial Learner Forecast Results



6. Robustness

In order to check the robustness of the models, we changed two main features of the analyses. First, we changed the train-test ratios of the machine learning algorithms. Second, we used an alternative measure for volatility and run machine learning algorithms on the volatility models with the new independent variable.

First of all, mcp models were re-estimated using the 2nd degree polynomial learner method, with the train-test ratios of 80/20% (Appendix 4) and 70/30% (Appendix 5). We again found most of the coefficients significant. Moreover, the signs of the coefficients are the same as before. The R^2 values of the models are high. The comparison of the explanatory power of the models are given in Table 6.

Table 6: Comparison of Explanatory Powers of Market-Clearing Price Models

R^2 (Explanatory Power) of the Comparison of Market-clearing Price Models			
	Main Model Results (90/10 Test-Train Ratio)	Robustness 1 (80/20 Test-Train Ratio)	Robustness 2 (70/30 Test-Train Ratio)
Model 1	0.90	0.79	0.89
Model 2	**0.93**	**0.92**	**0.91**
Model 3	0.90	0.91	0.88
Model 4	0.82	0.87	0.85
Model 5	0.88	0.89	0.89

Similarly, we re-ran the machine learning algorithm on the volatility models with train-test ratios of 80/20 (Appendix 6) and 70/30 (Appendix 7). We obtained consistent results with the initial estimations. Table 7 can be used to compare the explanatory power of the volatility models with Volvar at different train-test ratios. Besides, Dutch-ttf and wind generation increase mcp volatility, while solar generation reduces it as before. Therefore, the re-estimations of mcp and volatility models using different train-test ratios validate the results of the initial version of the models.

Table 7: Explanatory Power Comparison of Volatility Models with Volvar

R^2 (Explanatory Power) of the Comparison of Volatility Models with *Volvar*			
Volatility Variance Measure			
	Main Model Results (90/10 Test-Train Ratio)	Robustness 1 (80/20 Test-Train Ratio)	Robustness 2 (70/30 Test-Train Ratio)
Model 1	0.56	0.54	0.52
Model 2	**0.92**	**0.91**	**0.86**
Model 3	0.90	0.90	0.84
Model 4	0.90	0.90	0.84

Second, we used an alternative measure for volatility to Volvar. This time, we defined volatility by using the difference between the maximum and minimum vaue of the hourly prices (P) in a day. We called it "Vold":

$$Vold_d = max\{P_{t+23}, \dots, P_t\} - min\{P_{t+23}, \dots, P_t\}$$

We reached estimation results similar to the initial validity models. The R^2 statistics of the models are given in Table 8. The best fitting models' explanatory powers are 0.89, 0.82, and 0.73 at the 90/10 (Appendix 8), 80/20 (Appendix 9), and 70/30 (Appendix 10) train-test ratios, respectively. The cross-validation process yields that the difference between the explanatory powers of the models with *Volvar* and *Vold* is negligible. The signs of the coefficients are the same as those of the initial models' coefficients. Therefore, using an alternative measure of price volatility as the dependent variable in the volatility models did not change the results significantly.

Table 8: Explanatory Power Comparison of Volatility Models with Vold

R^2 (Explanatory power) of the Comparison of Volatility Models with *Vold*			
	Main Model Results (90/10 Test-Train Ratio)	Robustness 1 (80/20 Test-Train Ratio)	Robustness 2 (70/30 Test-Train Ratio)
Model 1	0.60	0.55	0.52
Model 2	**0.89**	**0.82**	0.72
Model 3	0.85	0.80	**0.73**
Model 4	0.87	0.81	0.73

7. Conclusion

Fighting against climate change has brought along the use of renewable resources more for electricity generation. However, incorporating these resources into the electricity market has far-reaching consequences. In this paper, we examined the effects of electricity generations from solar and wind energy on mcp and mcp volatility for the Turkish case. We applied the machine learning methodology to the daily data from 1/1/2016 to 07/31/2022.

In this paper, we compared several artificial intelligence methods and found the polynomial learner method as the best-fitting one. By using it, we found that electricity generation from wind and solar sources reduces mcp. Thus, this study provides evidence of the merit order effect for the Turkish case. We also showed that renewable energy incentive mechanisms in Turkey is useful to decrease mcp since the results suggest that electricity generation from all kinds of RES that are supported also reduces mcp.

The results of this study reveal that the effects of solar and wind on mcp depend on the level of demand. Wind generation affects the price more at low levels than at high levels of electricity demand. Increasing electricity generation from solar energy is effective on prices only at the high levels of demand. The difference between the merit order effect of solar and wind generations might be based on the distinctive feature of the Turkish wholesale electricity market. Wind generation is immediately incorporated into the day-ahead market on the supply side, which shift the supply curve outwards. Solar generation is integrated through the channels of retail companies, which shift the demand curve inwards. Thus, the intersection of demand and supply curves, i.e., mcp, depends not only on the shifts of the demand and supply curves but also on whether it happens when it is a low or high demand period.

Another important finding of this study is that the impacts of wind and solar generation on mcp volatility differ. While wind energy increases volatility, solar energy reduces it. This might be because their production patterns are different. Solar energy enters the day-ahead market with a regular pattern. On the other hand, wind generations are irregular at producing electricity. Therefore, it is a fact that solar generation is more predictable than wind generation. This might be the reason why solar generation reduces electricity mcp volatility whereas wind generation increases it.

This study has several policy implications. First, the price-reducing effect of the penetration of RES into the wholesale electricity market can be used to determine the feed-in tariffs. The lower feed-in tariffs might reduce the cost of incentive mechanisms and also lessen the burden of consumers who bear them in their bills. Second, incentive mechanisms for solar generation might be developed and reinforced since they decrease the volatility of mcp. This, in turn, attracts more investors to the market. Third, the results of this study imply that increasing the share of solar and wind generations in the wholesale electricity market results in less greenhouse gas emissions without harming market participants.

This study provides an empirical test of the penetration of solar and wind electricity generations into the wholesale electricity market on market dynamics such as mcp and mpc volatility. In this study, we used daily data. Using hourly data would refine the results even though trends would not change. Our study provides the groundwork for further studies in this direction.

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Çıkar Beyanı: Yazarlar arasında çıkar çatışması yoktur.

Etik Beyanı: Bu çalışmanın tüm hazırlanma süreçlerinde etik kurallara uyulduğunu yazarlar beyan eder. Aksi bir durumun tespiti halinde Fiscaoeconomia Dergisinin hiçbir sorumluluğu olmayıp, tüm sorumluluk çalışmanın yazarlarına aittir.

Yazar Katkısı: Yazarların katkısı aşağıdaki gibidir;

Giriş: 1. Yazar ve 2. Yazar

Literatür: Yazar ve 2. Yazar

Metodoloji: Yazar ve 2. Yazar

Sonuç: Yazar ve 2. Yazar

1. yazarın katkı oranı: %50. 2. yazarın katkı oranı: %50.

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Author Contributions: author contributions are below;

Introduction: 1. Author and 2. Author

Literature: 1. Author and 2. Author

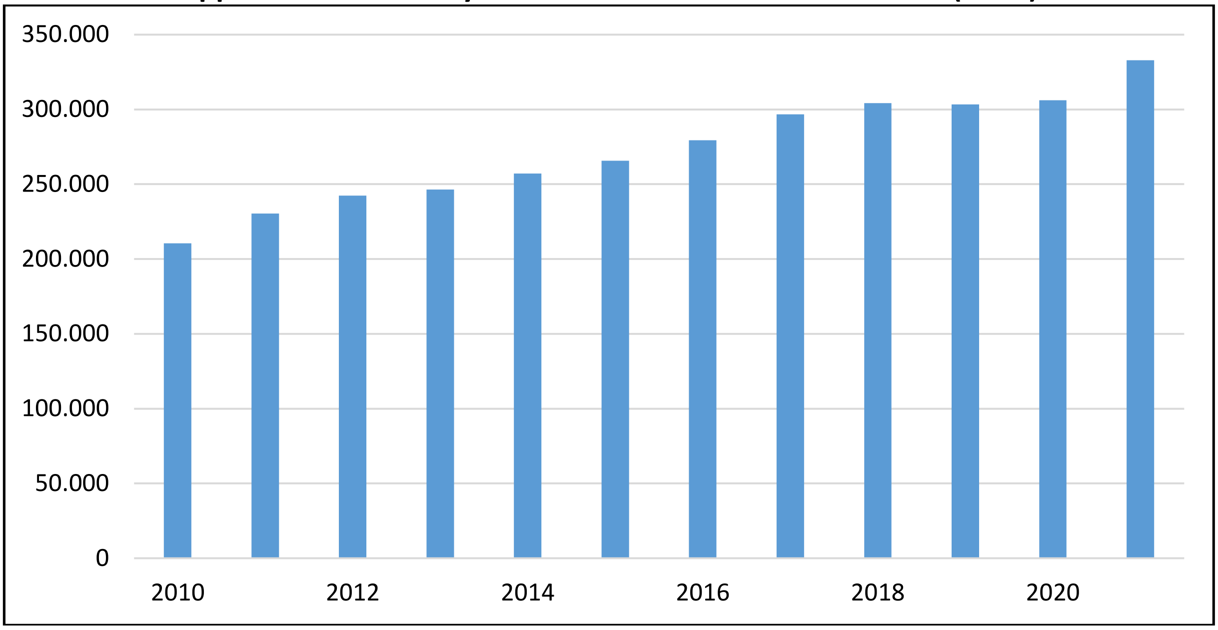
Methodology: 1. Author and 2. Author

Conclusion: 1. Author and 2. Author

1st author's contribution rate: %50, 2nd author's contribution rate: %50.

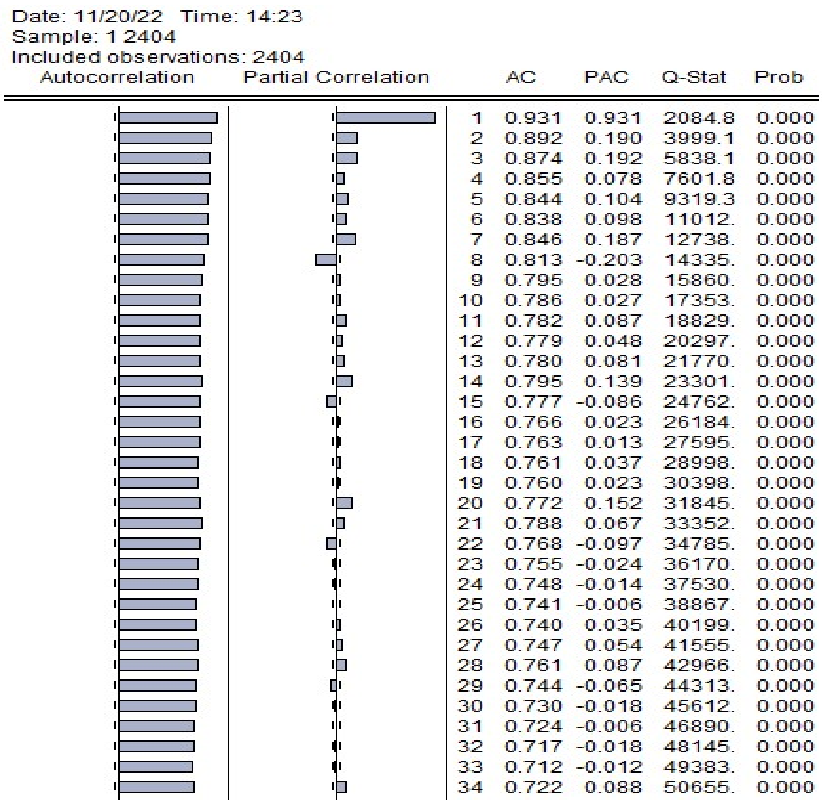
APPENDIX

Appendix 1: Electricity Demand Increase In Last Ten Years (GWh)



Source: http://emra.gov.tr/

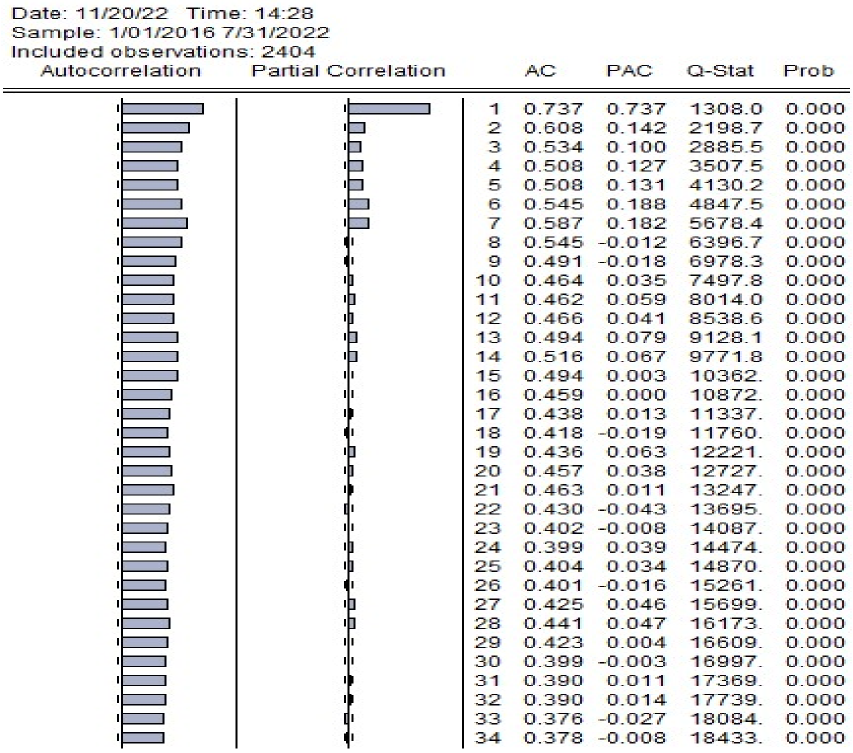
Appendix 2: Autocorrelation and Correlogram Results of the Market-clearing Price



Date: 11/20/22 Time: 14:23
Sample: 1 2404
Included observations: 2404

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.931	0.931	2084.8	0.000
		2	0.892	0.190	3999.1	0.000
		3	0.874	0.192	5838.1	0.000
		4	0.855	0.078	7601.8	0.000
		5	0.844	0.104	9319.3	0.000
		6	0.838	0.098	11012.	0.000
		7	0.846	0.187	12738.	0.000
		8	0.813	-0.203	14335.	0.000
		9	0.795	0.028	15860.	0.000
		10	0.786	0.027	17353.	0.000
		11	0.782	0.087	18829.	0.000
		12	0.779	0.048	20297.	0.000
		13	0.780	0.081	21770.	0.000
		14	0.795	0.139	23301.	0.000
		15	0.777	-0.086	24762.	0.000
		16	0.766	0.023	26184.	0.000
		17	0.763	0.013	27595.	0.000
		18	0.761	0.037	28998.	0.000
		19	0.760	0.023	30398.	0.000
		20	0.772	0.152	31845.	0.000
		21	0.788	0.067	33352.	0.000
		22	0.768	-0.097	34785.	0.000
		23	0.755	-0.024	36170.	0.000
		24	0.748	-0.014	37530.	0.000
		25	0.741	-0.006	38867.	0.000
		26	0.740	0.035	40199.	0.000
		27	0.747	0.054	41555.	0.000
		28	0.761	0.087	42966.	0.000
		29	0.744	-0.065	44313.	0.000
		30	0.730	-0.018	45612.	0.000
		31	0.724	-0.006	46890.	0.000
		32	0.717	-0.018	48145.	0.000
		33	0.712	-0.012	49383.	0.000
		34	0.722	0.088	50655.	0.000

Appendix 3: Autocorrelation and Correlogram Results of Volatility of the Market-clearing Price



Date: 11/20/22 Time: 14:28
Sample: 1/01/2016 7/31/2022
Included observations: 2404

	AC	PAC	Q-Stat	Prob
1	0.737	0.737	1308.0	0.000
2	0.608	0.142	2198.7	0.000
3	0.534	0.100	2885.5	0.000
4	0.508	0.127	3507.5	0.000
5	0.508	0.131	4130.2	0.000
6	0.545	0.188	4847.5	0.000
7	0.587	0.182	5678.4	0.000
8	0.545	-0.012	6396.7	0.000
9	0.491	-0.018	6978.3	0.000
10	0.464	0.035	7497.8	0.000
11	0.462	0.059	8014.0	0.000
12	0.466	0.041	8538.6	0.000
13	0.494	0.079	9128.1	0.000
14	0.516	0.067	9771.8	0.000
15	0.494	0.003	10362.	0.000
16	0.459	0.000	10872.	0.000
17	0.438	0.013	11337.	0.000
18	0.418	-0.019	11760.	0.000
19	0.436	0.063	12221.	0.000
20	0.457	0.038	12727.	0.000
21	0.463	0.011	13247.	0.000
22	0.430	-0.043	13695.	0.000
23	0.402	-0.008	14087.	0.000
24	0.399	0.039	14474.	0.000
25	0.404	0.034	14870.	0.000
26	0.401	-0.016	15261.	0.000
27	0.425	0.046	15699.	0.000
28	0.441	0.047	16173.	0.000
29	0.423	0.004	16609.	0.000
30	0.399	-0.003	16997.	0.000
31	0.390	0.011	17369.	0.000
32	0.390	0.014	17739.	0.000
33	0.376	-0.027	18084.	0.000
34	0.378	-0.008	18433.	0.000

Appendix 4: Robustness Check 2nd Degree Polynomial learner Model Results for Level of Market-clearing Price (%80/20 Train-Test Ratio)

MCP – LEARNING(%80)	Model 1(3)	Model 2(4)	Model 3(5)	Model 4(7)	Model 5(8)	Model 6(9)
mcp(t-2)			0.25*** (0.05)			
mcp(t-1)	0.47*** 0.04)	0.80*** (0.04)	0.53*** (0.05)	0.70*** (0.04)	0.68*** (0.04)	0.53*** (0.04)
ttf	0.25*** (0.02)	0.19*** (0.02)	0.19*** (0.02)	0.22*** (0.02)	0.18*** (0.02)	0.26*** (0.02)
demand	858.43** (412.03)					
wind	-36.79*** (10.88)	-37.80*** (11.40)	-46.70*** (11.97)	-35.50*** (11.86)		
solar	-1.85 (1.30)	-0.93 (0.91)	-1.17 (1.00)		-1.16 (0.95)	
$mcp(t-2)^2$			0.00 (0.00)			
$mcp(t-1)^2$	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ttf^2	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
$demand^2$	88.09* (45.66)					
$wind^2$	-6.73*** (1.68)	-6.49*** (1.75)	-8.03*** (1.84)	-6.21*** (1.83)		
$solar^2$	-0.55* (0.29)	-5.34** (2.45)	-6.45** (2.68)		-0.74** (0.37)	

supren						-109.74** (44.10)
supren²						-15.46** (5.77)
Intercept	-2109.54** (929.44)	-48.02** (18.58)	-59.15*** (19.46)	-39.77** (19.24)	10.62*** (1.29)	-178.65** (84.05)
R²	0.91	0.79	0.92	0.91	0.87	0.89
Mean Absolute Error	4.3930	5.0884	4.2311	4.5193	4.6688	5.0404
Mean Squared Error	41.8719	95.1032	40.0174	53.5078	72.0546	72.9457
Root Mean Squared Error	6.4709	9.7521	6.3259	7.3149	8.4885	8.5408
Mean Absolute Percentage Error	0.1008	0.1295	0.1109	0.0962	0.1047	0.1078

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Appendix 5: Robustness Check 2 - 2nd Degree Polynomial learner Model Results for Level of Market-clearing Price (%70/30 Train-Test Ratio)

MCP – LEARNING(%70)	Model 1(3)	Model 2(4)	Model 3(5)	Model 4(7)	Model 5(8)	Model 6(9)
mcp(t-2)			0.26*** (0.06)			
mcp(t-1)	0.45*** (0.04)	0.62*** (0.04)	0.50*** (0.06)	0.66*** (0.04)	0.65*** (0.04)	0.59*** (0.05)
ttf	0.26*** (0.02)	0.23*** (0.02)	0.20*** (0.03)	0.22*** (0.02)	0.24*** (0.02)	0.25*** (0.03)
demand	667.10** (212.31)					
wind	-47.31*** (12.13)	-44.83*** (12.08)	-41.38*** (13.00)	-39.02*** (12.76)		
solar	-1.10 (1.22)	-0.39 1.02)	-1.43 1.05)		-1.26 (1.13)	
mcp(t-2)²			0.00 (0.00)			
mcp(t-1)²	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ttf²	0.00 (0.00)	0.00 (0.0)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
demand²	66.57 (45.73)					
wind²	-8.46*** (1.87)	-7.63*** (1.86)	-7.20*** (2.00)	-6.72*** (1.96)		
solar²	-0.76** (0.33)	-6.02* (3.10)	-5.98** (2.13)		-0.57** (0.23)	
supren						-124.31** (50.59)
supren²						-17.35** (6.61)
Intercept	-1699.50* (929.41)	-52.71** (19.58)	-50.09** (21.15)	-44.68** (20.80)	11.08*** (1.35)	-208.12** (96.62)
R²	0.92	0.89	0.91	0.88	0.85	0.89
Mean Absolute Error	4.6573	4.9967	4.5862	4.8293	4.9806	4.9838
Mean Squared Error	55.3352	71.3842	52.2935	67.3373	78.9433	64.2528
Root Mean Squared Error	7.4388	8.4489	7.2314	8.2059	8.8850	8.0158
Mean Absolute Percentage Error	0.0946	0.1236	0.1022	0.1229	0.1227	0.1031

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Robustness Check Market-Clearing Price Volatility: Volatilityvar

Appendix 6: Robustness Check 1 - 1st Degree Polynomial learner Model Results for Volatility of Market-clearing Price (%80/20 Train-Test Ratio)

Volatility of MCP – LEARNING(%80)	Model 1	Model 2	Model 3	Model 4
volvar(t-3)				0.05** (0.02)
volvar(t-2)			0.14*** (0.03)	0.11*** (0.03)
volvar(t-1)		0.61*** (0.02)	0.51*** (0.02)	0.51*** (0.02)
ttf	0.12*** (0.01)	0.04*** (0.00)	0.04*** (0.00)	0.03*** (0.00)
wind	0.98* (0.58)	0.85* (0.45)	1.03** (0.45)	1.09** (0.45)
solar	-2.16*** (0.14)	-0.87*** (0.11)	-0.78*** (0.11)	-0.75*** (0.11)
Intercept	9.10*** (1.85)	2.13 (1.47)	0.95 (1.47)	0.58 (1.48)
R^2	0.54	0.91	0.90	0.90
Mean Absolute Error	4.3605	2.8305	2.8173	2.8024
Mean Squared Error	46.2083	22.3357	22.9927	22.6824
Root Mean Squared Error	6.7977	4.7261	4.7951	4.7626
Mean Absolute Percentage Error	8.3962	3.3345	2.9819	3.0960

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Appendix 7: Robustness Check 2 - 1st Degree Polynomial learner Model Results for Volatility of Market-clearing Price (%70/30 Train-Test Ratio)

Volatility of MCP – LEARNING(%70)	Model 1	Model 2	Model 3	Model 4
volvar(t-3)				0.07*** (0.02)
volvar(t-2)			0.18*** (0.03)	0.13*** (0.03)
volvar(t-1)		0.61*** (0.02)	0.50*** (0.03)	0.50*** (0.03)
ttf	0.12*** (0.01)	0.05*** (0.00)	0.04*** (0.00)	0.04*** (0.01)
wind	0.83* (0.63)	0.72** (0.49)	0.99** (0.49)	1.05** (0.49)
solar	-2.15*** (0.15)	-0.82*** (0.12)	-0.73*** (0.12)	-0.68*** (0.12)
Intercept	9.50*** (2.03)	2.33 (1.60)	0.74 (1.60)	0.27 (1.61)
R^2	0.52	0.86	0.84	0.84
Mean Absolute Error	4.4151	2.9394	2.9276	2.9132
Mean Squared Error	44.4905	24.0759	25.2714	25.1061
Root Mean Squared Error	6.6701	4.9067	5.0271	5.0106
Mean Absolute Percentage Error	6.1399	2.5750	2.2498	2.3641

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Appendix 8: Robustness Check 3 - 1st Degree Polynomial learner Model Results for Different Volatility of Market-clearing Price (%90/10 Train-Test Ratio)

Volatility of MCP – LEARNING(%90)	Model 1	Model 2	Model 3	Model 4
vold(t-3)				0.16*** (0.02)
vold(t-2)			0.16*** (0.03)	0.08** (0.03)
vold(t-1)		0.55*** (0.02)	0.45*** (0.02)	0.44*** (0.02)
ttf	0.38*** (0.02)	0.17*** (0.01)	0.15*** (0.02)	0.13*** (0.01)
wind	2.62** (1.75)	3.64** (1.45)	5.00*** (1.49)	4.53*** (1.42)
solar	-7.92*** (0.41)	-3.72*** (0.36)	-3.39*** 0.39)	-2.88*** (0.36)
Intercept	33.82*** (5.63)	7.41 (4.72)	0.87 (4.92)	-0.33 (4.70)
R^2	0.60	0.89	0.85	0.87
Mean Absolute Error	14.0659	10.0323	10.1017	9.7206
Mean Squared Error	392.8878	215.4822	238.4539	228.0061
Root Mean Squared Error	19.8214	14.6793	15.4420	15.0999
Mean Absolute Percentage Error	0.6453	0.4269	0.4612	0.4521

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Appendix 9: Robustness Check 4 - 1st Degree Polynomial learner Model Results for Different Volatility of Market-clearing Price (%80/20 Train-Test Ratio)

Volatility of MCP – LEARNING(%80)	Model 1	Model 2	Model 3	Model 4
vold(t-3)				0.16*** (0.02)
vold(t-2)			0.16*** (0.03)	0.07** (0.03)
vold(t-1)		0.54*** (0.02)	0.45*** (0.02)	0.44*** (0.02)
ttf	0.38*** (0.02)	0.18*** (0.02)	0.15*** (0.02)	0.13*** (0.02)
wind	3.45* (1.82)	4.49*** (1.50)	5.00*** (1.49)	5.47*** (1.47)
solar	-7.99*** (0.43)	-3.82*** (0.38)	-3.39*** (0.39)	-2.93*** (0.39)
Intercept	31.12*** (5.85)	5.09 (4.92)	0.87 (4.92)	-3.23 (4.89)
R^2	0.55	0.82	0.80	0.81
Mean Absolute Error	13.6583	9.8376	9.7269	9.4072
Mean Squared Error	437.1876	271.3395	280.0748	273.4844
Root Mean Squared Error	20.9090	16.4724	16.7354	16.5374
Mean Absolute Percentage Error	0.8030	0.5088	0.5035	0.5014

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**

Appendix 10: Robustness Check 5 - 1st Degree Polynomial learner Model Results for Different Volatility of Market-clearing Price (%70/30 Train-Test Ratio)

Volatility of MCP – LEARNING(%70)	Model 1	Model 2	Model 3	Model 4
vold(t-3)				0.18*** (0.02)
vold(t-2)			0.11*** (0.03)	0.02*** (0.03)
vold(t-1)		0.55*** (0.02)	0.49*** (0.02)	0.48*** (0.02)
ttf	0.39*** (0.02)	0.18*** (0.02)	0.17*** (0.02)	0.14*** (0.02)
wind	2.74* (1.95)	3.09* (1.57)	3.59** (1.56)	4.12** (1.54)
solar	-7.85*** (0.45)	-3.45*** (0.39)	-3.16*** (0.40)	-2.64*** (0.40)
Intercept	32.78*** (6.27)	8.12 (5.10)	4.63 (5.14)	0.01 (5.08)
R^2	0.52	0.72	0.73	0.73
Mean Absolute Error	13.9681	10.3210	10.1095	9.8767
Mean Squared Error	481.3308	351.2228	345.7308	343.3407
Root Mean Squared Error	21.9393	18.7409	18.5938	18.5295
Mean Absolute Percentage Error	0.8394	0.6026	0.5982	0.5729

***** denotes significance in %1, ** denotes significance in %5, * denotes significance in %10 confidence interval. The numbers in parenthesis are standard deviations.**