BASIC TIME SERIES PATTERNS OF TURKISH ELECTRICITY PRICES

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Abstract

After the deliberalization of the Turkish electricity market in the end of 2000s, hourly electricity prices has started to occur in the day-ahead electricity market according to the bids of the supply and demand sides. It is important for both parties to forecast hourly electricity prices to give accurate bids and avoid a lose of money in this market due to myopic forecasts. Therefore electricity price forecasts with different methods, such as time series statistical ones, have been done for Turkish market as well as the more developed electricity markets. Due to the nature of the electricity, electricity prices have some characteristics such as seasonality, high volatility, sharp price spikes and mean reverting processes. This paper mainly focuses on the seasonality effect. Electricity prices show a great variation according to the hours, days of the month, weekdays, months, years and holidays. The first purpose of this paper is to state this fact and give some descriptive information about the electricity prices. Second aim is to eliminate the deterministic seasonality by using a Uni-ANOVA process as a pre-whitening method. Our findings suggest that Uni-ANOVA process eliminates the deterministic seasonality substantially, however stochastic seasonality has still effect on the electricity price data.

Keywords: electricity prices, UNI-ANOVA, seasonality, pre-whitening

1. Introduction

Electricity is separated from other financial assets and even commodities due to its idiosyncratic features. Therefore, it needs a special effort and unique techniques to model the electricity prices. Non-storability, demand inelasticity, requirement of maintaining constant balance between demand and supply and oligopolistic generation side (Aggarwal et al., 2009) are among the features of electricity prices.

These features cause some electricity price characteristics: Seasonality, high volatility, sharp price spikes and mean reverting processes (Hayfavi and Talasli, 2014). Intra-daily, weekly, monthly and annual seasonality could be observed due to variables such as business activities, weather and industrial production, which affect the electricity prices. Non-storability and the requirement of having equilibrium between demand and supply sides cause supply and demand shocks on electricity prices. For low levels of demand; generators supply electricity by low marginal costs. However, for high levels of demand, higher marginal cost generators also provide energy for the system, which is the main reason of price shocks. Furthermore, plant failures or maintenance and repair activities also activate high cost generation plants and let the price spikes occur. When the reason for the price shocks disappear, prices tend to revert back to the long term equilibrium levels, which is formed mainly by the cost of production. Furthermore, an important element in the formation of electricity prices is temperature and it is also a mean reverting process like electricity prices, itself (Talasli, 2012).

Electricity price forecasting plays a major role in energy companies' decision making mechanisms (Bunn, 2004; Weron, 2006). For example, electric utilities are especially vulnerable, because they cannot pass their costs on the retail consumers. If they over contract/under contract and sell/buy in the balancing market, it might cause very huge losses to the companies. The enormous volatility of electricity prices compared to any other financial asset require companies to hedge not only against volume, but also against price movements. Therefore, price forecasting/modeling is very important for all the parties; generator, utility company or large industrial companies. If they forecast wholesale prices accurately, they can adjust their bidding strategy and also their own production or consumption schedule, which will decrease the risk and maximize the profits in day-ahead trading (Weron, 2014).

Turkish Day Ahead Electricity Market is an emerging spot market, where generators and demanders submit their bids in hourly time frequency and the hourly market clearing price is determined by the Market Financial Settlement Centre. The establishment of Turkish Day Ahead Electricity Market is due to several reasons: Firstly, it is an opportunity for the market participants to balance their portfolios in addition to bilateral contracts and providing the system operator with a balanced system. Secondly, it is used for power trading and balancing activities one day before the physical delivery of electricity. Furthermore, electricity future contracts are tradeable in Turkish Derivatives Exchange since 2011 to give the opportunity of risk-hedging to the market participants. Another breakthrough was happened in September 2015 by the establishment of Power Exchange. Turkish Power Exchange operates the day ahead and intraday markets and Borsa Istanbul has the operating right of derivatives market in current situation (Avci-Surucu et al., 2016).

This paper will focus on the seasonality effect in the Turkish Day Ahead Electricity Market hourly prices. First, it gives a detailed descriptive analysis of the hourly prices according to the hours, weekdays, days of the month, months, years and holiday effects. Furthermore, it analyses the outliers related to these effects. As a main purpose, it removes the deterministic seasonality by applying a Uni-ANOVA process as a pre-whitening method and gives the opportunity to forecast with this stationary series. Section 2 will give a literature review about the features of the electricity prices and Turkish Day Ahead Electricity Market. Section 3 explains the method and application and Section 4 shares the results. Last section concludes and gives has some further research suggestions.

2. Literature Review

Amjady and Hemmati (2006) mention the need of short-term price forecasts, review the problems related to electricity price forecasting techniques. One of the most important problems is the effect of the seasonality; in addition to sharp price spikes, mean-reverting processes etc.

Ziel et al. (2015) explains the features of the electricity prices very detailed as well as the difficulties of forecasting. Electricity prices are dependent on the days of the week and the seasons. There are two reasons. Firstly; solar, wind and water energy production depends on the weather conditions. Secondly; it is directly related to the working days, because of the energy requirement of the industrial machines. It also mentions the holiday effect, which will be discussed in this paper, as well.

These effects are discussed in literature, but one of the rare works about holiday effect is done by Cancelo et al. (2008). Karakatsani and Bunn (2008) works on the British half-hourly electricity prices and their model which includes time varying parameters outperform other types of autoregressive models. Another model with time-varying coefficient which include holidays as well is proposed by Koopman et al. (2007).

Fanone et al. (2013) work on the negative prices case in German EEX market. Due to the Renewable Energy Act (EEG) in Germany, modelling of electricity prices has an additional problem, negative prices. Their model captures negative and positive price spikes in addition to the response of negative prices. Keles et al. (2012) also shows that the inclusion of negative prices in the model gives better results for their simulation based model.

Another important feature is the inverse leverage effect, which is first detected by Knittel and Roberts (2005) and then supported with the works of Bowden and Payne (2008) and Liu and Shi (2013).

Cuaresma et al. (2004) apply AR(1) and general ARMA processes to hourly time frequency in German EEX market and find out that modeling the prices separately for each hour forecast better than modeling the prices for whole time series. Weron and Misiorek (2005) use various autoregression methods in the California market, which also include SARIMA. Garcia-Martos and Conejo (2013) review short- and medium-term electricity price forecasting and focus on time series models and variations of ARIMA models such as SARIMA calibrated to hourly prices.

Kim et al. (2002) and Conejo et al. (2005) use similar forecasting techniques and their independent variables are the predicted demand and try to forecast daily and hourly prices, respectively. Schmutz and Elkuch (2004) use multiple regression with gas prices, available nuclear capacity, temperatures and rainfall as regressors. Karakatsani and Bunn (2008) use a regression model for 48 half hourly load periods and compare their performance to time varying regression and regime switching regression models. Their conclusion is that the models, which invoke market fundamentals and time varying coefficients performs better than the various alternatives.

Although there are many papers about electricity price forecasting, only a limited amount of research has done about Turkish electricity market. In 2009 deregulated Turkish electricity market has a relatively developed literature for demand forecast (e.g. Ediger and Tatlidil, 2002; Altinay and Karagol, 2005; Akay and Atak, 2007; Hamzacebi, 2007; Boluk and Koc, 2010; Dilaver and Hunt, 2011; Hamzacebi and Es, 2014), however electricity price modelling research are very rare in Turkish electricity market. Some of the important ones are discussed below.

Ozyildirim and Beyazit (2014) forecast and model the electricity prices by radial basis function, which implement a totally new approach to electricity price forecasting, in addition to conventional linear regression technique. To my knowledge, this is the only paper that works with hourly data in Turkish electricity market. Consequently, out of sample performance of radial basis function method slightly outperforms the regression method for a specific estimation period.

Talasli (2012) models the electricity markets stochastically in her thesis and analyses the Turkish electricity market very detailed. The thesis tries to capture all the characteristics of the electricity prices such as mean reversion, seasonality and the spiky behaviour. The thesis is also concerned with the derivative electricity market and the pricing of the derivatives, but the lack of observations due to the infant Turkish derivative electricity market did not let the thesis to have clear results in this chapter.

Akyildirim et al. (2014) work on the electricity prices by modeling long-term seasonal components and use three different long-term seasonality models: Fourier series, dummies and wavelet-based methods and perform a back-testing for different forecasting horizons for the Turkish electricity market. The paper also involves in the price spikes, however by using five different outlier detection methods, it removes the outliers and does the modelling after that point. The problem is that removing the outliers endangers the forecast performance and does not take the most important characteristic, price spikes, of electricity prices into account.

Taysi et al. (2015) combine time series statistics with a neural network model in their paper for Turkish electricity market. The time series statistics method is SARIMA model, a seasonal approach of ARIMA, and the artificial intelligence model is named feed forward neural network. Both methods use historical electricity price data and the performance of them are very close to each other with the average error rate of 8.5% for weekly frequency forecasting.

In a very recent paper Avci-Surucu et al. (2016) works on the bidding structure, market efficiency and persistence in a multi-time tariff setting in Turkish electricity market. The paper divides the daily prices in three time zones and finds that in two time zone market participants bid hyperbolically and not at their marginal costs. These findings are important for policy makers and market participants to develop more accurate forecasting tools, market monitoring indexes and conduct ex-ante impact assessment.

3. Method and Application

The main purpose of this paper is to eliminate the deterministic seasonality by applying a Uni-ANOVA process to the hourly Turkish electricity prices. Therefore, hourly electricity prices of Turkish market from 01.01.2013 to 31.12.2015 is taken from EPİAŞ[1]. The market is started to operate in December 2011 and the data of 2011 and 2012 is excluded due to high volatility, which is probably because of “learning by doing”[2] fact. This hourly data, which consists of 26208 samples, is analysed according to the hours, days of the month, weekdays, months, years and holidays. The descriptive statistics of the hourly electricity price data is examined with a special care about the outliers. Due to the zeros, it is impossible to take logarithms and have stationary price series with the original data. There are also some peaks in the prices which cause problems. Therefore a Uni-ANOVA pre-whitening process is applied in SPSS 17 to eliminate the deterministic seasonality. The stationary series of residuals obtained from this process, descriptive statistics of which are given in the results part, can be used for forecasting. This process eliminates the deterministic seasonality and removing the stochastic seasonality requires another method.

4. Results

Prices vary a lot according to different time intervals of the day, week, month and also year. Range of the prices in regular times is roughly from 50-200 TL/MWh for hourly prices from 2013 to 2015. However, they positive and negative price shock occur sometimes. Figure 1 shows the graph of the prices from 2013 to 2015.

[1] https://seffaflik.epias.com.tr/transparency/
[2] Bowden and Payne (2007) and Hickey et al. (2012)

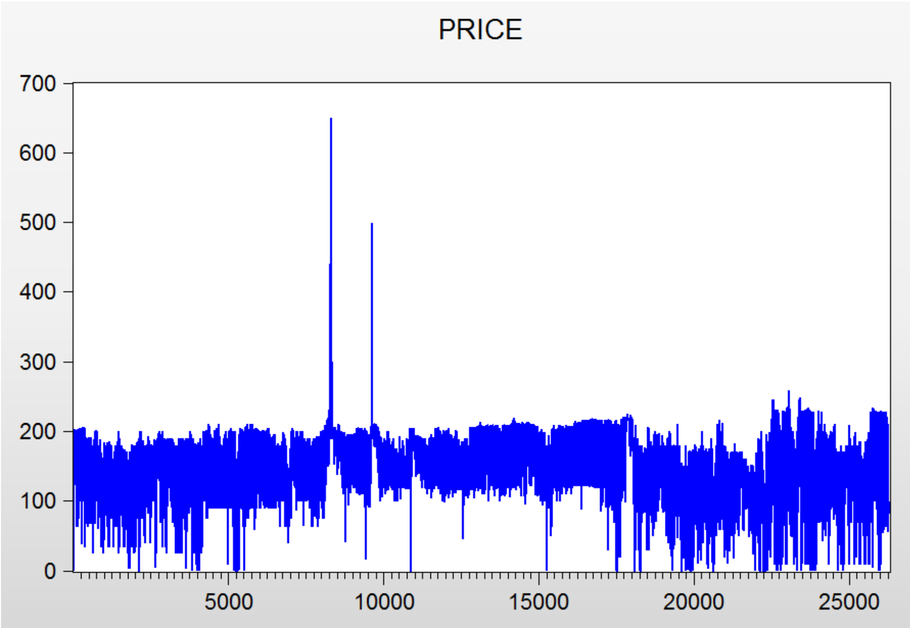

Figure 1 Hourly Prices (TL/MWh) for 2013-2015

Table 1 and Figure 2 give information about the descriptive statistics of electricity prices for 2013-2015 period. There are 26280 samples and the range[3] is 649.99 TL/MWh. Mean price is 150.70 TL/MWh with the standard deviation of 43.05. The histogram is quite left-skewed and the excess kurtosis is at about 0.52. Histogram of hourly electricity prices in Figure 2 also proves that the data is left-skewed. Furthermore; Table 2 shows that the hourly electricity price series has a unit root, which means the series is unstationary and should be differentiated or the logarithm of the series should be taken. However, due to many zeros in the series it is impossible to do any of them. Therefore, a Uni-ANOVA process is applied to eliminate the zeros as well as the deterministic seasonality.

Table 1 Descriptive Statistics of Hourly Electricity Prices for 2013-2015

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PRICE	26280	,00	649,99	150,6973	43,05545	-,390	,015	3,517	,030
Valid N (listwise)	26280								

[3] Negative prices are not allowed by the authority in the Turkish electricity market.

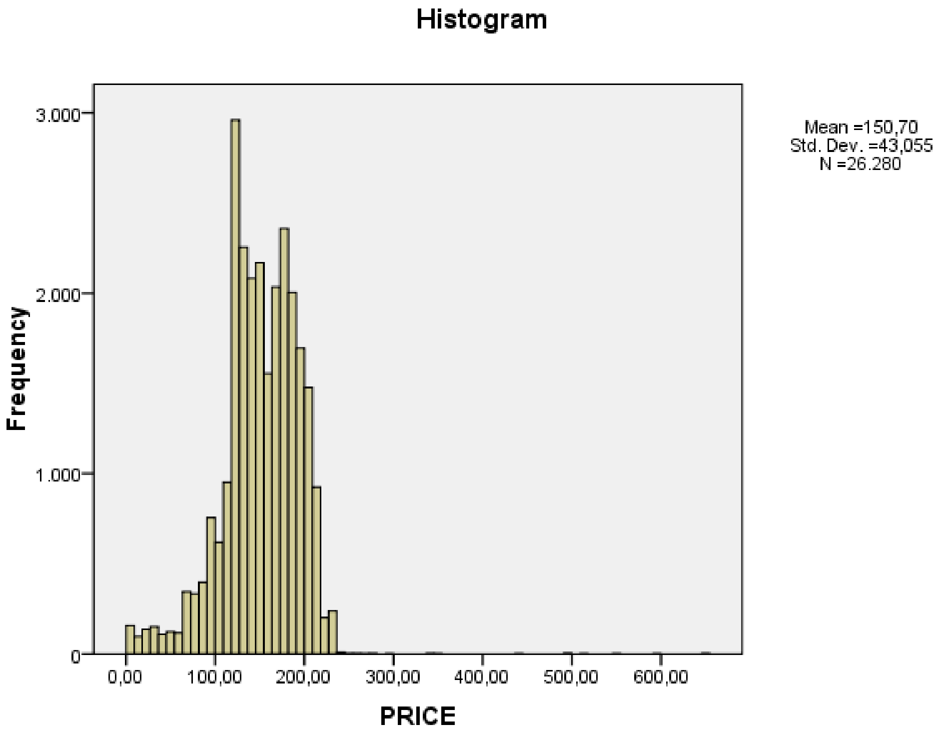

Figure 2 Histogram of the Hourly Electricity Prices for 2013-2015

Table 2 ADF Unit Root Test of Electricity Prices for 2013-2015

Null Hypothesis: SERIES01 has a unit root
Exogenous: None
Lag Length: 48 (Automatic - based on AIC, maxlag=48)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.534234	0.1175
Test critical values:	1% level	-2.565050	
	5% level	-1.940836	
	10% level	-1.616692	

*MacKinnon (1996) one-sided p-values.

Another important feature of the data is that it contains an important amount of outliers[4]. 248 of the outliers are on the negative side and 51 of them are in the positive side. 1.14% of the all sample is taken as outliers. Outliers are investigated according to the time frequencies. Figure 3 shows that outliers of the both sides occur mostly in the night and early morning hours. Both outliers make a peak at 6 o'clock. According to Figure 4 Monday and Sunday are keen to have outliers. An interesting observation is that Monday has the highest outliers in negative side, but the lowest in positive side. Figure 5 illustrates that the negative outliers have a higher frequency in the beginning and in the end of the months. Furthermore, the most expensive winter months have the highest positive outliers and quite surprisingly summer times have the highest number of negative outliers (Figure 6). Another important finding is that 206 of the 299 outliers occured in 2015 (Figure 7). Additionally, Figure 8 suggests that there are 76 outliers in holiday days and 223 in normal days. Although the number of the outliers in normal days are higher than the number of the outliers in holiday days, 7.28% of the holiday days are outliers compared to 0.89% of the normal days.

[4] The prices which exceed the student-t scores of 3 and -3 according to the applied Uni-ANOVA process from both, positive and negative, sides are named outliers.

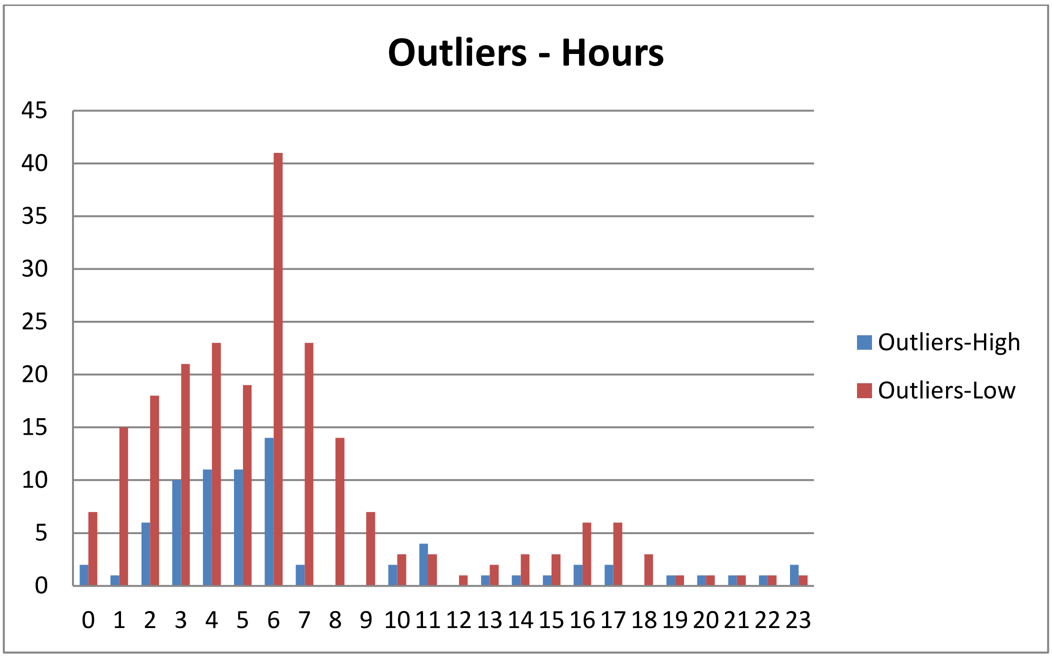

Figure 3 Histogram of Outliers (Hours of the Day)

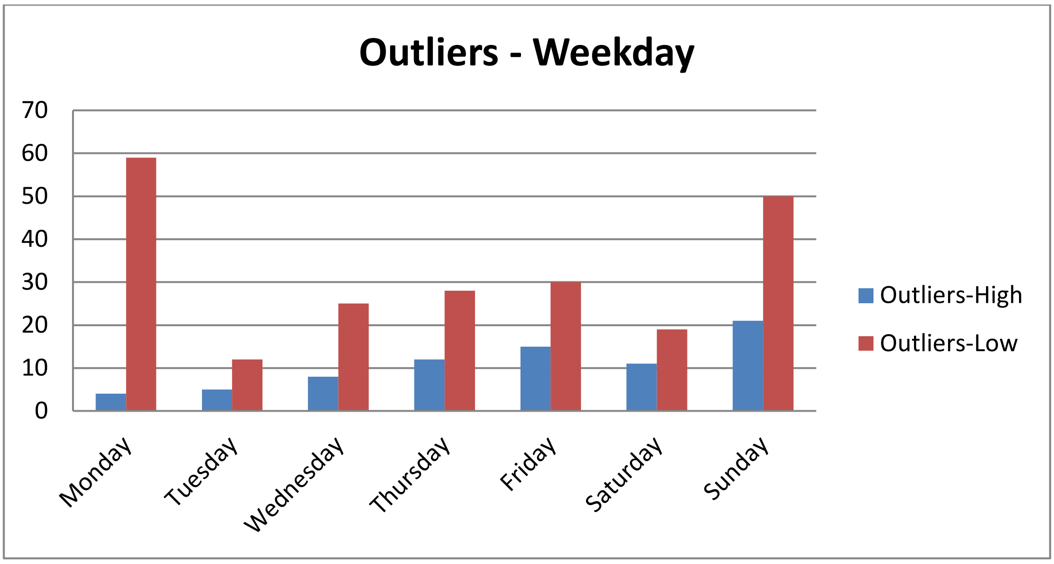

Figure 4 Histogram of Outliers (Weekday)

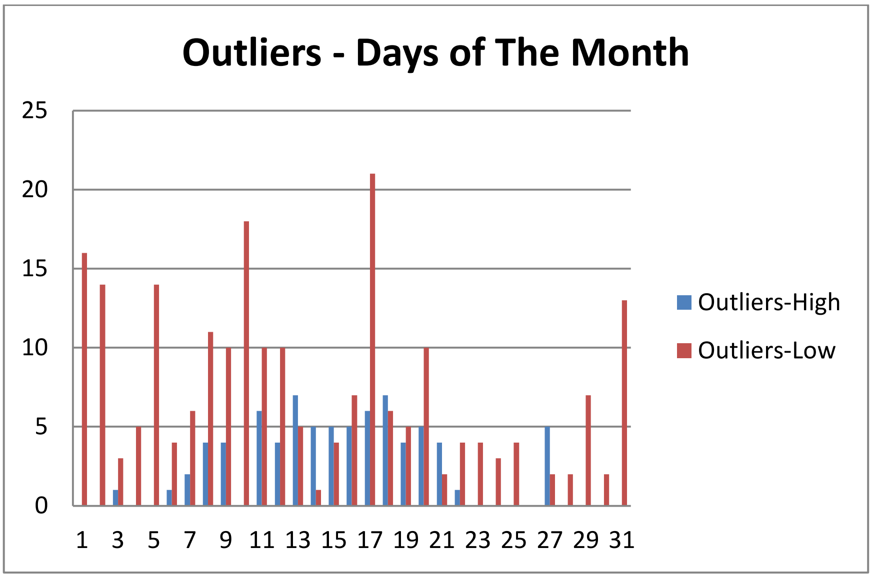

Figure 5 Histogram of Outliers (Days of the Month)

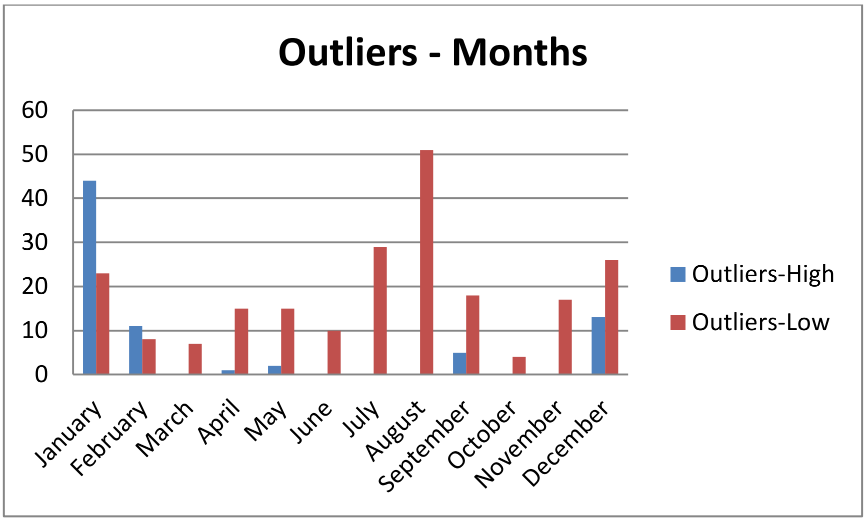

Figure 6 Histogram of Outliers (Months of the Year)

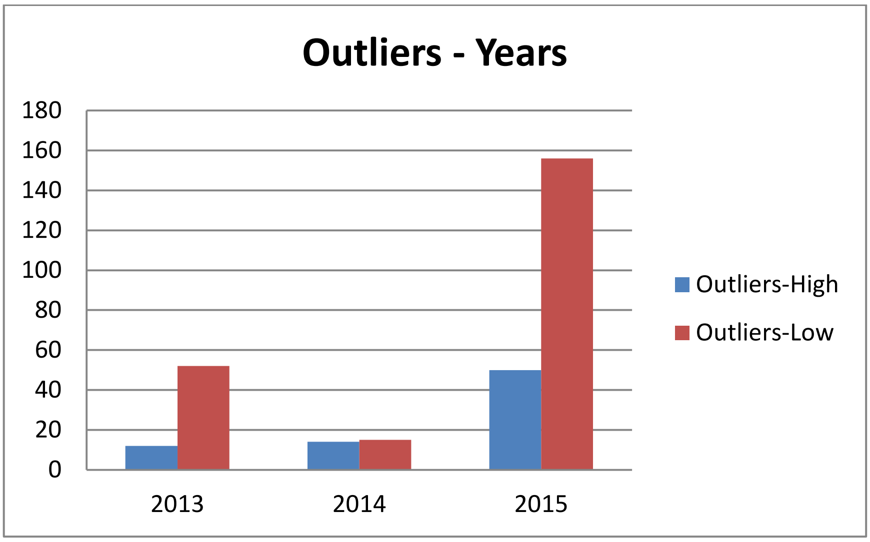

Figure 7 Histogram of Outliers (Years)

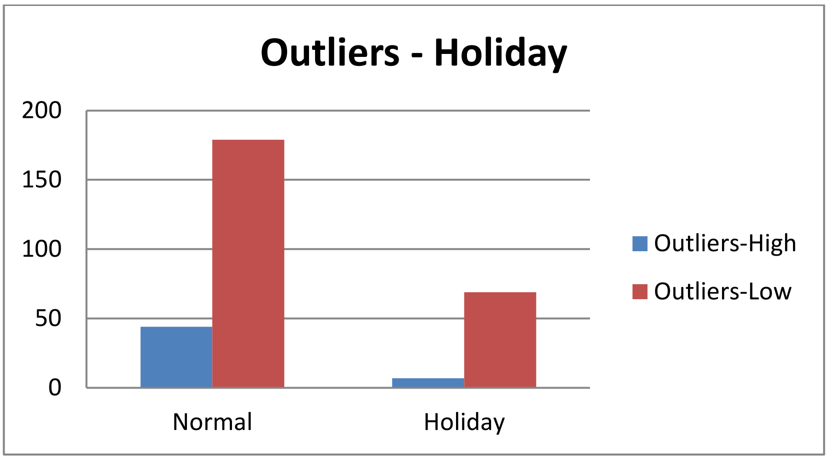

Figure 8 Histogram of Outliers (Holiday)

Following graphs illustrate the effects of the seasonality. Figure 9 illustrates the effect of the different hours of the day. Hourly mean prices have a global maximum at 11 o'clock by 181.80 TL/MWh and two local maximums at 14 o'clock by 176.95 TL/MWh and at 22 o'clock by 160.57 TL/MWh. The lowest mean prices occur at 4 and 5 o'clock in the morning by 103.25 TL/MWh and 103.68 TL/MWh, respectively. It is mainly due to the demand of the electricity. According to the working hours there is one peak in the morning and another one in the afternoon. Moreover, there is a small peak in the evening at 22 o'clock, when the people return their homes and the demand increases.

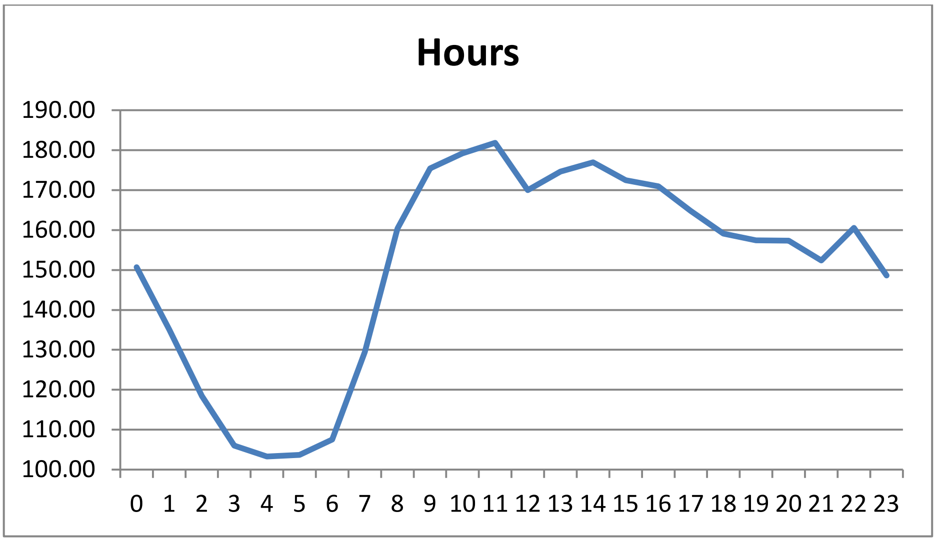

Figure 9 Price Distribution of Hourly Prices (TL/MWh) According to the Hours of the Day

Figure 10 also shows the effect of working days. Although Monday and Friday prices are quite lower than the other working days, working days have a stable mean price. Surprisingly, electricity prices do not drop on Saturday[5] and have almost the same level with the working days. A sharp decrease could be observed on Sundays and the mean price level is at 132.15 TL/MWh.

[5] In Turkey most of the private companies work half-day on Saturday and factories work all-day.

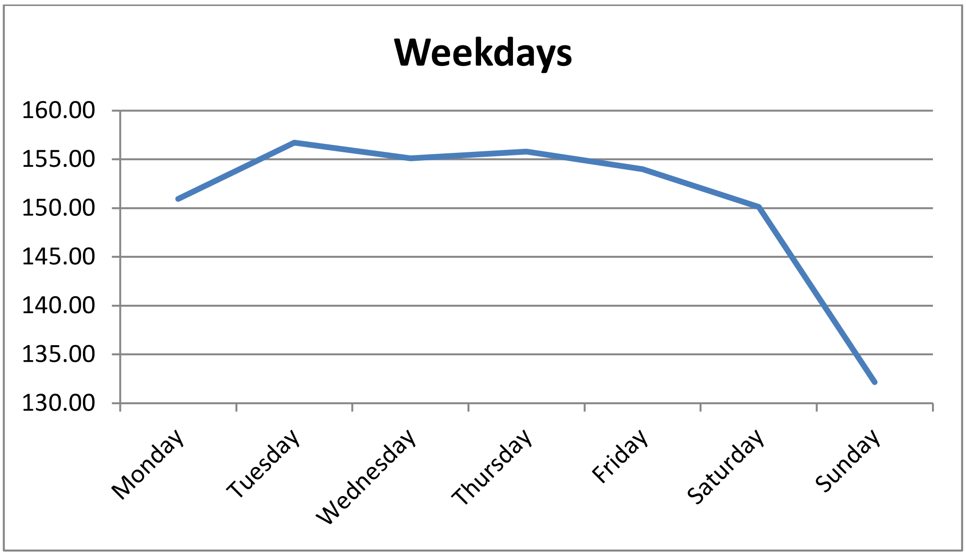

Figure 10 Price Distribution of Hourly Prices (TL/MWh) According to the Weekdays

Figure 11 shows the price distribution of hourly prices according to the days of the month. It could be mentioned that the electricity prices are quite low at the first and the last days of the months and the highest prices are in the middle of the month.

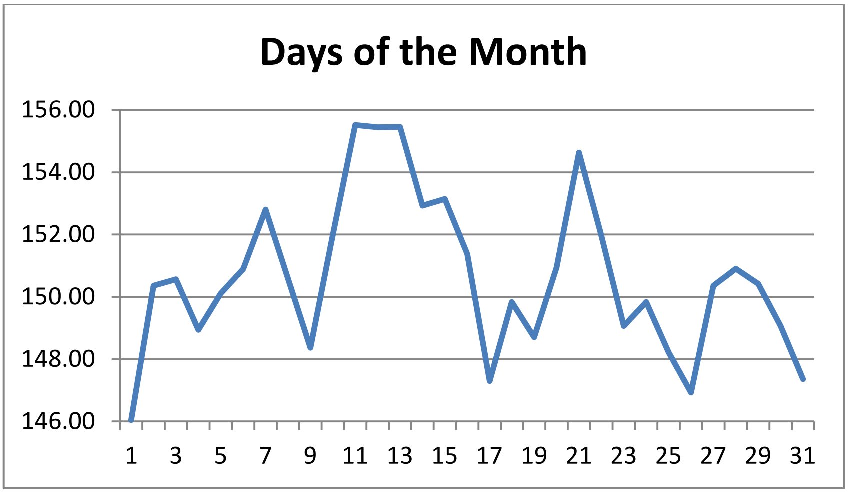

Figure 11 Price Distribution of Hourly Prices (TL/MWh) According to the Days of the Month

The effect of seasonality can also easily observed according to the months of the year. On the contrary[6] of more developed countries prices have a peak at winter time instead of summer time. The most expensive electricity is used in December at 175.97 TL/MWh. Even January mean price is higher than the summer months. The lowest prices are in Spring time, especially in March with the price of 133.85 TL/MWh. This monthly seasonality shows the effect of the cooling days and heating days in addition to the water effect and the use of cheaper hydroelectric plants in the Spring time (Figure 12).

[6] See Knittel and Roberts (2005)

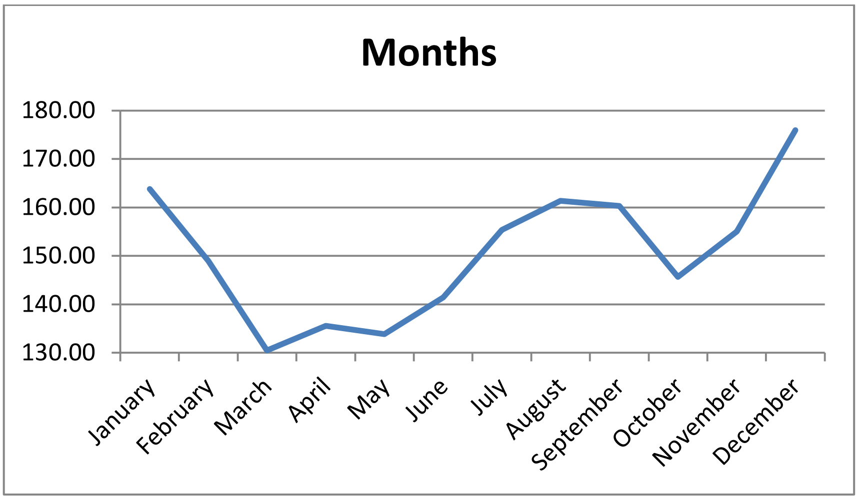

Figure 12 Price Distribution of Hourly Prices (TL/MWh) According to the Months of the Year

Another type of seasonality is seasonality of the years. According to the technological inventions; power plants have higher efficiency rates, hydrolelectric and solar energy has started to play an important role in electricity generation. Therefore there is a decreasing trend in the electricity prices[7]. However; due to the high temperatures and low rainfalls, 2014 prices do not show the regular trend (Figure 13).

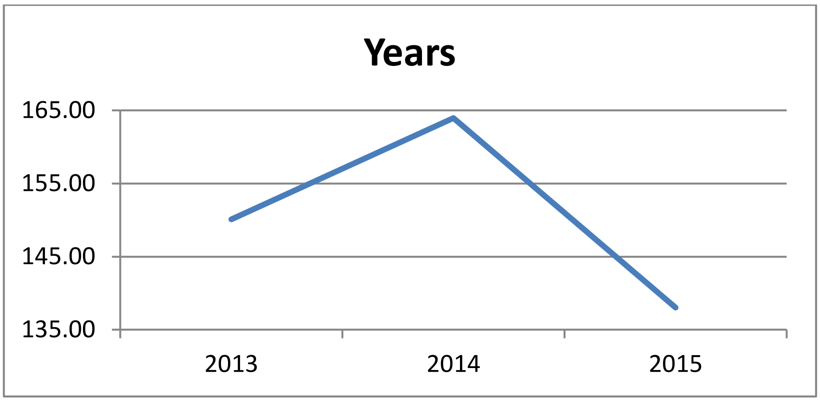

Figure 13 Price Distribution of Hourly Prices (TL/MWh) According to the Years

All the national holidays are taken as holiday days and there is a 31.14 TL/MWh difference between the means of normal and holiday days (Figure 14).

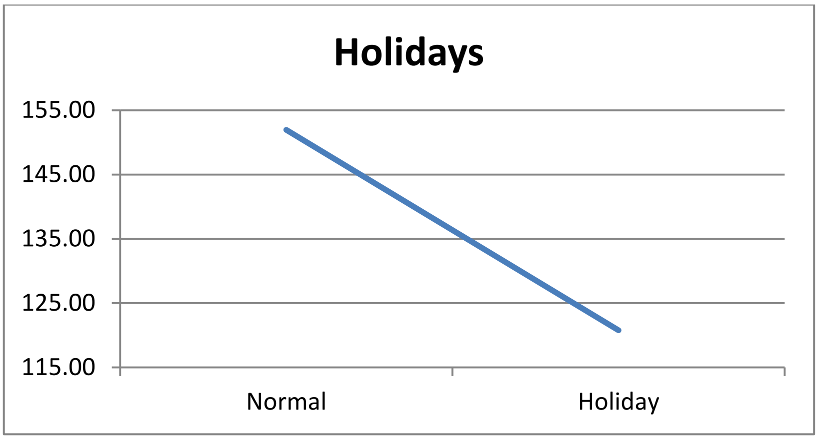

Figure 14 Price Distribution of Hourly Prices (TL/MWh) According to the Holidays

[7] This is also proved by the data of the first 5 months of 2016. Decreasing trend is expected to continue in following years.

A Uni-ANOVA process is implemented to the data and the parameter estimates of the days of the month, months, years, weekdays, holiday and hours can be found in Appendix part.

Figure 15 shows the mentioned effect of pre-whitening that resids are more stationary and capture the movement of the prices.

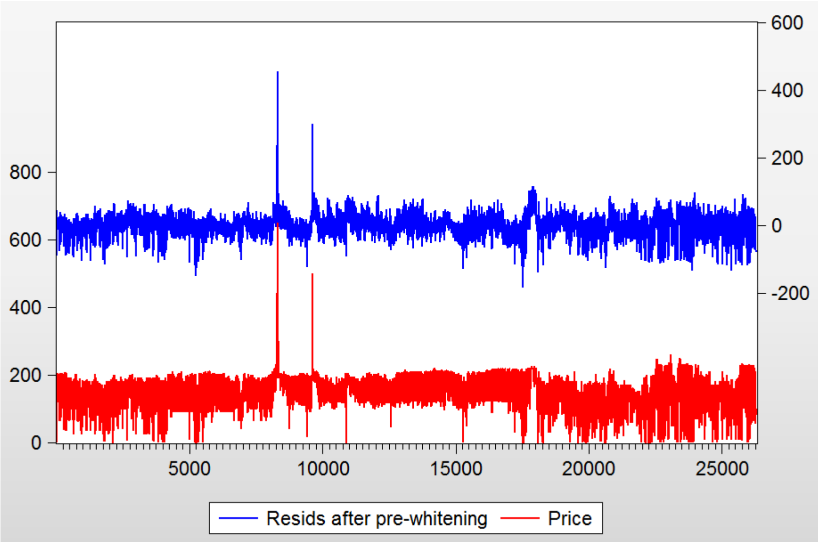

Figure 15 Prices and Resids after Pre-whitening for 2013-2015

Figure 16-21 illustrate the capturing ability of the pre-whitening. Blue graphs show the prices on the left axis and the red graphs show the parameters after pre-whitening on the right axis. Figure 9-14 represent the situation for hours, weekdays, days of the month, months, years and holidays, respectively. Red graphs are drawn by using the parameter estimates from Table A-1 for each and every time interval. As it is observed in the graphs, Uni-ANOVA process captures the deterministic seasonality quite successfully.

Figure 16 Prices and Parameters after Pre-whitening According to the Hours of the Day

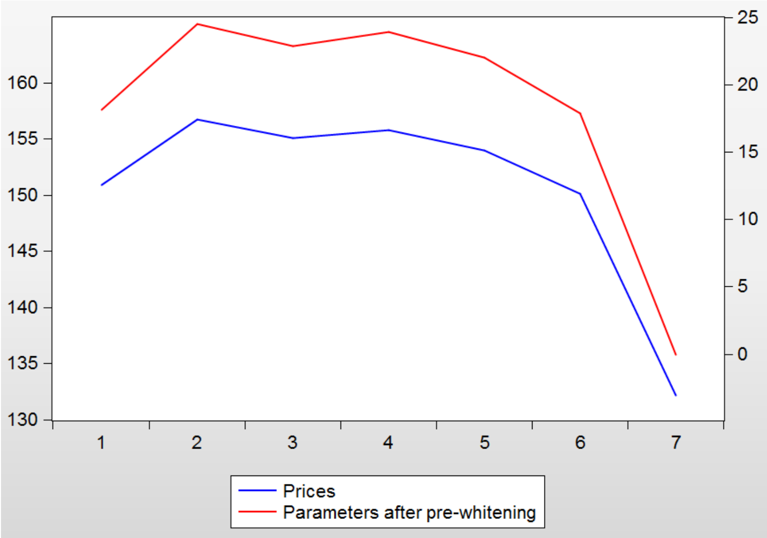

Figure 17 Prices and Parameters after Pre-whitening According to the Weekdays (1 shows Monday)

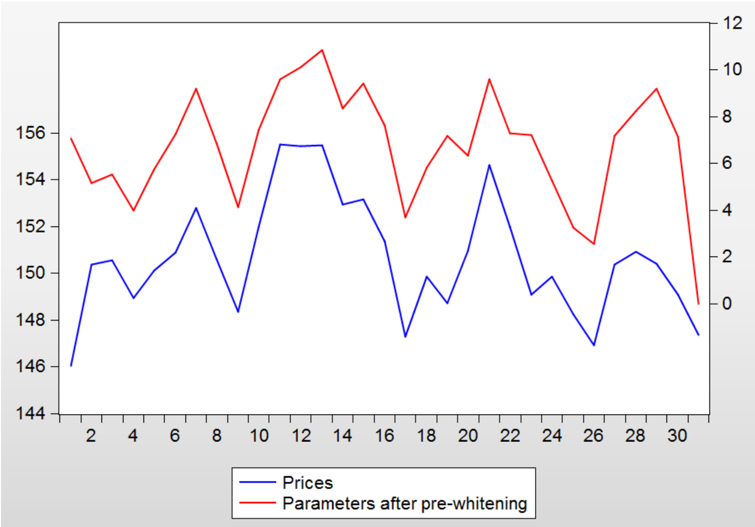

Figure 18 Prices and Parameters after Pre-whitening According to the Days of the Month

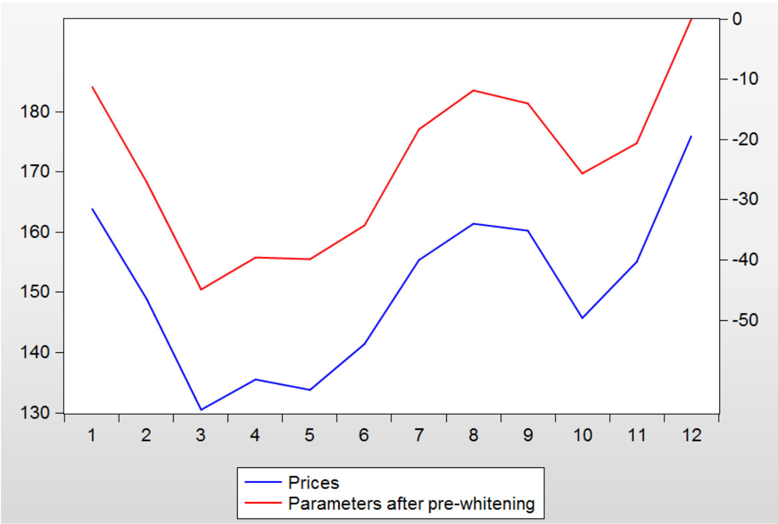

Figure 19 Prices and Parameters after Pre-whitening According to the Months of the Year (1 shows January)

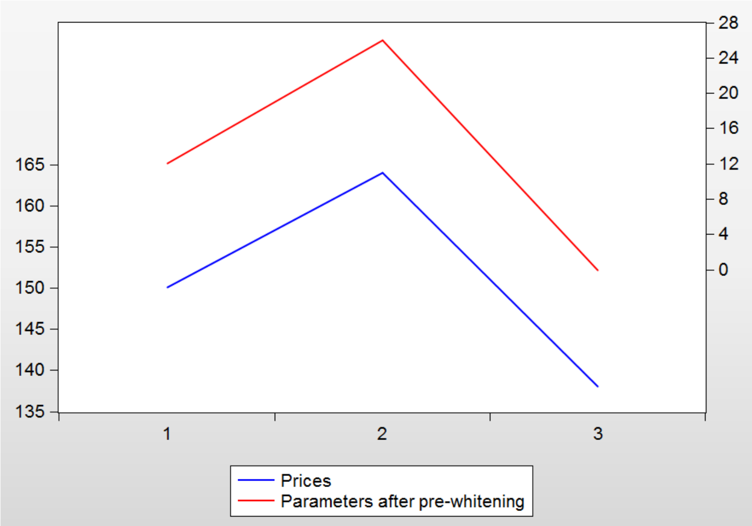

Figure 20 Prices and Parameters after Pre-whitening According to the Years 2013-2015 (1 shows 2013)

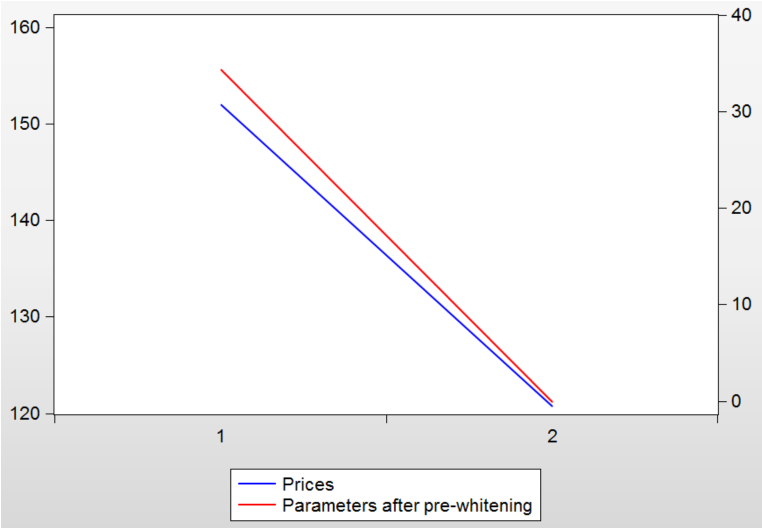

Figure 21 Prices and Parameters after Pre-whitening According to the Holidays (1 shows a normal day)

Table 2 shows the descriptive statistics of the residuals after the pre-whitening process. Mean of the residuals are 0 and the standard deviation is 28.44. It is a little right-skewed and the kurtosis increased to 10.05[8]. Moreover, Figure 22 illustrates the histogram of the residuals. This processed data, which does not have the deterministic seasonality, is much more available for the forecast of electricity prices.

Table 3 Descriptive Statistics of the Hourly Electricity Price Residuals after Pre-whitening for 2013-2015

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Residual for PRICE	26280	-184,09	452,86	,0000	28,44407	,310	,015	10,050	,030
Valid N (listwise)	26280								

[8] Due to the pre-whitening process, prices tend to gather around the price 0. This process takes into account all the seasonality effects and forms the residuals according to these effects. Therefore the frequency around the mean of 0 is much higher than the frequency of the original prices around the mean. Additionally, all the observations get closer to the mean due to the removing of the deterministic seasonality. For this reason, kurtosis increases in the price residuals.

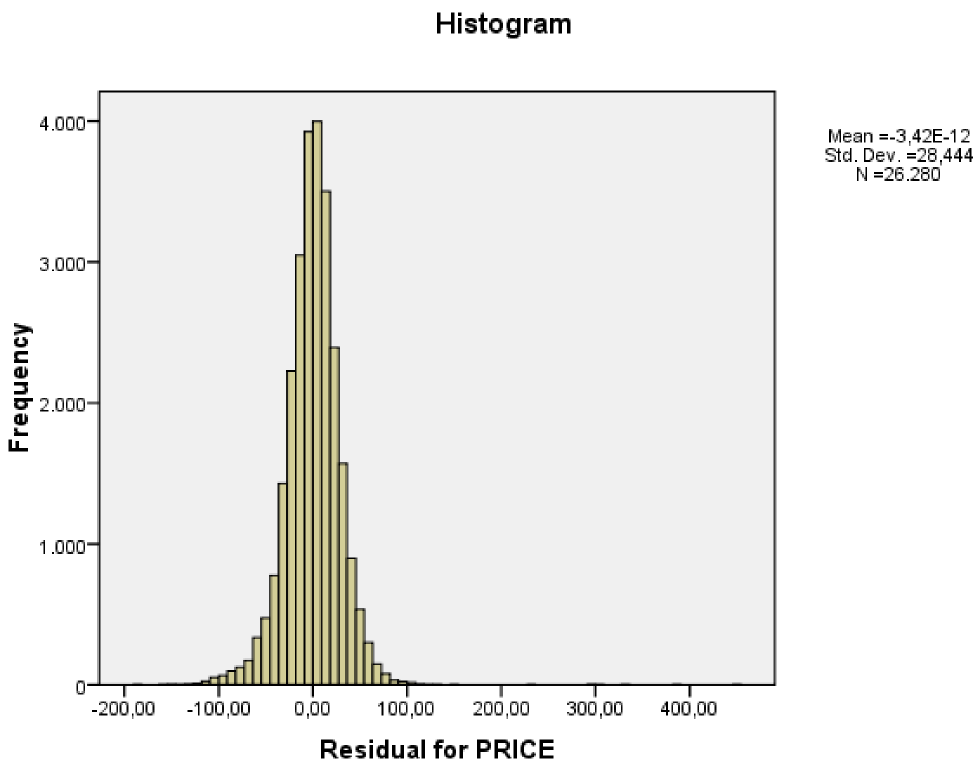

Figure 22 Histogram of the Hourly Electricity Price Residuals after Pre-whitening for 2013-2015

After the execution of the Uni-ANOVA process the price series become stationary (Table 4). It is possible to use this stationary series to forecast the hourly electricity prices by using the residuals.

Table 4 ADF Unit Root Test of Residuals Electricity Prices for 2013-2015

Null Hypothesis: RES has a unit root
Exogenous: None
Lag Length: 48 (Automatic - based on AIC, maxlag=48)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.32292	0.0000
Test critical values:	1% level	-2.565050	
	5% level	-1.940836	
	10% level	-1.616692	

*MacKinnon (1996) one-sided p-values.

5. Conclusions

Electricity prices have many extraordinary characteristics such as seasonality, high volatility, sharp price spikes and mean reverting processes. Therefore it is much more difficult to forecast electricity prices compared to other commodities. Especially seasonality has a tremendous effect on the electricity prices. The effect of seasonality is in various frequencies; such as hourly, daily, monthly and yearly. Furthermore, seasonality can be categorized under two titles: stochastic seasonality and deterministic seasonality.

Seasonality complicates the forecasting of the electricity prices. Time series of the electricity data become unstationary due to the seasonal movements in various frequencies. The main problem is that it is impossible to take the logarithm or the first difference of the series due to the zeros in the data. Hence, Uni-ANOVA method is applied as a pre-whitening method in this paper to have the stationary series of residuals in the hourly electricity price data. Then, it is possible to perform a forecast by using these stationary residuals.

Furthermore, this paper gives a detailed analysis of the seasonality effect on the hourly Turkish electricity market data in terms of hours, weekdays, days of the month, months, years and holidays. Moreover, it takes outliers into account and split them into the positive and negative outliers and categorize them according to time frequency. Additionally, it also shows that the pre-whitening method captures deterministic seasonality successfully for all the time frequencies. It should be kept in mind that the stochastic seasonality still stands in the data.

As a future work, by using a forecast method such as regression or ARIMA, this stochastic seasonality can also be removed from the data. These electricity price forecasts would also give the opportunity of pricing derivatives such as forward contracts or options.

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Appendix

Table A-1 shows the parameter estimates according to the pre-whitening for days of the month, months, years, weekdays, holidays and hours. Table A-2 explains how these parameters will be used for a specific hour. PTF (TL/MWh) shows the actual prices and all the known information such as days of the month, months, years, weekdays, holidays and hours let us calculate the unstandardized part. When we subtract the unstandardized part from the actual price we have the resids. It is possible to use these resids, which are stationary, for forecasting.

Table A-1 Parameter Estimates According to the Pre-whitening[9]

Parameter	B	Parameter	B	Parameter	B
Intercept	101,700				
[DAY=1]	7,076	[MONTH=1]	-11,290	[TIME=0:00]	1,811
[DAY=2]	5,159	[MONTH=2]	-27,030	[TIME=1:00]	-13,814
[DAY=3]	5,519	[MONTH=3]	-44,859	[TIME=2:00]	-30,491
[DAY=4]	3,971	[MONTH=4]	-39,600	[TIME=3:00]	-43,069
[DAY=5]	5,730	[MONTH=5]	-39,834	[TIME=4:00]	-45,508
[DAY=6]	7,245	[MONTH=6]	-34,226	[TIME=5:00]	-45,228
[DAY=7]	9,192	[MONTH=7]	-18,315	[TIME=6:00]	-41,349
[DAY=8]	6,849	[MONTH=8]	-11,799	[TIME=7:00]	-19,411
[DAY=9]	4,116	[MONTH=9]	-14,007	[TIME=8:00]	11,515
[DAY=10]	7,426	[MONTH=10]	-25,582	[TIME=9:00]	26,578
[DAY=11]	9,595	[MONTH=11]	-20,624	[TIME=10:00]	30,348
[DAY=12]	10,111	[MONTH=12]	0[a]	[TIME=11:00]	32,985
[DAY=13]	10,852	[YEAR=2013]	12,076	[TIME=12:00]	21,410
[DAY=14]	8,366	[YEAR=2014]	25,974	[TIME=13:00]	26,062
[DAY=15]	9,407	[YEAR=2015]	0[a]	[TIME=14:00]	28,321
[DAY=16]	7,603	[WEEKDAY=1]	18,151	[TIME=15:00]	23,866
[DAY=17]	3,678	[WEEKDAY=2]	24,514	[TIME=16:00]	22,376
[DAY=18]	5,823	[WEEKDAY=3]	22,886	[TIME=17:00]	16,155
[DAY=19]	7,191	[WEEKDAY=4]	23,917	[TIME=18:00]	10,510
[DAY=20]	6,342	[WEEKDAY=5]	22,029	[TIME=19:00]	8,799
[DAY=21]	9,594	[WEEKDAY=6]	17,905	[TIME=20:00]	8,764
[DAY=22]	7,273	[WEEKDAY=7]	0[a]	[TIME=21:00]	3,770
[DAY=23]	7,202	[HOLIDAY=0]	34,318	[TIME=22:00]	11,944
[DAY=24]	5,268	[HOLIDAY=1]	0[a]	[TIME=23:00]	0[a]
[DAY=25]	3,253				
[DAY=26]	2,549				
[DAY=27]	7,181				
[DAY=28]	8,245				
[DAY=29]	9,181				
[DAY=30]	7,152				
[DAY=31]	0[a]				
a. This parameter is set to zero because it is redundant.					

[9] This Uni-Anova process has the R^2 of 0.564

Table A-2 An Example of the Use of Pre-whitening Estimates

Time	PTF (TL/MWh)	Day of the month	Month	Year	Hour	Weekday	Holiday	Price	Unstd.	Res.
01012013	145	1	1	2013	00:00	2	1	145	135.89	9.11
02012013	184.79	2	1	2013	14:00	3	0	184.79	193.17	-8.38

01012013 00:00	Unstd= Intercept + First Day of the Month + January + 2013 + 00:00 + Tuesday + Holiday	
	Unstd= 101.700 +7.076 -11.290 +12.076 +1.811 +24.514 +0 = 135.887	
	Res= Price-Unstd	Res= 145.00 -135.89 = 9.11

02012013 14:00	Unstd= Intercept + Second Day of the Month + January + 2013 + 14:00 + Wednesday + Normal	
	Unstd= 101.700 + 5.159 -11.290 +12.076 + 28.321 + 22.886 +34.318	
	Res= Price-Unstd	Res= 184.79 -193.17 = -8.38

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