Analysis of Electricity Price In The Turkish Domestic Energy Market

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Abstract

Market participants across the variable electricity prices seek new ways to give an idea for operation planning in the future. Since the day-ahead market regulation met with Turkey's electricity market in 2011, electricity price forecasting has become a significant issue. Uncertainty in electricity prices caused investors to see pricing as a risk of economic loss. Therefore, the number of active participants in the market fell to about 60%. This paper aims to fit electricity price behavior to a statistical distribution in order to help market participants. We used a couple of statistical distribution functions in this study to determine electricity price behavior. The historical electricity price data were obtained from the website of PMUM, which consisted of hourly prices. Analyses were carried out for different intraday demand levels in different periods. The results indicated that the electricity price behavior best fits the GEV distribution in long-term analysis.

1. Introduction

In 2009, a new electricity market structure called day-ahead planning was founded in Turkey. Market investors were required to join this new market. Accordingly, training regarding the new structure was provided to various groups of market participants at different times and places. The training was designed to facilitate the transition to day-ahead market structures. Thus, the market participants would be ready for the day-ahead market, and they would be able to adapt quickly. Moreover, the balancing power market helped day-ahead planning to balance its system in the case of encountering a power surplus or power failure in real time. The balancing power market is still being used in Turkey's electricity market.

In 2011, the day-ahead market began to be implemented in Turkey's electricity market. This market is different from day-ahead planning in terms of willingness to participate. The other important difference is the demand side arranging the load consumption by price level in order to avoid economic losses. In this market structure, market power producers can receive power support from other producers if the cost of owning plants is greater than their own production rate. That is to say that one producer may owe another one. As an additional novelty compared to day-ahead planning, the intraday debts are paid the next day, which solves the cash shortage problems for market participants.

Despite all these innovations, participation in the market remains to a certain extent. Because of the price uncertainty, investors do not want to take risks for future operation planning. Consequently, the market needs reference prices to give way to participation. Many studies deal with short- and long-term electricity price forecasting in order to present a reference price or give an idea to investors for operation planning.

Due to various factors affecting electricity prices, it is very hard to make an accurate price forecast, especially when given unexpected generation outages or sudden load reductions or increases, which cause uncertainty in electricity prices. This electricity price uncertainty is described and presented in different studies in detail [1–6]. Next-day price forecasting using Artificial Neural Network has been proposed in [1,2]. Several statistical models[3] are used to predict electricity prices. Statistical and graphical analyses of electricity prices for Singapore's market are presented in[4,5]. Statistical analyses of electricity price forecasting methods are reviewed in [6].

This paper presents a statistical approach to Turkey's electricity market participants, especially for investors hesitant to join the market. Several statistical distributions were used to investigate whether the actual electricity price data fit any statistical representation, and the root mean square error (RMSE) values were calculated to make comparisons. The actual data were obtained from the website of the Market Financial Reconciliation Center (PMUM) [7], and analyses were carried out for different load levels throughout the day at different intervals, including annual and seasonal. It should be emphasized that the price behavior may vary from one market to another. Hence, different statistical functions may be used for the analyses to find the best fit. In this study, the analyses were performed for the electricity market in Turkey.

This paper is organized as follows: The Turkish electricity market structure and the next-day price determination details are given in Section 2. Section 3 details the analyses of electricity prices conducted to describe the favorable statistical representation of price behavior. The results of the analyses and conclusions are presented in Section 4.

2. Day-Ahead Electricity Market in Turkey

The day-ahead electricity market was first introduced in Turkey on December 1, 2011. With the establishment of the day-ahead market, Turkey's electricity market gained a new dynamism and vision. Also, the market's competitive spirit was first formed. It brought a lot of innovation to the market such as voluntary participation, adjusting the load demand by the price level, and doing the financial reconciliation the next day.

Offers in this market are under three headings: hourly, block, and flexible. The participants must send the next-day offers by 11:30 a.m., and the offers must be between 0 and 2000 TL/MWh. The offers are evaluated by an optimization tool between at 12:00 and 1:00 p.m., and the next-day hourly prices announced at 2:00 p.m.

Firstly, the optimization tool takes into account the hourly offers while determining the next-day hourly prices and then considers, respectively, the block and flexible offers. After these operations, the supply-demand curve is formed for every hour of the next day. At the intersection of the supply-demand curve, market clearing price (PTF) is determined and announced for market participants. Also, the PTF values are published on the Internet for the public.

In this study, the PTF values in 2014 were obtained from the related website and the prices were separated as seasonal and annual. Summer was selected for seasonal analysis.

Fig. 1 shows the variation of the hourly mean PTF value in 2014 for the two periods. The hourly mean prices are similar for each period. The prices are low at night because of low load demand; otherwise, the prices are high at noon because of high load demand.

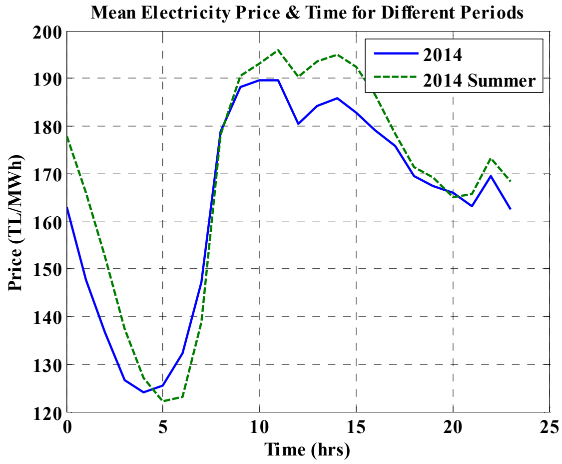

Fig. 1. Plot of hourly mean electricity price for different periods

Fig. 2 shows the electricity price at 8:00 a.m. for the year 2014. It shows that the price varies by days of the week. On weekdays, the prices are usually high in comparison with the weekends. Another factor is whether the price value is affected by holidays or not. During the holidays, people consume less power, and some companies may have a break or slow their production, which causes lower power consumption. Thus, the prices are low during this period due to low demand. These impacts are clearly seen in Fig. 2.

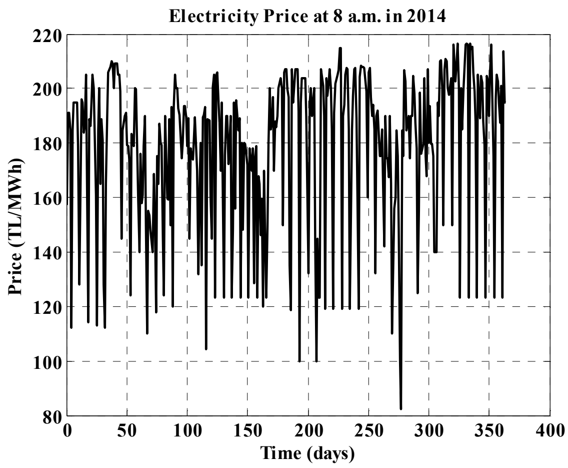

Fig. 2. Plot of electricity price at 8:00 a.m. for the year 2014

In Fig. 3, the estimated load demand is given at 8:00 a.m. for the year 2014. Because the electricity price is directly proportional to load demand, Fig. 2 and Fig. 3 are similar.

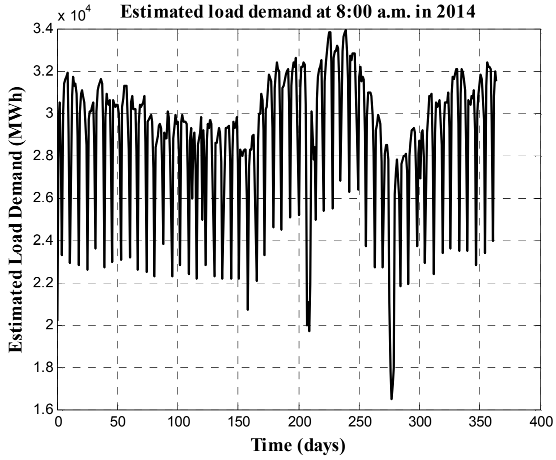

Fig. 3. Plot of estimated load demand at 8:00 a.m. for the year 2014

3. Analysis of Electricity Price Behavior

When examined, the hourly electricity prices obtained from the historical data are in between certain values except for the extreme ones. But these values are variable depending on the period length. If the price distribution indicates a particular characteristic, it can be analyzed statistically, and the price behavior may be represented as a particular statistical distribution that uses the mean and standard deviation parameters. These parameters can be calculated by using the historical price data.

For that purpose, the electricity price in Turkey's market is analyzed. The historical market clearing price data were obtained for different periods and the analyses were carried out for different load levels. The RMSE values between the actual price histogram and the fitting density functions of distributions are compared. All analyses were performed by using MATLAB and Microsoft Excel; the MATLAB Distribution Fitting Tool was especially helpful [8].

The price data histogram at 8:00 a.m. for the summer of 2014 and the entire year of 2014 are shown in Fig. 4.

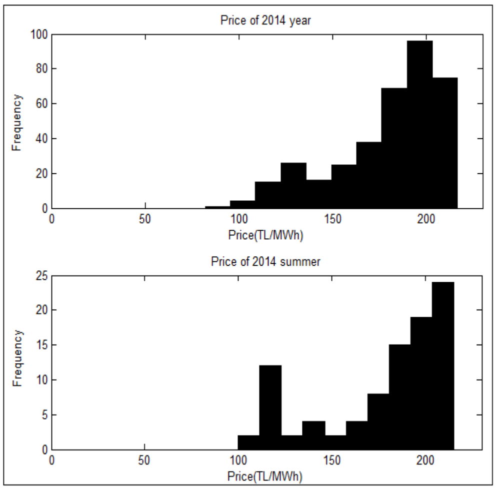

Fig. 4. Plot of electricity price distributions for different periods

The two distributions have a range of extreme values, and each period has different numbers of data samples such as 365 samples for the entire year of 2014 and 92 samples for the summer of 2014. However, in percentages, 86.57% of the price data for the entire year of 2014 and 81.52% of price data for the summer of 2014 are between 140 TL/MWh and 220 TL/MWh. These percentages show that the price behavior for the entire year of 2014 is more decisive. The results make the validity of the long-term analysis possible.

Also, the analyses were carried out for different intraday times such as 1:00 p.m. and 7:00 p.m., but the results are similar to each other. Annual price data are more useful for analyses and more helpful for getting an idea about the price behavior.

Although there are many different types of statistical distribution, this paper focuses on three of them that fit most closely to the actual price data in comparison to others. Generalized extreme value(GEV), Logistic, and Weibull distributions were used in this study. The probability density functions of the aforementioned are described by the following equations:

Generalized extreme value:

$$f(x;\mu,\sigma,\xi) = \frac{1}{\sigma}\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{\left(-\frac{1}{\xi}\right)-1} \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\} \tag{1}$$

where $\mu, v,$ and ξ are, respectively, the location, scale, and shape parameters. The quantity x is expressed as follows:

$$\begin{cases} x \in [\mu - \sigma/\xi, +\infty) \text{ when } \xi > 0 \\ x \in (-\infty, +\infty) \text{ when } \xi = 0 \\ x \in (-\infty, \mu - \sigma/\xi] \text{ when } \xi < 0 \end{cases} \tag{2}$$

Logistic:

$$f(x;\mu,s) = \frac{e^{-\frac{x-\mu}{s}}}{s\left(1+e^{-\frac{x-\mu}{s}}\right)^2}, x \in (-\infty,+\infty) \tag{3}$$

where μ, and s are, respectively, the location and scale parameters.

Weibull:

$$f(x;\gamma,\theta) = \frac{\gamma}{\theta} x^{\gamma-1} e^{-x^{\gamma}/\theta}, x \in (0,+\infty) \tag{4}$$

where γ, and θ are, respectively, the scale and shape parameters.

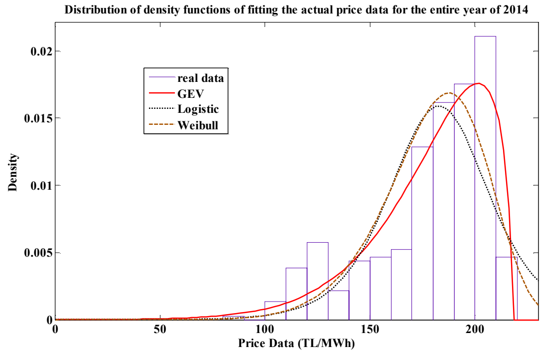

Fig. 5. Distribution of density functions fitting the actual price data for the entire year of 2014

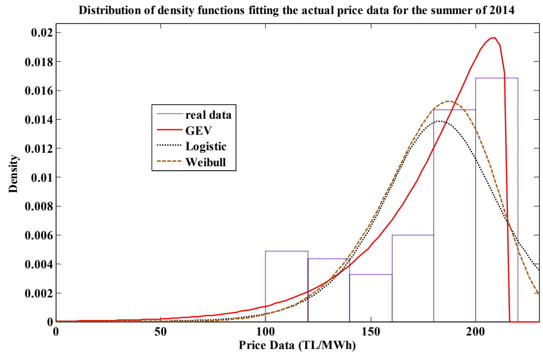

Fig. 6. Distribution of density functions fitting the actual price data for the summer of 2014

The density functions of these distributions with the price data histogram are shown in Figs. 5 and 6 for the different periods of data. The GEV distribution fits the best to the actual price histogram. Moreover, the calculated RMSE values in Table1 support the graphical analysis. The RMSE value is the smallest in the GEV distribution function for the entire year of 2014. If the extreme values are filtered, the results of analyses fit better.

Table 1. The RMSE results of the fitting equations

Distribution function	2014 year	2014 summer
GEV	0.00275	0.0214
Logistic	0.00419	0.0241
Weibull	0.00373	0.0234

If the density functions of distributions are examined, one can interpret that the rise and fall sides of the GEV distribution resemble the actual price data histogram. The same inferences can be made for the probability plot of distributions in Figs. 7 and 8. Even though some of the data are outside of the line, the best fit is seen in the GEV distribution in comparison to others. Also, one can see in the figure that the GEV distribution for the entire year of 2014 follows the price data much better than the other fittings.

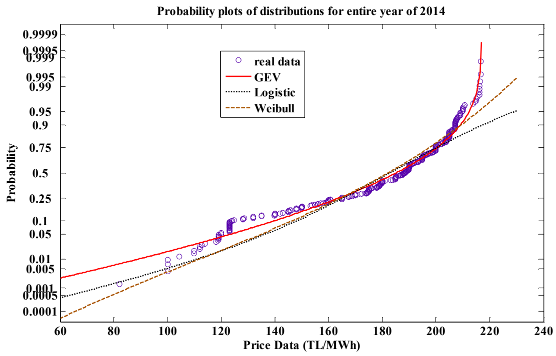

Fig. 7. Probability plots of distributions for entire year of 2014

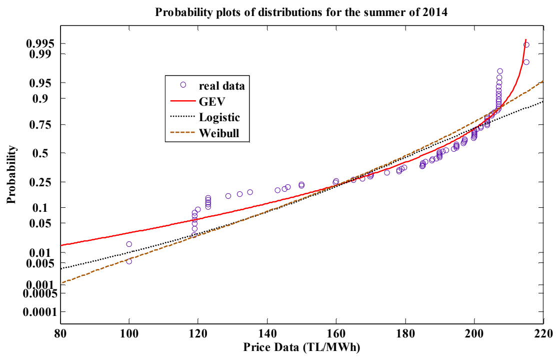

Fig. 8. Probability plots of distributions for the summer of 2014

4. Conclusions

After the day-ahead market was implemented in Turkey, the electricity market began to turn into a competitive structure. That was the solution to the economic loss problems for the consumer side, which was a positive impact; on the other hand, the participation in the market stayed at low levels, which was a negative impact. Because of the uncertainty of the prices, investors hesitated to participate in the market.

For the purpose of helpfulness to investors, this study investigated whether the electricity prices are represented probabilistically. Three types of distributions, namely generalized extreme value, Logistic, and Weibull distributions were analyzed for different times throughout the day in the long and short-term. Not all distributions fully fit with actual price data, but the GEV distribution adapted much better in comparison with other distributions. Also, the numeric analyses demonstrated that the RMSE value for GEV distribution is minimal in the long-term.

The results indicate that the electricity price behavior in a market can be forecasted by using statistical distributions that use the historical price data for fitting. In this context, this paper helps the investors to prudential system operation planning and risk estimation. Thus, the participation in the market can be increased.

5. References

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