Applied Energy 193 (2017) 287–296

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Forecasting electricity demand for Turkey: Modeling periodic variations and demand segregation

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HIGHLIGHTS

- We include the modulation of daily and weekly variations by seasonal harmonics.
- We forecast demand without physical parameters involved.
- We forecasted the demand 1-week and 1-day horizons with %3 MAPE.
- We propose a method to estimate the share of industrial electricity in total demand.
- We use special days, holidays and exceptional events to segregate demand.

ARTICLE INFO

Article history:
Received 29 September 2016
Received in revised form 3 February 2017
Accepted 18 February 2017
Available online 24 February 2017

Keywords:
Time series analysis
Fourier series
Electricity demand for Turkey
Demand segregation
Load forecast

ABSTRACT

In deregulated electricity markets the independent system operator (ISO) oversees the power system and manages the supply and demand balancing process. In a typical day the ISO announces the electricity demand forecast for the next day and gives participants an option to prepare offers to meet the demand. In order to have a reliable power system and successful market operation, it is crucial to estimate the electricity demand accurately. In this paper, we develop an hourly demand forecasting method on annual, weekly and daily horizons, using a linear model that takes into account the harmonics of these variations and the modulation of diurnal periodic variations by seasonal variations. The electricity demand exhibits cyclic behavior with different seasonal characteristics. Our model is based solely on sinusoidal variations and predicts hourly variations, without using any climatic or econometric information. The method is applied to the Turkish power market on data for the period 2012–2014 and predicts the demand over daily and weekly horizons within a 3% error margin in the Mean Absolute Percentage Error (MAPE) norm. We also discuss the week day/weekend/holiday consumption profiles to infer the proportion of industrial and domestic electricity consumption.

1. Introduction

"Poolco" is one of the main market competition structures used in deregulated markets [1]. Trading platforms such as the "day-ahead market", "balancing market" and "intra-day market" are developed to increase the functionality and success of the market mechanism.

The demand forecast has always played an important role in capacity and transmission planning, generation scheduling and pricing. However, the deregulation and privatization of the power markets increased the importance of demand or load forecasting since the success of the markets is highly related to their accuracy.

The demand forecast has different aspects at different forecast horizons. For example, for capacity planning one needs a long term forecast of aggregate demand as a function of economic or demographic parameters. On the other hand, short term (hourly) forecasts are essential for the efficiency of day-ahead markets. Short term variations have a "regular" component depending on daily routines and seasonal effects. Exceptional conditions (extreme weather conditions) and exceptional events (holidays, sports events) cause "irregular" variations that affect and modify this pattern. It is an interesting and challenging problem to forecast the "regular" component of the hourly demand for the planning of the day-ahead market over a long term i.e., year-long horizon. The model that we develop in this paper is based solely on sinusoidal variations and predicts hourly variations over a 1-year horizon, within a 3% Mean Absolute Percentage Error (MAPE),

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http://dx.doi.org/10.1016/j.apenergy.2017.02.054

without using any climatic or econometric information. The incorporation of the irregular variations to this model will be the subject of ongoing work. These irregular variations fall into "predictable" and "unpredictable" categories. The predictable variations are changes in the demand patterns that are tied to predictable natural or social events and they can be included in the basic model as a new set of regressors. Unpredictable irregular variations are changes in the demand that are of yet unknown origin and they have to be treated with special methods, such as the "feedback" method used in Bilge and Tulunay [2] or time series and stochastic approaches reviewed below.

In the literature, descriptions and comparisons of various forecast methods have been presented by a number of researchers. Linear models, Time Series Methods such as ARMA and ARIMA, statistical models and other numerical methods like Artificial Neural Networks (ANN), Genetic Algorithms (GA), Support Vector Machines (SVM) and Particle Swarm Optimization are common approaches that are used for electric demand forecasting.

Dyner and Larsen present an analysis for the liberalization of electricity markets and discuss the usability of "agent modeling", "simulation", "game theory" and "risk management" for taking into account stochastic characteristics of load and demand [3]. Anand and Suganthi present a review of energy demand forecasting models, discussing traditional methods such as "time series", "regression", ARIMA and new methods such as "Support Vector Machines", "Ant Colony" and "Particle Swarm Optimization" [4]. Hahn et al. present a survey of electricity load forecasting methods and tools for decision making [5]. Conejo et al. compare "time series analysis", "neural networks" and "wavelets" for electricity demand forecasting in the market. They conclude that time series methods provide more accurate results for short term forecasting [6].

Regression methods that are quite convenient and easy to implement have been applied widely for electricity demand forecasting. Vilar et al. use a "nonparametric regression" technique to forecast the next-day electricity demand and price with a semi-functional partial linear model. Their model is applied to Spanish data and the results are compared with that of "naïve" and "ARIMA" methods [7]. Taylor uses statistical forecasting methods for short term electricity demand forecasting. He extends the three double seasonal methods in order to accommodate the intra-year seasonal cycle and applies the method to six years of British and French data [8]. Clements et al., show that a multiple equation time-series model can forecast the load as accurately as complex nonlinear and nonparametric forecasting models. They apply the method to Australian data and they reach a very low MAPE using an 11-year data set [9]. Fan and Hyndman propose "semi-parametric additive models" to estimate the relationships between demand and inputs such as calendar variables, lagged actual demand observations, and historical and forecast temperature. Their method is applied to the Australian National Electricity Market to forecast half-hour electricity demand for up to one week [10]. Wang et al. use the "PSO optimal Fourier method", the "seasonal ARIMA" model and apply their combinations to the Northwest electricity grid of China for correcting the forecasting results of seasonal ARIMA. Their results show that the prediction accuracy of the combined models is higher than that of the single seasonal ARIMA [11,12]. A "semi-parametric additive regression" model is proposed to estimate the relationships between demand and temperatures, calendar effects and some demographic and economic variables in Hyndman and Fan [10], Fan and Hyndman [13]. Hyndman and Fan then calculate the density forecasts and full probability distributions of the possible future values of the demand while also considering the holidays and weekends. A similar regression approach is proposed in McSharry et al. [14] to analyze the relationship between demand and other variables. The author uses five different exponential smoothing methods to apply the methodology to British and French half-hourly load data in Taylor [15].

The application of time series methods to the forecast of the electricity demand is also popular in the literature. "ARIMA" is preferred mostly for short and long term electricity demand. Future demand is predicted using an ARIMA model and profit function is developed as an objective in Niu et al. [16]. Andersen et al. propose an econometric modeling approach for the long term forecasting of hourly electric consumption in local areas. Data from the Danish market is used for the analysis and the estimated load profiles are used by the transmission operator [17]. Lo and Wu examine local forecast uncertainty: Artificial Neural Networks and ARIMA models are used to calculate the load, highlight high risk in different periods and evaluate daily value at risk [18]. In Chakhchoukh et al. [19] the authors use statistical analysis methods to forecast the short term demand. They compare these methods with classical models like ARIMA and show that the proposed method can outperform the classical ones. The authors develop a multiple linear regression model based on calendar and weather related variables to analyze the relationship between meteorological variables and monthly electricity demand. The method is applied to forecast the electricity demand in Italy and returns promising results [20].

In addition to the basic approaches cited above, based on the problem scope and objective, a number of alternative methods are also proposed in the literature. Zhang and Dong use an "artificial neural network" model and wavelet transformed data together to forecast electricity demand for short periods [21]. Heuristic approaches such as "particle swarm optimization", "evolution algorithms" or hybrid approaches are also used to forecast the electricity demand [22,11,12,23]. Azadeh et al. use "neural networks" and "genetic algorithms" to predict the electrical energy consumption using economic indicators such as price, value added, number of customers and consumption in previous periods. The integrated GA and ANN method returns less (MAPE) when applied to the Iranian electricity market [24]. Pai and Hong propose a method to forecast the electricity load using recurrent Support Vector Machines (SVM) with Genetic Algorithms. They use electricity data from Taiwan and they show that the proposed method outperforms the SVM, neural network and regression models [25]. Wang and Ramsay develop a "neural network" based estimation for electricity spot prices, focusing particularly on weekends and public holidays [26]. A similar approach for electricity demand forecasting with a focus on weekends and public holidays is given in Srinivasan et al. [27].

It is true that the temperature and climate can affect electricity demand, and hence, can be included in the forecasting model. The effect of weather on electricity consumption is studied by Taylor and Buizz, who use weather conditions to forecast short term electricity demand for 1–10 days ahead. Various weather scenarios are included in their models and it is shown that the model that includes weather scenarios returns more accurate results for the short term than the traditional weather forecasts [28]. Felice et al. use statistical modeling to analyze the influence of temperature on load forecasting in Italy both at the national and regional level using unprecedented historical load data [29].

In Crowley and Joutz [30] the authors show that electricity consumption due to increased cooling needs continues even after the high temperatures return to normal due to the heat capacity of the buildings. This shows that the effects of weather conditions on electricity consumption is far from being simple. This is also to show that approaches that can capture the demand pattern without using physical parameters might return better forecasts, as we present in this research. Table 1 provides an overview of methods and resources.

Table 1
Overview of the forecasting methods and related resources.

Methods	Sources
Time series analysis	[10,4,9,16–18]
Statistical methods	[7,8,10–15,19,20]
Surveys	[3–5,10]
artificial neural network and simulation	[21,26,27],
Heuristic approaches	[11,12,22–25]
Temperature based methods	[28–30]

In our case, inclusion of the deviations from comfortable temperatures (heating degree day) and (cooling degree day) brought only a minor improvement to the model, possibly because the modulation regressors had already taken into account the effects of temperature.

As discussed in the following chapters, we also see that irregular holidays or special days have a strong impact on the electricity demand. The effect of holidays on electric power demand and prices has always been a topic of interest. The power companies use time of pricing tariffs for holidays and develop generation and transmission plans considering holiday effects [31,32],. The effect of irregular holidays on electricity demand is taken into account by Braubacher and Wilson in their model for hourly electricity demand, where they replace the data for the holidays with an interpolation of demand for the before and after holiday periods [33].

In this paper, we develop a linear model, as an expansion in Fourier series supplemented with a modulation by seasonal harmonics, in which the workdays and weekends form two nearly independent sets of variations. The model includes harmonics of daily, weekly and seasonal variations and a linear term to take into account the trends. The novelty of the model is the inclusion of the modulation of the high frequency harmonics (daily and weekly variations) by low frequency harmonics (seasonal variations). The method is completely generic and applicable to any load forecasting problem characterized by daily, weekly, and seasonal periods. The model may be supplemented by regressors such as time series for physical parameters (temperature and/or humidity in this case). However, the inclusion of such regressors added only a minor improvement to the results and they were omitted in the present model. We may thus claim that the modulation of diurnal variations by seasonal harmonics captures the essence of the seasonal effects in electricity demand. The daily variation patterns that play a crucial role reflect habits that are usually common to most countries, as work hours and off times are quite similar.

The model can be replicated for any country as it captures periodic variations based on the historical demand data only. Local features of the analysis are the regional and religious holidays. We took advantage of these features for demand segregation, but we interpolated data for these periods, hence we ignored them for prediction and forecast. A similar approach can be adopted in the application of the model to any other country. The next local feature is the weekday-weekend structure, which is taken into account by introducing harmonics of 7 days in the model. In Turkey, the weekend structure is the same as the European zone, but the model works for any country that has a 2 day weekend starting at a different day or even in countries with a 1 day weekend. Applying the model to the Turkish Power market, we were able to model and predict demand within 3% MAPE over a whole year without any climatic information. Here and in any other country, local features such as the low and high demand periods such as for national holidays, elections and competitions could be included in the model to make a better analysis.

In Section 2, we present an overview of the Turkish Power market, the data used for the validation of the model and a discussion of the structure of the daily variation curves and the effect of exceptional events. In Section 3 we present a linear regression model using low and high frequency harmonics and their interaction as modulated waves. In Section 4 we use various schemes for the forecasting of the demand and we present our forecast results for annual, weekly and daily demand within about 3% MAPE. In Section 5, we discuss predictions using these models to estimate the proportion of industrial versus household electricity demand. In Sections 6 and 7, we present the conclusion and suggestions for future directions respectively.

2. Data processing and the Turkish power market

In Turkey, the electric power market used to be state owned and controlled in generation, transmission and distribution until the beginning of the 2000s. The market design started in 2003 by transferring state monopoly rights to private companies for generation, transmission and distribution and by privatizing energy assets. The balance and conciliation phase was launched in 2006 and the participants carried out bidding and bilateral contracts until the end of 2009. The day-ahead planning was built in this year; as a result of the market's development, the day-ahead planning was converted to the day-ahead market in 2011. After successfully implementing the day-ahead market, the system operator established the intra-day market in 2014 under the control of the new market operator, the Market Financial Settlement Centre System (EPIAS).

The main goal of the day-ahead market is to increase the planning accuracy and reliability of the power system on an hourly basis. In the day-ahead market, the system operator announces the estimated day-ahead demand for each hour of the next day. The two parties can determine the power price and delivery conditions and they can have independent bilateral contracts. The total amount of power that will be provided with the bilateral contracts is determined and deducted from the total day ahead demand. Then the remaining power is open to the market to be supplied by competitive and reliable bids. The suppliers submit their hourly capacities and respective prices for the next day as a response to hourly demand forecasts that are announced by EPIAS. This process is called "bidding into market". Having details of generation capacities and price offers, the system operator sorts these on a merit based system. The algorithm stops where the cumulative generation capacities meet the forecasted hourly demand and the day-ahead price for that hour is determined. This price is accepted as the "marginal price" and announced as the "system day-ahead price" for that hour. The process is repeated for 24-h and participants are informed of the final day-ahead generation schedules and market prices.

The generation and demand of electricity possess stochastic features making them hard to estimate accurately in a typical day. The "balancing market (real time market)" is planned to manage such unexpected circumstances in both demand and generation. It is also possible that a market participant needs to adjust its supply and/or demand offer during a day. The "intra-day market" is designed for the participants who need to balance their contractual undertakings, generation or consumption plans. Another objective of the intra-day market is to decrease the imbalance in the system and to provide an alternative electricity purchase/sale option for the market participants. Hence, companies are able to provide additional generation capacity or decrease their excess generation for every hour.

The hourly demand data for the whole country is provided by the system operator in the EPIAS system. The data includes market prices, hourly imbalances and other related information without any demand or region segregation. We used data for the years 2012–2014 and we modeled the "finalized generation plan" section of this data.

In Fig. 1, we present an overview of the data for the years 2012–2014, after correcting for switching to daylight saving time. In these figures, the low-demand periods correspond to two religious holidays of durations 3 and 4 days respectively. These holidays are determined according to the lunar calendar and they are shifted back by 10 days each year. In day ahead forecasts using modulated Fourier expansions, these days will be treated as exceptional events and they will be replaced by appropriate averages. On the other hand, the demand data for these periods will be used for estimating the share of household and industrial electricity consumption, because it is known that most factories stop working in these days.

In Fig. 2 we present typical 4-week periods in winter and in summer, where we see that not only the amplitude but also the shape of the periodic variations for weekdays, weekends, summer and winter are different. For example, the intraday peak shifts to the afternoon in winter.

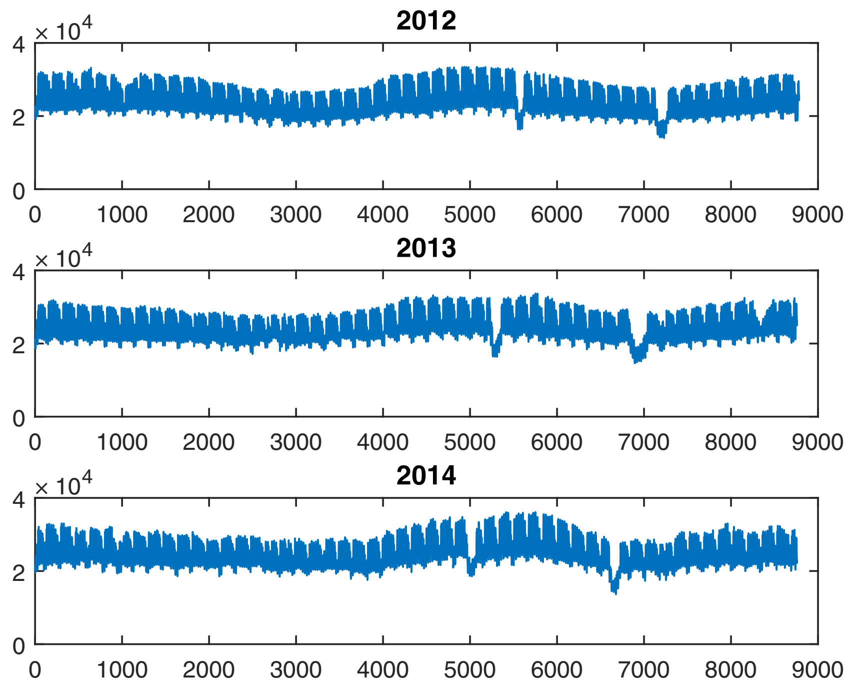

Fig. 1. Overview of the data after adjustment for daylight saving time. The low demand periods correspond to religious holidays.

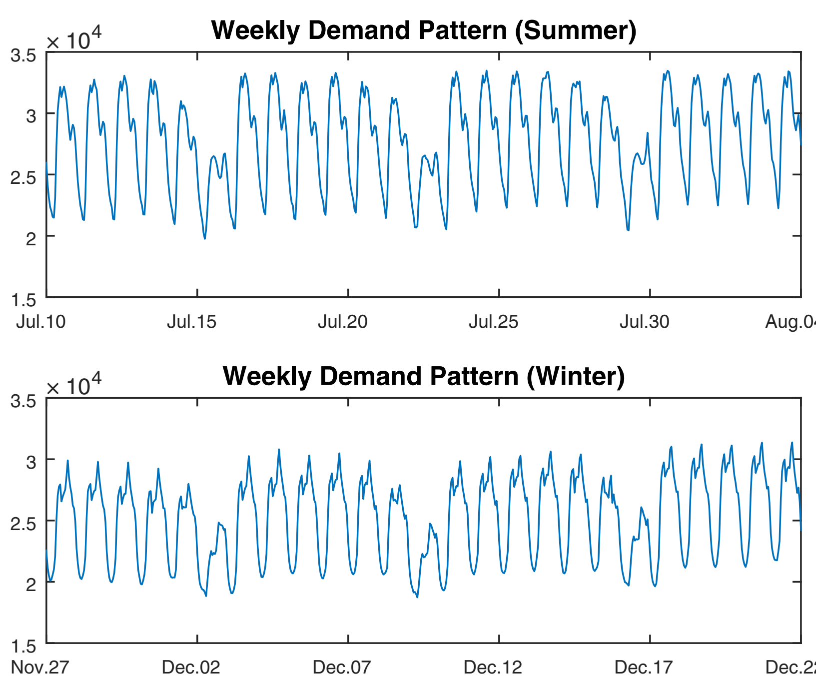

Fig. 2. Typical hourly demand data, for winter and summer for the year 2002.

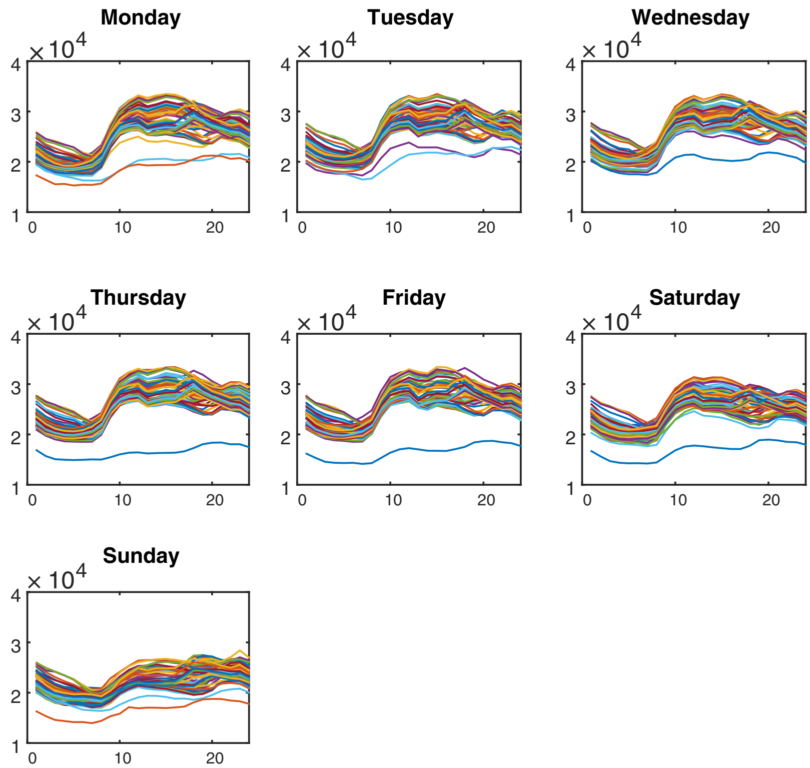

Fig. 3. Daily variation curves for electricity demand in the year 2012.

Fig. 3 shows the demand patterns for each day of the week for the year 2012. We note that except for Sunday, the curves have similar shapes. The demand profile for Saturday is similar to weekdays but it has lower amplitude. The days that have significantly lower demand correspond to January 1st and to the religious holidays as the demand decreases on these days. Moreover, the maximum demand values for graphs of Saturdays and Fridays correspond to the fourth week of July, which were the warmest days in 2012. In fact, this week's temperature was recorded as the warmest week since 1927 showing the effect of the temperature on the demand.

This preliminary analysis shows the importance of knowledge of local characteristics on the demand pattern. The work habits and work hours are usually similar throughout the world. The length of the days is different though. Once the demand pattern is identified and historical demand data is used, the model can be successfully replicated.

3. Modeling of periodic variations

A glance at the data as displayed in Figs. 1 and 2, shows that weekdays and weekends seem to form two independent sets of variations. At all times, diurnal variations are superimposed on seasonal variations, furthermore, diurnal variations have higher amplitudes in winter and in summer. In this section, we model the weekend effects and the modulation by seasonal variations using a standard linear regression model. The regressors are hourly samples of sinusoidal functions expressed as column vectors [34,35],. We denote the harmonics of sinusoidal functions with periods of 1 year (365×24 h), 1 week (7×24 h) and 1 day (24 h) respectively by X_i, Z_k, and Y_j. The modulation of the high frequency variations (Y_j) by the low frequency variation (X_i) is included by the component wise product of the corresponding vectors, denoted as X_iY_j respectively. The hourly electricity demand is denoted by S. These regressors are arranged as the columns of a matrix F, and the coefficient vector $\boldsymbol{a}$ and model vector $\boldsymbol{y}$ are calculated as below.

$$F = [X_iZ_kY_j \quad X_iY_j] \tag{1}$$

$$a = (F^tF)^{-1}F^tS \tag{2}$$

$$y = Fa \tag{3}$$

A linear trend is also added as a regressor but as its effect is minor it is not shown above. The model includes harmonics of sinusoidal variations of periods of 24 h (Y_i), 24×7 h (Z_i) and 24×365 h (X_i). The sampling theorem that states that the highest frequency that can be recovered from data sampled at Δt time intervals has period $2\Delta t$, limits the harmonics Y_i to sinusoidal functions with periods 24, 24/2 = 12, 24/3 = 8, ...24/12 = 2 h. The number of regressors should be large enough to capture the main features of the data but over-specification should be avoided. The number of harmonics of the weekly and annual variations are chosen by this rule. The model uses 96 time regressors and 160 modulation regressors. The detailed formulations are given in the Appendix.

The "modeling error" is measured by the "Mean Square Error (MSE)" and "Minimum Absolute Percentage Error (MAPE)". If S_h and y_h are the actual demand and the forecasted demand for hour h, they are defined as:

$$MSE = \frac{1}{N}\sum_{h=1}^{N}(y_h - S_h)^2 \tag{4}$$

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{|y_h - S_h|}{S_h} \tag{5}$$

where N is the total number of data items. In Fig. 4 we present the results of the proposed model in terms of the harmonics of the annual, diurnal and weekly variations and the modulation of the diurnal and weekly variations by seasonal harmonics for the year 2012. This model is quite satisfactory and shows the power of including modulation of the high frequency components by the

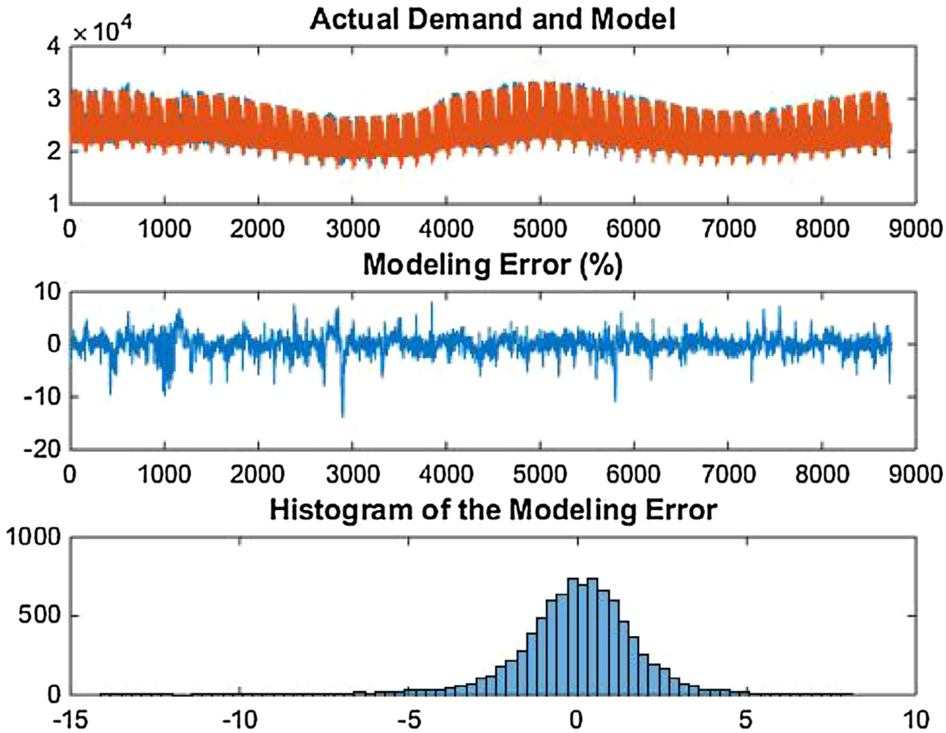

Fig. 4. (a) The model and the actual demand for the year 2012, (b) the modeling error, (c) histogram of the modeling error.

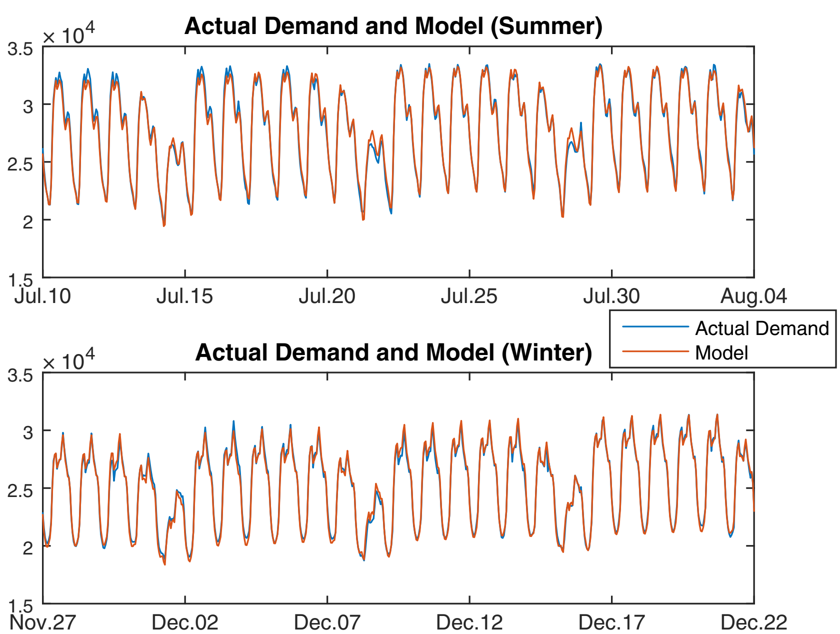

Fig. 5. The model and actual demand for the year 2012, for representative 4 week periods in winter and in summer.

low frequency variations. A close up given in Fig. 5 shows that both weekday and weekend intraday variations are faithfully reproduced.

The minimum absolute percentage (MAPE) and minimum square (MSE) errors of the model in each year are shown in Table 2.

Table 2
Modeling errors for each year.

Error types/years	2012	2013	2014
MSE	3.96%	4.81%	4.37%
MAPE	2.48%	3.04%	3.02%

4. Forecast

The “models” that we build should ultimately be used for “prediction”. For predicting data, we split the time axis into “past” (t_1) and “future” (t_2). The choice of relative proportions of (t_1) and (t_2) depends on the problem. As a first step, with the aim of obtaining a general model, we choose both as 1 year. We then make weak-ahead and day-ahead predictions. We note that in the context of day-ahead planning, one-hour-ahead predictions may not be meaningful. On the other hand, they are needed for the intra-day market.

Once we choose the splitting of the time axis into past and future, we have a corresponding splitting of the matrix F, into F_1, F_2. In our model the regressors that are harmonics of annual, diurnal and weekly variations are the same in F_1 and F_2.

In order to make a prediction, we use F_1 to compute the coefficient vector a but we use F_2 to compute the model vector y_2;

Table 3
New modelling and annual prediction errors after adjustments.

Error types/years	2012	2013	2014	2014 annual prediction
MSE	1.85%	2.83%	2.81%	4.75%
MAPE	1.34%	1.94%	2.12%	3.59%

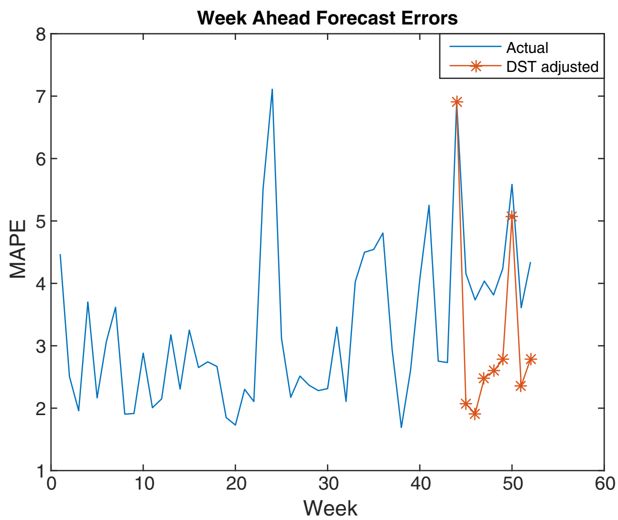

Fig. 6. Week-ahead forecast error ratios for actual and data shifted to correct the daylight savings time.

$$a_1 = (F_1^t F_1)^{-1} F_1^t S_1, \quad y_2 = F_2 a_1 \tag{6}$$

The prediction error of MSE and MAPE norms are based on the difference S_2-y_2. Usually the prediction error is larger than the modeling error. We test the forecast accuracy of the models for the annual, weekly and daily forecast periods in the following sections.

4.1. Annual forecast

The forecast error for the year 2014, which is found using the demand data for 2013, is around 9% which is not satisfactory compared to the modeling error [34]. These high prediction error percentages are tied to the time shift of the religious holidays and to the phase shift of the weekday-weekend structure when working on an annual basis. In order to cure the phase differences, we considered 3-year data as a concatenation of 52 week periods. Then, we corrected for the demand during the religious holidays and the first day of the year by using the average demands for the next and the previous weeks. With these adjustments, both the modeling and the prediction errors improved considerably as shown below in Table 3.

4.2. Week-ahead forecast

In this section we use a 2-year (104 weeks) observation period to predict next-week's hourly demand and repeat this for 52 consecutive weeks. This sliding window approach provides a dynamic forecast model by considering recent past period demand habits and events. Fig. 6 shows an overview of the week-ahead error ratios.

In the plot of the prediction errors we see that the prediction errors are higher for the period right after switching back from the daylight savings time in October. This effect can be seen clearly in the graphs. We have re-run the model after shifting data to take into account the switching from daylight savings time. As shown in Figs. 6 and 7, this process improves the forecast results. As shown

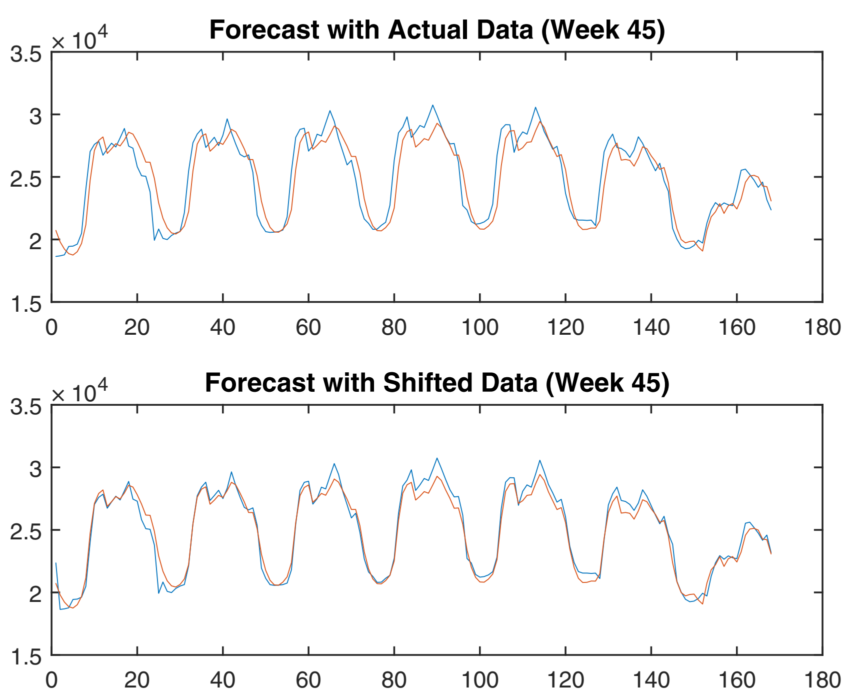

Fig. 7. Time domain plots of the original data and forecast for week 45 of the year 2014 (upper panel original data and lower panel after correcting for daylight savings time).

in Fig. 7, the left and right panels correspond to original and shifted data respectively.

4.3. Day-ahead forecast

For day-ahead forecasts, we applied the same method to a two-year period. Only the roll-over period changed from week to day. Similarly, day-ahead forecast results improved with shifting data after the daylight saving time ended in October as shown in Fig. 8.

Deviations from comfortable temperatures is known to affect electricity demand [28]. We clearly observed this effect when we observed that maximum demand occurs in the week with the warmest temperatures as shown in Section 2. We incorporated deviations from comfortable temperatures in our model but this resulted only in a minor improvement on the forecast. This might be due to the fact that modulation by seasonal harmonics models temperature effects adequately as the modulated Fourier expansion is used.

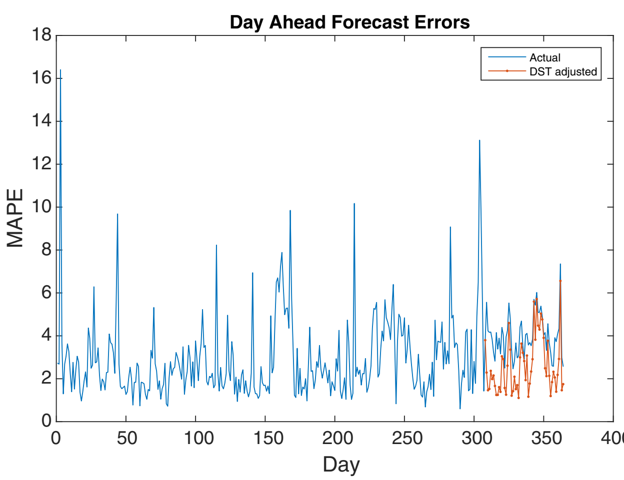

Fig. 8. Day-ahead error ratios for actual and shifted data.

Table 4
Forecast results in Model 2.

Error	MSE	MAPE
Daily roll-over	3.52%	3.06%
Daily roll-over(phase adjusted)	3.24%	2.86%
Weekly roll over	3.95%	3.27%
Weekly roll-over(phase adjusted)	3.65%	3.05%
Weekly roll-over(temperature added)	3.41%	3.04%

On the other hand, as seen in Table 4, with phase adjustment, we obtained considerable improvements in the accuracy of forecasting. When we checked all of the results, we see that the day-ahead forecast is the most accurate. This proves the power of the model in short term demand prediction.

Moreover, as we highlighted before, daily demand is affected by exceptional events. In order to increase forecast accuracy, we need to input more information about exceptional events such as high temperatures, the world cup, and elections that cause changes in daily life routines.

5. Demand segregation

In this section we focus on estimating the share of industrial and residential demand from the total demand data. As observed from the data, the demand is exceptionally low during two religious holidays determined according to the lunar calendar. It is known that, although some commercial institutions are active, almost all industry is shut down during these times, hence those days are considered to be good samples to distinguish between industrial and household electricity usage. In order to track the changes in demand, we first calculate the average demand for each day of the 3-year period and call it x_i. Then we calculate a running average using the averages of the same days for previous and next two weeks, e.g.

$$y_i = \frac{1}{5}(x_{i-14} + x_{i-7} + x_i + x_{i+7} + x_{i+14}) \tag{7}$$

Finally we find the ratio $z_i = \frac{x_i}{y_i}$. If there is nothing unusual, z_i is expected to be close to 1, but if the demand for the day i is low (high), then z_i is less than (greater than) 1. The resulting ratios are plotted in Fig. 9 where we clearly observe 6 exceptional regions corresponding to religious holidays over the 3 years. The decrease in the demand during these holiday periods is about 30%, 35%, 33%, for the years 2012, 2013 and 2014 respectively. These lowest demand profiles can be considered to be basic household demand for Turkey and provide an idea of the ratio of residential and industrial demand.

Given that such industrial demand is about 33% of the total, the expected electricity demand values can be updated based on the fact that 67% will be demanded by residential customers. It is also true that the transmission lines will be used more efficiently when the electricity transmitted to industrial zones and residential customers are considered and planned for well. Then, the expected deviation of predicted and measured electricity demand for the special holidays and occasions will be reduced. The peak power can also occur due to high or low temperature through the year. The proposed methodology could not provide a reliable recommendation for these cases and a method that includes physical parameters is needed.

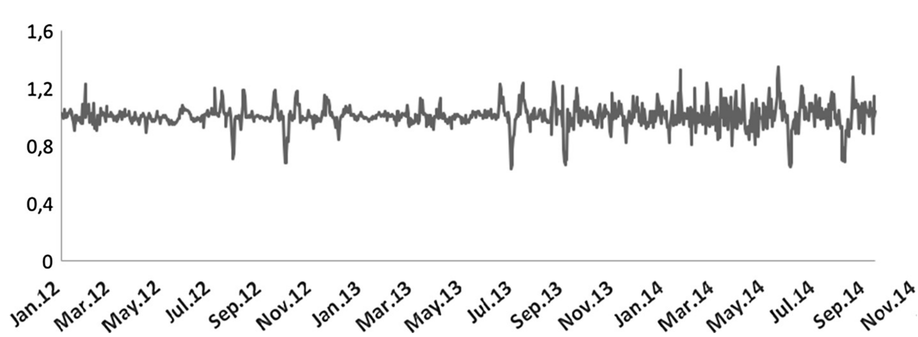

Fig. 9. Moving average values for two weeks before and after for a day, z_i values.

6. Conclusion

Electricity demand forecasting plays a key role for power companies as they need to develop long and short term strategies. In this work, aggregate electricity consumptions for the years 2012, 2013 and 2014 were analyzed and a linear regression model in terms of the harmonics of the daily, weekly and seasonal variations and a modulation by seasonal harmonics was developed. The hourly electricity demand was forecast for 1-week and 1-day horizons with 3% MAPE. The model is applicable to any country as long as there is a 7-day weekday/weekend structure.

Another contribution of this paper is to propose a method to estimate the expected share of the industrial electricity demand in total demand using special days such as religious holidays. We have used data 3 consecutive years and determined unusually low demand periods correspond to religious holidays and from this we conclude that the expected industrial demand is around 33%. A similar demand segregation and demand forecasting approach could be applicable to other international markets, provided there are holiday periods celebrated nationwide.

Electricity demand forecasting methods would usually require the knowledge of physical parameters such as temperature. Our contribution here is to incorporate the modulation of diurnal variations by seasonal harmonics to eliminate the need for weather information. This method needs no external information but still gives competitive results and helps to estimate a hourly demand profile for a specific hour for the whole year.

7. Future works

The proposed method can be designed as a decision support system and can be used by power companies for short and long term decisions. The historical demand data will be fed into the system and the method will return a short or long term demand profile that will ease decision making processes. The demand segregation method can also be implemented in this system.

The power companies can structure their offers using the demand profile in this paper. This information is also important for the system operator. The system operator can plan the reserves, generation schedules and planned outages according to short or long term demand profiles. We plan to develop the proposed method in future studies where physical parameters are not preferred.

Appendix A. Model parameters

Polynomial part:

$$Y_t^1 = 2.5665\alpha 10^4 - 0.1278t$$

Seasonal harmonics:

$$Y_t^2 = 10^3 \sum_{n=1}^{12} A_n \mathrm{Sin}(n\alpha t) + B_n \mathrm{Cos}(n\alpha t) \quad \text{where} \quad \alpha = \frac{2\pi}{364 \times 24}$$

Diurnal harmonics:

$$Y_t^3 = 10^3 \sum_{n=1}^{11} C_n \mathrm{Sin}(n\beta t) + D_n \mathrm{Cos}(n\beta t) \quad \text{where} \quad \beta = \frac{2\pi}{24}$$

Weekly harmonics:

$$Y_t^4 = 10^3 \sum_{n=1, n\neq 7}^{27} E_n \mathrm{Sin}(n\gamma t) + G_n \mathrm{Cos}(n\gamma t) \quad \text{where} \quad \lambda = \frac{2\pi}{7 \times 24}$$

Modulation terms:

$$Y_t^5 = \sum_{n=1}^{5}\sum_{m=1}^{8} H_{n,m} \mathrm{Sin}(n\alpha t)\mathrm{Sin}(m\beta t) + K_{n,m} \mathrm{Cos}(n\alpha t)\mathrm{Sin}(m\beta t)$$
$$+ P_{n,m} \mathrm{Sin}(n\alpha t)\mathrm{Cos}(m\beta t + Q_{n,m} \mathrm{Cos}(n\alpha t)\mathrm{Cos}(m\beta t)$$

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