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Forecasting Electricity Demand for Turkey Using Modulated Fourier Expansion

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Abstract

Turkish power market has undergone a restructuring and deregulation to reach a competitive and reliable electricity market. A typical day starts when the system operator announces the next day demand forecast for the electricity and participants submit offers in response to meet the demand. Accuracy in electricity demand forecast is essential for a reliable power system and successful market operation and mathematical models help market participants to forecast the electricity demand. We use hourly electricity demand data for Turkey, for the years 2012-2014 to make a linear model taking into account weekly and diurnal periodic variations modulated by seasonal effects. The model fits the data within %4 and predicts within %9.8 in the L_2 norm.

Keywords: Time series analysis; Fourier series; Hourly electricity demand for Turkey; deregulated electricity market; load forecast.

1. Introduction

Electricity markets used to be a monopoly in all areas of generation, transmission and distribution that were controlled by the state until the beginning of 2000s. In Turkey, state directed regulations for the restructuring of electricity markets started in 2001 with the founding of the Energy Market Regulatory Authority (EMRA) which is the main authority that manages the process of privatization and oversees all related activities.

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The monopoly of state-owned resources is divided up into different companies in order to increase efficiency and provide a competitive market environment which can lower the cost of electricity and increase the reliability of power supply. The first step of the market design, which involves financial transactions in a deregulated electricity market, started on December 1, 2003.

The power supplier and large number of consumers were encouraged to participate and invest in power markets at this time. The second step of the market design was defined as balance and conciliation, and it was launched on August 1, 2006. Participants carried out bidding and bilateral contracts in this step until the end of 2009. In order to construct free and competitive electricity markets, Turkish Government started to transfer its rights to private companies for generation, transmission and distribution and constructed day-ahead planning in 2009. As a result of step by step improvement of the market and experience gained from the daily operations, day-ahead planning is converted as to be day-ahead market in 2011. A new market called intra-day market was established in 2014 under the control of a new market operator.

The day-ahead market was established to increase the planning accuracy and reliability on hourly basis. On a typical day, the estimated day-ahead demand for each hour of the next day is announced by the system operator. All market participants submit their hourly generation capacities and unit prices to the system operator for the next day according to hourly electricity forecasts that are shared by Market Financial Settlement Centre System (PMUM). Each participant submits the amount of power they are willing to supply using bilateral contracts. Bilateral contracts are agreements between two parties that allow each participant to determine the power delivery conditions and price. The total amount of power that will be provided with the bilateral contracts is determined and deducted from the total estimated demand. The remaining amount should be supplied from competitive and reliable offers in the market. Once generation capacities and price offers are collected from all participants, they are sorted in merit based ascending orders by price. The day-ahead price for each hour is determined at the point where the cumulative hourly generation offers meet forecasted hourly electricity demand. The latest offer price is accepted as the final price and announced as the system day-ahead price for that hour. The process is repeated for every hour and participants are informed for conclusive day-ahead generation schedules and final market prices. Note that in this process load planning is carried out for real time demand and sudden load decreases or increases on transmission and distribution lines are managed efficiently.

As it is not possible to fully estimate the deviations in generation and demand in a typical day, deviations in demand and generation levels are expected and they have to be managed well. The balancing market aims to overcome such unexpected circumstances in both demand and generation. The balancing market starts once the day-ahead market process is finalized and the schedule is announced.

The success of the markets aforementioned above is highly related to the demand accuracy and the demand forecast plays an important role in generation schedule, market price determination and transmission planning. Forecast accuracy affects the profit of the market participants and effective usage of generation plants, transmission and distribution systems. In literature, there are a number of studies on the development of models for accurate electricity forecast. For example, Larsen and Dyner, present an analysis for the liberalization of electricity markets and discuss the usability of agent modelling, simulation, game theory and risk management for the electricity markets [1]. These methods are widely used for the load and demand forecast as the load shows stochastic characteristics. Another approach is to use Box-Jenkins models for the daily, weekly and annual demand forecasting [2]. In the present work, we will use a Fourier series expansion taking into account daily and weekly variations and we modulate them by seasonal variations in order to take into account seasonal effects. The novelty of our approach is to use modulation by seasonal variations for taking into account variable amplitude variations in different times of a year.

One of our crucial observations is the low demand during religious holidays. This problem has been taken into account by Braubacher and Wilson [3], who replaced the demand during irregular holidays by the interpolation of demands in before and after these periods. In our work, we didn't exclude or modify these exceptional days; for future work we are planning to use the demand during holidays as a baseline for household electricity demand to estimate of the percentage of industrial electricity consumption from this data.

Deviations from comfortable temperatures are also considered to have an impact on the electricity consumption [4]. These effects are taken into account by Toker and Korkmaz who use Artificial Neural Networks (ANN) and advanced signal method to forecast the short term and hourly electricity demand in Turkey [5]. They improve ARIMA and FFT models by including weather conditions and holiday effects. Also, in [6], Taylor works on weather effects on electricity demand by using various weather scenarios and conditions to forecast short term electricity demand starting from next day to tenth day. In our model, we have seen that the modulation by seasonal harmonics takes into account whether effects on a year-long scale. A preliminary analysis that included deviations from comfortable temperatures showed that the improvement for long term prediction was negligible and we postponed the incorporation of whether effects for short term prediction to a future work.

In Section 2, we present an overview of the data and preliminary data processing and we develop a linear regression model using low and high frequency harmonics and their interaction as modulated waves. The results are presented in Section 3.

2. Materials and Methods

2.1. Data Processing

The data for total hourly electricity demand of Turkey were obtained from PMUM system for the years 2012-2014. This data includes market prices, hourly imbalances and other related information but there are no classifications based on region or demand type. We used actual hourly demand figures for the daily generation plan provided by the system operator in our analysis (http://www.pmum.gov.tr/). An overview of the data for the years 2012-2014, after correcting for the daylight saving time by linear interpolation is given in Figure 1.

Demand data shows a clear weekend effect as shown from Figure 2, that presents typical 2-week periods for winter and summer. We see that the shapes of the periodic variations for weekdays and for the weekend are different. For example, during week days, the intra-day peak is in the morning while for the weekends it is in the afternoon. These differences are expected as the habits of the people are different during the weekdays and weekends. A daily schedule such as wake up times, work hours, shift changes, lunch breaks, leaving the job at the end of the days, using lights and heating/cooling when arriving homes are all related to total electricity demand and the schedule might be different in weekend. Another observation that can be made is that shapes of the curves are different in winter and summer both for weekdays and weekends. These observations suggest that the modelling of weekdays and weekends by a single Fourier expansion will be challenging.

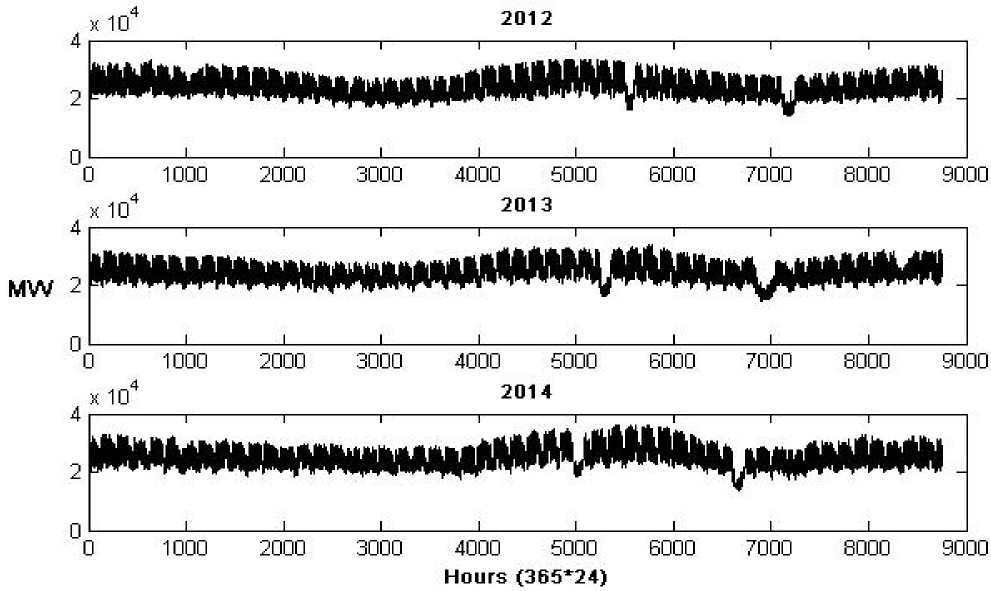

Figure 1 : Overview of the data after adjustment for the daylight saving time**.**

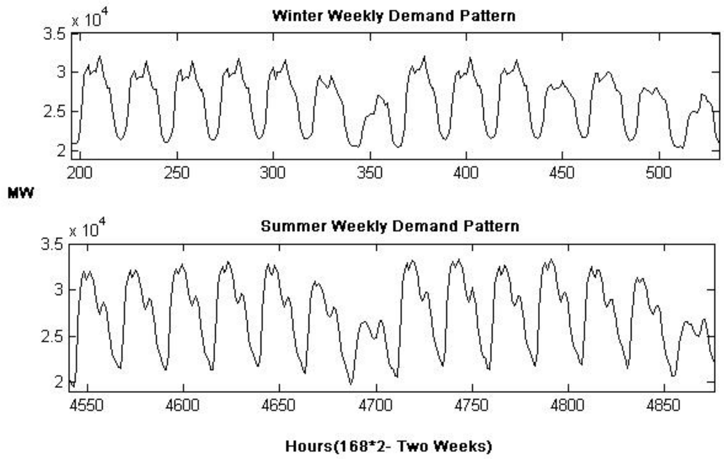

Figure 2 : Hourly demand data for two weeks in winter and summer.

2.2. Modeling of Periodic Variations

The demand patterns for each day of the week for the year 2012 are given below in Figure 3. We note that except for Sunday, the curves have similar shapes. The demand profile for Saturday is similar to weekdays but with lower amplitude. On the other hand, there are exceptionally high demand days on “Saturday” and “Friday” graphs which correspond to days with extremely high temperatures.

A glance to the data as presented in Figure 1 and 2 shows that diurnal variations are superimposed on seasonal variations and daily variations have higher amplitudes in winter and in summer. In addition, data for weekends, especially for Sundays has a different shape. In this section we develop a linear model in terms of the harmonics of the annual, diurnal and weekly variations and we include the modulation of the diurnal variation based on the annual variation in order to take into account seasonal effects. We group the regressors of our model as follows. We assume that the number of regressors should be large enough to capture the main features of the data but over-specification should be avoided.

$$X = Harmonics\ of\ 1\ year: \qquad X = \left[X_1 \cdots X_{12x2}\right] \tag{1}$$

$$Y = Harmonics\ of\ 1\ day: \qquad Y = \left[Y_1 \cdots Y_{11x2}\right] \tag{2}$$

$$Z = Harmonics\ of\ 1\ week: \qquad Z = \left[Z_1 \cdots Z_{23x2}\right] \tag{3}$$

$$U = Modulation\ of\ Y\ by\ X: \qquad U = \left[X_1 . Y_1 \cdots X_i . Y_j\right] \tag{4}$$

In the linear model the (column) vectors consisting of the samples of these regressors are arranged as the columns of a matrix F. If S is the time variation to be modeled in terms of these regressors, the coefficient vector a and model m are calculated as;

$$F = \left[X_i \quad Y_i \quad Z_i \quad X_i \times Y_i\right] \tag{5}$$

$$a = \left(F^t \times F\right)^{-1} \times F^t \times S \tag{6}$$

$$m = F \times a \tag{7}$$

The modeling error is the standard (L_2) norm of the difference between the data and the model.

For predicting data, we split the time axis as "past" (t_1) and "future" (t_2). The choice of relative proportions of (t_1) and (t_2) depends on the problem. Once we choose the splitting of the time axis as past and future, we have a corresponding splitting of the matrix F and of the observation vector S, as $F=[F_1 \ \ F_2]^t$, $S=[S_1 \ \ S_2]^t$. In our model the only difference between F_1 and F_2 is the last column that gives the weighted deviations from comfortable temperatures. To predict variations over the timespan t_2 based on a model on t1, we use the following formulations:

$$a_1 = \left(F_1^t \times F_1\right)^{-1} \times F_1^t \times S_1 \qquad (8)$$

$$m_2 = F_2 \times a_1 \qquad (9)$$

The prediction error now is the norm of the difference S_2-M_2. Usually the prediction error is larger than the modeling error.

In this work where we aimed to obtain a general model, we have chosen t_1 and t_2 both as 1 year and we have obtained reasonably good prediction errors. Normally we would expect our annual model work well for month ahead predictions, but it turned out that weekends were poorly predicted and we deferred the study of short term predictions to future work that would take into account weekend effects in a more sophisticated manner.

In Figure 4 we present the results of our modeling in terms of the harmonics of the annual, diurnal and weekly variations only for the year 2012. Our model uses 96 time regressors and 160 modulation regressors. The model is quite satisfactory and shows the power of including modulation of the high frequency components by the low frequency variations.

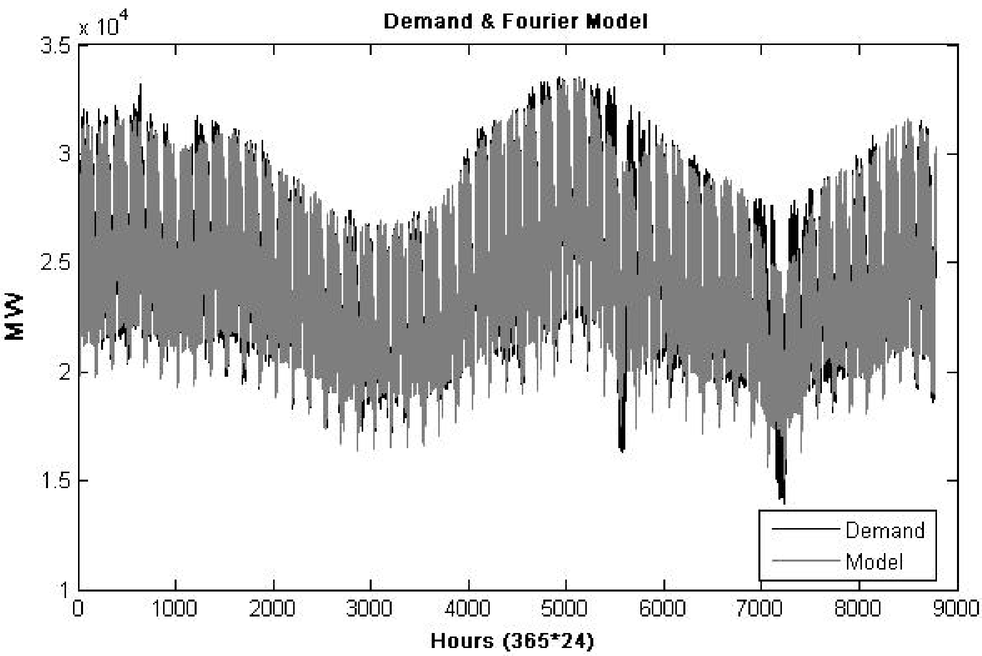

Figure 4 : The model and demand for a year period.

A close up to the model that includes 7 days for winter and summer is given in Figure 5. The figure shows that both weekday and weekend intraday variations are realistically reproduced. The L_2 norm of the modeling errors for each year is given Table 1.

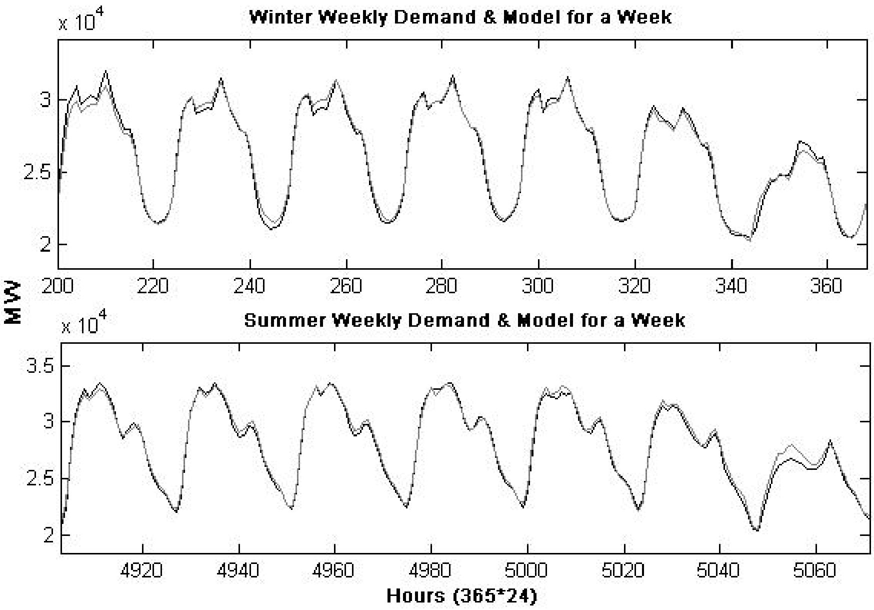

Figure 5 : The Model and Demand for a week.

In order to give an example of the long term prediction performance of our model, we use the electricity demands for 2013 and 2014 to build a model and we use this model to forecast the electricity demand for 2014 within 9.8% , as displayed in Table 1. We note that this 1-year ahead prediction is shown just to give an idea of the performance of the model; in a realistic situation it has to be supplemented with short term forecast models including possibly weather conditions and special events.

Table 1 : Modeling and prediction errors**.**

Error Types	2012	2013	2014
Modeling	3.96%	4.81%	4.37%
Prediction	-	-	9.80%

3. Conclusion

Forecasting the electricity demand plays a key role long term and short term strategies of companies. Long term electricity demand forecasts are required to make investment decisions and to add capacity.

In this paper electricity demand data of Turkey, for the years 2012, 2013 and 2014 were analyzed and a model was developed for the demand pattern. First, yearly harmonics were added to the model, and then daily and weekly harmonics were added to have better results. It is shown that the models give better result with adding weekly harmonics. The method returns promising results in terms of estimating the electricity price profile of a certain time period. The model captures the cyclical behavior of the daily and weekly routines.

The temperature is an important parameter to consider when evaluating the electricity demand as the temperature effects the consumption. We plan to analyze the effect of the temperature on the electricity demand and we would like to improve the model to have more reliable results. The share of the residential use and industrial consumption is also another important topic that we plan to work in future research. We will work on the methods to distinguish the share of the residential consumption from the share of the industrial consumption to make more reliable analysis.

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