Forecasting hourly Electricity demand in Egypt

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Abstract

Forecasting electricity demand is critical concerning future technical improvements. A notable feature of the electricity demand time series is the presence of both intraday and intraweek seasonal cycles. This study investigates using double seasonal Holt-Winters exponential smoothing method for forecasting hourly electricity demand in Egypt. A one year of hourly electricity demand measured in Megawatt from 7 January 2010 to 31 December 2010 is used. The mean absolute percentage error is used to compare forecasting accuracy between the double seasonal Holt-Winters method and the traditional Holt-Winters that considers only single seasonality pattern. The forecasts produced by the double seasonal Holt-Winters method outperform those obtained from single seasonal Holt-Winters methods.

Keywords: multiple seasonality pattern; double seasonal exponential smoothing; mean absolute percentage error; Egyptian electricity demand.

1. Introduction

Electricity is one of the ordinary life necessities, and a major driving force for economic growth and development. The unstorable nature of electricity means that the supply of electricity must be always available to satisfy the growing demand. Therefore, electricity utilities throughout the world have given a remarkable interest for forecasting electricity demand. Decision makers around the world widely use energy demand forecasting as one of the most important policy making tools. An accurate hourly demand forecasting up to one day ahead is a vital process in electricity industry planning. It is critical for nations in order to balance electricity produced and electricity consumed at any time in the day, to increase the reliability of power supply, to minimize costs and to provide correct decisions for future development [Bunn,D.W. (2000), Garcia,M.P. & Kirschen,D.S. (2006)] .

Several forecasting methods have been used for load forecasting including multiple linear regression [Hyde, O. & Hodnett, P.F. (1997), Al-Hamadi, H. M. & Soliman, S. A.(2005), and Aslan et al.(2011)] and Artificial Neural Network (ANN) with variety of approaches such as back propagation ANN [Al-Saba,T. & El-Amin, I.(1999)] , Elman ANN [Beccalia et al.2004] , Dynamic ANN [Ghiassi et al. 2006], and particle swarm optimization [El-Telbany, M. & El-Karmi,F. (2007)].

Electricity load demand is mainly influenced by seasonal effects (daily and weekly cycles, calendar holidays). A within-day seasonal cycle is apparent if similarity of the hourly demand from one day to the next exists, while a within-week seasonal cycle is apparent if similarity of the daily demand exists week after week. Therefore, using a forecasting method that is able to capture both seasonal patterns (daily and weekly) is mandatory.

Exponential smoothing for double seasonality has found widespread use for electricity demand forecasting. Taylor (2003) adopted a double seasonal Holt-Winters exponential smoothing method which captured the daily and weekly seasonal cycles. Taylor compared the hourly load forecasts produced by the double seasonal Holt-Winters method with traditional Holt-Winters and with a multiplicative double seasonal autoregressive integrated moving average (ARIMA) model. The forecasts produced by the double seasonal Holt-Winters method outperformed those from traditional Holt-Winters and from a multiplicative double seasonal ARIMA model.

Taylor et al. (2006) considered six forecasting methods including double seasonal ARIMA, double seasonal exponential smoothing, a method based on the principal component analysis (PCA), ANN, a random walk model and a seasonal version of the random walk for forecasting hourly electricity demand for the state of Rio de Janeiro in Brazil and half-hourly electricity demand for England and Wales. Among those forecasting methods, double seasonal exponential smoothing method performed best for Rio data and England and Wales data. Taylor, W.J. & McSharry, E.P. (2008) applied the same pervious methods on ten European countries. They concluded that double seasonal exponential smoothing method outperformed the others. On the other side, the Egyptian electricity demand series has not been analyzed using double seasonal exponential smoothing method. Therefore, our target is to investigate double seasonal Holt-Winters method in forecasting Egyptian electricity demand series. This paper is structured as follows: Section 2 describes the Egyptian electricity demand data, Section 3 describes Holt-Winters exponential smoothing method, while Section 4 discusses the results. Section 6 concludes the paper.

2. Egyptian Electricity Demand Series

The Egyptian electricity demand series consists of hourly time series data of Egyptian electricity demand measured in Megawatt (MW) for a one year starting on Saturday 7 January 2012 and ending on Friday 28 December 2012. All the data is used to estimate parameters except for the last 4 weeks that are put aside to evaluate accuracy of post-sample forecasts.

Figure 1 shows a time series plot of the Egyptian electricity demand series covering the period from Friday 1 June 2012 to Thursday 28 June 2012. In figure (1), from hour 1 till hour 24 represents the first day in this sub time series which is Friday 1 June 2012, while from hour 24 till hour 48 represents the second day and so on. Figure (1) shows a within-day seasonal cycle and a within-week seasonal cycle. A within-day seasonal cycle is apparent in this data set from the similarity of the demand from one day to the next. A within-week seasonal cycle is also apparent from comparing the demand on a certain day in different weeks. It is clear that the weekdays show similar patterns of demand, while the weekend days, have the lowest peak of electricity demand, have a different electricity demand.

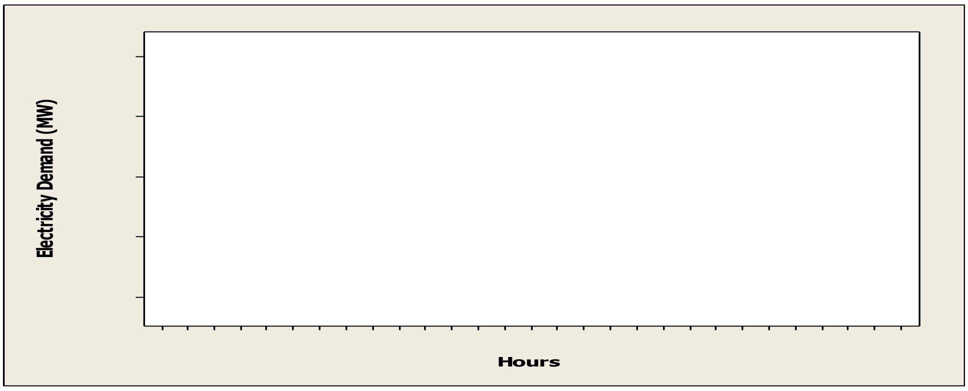

Figure (1): Time plot for the Egyptian electricity demand series from Friday 1 June 2012 to Thursday 28 June 2012

3. Holt-Winters Exponential Smoothing method

Exponential smoothing is a simple method for forecasting. The forecast is constructed from an exponentially weighted average of past observations. The name "exponential smoothing" reflects that the weights decrease exponentially as the observations get older which allows the recent values of the series to have greater influence on the forecast of future values than older values.

The traditional Holt-Winters exponential smoothing method was introduced by Winters (1960) for forecasting sales. The Holt-Winters exponential smoothing is a modification of the exponential smoothing method. Winters added a seasonal ratio and a linear trend to exponential smoothing method to accommodate seasonal variations and changes in the mean over time. The multiplicative seasonal Holt-Winters method is defined in four equations as following

Level $L_t = \alpha (Y_t / S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1})$ (1)

Trend $T_t = \gamma (L_t - L_{t-1}) + (1-\gamma) T_{t-1}$ (2)

Seasonality $S_t = \delta (Y_t / L_t) + (1-\delta) S_{t-1}$ (3)

Forecast $\widehat{Y}_t (k) = (L_t + k T_t) S_{t-s+k}$ (4)

where L_t is the smoothed level, T_t is a local trend which is the difference between local levels (L_t - L_{t-1}) , S_t is the seasonal index, s is the number of season periods, $\widehat{Y}_t$ (k) is the k step-ahead forecast and α, γ and δ are the smoothing parameters.

Double seasonal Holt-Winters exponential smoothing method had been adapted by Taylor (2003) in order to accommodate a two seasonal cycles (daily and weekly cycles) in electricity demand series. The major addition to Holt-Winters exponential smoothing method was a second seasonal index. The multiplicative double seasonal Holt-Winters was presented in five equations as following

Level $L_t = \alpha (Y_t / (D_{t-s_1} W_{t-s_2})) + (1-\alpha)(L_{t-1} + T_{t-1})$ (5)

Trend $T_t = \gamma (L_t - L_{t-1}) + (1-\gamma) T_{t-1}$ (6)

Seasonality 1 $D_t = \delta (Y_t / (L_t W_{t-s_2})) + (1-\delta) D_{t-s_1}$ (7)

Seasonality 2 $W_t = w (Y_t / (L_t D_{t-s_1})) + (1-w) W_{t-s_2}$ (8)

Forecast $\widehat{Y}_t (k) = (L_t + k T_t) D_{t-s_1+k} W_{t-s_2+k}$ (9)

where D_t and W_t are the seasonal indices for the intraday and intraweek seasonal cycles, respectively, s_1 is the number of periods of the first season, and s_2 is the number of periods of the second season. For example in our time series, s_1 would be 24 and s_2 would be 168. Finally, $\widehat{Y}_t$ (k) is the k step-ahead forecast where $k \leq s_1$ and α, γ, δ and w are the smoothing parameters, where each ranges between zero and one.

4. Results

The Egyptian electricity demand series is analyzed using three different methods: Holt-Winters for within-day seasonality, Holt-Winters for within-week seasonality and double seasonal Holt-Winters that capture both seasonal patterns (daily and weekly). Table (1) and Table (2) show the estimation of the parameters of these methods from our data set.

Table (1)

Parameter estimation for Holt-Winters for within-day seasonality method and Holt-Winters for within-week seasonality method

	Level (α)	Trend (γ)	Seasonality (δ)
Holt-Winters for within-day seasonality	0.71	0.00	0.73
Holt-Winters for within-week seasonality	0.54	0.00	1.00

Table (2)

Parameter estimation for Double seasonal Holt-Winters exponential smoothing method

	Level (α)	Trend (γ)	Daily seasonality (δ)	Weekly seasonality (w)
Double seasonal Holt-Winters	0.23	0.00	0.27	0.40

Figure (2) shows the actual values of the first week of the post-sample period of the Egyptian electricity demand series and the forecasts produced by these methods. The forecasts of the three methods are close to the actual values. However, the forecasts produced by double seasonal Holt-Winters are the closest to the Egyptian electricity demand series.

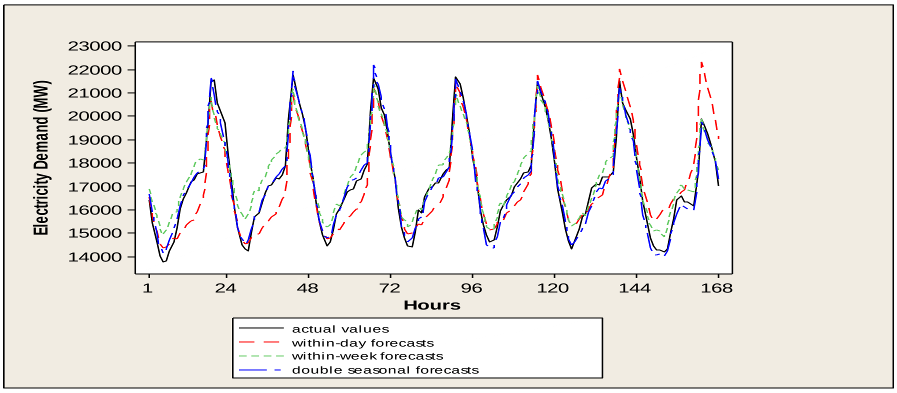

Figure (2): Time plot of the actual values of the first week of post-sample period versus the forecasts

This conclusion is confirmed by calculating the mean absolute percentage error (MAPE). The MAPE is calculated for different time horizons to evaluate the accuracy of the methods. Low values of MAPE are preferred. Table (3) and Figure (3) show the MAPE of out-sample forecasts of the three methods. We compared the forecasts at one week horizon, two weeks horizon, three weeks horizon and a month horizon.

Table (3) shows that forecasting accuracy was less for longer horizons. Holt-Winters for within-week seasonality method was worse than the competitive Holt-Winters for within-day seasonality method in some forecast horizons. The Holt-Winters for within-day seasonality method was the worst for out of sample forecasts for one-, two-, three- and four-weeks ahead. The MAPE of this method is higher than that of the Holt-Winters for within-week seasonality method, this is because the former method failed to capture within-week seasonality, which appeared to be high. However, Double seasonal Holt-Winters method outperformed both Holt-Winters for within-week seasonality and that for within-day seasonality.

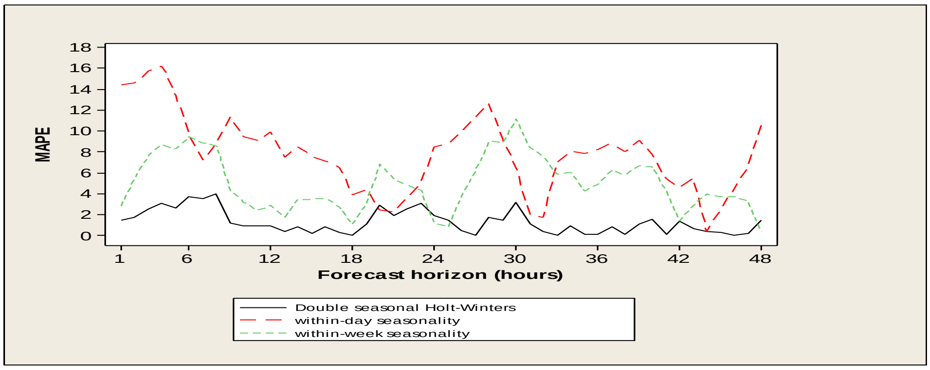

Figure (3):Comparison of MAPE results of two day forecasts for the three Holt-Winters methods

Table (3): The MAPE of out-sample forecasts of three methods

	Holt-Winters for within-day seasonality	Holt-Winters for within-week seasonality	double seasonal Holt-Winters
Out-sample 1 week forecast	8.156865	3.337798	1.334666
Out-sample 2 week forecast	9.015748	3.912223	1.706809

Out-sample 3 week forecast	9.547343	4.209455	1.804665
Out-sample 1 month forecast	9.833636	4.407725	2.258141

5. Conclusions

The double seasonal Holt-Winters method is used to forecast Egyptian electricity demand. Its forecasting performance is compared with the traditional Holt-Winters that captures only one seasonality pattern. Holt-Winters for within-day seasonality and Holt-Winters for within-week seasonality are compared to the double seasonal Holt-Winters. The MAPE of the three forecasting methods showed the superiority of double seasonal Holt-Winters in forecasting Egyptian electricity demand for different forecast horizons time. Different techniques and models may be used and compared with double seasonal Holt-Winters method in analyzing the Egyptian electricity demand series.

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