Seasonal Decomposition of Electricity Consumption Data

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ABSTRACT

Multiplicative decomposition model is compared with the Multiplicative Winter's Model for estimation of seasonal indices for monthly electricity consumption data the Muscat region of Oman. Based on three measures of forecast accuracy the Multiplicative decomposition model outperforms Multiplicative Winter's Model for forecasting monthly electricity consumption. Then using the Multiplicative decomposition model, it is observed that the demand for electricity is minimum in February and highest in July.

Keywords: Multiplicative decomposition; Multiplicative winter's Model; Seasonal indices; Forecast Accuracy.

1. INTRODUCTION

Electricity consumption plays a very vital role in economic development. The forecasting of electricity demand is fundamental leading factor for efficient planning because electricity is commodity which cannot be stored as it should be generated as soon as it is demanded. Moreover any commercial electric power company generally has it's one of the strategic objectives to provide end users (market demands) with safe and stable electricity. Therefore it becomes more important to have reasonably accurate estimates of electricity use in different seasons over any year in particular. Accurate forecasts lead to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. Zhou, P.; Ang, B.W.; Poh, K.L.(2006);

The electricity demand pattern is necessarily affected by several factors including time, social, economic, and environmental factors by which the pattern will form various complex variations. Social (such as behavior) and environmental actors are big sources of randomness (noise) found on the load pattern. Diversity and complexity in demand pattern have been leading to developing complicated electric energy demand forecasting methods such as autoregressive integrated moving average (ARIMA), Konarasinghe, K.M.U.B(2016). artificial neural network (ANN) and multiple linear regression (MLR). Abdel-Aal, R.E.; Al-Garni, A.Z.(1997). Although electricity demand is assessed by accumulating the consumption periodically; it is almost considered for hourly, daily, weekly, monthly, and yearly periods.

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But very little attention has been paid to investigate the seasonal patterns and seasonal models of forecasting. In the present study, the multiplicative decomposition and Holt Winter models of seasonal time series are applied to monthly electricity demand data and there forecasting ability are compared by taking monthly consumption data for eight years from Muscat OMAN. Cho, M.Y.; Hwang, J.C.; Chen, C.S.(1995).

2. METHODOLOGY

In this study we compared the forecasting performance of two seasonal models which explained as below.

2.1 Decomposition model:

This method is suitable to forecast time series that exhibit trend and seasonal effects. Decomposition models have been found to be useful when the parameters describing a time series are not changing over time. The idea of these models is to decompose the time series in to several factors: trend, seasonal, cyclical, and irregular.

These factors can be estimated to describe the time series if the parameters of time series are not changing, then the estimates can be used to compute point forecast. The time series model may be assumed to be additive or multiplicative. In this study, we have considered multiplicative model. The Multiplicative decomposition model is preferred when the data display increasing or decreasing seasonal variation.

The Multiplicative decomposition model can be written as:

$$Y_t = TR_t * CL_t * SN_t * \quad IR_t \qquad (1)$$

Where

TR_t denotes trend, SN_t represents seasonal effect, Cl_t is for cyclical component and IR_t the irregular movement. Let tr_t, sn_t , cl and ir be the trend and seasonal, cyclical and irregular estimates which were estimated by the method consisting of the following steps:

Step 1: Compute the moving average (MA): “12-period moving average” were computed because of the monthly seasonal effect i.e.

$$\text{MA}(12) = \frac{12-period\ moving\ total}{12} \qquad (2)$$

Step 2: Compute centered moving average (CMA): This was done by computing the two period moving average of MA(12) which represents the trend and cyclical effect i.e.

$$CM_t = tr_t * cl_t \qquad (3)$$

Step 3: Computation of seasonal variation (sn_t) was done by first de-trending the series and then averaging over years as:

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$$sn_t = \frac{L}{\sum_{t=1}^{L} \overline{snt}} * \overline{snt} \qquad (4)$$

Step 4: The series was the deseasonalized and least square method was used to find linear trend

$$tr_t = b_0 + b_1\ (t) \qquad (5)$$

2.2: Exponential smoothing:

Exponential smoothing is a forecasting method that weights the observed time series values unequally. More recent observations are weighted more heavily than more remote observation. The unequal weighting is accomplished by using one or more smoothing constants, which determine how much weight is given to each observation.

Exponential smoothing has been found to be most effective when the parameters describing the time series may be changing slowly over time. It has multi versions of informal models but we will use Holt Winter model.

2.2.1: Winter's Method:

It approaches to forecasting seasonal data and it have multiplicative and additive methods. For this study, we considered the multiplicative model. The multiplicative model is for increasing seasonal variation and additive is for constant seasonal variation. Multiplicative winter's Model has the form given as below.

$$y_t = (\beta_0 + \beta_1 t) \times SN_t + \varepsilon_t \qquad (6)$$

Where $\beta_0\ and\ \beta_1$ are level and growth parameters. $SN_t and\ \varepsilon_t$ are seasonal and irregular components.

Let these parameters are assumed to change over time therefore they need to be updated. Let $a_0(T), b_1(T), sn_T(T)\ be$ the estimates of level.

Trend growth and seasonal factor at time T, then the following formulae are used to update these estimates for time T+1.

The updated estimate:

1) $a_0(T) = \alpha \frac{y_T}{sn_T(T-L)} + (1-\alpha)[a_0(T-1) + b_1(T-1)]$ (7)

2) $b_1(T) = \beta[a_0(T) - a_0(T-1)] + (1-\beta)b_1(T-1)]$ (8)

3) $sn_T(T) = \gamma \frac{y_T}{a_0(T)} + (1-\gamma)sn_T(T-L)]$ (9)

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2.3: Forecast accuracy:
Three commonly used measures of forecast accuracy which are based on forecast errors are:

The mean absolute deviation (MAD),

The mean square error (MSE), and

The mean absolute percent error (MAPE).

MAD is the average absolute errors, MSE is the average of squared errors, and MAPE is the average absolute percent error. These measures were used to compare the forecasting performance of Holt Winter and Decomposition multiplicative models.

3. RESULTS AND CONCLUSION

Preliminary analysis of the data showed that it were non normal therefore the data was transformed by taking natural logarithm which made it normal. Plot of time series revealed linear trend and varying levels of seasonality. Therefor multiplicative decomposition and Holt Winter models were fitted by MIMITAB statistical software.

The estimates of seasonal components are presented in Table 1.

Table1. Seasonal Components estimates

Months	Decomposition	Holt-Winter
Jan	0.94538	**0.94263**
Feb	0.93237	**0.93122**
Mar	0.97348	**0.96933**
Apr	1.00141	**1.0016**
May	1.04651	**1.0402**
Jun	1.04109	**1.0402**
July	1.04977	**1.0452**
Aug	1.04137	**1.0399**
Sep	1.03175	**1.0294**
Oct	1.01563	**1.0095**
Nov	0.97068	**0.98207**
Dec	0.95056	**0.95760**

This table shows that the estimates of seasonal components are very similar by each method. The electricity consumption starts decreasing below a base of 100 in November. It keeps decreasing below that base until February. Then it starts increasing in March. From April up to October the seasonal component index of consumption remains above 100%. And it peaks in July.

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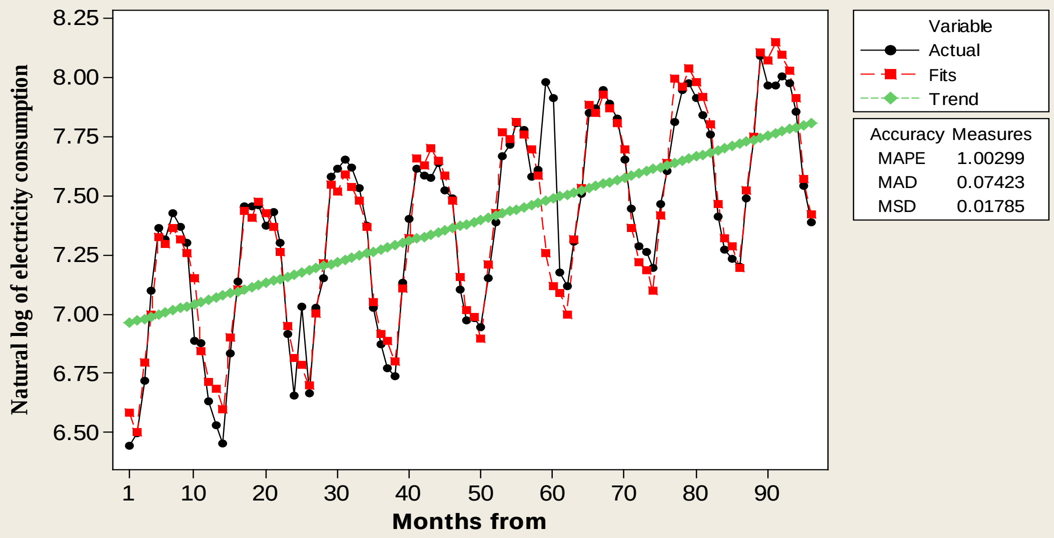
Therefor the demand for electricity is minimum in February and highest in July. Actually, April to October the index remains above 100 while November to March which are cooler months, the electricity demand remains low.

The forecasting performance as measured by mean absolute deviation (MAD), the mean square error (MSE), and the mean absolute percent error (MAPE) is graphically presented in figures 1 and 2 below. These figures clearly show that decomposition method gives better forecasts as compared to Holt Winter method. Karin Kandananond (2011).

Figure 1:Time Series plot for actual and fitted log transformed electricity consumption
Method of multiplicative seasonal decomposition



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