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RESEARCH ARTICLE | MAY 16 2023

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AIP Conference Proceedings 2683, 020015 (2023)
https://doi.org/10.1063/5.0125443

Forecasting Double Seasonal Electricity Consumption with TBATS Model

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Abstract. The percentage of electrical energy needs is the largest demand compared to other energy needs such as natural gas, fuel, and coal. This is due to various factors, including population growth, economic growth, industrial development, as well as the rapid development of electricity-based technology in almost every sector, especially in the household, industrial and commercial sectors. This condition has the potential to trigger an electricity crisis, but can be minimized if the required electricity consumption is known. One way to determine electricity demand is to build a predictive model that is accurate and flexible and able to accommodate the complexity of seasonal patterns, both seasonal in months and years as reflected in electricity consumption data. Therefore, in this study, the TBATS model was used to accommodate this. TBATS models will be used which is the development of the exponential smoothing model that can accommodate the occurrence of multiple seasonal patterns, both nested and non-nested, non-integer seasonal periods, and handle the possibility of non-linearity cases because it has a flexible seasonality The results of this study, the TBATS model built has a value of SMAPE by 8.13% has been able to capture fluctuating patterns in seasonal periods.

Keywords: TBATS; Doubel Seasonal; Prediction; Electrical Energy.

INTRODUCTION

The need for electrical energy is proven to continue to increase from year to year, and this is one of the key aspects of living standards and measuring the welfare effect of a country. However, unpreparedness to fulfill electricity needs is one of the main problems in the country. Therefore, it is important to plan anticipating surges in electricity demand accurately by optimizing energy generation and avoiding unexpected waste so that the sustainability of economic productivity goes well [1, 2]. One way to plan electricity needs is by building a prediction model based on previous data. The prediction model that is built can provide an overview of the electricity demand pattern in each certain period, so that it can be known the amount of electricity that must be provided to fulfill the demand and needs of electrical energy.

Study [3] mentioned that in the electricity demand data there are three seasonal patterns including daily seasonal patterns, weekly seasonal patterns and annual seasonal patterns. This causes the data on the demand for electrical energy to have complex seasonal effects such as non-integer seasonality, dual calendar effects, and non-nested seasonal patterns [4]. Therefore, some prediction models that have been built still have weaknesses in accommodating this seasonal complexity effect. For example, the double seasonal model cannot be developed for time series data with

The 6th International Conference on Energy, Environment, Epidemiology and Information System (ICENIS) 2021
AIP Conf. Proc. 2683, 020015-1–020015-6; https://doi.org/10.1063/5.0125443
Published by AIP Publishing. 978-0-7354-4517-8/$30.00

more than two seasonal patterns and is also unable to accommodate the occurrence of non-linearity. The exponential smoothing model for the non-linearity case has a weakness, the forecasting results have infinite variance and the prediction distribution is unknown [5-8]. Thus, an innovative approach was developed from existing methods in dealing with seasonal complexity cases [9-12].

In this study, the Trigonometric, Box-Cox transform, ARMA errors, Trend, and Seasonal components (TBATS) models will be used which is the development of the exponential smoothing model that can accommodate the occurrence of multiple seasonal patterns, both nested and non-nested, non-integer seasonal periods, and handle the possibility of non-linearity cases because it has a flexible seasonality [13-14]. Furthermore, the trigonometric formulation of the resulting parameters can be used to obtain better predictive results by modeling each season with trigonometric representations based on Fourier terms. Therefore the TBATS model can accommodate time series with high frequency and seasonal complexity

METHODS

This study used daily electricity demand data in MegaWatt (MW). The data is divided into two, in-sample data for the process of forming and testing the model from January 1, 2015 to November 30, 2015. While the period December 1, 2015 to December 31, 2015 is out-sample data used for selecting the best model in forecasting. After that, identify the characteristics and determine the TBTS model on the in-sample data of the electrical system load to obtain TBATS model [15].

1. Analyze the characteristics of electrical energy requirements
2. Establishing a flexible seasonality TBATS model on in-sample data which is divided into
    - Determine the indication of transformation,
    - Initial component of the seasonal component transformation,
    - Level component and trend component,
    - The number of harmonies for each seasonal period
    - Prediction of de-trend data
    - Optimizing initial values
    - Define the ARIMA model.
3. Make predictions based on the TBATS model, compare the predictions with out-sample data from the model that has been obtained and calculate the predicted SMAPE.

RESULT AND DISCUSSION

Characteristics of electrical energy requirements

The need for electrical energy is the amount of electrical energy consumption by customers which is influenced by their individual needs. The characteristics of the electricity demand in 2015 are descriptively shown in FIGURE 1.

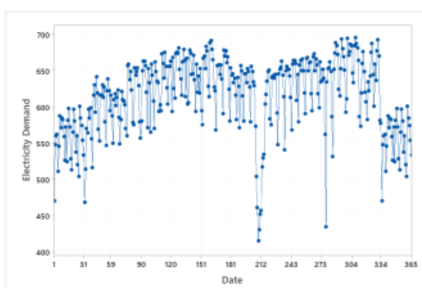


FIGURE 1. Annual Seasonal Pattern of Electricity Demand.

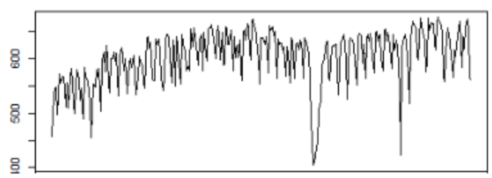
FIGURE 1 shows the amount of electricity consumption per day. In the figure, it can be seen that every week and month, electricity consumption has the same pattern, with low consumption every week, falling at the beginning of the week of each month, on the 5th, 12th, 19th and so on or seasonal seven days. Meanwhile, for high consumption each month it appears on the 36th, 72nd, 108th and so on or seasonal thirty-six days. This indicates that the electricity demand data has double seasonal characteristics, seasonal in weeks and months.

Formation of flexible seasonality TBATS model on in-sample data. TBATS modeling on electricity consumption data with seasonal periods of seven and thirty-six.

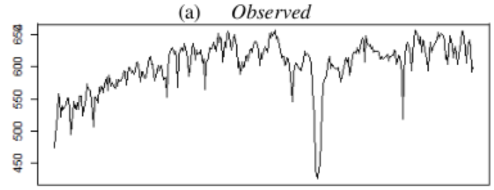
In this first stage, the TBATS modeling was carried out without including the Eid al-Fitr holiday as a fixed seasonal effect. The resulting TBATS modeling of the electrical system load is TBATS (0.995, 1, 1, 0.947, {7, 3}, {36, 1}). In this modeling 0.995 is the magnitude of the Box-Cox transformation for the data in the model and the residual correlation is indicated by the order of ARMA (1, 1). The value of 0.947 indicates the coefficient of the damping trend parameter in the model. Furthermore, {7.3} and {36, 1} show the seasonal period and the number of harmonies for each seasonal period.

TBATS parameter estimation results show that the Box-Cox transformation to handle the case of non-linearity in the data is not needed because the lambda value shows a number close to 1. The damping trend coefficient close to 1 indicates that the damping trend effect in the model is very small. Meanwhile, the number of harmonies to produce a smoother seasonal decomposition is obtained at $k_1 = 3$ dan $k_2 = 1$ where the number of harmonies for the two seasonal patterns produces the minimum AIC value. And furthermore, the residual correlation of the model is captured with the ARMA (1, 1).

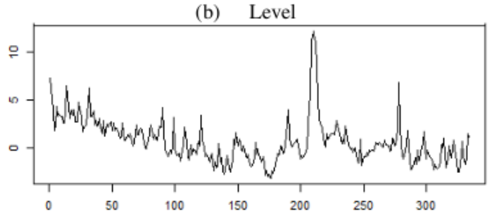
In (FIGURE 2) it can be seen the decomposition of the TBATS model with seasonal patterns of seven and thirty-six. (FIGURE 2 (a)) shows the Box-Cox transformation of the observation data which shows that the trend component is very small in the model. Meanwhile, the daily seasonal pattern decomposition is shown in (FIGURE 2 (d)) and the weekly seasonal pattern decomposition is shown in (FIGURE 2 (e)) is a strong and stable seasonal component over time.



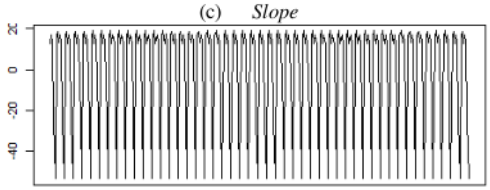
(a) *Observed*



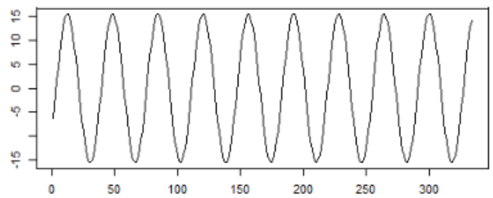
(b) Level



(c) *Slope*



(d) *Seasonal 1*



(e) *Seasonal 2*

FIGURE 2 (a). Observed of TBATS Model (0.995, 1, 1, 0.947, {7, 3}, {36, 1}) on Electrical System Load Data.

(b). Level of TBATS Model (0.995, 1, 1, 0.947, {7, 3}, {36, 1}) on Electrical System Load Data.

(c). Slope of TBATS Model (0.995, 1, 1, 0.947, {7, 3}, {36, 1}) on Electrical System Load Data.

(d). Seasonal 1 of TBATS Model (0.995, 1, 1, 0.947, {7, 3}, {36, 1}) on Electrical System Load Data.

(e). Seasonal 2 of TBATS Model (0.995, 1, 1, 0.947, {7, 3}, {36, 1}) on Electrical System Load Data.

Based on the modeling results, the TBATS (0.995, 1, 1, 0.947, {7, 3}, {36, 1}) can be written as follows.

$$y_t^{(0)} = l_{t-1} + 0{,}995 b_{t-1} + \sum_{i=1}^{2} s_{t-m_i}^{(1)} + d_t \tag{1}$$

$$y_t^{(0)} = l_{t-1} + 0{,}947 b_{t-1} + \sum_{i=1}^{2} s_{t-m_i}^{(1)} + d_t \tag{2}$$

Making predictions based on the TBATS model

After obtaining the TBATS model from the data on electricity consumption, short-term forecasts are then carried out for the next 1 month. This short-term forecasting is intended to determine the ability of the model. In this section, forecasting is performed using the TBATS model (0.995, 1, 1, 0.947, {7, 3}, {36, 1}). The results of the forecasting are shown in the following figure.

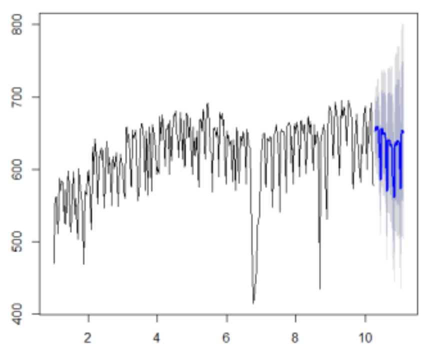


FIGURE 3. Short-term Forecast Results of Electrical System Load.

TABLE 1. Results of TBATS Forecast Out Sample Data.

Date	Actual	Forecast
December1, 2015	644.154	652.622
December 2, 2015	634.589	658.205
December 3, 2015	628.006	653.923
⋮	⋮	⋮
December 31, 2015	530.839	650.586
SMAPE	**8,13%**	

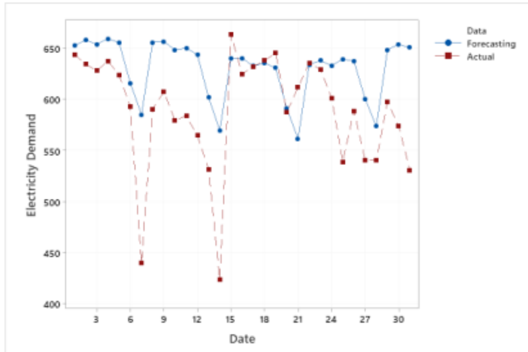


FIGURE 4. The Difference Between Forecast and Actual Data.

From (FIGURE 4) and (TABLE 1) the results of the short-term forecast of electricity consumption in the TBATS model have followed the pattern in the previous data. In addition, the upper and lower limits of the forecast do not have a small interval and are strengthened again with a SMAPE value of 8.13% which indicates that the forecast results are good forecast results. This is because, TBATS modeling uses harmony specification in trigonometric seasonal models which produce smooth forecasts, so that the pattern of decrease or increase in the resulting forecast is not as big or sharp as the pattern of decrease or increase in out-sample data.

In addition, the model has been able to predict seasonal patterns which are indicated by fluctuations every day and week. However, the results of this forecast cannot show fluctuations in each month that occur at an interval of one year and cannot be produced in the forecast, especially on Eid al-Fitr. Forecasting of electrical system load data with daily and weekly seasonal periods has previously been carried out by [16, 17]. This study used the Double Seasonal Holt Winter (DSHW) method on the electrical system load data per half hour with a Double Seosanal Block (DSB) and Percentile Error simulation approach. (PE) bootstrapping. The result is that DSB bootstrap has high accuracy which is more stable than PE bootstrap in electrical system load forecasting using the DSHW method. The implication of this research is that electricity consumption from year to year will increase by around 5% to 10%. Therefore, it is necessary to take steps to anticipate the electricity crisis, for example by utilizing new and renewable energy, urging people to save electricity and so on.

CONCLUSION

Based on the research conducted, descriptively, the in-sample data on the system load shows weekly and monthly seasonal pattern. In addition, the TBATS modeling pattern without including Eid al-Fitr as a seasonal effect also shows that a Box Cox transformation is needed based on a value of the order of 0.995. Furthermore, the residual correlation of the model was captured with the ARMA (1, 1) model.This model has been able to capture fluctuating patterns in seasonal periods but has not been able to accommodate the effects of holidays when using the hijri calendar for forecasting. So that in further research using TBATS modeling, it is recommended to add the amount of data and effects of dual calendars, the Hijri calendar and the Gregorian calendar so that the largest seasonal patterns can be captured by the model and produce better forecasts. In addition, it is also recommended to handle outliers and include seasonal effects in the residual ARMA model in the TBATS modeling so as to produce a better model.

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