State of the art in wind speed in England using BATS, TBATS, Holt’s Linear and ARIMA model

MOSTAFA ABOTALEB, TATIANA MAKAROVSKIKH, AYNUR YONAR*, AMR BADR **, PRADEEP MISHRA***, DHANANJAY KATHAL ***, A. J. WILLIAMS*# and HARUN YONAR*##

Department of System Programming, South Ural State University, Chelyabinsk, Russia

*Selçuk University, Faculty of Science, Department of Statistics, Konya, Turkey

** New England University, Science Faculty, School of Science and Technology, Armidale, NSW, Australia

*** College of Agriculture, Powarkheda, J.N.K.V.V. (M.P.), India

*BTC College of Agriculture & Research Station, IGKV, Sarkanda, Bilaspur, Chhattisgarh, India

**Selçuk University, Faculty of Veterinary Medicine, Department of Biostatistics, Konya, Turkey

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e mail : pradeepjnkvv@gmail.com

ABSTRACT. Wind energy is one of the most important renewable energy sources in the world. Hence, the prediction of wind speed is a highly significant subject with respect to both protecting the environment and economic development. England is among the countries with an increasing interest in the potential for wind energy systems. In this study, various time series models, including BATS, TBATS, Holt’s Linear Trend and ARIMA models were applied for wind speed prediction in England and their performance was compared. The available wind speed data between 1994-07-07 and 2015-12-31 were divided into two parts: training data that is used to build up the models and testing data that is used to measure the validity of a model forecast. The results of the testing data indicate that the BATS and ARIMA outperform the other time series models according to the root mean square errors.

Key words – ARIMA, BATS, TBATS, Forecasting, Wind speed.

1. Introduction

Wind energy is considered a renewable energy source as well as clean energy that does not pollute the environment and countries are currently tending to make great use of wind energy as a source of electricity generation. Because of the decline of non-renewable energy sources such as petroleum, coal, natural gas and other non-renewable sources, there is a need to invest in renewable energy sources. China has started a revolution in investing in its energy systems. China is the largest producer and consumer of coal, but today. (Lewis, 2012). China is the largest market for wind energy in the world. There is a study carried out on daily wind speed time series for Peninsular Malaysia from 18 meteorological stations. This study used Box-Jenkins ARIMA models for each meteorological station plus ARCH Effects. The problem is, we used the ARIMA-GARCH model for 15 stations. The results show that 10 of the stations were successfully designed using the ARIMA-GARCH model, while there were 5 stations. In other studies (Ray, 2021), they studied the monthly average rainfall and temperature...
of South Asian countries, which have been modelled using seasonal ARIMA for developing the forecasting model. This study has shown that all the data series for both rainfall and temperature contain three time-series components such as stochastic trend, seasonal and random. Other modeling methods are required (Hussin, 2020). Meteorological data was received from the Riga site (central Latvia). They can be denominated as all-Latvian averages. All the data is presented as hourly data. The investigation period covers the period 2012-2014.

The second Equation (2) represents the seasonal $M$ pattern global trends and local trends are Equations (3), (4) and (5).

$$y_t^{(\eta)} = l_{t-1} + \xi Z_{t-1} + \sum_{i=1}^{T} s_{t-\rho_i}^{(i)} + d_t$$

(2)

global trends and local trends are Eqns. 3, 4 and 5

$$l_t = l_{t-1} + \xi Z_{t-1} + \alpha d_t$$

(3)

$$b_t = \beta b_{t-1} + \beta d_t$$

(4)

$$s_{t}^{(i)} = s_{t-\rho_i}^{(i)} + \gamma d_t$$

(5)

Equation (6) error can be modeled by ARMA

$$d_t = \sum_{j=1}^{p} \phi_j d_{t-j} + \sum_{i=1}^{q} \theta_i e_{t-i} + e_t$$

(6)

From $\rho_1$... to, $\rho_T$ denote that seasonal period, level and trend of components of time series can be denoted by $l_t$ and $Z_t$ at time $t$, the seasonal component can be denoted by $s_{t}^{(i)}$ at time $t$, $d_t$ represents to ARMA $(p, q)$ component and $e_t$ is white noise process.

The smoothing parameters are given by $\alpha$, $\beta$, $\gamma$, for $i = 1...T$, and $\xi$ is the dampening parameter, which gives more control over trend extrapolation when the trend component is damped (Taylor, 2003). For seasonal data the following equations representing Trigonometric exponential smoothing models

$$s_{t}^{(i)} = \sum_{j=1}^{k_i} a_{j,t}^{(i)} \cos \left( \psi_j^{(i)} t \right)$$

(7)

$$a_{j,t}^{(i)} = a_{j,t-1}^{(i)} + k_{j,t}^{(i)} d_t$$

(8)

$$\beta_{j,t}^{(i)} = \beta_{j,t-1}^{(i)} + k_{j,t}^{(i)} d_t$$

(9)

The smoothing parameters are $k_{1}^{(i)}$ and $k_{2}^{(i)}$.

$$\psi_j^{(i)} = 2\pi / \rho_i$$. This is an extended, modified single source of error version of single seasonal multiple sources of error representation suggested by (Hannan, 1970) and is equivalent to index seasonal approaches when $k_i = \rho_i/2$ for even values of $\rho_i$, and when $k_i = (\rho_i - 1)2$ for odd values of $\rho_i$. But most seasonal terms will require much smaller

2. Materials and method

2.1. BATS and TBATS models

TBATS is an improvement modification of BATS that allows multiple seasonal incorrect cycles. TBATS has the following equation (De Livera, 2011) from figure number two that represented BATS and TBATS model.

The first Equation (1) is a Box-Cox transformation, error modeled by ARMA

$$Y_t^{(\eta)} = \begin{cases} y_t^{(\eta)} - \frac{1}{\eta} & \eta \neq 0 \\ \log y_t & \eta = 0 \end{cases}$$

(1)
Fig. 1. Schema for select best model for forecasting wind speed in England

Fig. 2. BATS and TBATS model
values of \( k_i \), thus reducing the number of parameters to be estimated. In the single seasonal multiple sources of error setting (Harvey, 1990) an alternative, but equivalent formulation of representation (2) is preferred (Durbin, 2012) which can be obtained hyper-parameterizing the single seasonal multiple sources of error version of (2) using:

\[
\begin{align*}
    a_{j,t}^{(i)} &= s_j^{(i)} + s_{j,t-1}^{(i)} \sin \Psi_j^{(i)} - s_{j,t-1}^{(i)} \sin \Psi_j^{(i)} \\
    \beta_{j,t}^{(i)} &= s_j^{(i)} \sin \Psi_j^{(i)} - s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} \\
    s_t^{(i)} &= \sum_{j=1}^{k} s_{j,t}^{(i)}
\end{align*}
\]

where,

\[
\begin{align*}
    s_{j,t}^{(i)} &= s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} + s_{j,t-1}^{(i)} \sin \Psi_j^{(i)} \\
    + k_1^{(i)} \cos \Psi_j^{(i)} + k_2^{(i)} \sin \Psi_j^{(i)} \\
    s_{j,t}^{(i)} &= -s_{j,t-1}^{(i)} \sin \Psi_j^{(i)} + s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} \\
    + k_1^{(i)} \cos \Psi_j^{(i)} - k_2^{(i)} \sin \Psi_j^{(i)} \\
    s_t^{(i)} &= \sum_{i=1}^{k} s_{j,t}^{(i)}
\end{align*}
\]

Equations (16) and (17) are seasonal patterns modeled by the Fourier model.

\[
\begin{align*}
    s_{j,t}^{(i)} &= s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} + s_{j,t-1}^{(i)} \sin \Psi_j^{(i)} + \gamma_1 d_t \\
    s_{j,t}^{(i)} &= -s_{j,t-1}^{(i)} \sin \Psi_j^{(i)} + s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} + \gamma_2 d_t
\end{align*}
\]

The notation of TBATS \([p, q, (p_1, k_1), (p_2, k_2), \ldots, (p_T, k_T)]\) is used for these trigonometric models.

2.2. Holt’s linear trend method

The exponentially weighted moving average is also the averages of smoothing random variability with the following advantages: (i) older data have a declining weight that is very important that; (ii) very simple to calculate; and (iii) the most important for data set is that minimal data is needed. Holt, 1957 had given three equations for forecast, level and trend (Holt, 1957).

\[
\begin{align*}
    \hat{X}_{t+1} &= M_t + \rho \theta_t \\
    M_t &= vX_t + (1 - \omega)(M_{t-1} + \theta_{t-1}) \\
    \theta_t &= \gamma^* (M_t - M_{t-1}) + (1 - \gamma^*) \theta_{t-1}
\end{align*}
\]

And an estimate of the level of series at time \( t \), \( b_t \) denotes an estimate of the trend (slope) of the series at time \( t \), \( \omega \) is the smoothing parameter for level, \( 0 \leq \omega \leq 1 \) and \( \gamma^* \) is the smoothing parameter for the trend, \( 0 \leq \gamma^* \leq 1 \) that’s with simple exponential smoothing.

2.3. ARIMA model

ARIMA model consist of three parts The first part is (AR) that is Autoregressive The second part is (I) integrated The third part is (MA) Moving Average so that model is named that Autoregressive integrated moving average (ARIMA). Some times data of time series not required integrated part to decline the seasonality and in that case ARIMA model represented as ARMA \((p, q)\) model where \( p \) is the order of the autoregressive part and \( q \) is the order of the moving average and integrated part is equal zero ARIMA \((p, 0, q)\) that represented as ARMA \((p, q)\).

The first part is autoregressive model

Equation (1) The autoregressive model of order \( p \) is written as AR\((p)\)

\[
X_t = K + \sum_{i=1}^{p} \omega_i X_{t-i} + \varepsilon_t
\]

where, \( \omega_1, \omega_2, \ldots, \omega_p \) are the parameters of the model, \( K \) is a constant and some times the constant term is avoided \( \varepsilon \) is white noise.

The second part is moving average model

Equation (2) the moving average model of order \( q \) is written as MA \((q)\) (Mishra et al., 2021)

\[
X_t = \mu + \sum_{i=1}^{q} \theta_i + \varepsilon_t
\]
where $\theta_1, \ldots, \theta_q$ are the parameters of the model, $\mu$ is the expectation of $X_t$ (often assumed to equal 0) and the $\epsilon_t$, $\epsilon_{t-1}$, 

Stationary time series can be modelled with ARIMA models. The non-seasonal ARIMA model can be written as in Equation 3.

$$
V_t' = K + \phi_1 V_{t-1}' + \phi_2 V_{t-2}' + \ldots + \phi_p V_{t-p}' + \epsilon_t + \theta_1 \epsilon_{t-1} \\
+ \theta_2 \epsilon_{t-2} + \ldots + \theta_p \epsilon_{t-p}
$$

(3)

The important of $V_t'$ is the difference in the series to eliminate the seasonality when that is required. The “predictors” on the right-hand side include both lagged values of $V_t$ and lagged errors. This is defined as the ARIMA $(p, d, q)$ model. ARIMA has four major steps as model building and identification, estimation, model diagnostics and forecast. Firstly, tentative model parameters are identified through ACF (Auto Correlation Function) and PACF (Partial Auto Correlation Function), then the best coefficients for the model are determined through MSE, MAPE etc. next steps involve is to forecast and finally validate and check the model performance by observing the residuals through Ljung Box test and ACF plot of residuals (Mishra, 2021). For steps and information about Box Jenkins method for time series data analysis (Young, 1977); (Frain, 1992); (Kirchgässner, 2012) and (Chatfield, 2019)

### 3. Results and discussion

All results were obtained using R programming and steps for different models in rpubs for BATS, TBATS and Holts linear trend models (Makarovskikh Tatyana Anatolyevna, 2021) and for the ARIMA model (akarovskikh Tatyana Anatolyevna, 2021). We find that: wind speed in England from "1994/07/07" to "2015/12/31", the Wind Speed has increased during the period from (0) to (16.42) meter per second. Average daily Wind speed is 3.10 meters per second. Kurtosis value is (5.06) indicates the data follows a platykurtic distribution which shows a tail that's thinner than a normal distribution which means the number of outliers will not be large. Followed by a positive value of skewness (1.31) which is between -0.5 and 0.5, the distribution is approximately symmetric and standard deviation is 2.17.

Wind Speed In England fit model BATS [1, {3, 2}, 0.958, -] In this model, Box-Cox transformation (lambda) equal 1 (doing nothing), the order of ARMA errors are present error is (3, 2) and Autoregressive coefficients are (-0.18, 0.14, 0.02) respectively and moving average coefficients are 0.64 and 0.09 respectively, the damping parameter for Trend is 0.95 . Optimized while fixing the values for $\alpha = 0.04$, $\beta = -0.001$ are smoothing parameters for the parameter that controls the smoothness of the fitted curve. Wind Speed In England fit model TBATS [1, {0,0}, 1, {<6,2>}] In this model, the value that provides the best approximation for the normal distribution Box-Cox transformation (lambda) equals 1 (doing nothing), ARMA (0,0) errors are present .the damping parameter equals 1 (doing nothing) and 2 Fourier pairs have a Seasonal period of $m = 6$ to be optimized while fixing the values for $\alpha =0.3745714$, $\beta =0.0004$, $\gamma_1=-0.00011$ and $\gamma_2 = 0.0001$ are smoothing parameters are the parameters that control the smoothness of the fitted curve. Here the one type of seasonality has been handled with 6 parameters (the four initial values for $s_{j,0}$ and $s_{j,0}$ and the two smoothing parameters $\gamma_1$ and $\gamma_2$).

Holt’s linear trend for wind speed in England. It becomes clear that the best values of the level smoothing and the trends are (Alpha) 0.6556 for level, meaning normal learning in the day-to-day wind speed in England and 1e-04 for trend (Beta), which means slow learning for the trend. The value that provides the best approximation of the normal distribution Box-Cox transformation (lambda) equals 0.0635. One model for wind speed in England is ARIMA (2, 1, 2) and the other is the Autoregressive from the second order. This means that the forecast of a new day’s wind speed in England is dependent on the previous two days and MA does not use previous forecasts to forecast future wind speeds in England. It indicates that the moving average is of the second order, indicating that there are fluctuations in the number of wind speeds in England. Fig. 3 shows the Root
Mean Square Error (RMSE) from testing data. It shows that the BATS model is the best model that achieves the least RMSE. Fig. 4 shows the training data for wind speed in England. Fig. 5 shows the decomposition of the wind speed time series by the BATS model to observed, level and slope. Fig. 6 shows the residuals from the BATS model and the ACF plot of the residuals from the BATS model shows that all autocorrelations are within the threshold limits, indicating that the residuals are behaving like white noise. Fig. 7 shows the forecast wind speed from the BATS model. Fig. 8 shows the decomposition of the wind speed time series by the TBATS model and Fig. 9 shows the residual from the TBATS model.
TBATS model into four components observed, level, slope and season. Fig. 9 shows the residual from the TBATS model. The ACF plot of the residuals from the TBATS model shows that all autocorrelations are within the threshold limits, indicating that the residuals are behaving like white noise. Fig. 10 shows the forecast wind...
TABLE 1
Descriptive statistics of Wind Speed in England

<table>
<thead>
<tr>
<th>Wind speed in England</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.01</td>
<td>0.00</td>
<td>16.42</td>
<td>2.17</td>
<td>1.31</td>
<td>5.60</td>
</tr>
</tbody>
</table>

TABLE 2
BATS model fitted for wind speed in England on training data 80% of data set (From 7 July, 1994 to 2 October 2011)

<table>
<thead>
<tr>
<th>Wind Speed In England</th>
<th>*Box-Cox transformation (Lambda)</th>
<th>Smoothing parameter</th>
<th>Damping Parameter for trend</th>
<th>Prediction error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Alpha Beta Gamma-1 Values Gamma-2 Values</td>
<td>Sigma AIC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BATS [1, {3,2}, 0.958, -1]</td>
<td>1 0.04 0.00 - 0.96 0.14 0.02</td>
<td>-0.18 0.64 0.09 1.46 58932.69</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Box-cox transformation (Lambda) is equal 1 that means no transformation is required

TABLE 3
TBATS model fitted for wind speed in England on training data 80% of data set (From 7 July, 1994 to 2 October 2011)

<table>
<thead>
<tr>
<th>Wind Speed In England</th>
<th>*Box-Cox transformation (Lambda)</th>
<th>Smoothing parameter</th>
<th>Damping Parameter for trend</th>
<th>Prediction error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Alpha Beta Gamma-1 Values Gamma-2 Values</td>
<td>Sigma AIC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TBATS (1, {0,0}, 1, {&lt;6,2&gt;})</td>
<td>1 0.37 0.00 0.00 0.00 1</td>
<td>1.58 59872.38</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Box-cox transformation (Lambda) is equal 1 that means no transformation is required

TABLE 4
Holt’s Linear trend model fitted for wind speed in England on training data 80% of data set (From 7 July, 1994 to 2 October 2011)

<table>
<thead>
<tr>
<th>Wind Speed In England</th>
<th>Smoothing parameters</th>
<th>Initial states</th>
<th>Sigma</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Alpha Beta L B</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.06 0.66 1e-04 0.10 1e-04</td>
<td>0.67 49313.13</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE 5
ARIMA model fitted for wind speed in England on training data 80% of data set (From 7 July, 1994 to 2 October 2011)

<table>
<thead>
<tr>
<th>Model</th>
<th>AR (1)</th>
<th>AR (2)</th>
<th>MA (1)</th>
<th>MA (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA (2, 1, 2)</td>
<td>-0.46</td>
<td>0.40</td>
<td>-0.05</td>
<td>-0.90</td>
</tr>
</tbody>
</table>
TABLE 6
Holt’s Linear trend models fitted for of wind speed in England on training data 80% of data set (From 7 July, 1994 to 2 October 2011)

<table>
<thead>
<tr>
<th>Model</th>
<th>ME</th>
<th>RMSE</th>
<th>MAE</th>
<th>MPE</th>
<th>MAPE</th>
<th>MASE</th>
<th>ACF1</th>
</tr>
</thead>
<tbody>
<tr>
<td>BATS</td>
<td>0.01</td>
<td>1.46</td>
<td>1.07</td>
<td>-</td>
<td>-</td>
<td>0.89</td>
<td>3.17</td>
</tr>
<tr>
<td>TBATS</td>
<td>-0.03</td>
<td>1.58</td>
<td>1.14</td>
<td>-</td>
<td>-</td>
<td>0.96</td>
<td>0.19</td>
</tr>
<tr>
<td>Holt’s linear Trend</td>
<td>0.13</td>
<td>1.60</td>
<td>1.13</td>
<td>-</td>
<td>-</td>
<td>0.94</td>
<td>-0.01</td>
</tr>
<tr>
<td>ARIMA(2,1,2)</td>
<td>0.01</td>
<td>1.46</td>
<td>1.07</td>
<td>-</td>
<td>-</td>
<td>0.90</td>
<td>0.01</td>
</tr>
</tbody>
</table>

TABLE 7
Fitted Holt’s Linear Trend, BATS, TBATS, ARIMA model fitted for wind speed in England on Testing data 20% of data set (3 October 2011 to 31 December 2015)

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>BATS</td>
<td>2.28</td>
</tr>
<tr>
<td>TBATS</td>
<td>3.59</td>
</tr>
<tr>
<td>Holt’s linear Trend</td>
<td>2.81</td>
</tr>
<tr>
<td>ARIMA(2,1,2)</td>
<td>2.30</td>
</tr>
</tbody>
</table>

speed from the TBATS model. Fig. 11 shows the residual from Holt’s linear trend model as well as the ACF plot of the residuals from the Holt’s linear trend model shows that all autocorrelations are within the threshold limits, indicating that the residuals are behaving like white noise. Fig. 12 shows the forecast wind speed from Holt’s linear trend model. Fig. 13 shows the first difference in wind speed time series data to be the wind speed time series stationary. The PACF shown in Fig. 14 is suggestive of an AR (2) model and the ACF suggests an MA (2) model, so an initial candidate model is an ARIMA (2, 1, 2) from Fig. 14 shows the residual from the ARIMA (2, 1, 2) model. The ACF plot of the residuals from the ARIMA (2, 1, 2) model shows that all autocorrelations are within the threshold limits, indicating that the residuals are behaving like white noise. Fig. 15 shows the forecast wind speed from the ARIMA (2, 1, 2) model.

4. Conclusions

This study is aimed at calculating wind speed predictions for England, where there is a great interest in developing wind energy. For this purpose, the wind speed data (1994-2015) were first divided into two groups: training data and test data. Then, using four different time series models: BATS, TBATS, Holt’s Linear Trend and ARIMA, the models for wind speed were constructed with the training data and the validity of the models was measured with the test data. The goodness of fit of the models established for training data is examined through ME, RMSE, MAE, MASE and ACF. The results show that among these models, the BATS model has the best performance with the smallest RMSE value for testing data. Furthermore, the ARIMA (2, 1, 2) model has an RMSE value very close to that of the BATS model.

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