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

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सार – पवन ऊर्जा दुनिया में सबसे महत्वपूर्ण अक्षय ऊर्जा स्रोतों में से एक है। इसलिए, पर्यावरण की रक्षा और आर्थिक विकास दोनों के संबंध में पवन की गति का पूर्वानुमान एक अत्यधिक महत्वपूर्ण विषय है। इंग्लैंड पवन ऊर्जा प्रणालियों की क्षमता वृद्धि में रुचि रखने वाले देशों में से एक है। इस शोध पत्र में, इंग्लैंड में पवन की गति के पूर्वानुमान के लिए BATS, TBATS, हॉल्ट्सल की रैखिक प्रवृत्तिो और ARIMA मॉडल सहित विभिन्न समय श्रृंखला मॉडल लागू किए गए और उनके प्रदर्शन की तुलना की गई। 1994-07-07 और 2015-12-31 के बीच उपलब्ध पवन की गति के आंकड़ों को दो भागों में विभाजित किया गया प्रशिक्षण डेटा जिसका उपयोग मॉडल बनाने के लिए किया जाता है और परीक्षण डेटा का उपयोग मॉडल पूर्वानुमान की वैधता को मापने के लिए किया जाता है। परीक्षण डेटा के परिणाम दर्शाते हैं कि वर्ग माध्य मूल त्रुटियों के अनुसार BATS और ARIMA अन्य समय श्रृंखला मॉडलों से बेहतर प्रदर्शन करते हैं।

**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 paper recommends the best model for forecasting wind speed is the ARIMA (3, 1, 1) forecast wind speed for the first 6-8 hours because the accuracy of the ARIMA Model is lower when it is used for longer periods of time. It also suggests choosing RMSE and MAE criteria for wind speed analysis and model selection Grigonyt (2016) defines formalized. Mishra *et al.* (2021) used the ARIMA and GARCH models for forecasting purposes for maximum, minimum and relative humidity. Lama *et al.* (2021) compared the forecasting performances of the SARIMA, TDNN and EXPAR models using monthly rainfall data from the sub Himalayan region. Several researchers have applied the SARIMA model to rainfall data from various locations and found satisfactory results (Akpanta *et al.*, 2015; Wanga *et al.*, 2013; Murthy *et al.*, 2018; Dabral and Murry, 2017). So in that paper, we are using ARIMA, BATS, TBATS (Trigonometric seasonality, Box-Cox transformation), ARMA errors, Trend and Seasonal components and Holt's linear model to improve the forecast wind speed in England and we selected the best model for forecasting by using the RMSE criterion and selecting the model which has the least RMSE. The study used daily wind speed data from England from 1994-07-07 to 2015-12-31) and used 80% of the data set for training (from 1994-07-07 to 2011-10-02) and 20% of the data set for testing (from 2011-10-03 to 2015-12-31) (Rennie, 2020).

## 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

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

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

$$Y_t^{(\eta)} = l_{t-1} + \xi Z_{t-1} + \sum_{i=1}^{T} s_{t-\rho_i}^{(i)} + d_t \tag{2}$$

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

$$l_t = l_{t-1} + \xi Z_{t-1} + \alpha d_t \tag{3}$$

$$b_t = \xi b_{t-1} + \beta d_t \tag{4}$$

$$s_t^{(i)} = s_{t-\rho_i}^{(i)} + \gamma_i d_t \tag{5}$$

Equation (6) error can be modeled by ARMA

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_{t'} \tag{6}$$

From $\rho_1,\ldots$ 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 $\varepsilon_t$ is white noise process.

The smoothing parameters are given by α, β, $\gamma_i$ for $i = 1\ldots T$ and ξ 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

$$s_t^{(i)} = \sum_{j=1}^{k_i} a_{j,t}^{(i)} \cos\left(\psi_j^{(i)} t\right) \tag{7}$$

$$a_{j,t}^{(i)} = a_{j,t-1}^{(i)} + k_1^{(i)} d_t \tag{8}$$

$$\beta_{j,t}^{(i)} = \beta_{j,t-1}^{(i)} + k_2^{(i)} d_t \tag{9}$$

The smoothing parameters are $k_1^{(i)}$ and $k_2^{(i)}$.

$\psi_j^{(i)} = 2\pi j / \rho_i$. 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
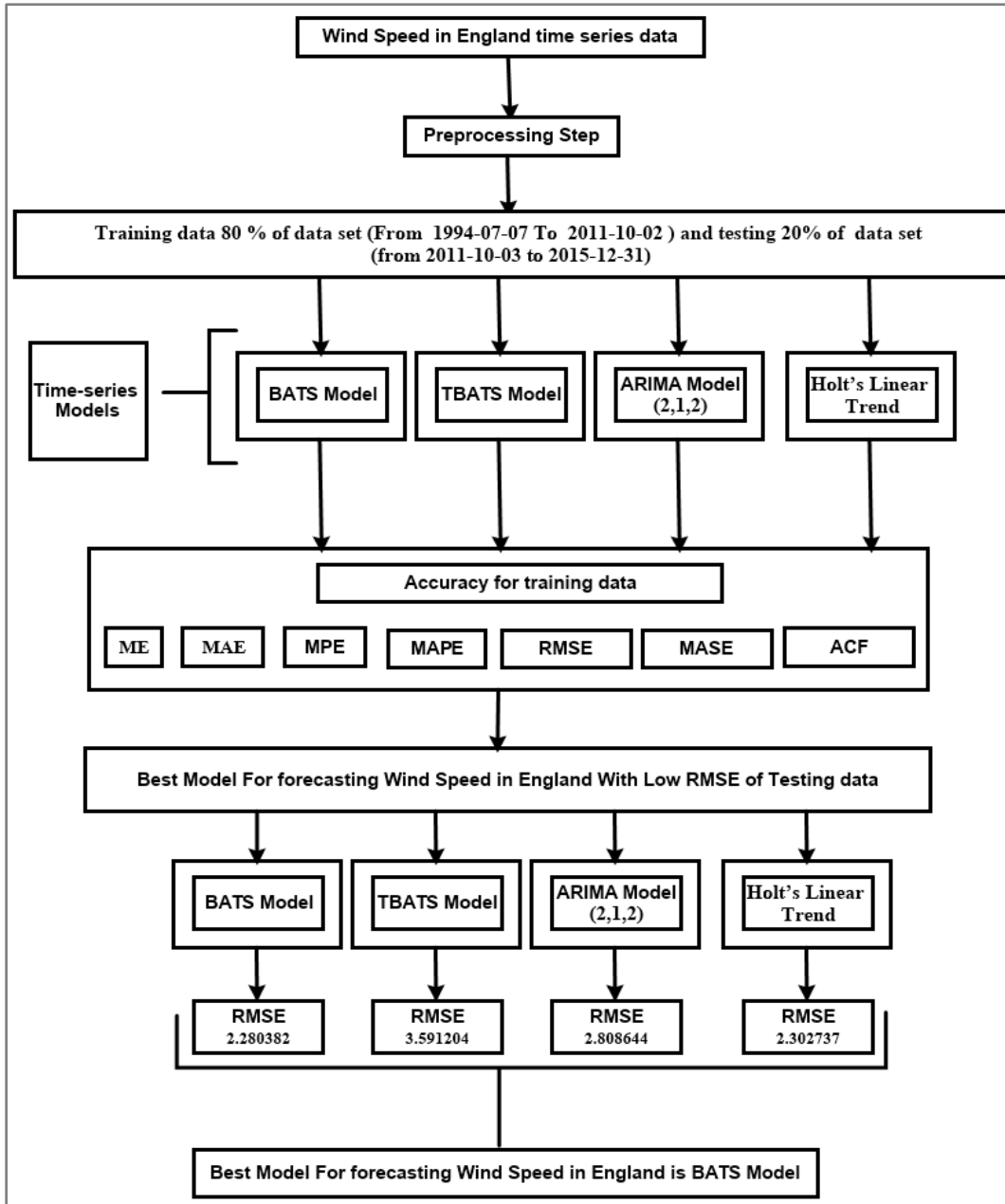
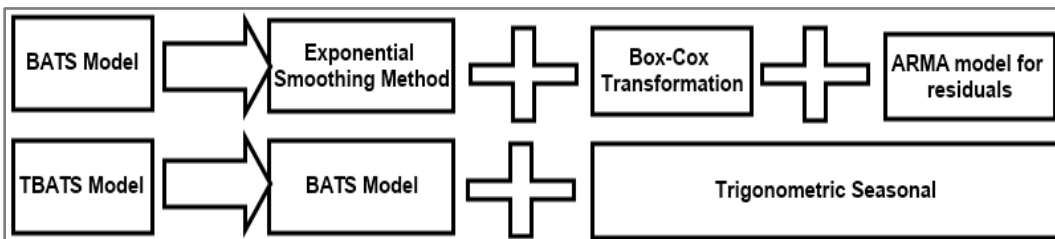**Fig. 1.** Schema for select best model for forecasting wind speed in England



**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 :

$$a_{j,t}^{(i)} = s_{j,t}^{(i)} \cos\left[\Psi_j^{(i)}t\right] - s_{jt}^{*(i)} \sin\left[\Psi_j^{(i)}t\right] \tag{10}$$

$$\beta_{j,t}^{(i)} = s_{j,t}^{(i)} \sin\left[\Psi_j^{(i)}t\right] - s_{jt}^{*(i)} \cos\left[\Psi_j^{(i)}t\right] \tag{11}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{12}$$

where,

$$\begin{aligned} s_{j,t}^{(i)} &= s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} + s_{j,t-1}^{*(i)} \sin \Psi_j^{(i)} \\ &+ \left\{ k_1^{(i)} \cos\left[\Psi_j^{(i)}t\right] + k_2^{(i)} \sin\left[\Psi_j^{(i)}t\right] \right\} d_t \end{aligned} \tag{13}$$

$$\begin{aligned} s_{j,t}^{*(i)} &= -s_{j,t-1} \sin \Psi_j^{(i)} + s_{j,t-1}^{*(i)} \cos \Psi_j^{(i)} \\ &+ \left\{ k_2^{(i)} \cos\left[\Psi_j t\right] - k_1^{(i)} \sin\left[\Psi_j t\right] \right\} d_t \end{aligned} \tag{14}$$

$$s_t^{(i)} = \sum_{i=1}^{k_i} s_{j,t'}^{(i)} \tag{15}$$

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

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \Psi_j^{(i)} + s_{j,t-1}^{*(i)} \sin \Psi_j^{(i)} + \gamma_1^{(i)} d_t \tag{16}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} \sin \Psi_j^{(i)} + s_{j,t-1}^{*(i)} \cos \Psi_j^{(i)} + \gamma_2^{(i)} d_t \tag{17}$$

The notation of TBATS $[p, q, (\rho_1, k_1), (\rho_2, k_2),\ldots, (\rho_T, k_T)]$ 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).

*Forecast equation*

$$\hat{\chi}_{t+\rho\backslash t} = M_t + \rho\theta_t \tag{i}$$

*Level equation*

$$M_t = v\chi_t + (1-\omega)(M_{t-1} + \theta_{t-1}) \tag{ii}$$

*Trend equation*

$$b_t = \gamma^*(M_t - M_{t-1}) + (1-\gamma^*)\theta_{t-1} \tag{iii}$$

And an estimate of the level of series at time $tM_t$, $b_t$ denotes an estimate of the trend (slope) of the series at time t, $\omega$ is the smoothing parameter for level, $0 \le \omega \le 1$ and $\gamma^*$ is the smoothing parameter for the trend, $0 \le \gamma^* \le 1$ 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*)

$$X_t = \mathrm{K} + \sum_{i=1}^{P} \omega_i X_t + \varepsilon_t \tag{1}$$

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 $\varepsilon_t$ 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)

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_t + \varepsilon_{t-i} \tag{2}$$

where, $\theta_1, ..., \theta_q$ are the parameters of the model, $\mu$ is the expectation of $X_t$ (often assumed to equal 0) and the $\varepsilon_t$, $\varepsilon_{t-1}$...

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

$$V_t^{`} = K + \phi_1 V_{t-1}^{`} + \phi_2 V_{t-2}^{`} + ... + \phi_p V_{t-p}^{`} + e_t + \theta_1 \varepsilon_{t-1} \\ + \theta_2 e_{t-2} + ... + \theta_p e_{t-p} \qquad (3)$$

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
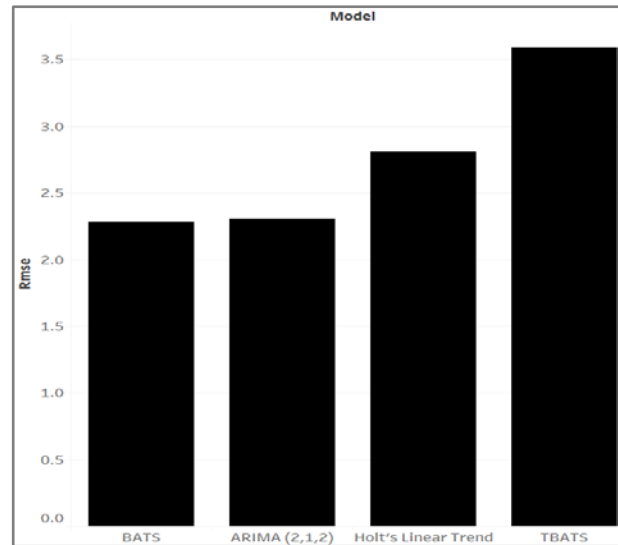


**Fig. 3.** RMSE form testing data

parameter for Trend is 0.95 . Optimized while fixing the values for $\alpha$ = 0.04, $\beta$ = -0.001 are smoothing parameters are 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, $\gamma1$=-0.00011 and $\gamma2$ = 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 $\gamma1$ and $\gamma2$).

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
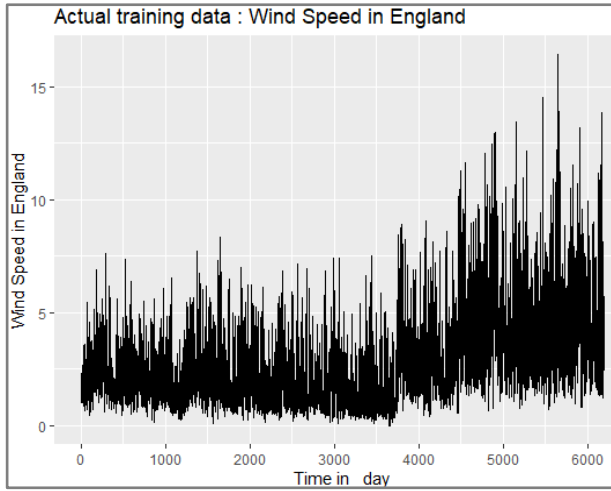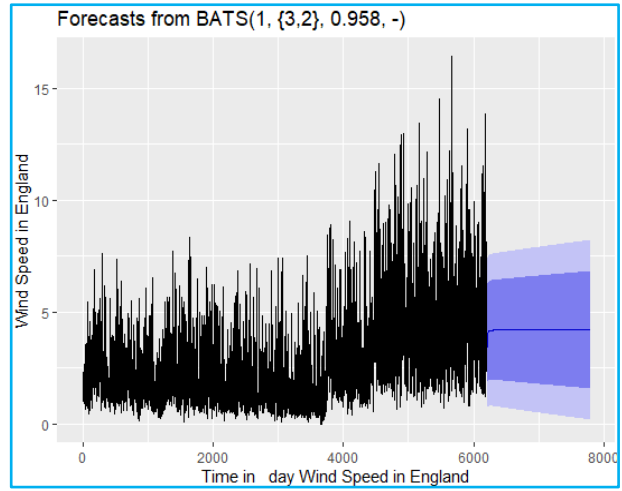
**Fig. 4.** Actual training data of wind speed



**Fig. 7.** Forecast wind speed from BATS model
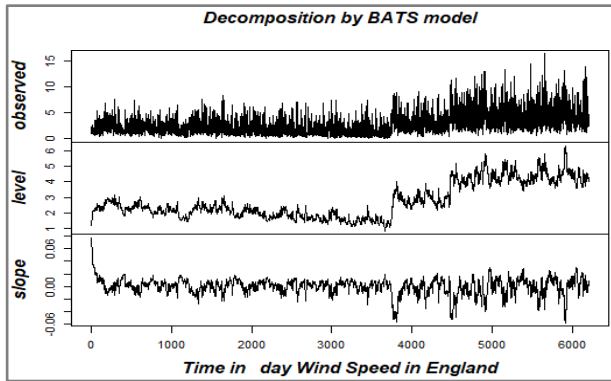


**Fig. 5.** Decomposition the wind speed time series by BATS model
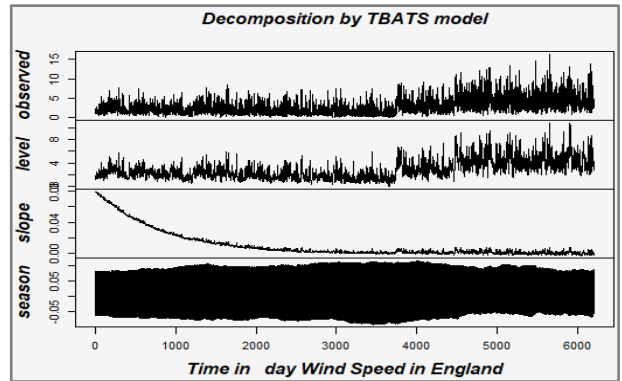


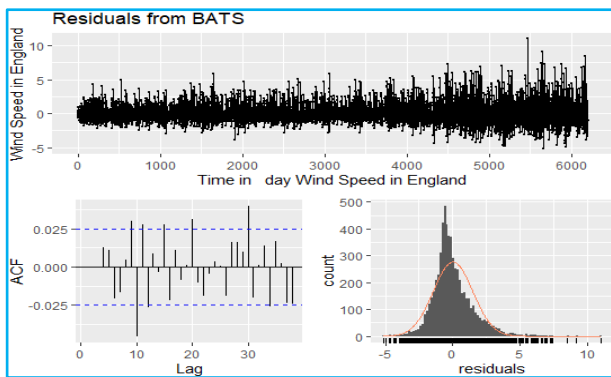**Fig. 8.** Decomposition wind speed time series by TBATS model
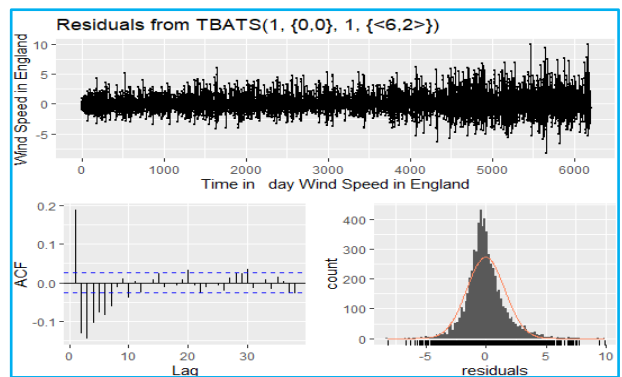


**Fig. 6.** Residual from BATS model



**Fig. 9.** Residual from TBATS model

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
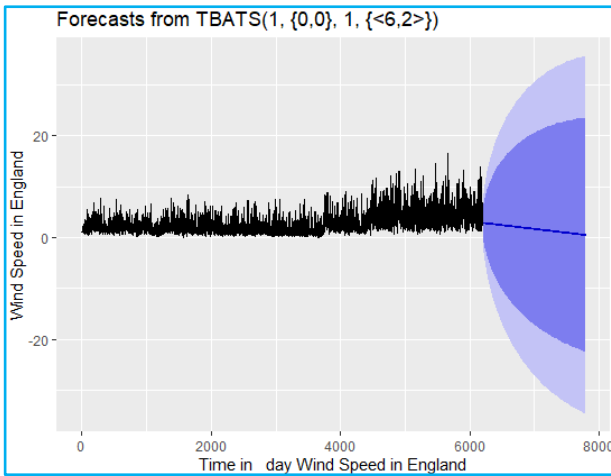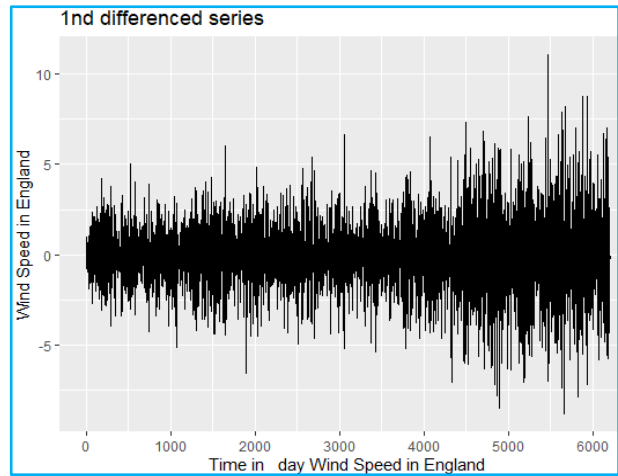
**Fig. 10.** Forecast wind speed from TBATS model



**Fig. 11.** Residual from Holt's linear trend model



**Fig. 12.** Forecast wind speed from Holt's linear trend model



**Fig. 13.** First differencing of wind speed time series data
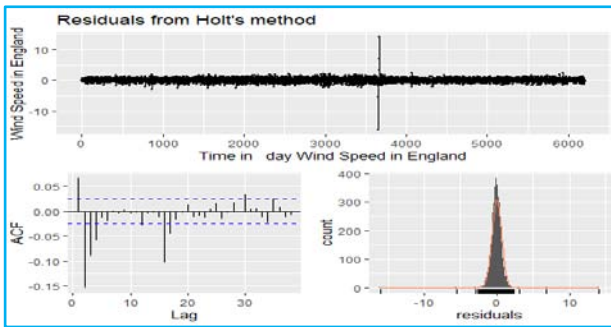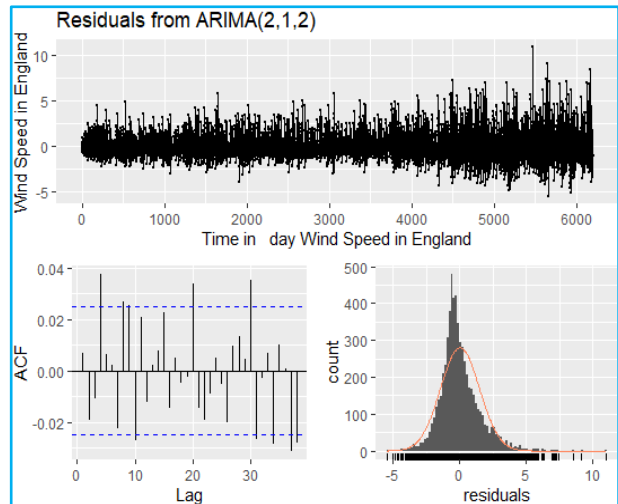


**Fig. 14.** Residual from ARIMA (2, 1, 2) model
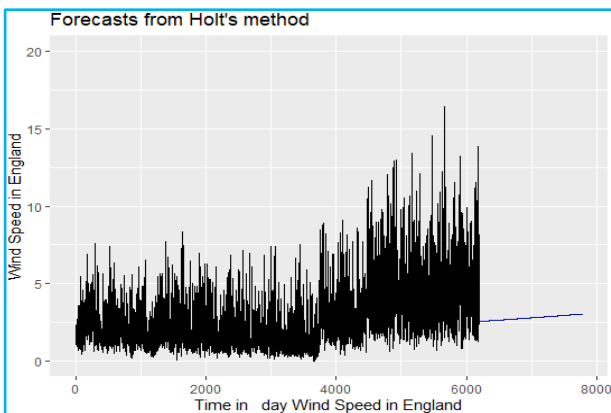


**Fig. 15.** Forecast wind speed from ARIMA model

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

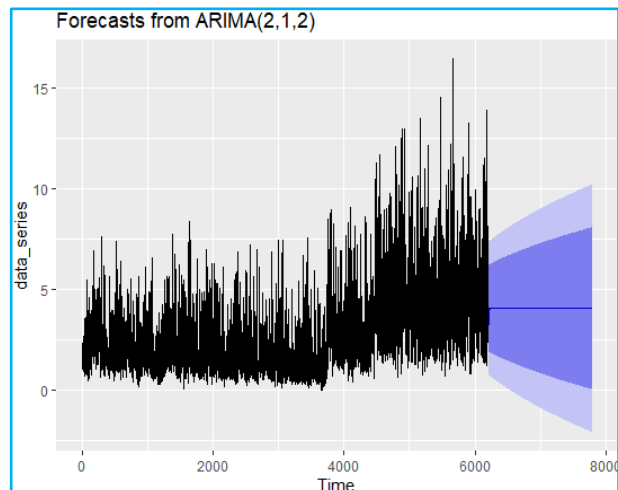**TABLE 1**

**Descriptive statistics of Wind Speed in England**

| Wind speed in England | Mean | Minimum | Maximum | Standard Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| | 3.01 | 0..00 | 16.42 | 2.17 | 1.31 | 5.6 0 |

**TABLE 2**

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

| Wind Speed In England | *Box-Cox transformation (Lambda) | Smoothing parameter | | | | Damping Parametr for trend | Prediction error | |
|---|---|---|---|---|---|---|---|---|
| | | Alpha | Beta | Gamma-1 Values | Gamma-2 Values | | Sigma | AIC |
| BATS [1, {3,2}, 0.958, -] | 1 | 0.04 | 0.00 - | 0.96 | -0.18 0.14 0.02 | 0.64 0.09 | 1.46 | 58932.69 |

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

**TABLE 3**

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

| Wind Speed In England | *Box-Cox transformation (Lambda) | Smoothing parameter | | | | Damping Parametr for trend | Prediction error | |
|---|---|---|---|---|---|---|---|---|
| | | Alpha | Beta | Gamma-1 Values | Gamma-2 Values | | Sigma | AIC |
| TBATS (1, {0,0}, 1, {<6,2>}) | 1 | 0.37 | 0.00 | 0.00 | 0.00 | 1 | 1.58 | 59872.38 |

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

**TABLE 4**

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

| Wind Speed In England | | Smoothing parameters | | Initial states | | Sigma | AIC |
|---|---|---|---|---|---|---|---|
| | | Alpha | Beta | L | B | | |
| | 0.06 | 0.66 | 1e-04 | 0.10 | 1e-04 | 0.67 | 49313.13 |

**TABLE 5**

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

| Model | AR (1) | AR (2) | MA (1) | MA (2) |
|---|---|---|---|---|
| ARIMA (2, 1, 2) | -0.46 | 0.40 | -0.05 | -0.90 |

**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)**

| Model | Wind speed in England | | | | | | |
|---|---|---|---|---|---|---|---|
| | ME | RMSE | MAE | MPE | MAPE | MASE | ACFl |
| BATS | 0.01 | 1.46 | 1.07 | - | - | 0.89 | 3.17 |
| TBATS | -0.03 | 1.58 | 1.14 | - | - | 0.96 | 0.19 |
| Holt's linear Trend | 0.13 | 1.60 | 1.13 | - | - | 0.94 | -0.01 |
| ARIMA(2,1,2) | 0.01 | 1.46 | 1.07 | - | - | 0.90 | 0.01 |

**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)**

| Wind speed in England | |
|---|---|
| Model | RMSE |
| BATS | 2.28 |
| TBATS | 3.59 |
| Holt's Linear Trend | 2.81 |
| ARIMA(2,1,2) | 2.30 |

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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