Wind Speed Forecasting Using Machine Learning Models

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Abstract

Wind energy is the strongest renewable energy source which ensures clean and safe production of energy. The wind speed prediction has an important place in wind energy systems and to drive turbines that further helpful for generating electricity, but the issue with the system is that power generated from wind is uncertain. So, accurate wind speed forecasting is required to produce more electric power. To address this issue, many approaches are presented by various researchers. This project describes an empirical study of modeling and forecasting of wind speed of Chennai city.. This project aims to build two wind speed prediction models The mean square error (MSE) and root mean square error (RMSE) are used to compare the performance of Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated

Moving Average (SARIMA) in order to determine which model is superior for wind speed forecasting.

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I. INTRODUCTION

The development of modern technology made 'electricity' as one of the essential element to lead a quality life. To reduce this we need to reduce the usage of fossil fuels and to find alternate energy sources. Due these reasons the importance of renewable energies has been increasing rapidly as it has less impact on environmental pollution. One of the best among such renewable energies is wind energy which ensures clean and safe production of energy. Wind is nothing but "Air in motion". Wind stations are to be constructed for using wind energy and for constructing wind stations proper and accurate investigation on wind speed at different regions need to be done. So we can reduce the operational cost. Electric power generation is mainly depends on the wind energy. The wind speed prediction has an important place in wind energy systems and to drive turbines that further helpful for generating electricity. Wind power forecasting is primarily depends of wind speed forecasting. Wind speeds will become uncertain due to climate change. So, accurate wind speed forecasting is required to produce more electric power. Many approaches have been described by many researchers to address this issue. These approaches are basically divided into structural methods, mathematical methods, time series methods. Combination of two or more different model to gain advantages of each model is known as hybrid method. ARIMA is one of the most widely used time series method which aims to find autocorrelation between the data. The structure of this model is described by p, d, and q, and these parameters were determined using the Partial Auto-Correlation Function (PACF) and the Auto-Correlation Function (ACF). Seasonal-ARIMA is an extension of ARIMA with a seasonality function, with the following parameters: auto regression (AR), degree of differencing (I), and moving average (MA), as well as a seasonality parameter. The mean square error (MSE) and root mean square error (RMSE) were used to assess the prediction accuracy of these models (RMSE). For wind speed predictions, the model with lower RMSE and MSE values was chosen as the best model.

II. RELATED WORK

Yanbin Cui, et al [1]. Prediction of wind speed using short term forecasting is important for decision making to run turbines so that operational cost can be reduced. For improving forecasting novel based model is used for this paper. The quick ensemble empirical mode decomposition method is used to handle data.The algorithm Bat was used for reducing the threshold caused by back propagation method. This method gave good accuracy. Zaher Mundher Yaseen, et al [2]. In the management of water resources prediction of evaporation is needed. Predicting the evaporation is done using various machine learning models on two different places in Iraq and compared among the models for finding the best model in this paper. All the models predicted good but among all models support vector machine model gave the best results. [13][14][15][16][17][18]19]. Mohammed Ali Jallal, et al [3].In this study, hourly global solar radiation (HGSR) is predicted using artificial multi-neural approach algorithm in three places. For evaluating the performance statistical indicators were used. This resulted a good performance for solar radiation prediction such that solar energy systems can be managed efficiently. Qiang Zhao, et al [4].Condition monitoring place an important role in reducing operational costs and in efficiently running the wind turbines. The temperature is predicted using an artificial model known as a neural network and memory long short term memory (LSTM) in this study. The variation model decomposition (VMD) technique is used to improve prediction accuracy. As a result, the performance and accuracy are excellent.Jiu Gu, et al [5]. Numerical weather prediction helps in many ways such as in generating electricity, management of water resources and so on. Processing of data is done using an embedding t-distributed neighbor stochastic (t-SNE) algorithm, principal of component and analysis (PCA) algorithm is used for comparing the results. For wind farm prediction long short term memory is used so that prediction of wind power increased. Mengning Wu, et al [6].Prediction of wind speed using short term forecasting is important for decision making to run turbines so that operational cost can be reduced. For prediction the combination of technique of decomposition and network adaptive based fuzzy (ANFIS) inference system technique used in this study. For finding stationarity of the time series the decomposition technique has been used and prediction is done using ANFIS.

P. A. Costa Rocha, et al [7].Prediction of solar energy plays an important role in electricity generation and helps in proper management of solar grids. In this three variables are trained represents daily , weekly and yearly predictions. In this study Artifcial neural networking model and (BFGS) Broyden, Fletcher, Goldfarb and Shanno algorithm •is used for solar energy prediction. Performance analyzing is based on using of mean error known as RMSE, Mean of absolute and percentage error (MAPE).Majid Jamil, et al [8]. In this paper, ANN was used to forecast wind speed. The original data is separated into two parts: training and testing.NAR and NARX models for predicting were helped for the studying of that data. Analysing the performanc is finished using mean error known as RMSE, Mean of absolute and percentage error (MAPE).Jian Jiao, et al [9]. For wind power generation predicting the speed of wind is necessary. This study, the hybrid model is used for prediction which contains combination of neural networking and (ARIMA) Auto regression of Integrating the moving speed or average algorithms. After analyzing this results hybrid model gave the best accuracy and performance.DAVID B. ALENCAR, et al [10].In this study, a hybrid model is used for prediction which contains combining the (SARIMA) Seasonality of Auto regression of Integrating the moving speed or average and neural networks algorithms. First explanatory variables are predicted and then multi step ahead forecasting is done. After analyzing the results hybrid model gave the best accuracy.Ernesta Grigonytė, et al [11]. This study of paper, time analysis methodology (ARIMA) Auto regression of integrating of moving speed or average method is utilized for short forecasting of speed of wind. Partially Auto Correlated Functionality and Completely Auto Correlated Functionality graphs were drawn for determining a model’s order and then performance analysis is done using mean error known as RMSE and then Mean absolute error (MAE).Erasmo Cadenas, et al [12]. In this study, for univariate model a linear Auto regression of moving speed or average and for multivariate model not a linear autoregressive exogenous artificial neural network (NARX) algorithms were used. Comparison of ARIMA and NARX is done on various meteorological variables impact. Based on error analysis best model is found. Many reviews of AI applications in various domains have been published in the literature by a variety of scholars. [20][21][22][23]. This study will undoubtedly provide scholars with an understanding of machine learning techniques in many applications. [24][25][26]. Machine learning approaches also address a variety of challenges. [27][28][29].

III. PROPOSED WORK

3.1 SYSTEM ARCHITECTURE:

The main structure of this project is presented in Fig.1, and the main steps involved in this are elaborated as follows.

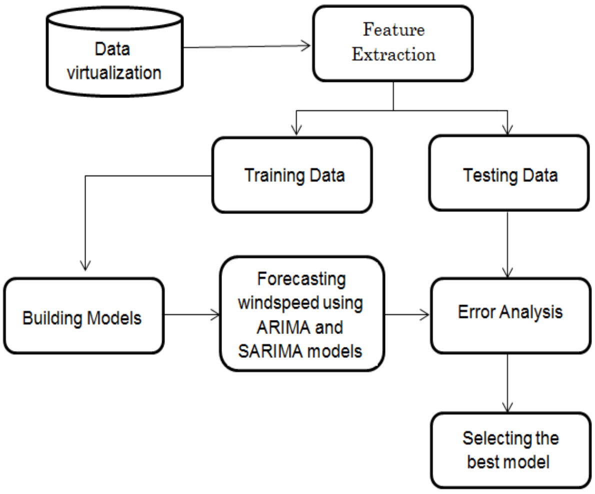

Fig.1 Overall system structure

A.Data Visualization:

An effective first and foremost step is visualizing the time series data to make sure the data which we imported is same as what we plan to use for forecasting and also we can detect initial parameters, identify its components and detect the problems by visualizing the time series. The best method for visualizing the data is Time plot which is presented in Fig. 2.a. Time plot is nothing but a graph that shows observations against time. Time plot is used to find whether the time series have trends and seasonality, if so then that must be removed. If the time series has too much variation, then we need to resample that by using rolling mean in time plot to determine trend. The time plot which uses rolling mean is presented in Fig. 2.b. Another method for data visualization is lag scatter plot. In time series the previous observation is referred as lag. The lag scatter plot is used to explore the relationship between an observation and the lag observation of that observation.

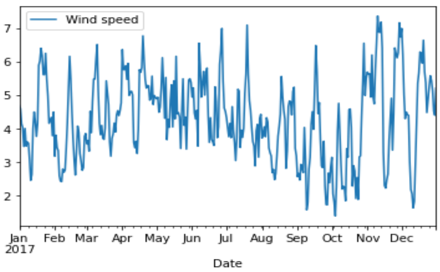

Fig.2a. Wind Speed Visualization

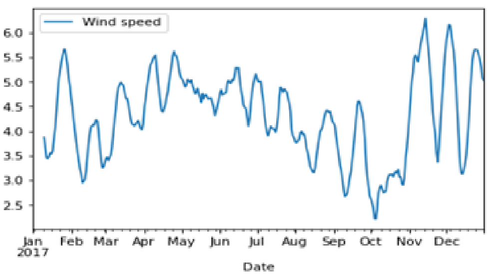

Fig2b. Wind speed visualization with rolling mean

A. Splitting Data:

The data was divided into two groups: training data and testing data. The training data set is a subset of data that is used to train the model; the model looks at and learns from this training set in order to predict future value.. The subset of the data set which is used for evaluation of the final model which learnt from training set is known as testing data set. In addition to the training and testing data, another set of observation called predicted data set is required to validate the behavior of the time series models.

3.2 ARIMA MODEL:

Because ARIMA models are resilient and easy to learn and execute, they are one of the most commonly used time series models, including Jian Jiao's approach [9].The ARIMA model sprang up with a point of performing various differencing methods to get stationary observations from the non-linear and non-stationary observations.

The ARIMA model is represented as ARIMA (p, d. q),
where p is the auto regression order,
d is the degree of differencing, and
q is the moving window order.

We can divide the ARIMA into three terms AR (p), I (d), MA (q).

Auto Regression Model (AR):

Auto Regression model is only applied on the data which do not have trend and seasonality. It tells as how many lagged values are used for forecasting that means p. It is basically a linear regression model. With the help of training data our software will train the model automatically and find the value p. Once we found the value of p, then we can start prediction.

Differencing part (I):

This is used to find how many differencing order used to make the time series stationary. In order to find a right order of differencing ACF plots are used.

Moving Average Model (MA):

This model inspects the relationship by applying moving average to lag values between the true value and a forecast error by applying moving average to lag values. It used to find number of lagged error (q).

The equation of ARIMA model with the parameters p, d, q can be expressed as

$$\mathbf{y_t = a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_p y_{t-p} + \varepsilon_t} \qquad (1)$$

The points (3, 0, 2) were taken as the best ARIMA (p, d, q) structure to forecast the wind speed, the points were calculated by plotting partial autocorrelation and autocorrelation graphs which are presented in Fig. 3a and 3b.

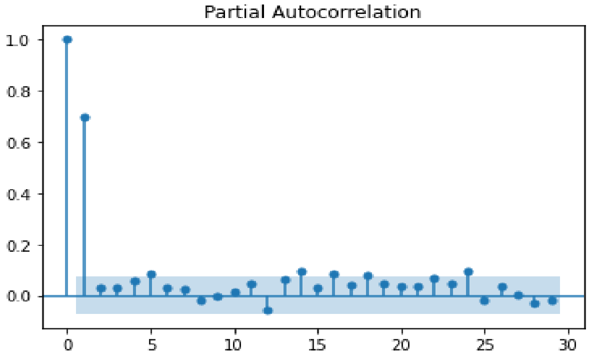

Fig 3a. Partial Autocorrelation plot of ARIMA model

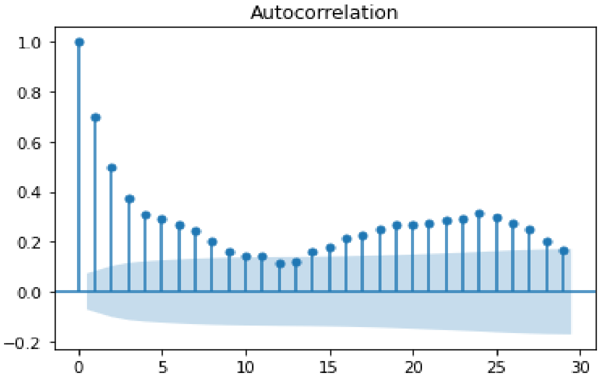

Fig 3b. Autocorrelation plot of ARIMA model

3.3 Seasonal-ARIMA MODEL

SARIMA is one of the frequently used time series model that uses past observations to forecast future values.

This model is an extension of the ARIMA with seasonality function is known as Seasonal - ARIMA which has all the parameters which is used in the ARIMA model and an additional parameter for the seasonality.

The disadvantage of ARIMA model is that doesn't support seasonal data. But Seasonal-ARIMA identifies the trend and seasonality in the time series with the help of a new seasonal component.

The auto correlation and partial autocorrelation graphs were plotted which were presented in Fig. 4a and 4b to identify the parameters of SARIMA.

Seasonal - ARIMA = Differencing (I) + combination of AR and MA parameters + seasonal component

The equation of SARIMA model is

$$(1-\phi_1\beta)(1-\phi_1\beta^4)(1-\beta)(1-\beta^4)Y_t = (1+\Theta_1\beta)(1+\Theta_1\beta^4)\varepsilon_t \qquad (2)$$

The points (0, 1, 2) x (0, 1, 2, 4) were taken as the best Seasonal - ARIMA (p, d, q) x (P, D, Q, s) structure to forecast the wind speed, the points were calculated by plotting partial autocorrelation and autocorrelation graphs.

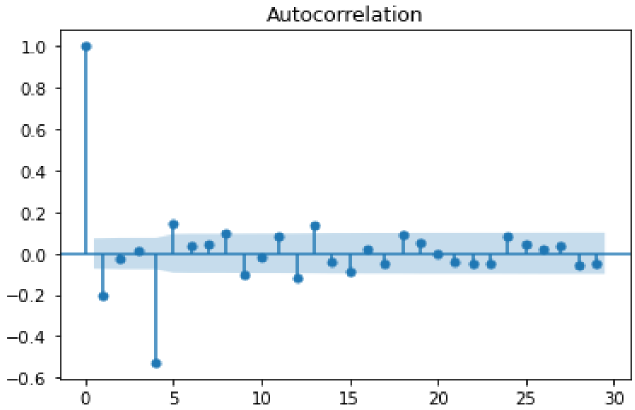

Fig 4a. Autocorrelation plot of SARIMA model

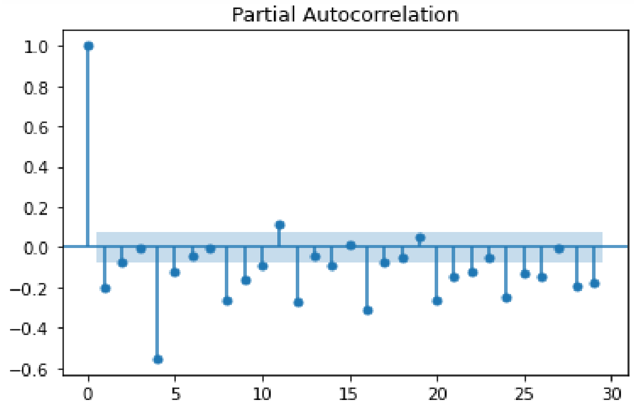

Fig 4.b. Partial Autocorrelation plot of SARIMA model

3.4. Auto correlation

The word autocorrelation is taken from Greek language. From the name itself we can find the meaning that term autocorrelation means the data corresponds with itself instead with some other data. The other name of Autocorrelation is serial correlation and it is a function that represents the time lag between various observations. The autocorrelation analysis is mainly done for finding the repetitive series or patterns and also the missed frequencies of a signal.

The term autocorrelation is generally termed as a variable using time series data. Generally it can be found by plotting ACF plot which is shown in Fig 4.a. and then tested with Durbin-Watson test.

Finally we can say that Autocorrelation is the degree of correspondence among same variable's values in different observations of the given data.

3.5. Partial Auto correlation

From the name itself we can find that it is partially correlated not complete unlike autocorrelation function.

In data analysis part partial autocorrelation has an important role and is used for identifying how far the lag is extended in auto regressive model. At first time this function is used in time series modeling for determining the lags p in AR (p) model by plotting PACF function.

3.6. Error Analysis

After predicting time series using ARIMA and Seasonal - ARIMA models, the accuracy of these models is determined by comparing the testing data set to the anticipated data set. To perform the evaluation, the mean square error (MSE) and root mean square error (RMSE) were determined. The squared difference between true and forecast values is measured by the Mean Square Error (MSE).

$$\text{MSE} = \frac{1}{\mathbb{N}} \sum_{j=1}^{\mathbb{N}} (\tilde{\text{Y}}j - \hat{\text{Y}}j)_2 \qquad (3)$$

Root Mean Square Error (RMSE) is the measure of square root of difference between the true values and forecast values.

$$\text{RMSE} = \sqrt{\frac{1}{\mathbb{N}} \sum_{j=1}^{\mathbb{N}} (\tilde{\text{Y}}j - \hat{\text{Y}}j)}_2 \qquad (4)$$

IV. PERFORMANCE ANALYISIS

The ACF and PACF graphs of both the ARIMA and SARIMA models were inspected inward to decide model fitting parameters. Then each model is fitted with parameters which were found by plotting ACF and PACF plots and predicted upcoming wind speed. The ARIMA and Seasonal- ARIMA models summaries were presented in Fig.5 and Fig.6.

Dep. Variable:	Wind speed	No. Observations:	701
Model:	ARMA(3, 2)	Log Likelihood	-1047.932
Method:	css-mle	S.D. of innovations	1.078
Date:	Tue, 02 Feb 2021	AIC	2109.865
Time:	22:18:48	BIC	2141.732
Sample:	01-01-2016	HQIC	2122.182
	- 12-01-2017		

	coef	std err	z	P>|z|	[0.025	0.975]
const	3.9444	0.331	11.930	0.000	3.296	4.592
ar.L1.Wind speed	0.7439	0.226	3.298	0.001	0.302	1.186
ar.L2.Wind speed	0.7088	0.356	1.992	0.046	0.011	1.406
ar.L3.Wind speed	-0.4647	0.139	-3.347	0.001	-0.737	-0.193
ma.L1.Wind speed	-0.1113	0.219	-0.509	0.611	-0.540	0.317
ma.L2.Wind speed	-0.7845	0.207	-3.790	0.000	-1.190	-0.379

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-1.2228	+0.0000j	1.2228	0.5000
AR.2	1.0160	+0.0000j	1.0160	0.0000
AR.3	1.7319	+0.0000j	1.7319	0.0000
MA.1	1.0603	+0.0000j	1.0603	0.0000
MA.2	-1.2022	+0.0000j	1.2022	0.5000

Fig 5. ARIMA MODEL SUMMARY

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                       Wind speed   No. Observations:                   726
Model:             SARIMAX(0, 1, 2)x(0, 1, 2, 4)   Log Likelihood                -429.491
Date:                          Wed, 24 Feb 2021   AIC                            868.982
Time:                                  11:49:08   BIC                            891.885
Sample:                                       0   HQIC                           877.823
                                          - 726
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -1.3865      0.024    -58.723      0.000      -1.433      -1.340
ma.L2          0.3956      0.020     19.428      0.000       0.356       0.436
ma.S.L4       -1.9963      0.090    -22.223      0.000      -2.172      -1.820
ma.S.L8        0.9973      0.090     11.117      0.000       0.821       1.173
sigma2         0.1801      0.017     10.803      0.000       0.147       0.213
===================================================================================
Ljung-Box (L1) (Q):                   2.83   Jarque-Bera (JB):               859.03
Prob(Q):                              0.09   Prob(JB):                         0.00
Heteroskedasticity (H):               0.92   Skew:                            -0.63
Prob(H) (two-sided):                  0.55   Kurtosis:                         8.20
===================================================================================
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Fig 6. SARIMA MODEL SUMMARY

Two tests were performed with two different datasets to verify performances each model. The predictive accuracy of these models was evaluated based on the mean square error (MSE) and root mean square error (RMSE) which were listed in table 1. From the results we concluded that the ARIMA model is more accurate than the SARIMA model.

Table1. Summary of test statistical errors

Test	Model	MSE	RMSE
Test 1	ARIMA	1.9469	1.3953
	SARIMA	2.2361	1.4953
Test 2	ARIMA	0.8840	0.9402
	SARIMA	0.9375	0.9682

V. CONCLUSION

Electric power generation is mainly depends on the wind energy. The wind speed prediction has an important place in wind energy systems and to drive turbines that further helpful for generating electricity The forecasting of wind speed is the most important factor in wind power forecasting. Models for analysing and forecasting wind speed were created and tested. The Autoregressive Integrated Moving Average (ARIMA) model is one option, while the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is another. Autocorrelation and partial autocorrelation plots can be made to check the authenticity of these models. The points (3, 0, 2) were taken as the best ARIMA (p, d, q) structure to forecast the wind speed and (0, 1, 2) x (0, 1, 2, 4) for SARIMA (p, d, q) x (P, D, Q, s). The predictive accuracy of these models was evaluated based on the mean square error (MSE) and root mean square error (RMSE). The ARIMA model poses with low RMSE and MSE values, so we determined that the ARIMA is the selected as better model for the forecasting of wind speed.

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