Wind Speed Forecasting using Time Series Methods: A Case Study

Sarita Sheoran*, Ritik Bavdekar, Sumanta Pasari, Rakhee Kulshrestha

Department of Mathematics,
Birla Institute of Technology and Science Pilani,
Pilani Campus, Jhunjhunu – 333031, Rajasthan, India.
Corresponding author's e-mail id: sheoransarita93@gmail.com

Abstract

This study focuses on hourly, daily and monthly forecasting of wind speed using various statistical methods, such as Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Prophet model and Holt Winter's technique. We choose these time series models since the dataset exhibits trend, seasonality, non-stationarity and randomness. For hourly forecasting, we additionally develop AR-24 and ARIMA-24 models to account for the high order of seasonality in hourly data. We adopt a grid search method to find optimum values of model parameters and use Root Mean Square Error (RMSE) to assess the performance of the studied models. For illustration, we consider 14 years (2000-2013) of hourly wind speed data from Panna, Madhya Pradesh, India. The results in terms of least RMSE values reveal that ARIMA-24 (2,1,2) has the best representation for hourly data, ARIMA (4,2,3) for daily data and SARIMA (2,1,8) (2,1,2,24) for monthly data. This study demonstrates the applicability of time series models in wind energy forecasting.

Keywords: Renewable Energy; Wind Speed; Forecasting; Time Series

1 Introduction

Reliable forecasting of renewable energy helps in planning and estimating the energy output on a short term to a long term basis. Among different renewable energy resources, the contribution of wind energy is remarkable. The wind energy forecasting is useful for several practical purposes, such as estimation of energy outputs of plants, marketing of wind energy and maintenance planning of wind farms. Hourly predictions of wind speed can be used for prompt and immediate planning by knowing the wind energy productions over the next few days; Daily forecasting can help decide the best months for wind energy productions, whereas monthly weather forecasting can be used for long-term planning of power plants.

In literature, various statistical, artificial intelligence and hybrid methods have been developed for wind speed forecasting. For example, Bhaskar and Jain [1] presented a comprehensive survey on wind speed forecasting including various statistical and soft computing models. Similarly, Saima et al. [2] provided a review on different weather forecasting techniques, highlighting the strengths and drawbacks of statisitical, hybrid and machine learning models. Nagaraja et al. [3] have also reviewed all types of forecasting models for wind energy. Recently, Jaseena et al. [4] have provided an extensive weather forecasting framework that guides us to choose suitable forecasting methods for wind speed data.

In this study, we implement various time series models for forecasting wind energy. For illustration purpose, we consider a study location from Panna, Madhya Pradesh, India. While we introduce the concept of wind speed forecasting in this section, the next section, Section 2, briefly describes the dataset and the proposed methodology. Section 3 presents the results of the implemented statistical models followed by the conclusions in Section 4.

2 Dataset and Methodology

The wind speed data for this study is obtained from National Solar Radiation Database (NSRDB; https://nsrdb.nrel.gov/) maintained by the US Department of Energy. The dataset is recorded at a location in Panna, Madhya Pradesh with its latitude 24.25°N and longitude 80.45°E. The state has the 7^{th} largest wind energy program in the country and thus is an important site to monitor and predict wind speed.

The proposed methodology comprises three steps. The first step performs an exploratory data analysis. It involves plotting the wind speed data (Figure 1) and performing an additive time series decomposition to observe any trend and seasonality. This provides some preliminary information on the model parameters of the time series methods. In the second step, we sample the dataset in an hourly, daily and monthly manner to train the models. We carry out model implementation in the third step. Several statistical models, namely Prophet [5], AR [6], MA, ARMA, ARIMA, SARIMA and Holt Winter's [7] technique are developed. For daily forecasting, five days of hourly data is predicted and compared with their actual values. A similar process is followed for the daily and monthly

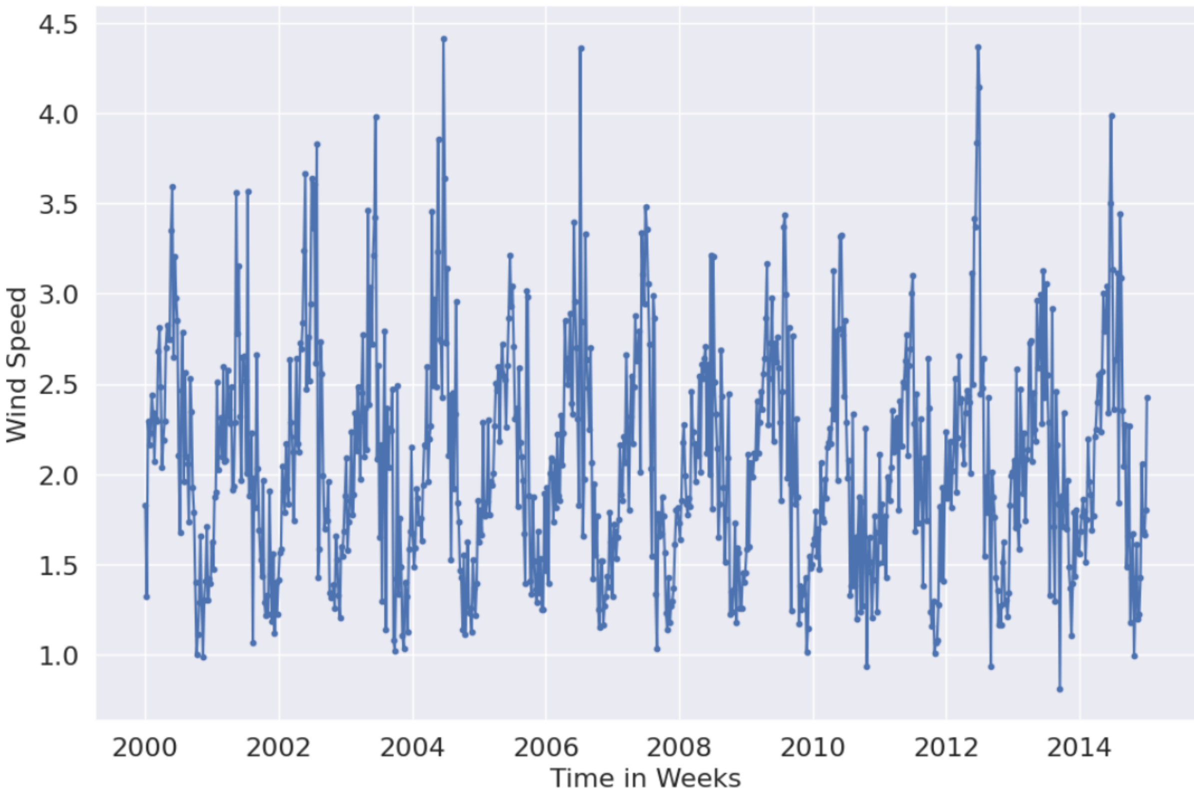

Figure 1: Wind speed data from 2000 to 2014

forecasting corresponding to 31 days of daily predictions and 12 months of monthly predictions. The RMSE value is calculated for each model. For hourly forecasting, AR-24 and ARIMA-24 are additionally developed to account for the high order of seasonality in the hourly data. For this, 24 different models are trained, each for a specific hour.

3 Results

The results of forecasting of the best three models (in terms of least RMSE values) corresponding to the hourly, daily and monthly predictions are represented in Figures 2, 3 and 4, respectively. The optimal values of the model parameters and the RMSE values of the implemented models are provided in Tables 1, 2 and 3, respectively.

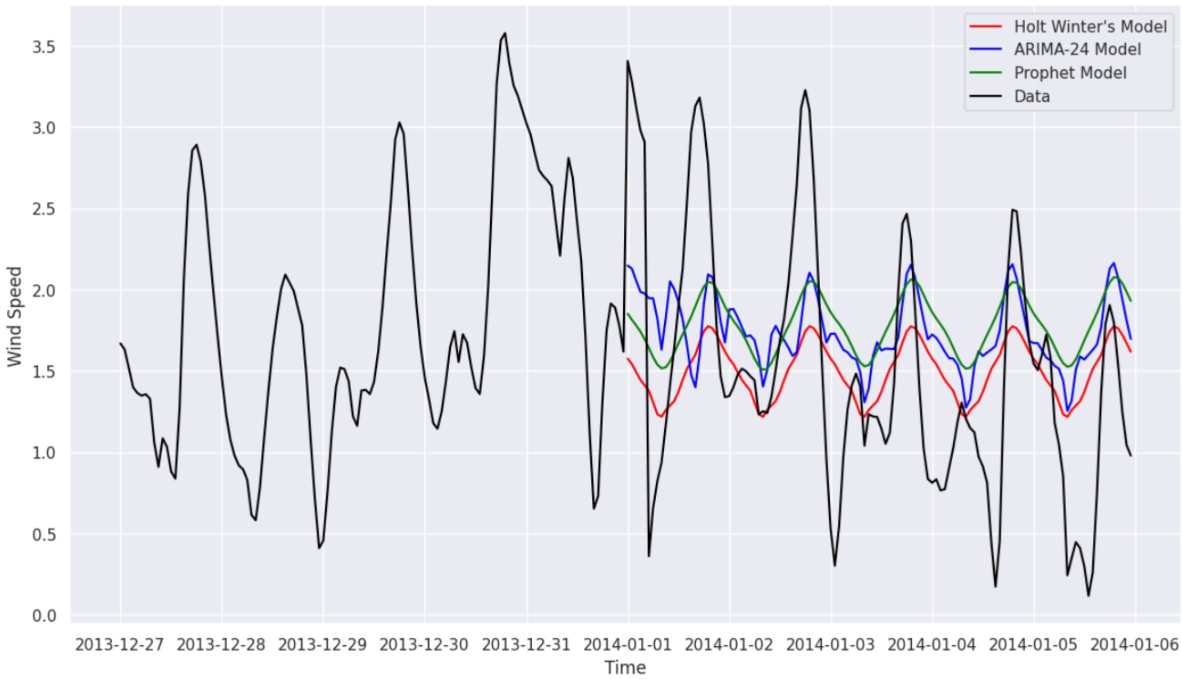

Figure 2: Hourly wind speed prediction using best three models

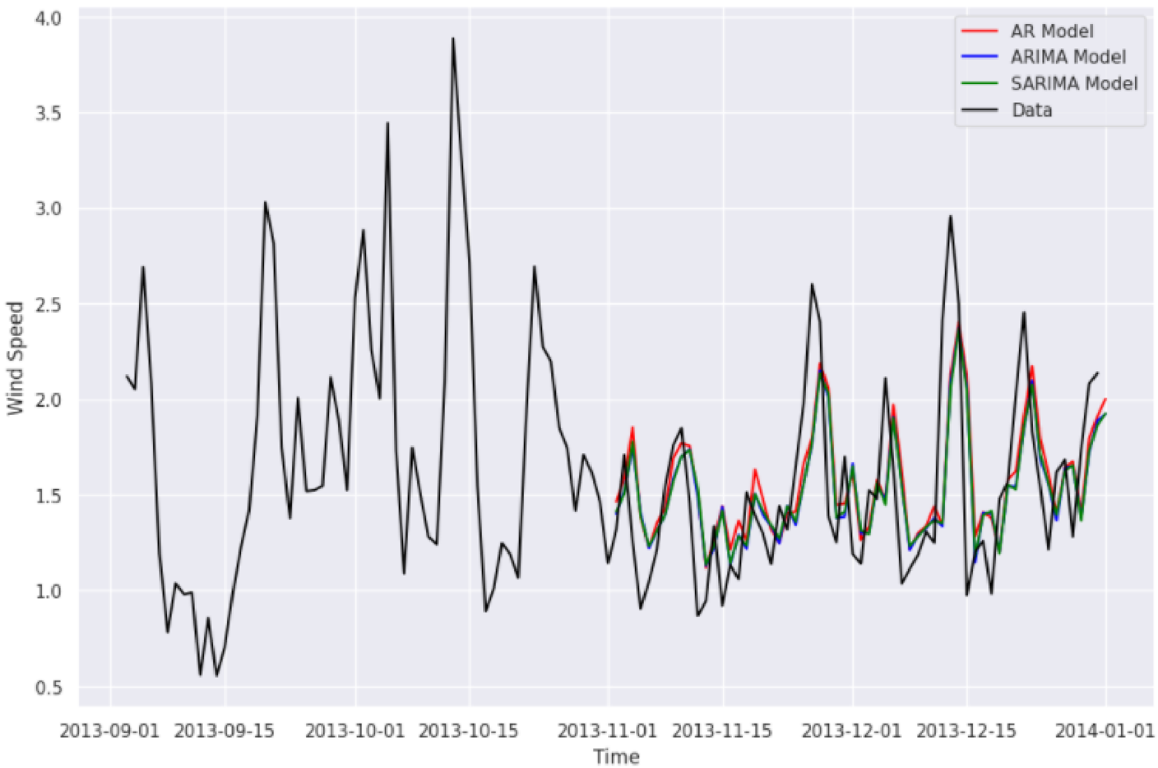

Figure 3: Daily wind speed prediction using best three models

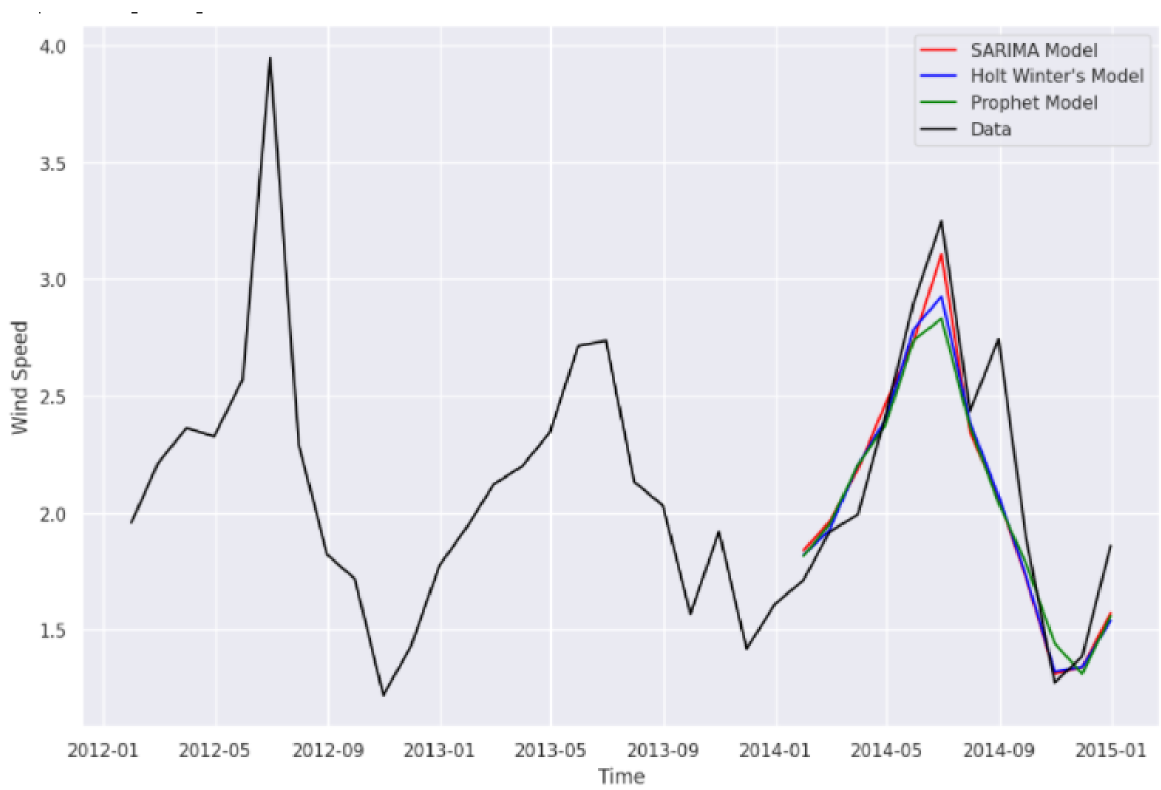

Figure 4: Monthly wind speed prediction using best three models

Table 1: Hourly Forecasting

Technique	RMSE	Best Parameters
Prophet	0.774	Automatic Tuning
AR	0.979	p=2
MA	0.971	q=2
ARMA	0.980	(p,q)=(2,1)
ARIMA	0.901	(p,d,q)=(2,1,2)
Holt Winter's Technique	0.723	Trend="add", seasonal="add", seasonal_periods=24
AR-24	0.836	p=10
ARIMA-24	0.741	(p,d,q)=(2,1,2)

Table 2: Daily Forecasting

Technique	RMSE	Best Parameters
Prophet	0.423	Automatic Tuning
AR	0.383	p=49
MA	0.521	q=2
ARMA	0.396	(p,q)=(4,3)
ARIMA	0.382	(p,d,q)= (4,2,3)
SARIMA	0.387	(p,d,q)(P,D,Q,s) = (4,2,3) (1,0,1,30)
Holt Winter's Technique	0.507	Trend="add", seasonal="add", seasonal_periods=30

Table 3: Monthly Forecasting

Technique	RMSE	Best Parameters
Prophet	0.272	Automatic Tuning
AR	0.288	p=24
MA	0.518	q=8
ARMA	0.336	(p,q)=(2,8)
ARIMA	0.331	(p,d,q)=(4,1,8)
SARIMA	0.240	(p,d,q)(P,D,Q,s) = (2,1,8) (2,1,2,24)
Holt Winter's Technique	0.251	trend="add", seasonal="add", seasonal_periods=24

4 Conclusions

The present study leads to the following conclusions:

- For hourly forecasting, conventional time series models have not provided satisfactory results due to higher order of seasonality in hourly dataset. However, the accuracy of ARIMA-24 (2,1,2) model is satisfactory.
- For daily forecasting, the AR (49) model and ARIMA (4,2,3) model provide the best results.
- For monthly forecasting, SARIMA (2,1,8) (2,1,2,24) and Holt Winter's Technique provide the best representations due to the clear monthly seasonality in the dataset.

Therefore, in summary, the present study provides a comprehensive analysis of time series models for wind speed forecasting based on desired time horizon. The proposed methodology and the emanated results are useful for better planning and management in energy sectors.

References

[1] Bhaskar M, Jain A, Srinath NV (2010), Wind speed forecasting: Present status. In 2010 International Conference on Power System Technology pp:1-6

[2] Saima H, Jaafar J, Belhaouari S, Jillani TA (2011), Intelligent methods for weather forecasting: A review. In 2011 National Postgraduate Conference pp:1-6

[3] Nagaraja Y, Devaraju T, Kumar MV, Madichetty S (2016), A survey on wind energy, load and price forecasting:(Forecasting methods). In 2016

International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT) pp:783-788

[4] Jaseena KU, Kovoor BC (2020), Deterministic Weather Forecasting models based on Intelligent Predictors: A Survey. Journal of King Saud University-Computer and Information Sciences.

[5] Taylor SJ, and Letham B (2018), Forecasting at scale. The American Statistician pp:37-45

[6] Adhikari R, Agrawal RK (2013), An introductory study on time series modeling and forecasting. arXiv preprint arXiv:1302.6613.

[7] Chatfield C (1978), The Holt-winters forecasting procedure. Journal of the Royal Statistical Society: Series C (Applied Statistics) pp:264-279