Review of Wind Forecasting Models

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Extended Abstract

1. Introduction

Wind energy is a valuable renewable source of energy that is available in abundance. The frequent wear and tear of the mechanical parts caused by the fluctuation in wind speed has limited the harvesting of this type of energy. On the other hand, availability of other sources of energy, like natural gas, at a much lower cost has significantly reduced the demand for wind energy in the market. With all these shortcomings, wind energy has still managed to contribute .19% of the total electricity generated in US for the year 2000[1] by producing 5.59 billion kilowatt-hours (kWh). This contribution was increased by 40-fold in the year 2016 with a total of 227 billion kilowatt – hours energy produced contributing to 5.6% of the total electricity produced in that year [2]. From these numbers, we can clearly see a tremendous development in the wind turbine technology, that led to reducing the complexity of installation and maintenance of wind farms at highly fluctuating and limited access locations.

The new developments involve usage of several microelectronics to monitor the input conditions and prepare the wind turbine for any unfavorable conditions, like wind gusts. This continuous data collection has opened a new path to analyze and predict wind speed to estimate the backup power available to match the market need immediately. This prediction helps prepare the contingency reserves, that may need up to an hour or two to start delivering the power. Hence, it is a good practice to predict the wind speed at least 2 hrs. ahead to plan for such difficult situations.

2. Objectives

Amongst all the forecasting models available, the Auto Regressive Moving Average (ARMA) model is chosen, along with the Weibull distribution to forecast the wind speed 2 hrs. into the future. In this paper, a detailed literature review was done to understand and implement the ARMA forecasting model. A comparison plot between the actual and predicted data, along with other findings of the same are discussed by assessing the accuracy of the prediction using standard performance metrics mentioned in the available literature.

3. Weibull Distribution

$$f(x) = \begin{cases} \left(\frac{\beta}{\eta}\right)\left(\frac{x}{\eta}\right)^{\beta-1} \exp\left\{-\left(\frac{x}{\eta}\right)^{\beta}\right\} & x \geq 0, \\ 0 & x < 0, \end{cases}$$

Where,

f(x) is the probability density function value of the given velocity x,

β is the shape factor and

η is the scale parameter.

The wind speed data is non-negative and right skewed, hence any distribution function that has right skewed with non-negative domain can be used for modelling wind speed data. Weibull is one such distribution that is popular amongst analysts. The Weibull parameters such as the shape parameter and the scale parameter are estimated by maximizing the log-likelihood function. Once these parameters are found the goodness of the fit is assessed using the chi squared test at a chosen confidence level.

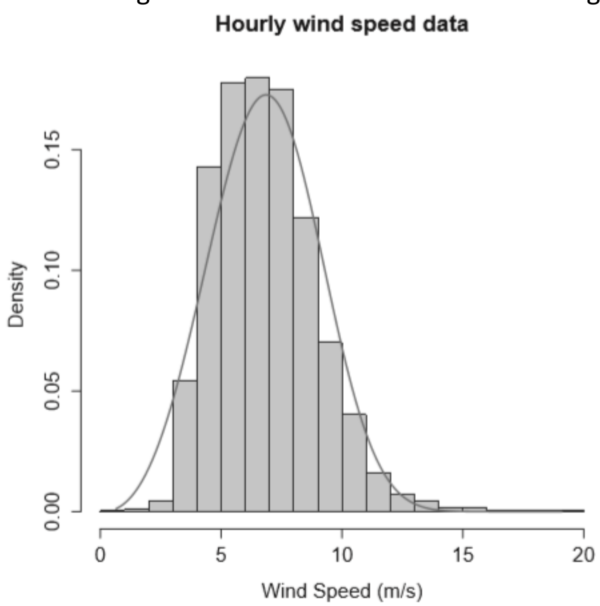

Figure 1 as imported from [3], The left panel is the fit to the hourly data. estimated parameters are: η= 7.60, β= 3.40, mean = 6.84, median = 6.69, mode = 6.5, and the standard deviation = 2.09. The right panel is the fit to the 10-min data. The estimated parameters are: η= 7.61, β= 3.41, mean = 6.86, median = 6.67, mode = 6.5, and the standard deviation = 2.06.

Figure 1, shows the Weibull distribution fit for an hourly data and 10 min data. From the analysis as discussed in [3], the shape parameter and scale factors are almost the same even when the time resolution of the data is different.

Auto Regressive Moving Average (ARMA) Model....

$$\begin{aligned} V_t &= a_0 + a_1 V_{t-1} + \ldots + a_p V_{t-p} + \varepsilon_t, \\ V_{t-1} &= a_0 + a_1 V_{t-2} + \ldots + a_p V_{t-1-p} + \varepsilon_{t-1}, \\ &\ldots \quad \ldots \quad \ldots \quad \ldots \\ V_{t-n} &= a_0 + a_1 V_{t-n-1} + \ldots + a_p V_{t-n-p} + \varepsilon_{t-n}. \end{aligned}$$

Before feeding the data into the ARMA model, the data is first cleaned by removing the unwanted data points, then the cleaned-up data is normalized and standardized before proceeding with the parameter estimation and forecasting model.

Preprocessing:

The wind data is first normalized using power transformation,

$$V_t' = V_t^m, \forall i,$$

Where,

m = estimated Weibull Shape factor/3.6,

$V_t^{'}$ is the transformed velocity data.

Deciding Model Order & Parameter estimation:

Once the data is cleaned up, the model order is found by maximizing the loglikelihood function for ARMA model and selecting the model with the least complexity. During this process, "overfitting" needs to be avoided, since focusing on maximizing the log likelihood function alone may result in reading too much into the noise part of the data. Hence to avoid such scenarios, additional criteria namely, the BIC and ACC were introduced to choose the right model.

4. References

1. U.S. Energy Information Agency. Annual Energy Review 2011: https: //www.eia.gov/totalenergy/data/annual/pdf/aer.pdf

2. U.S. Energy Information Agency. Electric Power Annual 2016, Chapter 1 National Summary Data: https://www.eia.gov/electricity/ annual/pdf/epa.pdf.

3. Ding Y. Data Science for Wind Energy: CRC Press; 2019.