Analysis of Statistical Techniques to Estimate Wind Turbine Power Generation

Rajesh Wadhvani†, Sanyam Shukla††, Manasi Gyanchandani†††, Akhtar Rasool ††††

Maulana Azad National Institute of Technology Bhopal, 462003, India

Summary
Accurate modeling of any system requires appropriate knowledge of all the factors affecting performance of the system. This paper provides the detail of the machine and site specific factors affecting the performance of the wind turbine power production. Various mathematical models have been compared, which were previously applied for power prediction of wind turbine. The recent developments in power prediction of wind turbine relied on power curve modeling technique. The wind turbine power curve shows the relationship between wind speed and power generated. The main objective of this paper is analysis of regression based statistical techniques for power prediction. In each technique, the power curves have been derived using the SCADA data obtained from resource file of NREL HOMER software.

Key words:
Power Curve; wind turbine; SCADA; NREL HOMER; Regression Techniques.

1. Introduction

Today our society needs renewable energy and clean source of energy for electricity generation. Among all the renewable energy sources, wind energy is the most promising source of energy. Wind energy has potential to satisfy future electricity need. Fast growing wind power industry has also raised challenges like turbine control, plant operation, production planning, condition monitoring, and maintenance. This motivates the analysis of wind power generation at given wind speed. Wind Energy holds out a promising energy source but there are uncertainties involved due to stochastic nature of wind. Accurate and reliable forecasting models are needed to optimize the operation cost and improve the reliability of power system with increased penetration of mechanical power to electric grid [1]. To improve the quality of life of the consumers and providers of wind energy, there is a need to study of the effects of various factors, which influence the performance of wind turbines and to predict the wind turbine energy for a given wind speed.

In [2], Thapar et al. stated that there are number of factors which affect the performance of wind turbine and are shown in fig.1.

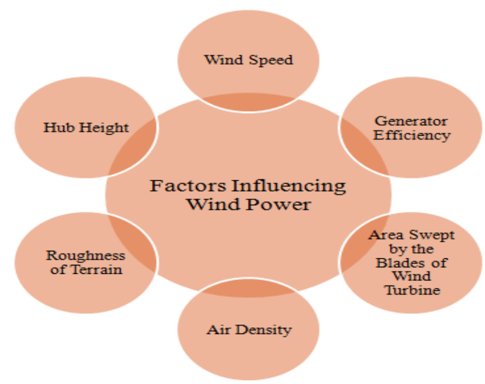

Fig. 1 Factors affecting wind power.

The power output of a wind turbine mainly depends on the local wind speed, and the physical and operating characteristics of the turbine. Wind speed changes according to weather conditions, It varies with time scales ranging from minutes to hours, days and years. This uneven behaviour induces a corresponding variability in the power output. It has been found from long term study of wind speed variation at many locations around the world, that the Weibull probability distribution function most suitably describes the wind speed distribution. The direction of wind also influences power generation. However, compared with wind velocity, wind direction has less influence on power output because each turbine is built to face the wind when operating. Generally, at the same wind speed, there is no great difference in the power generation for different wind directions. Finally, a model is need which considers machine and site specific factors to estimate the performance of the wind turbine.

2. Mathematical Models for Power Prediction

The theoretical power captured by the rotor of a wind turbine (Pw) is given by

$$Pw = [\ \tfrac{1}{2}\rho Av3\ ] \qquad (1)$$

Habib et al.[3] proposed that the maximum attainable power from a wind energy conversion system assuming

Manuscript received February 5, 2017
Manuscript revised February 20, 2017

mechanical electrical conversion efficiency of 100% is given by

$$Pe = 0.593[\frac{1}{2}\rho Av3] \qquad (2)$$

Kolhe et al.[4] stated that the power output of wind turbine is given by

$$Pe = Cp[\frac{1}{2}\rho Av3] \qquad (3)$$

El-Shatter[5] states that the captured power calculated of wind turbine as

$$Pe = 0.5\ Cp[\frac{1}{2}\rho\ \pi R2v3] \qquad (4)$$

Nelson[6] evaluated average hourly wind speed data and converted it to wind turbine power and stated that

$$Pe(t) = Cp\ Effad[\frac{1}{2}\rho Av3(t)] \qquad (5)$$

Ashok [7] states that the wind power output can be calculated by

$$Pe = Cp\ \eta m\ \eta g[\frac{1}{2}\rho Av3] \qquad (6)$$

In eq.(2)-eq.(7), Pe is electrical power produced by wind turbine, ɳg is generator efficiency, ɳm is Transmission efficiency, Cp is power coefficient of the turbine, Effad is Efficiency of AC/DC convertor (Effad is assumed as 95%), A is area swept by rotor blades, R is radius of turbine blade (m), ρ is air density, v is wind speed. The model discussed from eq.3- eq.7 suffers from number of limitations which are:

I. Fraction of wind power that gets converted into electric power depends on number of interdependent factors.
II. Variations in values of ɳg, ɳm and Cp with wind speed have not been taken into consideration.
III. Value of these factors with changing weather condition, time and turbine design is not taken into consideration, all the values are taken as a constant, so it doesn’t replicate actual behavior of wind turbines.
IV. These models are cumbersome due to mathematical calculations and moreover they do not give accurate results.

3. Power Prediction using Power Curve

In wind industry, the turbine power curve - a plot of power generated versus ambient wind speed, is an important indicator of wind turbine performance. Power curve predicts power produced by turbine far a given wind speed, without the technical details of components of wind power generating system. A turbine manufacturer usually provides a nominal power curve as a reference. The typical generic power curve is shown in fig.2.

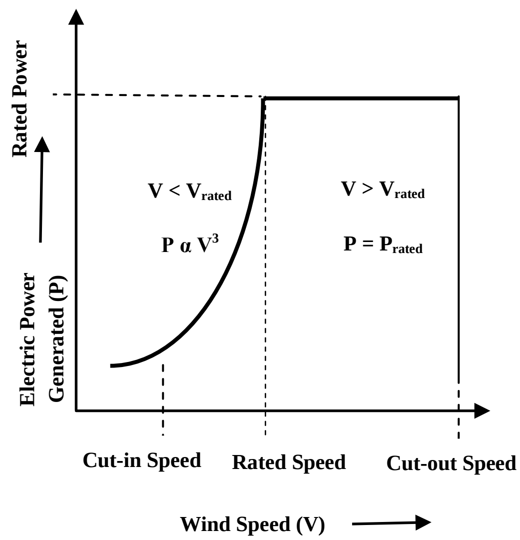

Fig. 2 Generic wind turbine power curve.

The minimum speed at which the turbine delivers useful power is known as the cut-in speed. Rated speed is the wind speed at which the rated power, which is the maximum output power of the electrical generator is obtained. The cut-out speed is usually limited by engineering design and safety constraints. It is the maximum wind speed at which the turbine is allowed to produce power. The actual power curve will vary from this nominal curve for a number of reasons. As stated earlier the power output of a wind turbine mainly depends on the local wind speed and the physical and operating characteristics of the turbine. For all these reasons, in power curve modeling a technique is required which can develop a site specific power curve of given wind turbine.

4. Power Curve Modelling Techniques

Earlier a number of studies have been done to develop the quality power curve which estimate the power production of wind turbine. Research started with various statistical models in which power curve is obtained by using various parametric regression methods. In these models relationship between dependent and independent variable is known but there are some parameters whose values are unknown and these value are estimated from training set by minimizing least square error. Regression tried to capture pattern information in parameters to predict future values. Techniques which aims to develop models based on parametric regression are discussed below.

4.1 Linear Regression

Yang et al. [8] have proposed a linear regression based model for power prediction in which output power increases linearly. It establishes a relationship between dependent variable (P) and one or more independent variables (V) using best fit straight line.

$$P = \beta_0 + \beta_1 V + \varepsilon \tag{7}$$

Where,

β0 – intercept, β1 – slope, ε – error

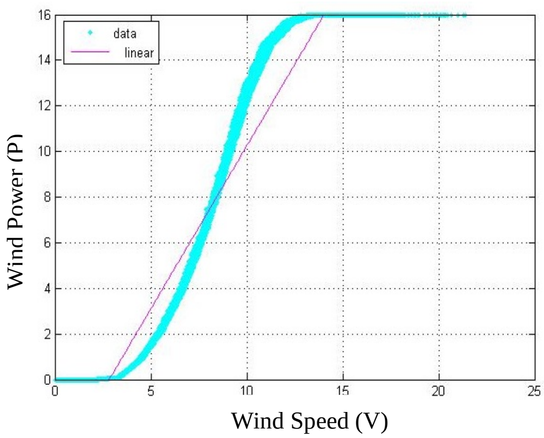

Fig. 3 Power Curve obtained from NREL 2012 dataset using linear regression.

Using the above approach, the power curve for SCADA (supervisory control and data acquisition) data provided in resource file of National Renewable Energy Laboratory's (NREL) HOMER software [9] of year 2012 is shown in fig [3].

The only advantage of linear regression is its simplicity, but it over-estimates the power available.

4.2 Polynomial Regression

Shokrzadeh et al. [10] have proposed a polynomial regression based model for power prediction, where relationship between dependent and independent variables is curvilinear. Following is the polynomial regression in one variable of kth order model.

$$P = \beta_0 + \beta_1 V + \beta_2 V^2 + \cdots + \beta_k V^k + \varepsilon \tag{8}$$

Coefficients $\beta_0, \beta_1, \ldots, \beta_k$ are called parameters of the polynomial equation. The power curve of 3rd order polynomial for SCADA data provided in NREL HOMER software of year 2012 is shown in fig [4].

Fitting a high degree polynomial regression model results in a good fit to the observed data set but may overfit data points. The fitted power curve will closely follow the noise of the power generating system. To compute value of power at a particular wind speed global data is taken into consideration.

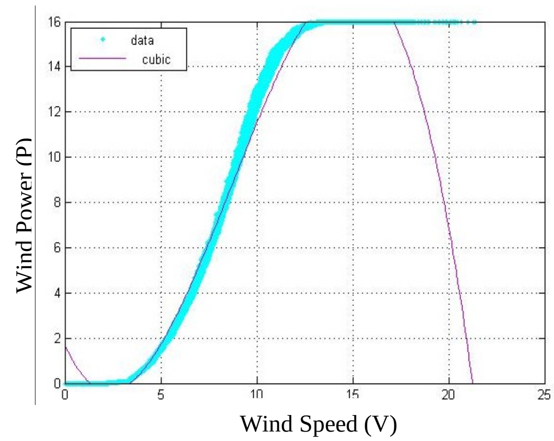

Fig. 4 Power Curve obtained from NREL 2012 dataset using cubic regression.

4.3 Cubic Spline Regression

Llombart et al. [11] have proposed piecewise polynomials based model for power prediction which achieve more flexibility and provide more control on the curvature of the fitted power curve. A piecewise polynomial regression involves fitting separate low-degree polynomials over different regions of the wind speeds. For this, one need to specify K different breakpoints, known as knots, throughout the range of the wind speeds and then fit K + 1 different polynomial regression models. The most popular spline regression is the cubic spline corresponding to the choice of k = 3. Spline regression often leads to superior results over polynomial regression. This is because spline regression introduces flexibility by increasing the number of knots but keeping the degree of polynomial fixed. Based on above approach, the power curve for SCADA data provided in NREL HOMER software of year 2012 is shown in fig [5].

This method suffers from two limitations, First, it tends to behave erratically beyond the boundary knots compared with the corresponding global polynomial regression in those regions. The second limitation is that, if the number and location of knots are chosen badly, spline regression will result in a poor fit.

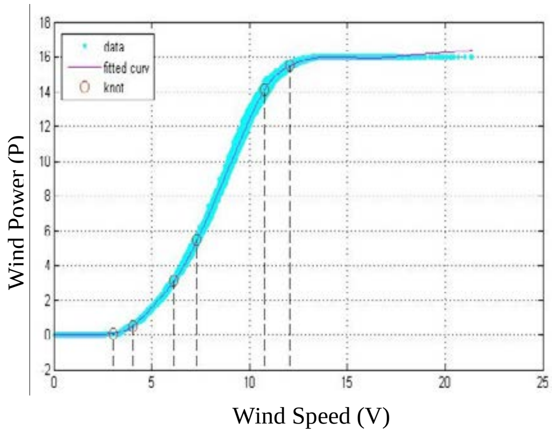

Fig. 5 Power Curve obtained from NREL 2012 dataset using cubic spline regression.

4.4 Four-Parameter Logistic Regression

In most real power curves, there is a point on the curve at which its changes its behavior known as inflection point of the curve. Lydia et al. [12] have proposed a model functions which has four-parameter for logistic approximations. This formula considers inflection point as a one of the parameters to model the power curve. The four-parameter logistics (4PL) regression function is given below

$$P = d + \frac{a-d}{1+(\frac{v}{c})^{b}}$$

Where a is the minimum asymptote, b is steepness of the curve, c is the inection point of the curve, and d is the maximum asymptote of 4PL functions. The four parameters of the function are obtained from the observational data of wind farms using a 4PL approximation. Based on above approach power curve have been obtained using SCADA data provided in resource file of NREL HOMER software is shown in fig [6].

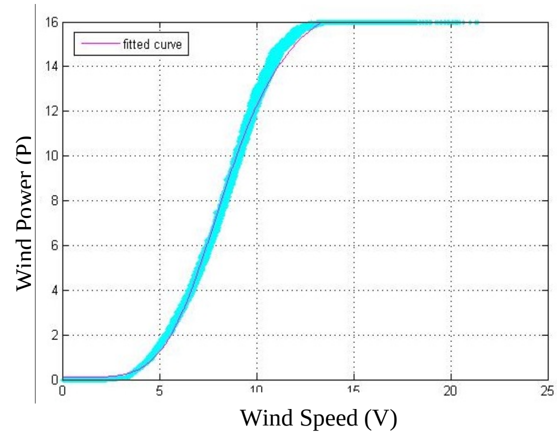

Fig. 6 Power Curve obtained from NREL 2012 dataset using cubic 4PL regression.

However a 4PL curve is symmetric about the inflection point whereas, the power curves are asymmetric. Models which can incorporate this asymmetry can therefore produce even better results.

3.1.2 Five-Parameter Logistic Regression

Sohoni et al. [13] have proposed a model for power prediction which approximates the power curve of wind turbine by a five-parameter logistics (5PL) regression method. In this model a typical 5PL function is given by

$$P = d + \frac{a-d}{\left(1+(\frac{v}{c})^{b}\right)^{g}}$$

Where a, b, c, and d parameters are same as in 4PL functions and g is the asymmetry factor of the 5PL function.

Based on above approach power curve have been obtained using SCADA data provided in resource file of National Renewable Energy Laboratory's HOMER software is shown in fig [7].

One of the difficulties in 5PL model is that evaluation of parameter vector is difficult.

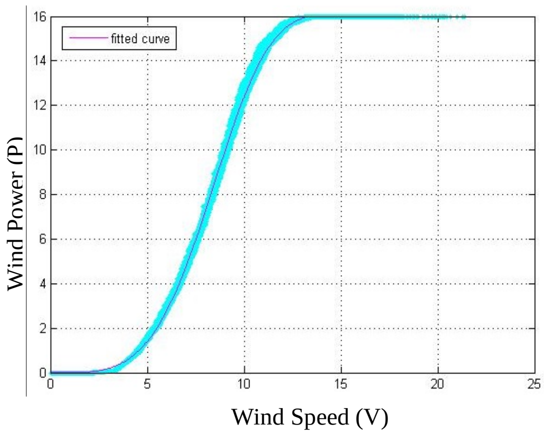

Fig. 7 Power Curve obtained from NREL 2012 dataset using cubic 5PL regression.

5. Conclusions

Accurate modelling plays a crucial role in designing an optimum system. Various methods for wind turbines modelling have been analyzed with reference to SCADA data of NREL 2012 datasets. Following conclusions are drawn from the study. The existing mathematical models for power prediction are cumbersome because it requires appropriate knowledge of all the parameters affecting the performance of the system. Modelling methods based on the concept of power curve are convenient to express the actual performance of wind turbine regardless of how it is operated The analyzed solution of the model based on actual data only focused on goodness of fit. Along with goodness of fit, through regularization complexity of the model can be reduced which may achieve the desired accuracy. The investigated research to model the power curve based on actual data of wind farm focused to improve the quality of the curve but the dynamic behaviour of the curve in different environment conditions is ignored.

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