ISSN:0975-9646

Swarna Jain et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 7 (4) , 2016, 1774-1778

Improvement Estimate Wind Turbine Power Generation Using Machine Learning Techniques

Swarna Jain
Dept. of Computer Science
Babulal Tarabai Institute of Research and Technology, Sagar, India

Anil Pimpalapure
Assist. Proff (CSE)
Babulal Tarabai Institute of Research and Technology Sagar, India.

ABSTRACT **This paper provides an overview of the recent developments in machine learning techniques focused on prediction using regression. The machine learning techniques rapidly developed and regression techniques have been used for prediction. The wind turbine power curve shows the relationship between wind turbine power and wind speed. Wind turbine captures the wind speed and mechanical power produced is given to electric grids, hence wind speed has been taken into consideration for prediction of power. The main objective of this paper is to review and summarize the recent achievements in machine learning techniques, especially regression for prediction, thus providing a referee for study on related topics both from practical and academic points of view. This paper begins with power estimation techniques using mathematical formulae, their advantages and disadvantages. The recent development in the field of prediction using Gaussian regression.**

Index Terms: -. Machine Learning, Power Curve, and wind turbine power curve.

1. INTRODUCTION

Increase in demand of renewable energy and clean source of energy for electricity generation and among all the renewable energy sources wind energy being most promising source of energy. Wind energy has potential to satisfy future electricity need. Wind Energy holds out a promising energy source but the uncertainties involved due to stochastic nature of wind accurate and reliable forecasting models are required to optimize the operation cost and improve the reliability of power system with increased penetration of mechanical power to electric grid [1][2][3]. Also by forecasting power one will be able expand the existing wind farms. In wind energy industry, the turbine power curve - a plot of generated power versus ambient wind speed, is an important indicator of wind turbine performance. Power curve predicts power produced by turbine 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 actual power curve will vary from this nominal curve for a variety of reasons-some inherent to the incoming wind and its characteristics such as turbulence, some due to the way the turbine actually responds to the observed wind, but some may also be caused by multiple system faults - sensor and control faults, turbine or generator faults, etc.

[1][2]The minimum speed at which the turbine delivers useful power is known as the cut-in speed (uc). Rated speed (ur) 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 (us) 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 typical power curve is shown in fig.1.

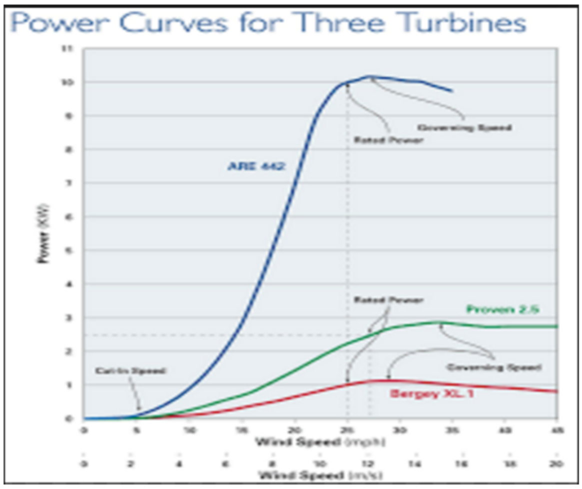

Fig.1: Typical wind turbine power curve.

2. FACTORS AFFECTING POWER OUTPUT

Wind speed, hub height, air density, area swept by blades of turbine, roughness of the terrain, generator efficiency, turbine efficiency, transmission system efficiency, temperature these are the factors affecting output power generated by wind turbine [2].

Given below is the equation specifying relationship between wind speed and height..

$$v_2 / v_1 = (h_2 / h_1)^{\alpha} \qquad (1)$$

Where,

v_1, v_2 – wind velocity

h_1, h_2 – height at which turbine is located

α – ground friction coefficient

From this equation it is clear that wind speed is directly related to the height at which turbine is located.

More turbine efficiency, generator efficiency, transmission system efficiency promises more electric power.

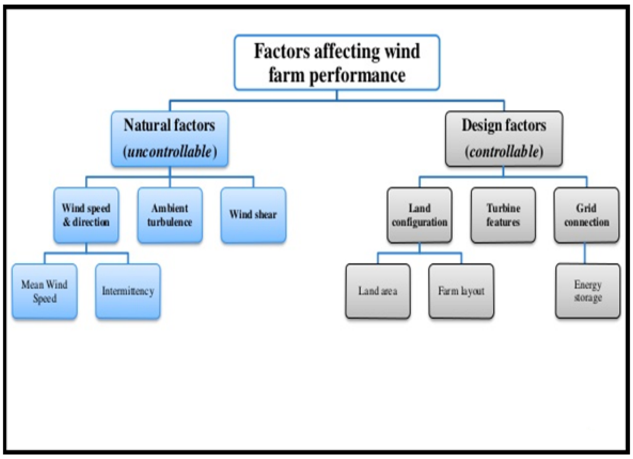

Fig. 2: Factors affecting wind power.

Air density changes with change in value of altitude, temperature, and pressure and weather condition [15]. Atmospheric pressure decreases with height. So, power output on the high mountain gets reduced as compared to power output at sea level. Increase in wind speed gives maximum power generated since wind speed is directly proportional to the power.

3. MODELS FOR PREDICTING POWER OUTPUT

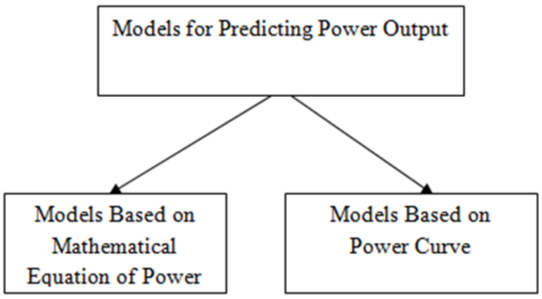

Fig. 3: Two broad categories of models for predicting power output.

3.1 Models Based On Fundamental Equation of Power Available in the Wind

Forecasting using power curve method preferred over mathematical model because of the complexity of mathematical calculations and since mathematical methods doesn't take speed, rotational speed of turbine, turbine blade parameters, mechanical transmission efficiency, generator efficiency, etc. included in the model variation according to the time and weather condition. Hourly calculation of electrical energy generated by wind turbines using these models does not give accurate results and is cumbersome.

3.2 Models Based on Power Curve

In models based on power curve the only factor considered for power output is wind speed. Wind energy i.e. kinetic energy is converted into electrical energy. Amount of kinetic energy in any mass is calculated as

$$\textbf{Kinetic Energy} = \mathbf{(0.5) * mass * (Velocity)^2}$$

In above equation, velocity might be considered as a wind speed and mass might be considered as a particular volume of air. As wind turbine extracts KE (kinetic energy) from wind, it doesn't consume air mass (since only nuclear reaction consumes mass). Air density remains almost constant at hub height; the power captured significantly depends on power coefficient (C_P) and wind speed. Thus, only wind speed has been taken into the consideration while calculating power generated.

The different techniques available in literature for wind turbine power curve modeling have been classified into parametric techniques and non-parametric techniques.

Parametric Methods

1. Linear Regression
2. Polynomial Regression
3. Locally Weighted Polynomial and Linear Regression Models
4. Cubic Spline Regression
5. Natural Cubic Spline Regression

Non – Parametric Methods

1. Multilayer Perceptron
2. Radial Basis Function
3. Extreme Learning Machine

3.2.1 Parametric Methods

Relationship between dependent and independent variable is known but contains some parameters whose value is unknown and its value is estimated from training set, it is known how the regression look like. Information is captured in parameters to predict future values only parameters need to be known.

3.2.1.1. Linear Regression

Linear regression is simple approach to supervised learning. It follows the propriety of linear equation and tries to fit best linear line over the data points.

Linear regression assume a model

$$Y = \beta_0 + \beta_1 x + \varepsilon$$

Where β0 and β1 are two unknown constants that represent the intercept and slope. Also known as coefficients or parameter, and the error term.

Given some estimates β0 and β1 for the model coefficients, we predict further point using

$$Y = \beta_0 + \beta_1 x + \varepsilon$$

Where Y is prediction

To estimate the value of coefficient (y intercept, slope) of linear line least square method is applied [4].

Least square method calculates the series of points on which the error is less. Here error if defined as the difference between actual value and the predicted value.

Let $y_i = \beta_0 + \beta_1 x_i$ be the prediction for Y based on the ith value of X.

Then $e_i = y_i - \bar{y}$ represents the residual.

Here residual sum of squares (RSS) as

$$RSS = e_1^2 + e_2^2 + \cdots + e_n^2$$

Or equivalent as

$$RSS = (y_1 - \beta_0 - \beta_1 x_1)^2 + (y_2 - \beta_0 - \beta_1 x_2)^2 + \cdots + (y_n - \beta_0 - \beta_1 x_n)^2$$

The least square approach choose β_0 and β_1 to minimize The RSS. The minimizing values can be shown to below

$$\beta_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

$$\beta_0 = \bar{y} - \beta_1\bar{x}$$

Where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ and $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ and the sample means.

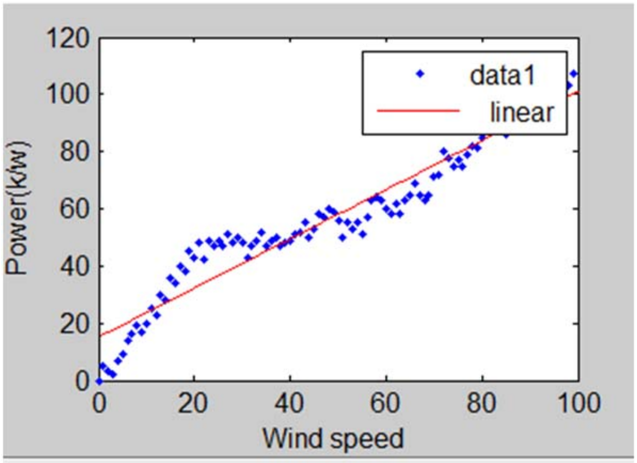

Fig.4: Output of linear regression plotted wind speed versus power in MATLAB

The only advantage of linear regression is simplicity, but this regression looks only at linear relationships, sensitive to the outliers and can affect the regression line and eventually forecasted values, so this method is not widely used.

Disadvantage of linear regression is that it takes only linear relationship into the consideration.

3.2.1.2 Polynomial Regression

It is used in situation where relationship between dependent and independent variables is curvilinear.

Following is the polynomial regression in one variable and is called second order model or quadratic model

$$Y=\beta_0 + \beta_1 X + \beta_2 X^2 + \varepsilon$$

Coefficients β1 and β2 is called linear effect parameter and quadratic effect parameter respectively.

Linear regression is best suitable for the data pointes which show the linear relationship. If the data points show the nonlinear relation linear regression is not suitable for this. So to deal with nonlinear nature of data points polynomial regression is preferred. Polynomial regression fit the relationship between the nonlinear data points [6].A polynomial equation with degree n is a function of the form

$$y_i = a_0 + a_1 x_i^2 + \cdots + a_m x_i^m + \varepsilon_i \quad (i = 1,2,3 \ldots\ldots..n)$$

Where, as are real numbers also called the coefficients of the polynomial. This general formula might look quite complicated. Degree of polynomial equation decides the number of turns in graph and value of coefficient decides the direction of turn and the slope of graph [6].

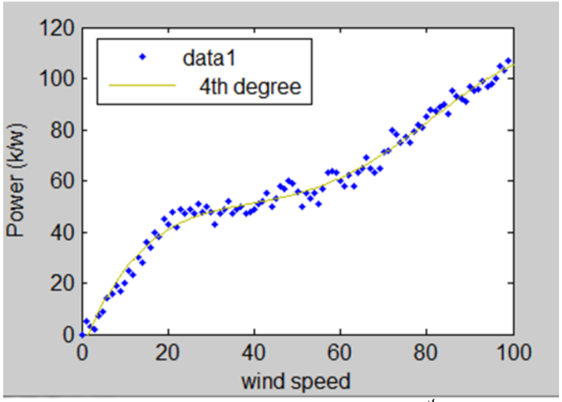

Fig.5: Output of polynomial regression of 4th degree plotted wind speed versus power in MATLAB

Fitting a high degree polynomial regression model results in a good fit to the observed data set but may over fit 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.

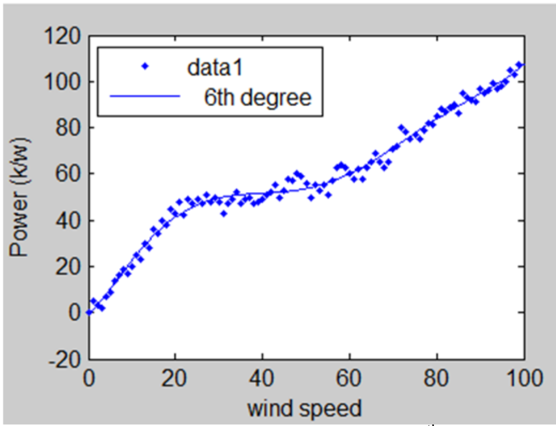

Fig.6: Output of polynomial regression of 6th degree plotted wind speed versus power in MATLAB.

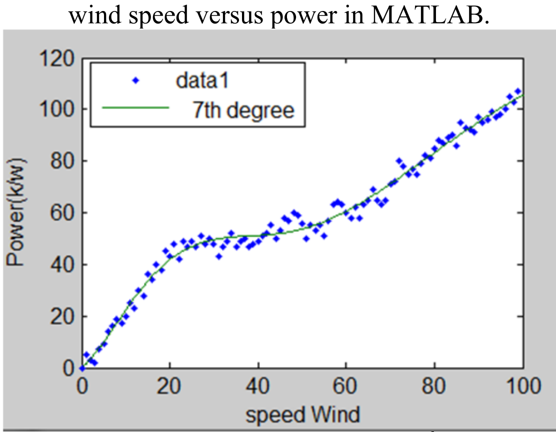

Fig.7: Output of polynomial regression of 7th degree plotted wind speed versus power in MATLAB.

3.2.1.3. Locally weighted polynomial & linear regression Models:

The fitted value of power at a given speed v_0 depends strongly on all data values even those v_i's that are far from v_0, polynomials are more sensitive to anomalies within the data. To avoid such problems is to fit a local regression model at a target point v_0. Data points nearest to v_0 are given the highest weight and those farther away are given lower weights. This method is resistant against outliers by assigning low weights to observations, which generate large residuals. To compute these weights kernel functions are used like tri-cube kernel function, Gaussian Kernel Function.

Advantage: locally weighted polynomial regression models reduce the bias of polynomial regression models, especially at the boundaries.

3.1.1.4 Gaussian regression

Gaussian regression uses probability distribution over functions y(x), such that the set of values of y(x) evaluated at an arbitrary set of point X1, Xu jointly have a Gaussian distribution. In mathematics a Gaussian function, often simply referred to as a Gaussian, is a function of the form [8]:

$$f(x) = ae^{-\frac{(x-b)^2}{2c^2}}$$

Where, a, b and c are real constant.

The graph of a Gaussian is generally known as "bell Type curve" shape. The parameter ‘a’ is the height of the curve's peak, ‘b’ is the position of the center of the peak and ‘c’ (the standard deviation, sometimes called the Gaussian RMS width) controls the width of the "bell"[9].

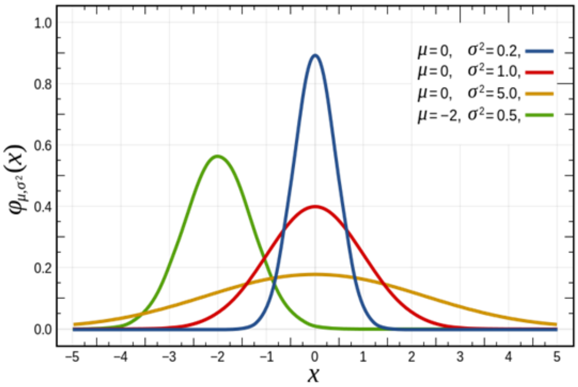

Fig 8 Gaussian function graph

Gaussian regression provide better curve fitting over the linear regression and sometimes better than the polynomial regression models.

Advantage of Gaussian regression is that it uses the probability distribution function so the movement of graph directly depends on the distribution of data.

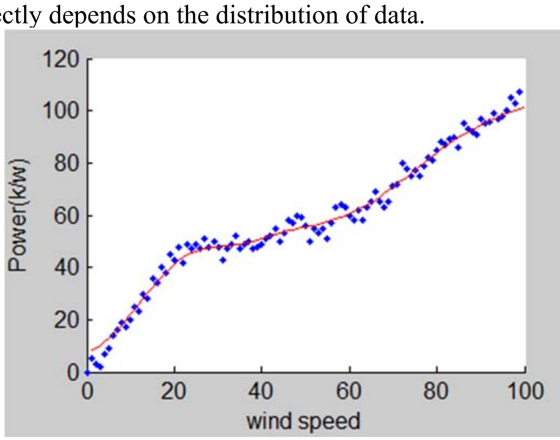

Fig.9: Output of Gaussian regression wind speed versus power in MATLAB

CONCLUSION

Wind power forecasting is critical to power system operation. However, wind power forecasting errors are unavoidable to some extent due to the nonlinear and stochastic nature of the weather system. This paper presents a comprehensive overview on the wind turbine power curve modelling techniques and mathematical models for wind power forecasting their advantages and disadvantages. These models assist the customers in making the appropriate choice of wind turbines, aid in wind energy assessment and prediction, and revolutionize wind turbine performance monitoring, troubleshooting and predictive control. The various parametric and non-parametric modelling techniques that have been employed for wind turbine power curve modelling have been presented in detail. Traditional neural network based forecasting models cannot provide satisfactory performances with respect to both accuracy and computing time needed. Thus, extreme learning machine applied for probabilistic interval forecasting of wind power. Comprehensive experiments using practical wind farm data of National Renewable Energy Laboratory of different season have been done in MATLAB2013a on Processor: Intel(R) Core(TM) i5-3210M CPU @ 2.50GHz, 2501 MHz, 2 Core(s), 4 Logical Processor(s).

REFERENCES

[1] Vinay Thapar, Gayatri Agnihotri, Vinod Krishna Sethi, “**Critical analysis of methods for mathematical modeling of wind turbines**”, 10 March 2011.

[2] M. Lydia , S.SureshKumar , .Immanuel Selvakumar , G.Edwin PremKumar , “**A comprehensive review on wind turbine power curve modeling techniques** ”, 21 October 2013.

[3] Shahab Shokrzadeh, *Student Member, IEEE*, Mohammad Jafari Jozani, and Eric Bibeau, ”**Wind Turbine Power Curve Modeling Using Advanced Parametric and Nonparametric Methods**”, IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, VOL. 5, NO. 4, OCTOBER 2014

[4] Guang-Bin Huang, Qin-Yu Zhu, Chee-Kheong Siew, “**Extreme learning machine: Theory and applications**”, 3 December 2005.

[5] Principe, J.C.; Dept. of Electrical & Computer Eng., Univ. of Florida, Gainesville, FL, USA; Badong Chen” **Universal Approximation with Convex Optimization: Gimmick or Reality?**” IEEE Computational intelligence magazine may 2015.

[6] Shuhui Li, Donald C. Wunsch, Edgar O’Hair Michael G. Giesselmann, “**Comparative Analysis of Regression and Artificial Neural Network Models for Wind Turbine Power Curve Estimation**”, November 2001.

[7] Erik Cambria, Guang-Bin Huang, ”**Extreme Learning Machines**”, IEEE Computational intelligence December 2013.

[8] Shuhui Li, *Member, IEEE*, Donald C. Wunsch, *Senior Member, IEEE*, Edgar A. O’Hair, and Michael G. Giesselmann, *Senior Member, IEEE*, “**Using Neural Networks to Estimate Wind Turbine Power Generation**”, IEEE TRANSACTIONS ON ENERGY CONVERSION, VOL. 16, NO. 3, SEPTEMBER 2001.

[9] Can Wan, Zhao Xu, Pierre Pinson, Zhao Yang Dong, Kit Po Wong,” **Probabilistic Forecasting of Wind Power Generation Using Extreme Learning Machine**”, IEEE TRANSACTIONS ON POWER SYSTEMS 3, May2014.

[10] Book: WEIFENG LIU, “**Adaptive Filtering In Reproducing Kernel Hilbert Spaces**”, 2008.

[11] Can Wan, student member; IEEE, Zhao Xu, Senior Member; IEEE, Pierre Pinson, Senior Member ; IEEE, Zhao Yang Dong, Senior Member; IEEE, and Kit Po Wong, Fellow; IEEE," **Probabilistic Forecasting of Wind Power Generation Using Extreme Learning Machine**", IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 29, NO. 3, MAY 2014.

[12] W. Frost and C. Aspliden, "**Characterics of the wind in Wind Turbine Technology**", D. A. Spera, Ed: AMSE Press, 1995, ch. 8, pp. 371–445.

[13] S. S. Haykin, "**Neural Networks: A Comprehensive Foundation**": Macmillan, 1994, p. 160.

[14] George Sideratos and Nikos D. Hatziargyriou, *Fellow, IEEE,* "**Probabilistic Wind Power Forecasting Using Radial Basis Function Neural Networks**", IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 27, NO. 4, NOVEMBER 2012

[15] P. Badari Narayana, R. Manjunatha, K. Hemachandra Reddy, "Wind Energy Forecasting Using Radial Basis Function Networks", IJRET: International Journal of Research in Engineering and Technology.