Front. Energy
https://doi.org/10.1007/s11708-018-0553-3

RESEARCH ARTICLE

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Comparison of modeling methods for wind power prediction: a critical study

Abstract Prediction of power generation of a wind turbine is crucial, which calls for accurate and reliable models. In this work, six different models have been developed based on wind power equation, concept of power curve, response surface methodology (RSM) and artificial neural network (ANN), and the results have been compared. To develop the models based on the concept of power curve, the manufacturer's power curve, and to develop RSM as well as ANN models, the data collected from supervisory control and data acquisition (SCADA) of a 1.5 MW turbine have been used. In addition to wind speed, the air density, blade pitch angle, rotor speed and wind direction have been considered as input variables for RSM and ANN models. Proper selection of input variables and capability of ANN to map input-output relationships have resulted in an accurate model for wind power prediction in comparison to other methods.

Keywords power curve, method of least squares, cubic spline interpolation, response surface methodology, artificial neural network (ANN)

1 Introduction

Demand for energy is observing a constant and steady growth worldwide due to increased industrial and agricultural activities. This indeed is increasing the environmental pollution and its ill effects. Thus it is a matter of concern for every developing country to focus more on renewable energy sources. Wind energy, a fastest growing source in electricity generation, can significantly contribute to relieving problems of global environmental pollution [1]. India, being one of the fastest growing economies, has a huge potential for renewable energy sources. The government of India is making efforts to promote renewable energy by issuing wind energy policies which are investor friendly [2]. Integration, penetration, and large-scale deployment of wind energy definitely can result in social and environmental impacts and hence it has gathered a greater momentum in the last decade [3,4]. The major issue which restricts the pace of development of wind power industry is the stochastic nature of wind and the uncertainty involved in the power produced because of this reason. Hence, it causes serious problems in wind power penetration, energy management systems, and reliability of the power grid [5–7]. This calls for accurate and reliable models that assist in operational management, performance monitoring, and prediction and forecasting in wind industry [8–11].

The manufacturer's power curve of a particular turbine provides the relationship between the wind speed and the power. But the manufacturer's power curve is usually derived under standard conditions [12]. Hence, it is not advisable to blindly apply the manufacturer's power curve as the actual working condition of a turbine is quite different. Thus, a strong need for developing site specific power prediction models has gained greater significance. Researchers have applied a variety of approaches in developing models for predicting the power output of wind turbines. These models can be broadly classified as models based on fundamental equations of power available in wind and models based on the concept of power curve of wind turbine [13]. The later can be further classified into parametric and nonparametric techniques [14]. The parametric techniques are based on mathematical models such as the linearized segmented model, the polynomial power curve, the maximum principle method, the dynamic power curve, the probabilistic model, the ideal power curve, the 4-parameter logistic function, and the 5-parameter logistic function etc. Nonparametric techniques, unlike parametric

Received Apr. 21, 2017; accepted Sep. 11, 2017; online Apr. 20, 2018

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techniques, do not impose any pre-specified model. The estimation of the power curve in this case is as close as possible to the available data subject to the smoothness of the fit. Nonparametric models include the cupola power curve, the cubic spline interpolation, the neural networks, the fuzzy methods, the response surface methodology, and the data mining algorithms (random forest, *k*-nearest neighbor), etc [14–18].

Thapar et al. [13] presented a comparative study of various methods for mathematical modeling of wind turbines. It was found that modeling methods which used actual power curve for developing characteristic equations, by utilizing curve fitting techniques such as method of least squares and cubic spline interpolation gave accurate results. Shokrzadeh et al. [14] analyzed polynomial regression, locally weighted polynomial regression, spline regression and the penalized spline regression methods for estimating the power curve of a wind turbine. It was found that penalized spline regression presents a better performance over the other analyzed methods. Marvuglia and Messineo [16] developed three different machine learning models, self-supervised neural network called generalized mapping regressor (GMR), a feed-forward multi-layer perceptron (MLP), and a general regression neural network (GRNN) to estimate the relationship between the wind speed and the power generated in a wind farm. It was observed that, if suitable pre-processing of the input data was accomplished, the non-parametric approach provided a fair performance. Kusiak et al. [18] integrated data mining and evolutionary computation for building models for prediction and monitoring of wind farm power output and concluded that *k*-nearest model combined with the principal component analysis performed well. Lydia et al. [19] developed parametric and nonparametric models. Application of the differential evolution algorithm to a five-parameter logistic function and neural network model gave the best parametric and nonparametric models of a wind turbine power curve respectively. Lydia et al. [15] in another study presented the review of parametric and non-parametric modeling techniques for modeling of the wind turbine power curve. Carrillo et al. [20] presented a review of the equations commonly used to represent the power curves of variable speed wind turbine generators. It was reported that, higher R^2 values and a lower error in energy estimation was observed for exponential and cubic approximations and the worst results were observed for the polynomial power curve, due to its sensitivity to the data given by the manufacturer. Gill et al. [21] proposed the application of empirical copulas to estimate bivariate probability distribution functions representing the power curve of turbines. Ouyang et al. [22] proposed an approach based on centers of data partitions and data mining to develop a model of a power curve and it was demonstrated that the model reflected the dynamic properties of a power curve. Goudarzi et al. [23] carried out a comparative analysis of various parametric and non-parametric techniques for modeling wind turbine power curves. It was found that the multilayer perceptron neural network model outperformed all other models.

Although the relationship between wind speed and power output of a wind turbine is modeled by using the best available technique, the power curve thus obtained is only a function of wind speed which certainly is a key factor, but completely ignores several other parameters that influence power production.

Hence, it is evident that, to bridge the gap between estimation of power by the power curve and actual power output of a turbine, the other parameters also have to be considered. Such a model will help in considering the dynamic behavior of the wind which otherwise is overlooked by the power curve.

Many researchers have worked in this direction. Tu et al. [24] presented a study on the suitable number of input neurons for the ANN model to estimate the energy outputs of a wind farm having short record of measured data. It was found that, among the input parameters used, current wind speed and previous power outputs are the most important. Li et al. [25] compared regression and ANN models for estimation of wind turbine power output by using the wind speed and wind direction data from two meteorological towers as inputs. It was reported that neural network possessed better performance than the regression model. Liu et al. [26] built a complex valued recurrent neural network model by using historical data of wind speed and direction to predict wind power, and the model proposed showed high accuracy. Schlechtingen et al. [27] built and compared cluster center fuzzy logic, neural network, and *k*-nearest neighbor models by using wind speed, ambient temperature and wind direction as input parameters to predict the power of a wind turbine. It was proved that ambient temperature and the wind direction were important parameters, when setting up data-mining models for wind turbine power curve monitoring. Lapira et al. [28] evaluated three different models by considering eight input parameters to predict the turbine power output. Mabel and Fernandez [29,30] considered three input variables — wind speed, relative humidity, and generation hours to predict the energy output of a wind farm by using MATLAB toolbox. A good agreement between simulated results and actual measured values were observed. Reddy et al. [31] used ANN and the weighted least square (WLS) technique to forecast the day-ahead electricity price and proved that the methods are effective. Han et al. [6] selected wind power, wind speed, and wind direction as inputs for wind power prediction by using back propagation (BP) and radial basis function (RBF) neural network and proved that RBF is superior to BP.

Based on the literature review, it is evident that there have been efforts in the use of different modeling methods for wind power prediction. There have been lesser efforts in attempting a critical comparison of different modeling techniques based on wind power equation, power curve, and use of ANN etc. to suggest the most suitable approach to wind power modeling. In this context, the present work compares various modeling methods to predict the power output of a wind turbine. The models developed include those based on the fundamental equations of power available in wind and those based on the concept of power curve of wind turbine. Further, models have also been developed using RSM and ANN by considering other input parameters along with wind speed that influence the power generation of a wind turbine, which is a major contribution of this work. Thus a comparison between statistical and non-statistical methods is attempted. Finally, different modeling methods have been studied to get a proper understanding of the effect of considering relevant input parameters in modeling wind power prediction, which is a novelty of this work. The methodology adopted in the present work is shown in Fig. 1.

2 Basics of wind power generation

In wind turbine, the kinetic energy in the wind is converted to mechanical and then to electrical energy. The power production in this prime mover is due to the interaction of wind with the rotor.

Theoretically, the power captured P by the rotor of a wind turbine in kW is given by Eq. (1)

$$P = 0.5\rho\pi R^2 C_{\mathrm{p}}(\lambda, \beta)v^3, \tag{1}$$

where ρ is air density in kg/m^3, R is the radius of the rotor determining the swept area in m, C_{p} is power coefficient, β is blade pitch angle in degree, λ is tip speed ratio, and v is wind speed in m/s.

The tip speed ratio is defined as the ratio of the tangential velocity of the blade tip to the effective wind speed. λ can

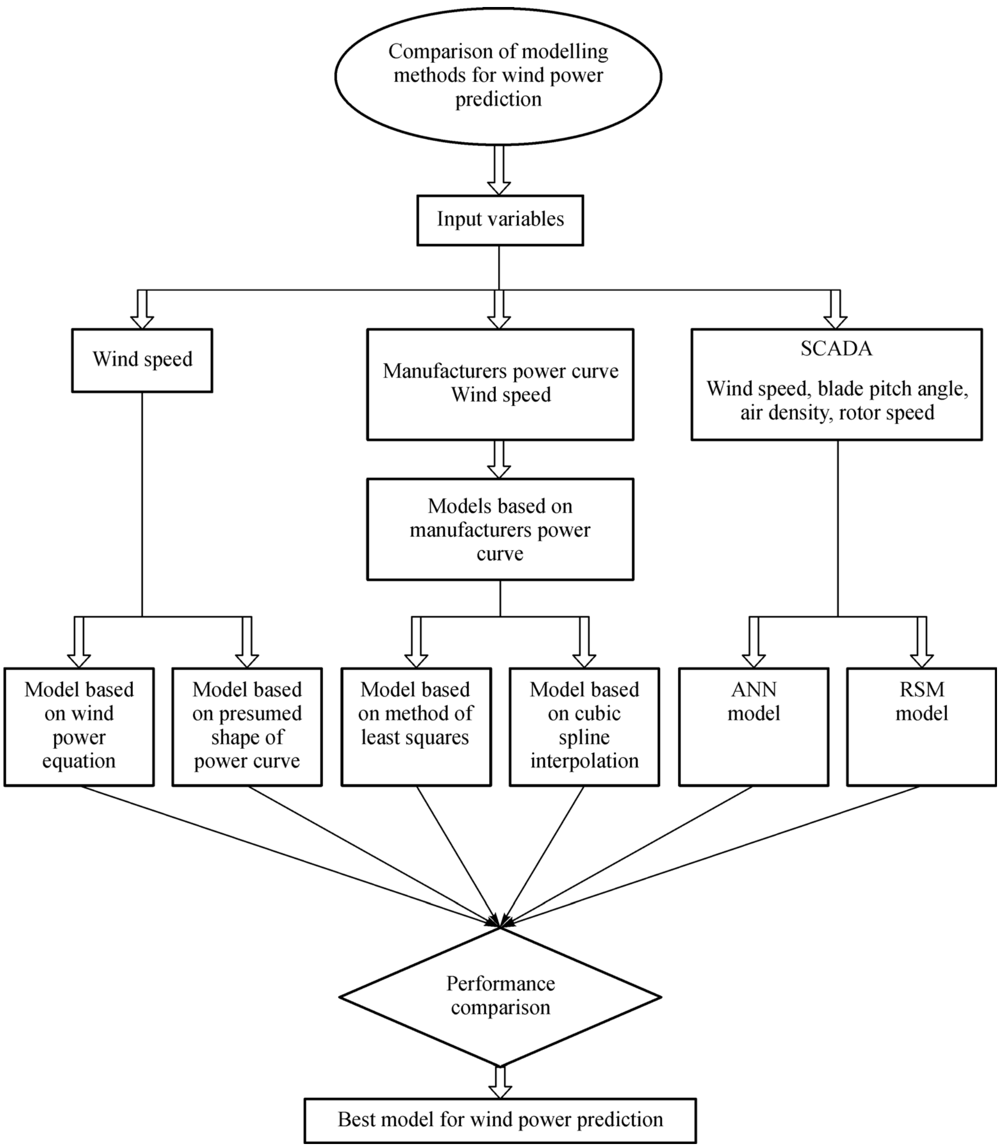

Fig. 1 Methodology adopted in this paper

be determined from Eq. (2) [32,33].

$$\lambda = \frac{R\Omega_r}{v_e}, \tag{2}$$

where R is rotor radius in meters, Ω_r is rotor speed in rad/s, and v_e is effective wind speed perpendicular to the rotor plane in m/s. From this it is noticeable that rotor speed, in turn, is an influencing parameter on wind power production.

The wind is generally assumed to be blowing orthogonally to the rotor, and hence, its direction is not considered in the power equation, but it is not true in operation. Hence, wind direction also is one among the important parameters affecting wind turbine power.

Thus, it can be observed that along with wind speed, air density, blade pitch angle, rotor speed, and wind direction are the other parameters influencing the wind power production, which when considered in modeling can result in more accurate modeling and prediction than only considering wind speed. Hence, in this study the above discussed parameters have been considered as inputs while developing RSM and ANN models.

To develop models based on the concept of power curve, the data from manufacturer's power curve of a 1.5 MW horizontal axis, pitch regulated, 3 bladed, upwind, wind turbine has been used. This has a cut-in, rated and cut-off wind speed of 4, 13 and 20 m/s respectively. Further, the data collected from the SCADA of this turbine over a period of six months (June–November 2013) has been used to develop ANN and RSM models. The manufacturer's power curve of the turbine considered for the present study has been shown in Fig. 2. A power curve is a graph showing the steady power delivered by the turbine as a function of wind speed between cut-in and cut-out. The values of power corresponding to various wind speeds from manufacturer's power curve are listed in Table 1. It can be observed from Fig. 2 that the power production starts only after cut-in speed and increases till rated wind speed, thereafter is maintained constant at the rated power till the cut-out wind speed. The sample data set collected from SCADA has been shown in Table 2. The raw data collected from SCADA contains errors due to the sensor and data collection system. After the data are averaged to 1 h interval, the missing and erroneous data have been removed. Out of the total data of 2966, 85%, i.e., 2522 data have been used for training and the rest 15% for testing the developed RSM and ANN models. The data has been normalized between 0 and 1 using suitable normalization method.

Table 1 Power values for various wind speeds from manufacturer's power curve

Sl. No	Wind speed/($m\cdot s^{-1}$)	Power/kW
1	5	250
2	6	250
3	7	480
4	8	730
5	9	980
6	10	1200
7	11	1400
8	12	1450
9	13	1500
10	14	1500
11	15	1500
12	16	1500

3 Modeling methods used for wind power prediction

Several efforts have been made in the literature regarding use of different models for predicting the power generated by a wind turbine. These can be broadly classified as

(1) Models based on wind power equation.

(2) Models based on the concept of power curve of wind turbine.

Models based on the concept of power curve that provides the relationship between the turbine power and wind speed are further classified as:

i) Models based on a presumed shape of power curve.

ii) Models based on actual power curves supplied by the manufacturer.

Under this class, two curve fitting techniques, namely the method of least squares and cubic spline interpolation have been investigated.

The non-parametric methods can be made use of, if more input parameters are to be considered. Hence, in the present work two such methods have been used, namely,

Table 2 Sample data set collected from the SCADA

Local time	Outdoor temp/°C	Wind direction degree	Wind speed/($m\cdot s^{-1}$)	Nacelle temp/°C	Blade pitch angle/(°)	Rotor speed/($r\cdot m^{-1}$)	Active power/kW
8/1/2013 0:10	22	−0.1	11.8	26	4.9	16.3	1347.7
8/1/2013 0:20	22	−0.8	13	26	9.7	16.5	1491.1
8/1/2013 0:30	22	−0.5	12.8	26	7.7	16.4	1448.7
8/1/2013 0:40	22	−0.4	12.4	26.1	7.2	16.4	1482.4
8/1/2013 0:50	22	−0.5	12.5	26	8	16.5	1481.3

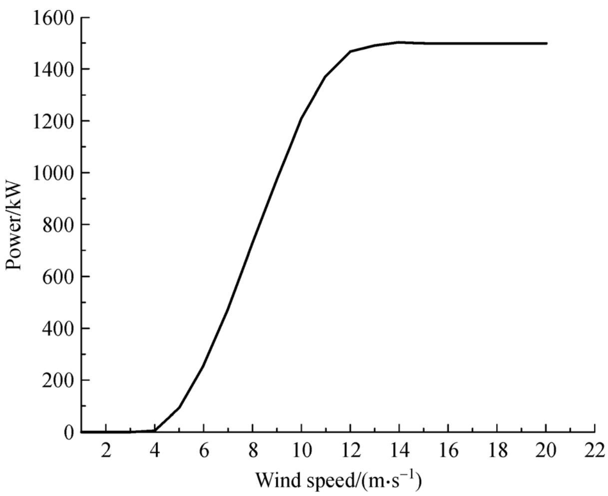

Fig. 2 Manufacturer's power curve of the turbine considered for this paper

(3) Response surface methodology.
(4) ANN.

The details of the models developed in the present study have been given in Table 3. A comparison of the results obtained from parametric and non-parametric models is presented.

Table 3 Details of the models developed

Model	Description
Model-1	Model based on wind power equation
Model-2	Model based on presumed shape of power curve
Model-3	Model based on method of least squares
Model-4	Model based on cubic spline interpolation
Model-5	Model based on response surface methodology
Model-6	Model based on ANN

3.1 Model-1

Many authors have developed equations for the power available from the wind [13]. Habib et al. [34] proposed that maximum possible power generation from a wind turbine assuming a mechanical to electrical conversion efficiency of 100% is given by Eq. (3).

$$P_{\mathrm{e}} = 0.593\left(\frac{1}{2}\rho A v^3\right). \tag{3}$$

The model takes the value of C_{p} as 0.593, which is the maximum possible theoretical value. Practically, 100% efficiency in mechanical to electrical conversion is impossible to be achieved, thus both of the above factors lead to inaccurate results.

3.2 Models based on the concept of power curve of wind turbine

3.2.1 Model-2

The power curve of a wind turbine is presumed to follow a typical shape in this concept. Hence, for different ranges of wind speed between cut-in and cut-out, a set of characteristic equations for power prediction are developed. One such model presented by Abouzaher and Ramakumar [35,36] and later used by Yang et al. [37–39] is very simple in predicting the performance of a wind turbine. In this model, it is assumed that, for a typical wind turbine, the power generation starts at cut-in wind speed v_{c}, the power output increases linearly for wind speed between cut-in and rated wind speed v_{r} and then, a constant rated power is produced between rated wind speeds v_{r} to cut-out wind speed v_{f}. The set of characteristic equations proposed are given in Eq. (4).

$$\left.\begin{array}{ll} P_{\mathrm{e}} = 0 & (\text{for } v < v_{\mathrm{c}}) \\ P_{\mathrm{e}} = P_{\mathrm{er}}\dfrac{v - v_{\mathrm{c}}}{v_{\mathrm{r}} - v_{\mathrm{c}}} & (\text{for } v_{\mathrm{c}} \leqslant v < v_{\mathrm{r}}) \\ P_{\mathrm{e}} = P_{\mathrm{er}} & (\text{for } v_{\mathrm{r}} \leqslant v \leqslant v_{\mathrm{f}}) \\ P_{\mathrm{e}} = 0 & (\text{for } v > v_{\mathrm{f}}) \end{array}\right\}, \tag{4}$$

These models are not very accurate, since the characteristic equations evolved are more general and not specific to any turbine, hence does not replicate the performance of a specific turbine very clearly.

3.2.2 Models based on actual power curves supplied by the manufacturer

Due to the drawback of the models based on presumed shape of power curve, many researchers have put forward methods that use the actual power curve of the individual wind turbine to develop the characteristic equations by using a variety of curve fitting techniques. In the present work, two curve fitting techniques, namely the method of least squares and cubic spline interpolation have been investigated.

3.2.2.1 Model-3

It is the mathematical procedure of fitting a best curve for the given set of data points in such a way that the sum of the squares of the offset of the points from the curve is minimum. The major advantage of this method is its simplicity. Three quadratic expressions are preferred for better fitting accuracy [13,40]. It has been proposed in Ref. [39] to use Eq. (5) to predict the power output of a wind turbine.

$$\left.\begin{array}{ll} P_e = 0 & (\text{for } v < v_c) \\ P_e = a_1v^2 + b_1v + c_1 & (\text{for } v_c \leqslant v < v_1) \\ P_e = a_2v^2 + b_2v + c_2 & (\text{for } v_1 \leqslant v < v_r) \\ P_e = a_3v^2 + b_3v + c_3 & (\text{for } v_r \leqslant v \leqslant v_f) \\ P_e = 0 & (\text{for } v > v_f) \end{array}\right\}, \tag{5}$$

where $a_1,b_1,c_1,a_2,b_2,c_2,a_3,b_3$ and c_3 are the coefficients.

The equations developed based on this approach for the turbine under study are given in Eq. (6).

$$\left.\begin{array}{ll} P_e = 0 & (\text{for } v < 4) \\ P_e = 35v^2 - 231v + 380 & (\text{for } 4 \leqslant v < 7) \\ P_e = -30v^2 + 786v - 3648 & (\text{for } 7 \leqslant v < 13) \\ P_e = 0v^2 + 0v + 1500 & (\text{for } 13 \leqslant v \leqslant 20) \\ P_e = 0 & (\text{for } v > 20) \end{array}\right\}, \tag{6}$$

3.2.2.2 Model-4

A cubic spline is a spline constructed of piecewise third-order polynomials which pass through a set of m control points. Efforts are found in the literature in using this technique to fit a power curve of a wind turbine [41,42]. The characteristic equations in their general form can be expressed as Eq. (7).

$$\left.\begin{array}{ll} P_e = 0 & (\text{for } v \leqslant v_c) \\ P_e = a_1v^3 + b_1v^2 + c_1v + d_1 & (\text{for } v_c \leqslant v < v_1) \\ P_e = a_2v^3 + b_2v^2 + c_2v + d_2 & (\text{for } v_1 \leqslant v < v_2) \\ \vdots & \\ P_e = a_nv^3 + b_nv^2 + c_nv + d_n & (\text{for } 6 \leqslant v < 7) \\ P_e = P_r & (\text{for } v_r \leqslant v \leqslant v_f) \\ P_e = 0 & (\text{for } v > v_f) \end{array}\right\}, \tag{7}$$

where $a_1, b_1, c_1, d_1, a_2, b_2, c_2, d_2, \ldots, a_n, b_n, c_n$, and d_n are the polynomial coefficients of cubic spline interpolation functions, n is the number of cubic spline interpolation functions corresponding to $n+1$ values of data points. The set of equations developed for the turbine under study using the above technique are given in Eq. (8).

$$\left.\begin{array}{ll} P_e = 0 & (\text{for } v < 4) \\ P_e = 11.33x^3 - 101.97x^2 + 314.58x - 331.92 & (\text{for } 4 \leqslant v < 5) \\ P_e = 3.27x^3 - 5.25x^2 - 72.287x + 183.865 & (\text{for } 5 \leqslant v < 6) \\ P_e = 5.34x^3 - 36.12x^2 - 88.61x + 928.54 & (\text{for } 6 \leqslant v < 7) \\ P_e = -20x^3 + 420x^2 - 2690x + 5590 & (\text{for } 7 \leqslant v < 8) \\ P_e = 2x^3 - 42x^2 + 542x - 1942 & (\text{for } 8 \leqslant v < 9) \\ P_e = -10x^3 + 246x^2 - 1762x + 4202 & (\text{for } 9 \leqslant v < 10) \end{array}\right\}. \tag{8}$$

A finite set of parameters are assumed in parametric models, hence, these are not very flexible and are restricted in their nature. But non-parametric models can be defined in terms of many parameters and they do not impose any pre-specified model, and hence, are more flexible.

Two such popular non-parametric models are response surface methodology and ANN which are investigated in this study.

3.3 Model-5

The response surface methodology (RSM) is a collection of mathematical and statistical techniques introduced by Box and Wilson in 1951 that explored the relationship between a response of interest and a number of input variables. The objective of optimizing the response which is influenced by several parameters in RSM is achieved with less effort for both linear and nonlinear problems.

The mathematical relationship between independent input variables and the dependent output variable have been obtained in terms of a second order model of the form

$$y = ax^2 + bx + c,$$

where y is predicted response and x is the input variable that influences the response variable.

The regression model development has been carried out using Statistica 12.0 (StatSoft) software[1)]. 99% of confidence level has been set and backward elimination method has been used in this work.

1) StatSoft, Inc, 2013. STATISTICA (data analysis software system) v. 12.0

3.4 Model-6

ANNs are the class of intelligent learning techniques that are inspired by biological neurons. ANN finds numerous applications in vast fields due to its ability to automatically approximate any nonlinear complex relationship between variables [43–45]. ANN, being a massively parallel distributed processor made up of simple processing units, stores the knowledge acquired through learning in the form of synaptic weights and biases [46]. There are two types of widely used feed forward networks, namely multilayer perceptron (MLP) and radial basis function neural networks (RBFNN). The feed forward network has the links that extend only in one direction. Except during training, there are no backward links in a feed forward network; all links proceed from input nodes toward output nodes. In MLP, non-linear elements (neurons) are arranged in successive layers and the information flow from the input layer to the output layer through hidden layers.

Each neuron in the network includes a nonlinear activation function. A commonly used form of nonlinearity is the sigmoidal nonlinearity defined by the logistic function: $y_j = \dfrac{1}{[1 + \mathrm{e}^{-v_j}]}$ where v_j is the net internal activity of neuron j and y_j is the output of the neuron.

The synaptic weights and bias of the network are updated during the process of learning in ANN. A popular BP algorithm is used in the present work. The algorithm works as follows:

The error signal is computed according to Eq. (9).

$$e_k(n) = o_k(n) - y_k(n). \tag{9}$$

The modification in the weights are calculated according to Eqs. (10) and (11).

$$\delta_k(n) = (o_k(n) - y_k(n))o_k(n)(1 - o_k(n)), \tag{10}$$

$$\Delta w_{kj}(n) = \delta_k(n)v_j(n)\alpha, \tag{11}$$

where α is momentum parameter, η is learning rate, v_j is hidden layer output, y_k is target output, and $\Delta w_{kj}(n)$ is the adjustment applied to the synaptic weights.

The synaptic weights are then updated in Eq. (12)

$$w_{kj}(n+1) = w_{kj}(n) + \Delta w_{kj}(n). \tag{12}$$

In the present work the MLP neural network model using gradient descent learning algorithm has been developed using customized codes written in MATLAB R2014a[1)]. The stopping criteria of minimum error of 1×10^{-3} or maximum 1000 epochs have been fixed. Various simulation parameters, learning and momentum coefficient η and α have been fixed on trial and error basis during training based on maximum prediction accuracy.

1) MATLAB R2014a @R, www.matheorks.com

4 Results and discussion

Models have been developed to predict wind turbine power based on the wind power equation and the concept of power curve of the wind turbine, using RSM and ANN. Wind speed, air density, blade pitch angle, rotor speed, and wind direction have been used as the input parameters in developing Model-5 and Model-6, in contrast to use of only wind speed in other models. The results have been discussed in this section with the help of randomly picked set of values as tabulated in Table 4, that cover cut-in to cut-out wind speed interval in the data collected from the SCADA of the wind turbine and that lies in the test set used in RSM and ANN modeling techniques. The direct comparison of predicted power with the actual power generated by the turbine helps in checking the relevance of different models.

Table 4 Data selected for comparison of performances of the models

Sl. No	Wind speed/(m·s^{-1})	Actual power/kW
1	5.667	250.85
2	6.017	289.383
3	7	447.433
4	8.033	637.133
5	9	820.9
6	10	981.15
7	11.017	1201.067
8	12	1392.217
9	13	1473.733
10	14	1500.183
11	15.233	1487.85
12	16.117	1475.533

The root mean square error (RMSE) which is defined as the square root of the mean of the squared difference between the actual and the predicted power values is used as the performance metric to evaluate the performance of the six models. The RMSE is expressed in Eq. (13)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(P_{\mathrm{e}}(i) - P_{\mathrm{a}}(i))^2}, \tag{13}$$

where P_{e} and P_{a} are the estimated and the actual power in kW respectively, and n is the total number of data.

4.1 Model-1

The model uses Eq. (3) and it results in wind power that is too far from the actual value. For example, for a wind speed of 5.667 m/s, the equation results in a wind power of 313924.6278 kW in contrast to 250.85 kW of the actual power produced by the turbine. This huge difference is caused by the assumption of 100% mechanical to electrical conversion efficiency by the turbine and the theoretical highest value of C_p of 0.593 used in this model. Both of the assumptions lead to inaccurate results as these assumptions depict the ideal condition and are impossible to be attained in practice. Some of the other models based on wind power equation take into consideration the efficiencies (mechanical transmission and generator) and the power factor which is a function of the blade pitch angle, the rotational speed of the turbine as well as the angle of attack. The interdependency of the above mentioned parameters and their variations based on the wind speed and other climatic conditions make these models complex and inaccurate [13].

4.2 Models based on the concept of power curve of wind turbine

Power curve can be one of the tools to predict the power generation of a wind turbine if accurately modeled. These models relate the power generated with the wind speed. The results of two categories under this concept have been discussed. These models have been derived by making use of the data from manufacturer's power curve.

4.2.1 Model-2

A model based on linear power curve proposed by Abouzaher and Ramakumar [35,36] has been used. The resulting power output values are comparable with the actual values as shown in Table 5.

4.2.2 Models based on actual power curves supplied by the manufacturer

The wind turbine power curves are made available by the manufacturer under standard conditions. Various curve fitting techniques can be made use of in order to model these power curves. The results of two models based on this concept have been discussed below.

The predicted values of power by Model-3 and Model-4 have been presented in Table 5. Although the techniques are efficient in fitting the curve as is evident from the predicted power and values of the power provided by manufacturer's power curve in Tables 1 and 5. The RMSE values for both the techniques are quite high with respect to the actual power values. One of the primary reasons for this is a difference between the power values provided in manufacturer's power curve and the actual power produced by the turbine. It can be observed from Tables 1 and 4, that for a wind speed of 10 m/s, the value of power in manufacturer's power curve is 1200 kW and the actual power produced is 981.15 kW. In addition to this, there could be errors due to the curve fitting method adopted in the models.

4.3 Model-5

The analysis of response variable, namely wind turbine power, can be explained through the surface plots obtained from the RSM study. The typical three-dimensional (3D) surface plots for wind turbine power in terms of the process variables are shown in Figs. 3–6. Figure 3 illustrates the surface plot for power by varying two variables using wind speed and pitch angle. It is clearly observed from Fig. 3 that the power increases with the increase in both wind speed and pitch angle. It can be established from Figs. 4 and 5 that air density and wind direction have not much effect on power. It is clearly seen from Fig. 6 that the power of a wind turbine increases with the rotor speed. The R^2 value obtained is 0.9954.

The resulting RSM equation considering second order model is given by Eq. (14)

Table 5 Comparison of power predicted by different modeling methods

Sl. No	Wind speed /($m \cdot s^{-1}$)	Actual power/kW	Model-2		Model-3		Model-4		Model-5		Model-6	
			Power/kW	RMSE	Power/kW	RMSE	Power/kW	Power/kW	Power/kW	RMSE	Power/kW	RMSE
1	5.667	250.85	250.05	0.565	200.61	35.52	200.73	35.43	222.28	20.19	269.01	12.84
2	6.017	289.38	302.55	9.31	263.24	18.48	253.24	25.55	280.07	6.57	282.42	4.92
3	7	447.43	450	1.81	485	26.56	480	23.02	425.91	15.21	432.50	10.55
4	8.033	637.13	604.95	22.75	730.06	65.71	716.20	55.91	625.30	8.36	635.84	0.91
5	9	820.9	750	50.13	996	123.81	992	120.98	786.48	24.33	793.43	19.42
6	10	981.15	900	57.38	1212	163.23	1278	209.90	960.39	14.67	963.64	12.37
7	11.017	1201.06	1052.55	105.01	1370.13	119.54	1401.78	141.92	1171.69	20.76	1182.68	12.99
8	12	1392.21	1200	135.91	1464	50.75	1450	40.85	1346.63	32.23	1359.93	22.82
9	13	1473.73	1350	87.49	1500	18.57	1500	18.57	1437.08	25.91	1440.81	23.27
10	14	1500.18	1500	0.129	1500	0.12	1500	0.129	1476.85	16.49	1491.60	6.06
11	15.233	1487.85	1500	8.59	1500	8.59	1500	8.59	1478.45	6.64	1487.69	0.11
12	16.117	1475.53	1500	17.30	1500	17.30	1500	17.30	1468.35	5.07	1470.87	3.29

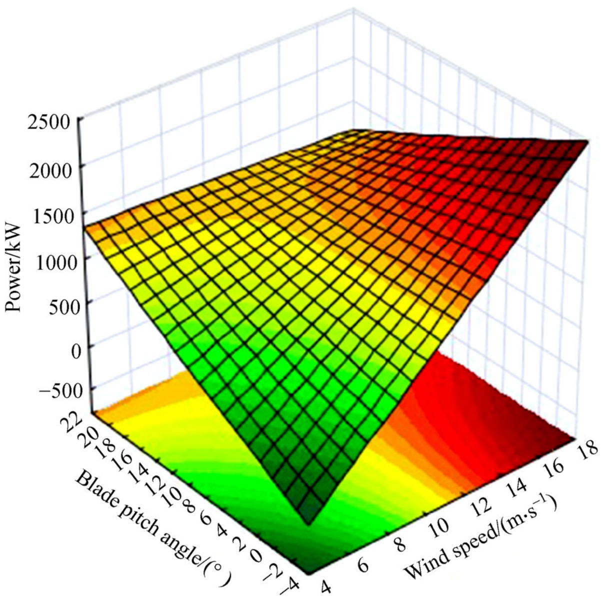

Fig. 3 Surface plot for power by varying two variables: wind speed and pitch angle

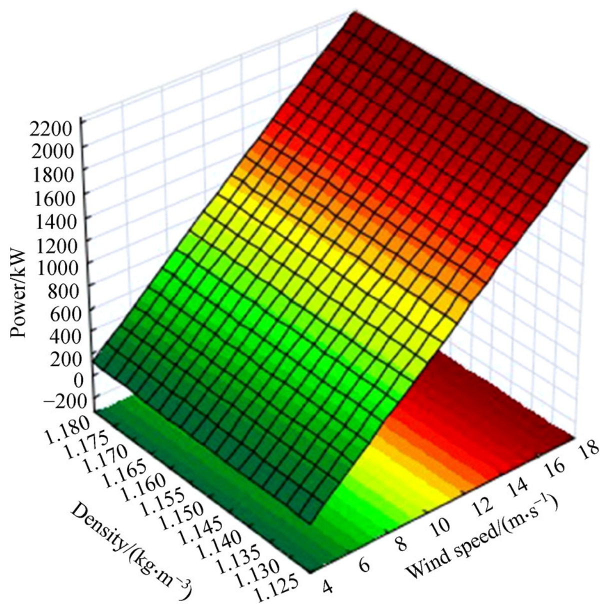

Fig. 5 Surface plot for power by varying two variables: wind speed and density

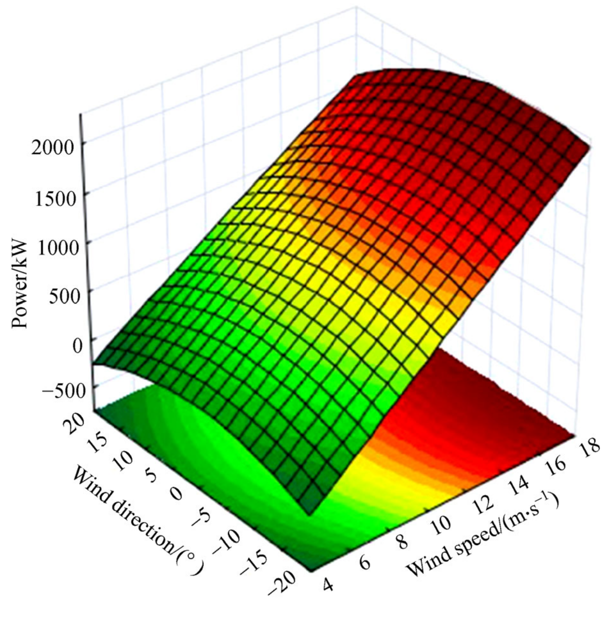

Fig. 4 Surface plot for power by varying two variables: wind speed and wind direction

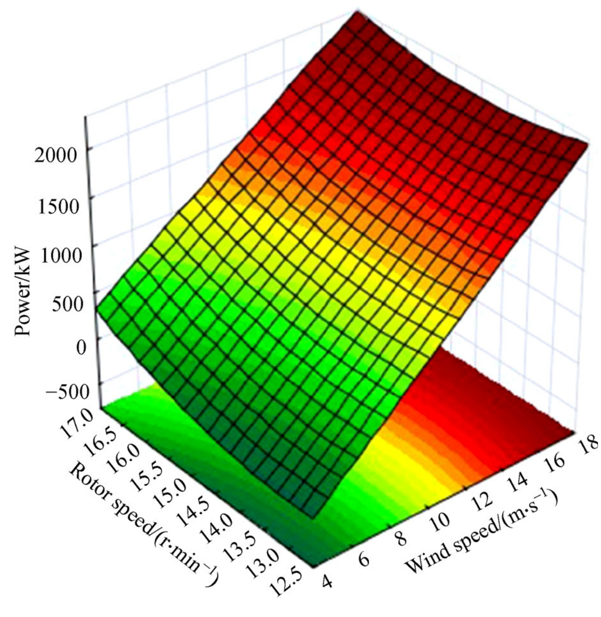

Fig. 6 Surface plot for power by varying two variables: wind speed and rotor speed

$$
\begin{aligned}
Y = {} & 3356 + 310.8X_1 + 126.2X_2 + 1.34X_3 + 738.4X_4 \\
& -866X_5 - 0.8122X_3^2 + 35.02X_5^2 - 7.7526X_1X_2 \\
& -0.882X_1X_3 - 8.99X_1X_5 - 2.434X_2X_5,
\end{aligned} \tag{14}
$$

where X_1, X_2, X_3, X_4, and X_5 are wind speed, blade pitch angle, wind direction, density, and rotor speed respectively, and Y is the wind power output. From Table 5, it can be noted that the values of the power predicted by the RSM model are much closer to those of the actual power. Since 2522 and 444 data collected from SCADA have been used for training and testing the RSM and ANN models, the mean RMSE for training and test data are 14.07 and 15.29 respectively for Model-5.

4.4 Model-6

The MLP neural network model using gradient descent learning algorithm has been developed. The variation of

MSE with the number of hidden neurons is presented in Fig. 7. It can be observed that there is a steady decrease in MSE till 25 hidden neurons, and there onwards it increases. The MLP neural network model with 25 hidden neurons, with η and α values of 0.019 and 0.002 respectively produces the best results. Thus the configuration of the developed model is 5-25-1.

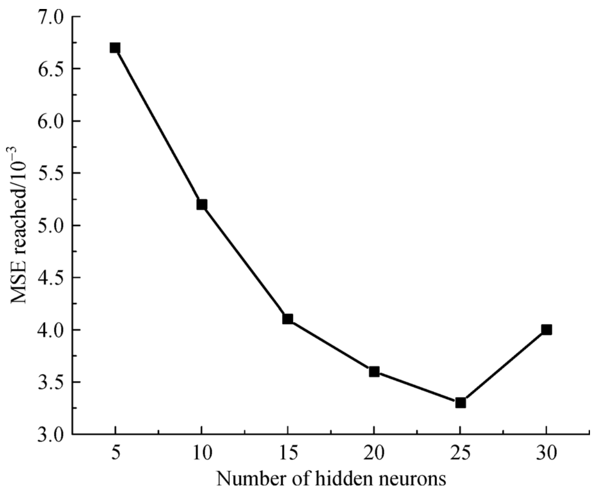

Fig. 7 Variation of MSE with number of neurons in the hidden layer for MLP model

The simulated values of power presented in Table 5 are satisfactorily close to the actual power values with a relatively small RMSE, proving the superiority of the model. The mean RMSE for training and test data are 13.63 and 14.33 respectively for Model- 6.

5 Comparison of modeling methods

Comparison of different modeling methods for wind power prediction is the main focus of the present study. Six different parametric and non-parametric models have been studied. Model-1 which is based on the concept of wind power equation results in nonrealistic values of power due to the theoretical assumptions with respect to C_p and mechanical to electric conversion efficiencies. The results of five different models other than the first one along with the actual power values have been presented in Table 5. The RMSE values of the models have been plotted in Fig. 8. It can be observed from Fig. 8 that Model-3 and Model-4 have resulted in a higher RMSE, Model-5 has resulted in a moderate, and Model-6 has resulted in the lowest values of RMSE. It can be observed from the power curve in Fig. 2 that between the wind speed of 6 m/s to 12 m/s, the power increases linearly, and for wind speeds above and below this range, the variation in power is negligible. By comparing the values of power from manufacturer's power curve and the actual power, it is clearly observed that the power of a wind turbine under actual working conditions is quite different from that of standard conditions and there are various other parameters affecting power generation other than wind speed. This is one of the reasons for the higher error for Model-2, Model-3, and Model-4 which are based on the concept of power curve.

It is worth noting form Tables 1 and 4 that the difference between the power from manufacturer's power curve and the actual power is large for data number 4–9 (corresponding to a wind speed of 8–13 m/s), thus resulting in higher errors in power prediction by the models as shown in Fig. 8. Further, the curve fitting methods are based on certain assumptions [47]. The limitations of these models have been overcome in Model-5 and Model-6 by considering several other variables along with wind speed. Model-6 give superior results in comparison with Model-5 and has resulted in lower values of RMSE. The reason behind this is that ANN has a universal approximation capability to approximate all kinds of nonlinear functions and it does not require any prior specification of suitable fitting functions, whereas RSM is restricted only for quadratic approximations [48].

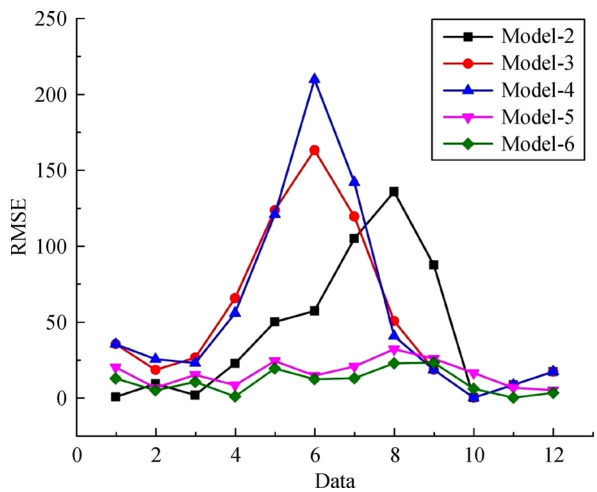

Fig. 8 Comparison of RMSE of different modeling methods

6 Conclusions

An efficient model to predict the power output of a wind turbine is of great importance to the wind industry. Various parametric and nonparametric models, based on wind power equation, based on concept of power curve, such as RSM and ANN have been developed and the results have been compared in this study. To develop and analyze the models, the power curve and SCADA data collected from a 1.5 MW commercially available wind turbine has been used.

The following conclusions can be drawn.

(1) Modeling methods based on fundamental equation of the wind power are complex to use and are based on

certain theoretical assumptions which make them inaccurate.

(2) The actual power derived from the turbine differs from that based on the manufacturer's power curve, due to the difference in conditions in which it operates. This leads to the error in the models derived from manufacturer's power curve.

(3) Curve fitting techniques are restricted in nature due to the finite number of parameters and thus are not flexible.

(4) A careful consideration of selected variables affecting the power output of a wind turbine along with wind speed has a definite impact in wind power modeling.

(5) Model-5 and Model-6 have shown good agreement between simulated and measured values of power.

(6) Model-6, which is based on ANN, has outperformed Model-5 as well as all the other models due to its capability to approximate any nonlinear function.

Notations

P	Power output of a wind turbine/kW
ρ	Air density/($\mathrm{kg \cdot m^{-3}}$)
R	Radius of the rotor/m
C_p	Power coefficient
β	Blade pitch angle/(°)
λ	Tip speed ratio
v	Wind speed/($\mathrm{m \cdot s^{-1}}$)
Ω_r	Rotor speed/($\mathrm{rad \cdot s^{-1}}$)
v_e	Effective wind speed perpendicular to the rotor plane/($\mathrm{m \cdot s^{-1}}$)
P_e	Estimated power/kW
v_c	Cut-in wind speed/($\mathrm{m \cdot s^{-1}}$)
v_r	Rated wind speed/($\mathrm{m \cdot s^{-1}}$)
v_f	Cut-out wind speed/($\mathrm{m \cdot s^{-1}}$)
a	Momentum parameter
η	Learning rate

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