WIND ENERGY FORECASTING USING RADIAL BASIS FUNCTION NEURAL NETWORKS

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Abstract

Wind power forecast is essential for a wind farm developer for comprehensive assessment of wind potential at a particular site or topographical location. Wind energy potential at any given location is a non –linear function of mean average wind speed, vertical wind profile, energy pattern factor, peak wind speed, prevailing wind direction, lull hours, air density and a few other parameters. Wind energy pattern data of various locationsis collected from a published resource data book by Centre for Wind Energy Technology, India.Modeling of wind energy forecasting problem consists of data collection, input-output selection, mappingand simulation. In this work, artificial neural networks technique is adopted to deal with the wind energy forecasting problem.After normalization, neural network will be run with training dataset.Radial Basis function based Neural Networks is a feed-forward algorithm of artificial neural networks that offers supervised learning.It establishes local mapping with two fold learning quickly.Wind power densities predicted for new locationsare in agreement with the measured values atthewind monitoring stations.MAPE was found out to be less than 10% for all the values of Wind Power Density predictions at new topographical locations and R^2 is found to be nearer to unity.WPD values are multiplied by wind availability hours (generation hours) in that particular location to give number of energy units at the turbine output. These values are compared to the output of the wind turbine model installed in the same region, so as to assess the number of units generated by that particular wind turbine in the respective locations.This kind of assessment is useful for wind energy projects during feasibility studies. With this work, it is established that radial basis function neural netscan be used as a diagnostic tool for function approximation problemsconnected towind energy resourcemodeling& forecast.

Keywords: *Wind power density, wind energy, forecast, modeling, air density, peak wind speed, radial basis function, neural network, CoD, MAPE*

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I. INTRODUCTION

Wind resource assessment is a preliminary requirement for a wind farm developer.Identification of potential windy sites is made within a fairly large region of several kM^2 by analyzing data comingfrom meteorological stations. Climatological data obtained from these stations along with topographical maps and satellite images is combined for this purpose. During this stage, wind resource assessment methodology is termed as Prospecting. The next stage is Validation Process.It involves more detailed investigation such as wind measurements and data analysis. The final and necessary step is Micro survey and Micro siting. The main aim of this step is to quantify the small scale variability of the wind resource over the region of interest, i.e. 10 KM radius from wind monitoring station taken vertically and horizontally.At the end, micro siting is carried out to position the wind turbine in a given area of land. Efficient modeling of wind resource data post the Validation Process maximizes the comprehensive energy output of the wind farm [20].Wind velocity and direction measurements are obtainedas every 1 second or 2second datasets and areadjusted as 10 minute average values. These valueswill be mentioned withminimum, maximum and standard deviations. This data will be used by Wind generator manufacturers to validate the power curve of their turbine models. Actual energy generated by the wind turbine will surely show some deviation from the manufacturer's power curve due to many reasons. Probabilistic determination of wind speed data above 25 m level, standard deviation methodology, error in air density extrapolation across the height and measurement slags are some of the reasons for these deviations [16]. Also, wind power economics is greatly influenced by mean annual energy produced per turbine which in turn depends on wind resource variation across different topographical locations vis-à-vis seasonal variations. Hence wind resource assessment and forecasting is a prima facie activity for the development of a wind farm.Selection of a suitable location for a wind plant primarily depends on wind resource estimation at a particular topography based on meteorological, atmospheric and geographical parameters. Wind resource assessment of any place is characterized by wind speed, direction, vertical wind profile, turbulent intensity, air density and topography.Terrain roughness, tunnel formations, nocturnal variation, diurnal variation, monsoon variation and many other climatological factors also contribute for wind energy assessment.In this paper, artificial neural network technique is adapted to model wind power density prediction problem with influencing factors being considered from wind resource mapping data of monitoring stations.

II. WIND RESOURCE PARAMETERS

The basic data required to estimate wind energy potential for any topographical region consists of wind velocity and wind power density values. They are determined at the hub height of the turbine. The resolution available should be 20mtrs or 50 mtrs. The wind resource parameters measured during the wind resource assessment programmes are as briefed below:

A) Mean annual wind speed: This is the mean value of measured wind speeds across one year data points. Mean annual value wind speed is defined as*u.*
$u = {}^{1}/_{n} \sum_{i=1}^{n} u_i$ where u_i = individual wind speed
n is sample size of wind patterns.

B) Wind power density
The wind power at any location is given by

$$U = \rho w^3/2$$

-here p is the air density. So the available mean wind power at any location is given by
E(U)=ρE(w^3)/2

C) Power Law Index:
Power Law wind profile is expressed as:
$U_2 = U_1 (Z_2/Z_1)^{\alpha}$
U_2= wind speed taken at level Z_2
U_1 = wind speed taken at level Z_1
Z_1 = Reference height
Z_2 = Computed height
-where ‘α’ is power law exponent. The power law index is a function of surface roughness and stability. Empirical studies have found that a value of 0.14 best fits to most of the sites. This method is always referred to as one-seventh power law.

D) Energy Pattern Factor:
Energy pattern factor (EPF) is a useful parameter to determine energy in the wind from the values of mean wind speeds.

$$\text{EPF}=\frac{\sum_{i=1}^{n} ui^3}{n(\bar{\upsilon})^3}$$

Where u_i=discrete wind velocity values (m/s)
ῡ=Mean annual or monthly wind velocity (m/s)
n=sample size
EPF values will be generally in the range of 1.5 to 2.50

E)Density of Air:
Density of airwill varywithchanges in altitude, temperature and pressure. It is susceptible todiurnal and seasonal variations also.The atmospheric pressure decreases with height,the power output of wind turbines on high mountains gets reduced compared to power that could be produced at the same wind velocity at sea level.

$$\rho=P/RT$$

-where ρ=Air density (Kg/m^3)
P=measured atmospheric pressure (mb)
T=Temperature of air in Kelvin (ºc+273)
R=Universal gas constant

E) Turbulent intensity:
The short time perturbations of wind speed at a given point in space over a time averaged mean value is characterized by rapid changes in three dimensional spaces.

$$T.I=(\sigma/\bar{\upsilon})$$

Where σ=Standard deviation
ῡ=Mean wind speed

F) Weibull parameters:
Weibull distribution function is obtainedby performing mathematical approximationson theactualvalues of wind speed frequencies. It is defined by two-parameters known as shape factor (ƙ) and scale factor (Ś).

$$f(\bar{u})=(ƙ_S/Ś)(\tfrac{\bar{u}}{Ś})^{ƙ-1}\exp[-(\bar{u}/Ś)^{ƙ}] \quad (ƙ>0,\bar{u}>0,Ś>1)$$

Where f(ū)=Probability density function
Ś=Scale Factor
ƙ=Shape Factor
= Standard deviation / mean wind velocity
Ś =1.12ῡ. Where, 1.5≥ƙ ≤3.0; ῡ=Mean wind speed

III. MODELLING OF WIND POWER DENSITY USING ANN

Wind resource assessment & forecasting is a non-linear mapping problem involving various parameters related to climatic data and atmospheric modeling. For analyzing wind resource assessment & forecasting problem, various mathematical, probabilistic and statistical models weredeveloped by researchers. These give predictions based on extrapolation of data. But, an artificial neural network (ANN) is a computing technique which has inherent ability to interpret nonlinearities of prediction problem. ANN can derive the required information directly from the datasetswith fast response and generalization capabilities. During training, ANNs will map the non-linearties of input and output variables. After training the neural network for certain amount of duration, complexities in input-output mapping are understood by the network indicating the stabilization of minimized error.Now, ANN can make predictions or approximations of desired variables for new values of inputs. Successful predictions will result if mapping is perfectand complete. Radial Basis Networks is a special technique of artificial neural network technology which was adopted in function-approximation problems related to wind energy resource assessment and wind power forecastmodeling [1, 5]. In this work, radial basis neural network is designed &developed for prediction &modeling of wind resource data of target topographical locations.

A. Data preparation & analysis

Variability in wind power resource greatly influences the overall power plant output for megawatt range wind projects.These fluctuations must be predicted accurately as wind power distribution is highly non- linear in nature.National Institute of Wind Energy, Chennai formerly known as CWET has established wind monitoring stations as part of their wind energy survey programmes since 1985. This work utilizes the wind resource mapping data bank of 76 wind monitoring stations under the published series viz., Wind Energy Survey – VIII. The collected data consisted of measured wind parameters recorded during the years 1995 to 2011.In this work, wind data of 24 topographical locations of Telangana and Andhra Pradesh states has been utilized for modeling.In neural network modeling, problem definition is a first step followed by systematic arrangement of data. This step involves arranging all the wind parameters data in time series chronology.As per the requirement of ANN methods,data is processed using normalization before being used in the modeling. This exercise involves filling the missing values, smoothening of data and rescaling the input output vectors. Most of the activation functionsof neural networks demandthat the input-output values are in specific range. Hence, input and output vectorsare rescaledby dividing each dataset value with a scalar constant. This process is known is data normalization. After normalization, entire set of data patterns are divided into training and testing data sets in the ratio of 80% and 20%. In this problem, data pertaining to 19 stations is used for training the neural network and data pertaining to 5 target stations is used for testing or prediction phase.

B. Radial basis neural networks

Neural network modifiesthe values of certain variables with respect to an input and output mapping. It begins with initialization of weights associated with input& output vectors and proceeds in the direction of finding a best fit of the relationship.Thismodification of weights continues during the feed forward movement of the neural network, termed as epoch. Root mean square error (RMSE)is evaluated in each training epoch and the network is run until this error is minimized and stabilized. Many researchers have designed and developed Multi-Layer perceptron models for solving complex problems of large data patterns.Back Propagation based Neural Networks have already been used for predicting wind speeds for a new topographical location [1]. Multilayer perceptron neural network will have a nonlinear sigmoidal activation function. Faster response of the neural network and better approximation of the desired outputs is achieved through radial basis function neural networks. Radial basis neural network employs a linear learning rule that prevents the networks to get struck up in local minima. It is an enhanced algorithm giving improved accuracies by probabilistically relating the outputs of each training epoch.

Radial basis neural networks are useful in performing the exact interpolation of dataset points in any high-dimensional space [17]. Thesewill have three layers- an input layer, a hidden layer and a linear output layer. Hidden layer consists of radial basis function implementation. At each value of input of middle layer neuron, the radial distance between the neuron centre and the input vector is determined. Radial basis function is applied on this distance to evaluate the output of the neuron in each epoch. Many radial basis functions given belowhave been tried as activation functions. A function S in linear space is defined as an interpolation of radial basis vectors such that $S_R(x_i) = t_i$, ; i = 1, …n.

$$S_R(x) = \sum_{i=1}^{n} W_i \upsilon_i \qquad \text{-------------} \quad (1)$$

And the basis function of the form is given by

$$\upsilon_i\,(x) = f\,(\|\,(x - x_i)\|)$$

Where f is to map R+ → R and the norm is Euclidean distance. Radial basis functions tried here are listed below.

(i) Thin Plate Spline Function
$f(\acute{r}) = \acute{r}^2 \log(\acute{r})$

(ii) Gaussian approximation function
$f(\acute{r}) = e^{-(\acute{r}^2/\tau^2)}$

(iii) Multiple quadratic function
$f(\acute{r}) = (\acute{r}^2+\tau^2)^{1/2}$

(iv) Inverse Multiple quadratic function
$f(\acute{r}) = 1/(\acute{r}^2+\tau^2)^{1/2}$

Where ŕ is the distance between from centre, τ is the width of radial basis function.

C. SelectedArchitecture

To model the predictionproblem of wind power densitiesat new locations, radial basis neural network is developed. This consists of a hidden layer with built-in radial basis function. Many trials were conducted by changing the number of neurons in the hidden layers to find out the optimum. 14-142-1 is derived to be the bestoptimal neural networkarchitectureafterrunning the neural nets for various combinations.

D. ANN Parameters

Fixing correct values for learning parameters, neural network architecture is a herculean task and requires many experimental trials. Speed of convergence, computational accuracy, and neural network performance parameters are importantin designing a best optimal network. Root Mean Square Error is represented by ‘e’and is calculated per training iteration as given below:

Table 1. Input- Output Mapping of wind resource assessment & forecasting in neural network design

S.no.	Input Parameter	Output Parameter
1	Latitude	Mean Monthly Wind Power Density (WPD) in Watt/ m^2
2	Longitude	
3	Altitude	
4	Month	
5	Height	
6	Power Law Index	
7	Energy Pattern Factor	
8	Peak Wind Speed	
9	Year	
10	Date	
11	Prevailing Wind Direction	
12	Lull Hours of percentage frequency Distribution	
13	Air Density	
14	Monthly Mean Average Wind Speed	

Table 2.ANN architecture

S.no	Algorithm	ANN Architecture	Activation Function
1	Back Propagation Feed Forward Neural Network	14-10-8-6-1	Input- Linear Hidden- Sigmoidal Output- Linear
2	Radial Basis Function Neural Network	14-142-1	Input- Linear Hidden- Radial basis Output- Linear

$$e= \left(\sum_k |(p_k - q_k)|^2 \right)^{1/2} \quad \text{-------} \quad (2)$$

Where p_k is the actual target vectorof supervised learning and q_k is the output vector of each training epoch.

14-142-1 is finally selected as an optimum neural net architecture after many trial and error exercises to run for 10000 training cycles. Learning rate isa constant whose value is 0.6. Momentum isanother parameter for which 0.9 isfound to be suitable. Lesser value of learning rate slows down running of neural network. But, a higher value for learning rate enables the weights and error function to diverge, thereby to stop learning at some point. A learning rate of 0.6 is found to be optimal during this modeling exercise. Table 2 lists the network architecture finally designedas part of the modeling. Convergence of the neural network program is linked to the fast response of the chosen algorithm. Radial basis neural network is able to sense and quickly understand the complexity of the data efficiently than a traditional back propagation neural network.

E. Evaluating ANN results

Neural network tool box of MATLAB facilitates to validate the data patterns during the evaluation phase. This is performed to prevent over training. After this stage, testing is performed by making predictions on new input datasets. The predicted new wind power density values are compared to the actual measured values of wind monitoring stations.This is done as part of the regression analysis. Table 3 consists of predictions performedat target wind stations endorsed by performance criterion of the neural nets. Other important neural network performance parameters are Coefficient of Determination (D_r) and Mean Average Percentage error (M).These are calculated for both the back propagationand radial basis neural nets using ORIGIN 6.0 software.

$$D_r = 1- \sum_{k=1}^{n} (pk - qk)^2$$

$$M= \quad (q\text{-}p)/p*100 \left(\qquad \right)$$

Table 3. Neural Network training results

Village Name	Back Propagation Neural Net			Radial Basis Neural Net		
	M	R	R^2	M	R	R^2
Kotrathanda	12.7068	0.9949	0.9898	40.3534	0.9987	0.9974
Kotturu	13.9735	0.9856	0.9714	70.6705	0.9953	0.9907
Shahapuram	11.8347	0.9986	0.9973	40.7337	0.9997	0.9995
Singarikonda	10.7298	0.9992	0.9985	60.7822	0.9990	0.9980
Tarennapallle	9.5281	0.9985	0.9970	80.6962	0.9990	0.9981
Total AP	11.7544	0.9954	0.9908	60.4472	0.9983	0.9967

Table 4. Predicted values of wind power densities

Back Propagation	**Radial Basis**	**Actual WPD** in Kg/m3
WPD in Kg/m^3	WPD in Kg/m^3	
56.61	57.49	58.83
89.86	94.90	94.75
101.46	100.51	103.16
79.70	81.89	84
79.04	78.18	82.5
81.33	82.59	84.65

Actual and predicted values for wind power densities under changing topographical conditions are represented in Fig. 1. This shows that neural network was able to predict the wind power density value at the target location with at most accuracy.Generalization capability of neural network depends on the mode of training, the selection of training data patterns covering most of the input-output variations and activation function used. Here, Radial basis neural network algorithm was successful in interpreting the non-linear mapping between wind speed & other parameters and wind power density at the target location.

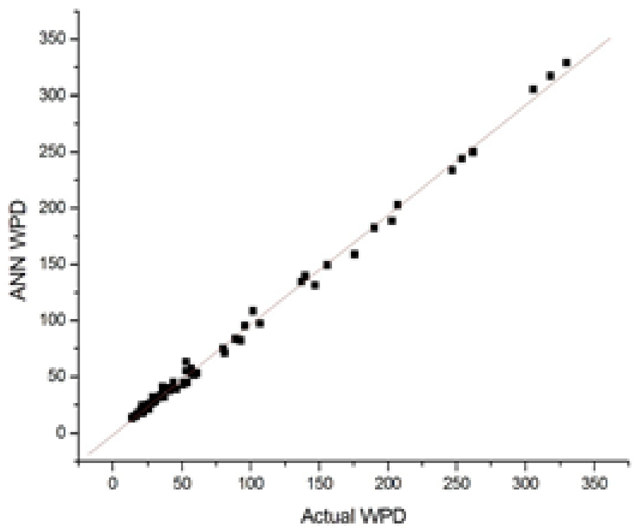

Fig: 1. WPD values predicted Vs actual

IV. WIND ENERGY GENERATION ESTIMATES

Wind turbine power generation will not always follow Manufacturer's power curve. This exercise helps to understand the overall energy generation that may be possible at the selected area per year. Wind energy generated at the new locations is estimated by analyzing the manufacturer's curves of horizontal axis wind turbines at the average wind speed. Wind power density values are taken from wind energy resource survey data.Power curves of NORDEX 29 of 250 KW, ENERCON 33of 330kW, Enercon82of 700 KW horizontal axis turbines are referred for this purpose.Wind power density values estimated from the modeling of radial basis neural networks along with generation hours are mapped to the power curve equation to estimate the wind energy generated in thatyear. This power curve modeling exercise takes into account the performance coefficients of the respective models of wind turbines given by the manufacturer. Predicted wind power density values along with the wind generation hours in that location multiplied by swept area of the turbine give rise to the energy units generated by the turbine. The graphs indicate that in June and July, the number of units generated is highest and contribute to 30% of overall energy that can be generated in a year. The entire generation year may be split up in to three regimes – low, high and moderate wind. Low wind regime is during January to April. High wind season is from May to August and moderate wind season is from September to October. This variation pattern is almost similar in Indian subcontinent.

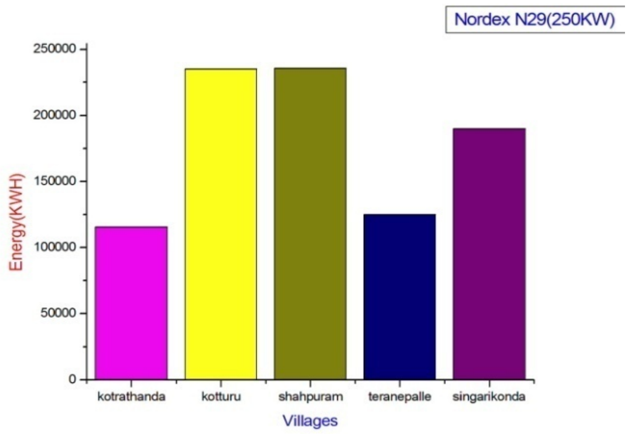

Fig.2 Energy Predictions with Nordex N29 turbine

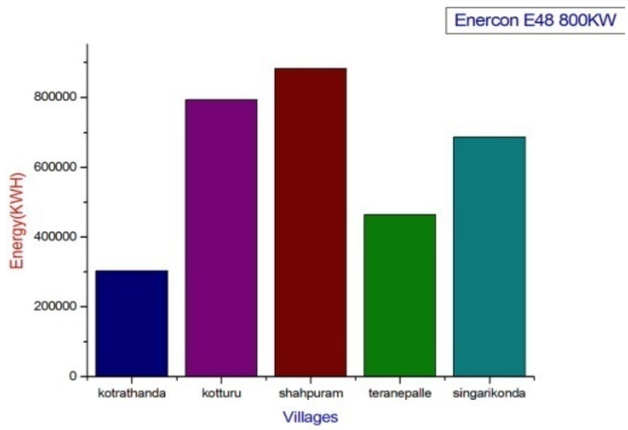

Fig.3 Energy Predictions with Enercon E48 turbine

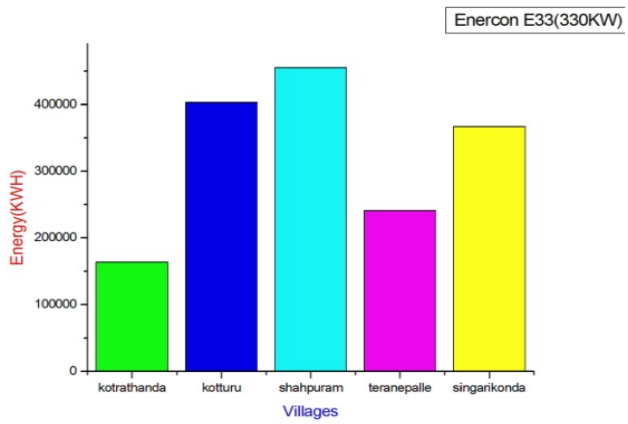

Fig.4 Energy Predictions with Enercon E33 turbine

V. CONCLUSIONS

Wind power resource assessment and forecasting helps wind farm developers to make rational decisions for the selection of wind sites. Processing of topographical information along with wind monitoring data with seasonal variations underconsideration, will be crucial to developers during the assessment of energy yield per season, month or year. These variations will significantly influence wind energy economics, energy trading,gridintegrationand transmission requirements.Wind power forecasting is an important tool for turbine manufacturers to select the wind power systems with high efficiency and reliability. The developed RBFNN can be used to predict the wind power density at a target topographical location.Itgives a better estimate of wind power resource characterized by wind speed and other important parameters at that specific location.In this work, the deviations of wind power generation with manufacturer's power curve were also interpreted. The performance of RBFNN is found to be satisfactory in predicting the wind power densities across fivetarget villages (Kotrathanda, Kotturu of the state of Telangana, Shahapuram, Singarikonda and Teranapallle of the state ofAndhra Pradesh) during the testing phase. Sensitivity analysis was also performed to identify the effect of influencing parameters viz., wind speed, direction, air density, energy pattern factor, seasonal variation, turbulent intensity etc.Predicted values of wind power densities are utilized to map with power curves of wind turbines, to estimate the number of units generated at eachtarget site if that particular model of wind turbine is installed. Thisresearch will go a long way inwind farm development, turbine manufacturing and helps independent system operators in finding risks of uncertainties due to variability of wind source at selected locations.This work willalso be a stimulus to wind energy market management in fixing a proper value for energy priceindex.

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