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Computer Aided Technique for Energy Estimation

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***Abstract*—**.In this paper, the estimation of electric energy output for a wind farm is carried out by using a computer aided technique which uses unpublished collected field data for 3 years 10 months from October 2010 to August 2014 at Satara, India. The inputs for this analysis are such as temperature, pressure, wind speed, wind direction and wind turbine power curve. The results demonstrate that this is an efficient methodology for taking techno commercial decisions.

Keywords- wind energy estimation; energy output; computer aided technique; wind energy prediction

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I. INTRODUCTION

Increased energy consumption, rising fuel costs and environmental concerns have led the mankind to look at alternative sources of energy apart from conventional fuels. One of the promising renewable energy sources is wind energy. To maximize the use of wind generated electricity, when connected to the electric grid, it is important to estimate and predict power produced by wind energy converter. The power generated by the wind turbines changes rapidly because of continuous fluctuation of wind speed and wind direction. Wind power can be affected by many factors such as air density, vertical wind profile, time of a day and seasons of a year and usually fluctuates rapidly, imposing considerable difficulties on the management of combined electric power system. It is important for the power industry to have a capability to perform prediction for diagnostic purposes and schedule for maintenance of the system. Scheduling and forecasting of power generation from wind are critical for economic viability, system reliability and long range planning. Proper siting in windy locations, away from large obstructions, enhances the wind turbine performance. It is vital to assess the wind power potential of the place as much as accuracy as possible, taking in to account of seasonal as well as yearly variations in the local wind climate. For proper and beneficial development of wind power at any site, wind data analysis and accurate wind energy potential assessment are the key requirements. An accurate wind resource assessment is an important and critical factor to be well understood for harnessing the power of the wind. The reason is that an error of 1% in wind speed measurement leads to a 3% error in energy output since energy is proportional to the cube of wind speed [1-3]

During the past two decades, wind energy technology has evolved to the point where it can compete with conventional forms of power generation at good sites [4]. Costs have declined 12–18% for each doubling of global capacity. The average cost of wind-generated electricity has fallen. The Global Wind Energy Council [5] states that wind energy developments have occurred in more than 70 countries around the world.

There are different types of models available for wind energy estimation. They are classified as Statistical, Intelligent systems, Time series, Fuzzy logic. Models constructed based on meteorological, topological data and wind turbine technical information using numerical methods, are suited for long term predictions.

Many techniques have been emerged to estimate the power produced by wind turbines. The estimation of power generation is carried out by comparing generated power to the manufacturers rating for a given wind speed[6]. Many input variables can be used that are related to weather at site, geography and operational aspects[7].Variables such as 10 minutes average wind velocity, its standard deviation, wind direction, air density, seasons of a year, time of a day are used as input parameters for energy estimation[8],[9],[10]. Input variables such as longitude, latitude, altitude and tower height are used to estimate wind energy potential by the authors of [11].

In this paper, the estimation of energy output is carried out by using a computer aided technique. The inputs for these analyses are such as temperature, pressure, wind speed, wind direction and wind turbine power curve. It presents a methodology to estimate the output energy which can be predicted well in advance and can be used for taking techno commercial decisions.

This paper present a method to evaluate the long-term wind resource and energy production potential of the Satara Wind Project. This paper presents the results of the analysis and discusses the methods used to develop the wind resource, energy production. Unpublished collected field data for a period of 3 years 10 months from October 2010 to August 2014 for UTM coordinates E437812, N1972521 near Satara is used in this model.

II. WIND MEASUREMENT

Meteorological data is provided from a 78m tower. Information about the mast including its geographic coordinates, elevations, periods of record, sensor heights are as mentioned in Table 1.

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TABLE I. MAST DETAILS

Site UTM Coordinates		Elevation (m)	Period of Record	Monitoring Heights (m)		
Easting	*Northing*			*Wind Speed sensors*	*Wind Direction sensors*	*Temp sensor*
437812	1972521	1052	10/10/2010-10/8/2014	78, 55, 40	78, 55	15

Raw binary files which contained 10- minute average wind speed, direction, barometric pressure, mast details and temperature records, along with their standard deviations are used.

The data is verified for completeness and reasonableness where the main issues addressed were sensor failures and missing data. The characteristics include the average and annualized average wind speeds, data recovery, shear exponent, turbulence intensity, Weibull parameters, air density, and wind power density. The observed mean wind speed is 5.94 m/s. The annualized mean speeds, which take into account repeated months in the data record and weight each calendar month by its number of days, were 6.00 m/s.

The wind shear exponent represents the rate of increase of wind speed with height above ground according to the power law. The observed shear exponent is 0.178. The shear was calculated from the mean wind speeds at the monitoring levels based on concurrent valid records at both heights. Only wind speeds greater than 4 m/s, the range of interest for energy production, were used in the calculations.

The turbulence intensity measures fluctuations in the wind speed recorded by the anemometer in each 10-minute interval as a fraction of the average speed. The observed turbulence intensity values at 15 m/s, 0.114 is consistent with the sites surrounding terrain and surface roughness.

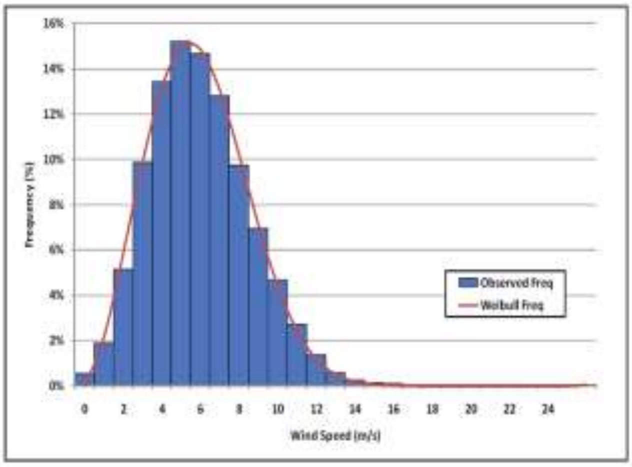

Figure1. Monitoring mast observed Wind speed Frequency Distribution and fitted Weibull Curves

The Weibull function is an analytical curve that describes the wind speed frequency distribution, or number of observations in specific wind speed ranges. Its two adjustable parameters allow a reasonably good fit to a wide range of actual distributions. *A* is a scale parameter related to the mean wind speed while *k* controls the width of the distribution. Values of *k* typically range from 1 to 3.5, the higher values indicating a narrower distribution. The observed *k* value at the mast is 2.50. This value indicates a mostly consistent wind resource with occasional high wind events. Fig.1 contains charts showing the observed frequency distribution and the fitted Weibull curve.

Monthly patterns of variation are also useful indicators of the wind resource. The observed pattern of monthly mean wind speed is shown in Fig.2. The period of record at the masts indicate that the strongest winds normally occur during the summer while the weakest winds occur during the winter. The range of variation in the monthly average wind speeds at the mast is about 2.9 m/s

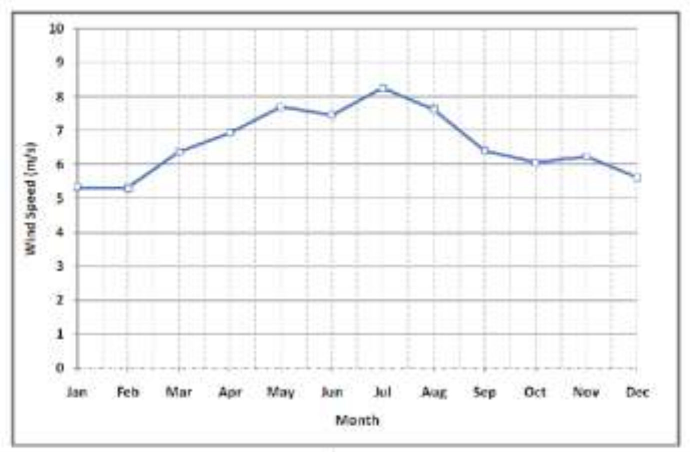

Figure 2. Monitoring Mast observed Monthly mean Wind speed

Fig.3 depicts the variation in the 78 m average wind speed with time of day at the mast, as well as the variation in mean wind shear exponent between 78 m and 55 m. The average wind speed varies by about 0.9 m/s throughout the day, and is highest during the early morning hours. The average wind shear exponent varies from a minimum of 0.119 in the late morning hours to a maximum of 0.229 in the early morning hours. Considering the mean speed and shear patterns, it is likely that energy production is peak during the late night and early morning hours.

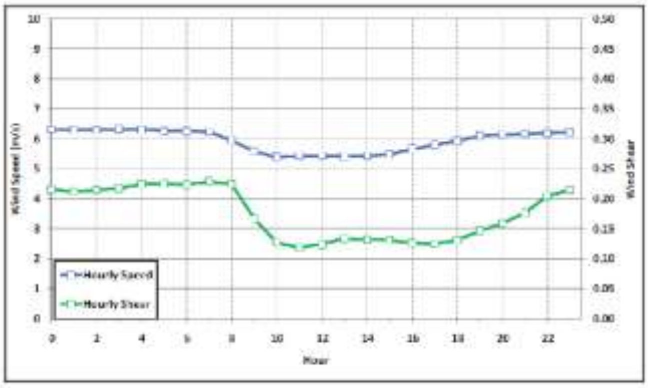

Figure3.Monitoring Mast Diurnal Wind speed and shear pattern

The annualized wind frequency and energy distribution by direction plot (wind rose) is presented in Figure 4. The wind roses indicate that the prevailing wind direction is from the west and west-northwest.

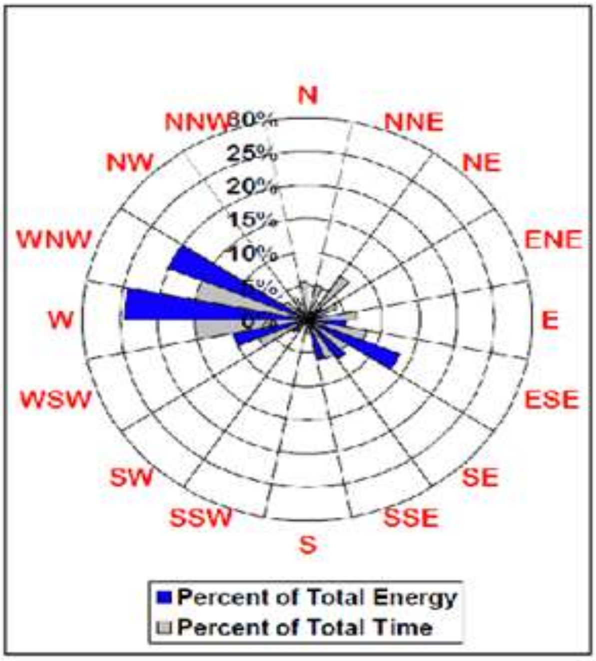

Figure 4. Monitoring mast annual wind rose

The air density directly affects the energy production: the greater the density, the greater the power output of a wind turbine for the same speed distribution. The estimated air density is calculated from the following equation:

$$\rho = \frac{P_o e^{\left[\frac{gz(1.0397-0.000025z)}{RT}\right]}}{RT} \qquad (1)$$

where

ρ = Air density (kg/m³)

P_o=Standard sea-level atmospheric pressure in Pascals (101325 Pa)

R = Specific gas constant for dry air (287 J/Kg·K)

T = Air temperature (°K)

g = Acceleration due to gravity (9.8 m/sec2)

z = Elevation of temperature sensor (m)

This equation was applied to each 10-minute data record, and a weighted average was calculated in which the weight was proportional to the energy content of the wind.

To assess the wind resource available at the site the wind power density should be calculated.

$$WPD = \frac{1}{2}\rho V^3. \qquad (2)$$

where

ρ = Air density (kg/m³)

V=wind speed (m/s)

Wind power density is a measure of the amount of energy available in the wind for conversion by the wind turbine over the cross sectional area swept by the turbine blades. The average wind power density is 187 W/m^2.

III. ESTIMATION

A. long term mean wind speed at mast height

Since the wind climate can vary considerably over time scales of months to years, it is important to adjust the data collected at the site to represent historical wind conditions as closely as possible. The method we used to make this adjustment is known as measure-correlate- predict, or MCP. In MCP, a linear regression or other relationship is established between two meteorological stations (or other sources of wind data, such as modelled data). One, the target site, spans a relatively short period and the other, the reference site, spans a much longer period. The complete record at the reference station is then applied to this relationship to estimate the long-term historical wind climate at the target site.

We obtained historical wind speed data for potential reference stations located within 160 km of the project area and assessed those sites for suitability as long-term references. Three-hourly observations of wind speed, wind direction, and temperature were acquired for each surface station from the National Climatic Data Center (NCDC)

B. Extrapolation to Hub Height

. We extrapolated the mean wind speed to the anticipated 95-m hub height using the power law equation:

$$U = U_0 (Z/Z_0)^p \qquad (4)$$

where

U=unknown wind speed at height Z above ground

U_0=the known speed at a reference height Z_0

p=shearexponent

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The main challenge is to determine the shear exponent between the top anemometer on the mast and the turbine hub height.

The resulting shear exponent used to extrapolate the mast top speeds to the 95-m hub height is 0.178.

C. Long –Term Energy Production

The energy production is estimated using a tool called openWind The primary input into openWind is a wind resource grid formed by site wind. Other inputs include details of the project design such as the turbine locations, hub height, power curve, and thrust coefficients. Once the wind resource model has been run, the resource grid file is imported into openWind to define the wind resource for the project area. The Weibull parameters in the file are converted to directional speed-up ratios relating the wind speed at each grid point to the speed at a reference mast. By associating the model data to a wind speed histogram file for the reference mast, the program is able to adjust the modeled speed distribution to the true speed distribution observed at a point. This method produces a more accurate estimate of the energy production than relying on the modelled distributions alone.

IV. RESULTS

The energy production was simulated for aV100, 1.8 MW, 100-m rotor diameter turbine model at a 95-m hub height for 54 MW. The average air density was calculated from the wind speed and temperature data and adjusted to the mean elevation of the turbines using a standard atmospheric lapse rate. The result was 1.048 kg/m3 at the average turbine elevation, with a range from 1.046 kg/m3 to 1.050 kg/m3 .

The long-term wind resource was estimated using data from an onsite monitoring mast. The site's energy production was simulated using a wind resource grid and the openWind. The expected average capacity factor of annual net production for the plant is 26.1% and the predicted average wind speed is 6.21 m/s.

V. CONCLUSION

The above results are in fair agreement with the measured output and the above methodology is best suited for making techno commercial decisions.

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