# CHAPTER-V

# Estimation of wind energy potential

## 5.1. Introduction

In recent past, rapidly growing global warming has been the major threat to the human being. Overcoming from global warming issues, globally all developed and developing countries meet each year in a summit of environmental issues. Where they do policy revision to improve the current environmental condition and maintain our ecology system. With this kind of global meets, the world came together for achieving a milestone in renewable energy sector to reduce the load of carbon emissions and improving world environment condition. For promoting renewable energy, developed countries are supporting developing countries for increasing utilization of renewable energy sources with technological and financial support. Environmental friendly nature of renewable energy sources is increasing their importance globally despite their high initial setup cost which is going down with technological advancement. Initially, our attraction over renewable energy sources was due to abundant availability of this and limited conventional fossil fuels. Now, environmental issues are being more concerned area to motivate for the adoption of renewable energy sources in the power sector. With the use of wind energy based renewable distributed generation technology concept, we can reduce green house gasses and adverse environmental effects with power quality improvement (Atwa and El-Saadany, 2011). With technological advancement, increased renewable energy based generation capacities are also helping to reduce per unit cost.

Small-scale generating the capacity of renewable energy based technology gives us the freedom of setting up decentralized generating units, which is called renewable distributed generation technology. This new renewable distributed generation technology concept is helping us to have access to rural or remote areas, where to set up of transmission line would not be possible or feasible (Ansari et al., 2012; Rajanna and Saini, 2016). Integration of renewable energy sources to the urban building in India has been discussed in the work of Kumar and Ravikumar (2015). Amongst the different alternatives of renewable energy sources, wind energy is one of the major sources and having the maximum contribution in power generation. In a work of Sholapurkar and Mahajan (2015), the potential of wind energy and their growth in India has been discussed. Kose et al. (2014) analysed the potential of wind energy at Selcuk University, Turkey in their work. Integration of wind generators with distribution networks can improve voltage stability through reactive power management (Roy et al., 2013). For the reactive power management, a new distributed multi-agent scheme has been developed by Rahman et al. (2014) to integrate the renewable energy sources in distribution networks. Maintaining resilience of transmission and distribution networks with increasing penetration of renewable distributed generation is very important (Akter et al., 2014). Managerial challenges of wind energy are the availability of wind speed and economical feasibility of the desired location. Developing countries are also following footsteps of developed countries to have adoption of renewable energy technologies and reducing load over conventional energy sources. Attention over renewable distributed generation technology has also been growing at the institutional and industrial level. Researchers are investigating to harness more energy from the renewable sources and reducing its per unit cost.

Optimal utilization of wind energy demands a good knowledge base for the installation areas. For this, wind speed distribution plays a key role to have optimal utilization of wind energy. In this work, authors have investigated the BHU region for the feasibility analysis of wind energy potential to install renewable distributed generation units. Hourly data of wind speed of BHU area has been collected from the National Renewable Energy Laboratory (NREL) for the period of twelve months in between the year 2002 to 2011 (India Solar Resource Data: Hourly Data and TMYs). Authors proposed different probability density functions for statistical analysis and computed with R programming language. For the statistical analysis, authors applied Weibull, Gamma, and Lognormal distributions which vary between zero to infinity. With the help of goodness-of-fit test, authors identified the best-fitted probability density function for wind speed data of BHU area. Authors used Kolmogorov, Anderson-Darling, and Cramer-von Mises tests for the goodness-of-fit test.

In this work, our objective of this study is to statistically analyze the wind speed data of BHU area to predict the wind speed distribution and be able to estimate the wind energy potential. We will have to identify the best-fitted probability density function for the BHU campus.

### 5.2. Data Collection and organization

Estimation of wind energy potential for a particular location requires analysis of available wind speed data for long or small periods. Lalas (1985) stated that the drawing out of meteorological data based on average wind speed for a period, duration curves, direction, power spectra of wind speed and its variation with heights. Generally, for the assessment of wind speed at desired location 10 year period of measurement will be required (Nfaoui, 1998). As per Frandsen and Christensen (1992), with the comparison of long period wind speed data a short period, for example, one-year wind speed data may be suitable for wind energy potential estimation with 5-15% uncertainty. Use of the various types of instruments, types of equipment and site specifications for assessment of wind energy has been briefly explained in the work of Alawaji (1996). For getting wind speed data for a specific location, Meteorological towers with cup anemometers and wind vanes are the major factors for getting the information of wind energy potential at measurement height from the ground level.

Recently National Centres for Environmental Prediction (NCEP) or National Centre for Atmospheric Research (NCAR) and European Centre for Medium-Range Weather Forecasts (ECMWF) databases of wind speed have been developed globally for many regions (Landberg et al., 2003). With high-resolution Sonic Detection And Ranging (SODAR), Light Detection And Ranging (LIDAR) or satellite like ground-based remote sensing instruments have used as alternatives to meteorological towers for assessment of wind energy potential (Angelis-Dimakis et al., 2011). Choisnard et al. (2004) and Christiansen et al. (2006) presented a methodology for assessment of wind energy potential using a series of satellite synthetic aperture radar (SAR) images; this technique is particularly useful for regions where unavailability of year-long time series data, such as offshore regions. A method of "round robin site assessment" has been investigated by Lackner et al. (2008) for the use of alternative monitoring strategy in wind energy potential assessment. After collecting wind speed data from any given methods described above will further utilized for feasibility analysis. Figure-5.1, 5.2 and 5.3 show availability of wind energy potential at the different region for mast height. Figure-5.1 shows the regional distribution of wind energy potential at 50 meter height, where Figure-5.2 and Figure-5.3 shows wind energy potential in India for the different region at height 80 meter and 100 meter. This shows wind energy potential at BHU campus lies in the moderate region.

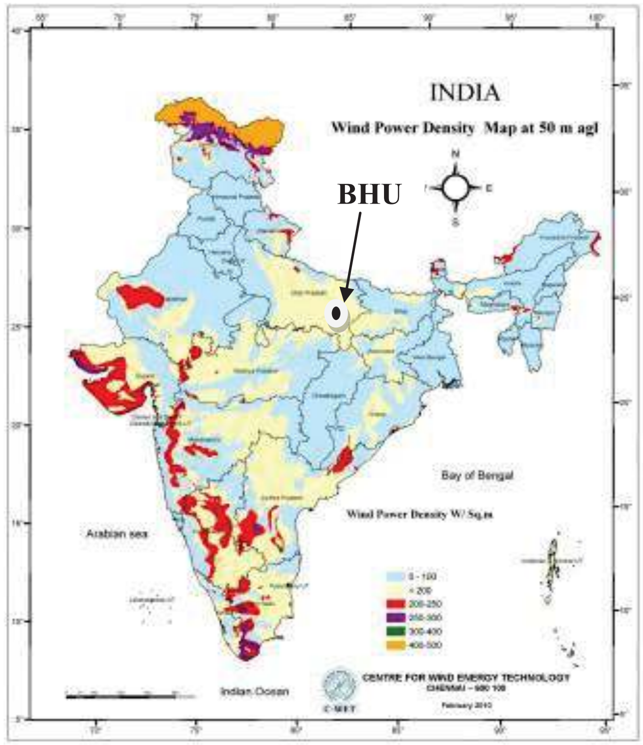


**Figure 5.1:** Indian wind power density map at 50meter height
(Source: India's Wind Power Potential)

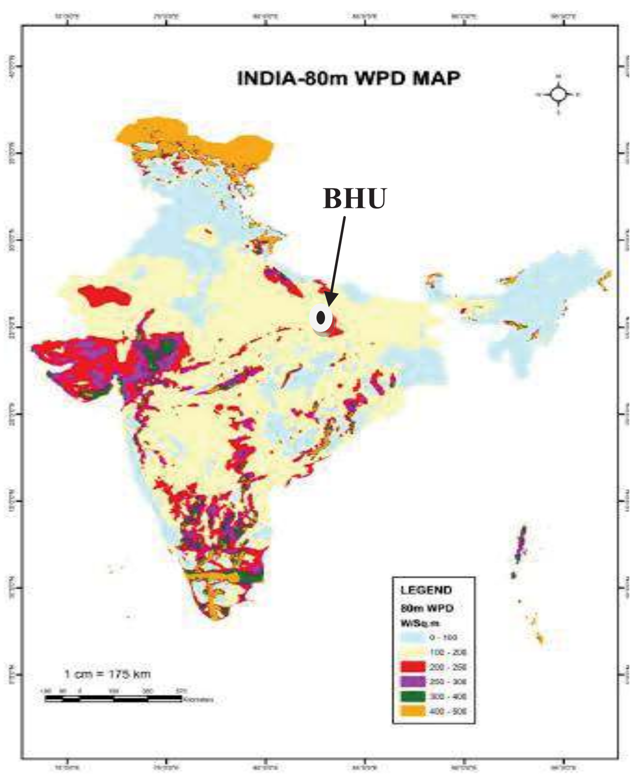


**Figure 5.2:** Indian wind power density map at 80meter height
(Source: India's Wind Power Potential)

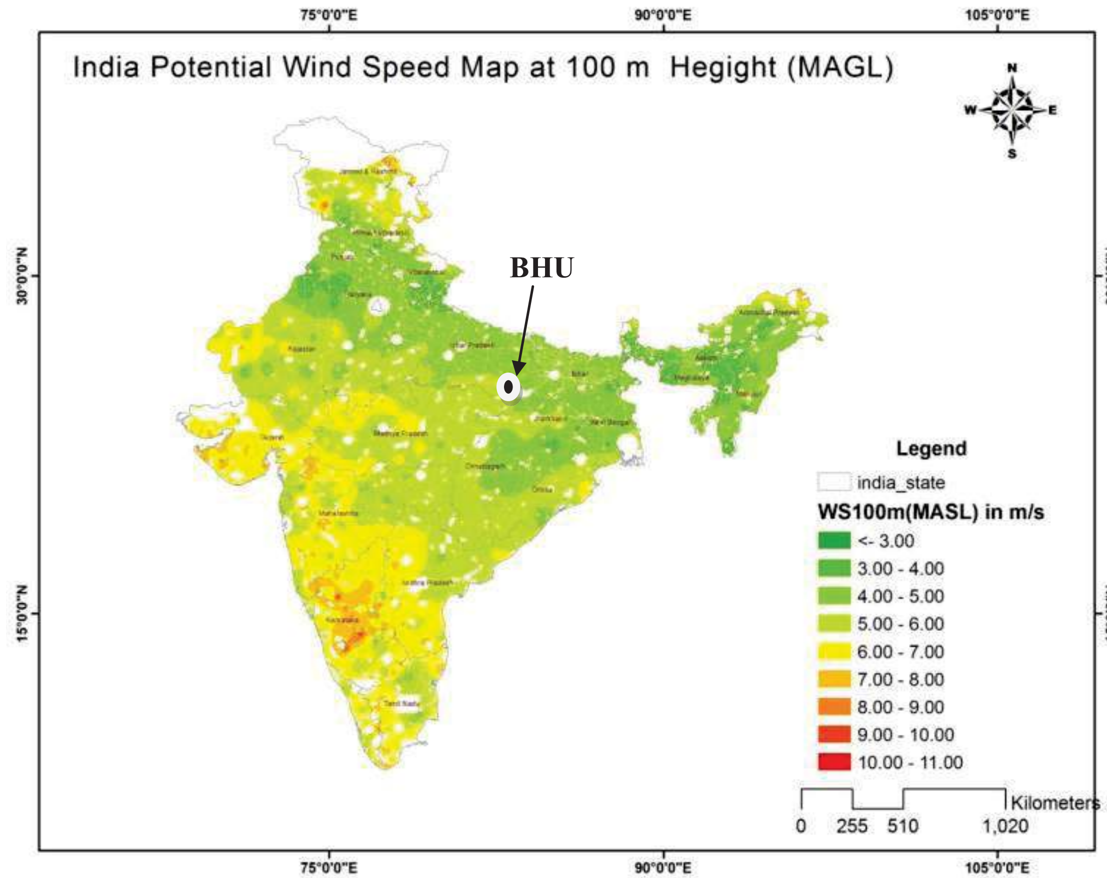


**Figure 5.3:** Indian wind speed potential map at 100meter height
(Source: Re-assessment of India's On-shore Wind Power Potential)

All the data has been taken in Local Standard Time (LST). India is ahead of Greenwich Mean Time (GMT) with 5.5 or five and a half (5:30) hours. All the data is given in the form of Cells with the particular latitude and longitude information. LST is selected based on the cells location with referenced coordinate information. Twelve-month hourly data files in between the period 2002-2011 are available for download in a compressed archive (tar.gz) files, and each archive file contains a list of comma separate values (CSV) files (India Solar Resource Data: Hourly Data and TMYs). Here file names show our location longitude and latitude of the wind speed cell centre which is determined to be the nearest coordinates entered into the Indian wind energy resource and that produce hourly computer generated imagery (CGI) data. Every cell covers an area on the surface of the Indian continent measuring $0.1^o$ of latitude by $0.1^o$ of longitude with the given cell coordinate which represents the cell's centre point. In this study, the cell of BHU area represents the area of $25.16^o$ N to $25.26^o$ N and $82.89^o$ E to $82.99^o$ E.

We considered at least one-year long measurement of data from an observation centre is required to determine the wind power potential and project feasibility. Wind speed data of the BHU region has been taken from the source centre by use of anemometers placed at the 2 meter height of the measurement mast from the ground level. Elevation of the BHU centre is 265 feet from the sea level, and it is located in the centre of the gangatic region. With ten minute intervals, data logger recorded measurement of the parameters at the observation centre in every second, their average values, minimum and maximum values with their standard deviation. For computing purpose, CALLaLOG 98 software program was used. Hourly data has been recorded in archive file by the CALLaLOG 98 software and stored in daily and monthly folders. Statistical analysis of wind speed data given by CALLaLOG 98 software has been done from the statistical analysis tool R programming language. Statistical R programming language is widely using by modern time researcher for the statistical analysis of data or pattern recognition. Missing data has been interpolated in this work, and this was only 0.06% in proportion, which was within the acceptable limit of 10% (Scientific, 1997). Twelve-month period of hourly data of meteorological parameters like air temperature, solar irradiation, barometric pressure and relative humidity apart from the wind speed data has been measured by the CALLaLOG 98 software and cup anemometer. The temperature variation at BHU area lies between the maximum and minimum monthly average temperature $44^oC$ in summer and $6^oC$ in winter respectively.

An important factor for the characterization of the wind resource is the variation of wind speed with height above the ground. In this respect, the wind speeds were measured by one anemometer located at 2 meter height on the mast. The sample of hourly distributed wind speeds measured between 1st January 2002, and 31st December 2011. For the conversion of wind speed data from the reference point to the desired level, we used power law. In Figure-5.4, we can see the monthly variation of average wind speed at BHU area, where maximum speed in month April and minimum in January month with 1.29 standard deviation.

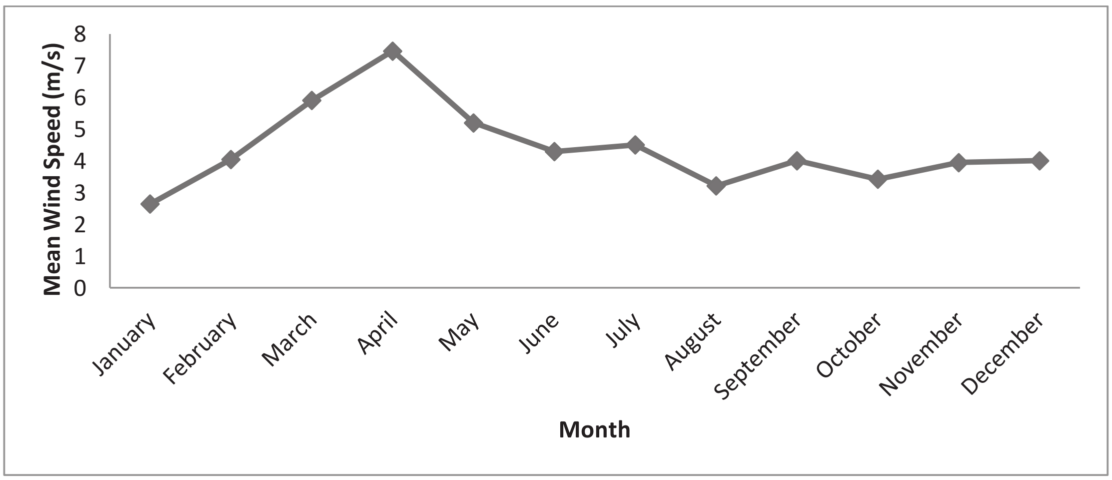


**Figure 5.4:** Monthly average wind speed values at BHU campus

The power law is used in wind power assessments for getting the wind speed values at wind turbine height from the surface level observation. Based on the design of different kind of wind turbines it range in between 50 and 100 meter heights, whereas observation of data may be over 2 meter or 10 meter height in normal cases (Manwell et al., 2010). For analysis purpose, we use a standard height to convert ground level data to the standard level, which is 100 meter in our case, because of normal height of maximum wind turbines and limitation of the logarithmic profile of wind speed within the surface layer of the atmospheric boundary layer.

We use generated wind profiles in the form of numerous atmospheric pollution dispersion models. Wind profile gives the variation or changes in horizontal wind speed with vertical distribution. The wind profile of the atmospheric boundary layer is logarithmic which is best represented by the log wind profile equation with consideration of surface roughness and atmospheric stability. In unavailability of surface roughness and atmospheric stability information, the wind profile power law equation is often used in a place of log wind profile. Representation of the wind profile power law is (Justus and Mikhail, 1976):

$$\frac{u}{u_r} = \left(\frac{h}{h_r}\right)^p \tag{5.1}$$

Here u is the wind speed (m/s) of the desired level of height h (meters), and $u_r$ (m/s) represents the available wind speed information of the reference level height $h_r$ (meters). An empirically derived coefficient p (unit-less) varies with the stability of the atmosphere. In neutral stability conditions, the value of p is approximately 1/7, or 0.143 (Hsu et al., 1994). In simplified form, estimation of the wind speed at the desired level of height $z$, the above power law relationship would be rearranged to:

$$u = u_r \left(\frac{h}{h_r}\right)^p \tag{5.2}$$

The difference between the reference level and desired level is less (<100 meter) for introducing substantial errors into the estimation of wind speed at the desired level, so 1/7 value of p becomes constant in wind resource assessments. The constant value of p does not account for the roughness of the surface, the stability of the atmosphere, or in the presence of obstacles the displacement of calm winds from the surface. In places like mountain or forest regions, where trees or structures impede wind speed near the surface level, the use of constant value 1/7 of p may yield an error in estimates; the log wind profile would be preferable. Even in neutral stability conditions, for offshore wind farms over open water, 0.11 would be more appropriate rather than 0.143 (1/7). In our case, we have the wind speed data at the height of 2meter and the requirement is at 100 meter and our location lies in a plane area with the neutral condition. So, from the power law with p-value 1/7, we have calculated the hourly wind speed data of BHU area at 100 meter height.

Measured wind speed data are commonly available in the time-series format, in which each data point represents either an instantaneous sample wind speed or an average wind speed over a given period. In some places, we can see wind speed data in frequency distribution format. This represents the frequency of wind speed distributed within various ranges (bins).

### 5.3. Wind Speed Distribution Models

#### 5.3.1. Statistical Analysis

Wind speed distribution modeling requires analysis of hourly distributed wind speed data for the analysis period. For minimizing the expenses and time to process long-term wind speed data, we can use statistical probability density functions for the prediction of randomly distributed wind speed data. The primary tools to describe wind speed characteristics are probability density functions. The parameters of probability density functions which describe wind speed frequency distribution are estimated using statistical data of analysis period. Many probability distribution functions have been proposed in recent past, but in the present study for the statistical analysis Weibull, Gamma, and Lognormal distributions are used to identify the appropriate probability distribution. For this, authors used R programming language to analyze the distribution of wind speed data and goodness-of-fit tests results. Parameters of each distribution have been calculated from the same computational tool. Representations of the mathematical formulation of Weibull, Gamma, and Lognormal distributions are:

#### 5.3.1.1. Weibull distribution

Mathematical representation of the probability density function of two parameters Weibull distribution with c being the scale parameter and k the shape parameter is

$$f(x;c,k) = (\frac{k}{c})(\frac{x}{c})^{k-1} exp\left[-(\frac{x}{c})^k\right] \quad (5.3)$$

Weibull CDF is written as

$$F(x;c,k) = 1 - e^{-(\frac{x}{c})^k} \quad (5.4)$$

where mean and variance of the distribution with Γ (Gamma function) are

$$E[X] = c\Gamma(1 + \frac{1}{k}) \quad (5.5)$$

$$Var[X] = c^2 \left[\Gamma\left(1 + \frac{2}{k}\right) - \left(\Gamma\left(1 + \frac{1}{k}\right)\right)^2\right] \quad (5.6)$$

#### 5.3.1.2. Gamma distribution

Probability density function of Gamma distribution with α (shape) and β (rate) parameters is

$$f(x;\ \alpha,\beta) = \frac{\beta^\alpha x^{\alpha-1} e^{-x\beta}}{\Gamma(\alpha)} \quad (5.7)$$

Gamma CDF is written as

$$F(x;\ \alpha,\beta) = \frac{\gamma(\alpha,\beta x)}{\Gamma(\alpha)} \quad (5.8)$$

where mean and variance of the distribution is

$$E[X] = \frac{\alpha}{\beta} \quad (5.9)$$

$$Var[X] = \frac{\alpha}{\beta^2} \quad (5.10)$$

### 5.3.1.3. Lognormal distribution

The lognormal distribution is a probability distribution of a random variable whose logarithm is normally distributed. Lognormal probability distribution function with μ as location and σ as scale parameters is given by

$$\ln(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right] \tag{5.11}$$

Lognormal CDF is written as

$$LN(x;\mu,\sigma) = \frac{1}{2}\left[1 + \text{erf}\,(\frac{\ln x-\mu}{\sigma\sqrt{2}})\right] \tag{5.12}$$

where mean and variance of the distribution is

$$E[X] = e^{\mu+\frac{1}{2}\sigma^2} \tag{5.13}$$

$$Var[X] = (e^{\sigma^2} - 1)e^{2\mu+\sigma^2} \tag{5.14}$$

### 5.3.2. Goodness-of-fit tests

Goodness-of-fit tests allow us to identify the suitable distribution function among the different alternatives. In reality, there is no any perfectly matched distribution. Probability density function is the most used tools to estimate and model the wind speed distribution. Many authors proved Weibull distribution as a best-fitted probability density function for the wind speed distribution in their work. Based on the suitability of data, authors proposed Weibull, Gamma and Lognormal distributions for the study to identify best-fitted distribution in this case. It would be wrong to choose from the list of previous results of specific areas in a different environment. Because the variation of wind speed depends on their regional factors and it may vary region to region and may not fit with respective referenced regional distribution. For error minimization, we should have to analyze the data and get best-fitted probability distribution. In this work author selected continuous distribution functions lies between zero and infinity and have been investigated with the aid of three goodness-of-fit tests namely; Kolmogorov-

Smirnov, Anderson-Darling and Cramer-von Mises tests. Brief information on selected goodness-of-fit tests is given below:

#### 5.3.2.1. Kolmogorov - Smirnov test

The Kolmogorov-Smirnov test is useful when parameters of the distribution did not estimate. With modified Kolmogorov-Smirnov test we can use this where the parameters are estimated from the data. The Kolmogorov-Smirnov test is mainly based on empirical cumulative distribution function. For the given *n* ordered data points $X_1$, $X_2$,…, $X_n$, the empirical cumulative distribution function is defined as (Daniel, 1990)

$$E_n = n(i)/N \tag{5.15}$$

Where n(i) represents the number of points less than $X_i$ and $X_i$ are ordered between smallest and largest value. This increases by 1/N for each value of ordered data between smallest to largest.

The advantage of this test is that the distribution of Kolmogorov-Smirnov test statistic will not need cumulative function distribution test. Compared to Cramer-von Mises test, it is an exact test. It only applies to continuous distributions. The test is calculated as

$$D = \max_{1 \le i \le N} \left\| F(X_i) - \frac{i}{N} \right\| \tag{5.16}$$

Where $F$ is the theoretical cumulative distribution for what we are conducting this test which must be a continuous distribution.

#### 5.3.2.2. Anderson- Darling test

Anderson-Darling tests the data whether this lies in the given probability distribution. The test is most often used to test of a given family of distribution, in which case parameters of that family needs to be estimated. Anderson-Darling is a modification of the Kolmogorov-Smirnov test and gives more weight to the tails where as Kolmogorov-Smirnov test gives more to the centre of the distribution. This has the advantage of allowing a more sensitive test. The Anderson - Darling test statistic is defined by (Anderson and Darling, 1952)

$$A^2 = -n-S \tag{5.17}$$

where

$$S = \sum_{i=1}^{n} \frac{2i-1}{n} [\ln F(X_i) + \ln(1 - F(X_{n+1-i}))] \tag{5.18}$$

And $F$ represents the theoretical cumulative distribution function of the given family of distribution. Note that the $X_i$ is the ordered data.

### 5.3.2.3. Cramer-von Mises test

The Cramer-von Mises test is used to test the fitness of distribution of a given family of distribution. In statistics the Cramér–von Misestest is used for testing the goodness-of-fit for a cumulative distribution function $F$ compared to an empirical distribution function$F_n$ for the given data, or comparing of two empirical distributions. It is also used in part of another algorithm as minimum distance estimation. This is represented as (Anderson, 1962)

$$w^2 = \int_{-\infty}^{\infty} \{F_n(x) - F(x)\}^2 dF(x) \tag{5.19}$$

In this study, here $F$ is the theoretical cumulative distribution function for the wind speed data of BHU region, and $F_n$ is the empirically observed distribution. Two distributions can be empirically estimated ones in a two-sample case. This Cramér–von Mises test is an alternative to the Kolmogorov–Smirnov test.

Let $x_1$, $x_2$,....,$x_n$ are the observed values, in ascending order. The numerical values of test statistic is found as

$$T = nw^2 = \frac{1}{12n} + \sum_{i=1}^{n} \left[\frac{2i-1}{2n} - F(x_i)\right]^2 \tag{5.20}$$

In equation (5.19) $w^2$ is derived as the difference between empirical distribution function and cumulative distribution for one sample application. Integration of equation (5.19) and multiply with n will give T as total differences for n observed values.

### 5.4. Results and discussions

Figure-5.5 shows a histogram of wind speed data in ninety-four class intervals. The histogram has been drawn from the use of R programming language computation. Hines et al. (2008) state that choosing the number of class intervals approximately equal to the square root of the sample size often works well in practice. Authors used this theory to find out the class intervals to draw the Histogram for wind speed data. If you have very few intervals for the larger data, then this will give you the blocky or coarse figure, or if you have very large intervals compared to not much larger data, then this will show you ragged figure. For the selection of best fit, we should choose appropriate class intervals for the given sample size. In this case, authors have total sample size equal to eight thousand seven hundred and sixty-two which gives the value of ninety-four with approximation after the square root of sample size. Figure-5.6 is showing graphical representations of Weibull, Gamma and Lognormal distributions of the given data with the help of Histogram and theoretical density plots. Authors have drawn the Histogram and density curves in ninety-four class intervals for the given three distributions. From the Figure-5.6 given below, we can see Weibull is the best-fitted curve among the other proposed distributions. It is very easy to see that the other two, i.e., Gamma and Lognormal distributions are not showing a best-fitted curve for the given data. Figure shows, if we will have the wrong selection, there will be more risk. Wrong selections will lead more chances of error to occur. If we rank them from the Figure-5.6 given below, then there will be Weibull leads to Gamma followed by Lognormal distribution.

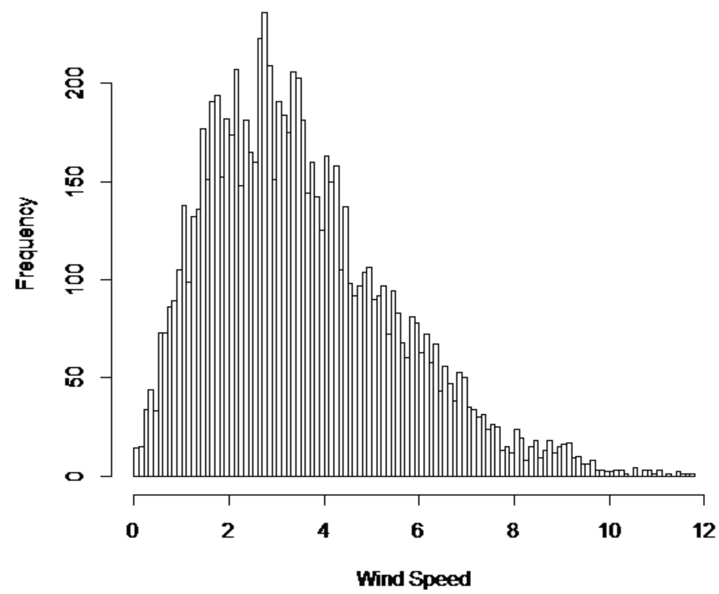


**Figure 5.5:** Histogram of hourly wind speed data

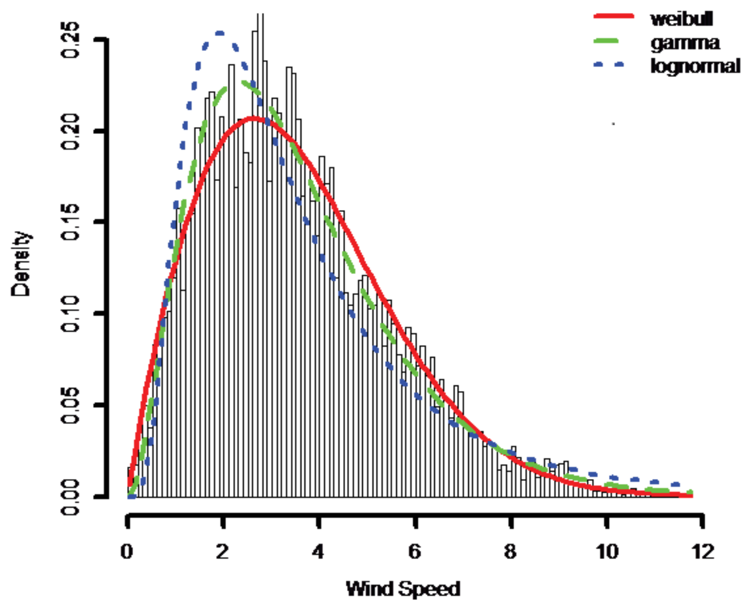


**Figure 5.6:** Density plots of theoretical distributions with wind speed data

The result showing in Figure-5.7 is the graphical representation of empirical and theoretical cumulative distribution functions (CDFs). Variation of theoretical cumulative distribution functions of these three proposed distributions with empirical distribution function is showing fitness of probability distribution of given data. From this, we can identify Weibull distribution is more fitted with empirical distribution function. Based on this, we can say Weibull distribution is best-fitted one in a case of BHU area.

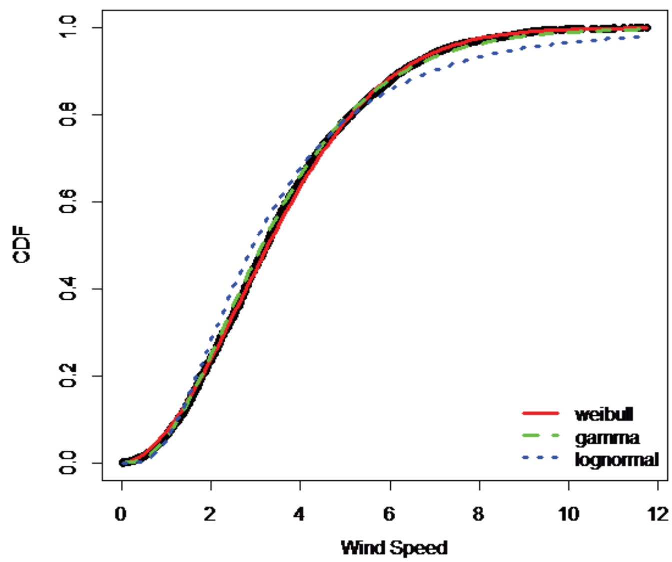


**Figure 5.7:** Empirical and theoretical CDFs

Figure-5.8 shows P-P (probability-probability) plot of the given data. In a P–P plot, this assesses how closely two data sets agree for the two cumulative distribution functions against each other. Here in Figure-5.8, Weibull distribution is showing a close relation with the given dataset for the cumulative distribution function compared to other two Gamma and Lognormal distributions. With the help of P-P plots, we can evaluate the skewness of the distribution. Figure-5.9 is showing the Q-Q (quantile-quantile) plot. In a Q–Q plot, this also assess how closely two data sets agree for the two cumulative distribution functions against each other with their quantile plots. Q–Q plot also helps to compare the shapes of distributions with the graphical presentation to view how properties like location, scale, and skewness are similar or different in the two distributions. Q–Q plots compared to collected data and theoretical distributions. Q-Q provides an assessment of "goodness of fit" graphically, rather than having a numerical summary. With the interpretation of Figure-5.9, we can find the best-fitted Weibull distribution in this study compared to other two Gamma and Lognormal distributions.

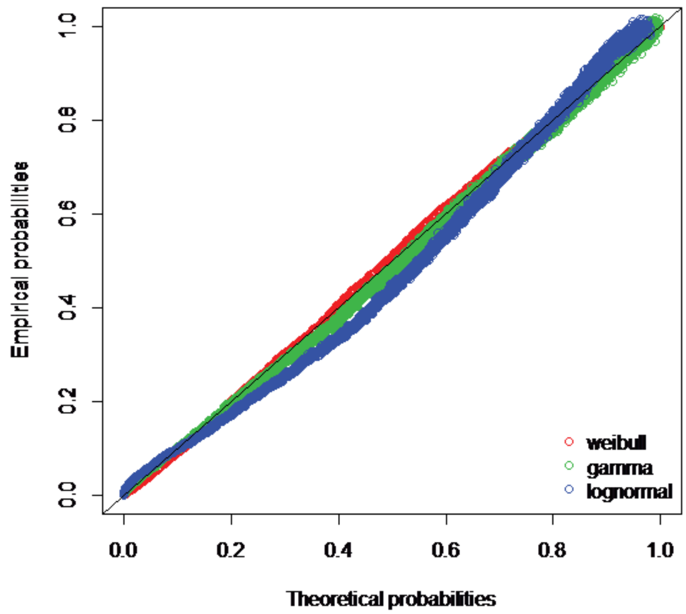


**Figure 5.8:** P-P Plot

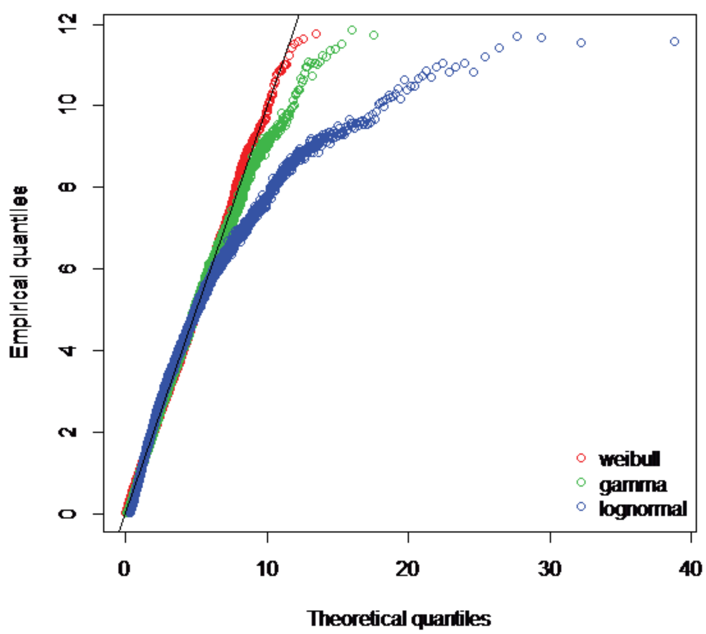


**Figure 5.9:** Q-Q Plot

Table-5.1 is showing the results of parameters for the proposed distributions. Mean and standard deviation of one-year period hourly wind speed data of BHU campus is 3.53 and 1.87 respectively. These parameters have been calculated by the maximum likelihood methods because of its more accurate values.

**Table 5.1:** Parameter results for the proposed distributions

| Weibull | | Gamma | | Lognormal | |
|---|---|---|---|---|---|
| Shape | scale | Shape | Rate | mean log | Slog |
| 1.874745 | 3.979186 | 2.8788796 | 0.8156843 | 1.0774736 | 0.6688455 |

With goodness-of-fit test results in Table-5.2, authors have ranked these three distributions as per the individual test results of Kolmogorov-Smirnov, Anderson-Darling and Cramer-von Mises test. In Table-5.2, we can see all these three tests are showing Weibull distribution is best one with less error value and ranked them in the order of Weibull, Gamma, and Lognormal distribution. From this, we can say that the Weibull distribution is the better one amongst the proposed three distributions.

**Table 5.2:**Goodness-of-fit test results

| Distribution function | Kolmogorov-Smirnov | Anderson-Darling | Cramer-von Mises |
|---|---|---|---|
| Weibull | 0.02106212 | 3.87999752 | 0.65250478 |
| Gamma | 0.02778126 | 7.76586366 | 1.22543889 |
| Lognormal | 0.06997673 | 78.86732540 | 12.59881876 |

## 5.5. Theoretical power density

Estimation of the wind power depends on wind turbine blade rotational cross-section area, wind speed and wind flow kinetic energy. It can also be represented by multiplication of kinetic energy with total swept volume of the wind per unit time (Ackermann, 2005; Ramirez and Carta, 2005)

$$P(v) = (0.5\rho v^2)vA = 0.5\rho v^3 A \text{ [W]} \quad (5.21)$$

where ρ is the air density (kg $m^{-3}$).

Variation of air density depends on upon pressure, temperature, and humidity. For the first attempt of resource calculation variation of air, density is not greatly significant. With this assumption on a constant pressure surface, the error is probably less than 5% (Hennessey Jr, 1977). In standard conditions at sea level with 15°C temperature, a typical value of air density is $\bar{\rho} = 1.225\ kgm^{-3}$.

Statistical analysis of wind power potential with mean air density $\bar{\rho}$ is proportional to the cube of the random variable wind speed values. We can calculate the distribution of wind power with random wind speed values by multiplying the wind power density of each wind speed with the probability of each wind speed. So, this can be written in mathematical term

$$P(v) = 0.5\bar{\rho}v^3 f(v;\alpha,\beta)[\text{Wm}^{-3}\text{s}] \quad (5.22)$$

With this, we can calculate the annual mean wind power potential from the wind resources available at a potential site. This can be determined through

$$\bar{P} = 0.5\bar{\rho}\int_0^\infty v^3 f(v;\alpha,\beta)dv = 0.5\bar{\rho}\mu_3' \text{ [Wm}^{-2}\text{]} \quad (5.23)$$

where$\mu^/$ represents the mean of the cube of the wind speed ($m^3s^{-3}$ )

$$\mu^/ = \beta^3\Gamma\left(1+\frac{3}{\alpha}\right) \quad (5.24)$$

An annual power production from the wind turbines is a maximum wind power density for the aerodynamically efficient design at $v = v_{me}$

$$v_{me} = \beta\left(1 + \frac{2}{\alpha}\right)^{\frac{1}{\alpha}} [\mathrm{ms^{-1}}] \tag{5.25}$$

**5.6. Wind energy potential**

Potential of wind energy can be estimated with randomly distributed wind speed by multiplication of power output from the hourly wind speed dataset and their probability distribution (Kwon, 2010),

$$\frac{E_{actual}}{A} = \frac{T}{A}\int_0^\infty P(v)f(v)dv \tag{5.26}$$

Where T denotes hours, and $A$ equals to the total area swept by wind turbine blades. In wind energy estimation we neglect the value of air density because it does not affect the wind speed values. In unavailability of wind speed situation, we can exclude that period and can identify total number of hours for availability of wind speed in a year,

$$T = 365 \times 24 \times \{1 - f(v = 0)\} \tag{5.27}$$

Here $f_v(v = 0)$ means the probability of hours for unavailability of wind speed. We can calculate annual wind energy potential for the T hours without having any probability distribution from this equation,

$$E = \sum_{i=1}^{T} P(v_i)\,\bar{\rho} \tag{5.28}$$

Here Figure-5.10 is showing mean monthly wind power density distribution for BHU area. We can see maximum potential of wind power for the April month and minimum in January month with the 67.09 standard deviation. This will help in optimal capacity installation of renewable distributed generation unit at BHU campus and have better demand – supply management.

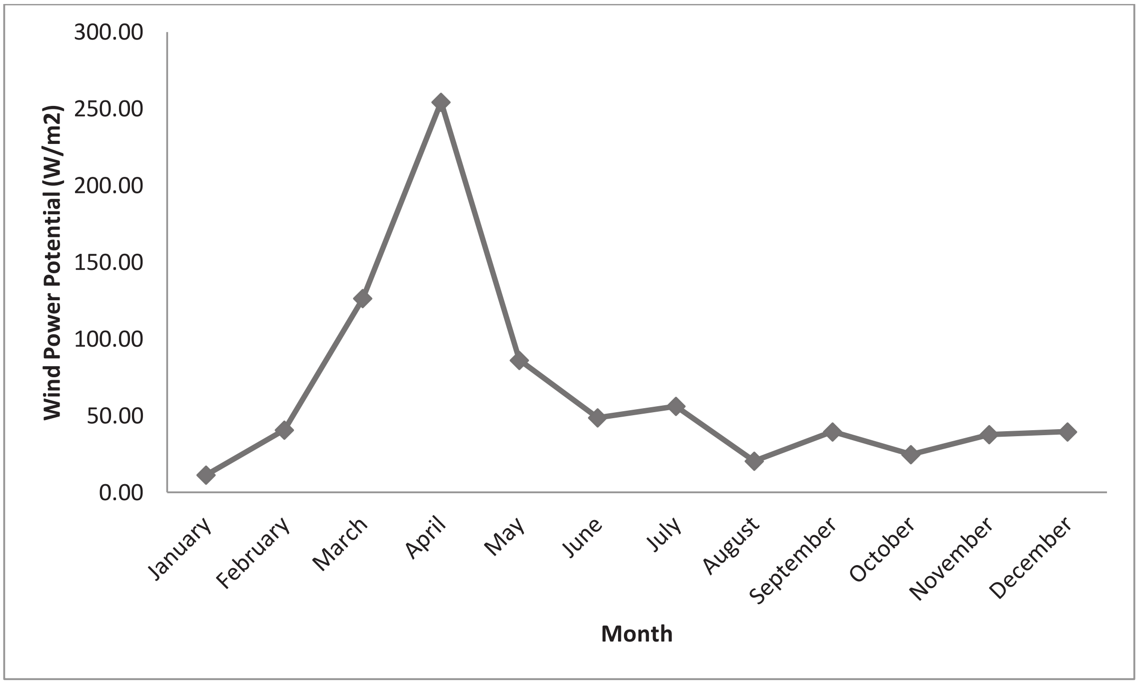


**Figure 5.10:** Monthly average wind power potential at BHU campus

## 5.7. Conclusion

A decision on making an investment in the renewable distributed generation technology planned to be built at BHU region will be made with the help of wind speed data measured from the region. Therefore, distribution of the wind speed at BHU region is statistically analyzed for twelve months in between 2002-11 on an hourly basis. Because of randomness of the wind speed values, it is expected to fit a probability density function which will give better fitness. For that, three probability density functions have been proposed in this analysis which is Weibull, Gamma and Lognormal distributions. Significance level alone cannot help to decide for selection of any distribution without going for any statistical goodness-of-fit test and graphical analysis. For making scientific decisions, the reliability of the decision is very important factor in estimation and investment projects to be made with the help of this decision. Since decisions made with the help of statistical analysis are in certain confidence level, in this case, there was 95% confidence level. In this study, authors used three goodness-of-fit tests named Kolmogorov-Smirnov, Anderson-Darling and Cramer-von Mises along with the graphical analysis to identify the fittest distribution. At the end of the comparison, Weibull has been determined to be the best-fitted distribution representing given wind speed data of the BHU region. Best fitted distribution will reduce chances of error and risk in making an investment decision for setup of renewable distributed generation units.