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ORIGINAL RESEARCH

Estimation of wind energy potential and comparison of six Weibull parameters estimation methods for two potential locations in Nepal

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Abstract
This study analyzes the wind speed characteristics, compares the six different methods (graphical, method of moment, wind energy pattern factor, empirical method of Justus and Lysen, and maximum likelihood method) of estimating Weibull parameters and calculates wind power density using daily mean wind speed data collected, at a height of 2 m, over a period of seven and eight years for Jumla and Okhaldhunga, respectively. Wind data were estimated at a height of 50 m to calculate average wind speed, Weibull parameters, and wind power density. Based on the results, Jumla has an average monthly maximum wind speed of 9.78 m/s in June and minimum wind speed of 6.71 m/s in December, whereas Okhaldhunga has an average monthly maximum wind speed of 10.95 m/s in April and minimum wind speed of 4.52 m/s in October. Jumla has an average annual wind speed of 8.11 m/s while Okhaldhunga has an average annual wind speed of 6.89 m/s. The accuracy of estimation methods was statistically tested using root mean square error and coefficient of determination. The empirical method of Justus and Lysen was found to be the best performing while the graphical method performed the poorest. By using the best method, an average wind power density has been estimated as 336.07 W/m^2 and 326.73 W/m^2 for Jumla and Okhaldhunga, respectively, indicating that both locations belong to wind power class III and have a moderate potential for wind energy harvesting.

Keywords Wind energy · Wind speed · Weibull distribution · Nepal

Introduction

Fossil fuels like, petroleum products, coal, and natural gas make a significant portion of non-renewable energy sources and account for 84.3 % of worldwide energy usage [1]. When these are burned, large amount of greenhouse gases are released into the atmosphere causing serious health and environmental consequences. Hence, alternative sources of energy such as solar, wind, hydropower, geothermal, tidal, and biomass energy have become imperative now more than ever. The world energy scenario today has seen a growing investment in renewable energy sector, ranging from small household-based projects to large utility-scale power plants. As a result, the contribution of renewable energy in global electricity generation grew from 27% in 2019 to 29% in 2020 and is projected to supply more than half of the increase in global electricity supply in 2021 with solar and wind energy predicted to account for two-thirds of the growth [2]. The total installed wind energy capacity saw a major growth from 622 GW in 2019 to 733 GW in 2020 [3]. In fact, year 2020 saw the largest year-over-year growth of 53% [4], and the generation is further projected to grow by 17% in 2021 [2].

The potential of harnessing a wind energy in any location depends on the site specific Wind Power Density (WPD). Furthermore, the system design requirement entails an understanding of the averaged wind speed and its distribution characteristics throughout a year. To date, several techniques have been established to model the wind speed distribution for better understanding the local wind characteristics and estimating the wind power density as accurately as possible. In the literature, Weibull and Rayleigh's distributions are two of the most commonly utilized probability distribution functions [5–8].

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Fyrippis et al. [6] applied both Weibull and Rayleigh distributions to study the wind energy potential of the Greeek island of Naxos. They found an average wind power density of 420 W/m^2 and a yearly average wind speed of 7.4 m/s. Statistical tests to assess the performance of the distributions showed the Weibull distribution to be a better fit to the actual data. Similar research was conducted by Ucar and Balo [9] in two locations of Turkey; Ankara, and Polati, using Weibull and Rayleigh distribution to understand the wind characteristics and its potential. Hourly wind speed data collected from the year 2000 to 2006 was used to determine the fluctuation in wind power density over the course of a year. The maximum wind power density value was estimated to be 42.40 W/m^2 in Ankara during the winter season, and 41 W/m^2 in Polati during the summer season. Another study [10] in Bishkek, Kyrgyzstan, modeled the average daily wind speed data spanning over three years, with Weibull and Rayleigh distributions to estimate maximum wind power density, whose value was found to be 4.04 W/m^2. This low value demonstrates the region's poor wind power potential. To determine the wind power density, Soulouknga et al. [11] used data on wind speed obtained for eighteen years and modeled it adopting the Weibull distribution to obtain the annual power density of 343.31 W/m^2. Numerous studies have reported the superior performance of Weibull distribution compared to Rayleigh distribution [6, 7, 12].

The majority of the authors have preferred Weibull distributions, and various techniques are described in the literature for the estimation of Weibull parameters in different areas across the world. Chang [13] in his quest to identify the best estimation method compared six methods of estimation: method of moment, graphical method, energy pattern factor, method empirical method, maximum likelihood method, and modified maximum likelihood method for three different stations in Taiwan. A Monte-Carlo simulation was then performed so that the performance of each method could be assessed with respect to real wind speed data, by using different statistical tests. Results revealed the superior performance when using maximum likelihood method. Rocha et al. [14] compared seven different approaches to calculate the Weibull parameters in the Brazilian coastline region. The evaluation of the accuracy of the procedures was done with chi-square and RMSE (Root Mean Square Error) as statistical tools. The Equivalent Energy Method (EEM) matched the real wind distribution with best fit, while the Wind Energy Pattern Factor (WEPF) and graphical method were the worst fit. In Halabja, Iraq, Ahmed [15] performed statistical analysis on four years of monthly time series wind data to measure the accuracy of four different estimation methods, namely power density method, rank regression methods, mean-standard deviation method, and maximum likelihood method. The actual wind data were best fitted by the power density method. Werapun et al. [16] examined the efficiency of five different methods of estimation for Phagan island in Thailand. The energy pattern factor matched excellently with the data whereas the graphical method approach provided the worst fit. In recent research, Weibull parameters were evaluated using a variety of methods by Shaban et al. [17] and Ben et al. [18] in Nigeria and AL-Najaf, respectively. In their study, Shaban et al. [17] applied six evaluation methods to estimate the Weibull parameters and discovered that the EEM outperformed the rest of the methods. Ben et al. [18] analyzed wind speed data for a period of ten years at thirteen different cities in Nigeria using six estimation methods. Interpretation of the results on the basis of goodness of fit tests revealed the maximum likelihood technique to be the best performing while the graphical method produced the worst fit.

Wind energy is set to become one of the major generation sources and is projected to generate about 35 % of the total electricity demand by 2050 [19]. The boost in wind energy supply is also assisted by the decreasing cost of wind energy production. The Levelized Cost of Electricity (LCOE) for offshore wind power generation decreased from USD 0.162/kWh in 2010 to USD 0.084/kWh in 2020 [20], and this decreasing trend will help to drive the world toward fulfilling the net zero emissions target by 2050 set by international communities after Paris Agreement. However, the massive establishment of wind power plants is limited by the unavailability of time series wind maps or wind data mostly in the developing countries. As for Nepal, there are very few studies on estimating the wind power potential resulting few micro wind projects for distributed community electrification in the country. As steep topography and rough terrain pose a challenge for mainline electrification of numerous isolated rural areas in higher elevations, independent energy projects capable of sustaining an entire locality are getting more and more accentuated. In line with this, the Government of Nepal, assisted by ADB (Asian Development Bank), established a 20 kW combined wind-solar power system to electrify a village in the Sindhuli district [21]. Existing researches conducted by Dhakal et al. [22] and Parajuli [5], have focused on estimating the wind energy potential of a single location but they have not done detail performance analysis using Weibull parameter estimation methods.

The present study carries out a comparative analysis of six different approaches to estimate the Weibull parameters at two selected locations (Jumla and Okhaldhunga) in Nepal based on daily mean wind speed data collected and recorded over a period of seven and eight years, respectively. Along with that, a wind resource evaluation is also conducted by using the best-performing method to estimate the Wind Power Density (WPD) for both locations. The output of the study is expected to help during choosing the best methods under the availability of primary wind data at low height (2 m) for establishing the wind energy potential in Nepal and other part of the world with similar geographical and climatic conditions.

Methodology

Description of the study site

Both the sites, Jumla and Okhaldhunga, situated in the mid-hills of Nepal, ranging from an altitude of 610 m to 4800 m, are characterized by elevated flatlands and hills. The hilly region mainly consists of rough terrain with steep hills and lowland valleys. Measuring stations in Jumla and Okhaldhunga are located at an elevation of 2300 m in Western part and 1720 m in Eastern part of Nepal, respectively. Okhaldhunga experiences strong wind in the months from March to May whereas Jumla experiences more stable wind conditions throughout the year.

Figure 1 shows the study site marked with dots within the elevation map of the districts inside the map of Nepal. It is to note that both the measuring stations are of synoptic type. The density of air is calculated using the equation [11]:

$$\rho = \rho_o - 1.194 \times 10^{-4} H_m \tag{1}$$

where H_m denotes the elevation of sites in meters. Table 1 shows latitude and longitude along with the density of air calculated at the locations.

Table 1 Location details

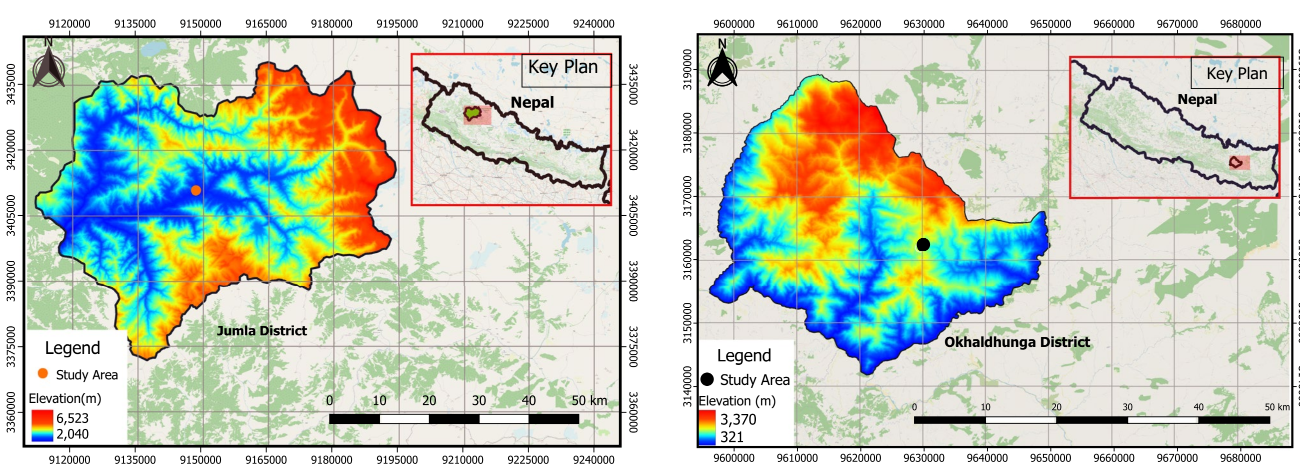
S.N	Location	Latitude	Longitude	Air density (kg/m^3)
1	Jumla	29°17′	82°10′	0.944
2	Okhaldhunga	27°19′	86°30′	1.0136

Wind speed data collection

Daily mean wind speed data, measured and recorded through the synoptic stations located 2 m above the ground surface, were obtained from the Department of Hydrology and Meteorology under the Ministry of Energy, Water Resources and Irrigation, Government of Nepal. For Jumla, the study data span a seven-year cycle (2011–2018) excluding the year 2012 due to non-availability of data whereas, for Okhaldhunga, the wind speed during an eight-year period (2011–2018) was analyzed. A total of 72 (Jumla) and 67 (Okhaldhunga) wind speed data were missing for the locations, giving the data recovery rate of 97.70% and 97.18%, respectively. Since majority of wind turbines can't be installed at the height of 2 m, the wind speed is extrapolated to a height of 50 m to assess the wind potential at the turbine's hub height. This extrapolation from a lower height of 2 m was carried out using the power rule as followed by Rahman and Chattopadhyay [23] and Ben et al. [18] which is expressed as:

$$\frac{V_2}{V_1} = \left(\frac{H_2}{H_1}\right)^{\alpha}. \tag{2}$$

Here, V_1 denotes the velocity of wind measured by a measuring station at height H_1. V_2 is the speed to be calculated at the hub height, H_2. The coefficient α is friction coefficient or Hellman exponent determined by the topography of a location and varies numerically from 0.1 to 0.4. "The value 0.1 is for lakes, oceans, and smooth hard ground to 0.40 for



(a) Jumla (b) Okhaldhunga

Fig. 1 Map of individual districts showing the study site a city with tall buildings" [24]. Since both the stations are surrounded by structures resembling shrubs and hedges, the value of α was taken as 0.2 for both of them.

Weibull distribution and parameter estimation methods

Various methods are used to model the actual wind speed data in terms of probability distribution or speed frequency distribution. These give insights into the probability of a certain wind speed occurring or the most frequent wind speed. Additionally, determining the wind power output requires a thorough understanding of the speed frequency distribution. Weibull distribution, which requires two parameters i.e., k, a non-dimensional shape factor, and c, a scale factor, is a regularly used mathematical technique to define the wind frequency distribution. Higher values of k show a sharper peak or narrow frequency distribution and indicate less variation in the speed of wind.

The probability density function i.e., the probability that the speed will fall in a bin for a Weibull distribution is given by Eq. (3) and can be written as [6, 9]:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{(k-1)} e^{-\left(\frac{v}{c}\right)^{k}} \tag{3}$$

where v denotes the wind speed. Equation (3) can be integrated to determine the cumulative function, $F(v)$ of the velocity which measures the likelihood of wind speed occurring in a certain wind speed range and is given by following expression [6, 9]:

$$F(v) = P(v < v_x) = \int_0^{v_x} f(v)dv = 1 - e^{-\left(\frac{v_x}{c}\right)^{k}}. \tag{4}$$

Parameter estimation methods

Various approaches to estimating the Weibull parameters, k and c, have been presented in the literature. Among the widely used methods, this study assess the performance of six methods, which are briefly described below.

1. Graphical Method The Graphical method uses measured data to generate a cumulative distribution function that is plotted as a nearly straight line in the form of Eq. (5). After some computation, k and c can be calculated. Equation (5) is obtained by taking natural log twice on Eq. (4) and then rearranging as [13] :

$$\ln\left[-\ln\left[1 - F(v)\right]\right] = k\ln(v) - k\ln(c) \tag{5}$$

   where $\ln(v)$ and $\ln\left[-\ln\left[1 - F(v)\right]\right]$ are plotted along the x-axis and y-axis, respectively. The resulting graph is a straight line having slope k and intercept $-kln(c)$.

2. Method of Moment (MOM) The Method of Moment has been proposed as a substitute to the maximum likelihood method.The parameters k and c can be determined using the equations [14]:

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{6}$$

$$\sigma = c\left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)\right]^{\frac{1}{2}} \tag{7}$$

   where $\overline{v}$ is the average wind speed calculated as:

$$\overline{v} = \frac{1}{n}\sum_{i}^{n} v_i \tag{8}$$

   and σ is the standard deviation of wind speed for a certain time duration given by:

$$\sigma = \left[\frac{1}{n-1}\sum_{i=1}^{n}(v_i - \overline{v})^2\right]^{\frac{1}{2}}. \tag{9}$$

   From Eqs. (6) and (7), the shape parameter can be determined by [25]:

$$k = \left(\frac{0.9874}{\frac{\sigma}{\overline{v}}}\right)^{1.0983} \tag{10}$$

   and $\Gamma(x)$ is the gamma function written as:

$$\Gamma(x) = \int_0^{\infty} \exp(-t)t^{x-1}dt. \tag{11}$$

3. Empirical Method of Justus (EMJ) Justus et al. [26] established the empirical method of Justus, where the shape parameter (k) and scale parameter (c) are calculated as:

$$k = \left(\frac{\sigma}{\overline{v}}\right)^{-1.086} \tag{12}$$

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)}. \tag{13}$$

4. Empirical Method of Lysen (EML) The empirical method of Lysen calculates the shape parameter (k) by using Eq. (12) same as the Justus method. The scale parameter (c) is evaluated by the following expression [27]:

$$c = v_m\left(0.568 + \frac{0.433}{k}\right)^{-\frac{1}{k}}. \tag{14}$$

5. Wind Energy Pattern Factor (WEPF) Method The energy pattern factor, E_{pf}, is used in this method to estimate the scale and shape parameters. This method is simple and requires less computation. E_{pf} for a specific duration is calculated as a ratio of the cube of the mean wind speed to the mean of cubic wind speed and determined by the Eq. (15) [28] :

$$E_{pf} = \frac{\frac{1}{n}\sum_{i=1}^{n} v_i^3}{\left(\frac{1}{n}\sum_{i=1}^{n} v_i\right)^3} = \frac{\overline{v^3}}{(\overline{v})^3}. \tag{15}$$

The Weibull shape factor (k) and scale factor (c) may be computed after calculating the energy pattern factor, using the expressions below [28]:

$$k = 1 + \frac{3.69}{E_{pf}^2} \tag{16}$$

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)}. \tag{17}$$

6. Maximum Likelihood Method (MLM) This method is a frequently used technique to estimate the Weibull parameters. The likelihood function of Weibull probability density function in Eq. (3) can be written as [17]:

$$L(v_i, k, c) = \prod_{i=1}^{n}\left[\left(\frac{k}{c}\right)\left(\frac{v_i}{c}\right)^{k-1}\exp\left[-\left(\frac{v_i}{c}\right)^k\right]\right] \tag{18}$$

where k and c denote the shape and scale parameters, respectively, and v_i is the wind speed value in time step i. n represents total non-zero wind speed values in the sample. Taking logarithm of both sides, a log-likelihood function is obtained as:

$$\ln(L) = n\ln(k) - nk\ln(c) + (k-1)\sum_{i=1}^{n}\ln(v_i) - \sum_{i=1}^{n}\left(\frac{v_i}{c}\right)^k. \tag{19}$$

Equation (19) is differentiated with respect to k and c and equated to zero to obtain the following expressions for the parameters [17]:

$$k = \left[\frac{\sum_{i=1}^{n}\ln(v_i)}{\sum_{i=1}^{n}(v_i^k)} - \frac{\sum_{i=1}^{n}(v_i^k)\ln(v_i)}{n}\right]^{-1} \tag{20}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{\frac{1}{k}}. \tag{21}$$

Equation (20) was solved with the help of an iterative procedure. After the shape parameter was determined, Eq. (21) was used to calculate the scale parameter.

Evaluation of Weibull parameter estimation methods

The correctness of the projected wind speed distribution resulting from the aforementioned methods is validated using two tests: Root mean square error (RMSE) and Coefficient of determination (R^2) [15, 29].

1. Root mean square error (RMSE) This method examines the goodness of fit between the actual measured values and the predicted values of the model. In this study, it is used to estimate the accuracy between the values achieved by Weibull functions, obtained using different approaches, with the actual measured data. RMSE value is always non-negative and smaller RMSE values mean better model efficiency. The measurement depends on the scale of the number used [30]. RMSE is calculated from the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \tag{22}$$

where x_i and y_i represent the actual data measured and the data predicted from Weibull distribution, respectively, and n represents the number of wind speed dataset (bins).

2. Coefficient of determination (R^2) It is another statistical tool to explain the relationship between the two variables. Its value lies between 0 and 1. Values nearer to 1 indicate that the model explains much of the proportion of variance in the dependent variables. The R^2 value can be expressed as [31]:

$$R^2 = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2 - \sum_{i=1}^{n}(X_i - x_i)^2}{\sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{23}$$

where X_i represents the recorded wind data frequency in the wind speed bin, $(\bar{X})$ represents the average of X_i values, x_i represents the frequency estimated from the Weibull distribution, and n represents the number of bins.

Calculation of wind power density (WPD)

The calculation of WPD is done in order to approximate the power potential that can be derived from Wind Turbine Generator. It relies upon the kinetic energy of the air mass and hence is proportional to the cube of the wind speed. The kinetic energy of air mass can be written as:

$$K.E = \frac{1}{2}\rho v^3 At \tag{24}$$

where ρ represents the density of air, A denotes the normal section of the area of the rotor, and t represents the time period at a constant wind speed v. The expression for wind power (P) is obtained by dividing Eq.

(24) by the rotor area per second:

$$P = \frac{1}{2}\rho v_{avg}^3. \tag{25}$$

Equation (25) is an expression for wind power at a constant speed. In fact, the wind speed is constantly changing. To incorporate this effect, the wind power density equation is derived using the mean speed expression from the Weibull distribution curve. The mean speed of wind can be expressed as:

$$v_{avg} = c\Gamma\left(1 + \frac{1}{k}\right). \tag{26}$$

Substituting the value of v_{avg} in Eq. (25), we get,

$$P = \frac{1}{2}\rho c^3\Gamma\left(1 + \frac{3}{k}\right). \tag{27}$$

Equation (27) is an expression for Weibull Wind Power Density (WPD). The air density corresponding to standard conditions i.e., at the sea level (0 m.a.s.l.) 15^oC is 1.225 kg/m^3 [32]. For a more accurate prediction of wind potential, the corrected density is to be calculated at the turbine's hub height. This can be calculated through a simple expression shown in Eq. (1).

Results and discussion

In order to understand the wind characteristics, monthly and annual mean wind speed was calculated over a period of seven years (2011, 2013–2018) for Jumla and over a period of eight years (2011–2018) for Okhaldhunga. Six different numerical methods were used to estimate Weibull parameters and consequently the wind power density. A performance evaluation was conducted to find out a method providing a best fit to the actual data.

Wind speed characteristics

Monthly wind speed variation

The average monthly wind speed during a seven-year period (2011-2018) excluding 2012 for Jumla and a period of eight years (2011-2018) for Okhaldhunga is plotted in Fig.2. Wind speed increases in both locations beginning in January. However, compared to Jumla, the wind speed

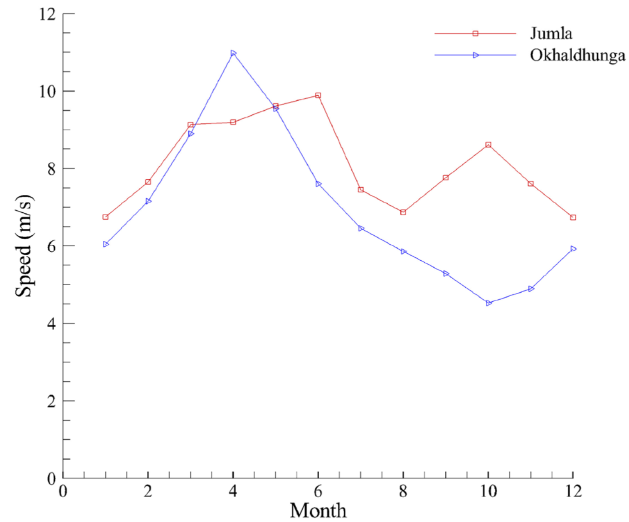


Fig. 2 Monthly wind speed variation at height of 50 m

in Okhaldhunga then subsides to lower values in the following months until August. The wind characteristic variations on both locations are result of the differences in geography, temperature, rainfall, and other parameters.

Based on the evaluation of the data, Jumla was observed to have minimum wind speed in December and January. Beginning in January, the wind speed rose gradually and reached its maximum value of 9.78 m/s in June. Thereafter, the wind speed continued to decline until August. This may be attributed to the monsoon rainfall prevailing from the month of June till the end of August. The wind distribution pattern shows that the wind speed picked up again and had a relatively higher value for September and October. From then on, the wind speed decreases and reaches 6.71 m/s in December which is the minimum.

The monthly wind speed variation in Okhaldhunga can be understood by dividing the year into two distinct phases. The first one is the warmer season between April and October, and the second one is the colder months of November to March. A maximum mean wind speed of 10.95 m/s was observed in April. The wind speed then showed a decreasing trend reaching its lowest value of 4.52 m/s in October. This is due to the gain in significant rainfall after April to October in Okhaldhunga. After October, the wind speed rose again until April. The maximum mean wind speed is twice the value of minimum wind speed. The range of mean wind speed for Okhaldhunga is greater than that of Jumla.

Both locations experienced higher wind speed in the months of March, April, and May. This may be credited to the seasonal transition from winter to summer. The air in the tropic region starts to warm up as the Northern hemisphere gets more sunlight. This warm low-pressure air moves northward to meet cold high-pressure air in the artic and creates a pressure gradient which results in higher wind speed.

Annual variation of wind speed parameters

Since wind speed is affected by various weather phenomena, reliable wind resource assessment demands the study of year-to-year variation. To get a basic notion of such variations, general wind speed parameters, annual values of mean speed (v_m), maximum speed (v_{max}), and minimum speed (v_{min}) are calculated and listed in Table 2.

Throughout the years of study, Jumla shows a more consistent mean wind speed while Okhaldhunga experiences fairly steady values only in the last few years of study. If the last three years (2015-2018) of study are taken into account, Okhaldhunga has an average wind speed value of 8.56 m/s, which is slightly higher than that of Jumla with a value of 7.96 m/s.

However, calculations for the entire study period indicate the average wind speed of Jumla to be greater than that of Okhaldhunga by a margin of 1.22 m/s. But Okhaldhunga shows higher values of maximum wind speed in a majority of years along with the average ones, showing that it sustains greater wind speed values but for a relatively shorter duration. Even though Okhaldhunga has a higher maximum value of wind, Jumla has a fairly constant wind speed value and does not fluctuate as much as Okhaldhunga which has much importance in wind energy generation.

Wind availability analysis

Generally, a wind speed of 3 m/s is taken as cut-in speed for the wind turbine to generate energy and wind speed greater than 6 m/s is considered to have appreciable energy production [33]. For Jumla, 96.79% of the wind speed data were greater than 3 m/s, and 78.80% of data were greater than 6 m/s, indicating that 96.79% of the time throughout the year wind energy can be produced and appreciable energy production for 78.80% of the time. In the case of Okhaldhunga, 85.70% of the wind speed data was greater than 3 m/s indicating that 85.70% of the time throughout the year energy generation can be feasible, and 56.63% of the time wind speed was greater than 6 m/s. Both locations have good potential for wind energy generation.

Weibull parameters and performance evaluation

Tables 3 and 4 list the values of k and c obtained after each estimation method was applied to the annual wind speed data set.

Table 2 Yearly trend for wind speed parameters

Location	Wind speed parameters	2011	2012	2013	2014	2015	2016	2017	2018	Average
Jumla	v_m	7.94	–	8.24	8.00	8.66	8.11	7.72	8.07	8.11
	v_{max}	17.13	–	17.70	17.13	19.04	19.80	15.99	16.75	17.65
	v_{min}	1.52	–	1.52	0.76	1.33	1.52	0.76	1.52	1.28
Okhaldhunga	v_m	3.80	6.45	7.59	5.93	5.69	8.84	8.75	8.11	6.89
	v_{max}	17.51	19.80	20.18	20.18	18.08	19.99	19.42	18.28	19.18
	v_{min}	0.19	0.62	0.38	0.19	0.48	0.95	2.28	1.33	0.80

Table 3 Yearly Weibull parameters of Jumla

Method	Parameter	Year							
		2011	2012	2013	2014	2015	2016	2017	2018
EML	k	3.22279	–	3.31407	3.09377	3.35980	3.40298	3.35206	3.54006
	c	8.85844	–	9.18444	8.95012	9.63729	9.02376	8.60172	8.95884
EMJ	k	3.22279	–	3.31407	3.09377	3.35980	3.40298	3.35206	3.54006
	c	8.86044	–	9.18686	8.95162	9.64000	9.02645	8.60411	8.96194
MOM	k	3.22062	–	3.31289	3.09026	3.35912	3.40552	3.35130	3.54144
	c	8.86073	–	9.18702	8.95209	9.64010	9.03270	8.60421	8.96175
MLM	k	3.20164	–	3.22282	3.08877	3.32601	3.34077	3.37446	3.54751
	c	8.85640	–	9.18226	8.94120	9.62102	9.00647	8.59017	8.95496
WEPF	k	3.01514	–	3.04675	2.94481	3.11011	3.12491	3.11949	3.21283
	c	8.88807	–	9.22399	8.97128	9.67656	9.07125	8.63451	9.00660
Graphical	k	3.10273	–	3.17011	2.86349	2.89181	2.99798	2.99670	3.41902
	c	8.95377	–	9.39159	8.87142	9.61950	9.16903	8.58010	8.97646

Table 4 Yearly Weibull parameters of Okhaldhunga

Method	Parameter	Year							
		2011	2012	2013	2014	2015	2016	2017	2018
EML	*k*	1.26537	1.55374	2.25852	1.60868	2.11679	2.64060	3.24234	3.26280
	c	4.09365	7.17904	8.56834	6.61926	6.42888	9.95018	9.76466	9.04353
EMJ	*k*	1.26537	1.55374	2.25852	1.60868	2.11679	2.64060	3.24234	3.26280
	c	4.09141	7.17311	8.56523	6.61384	6.42581	9.94933	9.76694	9.04573
MOM	*k*	1.25120	1.53992	2.24793	1.59500	2.10532	2.63288	3.24038	3.26106
	c	4.08113	7.16627	8.56555	6.60867	6.42562	9.95025	9.76723	9.04597
MLM	*k*	1.26275	1.54702	2.23407	1.64382	2.09935	2.57520	3.05871	3.27125
	c	4.09200	7.17936	8.56491	6.65478	6.42974	9.96644	9.77832	9.17095
WEPF	*k*	1.2684	1.53989	2.22026	1.55772	2.05109	2.49828	2.93460	2.92932
	c	4.09356	7.16625	8.56619	6.59330	6.42410	9.96485	9.81181	9.09080
Graphical	*k*	1.21162	1.54519	2.21596	1.69217	2.11726	2.87490	3.61312	3.57488
	c	4.05126	7.21796	8.74919	6.92088	6.74750	10.59026	10.47175	9.86509

The shape of a Weibull distribution is dependent on the value of k. Lower values of this parameter relate to a wider Weibull curve which in turn infers that the wind speed falls upon a larger range whereas greater values designate a narrow Weibull curve indicating that the speed falls upon a smaller range. The other parameter, c, correlates with the average wind speed and represents the magnitude of wind speed in the site.

In terms of shape parameter k, it is observed that it's value ranges from 2.863–3.547 for Jumla, while Okhaldhunga presents values ranging from 1.211–3.574 inferring that the wind speed in Jumla is more consistent. The shape parameter in Okhaldhunga shows an increasing trend over the study period indicating more steadiness in the wind speed in recent years. Scale parameter for Jumla ranges from 8.590–9.640 m/s while Okhaldhunga shows c values ranging from 4.051–10.590 m/s. Similar to the shape parameter, the scale parameter for Okhaldhunga also shows an increasing trend during the study period, suggesting an increasing potential for producing wind energy. The shape and scale factor in conjunction offer an approximation of the wind turbine's operating range of speed.

Weibull distributions in Fig. 3 are the results of the plot between probability density function and wind speed data collected annually for the study period using the parameters calculated from six different numerical methods as listed in Tables 3 and 4. The Graphical method used a bin size of 1 m/s in the calculation of the parameters. Only years 2011 and 2018 are included here for a general insights.

The curves created by different methods shown in Fig.3 appear to be either underestimating or overestimating the wind speed data for both study stations. For Jumla 2018, all methods underestimated the speed in 2-4 m/s, 5 m/s, 9-10 m/s, 12-14 m/s, and 16 m/s ranges whereas overestimation was observed in 1 m/s, 6-8 m/s, 11 m/s, 15 m/s, and 17 m/s ranges with WEPF method resulting in the largest error of overestimation and underestimation of 3.07% at 5 m/s and 3.94% at 8 m/s, respectively. For Okhaldhunga 2018, all the methods overestimated the wind speed in the 1-5 m/s and 10-15 m/s ranges, while underestimation was observed in the 6-9 m/s and 16-19 m/s ranges, with graphical method resulting in the largest error of overestimation and underestimation of 8.03% at 11 m/s and 9.03% at 7 m/s speed, respectively.

The distributions aid in the visualization of the match between the Weibull probability density curve and the actual wind speed data collected, providing insights into the methods performing the best. Graphically, Fig.3 demonstrates that all estimation methods produced a good curve fit to the histogram of actual wind speed data. However, the aforementioned statistical tests are carried out to further analyze the six methods of estimation, the results of which are shown in Tables 5 and 6.

From the statistical analysis of methods shown in Tables 5 and 6, it is evident that all the considered methods provide acceptable effectiveness in estimating the Weibull distribution parameter for data under consideration. Statistical testing parameters, RMSE and R^2 have been used collectively to accurately decide the best method.

As shown in Table 7, all of the methods were ranked to determine the best estimating model by choosing the model with the least value of RMSE and the highest R^2 value. In case of Jumla, EMJ has been ranked first followed by EML, MOM, MLM, WEPF, and Graphical, respectively. EMJ and EML shared a slight variation. For Okhaldhunga, both EMJ and EML performed equally well followed by MOM, MLM, WEPF, and Graphical method. EMJ performed better based on RMSE and EML performed better in R^2. Therefore, based on these statistical rankings, EMJ and EML provided the best accuracy estimation models, whereas the Graphical method provided the worst fit for Jumla and Okhaldhunga.

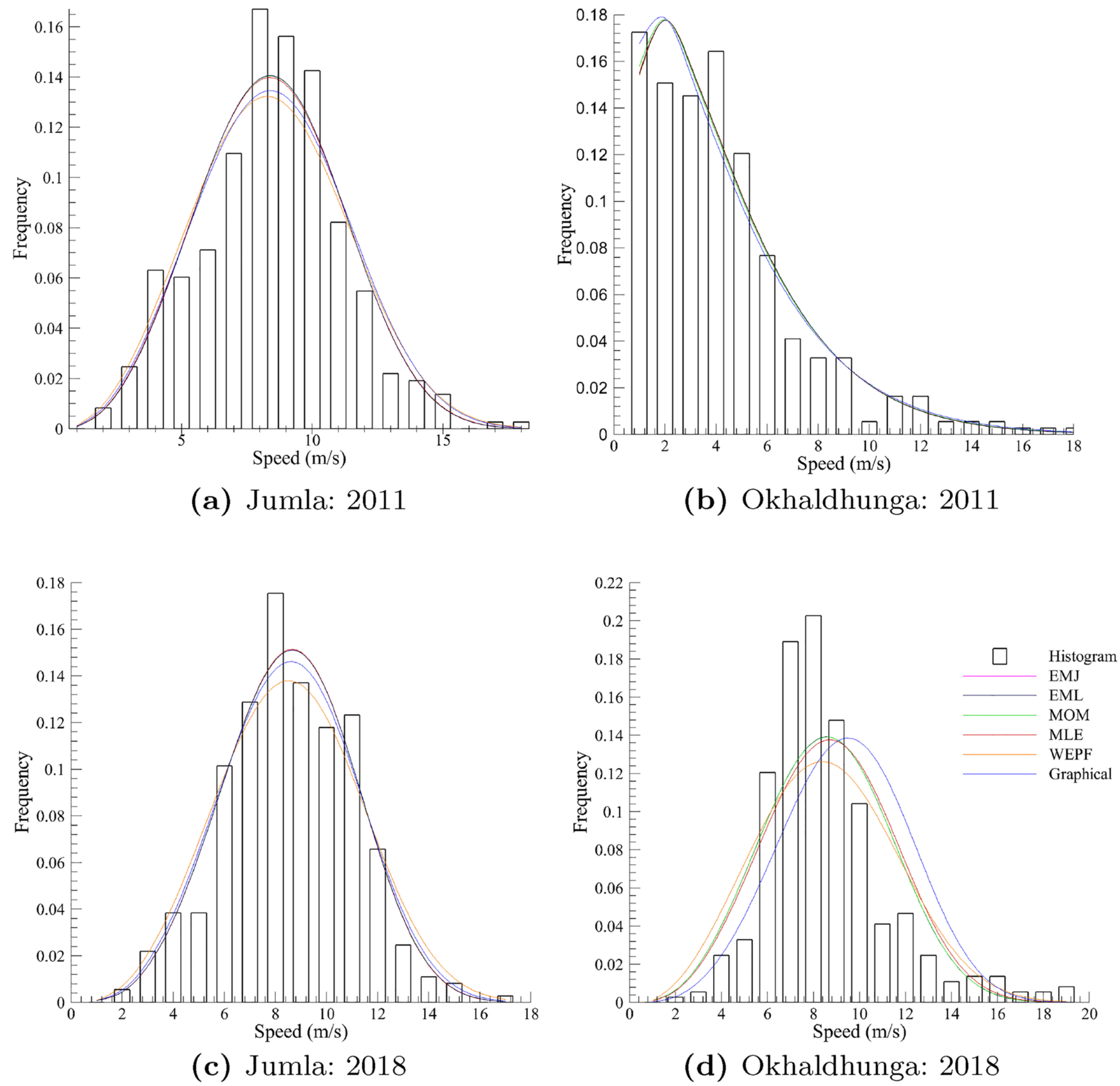


Fig. 3 Profiles of Weibull distribution for Jumla and Okhaldhunga in 2011 and 2018

Table 5 Coeff. of Determination and RMSE along different years at Jumla

Method	Parameter	Year							
		2011	2012	2013	2014	2015	2016	2017	2018
EML	R^2	0.92536	–	0.91318	0.96303	0.89501	0.89925	0.88085	0.95172
	RMSE	0.01452	–	0.01635	0.00918	0.01697	0.01829	0.01968	0.01222
EMJ	R^2	0.92536	–	0.91305	0.96303	0.89496	0.89917	0.88096	0.95155
	RMSE	0.01452	–	0.01637	0.00918	0.01698	0.01831	0.01968	0.01223
MOM	R^2	0.92522	–	0.91298	0.96298	0.89491	0.89913	0.88090	0.95157
	RMSE	0.01454	–	0.01637	0.00919	0.01699	0.01831	0.01969	0.01222
MLM	R^2	0.92390	–	0.90830	0.96289	0.89240	0.89545	0.88212	0.95172
	RMSE	0.01470	–	0.01707	0.00920	0.01724	0.01880	0.01955	0.01219
WEPF	R^2	0.90722	–	0.88380	0.95909	0.86421	0.86484	0.86151	0.93206
	RMSE	0.01656	–	0.01903	0.00996	0.01960	0.02139	0.02187	0.01485
Graphical	R^2	0.91636	–	0.89106	0.95239	0.84142	0.86200	0.84303	0.94894
	RMSE	0.01575	–	0.01894	0.01084	0.02234	0.02339	0.02341	0.01287

It was clear that among the six methods studied, the EMJ and EML offered the best accuracy, with very close results from MOM, whereas the graphical method appeared to be the worst-performing. The EMJ providing the best accuracy for a height of 50 m is mentioned by Rocha et al. [14]. Additionally, EMJ and EML performing the best among others is observed by Teyabeen et al. [34]. Poor performance of the graphical method against other methods is also observed by Werapun et al. [16], Ben et al. [18], and Mohammadi et al. [27].

Estimation of wind power potential

Wind Power Densities (WPD) calculated using the values of *k* and *c* from the Empirical Method of Lysen for a height of 50 m during the study period for Jumla and Okhaldhunga are shown in Table 8.

Results show that Jumla has a consistent wind potential throughout the years with a mean WPD of 336.07 W/m^2. The lowest potential of value 288.52 W/m^2 was observed in the year 2017 which is still promising indicating a marginal potential for harnessing wind energy [35]. The year 2015 experienced the highest value of 405.49 W/m^2.

Meanwhile, Okhaldhunga shows a larger variation in WPD ranging from a minimum value of 100.49 W/m^2 in 2011 to a maximum of 531.95 W/m^2 in 2016. The mean WPD is obtained to be 326.73 W/m^2 which is slightly lower than that of Jumla. Based on the mean values, it can be concluded that both the locations belong to wind resource of Class 3 and have a good potential for wind energy generation [35]. Therefore, a wind turbine having capacity of around 100 kW and low operating wind speed could be considered for installation [36].

Table 6 Coeff. of Determination and RMSE along different years at Okhaldhunga

Method	Parameter	Year							
		2011	2012	2013	2014	2015	2016	2017	2018
EML	R^2	0.94874	0.86086	0.89595	0.85443	0.93827	0.75086	0.76410	0.79303
	RMSE	0.01370	0.01419	0.01328	0.01811	0.01423	0.02388	0.02805	0.02929
EMJ	R^2	0.94874	0.86101	0.89598	0.85457	0.93839	0.75096	0.76378	0.79269
	RMSE	0.01370	0.01419	0.01328	0.01809	0.01422	0.02388	0.02807	0.02932
MOM	R^2	0.94884	0.86035	0.89587	0.85311	0.93737	0.75096	0.76376	0.79261
	RMSE	0.01369	0.01423	0.01331	0.01821	0.01437	0.02391	0.02807	0.02933
MLM	R^2	0.94879	0.86052	0.89566	0.85602	0.93668	0.74976	0.76162	0.77197
	RMSE	0.01369	0.01422	0.01334	0.01797	0.01448	0.02418	0.02873	0.03064
WEPF	R^2	0.94866	0.86035	0.89536	0.84758	0.93171	0.74933	0.75521	0.77288
	RMSE	0.01371	0.01423	0.01338	0.01859	0.01520	0.02452	0.02957	0.03189
Graphical	R^2	0.94672	0.85952	0.89253	0.84246	0.91974	0.63341	0.60469	0.59787
	RMSE	0.01396	0.01429	0.01372	0.01892	0.01671	0.02836	0.03572	0.03956

Table 7 Rank of different estimation methods

Methods	Jumla				Okhaldhunga			
	R^2	Rank	RMSE	Rank	R^2	Rank	RMSE	Rank
EML	0.91832	1	0.01530	1	0.85078	1	0.01935	2
EMJ	0.91830	2	0.01532	2	0.85076	2	0.01934	1
MOM	0.91824	3	0.01533	3	0.85036	3	0.01939	3
MLM	0.91668	4	0.01554	4	0.84763	4	0.01966	4
WEPF	0.89610	5	0.01761	5	0.84514	5	0.02014	5
Graphical	0.89360	6	0.01822	6	0.78712	6	0.02266	6

Table 8 Wind power density estimations

Year	2011	2012	2013	2014	2015	2016	2017	2018	Average
Jumla	319.29	–	352.51	334.34	405.49	331.56	288.52	320.81	336.07
Okhaldhunga	100.49	352.20	378.43	260.47	169.19	531.95	458.04	363.09	326.73

Conclusions

With the growing demand for cleaner energy sources, Nepal has emphasized to promote wind energy where ever possible to improve energy mix and supply security within the country. This study explores the preliminary steps for determining the wind energy potential in Jumla and Okhaldhunga districts of the country. It conducted the analysis of various Weibull estimation methods and determined the best option for assessment of wind energy potential for Jumla and Okhaldhunga. Daily wind speed data of Jumla and Okhaldhunga for 7 years and 8 years, respectively, at a height of 2 m were collected and extrapolation was carried to a height of 50 m using the power-index law for further analysis.

The average wind speed of Jumla is observed to be 8.11 m/s with a maximum average wind speed of 9.89 m/s in June and a minimum average wind speed of 6.74 m/s in December. Similarly, the average wind speed of Okhaldhunga is observed to be 6.89 m/s with a maximum average wind speed of 10.98 m/s in April and a minimum average wind speed of 4.52 m/s in October. At 50-m-height, the annual average of the Weibull shape parameter k for Jumla and Okhaldhunga are 3.327 and 2.244, respectively, and the scale parameter c for Jumla and Okhaldhunga are 9.033 m/s and 7.704 m/s, respectively. This shows that wind is more uniform and steady in Jumla in comparison to Okhaldhunga. Wind power density is calculated using the EML for both locations, and Jumla seems to have a similar WPD for the seven years study period with an average of 336.07 W/m^2. However, in the case of Okhaldhunga WPD seems to be varying with recent data showing good wind potential. Eight years average WPD for Okhaldhunga is 326.73 W/m^2. The study shows that both Jumla and Okhaldhunga lie in wind class 3 suggesting that both locations have moderate suitability for wind energy harvesting. From the analysis of RMSE and coefficient of determination for the six Weibull parameters estimation methods, the Empirical method of Justus was observed to be the best fit for Jumla whereas EMJ and EML ranked equally for Okhaldhunga. The Graphical method gave the worst fit. Further, Empirical, MOM, and MLM techniques all provided similar results.

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