Analysis of Wind Speed Data and Energy Potential Using Weibull Distribution Method: A Case Study of Damaturu, Yobe State, North-East, Nigeria

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Abstract

In this study, the wind speed characteristics and energy potential in Yobe State University area, Damaturu were investigated using wind speed data that span for 4 years from 2016 to 2019 and was measured at a height of 10 meters from the ground level using cup anemometers and modeled via the Weibull probability framework. The Maximum Likelihood Estimation (MLE) method were deployed to compute the Weibull shape (k) and scale (c) parameters. These parameters facilitated a detailed evaluation of temporal wind dynamics. It was observed that the maximum wind speed (3.21–4.80 m/s), energy density ranges (15.07–50.40 kWh/m^2), and power density (20.26–67.74 W/m^2) peaked between January and April, whereas July to October exhibited significantly reduced performance. The years 2017 and 2018 proved most favorable for energy extraction, driven by elevated scale parameters ($c = 2.70$) and consistent mean speeds (2.44 m/s). In contrast, 2016 recorded the highest shape factor ($k = 4.14$), reflecting stable yet slower winds ideal for low power, steady output applications. Although annual wind speeds remained below 3 m/s, the region shows promise for small-scale wind energy installations employing turbines with low activation thresholds, especially during months with extended wind duration (January's, $T(V) = 368.61$). However, periods such as September 2019 marked by minimal speeds (0.86 m/s) and high probability density values ($F(V) = 0.92$) highlight challenges in energy predictability, necessitating turbines optimized for variable conditions. Damaturu holds some potential for wind energy development, achieving maximum power density of 67.74 W/m^2 and an energy density of 50.40 kW h/m^2, positioning it below the Class I threshold. This suggests its suitability for low energy applications such as water pumping, battery charging, and powering small electronic devices.

Keywords**:** Wind Power Density, Wind Energy Potential, Weibull Parameters (Shape and Scale), Probability Distribution Function, Probability Duration Function.

1. Introduction

The increasing global energy demand, coupled with concerns over depleting fossil fuel re- serves and the severe environmental consequences associated with their use, necessitates a urgent transition towards sustainable and renewable energy sources [1]. Among these alternatives, wind energy has emerged as a crucial and increasingly adopted option, converting the kinetic energy of wind into electricity. The successful planning and implementation of wind energy projects rely heavily on an accurate assessment of the wind resource available at a particular site. This assessment involves understanding and characterizing the natural variability of wind speed over time and space [1]. Statistical models play a vital role in this characterization. The two-parameter Weibull distribution is widely recognized and frequently employed for modelling wind speed frequency distributions and estimating wind energy potential [2]. Its popularity stems from its analytical tractability and demonstrated effectiveness in representing observed wind speed data. The Weibull distribution is mathematically defined by two key parameters: the shape parameter (k) and the scale param- eter (c), which together describe the distribution’s form and magnitude [3]. The reliability of wind energy potential assessments is highly dependent on the accuracy of the estimated Weibull parameters. Consequently, numerous methods have been developed over time for estimating the k and c parameters. These methods encompass a wide range of approaches, including Graphical Methods, various Empirical Methods (such as those based on mean wind speed and standard deviation like the Empirical Method of Justus and the Empirical Method of Lysen), the Maximum Likelihood Method and its variations, Least Square Methods, the Energy Pattern Factor Method, the Moment Method, the Curve Fitting Method, the Wind Variability Method, the Moroccan Method, and the Median and Quartile Method, among others [4]. However, studies comparing these different estimation techniques have consistently shown variations in their performance and accuracy. For example, some comparisons have found specific methods like the Energy Pattern Factor Method or Maximum Likelihood Method to perform favourably in certain contexts, while others have highlighted the superiority of different methods or concluded that the most suitable method can vary depending on the specific site and the characteristics of the available wind data [3]. Selecting an unsuitable estimation method could lead to inaccurate parameter values, resulting in an unreliable assessment of wind energy potential and potentially suboptimal or uneconomical wind power system designs [3]. This study aims to analyze wind speed data and assess the energy potential using the Weibull distribution method. The Weibull parameters will be estimated using the Maximum Likelihood Estimation (MLE) method for the observed location.

2. Methodology

2.1 Description of Location

Damaturu is the capital city of Yobe State located in the North-Eastern of Nigeria. It lies approximately at Latitude 11.74ºN and Longitude 11.96ºE with an average elevation of 414.8 meters above sea level Table 1.

Table 1: Geographic Coordinates and Elevation of the Study Area

State	Station's Location	Latitude (N)	Longitude (E)	Air Density (kg/m^2)	Elevation (m)
Yobe	Yobe State University	11.66º	11.95º	1.225	414.8

2.2. Data Collection

The wind speed data was recorded for four years from 2016 to 2019 using cup anemometer as shown in Figure 1. The wind speed data were collected on a daily basis, and monthly mean wind speed were computed for further analysis. The anemometer was located 10 meters above the ground level at the Desert Research Center, Yobe State University, Damaturu, Yobe State, Nigeria. The cup anemometer, widely used for measuring wind speed, typically features three cups on a shaft that rotate in proportion to wind velocity, generating a signal. Rotation speed is measured through mechanical counters tracking rotations, electrical voltage changes (AC or DC), or photoelectric switches [5].

Figure 1: Cup Anenometer at Desert Research Center, Yobe State University

2.3. Data Analysis

Wind Power (P)

Is the total mechanical power available in the wind. It depends on the cross-sectional area swept by the turbine blades, the air density, and the cube of the wind speed [5].

$$P = \frac{1}{2}\rho A V^3 \qquad (1)$$

Where:

P is the wind power (W),

ρ is the air density (kg/m^3),

A is the swept area of the turbine blades (m^2),

V is the wind speed (m/s).

Wind Power Density (P_d)

refers to the amount of kinetic energy carried by the wind that passes through a unit area oriented perpendicular to the wind flow, typically measured in watts per square meter [6].

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

Where:

P_d is the wind power density (W/m^2),

ρ is the air density (kg/m^3),

V is the wind speed (m/s).

Power density represents the available wind power per unit area.

Maximum Likelihood Estimation (MLE) Method for Weibull Parameters

The Maximum Likelihood Method (MLM) is an iterative numerical approach used to estimate the Weibull parameters (k and c) by maximizing the likelihood function derived from observed wind speed data. It is widely applied in wind energy studies due to its statistical robustness [3].

The shape parameter k is estimated by solving the following equation iteratively:

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

The scale parameter c is then calculated as:

$$c = \left(\frac{1}{m}\sum_{i=1}^{m} v_i^k\right)^{1/k}$$

where: v_i= observed wind speed data points,

m = number of data points.

Empirical Method for the Estimation of Weibull Shape and Scale Parameters

The shape parameter k can be estimated using the mean wind speed v_m and standard deviation σ:

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.086} \tag{3}$$

This empirical relationship is commonly used to estimate k [7][6].

The scale parameter c can be estimated as:

$$c = \frac{v_m}{\Gamma\left(1+\frac{1}{k}\right)} \tag{4}$$

This provides a direct relationship between the scale parameter and the mean wind speed [7][6][1].

Weibull Probability Density Function

The Weibull probability density function (PDF) describes the probability of observing a particular wind speed v. It is given by:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{5}$$

where f (v) is the probability density of wind speed v, k is the dimensionless Weibull shape parameter, and c is the Weibull scale parameter (in m/s) [7][6][1].

Frequency Distribution Duration Function T(V)

The frequency distribution duration function T(V) is given by the formula [8].

$$T(V) = 8760exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{6}$$

The T(V) estimates the number of hours in a year (8760 hours) that the wind speed exceeds a specific value V. It provides insight into how long wind speeds remain above a certain threshold, which is crucial for assessing the feasibility of wind energy projects.

3. Results and Discussion

This research involved a statistical analysis of wind speed measurements collected from Desert Research Center located at Yobe State University, Damaturu, in north-eastern Nigeria over the period of four (4) years from 2016 to 2019. Using both spreadsheet tools and the Wind Information and Python Programming software, the wind speed data from the site were evaluated and processed. A summary of the key findings from the analysis is presented from Table 2 to Table 6 and Figure 2.

3.1. Figures and Tables

In Table 2, the monthly mean wind speed in meters per second (m/s) was calculated which varies significantly across the year 2016, reflecting seasonal changes in wind patterns. The highest mean wind speed was observed to be 3.21m/s in January while September has the lowest wind speed at 1.37m/s. Other months, such as July (1.58m/s) and October (1.57m/s), also indicates low wind speeds, while February (2.5m/s) and April (2.56m/s) show moderate values. This variation suggests a seasonal trend, with higher wind speeds in winter and early spring and lower speeds in summer and autumn.

The highest Power density in watts per square meter (W/m^2), was observed to be in

January with 20.26 (W/m^2), due to its high wind speed, while September records the lowest at 1.57 (W/m^2).

In the calculated Energy density, January has the highest value of 15.07 kW h/m^2) due to it its high-power density and wind speed. September has the lowest energy density at 1.17 kW h/m^2), consistent with its low wind speed and power density April (7.40 kW h/m^2).

From the probability density function, F(V), the highest PDF was observed in September at 0.6185, showing a higher probability of low wind speeds, due to its low mean speed of 1.37 m/s. October (0.5647) and August (0.5042) show higher F(V) values, indicating frequent low wind speed. April has the lowest F(V) at 0.1470, indicating a broader or less concentrated wind speed distribution. While January (0.3426) and December (0.3835) show moderate probabilities, indicating more variable wind conditions.

In the frequency distribution duration function, T(V), October shows the highest T(V) at 354.92, suggesting prolonged periods of consistent wind speeds, despite its low mean speed. September (351.77) and November (348.98) also show high T(V) values, indicating stable wind conditions. March has the lowest T(V) at 265.50, implying shorter duration of consistent wind speeds, possibly due to variable spring weather. January (368.61) has the highest T(V), indicating sustained high wind speeds. This parameter is essential for assessing the consistency of wind resources for energy applications.

In conclusion the data shows difference in seasonal patterns and wind characteristics, with January being the most likely suitable month for wind energy due to high wind speed, power density, and energy density, while September is the least favorable. The probability and frequency distributions further highlight the reliability and duration of wind speeds, providing valuable insights for wind energy system design and site assessment.

Table 2: Estimation of Power and Energy Density for the year 2016

Months	**Wind Speed** (m/s)	**Power Density** (W/m^2)	**Energy Density** (kWh/m^2)	**F(V)**	**T(V)**
Jan	3.21	20.26	15.07	0.3426	368.61
Feb	2.5	9.57	6.66	0.2824	316.27
Mar	1.84	3.82	2.84	0.1867	265.50
Apr	2.56	10.28	7.40	0.1470	267.45
May	2.09	5.59	4.16	0.2719	319.55
Jun	1.82	3.69	2.66	0.2402	283.83
Jul	1.58	2.42	1.80	0.3792	324.30
Aug	1.75	3.28	2.36	0.5042	343.16
Sep	1.37	1.57	1.17	0.6185	351.77
Oct	1.57	2.37	1.76	0.5647	354.92
Nov	2.1	5.67	4.08	0.4598	348.98
Dec	1.93	4.40	3.28	0.3835	341.78

It can be seen from Table 3, that the highest mean wind speed occurred in February with 4.1 m/s while October has the lowest mean wind speed of 1.46 m/s. January (3.16 m/s) and March (2.8 m/s) show relatively high wind speeds, while months like November

(1.84 m/s) and May (2.06 m/s) show lower values. These fluctuations highlight a seasonal pattern.

The highest probability density function F (V) occurred in October with 0.6843, indicating a high probability of low wind speeds, in line with its mean speed of 1.46 m/s. Although June has the lowest F(V) at 0.1109, implying a wider or less concentrated wind speed distribution.

It was also observed that January has the longest duration function of 385.79, suggesting prolonged periods of consistent wind speeds, although it does not have the highest mean wind speed. October (362.79) and May (357.80) also show high T(V) values, indicating stable wind conditions. June has the lowest T(V) at 237.27, indicating shorter durations of consistent winds.

Hence, the 2017 year data show pronounced seasonal trends, with February being the most favorable month for wind energy due to its high wind speed, power density, and energy density, while October is the least favorable.

Table 3: Estimation of Power and Energy Density for the year 2017

Months	**Wind Speed** (m/s)	**Power Density** (W/m^2)	**Energy Density** ($kW\,h/m^2$)	**F(V)**	**T(V)**
Jan	3.16	19.33	14.38	0.4983	385.79
Feb	4.1	42.21	28.37	0.2808	335.31
Mar	2.8	13.45	10.00	0.3092	353.28
Apr	2.3	7.45	5.37	0.2095	293.75
May	2.06	5.35	3.98	0.4491	357.80
Jun	2.63	11.14	8.02	0.1109	237.27
Jul	2.47	9.23	6.87	0.2128	312.22
Aug	2.22	6.70	4.83	0.3241	328.62
Sep	2.13	5.92	4.40	0.3562	343.67
Oct	1.46	1.91	1.42	0.6843	362.79
Nov	1.84	3.82	2.75	0.5436	351.16
Dec	2.08	5.51	4.10	0.2368	305.77

In the year 2018, as shown in Table 4, a distinct seasonal pattern is highlighted, with September having the highest mean wind speed of 4.8 m/s, with the highest energy density of 50.40 kW h/m^2, frequency distribution function of 260.67, and probability density function of 0.0688. while November shows the lowest mean wind speed of 1.51 m/s, with energy density of 1.43 kW h/m^2, frequency distribution function of 287.43, and probability density function of 0.3088.

Table 4: Estimation of Power and Energy Density for the year 2018

Months	**Wind Speed** (m/s)	**Power Density** (W/m^2)	**Energy Density** ($kW\,h/m^2$)	**F(V)**	**T(V)**
Jan	1.74	3.23	2.40	0.5903	364.51
Feb	1.61	2.56	1.72	0.4684	309.99
Mar	2.99	16.37	12.18	0.1183	268.97
Apr	2.43	8.79	6.33	0.1100	226.77
May	2.96	15.88	11.82	0.0903	234.38
Jun	2.49	9.46	6.81	0.1142	234.26
Jul	2.74	12.60	9.37	0.1203	260.41
Aug	2.26	7.07	5.09	0.1795	275.85
Sep	4.8	67.74	50.40	0.0688	260.67

Oct	1.51	2.11	1.57	0.5522	350.63
Nov	1.48	1.99	1.43	0.3057	287.43
Dec	2.26	7.07	5.26	0.3088	337.16

Table 5 indicates that the month of January has the highest wind speed at 4.06 m/s, while October has the lowest wind speed at 0.83 m/s. January leads with a power density of 40.99 W/m^2 and Energy density at 30.50 kW h/m^2 making it optimal for sustained energy production. In contrast, October has the lowest power density at 0.35 W/m^2 and an energy density of 0.26 kW h/m^2, consistent with its minimal wind speed.

The probability density function F(V), is highest in September at 0.9248, suggesting a very high probability of low wind speeds, which aligns with its mean speed of 0.86 m/s. In contrast, July has the lowest F(V) at 0.0272, indicating a broader or less concentrated wind speed distribution. January (0.0907) and June (0.1642) also have low F(V) values, reflecting more variable wind conditions.

Table 5: Estimation of Power and Energy Density for the year 2019

Months	**Wind Speed** (m/s)	**Power Density** (W/m^2)	**Energy Density** $(kW\,h/m^2)$	**F(V)**	**T(V)**
Jan	4.06	40.99	30.50	0.0907	273.86
Feb	2.33	7.75	5.21	0.2917	302.61
Mar	2.81	13.59	10.11	0.1809	308.95
Apr	2.82	13.74	9.89	0.1753	296.28
May	3.28	21.61	16.08	0.2204	339.96
Jun	2.6	10.77	7.75	0.1642	281.38
Jul	2.38	8.26	6.14	0.0272	135.77
Aug	1.14	0.91	0.65	0.5732	321.06
Sep	0.86	0.39	0.29	0.9248	347.20
Oct	0.83	0.35	0.26	0.8754	340.34
Nov	1.74	3.23	2.32	0.5038	342.72
Dec	2.33	7.75	5.76	0.3671	352.44

It was observed that the frequency distribution duration function T(V), is highest in December at 352.44, indicating prolonged periods of consistent wind speeds, despite its moderate mean speed. September (347.20) and November (342.72) also show high T(V) values, suggesting stable wind conditions. July has the lowest T(V) at 135.77, implying significantly shorter durations of consistent winds.

The annual average wind speed was estimated from the year 2016 to 2019 and the Weibull parameters (Shape and Scale Parameters) were calculated for each year as shown in Table 6. The analysis of the wind speed using Weibull distribution method reveals significant year to year variability in the wind characteristics. In the year 2017 and 2018 the highest wind energy potential were observed, supported by high scale factors of 2.69 and 2.74 respectively with an average wind speeds 2.44 m/s.

2016 presents consistent wind speeds with the highest shape factor, suggesting it is best suited for stable, moderate-power applications.

2019 shows greater variability, which may reduce energy predictability but still offers reasonable potential.

In general, the Weibull-based method works well for calculating the feasibility of wind energy and predicting the distribution of wind speeds. Despite Damaturu's low wind speeds (less than 3 m/s), the region offers the potential for small to medium-sized wind energy systems, especially when combined with low cut-in speed turbines, according to the consistent annual trends, particularly in 2017 and 2018

Table 6: Annual Average Wind Speed and Corresponding Shape Factor (k) and Scale Factor (c)

Years	**2016**	**2017**	**2018**	**2019**
Average Wind Speed	2.03	2.44	2.44	2.26
Shape Factor (k)	4.14	3.72	2.85	2.65
Scale Factor (c)	2.22	2.69	2.74	2.55

Figure 2 shows the Weibull probability density function (PDF) graphically illustrates the variation in wind speed distributions recorded in Damaturu, Yobe State, between 2016 and 2019. Key parameters such as the shape factor (k) and scale factor (c) essential for assessing wind patterns and their energy potential are used to differentiate the annual datasets, with each curve in the plot corresponding to a specific year within the studied period.

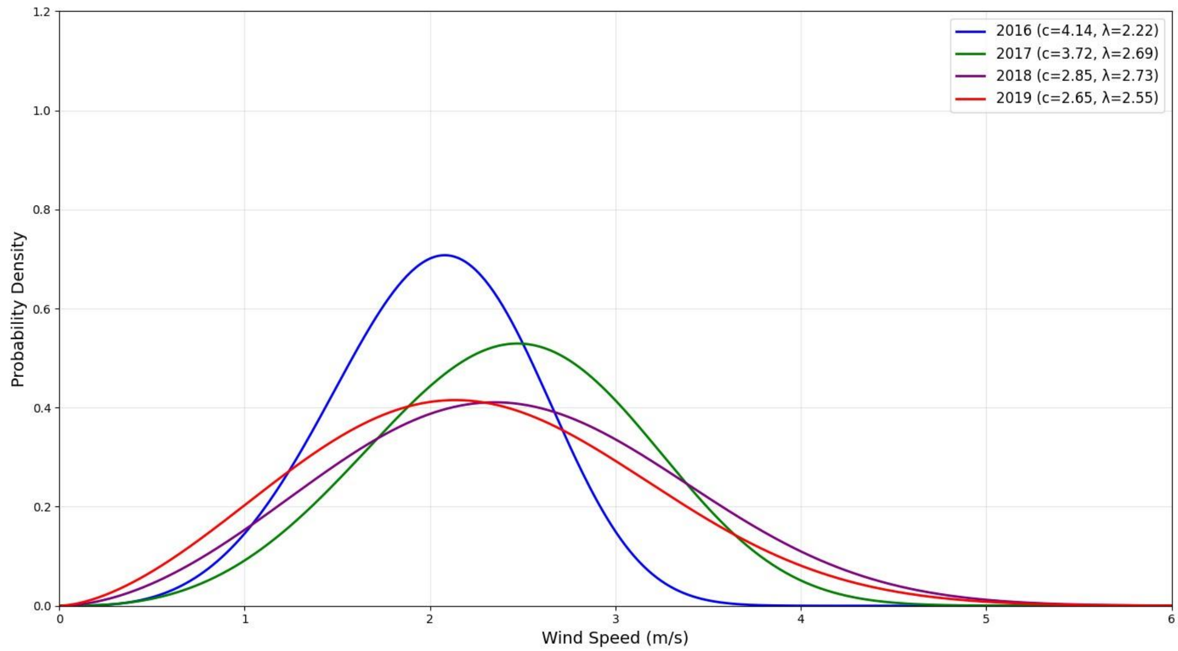

Figure 2: Wind Speed against Probability Density Function

4. Conclusion

This research presents statistical evaluation of wind speed data in Damaturu, Yobe State, located in north-eastern region of Nigeria. The Wind speed data were obtained from Desert Research Center located at Yobe State University, Damaturu, Nigeria using Cup Anemometer for the duration of four (4) years covering the years from 2016 to 2019. The data were used to calculate the Weibull probability distribution function (F (V)) and the duration function (T (V)), and the Weibull Parameters (Shape (k) and Scale (c)) were estimated using Maximum Likelihood Estimation (MLE) method. The findings indicate that Damaturu holds some potential for wind energy development, achieving maximum power density of 67.74 W/m^2 and an energy density of 50.40 kW h/m^2, positioning it below the Class I threshold. This suggests its suitability for low-energy applications such as water pumping, battery charging, and powering small electronic devices. To enhance the viability of wind energy deployment in Damaturu, the study recommends the use of low-startup-speed turbines and encourages further research into wind behavior at higher altitudes greater than 10 meters, as well as the integration of wind with complementary renewable sources to ensure a more dependable energy supply.

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