



WIND ENERGY ASSESSMENT IN AUCHI, NIGERIA USING WEIBULL DISTRIBUTION AND NASA DATA

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ARTICLE INFORMATION ABSTRACT

Submitted 10 January, 2024
Revised 18 February, 2024
Accepted 25 February, 2024

Keywords:

Wind energy potential
Weibull distribution
pdf
RMSE
Wind speed

The advancements in wind energy farms in the developed world have significantly reduced the cost of wind energy turbine systems, making them more competitive and contributing to a reduction in global warming, which has a widespread impact on the global population. This study evaluates the wind energy potential of Auchi, a community in Edo State, Nigeria, using the Weibull distribution function. Wind speed data from NASA spanning an 11-year period (2012-2022) at a height of 10 m is utilized, and statistical methods are employed to estimate the Weibull parameters (scale and shape), which are then used to calculate the wind power density and the probability density function which was validated using root mean square error (RMSE) and coefficient of determination R^2 . The results indicate that Auchi possesses favorable wind conditions for power generation, with an average wind speed of 6.07 m/s and an average power density of 153.64 W/m². Additionally, the study examines the influence of surface roughness and height on wind speed and power density, highlighting the potential for harnessing wind energy for electrification purposes in Auchi, thereby offering a solution to Nigeria's energy challenges.

1.0 Introduction

The increasing global demand for energy, along with concerns about climate change from fossil fuel emissions, necessitates a shift to sustainable power generation (Akdağ and Dinler, 2009). Wind energy, as a renewable and environmentally friendly source, stands out amidst this backdrop. Unlike fossil fuels, wind energy offers a perpetually renewable option for power generation (Mudasiru et al., 2018). Renewable energy sources (RES), including wind, geothermal, hydroelectric, and solar energy, present varied options with differing viability based on geographical context. Developing nations, particularly those with limited access to non-renewable resources, are significantly impacted by the global energy crisis, prompting the adoption of alternative energy sources (Mohammadi et al., 2016).

In Nigeria, unreliable electrical power supply has hindered socioeconomic progress and increased air pollution. Government efforts have seen limited success, necessitating an independent power supply (Amadi, 2018). Renewable technologies, like wind turbines (WT), offer a solution due to their independence from traditional sources and unlimited renewability (Khan et al., 2018).

Despite extensive global research on wind energy potential, studies specific to the Auchi community in southern Nigeria are lacking. This study aims to fill this gap by analyzing wind energy potential in Auchi, Edo State, Nigeria from 2012 to 2022, using Weibull distribution

functions. The objective is to assess its appropriateness for an independent wind turbine power supply system that is free of carbon emissions

2.0 Materials and Method

Statistical methods, particularly the Weibull distribution, were employed to assess wind energy potential at selected sites, aiming to estimate wind power. This approach, known for its precision and simplicity, surpasses alternative methods such as Gaussian, Beta, Gamma, Poisson, Rayleigh, Normal, and lognormal distributions (Amadi, 2018). The statistical analysis is based on wind data collected over 11 years (2012-2022) at a height of 10 m, obtained from the official website of the National Aeronautics and Space Administration (NASA).

2.1 Theory of Weibull and its Parameters for Wind Energy Assessment

To comprehensively assess the potential of wind power at a specific location, it is necessary to conduct a statistical analysis of the recorded data on wind speeds, depicting the frequency distribution influenced by factors like location, climate, terrain, and surface profiles (Mohammadi et al., 2016). Selecting a distribution function depends on data characteristics such as discreteness, symmetry, and skewness. For continuous data, the Weibull distribution is particularly suitable, excelling in modeling wind speed distribution, even with infrequent extreme values (Adedipe et al., 2018). The Weibull distribution relies on scale (c) and shape (k) parameters (Sedzro et al., 2022). According to IEC 61400-12, It is advisable to utilize the Weibull function with two parameters for accurately approximating recorded wind speed data. It adapts to the distribution shape by adjusting its parameters, offering reliable outcomes (Ma et al, 2022).

To account for wind's inherent unpredictability, statistical approaches based on probability distribution functions are critical for assessing wind energy potential at a specific height.

Equation (1) and (2) depict the Weibull probability density function (PDF), represented as $f(v)$, and the cumulative distribution function (CDF), denoted as $F(v)$ [1].

$$f(v) = \frac{k}{c} (v/c)^{k-1} \times \exp[-(v/c)^k] \quad (1)$$

$$F(v) = 1 - \exp[-(v/c)^k] \quad (2)$$

In (3), v corresponds to wind speed, k is a parameter without units, and c possesses the same dimensions as v . By assigning a value of 2 to k , the distribution function undergoes a transformation into the Rayleigh distribution function. The expressions for the values of k and c are given in equations (6) and (7), respectively.

$$v = \frac{v}{c} \quad (3)$$

The average monthly wind speed and the standard deviation (S.D) of the collected data, both expressed in m/s, were calculated from the wind data, also in m/s, using (4) and (5), respectively (Mudasiru et al, 2018).

$$V_{mean} = \frac{1}{n} \sum_{i=1}^n V_i \quad (4)$$

$$S.D = \left[\frac{1}{n-1} \sum_{i=1}^n (V_i - V_{mean})^2 \right]^{1/2} \quad (5)$$

In this context, n represents the number of observed monthly wind speed data points.

$$k = \left(\frac{S.D}{v} \right)^{-1.086}, \quad (1 \leq k \leq 10) \quad (6)$$

$$c = \frac{v}{\Gamma(1 + \frac{1}{k})} \quad (7)$$

where $\Gamma(x)$ is gamma function of expressed in (8).

$$\zeta(x) = \int_0^{\infty} t^{x-1} \exp(-t) dt \quad (8)$$

According to (1), the calculated mean wind speed, determined using the Weibull parameters, is approximated using (9), derived from (7).

$$v_a = c\zeta \left(1 + \frac{1}{k}\right) \quad (9)$$

In order to assess the effectiveness of the Weibull distribution model in estimating wind speeds concerning acquired meteorological data, it is common to analyze the root mean square error (RMSE), coefficient of determination (R^2), and relative error (RE) (Aziz et al., 2023). However, for our study, we will specifically focus on the RMSE and R^2 metrics, as described in equations (10) (Teimouriane et al., 2022) and (11) (Mohammadi et al., 2016).

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (y_i - x_j)^2\right]^{1/2} \quad (10)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - x_j)^2}{\sum_{i=1}^n (y_i - y_m)^2} \quad (11)$$

R^2 , also known as the coefficient of determination, is the statistic that assesses the goodness-of-fit of a regression model, indicating the portion of dependent variable variation explained by the independent variable(s) (Abou et al., 2023). It is a value that ranges from 0 to 1, with 0 indicating that the independent variable(s) have no explanatory power, and 1 indicating a perfect fit where the independent variable(s) can explain all of the variance in the dependent variable (Zambak et al., 2023). RMSE quantifies the average disparity between predicted and actual values in a dataset, making it a widely employed metric for evaluating the accuracy and suitability of regression models (Teimourian et al., 2022). Where y_m , represents the mean frequency, y_i , corresponds to the observed frequency, and x_j pertains to the estimated frequency of wind speed.

2.2. Site and Data Description

This study centers on Auchi, a community in Edo state, Nigeria, located at approximately 7.0669° N latitude and 6.2748° E longitude. Monthly wind speed data for energy assessment over 11 years (2012 to 2022) were obtained from NASA and measured at a height of 10 m.

2.3 Vertical wind speed profile modelling

Wind speed exhibits vertical variability, gradually increasing with altitude until reaching a maximum value at a specific height. Establishing the wind speed at the wind turbine's hub height is essential. This relationship is described by a power law, as shown in (12) (Adedipe et al., 2018).

$$V_2 = V_1 \times \left(\frac{H_2}{H_1}\right)^\alpha \quad (12)$$

In this context, the estimated wind speed V_2 at the desired practical height H_2 , is derived from the measured wind speed V_1 at a known height H_1 by accounting for the influence of surface roughness coefficient α on the wind profile. Its value varies with factors like height, time, season, terrain, wind speed, and temperature, calculated using (13) (Aljeddani et al., 2023).

$$\alpha = \frac{0.37 - 0.088 \ln V_1}{1 - 0.088 \ln \left(\frac{H_1}{10}\right)} \quad (13)$$

2.4 Wind power density prediction

Wind power potential at a site (14) is determined by analyzing the average wind speed V_{mean} swept by the rotor blades (Akdağ and Dinler, 2009).

$$P(v) = \frac{A \times \rho \times V_{mean}^3}{2} \quad (14)$$

Here, ρ (1.225 kg/m^3) denotes air density, considering variations with factors like air pressure, temperature and altitude. The rotor blade swept area A in m^2 . Wind power density, calculated using the formula in (15) with the Weibull PDF (Parvin et al., 2023), represents wind power per unit area.

$$P(v) = \frac{P(v)}{A} = \frac{\gamma \times c^3 \times \rho \left(\frac{v}{c}\right)^{\gamma-1}}{2} \quad (15)$$

The general sequence of stages in the assessment process for potential power evaluation is shown in Figure 1.

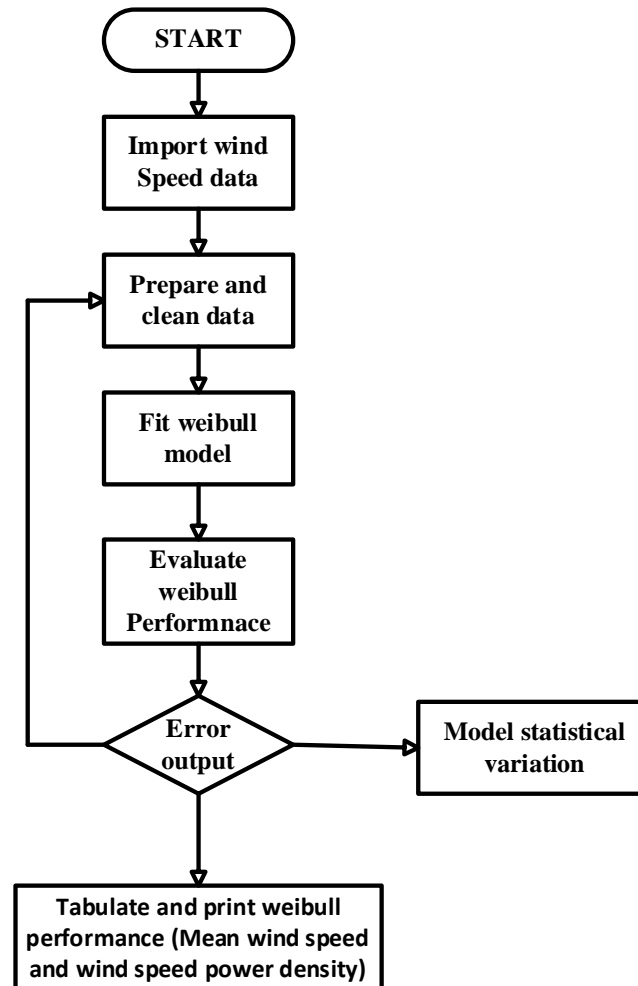


Figure 1: Methodology flow chart

3. Results and Discussion

In 2015, the highest average wind speed was recorded, while 2013 had a moderate mean speed. Notably, October and November showed the lowest mean speeds at 3.94 m/s and 4.62 m/s, respectively, which corresponds to the findings of (Ogbeide et al., 2018) while January, February, and December exhibited high mean speeds at 10.59 m/s, 9.45 m/s, and 8.04 m/s. The surface roughness coefficients obtained using (13) for each year are listed in Table 1.

Table 1. Surface Roughness Coefficient value

year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
α	0.212	0.208	0.218	0.203	0.209	0.216	0.210	0.217	0.207	0.217	0.213
V_{mean}	6.049	6.332	5.642	6.636	6.263	5.748	6.172	5.704	6.400	5.716	5.940

3.1 Parameters of the Weibull Distribution and Density Function

Table 2 presents the Weibull parameters c and k , power density (P), and the error measure RMSE and R^2 for wind speed data collected at 10 m for 11 years.

Table 2. Annual Performance Metrics for the Weibull Distribution

Year	(m/s)	K	c (m/s)	P(W)	R ²	RMSE
2012	6.049	8.5164	6.3490	149.3785	1.00000	0.251
2013	6.332	4.9512	6.8597	175.8379	1.00000	0.168
2014	5.642	9.1577	5.9634	124.3886	1.00000	0.258
2015	6.636	4.3593	7.2240	202.416	1.00000	0.164
2016	6.263	6.2782	6.7209	170.1381	0.99999	0.237
2017	5.748	10.4829	6.0298	131.5783	0.99991	0.252
2018	6.172	8.8483	6.5346	162.8481	1.00000	0.172
2019	5.704	4.7162	6.2051	128.5687	1.00000	0.496
2020	6.400	5.5440	6.9074	181.5927	1.00000	0.300
2021	5.716	7.6065	6.0688	129.3591	1.00000	0.184
2022	5.940	5.8440	6.4074	145.8137	1.00000	0.260

3.2 Wind Speed Variation

The data for the eleven-year period, showing the average monthly wind speed at a 10-meter height, indicates that October and November exhibited the lowest mean wind speeds throughout the given years, whereas December to March displayed the highest mean wind speeds on average. These fluctuations can be ascribed to the shifts between the Dry season and Harmattan season, along with the transition from the hot season to the Rainy season. During the intermediate periods, the mean wind speed remains relatively moderate. Figure 2 – 12 shows the mean monthly speed obtained from NASA.

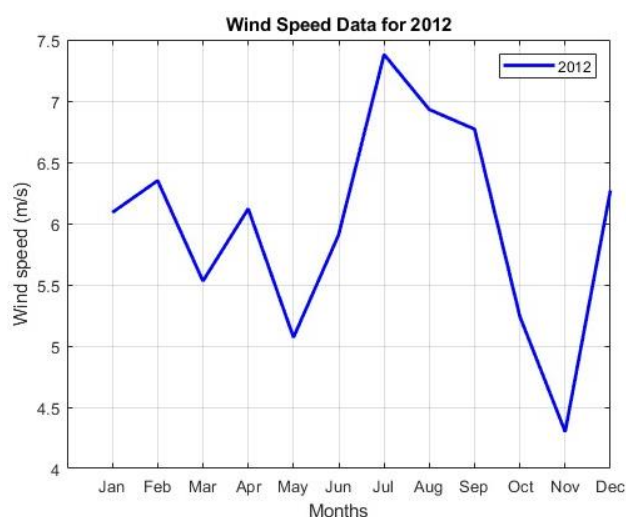


Figure 2: Wind speed data 2012

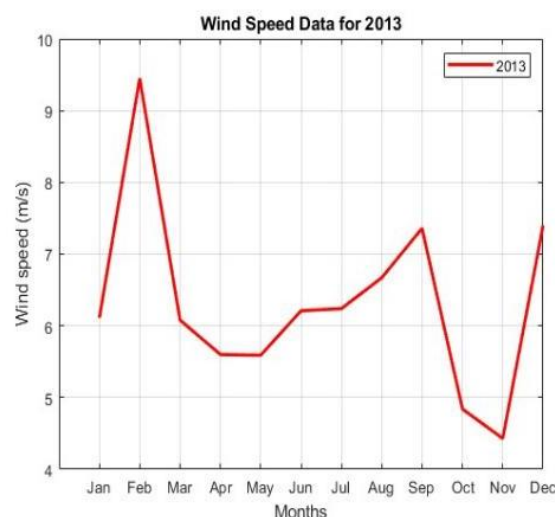


Figure 3: Wind speed data 2013

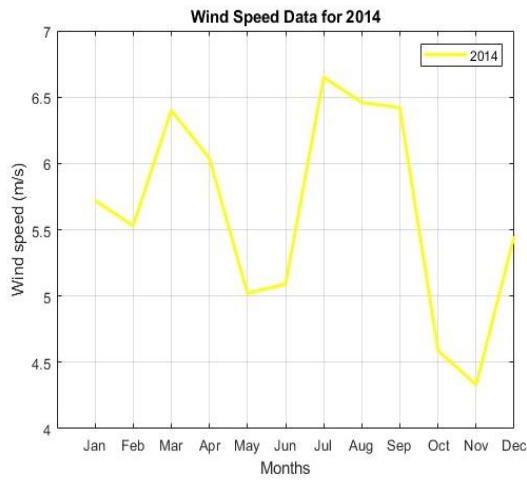


Figure 4: Wind speed data 2014

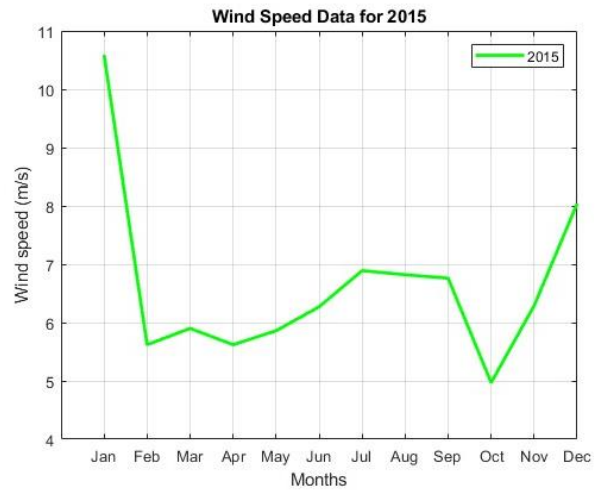


Figure 5: wind speed data 2015

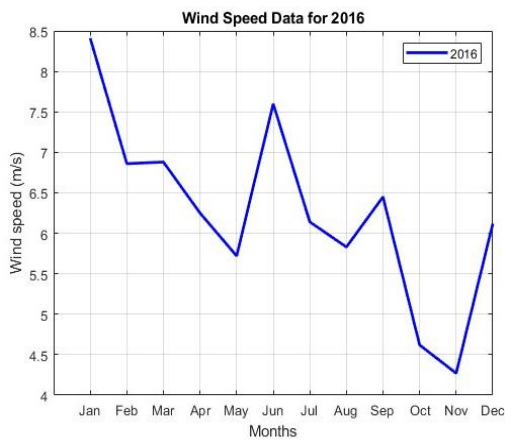


Figure 6: wind speed data 2016

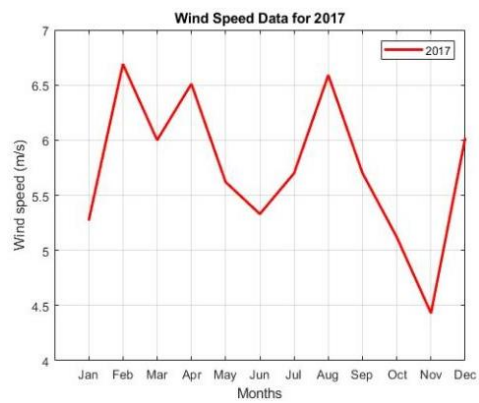


Figure 7: wind speed data 2017

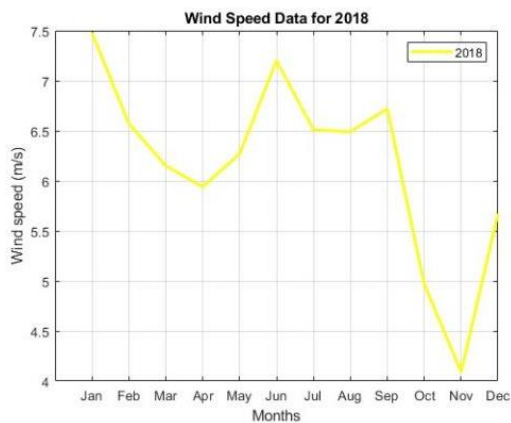


Figure 8: Wind speed data 2018

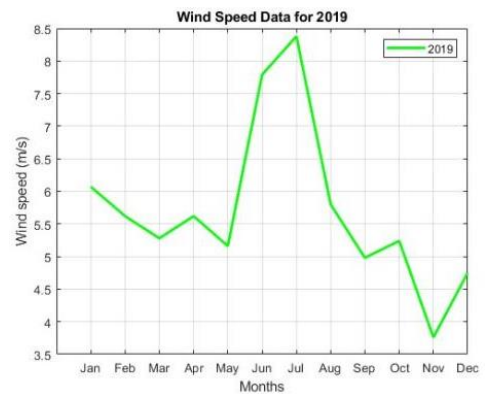


Figure 9: Wind speed data 2019

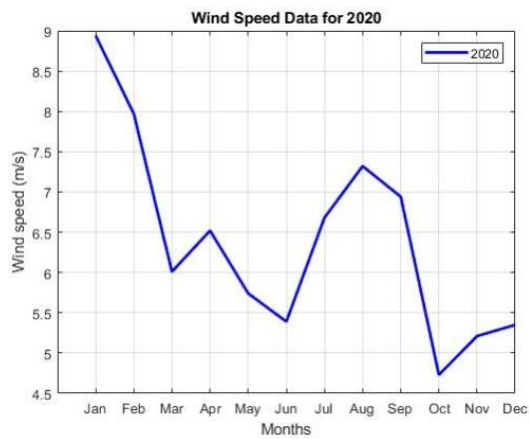


Figure 10: Wind speed data 2020

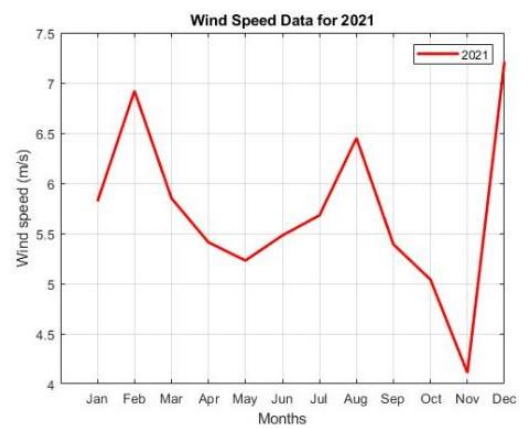


Figure 11: Wind speed data 2021

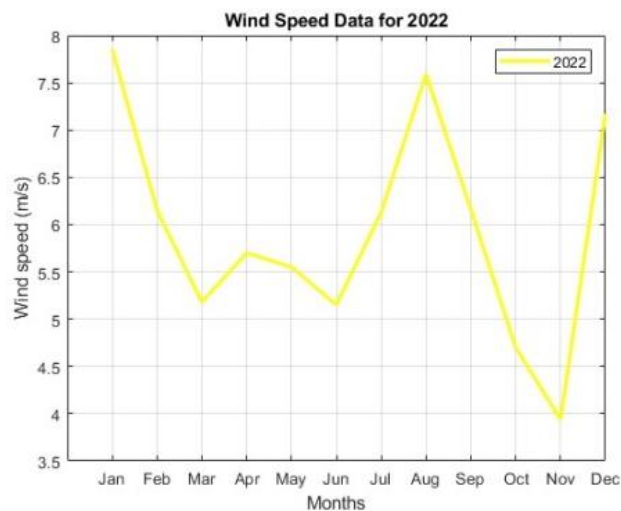


Figure 12: Wind speed data 2022

The Weibull scale parameter (c) ranges from 5.9634 m/s to 7.2240 m/s, c tends to be smaller than k for wind speed data, with k ranging from 4.9512 to 10.4829. The annual power density varies from 124.3886 W/m² to 181.5927 W/m², as illustrated in Figure 13 for each year.

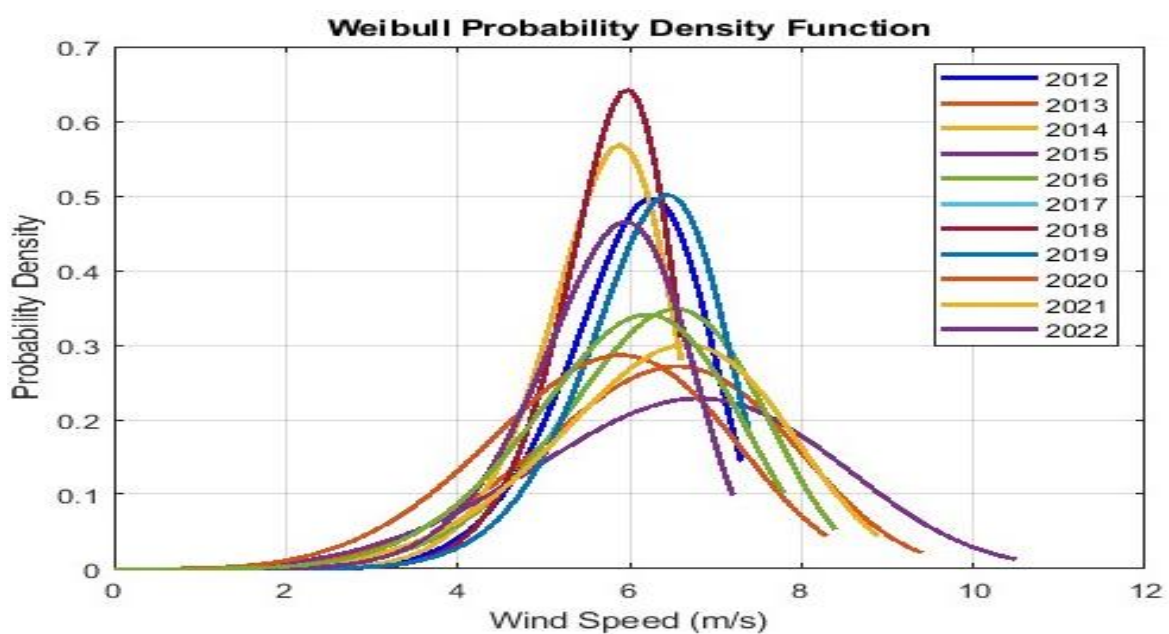


Figure 13: Annual Weibull probability density function

The highest peak wind speed was observed in 2018, which was closely followed by 2014, both exhibiting more focused distributions. In contrast, 2022 and 2020 show lower and broader distributions, indicating fewer instances of high wind speeds. Meanwhile, 2016 falls in between, signifying a transitional phase. The wind speed distribution in this study best fits within the 3 m/s to 7 m/s interval. Figure 14 illustrates the cumulative probability distribution of the Weibull function for wind speed data at a 10 m height from 2012 to 2022.

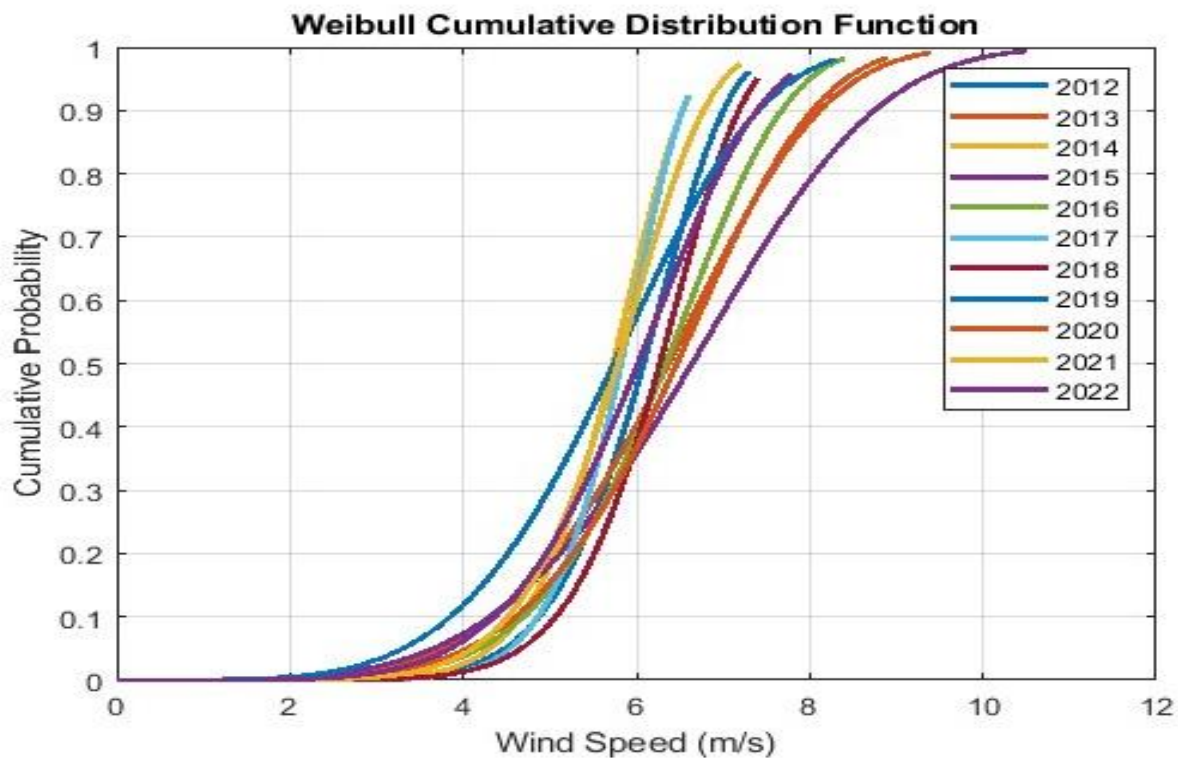


Figure 14: Annual Weibull wind speed probability distribution

By setting a wind speed threshold of 3.5 m/s, the frequency spans from 0% to 5%. Raising the threshold to 5 m/s expands the range to 10% to 30%. At 7 m/s, the frequency extends from 60% to 96%, and at 10 m/s, it sharply concentrates around 98%. Based on the cumulative probability, it is indicated that at a wind speed of approximately 3.5 m/s, there exists a potential to generate a substantial amount of wind energy, ranging from 10% to 30%, from the wind farm, varying by year. Moreover, an escalation in wind speed will result in an increase in the harvestable wind energy. This is in agreement with the findings of (Abdulkarim *et al.*, 2017) and (Gaddafi *et al.*, 2017).

3.3 Wind speed power density

Figure 15 depicts wind speed data over eleven years (2012 to 2022), highlighting variations in annual wind speed power density at both 10 m and 100 m height levels based on annual averages.

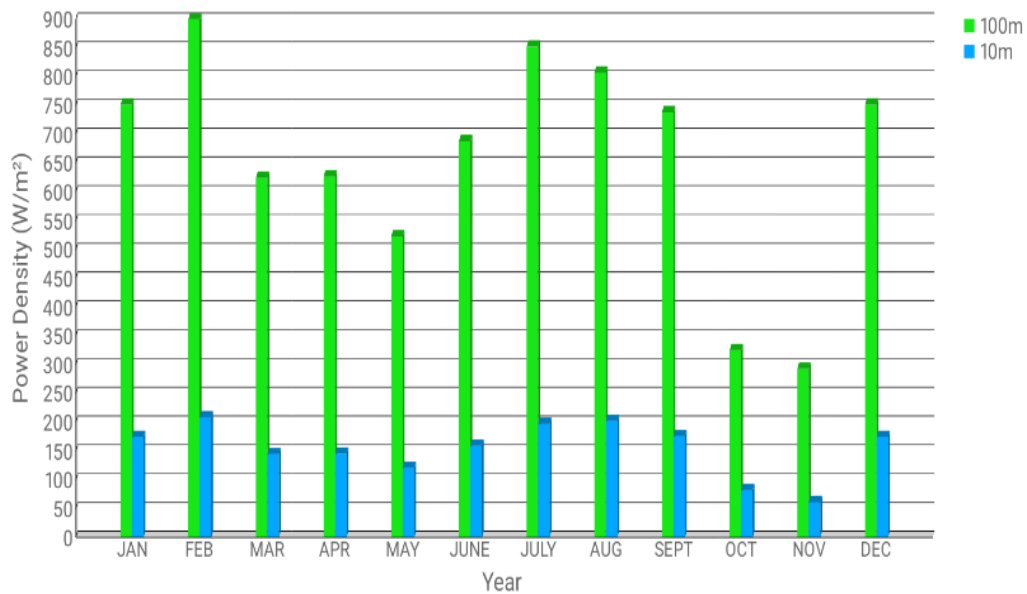


Figure 15: Annual wind speed power density

At 10 m and 100 m, November and May had the lowest power density (61.8324 W/m², 82.2259 W/m²) and (293.1663 W/m², 325.2405 W/m²), respectively. February and August recorded the highest power density at 10 m (208.5994 W/m², 202.6488 W/m²) and at 100 m (899.5688 W/m², 852.6808 W/m²) for February and July. Power density at 100 m is about four times higher than at 10 m, representing average monthly values.

4. Conclusion

The study assessed the wind energy potential in Auchi community in Edo State, utilizing the Weibull distribution function and NASA wind speed data from 2012 to 2022. Results indicate that Auchi experiences moderate and consistent wind speeds (ranging from 5.642 m/s to 6.636 m/s) that increase with altitude, indicating favorable conditions for wind energy generation and electrification. Additionally, the analysis explored the influence of seasonal fluctuations and surface roughness on wind speed distribution and power density. These findings augment the existing body of knowledge on wind energy assessment in Nigeria and offer valuable insights for prospective wind farm projects in the area. Nevertheless, further investigation is necessary to evaluate the economic viability and environmental ramifications of implementing wind turbines in Auchi, alongside determining optimal design and configuration for the wind energy system.

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