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Evaluation of Wind Energy Potential in Omu Aran, Nigeria Using Weibull and Rayleigh Models

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Abstract: The depletion of resources and emission of hazardous gases have been identified with conventional sources of energy. The negative influence of conventional sources of energy on the environment necessitates the call for the use of renewable and sustainable energy sources, such as wind. Wind power is one of the available renewable energy sources in Nigeria with huge potential that can be tapped in order to contribute to its energy mix. Wind energy utilization in Nigeria is poor because the available data in all six geopolitical political regions for system design have not been fully analyzed and implemented. Wind energy projects are liable to failure if proper analysis is not done. Therefore, before any location could be considered suitable or unsuitable for wind power generation, the power density must be determined using the standard approach. This study, therefore, evaluated the wind energy potential of Omu Aran, Nigeria using Weibull and Rayleigh models. Five-year data collected from the metrological station of the Landmark University on Lat. 8.14 °N; Long. 5.10 °E were processed and analyzed in Matlab computer software using a code developed for two statistical modeling methods (Weibull and Rayleigh). The actual mean yearly wind speed of 3.964 m/s for Kwara falls in the low wind speed. Although the power density for hours of the day, months, and seasonal variation ranged from 24 to 141 W/m^2, more than 50% of the power density for daily hours was less than 100 W/m^2 which indicated that Omu Aran, Nigeria belongs to class 1. The coefficient of efficiency for Weibull probability distribution ranged from 39.95 to 94.9, while the coefficient of determination (COD) R^2 ranged from 0.66 to 0.98. This range of performance values for the Weibull model, when compared to the Rayleigh model, was within the acceptable limits for prediction accuracy; hence, the Weibull probability distribution function can be used for the preliminary design of wind power plants for Kwara State, Nigeria. Therefore, it would help the relevant stakeholders in wind power project investment to make the appropriate decision.

Keywords: wind, energy, Weibull, Rayleigh, modeling, power density, Omu Aran

1. Introduction

For decades, fossil fuels in the form of coal, natural gas, crude oil, and renewable energy resources like solar, hydro, biomass, and wind energy have been the major source of primary energy in Nigeria (Fadare, 2008). However, due to the negative environmental impact of fossil fuel on the environment, its global usage as a source of primary energy or input resources to power plants is on the decline, Nigeria inclusive. For this reason, renewable energy sources have become the mainstream energy source, leading to worldwide attention (Dokur & Kurban, 2015).

Renewable energy is one of the core drivers of sustainable development. It is recognized as a fundamental element of economic growth that drives the nation's economy and technological progress. Nigeria's energy demand outmatches the energy supply, which has been a major setback for industrial and economic development (Falobi, 2019). To improve power supply, the Nigerian Government developed a long-term solution adopted through the Renewable Energy master plan (REMP) in 2005, which was revised in 2012 and targeted to increase on-grid renewable energy supply from 13% to 25% in 2025 and then 30% in 2025 (Falobi, 2019; Akorede et al., 2017). In the revised REMP, estimated potentials (percentage and Megawatt) for renewable energy resources for wind (onshore), wind (offshore), solar PV, geothermal, biomass, small, and large hydro and nuclear power are 1.7% (1600 MW), 0.85% (800 MW), 7.45% (7000 MW), 0.53% (500 MW), 0.05% (50 MW), 68.12% (64,000 MW), and 21.29% (20,000 MW), respectively. Out of the total 93,950 MW of renewable energy potential estimated, wind energy accounted for only 2.25% (The International Energy Agency, 2013). The current state of wind energy research in Nigeria, especially in rural communities, is inadequate, creating a significant research gap that needs to be filled. Reliable data on wind speed, direction, and variability in many parts of the country are sorely lacking, making it

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difficult to accurately assess the potential for wind energy production. In order to fully harness the wind energy potentials in Nigeria, understanding of the wind pattern of the border states between the geopolitical zones is also required. Omu Aran, Kwara State, in the North central part of Nigeria is located in the transition zone between the tropical and subtropical climate zones. Among the States in the Northern part of Nigeria, Kwara is the closest state to the south western part. This does not mean that they would have exactly the same meteorological variables such as wind speed, temperature, humidity, and rainfall. It should be noted that the South Western region of Nigeria is closer to the equator and characterized with a hot and humid climate, and a higher level of rainfall, while the Northern part has a hot and dry climate with lower rainfall and higher temperatures. Also, since the topography is a factor that can significantly affect the wind patterns (Tang et al., 2022). As a result, there is an urgent need for more research into the most appropriate models for predicting wind energy potential in Nigeria. The study aims to determine the most suitable wind energy model for the state and provide recommendations for the development of a sustainable wind energy system in the community.

The objective of this study is to assess the wind energy potential of Omu Aran, a rural community in Kwara State, Nigeria. This study aims to determine the most suitable wind energy model for the region and provide recommendations for the development of a sustainable wind energy system in the community.

2. Literature Review

Considerable efforts have been made on solar, hydro, and biomass, but wind energy utilization in Nigeria is minimal. For few implemented wind projects, most are ill-maintained or abandoned (The International Energy Agency, 2013). Also, Nigeria as a developing country is endowed with abundant wind energy, but practically wind utilization is minimal and relatively insignificant. Since wind power is needed to be integrated into the energy mix for economic purposes, all available resources must be put into consideration (Akpinar & Akpinar, 2004). According to the Akorede et al. (2017), wind power is one of the renewable energy technologies that has the lowest price since the cost per kilowatt-hour is between 4 and 6 cents. In addition to that, the construction time is less than any other technology.

Even at that, only a few of the government standalone wind power plants had been installed for over 50 years, mostly in the northern part of the country which is attributed to high wind speed in the northern geographical location at Sokoto, Jigawa, and Kano (Fadare, 2008; Dokur & Kurban, 2015; Falobi, 2019; Akorede et al., 2017). Ideally, wind energy is characterized by variability of wind speed and power generated at different sites. For this reason, it becomes imperative to evaluate and characterize the variability of wind energy at different sites (Akpinar & Akpinar, 2004; Fadare, 2008). The stochastic nature of wind energy prompted the need to develop methods for effective prediction of its properties. Statistical analysis has been widely adopted and accepted in modeling wind speed characteristics.

The statistical approximation has a better approximation than gamma and the square root normal distribution. Also, it was recommended because of its flexibility in determining model parameters. Among the various models, Weibull and Rayleigh probability distribution functions are the most widely used, based on their better way of describing and predicting wind speed distribution worldwide (Safari & Gasore, 2010). Studies on the assessment of wind speed characteristics for different locations around the world have been reported (Ahmed & Mahammed, 2012; Akinsanola et al., 2017; Argungu et al., 2013; Bertrand et al., 2020; Fadare, 2008; Kantar et al., 2016; Kidmo et al., 2015; Kidmo et al., 2016; Medugu & Jauro, 2002; Kumar et al., 2019; Osmanaj et al., 2018; Tizgui et al., 2017; El Khchine et al., 2019). In these studies, statistical models which include Rayleigh, Weibull distribution, linear and multiple regression models, artificial neural network, and seasonal auto-regression moving average have been adopted to model wind speed (Fadare, 2008).

Richard and Eseosa (2022) also evaluated wind energy utilization in six geopolitical zones, which include Gumel in Jigawa state, Maiduguri, Gamboru and Baga in Bornu State and Kumagunnam in Yobe State, Pankshin and Biu in Plateau State, Lagos State, Ihiala in Anambra State, and Buguma in Rivers State using RETScreen. Similarly, Saleh et al. (2022) investigated the wind speed data collected from the Anyigba region in Kogi State, Nigeria, to evaluate its potential for wind energy generation. The study utilizes statistical analysis methods such as the Weibull and Rayleigh models to determine the wind speed distribution and energy potential of the region.

In Nigeria, statistical analysis of wind energy potentials of Ibadan, Jos, Maiduguri, and Koluama using either Weibull or a combination of Weibull/Rayleigh distribution functions has been reported (Akinsanola et al., 2017; Argungu et al., 2013; Fadare, 2008; Medugu & Jauro, 2002). Nevertheless, none of the studies in the literature has neither considered Omu Aran, Kwara State, Nigeria for its wind data assessment nor modeled its data with Rayleigh and Weibull distribution. Hence, the main objective of this study is to evaluate the wind characteristics of the wind speed and its variation at Omu Aran, Nigeria using Rayleigh and Weibull distribution statistical models.

3. Research Methodology

3.1. Data measurement

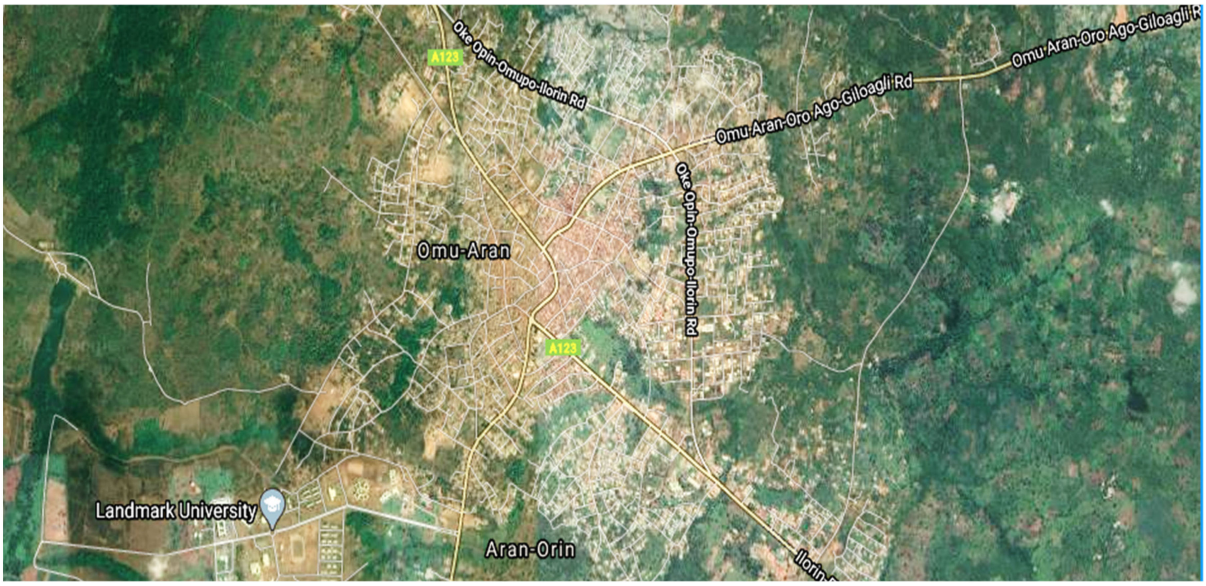
In this study, time series of measured hourly daily raw wind speed data for the period 2014–2018 (5 years) were collected at a height of 10 m by a cup generator anemometer on the Campbell meteorological station at Landmark University, Omu Aran, Nigeria on Lat. 8.14 °N; Long. 5.10 °E and transferred into Matlab computer software. The transferred data were processed using a developed Matlab code for Weibull and Rayleigh models. The results produced by the models were extracted into Excel 2013 version for analysis and creation of charts and tables. The continuously recorded wind speed (m/s) data within that period at a height of 10 m by a cup generator anemometer on a meteorological station at Landmark University, Omu Aran, Kwara State, Nigeria were averaged over 1 hour and stored as hourly data. Figure 1 shows the geographical location of Omu Aran. Figure 2 shows five directional wind rose diagrams plotted with WRPLOT View Version 7.0.0© 1998–2011 to represent frequencies of the direction of each wind speed for the years 2014, 2015, 2016, 2017, and 2018. Data were processed using Excel 2013 and a self-developed Matlab code.

3.2. Wind analysis theory

Three major statistical variables provide substantial information collected on the wind speed data. They are the average wind speed, variance, and standard deviation (El-Sharkawi, 2015). In this study, the wind average speed, variance, and standard deviation are calculated using equations (Dokur & Kurban, 2015; Fadare, 2008; Falobi, 2019).

$$U_{ave} = \frac{1}{n} \sum_{i=1}^{\infty} n_i \; u_i \tag{1}$$

Figure 1
Geographical location of Landmark University meteorological station, Omu Aran



$$Var = \frac{1}{N}\sum_{i=1}^{\infty} n_i\,(u_i - u_{ave})^2 \qquad (2)$$

$$\sigma = \sqrt{Var} = \sqrt{\frac{1}{N}\sum_{i=1}^{\infty} n_i(u_i - u_{ave})^2} \qquad (3)$$

where U_{ave} is the average wind speed in m/s, Var is the variance, σ is the standard deviation, N is the total number of observations in consideration, and Vi is the recorded wind speed value in m/s.

3.3. Frequency of wind speed distribution

Functions representing wind speed probability and distribution are essential elements used in wind speed analysis literature. They have wide applications ranging from statistical methods used in identifying statistical parameters of the distribution functions to wind speed analysis and energy economics (Dokur & Kurban, 2015). Statistical analysis of wind speed, its characteristics, and energy potential is based on Weibull and Rayleigh approximations (Dokur & Kurban, 2015; Fadare, 2008).

In the recent studies, Ahmed and Kunya (2019), Bertrand et al. (2020), and Gul et al. (2020) recommended Rayleigh and Weibull distribution for fitting the probability of measured wind speed in a given location over some time.

3.4. Computation of Weibull and Rayleigh parameters

To use Weibull distribution in the statistical modeling of wind data, it has two parameters: scale parameter (c) and shape parameter (k). c parameter adjusts the shape of the function while the k parameter adjusts the peak of the function.

3.4.1. Computation of Weibull statistical parameters

The probability density function for Weibull distribution is given as (Akpinar & Akpinar, 2004; Bertrand et al., 2020; Bidaou et al., 2019; Fadare, 2008; Safari & Gasore, 2010)

$$f_w(u) = \left(\frac{k}{c}\right)\left(\frac{u}{c}\right)^{k-1}\exp\left[-\left(\frac{u}{c}\right)^k\right] \qquad (4)$$

where fw(u) is the probability of observing wind speed u. The corresponding cumulative probability function of observed wind speed u is given by Equation (5) (Akpinar & Akpinar, 2004; Bertrand et al., 2020; Bidaou et al., 2019; Fadare, 2008; Safari & Gasore, 2010)

$$F_W(u) = 1 - \exp\left[-\left(\frac{u}{c}\right)^k\right] \qquad (5)$$

To evaluate the shape k and scale c parameters in the Weibull distribution function, it is important to have a good fit for Equation (5) to the recorded discrete cumulative frequency distribution (Fadare, 2008). Linearizing Equation (5) by taking its double logarithm gives Equation (6), which results in:

$$\ln(-ln[1 - F_W(u)]) = k\ln(u) - k\ln c \qquad (6)$$

The plot of Equation (6) against $\ln v$ gives a straight line where the gradient of the line is k and the intercept is $-k\ln c$. Analytically, the Weibull scale and shape parameter are calculated using Equations (7) and (8), respectively (Ahmed & Kunya, 2019)

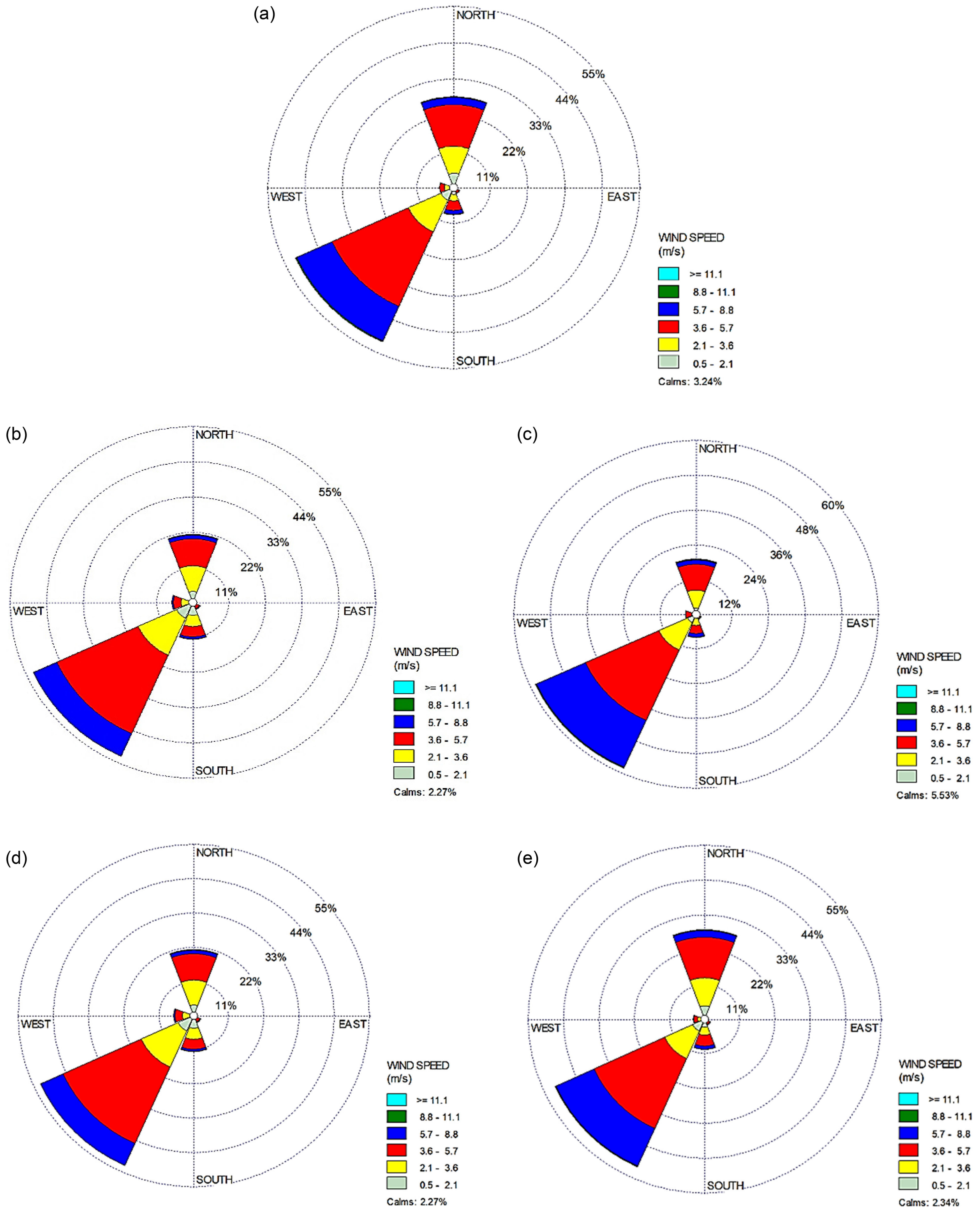
$$c = \left(\frac{k^{2.6674}}{0.184 + 0.816^{\,2*2.73859}}\right) \qquad (7)$$

$$k = \left[\frac{\sigma}{u}\right]^{-1.090} \qquad (8)$$

3.4.2. Computation of Rayleigh statistical parameters

A special case of Weibull distribution where the shape parameters are fixed at 2 is Rayleigh distribution (Dokur & Kurban, 2015; Fadare, 2008; Falobi, 2019). It is simpler than Weibull in determining velocity probability distribution because it only requires the knowledge of the wind mean speed u_{ave} (m/s). For the Rayleigh model, the probability density function and cumulative distribution functions are shown in Equations (9) and (10).

Figure 2
Wind rose diagram for Omu Aran, Kwara State, Nigeria (a) 2014, (b) 2015, (c) 2016, (d) 2017, and (e) 2018



$$f_R(u) = \left(\frac{\pi}{2}\right)\left(\frac{u}{u_m^2}\right)\exp\left[-\left(\frac{\pi}{4}\right)\left(\frac{u}{u_m^2}\right)^k\right] \quad (9)$$

$$F_R(u) = 1 - \exp\left[-\left(\frac{\pi}{4}\right)\left(\frac{u}{u_m}\right)^k\right], u \le u_{ave} \quad (10)$$

The two significant parameters k and c are closely related to the mean of wind speed u_{ave} (m/s)

$$u_{ave} = c\,\Gamma\left(1 + \frac{1}{k}\right) \quad (11)$$

where Γ (standard formula) is the gamma function for $\left(1 + \frac{1}{k}\right)$(Dokur & Kurban, 2015; Akpinar & Akpinar, 2004; Bertrand et al., 2020; Ayodele et al., 2012).

3.5. Wind power density

Wind power density is the most important for wind characteristics and its assessment is essential for the wind power project. It depends on the air density, cube of wind speed, and wind speed distribution, and it is then considered as a better indicator of wind resources than wind speed (Akpinar & Akpinar, 2004).

The available power in the wind that is flowing at a mean speed of u_{ave} in (m/s) through a wind rotor blade of swept area A in (m^2) at any given site is expressed by Equation (12) (Ahmed & Kunya, 2019; Akpinar & Akpinar, 2004; Bidaou et al., 2019; Bertrand et al., 2020; Dokur & Kurban, 2015; Fadare, 2008; Safari & Gasore, 2010)

$$P(u) = \left(\frac{1}{2}\right)\rho A u_{ave}^3 \quad (12)$$

The power density which is defined as the wind power per unit area based on the Weibull probability distribution function can be expressed by Equation (13) (Akpinar & Akpinar, 2004; Fadare, 2008).

$$P_W(u) = \left(\frac{(P_u)}{A}\right) = \frac{1}{2}\rho c^3\left(1 + \frac{3}{k}\right) \quad (13)$$

where $P(u)$ is the wind power in (W) and ρ is the air density of the site or location in consideration (kg/m^3). While setting k equals 2, the power density for Rayleigh density function is expressed by Equation (14) (Ahmed & Mahammed, 2012; Akpinar & Akpinar, 2004; Almetwally & Almongy, 2019; Ayodele et al., 2012; Corke & Nelson, 2018; Fadare, 2008).

$$P_R = \frac{3}{\pi}\rho u_{ave}^3 \quad (14)$$

3.6. Prediction performance of Weibull and Rayleigh distribution

To know the accuracy of the model used in estimating wind speed parameters and their corresponding power density which are related to the actual values, coefficient of determination (COD) (R^2), root mean square error (RMSE), and coefficient of efficiency (COE) of the models are evaluated using Equations (15), (16), and (17), respectively (Fadare, 2008).

Table 1
Monthly average wind speed and standard deviations in Omu Aran, Kwara State, Nigeria from 2014 to 2018

Month	Parameters	2014	2015	2016	2017	2018	Whole year
January	V_{mean}	0.000	3.387	3.029	3.163	3.163	3.039
	Std	0.000	1.579	1.602	1.657	1.510	1.614
February	V_{mean}	0.000	4.167	3.425	3.224	4.240	3.761
	Std	0.000	1.700	1.711	1.518	1.962	1.785
March	V_{mean}	0.000	4.426	5.332	5.178	5.394	5.082
	Std	0.000	1.780	1.788	1.836	1.669	1.825
April	V_{mean}	0.000	4.384	5.102	5.483	5.487	5.114
	Std	0.000	1.754	1.836	1.669	1.517	1.756
May	V_{mean}	0.000	4.663	4.802	4.475	4.848	4.697
	Std	0.000	1.774	1.579	1.976	1.939	1.829
June	V_{mean}	4.752	4.752	4.353	3.874	4.552	4.697
	Std	1.631	1.428	1.510	1.726	1.696	1.829
July	V_{mean}	4.413	4.413	4.542	4.587	4.402	4.370
	Std	1.371	1.753	1.463	1.373	1.555	1.628
August	V_{mean}	4.333	4.333	4.468	4.398	4.521	4.473
	Std	1.575	1.249	1.616	1.624	1.554	1.533
September	V_{mean}	3.989	3.989	3.783	3.704	3.158	3.682
	Std	1.537	1.497	1.458	1.795	1.754	1.637
October	V_{mean}	3.517	3.517	3.116	2.915	2.882	1.650
	Std	1.490	1.603	1.609	1.670	1.789	3.134
November	V_{mean}	3.242	3.242	3.115	3.160	2.283	3.020
	Std	1.660	1.268	1.756	1.626	1.805	1.635
December	V_{mean}	3.107	3.107	2.791	2.850	0.000	2.827
	Std	1.459	1.693	1.602	1.689	0.000	1.624
Yearly	Vmean	3.908	4.059	4.074	4.038	3.878	3.964
	Std	1.532	1.577	1.618	1.683	1.573	1.820

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y_i - z)^2 - \sum_{i=1}^{N}(X_i - z)^2}{\sum_{i=1}^{N}(y_i - z)^2}\right] \tag{15}$$

$$\text{RMSE} = \sqrt{\left[\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2\right]} \tag{16}$$

$$\text{COE} = \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(y_i - z_i)^2} \tag{17}$$

y_i is the Ith actual data, x_i is the Ith predicted data for Weibull distribution, z_i is the equal mean of actual data, and N is the equal number of observations.

4. Result and Discussion

Figure 2 shows the wind rose charts indicating the wind direction of the site. It can be seen in all the roses that the wind flows toward the North and Southwest but dominantly in the Southwest throughout the years for the site under consideration. Similar patterns were observed by Bidaou et al. (2019). The highest direction of wind flow which occurred in the year 2016 originated at 40° South and West direction (clockwise) with 55 and 12% of occurrence. Also, the highest wind speed in all the roses ranged from 5.7 to 8.8 m/s. Table 1 presents the average monthly wind speed for the period under consideration (2014–2018) The highest monthly wind speed occurred in April (5.114 m/s), March (5.082 m/s), and May (4.697 m/s), while the lowest monthly wind speed occurred in October (1.650 m/s), December (2.827 m/s), and November (3.020 m/s). Fadare et al. (2018) reported similar months, but the average wind speed values presented here are slightly higher. This could be due to the geographical location and topography of the site (Omu Aran). Also, Figure 3 shows the yearly variation of average wind speed between 2014 and 2018 and the whole year. It is glaring that the highest wind speed of 4.074 occurred in the year 2016, while the minimum wind speed of 3.878 occurred in the year 2018.

Figure 3
Yearly average wind speed in Omu Aran, Kwara State, Nigeria from 2014 to 2018

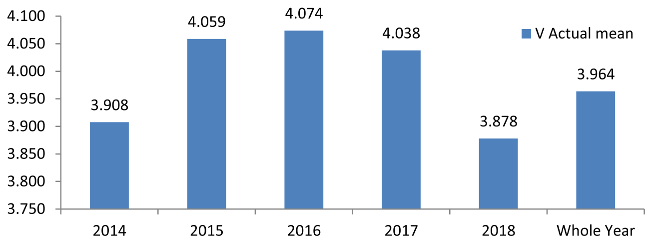


Figure 4
Monthly probability density function as a function of wind speed

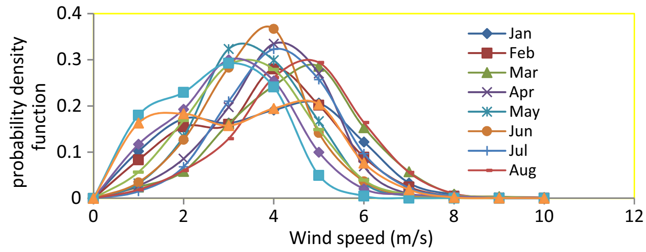


Figure 5
Cumulative density function against wind speed

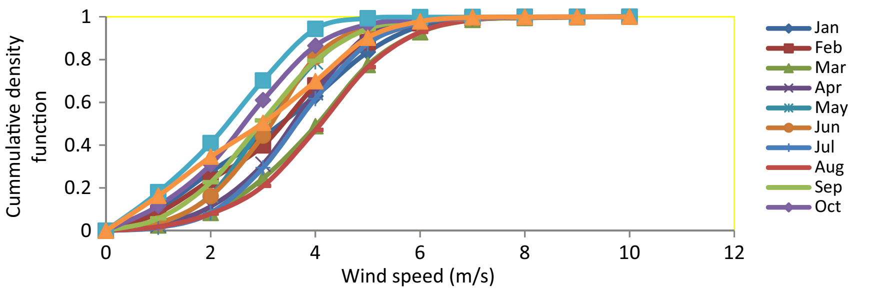


Figure 6
Probability density function for seasonal variation as a function of wind speed

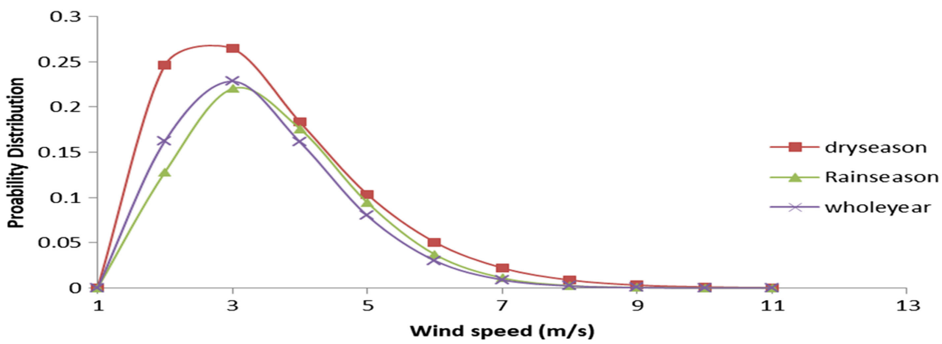


Figure 7
Comparison of monthly actual values to Weibull and Rayleigh models

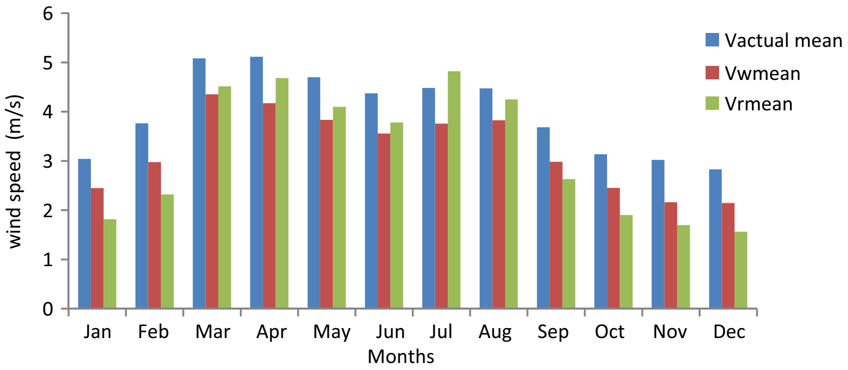


Figure 8
Coefficient of determination for Weibull and Rayleigh models against actual monthly wind speed

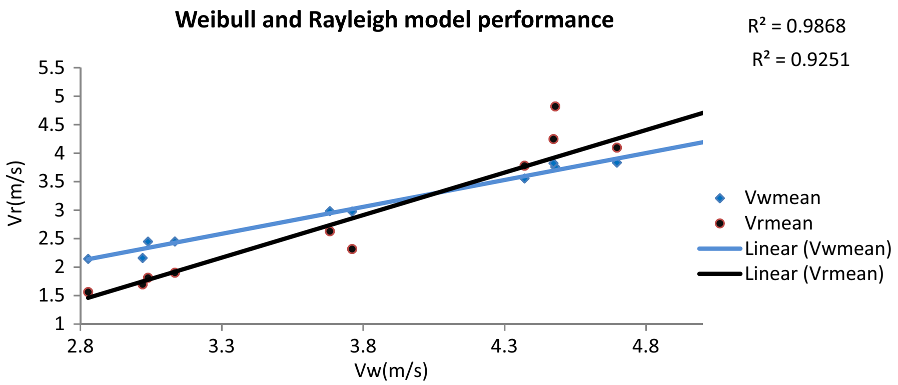
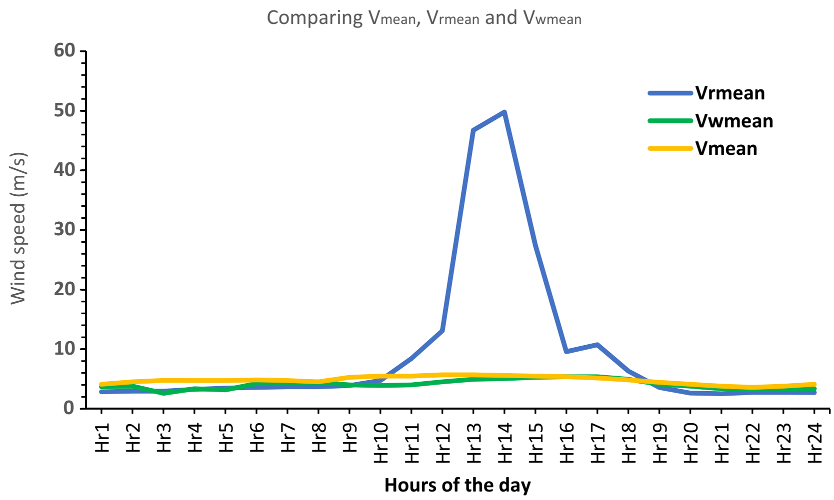


Figure 9
Comparison of hours of the day's actual values to Weibull and Rayleigh models

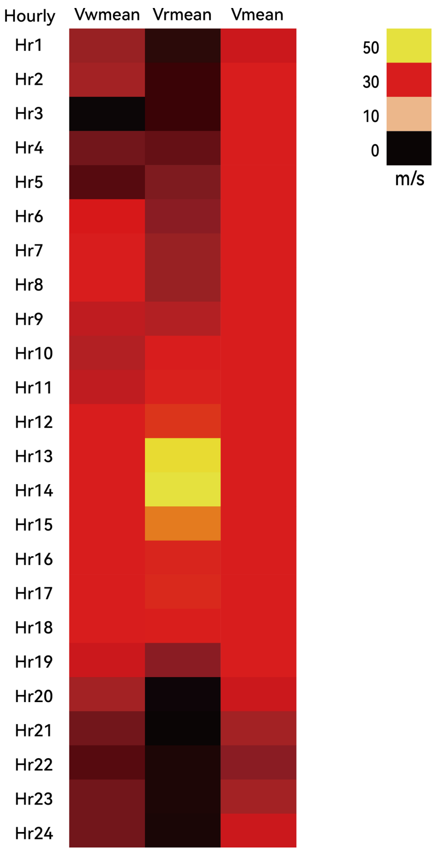


However, the overall average yearly wind speed for the whole year in Omu Aran, Nigeria was found to be 3.964 m/s.

To compare the behavior and performance of Rayleigh and Weibull distribution in predicting monthly and seasonal variation wind speed, Figures 4, 5, and 6 are the key elements required. Figures 4 and 5 show the probability density distribution and cumulative distribution of the average wind speed for all the months while Figure 6 depicts the probability density function for seasonal variation. As indicated in Figure 3, the maximum probability density function of 0.3671 at a wind speed of 4 m/s occurred in June. In general, from the three figures, it can be seen that all the curves exhibit a similar wind speed pattern. Curves of similar wind speed patterns have been reported (Akpinar & Akpinar, 2004; Ayodele et al., 2012; Fadare, 2008).

Figures 7 and 8 compare the predicted monthly and hour of the day values for Weibull and Rayleigh models with the actual wind

Figure 10
Heatmap comparison of hours of the day's actual values to Weibull and Rayleigh models



speed values. Comparing the observed monthly wind speed data with Weibull and Rayleigh models for the investigated site as shown in Figure 7, it can be seen that Weibull and Rayleigh had a COD of 0.98 and 0.92, respectively. Although they both performed well in modeling the monthly wind speed data for the site considered in this project, Weibull performed better than Rayleigh. The relationship between the actual data, Weibull and Rayleigh models showed that Weibull provides a better fit of the observed wind speed monthly data. In addition to that, it explains more than 98% of the values of the variability of the actual data points.

Considering Figure 9, it is obvious that Rayleigh was able to model the hourly data well from the first 10 hours of the day (hour 1 to hour 10) and also at the last 4 hours of the day (hour 20 to hour 24). However, the model performed woefully for about 8 hours during the day ranging between 10 AM to 8 PM. Hence, Rayleigh was not reliable for one-third hours of the whole day (8 hours). This model was unable to handle the daily unique characteristics of wind speed in Omu Aran. Nonetheless, Weibull model maintained high accuracy and reliability of prediction as shown in Figure 8 while also maintaining a good accuracy for the hourly model throughout the day. The implication is that, in Figure 10, the visible part of the heat map clearly shows that Rayleigh deviated widely from 12:00 to 18:00 from the actual data. Fadare (2008), and Dokur and Kurban (2015) also carried out the month-to-month comparison of Weibull and Rayleigh distribution of different locations and they reported that the Weibull model indicated a better fit of the observed data than Rayleigh. In this study, Weibull performed better than Rayleigh in predicting hourly and monthly wind speed. This result is in tandem with what was reported by Fadare (2008), Dokur and Kurban (2015), and Bertrand et al. (2020).

Table 2
Hourly power density prediction

Hours	K		C		Model performance parameter						Model prediction	
	Kw	Kr	Cw	Cr	Rsquare W	Rsquare R	RMSE W	RMSE R	COE W	COE R	Pw density (W/m^2)	Pr density (W/m^2)
Hour 1	1.11	2	2.99	1.84	0.82	0.67	0.05	0.12	0.42	−2.41	60	9.4
Hour 2	1.16	2	3.17	1.96	0.74	0.49	0.05	0.12	0.36	−2.31	69	11.3
Hour 3	1.36	2	3.21	2.21	0.72	0.47	0.07	0.11	0.4	−0.87	64.2	16.2
Hour 4	1.38	2	3.73	2.49	0.65	0.41	0.06	0.11	0.31	−1.78	99.6	23.3
Hour 5	1.52	2	3.73	2.71	0.7	0.49	0.06	0.1	0.42	−0.8	93.7	30.2
Hour 6	1.49	2	3.87	2.75	0.66	0.45	0.06	0.1	0.38	−1.09	105.5	31.4
Hour 7	1.69	2	3.26	2.72	0.74	0.6	0.07	0.1	0.49	0.11	58.2	30.4
Hour 8	1.68	2	3.24	2.68	0.73	0.58	0.08	0.1	0.48	0.11	57.1	29.2
Hour 9	1.68	2	3.52	2.87	0.07	0.57	0.09	0.48	0.48	−0.03	73.4	35.9
Hour 10	1.88	2	4.11	3.77	0.77	0.71	0.06	0.07	0.58	0.47	109	81.2
Hour 11	2.6	2	4.77	7.63	0.94	0.71	0.03	0.07	0.87	0.32	141.9	672.6
Hour 12	3.22	2	4.74	12.27	0.96	0.05	0.03	0.12	0.9	−0.21	124.7	2796
Hour 13	4.3	2	4.89	30.25	0.98	−0.39	0.02	0.14	0.95	−0.72	119.8	41876.5
Hour 14	4.82	2	4.93	46.81	0.97	−0.38	0.05	0.14	0.73	−1.01	117.6	155126.6
Hour 15	4.88	2	4.97	50.17	0.97	−0.45	0.04	0.14	0.84	−0.84	119.9	190946.1
Hour 16	4.07	2	4.96	26.01	0.98	−0.54	0.03	0.16	0.95	−0.47	128.3	26615.6
Hour 17	2.81	2	4.77	9.01	0.93	0.47	0.08	0.14	0.7	0.07	135.6	1105.2
Hour 18	2.96	2	4.72	9.93	0.15	0.2	0.07	0.15	0.76	−0.02	127.8	1479.7
Hour 19	2.4	2	4.08	5.42	0.94	0.87	0.06	0.09	0.76	0.52	92.7	240.6
Hour 20	1.7	2	3.25	2.73	0.89	0.86	0.06	0.07	0.73	0.7	57.5	30.8
Hour 21	1.33	2	2.6	1.88	0.83	0.83	0.06	0.08	0.66	0.36	34.5	10.1
Hour 22	1.24	2	2.34	1.69	0.84	0.78	0.06	0.1	0.66	0.19	26.5	7.3
Hour 23	1.3	2	2.45	1.79	0.86	0.78	0.06	0.09	0.66	0.04	29.6	8.7
Hour 24	1.21	2	2.47	1.73	0.87	0.73	0.05	0.1	0.66	−0.19	31.9	7.9

Table 3
Monthly power density prediction

	K		C		Model performance parameter						Model prediction	
					Rsquare		RMSE W		COE			
Months	Kw	Kr	Cw	Cr	Rsquare W	Rsquare R	RMSE W	RMSE R	COE W	COE R	Pw density (W/m^2)	Pr density (W/m^2)
Jan	1.4431	2	2.6981	2.0466	0.7239	0.5634	0.0682	0.1198	0.2488	−1.3182	36.58636	12.96565
Feb	1.6021	2	3.3198	2.6148	0.6838	0.4988	0.0709	0.1055	0.4047	−0.3176	63.58542	27.04026
Mar	2.0458	2	4.911	5.0931	0.7747	0.7962	0.0677	0.0668	0.5335	0.5455	176.7389	199.8214
Apr	2.1476	2	4.7105	5.2811	0.7453	0.813	0.086	0.0837	0.4616	0.4902	151.5681	222.7761
May	2.09	2	4.3277	4.6225	0.8358	0.8671	0.0781	0.0772	0.5709	0.5802	119.4258	149.3916
Jun	2.0875	2	4.0135	4.2652	0.7819	0.8151	0.0843	0.0824	0.5372	0.5589	95.32419	117.3582
Jul	2.3448	2	4.2395	5.4381	0.8442	0.9062	0.065	0.0722	0.6739	0.5974	105.0812	243.2411
Aug	2.1432	2	4.3162	4.7925	0.7788	0.8299	0.0654	0.0634	0.596	0.621	116.743	166.4875
Sep	1.7977	2	3.353	2.9668	0.808	0.7359	0.0662	0.0786	0.6259	0.4727	60.8656	39.49664
Oct	1.5258	2	2.719	2.1449	0.7482	0.5982	0.075	0.1097	0.5162	−0.0369	36.07287	14.92508
Nov	1.4901	2	2.3912	1.9146	0.7354	0.5817	0.0842	0.118	0.4606	−0.0598	24.92549	10.61523
Dec	1.3363	2	2.3345	1.7621	0.7407	0.5699	0.0749	0.131	0.2033	−1.4356	24.9777	8.275363

Figure 11
Comparison between Weibull and Rayleigh's monthly performance

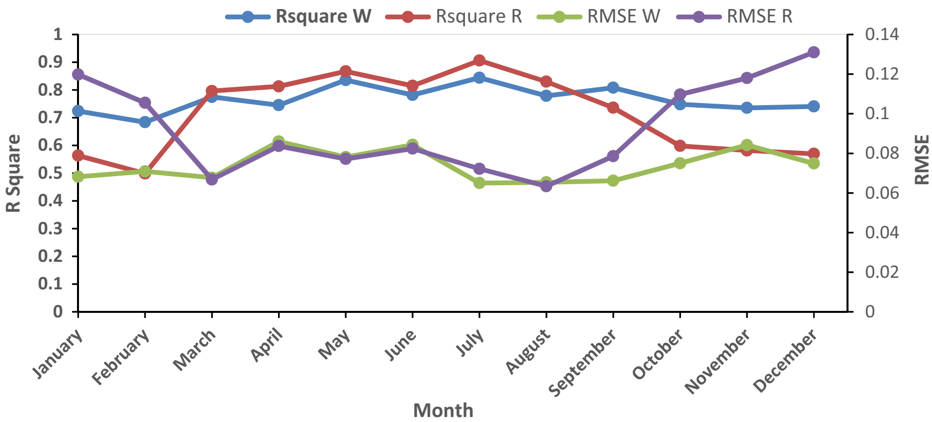


Table 4
Days of the week power density prediction

	K		C		Model performance parameter						Model prediction	
					Rsquare		RMSE		COE			
Days of the week	Kw	Kr	Cw	Cr	Rsquare W	Rsquare R	RMSE W	RMSE R	COE W	COE R	Pw density (W/m^2)	Pr density (W/m^2)
Mon	3.51	2	4.04	11.62	0.85	0.12	0.11	0.07	4.87	−1.28	73.86	2374.13
Tue	3.7	2	4.15	13.93	0.9	−0.2	0.1	0.09	2.34	−1.3	78.06	4092.14
Wed	3.77	2	3.75	14.65	0.95	−0.6	0.07	0.11	0.27	−0.73	57.37	4760.21
Thu	3.79	2	4.06	14.25	0.96	−0.06	0.08	0.1	0.22	−0.81	72.4	4379.49
Fri	3.55	2	4.06	12	0.98	−0.47	0.11	0.07	4.13	−1.4	74.55	2612.95
Sat	3.91	2	4.03	15.25	0.89	−0.19	0.13	0.09	5.45	−2.02	70	5362.51
Sun	3.77	2	4.08	14.15	0.86	−0.17	0.12	0.08	4.54	−1.67	73.65	4287.14

Tables 2 and 3 present the predicted hourly and monthly for the models, respectively. The negative COE values in Tables 2 and 3 for the Rayleigh model showed high level of inconsistency and therefore considered not reliable, while the obtained hourly and monthly COE values for the Weibull model ranged from 30% to 95%, and 20.33% to 67.3%, respectively. The consistency level in this case made Weibull model to provide better prediction than Rayleigh model. The COE for hourly wind speed modeling in Figure 2 shows the COE for Rayleigh distribution ranges from −0.02 to 0.52 and 0.31 to 0.95 for Weibull distribution. In addition to that, the COE values for most of the

Table 5
Seasonal variation power density prediction

	K		Cw		Model performance parameter						Model prediction	
					Square		RMSE		COE			
Season	Kw	Kr	Cw	Cr	Rsquare W	Rsquare R	RMSE W	RMSE R	COE W	COE R	Pw density (W/m^2)	Pr density (W/m^2)
Rainy season	1.829	2	3.6739	3.274	0.7634	0.681	0.0854	0.0944	0.4953	0.38	79.37	53.08
Dry Season	1.4602	2	2.6429	2.0332	0.7251	0.5494	0.0734	0.1166	0.4044	−0.5	34.11	12.71

hourly data from hour 11 to hour 18 are negative which returns outrageous values for Pr density (W/m^2). For this reason, it is safe to conclude that the Rayleigh power density (W/m^2) for most of the daily hours is unreasonable. Comparison of the R^2 and RMSE graphical pattern in Figure 11 further revealed the level of the superiority of Weibull model over the Rayleigh. With 33% of daily hours modeled wrongly, monthly power projection which is a cumulative of daily power projected has tendency for high error margin which might impact the applicability and integration of wind power system into renewable energy mix for Omu Aran. His results showed consistency with Weibull model. In Table 3, the predicted power density (W/m^2) values for March, April, May, June, July, and August are 176.73, 151.56,119.42, 95.32, 105.08, and 116.74, respectively. The high values predicted for the monthly wind analysis by Weibull fall mostly in the rainy season.

The same trend of COE values is observed in Table 4 where all values of COE are negative. Considering days of the week analysis, the Weibull model predicted that more power is generated on Tuesday than every other day. In this modeling, the values of the R^2, RMSE, and COE range from 0.845 to 0.977, 0.07 to 0.12, and 4.45 to 0.28, respectively.

Table 4 shows the model's wind power density prediction for the hours of the day. The power density predicted for the hours of the day ranges from 57.36 W/m^2 to 78.05 W/m^2 for Weibull only. The wind power density is predicted to fall into a class I considering their ranges (Wind Energy Resources, 2005). Similarly, Ahmed and Kunya (2019) in their study reported Bauchi with a wind power density of less than 100 W/m^2 to be class I.

Table 5 shows the model's wind power density prediction for the seasonal variation (rainy and dry season). The power density predicted for the rainy season and dry season was 79.3 W/m^2 and 34.1 W/m^2, respectively, that is, more power is generated during the rainy season than in the dry season. This result is coherent with Table 3 discussion since most of the high values predicted by the Weibull distribution fall in the rainy season. It is interesting to know that the power density of the wind speed during the rainy season doubled that of the dry season. Comparing the performance efficiency of Weibull and Rayleigh, the values of R^2, RMSE, and COE for Rayleigh are (0.681, 0.094, and 0.38) and (0.5494, 0.1166, and -0.5) for the rainy season and dry season, respectively, while the values of R^2, RMSE, and COE for Weibull model are (0.7634, 0.085, and 0.495) and (0.725, 0.073, and 0.404) for the rainy and dry season, respectively.

5. Conclusion

Daily observed time series wind speed data for Omu Aran, Kwara State, Nigeria have been analyzed statistically using Weibull and Rayleigh probability distribution models. In this study, the hourly (hours of the day), daily (days of the week), monthly, and yearly Weibull probability distribution function parameters, average wind speed, and wind power density were determined. Considering the analysis of the Landmark University wind speed data, the following conclusion can be made about Kwara State, Nigeria.

The actual mean yearly wind speed of 3.964 m/s for Kwara is in the low wind speed region.

The Weibull probability density distribution scale parameters are of higher values and higher variability than shape parameters for hours of the day, daily, and monthly distribution.

The range of power density for hours of the day, months, and seasonal variation falls within the range of 24–141 W/m^2. However, more than 50% of the daily hours were less than 100 W/m^2 which does indicate that Omu Aran, Nigeria belongs to class 1 because it is less than 100 W/m^2. Wind power availability in Kwara cannot be used for grid connection applications, but it could only be utilized to power standalone systems, for example, water pumping and charging of the battery. Thus, it could be utilized for the mini-grid, but the financial justification must be favorable.

The COE ranged from 39.95 to 94.9, while the COD R^2 ranges from 38.4 to 0.985. This range of performance values of Weibull is within acceptable limits for prediction accuracy; hence, the Weibull probability distribution function is sufficient for the preliminary design of a wind power plant and any other related project that require wind speed analysis in Kwara State, Nigeria.

Nomenclature

COD: Coefficient of determination
COE: Coefficient of efficiency
RMSE: Root mean square error
REMP: Renewable Energy master plan
Vmean: Average wind speed
Vwmean: Average mean speed for Weibull model
Vrmean: Average mean speed for Rayleigh model
Std: Standard deviation

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

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