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Assessment of Wind Speed Distributions and Turbine Characteristics in Equatorial West Africa

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ABSTRACT

Wind nullity, low wind, and bi- or multi-modality are common characteristics at high temporal resolution, especially in Equatorial regions. The traditional two-parameter Weibull (Weibull) distribution function (DF) is not designed to capture such peculiarities. Hourly mean wind speed data for eight locations that cut across different climate zones in an Equatorial region of West Africa have been analyzed using Weibull and Maximum Entropy Principle-based (MEP) distribution functions (DFs). Wind characteristics, such as power density, null wind speed, and modal distributions, together with turbine efficiency, capacity, and availability factors, were also assessed at a wind turbine hub height of 73 m using standard statistical tools. The results indicated that null wind speed and/or bimodality were present in the wind distributions at Abuja, Akure, Akungba, Nsukka, Makurdi, and Yola. The results of the assessments of the two DFs show that the MEP DF generated much better results across all time scales (R^2: 0.83 - 0.98; RMSE: 0.0037 - 0.0109 m/s^2) than the Weibull DF (R^2: 0.47 - 0.98; RMSE: 0.0038 - 0.0191 m/s^2), especially for locations where null wind speed and bimodality were prominent in the wind data distribution. MEP DF results further indicated that annual and rainy season periods were better modeled than the dry season in all the locations. The overall effect of all the turbine characteristics on annual and seasonal scales is that sufficient winds were available (Availability factor: 0.733 - 0.97; Capacity factor: 0.350 - 0.778) at the rated power for energy production in all the climate zones.

Keywords:
Null wind,
Modality,
Probability distribution functions,
Turbine Efficiency.

INTRODUCTION

Availability of stable and secure energy is the backbone of industrialization, which has played a key role in stimulating economic growth and employment generations in several countries (Csereklyei et al., 2014; Alrashidi et al., 2020). However, the main chunk of this energy is from thermal sources such as petroleum, coal, and natural gas, which are not only finite but also pose serious environmental concerns associated with global warming and climate change. The Cost-effectiveness of clean, greener renewable energy sources and commitment to reverse the adverse effects of climate change have led several countries to make significant investments to increase the penetration of hydropower, solar, and wind energy into their electrical power system. For instance, hydropower is the world's most widely used renewable energy resource, contributing about 16.6% of electricity generation worldwide, and this is expected to increase approximately by 3.1% each year for the next 25 years (Donoghue, 2012). This renewable energy source, therefore, plays an important role in enabling countries and communities around the world to meet their power and water needs. As of 2019, in Europe, 10% of the energy mix is also from wind energy alone, and this is expected to increase significantly towards 2030 (Europe, 2017). Several developing countries are also making frantic efforts to grow their economy by investing in energy production, transmission, and distribution. A choice has to be made between the cost-effectiveness of energy resources and emerging and ever-growing environmental issues. Most of the electrical energy production in the equatorial regions of West Africa is from non-renewable sources. One clear effort to reverse this trend, for instance, is the huge investment in hydropower plants at locations such as Kanji, Jebba, Shiroro, and some other smaller schemes, all situated in Nigeria, an equatorial region of West Africa. This renewable source adds about one-fifth of the total energy mix in Nigeria (Olaniyi et al., 2025). Notwithstanding the significant contribution from this source, there is still a wide gap between energy demand and supply in Nigeria. In addition to this, Hydropower sources are susceptible to climate variations, seasonal changes, drought, flooding, etc. In a study carried out by Ladokun et al., (2018) using 27 years of data on turbine discharges, it was shown that the lowest averaged values of the hydro-turbine discharges were obtained during the rainy season in July for Kanji and Jebba, and May for Shiroro. The observed fluctuation patterns in turbine discharges were linked to the inflow patterns, which are also connected to seasonal variation in rainfall and other climatic factors at the hydropower stations (Ladokun et al., 2018; Adegbehin et al., 2016). Besides, Nigeria, being a vast country, has many zones that are far away from the hydropower stations, and the cost of transmission could be daunting. One of the viable ways to increase the amount of energy generated and to ameliorate the observed power fluctuations associated with hydropower sources is to explore the complementary advantages of other renewable sources, such as wind and solar (Ajayi et al., 2013; Okeniyi et al., 2015; Oyedepo et al., 2012; T.A. Otunla & A.K. Umoren, 2022; Otunla & Kolebaje, 2015; Otunla, 2019). Wind sources, if properly exploited, could have some obvious advantages over hydropower, for instance, they could be less susceptible to seasonal variations. It can also be used to power rural communities that are far away from the national grid. Incidentally, above 50% of Nigerians live in rural communities (Ajayi et al., 2013; Okeniyi et al., 2015). Celik, (2003) states that electrical energy from medium-scale wind turbines is preferable in remote locations because it is socially valuable and economically competitive.

Wind turbines, when sited properly and used at optimal working conditions, could be a reliable energy source and produce socio-economically valuable energy. However, the utilization of wind resources is not without some inherent problems, among which are: the wind intensity of the site for the wind turbine, the wind distribution of the region proposed for the siting of the turbine, and frictional drag due to topography and other physical structures. The problem of frictional drag is easily solved since the atmosphere becomes freer of the effect of surface structures with an increase in height, and the wind also intensifies.

The parameter Weibull (Weibull) distribution function (DF) has been the probability distribution of choice when it comes to analyzing the frequency distribution of wind speed to extract its energy (Weibull, 1951; Okeniyi et al., 2015; Dorvlo, 2002; Li & Li, 2004; Akpinar & Akpinar, 2004; Kavak Akpinar & Akpinar, 2005), reportedly due to the ease of its estimation and also for being a positively skewed distribution that favors moderate wind speeds. However, regional, climatic, seasonal, and diurnal effects can be observed when the nature of wind speed is considered (Yürüşen & Melero, 2016). Weibull DF often fail to understand such nonlinear spatiotemporal variations (Okpala et al., 2026). For instance, Carta & Ramírez, (2007) applied Weibull DF in an analysis of hourly mean wind speed data recorded at the various weather stations located throughout the Canarian Archipelago islands, and it was found that the typical two-parameter Weibull DF does not accurately represent all the wind regimes observed in that region. Thus, Weibull DF is not suitable for some wind regimes encountered in nature, such as, for instance, those with high percentages of null wind speeds (Takle & Brown, 1978; Chang, 2011), Bimodal distributions (Jaramillo & Borja, 2004), etc (Li & Li, 2004; Ramírez & Carta, 2005; Garcia et al., 1998; Li & Li, 2005a; Li & Li, 2005b). Weibull DF will, in fact, give a probability of zero for null wind speed. The magnitude of these types of wind regimes could increase significantly as the resolution of the data increases from monthly to hourly time scale. Oyedepo et al., (2012) indicated that using monthly data for analysis of wind resources has the limitation of losing extremely low and high wind speeds within the month, as well as diurnal variations in the wind. Thus, wind energy resources are best assessed using hourly time series data; however, with the consequences of deprecation in the accuracy of Weibull DF, especially in regions of the world where there is a significant amount of null wind speed or bimodality in the frequency distribution of the wind.

All existing literature on the assessment of wind energy characteristics in the region used in this study either used monthly or daily time series data, probably due to the paucity of data with higher resolution, and this has the potential of averaging out low and high wind speed events and hence, avoided the deprecation in the accuracy of Weibull DF (Oyedepo et al., 2012). Some studies claimed that the Mixture Weibull distribution is superior to the traditional two-parameter Weibull DF, especially for bi-modal wind regimes (Carta et al., 2009; Celik et al., 2010), also, for multi-modal wind regimes (Carta et al., 2009), but with the disadvantage of an increased number of parameters and model complexity. Maximum Entropy Probability-based (MEP) DF has been shown to have a comparative advantage over all distributions that give a probability of zero for null wind speed (Li & Li, 2005a). Surface wind speeds are generally low in the equatorial region (Milone & William J.F. Wilson, 2008; Milone, & Wilson, 2014). Low wind at a measuring height of 2 m has been reported for some locations in the region (Otunla T.A. & Umoren A.K, 2022). This present study aims to assess both wind and turbine characteristics in many locations in the same region from high-resolution time series data using both MEP and two-parameter Weibull DFs.

MATERIALS AND METHODS

Regions of Study and Data

Eight locations within the major climate zones in the equatorial region of West Africa were used in the study. Four of the locations: Akure, Akungba, Anyigba, and Nsukka were within the Transitional Equatorial Zone, three locations: Lapai, Abuja, and Makurdi were in the Transitional Tropical Zone, and one location: Yola, was in the Pure Tropical Zone (Figure 1). The choice of each location was not only based on climate representativeness and data availability, but some of them were also within the same state/province where hydropower plants were sited. For example, the Kanji hydropower plant and Lapai are both in Niger state, while the Jebba hydropower plant and Anyigba are both in Kogi state. Table 1 gives the climate, the coordinates, the altitudes, and the wind data time series duration for all the locations. The study locations have two predominant climatic conditions, namely, rainy and dry seasons. The rainy season commenced around March/April with convective rainfall, characterized by wind gusts and intense monsoon rainfall that follows in June and July. A cessation or a lower rainfall amount is usually observed down south, locally known as the August break or the little dry season, and finally, thunderstorms set in September/October as the dry season approaches. The dry season is characterized by intense sunshine with little or no rainfall between the months of November and March of the following year (Akpinar & Akpinar, 2004). The wind in December and January is usually dry, cold, and gusty, especially when the Northeasterly wind is intense.

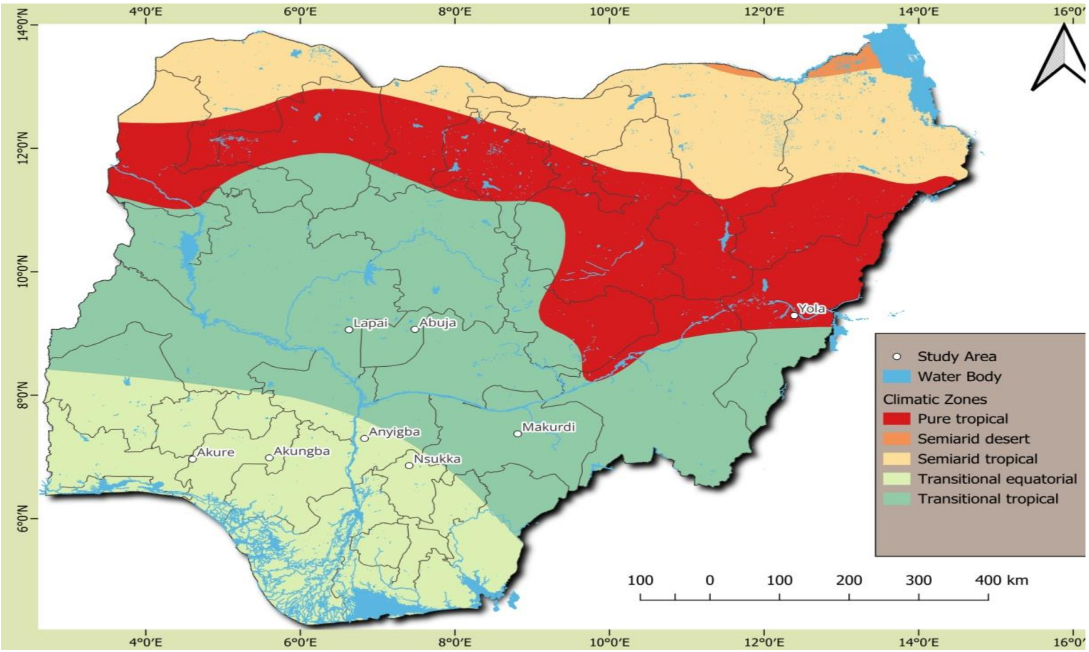

Figure 1: Map of Nigeria showing the spread of the study locations: Abuja, Akure, Lapai, Makurdi, Anyigba, Akungba, Yola, and Nsukka across various climatic zones

Time series data of wind speed of the duration specified Table 1 were obtained from the TRODAN data sets situated in the Centre for Atmospheric Research and Development Agency (CAR-NSRDA) in Nigeria and used in this study. The duration of the datasets was carefully selected for each location to avoid any significant data gaps. Notwithstanding, the data for some of the locations did not start in January of the beginning year nor end in December of the end year. Measurements were originally taken in five-minute intervals using anemometers and logged and stored using Campbell Scientific. The hourly time resolution of wind data commonly used in wind energy assessment (Kavak Akpinar & Akpinar, 2005) was obtained from these five-minute averaged records. The wind speed data, which were originally measured and recorded at 2 m above the ground level, were extrapolated to a wind turbine hub height of 73 m using the power law (Peterson & Hennessey, 1978; Ramírez & Carta, 2005):

$$\frac{v}{v_\mathrm{h}} = \left(\frac{H}{\mathrm{h}}\right)^{\alpha} \qquad (1)$$

Where v and v_h are wind speeds at 73 m and 2 m above the ground, H and h are the extrapolated height of 73 m and the measurement height of 2 m respectively. α is the surface roughness coefficient, and it is usually taken to be 1/7, but to reflect its dependence on wind hub height, it can be determined from (Ucar & Balo, 2009)?

$$\alpha = \frac{0.37\text{-}0.088 ln V_\mathrm{h}}{(1\text{-}0.088\ln \boxed{f()} (\frac{\mathrm{h}}{H})} \qquad (2)$$

Table 1: Climate zone, Latitude, Longitude, Altitude, and Time Duration at the study locations

Climate Zone	Locations	Latitiude(degN)	Longitude(degE)	Altitude(m)	Time Duration
Transitional Equatorial	Akungba	6.984	5.599	175	2008-2011
	Akure	6.958	4.605	131	2010-2011
	Nsukka	6.883	7.433	359	2007-2013
	Ayingba	7.25	7.183	420	2010-2013
Transitional Tropical	Lapai	9.122	6.898	442	2011-2012
	Abuja	9.067	7.483	536	2007-2012
	Makurdi	7.372	8.812	140	2008-2011
Pure Tropical	Yola	9.293	12.391	260	2009-2013

Mathematical Analysis

Probability Density Functions

The probability of wind speed of particular value occurring at a location is modeled mathematically using probability density functions such as two-parameter Weibull (Okeniyi et al., 2015; Dorvlo, 2002; Li & Li, 2004; Akpinar & Akpinar, 2004; Kavak Akpinar & Akpinar, 2005, Rayleigh (Kavak Akpinar & Akpinar, 2005), Gumbel (Okeniyi et al., 2015), lognormal (AKYUZ & GAMGAM, 2017, Maximum Entropy Principle-based (MEP) (Li & Li, 2004; Li & Li, 2005a) and Gamma DFs (AKYUZ & GAMGAM, 2017). Previous studies had shown that both two parameters Weibull and Maximum Entropy Principle-based DFs are superior to others. The two of them are used in this study.

Maximum Entropy Principle-based Distribution Function

Jaynes, (1957) developed the concept of information entropy originally proposed by Shannon & Weaver, (1949) into the Maximum Entropy Principle(MEP). This principle can be used to determine the most unbiased probability DF for a system when the information available is subjected to some constraints (Li & Li, 2005a). The MEP DF has been widely used to fit the distributions of wind speed and some of the locations are Algeria (Chellali et al., 2012), Taiwan (Chang, 2011), Canada (Li & Li, 2005a) and Turkey (Akpinar & Kavak Akpinar, 2007). The entropy of a probability function g(x) is given as (Chang, 2011):

$$S=-\int g(x) \ln g(x)dx \qquad (3)$$

Suppose the information available for the physical system of interest exists in the form of moments $\phi_n(x), n = 0, 1,\ldots, N$ with $\phi_0(x)=1$, the most probable density function can be found by maximizing the entropy in equation (3).

The (N+1) constraints of the maximum entropy for the physical system are given as:

$$D(\phi_n(x))=\int \phi_n(x)g(x)dx=\Omega_n \text{ ;n=0,1,...,N} \qquad (4)$$

Where$\phi_n(x), n = 0, 1,\ldots, N$ with $\phi_0(x)=1$ are the known functions for the systems;Ω_n,n=0,1,...,Nwith $\Omega_0=1$, are the expectation data.

The analytical solution to the maximum entropy problem can be written as:

$$g(x)=\exp(-\Sigma_{n=0}^{N}\beta_n\phi_n(x)) \qquad (5)$$

where β_n are Lagrangian multipliers that can be obtained by solving the $(N+1)$ nonlinear equations:

$$G_n(\beta)=\int \phi_n(x)\exp(-\Sigma_{n=0}^{N}\beta_n\phi_n(x)dx=\Omega_n\text{; n=0, 1, N} \qquad (6)$$

For the case of wind distribution $\phi_n(x)$can be taken as powers of wind speed (v) such that:

$$\phi_n(x), =(v)^n; n= 0, 1,\ldots, N \qquad (7)$$

and Ω_n ;n=0,1,...,Nwith $\Omega_0=1$ are the moments of the distribution representing the mean values of n power of wind speed observation data and hence, correspondingly, $g(v)$, and can be calculated from the wind data as (Akpinar & Akpinar, 2004):

$$g(x)=\exp(-\Sigma_{n=0}^{N}\beta_n v^m) \qquad (8)$$

Details of numerical methods entailed in the calculation of Lagrangian multipliers are given in (Saad & Ruai, 2019). The numerical method was into a Python code to generate the necessary Lagrangian multipliers when moments of n power of wind speed are supplied. The code was used in this study.

The Weibull Distribution Function

The Weibull two-parameter probability distribution function (Weibull DF) is given as (Akpinar & Akpinar, 2004; Paul et al., 2012; Okeniyi et al., 2015; Ben et al., 2021:

$$g(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\exp\left(-\left(\frac{v}{c}\right)^{k}\right) \qquad (9)$$

Where $g(v)$is the probability of wind speed (v), c is the scale parameter (m/s), and k is the dimensionless shape parameter. The cumulative density function $G(v)$ is given by integral of the probability distribution function $g(v)$ as:

$$G(v)=1-\exp\left(-\left(\frac{v}{c}\right)^{k}\right) \qquad (10)$$

The Weibull shape and scale parameters are given as(Justus et al., 1978; Ouammi et al., 2010):

$$k=\left(\frac{\sigma}{v_m}\right)^{-1.086} \qquad (11)$$

$$c=\frac{v_m}{\Gamma\left(1+\frac{1}{k}\right)} \qquad (12)$$

Where σ and v_m are the standard deviations and the first moment of the wind speed data set, respectively. $\sigma$is gamma function defined as (Chang et al., 2003)?

$$\Gamma(x)=\int_0^{\infty} t^{x-1}e^{-t}dt \qquad (13)$$

Wind Turbine Characteristics

The energy generated by an ideal wind turbine is given as (Chang et al., 2003):

$$Eti=T\int_0^{\infty}P(v)g(v)dv=T\left(\int_{v_i}^{v_R}P(v)g(v)+\int_{v_R}^{v_c}P_R g(v)\right) \quad (14)$$

where $P(v)=0.5\rho Av^3$, $P_R=0.5\rho Av_R^3$, and T is the time duration of the turbine operation.

The wind power density for probability DF is:

$$P/A=\left(\int_0^{\infty}P(v)g(v)dv\right)/A \quad (15)$$

Where A is the area swept by the rotor of the turbine and ρ is the air density at the turbine hub height given as $\rho=\rho_0+10^{-10}\times H^*$. Where ρ_0 is the air density at sea level and H^* is the hub height.

A 3.4M104 S104/3400 wind turbine machine was used in this study as a test case. It operates at increasing power between cut-in wind speed (v_i) 3.5 m/s and rated speed(v_R) 14 m/s, and at constant power P_R=3400 kW with maximum efficiency between the rated speed, and cut-out speed(v_C) 25 m/s. The actual wind power output from the wind turbine P_T is determined by the turbine performance curve, which is well described by the following expression:

$$P_T=\begin{cases}0, & v<v_i\\ (a_0 v^3+a_1 v^2+a_2 v+a_3)P_R, & v_i\le v<v_R\\ 0, & v\ge v_c\end{cases} \quad (16)$$

Where a_0=-0.0023, a_1=0.0619, a_2=-0.397 and a_3=0.7739 are the regression coefficients for the turbine performance curve. The actual wind energy from the turbine can be determined from:

$$Eta=\int_{v_i}^{v_c}P_T(v)g(v)dv=TP_R\int_{v_i}^{v_c}(a_0 v^3+a_1 v^2+a_2 v+a_3)g(v)dv+TP_R\int_{v_R}^{v_c}g(v)dv \quad (17)$$

Three complementary but fundamental turbine characteristics that are used in this study are Turbine Efficiency, Availability, and Capacity Factors. Chang (Chang et al., 2003) defined them as:

Turbine Efficiency, *eff*, is the ratio of actual energy produced by a wind turbine to the energy generated by an ideal wind turbine. It is given as:

$$eff=\frac{Eta}{Eti} \quad (18)$$

The Capacity Factor, *CF*, is the ratio of actual energy output by a wind turbine to the rated energy. The rated energy for a turbine operating at full capacity for a duration T is *EtR=TPR*. Hence,

$$CF=\frac{Eta}{EtR} \quad (19)$$

The Availability Factor, *AF*, is the fraction of time the wind turbine is operating. It is given as the probability $p(v_i\le v<v_c)$ and hence:

$$AF=p(v_i\le v<v_c)=\int_{v_i}^{v_c}g(v)dv \quad (20)$$

The integrals in equations 14, 15, 17, and 20 were calculated by implementing the Gauss-Legendre quadrature in Python coding.

Test of goodness of fit

The coefficient of determination (R^2) is used to evaluate the performance of both Weibull and MEP DFs against the measured data. The higher the R^2, the better the fit between measured data and theoretical distributions. The R^2 is given as:

$$R^2=1-\frac{\sigma_{x,y}^2}{\sigma_y^2} \quad (21)$$

Where σ_y^2 is the variance of measured data from mean value and $\sigma_{x,y}^2$ is the covariance.

To further evaluate the performance of the distribution functions, mean bias error (MBE) and root mean square error (RMSE) were also introduced. The smaller the values of the RMSE parameter, the better the proposed distribution function approximates the measured data. The sign of MBE indicates over-estimation or underestimation of the measured data by the DF functions. The expression for RMSE and MBE are given as:

$$MBE=\frac{1}{N}\Sigma(y-y_m) \quad (22)$$

$$RMSE=\sqrt{\frac{1}{N}\Sigma(y-y_m)^2} \quad (23)$$

Where y and y_m are the measured and model values respectively. N is the number of data points.

RESULTS AND DISCUSSION

Annual and Seasonal Assessment of Wind and Turbine Characteristics

The potentials of both Weibull and MEP DFs to model wind speed distributions in all the locations of the study were compared on the annual, rainy, and dry season time scales (Figures 2-4 and Table 2). Figures 2-4 indicated similar wind distribution patterns on annual, rainy, and dry season time scales for all the locations used in the study except Akure, Makurdi, Akangba, and Nsukka in the dry season. Diurnal and seasonal effects, which usually manifest in the form of nullity and bimodality in wind speed and distribution, were observed in all the locations used in the study except in Lapai and Anyigba(Figures 2-4) as pointed out by Yürüşen & Melero, (2016). Abuja had the highest amount of null wind and was poorly modeled by Weibull DF when compared with MEP DF. Takle & Brown, (1978) and Chang (Chang, 2011) had already pointed out that the two-parameter Weibull DF may not be suitable for modeling wind speed distribution when the percentage of null wind speed is high. Bimodality was significantly present in the wind distributions, especially in Akure, Makurdi, Akungba, and Nsukka during the dry season period, and this could be responsible for the poor performance of Weibull DF (Carta & Ramírez, 2007; Li & Li, 2005b). The two DFs modeled both the annual and rainy season periods better than the dry season (Table 2). The MEP DF generally outperformed the Weibull DF with higher values of R^2 and lower values of RMSE. The RMSE values were almost an order of magnitude lower in Abuja, Makurdi, Akungba, and Nsukka, irrespective of the symmetry and asymmetry of the distribution histograms and regardless of whether they are unimodal or bimodal. The lowest values of R^2=0.83 and R^2=0.47 were obtained during the dry season for the MEP and Weibull DFs at Makurdi, respectively.

Tables 3-5 gave the annual wind and turbine characteristics computed from Weibull and MEP DFs distributions. As would be expected, the values of both the wind speeds and Power Density (P/A) were very close for the two DFs in Lapai and Anyigba, where null wind and bi-modality were very low, and the values were far apart as the nullity and bi-modality in the wind distributions increased in Abuja, Nsukka, and Makurdi (Jaramillo & Borja, 2004; Li & Li, 2005b; Carta & Ramírez, 2007). The Turbine Efficiency and Availability Factor were higher and possibly over-estimated while the Capacity Factor was lower and possibly under-estimated in the Weibull DF when compared with MEP DF, which have higher R^2 and lower RMSE values, especially in locations with higher nullity and bimodality.

Tables 4-6 indicated that, on both annual and seasonal time scales, the wind was generally available in all the locations, with the lowest value of Availability Factor (0.733) in Abuja and the highest value (0.970) in Anyigba. Tables 4-6 further indicated that Turbine Efficiency has its lowest value (0.284) in Akungba during the rainy season and its highest value (0.352) in Abuja during the rainy season. The values of the Capacity Factor ranged between 0.35 (Abuja) and 0.778 (Anyigba) and were reciprocal to the values of Turbine Efficiency. This implied that the values of the former were high when the values of the latter were low. The Tables further show that Availability and Capacity Factors were generally higher in the rainy season, while Turbine Efficiency was very close in the two seasons. The values of wind power density (P/A), a measure of the potential of wind for wind energy prospecting, were higher in the rainy season than in the dry season (Table 6).

Table 2: Root Mean Square Error (RMSE)and Coefficient of Determination (R^2) for Annual, Rainy, and Dry Season Time Scale of Weibull and Maximum Entropy Principle-based (MEP) distribution functions respectively, at the study locations

Location	Time Scale	Weibull		Maximum Entropy	
		RMSE(ms^{-2})	R^2	RMSE(ms^{-2})	R^2
Abuja	Annual	0.016	0.78	0.0044	0.98
	Rainy	0.0156	0.78	0.0047	0.98
	Dry	0.0168	0.91	0.0041	0.95
Makurdi	Annual	0.0144	0.77	0.0086	0.91
	Rainy	0.0091	0.91	0.0065	0.95
	Dry	0.0211	0.47	0.0109	0.83
Akure	Annual	0.0093	0.9	0.0057	0.96
	Rainy	0.0065	0.95	0.0054	0.97
	Dry	0.0145	0.75	0.0066	0.94
Akungba	Annual	0.0106	0.81	0.0047	0.96
	Rainy	0.0082	0.88	0.0037	0.97
	Dry	0.0191	0.47	0.0082	0.88
Nsukka	Annual	0.0135	0.76	0.005	0.97
	Rainy	0.0125	0.81	0.005	0.97
	Dry	0.0154	0.64	0.0055	0.95
Lapai	Annual	0.0038	0.98	0.004	0.98
	Rainy	0.0041	0.98	0.005	0.97
	Dry	0.005	0.96	0.0038	0.98
Anyigba	Annual	0.0053	0.96	0.0046	0.97
	Rainy	0.0056	0.96	0.0049	0.97
	Dry	0.0053	0.96	0.0045	0.97
Yola	Annual	0.0089	0.9	0.0048	0.97
	Rainy	0.0072	0.93	0.0051	0.97
	Dry	0.0114	0.86	0.0061	0.96

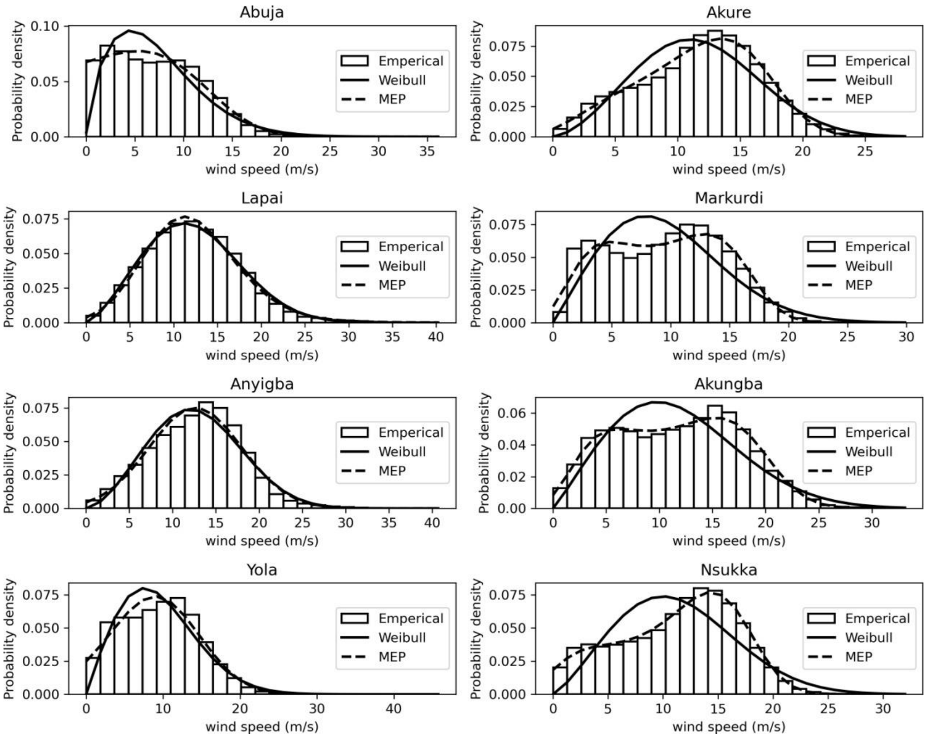

Figure 2: Annual probability distribution of actual data, the Weibull distribution and Maximum Entropy principle-based distribution for Abuja, Akure, Lapai, Makurdi, Anyigba,Akungba,Yola and Nsukka

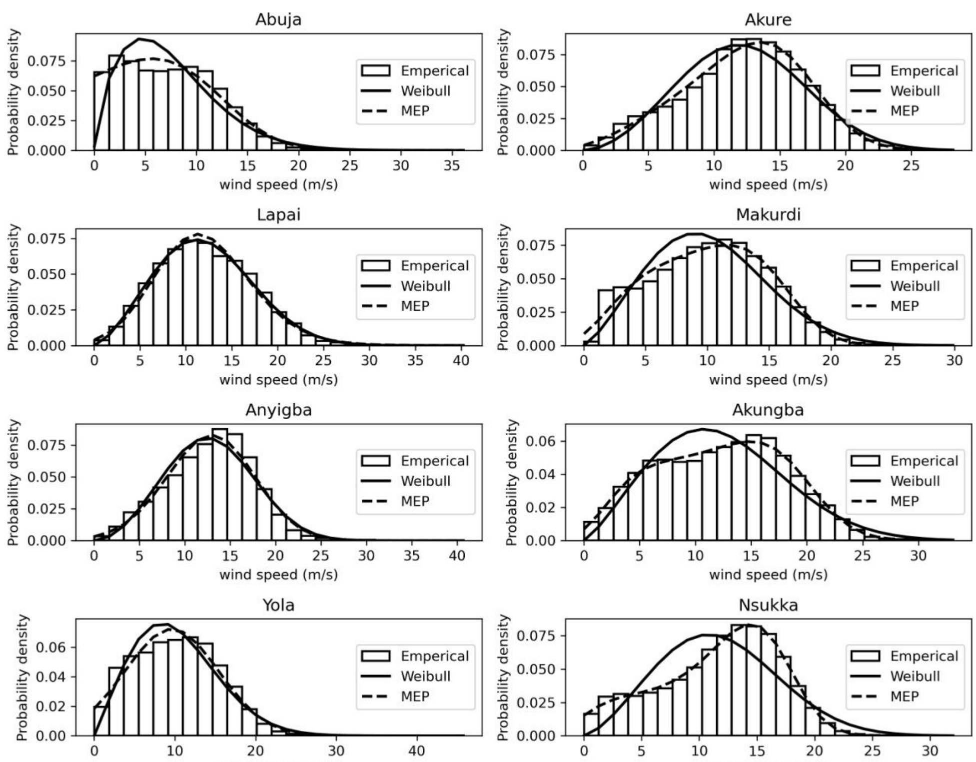

Figure 3: Rainy Season probability distribution of actual data, the Weibull distribution and Maximum Entropy principle-based distribution for Abuja, Akure, Lapai, Makurdi, Anyigba,Akungba, Yola and Nsukka

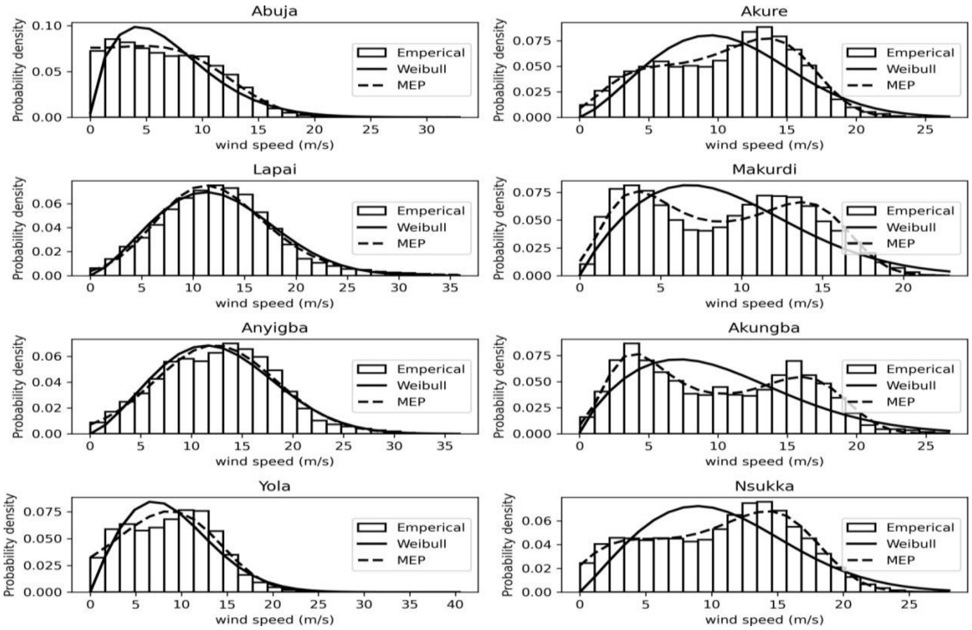

Figure 4: Dry Season probability distribution of actual data, the Weibull distribution and Maximum Entropy principle-based distribution for Abuja, Akure, Lapai, Makurdi, Anyigba, Akungba, Yola and Nsukka

Table 3: Annual wind characteristics and wind turbine characteristics from Weibull two- parameter distribution function the study locations

	K	C(m/s)	V(m/s)	P/A(W/m)	Eti(kWh)	Eta	eff	AF	CF
Nsukka	11.4	2.3	12.82	835.4	6.22E+07	1.93E+07	0.31	0.941	0.647
Akure	11.7	2.65	13.14	921.3	6.86E+07	2.07E+07	0.302	0.966	0.696
Akungba	11.8	2.11	13.29	853.1	6.35E+07	1.90E+07	0.299	0.92	0.637
Ayingba	12.8	2.67	14.28	990.5	7.37E+07	2.21E+07	0.3	0.965	0.741
Makurdi	9.5	2.08	10.78	655.7	4.88E+07	1.57E+07	0.322	0.905	0.528
Abuja	7.2	1.65	8.03	380.4	2.83E+07	1.01E+07	0.358	0.773	0.34
LApai	12.3	2.46	13.89	923.5	6.87E+07	2.09E+07	0.304	0.953	0.702
Yola	9.5	2	10.71	638.2	4.75E+07	1.54E+07	0.325	0.894	0.517

Table 4: Annual wind turbine characteristics from Maximum Entropy Principle)-based (MEP) distribution function at the study locations

Location	Multiplier	P/A(W/m2)	Eti(kWh)	Eta(kWh	eff	AF	CF
Nsukka	-3.9992 0.4166 -0.0979 0.01104 -0.00051 0.000007	928.9	6.91E+07	2.03E+07	0.294	0.899	0.682
Akure	-5.0763 0.6858 -0.1076 0.00997 -0.00043 0.000006	973.9	7.25E+07	2.12E+07	0.293	0.944	0.713
Akungba	-4.7918 0.8878 -0.1626 0.01352	920.8	6.85E+07	1.95E+07	0.284	0.906	0.654

Ayingba	-0.0005 0.000006 -5.4063 0.4478 -0.0179 0.00001	1008.1	7.50E+07	2.23E+07	0.298	0.955	0.75

Table 5: Annual wind turbine characteristics from Maximum Entropy Principle-based (MEP) distribution function at the study locations

Location	Multiplier	P/A(w/m)	Eti(kWh)	Eta(kWh	eff	AF	CF
Makurdi	-4.4155 0.991 -0.2192 0.0215 -0.00092 0.000013	724	5.39E+07	1.65E+07	0.307	0.868	0.555
Abuja	-2.6949 0.0355 0.0011 -0.00055	411..8	3.06E+07	1.09E+07	0.357	0.749	0.367
Lapai	-5.5915 0.5886 -0.033 0.00041	917.6	6.83E+07	2.10E+07	0.307	0.946	0.704
Yola	-3.6989 0.2337 -0.0114 -0.00012	670.4	4.99E+07	1.06E+07	0.321	0.872	0.537

Table 6: Seasonal wind characteristics and wind turbine characteristics from Maximum Entropy Principle-based (MEP) distribution function at the study locations

Location	Season	V(m/s)	P/A(W/m)	Eti(kWh)	Eta	eff	AF	CF
Nsukka	Dry	10.3	855.6	2.62E+07	7.74E+07	0.296	0.874	0.633
	Rainy	11.8	982.5	4.21E+07	1.23E+07	0.292	0.917	0.717
Akure	Dry	10.6	855.8	2.62E+07	7.81E+07	0.298	0.908	0.638
	Rainy	12.2	1037.9	4.45E+07	1.29E+07	0.291	0.962	0.754
Akungba	Dry	10	758.7	2.32E+07	6.61E+07	0.285	0.845	0.54
	Rainy	12.3	974.3	4.17E+07	1.18E+07	0.284	0.923	0.691
Ayingba	Dry	12.7	966.7	2.96E+07	8.78E+07	0.297	0.934	0.717
	Rainy	12.8	1046.1	4.48E+07	1.33E+07	0.298	0.97	0.778
Makurdi	Dry	9	674.7	2.06E+07	6.25E+07	0.303	0.823	0.511
	Rainy	10.1	777.2	3.33E+07	1.03E+07	0.311	0.913	0.603
Abuja	Dry	6.9	397.9	1.22E+07	4.28E+07	0.352	0.733	0.35
	Rainy	7.4	442.5	1.90E+07	6.51E+07	0.343	0.76	0.379
Lapai	Dry	12.5	936.9	2.86E+07	8.59E+07	0.3	0.94	0.701
	Rainy	12.1	937.2	4.02E+07	1.21E+07	0.301	0.95	0.706
Yola	Dry	8.9	608.2	1.86E+07	6.12E+07	0.329	0.851	0.5
	Rainy	10.2	744.8	3.19E+07	9.99E+07	0.313	0.894	0.583

Monthly Assessment of Wind and Turbine Characteristics

The monthly wind characteristics, as typified by wind power density (P/A) and three fundamental wind turbine characteristics: Turbine Efficiency, Capacity Factor, and Availability Factor, were further analyzed for all the locations to investigate their temporal and spatial variations on a monthly time scale in and across the climate zones. Figure 5a-d showed the monthly variations of Turbine Efficiency, Capacity Factor, and Availability Factor for all the locations used in the study. The Turbine Efficiency tends to indicate a similar trend within the same climate zones, with values that were very close for locations within the Transitional Equatorial zone. The range of values for Turbine Efficiency was: 0.275 - 0.318, 0.282 - 0.382, and 0.302 - 0.350 for Transitional Equatorial, Transitional Tropical, and Pure Tropical zones, respectively (Figure 5a). The Availability Factor indicated that wind was generally available in all the climate zones, with the lowest value (0.67) in January and the highest value (0.992) in March, both of them in the Transitional Equatorial zone (Figure 5b). Lesser variations in values of the Availability Factor were indicated for rainy season months, especially if Abuja in the Transitional Tropical zone was to be excluded.

The trend of the Capacity Factor was the same as that of wind characteristics, as typified by Power Density, but opposite to that of Turbine Efficiency in all the climate zones (Figures a,c-d). This was also in agreement with Chang et al., (2003), who reported opposite trends for both Turbine Efficiency and Capacity Factor for the work that was carried out in Taiwan. The locations in the Transitional Equatorial zone generated the highest wind Power Density for each month, with values that were very close for all the locations and for most of the months. As already reported in Ben et al., (2021) for some of the locations used in this study, the Power Density peaked in March and April, and also in the Transitional Equatorial zone. The range of values for Capacity Factor was: 0.571 - 0.903, 0.276 - 0.765, and 0.449 - 0.662 for Transitional Equatorial, Transitional Tropical, and Pure Tropical zones, respectively (Figure 5c). Thus, indicating more and sufficient wind speed at the rated power for the wind turbine in the Transitional Equatorial zone than in the other zones. However, it should be noted that only one location is used to characterise the Pure Tropical zone. The results could therefore be significantly different as more locations are used for the zone. Notwithstanding, the values of the Turbine Efficiency, Availability Factor, Capacity Factor, and Power Density in all the zones indicated that wind was generally available for wind energy extraction in the region of study.

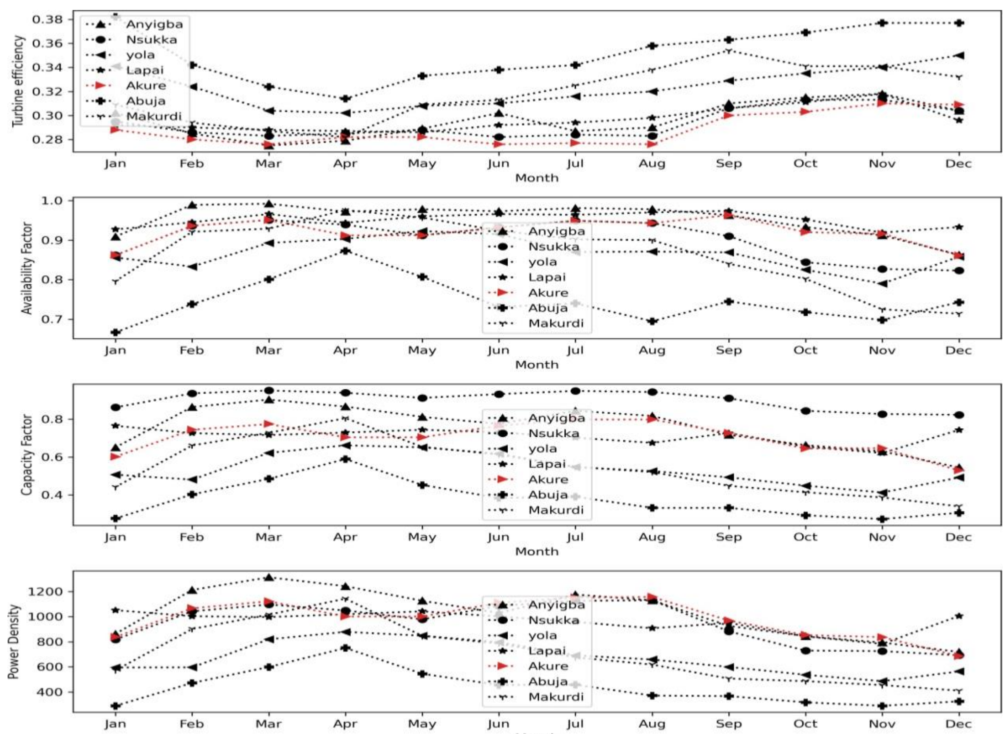

Figure 5: Monthly Turbine Efficiency, Availability Factor, Capacity Factor, and Power Density using Maximum Entropy principle-based distribution for Abuja, Lapai, Makurdi, Anyigba, Akungba, Yola and Nsukka

CONCLUSION

Hourly mean wind speed data for periods ranging from two to seven years in eight locations that cut across different climate zones in an equatorial region of West Africa have been analyzed and used to assess wind characteristics such as nullity and modality in the speed and distributions of wind, respectively. The wind distributions and power densities in all the locations used in the study were modeled using two parameters: Weibull and Maximum Entropy Principle-based distribution functions. The accuracy of the two distribution functions was assessed using the coefficient of determination, root mean square error, and mean bias error. Furthermore, three fundamental wind turbine characteristics: Turbine Efficiency, Capacity Factor, and Availability Factor, were computed and analyzed for annual, seasonal, and monthly time scales. It should however be noted that the two to seven years of wind data used in power density calculation and turbine characterization is not enough for long term trend analysis. Hence, only monthly and seasonal changes were examined across the different climate zones. The conclusions that were drawn from all the analyses are given as follows:

Diurnal and seasonal effects that manifest in the form of null wind speed and bimodality in the distribution were observed in Abuja, Akure, Akungba, Nsukka, Makurdi, and Yola.

The results of the assessments of the two distribution functions showed that the Maximum Entropy Principle-based distribution function generated much better results than the two-parameter Weibull distribution function, especially for locations where null wind speed and bi-modality were prominent in the wind data distribution. The annual and rainy season periods were better modeled than the dry season in all the locations.

The values of the Power Density calculated from the two distribution functions were close at Lapai and Anyigba, where wind nullity and bi-modality in the distributions of actual data were low. The converse is correct for all other locations.

The values of Availability Factor (0.733 - 0.97), Capacity Factor (0.350 - 0.778), and Turbine Efficiency (0.284 - 0.3552) calculated on annual and seasonal time scales indicated that wind was generally available in all the locations used in the study.

Using the monthly time scale, the values of the Availability Factor indicated that winds were generally available in all the climate zones, with the lowest Availability Factor value (0.67) and the highest (0.992) in January and March, respectively. These values were obtained in locations situated in the Transitional Equatorial zone.

The ranges of values of Turbine Efficiency using a monthly time scale were: 0.275 - 0.318, 0.282 - 0.382, and 0.302 - 0.350 for locations in Transitional Equatorial, Transitional Tropical, and Pure Tropical zones, respectively.

The ranges of values of Capacity Factor using a monthly time scale were: 0.571 - 0.903, 0.276 - 0.765, and 0.449 - 0.662 for locations in Transitional Equatorial, Transitional Tropical, and Pure Tropical zones, respectively.

Turbine Efficiency, Capacity and Availability factors may also depend on the rated power, hub height, cut-in and cut-out wind speeds of the turbine, among other factors. Hence, type of turbines may also influence these values.

Locations in the Transitional Equatorial zone generated the highest wind power density for each month. The overall effect of all the turbine characteristics is that sufficient winds were available at the rated power for energy production in all the climate zones.

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