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Wind Characteristics and Potentials of Two-Parameter Weibull Distribution and Maximum Entropy-Based Distribution Functions at an Equatorial Location

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Abstract: Thorough knowledge of the wind characteristics and variations are of great importance in the development of wind energy resource in any location. This study examines the wind characteristics and assess the potential of two distribution functions in a low wind equatorial region of West Africa. High resolution wind speed and direction data were obtained from a site in Nsukka, a location chosen in the region of study. Diurnal, seasonal and annual variations of both the wind speed and directions were examined. The potentials of two-parameter Weibull distribution and another distribution function based on Maximum Entropy principle (MEP) were assessed using R^2 and root mean squared error (RMSE). The results indicated that day-time is windier than night-time. The transitions months of February, March and April have the highest wind speed. The dry season has greater energy potential than rainy season. The predominant wind direction lay within the sectors: South-South-West and East. The predominant wind sector for February, March and April is South-East. The R^2 for daily, sub-seasonal day-time and night-time, monthly, and annual ranged between 0.90 and 0.99 for both MEP-based and Weibull distributions. The daily, sub-seasonal day-time and night-time, monthly, and annual RMSE also ranged between 0.011 to 0.075 for MEP-based and Weibull distribution respectively. Thus, both MEP-based and Weibull two-parameter distribution functions can be used to model wind data at the location of study.

Keywords: Wind energy, weibull distribution, maximum entropy principle, equatorial region

1. Introduction

Industrialization and technological advancement have caused a massive surge in global energy demand. The challenge of providing the much-needed energy has become a cause of global concern. Therefore, there is a need to adequately meet the rising energy demand of the global population (Lee & Zhao 2021). Fossil fuel has remained the main source of global energy for a long time and over-dependence on these non-renewable sources has led to its depletion. Moreover, environmental problems resulting from the burning of such fuels which include the emission of carbon dioxide and other dangerous anthropogenic greenhouse gases is the main cause of global warming with the attendance impact on the climate("Global Energy Review 2020" 2020). These issues have made the world to focus on alternative energy sources that are both eco-friendly and renewable. The generation of energy from sustainable as well as renewable sources like hydropower, wind, the sun, and biomass, has been recognized as the most feasible alternatives to generating clean, free, and eco-friendly energy (Ellabban, Abu-Rub, & Blaabjerg 2014). Many dams have been constructed for hydropower generation and photovoltaic cells have been widely deployed to tap solar energy across West Africa.

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In Nigeria, for instance, significant and commendable initiatives have been made to improve the energy infrastructure. Energy has been generated and transmitted to millions of consumers from the grid by connecting to various energy sources. Some of these energy sources are not eco-friendly. Energy generated from fossil fuels, which include coal and petroleum products, still form a good part of energy mix in Nigeria (Ben et al. 2021). In the renewable energy sector, many solar energy projects have been completed and deployed in addition to the primary and traditional hydropower sources. Little attention has however been given to wind energy, except for the 10 MW wind farm in Katsina State (Idris, Ibrahim, & Albani 2020). Wind is generated due to the pressure gradient from uneven heating of the earth's surface by the sun. As the very driving force causing this movement is derived from the sun, wind energy is an indirect form of solar energy (Masters 2004). To effectively utilize wind energy at any given location, accurate analyses of wind data and knowledge of wind characteristics is required. Wind speed characteristics is necessary for the choice of turbine for any selected installation site. It has been recorded that patterns of wind flow can be affected by topography, vegetation and water bodies (Oyedepo, Adaramola & Paul 2012). Several analyses have been done on available wind data, which are mostly in daily and monthly resolution, in different locations in Nigeria, and it has been pointed out that Nigeria has some prospect for wind energy development (Ajayi et al. 2013; Fagbenle et al. 2011; Oyedepo, Adaramola & Paul 2012; Ben et al. 2021). Most of these analyses used Weibull distribution function which has been widely considered to be the appropriate distribution function for the analysis of wind speed data (Hasan, Guwaeder, & Gao 2017; Janajreh 2012; Okorie et al. 2018; Ajayi *et al.* 2013; Bassyouni et al.,2015; Baseer et al., 2017; Idris; Zahid *et al.*,2019; Idris *et al.*, 2020; Shoaib e*t al*. 2020). Many studies have adopted the two-parameter Weibull probability distribution function. For two-parameter Weibull distribution, the shape parameter is used to describe the width of data distribution, while the scale parameter controls the scale of the plot. However, a number of studies have also indicated that maximum entropy-based distribution can out-performed Weibull distribution (Li and Li 2005b; Zhou *et al.*, 2010; Zhang *et al.*, 2014). In a recent study of wind distribution at Keti Bandar in Pakistan, Shoaib *et al.*, 2017 concluded that maximum entropy-based distribution can be used as alternative Weibull. Weibull distribution function however, has been shown to be unable to effectively predict or describe low or calm wind conditions accurately (Li and Li 2005b). Low and calm wind conditions are however common, if not prevalent in the equatorial region of West Africa. Maximum entropy-based distribution has been pointed out to have potential to predict this type of condition accurately (Li, M. & X.Li. 2005a). The potential of this distribution is yet to be assessed in the equatorial region.

The objective of this study is to use high resolution wind data to carefully examine the wind characteristics such as diurnal, monthly, seasonal and annual variations and to assess the potential of both two-parameter Weibull distribution and maximum entropy-based distribution functions at an equatorial location in West Africa where calm conditions are minima but where wind speed is generally low.

2. Site Description

The study location is at Longitude 7.373266°E and Latitude 6.842942°N in Nsukka city. It is an equatorial site located in Enugu state, south-eastern region of Nigeria. It has elevation of 423m above sea level. The study location has two predominant climatic conditions comprising of rainy and dry seasons. The rainy season is a period of intense rainfall between the months of April and October. The dry season is characterized by intense sunshine with little or no rainfall between the months of November and March (Iloeje 1986).

2.1 Wind Speed Data

Five years (2008-2012) wind data comprising of both wind speed and direction were obtained from the TRODAN data sets situated in Centre for Atmospheric Research and Development Agency (CAR-NSRDA) in Nigeria and used in this study. The measurement was taken using an automatic weather station and logged at five minutes interval. Hourly time resolution of wind data commonly used in wind energy assessment (Celik 2003) were obtained from these five minutes averaged records. Table 1 shows the yearly cumulative times the wind blows according to the wind speeds. The wind speed data which were originally made and recorded at 2 m above the ground level were extrapolated to 10m using the power law (Ben et al. 2021).

$$\frac{V}{V_o} = \left(\frac{h}{h_o}\right)^{\alpha} \qquad (1)$$

Where V and Vo are wind speeds at 10 m and 2 m above the ground, h and h_o are the extrapolated height of 10 m and the measurement height of 2 m respectively.
The roughness coefficient α was determined from (Okorie et al. 2018):

$$\alpha = \frac{[0.37 - 0.088\ln(V_o)]}{[1 - 0.088\ln(\frac{h_o}{10})]} \qquad (2)$$

Table 1 - Yearly cumulative times the wind blows according to wind speeds at 10 m

Wind speed(m/s)	5-year	2008	2009	2010	2011	2012
0-1	92	1016	963	1028	998	1061
1-2	2747	2082	2308	2421	2406	2294
2-3	4915	3167	3325	3395	3451	3520
3-4	977	1897	1727	1557	1521	1492
4-5	28	495	350	305	329	335
5-6	1	83	73	47	44	40
6-7	0	18	10	6	8	12
7-8	0	7	4	1	3	6

2.2 Mathematical Model

A probability density function is a mathematical model that describes the likelihood of a random variable to occur at any given point in an observation space (Chang 2011). A probability distribution function is used to model the wind characteristics of a location so as to effectively determine the wind energy potential of that location. Many probability density functions have been used to describe wind speed distributions and these include: Weibull (Hasan, Guwaeder& Gao 2017), Rayleigh (Kisito et al. 2015) , Gumbel (Okeniyi, Ohunakin & Okeniyi 2015), lognormal (Akyuz & Gamgam 2017), Maximum Entropy (Li & Li 2005a) and Gamma (Akyuz & Gamgam 2017) distribution functions. Most of these previous studies had shown that both Weibull and Maximum Entropy-based distribution functions are superior to others. The two of them are used in this study.

2.2.1 Maximum Entropy Principle-based Distribution Function

Shannon (Shannon 1948) proposed the concept of information entropy based on a measure of uncertainty for any probability distribution function. This concept was further extended by Jaynes (Jaynes 1989) into the maximum entropy principle, which is commonly applied to problems involving probability. The maximum entropy principle (MEP) allows for the determination of the most unbiased probability density function when information known about the system is subject to some constraints (Li & Li 2005a). The Maximum Entropy distribution model has been used to fit the distributions of wind speed in several locations globally such as Algeria (Chellali et al. 2012), Canada (Li & Li 2005a), Turkey (Akpinar & Akpinar 2007), Taiwan (Chang 2011), the Canary Island (Ramírez & Carta 2006). The entropy of a probability function *f(x)* is given as (Chang 2011):

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

Suppose the information available for the physical system of interest exist inform of moments $\varphi_n(x)$, n = 0, 1,…,N with $\varphi_0(x) = 1$, 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 is given as:

$$E\{\varphi_n(x)\} = \int \varphi_n(x) f(x) dx = \gamma_n \text{ for n = 0, 1,…, N} \qquad (4)$$

Whereγ_n, n = 0, 1, …,N with $\gamma_0 = 1$ are the expectation data.
The analytical solution of the maximum entropy problem can be written as:

$$f(x) = \exp\left[-\sum_{n=0}^{N} \alpha_n\ \varphi_n(x)\right] \qquad (5)$$

where α_n are Lagrange multipliers that can be obtained by solving the (N+1) nonlinear equations:

$$Z_n(\alpha) = \int \varphi_n(x) \exp\left[-\sum_{n=0}^{N} \alpha_n\ \varphi_n(x)\right] dx = \gamma_n \text{ for n = 0,1,…, N} \qquad (6)$$

For the case of wind distribution φ_n(x) can be taken as powers of wind speed (*v*) such that:

$$\varphi_n(v) = v^n \text{ for n = 0,1,…,N} \qquad (7)$$

Then γ_n, n = 0,1,…,N with γ_0 = 1 are the moments of the distribution representing the mean values of n power of wind speed observation data and hence, correspondingly, *f(v)* and $Z_n(\alpha)$ can be calculated from the wind data as(14) :

$$f(v) = \exp\left[-\sum_{m=0}^{N} \alpha_m v^m\right] \quad (8)$$

$$Z_n(\alpha) = \int v^n \exp\left[-\sum_{m=0}^{N} \alpha_m v^m\right] dv = \gamma_n \text{ for } n = 0, 1, \ldots, N \quad (9)$$

In this study, the python pymaxent software authored by Saad (Saad & Ruai 2019) was used to compute the Lagrange multipliers of the maximum entropy probability density distribution. Details of the numerical method used in the determination of the Lagrange multipliers is given in Refs. (Saad & Ruai 2019).

2.2.2 The Weibull Distribution Function

The Weibull probability distribution function is given as (Fagbenle et al. 2011; Oyedepo, Adaramola & Paul 2012; Hasan, Guwaeder & Gao 2017):

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (10)$$

Where *f (v)* is the probability of wind speed (*v*), c is the scale parameter (m/s), k is the dimensionless shape parameter. Integral of the probability distribution function *f(v)* gives the cumulative density function F(v) expressed as:

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (11)$$

The Weibull shape and scale parameter are given as:

$$k = \left(\frac{\sigma}{Vm}\right)^{-1.086} \quad (12)$$

$$c = \frac{Vm}{\Gamma\left(1+\frac{1}{k}\right)} \quad (13)$$

where σ is standard deviation, V_m is mean wind speed (m/s) and Γ is gamma function defined as (Paul, Oyedepo, and Adaramola 2012):

$$\Gamma(x) = \int_0^{\infty} t^{x-1} e^{-t}\, dt \quad (14)$$

3. Test of Goodness of Fit

The coefficient of determination (R^2) is used to evaluate the performance of modelled values obtained from the proposed distribution function in comparison with measured data. The higher the R^2, the better is the fit between measured data and theoretical distribution. Ideally, a value higher than 0.7 of R^2 is acceptable (Li & Li 2005a). The R^2 is given as:

$$R^2 = 1 - \frac{\sigma_{y,x}^2}{\sigma_y^2} \quad (16)$$

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

$$\sigma_y^2 = \left[\frac{\sum_{i=1}^{N}(y_i - \bar{y})^2}{N-1}\right] \quad (17)$$

$$\sigma_{xy}^2 = \left[\frac{\sum_{i=1}^{N}(y_i - y_m)^2}{N-1}\right] \quad (18)$$

Where N is the total number of measurements y_i and y_m are the measured and modelled values respectively. To further evaluate the performance of the models, the root mean square error (RMSE) is also introduced. The smaller the values of the RMSE parameter, the better the proposed distribution function approximates the measured data. The expression for RMSE is given as:

$$\text{RMSE} = \left[\frac{1}{N} \sum_{i=1}^{N} (y_i - y_m)^2 \right]^{1/2} \tag{19}$$

4. Results and Discussion

4.1 Annual and Overall Mean Wind Speeds

The annual wind speed was obtained by averaging available wind speed for the year. The averaged wind speed for each year from 2008 to 2012 and the overall five-year wind speed average at 10 m are given in table 2.

Table 2 - Yearly and 5-Year mean wind speed at Nsukka

Year	Mean wind speed (m/s)
2008	2.5
2009	2.4
2010	2.3
2011	2.3
2012	2.3
5-Year	2.3

4.2 Monthly and Seasonal Wind Speed Variations

Monthly mean wind speed variations for the 5-year average and individual year at Nsukka are presented in Fig. 1. The monthly variations ranged between 2 m/s and 3.4 m/s. The variation is higher between February and April, and peaked at 3.4 m/s for 2008. These months coincide with the transition period from dry to rainy season. In this study, November to March is defined as the dry Season. The monthly average wind speed for November and December is between 2 m/s and 2.3 m/s. A rise in the wind speed was noticed from January to April. It is observed that the Year 2008 is the windiest in comparison with the other four years. The seasonal mean wind speed is presented in table 3. The dry season has relative higher wind speed compared with rainy season.

Table 3 - Yearly mean wind speed variations for rainy season (April-October) and dry season (November-March) based on 5-year data (2008-2012) at Nsukka

	Wind speed (m/s)	
	Rainy Season	Dry Season
2008	2.4	2.5
2009	2.3	2.5
2010	2.3	2.3
2011	2.3	2.4
2012	2.3	2.3
5-year	2.3	2.4

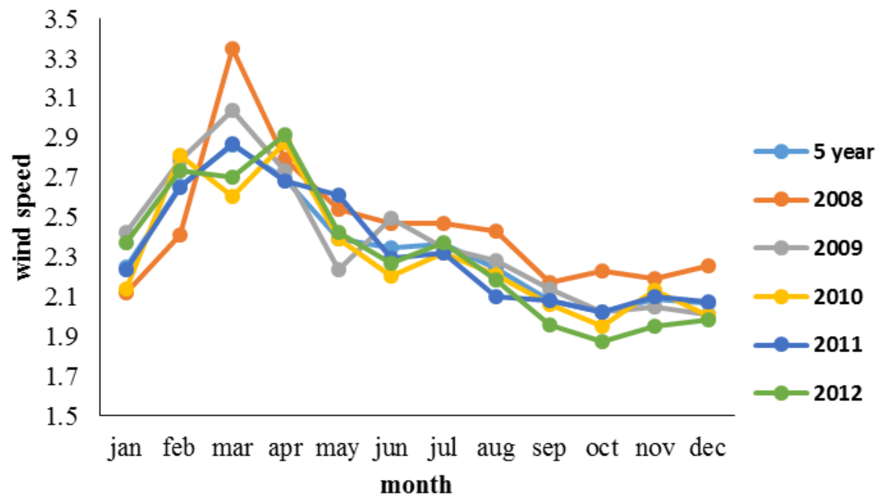

Fig. 1 - Monthly mean wind speed variations for 5-years and individual year at Nsukka, Nigeria

4.3 Diurnal Wind Speed Variations

The diurnal wind speed variations are illustrated in Fig. 2 for the 5-year average and the two seasons based on the 5-year data. A similar trend can be found for all the three curves. It can be seen that the day-time, from 8 a.m. to 3 p.m. is windy for all seasons peaking at 3.0 m/s between 10 am and 11 am. This is a good coincidence between the energy demands and the characteristics of the wind speeds since normally the energy demand is higher in the daytime. Therefore, wind energy can be used to supplement the regular energy generation. Wind speed at night is peaked at 2.5 m/s at midnight. It is worthy of note that the transition hours of 5-6 am and 5-6 pm, usually characterised with neutral stability due to extensive cloud cover have the least wind speed. The individual monthly diurnal variation is shown in Fig. 3. It can be seen that wind speeds for February, March, and April, are almost approximately 3 m/s for most of the time. These months coincides with dry to rainy season transition period. There is a marked phase shift of about 2 hours during the day-time hours between these group of months together with January and the remaining other months. The night-time hours are equally as windy as the day-time hours from the month of February through to April with the exception of transition hours of 5-6 am and 5-6 pm. It is worthy of note that the highest recorded wind speed of about 3.6 m/s occurred at 11 pm for March and the lowest recorded wind speed value of 1.3 m/s was in January at 6 pm. The day-time peak value of the wind speed was lowest in October.

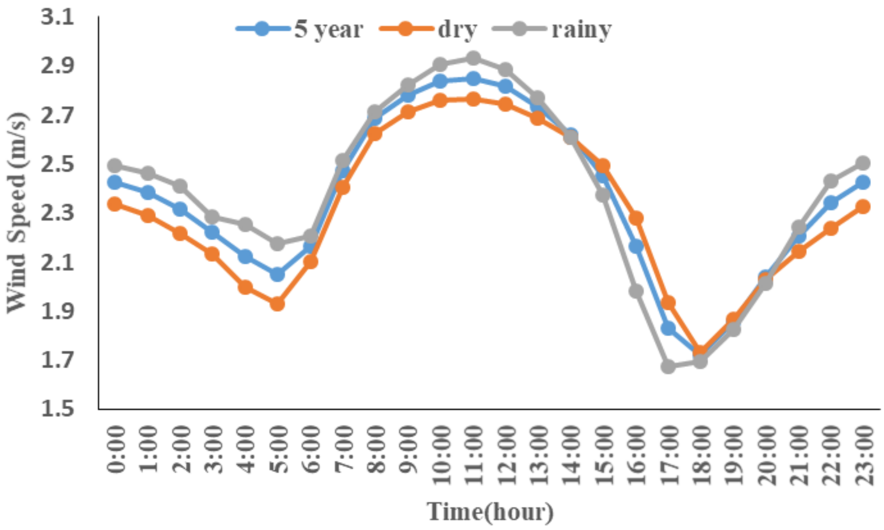

Fig. 2 - Diurnal mean wind speed variations for rainy season (April-October), dry season (November-March), and annual based on 5-year data average

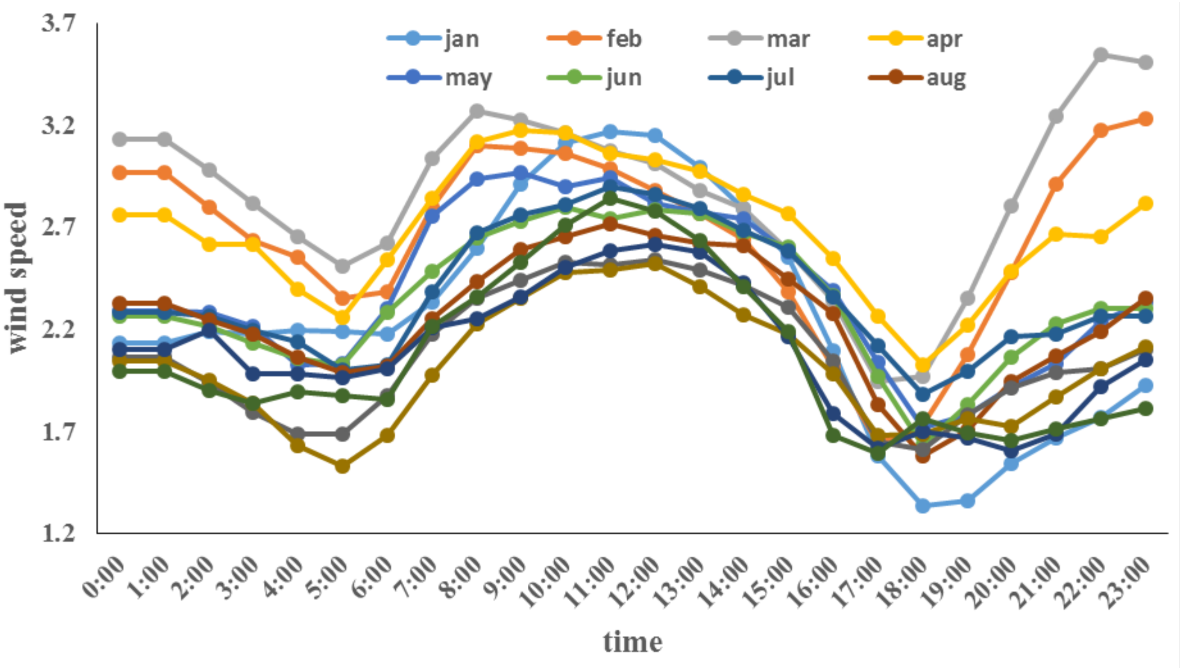

Fig. 3 - Diurnal wind speed variations for the individual months based on 5-year data at Nsukka

4.4 Wind Direction

Wind direction analysis is of great importance for planning of wind turbine installations. Wind direction frequency distribution for the 5-year annual averaged values is shown in Fig. 4. The predominant classes of wind speed of 2 m/s and 3 m/s lay within the sectors that were bounded by South-South-West and East. The wind sectors where the predominant wind speed classes situated were further delineated as the wind moved from January to December (the figures are not shown). The predominant wind speed classes of 2 m/s and 3 m/s rotated from South-South-West in January to South-East in February and through to East in August. These predominant wind speed classes rotated back from East in August to South-South-West in January. The 3 m/s wind speed and higher dominated over 2 m/s wind speed class from January through to May while 2 m/s wind speed and lesser dominated for the remaining months.

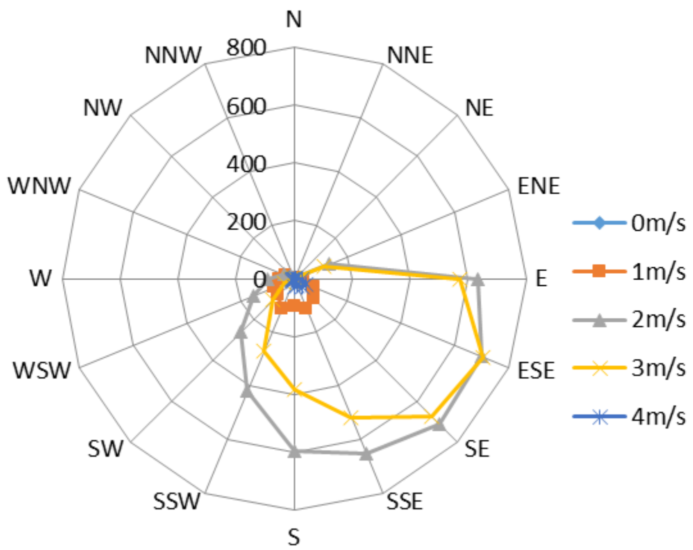

Fig. 4 - Wind direction frequency distributions for 5-year averaged data at Nsukka

4.5 Comparison of MEP-Based and Weibull Wind Speed Distribution with Data

The Lagrangian multipliers for different time-averaged period in MEP-based distribution at Nsukka are listed in table 4. The annual probability distribution of the actual data, MEP-base and Weibull distribution functions based on five-year hourly averages are given in figure 5. Figure 5 indicated 2 and 3 m/s wind speeds as dominant. The wind data were further divided into seasons, day-time and night-time hours. The corresponding probability distribution of the actual data, MEP-based and Weibull distribution functions indicated day-time hours to be windier than night-time with 3 m/s wind speed dominating in the day-time hours and 2 m/s wind speed dominating in the night-time (Figure 6). The monthly probability distribution of the actual data, MEP-base and Weibull distribution functions based on five-year hourly averages are also plotted but not shown in this paper. Comparing these plots with Figure 6 indicated that the 3m/s wind speed was again dominant from January through to May while 2 m/s wind speed dominated for the remaining months.

The parameters for the statistical analysis: the R^2 and RMSE are given in table 5 for all the time-average periods for MEP-based and Weibull distribution functions. It can be seen that the R^2 values vary from 0.91 to 0.99 for the MEP-based distribution and 0.90 to 0.99 for the Weibull distribution. Similarly, for the RMSE, the smaller the values of the RMSE parameter, the better the proposed distribution function approximates the actual data. The values of the RMSE for the MEP-based and Weibull distribution functions are very small in order of magnitude compared with the actual data.

Table 4 - The computed MEP Lagrangian multipliers for different periods based on 5-year data (2008-2012) for Nsukka

Period	alpha0	alpha1	alpha2	alpha3
Annual	7.57026526	-5.8926102	1.1278387	0.03553219
January	2.55903435	1.646553	-2.35145794	0.53955094
February	9.19804013	-5.7097842	0.59012284	0.11565725
March	6.74921503	-1.2551929	-1.36723137	0.35670651
April	1.52790054	10.112633	-7.71172291	1.39144349
May	4.31326307	0.450499	-2.25854704	0.57172369
June	16.55232949	-17.400143	5.78948174	-0.56383643
July	24.36422775	-26.841733	9.43062774	-1.01494881
August	1.92583731	9.5459759	-9.24609615	2.04266954
September	9.06882212	-8.9201576	2.42825231	-0.08563993
October	4.32163933	-0.4567353	-2.31024272	0.75409042
November	29.79624834	-38.431678	15.80656235	-2.0221045
December	5.51153792	-3.0995973	-0.5257097	0.38612352
Rainy season	5.674246707	0.5078239	-3.45309322	0.453488924
Dry season	6.90729246	-5.2614430	1.04091552	0.01616176
Rainy Season Day Time	25.64322552	-26.989678	9.09573041	-0.94503361
Rainy Season Night Time	2.2613	3.129173	-3.84371451	0.91177668
Dry Season Day Time	18.52355149	-18.207789	5.59956932	-0.49433013
Dry Season Night Time	9.00984321	-9.213035	2.99756287	-0.26073802

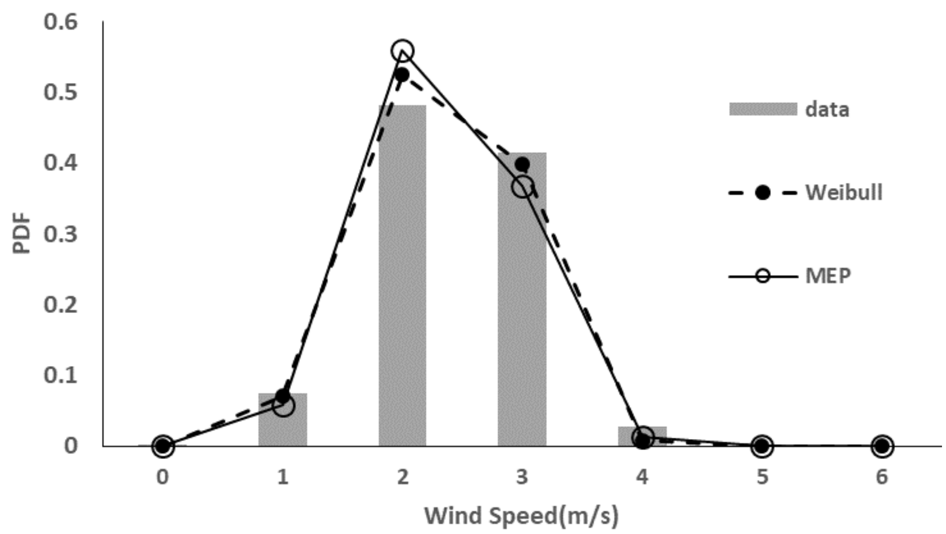

Fig. 5 - Annual probability distribution of actual data, the Weibull distribution and Maximum Entropy principle-based distribution at Nsukka using five-year data (2008 - 2012)

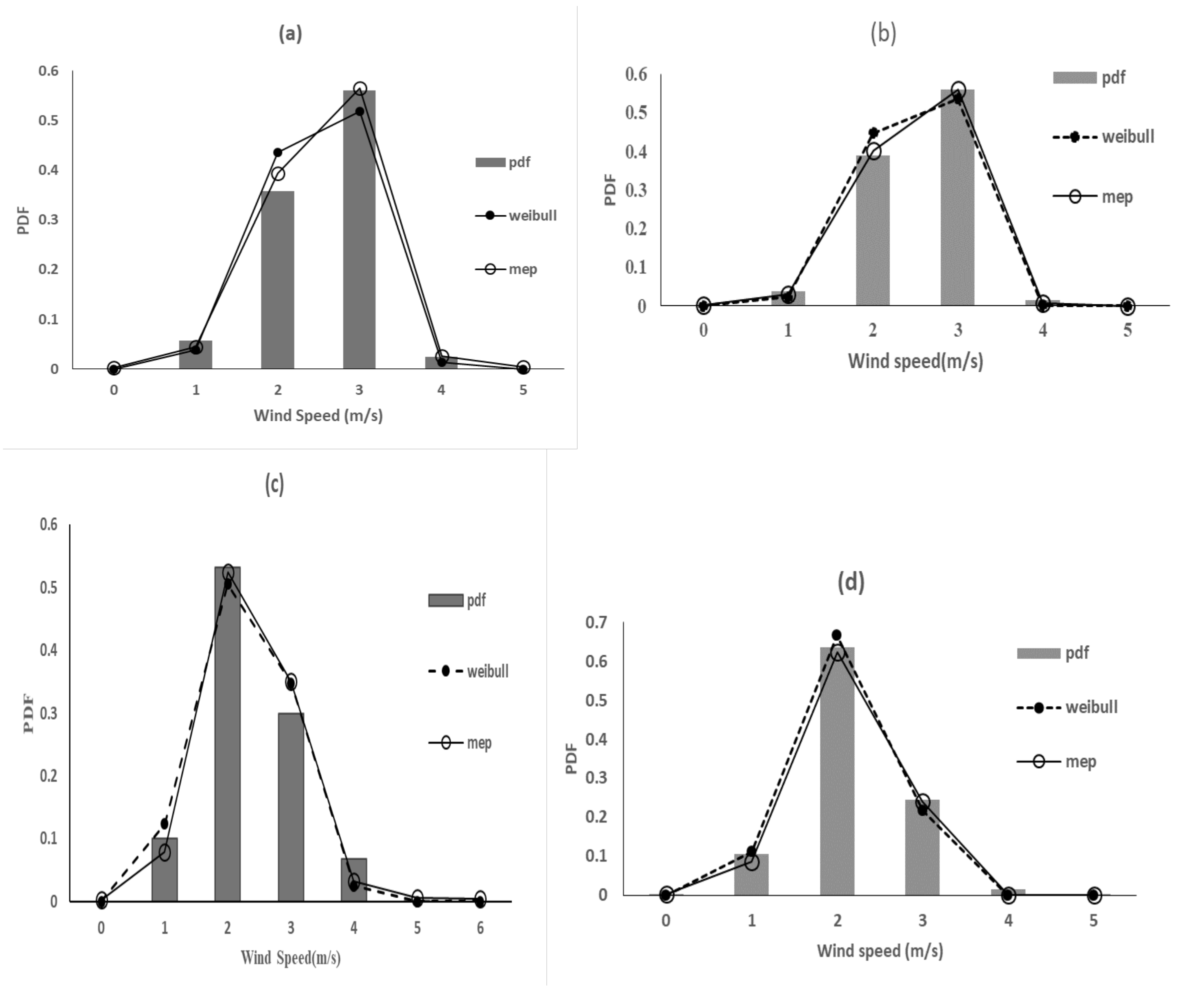

Fig. 6 - The probability distribution of actual data, Weibull distribution and Maximum Entropy principle-based distribution (a) dry season day-time hours; (b) rainy season day-time hours; (c) dry season night-time hours and; (d) rainy season night-time hours at Nsukka using five-year data (2008 - 2012)

Table 5 - The statistical analysis parameters for monthly wind speed distribution at Nsukka based on 5years data (2008 -2012) at Nsukka

Period	R^2 (MEP)	R^2 (Weibull)	RMSE (MEP)	RMSE (Weibull)
Annual	0.97	0.99	0.035	0.019
January	0.94	0.94	0.047	0.047
February	0.99	1.00	0.019	0.021
March	0.99	0.99	0.044	0.032
April	0.98	1.00	0.037	0.025
May	0.99	0.98	0.019	0.032
June	0.99	0.97	0.025	0.037
July	0.98	0.95	0.049	0.036
August	0.91	0.90	0.075	0.08
September	0.96	0.97	0.072	0.059
October	0.94	0.97	0.091	0.061
November	0.95	0.94	0.060	0.085
December	0.96	0.98	0.060	0.046
Rainy season	0.99	0.99	0.023	0.025
Dry season	0.98	0.99	0.027	0.016
Rainy Season Day Time	0.99	0.99	0.007	0.027
Rainy Season Night Time	0.99	0.99	0.011	0.018
Dry Season Day Time	0.99	0.97	0.016	0.037
Dry Season Night Time	0.98	0.98	0.027	0.030

5. Conclusion

Wind characteristics were analysed at a low wind equatorial location, Nsukka, Nigeria using a five year data (2008-2012). The diurnal, monthly, seasonal and annual variations of wind speed and directions were examined. The five-year average wind speed of approximately 2.3 m/s at 10 m can be scaled up with height to extract energy for domestic use especially in remote locations where conventional energy transmission could be prohibitively high. The analysis of the wind speed characteristics indicated that day-time are windier than night-time. The transition months of February, March and April are the windiest months with diurnal wind speed ranging between 2.3 and 3.7 m/s. There is usually heavy demand on the conventional means of energy supply due to industrial related activities during the day-time hours and this can be supplemented with the wind energy source. Also, the hydro-based, conventional means of energy supply are at the lowest performance during the transitional months due to low level of water in the dam. Wind energy will be a beneficiary addition during these months by using turbines that have low cut-in wind speed of 3 m/s at appropriate heights of 32 m or 64 m and so on. The predominant wind direction for these three months is South-East. The general predominant wind directions for all the months lay within the sectors South-South-West and East Wind distribution at the study location were modelled using Weibull two-parameter distribution and Maximum Entropy Principle (MEP) based distribution. Analysis of the two distribution models indicated that the two distributions can be used to model low wind regime accurately.

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