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GOODNESS OF FIT TEST FOR WIND ENERGY POTENTIAL USING FIVE PROBABILITY DENSITY FUNCTIONS FOR SOME SELECTED CITIES IN NIGERIA

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ABSTRACT

This research gives a better understanding on wind energy availability for some selected cities in Nigeria, such as Katsina, Sokoto, Bauchi, Maiduguri, Abuja, Jos, Abeokuta, Lagos, Enugu, Owerri, Calabar and Benin City respectively. Twenty Years (2000-2020) average wind speed data obtained from NIMET Headquarters Abuja, were analysed and fitted with five probability density functions such as normal, Weibull, Rayleigh, lognormal and Gamma Function with fixed shape parameter (K), but different scale parameters (C) in the model. The results of goodness of fit test based on Kolmogorov-Smirnov and Anderson – Darling shows that all the probability distribution functions are accepted at maximum difference, (D_n) less than their critical values, $D_n^{0.05}$ (= 0.0853 and 0.0855). While in the A-D tests, all the distribution functions hold except lognormal distribution function which is satisfactory for Jos and Abuja with an observed significant level (OSL) ranging from (0.7497 - 0.7497). Therefore, this results can be used for investors on wind power and also improve wind farm project for surface wind electrification.

Keywords: Goodness of fit test; A-D test; K-S Test; Wind Power Potential and Probability distribution functions

INTRODUCTION

Due to high cost of fossil fuel, its health hazard and related greenhouse gases cases made renewable energy resources more attractive as a source of alternative energy to meeting the energy demand of our country Nigeria. Ramirez, P., and Carta, J. A. (2OO5). On the other hand, for the past decade fossil fuel is finite and recorded as the world source of energy its consumption which is on an increased daily. Gupta, A. K., (1997) and thus, wind energy which is a clean source of energy, available throughout all seasons are of great interest in this work. Moreover, wind power provides power generation by converting kinetic energy of the wind through rotating shaft near load centres and lower transmission losses on lines passing through remote areas Gupta, A. K., (1997) North –East and North – West of Nigeria, has an enormous wind energy potential in terms of wind power generations (Ucar and Balo 2009, Genç *et, al.,* 2012a, 2012b), due to its geographical features and semi-arid region with enormous sun (solar radiation for 4-5hours daily (Jowder 2009).

Statistical analysis of wind speed plays important role for structures, designing, and power generators, and helps investors to have enough knowledge on characteristics of wind speed, wind generation, wind directions are important to any given location for perfect installation of wind farms (Ozgener 2010) and (Genç and Gökçek 2009, Genç 2011). Wind analysis also provides valuable information for researchers in this field (Eskin *et, al.,* 2008). The assessment of the effect of regional wind on structure is achieved whenever the analysis of basis wind speed is properly done (Lagomarsino *et, al.,* 1999, Quan *et, al.,* 2017). Also, basic wind characteristics measured at the field are important component of wind turbine constructions (Zidong *et, al.,* 2017). This assessment reduces the Damage caused by extreme wind events to the wind turbine component in any potential site (Elshaer *et, al.,* 2019).

The forces induced by the wind are of great impact to the aerodynamic performance of the small or large scale wind turbine / wind farm (Ke et al. 2019). It is difficult to predict the wind pattern of a place without the measured wind speed data of such location, due to nonlinear and fluctuation characteristics (Ye *et, al.,* 2019). So, many researchers predict that the main wind data is generally considered to be Weibull probability distribution satisfactory (Harris *et, al.,* 2006). However, this may fit into different probability distributions among the five probability distribution functions such as Weibull, Rayleigh, normal, gamma, lognormal, logistic according to the variability of wind speeds in different regions. In Nigeria, many studies were carryout on aerodynamic analysis, wind characteristics, cost analysis estimation and evaluation of wind potential for different locations across the country. Bajic and Peros (2005). According to Asiegbu and Iwuoha (2007) there is deficit wind resource availability in Umudike, South-East, Nigeria using 10 years (1994–2003) wind speed data. They found that the economic viability of the site required a hub height of 65 m above the ground with an annual mean wind speed of 5.36 m/s.

Fadare (2008) carried out a statistical analysis of wind energy potential in Ibadan, using a Weibull distribution function on 10 years (1995–2004) of daily wind speed data. The outcome showed that the city experienced an average wind speed and power density of 2.947 m/s and 15.484 W/m2. Ogbonnaya *et al.* (2009), on the other hand, worked on the prospects of wind energy in Nigeria. Four years' wind data from six cities (Enugu, Jos, Ikeja, Abuja, Warri, and Calabar) cutting across the different geopolitical zones of the federation were employed. The outcome showed that the annual wind speed at 10 m height for the cities varied from 2.3 to 3.4 m/s for sites along the coastal areas and 3.0–3.9 m/s for high land areas and semi-arid regions. Also, Ngala *et, al*. (2007) did a statistical analysis of the wind energy potential in Maiduguri (Borno State). It employed the Weibull distribution with 10 years (1995–2004) of wind data he found out that Weibull distribution functions is best fit for Maiduguri Metropolis . Further reports on the various assessment studies both by researchers and government agencies are profiled in (Ajayi, 2009).

In the present research, we used Kolmogorov- Smirnov (K-S TEST) and Anderson - Darling (A-D TEST) statistical goodness of fit test to predict the linear relationship between experimental model and observed model by arranging the wind speed data in ascending and descending order to check which one among the five probability distribution functions will be best fit for surface wind electrification across some selected cities Nigeria.

MATERIALS AND METHODS

Wind speed measurements have great importance in analysing the wind potential of a given region. The other important parameters are speed distribution, meteorological statistics and topographical data (Ajayi, 2009). Time series of wind speed is more suitable for statistical analysis Ngala *et al*. (2007). The time series of wind speed are analysed annually based on five probability density functions, namely Weibullx Rayleigh, Normal, Log`-Normal and Gamma distributions were selected for the estimation of wind speed in Katsina, Sokoto, Bauchi, Maiduguri, Abuja, Jos, Abeokuta, Lagos, Enugu, Owerri, Calabar and Benin city respectively.

Table 1: Geographical data for the locations in Nigeria

Locations	State	LAT (N)	LONGITUDE (E)	ALTITUDE (M)	ALTITUDE (FT)
KATSINA	KATSINA	$12^0 59'7$	$7^0 37'1$	513	1683
SOKOTO	SOKOTO	$13^0 3'5$	$5^0 13'45$	272	895
BAUCHI	BAUCHI	$10^0 18'57$	$9^0 50'39$	615	2020
MAIDUGURI	BORNO	$11^0 50'47$	$13^0 9'37$	299	984
ABUJA	ABUJA	$9^0 15'0$	$6^0 55'60$	246	810
JOS	PLATEAU	$9^0 55'0$	$8^0 54'$	1217	3996
ABEOKUTA	OGUN	$7^0 9'0$	$3^0 21'0$	66	219
LAGOS	LAGOS	$6^0 27'11$	$3^0 23'45$	34	114
ENUGU	ENUGU	$6^0 26'25$	$7^0 29'39$	247	813
OWERRI	IMO	$5^0 28'60$	$7^0 1'60$	158	521
CALABAR	CROSSRIVER	$4^0 34'27$	$6^0 58'33$	380	1249
BENIN CITY	EDO	$6^0 20'21$	$5^0 37'2$	122	400

Goodness-of-fit Test

When a model of random phenomenon has displayed to be of a particular probability distribution, is determined perhaps on the basis of available data plotted on a given probability paper, or through visual inspection of the shape of the histogram, the validity of the specified or assumed distribution model may be verified or disproved statistically by goodness-of-fit tests (Chang & Tu, 2007). In this study we used two goodness of fit test. The Kolmogorov-Smirnov (or K-S Test), and the Anderson-Darling (or A-D Test) methods; this two methods may be used to validate a specified or assumed probability distribution model. When two (or more) distributions appear to be credible models, the same test may be used also to distinguish the relative high quality between (or among) the assumed distribution models (Chang and Tu, 2007).

Kolmogorov-Smirnov (K-S) Test for Goodness-of-Fit

Kolmogorov-Smirnov (K-S test) is another widely used goodness-of-fit test. In K-S Test is to compare the maximum difference between experimental cumulative frequencies with that of the CDF of an assumed theoretical distribution. If the maximum discrepancy is large than the normal expected for a given sample size, the proposed model will not be accepted for the modelling of the underlying population. On the other hand, if the discrepancy is less than a critical value, the proposed model will be accepted at significance level α (Aidan and Ododo, 2010).

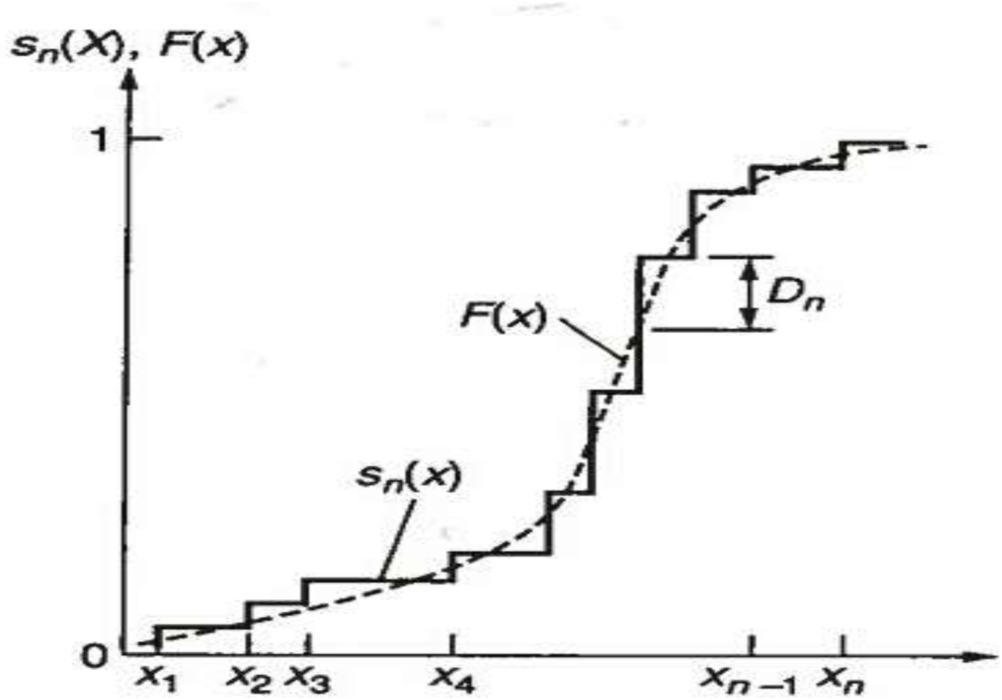

Figure 1: Empirical Cumulative Frequency versus Theoretical CDF. (Chand and Tu, 2007)

The set of the observed data is rearranged, for a given sample of size (n). From this ordered set of sample data, a step by step experimental cumulative frequency function is developed as given by equation (2.53) (Aidan and Ododo, 2010) as:

$$S_n(x) = \begin{cases} 0 & x \geq x_n \\ \frac{K}{n} & x_K \leq x < x_{k+1} \\ 1 & x \geq x_n \end{cases} \quad \ldots (1)$$

Where $x_1, x_2, \ldots, x_n$the observed ordered set of the data of a given sample size (n). it was also shown in Figure 1 which is a step-function plot of S_n with an assumed theoretical CDF $F_X(x)$. In the K-S test, the maximum difference between $S_n(x)$ and $F_X(x)$ over the entire observed data.

$$D_n = max\left|F_x - S_{n(x)}\right| \quad \text{... (2)}$$

Theoretically, in K-S test D_n the compares the observed maximum difference at significance level α as in equation (2.2) and equation (2.3) at critical valueD_n^α:

$$P(D_n \leq D_n^\alpha) = 1 - \alpha \quad \text{... (3)}$$

In this case if the observed data is less than the critical value D_n^α , the proposed theoretical distribution is acceptable at the specified significance level α; otherwise, the assumed theoretical distribution would be rejected.

Anderson-Darling (A-D) Test for Goodness-of-Fit

In (1954) Anderson-Darling (A-D) introduced (A-D) goodness-of-fit test in other to place more weight or discriminating power at the tails of distribution. This can be important when the tails of a selected theoretical distribution are of practical significance. Below steps are required when applying A-D method as follows:

i. Arrange the observed data in an increasing order: $x_1, x_2 \ldots \ldots .. x_i, \ldots \ldots .. x_n$, with x_n as the largest value.
ii. Evaluate the proposed distribution $F_X(x_i)$ at x_i, for $i = 1.2, \ldots . n$.
iii. A-D statistics is done by the given equation

$$A = -\sum_{i=1}^{n}\left[\left(\frac{(2i-1)}{n}\right)\{\ln F_X(x_i) + \ln[1 - F_X(x_{n+1-i})]\}\right] - n \quad \text{.... (4)}$$

i. Firstly compute the adjusted test statistic A^* which will account the effect of the sample size n. this adjustment is done based on the selected form of distribution.
ii. Select a significance level α under a determined critical value C_α for the appropriate distribution type.
iii. For a given distribution, compare A^* with the appropriate critical value C_α. In the case that A^* is less than C_α, the proposed distribution is acceptable at the significance level α, if $n > 7$.

For normal distribution, the critical value C_α is given by equation (2.5), (Chang and Tu, 2007) as:

$$C_\alpha = a_\alpha\left(1 + \frac{0.75}{n} + \frac{2.25}{n^2}\right) \quad \ldots (5)$$

And the adjusted A-D statistic for normal distribution of a sample size n is given by (Chang and Tu, 2007) as:

$$A^* = A\left(\frac{0.75}{1+\frac{0.75}{n}+\frac{2.25}{n^2}}\right) \quad \ldots (6)$$

In the case of gamma distribution, the critical value of C_α depends on the parameter k as given by equation (2.59) (Chang and Tu, 2007) as:

$$A^* = A^2\left(1.0 + \frac{0.6}{n}\right), \qquad For\ k = 1 \quad \ldots (7)$$

$$A^* = A^2 + \frac{\left(0.2+\frac{0.3}{K}\right)}{n}, \qquad For\ k \geq 2 \quad \ldots (8)$$

For the extremal distributions, of Gumbel and Weibull types, the adjusted A-D statistic is given by equation (2.61) (Chang and Tu, 2007) as:

$$A^* = A\left(1.0 + 0.2/\sqrt{n}\right) \quad \ldots (9)$$

Distribution Functions

Five different distribution functions used in this research are: Weibull, *f(v),* Rayleigh, *R(v),* normal, *n(f),* gamma, *g(v),* lognormal, *l(v)* and their probability density function (PDF) express for the i^{th} wind speed, v_i are given by (Aidan, 2010):

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v_i}{c}\right)^{k-1} e^{\left[-\left(\frac{v_i}{c}\right)^k\right]} \quad v \geq 0\,; k, c > 0 \quad \ldots (10)$$

$$R(v) = \frac{2}{c^2} v_i e^{\left[-\left(\frac{v_i}{c}\right)^2\right]} \qquad v \geq 0, c > 0 \quad \ldots (11)$$

$$n(v) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left[-\frac{1}{2}\left(\frac{v_i-\mu}{\sigma}\right)^2\right]} \qquad 0 \leq v \leq \infty \quad \ldots (12)$$

$$g(v) = \frac{{v_i}^{\alpha-\beta}}{\beta^\alpha \Gamma(\alpha)} e^{\left[\frac{v_i}{\beta}\right]} \qquad \alpha, \beta, v > 0 \quad \ldots (13)$$

$$l(v) = \frac{1}{\sigma\sqrt{2\pi v_i}} e^{\left[\frac{[\ln(v_i-\mu)]^2}{2}\right]} \qquad 0 \leq v \leq \infty \quad \ldots (14)$$

Where k, c, σ, μ, α, β and are the distribution function parameters.

A widely accepted empirical relation for the values of k and c are given by equation (2.15) and (3.7) Luna and Church (1974), Garcia *et al.* 1998).

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086} \quad \ldots (15)$$

$$c = \bar{v}\frac{k^{2.6674}}{0.184+0.816k^{2.73859}} \quad \ldots (16)$$

Where σ is the standard deviation and $\bar{v}$ is annual mean wind speed for the selected site

RESULTS AND DISCUSSIONS

Kolmogorov- Smirnov and Anderson Darling Goodness of Fit Test

It is clear that from Table (2-4) that the wind speed distributions shows that Katsina, Sokoto, Bauchi, Maiduguri, Abuja, Abeokuta, Lagos, Enugu, Owerri, Calabar and Benin City are fitted by normal distribution functions at 5% significant level while Jos is well fitted by lognormal distribution function at 5% significance level. The selected stations have shown that, all the accepted probability distribution functions have their values less than the KS test, similarly both values of their maximum difference, D_n less than their critical values, $D_n^{0.05}$ (= 0.0853 and 0.0855). The AD tests, though distribution specific, lognormal and distribution function are satisfactory for Jos and Abuja, while normal, Weibull and Rayleigh distribution function only can be satisfactory for Katsina, Sokoto, Bauchi, Maiduguri, Abuja, Abeokuta, Lagos, Enugu, Owerri, Calabar and Benin City. This shows that AD < CV in the case of distributions function for both stations were accepted at observed significant level (OSL) (0.7497 and 0.7497). With the favourable KS and AD test result together in table **(2-4),** with Figure **(2-4),** the wind speed distributions for Katsina, Sokoto, Bauchi, Maiduguri, Abuja, Abeokuta, Lagos, Enugu, Owerri, Calabar and Benin City can be satisfactory represented by normal distribution function while Lognormal can be satisfactory for Jos.

Table 2: Goodness-of-Fit Test Results for Sokoto, Katsina, Bauchi and Maiduguri

Stations	Distribution function	Kolmogorov-Smirnov test		Anderson-Darling tes6t		
		D_n	Decision rule	Test value	CV	Decision rule
Sokoto	Weibull	0.0617	Accept	2.689×10^{-17}	0.7497	Reject
	Rayleigh	0.2000	Accept	8.332×10^{-12}	0.7498	Reject
	Normal	0.0688	Accept	0.0037	0.7497	Accept
	Gamma	0.9998	Reject	1.945×10^{-5}	0.7497	Reject
	Lognormal	0.0986	Reject	3.138×10^{-43}	0.7497	Reject
	CV	0.0855				
Katsina	Weibull	0.0499	Accept	0.0058	0.7498	Accept
	Rayleigh	0.2455	Reject	3.103×10^{-11}	0.7498	Reject
	Normal	0.0629	Accept	0.0047	0.7498	Accept
	Gamma	0.9997	Reject	2.4922×10^{-93}	0.7498	Reject
	Lognormal	0.0897	Reject	7.0972×10^{-5}	0.7498	Reject
	CV	0.0853				
Bauchi	Weibull	0.0739	Accept	0.00018	0.7497	Accept
	Rayleigh	0.2721	Accept	5.0571×10^{-13}	0.7497	Reject
	Normal	0.0637	Accept	2.1506×10^{-26}	0.7497	Reject
	Gamma	1.000	Reject	---	---	---
	Lognormal	0.0685	Accept	0.00306	0.749	Accept
	CV	0.0855				
Maiduguri	Weibull	0.0699	Accept	0.00331	0.749	Accept
	Rayleigh	0.2205	Reject	1.101×10^{-12}	0.749	Reject
	Normal	0.0752	Accept	0.00063	0.749	Accept
	Gamma	0.8233	Reject	---	---	---
	Lognormal	0.1137	Reject	5.6739×10^{-75}	0.749	Reject
	CV	0.0855				

Table 3: Goodness-of-Fit Test Results for Plateau, Abuja, Lagos and Abeokuta

Stations	Distribution function	Kolmogorov-Smirnov test		Anderson-Darling test		
		D_n	Decision rule	Test value	CV	Decision rule
Plateau	Weibull	0.1458	Reject	3.9071×10^{-8}	0.7498	Reject
	Rayleigh	0.2737	Reject	1.878×10^{-11}	0.7498	Reject
	Normal	0.1531	Reject	4.174×10^{-8}	0.7498	Reject
	Gamma	0.9998	Reject	8.778×10^{-106}	0.7498	Reject
	Lognormal	0.0045	Accept	0.0037	0.7498	Accept
	CV	0.0853				
Abuja	Weibull	0.0482	Accept	0.00916	0.749	Accept
	Rayleigh	0.3115	Reject	1.7536×10^{-16}	0.749	Reject
	Normal	0.0357	Accept	0.12224	0.749	Reject
	Gamma	0.9872	Reject	0.00031	0.749	Accept
	Lognormal	0.0665	Accept	0.0134	0.749	Accept
	CV	0.0855				
Lagos	Weibull	0.0655	Accept	0.00233	0.749	Accept
	Rayleigh	0.2810	Reject	7.090×10^{-15}	0.749	Reject

	Normal	0.0581	Accept	0.00901	0.749	Reject
	Gamma	1.0000	Reject	---	---	---
	Lognormal	0.0614	Accept	0.00107	0.749	Accept
	CV	0.0855				
Abeokuta	Weibull	0.0024	Accept	0.0589	0.749	Accept
	Rayleigh	$8.37\text{x } 10^{-16}$	Reject	0.7438	0.749	Accept
	Normal	0.0326	Accept	0.0479	0.749	Accept
	Gamma	---	---	1.000	0.749	Reject
	Lognormal	0.0052	Accept	0.0521	0.749	Accept
	CV	0.0855				

Table 4: Goodness-of-Fit Test Results for Owerri, Benin City, Enugu and Cross River

Stations	Distribution function	Kolmogorov-Smirnov test		Anderson-Darling test		
		D_n	Decision rule	Test value	CV	Decision rule
Owerri	Weibull	0.0889	Accept	$4.087 \text{ x } 10^{-5}$	0.7498	Reject
	Rayleigh	0.3239	Reject	$9.904 \text{ x } 10^{-17}$	0.7498	Reject
	Normal	0.0632	Accept	0.0037	0.7498	Accept
	Gamma	1.0000	Reject	---	---5	---
	Lognormal	0.0489	Accept	0.0264	0.7498	Accept
	CV	0.0853				
Benin City	Weibull	0.0901	Reject	0.0012	0.7498	Accept
	Rayleigh	0.3378	Reject	$1.224 \text{ x } 10^{-17}$	0.7498	Reject
	Normal	0.0661	Accept	0.0044	0.7498	Accept
	Gamma	0.9800	Reject	1.000	0.7498	Reject
	Lognormal	0.0499	Accept	0.0489	0.7498	Accept
	CV	0.0853				
Enugu	Weibull	0.0437	Accept	$4.087 \text{ x } 10^{-5}$	0.7498	Accept
	Rayleigh	0.2786	Reject	$9.904 \text{ x } 10^{-17}$	0.7498	Reject
	Normal	0.0619	Accept	0.0037	0.7498	Accept
	Gamma	1.0000	Reject	---	---	---
	Lognormal	0.0944	Reject	0.0264	0.7498	Accept
	CV	0.0853				
Cross-River	Weibull	0.0593	Accept	$5.1902 \text{ x } 10^{-8}$	0.7498	Reject
	Rayleigh	0.3198	Reject	$3.3520 \text{ x } 10^{-17}$	0.7498	Reject
	Normal	0.0419	Accept	$7.8265 \text{ x } 10^{-6}$	0.7498	Reject
	Gamma	---	---	---	---	---
	Lognormal	0.0835	Reject	0.00025	0.7498	Accept
	CV	0.0853				

Wind Speed Data and Frequency Distribution Analysis

The sample estimated parameters of the distribution functions are presented in Table 2. Figure **(2-13)** shows the fitted probability distribution functions (PDF) onto the constructed frequency diagram of the observed wind speed data for Katsina, Sokoto, Bauchi, Maiduguri, Abuja, Jos, Abeokuta, Lagos, Enugu, Owerri, Calabar and Benin City respectively. It was also shown from Figure **(2-4)** only on the plots of probability distribution functions it could be seen that normal distribution function is the most fitted function onto the constructed data histograms across the above mentioned state. These are validated by the statistical goodness-of-fit test results in Table (2-4).

Table 5: Estimates of the parameters of the distribution function across six geopolitical zones

Stations	Weibull		Rayleigh		Normal		Log-Normal		Gamma	
	K	C	K	C	μ	σ	μ	σ	α	β
Abuja	7.197	2.224	2	2.359	2.091	0.339	0.725	0.161	0.026	0.055
Plateau	1.995	3.565	2	3.565	3.159	1.673	1.026	0.497	0.280	0.886
Abeokuta	4.098	2.465	2	2.521	2.234	0.609	0.767	0.267	0.074	0.325
Bauchi	4.059	4.671	2	4.356	4.285	1.179	1.418	0.270	0.075	0.324
Maiduguri	4.700	3.962	2	4.087	3.622	0.871	1.258	0.237	0.057	0.209
Katsina	4.119	3.579	2	3.662	3.245	0.881	1.142	0.266	0.073	0.239
Sokoto	2.543	3.844	2	3.849	3.411	1.444	1.144	0.164	0.179	0.611
Lagos	4.039	0.839	2	3.426	3.036	0.839	0.191	1.073	0.232	0.076
Cross- River	4.993	1.948	2	2.017	1.788	0.406	0.555	0.224	0.052	0.092
Owerri	4.439	2.488	2	2.557	2.266	0.574	0.787	0.249	0.064	0.145
Enugu	3.746	2.960	2	3.013	2.669	0.791	0.9399	0.290	0.087	0.234
Edo	3.909	2.505	2	2.336	2.298	0.654	0.793	0.279	0.081	0.186

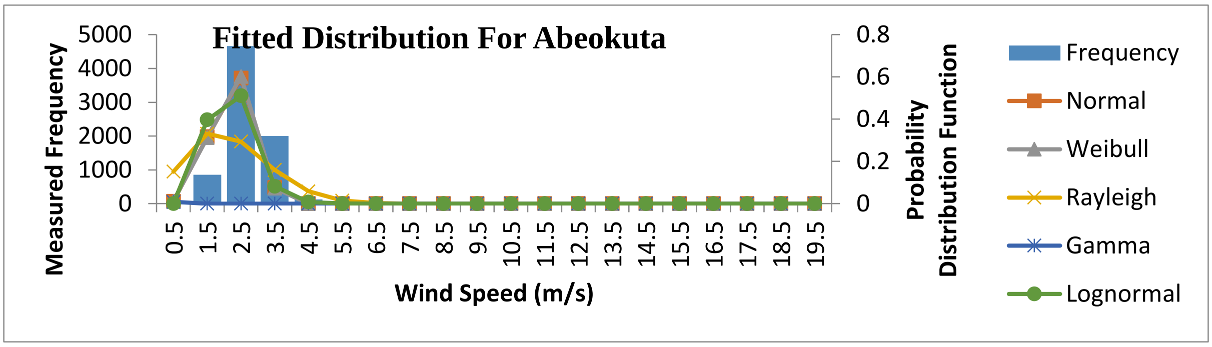

Figure 2: Fitted probability density function for Abeokuta

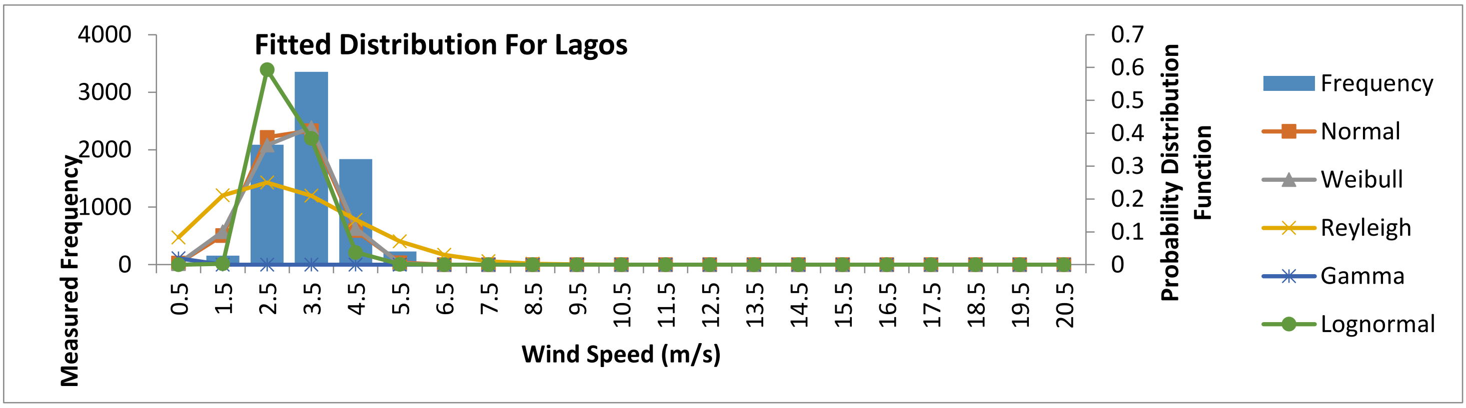

Figure 3: Fitted probability density function for Lagos

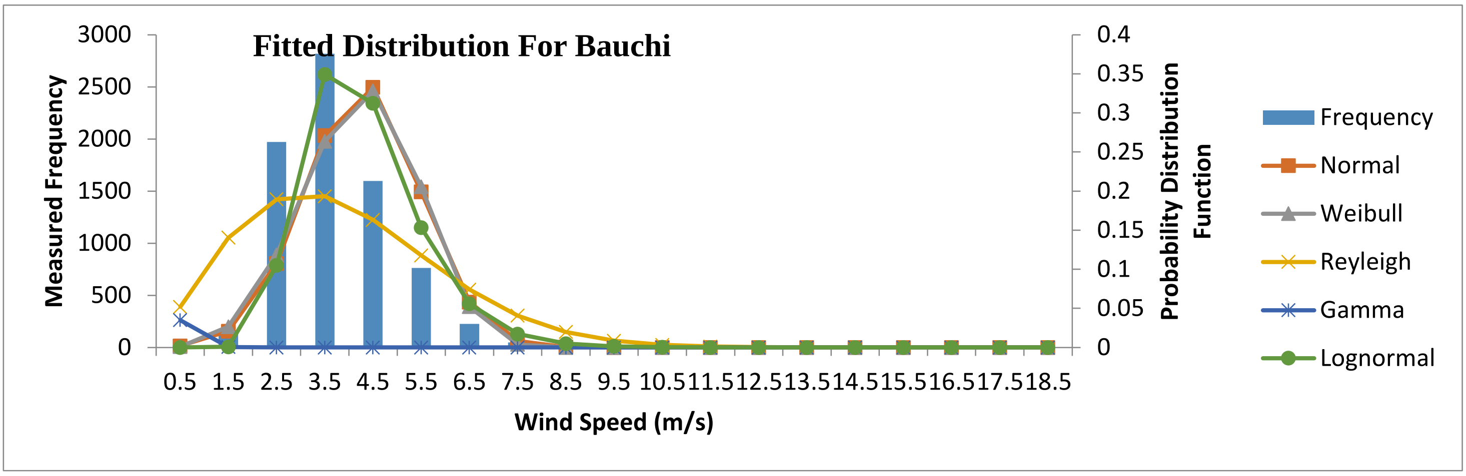

Figure 4: Fitted probability density function for Bauchi

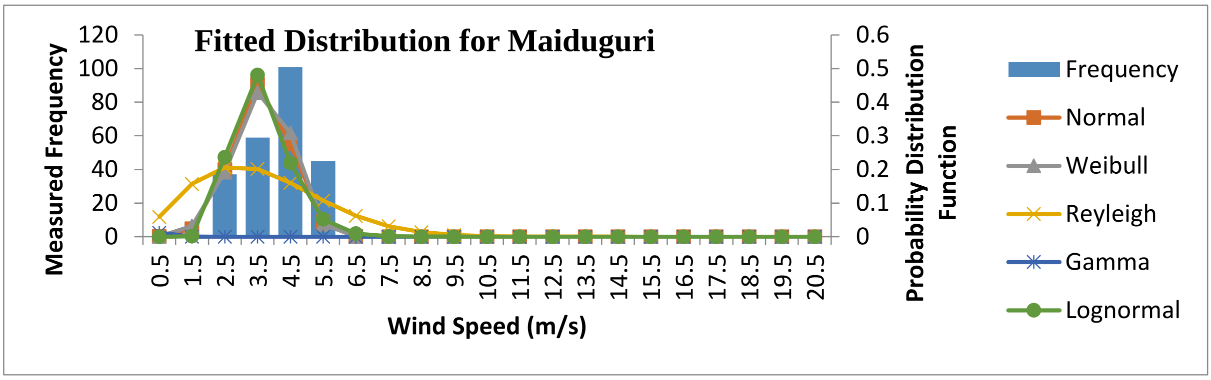

Figure 5: Fitted probability density function for Maiduguri

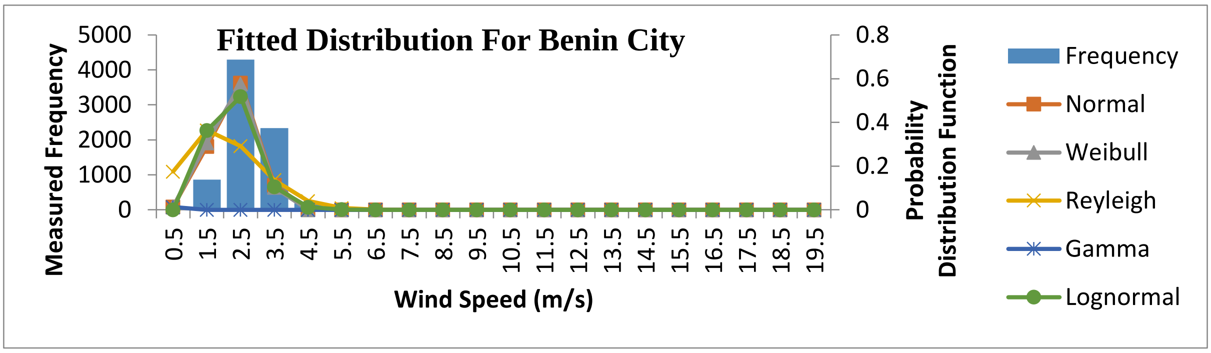

Figure 6: Fitted probability density function for Benin City

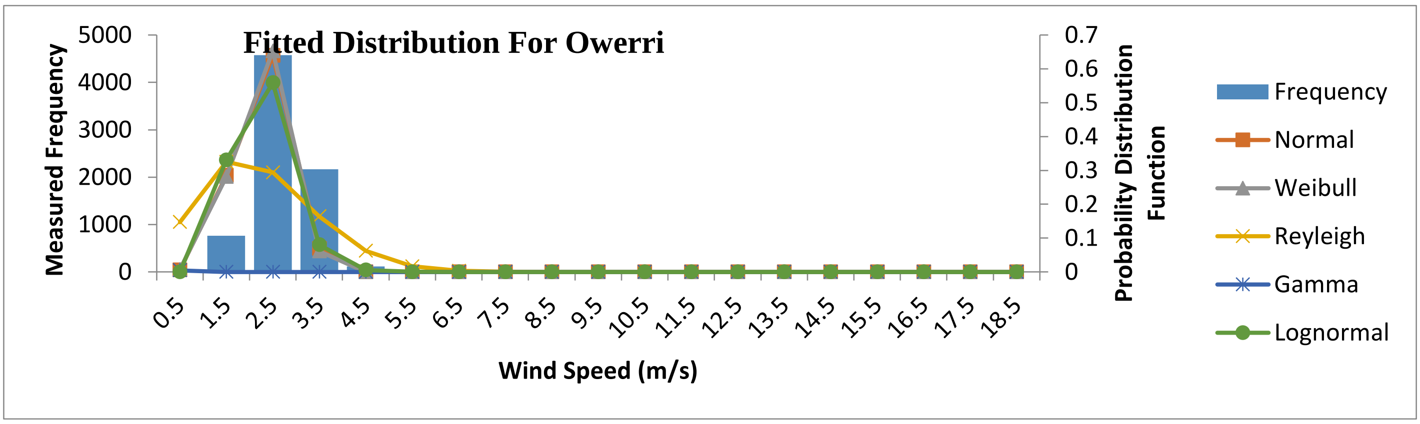

Figure 7: Fitted probability density function for Owerri

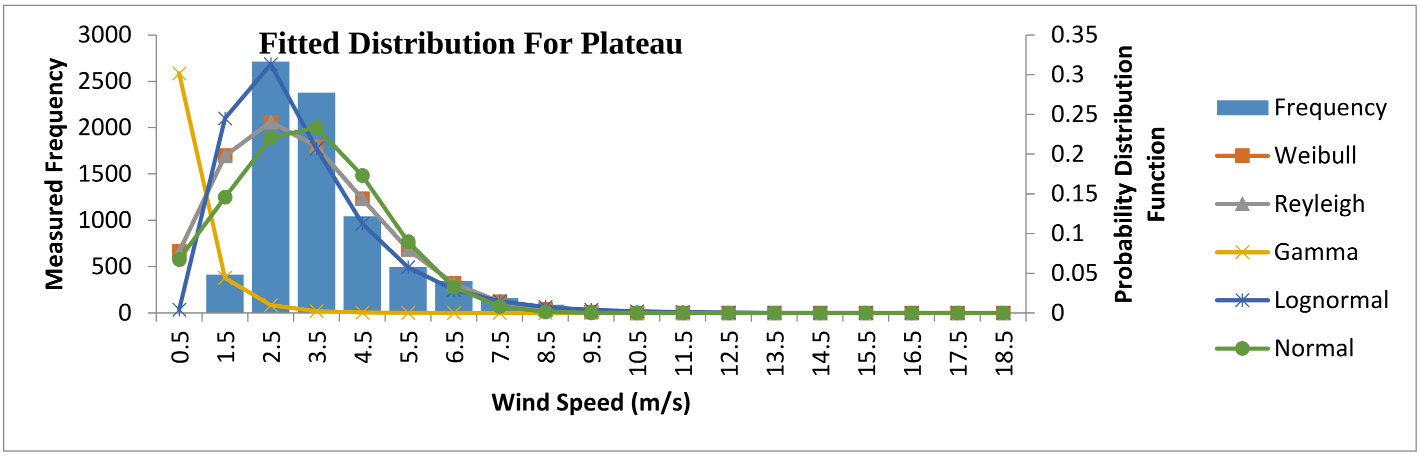

Figure 8: Fitted probability density function for Plateau

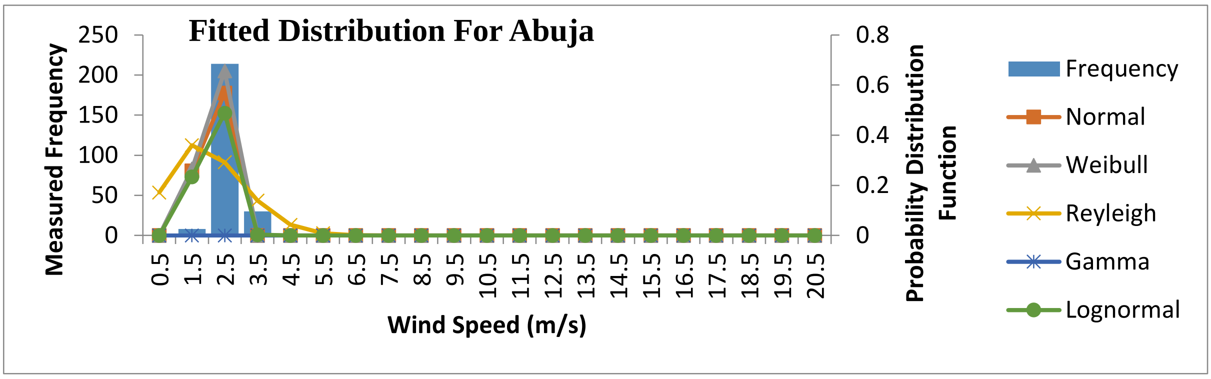

Figure 9: Fitted probability density function for Abuja

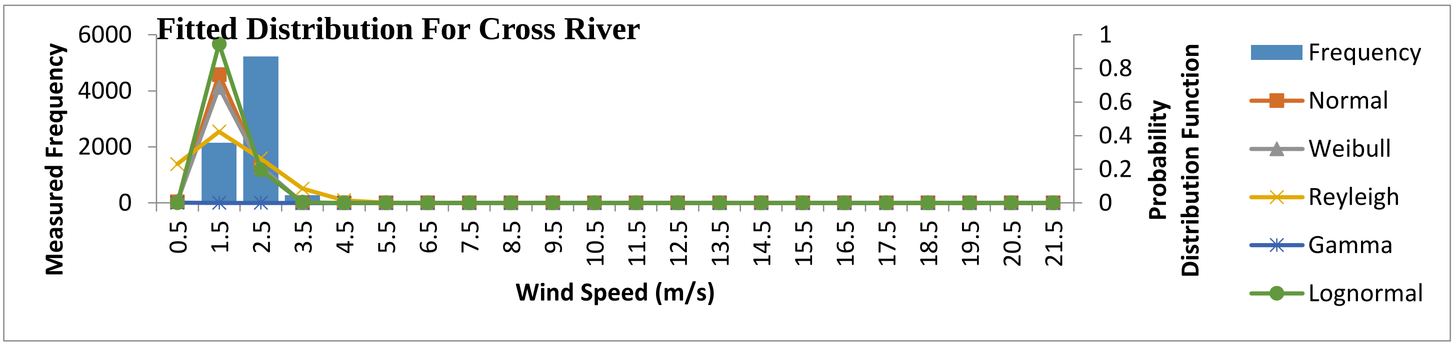

Figure 10: Fitted probability density function for Cross River

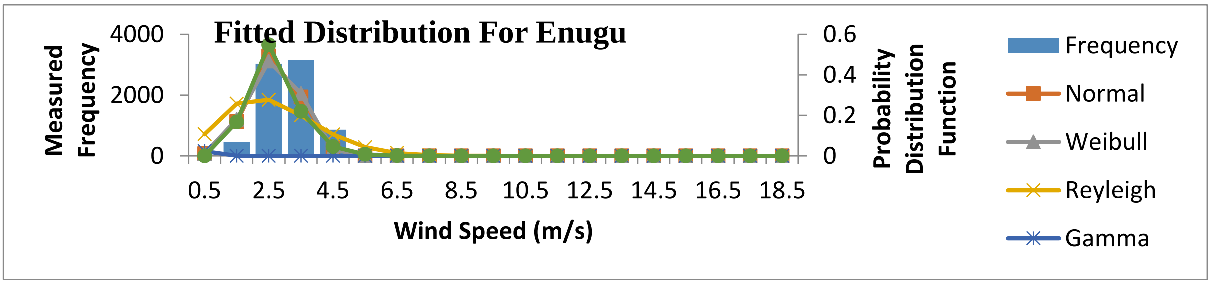

Figure 11:Fitted probability density function for Enugu

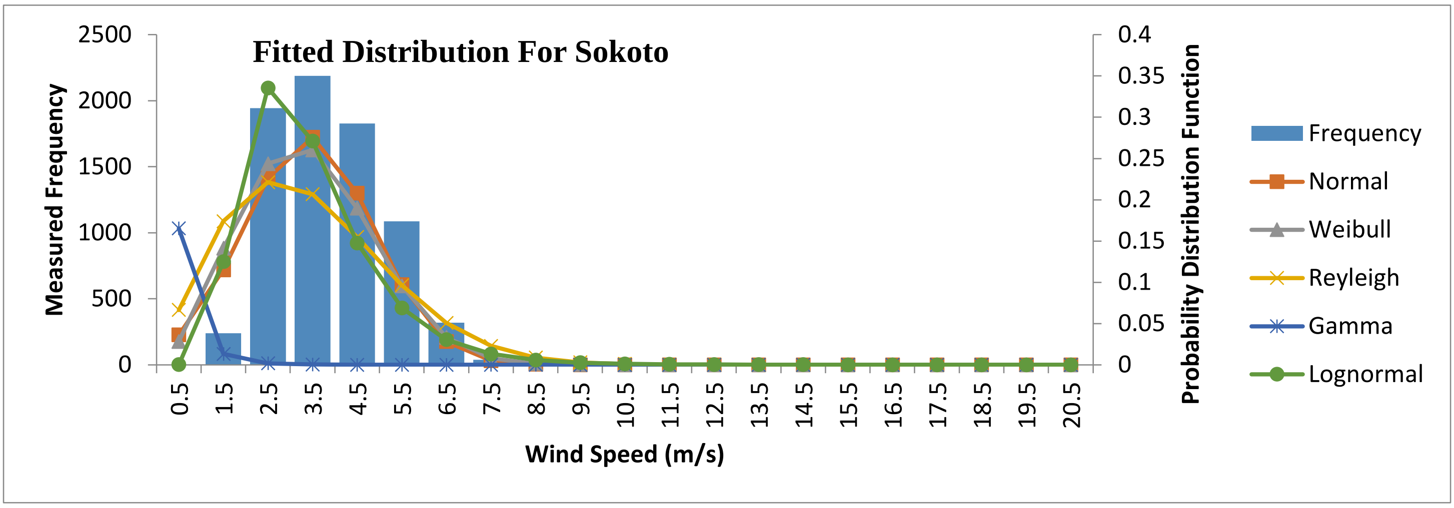

Figure 12: Fitted probability density function for Sokoto

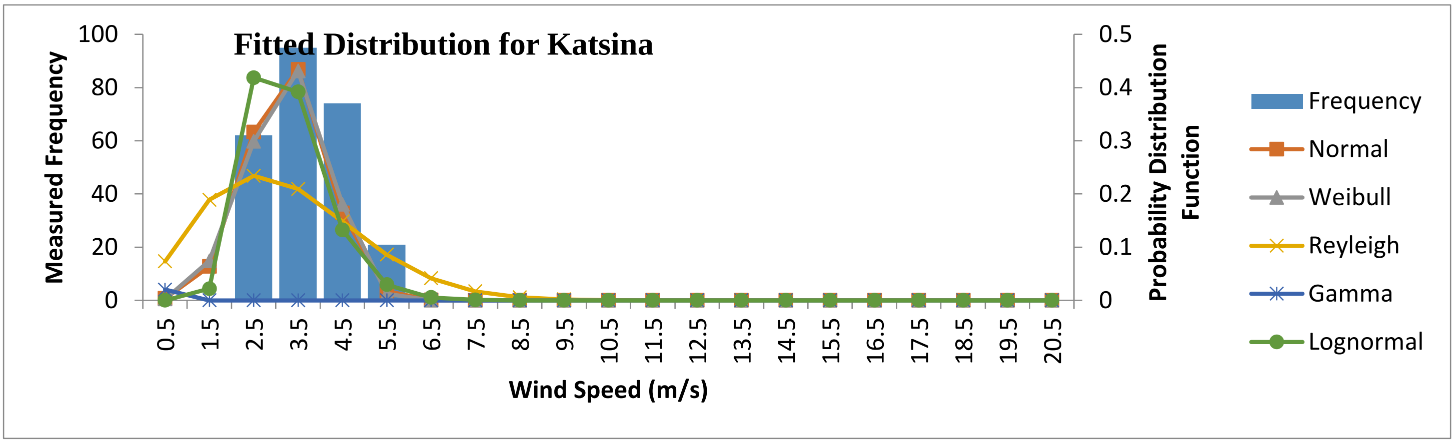

Figure 13: Fitted probability density function for Katsina

CONCLUSION

The wind speed data for the twelve stations has been fitted to five distribution functions (normal, Weibull, Rayleigh, lognormal and Gamma) with fixed shape parameter, k but different scale parameters, c. The goodness-of-fit at the 5% significance level has been determined by using Kolmogorov and Anderson-Darling tests. Normal distribution function is found to give the best fit for all the selected cities for surface wind electrification.

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