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Mathematical Differential Analysis of Atlantic Ocean Wind to Electrical Energy Generation in Lekki Peninsular Lagos Nigeria.

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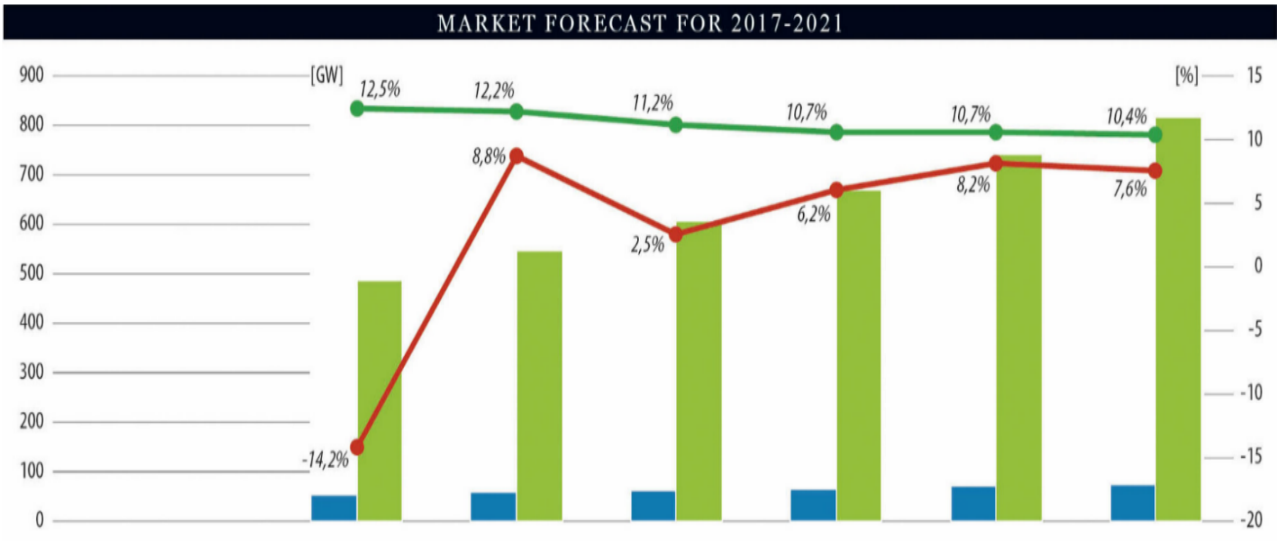
Abstract

This article is a pragmatic approach on the evaluation of wind energy production and it's estimation in the coastal area of Lagos Nigeria. The work focuses on the accessibility of wind energy production in Lagos Nigeria through analyzing wind data in the look up tables using proficient probability function. Here, three approaches are itemized; Analysis of sets of actual time series data, theoretical Weibull probability function using seven numerical methods and the comparison of theory and the analysis. Two important parameters are used in this analysis are the Weibull shape factor "k" and Weibull scale factor "c". Theory involves the calculation using seven popular methods of moments (MM), standard deviation method (STDM) or empirical method (EM), maximum likelihood method (MLM), modified maximum likelihood method (MMLM), second modified maximum likelihood method (SMMLM), graphical method (GM) or least mean square method (LSM), energy pattern factor method (EPFM). The performance of the numerical methods has been tested by five methods; RMSE, X^2, IA, MAPE and RRMSE. The results expatiate on Actual and theoretical technique being used to find out wind energy conversion per 1 km^2. In this paper, a differential performance method for accuracy check has been proposed as an error indicator between the wind energy calculated by theoretical Weibull function and the one by actual time-series data. The wind speed data was measured from January 2018 to December 2021 in the Lekki peninsular area of Lagos State. The suitability values for these parametric; shape and scale parameters of Weibull distribution are determined in selecting the best location for the installation the wind turbine generators. The measured annual mean wind speed and mean wind power are 10.11 ms^{-1} and 10.4 KWm^{-2}, respectively.

Keywords: Wind turbine, Artificial Neural Networks, Modelling and simulation, Wind speed, Wind energy, Weibull probability distribution, scale factor (c), shape factor(k), mean wind speed (MWS), probability distribution function (PDF).

1. Introduction

Renewable energy such as solar. Wind, tidal, geothermal, hydroelectric, biomass, Ocean thermal etc are obviously becoming the alternative sources of energy. Notable among these renewable energy are wind energy for electricity production and distribution. The energy demand and consumption have increased rapidly in the last few years as a result of increased housing scheme due to rapid population growth in Lagos Nigeria. Unfortunately, most of this demand are met using fossil fuels which are non-renewable sources of energy. Undoubtedly, the non-renewable form of energy has shown potential environmental damage, climate change and the degredation of the ecosystem through pollution. Most developed nations are taking steps in dealing with this menance by using renewable form of energy to solve the afforementioned drawback.. These renewable sources have drawn significant consideration as alternatives to its counterpart sources because of their reliability and environmental friendliness [Mazin A., Min G. (March 2023), Ziyuan Z., Jianzhou W., Danxiang W., Tianrui L., Yurui X., (2023), Parajuli, A., A (2016), Albuhairi, M.H. (2006), Ghosh, S.K., et al. (2014), Azad, A.K., et al.(2015), Badawi, A.S.A. (2013)]. Wind energy is considered one of the most common renewable energy resources. In recent times, research on wind power technology has been getting increasingly significance all over the world. At the end of year 2021, worldwide nameplate capacity of wind powered generation was around 900 Giga Watts (GW). Thus wind energy has been accepted with highly potential prospective of all energies throughout the world with basically three main purposes : 1)electricity generation and 2) water pumping and 3) water desalination .The obvious use of wind energy depends on the capacity and the variety of wind speed in any given area. Abdulwahab, D., (2011), Abdulwahab D. (2016). The installed global wind capacity from 2018 to 2021 is shown in Fig. 1.

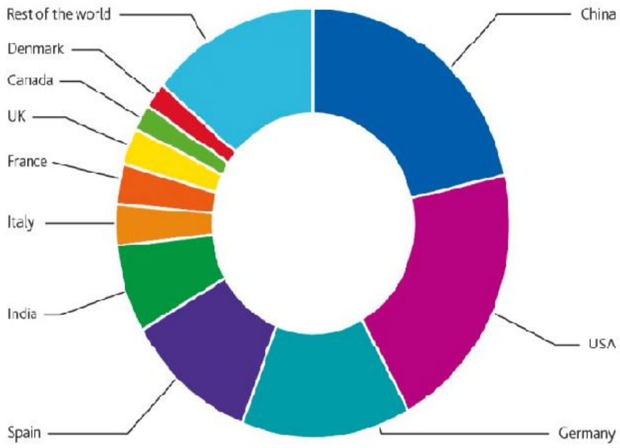


	2016	2017	2018	2019	2020	2021
Cumulative [GW]	486.8	546.1	607.0	671.7	741.7	817.0
Cumulative capacity growth rate [%]	12.5%	12.2%	11.2%	10.7%	10.7%	10.4%
Annual installed capacity [GW]	54.6	59.4	60.9	64.7	70.0	75.3
Annual installed capacity growth rate [%]	-14.2%	8.8%	2.5%	6.2%	8.2%	7.6%

Figure1. Global cumulative installed wind capacity 2018-2021[1-4].

Figure 2. and table 1 show the top comulative capacity of the PR China, USA, Germany, Spain, India etc and how they have accomplished high level of wind power penetration. However, the shortage of electricity is becoming one of the mainstay problem around the world especially in the third world nations. Arslan, T., Y.M .Bulut, and A. Altın Yavuz (2014), Mohammadi, K. and Mostafaeipour A. (2013), Celik, A., Makkawi, A. and Muneer T. (2010), Ohunakin, O., Adaramola M.S. and .Oyewola O.M., (2011), Carrasco-Díaz, M., et al. (2015),

Table 1: Countries capacity of Wind Enegy



Country	MW	%
China	42,287	21.8
USA	40,180	20.7
Germany	27,214	14.0
Spain	20,676	10.6
India	13,065	6.7
Italy	5,797	3.0
France	5,660	2.9
UK	5,204	2.7
Canada	4,009	2.1
Denmark	3,752	1.9
Rest of the world	26,546	13.7
Total TOP 10	**167,844**	**86.3**
World Total	**194,390**	**100**

Figure 2. Top 10 cumulative capacity Dec 2018 [1-2].

Nigeria is a country of about 230 million people with a barely 4000MW of electricicity distributed. By standard, 1 million people are entitled to 1,000MW of electricity and 230 million are entitled to 230,000MW. So as it stands, Nigeria needs huge investment in electricity and renewable energy is undoutedly a source that has been undertapped in the generation of electricity in Africa. The alternative source of energy e.g. wind power becomes more intensely needed than ever before, as the Nigeria is faced with the continued interruption of fuel due to Niger Delta vandalism of fuel pipeline, banditry and kidnapping of electric power manpower and machinaries [1-5]. Khan S., A. Deji, A.H.M Zahirul, J. Chebil, M.M Shobani, A.M Noreha. (Setember 2012),

Hence, we commence the wind energy research by obtaining (1) the wind power density (wpd) based on the measurement, (2) wind power density using frequency distribution function [1, 4, 6 and 9]. Recent researches show that the Weibull function suits the wind probability distribution very accurately when compared to other methods [7-10]. The Weibull function helps to fit time series data. This probabilistic distribution is significant mainly for maintainability and reliability analysis. The appropriate values for both scale parameters and shape parameter of Weibull distribution are immensely important in choosing sites for the installation of the wind turbine generators. Again, the scale parameter of Weibull distribution is cognizant in determining the usefulness of the resulting wind farm. Deji, A., Khan, S., Habaebi, H.M., Musa. O.S. (2024), Deji A., Sheroz K., Musse M.A., (December 2023, D. Abdulwahab et al. (2010), D. Abdulwahab, S. Khan, J. Chebil and A. H. M. Z. Alam (2011).

The amount of electricity generated by wind power generator model depends on three factors; the mean wind speed (MWS), standard diviation of wind speed, and the location characteristics. As the values of annual MWS becomes hard to predict yearly, then the variations of wind speed during the year can be clearly characterized in terms of a probability distribution function (PDF). Moreover this study explores finding the relationship between MWS, its common deviation, and two significant parameters of Weibull distribution. Deji A., Sheroz K., Musse M.A., (December 2023), Deji A., Hanifah A.M., Sherifah O.M., (December 2023). Therefore, this research work centralizes on the wind energy production in Lekki Pennisular area of Lagos state, Nigeria by analyzing wind data, using proficient probability function.. This research has been carried out using information recorded from three coastal cities: Lagos Island and Eti-Osa from January 2018 untill December 2021. Such information is required to optimize the design of wind turbines, so as to minimize energy generating costs. This research study focuses on estimating the wind energy potential in the Atlantic coast of Lagos. It describes how variation in wind speeds is useful in optimizing the wind energy turbine designs for cost effective wind energy generation.

2. Estimation of Wind Power Density (WPD)

The wind power density (WPD) is an indicator reflecting the capacity of wind energy resources in a particular target location[12]. The wind Power density could be measured based on two approaches: 1) available power based on the measured mean wind speed of the meteorological station, and 2) The frequency distribution function (Weibull two parameter method) Rocha, P.A.C., et al., (2012).

The wind power density is an important indicator to determine the potential of wind resources and to represent the amount of wind energy at different wind speed values in a specific location. The knowledge of wind power density is also helpful to evaluate the performance of wind turbines while selecting the optimum wind turbines. Wind power density identifies the level of accessible energy at the location. Researchers chose two methods to calculate wind power density. The first, the wind power density is calculated based on measured wind speed data. Nevertheless, as an alternative approach, the wind power density can also be computed using a proper distribution function. Through many probability distribution functions suggested in the literature for various applications of wind energy, the Weibull function, which is unarguably one of the most common ones widely used based on statistical distributions. The major merits of the Weibull function have been characterized extensively in[12, Andrade, C.F.d., et al. (2014), Yildirim, U., F. Kaya, and A. Gungor, (2012).

Additionally, it should be mentioned that adaptability, simplicity, favorability, flexibility, and capability to fit with wind data are considered throughout in this course of study as the major advantages of this function[16]. Accordingly, distribution function of Weibull is adopted for the calculation of wind power density. It is used for illustrating the wind speed frequency distribution. This paper has adopted these seven methods as a recommendation and contribution for estimating Weibull parameters. These methods are: Moment method (MM), Empirical method (EM), Maximum likelihood method (ML), Modified maximum likelihood method (MML), Graphical method (GP), Energy pattern factor method and Equivalent energy method. The goals of estimation are to: a) retrospectively distinguish past conditions; b) predict future power generation at one site; c) predict power generation among a grid of wind turbines, and to d) calibrate meteorological records[1] and [Deji A., Sheroz K., Musse M.A., (Jan-Feb 2024), Deji A., Sheroz K, Musse M.A, Jalel C. (August 2014), Deji A., Sheroz K, Musse M.A, Jalel C. (2011), Deji A., Sherifah OM., 2023, Elfaki Ahamed, O.M.H., Musa O.S, Deji A., (2023),.

3. Methodology and Statistical Analysis of Measured Wind Data

Assuming wind speed in $\upsilon\ (m/s)$, the wind power is proportional to cube of wind speed and can be calculated using the following equation Shu, Z., Li Q., and Chan P. (2015), Boudia S.M. and Guerri O., (2015)

$$P(V) = \frac{1}{2}\rho A \upsilon_{avg}^{3} \tag{1}$$

Where ρ is the air density for standard enviromental conditions, for example, at sea level with temperature of 15^o and pressure of 1 atmosphere is equal ρ=1.21kg/m^3.Thus, the power density for actual time series wind speed data can be calculated using the following equation[12, 17]:

$$\overline{P} = \frac{1}{2n}\rho\sum_{i=1}^{n}\upsilon^{3} = \frac{1}{2}\rho A(\overline{\upsilon^{3}}_{avg}) \qquad (2)$$

Where, ρ is the air density, υ is the wind speed (m/s) and n is the number of all data in the specified period of time Shu, Z., Li Q., and Chan P. (2015), Boudia S.M. and Guerri O., (2015)

3.1 Calculation using Weibull distribution

The wind speed is a random variable and its use in determining the wind potential of a region. The Weibull distribution can be described as a Cumulative Distribution Function (CDF), F(υ) and a Probability Density Function (PDF), f(υ). The cumulative distribution function can be attained by computing the integral of the probability density function [12, 20, 21], which is ultimately determined by the following equations [3, 11, 12, 20-23]. Celik, A., Makkawi, A. and Muneer T. (2010),

$$F(\upsilon) = 1 - \exp\left(-\left(\frac{\upsilon}{c}\right)^{k}\right) \qquad (3)$$

And the probability function is given by

$$f(\upsilon) = \frac{dF(\upsilon)}{d(\upsilon)} = k\frac{v^{(K-1)}}{c^{K}}e^{-\left(\frac{\upsilon}{C}\right)^{K}} \qquad k > 0, \upsilon > 0,\ c > 1 \qquad (4)$$

Where v, k and c are care wind speed (m/s), shape factor (dimensionless) and scale factor (m/s). The parameter, k, indicates the width of wind speed distribution, [12, 24]. The parameter, c, identifies the abscissa scale of the wind distribution, hence showing how windy the location is [12, 25]. Parameter c and k are popularly obtained using these methods: Moment method, Graphical method (GP), Maximum likelihood Modified, Maximum likelihood method (MML), and Empirical method (EMJ). The wind power density on the basis of Weibull probability density function is estimated using the following equation [12, 27, 28, 70-75]:

$$\overline{P} = \frac{1}{2}\rho\int_{0}^{\infty}\upsilon^{3} f_{w}(\upsilon)d\upsilon = \frac{1}{2}\rho c^{3}\Gamma\left(1+\frac{3}{k}\right) \qquad \left(\frac{w}{m^{2}}\right) \qquad (5)$$

To simulate the electrical power output of a model wind turbine is required using Celik, A., Makkawi, A. and Muneer T. (2010), .

3.2 Turbine power output

The power output of a wind turbine generator can be expressed as in equation (1) and its shown in Fig.3.

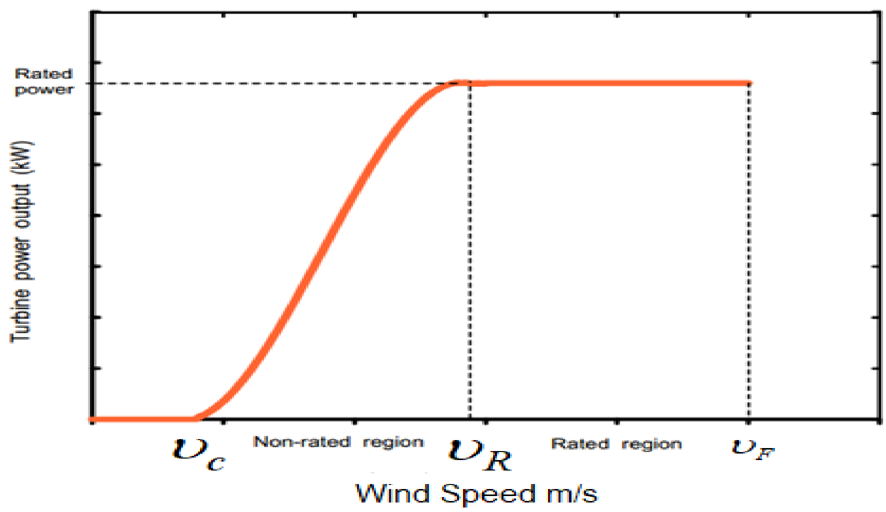


Fig. 3. Relationship between wind speed and output power [31].

Figure 3 shows the relation between wind speed and power, indicating how large the electrical power output will be for the turbine at different wind speeds. The power curve of a wind turbine follows this relationship between cut-in wind speed (the speed at which the wind turbine starts to operate) and the rated capacity, approximately. The wind turbine usually reaches rated capacity at a wind speed of between 12ms^{-1}to 16ms^{-1}, depending on the design of the individual wind turbine [75].

3.2.1 Max power output V_r

This power is also known as a rated power of the turbine, which is the constant power output maintained above the rated wind speed. This is used in calculating the rated electrical power as shown in equation 6.

3.2.2 The Cut in Wind Speed V_c

Wind speed at which the wind turbine is designed to start running. It is used as a parameter in determining the rated output power as shown in equation 6.

3.2.3 The Cut out Wind Speed V_f

The wind turbine will be programmed to stop at high wind speeds above, say 25 metres per second. This so as to avoid damaging the turbine or its surroundings. The stop wind speed is called the cut out wind speed.

$$Pe = \begin{cases} 0 & (\upsilon < \upsilon_c) \\ P_{eR}\dfrac{\upsilon^k - \upsilon_c{}^k}{\upsilon_R{}^k - \upsilon_c{}^k} & (\upsilon_c \le \upsilon \le \upsilon_R) \\ P_{eR} & (\upsilon_R \le \upsilon \le \upsilon_F) \\ 0 & (\upsilon > \upsilon_F) \end{cases} \tag{6}$$

Where P_{eR} is the rated electrical power, v_c is the cut-in wind speed, v_R is the rated wind speed and v_F the cut-out speed of the model wind turbine respectively.

3.3 Wind potential energy

Based on the Weibull probability function, the theoretical wind energy per unit area for a given time period T, is calculated by:

$$E_w = \frac{1}{2}\rho c^3 \Gamma\left(1+\frac{3}{k}\right) T \tag{7}$$

Where ρ is the air density.

Similar energy based on actual time-series data can be obtained by:

$$E_a = \frac{1}{2}\rho \upsilon^3 T \tag{8}$$

Where υ^3 is the mean of wind speed cubes [31]

Basically, there are two wind speeds that are of utmost interest to wind resource assessors. These are the maximum energy carrying wind speed ($\upsilon_{E\max}$) and the most probable wind speed (υ_{mp}). While the former is described as the wind speed carrying maximum wind energy, the latter represents the modal wind speed for the given wind distribution[29, 30]. They are expressed as:

$$\upsilon_{E\max} = c\left(\frac{k+2}{k}\right)^{\frac{1}{k}}$$ (9)

$$\upsilon_{mp} = c\left(\frac{k-1}{k}\right)^{\frac{1}{k}}$$ (10)

4. Numerical Methods For Determining Weibull Parameters

The followings are the different methods for obtaining Weibull Parameters.

4.1 Moment method

The moment method is recommended by Justus and Mikhail 2012. Here, it is suggested when the standard and the mean deviations of the elements are noted initially at a suitable scale Moment method. This is based on the numerical iteration of the following two equations, related to the mean ($\bar{\upsilon}$) and standard deviation (σ) of wind speeds are available Celik, A., Makkawi, A. and Muneer T. (2010),. The method of moments is an effective tool for finding Weibull parameters. The first moment is about origin and second moment is about mean. They are used to measure the parameters k and c, as given in equations (3) and (4). The calculation include mean wind speed and standard deviation which are obtained from calculated wind speed[38, 39].

$$\bar{\upsilon} = c\Gamma(1+1/k) \tag{11}$$

$$\sigma = c[\Gamma(1+2/k) - \Gamma^2(1+1/k)]^{1/2} \tag{12}$$

Where

$$\bar{\upsilon} = \frac{1}{n}\sum_{i=1}^{n} \upsilon i \tag{13}$$

$$\sigma = \left[\frac{1}{n-1}\sum_{i=1}^{n}(\upsilon i - \bar{\upsilon})^2\right]^{1/2} \tag{14}$$

Where Γ(x) is the gamma function expressed by:

$$\Gamma(x) = \int_0^\infty t^{x-1}\exp(-t)dt \tag{15}$$

4.2 Empirical method (EM)

EPM also commonly known as power density method. It is easy and simple to implement [38]. The empirical approach has a straight forward and practical solution only requiring the knowledge of the wind mean speed $\bar{\upsilon}$ and the standard deviation σ [31]. It uses mean of wind speed cubes (υ^3) and cube of mean wind speed $\bar{\upsilon}^3.\frac{\bar{\upsilon}^3}{\bar{\upsilon}^3}$ known as (E_{pf}). The scale factor is determined from energy pattern factor. The equations for finding scale parameters are identical to those used for method of moments and empirical method[40]. So The empirical method is considered a special case of the moment method [3, 33]. Based on the empirical method introduced by Justus [12, 41, 4273-85], the k and c parameters are computed in Eqs.(6) and (7)as [12, 34, 41, 42] respectively. EM can also be called STDM. Quite a number of authors uses STDM numerical methods to calculate Weibull parameters. Rreference [34] authors made a statistical study to compare the performance of six numerical methods in estimating Weibull parameters for wind energy application. In the STDM, the Weibull factors can be obtained as follows:

$$k=\left(\frac{\sigma}{\bar{\upsilon}}\right)^{-1.086} \quad , \quad 1\le k\le 10 \tag{16}$$

$$c=\frac{\bar{\upsilon}}{\Gamma\left(1-\frac{1}{k}\right)} \tag{17}$$

4.3 Maximum Likelihood Method (ML)

The maximum likelihood method was invented by Fisher [31, 43]. It was introduced as an application to wind speed information by Stevens and Smulders [31, 44]. It is based on indirect result of numerical iteration method for the determination of parameter k. It is, therefore, a more laborious and complex procedure, but very effective[31]. It is a mathematical expression technique which is also known as likelihood function of the wind speed data in time series format[12]. It requires extensive numerical iteration[33]. In this method, extensive numerical iterations are needed to determine the k and c parameters of the Weibull function. Using this method, k and c are shown as follows;

$$k=\left[\frac{\sum_{i=1}^{n}\upsilon_i^k\ln(\upsilon_i)}{\sum_{i=1}^{n}\upsilon_i^k}-\frac{\sum_{i=1}^{n}\ln(\upsilon_i)}{n}\right]^{-1} \tag{18}$$

$$c=\left[\frac{\sum_{i=1}^{n}\upsilon_i^k}{n}\right]^{1/k} \tag{19}$$

Where vi the wind speed in time step i (m/s) and n is the number of non-zero wind speed data points.

4.4 Modified Maximum Likelihood Method (MML)

This method can only be applied if the wind speed data are available in the format of frequency distribution. Like the maximum likelihood method, a remarkable number of iterations should be considered to determine the Weibull parameters. The k and c are obtained using the following equations:

$$k=\left[\frac{\sum_{i=1}^{n}\upsilon_i^k\ln(\upsilon_i)f(\upsilon_i)}{\sum_{i=1}^{n}\upsilon_i^k f(\upsilon_i)}-\frac{\sum_{i=1}^{n}\ln(\upsilon_i)f(U\upsilon_i)}{f(\upsilon\ge 0)}\right]^{-1} \tag{20}$$

$$c=\left[\frac{1}{f(\upsilon\ge 0)}-\sum_{i=1}^{n}\upsilon_i^k f(\upsilon_i)\right]^{1/k} \tag{21}$$

Where vi is the wind speed central to bin i and n is the number of bins. Also, $f(vi)$ is the frequency for wind speed falls within bin i and $f(v\ge 0)$ is the probability that wind speed reach or exceeds zero.

4.5 Second Modified Maximum Likelihood Method (SMMLM).

This method was modified by Christofferson and Gillette [1987] by replacing the iterative calculation of the shape parameter by[49]

$$k=\frac{\pi}{\sqrt{6}}\left[\frac{N(N-1)}{N\left(\sum_{i=1}^{N}\ln^2 vi\right)-\left(\sum_{i=1}^{N}\ln vi\right)^2}\right]^{0.5} \tag{22}$$

which requires neither iteration nor sorting of data. For this reason, this method has been selected by Ahmed Shata and Hanitsch[2006].[50, 72-75]

4.6 Graphical Method (GPM)

It is attained using the cumulative distribution function. In this method, the wind speed data are interpolated based upon the least squares regression. Accordingly, the wind speed data should be categorized into bins first. By taking twice logarithm of Eq. (3), the equation for the graphical method is obtained as shown in 33 [40,61]:

The graphical method is used by a logarithmic function of the cumulative Weibull distribution F(v), i.e., the cumulative distribution function F(v) is modified for the insertion of a double logarithmic transformation[31].

$$\ln\{-\ln[1-F(\upsilon)]\} = k\ln(\upsilon) - k\ln(c) \quad (23)$$

Plotting the $\ln(\upsilon)$ as x axis versus $\ln\{-\ln[1-F(\upsilon)]\}$ as y axis shows a straight line in which k is the slope of line and the y-intercept is $k\ln(c)$ [12, 33, 51]. Many outhors call GM as least mean squre method (LMS).[6]

4.7 Energy pattern factor method

This method is related to the mean records of wind speed and is described by the following equations[3, 26]

$$E_{pf} = \frac{\overline{\upsilon^3}}{\bar{\upsilon}^3} \quad (24)$$

Where, $\bar{v}$ is given in equation (11).

$$k = 1 + \frac{3.69}{(E_{pf})^2} \quad (25)$$

Where E_{pf} is the energy pattern factor and is the gamma function represented by equation (15).

5 Statistical Error Analysis and Goodness of best Fit

To evaluate and assess the performance of the seven parameters estimation methods of Weibull distribution for the estimation of wind power density, different statistical approaches including seven reliable statistical indicators have been used. In this study, several statistical parameters consisting relative percentage error (RPE), mean absolute percentage error (MAPE), mean absolute bias error (MABE), root mean square error (RMSE), relative root mean square error (RRMSE), correlation coefficient (R) and index of agreement (IA) along with some other statistical tools have been utilized to offer an appropriate comparative assessment. In the aforementioned subsections, a brief description of the statistical parameters considered is presented vividly. Mazin A., Min G. (March 2023)
Ziyuan Z., Jianzhou W., Danxiang W., Tianrui L., Yurui X., (2023)

5.1 Root mean square error (RMSE)

The RMSE identifies the model's accuracy by comparing the deviation between the values achieved by

Weibull function and those obtained from measurement data. The RMSE has a positive value and is calculated by[12]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{i,W} - P_{i,M}\right)^2} \tag{26}$$

5.2 Chi-square test X^2

This method is recommended to analyse proportions of independent variables, that is, possible discrepancies between the observed frequencies and the expected frequencies of the events of occurrence [52]. It is not appropriate to certify phenomena with small samples less than twenty (sample space) individuals. It is a nonparametric test which is independent of factors such as the population mean and variance. Obviously, two groups behave similarly if the differences between the frequencies of each category are negligible, close to zero. As stated by Souza [52], for this model the following propositions must be met: the groups should be independent; the items should be randomly selected from each group; the observations should be frequency counted and that each observation should belong to only one category[31, 86].

Let $F(v)$ the empirical distribution obtained from any wind speed data. Then, the parameters k and c are estimated such that is a minimum[53].

$$\chi^2 = \sum_{i=1}^{N}\frac{(y_{i,m} - x_{i,m}}{x_{i,m}} \tag{27}$$

Where, y is observed value, x is expected value.

5.3 Index of agreement (IA)

The IA generally shows the degree of precision of the predicted values compared to the measured values. The IA which varies from 0 to 1 is calculated by[12, 54]:

$$IA = 1 - \frac{\sum_{i=1}^{n}\left|P_{i,W} - P_{i,M}\right|}{\sqrt{\sum_{i=1}^{n}\left|P_{i,W} - P_{M,avg}\right| + \left|P_{i,M} - P_{M,avg}\right|}} \tag{28}$$

In the equations shown above (15)–(21), $P_{i,w}$ and $P_{i,M}$ are the ith calculated wind power density via Weibull distribution function and ith calculated wind power density by measured data, respectively. Also, $P_{W;avg}$ and $P_{M;avg}$ are the average of $P_{i,W}$ and $P_{i,M}$ values and n is the total number of observations.

5.4 Mean absolute percentage error (MAPE)

The MAPE shows the mean absolute percentage difference between the computed wind power using Weibull function and those attained by measured values. The MAPE is calculated by[12]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_{i,W} - P_{i,M}}{P_{i,M}}\right| \times 100 \tag{29}$$

5.5 Relative root mean square error (RRMSE)

The RRMSE is obtained by dividing the RMSE with the average of wind powers obtained by measured values as follows:

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{i,W} - P_{i,M}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}P_{i,M}} \times 100 \tag{30}$$

Different ranges of RRMSE can be defined to represent the models precision as [12, 55, 56]:
Excellent for RRMSE < 10%; Good for 10% < RRMSE < 20%; Fair for 20% < RRMSE < 30%; Poor for RRMSE > 30%

6. Wind speed for coastal plain in Lekki Lagos as a case study

Lekki Lagos is located in West Africa along the Atlantic coast. This study will focus on the south coast of Atlantic Ocean. The climate of the coastal area is hot and dry in summer, warm and rainy in autumn and cold and dry in the winter. Wind speeds in the coastal area are generally below 15 m/s for most of the year, while strong winds have mean speeds not exceeding 25m/s.

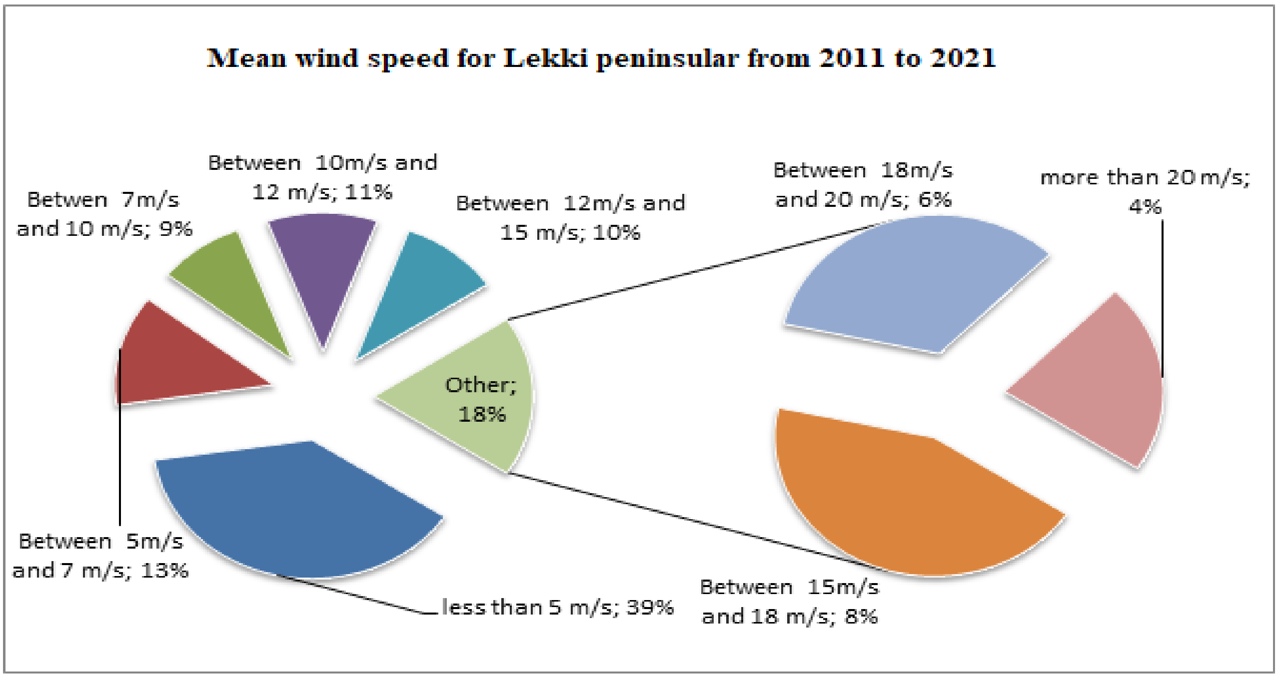


Figure 4. Actual mean wind speed percentage in the Lekki Peninsular during 10 years.

The pie-charts in the Figure 4 demonstrates changes in the different actual mean wind speed over a ten-year period between 2011 and 2021 in the south coastal area of Lagos. According to the charts mean wind speed equivalently 5m/s are slightly below 40% of the total and are approximately140 days of total. The mean average wind speed between 7 and 15 m/s are around 110 days, which are equivalently 30% of the total. Exactly 30 % of the total wind speed was between 7m/s to 15m/s, and this is the best wind speed to generate electricity, which is considered the rated power especially for small scale. Mean wind speeds in the coastal area above 15 m/s are generally just over 20% of the total. The characterization of the wind speed and their corresponding number of days is shown in table 2 below.

Table 2. Lists the actual MWS in the Lekki Peninsular over a ten year.

Wind Speed	Days of the year
less than 5 m/s	140
Between 5 m/s and 7m/s	47
Between 7 m/s and 10 m/s	32
Between10 m/s and 12 m/s	41

Between 12 m/s and 15 m/s	37
Between 15 m/s and 18 m/s	30
Between 18 m/s and 20 m/s	23
more than 20 m/s	15

Table 2 clarifies the figure for the daily MWS during the ten (10) years consideration in Lekki Peninsular. The highest average wind speed in winter reaches to 25 m/s.

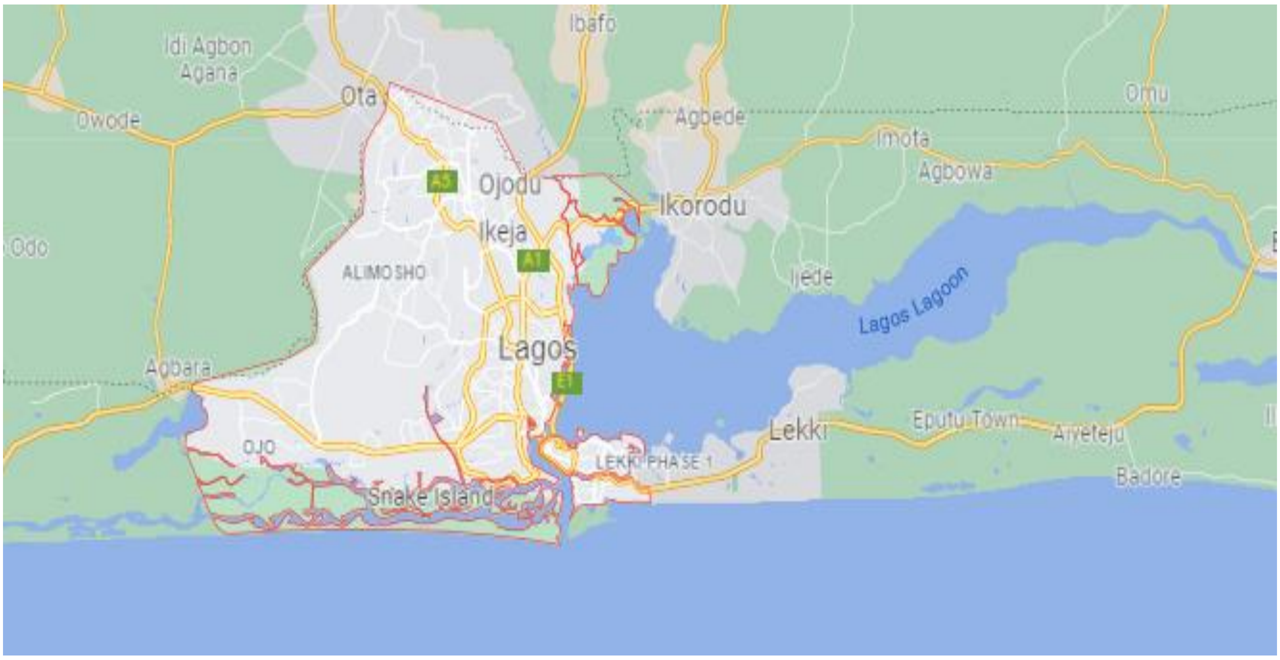


Figure 5: The Atlanntic Coast of Lagos Nigeria

Figure 6: The MWS from January 2018 to December 2021 for Lagos State

Figure 4 shows the percentage of monthly MWS of coastal area- Lagos city between 2018 and 2021. The recorded sources of meteorological data in the city of Lagos,, is carried out on a daily basis form the bases of the MWS which is usually calculated per month. According to the graph, during the 2018, there was a dramatic decrease from February to April reaching an all-time low of 3.2m/s. It goes as high as or more than 5 m/s during the month of January. MWS increases steadily reaching approximately 4 m/s. However, the curve went down during the last three months. In 2019 MWS rose dramatically to reach around 4.7m/s in April. Suddenly, the curve fluctuates during the last eight months of the year. In 2020, there was significant increase from January to August reaching 4.8 m/s before it dropped in the last four months of that year. In 2021, MWS jumped during January to reach 5.1 m/s, and then fluctuated significantly to reach the peak point in June. However, there was a gradual decline MWS between July and December to all-time low of 3 m/s. Over all, MWS fluctuates during this period between 3m/s to 5m/s. This values fluctuate in similar manner from 2016 to 2022 Deji A., Sheroz K., Jalel C., and Alam A. H. M. Z. (2011), Deji Abdulwahab et al. (2010).

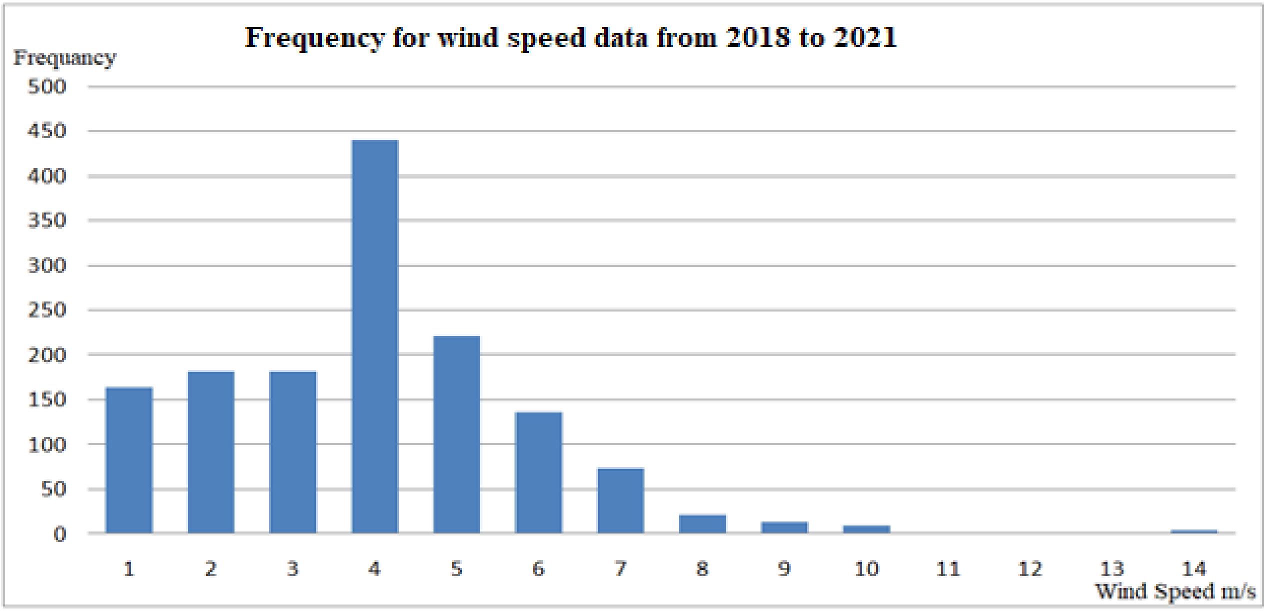


Figure 7: Frequency of actual MWS records from January 2018 to December 2021.

Figure 7 bar graph illustrates the frequency of the actual MWS records between January 2018 and December 2021 of coastal area of Ikoyi-Lekki city of Lagos state. According to the bar graph, the frequency has increased slightly from 1 m/s to 2 m/s reaching above 150 Hz. In MWS records of 2 m/s and 3 m/s, the graph in both cases is similar. MWS 4 m/s records the greatest percentage thereby reaching over 400 Hz. There was a significant decrease on MWS of 5m/s reaching a low frequency value of 250 Hz. The chart decreased gradually after reaching around 10m/s MWS.

Table.3: Lists of the frequency of actual MWS records from January 2011 to December 2021.

Wind Speed (m/s)	Jan	Feb	Mar	April	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1.0615	13	6	5	4	3	1	0	0	1	2	10	11
2.0734	7	2	3	1	0	1	0	0	1	2	3	4
3.0853	3	4	7	4	4	3	1	1	2	3	2	7
4.0972	3	11	11	11	11	12	17	15	9	13	4	6
5.1091	2	2	1	4	4	7	8	8	10	4	1	1
6.121	1	0	2	3	6	5	5	4	6	6	3	2
7.1329	2	2	2	3	3	1	0	3	1	0	3	0

8.1448	0	1	0	0	0	0	0	0	0	0	0	0
9.1567	0	0	0	0	0	0	0	0	0	0	0	0
10.1687	0	0	0	0	0	0	0	0	0	0	0	0
11.1806	0	0	0	0	0	0	0	0	0	0	0	0
12.1925	0	0	0	0	0	0	0	0	0	0	0	0
13.2044	0	0	0	0	0	0	0	0	0	0	0	0
14.2163	0	0	0	0	0	0	0	0	0	1	0	0

Table 3 clarified the bar graph on Figure 7 and illustrate the frequencies per months of the ten years MWS Measurement.

7. Results and Discussion

From wind speed data measured from January 2018 until 2021 in Lagos, a sample data is selected to test the performance. The southern Nigeria coastal area is presented here for all months using the seven numerical methods. This study is dependent on actual data to calculate actual maximum wind speed, MWS and standard deviation for every single month over a period of four years as shown in Table 3. The maximum wind speed for 2018, 2019, 2020 and 2021 has been 8.54, 7.98, 7.87 and 8.47m/s respectively. The average maximum wind speed for the four years has been around 8.22 m/s. The mean wind speed is 4.08, 3.82, 4.02 and 4.53 m/s for 2018, 2019, 2020 and 2021 respectively. The average mean wind speed for the four years has been recorded around 4.11 m/s. Based on MWS records, wind speed in coastal area is observed to be affected which result to downsizing the amount of electricity generation on large scale. This creates challenges for power production over the years. The cut in wind speed for the large-scale wind turbine is equal to at least 9 m/s. However, small-scale wind generation is currently possible.

Table 4: Lists of actual maximum wind speed, MWS records and standard deviation from January 2018 to December 2021.

period	Actual data for wind speed (m/s)														
	Maximum wind speed (m/s)					MWS(m/s)					Standard deviation (m/s)				
Years Months	2018	2019	2020	2021	All year	2018	2019	2020	2021	All years	2018	2019	2020	2021	All years
Jan	11.39	7.22	7.22	10.83	9.17	5.28	2.97	2.48	3.80	3.63	2.1771	2.0640	1.8853	2.1771	2.075875
Feb	15.00	8.06	8.06	9.72	10.21	5.29	3.71	3.42	5.02	4.36	3.0578	2.1333	1.8962	3.0578	2.536275
Mar	9.17	9.17	7.50	8.89	8.68	4.31	4.31	3.45	4.88	4.24	2.3936	2.4573	1.6586	2.3936	2.225775
Apr	5.56	10.78	7.22	10.83	8.60	3.19	4.60	4.08	5.36	4.31	1.9926	2.5309	1.6637	1.9926	2.04495
May	9.72	6.67	6.67	8.89	7.99	3.83	3.76	4.48	5.13	4.30	1.5874	1.6633	1.5726	1.5874	1.602675

Jun	5.56	7.78	6.67	6.67	6.67	3.95	4.09	4.60	5.53	4.54	0.9266	1.4895	1.2879	0.9266	1.157650
Jul	5.56	5.56	6.39	6.67	6.05	4.09	4.31	4.78	5.11	4.58	0.8507	1.4895	0.8884	0.8507	1.019825
Aug	6.67	5.28	7.50	6.67	6.53	4.04	3.29	4.87	4.78	4.24	0.8679	0.9103	1.0827	0.8679	0.932200
Sep	6.67	6.39	6.67	6.38	6.53	4.05	3.95	4.77	4.35	4.28	0.9208	1.1550	1.2658	0.9208	1.065600
Oct	7.78	9.72	14.72	6.38	9.65	4.04	4.13	4.61	3.89	4.17	1.3264	1.7579	2.3828	1.3264	1.698375
Nov	9.72	8.89	9.44	10.83	9.72	3.51	3.23	4.00	3.50	3.56	2.5956	2.0104	2.8651	2.5956	2.516675
Dec	9.72	10.28	6.39	8.89	8.82	3.39	3.48	2.68	2.98	3.13	1.9752	2.5305	1.6046	1.9752	2.021375
Mean	8.54	7.98	7.87	8.47	8.22	4.08	3.82	4.02	4.53	4.11	1.9873	1.9179	1.8993	1.9873	1.741438

Actual Wind power can be calculated directly by using equation (1) as shown in Table 5. The maximum amount of power for mean wind speed in 2021 has been around 1084 W/m^2. This is due to highest mean wind speed in the aforementioned year. The total amount of wind power from 2018, 2019 and 2020 has been approximately 977, 744 and 808 W/m2 respectively. Wind energy from 2018 to 2021 was found to be around 23.45, 17.86, 19.40 and 26.02 KWm-2 respectively.

Table 5. Lists of actual wind power evaluation and energy from January 2018 to December 2021.

period	Actual data- Wind Power and Wind Energy from MWS per 1 m^2 for every single month							
	Wind Power (Wm^{-2})				Wind Energy ($KWm^{-2}h$)			
Years Months	2018	2019	2020	2021	2018	2019	2020	2021
Jan	156.1947	41.7336	29.0061	71.1442	3.7487	1.0016	0.69615	1.7075
Feb	255.5118	64.6195	47.9561	161.3793	6.1323	1.5509	1.1509	3.8731
Mar	97.4782	97.4782	42.5238	121.8650	2.3395	2.3395	1.0206	2.9248
Apr	30.3390	115.4003	61.0719	133.5769	0.72813	2.7696	1.4657	3.2058
May	61.8241	51.0441	72.6317	103.0403	1.4838	1.2251	1.7432	2.4730
Jun	42.5978	57.9057	71.8563	110.0621	1.0223	1.3897	1.7246	2.6415
Jul	47.9119	52.1848	72.6806	87.0722	1.1499	1.2524	1.7443	2.0897
Aug	47.8722	26.2754	80.0334	72.4121	1.1489	0.63061	1.9208	1.7379
Sep	48.2818	46.5969	78.0520	56.5640	1.1588	1.1183	1.8732	1.3575
Oct	54.7138	67.5857	123.2901	47.4861	1.3131	1.6221	2.9590	1.1397
Nov	66.0400	48.5239	104.1244	78.3889	1.5850	1.1646	2.4990	1.8813
Dec	68.2613	74.6780	24.9695	41.3751	1.6383	1.7923	0.59927	0.99300
Total	977.0266	744.0261	808.1959	1084.366	23.44873	17.85671	19.39672	26.0248

Wind speed in any specific area changes rapidly. The relation between power and energy is proportional to the cube of wind speed. This study has considered the maximum wind speed in power and energy evaluations. The actual wind power evaluation for maximum wind speed was 6024.1, 4119.1, 4576.2 and 4991.6 from 2018 to 2021 respectively; while the greatest amount of wind energy has been in 2018 due to highest wind speed value. The wind energy evaluation for 2018 to 2021 was 52771.12, 36083.19, 40087.51 and 43726.76 kW/m^2 respectively as shown in Table 6.

Table 6: Lists of actual wind power evaluation and energy for maximum wind speed from January 2018 to December 2021.

period	Actual data from maximum w per 1 m^2 for every single month							
Years	Wind Power (Wm^{-2})				Wind Energy ($KW^{m-2}h$)			
Months	2018	2019	2020	2021	2018	2019	2020	2021
Jan	893.7	227.9124	227.9	769.2043	7828.812	1996.513	1996.404	6738.23
Feb	2042	316.2583	316.3	555.9708	17887.92	2770.423	2770.788	4870.304
Mar	466.0	466.0041	255.2	424.9108	4082.16	4082.196	2235.552	3722.219
Apr	103.7	656.8301	227.9	769.2043	908.412	5753.832	1996.404	6738.23
May	556.0	179.2593	179.3	424.9108	4870.56	1570.311	1570.668	3722.219
Jun	103.7	284.6571	179.3	179.2593	908.412	2493.596	1570.668	1570.311
Jul	103.7	103.7380	157.8	179.2593	908.412	908.7449	1382.328	1570.311
Aug	179.3	88.9424	255.2	179.2593	1570.668	779.1354	2235.552	1570.311
Sep	179.3	157.7725	179.3	157.7725	1570.668	1382.087	1570.668	1382.087
Oct	284.7	555.9708	1930.5	157.7725	2493.972	4870.304	16911.18	1382.087
Nov	556.0	424.9108	509.7	769.2043	4870.56	3722.219	4464.972	6738.23
Dec	556.0	656.8301	157.8	424.9108	4870.56	5753.832	1382.328	3722.219
Total	6024.1	4119.1	4576.2	4991.6	52771.12	36083.19	40087.51	43726.76

Measured and theoretical curves of Weibull probability density function (PDF) are shown below in Figure 8 for 2018 using actual measured wind speed data. The Theoretical estimated curves based on generated data using seven numerical different methods of MM, EM, GM, MLH,MLH, SMLH and EPF (STDM and EM, LSM and GM are considered the same methods). Figure 8 shows that the MMLHM predict that the measured data are more accurate for speed below 5 m/s. However, for higher speed values, all the methods over-estimated the measurements except the second modified method. PDF of measured data curve for 2018 is given in Figure 8.

It is clear that the second modified likelihood method is the most accurate estimation methods in 2019 as shown below in Figure 9. While in Figure 9, the most accurate methods are EPF and MLHM compared to the observed data curve of 2020 in Figure 10. The most accurate predicted methods are MLHM and EPF followed by FMLHM and SMLHM compared to the measured data curve in 2021 of Figure 11.

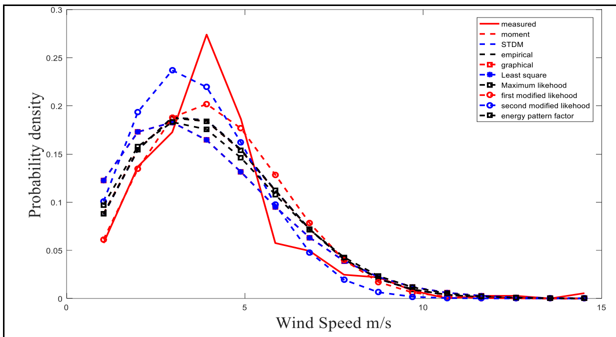


Figure 8: Comparison between Probability density function (PDF) of measured and estimation curve for Lekki site 2018.

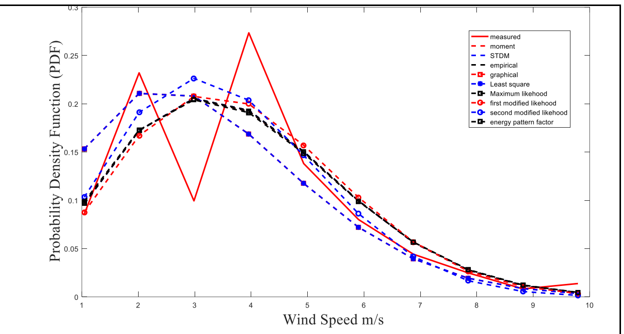


Figure 9: Comparison between Cumulative Distribution Function (PDF) and estimation curve for Lekki 2019.

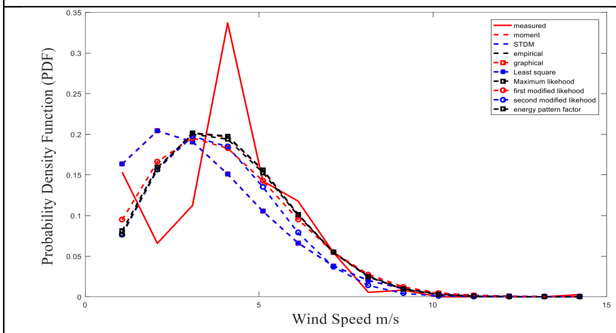


Figure 10: comparison between Probability density function (PDF) measured and estimation curve for Lekki site 2020.

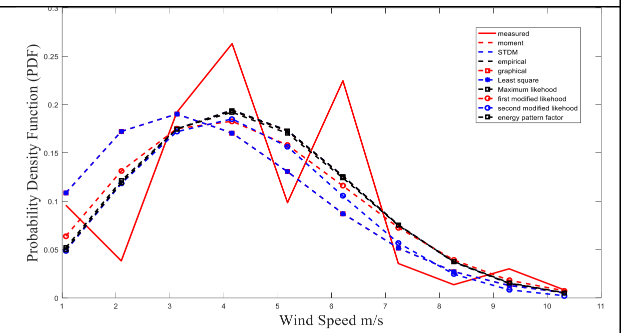


Figure 11: Comparison between Probability density function (PDF) measured and estimation curve for Lekki site 2021.

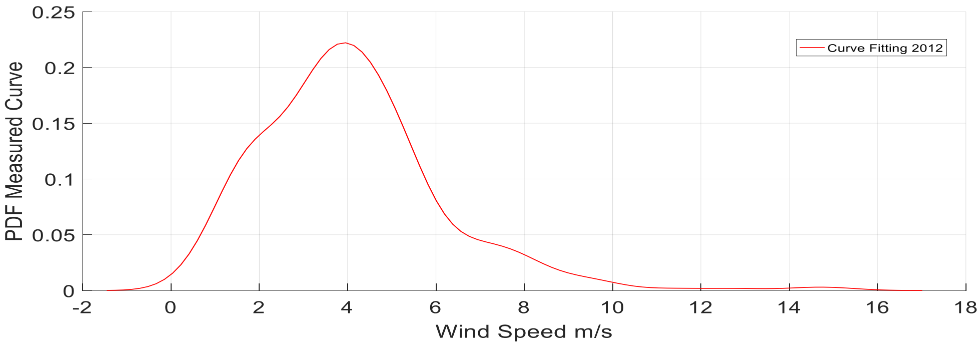


Figure12: Probability density function (PDF) Curve Fitting for measured data for 2018.

Measured and estimated CDF for 2018 are shown in Figure 13. Estimated CDF curves are based on generated data using seven numerical different methods MM, EM, GM, MLH, MLH, SMLH and EPF. The second modified curve show the best estimation performance when compared with other methods. As shown in Figure 14 the LSM is the the most accurate method followed by SMLHM. LMS is the most accurate method for speed higher than 4m/s as shown in Figures 15 and Figure16.

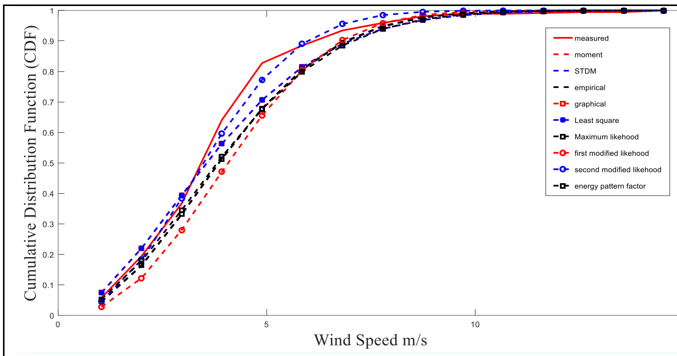


Figure13: Comparison between Cumulative Distribution Function (CDF) and estimation curve for Lekki 2018.

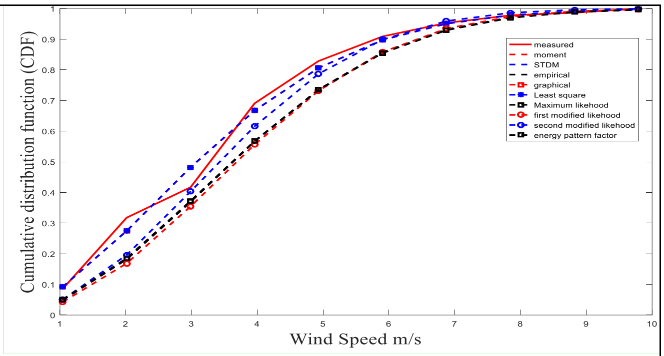


Figure14: Comparison between Cumulative Distribution Function (CDF) and estimation curve for Lekki 2019.

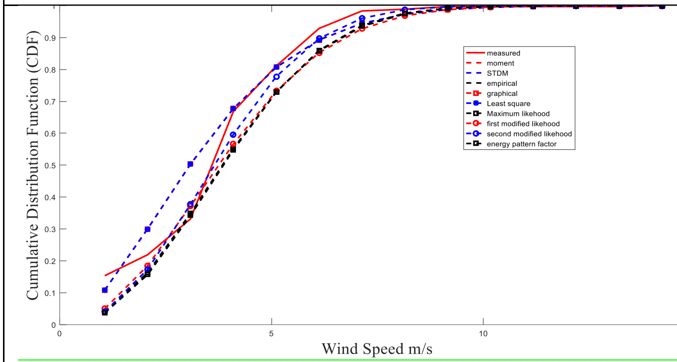


Figure15: Comparison between Cumulative Distribution Function (CDF) and estimation curve for Lekki 20220.

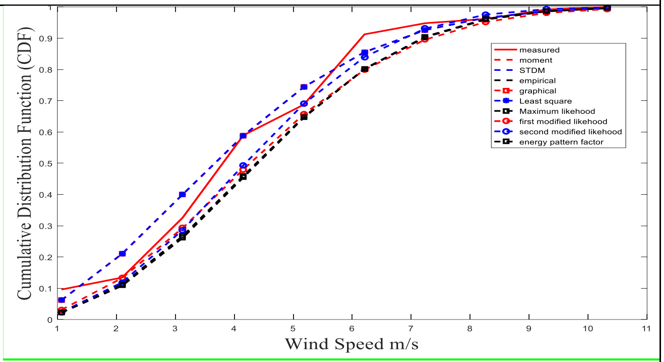


Figure16: Comparison between Cumulative Distribution Function (CDF) and estimation curve for Lekki 2021.

Table 7: Lists of estimation of Weibull parameters and the estimation of wind power and energy for maximum wind speed for 2018.

Years 2018	Estimated shape factor and scale factor using 7 numerical methods for Lekki 2018						
	c	*k*	MWS(m/s)	Standard divination σ(m/s)	Variation Coefficient %	Power density (Wm^{-2})	Energy Wm^{-2}
1. *MM*	4.5988	2.0608	4.0738	2.0729	50.8836	75.8631	6.6456e+05
2. *EM, STDM*	4.5991	2.0725	4.0738	2.0624	50.6248	75.4533	6.6097e+05
3. *MLHM*	4.6053	2.0616	4.0795	2.0751	50.8663	76.1557	6.6712e+05
4. *MMLHM*	4.7555	2.3526	4.2142	1.9041	45.1831	74.8012	6.5526e+05
5. *SMMLHM*	4.1000	2.2322	3.6313	1.7198	47.3613	49.9757	4.3779e+05
6. *GM,LSM*	4.3642	1.7848	3.8827	2.2492	57.9291	76.5093	6.7022e+05
7. *EPF*	4.5946	1.9559	4.0738	2.1727	53.3336	79.9115	7.0003e+05
Measured	4.6053	2.0616	4.0800	1.9873	51.1173	80.3672	7.04016e+5

Table 8: Lists of estimation of Weibull parameters and the estimation of wind power and energy for maximum wind speed for 2019.

Years 2019	Estimated shape factor and scale factor using 9 numerical methods for Lekki 2019						
	c	*k*	MWS(m/s)	Standard divination σ(m/s)	Variation Coefficient %	Power density (Wm^{-2})	Energy Wm^{-2}
1. *MM*	4.3076	2.0990	3.8152	1.9095	50.0496	61.2387	5.3204e+05
2. *EM, STDM*	4.3077	2.1105	3.8152	1.9002	49.8045	60.9279	5.2934e+05
3. *MLHM*	4.3119	2.1006	3.8190	1.9101	50.0166	61.3785	5.3326e+05
4. *MMLHM*	4.3513	2.1937	3.8536	1.8538	48.1071	60.6325	5.2677e+05
5. *SMMLHM*	4.0403	2.1865	3.5781	1.7264	48.2480	48.6784	4.2292e+05
6. *GM , LSM*	3.7570	1.8225	3.3391	1.8981	56.8458	47.5057	4.1273e+05
7. *EPF*	4.3074	2.0834	3.8152	1.9224	50.3863	61.6694	5.3578e+05
Measured	4.3119	2.1006	3.8200	1.9179	50.2685	62.0054	5.3870e+05

Table 9: Lists of estimation of Weibull parameters and the estimation of wind power and energy for maximum wind speed for 2020.

Years 2020	Estimated shape factor and scale factor using 9 numerical methods for Lekki 2020						
	c	*k*	MWS(m/s)	Standard divination σ(m/s)	Variation Coefficient %	Power density (Wm^{-2})	Energy Wm^{-2}
1. *MM*	4.5376	2.2464	4.0190	1.8927	47.0934	67.3882	5.9032e+05
2. *EM, STDM*	4.5374	2.2570	4.0190	1.8847	46.8951	67.1206	5.8798e+05
3. *MLHM*	4.5231	2.2089	4.0058	1.9152	47.8094	67.6972	5.9303e+05
4. *MMLHM*	4.4696	2.0668	3.9592	2.0093	50.7497	69.4444	6.0833e+05
5. *SMMLHM*	4.2750	2.2924	3.7872	1.7514	46.2446	55.4362	4.8562e+05
6. *GM , LSM*	3.8086	1.6942	3.3990	2.0644	60.7359	54.6827	4.7902e+05
7. *EPF*	4.5375	2.2536	4.0190	1.8873	46.9588	67.2064	5.8873e+05
Measured	4.5231	2.2089	4.0200	1.8993	47.2570	67.3838	5.9028e+05

Table 10: Lists of estimation of Weibull parameters, the estimation of wind power and energy for maximum wind speed for 2021.

Year 2021	Estimated shape factor and scale factor using 9 numerical methods for Lekki 2021						
	c	*k*	MWS (m/s)	Standard divination σ(m/s)	Variation Coefficient %	Power density (Wm^{-2})	Energy Wm^{-2}

1. MM	5.0981	2.4321	4.5205	1.9827	43.8593	89.9802	7.8823e+05
2. EM, STDM	5.0977	2.4414	4.5205	1.9759	43.7096	89.7214	7.8596e+05
3. MLHM	5.0839	2.3990	4.5068	2.0010	44.3994	90.0969	7.8925e+05
4. MMLHM	5.0234	2.2321	4.4491	2.1073	47.3645	91.9197	8.0522e+05
5. SMMLHM	4.8565	2.4650	4.3075	1.8666	43.3344	77.0699	6.7513e+05
6. LSM, GM	4.4173	1.9389	3.9174	2.1057	53.7534	71.7013	6.2810e+05
7. EPF	5.0981	2.4315	4.5205	1.9831	43.8692	89.9973	7.8838e+05
Measured	5.0839	2.3990	4.5300	1.9873	43.9606	89.7332	7.8606e+05

From table 7, 8, 9 and 10 of Weibull parameter for the calculated data using seven numerical methods. The estimated MWS from 2018 to 2020 shows the same behavior as the minimum MWS was observed in 2019 and the maximum for the four years was observed in 2021. The maximum estimated MWS was 4.5300 m/s in 2021. The maximum estimated power in 2021 due to the highest wind speed is power proportional to the cube of MWS. Generally, it is noted that the measured MWS value is very close to estimated value. MLHM shows the best predicted value due to its calculated parameter from the measurements.

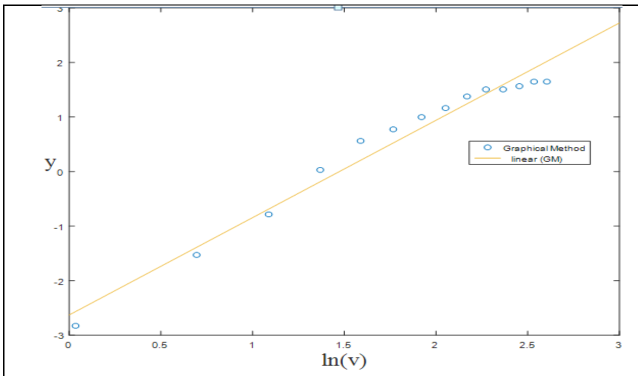


Figure 17: Graphical method estimated for Lekki 2018.

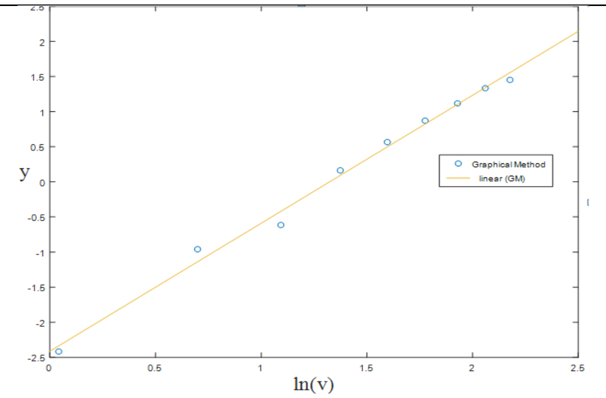


Figure18: Graphical method estimated for Lekki 2019.

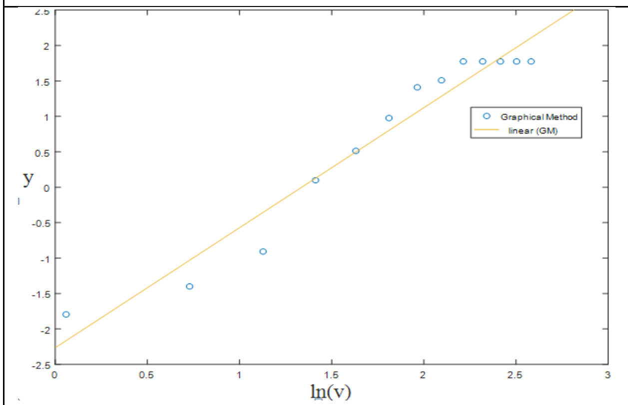


Figure: 19 Graphical method estimated for Lekki 2020.

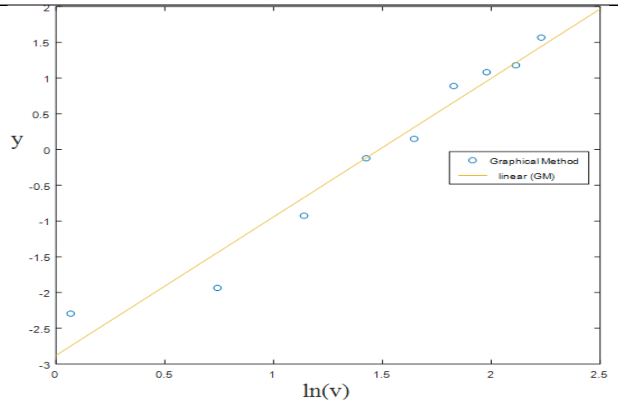


Figure: 20 Graphical method estimated for Lekki 2021.

Weibull parameters can be estimated using GM of every year from Figures 17, 18, 19 and 20. The first step is to plot natural logarithmic measured speed versus ln(-ln(1-F(measured speed)). Then, to find the

Weibull parameters, it is required to linearly fit the plotted points, where k is the slope of fitted line and c is equal exp(b/k), where b is y-intercept of the fitted line.
Where, $\ln(\upsilon)$ as x axis versus $\ln\{-\ln[1-F(\upsilon)]\}$

$y = mx - b$, Where, $x = slope,\ k = slope\ b = k\ln(c),\ln(c) = \frac{b}{k},\ c = e^{\frac{b}{k}}$

The histogram for wind speed records of 2018 is shown below in Figure 20. This figure is very close to Weibull distribution function. Around 82% of wind speed readings are located at range value of 2 to 5 m/s, the same observation is noted for the years 2019 and 2020. In 2021 the most frequent speed is still 4 m/s like the previous years. However, the frequency of the higher wind speeds such as 6 m/s is higher than the previous years. The maximum observed wind speeds during the four years are 15, 10, 14 and 10 m/s in 2018, 2019, 2020 and 2021 respectively. The observed mean wind speed is found to be 4.08, 3.82, 4.02 and 4.53 m/s and the measured maximum wind speed is 8.54, 7.98, 7.87 and 8.47 m/s for 2018, 2019, 2020 and 2021 respectively. The MWS and maximum wind speed is considered appropriate to be applied in the small-scale wind turbine generation. [62-75].

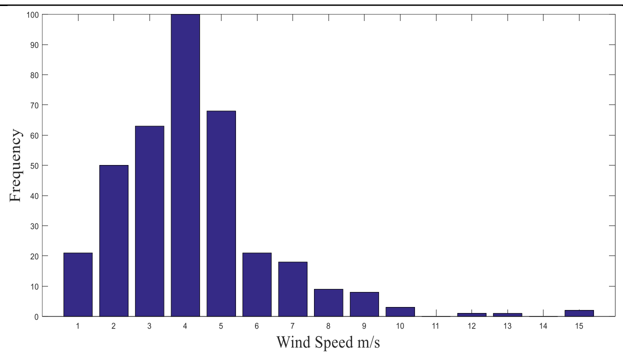


Figure 20: Histogram for MWS for Lekki 2018.

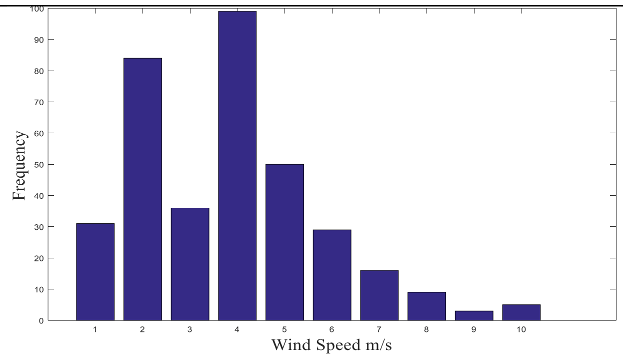


Figure 21: Histogram for MWS for Lekki 2019.

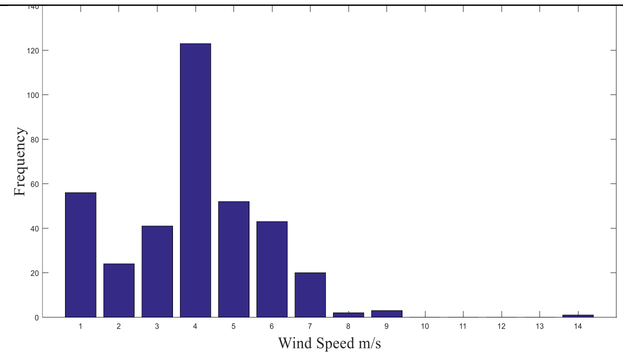


Figure 22: Histogram for MWS for Lekki 2020.

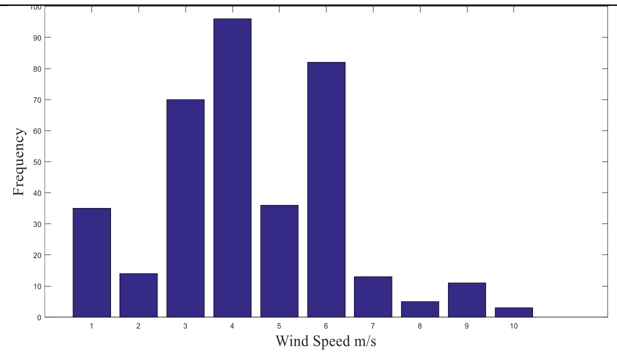


Figure 23: Histogram for MWS for Lekki 2021.

The statistical Error analysis of five different statistical techniques is presented in Tables 11-14 It is observed from table 11 as an example that in general a method could be the best using one statistical technique but the worst using another. From Table 11 the GM shows the best predicted technique using RMSE, X2, IA and RRMSE but the worst predicted technique using MAPE. Moreover, some technique such as MM, MLM and EPFM show an average prediction accuracy using all statistical techniques. On the other hand MMLM shows the worst prediction performance using all statistical technique except MAPE.

Table11: Lists of the error percentage for checking more accurate numerical methods for 2018

2018		Goodness of fit tests for Coastal area of Lekki 2018									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0074	3	0.9780	4	0.7893	3	0.0196	3	11.1391	3
2	STDM,EM	0.0075	4	1.0926	5	0.7912	5	0.0194	2	11.2563	5
3	MLM	0.0074	3	0.9610	3	0.7895	4	0.0196	3	11.1577	4
4	MMLM	0.0089	5	13.5805	6	0.8316	6	0.0158	1	13.3614	6
5	SMMLM	0.0223	6	222.8923	7	0.7795	2	0.0215	5	33.3957	7
6	GM,LSM	0.0043	1	0.3073	1	0.7415	1	0.0239	6	6.4394	1
7	EPFM	0.0066	2	0.4346	2	0.7705	2	0.0212	4	9.9210	2

Table 12: Lists of the error percentage for checking more accurate numerical methods for 2019.

2019		Goodness of fit tests for Coastal area of Lekki 2019									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0053	3	0.1393	2	0.7229	4	0.0317	3	5.2971	5
2	STDM,EM	0.0054	4	0.1402	3	0.7239	5	0.0316	2	5.4297	4
3	MLM	0.0053	3	0.1393	2	0.7224	3	0.0318	4	5.3135	3
4	MMLM	0.0063	5	0.1493	4	0.7254	6	0.0317	3	6.2557	6
5	SMMLM	0.0071	6	0.2126	6	0.7509	7	0.0295	1	7.1193	7
6	GM,LSM	3.2001e-04	1	0.1916	5	0.7027	1	0.0352	5	0.3200	1

7	EPFM	0.0051	2	0.1383	1	0.7214	2	0.0318	4	5.1099	2

Table 13: Lists of the error percentage for checking more accurate numerical methods for 2020.

2020		Goodness of fit tests for Coastal area of Lekki 2020									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0046	2	1.9073	6	0.6761	5	0.0323	1	6.4148	3
2	STDM, EM	0.0045	1	2.1563	5	0.6764	6	0.0323	1	6.3530	1
3	MLM	0.0048	3	1.3660	3	0.6751	4	0.0324	2	6.6635	4
4	MMLM	0.0056	4	0.5520	1	0.6723	3	0.0325	3	7.8650	5
5	SMMLM	0.0304	6	22.2735	7	0.6501	2	0.0347	4	42.6080	7
6	GM,LSM	0.0117	5	0.5048	2	0.6119	1	0.0389	5	16.3687	6
7	EPFM	0.0046	2	2.0717	4	0.6764	6	0.0323	1	6.3728	2

Table 14. Lists of the error percentage checking more accurate numerical methods for 2021.

2021		Goodness of fit tests for Coastal area of Lekki 2021									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0098	2	0.2858	2	0.5991	3	0.0468	5	9.7861	2
2	STDM,EM	0.0097	1	0.2867	4	0.5997	4	0.0468	5	9.7396	1
3	MLM	0.0099	3	0.2838	1	0.5987	2	0.0467	4	9.9406	4
4	MMLM	0.0110	4	0.2863	3	0.5948	1	0.0466	3	11.0351	5
5	SMMLM	0.0384	6	0.3746	5	0.6035	5	0.0462	2	38.4354	7
6	GM,LSM	0.0137	5	0.4159	6	0.6040	6	0.0460	1	13.6533	6

7	EPFM	0.0098	2	0.2858	2	0.5991	3	0.0468	5	9.7892	3

8. Conclusion

In this paper wind speed data, obtained through using Weibull factors, has been statistically analyzed for long-term of ten and four years making fourteen (14) years. The mean wind power of the region indicates that the location may not be ideal for grid-connected electricity production, but has sufficient wind for small wind turbines-based power generation ansd a fractional contribution to the mainstream grid. As an investigation study, it is done for estimating wind energy potential of the Lekki Peninsular area of Lagos Nigeria. The above results help the scientists and the technocrats to select the location for wind turbine generators. Moreover, mean wind speed, and coefficient of variation (COV) have been obtained. Also, the mean and maximum wind power based on actual measured data, Weibull distribution function and cumulative distribution function have been obtained. It is observed that the use of wind power on a commercial scale and connecting it to the main electricity network would be a fraction of Megawatts. However, it's very beneficial for small-scale wind turbine installations. Thus, the idea of wind-generation can be a possibility of energy generation for houses or organizations as an alternative resource. Analyzing wind data and using Weibull probability function to find out wind energy conversion characteristics of Lekki-Ikoyi and Ikorodu areas of Lagos Nigeria proves the obvious. The Weibull function parameters were calculated analytically, using the seven different methods; method of moments (MM), standard deviation method (STDM) or empirical method (EM), maximum likelihood method (MLM), modified maximum likelihood method (MMLM), second modified maximum likelihood method (SMMLM), graphical method (GM) or least mean square method (LSM). The energy pattern factor method (EPFM) is used to find shape factor (k) and scale factor (c), from the measured data. Thereafter, the study also helped in calculating the percentage error using five different tests (Goodness of fit tests) for Coastal area of Lekki -Ikoyi-Ikorodu area of Lagos state Nigeria for four years. Finally, the calculated wind power resource is proven to be very low, but it is possible to harness the wind energy by small wind turbine-generators. This paper, none the less, presents a first step for feasibility of installing wind turbines in Lagos. Based on the mean value, PDF and CDF of relevant wind-data, the results are analyzed and illustrated in tabular form as well as in graph.

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