International Journal of Engineering &Technology, 7 (4) (2018) 6631-6648

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i4.27832
Research paper

Maximum Likelihood Based Approach for Weibull's Distribution Parameters Estimation for Wind Energy Applications

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Abstract

In this article, a new computational approach is proposed to estimate the Weibull's distribution parameters. The method is dependent on the Maximum Likelihood (MLM) using the even and odd classes of wind speed's distribution. This new approach is referred to either as Maximum Likelihood with Odd Bins time series Method (MLOBM) or Maximum Likelihood with Even Bins time series Method (MLEBM). It comprises the data size reduction, which in turns may lead to a fast processing time. This method was evaluated in a comparative analysis of MLOBM and MLEBM against the proposed theoretical model. The obtained results on the mean wind speed, standard deviation, and power density on monthly and annual scales for different geographical locations may indicate that the MLOBM or MLEBM may give a better estimate of the Weibull parameters with a low error.

Keywords: *Comparative Evaluation; Even Bins Wind Speed Series; Maximum Likelihood Method (MLM); Odd Bins Wind Speed Series; Statistical Analysis.*

1. Introduction

Renewable energy sources such as wind and solar are naturally environmental clean; and can provide a sustainable solution to the world energy demands [1]. The electrical energy from wind is generated from the kinetic energy of the wind due to the wind speed that is a random variable. The knowledge of wind's distribution is critical for many applications of wind energy [2-5]. Various statistical distribution models, including the log-normal model, bivariate Gaussian distribution, Rayleigh distribution were used in the literature to characterize the probability distribution of the mean wind speed [6-8]. However, Weibull distribution model is the most widely used and designated as appropriate in representing the statistical properties of wind [9, 10]. Weibull distribution, a particular case of the generalized gamma distribution law, is characterized by the shape parameter K and the scale parameter C. The two Weibull parameters help to determine wind characteristics and wind power potential. Detailed knowledge of wind characteristics and distribution is crucial to selecting the optimal wind energy conversion system that maximizes energy output and minimizes electricity generation costs [11]. Thus the correct estimation of parameters (K and C) is very important in evaluating the wind power density of a prospective wind farm location and assessing the economic viability of a wind project [12]. Several methods have been proposed to estimate the Weibull parameters namely the graphical method, the Maximum Likelihood Method (MLM), the method of moments (MOM), the empirical methods (EM), the modified maximum likelihood method (MMLM), the equivalent energy method (EEM) and the energy pattern factor method (EPFM) [6], [13-24].

Akdag and Dinler [14] have compared the performance of the energy's pattern factor method with some other methods such as graphical method and Maximum Likelihood Method (MLM) based on measured wind data of different locations in Turkey. Their results indicated that the energy's pattern factor method is more suitable in comparing the mean wind speed and wind power. Jowder et al., [15] used graphical and empirical methods to determine the Weibull parameters using the wind speed distribution, mean wind speed and wind power in kingdom of Bahrain at three heights of 10, 30 and 60 m. It was found that the empirical method was more efficient. Bonfils Safari in his study [6], has compared the least square and maximum likelihood methods for the determination of the best method in estimation of the Weibull's parameters. The results showed that the maximum likelihood method (MLM) outperformed the least square method. Chang [16] compared the performance of six different methods by computing the shape and scale parameters for wind speed's distribution. The probability density and cumulative distribution functions were compared against the measured data. According to the attained results, the maximum likelihood method (MLM) have indicated that the modified maximum likelihood method achieved the highest performances while the graphical methods had the lowest performance. Rocha et al. [17] evaluated the performance of seven different methods for the assessment of the effectiveness the Weibull's distribution parameters, using some wind speed data collected in Camocim and Paracuru cities, State of Ceará, in the northeast region of Brazil. The results showed that:

i) The equivalent energy method is an effective method to determine the parameters (K and C).

ii) The graphical and energy pattern factor methods are less effective to adjust distribution of wind speeds.
iii) The numerical iterative methods such as Maximum Likelihood Method (MLM) and the method of modified maximum likelihood are recommended where better accuracy is desired.

In [18], Ahmed et al., evaluated the performance of four parameter estimation methods of Weibull function for modeling monthly wind speed distribution in Halabja, Pakistan. The results showed that more accuracy can be achieved by empirical method. Along the same lines, Azad et al. [19] used the seven methods applied by Rocha et al. [17] to estimate Weibull parameters and used six statistical tools to rank the methods precisely. They found that MOM and MLM are the most efficient methods for estimating parameters of Weibull distribution. Arslan et al. [20] compared MOM, ML and the LMOM (L-moment method) for estimation of wind speed parameters relevant to Weibull distribution. They also found that when the sample size is greater than 100, MLM is preferable in comparison to other methods for the estimation of shape parameter in terms of the MSE (mean square error) criteria. George [21] compared the performance of five methods to calculate the shape and scale parameters of Weibull function for determining the wind speed distribution. The results indicated that the maximum likelihood method (MLM) outperforms other methods in terms of representing the distribution of wind speed. Kidmo et al., [22] assessed the ability of six methods to calculate Weibull parameters for representing the distribution of wind speed in Garoua, Nigeria. Their results demonstrated that the wind energy's pattern factor method had more suitability over other examined methods. Moreover, the graphical method may not be adequate in determining the wind speed's distribution. Ilhan Usta [23] proposed an innovative estimation method regarding Weibull parameters for wind energy applications. This innovative method, namely the probability weighted moments based on the power (PWMBP) density method is compared to six other commonly-used methods such as the maximum likelihood (MLM), modified maximum likelihood (MMLM), graphical, moment, power density and probability weighted moments methods for actual wind data, based on different time periods and regions according to various goodness of fit criteria. The obtained results have indicated that PWMBP, MLM, EPM and MOM may provide more accurate and efficient estimation than other methods in the estimation of the parameters of Weibull distribution. Mohammadi et al., [24] evaluated the effectiveness of six numerical methods to determine the shape (k) and scale (c) parameters of Weibull distribution functions for calculating the wind power density in four stations distributed in Alberta province of Canada. The selected methods are graphical method (GP), empirical method of Justus (EMJ), empirical method of Lysen (EML), energy's pattern factor method (EPFM), maximum likelihood method (MLM) and modified maximum likelihood method (MMLM). The results indicate that the precision of computed wind power density values change when different parameters estimation methods are used to determine the K and C parameters. EMJ, EML, EPFM and MLM present very favorable efficiency while the GP method shows weak ability for all stations.

From the above survey, it is clear that the rich existing body of research agrees that the choice of the parameter estimation method is critical in achieving a trustworthy evaluation of wind energy potential of a prospective wind farm. In addition, the Maximum Likelihood Method (MLM) has proven to be a decent choice throughout the literature especially when higher accuracy is preferred. However, in [25] and [26], the authors pointed out that the Maximum Likelihood Method (MLM) is an iterative method. Consequently, the MLM is expensive in processing time especially when the data size is large. The study has shown that accuracy is then achieved at the cost of computational efficiency. Thus, there is a need to devise an estimation method that allies acceptable accuracy with computational efficiency. A study conducted by Yuan et al. [27] aimed at comparing the performance of the maximum parameter estimation method (MLE) and the moment parameter method. The results have shown that for the extreme likelihood small data size outperformed over the moment method. The likelihood had advantage for the middle and large data size. Conclusively, for life data analysis, it suggested the use of the maximum likelihood parameter method for the two-parameter Weibull's distribution.

A reduction in the data size will lead to a high computational efficiency in time. The key parametersfor the estimation of Weibull function are the average speed, standard deviation and power density. The main challenge is about the data filtering process and the sampling size for acceptable estimation accuracy. According the best of our knowledge, there is no existing work that proposes a filtering MLM-based method that allies accuracy and efficiency for Weibull parameter estimation in wind energy applications.

In order to reduce the data size and therefore the parameter estimation time, while maintaining a high accuracy of wind power density, mean wind speed and standard deviation, a new ML-based approach is proposed. Indeed, the series of wind speed is grouped in classes (or bins), each class being represented by a bin in the distribution histogram. The set of classes is divided into two subsets: even and odd order speed classes. In this paper. The paper aims at adequately determining the overall Weibull parameters (K and C) using the subsets of odd and even speed classes. For each subset, the Weibull parameters are estimated using the Maximum Likelihood (ML) Method. The accuracy of the proposed methods was assessed against some performance metrics such as the root mean squared error (RMSE), and the correlation coefficient R^2. Furthermore, the power density, the mean wind speed and the wind speed standard deviation estimation capabilities are compared for some selected cities alike Lome, Accra and Cotonou sites in the Gulf of Guinea.

The rest of this paper is structured as follows. Section 2 describes the applications of the Weibull distribution function in wind energy. In Section 3, the estimation process of Weibull parameters using the Maximum Likelihood Method (MLM) is described. Section 4 presents in detail the proposed approach to estimate Weibull parameters. In Section 5, statistical indicators for performance evaluation are illustrated. The results and discussions along with the underlying case study are given in Section 6. Finally, conclusions are drawn in Section 7.

2. The weibull's distribution function in some wind energy applications

The wind speed data on a site are often vague to provide a clear vision of the wind power potential available on it. Hence, there is a need to compute key parameters that allow a quick assessment of power characteristics hidden in the measured wind speed data [28]. Since wind is a stochastic valued event, it is better to describe the variation of wind speeds by a statistical function. The probability distribution function (pdf) of the two-parameter Weibull distribution (Equation (1)) is often used in characterizing the distribution of wind speeds measured frequently over a period of a month, a year, or several years [29-32].

$$f(V) = \left(\frac{K}{C}\right)\left(\frac{V}{C}\right)^{K-1} \cdot \exp\left[-\left(\frac{V}{C}\right)^{K}\right] \qquad (1)$$

Equation (2) gives the cumulative distribution function (cdf) of the wind speed,

$$F(V) = \left(1 - \exp\left[-\left(\frac{V}{C}\right)^{K}\right]\right) \qquad (2)$$

The mean and standard deviation of the wind speed series are given by equations (3) and (4):

$$\bar{V} = \frac{1}{n}\sum_{i=1}^{n} V_i \qquad (3)$$

$$\sigma = \left[\frac{1}{n-1} \sum_{i=1}^{n} (V_i - \overline{V}) \right]^{1/2} \tag{4}$$

Knowing the Weibull parameters (K and C), the mean and standard deviation can be quickly calculated using equations (5) and (6) [33]:

$$\overline{V_c} = C \cdot \Gamma(1 + \frac{1}{K}) \tag{5}$$

$$\sigma_c = C \cdot \left[\Gamma(1 + \frac{2}{K}) - \Gamma^2(1 + \frac{1}{K}) \right]^{1/2} \tag{6}$$

The wind power density is an important indicator to determine the potential of wind resources and to describe the amount of wind energy at various wind speed values in a particular location. The knowledge of wind power density is also useful to evaluate the performance of wind turbines and nominate the optimum wind turbines. Wind power density resembles the level of accessible energy at the site, which can be converted to electricity by using wind turbines. The mean kinetic energy, available on a site per unit time and per unit area is expressed in [34] as:

$$P = \frac{1}{2} \rho \int_0^{+\infty} V^3 f(V) dv = \frac{1}{2} \rho \overline{V^3} \tag{7}$$

Where: ρ is the density of air (kg m^{-3}), V is the wind speed and $f(V)$ is the probability distribution function (pdf) of Weibull (1) and $\overline{V^3}$ is the cubic mean wind speeds.
If the parameters (K and C) are estimated for a wind farm, mean wind power density (7) are calculated in [33], [35] and given by.

$$P_c = \frac{1}{2} \rho C^3 \Gamma\left(1 + \frac{3}{K}\right) \tag{8}$$

Where: Γ represents the gamma function defined by the Euler integral of the second kind.
In short, the estimated Weibull parameters (K and C) are very important for applications in the field of wind energy. Many methods were developed to estimate the parameters of the Weibull's probability distribution function (pdf), namely method of moments, the Maximum Likelihood Method (MLM), the least square method and Chi-square method. Among these methods, the Maximum Likelihood Method (MLM) is considered as one of the most reliable [6, 36].

3. The weibull's parameters using the maximum likelihood method

The Maximum Likelihood (ML) technique, with many required features, is the most widely used technique among parameter estimation techniques. The MLM has many large sample properties that make it attractive for use; it is asymptotically consistent, which means that as the sample size gets larger, the estimate converges to the true values.
Let $V_1, V_2, V_3, \cdots, V_n$ be a random sample size n drawn from a probability density function $f(V, \theta)$ where θ is an unknown parameter. The likelihood function of this random sample is the joint density of the n random variables and is a function of the unknown parameter. Thus, according to [37], [38],

$$L = \prod_{i=1}^{n} f(V_i, \theta) \tag{9}$$

The Maximum Likelihood (ML) estimator of θ say $\hat{\theta}$ is the value of L that maximizes L or, equivalent, the logarithm of L. Often but not always, the MLM of θ is a solution of equation (10)

$$\frac{d \log(L)}{d\theta} = 0 \tag{10}$$

Now, we apply the MLM to estimate the Weibull parameters, K and C. Consider the Weibull probability density function given in equation (1), the likelihood function will be (11):

$$L(V_1, V_2, V_3, \cdots, V_n, K, C) = \prod_{i=1}^{n} \left(\frac{K}{C}\right)\left(\frac{V_i}{C}\right)^{K-1} \cdot \exp\left[-\left(\frac{V_i}{C}\right)^K\right] \tag{11}$$

Taking the logarithms of equation (11), differentiating with respect to K and C, and equating to zero, one can obtain the estimating equations (12) and (13),

$$\frac{\partial Ln(L)}{\partial K} = \frac{n}{K} + \sum_{i=1}^{n} Ln(V_i) + \frac{1}{C} \sum_{i=1}^{n} V_i^K Ln(V_i) = 0 \tag{12}$$

$$\frac{\partial Ln(L)}{\partial C} = -\frac{n}{K} + \frac{1}{C^2} \sum_{i=1}^{n} v_i^K = 0 \tag{13}$$

After eliminating C, equations (12) and (13) become (14),

$$\frac{\sum_{i=1}^{n} V_i^K Ln(V_i)}{\sum_{i=1}^{n} Ln(V_i)} - \frac{n}{K} - \frac{1}{n} \sum_{i=1}^{n} Ln(V_i) = 0 \tag{14}$$

The estimated value of K, is found by the use of standard iterative procedures, which can be written as

$$X_{n+1} = X_n + \frac{g(X_n)}{g'(X_n)} \tag{15}$$

Where

$$g(K) = \frac{\sum_{i=1}^{n} V_i^K Ln(V_i)}{\sum_{i=1}^{n} Ln(V_i)} - \frac{n}{K} - \frac{1}{n} \sum_{i=1}^{n} Ln(V_i) \tag{16}$$

And

$$g'(K) = \sum_{i=1}^{n} V_i^K (Ln(V_i))^2 - \frac{1}{K^2} \sum_{i=1}^{n} V_i^K (Ln(V_i) - 1) - (\frac{1}{n} \sum_{i=1}^{n} Ln(V_i))(\sum_{i=1}^{n} V_i^K Ln(V_i)) \tag{17}$$

The shape parameter K is derived using equations (16) and (17) with equation (15) as:

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

Once K is determined, C can be estimated using equation (19) as follows:

$$C = \left[\frac{\sum_{i=1}^{n} V_i^K}{n} \right]^{1/K} \tag{19}$$

4. The proposed method to estimate the weibull's parameters

The information contained in the wind measurements at a given site can be represented as a histogram. Given $V_1, V_2, V_3, \cdots, V_r$, r wind speeds measured on a site, this sequence can be grouped into

m ($m \le r$) classes ($Bin_0, Bin_1, Bin_2, \cdots, Bin_{m-1}$); let $f_{j,}$ be the relative frequency of class Bin_j , the graph $(Bin_j \times f_{j,})$ represents the histogram of the distribution of relative frequencies of wind speed on this site. It may represent the variation of the relative frequency of wind speeds. If the speed intervals are dwindling, the limit of the histogram is a probability density function (pdf). In practice, the probability density function (pdf) of the wind speed is obtained by fitting the histogram with a function. In the case of wind speeds, a log-normal, gaussian or Rayleigh distribution function is not always appropriate [39]. According to [40, 41], a better solution is to use the Weibull distribution [42]. The probability density function (pdf) of the wind speed of a site can be approximated by a Weibull pdf for measurements averaged over periods of 1 to 30 min [43]. [44] is the first atlas to use the Weibull distribution. The use of Weibull distribution has become a standard for representing the climatology of a wind site, especially thanks to [45]. This representation has the advantage of allowing a quick assessment of the mean power density, the standard deviation and mean wind speed, for e.g., knowing the Weibull K and C parameters of the site, as detailed in [45] and [46].
Several studies have shown that estimating Weibull parameters using the Maximum Likelihood Method (MLM) is reliable, however, this method according to Section 4, is an iterative method, that is to say time consuming compared to other methods (graphic, moment, empirical, modified maximum likelihood, equivalent energy and power density) especially for large numbers of wind measurements.
Thus for all n samples of wind measurements $(V_1, V_2, V_3, \cdots, V_n)$ such that V_i is non-zero, obtained during a period of time on a given site, the application of the Maximum Likelihood Method (MLM) (equations (18) and (19)) gives the shape and scale parameters K_{all} and C_{all} respectively according to equations (20) and (21).

$$K_{all} = \left[\left[\frac{\sum_{i=1}^{n} V_i^{K_{all}} \ln(V_i)}{\sum_{i=1}^{n} V_i^{K_{all}}} \right] - \left[\frac{\sum_{i=1}^{n} \ln(V_i)}{n} \right] \right]^{-1} \tag{20}$$

$$C_{all} = \left[\frac{\sum_{i=1}^{n} V_i^{K_{all}}}{n} \right]^{1/K_{all}} \tag{21}$$

In order to reduce the estimation time of Weibull parameters (K_{all} and C_{all}) using the Maximum Likelihood Method (MLM) for its desired high acuracy, we propose to reduce the number of data to be processed while maintaining accurate power density, standard deviation and mean wind speed. Indeed all samples of n wind measurements $(V_1, V_2, V_3, \cdots, V_n)$ obtained during a period of time on a given site are grouped into classes and represented as a histogram (the graph $(Bin_j \times f_{j,})$). The obtained wind speed classes can be divided into two groups: the even speed classes (Bin_{2k}) and the odd classes (Bin_{2k+1}).
Samples of p wind speed measurements ($X_1, X_2, X_3, \cdots, X_p$) of the group of even classes group (Bin_{2k}), subsets of $(V_1, V_2, V_3, \cdots, V_n$), are used to estimate the shape parameter (K_{even}) and scale parameter (C_{even}) given in (22) and (23).

$$K_{even} = \left[\left[\frac{\sum_{i=1}^{p} X_i^{K_{even}} \ln(X_i)}{\sum_{i=1}^{p} X_i^{K_{even}}} \right] - \left[\frac{\sum_{i=1}^{p} \ln(X_i)}{p} \right] \right]^{-1} \tag{22}$$

$$C_{even} = \left[\frac{\sum_{i=1}^{p} X_i^{K_{even}}}{p} \right]^{1/K_{even}} \tag{23}$$

This new approach is referred to as Maximum Likelihood with Even Bins time series Method (MLEBM).
In case K_{even} and C_{even} allow a quick and accurate estimation of the mean power density using (7) and (8). The mean wind speed is given in (3) and (5); and the standard deviation in (4) and (6) for the set $(V_1, V_2, V_3, \cdots, v_n)$ of the obtained wind measurements during a period of time on a given site, is used for the estimation. The time is reduced, since the size of the dataset ($X_1, X_2, X_3, \cdots, X_p$) used to estimate these parameters is less than 100% of the size of the full set $(V_1, V_2, V_3, \cdots, V_n)$ as expressed in (24).

$$td_{even}(\%) = 100 \frac{p}{n} \tag{24}$$

Likewise, samples of q wind measurements $(Y_1, Y_2, Y_3, \cdots, Y_q)$ of the group of odd classes (Bin_{2k+1}), subsets of $(V_1, V_2, V_3, \cdots, V_n)$, are used to estimate K_{odd} and C_{odd} (shape and scale parameters) according to equations (25) and (26)

$$K_{odd} = \left[\left[\frac{\sum_{i=1}^{q} Y_i^{K_{odd}} \ln(Y_i)}{\sum_{i=1}^{q} Y_i^{K_{odd}}} \right] - \left[\frac{\sum_{i=1}^{q} \ln(Y_i)}{q} \right] \right]^{-1} \tag{25}$$

$$C_{odd} = \left[\frac{\sum_{i=1}^{q} Y_i^{K_{odd}}}{q} \right]^{1/K_{odd}} \tag{26}$$

This new approach is referred to as Maximum Likelihood with Odd Bins time series Method (MLOBM).
The use of K_{odd} and C_{odd} may allow a quick and reasonably accurate estimation of the mean power density. The equations that are used for the computaions equations (7) and (8), the mean wind speed (equations (3) and (5)) and the standard deviation (equations (4) and (6)) for the set $(V_1, V_2, V_3, \cdots, V_n)$ of wind measurements obtained during a period on a given site. It is clear that the estimation time is reduced, since the size of the dataset $(Y_1, Y_2, Y_3, \cdots, Y_q)$ used to estimate these parameters is less than 100% of the size of the full set $(V_1, V_2, V_3, \cdots, V_n)$ as expressed by the equation (27).

$$td_{odd}(\%) = 100 \frac{q}{n} \tag{27}$$

Thus, this study aims to verify if, from each speed class group (even or odd) taken individually, it is possible to estimate the parameters (K and C) suitable for a fast and accurate estimation of the mean power density, the mean wind speed and standard deviation on the Lome, Accra and Cotonou sites in the Gulf of Guinea.

Some performance metrics are used to evaluate each method namely the root mean squared error (RMSE), the correlation coefficient R^2 and the absolute value of the relative error.
The RMSE parameter, whose ideal value is zero (0), gives the difference between the predicted or expected value vp_i and observed value vo_i for n_e data samples [16], [24], [47]. It is given by equation (28)

$$RMSE = \sqrt{\frac{1}{n_e} \sum_{i=1}^{n_e} (vo_i - vp_i)^2} \tag{28}$$

The correlation coefficient whose ideal value is one (1) gives the correlation between the predicted or expected and observed values [16], [24], [47]. It is given by the relationship (29)

$$R^2 = \frac{\sum_{i=1}^{n_e}\left(vp_i - \overline{vp_i}\right)\cdot\left(vo_i - \overline{vo_i}\right)}{\sqrt{\sum_{i=1}^{n_e}\left(vp_i - \overline{vp_i}\right)^2 \cdot \sum_{i=1}^{n_e}\left(vo_i - \overline{vo_i}\right)^2}} \quad (29)$$

The absolute value of the relative error between the predicted value and the observed value is given by equation (30), it is considered acceptable if less or equal to 10% [24].

$$Error\ (\%) = 100\left|\frac{vo_i - vp_i}{vo_i}\right| \quad (30)$$

5. The methodology

5.1. The data collection

The hourly mean wind data used for the sites Lomé, Accra and Cotonou were obtained through the meteorological database at 'http://weather.uwyo.edu/area/meteorogram/' [48]. The coordinates of the three sites are given in Table 1. The data is recorded every day at one hour interval (this is the mean over the 10 minutes before the hour) at a height of 10 m above the ground.
The provided data sheet in [48] includes, respectively, for each record: the site name (STN), the date and recording time (TIME), atmospheric pressure (ALTM), room temperature (TMP) the dew temperature (DEW), relative humidity (RH), wind direction (DIR), wind speed (SPD), visibility (VIS) and the nature of clouds (CLOUDS).
Data collected for the three stations cover the period from January 2000 to December 2012, a record length of approximately thirteen (13) years. In our current work, we are interested only in the columns TIME (recording date and time) and SPD (wind speed). Fig. 1 shows the geographical location of the three (03) sites.

Table 1: Coordinates of the Case Study Sites [48]

Sites	Coordinates
Accra (Kotoka)	5.60N, 0.17W, 69 meters
Cotonou (Cadjehoun)	6.35N, 2.38E, 9 meters
Lomé (Tokoin)	6.17N, 1.25E, 25 meters

5.2. The data sampling and filtering

The mean wind speed data, the standard deviation data and mean power density data observed on the three sites for even, odd and all classes wind speed data subset of all data collected are shown in Table 2. The average wind speed, standard deviation and power density are similar for all three data classes considered. This is a preliminary indication that Weibull parameters estimated from either even or odd class speed data subset might yield similar average wind speed, standard deviation and mean power density as the entire dataset (all data).
Using the earlier described methods, we processed the 10-minutes averaged hourly wind speed data collected on the sites Lomé, Accra and Cotonou for 13 years. The data are sampled in monthly size such that each month (the entire 13-years data set is grouped monthly into 12 study periods: January, February, March, April, May, June, July, August, September, October, November, December), each year from 2000 to 2012 (13 periods) and the 13-years aggregate period amounting to 26 periods total. For each period of the three sites considered, the wind speeds data are classified as follows.

- The adjustment of even class (Bin_{2k}), odd class (Bin_{2k+1}) and all classes (Bin_k) histograms with their corresponding Weibull distribution functions;
- The estimation time of the Weibull parameters by considering the even class (Bin_{2k}), odd class (Bin_{2k+1}) and all classed (Bin_k) wind speed data;
- Details on fitting even class (Bin_{2k}), odd class (Bin_{2k+1}) and all classes (Bin_k) histograms with three Weibull distribution functions;
- The comparison of the mean power densities calculated using Weibull parameters estimated from even class (Bin_{2k}), odd class (Bin_{2k+1}) and all classes (Bin_k) wind speed data against the observed power density;
- The comparison of the mean wind speed calculated using Weibull parameters estimated from even class (Bin_{2k}), odd class (Bin_{2k+1}) and all classes (Bin_k) wind speed data against the observed mean wind speed;
- The comparison of the standard deviations calculated using Weibull parameters estimated from even class (Bin_{2k}), odd class (Bin_{2k+1}) and all classes (Bin_k) wind speed data against the observed standard deviation.

This classification is further given in Table 3.

6. Results and discussion

6.1. Histograms of the weibull functions: fitting the even, odd and all classes

Fig. 2, Fig. 3 and Fig. 4 show the Weibull probability density functions respectively for Lomé, Accra and Cotonou that are adjusted to the even class ( ), odd class ( ) and all classes ( ) histograms corresponding to the 13 years aggregated wind speed data. From these three figures it may be concluded that each histogram is well fitted since largest RMSE value is about 0.09573; and the lowest R2 value is 0.92421.
For each period and each site of the study, the Weibull parameters are estimated for series of wind speeds belonging to even (Bin_{2k}), odd (Bin_{2k+1}) and all (Bin_k) classes. The performance indicators R^2 and RMSE used to assess the estimated Weibull parameters in Lomé, Accra and Cotonou are recorded in Table 4.
The results in Table 4 may indicate that a good adjustment was achieved for each histogram.

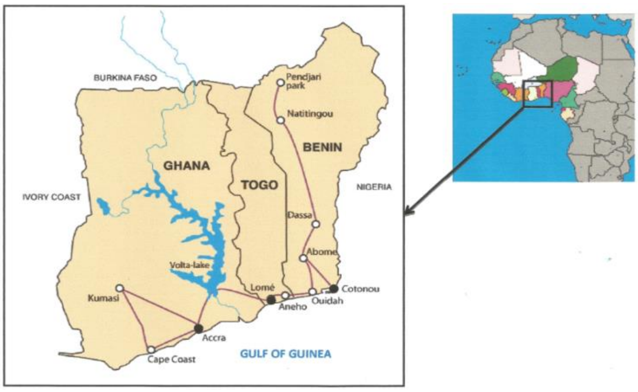

Fig. 1: Geograpgical Locations of the Study Sites.

Table 2: Mean Wind Speed, Wind Speed Standard Deviation and Mean Wind Power Densty According for the Group of Data Series for the Three Stations

	Mean wind speed (m/s)			Standard deviation (m/s)			Mean power density (W/m²)		
Site	All Bins	Even Bins	Odd Bins	All Bins	Even Bins	Odd Bins	All Bins	Even Bins	Odd Bins

Lome	3.52013	3.49066	3.54807	2.04755	2.05346	2.04156	55.45392	54.55148	56.30900
Accra	4.16032	4.00684	4.30235	2.21591	2.46834	1.94271	82.22761	84.87287	79.77961
Cotonou	3.99340	3.97250	4.01390	1.81220	1.80910	1.81510	62.70380	61.79640	63.59710

Table 3: Wind Speed Classes Adopted for the Three Sites.

Wind speed (m/s)	Bins	Type
]0, 1[	Bin_0	Even bin
[1, 2[	Bin_1	Odd bin
[2, 3[	Bin_2	Even bin
[3, 4[	Bin_3	Odd bin
[4, 5[	Bin_4	Even bin
[5, 6[	Bin_5	Odd bin
[6, 7[	Bin_6	Even bin
…	…	…
…	…	…
…	…	…
[21], [22]	Bin_{21}	Odd bin

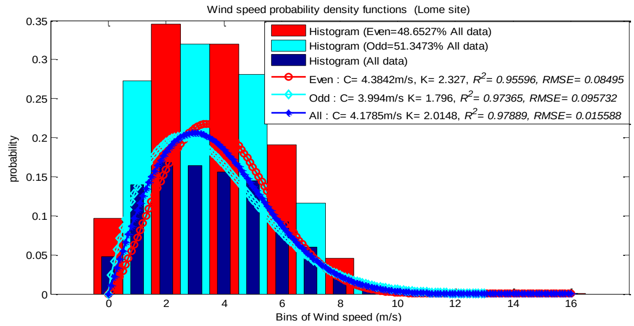

Fig. 2: Wind Speed Probability Density Function of Lomé Site for Whole Years 2000 to 2012.

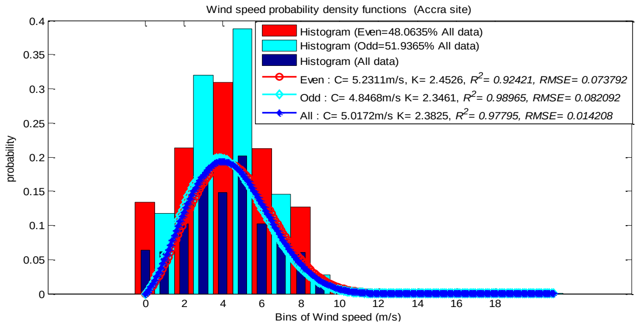

Fig. 3: Wind Speed Probability Density Function of Accra Site for Whole Years 2000 to 2012.

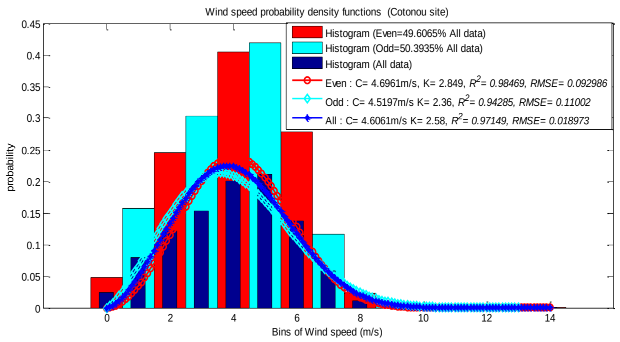

Fig. 4: Wind Speed Probability Density Function of Cotonou Site for Whole Years 2000 to 2012.

The tuned parameters in the Weibull distribution function for each period and site are tabulated. On the site of (Lomé, Accra, Cotonou) the highest RMSE value is 0.1469. For the march's data March, Cotonou site recorded a correlation coefficient of $R^2 = 0.9151$; and the lowest R^2 value is 0.6022 obtained for the same period in 2005 on the Lome's site (with RMSE = 0.1302).

6.2. Weibull parameter estimation time

The estimation time of Weibull parameters (K and C) was performed by using the Maximum Likelihood Method (MLM). A comparison was conducted on the derived times of Weibull parameters (K and C) for even (Bin_{2k}), odd (Bin_{2k+1}) and all (Bin_k) classes of wind speed data. The proposed approach is implemented in Matlab on a computer processor (Intel® Celeron® B840 CPU @ 1.90 GHz 1.90 GHz) with a 4 GB RAM. The Table 5, Table 6 and Table 7 illustrate the processing times of the Weibull parameters estimation for the three configurations of speed data (Bin_{2k} , Bin_{2k+1} and Bin_k) in Lomé , Accra and Cotonou respectively. The results in Tables 5, 6 and 7, may point out that the processing time of all (100%) speed wind data (Bin_k -class) in respect to a given period is approximately twice that of the even (Bin_{2k}) and odd (Bin_{2k+1}) class data. For example, it can be noted in the Table 4, for the period of January in Lomé, K_{all} and C_{all} (all class data shape and scale Weibull parameters) are estimated in 9 ms; while K_{odd} and C_{odd} (odd class data shape and scale Weibull parameters) in 5.5 ms, and K_{even} and C_{even} (even class data shape and scale Weibull parameters) in 4.8 ms.

6.3. Adjustment of the distribution histograms with weibull distribution functions

The work evaluates the time for computing the Weibull parameters based on the proposed sampling. It is observed that a less computation time was achieved based on the proposed Maximum Likelihood Method (MLM) to estimate the Weibull parameters with acceptable accuracy on the various sites located in the Gulf of Guinea Lome, Accra and Cotonou. For each site; and for a given period, the wind speeds series are divided into two groups of classes (even and odd classes). The parameters of three Weibull functions are estimated for even class (K_{even} and C_{even}), odd class (K_{odd} and C_{odd}) and for all class (K_{all} and C_{all}) data. Performance indicators RMSE and R^2 of the Weibull adjustment distribution functions of all the wind measurement data are calculated and presented in Tables 8, 9 and 10. Figures 5, 6 and 7 present (a) the three Weibull probality density functions and (b) the three Weibull cumulative distribution functions respectively for Lomé, Accra and Cotonou over 13-year time period (2000 -2012). For this study period and for all locations, figures 5, 6 and 7 show:

- A quasi-perfect fitting of the distribution histograms by the pdf and cdf curves obtained using the entire dataset ($K_{all} = 2.0148$ and $C_{all} = 4.1785\, m/s$ for Lomé, $K_{all} = 2.3825$ and $C_{all} = 5.0172\, m/s$ for Accra, and $K_{all} = 2.5800$ and $C_{all} = 4.6061\, m/s$ for Cotonou), with minimum correlation coefficient R^2 of 0.97149 and maximum RMSE of 0.018973;
- An acceptable fitting of the distribution histograms by the pdf and cdf curves obtained using the even class dataset ($K_{even} = 2.3270$ and $C_{even} = 4.3842\, m/s$ for Lomé, $K_{even} = 2.4526$ and $C_{even} = 5.2311\, m/s$ for Accra, and $K_{even} = 2.8490$ and $C_{even} = 4.6961\, m/s$ for Cotonou), with minimum correlation coefficient R^2 of 0.9382 and maximum RMSE of 0.02716;
- An acceptable fitting of the distribution histograms by the pdf and cdf curves obtained using the odd class dataset ($K_{odd} = 1.7960$ and $C_{odd} = 3.9940\, m/s$ for Lomé, $K_{odd} = 2.3461$ and $C_{odd} = 4.8468\, m/s$ for Accra, and $K_{odd} = 2.360$ and $C_{odd} = 4.5197\, m/s$ for Cotonou), with minimum correlation coefficient R^2 of 0.9520 and maximum RMSE of 0.02075.
- Tables 8, 9 and 10 show the Weibull parameters estimated by the Maximum Likelihood Method (MLM) for three sets of speed data (Bin_{2k} , Bin_{2k+1} and Bin_k) and the results of statistical tests respectively for Lome, Accra and Cotonou.

- Analysis of the results of Tables 7, 8 and 9 for all three sites, may indicate that:
- the fitting curves with Weibull parameters K_{all} and C_{all} accurately adjust the distribution histograms of all wind measurement data for each period, since the minimum R^2 value is 0.8797 and the maximum RMSE value is 0.0350;
- The curves with Weibull parameters K_{even} and C_{even} adjust with an acceptable accuracy the distribution histograms of all wind measurement data for each period, since the minimum R^2 value is 0.7820 and the maximum RMSE value is 0.0583;
- The curves with Weibull parameters K_{odd} and C_{odd} adjust with an acceptable accuracy the distribution histograms of all wind measurement data for each period, since the minimum R^2 value is 0.7793 and the maximum RMSE value is 0.0519.

Table 4: Statistical Analysis

Period	Lomé Even bins data RMSE	R^2	Lomé Odd bins data RMSE	R^2	Accra Even bins data RMSE	R^2	Accra Odd bins data RMSE	R^2	Cotonou Even bins data RMSE	R^2	Cotonou Odd bins data RMSE	R^2
Jan.	0.1291	0.8557	0.1198	0.9950	0.1085	0.7810	0.0836	0.9873	0.1224	0.9775	0.1293	0.9765
Feb.	0.0970	0.9357	0.1133	0.9326	0.0952	0.8975	0.1109	0.9809	0.1172	0.9590	0.1341	0.8980
Mar.	0.0991	0.9371	0.1132	0.9369	0.0951	0.8975	0.1016	0.9834	0.1231	0.9571	0.1469	0.9151
Apr.	0.0835	0.9544	0.0945	0.9692	0.0904	0.8401	0.0972	0.9950	0.1018	0.9809	0.1162	0.9313
May	0.1067	0.8970	0.0981	0.9842	0.0845	0.8697	0.0937	0.9881	0.1013	0.9836	0.1053	0.9636
Jun.	0.1048	0.9309	0.1054	0.9807	0.0911	0.8814	0.0952	0.9854	0.1043	0.9712	0.1138	0.9397
Jul.	0.1040	0.9916	0.1060	0.9835	0.0888	0.9542	0.0865	0.9930	0.1173	0.9862	0.1256	0.9810
Aug.	0.1100	0.9988	0.1027	0.9939	0.0768	0.9792	0.1231	0.9862	0.1269	0.9982	0.1381	0.9993
Sep.	0.1028	0.9818	0.1135	0.9796	0.0953	0.9645	0.1198	0.9798	0.1203	0.9770	0.1332	0.9370
Oct	0.1111	0.9330	0.0974	0.9758	0.0942	0.9163	0.0866	0.9926	0.0928	0.9796	0.1236	0.9393
Nov.	0.1201	0.9420	0.1227	0.9516	0.0815	0.9064	0.0988	0.9938	0.1081	0.9944	0.1333	0.9306
Dec.	0.1235	0.9096	0.1227	0.9586	0.0906	0.9025	0.1229	0.9909	0.1186	0.9944	0.1217	0.9546
Whole years	0.0850	0.9560	0.0957	0.9736	0.0738	0.9242	0.0821	0.9896	0.0930	0.9847	0.1100	0.9429
2000	0.1009	0.9540	0.0981	0.9780	0.1077	0.6673	0.1023	0.9772	0.1129	0.9553	0.1215	0.9434
2001	0.0961	0.9585	0.1131	0.9316	0.1220	0.7702	0.0938	0.9873	0.0949	0.9706	0.1202	0.9696
2002	0.1178	0.9277	0.1043	0.9679	0.0964	0.9018	0.1258	0.9902	0.0963	0.9737	0.1165	0.9491
2003	0.1057	0.9745	0.1167	0.9380	0.0938	0.9550	0.1219	0.9979	0.1160	0.9857	0.1225	0.9412
2004	0.1046	0.8484	0.1140	0.9701	0.0908	0.9546	0.0907	0.9947	0.1014	0.9883	0.1196	0.9535
2005	0.1302	0.6027	0.1006	0.9969	0.0948	0.9035	0.1040	0.9878	0.1111	0.9891	0.1357	0.8941
2006	0.0950	0.9430	0.1442	0.9891	0.0964	0.8587	0.0854	0.9751	0.1102	0.9869	0.1203	0.9266
2007	0.1200	0.7299	0.1057	0.9879	0.0878	0.8698	0.1038	0.9662	0.1008	0.9911	0.1125	0.9512
2008	0.1229	0.9484	0.0985	0.9693	0.0917	0.7891	0.0926	0.9643	0.1007	0.9871	0.1072	0.9472
2009	0.0979	0.9675	0.0956	0.9600	0.1024	0.7357	0.1089	0.9511	0.1115	0.9801	0.1158	0.9569
2010	0.10	0.95	0.10	0.95	0.08	0.79	0.11	0.95	0.0923	0.97	0.11	0.92

Period	Lomé Even bins data RMSE	Lomé Even bins data R^2	Lomé Odd bins data RMSE	Lomé Odd bins data R^2	Accra Even bins data RMSE	Accra Even bins data R^2	Accra Odd bins data RMSE	Accra Odd bins data R^2	Cotonou Even bins data RMSE	Cotonou Even bins data R^2	Cotonou Odd bins data RMSE	Cotonou Odd bins data R^2
	67	65	47	09	09	60	34	55		40	88	22
2011	0.0982	0.9684	0.1039	0.9659	0.0978	0.9642	0.1177	0.9959	0.1090	0.9829	0.1183	0.9342
2012	0.0973	0.9596	0.1023	0.9581	0.0962	0.9835	0.0898	0.9936	0.0995	0.9777	0.1180	0.9044

Table 5: Time Calculating Weibull Parameters for Lomé Site

Period	Lomé All data Time (s)	Even bins data td (%)	Even bins data Time (s)	Odd bins data td (%)	Odd bins data Time (s)
Jan.	0.0090	49.7089	0.0048	50.2911	0.0055
Feb.	0.0091	49.6086	0.0048	50.3914	0.0049
Mar.	0.0070	49.7258	0.0052	50.2742	0.0056
Apr.	0.0093	48.9074	0.0053	51.0926	0.0051
May	0.0109	48.3258	0.005	51.6742	0.0058
Jun.	0.0080	48.4074	0.0051	51.5926	0.0060
Jul.	0.0082	49.0373	0.0056	50.9627	0.0057
Aug.	0.0075	48.2338	0.0053	51.7662	0.0065
Sep.	0.0084	49.5426	0.0057	50.4574	0.0053
Oct.	0.0118	46.6527	0.0051	53.3473	0.0069
Nov.	0.0105	47.6500	0.0046	52.3500	0.0055
Dec.	0.0105	48.1620	0.0046	51.8380	0.0059
Whole years	0.0948	48.6527	0.0309	51.3473	0.0495
2000	0.0062	49.1760	0.0039	50.824	0.0049
2001	0.0067	49.1602	0.0043	50.8398	0.0059
2002	0.0043	49.9612	0.0030	50.0388	0.0027
2003	0.0050	47.0345	0.0034	52.9655	0.0034
2004	0.0064	51.4947	0.0038	48.5053	0.0039
2005	0.0063	52.9999	0.0033	47.0001	0.00400
2006	0.0055	48.8818	0.0035	51.1182	0.0036
2007	0.0075	52.9132	0.0042	47.0868	0.0046
2008	0.0100	46.9015	0.0061	53.0985	0.0076
2009	0.0101	47.2186	0.0071	52.7814	0.0076
2010	0.0087	47.1710	0.0070	52.829	0.0076
2011	0.0100	47.3443	0.0069	52.6557	0.0080
2012	0.0073	48.7763	0.0064	51.2237	0.0062

Table 6: Time Calculating Weibull Parameters for Accra Site

Period	Accra All data Time (s)	Even bins data td (%)	Even bins data Time (s)	Odd bins data td (%)	Odd bins data Time (s)
Jan.	0.0069	47.8993	0.0037	52.1007	0.0039
Feb.	0.0053	47.7375	0.0033	52.2625	0.0037
Mar.	0.0058	49.2586	0.0036	50.7414	0.0045
Apr.	0.0053	49.1022	0.0033	50.8978	0.0039
May	0.0062	51.1736	0.0034	48.8264	0.0043
Jun.	0.0057	48.3131	0.0034	51.6869	0.0037
Jul.	0.0070	44.8792	0.0034	55.1208	0.0046
Aug.	0.0067	46.0611	0.0039	53.9389	0.0047
Sep.	0.0058	48.0346	0.0034	51.9654	0.0039
Oct.	0.0057	48.4899	0.0032	51.5101	0.0035
Nov.	0.0066	48.5719	0.0034	51.4281	0.0041
Dec.	0.0077	47.8538	0.0036	52.1462	0.0039
Whole years	0.0381	48.0635	0.0154	51.9365	0.0207
2000	0.0032	51.0446	0.0027	48.9554	0.0025
2001	0.0035	53.4393	0.0025	46.5607	0.0025
2002	0.0035	53.8105	0.0029	46.1895	0.0025
2003	0.0076	48.4461	0.0037	51.5539	0.0039
2004	0.0058	48.241	0.0035	51.759	0.0037
2005	0.0052	46.8777	0.0032	53.1223	0.0035
2006	0.0054	45.9614	0.0031	54.0386	0.0036
2007	0.0038	46.8401	0.0025	53.1599	0.0031
2008	0.0046	42.7759	0.0025	57.2241	0.0033
2009	0.0069	43.0155	0.0032	56.9845	0.0048
2010	0.0065	49.4031	0.0046	50.5969	0.0045
2011	0.0059	51.1494	0.0036	48.8506	0.0036
2012	0.0064	49.4571	0.0037	50.5429	0.0042

Table 7: Time Calculating Weibull Parameters for Cotonou Site

Period	Cotonou All data Time (s)	Even bins data td (%)	Even bins data Time (s)	Odd bins data td (%)	Odd bins data Time (s)
Jan.	0.0076	49.3485	0.0030	50.6515	0.0035
Feb.	0.0090	49.6431	0.0052	50.3569	0.0059
Mar.	0.0087	49.9471	0.0049	50.0529	0.0054
Apr.	0.0087	49.9408	0.0058	50.0592	0.0062
May	0.0082	49.1730	0.0046	50.8270	0.0055
Jun.	0.0079	50.8499	0.0048	49.1501	0.0041
Jul.	0.0084	49.2415	0.0043	50.7585	0.0053
Aug.	0.0088	48.5408	0.0056	51.4592	0.0059
Sep.	0.0114	48.4371	0.0048	51.5629	0.0058
Oct.	0.0078	48.8112	0.0046	51.1888	0.0048
Nov.	0.0083	50.7937	0.0047	49.2063	0.0051
Dec.	0.0084	50.4787	0.0050	49.5213	0.0052
Whole years	0.0935	49.6065	0.0342	50.3935	0.0455
2000	0.0042	51.3073	0.0030	48.6927	0.0027
2001	0.0071	52.0724	0.0043	47.9276	0.0041
2002	0.0073	51.1300	0.0046	48.8700	0.0042
2003	0.0070	51.2827	0.0041	48.7173	0.0043
2004	0.0070	48.9999	0.0041	51.0001	0.0045
2005	0.0069	47.7298	0.0040	52.2702	0.0044
2006	0.0059	48.0932	0.0036	51.9068	0.0039
2007	0.0081	49.6683	0.0048	50.3317	0.0053
2008	0.0087	48.6081	0.0053	51.3919	0.0058
2009	0.0092	49.8892	0.0061	50.1108	0.0065
2010	0.0087	49.6608	0.0056	50.3392	0.0060
2011	0.0096	49.0356	0.0042	50.9644	0.0052
2012	0.0117	49.3521	0.0073	50.6479	0.0078

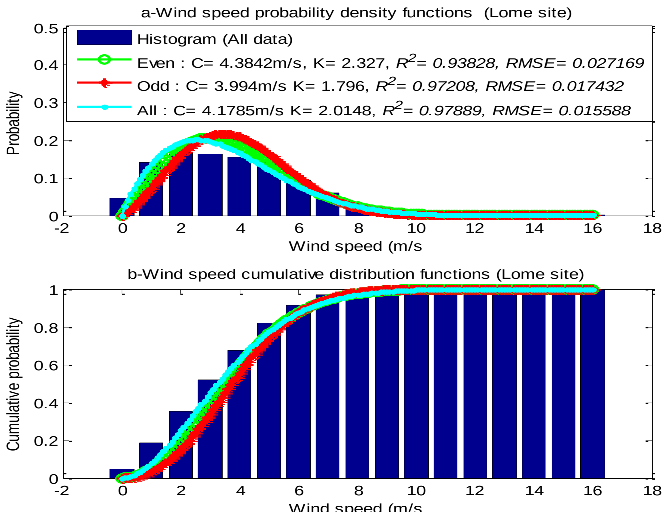

Fig. 5: Suitability of Weibull Distributions for Lomé Site for Whole Years 2000 to 2012.

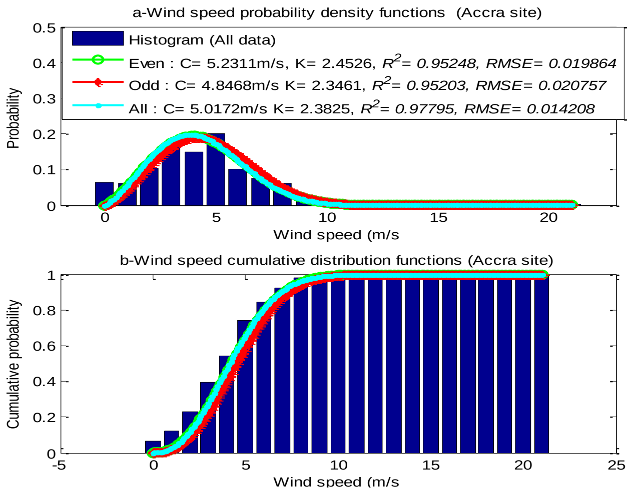

Fig. 6: Suitability of Weibull Distributions for Accra Site for Whole Years 2000 to 2012.

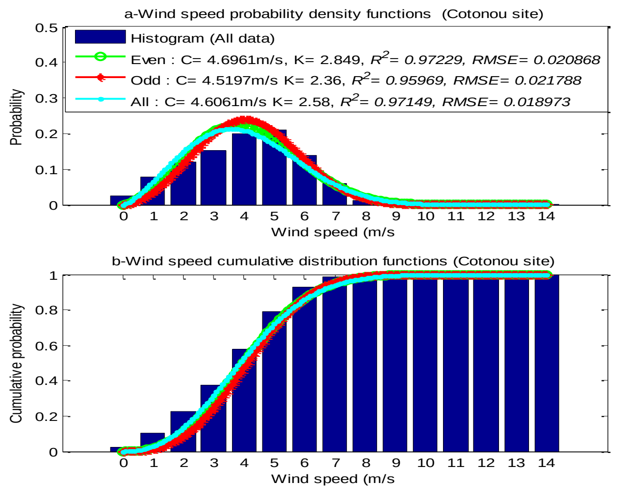

Fig. 7: Suitability of Weibull Distributions for Cotonou Site for Whole Years 2000 to 2012.

Table 8: Weibull Analysis and Estimation Parameters for Lomé Site

	Lomé All data				Even bins data				Odd bins data			
Period	C_{all} (m/s)	K_{all}	RMSE	R^2	C_{even} (m/s)	K_{even}	RMSE	R^2	C_{odd} (m/s)	K_{odd}	RMSE	R^2
Jan.	3.4266	1.9436	0.0205	0.9778	3.7035	2.3351	0.0508	0.8456	3.1897	1.7032	0.0311	0.9475
Feb.	4.4125	2.0843	0.0200	0.9619	4.5075	2.3068	0.0290	0.9317	4.3228	1.9068	0.0206	0.9583
Mar.	4.6683	2.1551	0.0193	0.9594	4.8058	2.3544	0.0274	0.9358	4.5426	1.9945	0.0223	0.9489
Apr.	4.3296	2.0122	0.0155	0.9778	4.5100	2.2932	0.0259	0.9407	4.1662	1.8060	0.0179	0.9682
May	3.6654	1.8625	0.0199	0.9707	3.9296	2.2240	0.0407	0.8781	3.4419	1.6384	0.0230	0.9614
Jun.	3.7569	1.9199	0.0187	0.9738	3.9781	2.2598	0.0370	0.9035	3.5613	1.6940	0.0198	0.9721
Jul.	4.8341	2.4445	0.0112	0.9901	4.8678	2.6114	0.0158	0.9858	4.8016	2.3022	0.0113	0.9881
Aug.	5.2592	2.8551	0.0077	0.9953	5.2526	2.9069	0.0087	0.9948	5.2653	2.8074	0.0073	0.9956
Sep.	4.7209	2.2841	0.0126	0.9866	4.8471	2.4899	0.0190	0.9757	4.5999	2.1132	0.0135	0.9830
Oct	3.8299	1.8836	0.0199	0.9670	4.1058	2.2434	0.0366	0.8956	3.6011	1.6623	0.0191	0.9719
Nov.	3.5383	1.9185	0.0319	0.9228	3.9089	2.4703	0.0583	0.7820	3.2183	1.6243	0.0313	0.9393
Dec.	3.4481	1.9528	0.0297	0.9407	3.7420	2.4559	0.0575	0.8074	3.1977	1.6715	0.0326	0.9371
Whole years	4.1785	2.0148	0.0156	0.9789	4.3842	2.3270	0.0272	0.9383	3.9940	1.7960	0.0174	0.9721
2000	4.7430	2.1757	0.0202	0.9564	4.5967	2.1464	0.0215	0.9546	4.8757	2.2096	0.0215	0.9508
2001	4.7254	2.2093	0.0228	0.9472	4.6701	2.1895	0.0231	0.9467	4.7765	2.2296	0.0230	0.9468
2002	4.4004	2.0058	0.0232	0.9430	4.2880	2.0539	0.0258	0.9389	4.5042	1.9624	0.0241	0.9379
2003	4.5189	2.1574	0.0179	0.9676	4.6295	2.3508	0.0230	0.9563	4.4229	2.0070	0.0178	0.9675
2004	4.3666	2.1366	0.0183	0.9791	4.4889	2.3583	0.0370	0.8920	4.2562	1.9639	0.0315	0.9044
2005	3.8384	2.0387	0.0235	0.9773	4.1228	2.4408	0.0570	0.7552	3.6104	1.8047	0.0519	0.7793
2006	3.1649	2.2002	0.0229	0.9743	3.4618	2.7165	0.0420	0.9085	2.9094	1.8870	0.0312	0.9450
2007	3.7944	1.9723	0.0230	0.9726	4.0898	2.3545	0.0525	0.7934	3.5309	1.7279	0.0416	0.8660
2008	3.8451	1.9513	0.0216	0.9621	4.1138	2.3850	0.0381	0.8952	3.6075	1.6883	0.0188	0.9723
2009	4.2694	2.0003	0.0209	0.9583	4.5469	2.4031	0.0327	0.9105	4.0208	1.7439	0.0201	0.9617
2010	4.1227	2.0009	0.0243	0.9458	4.3981	2.4287	0.0387	0.8837	3.8781	1.7359	0.0232	0.9527
2011	4.1151	2.0060	0.0202	0.9641	4.4027	2.3988	0.0337	0.9112	3.8611	1.7553	0.0202	0.9659
2012	4.5028	2.1131	0.0185	0.9667	4.6496	2.3748	0.0266	0.9417	4.3650	1.9115	0.0176	0.9692

Table 9: Weibull Analysis and Estimation Parameters for Accra Site

	Accra All data				Even bins data				Odd bins data			
Period	C_{all} (m/s)	K_{all}	RMSE	R^2	C_{even} (m/s)	K_{even}	RMSE	R^2	C_{odd} (m/s)	K_{odd}	RMSE	R^2
Jan.	4.3869	2.2015	0.0158	0.9780	4.5635	2.3282	0.0267	0.9243	4.2596	2.1230	0.0266	0.9255

Pe-riod	Accra All data C_{all} (m/s)	K_{all}	RMSE	R^2	Even bins data C_{even} (m/s)	K_{even}	RMSE	R^2	Odd bins data C_{odd} (m/s)	K_{odd}	RMSE	R^2
Feb.	5.1646	2.4268	0.0207	0.9497	5.4195	2.5065	0.0268	0.9157	4.9595	2.3913	0.0279	0.9219
Mar.	5.0388	2.3179	0.0176	0.9669	5.2224	2.3702	0.0234	0.9388	4.8823	2.2884	0.0242	0.9420
Apr.	5.0727	2.2507	0.0177	0.9661	5.3793	2.3971	0.0283	0.9041	4.8228	2.1646	0.0279	0.9170
May	4.6051	2.1956	0.0134	0.9885	4.7568	2.3006	0.0268	0.9283	4.4760	2.1135	0.0263	0.9316
Jun.	4.7892	2.3300	0.0165	0.9763	5.0146	2.4371	0.0254	0.9351	4.6131	2.2657	0.0263	0.9350
Jul.	5.6171	2.8180	0.0183	0.9621	5.8775	2.8932	0.0202	0.9534	5.4178	2.7970	0.0209	0.9525
Aug.	5.8691	3.1425	0.0189	0.9654	6.1221	3.1907	0.0222	0.9515	5.6637	3.1507	0.0209	0.9595
Sep.	5.7381	2.9325	0.0212	0.9540	5.9636	2.9952	0.0246	0.9383	5.5426	2.9144	0.0251	0.9419
Oct	5.0165	2.3886	0.0137	0.9803	5.2411	2.4905	0.0195	0.9572	4.8312	2.3285	0.0201	0.9575
Nov.	4.3677	2.2845	0.0146	0.9832	4.4388	2.2697	0.0236	0.9471	4.3127	2.3048	0.0243	0.9480
Dec.	4.2650	2.2473	0.0160	0.9823	4.4194	2.3203	0.0264	0.9415	4.1480	2.1993	0.0263	0.9462
Whole years	5.0172	2.3825	0.0142	0.9779	5.2311	2.4526	0.0199	0.9525	4.8468	2.3461	0.0208	0.9520
2000	4.8792	2.1838	0.0201	0.9631	5.0076	2.2772	0.0376	0.8310	4.7745	2.1109	0.0367	0.8383
2001	3.7999	2.1722	0.0122	0.9943	3.9104	2.4389	0.0327	0.9119	3.7050	2.0019	0.0316	0.9087
2002	3.8119	1.9890	0.0118	0.9911	3.9419	2.0998	0.0271	0.9394	3.6856	1.8836	0.0249	0.9492
2003	4.4268	2.1673	0.0128	0.9855	4.6907	2.2611	0.0210	0.9576	4.2026	2.1150	0.0182	0.9759
2004	4.6700	2.1766	0.0116	0.9878	4.9077	2.3407	0.0188	0.9658	4.4681	2.0604	0.0162	0.9763
2005	5.2727	2.4594	0.0216	0.9478	5.5725	2.5447	0.0260	0.9227	5.0335	2.4306	0.0265	0.9296
2006	5.2409	2.4855	0.0188	0.9586	5.4805	2.6491	0.0239	0.9318	5.0684	2.3955	0.0249	0.9262
2007	5.4312	2.5056	0.0223	0.9424	5.6878	2.6427	0.0290	0.9033	5.2392	2.4290	0.0307	0.8950
2008	5.3536	2.5132	0.0294	0.9006	5.8172	2.6353	0.0328	0.8722	5.0589	2.5107	0.0357	0.8617
2009	5.5190	2.7670	0.0350	0.8797	5.9933	2.9682	0.0396	0.8433	5.2210	2.7380	0.0435	0.8236
2010	5.2563	2.5212	0.0249	0.9334	5.5292	2.4656	0.0327	0.8710	5.0398	2.6363	0.0360	0.8680
2011	5.0191	2.5916	0.0101	0.9919	5.1283	2.6439	0.0185	0.9697	4.9157	2.5505	0.0175	0.9750
2012	5.3025	2.7730	0.0105	0.9897	5.3075	2.8030	0.0108	0.9889	5.2978	2.7466	0.0109	0.9889

Table 10: Weibull Analysis and Estimation Parameters for Cotonou Site.=

Pe-riod	Cotonou All data C_{all} (m/s)	K_{all}	RMSE	R^2	Even bins data C_{even} (m/s)	K_{even}	RMSE	R^2	Odd bins data C_{odd} (m/s)	K_{odd}	RMSE	R^2
Jan.	3.7698	2.4047	0.0175	0.9855	3.8554	2.6622	0.0287	0.9686	3.6907	2.1987	0.0210	0.9751

Period	Cotonou All data C_{all} (m/s)	K_{all}	RMSE	R^2	Even bins data C_{even} (m/s)	K_{even}	RMSE	R^2	Odd bins data C_{odd} (m/s)	K_{odd}	RMSE	R^2
Fev.	4.9260	2.9502	0.0299	0.9373	5.0204	3.2457	0.0273	0.9537	4.8351	2.7093	0.0340	0.9159
Mar.	5.2097	3.2438	0.0293	0.9441	5.2530	3.4715	0.0266	0.9573	5.1676	3.0440	0.0327	0.9286
Apr.	4.8748	2.7316	0.0215	0.9631	4.9696	3.0060	0.0205	0.9717	4.7828	2.5097	0.0255	0.9462
May	4.1217	2.2518	0.0165	0.9797	4.2512	2.5242	0.0229	0.9672	3.9986	2.0364	0.0187	0.9720
Jun.	4.3325	2.3340	0.0207	0.9662	4.4495	2.6090	0.0275	0.9540	4.2164	2.1074	0.0239	0.9517
Jul.	5.4662	3.4081	0.0155	0.9839	5.4753	3.4807	0.0149	0.9856	5.4579	3.3400	0.0169	0.9806
Aug.	5.5201	3.9497	0.0054	0.9985	5.5082	4.0979	0.0078	0.9977	5.5306	3.8217	0.0063	0.9980
Sep.	5.1439	3.0413	0.0223	0.9606	5.2138	3.3516	0.0222	0.9752	5.0804	2.8047	0.0276	0.9359
Oct	4.0340	2.2636	0.0195	0.9726	4.2234	2.6522	0.0283	0.9515	3.8574	1.9897	0.0226	0.9597
Nov.	3.9457	2.5516	0.0235	0.9673	4.0493	2.9156	0.0282	0.9634	3.8372	2.2485	0.0270	0.9527
Dec.	3.7844	2.5567	0.0243	0.9683	3.8885	2.9407	0.0313	0.9600	3.6767	2.2462	0.0268	0.9572
Whole years	4.6061	2.5800	0.0190	0.9715	4.6961	2.8490	0.0209	0.9723	4.5197	2.3600	0.0218	0.9597
2000	4.9448	2.8651	0.0266	0.9463	4.8255	2.8448	0.0297	0.9353	5.0642	2.8968	0.0249	0.9529
2001	4.9115	2.8758	0.0207	0.9676	4.8092	2.7923	0.0253	0.9523	5.0108	2.9689	0.0222	0.9641
2002	4.8388	2.6968	0.0221	0.9601	4.7712	2.6876	0.0248	0.9520	4.9039	2.7074	0.0226	0.9587
2003	4.5573	2.6640	0.0197	0.9722	4.6200	2.8769	0.0224	0.9724	4.4949	2.4753	0.0232	0.9584
2004	4.2952	2.5869	0.0198	0.9736	4.4718	2.9840	0.0234	0.9737	4.1319	2.3015	0.0275	0.9449
2005	4.4199	2.6248	0.0263	0.9509	4.5667	3.0300	0.0277	0.9611	4.2866	2.3390	0.0314	0.9254
2006	4.4454	2.5292	0.0232	0.9598	4.6026	2.8566	0.0245	0.9645	4.3016	2.2841	0.0273	0.9412
2007	4.3471	2.3894	0.0179	0.9758	4.4616	2.6917	0.0228	0.9701	4.2337	2.1446	0.0206	0.9646
2008	4.4357	2.4503	0.0193	0.9710	4.5434	2.7593	0.0227	0.9686	4.3338	2.2126	0.0217	0.9603
2009	4.7696	2.6881	0.0185	0.9737	4.8197	2.9248	0.0203	0.9759	4.7195	2.4874	0.0202	0.9660
2010	4.5990	2.5497	0.0215	0.9624	4.7326	2.8518	0.0236	0.9633	4.4717	2.3103	0.0249	0.9465
2011	4.5734	2.5843	0.0221	0.9624	4.7312	2.9415	0.0238	0.9683	4.4237	2.3163	0.0271	0.9396
2012	4.7542	2.5631	0.0240	0.9511	4.8648	2.9164	0.0259	0.9573	4.6465	2.2909	0.0275	0.9310

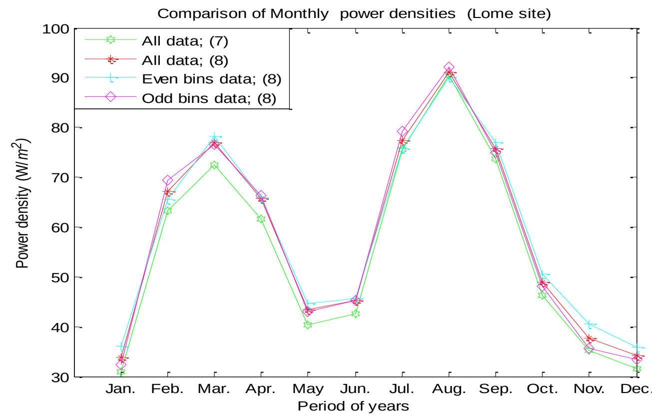

Fig. 8: Wind Power Density Obtained from the Measured Data (Eq. (7)) Versus Those Obtained From the Weibull Models (Eq. (8)), on A Monthly Basis for Lomé Site.

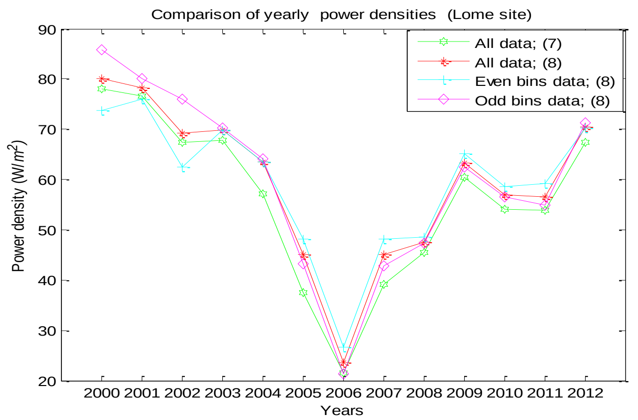

Fig. 9: Wind Power Density Obtained from the Measured Data (Eq. (7)) Versus Those Obtained from the Weibull Models (Eq. (8)), on A Yearly Basis for Lomé Site.

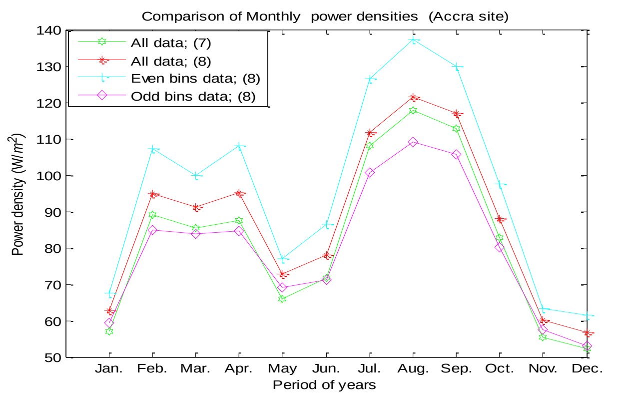

Fig. 10: Wind Power Density Obtained from the Measured Data (Eq. (7)) Versus Those Obtained from the Weibull Models (Eq. (8)), on A Monthly Basis for Accra Site.

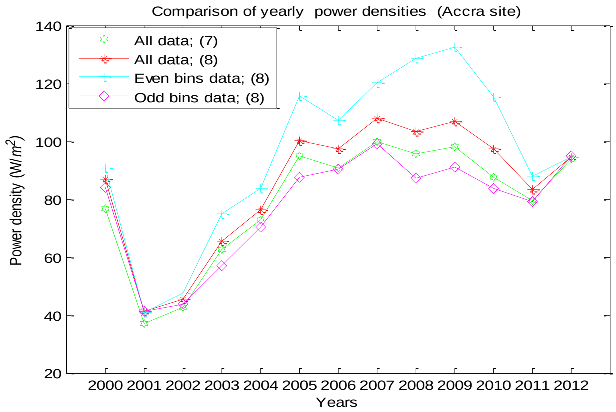

Fig. 11: Wind Power Density Obtained from the Measured Data (Eq. (7)) Versus Those Obtained from the Weibull Models (Eq. (8)), on A Yearly Basis for Accra Site.

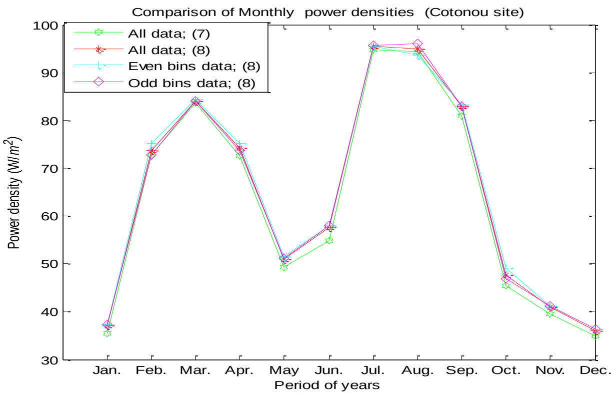

Fig. 12: Wind Power Density Obtained from the Measured Data (Eq. (7)) Versus Those Obtained from the Weibull Models (Eq. (8)), on A Monthly Basis for Cotonou Site.

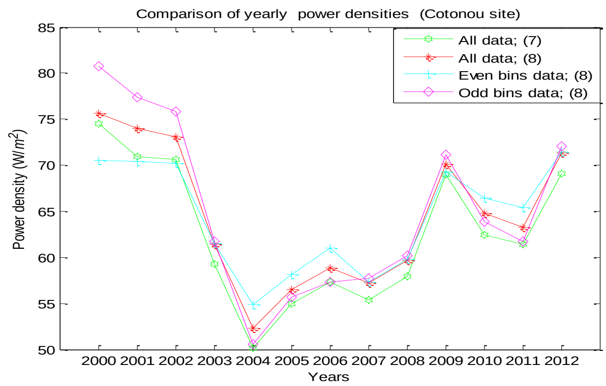

Fig. 13: Wind Power Density Obtained from the Measured Data (Eq. (7)) Versus Those Obtained from the Weibull Models (Eq. (8)), on A Yearly Basis for Cotonou Site.

6.4. Comparison of estimates of wind power density

One of the objectives of this work is to determine adequate Weibull parameters (K and C) among K_{even} and C_{even}, K_{odd} and C_{odd}, and K_{all} and C_{all} of each speed class group (even, odd or all) for a quick computation of the mean wind power density on the sites (Lomé, Accra and Cotonou in the Gulf of Guinea). As exposed in section 3, obtaining the appropriate Weibull parameters (K and C) of a wind site should lead to an accurate estimate of the mean power density. In this study, Weibull parameters from even class data (K_{even} and C_{even}), odd class data (K_{odd} and C_{odd}) and all class data (K_{all} and C_{all}) are estimated by the MLM. These parameters estimated for each period (26 periods total) are used to calculate the mean wind power density on each site (Lomé, Accra and Cotonou) according to equation (8). Figures 8, 9, 10, 11, 12 and 13 compare the mean power densities calculated (equation 8) and observed (equation 7) respectively on a monthly scale and on an annual basis in Lomé (Figures 8 and 9), Accra (Figures 10 and 11) and Cotonou (Figures 12 and 13).

The absolute value of the relative errors on the mean wind power densities estimated over 26 periods for the three study sites are calculated and presented in Table 11.

In the case of Lomé:

- The parameters K_{all} and C_{all} were used to calculate the mean wind power density with the lowest relative error for 8 periods out of 26;
- The parameters K_{even} and C_{even} were used to calculate the mean wind power density with the lowest relative error for 3 periods out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the mean wind power density with the lowest relative error for 15 times out of 26.
- Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind power density compared to others on the Lomé site. This is confirmed by the fact that the least mean relative error of 5.9091% committed in the calculation of mean wind power densities over 26 periods is obtained using K_{odd} and C_{odd}.
- In the case of Accra:
- The parameters K_{all} and C_{all} were used to calculate the mean wind power density with the lowest relative error for 7 periods out of 26;
- The parameters K_{even} and C_{even} were used to calculate the mean wind power density with the lowest relative error for 1 period out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the mean wind power density with the lowest relative error for 18 times out of 26.

Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind power density compared to others on the Accra site. This is confirmed by the fact that the least mean relative error of 4.5101% committed in the calculation of mean wind power densities over 26 periods is obtained using K_{odd} and C_{odd}.

In the case of Cotonou:

- The parameters K_{all} and C_{all} were used to calculate the mean wind power density with the lowest relative error for 11 periods out of 26;
- The parameters K_{even} and C_{even} were used to calculate the mean wind power density with the lowest relative error for 5 periods out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the mean wind power density with the lowest relative error for 10 times out of 26.

Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind power density compared to others on the Cotonou site. This is confirmed by the fact that the least mean relative error of 2.9566% incurred in the calculation of mean wind power densities over 26 periods is obtained using K_{odd} and C_{odd}.

6.5. The estimated mean wind speed

The quick assessment of the mean wind speed at a prospective wind farm location with a small error is important. It is crucial to identify adequate Weibull parameters (K and C) among K_{even} and C_{even}, K_{odd} and C_{odd}, and K_{all} and C_{all} of each speed class group (even, odd or all) for a quick computation of the mean wind speed on the

sites (Lomé, Accra and Cotonou in the Gulf of Guinea). As exposed in Section 3, obtaining the appropriate Weibull parameters (K and C) of a wind site should lead to an accurate estimate of the mean wind speed. In this study, Weibull parameters from even class data (K_{even} and C_{even}), odd class data (K_{odd} and C_{odd}) and all class data (K_{all} and C_{all}) are estimated by the MLM. These parameters estimated for each period (26 periods total) are used to calculate the mean wind speed on each site (Lomé, Accra and Cotonou) according to equation (5). Figures 14, 15, 16, 17, 18 and 19 compare the mean wind speed calculated (Equation (5)) and observed (equation 3) respectively on a monthly scale and on an annual basis in Lome (Figures 14 and 15), Accra (Figures 16 and 17) and Cotonou (Figures 18 and 19).
The absolute value of the relative errors on the mean wind speed estimated over 26 periods for the three study sites are computed and presented in Table 12.
In the case of Lomé:

- The parameters K_{all} and C_{all} were utilized to calculate the mean wind speed with the lowest relative error for 1 periods out of 26;
- The parameters K_{even} and C_{even} helped in calculating the mean wind speed with the lowest relative error for 3 periods out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the mean wind speed with the lowest relative error for 22 periods out of 26.

Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind speed compared to others on the Lomé site. This is confirmed by the fact that the least mean relative error of 2.8488% committed in the calculation of mean wind speed over 26 periods is obtained using K_{odd} and C_{odd} .
In the case of Accra:

- Only K_{odd} and C_{odd} led to the mean wind speed with the lowest relative error for 26 priods out of 26.

Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind speed compared to others on the Accra site. This is confirmed by the fact that the least mean relative error of 3.7579% committed in the calculation of mean wind speed over 26 periods is obtained using K_{odd} and C_{odd} .
In the case of Cotonou:

- The parameters K_{all} and C_{all} were used to calculate the mean wind speed with the lowest relative error for 1 periods out of 26;
- The parameters K_{even} and C_{even} were used to calculate the mean wind speed with the lowest relative error for 3 periods out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the mean wind speed with the lowest relative error for 22 periods out of 26.

Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind speed compared to others on the Cotonou site. This is confirmed by the fact that the least mean relative error of 1.2126% committed in the calculation of mean wind speed over 26 periods is obtained using K_{odd} and C_{odd}

6.6. Comparison of the estimateds tandard deviations

As exposed in Section 3, obtaining the appropriate Weibull parameters (K and C) of a wind site should lead to an accurate estimate of the standard deviation of wind speeds.
In this study, Weibull parameters from even class data (K_{even} and C_{even}), odd class data (K_{odd} and C_{odd}) and all class data (K_{all} and C_{all}) are estimated by the MLM. These parameters are estimated for each period (26 periods total) are used to calculate the standard deviation on each site (Lome, Accra and Cotonou) according to equation (6). Figures 20, 21, 22, 23, 24 and 25 compare the standard deviations calculated (equation 6) and observed (equation 4) respectively on a monthly scale and on an annual basis in Lome (Figures 20 and 21), Accra (Figures 22 and 23) and Cotonou (Figures 24 and 25).
The absolute value of the relative errors on the standard deviation estimated over 26 periods for the three study sites are computed and presented in Table 13.
In the case of Lomé:

- K_{odd} and C_{odd} are the only ones who led to a standard deviation with the lowest relative error for 26 priods out of 26.

Thus the estimated parameters K_{odd} and C_{odd} enabled a fast and accurate computation of the mean wind speed compared to others on the Lome site. This is confirmed by the fact that the least mean relative error of 2.3424% committed in the calculation of mean wind speed over 26 periods is obtained using K_{odd} and C_{odd} .
In the case of Accra:

- The parameters K_{all} and C_{all} were used to calculate the standard deviation with the lowest relative error for 1 periods out of 26;
- The parameters K_{even} and C_{even} were used to calculate the standard deviation with the lowest relative error for 17 periods out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the standard deviation with the lowest relative error for 7 periods out of 26.

Thus the estimated parameters K_{even} and C_{even} enabled a fast and accurate computation of the standard deviation compared to others on the Accra site. This is confirmed by the fact that the least mean relative error of 9.6215%% committed in the calculation of the standard deviation over 26 periods is obtained using K_{even} and C_{even} .
In the case of Cotonou:

- The parameters K_{all} and C_{all} were used to calculate the mean wind speed with the lowest relative error for 1 periods out of 26;
- The parameters K_{even} and C_{even} were used to calculate the mean wind speed with the lowest relative error for 3 periods out of 26;
- The parameters K_{odd} and C_{odd} were used to calculate the mean wind speed with the lowest relative error for 22 periods out of 26.

Thus the estimated parameters K_{odd} et C_{odd} enabled a fast and accurate computation of the mean wind speed compared to others on the Cotonou site. This is confirmed by the fact that the least mean relative error of 1.2126% committed in the calculation of mean wind speed over 26 periods is obtained using K_{odd} and C_{odd} .
The case studies conducted in this paper on three sites (Lomé, Accra and Cotonou) located in the Gulf of Guinea reveals that:

- The estimation time of the Weibull parameters K_{odd} and C_{odd} or K_{even} and C_{even} , using our approach, is reduced compared to the time required to estimate K_{all} and C_{all} for each period and site.
- The parameters K_{odd} and C_{odd} estimated from series of odd classes for a given period are adequate for a quick and a fairly accurate calculation of the mean wind power density, mean wind speed and the standard deviation of wind speeds on the Lomé site.

- For Accra, the parameters K_{odd} and C_{odd} estimated from series of odd classes for a given period are adequate for a quick and a fairly accurate calculation of the mean wind power density and mean wind speed, while K_{even} and C_{even} estimated from series of even classes give a better estimate of the standard deviation of wind speeds.
- The parameters K_{odd} and C_{odd} estimated from series of odd classes for a given period are adequate for a quick and a fairly accurate calculation of the mean wind speed and the standard deviation of wind speeds, while K_{all} and C_{all} estimated from series of even classes give a better estimate of the mean wind power density on the Cotonou site.

Table 11: Error Values in Calculating the Wind Power Density Obtained from the Weibull Models in Reference to the Wind Power Density Obtained from the All Measured Data, on Monthly and Yearly Basis

	Absolute Relative Error (%)								
	Lomé			Accra			Cotonou		
Period	All data	Even bins data	Odd bins data	All data	Even bins data	Odd bins data	All data	Even bins data	Odd bins data
Jan.	9.1274	16.1643	4.2158	10.0007	18.3243	4.0417	4.9221	5.1973	5.6457
Feb.	6.1367	3.5662	9.7014	6.3490	20.2392	4.8327	1.2989	3.2986	0.1230
Mar.	6.1176	7.6465	5.4841	6.5759	16.6789	2.0698	0.4556	0.8021	0.4107
Apr.	6.4177	6.7680	7.5292	8.6971	23.4812	3.4097	2.2573	3.5262	1.5122
May	7.6553	10.6583	6.4503	10.1866	16.838	4.7251	3.3964	4.4041	3.5240
Jun.	6.1160	7.4924	6.3726	8.6961	20.7608	0.6940	5.0133	5.5284	5.5850
Jul.	2.3633	0.2089	4.8327	3.4311	17.0117	6.8436	0.8562	0.7335	1.0268
Aug.	0.5950	0.6238	1.7790	3.324	16.6142	7.2428	0.5974	0.7233	1.8539
Sep.	2.8268	4.5316	1.7605	3.7117	15.3529	6.2704	2.5778	3.1356	2.5124
Oct.	5.7511	9.3655	4.0596	6.2909	17.7675	3.2388	5.0224	8.1110	3.5981
Nov.	7.4144	15.5783	1.3437	8.3365	14.307	3.5627	3.4813	4.1449	4.2637
Dec.	8.9410	13.8122	6.3236	8.5227	17.7044	1.6761	3.3619	4.1292	4.0503
Whole years	6.2925	7.8950	6.1817	7.1543	18.9931	2.2970	3.1098	3.5468	3.4392
2000	2.6232	5.4440	9.9890	13.1334	18.0786	9.3350	1.5158	5.3323	8.4914
2001	1.9225	0.8437	4.4466	11.1738	10.6151	11.5392	4.2758	0.6934	9.1452
2002	2.7715	7.1853	12.8319	6.5399	11.5433	2.3920	3.4729	0.6154	7.4793
2003	2.9475	3.1334	3.5520	4.1444	19.4995	8.8780	3.6991	3.8407	4.0963
2004	10.9494	11.0613	11.8361	4.8169	14.6173	3.3529	4.3312	9.4238	0.6949
2005	20.4826	28.2700	15.3524	5.2124	21.4702	7.7240	2.7881	5.6021	1.2728
2006	9.2339	23.5581	0.7778	7.6074	18.3118	0.1670	2.6156	6.4660	0.0021
2007	15.3833	23.0265	9.5861	8.1109	20.1891	0.9032	3.2219	3.4778	4.1324
2008	4.7409	6.9225	4.1896	7.8987	34.468	8.8975	2.9728	3.0635	3.8527
2009	4.7127	7.7198	3.3140	8.8879	34.8767	7.3101	1.6572	0.5638	3.2256
2010	5.4900	8.3032	4.4223	11.3605	31.5424	4.4713	3.7472	6.3064	2.171
2011	4.9588	9.9393	1.7961	4.9807	10.6789	0.4032	2.8963	6.4765	0.3980
2012	4.2928	4.1758	5.5086	0.7488	0.4889	0.9849	3.3263	3.3510	4.3770
Mean	6.3948	9.3805	5.9091	7.1497	18.4790	4.5101	2.9566	3.9421	3.3417

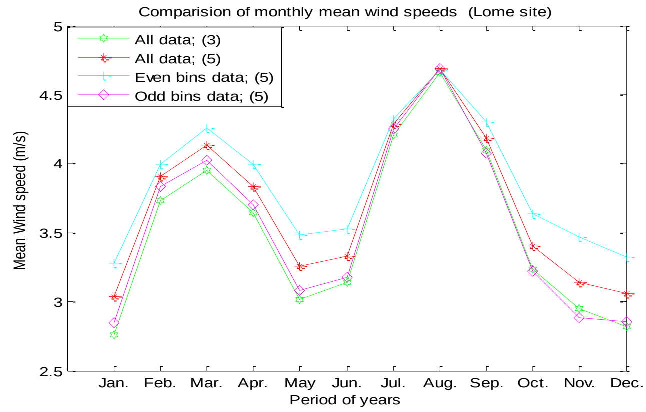

Fig. 14: Mean Wind Speed Obtained from the Measured Data (Eq. (3)) Versus Those Obtained from the Weibull Models (Eq. (5)), on A Monthly Basis for Lomé Site.

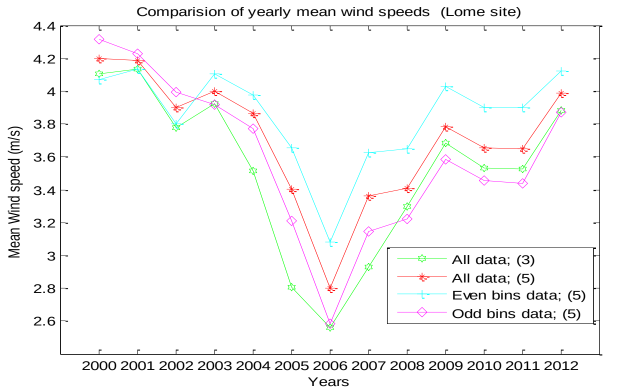

Fig. 15: Mean Wind Speed Obtained from the Measured Data (Eq. (3)) Versus Those Obtained from the Weibull Models (Eq. (5)), on A Yearly Basis for Lomé Site.

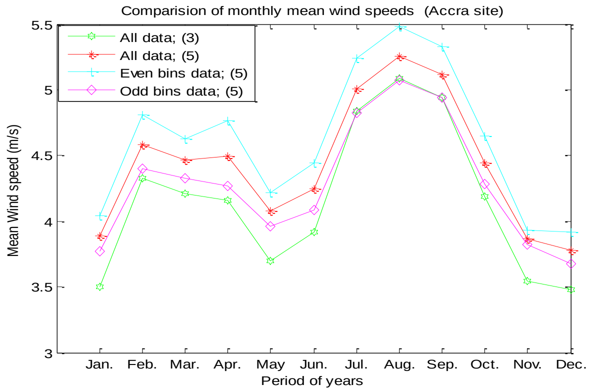

Fig. 16: Mean Wind Speed Obtained from the Measured Data (Eq. (3)) Versus Those Obtained from the Weibull Models (Eq. (5)), on A Monthly Basis for Accra Site.

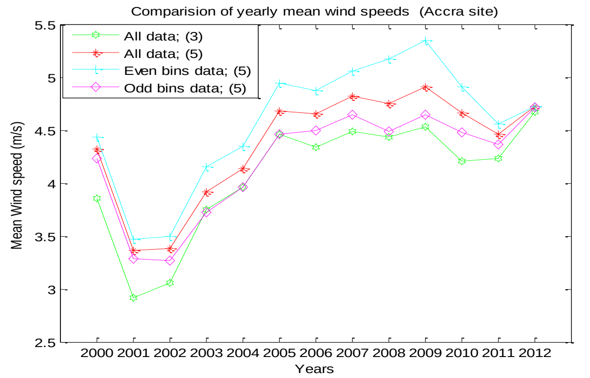

Fig. 17: Mean Wind Speed Obtained from the Measured Data (Eq. (3)) Versus Those Obtained from the Weibull Models (Eq. (5)), on A Yearly Basis for Accra Site.

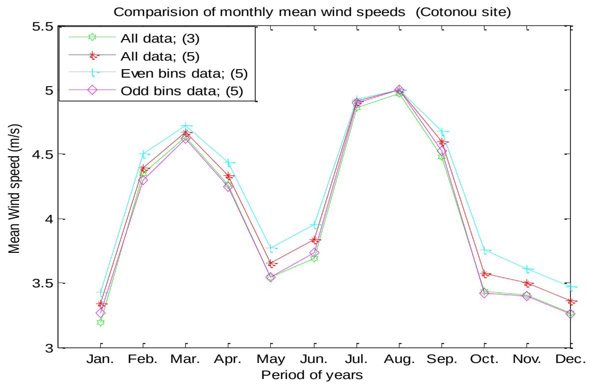

Fig. 18: Mean Wind Speed Obtained from the Measured Data (Eq. (3)) Versus Those Obtained from the Weibull Models (Eq. (5)), on A Monthly Basis for Cotonou Site.

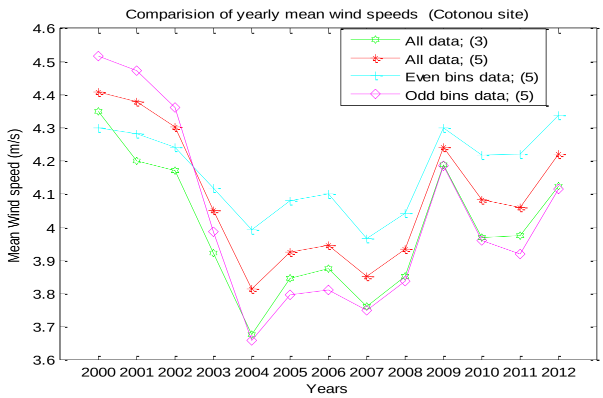

Fig. 19: Mean Wind Speed Obtained from the Measured Data (Eq. (3)) Versus Those Obtained from the Weibull Models (Eq. (5)), on A Yearly Basis for Cotonou Site.

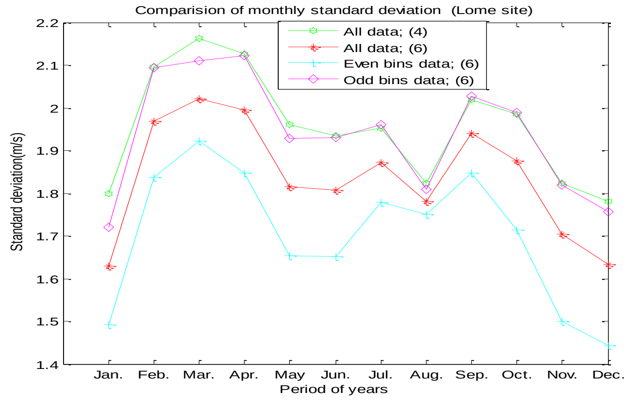

Fig. 20: Wind Speed Standard Deviation Obtained from the Measured Data (Eq. (4)) Versus Those Obtained from the Weibull Models (Eq. (6)), on A Monthly Basis for Lomé Site.

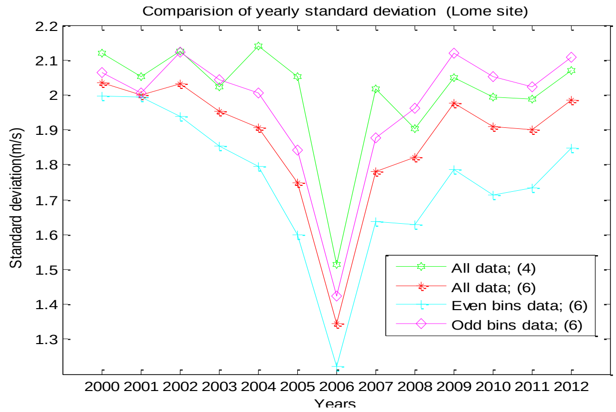

Fig. 21: Wind Speed Standard Deviation Obtained from the Measured Data (Eq. (4)) Versus Those Obtained from the Weibull Models (Eq. (6)), on A Yearly Basis for Lomé Site.

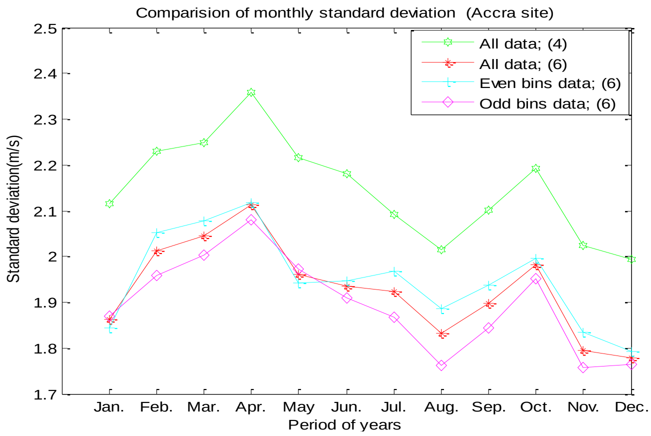

Fig. 22: Wind Speed Standard Deviation Obtained from the Measured Data (Eq. (4)) Versus Those Obtained from the Weibull Models (Eq. (6)), on A Monthly Basis for Accra Site.

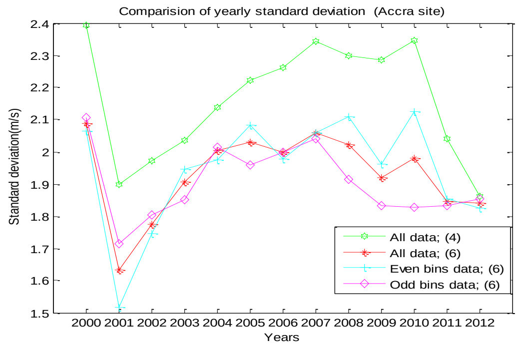

Fig. 23: Wind Speed Standard Deviation Obtained from the Measured Data (Eq. (4)) Versus Those Obtained from the Weibull Models (Eq. (6)), on A Yearly Basis for Accra Site.

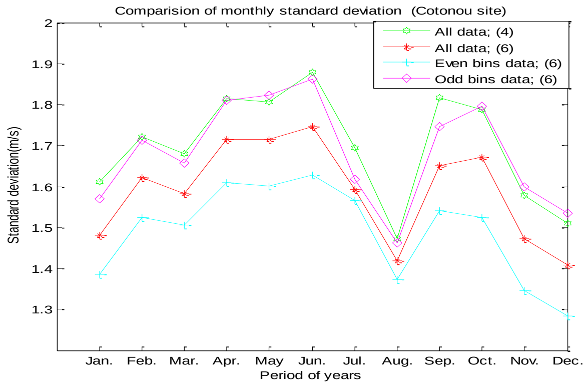

Fig. 24: Wind Speed Standard Deviation Obtained from the Measured Data (Eq. (4)) Versus Those Obtained from the Weibull Models (Eq. (6)), on A Monthly Basis for Cotonou Site.

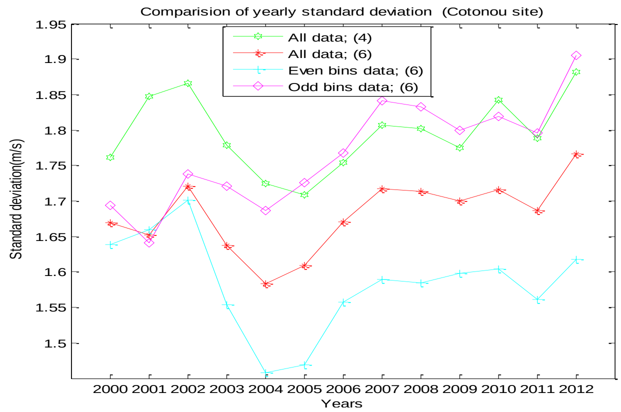

Fig. 25: Wind Speed Standard Deviation Obtained from the Measured Data (Eq. (4)) Versus Those Obtained from the Weibull Models (Eq. (6)), on A Yearly Basis for Cotonou Site.

Table 12: Error Values in Calculating the Mean Wind Speed Obtained from the Weibull Models in Reference to the Mean Wind Speed Obtained from the All Measured Data, on Monthly and Yearly Basis

	Absolute Relative Error (%)								
	Lomé			Accra			Cotonou		
Period	All data	Even bins data	Odd bins data	All data	Even bins data	Odd bins data	All data	Even bins data	Odd bins data
Jan.	10.1541	18.9617	3.1579	10.9013	15.4226	7.6866	4.6350	7.2960	2.3359
Feb.	4.7057	6.9841	2.7542	5.9144	11.223	1.6800	1.0997	3.4909	1.0943
Mar.	4.6891	7.8442	1.9471	6.1270	10.0311	2.8160	0.6996	1.8883	0.4136
Apr.	5.3806	9.7406	1.7463	8.1309	14.7604	2.7880	1.788	4.1652	0.3902
May	8.0721	15.5601	2.2532	10.2833	13.9549	7.1965	3.0278	6.474	0.0218
Jun.	6.1918	12.276	1.2736	8.2323	13.4132	4.2200	4.0948	7.1747	1.2594
Jul.	1.8347	2.7219	1.0494	3.3241	8.2280	0.3697	1.0622	1.3409	0.8039
Aug.	0.5472	0.4942	0.5980	3.2289	7.7573	0.3723	0.6273	0.6203	0.6316
Sep.	2.0403	4.9247	0.5964	3.6665	7.8372	0.1084	2.5260	4.4066	0.9174
Oct.	5.2134	12.5488	0.3973	6.1911	11.0417	2.2278	4.0224	9.2751	0.4690
Nov.	6.317	17.4415	2.3951	9.0487	10.8171	7.6843	2.9252	6.1232	0.1305
Dec.	8.4119	17.6836	1.2925	8.6792	12.6506	5.6866	2.8375	6.1925	0.3210
Whole years	5.1831	10.3525	0.9098	6.8933	11.5130	3.2356	2.4271	4.7849	0.3025
2000	2.4011	0.7582	5.2699	12.1045	15.0841	9.7075	1.3170	1.1541	3.8109
2001	1.2974	0.1093	2.3953	15.5269	19.0422	12.7213	4.1836	1.8953	6.4315
2002	3.2028	0.5312	5.6838	10.5194	14.2081	7.0139	3.1482	1.696	4.5515
2003	1.9973	4.5594	0.1056	4.5954	10.8499	0.6967	3.2662	4.9837	1.6419
2004	10.1028	13.2621	7.4340	4.3839	9.7594	0.1026	3.7629	8.5989	0.4248
2005	21.1399	30.2372	14.3565	4.9036	10.9627	0.1188	2.0538	6.0253	1.2862
2006	9.5069	20.3013	0.8870	7.2431	12.3453	3.6314	1.7909	5.8206	1.6875
2007	14.8566	23.7587	7.4629	7.4442	12.6912	3.5737	2.4140	5.4408	0.3465
2008	3.4575	10.6460	2.2810	7.1337	16.5683	1.2336	2.1283	4.9751	0.3522
2009	2.6918	9.4008	2.7891	8.3222	17.9624	2.4329	1.1983	2.5909	0.0890
2010	3.3927	10.3595	2.2113	10.8547	16.549	6.4258	2.8629	6.2531	0.1825
2011	3.3607	10.6214	2.5506	5.2318	7.5885	3.0177	2.1352	6.1544	1.4368
2012	2.7013	6.1264	0.2704	1.0810	1.2188	0.9575	2.3453	5.2037	0.1941
Mean	5.7250	10.7002	2.8488	7.3064	12.0569	3.7579	2.4761	4.7702	1.2126

Table 13: Error Values in Calculating the Wind Speed Standard Deviation Obtained from the Weibull Models in Reference to the Wind Speed Standard Deviation Obtained from the Measured Data, on Monthly and Yearly Basis

	Absolute Relative error (%)								
	Lomé			Accra			Cotonou		
Period	All data	Even bins data	Odd bins data	All data	Even bins data	Odd bins data	All data	Even bins data	Odd bins data
Jan.	9.3687	16.9923	4.3503	11.8948	12.7877	11.6136	8.1094	13.9753	2.6174
Feb.	6.1187	12.416	0.1808	9.7165	7.8954	12.1738	5.7481	11.4367	0.4825
Mar.	6.5256	11.0486	2.4146	9.1189	7.6407	10.9378	5.8060	10.3317	1.3782
Apr.	6.2058	13.1404	0.1621	10.4668	10.196	11.8603	5.5019	11.2416	0.2375

Period	Absolute Relative error (%) Lomé All data	Even bins data	Odd bins data	Accra All data	Even bins data	Odd bins data	Cotonou All data	Even bins data	Odd bins data
May	7.4246	15.6091	1.6012	11.5553	12.362	11.0389	5.0182	11.3841	0.8766
Jun.	6.5232	14.6362	0.1524	11.2665	10.6867	12.3870	7.0483	13.3815	0.9095
Jul.	4.1735	8.8892	0.3361	8.0728	5.9555	10.7627	6.0685	7.5788	4.5933
Aug.	2.2931	3.9059	0.7585	9.1058	6.4077	12.4834	3.6452	6.8102	0.7305
Sep.	3.9036	8.5342	0.3758	9.6347	7.7638	12.2499	9.1394	15.2016	3.8333
Oct.	5.5046	13.6208	0.1917	9.5692	8.9087	10.9325	6.5168	14.7855	0.4294
Nov.	6.5275	17.7074	0.1986	11.3262	9.3638	13.1285	6.7745	14.6967	1.3080
Dec.	8.2842	18.9535	1.3452	10.8363	10.1849	11.5953	6.7367	15.0342	1.5164
Whole years	6.1015	13.4339	0.0699	10.3399	8.8623	12.2075	6.1049	12.1058	0.4136
2000	3.9827	5.8071	2.6520	12.7705	13.7537	11.9972	5.2468	6.9690	3.8676
2001	2.5657	2.9270	2.3127	14.0065	20.1244	9.7070	10.5244	10.1503	11.1677
2002	4.4020	8.8411	0.1564	9.9724	11.3936	8.4443	7.7935	8.8135	6.8675
2003	3.3549	8.2683	1.0010	6.3917	4.4924	9.1583	7.9296	12.626	3.2152
2004	10.9613	16.1625	6.2764	6.2525	7.6433	5.7490	8.1981	15.4537	2.1817
2005	14.8814	22.132	10.3081	8.6717	6.3017	11.9118	5.8787	14.0161	0.9400
2006	11.2085	19.2378	6.0829	11.5574	12.4872	11.6653	4.7754	11.2272	0.7616
2007	11.7862	18.9241	6.9788	12.2068	12.2079	12.9844	4.9807	12.0703	1.8641
2008	4.2876	14.516	3.0620	11.9580	8.1889	16.7310	4.8767	12.0885	1.6974
2009	3.5407	12.8384	3.3588	15.9865	14.0859	19.8012	4.2130	9.9614	1.3724
2010	4.3057	14.1558	2.9081	15.5596	9.4309	22.1093	6.8440	12.954	1.2602
2011	4.3259	12.7849	1.7612	9.5362	9.1509	10.1638	5.6992	12.7171	0.3796
2012	4.1125	10.7639	1.9074	1.0678	1.8842	0.3393	6.1078	14.0245	1.2491
Mean	6.2565	12.9326	2.3424	10.3401	9.6215	11.6974	6.3571	11.9629	2.1596

7. Conclusion

In this study, a new ML-based approach is proposed to estimate the Weibull's distribution parameters with time efficient assessment. These parameters are namely the mean wind power density, mean wind speed and wind speed standard deviation. This new approach consists in applying the classic MLM to either even or odd class wind speed data subset with the objective of reducing the prediction error and gain in the computational time. This new approach is either referred to as Maximum Likelihood with Odd Bins time series Method (MLOBM) or Maximum Likelihood with Even Bins time series Method (MLEBM). MLOBM and MLEBM are compared with the Maximum Likelihood Method (MLM) considering power density, standard deviation and mean wind speed estimation capability for different geographical locations. It is worth to indicate that superiority of MLOBM or MLEBM over MLM can be obviously seen with estimation capability of power density, mean wind speed and wind speed standard deviation. Then it is concluded that MLOBM or MLEBM is very suitable and efficient in order to estimate Weibull parameters for wind energy applications with time efficiency.

Acknowledgments

The authors want to thank the University of Lomé for providing enabling environment during the research.

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