Contents list available at IJRED website
Int. Journal of Renewable Energy Development (IJRED)
Journal homepage: http://ejournal.undip.ac.id/index.php/ijred

Research Article

Estimating Weibull Parameters for Wind Energy Applications Using Seven Numerical Methods: Case studies of Three Coastal Sites in West Africa

Agbassou Guenoukpati [a], Adekunlé Akim Salami[a*], Mawugno Koffi Kodjo[a], Kossi Napo[b]

[a]*Laboratoire de Recherche en Sciences de l'Ingénieur (LARSI), Department of Electrical Engineering, Ecole Nationale Supérieure d'Ingénieurs (ENSI), University of Lomé, BP 1515, Lomé, Togo*

[b]*Laboratoire* sur l'*Energie Solaire* (LES), Faculté Des Sciences (FDS)), University of Lomé, BP 1515, Lomé, Togo

ABSTRACT. In this study, the effectiveness of seven numerical methods is evaluated to determine the shape (K) and scale (C) parameters of Weibull distribution function for the purpose of calculating the wind speed characteristics and wind power density. The selected methods are graphical method (GPM), empirical method of Justus (EMJ), empirical method of Lysen (EML), energy pattern factor method (EPFM), maximum likelihood method (MLM) moment method (MOM) and the proposed. Hybrid method (HM) derived from EPFM and EMJ. The purpose is to identify the most appropriate method for computing the mean wind speed, wind speed standard deviation and wind power density for different costal locations in West Africa. Three costal sites (Lomé, Accra and Cotonou) are selected. The input data was collected, from January 2004 to December 2015 for Lomé site, from January 2009 to December 2015 for Accra site and from January 2009 to December 2012 for Cotonou. The results indicate that the precision of the computed mean wind speed, wind speed standard deviation and wind power density values change when different parameters estimation methods are used. Five of them which are EMJ, EML, EPF, MOM, ML, and HM method present very good accuracy while GPM shows weak ability for all three sites.

Keywords: Modeling, Histogram of wind speed distribution, Weibull parameters estimation methods, Comparative evaluation.

Article History: Received: 21st April 2019; Received: 1st January 2020; Accepted: 19th February 2020; Available online: 4th May 2020
How to Cite This Article: Guenoukpati, A., Salami, A.A., Kodjo, M.K., and Napo, K. (2020) Estimating Weibull Parameters for Wind Energy Applications Using Seven Numerical Methods: Case studies of Three Coastal Sites in West Africa. *International Journal of Renewable Energy Development*, 9(2), 217-226
https://doi.org/10.14710/ijred.9.2.217-226

1. Introduction

Nowadays, West Africa faces the challenge of generating more electricity to meet existing and future demand in a sustainable way (Brew-Hammond and Kemausuor 2009; Deichmann et al. 2011). Wind is an inexhaustible resource whose energy utilization has been increasing around the world at an accelerating pace while the development of new wind projects continues to be hampered by the lack of reliable and accurate wind resource data in many parts of the world, especially in the developing countries (Ayenagbo, Kimatu, and Rongcheng 2011; Mentis et al. 2015).

Commonly used functions for fitting the measured wind speed probability distribution in a given location over a certain period of time, typically monthly or yearly, are the Weibull, the Rayleigh and Lognormal. Amongst the most common distribution models, the Weibull function is accepted as the best model. 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 determine wind characteristics. Thus, the various estimation methods for Weibull parameters have been proposed. Justus et al. (Justus et al. 1978) presented the four different estimation methods and the GPM (graphical method) based on the concept of least squares method and also compared them. Stevens and Smulders (Stevens, M. J. M., & Smulders 1979) suggested the MLM (maximum likelihood method) for the estimation of the parameters of Weibull wind speed distribution. Seguro and Lambert (Seguro and Lambert 2000) compared the commonly-used (MLM), (GPM) and the proposed MMLM (modified maximum likelihood method). As a result, they concluded that MLM performs better than GPM. Dorvlo (Dorvlo 2002) estimated the Weibull parameters used to model wind speeds in Oman using three methods, the Chi-square method, moment method (MOM) and GPM. The results showed that the Chi-square method gives better estimates for Weibull parameters than the other methods. Rocha et al. (Rocha et al. 2012) studied seven methods GPM, MLM, MMLM, MOM, EPFM, EM and

* Corresponding author: akimsalami11@gmail.com

EEM (equivalent energy method). They aimed to analyze and compare these seven numerical methods for assessing effectiveness in determining parameters of Weibull, using wind data collected in the northeast region of Brazil. Jowder (Jowder 2009) compared the EM (empirical method) and GPM for prediction of the average wind speed and power density, using wind data measured in the Kingdom of Bahrain. The results indicated that EM provides more accurate prediction than GPM. Akdag and Dinler (Akdağ, S. A., & Dinler 2009) used three conventional methods, namely GPM, MLM and MOM to compare the proposed EPFM (energy pattern factor method) for estimating Weibull parameters. Their results show that the EPFM has better suitability than others according to power density and mean wind speed. Furthermore, Chang conducted a comparative study to show the performance of GPM, MLM, MMLM, MOM, EPFM and EM, in estimating Weibull parameters for wind energy application (Chang 2011). Along the same lines, Azad et al. (Azad, A., Rasul, M., & Yusaf 2014) used the seven methods applied by Rocha et al. (Rocha et al. 2012) 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. In addition, Arslan et al (Arslan, Bulut, and Yavuz 2014) compared MOM, MLM 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.

Assessing the existing numerical methods to determine the most appropriate one for estimating of Weibull parameters is truly important in different applications of wind energy. Nevertheless, to the best of our knowledge, there is a lack of study in the literature on determining the most accurate Weibull parameter estimation methods to fit wind speed probability distribution histograms. Consequently, in this study, we evaluate the capability of six methods in estimating the K and C parameters of Weibull distribution function.

The chief goal of this work is to identify the most appropriate method for fitting wind speed probability distribution histograms for wind energy applications at different locations of West Africa. To achieve this, a comprehensive statistical analysis based upon several statistical parameters and approaches applied for three costal sites in West Africa: Lomé (Togo), Accra (Ghana) and Cotonou (Benin) is conducted among six well known methods namely GPM, EMJ, EML, EPFM, MLM MOM and the proposed Hybrid method (HM) derived from EPFM and EMJ.

The rest of this paper is structured as follows: the wind speed data of each site is presented in Section 2. Section 3 describes methods for calculation of Weibull parameters. In Section 4, statistical indicators for performance evaluation are illustrated. In Section 5, results and discussion are presented. Finally, conclusion is drawn in Section 6.

2. The data

The data is saved every day at one hour interval (this is the average over the 10 minutes before the hour) at a height of 10 m above the ground. Note that the measuring point of these weather data for each station is in an airport area which theirs coordinates are presented in Table 1. Data collected cover the period, from January 2004 to December 2015 for Lomé site (record length of approximately twelve (12) years), from January 2009 to December 2015 for Accra site (record length of approximately seven (7) years) and from January 2009 to December 2012 for Cotonou site (record length of approximately four (4) years).

Table 1
Coordinates of the case study site

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

Table 2 presents statistical parameters and the mean power density for the three (03) studied sites, (Lomé site, Accra site, and Cotonou site). As noticed, Accra site has the highest mean wind speed with the value of 4.1603 m/s and Lomé site has the lowest wind speed with the value of 3.5287 m/s. According to values of mean power density (< 100 W/m^2) obtained in Table 2 we concluded that the three sites are not suitable for large-scale electric wind application (Celik 2003; Keyhani et al. 2010). But, small-scale wind turbines could be good option for the three sites (Lomé, Accra and Cotonou sites) in order to supply power for lightings, electric fans, chargers and air conditioning units for small houses (Mostafaeipour et al. 2011).
Figures 1 to 3 offer respectively the probability and cumulative probability densities of the utilized wind speed data for selected sites. The descriptive statistics presented in Table 2 as well as the probability and cumulative probability distribution of the wind speed provided by that figures give a good insight on the characteristics of wind speed in the selected site.

3. Methods for calculation of Weibull parameters

The wind speed measurement data obtained 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(Genc et al. 2005; Lu, Yang, and Burnett 2002; Salami et al. 2013). 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 (Ajavon et al. 2015; Safari 2011).

Table 2
Descriptive statistics of the used wind speed data according to geographical locations

Sites	Periods	Maximum wind speed (m/s)	Mean wind speed (m/s)	Standard deviation (m/s)	Power density (W/m^2)	Kurtosis	Skewness
Lomé	2004-2015	16	3.52870	2.02964	54.96667	2.33358	0.26247
Accra	2009-2015	21	4.16032	2.21591	82.22761	2.76699	0.08801
Cotonou	2009-2012	14	4.01159	1.81438	63.35978	2.49218	-0.12249

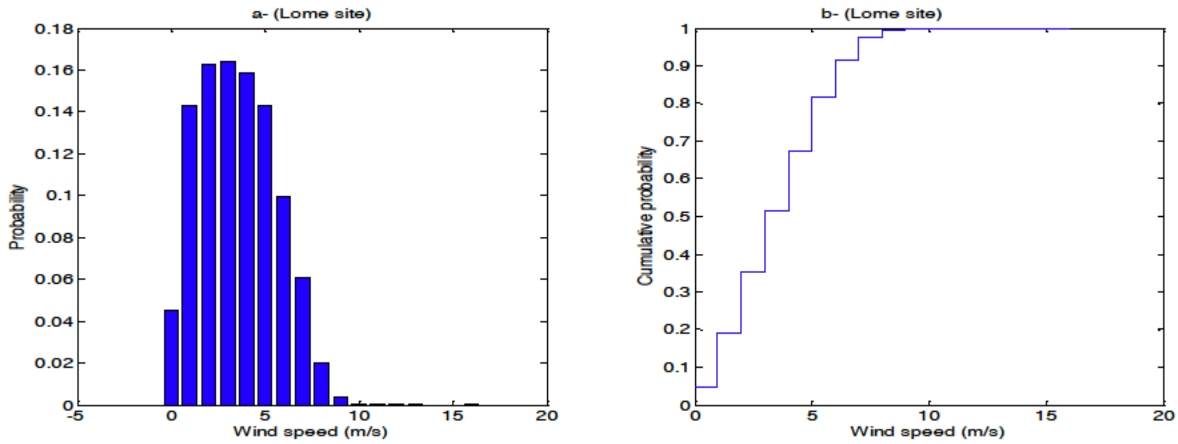

Fig. 1 Probability (a) and cumulative probability (b) densities of the measured wind speed at 10 m for Lome site

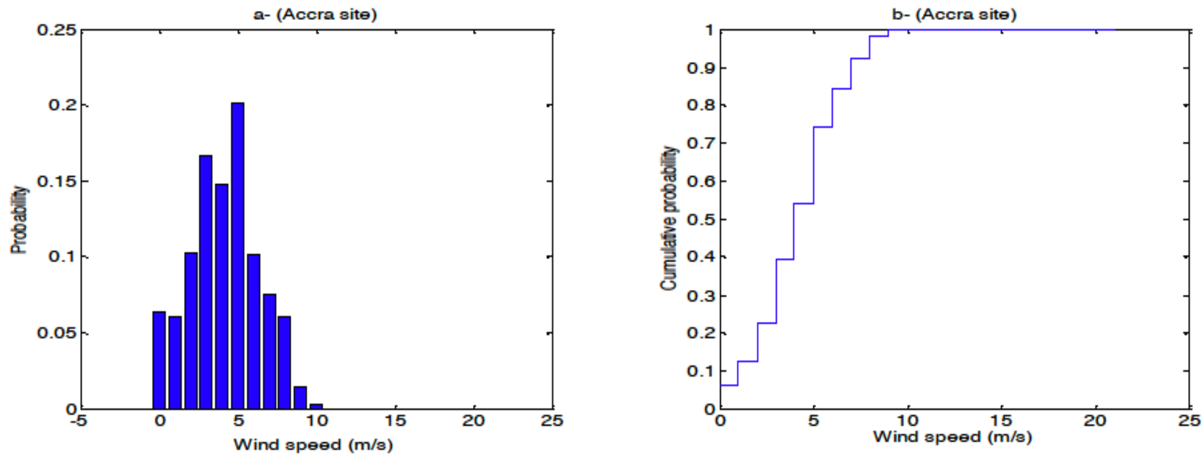

Fig. 2 Probability (a) and cumulative probability (b) densities of the measured wind speed at 10 m for Accra site

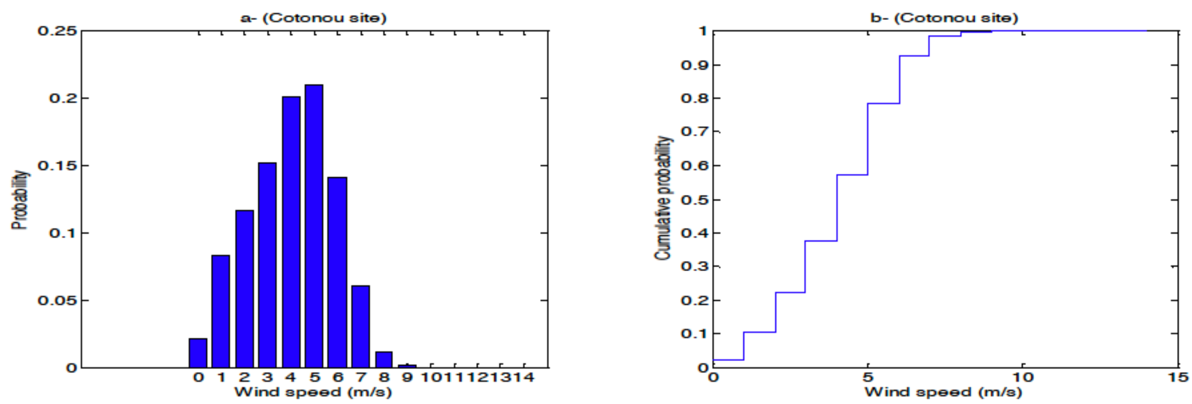

Fig. 3 Probability (a) and cumulative probability (b) densities of the measured wind speed at 10 m for Cotonou site

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

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

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

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

$$\overline{V}=\frac{1}{n}\sum_{i=1}^{n}V_i=C\cdot\Gamma(1+\frac{1}{K}) \tag{3}$$

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

where:

- $\overline{V}$ is the mean wind speed,
- σ is the standard deviation of the observed data of the wind speed,
- Γ is the gamma function defined by the Euler integral of the second kind.

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 represents the amount of energy available on the site which can be converted to electricity by using wind turbines. Indeed, the mean kinetic energy, available on a site per unit time and per unit area is expressed by Equation (5) (Celik 2003):

$$P=\frac{1}{2}\rho\int_{0}^{+\infty}V^3 f(V)dv=\frac{1}{2}\rho\overline{V^3}=\frac{1}{2}\rho C^3\Gamma\left(1+\frac{3}{K}\right) \tag{5}$$

where:

- ρ is the air density (kg.m^{-3}),
- V is the wind speed and,
- $f(V)$ is the probability distribution function (pdf) of Weibull (Equation (1)),
- $\overline{V^3}$ is the cubic mean wind speeds.

There are some methods introduced in the literature to calculate the K and C parameters of Weibull distribution function. In this study, we introduced a Hybrid method (HM) derived from EPFM and EMJ. Seven methods including graphical method (GPM), empirical method of Justus (EMJ), empirical method of Lysen (EML), energy pattern factor method (EPFM), maximum likelihood method (MLM), moment method (MOM) and Hybrid method (HM) are selected for comparative evaluation. The descriptions of these seven methods are provided briefly in the following.

3.1. Graphical method (GPM)

The graphical method is achieved through the cumulative distribution function. In this distribution method, the wind speed data are interpolated by a straight line, using the concept of least squares. The Equation for this method can be represented by a double logarithmic transformation (Celik 2003; Dorvlo 2002) as follows:

$$\ln\{-\ln[1-F(V)]\}=K\ln(V)-K\ln(C) \tag{6}$$

3.2. Empirical method of Justus (EMJ)

Based on the empirical method introduced by Justus (Justus et al. 1978), the K and C parameters are computed, respectively by Equations (7) and (8) as:

$$K=\left(\frac{\sigma}{\overline{V}}\right)^{-1.086} \tag{7}$$

$$C=\frac{\overline{V}}{\Gamma(1+\frac{1}{K})} \tag{8}$$

3.3. Empirical method of Lysen (EML)

In the empirical method suggested by Lysen, K is calculated by Equation (7) as in the Justus method. In fact, the only difference is the Equation of C. In the empirical method of Lysen, C is obtained by Equation (9):

$$C=\overline{V}\cdot\left(0.568+\frac{0.433}{K}\right)^{-\frac{1}{K}} \tag{9}$$

3.4. Energy pattern factor method (EPFM)

The energy pattern factor method is related to the averaged data of wind speed and is defined by the following Equations (Seguro and Lambert 2000):

$$E_{pf}=\left(\frac{\overline{V^3}}{\overline{V}^3}\right) \tag{10}$$

$$K=\left(1+\frac{3.69}{E_{pf}{}^2}\right) \tag{11}$$

C parameter is also computed similar to empirical method of Justus by Equation (8).

3.5. Maximum likelihood method (MLM)

The maximum likelihood estimation method is difficult to solve, since numerical iterations are needed to determine the parameters of the Weibull distribution (Chang 2011; Salami et al. 2013). In this method, the parameters K and C are determined according to the Equations below (Dorvlo 2002):

$$K = \left[\left[\frac{\sum_{i=1}^{n} V_i^K \ln(V_i)}{\sum_{i=1}^{n} V_i^K}\right] - \left[\frac{\sum_{i=1}^{n} \ln(V_i)}{n}\right]\right]^{-1} \quad (12)$$

$$C = \left[\frac{\sum_{i=1}^{n} V_i^K}{n}\right]^{1/K} \quad (13)$$

3.6. Moment method (MOM)

The moment method can be used as an alternative to the maximum likelihood method (Rocha et al. 2012) and, in this case, the parameters K and C are determined by the following Equations:

$$\overline{V} = C\cdot\Gamma(1+\frac{1}{K}) \quad (14)$$

$$\sigma = C\cdot\left[\Gamma(1+\frac{2}{K}) - \Gamma^2(1+\frac{1}{K})\right]^{1/2} \quad (15)$$

3.7. Proposed method (Hybrid EPFM-EMJ)

A hybrid method (HM) derived from EPFM and EMJ permit to find a formula to determine the shape parameter as follows:

$$K = \frac{1}{2}\left(1 + \frac{3.69}{{E_{pf}}^2} + \left(\frac{\sigma}{\overline{V}}\right)^{-1.086}\right) \quad (16)$$

and C parameter is computed similar to empirical method of Justus by Equation (8).

4. Performance Indicators

To evaluate the performance of each method, the root mean squared error (RMSE), the correlation coefficient R^2 the relative percent error (RPE) and Relative root mean square error (RRMSE) are used.

The RMSE parameter, whose ideal value is zero (0), gives the difference between the predicted or expected value $x_i$and observed value y_i for N data samples (Akdağ, S. A., & Dinler 2009; Rocha et al. 2012). It is given by Equation (17)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - x_i\right)^2} \quad (17)$$

The correlation coefficient whose ideal value is one (1) gives the correlation between the predicted or expected and observed values (Leung and Yang 2012; Stevens, M. J. M., & Smulders 1979). It is given by the relation (18).

$$R^2 = \frac{\sum_{i=1}^{N}\left(x_i - \overline{x_i}\right)\cdot\left(y_i - \overline{y_i}\right)}{\sqrt{\sum_{i=1}^{N}\left(x_i - \overline{x_i}\right)^2 \cdot \sum_{i=1}^{N}\left(y_i - \overline{y_i}\right)^2}} \quad (18)$$

The relative percent error (RPE) between the predicted value and the observed value is given by Equation (19), it is considered acceptable if its absolute value is less or equal to 10% (Chang 2011; Dorvlo 2002; Seguro and Lambert 2000).

$$RPE\ (\%) = 100\cdot\left(\frac{y_i - x_i}{y_i}\right) \quad (19)$$

The RRMSE is obtained by dividing the RMSE of wind speed characteristics (Means, standard deviations and power densities of wind speed) obtained by the average measured values as follows:

$$RRMSE\ (\%) = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - x_i\right)^2}}{\frac{1}{n}\sum_{i=1}^{n} y_i}\cdot 100 \quad (20)$$

Different ranges of RRMSE can be defined to represent the models' precision (Jamieson, Porter, and Wilson 1991; Li et al. 2013; Mohammadi et al. 2016) as:

- Excellent for RRMSE < 10%;
- Good for 10% < RRMSE < 20%;
- Fair for 20% < RRMSE < 30%; Poor for RRMSE > 30%.

5. Results and discussion

Given the importance of the analysis of monthly and global variations of wind characteristics on a given site, our case study covers a global dataset for each site and each month (the entire dataset is grouped monthly into 12 study periods: January, February, March, April, May, June, July, August, September, October, November, December).

5.1 Global Analysis

Our goal in this article is to identify the most appropriate method for fitting wind speed probability distribution histograms for wind energy applications on three costal sites in West Africa: Lomé (Togo), Accra (Ghana) and Cotonou (Benin). From Figures 4, 5 and 6 it is possible to verify how the curves representing the Weibull probability density function, for each of the six numerical methods considered in the analysis, match the histograms, giving an idea of which method yields the best fit to the data of wind speed collected.

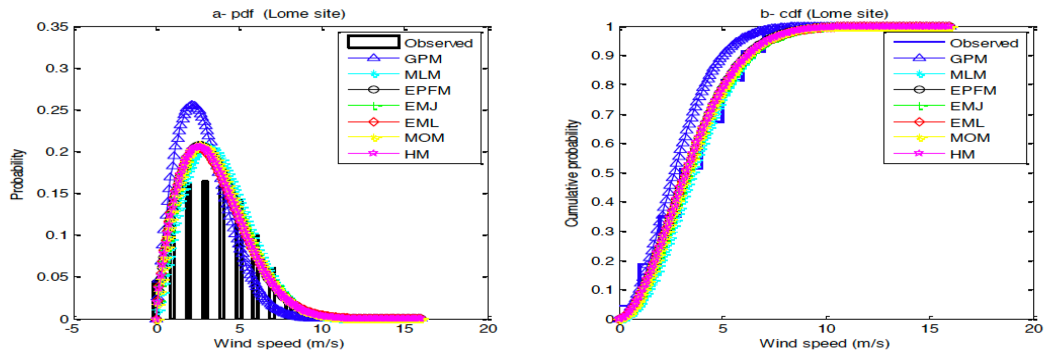

Fig. 4 Weibull distribution (a) and cumulative distribution (b) functions - Lomé (years 2004-2015)

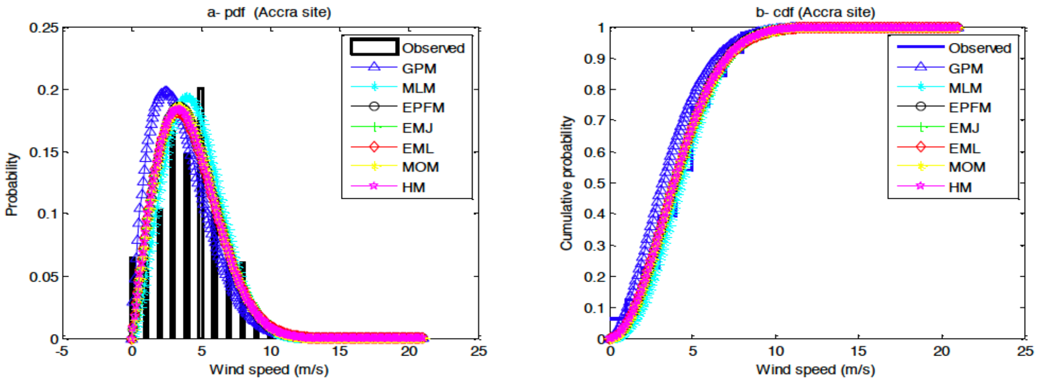

Fig. 5 Weibull distribution (a) and cumulative distribution (b) functions - Accra (years 2009-2012)

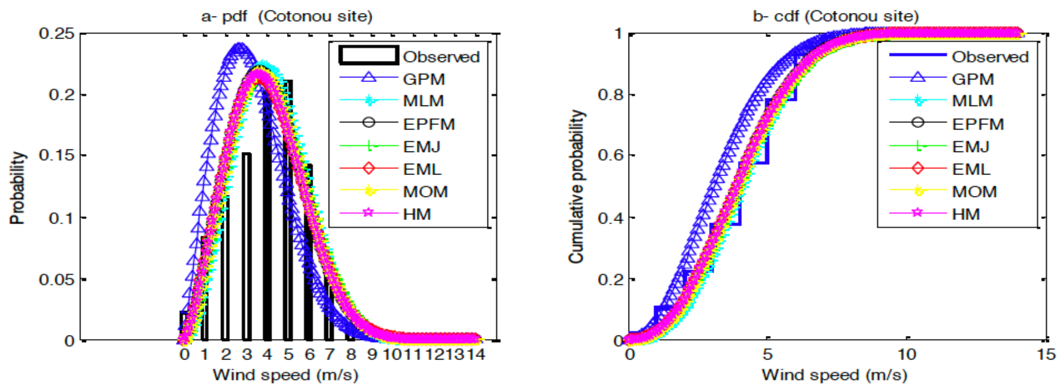

Fig. 6 Weibull distribution (a) and cumulative distribution (b) functions - Cotonou (years 2009-2015)

Graphically, it is observed that six methods (MLM, EPF, EMJ, EML MOM and HM), expected GPM present a better curve fit with the histogram of the wind speed on the three sites. To choose adequate method that adjusts better the histogram of the wind speed on each site, we calculated the RMSE and R^2. The results in Table 3 show that:

- on Lomé site, only two methods (EMJ and EML) have RMSE below 0.0200 and R^2 which are above 0.9660. EMJ and EML are followed by HM with RMSE of 0.0203 and R^2 of 0.9658;
- on Accra site, only MLM and EPFM have RMSE below 0.0210 and R^2 which are above 0.9500. MLM and EPFM are followed by HM with RMSE of 0.0241 and R^2 of 0.9299;
- on Cotonou site, only MLM has RMSE below 0.0210 and R^2 which are above 0.9600. . MLM is followed by HM with RMSE of 0.0224 and R^2 of 0.9588.

The predicted values for K and C permitted the computation of the mean wind speed, standard deviation and its mean power density for each method, and the results are presented in Tables 4, 5 and 6.

Table 3
Comparison of methods for different sites

Methods	Lomé				Accra				Cotonou			
	K	C	RMSE	R^2	K	C	RMSE	R^2	K	C	RMSE	R^2
GPM	1.8961	3.2471	0.0407	0.9061	1.7332	3.9821	0.0388	0.8305	2.0705	3.7028	0.0487	0.8219
MLM	2.0310	4.1788	0.0213	0.9621	2.3825	5.0172	0.0207	0.9527	2.5722	4.6173	0.0206	0.9670
EPFM	1.8846	3.9755	0.0207	0.9652	2.0616	4.6965	0.0238	0.9329	2.4372	4.5239	0.0224	0.9588
EMJ	1.8233	3.9704	0.0199	0.9662	1.9820	4.6936	0.0245	0.9265	2.3671	4.5264	0.0225	0.9570
EML	1.8233	3.9732	0.0198	0.9663	1.9820	4.6963	0.0245	0.9266	2.3671	4.5276	0.0225	0.9571
MOM	1.8866	3.9756	0.0208	0.9651	2.0636	4.6965	0.0238	0.9330	2.4392	4.5239	0.0224	0.9588
HM	1.8539	3.9731	0.0203	0.9658	2.0218	4.6953	0.0241	0.9299	2.4022	4.5252	0.0224	0.9588

Table 4
Comparison of methods according to mean speed, standard deviation and power density for Lomé site

Methods	Mean speed		Standard deviation		Mean power density	
	Predicted (m/s)	RPE (%)	Predicted (m/s)	RPE (%)	Predicted (W/m^2)	RPE (%)
GPM	2.8816	-18.3389	1.5804	-22.1324	29.5832	-46.1798
MLM	3.7025	4.9246	1.9088	-5.9556	58.4754	6.3835
EPFM	3.5287	0.0000	1.9461	-4.1173	54.6857	-0.5111
EMJ	3.5287	0.0000	2.0051	-1.2091	56.7331	3.2137
EML	3.5312	0.0708	2.0065	-1.1392	56.8536	3.4329
MOM	3.5286	-0.0018	1.9442	-4.2108	54.6198	-0.6310
HM	3.5287	0.0000	1.9751	-2.6869	55.6799	1.2975

Table 5
Comparison of methods according to mean speed, standard deviation and power density for Accra site

Methods	Mean speed		Standard deviation		Mean power density	
	Predicted (m/s)	RPE (%)	Predicted (m/s)	RPE (%)	Predicted (W/m^2)	RPE (%)
GPM	3.5485	-14.7054	2.1111	-4.7292	61.2424	-25.5209
MLM	4.4471	6.8933	1.9868	-10.3399	88.1104	7.1543
EPFM	4.1603	0.0000	2.1162	-4.5016	81.7690	-0.5577
EMJ	4.1603	0.0000	2.1925	-1.0576	85.0041	3.3766
EML	4.1628	0.0587	2.1938	-0.9996	85.1538	3.5587
MOM	4.1603	-0.0005	2.1143	-4.5853	81.6918	-0.6516
HM	4.1603	0.0000	2.1536	-2.8125	83.3325	1.3439

For the mean wind speed, only the graphical method presented a remarkable error. All the other methods have shown a good accuracy. Finally, we note that the Weibull parameters estimated by HM, EMJ and EPFM are adequate for predicting the average value with relative percent error (RPE) lower than 0.0301% in the three study sites.

The standard deviation analysis permits similar conclusion, in spite of MLM, which predicted the standard deviation with relative percent error (RPE) greater than 10% in Accra and Cotonou sites. Thus the EMJ, EML and HM methods are most appropriate to predict the standard deviation of wind speeds at the three sites.

For the mean power density, only the graphical method presented a remarkable error. All the other methods have shown a good accuracy. But the power densities calculated from Weibull parameters estimated by EPFM, MOM and HM best predicts the power densities with relative percent error (RPE) lower than 1.3% in the three study sites.

5.2 Monthly Analysis

In this part, the obtained results on the monthly basis evaluation are presented. Figures 7 through 12 illustrate the average of monthly values of C and K for Lomé, Accra and Cotonou sites, respectively. It is seen that for all sites the values of C parameter from all methods are very close to each other and only some major differences are noticed for GPM. Nevertheless, the values of K parameter for GPM, EMJ, EML, EPFM, MOM and HM methods are in the same range for all months while for the MLM methods the K takes higher values compared to other methods. These differences in K and C values for the methods lead to larger differences in the calculated values of wind speed average, standard deviation and wind power density.

Table 6
Comparison of methods according to mean speed, standard deviation and power density for Cotonou site

Methods	Mean speed		Standard deviation		Mean power density	
	Predicted (m/s)	RPE (%)	Predicted (m/s)	RPE (%)	Predicted (W/m^2)	RPE (%)
GPM	3.0520	-23.9213	1.5279	-15.7874	31.7458	-49.8960
MLM	4.2210	5.2199	1.5852	-12.6319	66.0511	4.2477
EPFM	4.0237	0.3018	1.7375	-4.2396	63.4089	0.0776
EMJ	4.0237	0.3018	1.7825	-1.7547	64.7902	2.2576
EML	4.0247	0.3269	1.7830	-1.7301	64.8388	2.3344
MOM	4.0237	0.3027	1.7362	-4.3080	63.3730	0.0208
HM	4.0116	0.0000	0.1791	1.9469	64.2653	1.4293

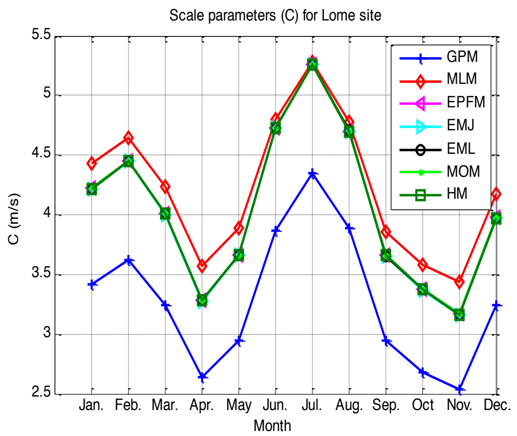

Fig. 7 Average of monthly values of C (m/s) for Lomé

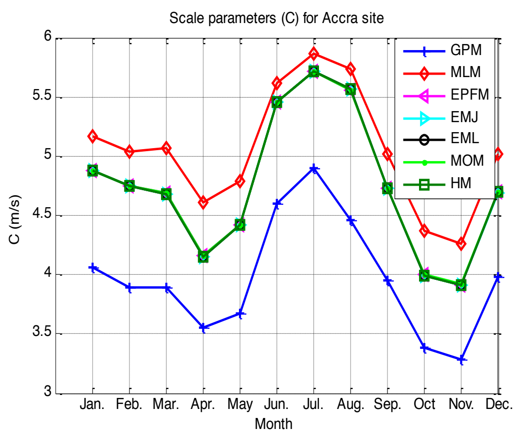

Fig. 8 Average of monthly values of C (m/s) for Accra

In order to provide a month by month comparison and assessment between measured and estimated values of wind speed average, standard deviation and wind power, a statistical frequency analysis was performed using the RPE indicator. The results of Tables 4, 5 and 6 show that only EPFM, EMJ, EML, MOM and HM methods are recommended to estimate Weibull parameters to predict the monthly average wind speeds, the monthly standard deviations of wind speeds and monthly power densities with RPE lower than 10% on Lomé site.

Therefore EPFM, EMJ, EML, MOM and HM methods are recommended to estimate Weibull parameters to predict the monthly average wind speeds, the monthly standard deviations of wind speeds and monthly power densities with RPE lower than 10% on Accra site.

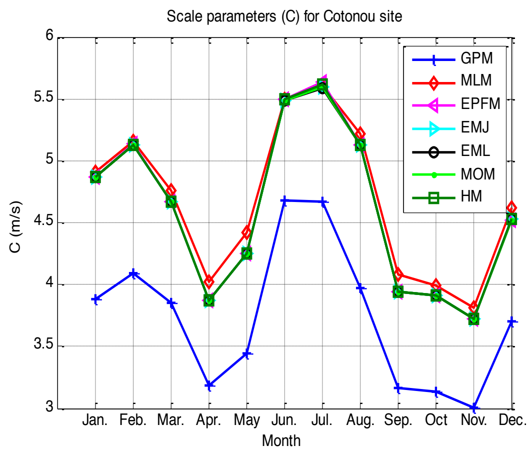

Fig. 9 Average of monthly values of C (m/s) for Cotonou

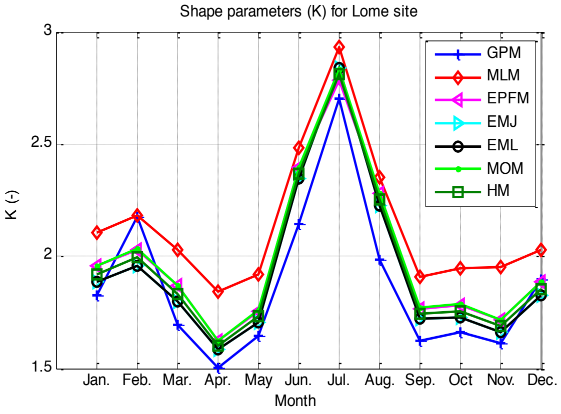

Fig. 10 Average of monthly values of K (–) for Lomé

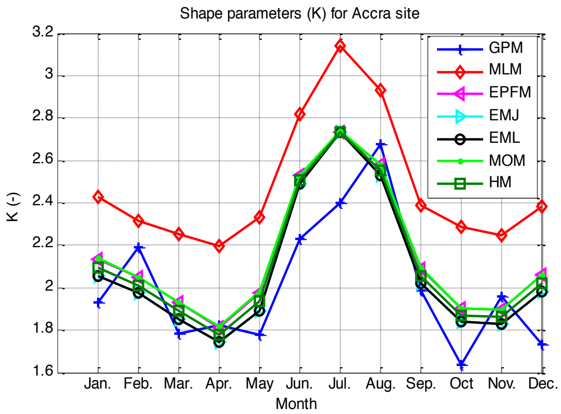

Fig. 11 Average of monthly values of K (–) for Accra

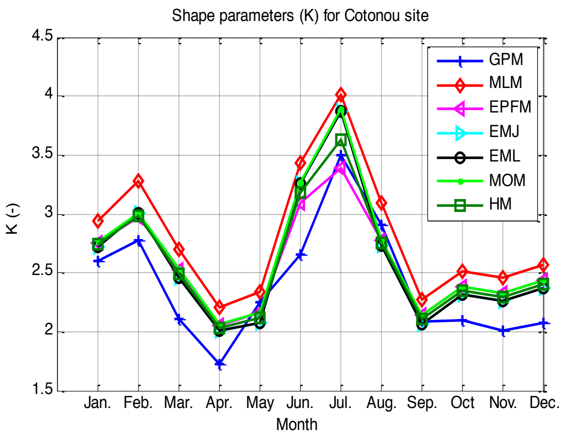

Fig. 12 Average of monthly values of K (–) for Cotonou

According to above results, we notice that only EPFM, EMJ, EML, MOM, MLM and HM methods are recommended to estimate Weibull parameters to calculate average wind speeds, with RPE lower than 10% on Cotonou site for all the twelve months. Additionally to calculate the monthly standard deviations and wind power densities on the site of Cotonou, it is preferable to use the Weibull parameters estimated by EPFM, EMJ, EML and MOM.

Among the calculated parameters (mean of wind speed, standard deviation of wind speed and wind power density), wind power density plays a critical role in wind energy applications.The wind power density portrays 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 for evaluating the performance of wind turbines and choosing the optimal wind turbines. Wind power density indicates the level of energy available that can be converted into electricity by using wind turbines. That is why the result of our analysis focuses on calculations of monthly power densities on the three sites using the six methods.

6. Conclusion

The purpose of this article is to determine a suitable method for estimating Weibull parameters for wind energy applications on three costal sites in West Africa. For this, six methods often used in the literature are applied to wind speed data collected at each site. These are: the graphical method (GPM), maximum likelihood method (MLM) moment method (MOM), energy pattern factor method (EPFM), empirical method of Justus (EMJ) and empirical method of Lysen (EML). Moreover, a hybrid method derived from EPFM and EMJ is proposed to also determine Weibull distribution function parameters. The results reveal that only GPM does not yield acceptable adjustment errors on the three sites and often the MLM has the lowest error adjustment of the distribution histogram of wind speeds at the three sites.

The Weibull parameters estimated by the methods EMJ, EML, EPFM, MOM and HM are recommended for predicting wind speed average, standard deviation and mean wind power density on Lomé, Accra and Cotonou sites located in West Africa. Thus for wind energy applications for costal sites in West Africa, we recommend using:

- MLM method to estimate Weibull parameters that best fit the histogram of wind frequency distributions;
- HM, EMJ, EML, EPFM, MLM, or MOM method to estimate Weibull parameters for better prediction of mean wind speeds, the standard deviation and mean wind power density.

Acknowledgments

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

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