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Research Article

Influence of the Random Data Sampling in Estimation of Wind Speed Resource: Case Study

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Abstract. In this study, statistical analysis is performed in order to characterize wind speeds distribution according to different samples randomly drawn from wind speed data collected. The purpose of this study is to assess how random sampling influences the estimation quality of the shape (k) and scale (c) parameters of a Weibull distribution function. Five stations were chosen in West Africa for the study, namely: Accra Kotoka, Cotonou Cadjehoun, Kano Mallam Aminu, Lomé Tokoin and Ouagadougou airport. We used the energy factor method (EPF) to compute shape and scale parameters. Statistical indicators used to assess estimation accuracy are the root mean square error (RMSE) and relative percentage error (RPE). Study results show that good accuracy in Weibull parameters and power density estimation is obtained with sampled wind speed data of 30% for Accra, 20% for Cotonou, 80% for Kano, 20% for Lomé, and 20% for Ouagadougou site. This study showed that for wind potential assessing at a site, wind speed data random sampling is sufficient to calculate wind power density. This is very useful in wind energy exploitation development.

Keywords: Weibull parameter, wind speed, wind energy, back-up electric power, random sample, statistical analysis

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1. Introduction

The main drivers of the renewed interest in renewable energy sources in recent years, are conventional energy resources depletion and their greenhouse gas emissions which are responsible for climate change. So, the adoption of alternative energy sources that enable the reduction of greenhouse gas emissions is essential (Gabbasa *et al.* 2013). For this, many scientists and governments around the world have paid particular attention to renewable energy. Among green energy sources, there is wind energy (Mostafaeipour 2010). With rapid technology development, wind machines have reached higher level of industrial reliability, which makes wind power more profitable. Wind is mainly characterized by its speed, which determines its strength. However, wind speed varies during different seasons (Seguro *et al.* 2000). Knowledge of certain parameters such as frequency, average speed, wind power density at a site, is important for wind resources exploitation (Shu 2013). Modelling wind speed distribution can help control seasonal variations in wind potential at a site (Al Zohbi *et al.* 2014; Salami *et al.* 2016; Sadam *et al.* 2020). Large number of studies have been published in scientific literature which proposes variety of probability density functions to describe wind speed frequency distributions (Warit *et al.* 2015). For statistical analysis of wind speed data distribution, Weibull probability density function is generally considered the most suitable function due to its simplicity, and its high precision (Mostafaeipour *et al.* 2014; Salami *et al.* 2013). According to international standard IEC 61400-12 and other international recommendations, two-parameter Weibull probability density function is the most appropriate distribution function for wind speed data. Weibull probability density function corresponds perfectly to the wind speed data observed on a site (Mouangue, 2014). These Weibull function parameters are called shape and scale parameters. Several numerical methods have been proposed in the literature to calculate Weibull shape and scale parameters (Arslan *et al.* 2014; Guarienti *et al.* 2020; Kapen et al. 2020; George *et al.* 2014; Ahmed 2013; Signe *et al.* 2019). Akdag and Dinler proposed a new method called power density method for calculating Weibull parameters (Akdag 2009). Their results indicate that this method is more appropriate in terms of comparing wind speed average and wind energy. Jowder (2009) used graphical and empirical method to determine Weibull parameters to calculate wind speed and wind power

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distribution in kingdom of Bahrain at three heights of 10, 30 and 60 m. Other methods allow to evaluate Weibull function parameters in different regions (Razavieh *et al.* 2014; Khahro *et al.* 2014; Adaramola *et al.* 2014). Kidmo *et al.* evaluated six methods to calculate Weibull parameters to represent wind speed distribution at Garoua in Cameroon (Kidmo *et al.* 2015). Their results have shown that the power density method is more suitable than other methods. Generally, estimating Weibull parameters at a site requires large amount of data over a long period. Researchers have estimated these parameters from hourly data (Usta *et al.* 2016). Others, however, used three-hour data. Three-hour data use to determine Weibull parameters has shown that error made is negligible (Ouedraogo *et al.* 2017). Scientists used wind speed data in 174 hours steps, which made it possible to confirm the independence hypothesis of wind speed data on Weibull parameters estimation (Ramirez 2005). Wind speed data sampling is important in order to gain computing time when estimating Weibull parameters (Salami *et al.* 2018). The main objective of this study is to assess the influence of wind speed data random sampling on Weibull shape and scale parameters estimation and on wind power density calculation precision.

2. Case study and wind speed data

Africa is the continent with the lowest electrification rate in world. Only 42% of population has access to electricity, against 75% in developed countries. In West Africa, electrical energy is mainly produced by thermal and hydraulic power stations and through imports from neighboring regions. Thermal power plants mainly use fossil fuels. Electricity demand always exceeds supply and power plant outages are common during peak periods. Today, the gap between electricity supply and demand in West Africa is estimated to be more than 40% (IEMSPR 2019). West Africa is one of fastest growing economic regions on the African continent and electric power insufficiency turns out to be heavy constraint. However, as pointed out in the third issue of the review "The West African Observatory", devoted to energy issue in West Africa, the region is rich in energy resources. Indeed, it has a significant hydroelectric potential, wind energy potential that would allow wind farms deployment, high solar radiation, as well as considerable hydrocarbon resources. In sub-Saharan Africa, only 43 megawatts of installed wind power were deployed, and another 230 megawatts were being installed in 2011. The only functional wind farm that is on commercial scale is that of Cabeolica in Cape Verde. Cape Verde has the largest installed capacity with more than 28 MW, followed by South Africa with 8.6 MW for two pilot projects. West Africa lags the continent, as fewer projects are completed, in progress or planned. It is becoming necessary for West Africa to find solution to exploit all the potential it has in terms of clean and renewable energy, in particular wind energy. West Africa can tap into its wind energy potential all year round. The sites considered in this study are those of Accra Kotoka, Cotonou Cadjehoun, Kano Mallam Aminu, Lomé Tokoin and Ouagadougou Airport, all located in West Africa.

Accra Kotoka is home to Kotoka International Airport which is the main airport in Ghana. Accra is influenced by local steppe climate. Annual temperature average is 26.6°C. Precipitation averages are 809 mm per year.

Cotonou International Airport is located to Cotonou Cadjehoun. Cotonou is the economic capital and the largest city in Benin. The climate is tropical. Temperature average throughout year is 26.8°C. The annual rainfall average is 1244 mm. Mallam Aminu is home to international airport serving Kano, capital of Kano state and the most populous city in northern Nigeria. Kano is influenced by local steppe climate. There is little rainfall in Kano. Temperature average in Kano is 26.1°C. Annual average rainfall is 752 mm. Lomé Tokoin is a locality which is home to Gnassingbé Eyadema International Airport located northeast of Lomé city, capital of Togo. Prevailing climate is tropical. Annual average precipitation is 859 mm. Temperature average in Lomé is 26.8°C. Ouagadougou is Burkina Faso capital and the largest city. The city is in the center of Burkina Faso, in the middle of intertropical zone. This is where Ouagadougou International Airport is located, which is the largest airport in Burkina Faso. Ouagadougou has steppe climate. There is little rainfall in Ouagadougou, averaging 788 mm per year. Annual temperature average is 28.2°C. Table 1 shows geographic coordinates and Figure 1 illustrates selected sites locations on West Africa map (Climate-data 2019).

Wind speed data used in this study are provided by meteorological databases of Wyoming University in United States (Meteorogram 2019). For each selected site, data collected covers period from January 2005 to December 2017 or twelve-year registration period. Wind speed data is recorded every day at one-hour intervals at 10 meters height above ground. Table 2 presents some statistics descriptive: wind speed average, standard deviation, asymmetry, flattening, wind power density and Weibull parameters (k and c) of wind speed data at selected sites. According to Table 2, a low number of data are collected on the sites of Accra (68732) and Kano (24283) compared to the sites of Cotonou (150660), Lomé (171493) and Ouagadougou (102127). Also Kano, Accra, and Cotonou sites have the highest average wind speeds at values of 4.9993 m/s, 4.6965 m/s and 4.5460 m/s, respectively. On the other hand, the lowest wind speed is observed on the Ouagadougou site. Power densities vary in proportion to average speeds. Descriptive statistics presented in Table 2 give an overview of wind speed characteristics at selected sites.

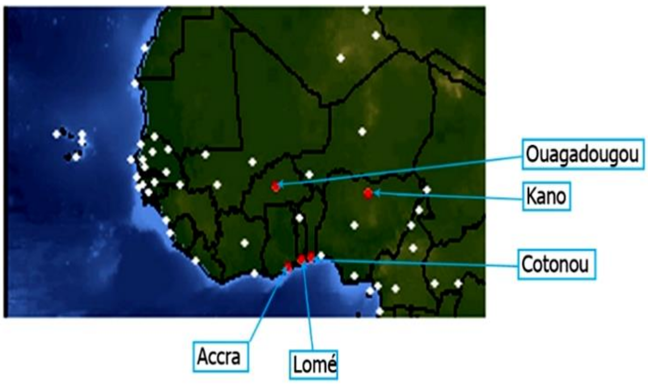


Fig. 1 Selected sites location

Table 1
Studied sites geographic coordinates

Country	Sites	OACI code	Latitude	Longitude	Altitude (m)
Ghana	Accra Kotoka	DGAA	5.60°N	0.17 °W	69
Benin	Cotonou Cadjehoun	DBBB	6.35°N	2.38°E	9
Nigeria	Kano Mallam Aminu	DNKN	12.05°N	8.53°E	481
Togo	Lomé Tokoin	DXXX	6.17°N	1.25°E	25
Burkina Faso	Ouagadougou	DFFD	12.35°N	1.52 °W	306

Source: Meteorological databases of Wyoming University, United States (2017).

Table 2
Weibull parameters and statistics descriptive of wind speed at selected sites

Sites	Number of data	K (-)	C (m/s)	Mean (m/s)	Standard deviation (-)	Kurt (-)	Skew (-)	Power density (W/m²)
Accra	68732	2.0616	4.6965	4.1603	2.2159	2.7670	0.0880	81.7700
Cotonou	150660	2.4391	4.5460	4.0312	1.8238	2.4916	0.1378	64.4602
Kano	24283	2.0574	4.9993	4.4287	2.3016	4.3208	0.4118	98.8275
Lomé	171493	1.9172	4.0329	3.5777	2.0257	2.3283	0.2425	55.9525
Ouagadougou	102127	1.8471	3.3557	2.9808	1.6747	4.6219	0.7901	33.6992

3. Method

To assess wind potential on a site, wind speed frequency distribution must be expressed (Saeed *et al.* 2020; Shoaib *et al.* 2019). Weibull distribution is the most used and recommended in the literature to express wind speed frequency distribution (Houekpoheha *et al.* 2014).

3.1 Weibull distribution

Weibull distribution is a special case of Pearson distribution (Chang 2011). In this distribution, wind speed variations are characterized by two functions: probability density function and cumulative distribution function (Sathyajith and Geeta 2011). Probability density function indicates probability for which wind gave speed V. Weibull distribution probability density function *f(v)* is given by relation (1) (Wais 2017; Mathew 2006).

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{1}$$

Cumulative speed distribution function gives probability that wind speed is less than or equal to speed V. Cumulative distribution function *F(v)* is given by relation (2).

$$F(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{2}$$

3.2 Weibull parameters estimation

There are several methods for estimating Weibull parameters from wind data at a site (Kang *et al.* 2018; Kasra *et al.* 2016; Masseran 2015). In this study, energy pattern factor method is used (Tizpar *et al.* 2014). Energy pattern factor E_{pf} is given by equation (3) (Boudia *et al.* 2015).

$$E_{pf} = \frac{\overline{V^3}}{\overline{V}^3} \tag{3}$$

With gamma function *Γ(x)* given by relation (4).

$$\Gamma(x) = \int_0^{\infty} \exp(-t)\, t^{x-t}\, dt \tag{4}$$

The parameter *k* is obtained by relation (5).

$$k = \left(1 + \frac{3,69}{\left(E_{pf}\right)^2}\right) \tag{5}$$

The scale parameter *c* is given by equation (6).

$$c = \frac{\bar{v}}{\Gamma(1+1/k)} \tag{6}$$

3.3. Wind speed average

Wind speeds mean $\bar{v}$ value is given by equation (7).

$$\bar{v} = c\Gamma\left(1 + \frac{1}{k}\right) \tag{7}$$

3.4 Wind power density

Wind energy power density represents amount of energy produced by wind (Ouarda *et al.* 2015). It is the most important characteristic of wind (Fagbenle *et al.*; 2011). Suppose that S is a cross section through which wind flows perpendicularly with a speed v, wind power P (v) is given by relation (8) (Prem *et al.* 2018).

$$P(v) = \frac{\rho v^2}{2} vS \quad \text{[W]} \tag{8}$$

Wind energy distribution density is obtained by multiplying wind power density by each wind speed probability according to equation (9) (Mohammadi *et al.* 2015).

$$\frac{P(v)}{S} f(v,k,c) = \frac{1}{2}\bar{\rho} v^3 f(v,k,c) \quad \text{[W/m}^2\text{]} \tag{9}$$

By integrating equation (9) for study period, wind power density average is obtained according to equation (10) (Hennessey 1977).

$$\bar{P} = \frac{1}{2}\bar{\rho}\int_0^{+\infty} v^3 f(v,k,c) dv \tag{10}$$

3.5 Statistical performance indicators

To evaluate Weibull distribution parameters and wind power density computational performance, different statistical indicators were used in this study. Standard deviation is used to measure data dispersion. Relation (11) gives it.

$$\sigma_v = \left[\int_0^{\infty} (v - \bar{v}) f(v) dv\right]^{1/2} \tag{11}$$

Kurtosis coefficient or Pearson flattening coefficient measures distribution overwriting degree of a real random variable. It is given by relation (12).

$$K = \frac{E(v-\bar{v})^4}{\left[E(v-\bar{v})^2\right]^2} \tag{12}$$

Skewness coefficient or asymmetry coefficient measures distribution asymmetry degree of a real random variable. It is defined by expression (13).

$$S = \frac{\left[E(v-\bar{v})^3\right]}{\left[\sqrt{E(v-\bar{v})^2}\right]^3} \tag{13}$$

Relative Percentage Error (RPE) shows the difference between wind power density calculated from sample and power density calculated with the full dataset of wind speed collected from which sample is taken. RPE is defined by relation (14) (Sabzpooshani *et al.* 2014).

$$RPE = \left(\frac{P - P_t}{P}\right) * 100 \tag{14}$$

where:

- P_t is sample power density,
- P is total data power density.

Root Mean Square Error (RMSE) assesses error made when calculating statistical parameters of sample drawn from data collected. Relation (15) gives the RMSE.

$$RMSE = \left(\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2\right)^{0.5} \tag{15}$$

where:

- N is intervals total number,
- y_i is observed value frequency,
- x_i is the frequency value obtained by Weibull distribution.

Confidence interval is used to assess estimation precision of sample statistical parameter, as given by relation (16).

$$IC = m_x \pm t * \frac{s}{\sqrt{n}} \tag{16}$$

where:

- IC is confidence interval,
- t is confidence level value,
- s is sample standard deviation,
- n is sample size,
- m_x is sample mean.

3.6 Methodology

This involves taking different sizes of random samples from wind speed data collected, then estimating Weibull distribution parameters and wind power density of each sample at five studied sites. A simulation program is configured in Matlab environment.

The program accesses files in database and performs wind speeds random sampling according to data percentage predefined by the user. For each sample, RMSE on Weibull parameters and the RPE on wind power density estimation are calculated at five the studied sites. Several series of simulations are carried out. For each series of simulations, parameters k and c mean and standard deviation for 100 simulations are used to calculate estimation confidence interval.

4. Results and discussions

Five sites from West Africa were chosen for this study. Several simulations were performed for Weibull parameters estimation and for power density evaluation at all sites. Weibull parameters and wind power density statistical precision parameters were calculated.

Figures 2.d to 2.f present Weibull parameters and wind power density for sampled wind data of size: 90%, 80%, 70%, 60%, 50%, 40%, 30%, 20%, 10% of collected data, as well as statistical indicators for the five study sites.

In view of the results in Figures 2.d to 2.f, for all sites, the root mean squared error (RMSE) made on Weibull parameters k and c estimation in the order of magnitude of the thousandth (1/1000) for some samples and of the hundredth (1/100) for others. For the relative percentage error (RPE) made on calculated wind power density is between -1% to 1% for all data samples and at all sites. The statistical parameters are calculated with an acceptable precision of 0.01. The RPE on power density is very close to zero. These errors are therefore negligible. Consequently, the impact of these wind speed data samplings on the Weibull parameters estimation is insignificant.

Figures 2.a to 2.c present Weibull parameters and wind power density for 9%, 8%, 7%, 6%, 5%, 4%, 3%, 2%, 1% wind speed data samples, as well as statistical indicators at Accra, Cotonou, Kano, Lomé, and Ouagadougou site. Results in Figures 2.d to 2.f show that, at all sites, error made on Weibull parameters k and c estimations is in the order of the hundredth, except at Kano site, where already at 2% wind speed data, RMSE on k and c are order of tenth. For relative percentage error made on calculated wind power density is between -1% to 1%, for all samples and at all sites. At Kano site, for samples less than or equal 2% of wind speed data, error made in parameters k and c estimation is not negligible. For 0.9%, 0.8%, 0.7%, 0.6%, 0.5%, 0.4%, 0.3%, 0.2%, 0.1% data samples, tables 3 to 6 present Weibull parameters and wind power density, as well as statistical indicators at Accra, Cotonou, Lomé, and Ouagadougou site.

The Weibull distribution curves for all the five sites correspond to maximum and minimum confidence intervals, as shown in Figures 3a to 3.f. The results of Table 3 show that for Accra site, RMSE on c is in the order of tenth for sample sizes less than 0.9%. Distribution function and Weibull distribution curves for the Accra site do not fit the histograms of k and c, as shown in Figure 3.g. On the Cotonou site (Table 4), RMSE on k and c are around tenth for sample sizes less than 0.2%. Distribution function and Weibull distribution curves on the Cotonou site do not fit the histograms of k and c, as shown in Figure 3.h. At the Lomé site (Table 5), RMSE on c is around tenth for sample sizes less than 0.3%. Distribution function and Weibull distribution curves on the Lomé site do not fit the histograms of k and c, as shown in Figure 3.i. On the Ouagadougou site (Table 6), RMSE on k is in the order of one tenth for sample sizes less than 0.5%. Distribution function and Weibull distribution curves at Ouagadougou site do not fit the histograms of k and c, as shown in Figure 3.h.

For all sites, the relative percentage error (RPE) made on power density calculation is between -1% to 1% for all samples between 0.1% and 0.9% of wind speed data. Therefore, their results are biased and should not be considered.

The Weibull distribution curves correspond to linked curves to maximum and minimum confidence intervals, and Weibull distribution curve, considering all data, is practically the same in figures 3.a to 3.e respectively at Kano, Accra, Cotonou, Lomé, and Ouagadougou site. These obtained results show that Weibull parameters k and c, can be estimated with an acceptable accuracy at the five sites by considering a part of measured data at each site and not all wind measured data.

Table 3
Weibull parameters, power density and statistical indicators at Accra site

Data sample	k [-]	c [m/s]	Power density [W/m²]	RMSE for k [-]	RMSE for c [-]	RPE for power density [-]
0.9%	2.0590	4.7004	82.3415	0.0841	0.1121	0.6953
0.8%	2.0798	4.7170	82.4039	0.0840	0.1046	0.7705
0.7%	2.0687	4.6876	81.2820	0.0818	0.1070	-0.5992
0.6%	2.0608	4.6945	82.1508	0.1040	0.1183	0.4648
0.5%	2.0725	4.6903	81.4197	0.1008	0.1378	-0.4290
0.4%	2.0626	4.6765	81.2014	0.1109	0.1497	-0.6990
0.3%	2.0666	4.7094	83.0732	0.1277	0.1782	1.5699
0.2%	2.0981	4.6921	80.8987	0.1467	0.2010	-1.0758
0.1%	2.1034	4.7017	82.1218	0.2194	0.3294	0.4296

Table 4
Weibull parameters, power density and statistical indicators at Cotonou site

Data sample	k [-]	c [m/s]	Power density [W/m²]	RMSE for k [-]	RMSE for c [-]	RPE for power density [-]
0.9%	2.4364	4.5414	64.3562	0.0473	0.0508	-0.1615
0.8%	2.4351	4.5426	64.4408	0.0503	0.0690	-0.0299
0.7%	2.4487	4.5500	64.5093	0.0587	0.0634	0.0762
0.6%	2.4370	4.5405	64.3329	0.0632	0.0697	-0.1978
0.5%	2.4358	4.5329	64.0391	0.0593	0.0758	-0.6575
0.4%	2.4382	4.5416	64.3824	0.0739	0.0807	-0.1208
0.3%	2.4516	4.5452	64.3255	0.0821	0.0897	-0.2093
0.2%	2.4284	4.5317	64.2666	0.1033	0.1344	-0.3011
0.1%	2.4523	4.5342	64.0817	0.1342	0.1685	-0.5906

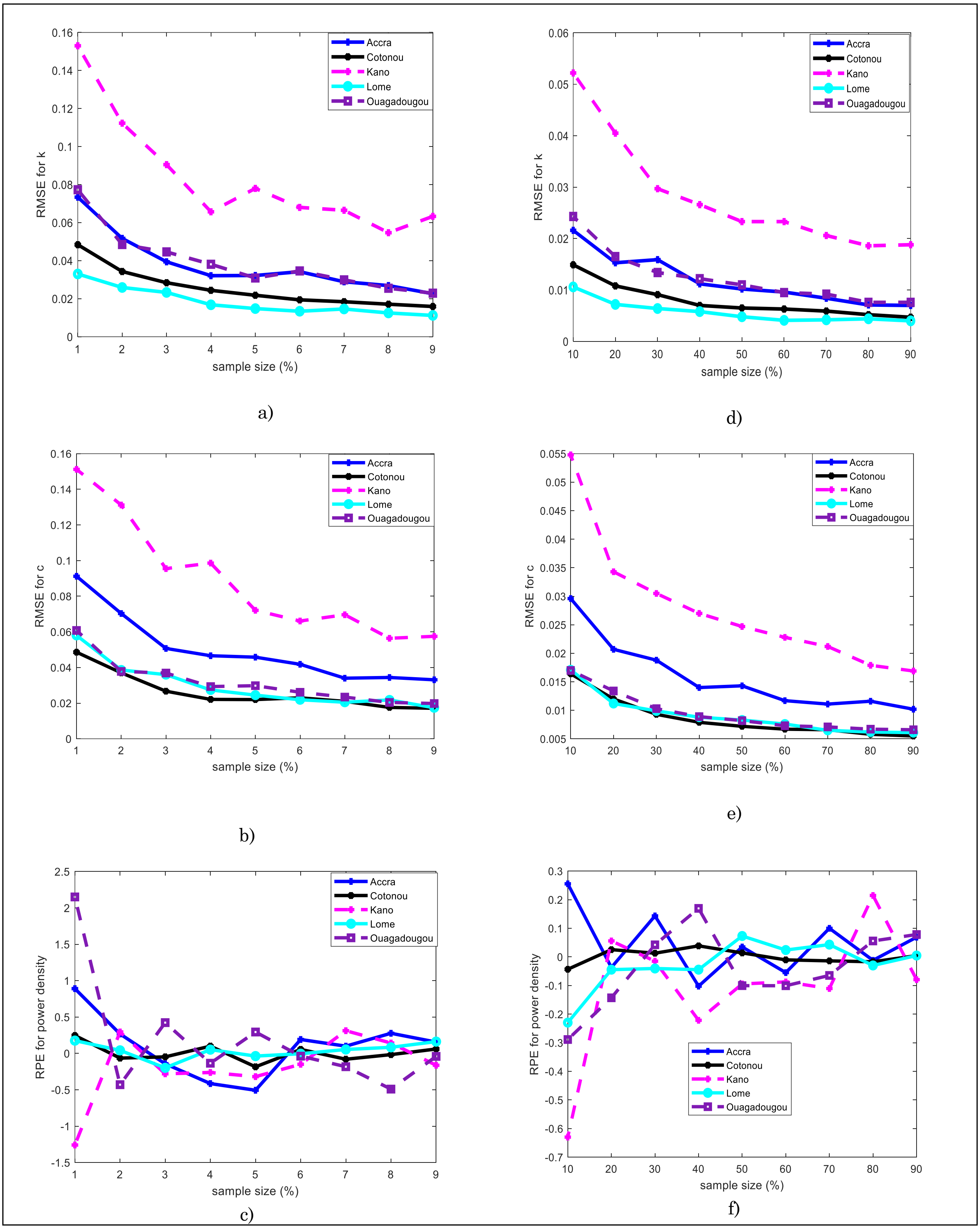
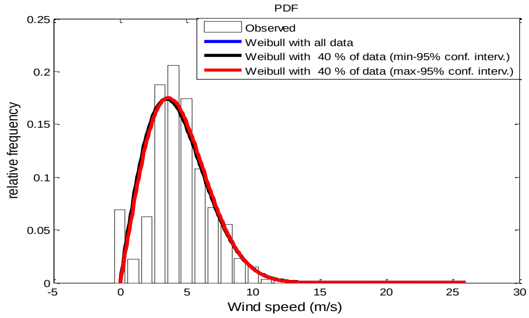
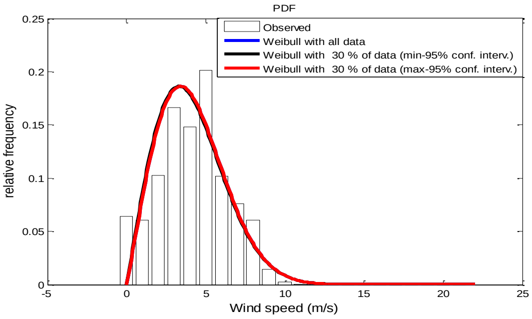


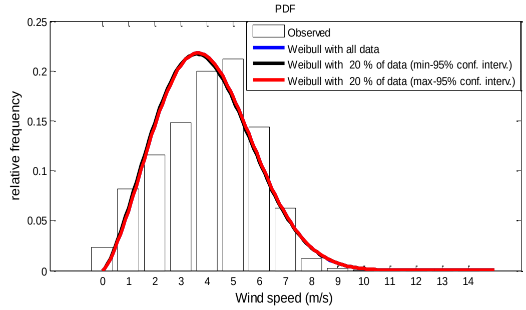
Fig. 2 Error (RMSE, REP) curves for wind speed on the five sites according to data sample size



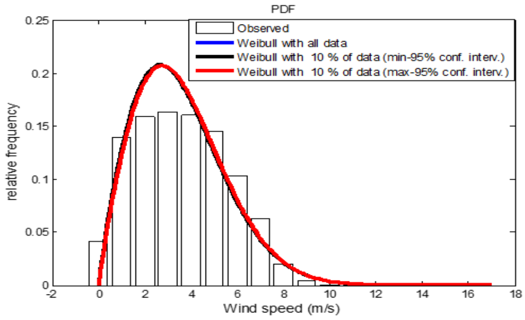
a) Kano site for 40% sample data



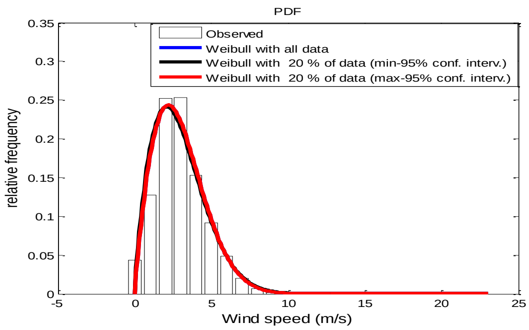
b) Accra site for 30% sample data.



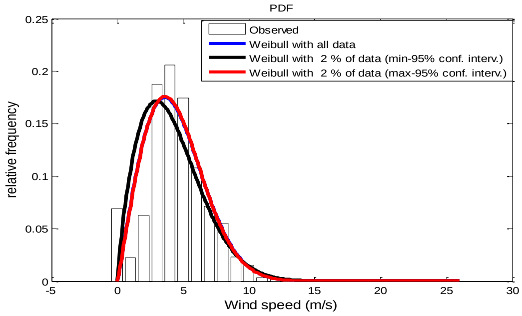
c) Cotonou site for 20% sample data



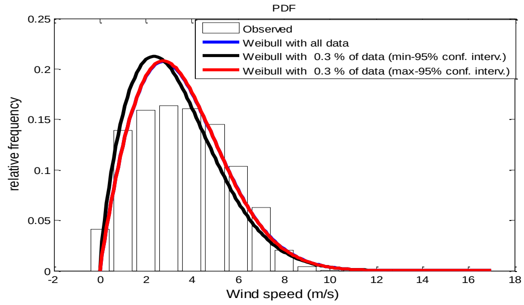
d) Lomé site for 10% sample data.



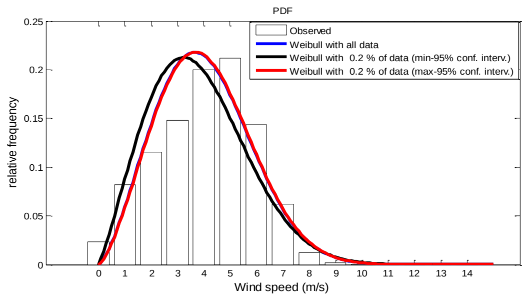
e) Ouagadougou site for 20% sample data.



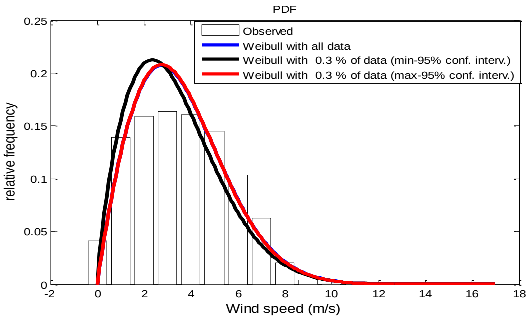
f) Kano site for 2% sample data.



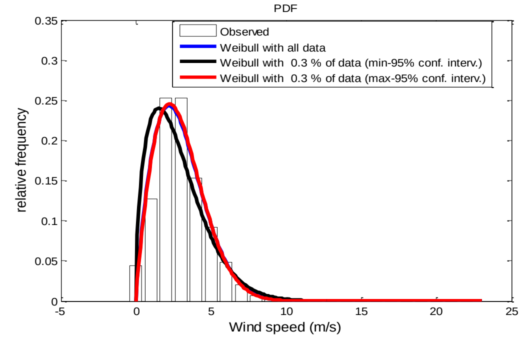
g) Accra site for 0.3% sample data



h) Cotonou site for 0.2% sample data.

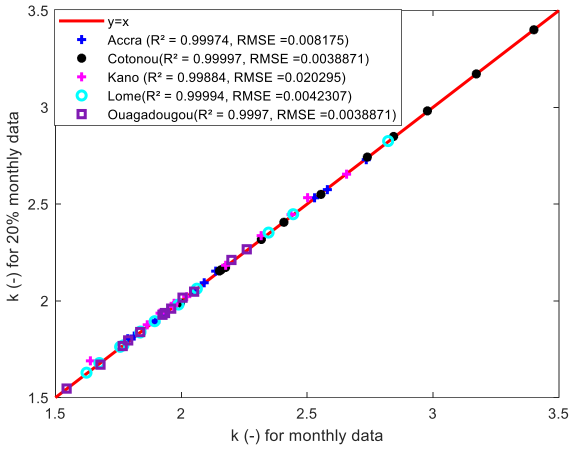


i) Lomé site for 0.3% sample data.

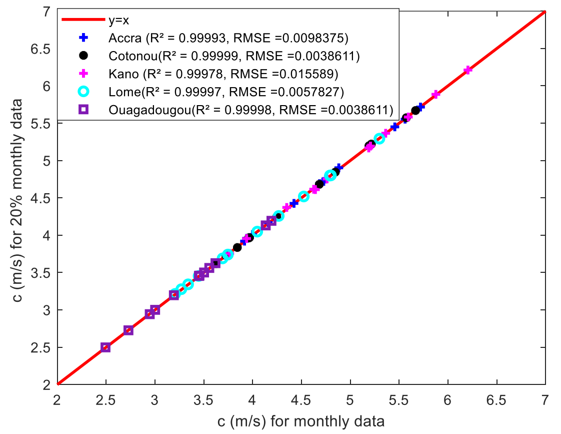


j) Ouagadougou site for 0.3% sample data.

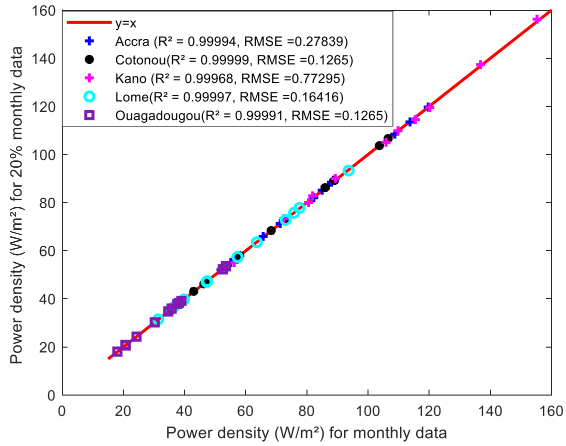
Fig. 3 Weibull distribution curves for wind speed on the five sites according data sample size.



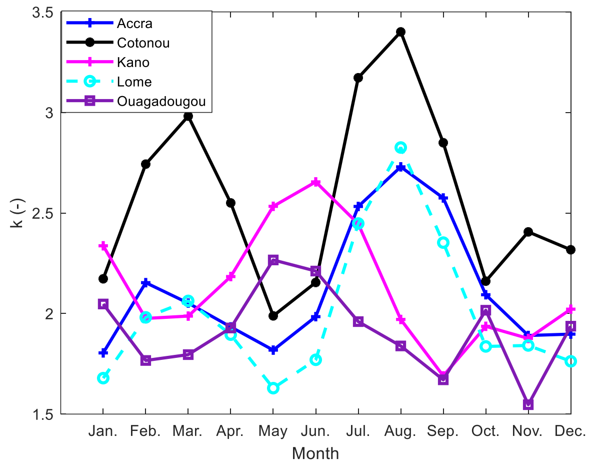
a) k using all monthly data vs. k using 20% of monthly data



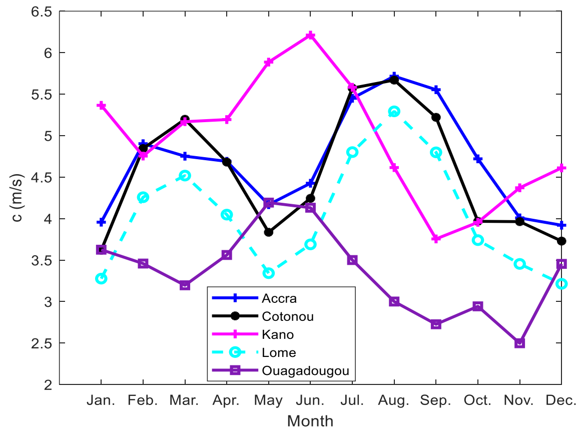
b) c using all monthly data vs. c using 20% of monthly data



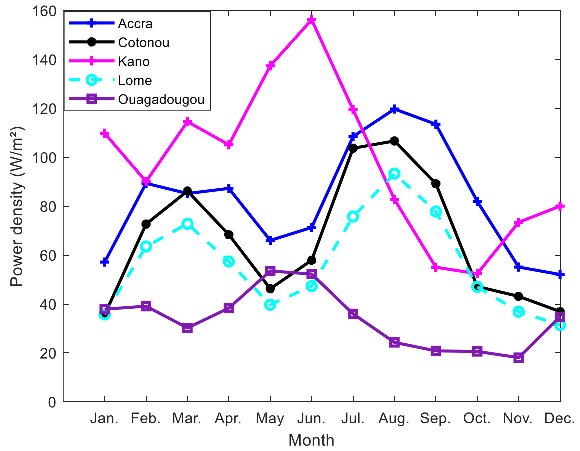
c) Power density using all monthly data vs. Power density using 20% of monthly data



d) k using 20% of monthly data



e) c using 20% usi monthly data



f) Power density using 20% of monthly data

Fig. 4 Monthly variation of Weibull distribution parameters (k and c) and power densty on the five sites using 20% data sample size.

Table 5
Weibull parameters, power density and statistical indicators at Lomé site

Data sample	k [-]	c [m/s]	Power density [W/m²]	RMSE for k [-]	RMSE for c [-]	RPE for power density [-]
0.9%	1.9182	4.0273	55.7349	0.0385	0.0525	-0.3914
0.8%	1.9189	4.0333	55.9651	0.0401	00574	0.0215
0.7%	1.9158	4.0231	55.6528	0.0371	0.0647	-0.5396
0.6%	1.9150	4.0255	55.7933	0.0454	0.0708	-0.2863
0.5%	1.9217	4.0280	55.6816	0.0478	0.0730	-0.4875
0.4%	1.9241	4.0400	56.1474	0.0608	0.0895	0.3460
0.3%	1.9195	4.0388	56.2668	0.0653	0.1007	0.5575
0.2%	1.9233	4.0151	55.2143	0.0788	0.1139	-1.3380
0.1%	1.9323	4.0380	56.1602	0.1200	0.1696	0.3689

Table 6
Weibull parameters, power density and statistical indicators at Ouagadougou site

Data sample	k [-]	c [m/s]	Power density [W/m²]	RMSE for k [-]	RMSE for c [-]	RPE for power density [-]
0.9%	1.8537	3.3581	33.7792	0.0725	0.0705	0.2350
0.8%	1.8412	3.3600	34.1309	0.0697	0.0659	1.2632
0.7%	1.8656	3.3448	33.1835	0.0902	0.0728	-1.5559
0.6%	1.8568	3.3501	33.5919	0.0997	0.0766	-0.3210
0.5%	1.8601	3.3639	34.0461	0.1185	0.0958	1.0173
0.4%	1.8580	3.3385	33.2936	0.1096	0.0973	-1.2199
0.3%	1.8730	3.3724	34.3112	0.1485	0.1148	1.7820
0.2%	1.8711	3.3500	33.6287	0.1356	0.1372	-0.2114
0.1%	1.8680	3.3419	34.2772	0.2051	0.2267	1.6846

Figures 4.d through 4.f present the monthly variations of the parameters k, c and the wind power density, respectively, estimated using only 20% of the monthly data collected on the five wind sites considered in this study. To appreciate the estimates of these parameters, its compared them to the parameters calculated using all 100% of the monthly data collected. The results of these comparisons are shown in Figures 4.a through 4.c. In these figures, a perfect linear correlation (R^2 almost equal 1) between the parameters estimated using only 20% of the monthly data collected and the parameters calculated using all 100% of the monthly data collected is observed. The RMSE calculated on the estimate of the k parameters using 20% of the data are less than 0.01 except for the Kano site for which the RMSE is equal to 0.020295 (Fig 4.a). The same thing is observed for the estimation of the parameters c where all the RMSE are less than 0.01 except for the Kano site for which the RMSE is equal to 0.015589 (Fig 4.b). Thus, a 20% sample of data collected on these four sites (Accra, Cotonou, Lomé, and Ouagadougou) can used to estimate Weibull's k and c parameters with an RMSE less than 0.01. The parameters k and c being parameters which are used for the estimation of the power density (equation (9)) on a site, we can further derive that the estimations of the power densities using the 20% of data collected on the four (04) sites (Accra, Cotonou, Lomé and Ouagadougou) are acceptable as confirmed in Figure 4.c. The power density variation curves (Fig. 4.f) on the five study sites show that the power densities differ appreciably from one month to another, especially in Kano. Only the Ouagadougou site has a power density of less than 60 m²/W throughout the year. In Lomé, Cotonou, and Accra, the greatest power densities occur during the months of February, March, April, July, August and September. This observation confirms the results obtained in (Salami et al. 2016). Optimal use of wind energy can therefore be envisaged on these sites during these six months.

To validate this present study method, the obtained results are compared to results of other methods such as that used odd and even class wind speed time series of the Weibull distribution histogram to estimate Weibull parameters (Salami *et al.* 2018), the one which also uses numerical methods for determining Weibull distribution parameters (Guarienti *et al.* 2020) and to results of Analysis and efficient comparison of ten numerical methods in estimating Weibull parameters for wind energy potential (Kapen *et al.* 2020). This comparison allows to say that the random sampling of the wind speed data for shape and scale parameters calculation gives results as precise as use of odd and even class wind speed time series of distribution histogram or all wind speed data collected at a site to estimate Weibull parameters. This approach makes it possible to precisely determine Weibull parameters with a reduced size of wind speed collected data and ultimately leads to a reduced computation time.

5. Conclusion

The main objective of our study is to assess the impact of wind speed data random sampling on the quality of Weibull shape and scale parameters estimation. The study considered the wind sites of Accra in Ghana, Cotonou in Benin, Kano in Nigeria, Lomé in Togo, and Ouagadougou in Burkina Faso. In general, the study shows that samples larger than 20% of wind speed data collected give Weibull parameters k and c approximately equal to those of all wind speed data collected, with maximum error around 0.05. With this very small difference we can conclude that Weibull parameters estimation is acceptable.

Study results show that good accuracy in Weibull parameters and power density estimation is obtained with the following sampled data sizes: 30% of wind speed data for Accra, 20% for Cotonou, 80% for Kano, 20% for Lomé, and 20% for Ouagadougou.

This study results are very useful in the development of wind energy. In the case of wind potential assessment which is necessary for any wind turbine installation project, wind speed data random sampling may be sufficient to calculate wind power density. This saves computing time. Better yet, this result enables wind project developers to confidently compress wind data through sampling prior to any extensive energy potential evaluation while still expecting the same results as when working with full datasets.

Nomenclature

f(v)	:	Weibull distribution probability density function
F(v)	:	cumulative distribution function
E*pf*:	:	energy pattern factor
Γ(x):	:	gamma function
k	:	shape parameter
c	:	scale parameter (m/s)
v	:	wind speed (m/s)
$\bar{v}$	:	wind speeds mean (m/s)
P(v):	:	wind power (W/m²)
$\bar{P}$:	:	wind power density average (W/m²)
ρ	:	air density (kg/m³)
σ_v	:	standard deviation
K	:	kurtosis coefficient
S	:	skewness coefficient
RMSE	:	root mean square error
RPE:	:	relative percentage error
IC	:	confidence interval

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