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Research Article

Estimating mixture hybrid Weibull distribution parameters for wind energy application using Bayesian approach

Agbassou Guenoupkati[a,b,c], Adekunlé Akim Salami[a,b,c,*], Yao Bokovi[a,b,c], Piléki Xavier Koussetou[b], Seydou Ouedraogo[c,d]

[a]Centre d'Excellence Régional pour la Maîtrise de l'Electricité (CERME), University of Lome, Lome, P.O. Box 1515, Lome Togo

[b]Department of Electrical Engineering, Ecole Polytechnique de Lomé (EPL), University of Lome, P.O. Box 1515, Lome Togo

[c]Laboratoire de Recherche en Sciences de l'Ingénieur (LARSI), University of Lome, P.O. Box 1515, Lome Togo

[d]Polytechnic University of bobo-Dioulasso, Burkina-Faso

Abstract. The Weibull distribution function is essential for planning and designing wind-farm implementation projects and wind-resource assessments. However, the Weibull distribution is limited for those areas with high frequencies of calm winds. One solution is to use the hybrid Weibull distribution. In fact, when the wind speed data present heterogeneous structures, it makes sense to group them into classes that describe the different wind regimes. However, the single use of the Weibull distribution presents fitting errors that should be minimized. In this context, mixture distributions represent an appropriate alternative for modelling wind-speed data. This approach was used to combine the distributions associated with different wind-speed classes by weighting the contribution of each of them. This study proposes an approach based on mixtures of Weibull distributions for modelling wind-speed data in the West Africa region. The study focused on mixture Weibull (WW-BAY) and mixture hybrid Weibull (WWH-BAY) distributions using Bayes' theorem to characterize the wind speed distribution over twelve years of recorded data at the Abuja, Accra, Cotonou, Lome, and Tambacounda sites in West Africa. The parameters of the models were computed using the expectation-maximization (E-M) algorithm. The parameters of the models were estimated using the expectation-maximization (E-M) algorithm. The initial values were provided by the Levenberg-Marquardt algorithm. The results obtained from the proposed models were compared with those from the classical Weibull distribution whose parameters are estimated by some numerical method such as the energy pattern factor, maximum likelihood, and the empirical Justus methods based on statistical criteria. It is found that the WWH-BAY model gives the best prediction of power density at the Cotonou and Lome sites, with relative percentage error values of 0.00351 and 0.01084. The energy pattern factor method presents the lowest errors at the Abuja site with a relative percentage error value of -0.54752, Accra with -0.55774, and WW-BAY performs well for the Tambacounda site with 0.19232. It is recommended that these models are useful for wind energy applications in the West African region.

Keywords: Wind speed, hybrid Weibull distribution; Numerical methods; Mixtures models; Bayes theorem; E-M algorithm; Levenberg-Marquardt algorithm

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1. Introduction

Environmental problems are currently of great concern on a global scale; for example, the problem of the depletion of certain resources of fossil origin and the pollution of the environment (Zhou *et al.*, 2015). Then the use of renewable energies is an alternative to ensure both energy transition and sustainable development. In this case, solar and wind power are commonly used (García-caballero *et al.*, 2023; Höök & Tang, 2013; Speirs *et al.*, 2015). In the case where the energy needs should be ensured by wind power, knowledge about the wind is essential. However, the wind is characterized by its variability, non-linearity, and intermittence (Bastin *et al.*, 2023). Therefore, wind modeling is required to size the wind turbines. To this end, the first approach consists to exploit wind speed data over a given period and the second is to use the distribution function that provides information on the probabilities of the occurrence of wind speeds. Moreover, during these decades, West Africa has benefited from wind farm projects in some of its countries to fill the energy gap characterized by a large part of its population with no access to electricity (Salami *et al.*, 2018).

For the optimal use of wind energy, the choice of the appropriate distribution function is very important (Alcalá *et al.*, 2019). Therefore, the Machine Learning method, Rayleigh, log-normal, Gaussian, and Weibull distributions are most often found in the literature (Elamouri & Ben Amar, 2008; Elmahdy, 2015; Kiss & Jánosi, 2008; Liu *et al.*, 2023; Mohammadi *et al.*, 2015; Adekunlé Akim Salami *et al.*, 2018; Sedzro *et al.*, 2022). Among them, the Weibull distribution function is widely used for wind energy applications because of its adaptability to multiple wind speed regimes and allows to have better results (Albani & Ibrahim, 2013; Celik, 2004; Morgan *et al.*, 2009; Salami *et al.*, 2013; Ucar & Balo, 2009). However, (Carta & Ramírez, 2007; Jaramillo & Borja, 2004b; Salami *et al.*, 2016) highlighted

* Corresponding author
Email: akimsalami11@gmail.com (A. A.Salami)

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that the conventional Weibull distribution should not use in a generalized way when wind speed distribution on certain sites is multimodal. The Mixture distributions are a viable alternative for modeling wind speed data. The mixture model is a linear combination of other distribution functions called mixture components (Jaramillo & Borja, 2004a; Kollu *et al.*, 2012). In the case of the mixture model, the estimation errors vary according to the method of estimation of its parameters.

This study aims to investigate the potential of mixture distributions for modeling wind speed data in a West African environment. To take into account calm winds in wind speed characterization, this study proposed two mixture models named mixture Weibull (WW-BAY) and mixture Hybrid Weibull (WWH-BAY) distributions using Bayes' approach to characterize the wind speeds at five sites in West Africa such as Abuja (Nigeria), Accra (Ghana), Cotonou (Benin), Lome (Togo) and Tabacomda (Senegal). A comparison was carried out to the Weibull distribution which parameters are estimated by Energy Pattern Factor (EPF), Empirical Method of Justus (EMJ), and Maximum Likelihood Method (ML). The contributions made by this research are promising with huge academic and economic impacts such as the proposal of an innovative approach using a mixture of Weibull distribution and Bayes' theorem for wind energy modeling, the highlight of the limits of the Hybrid Weibull distribution for areas with calm winds, decision making during the design and implementation of wind power plant projects, reduction of financial risks due to the variability of the wind, the optimization of the power generated by wind farms, evaluation of the wind potential, and the comparative basis of methods for modeling wind speed. Moreover, this is the first time these methods have been applied specifically in the West Africa area.

The rest of the paper is organized as follows: Section 2 formulates the problem descriptions in the context of slower windy sites. Section 3 exhibits wind power density calculation, Section 4 presents some numerical methods for estimation of Weibull parameters, hybrid Weibull mixture distribution followed by the model presentation in Section 5, the Bayesian approach in Section 6, and the expectation-maximization (E-M) algorithm in Section 7. Section 8 is dedicated for mixture Weibull distribution parameter estimation. In Section 9, the methodology is exposed. Section 10 presents the results and discussions, and ended the conclusion in Section 11.

2. Problem Description

The classical Weibull distribution function is the most widely used for modeling wind speed data. However, for multiple wind regimes, it presented errors in estimating wind occurrence probabilities that vary with the nature of the frequency histogram. The classic Weibull distribution is ill-suited to regions with relatively high calm frequencies. In this case, it is advisable to process the data by removing the calm wind values from the data series and indicating them separately using the Hybrid Weibull distribution (Salami *et al.,* 2013). In this circumstance, mixture models using Expectation-Maximization (E-M) algorithm based on Bayes' theorem are suitable for the heterogeneous aspects of the distribution (Akpinar & Akpinar, 2009; Elmahdy & Aboutahoun, 2013; Mazzeo *et al.*, 2018). To increase the power of this iterative method, Bayes' theorem, has been developed, taking into account the conditional probabilities of membership of wind speeds to predefined classes. This alternative proves its performance in the modeling of multimodal failures of industrial materials for the fitting of frequency histograms. (Elmahdy, 2015; Kececioglu & Wang, 1998). To utilize the advantages of the Bayesian estimation method for wind energy applications, we use it to model wind speed data by combining it with its hybrid variant due to the sensitivity of the model to calm winds to provide a better prediction of wind energy in the West African region.

3. Wind power density calculation

Wind energy density is an important indicator to evaluate wind resources and to describe the amount of wind energy at different values of wind speed in a particular location. Knowledge of wind energy density is also useful for evaluating the performance of wind turbines and for naming the optimal wind turbine wind. Wind power density is similar to the level of energy available at the site that can be converted into electricity using a wind turbine. The wind power density is calculated from the measured wind speed data. The wind energy at a given location depends on the wind speed cube. Thus, the power density for the time series of actual wind speed data can be calculated using Equation (1) (Sedzro *et al.*, 2022).

$$\bar{P} = \frac{1}{2}\rho S\overline{v^3} \tag{1}$$

where ρ denotes the air density, a parameter that varies with latitude and temperature, but is generally considered to be constant and averages about 1.25 kg/m^3 which depends on altitude, air pressure, and temperature; and v is the wind speed in m/s. S is the swept area by the wind turbine. The previous expression shows that the available power varies with the average cubic speed of the observed wind. The other expression is based on a statistical analysis of the raw wind data and the calculation of frequencies at a given threshold of speed. The classical Weibull probability density function is given by Equation (2) (Alavi et al., 2016).

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

where k is the shape parameter that indicates the wind distribution of any region, and c is the scale parameter in m/s indicates how windy the location is. The cumulative function can be obtained by calculating the integral of the probability density function. The cumulative distribution function is expressed by Equation (3).

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

The wind density energy calculated from the density of the Weibull probability density function is estimated using the following Equation (4) (Tizpar *et al.* 2014), where Γ denotes the Gamma function.

$$P = \frac{1}{2}\rho c^3\Gamma\left(1+\frac{3}{k}\right)\left[\frac{W}{m^2}\right] \tag{4}$$

4. Weibull parameters estimating methods

The Statistical estimation of the unknown parameter from random variables is an important problem that can be solved by numerical methods. In the case of Weibull distribution parameters estimated from wind speed data (Aras *et al.*, 2020; Guenoukpati *et al.*, 2020; Nage, 2016) several numerical methods are used. There are several methods in the literature to compute the parameters k and c of the Weibull distribution function. We have the graphical method (GP), the empirical method of Justus (EMJ), the empirical method of Lysen (EML), the energy pattern factor method (EPF), the maximum likelihood method (ML), and the Moroccan method (MMa) are used to calculate these parameters. The EPF, EMJ, and ML methods are recognized as those that minimize errors in wind characterization (Mostafaeipour, 2016). The three numerical methods used in this study to estimate the parameters of the Weibull distribution are the Energy Pattern Factor Method (EPF), the Empirical method of Justus (EMJ), and the Maximum Likelihood method (ML). Other variants can be found in the literature (Akdağ & Güler, 2018; Arrabal-Campos *et al.,* 2020).

4.1. Empirical method of Justus (EMJ)

Based on the empirical method introduced by Justus, the parameters, *k,* and *c* are calculated respectively by Equation (5) and Equation (6).

$$k = \left(\frac{\rho}{\bar{v}}\right)^{-1{,}086} \tag{5}$$

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

4.2. Energy Pattern Factor Method (EPF)

To calculate the parameters c and k by this process, the Energy pattern factor as a parameter used for the aerodynamic design of the turbines must be defined first. The energy pattern factor is obtained by using Equation (7) (Salami *et al.*, 2022).

$$E_{pf} = \frac{\frac{1}{n}\sum_{i=1}^{n} v_i^3}{\frac{1}{n}\sum_{i=1}^{n} v_i} = \frac{\overline{v^3}}{\bar{v}^3} = \frac{\Gamma\left(1+\frac{3}{k}\right)}{\Gamma^3\left(1+\frac{1}{k}\right)} \tag{7}$$

where $\overline{v^3}$ is the average wind speed cube, $\bar{v}^3$ is the cube of the average speed. Then, the parameter can be calculated by Equation (8). The parameter c is also calculated in the same way using Justus empirical method.

$$k = \left(1 + \frac{3{,}69}{\left(E_{pf}\right)^2}\right) \tag{8}$$

4.3. Maximum likelihood method

The maximum likelihood method is a mathematical expression recognized as a likelihood function of wind speed data in time series format. In this method, extended numerical iterations are required to determine the k and c parameters of the Weibull distribution. Using the maximum likelihood method, the parameters k and c are respectively calculated by Equation (9) and Equation (10) (Salami *et al.*, 2018; Salami *et al.*, 2013).

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} \ln(v_i)}{n}\right]^{-1} \tag{9}$$

$$c = \left[\frac{\sum_{i=1}^{n} v_i^k}{n}\right]^{\frac{1}{k}} \tag{10}$$

where v_i is the wind speed at time i in m/s and n is the number of non-zero wind speed data.

5. Theorical background of the proposed model

In statistics, the probability function of the mixture of Weibull distributions is a linear convex combination of two or more Weibull probability density functions (Elmahdy, 2017). Its probability density function is sometimes called the mixture distribution. The individual distributions that are combined to form the mixture distribution have the mixture components, and the probabilities associated with each component of the mixture probabilities (Jaramillo & Borja, 2004a). The number of components in the mixture distribution is often limited. The distribution function is expressed as a weighted sum with positive probabilities of other distribution functions. For an m-components mixture model, the probability density function is expressed by Equation (11).

$$f(v|\mu) = \sum_{i=1}^{m} \omega_i f_i(v|k_i, c_i) \tag{11}$$

With:

$$\sum_{i=1}^{m} \omega_i = 1 \tag{12}$$

w_i is the i_{th} mixing proportion associated with the hybrid Weibull distribution function f_i, μ is the complete set of parameters and F_0 the frequency of calms for the model with m component given by Equation (13).

$$\mu = (\omega_1, \omega_2, .., \omega_m, k_1, k_2, .., k_m, c_1, c_2, .., c_m, F_0) \tag{13}$$

This study is limited to $m = 2$. The Weibull PDF and CDF become the expressions given by Equations (14) and Equation (15). The wind power density is expressed by Equation (16).

$$f(v) = \omega\left(\frac{k_1}{c_1}\right)\left(\frac{v}{c_1}\right)^{k_1-1} exp\left[-\left(\frac{v}{c_1}\right)^{k_1}\right] + (1 - \omega)\left(\frac{k_2}{c_2}\right)\left(\frac{v}{c_2}\right)^{k_2-1} exp\left[-\left(\frac{v}{c_2}\right)^{k_2}\right] \tag{14}$$

$$F(v) = \omega\left(1 - exp\left(-\left(\frac{v}{c_1}\right)^{k_1}\right)\right) + (1 - \omega)\left(1 - exp\left(-\left(\frac{v}{c_2}\right)^{k_2}\right)\right) \tag{15}$$

$$P = \frac{1}{2}\rho\left[\omega c_1^3 \Gamma\left(1 + \frac{3}{k_1}\right) + (1 - \omega) c_2^3 \Gamma\left(1 + \frac{3}{k_2}\right)\right]\left[\frac{W}{m^2}\right] \tag{16}$$

The expression of the Mixture Hybrid Density function and its cumulative distribution function are respectively given by Equations (17) and (18). The wind power density is calculated by Equation (19).

$$f(v) = \begin{cases} F_0 \quad for \quad v < 1 \\ (1 - F_0)\begin{pmatrix} \omega\left(\frac{k_1}{c_1}\right)\left(\frac{v}{c_1}\right)^{k_1-1} exp\left[-\left(\frac{v}{c_1}\right)^{k_1}\right] + \\ (1-\omega)\left(\frac{k_2}{c_2}\right)\left(\frac{v}{c_2}\right)^{k_2-1} exp\left[-\left(\frac{v}{c_2}\right)^{k_2}\right] \end{pmatrix} \quad for \quad v \geq 1 \end{cases} \tag{17}$$

$$F(v) = (1 - F_0)\left(\omega\left(1 - exp\left(-\left(\frac{v}{c_1}\right)^{k_1}\right)\right) + (1 - \omega)\left(1 - exp\left(-\left(\frac{v}{c_2}\right)^{k_2}\right)\right)\right) + F_0 \tag{18}$$

$$P = \frac{1}{2}\rho(1-F_0)\left[\omega c_1^3 \Gamma\left(1+\frac{3}{k_1}\right) + (1-\omega)c_2^3\Gamma\left(1+\frac{3}{k_2}\right)\right]\left[\frac{W}{m^2}\right] \tag{19}$$

where F_0 represents the frequency of calms, which is determined from the wind data. To fit a mixture model from data, the ML method could be used. This process consists to search the parameters that maximize the logarithm of the likelihood function. Setting partial derivatives of the log-likelihood to zero leads to a set of n-nonlinear equations which become complex to solve using a gradient descent algorithm. A wide-use alternative in this context is the Expectation – Maximization (E-M) algorithm based on the Bayes rule (Bishop & Nasrabadi, 2006; Dempster et al., 1977).

6. Bayesian Method Formulation

Let X be a set of n data samples with incomplete distributions such that $X = \{x_1, x_2, ..., x_n\}$ and $Y = \{y_1, y_2, ..., y_n\}$ an unknown vector, such that $y \in \Gamma$. Each y_i refers to a component of the mixture through which an observation x_i is evaluated. Let's assume that complete data exists $D = (X, Y)$, and let's assume a joint probability density function with parameter μ.

$$f(X,Y|\mu) = f(Y|X,\mu)\cdot f(X|\mu) \tag{20}$$

Our goal is to find the parameter γ that will maximize the log-likelihood defined by Equation (21). The estimation of the parameters by the E-M will therefore go through the Estimation and Maximization stages until the optimal parameters are obtained.

$$L(\mu|X,Y) = \sum_{i=1}^{n}\left(log\left(f(y_i|x_i,\mu)\right) + log\left(f(x_i|\mu)\right)\right) \tag{21}$$

7. Expectation – Maximization (E-M) algorithm

The E-M algorithm is an iterative algorithm that starts from some initial estimate of parameter μ using random initialization and other algorithms and then proceeds to iteratively update μ until convergence is detected. Each iteration operates in two steps: first, E-M finds the expected values of the completed log-likelihood $log(f(x_i|\ \mu))$; Y being the unknown data or the latent variable, X the given observation, and μs the estimated parameters. The expectation of the likelihood function is calculated using Equation (22).

$$Q(\mu,\mu^s) = \mathrm{E}\left[L(\mu|X,Y),\mu^s\right] \tag{22}$$

Second, the expected values compiled in the first step are maximized $Q(\mu, \mu^s)$ according to the relation (23), which defines a set of values Ψ.

$$\mu^{s+1} = \arg\max_{\mu\in\psi} Q(\mu,\mu^s) \tag{23}$$

These two steps are iterated until convergence is obtained. In practice, if the local maximum is to be reached, the E-M algorithm runs a large number of times from different initial values to have a greater chance of reaching the global maximum likelihood.

8. Mixture hybrid Weibull parameters estimation

The E-step computes the posterior probability using Bayes theorem at each iteration with the order l using Equation (24).

$$f_i(v_j;\mu^{(l)}) = \frac{\omega_i^{(l)} f_i\left(v_j|k_i^{(l)};c_i^{(l)}\right)}{\sum_{i=1}^{m}\omega_i^{(l)} f_i\left(v_j|k_i^{(l)};c_i^{(l)}\right)} \tag{24}$$

In the M-step the algorithm computes the new parameter values that maximize the likelihood, now made possible by using the estimation of the data made in the previous step, and updates the values of the parameters for the next order iteration. The optimal value of the proportion parameter or responsibility is obtained by Equation (25).

$$\omega_i^{(l+1)} = \frac{1}{n}\sum_{i=1}^{n} f_i(v_j;\mu^{(l)}) \tag{25}$$

Similarly, the optimal values of shape and scale parameters are respectively given by Equations (26) and (27).

$$c_i^{(l+1)} = \left[\frac{\sum_{i=1}^{n} f_i(v_j;\mu^{(l)})(v_j)^{k_i^{(l+1)}}}{\sum_{i=1}^{n} f_i(v_j;\mu^{(l)})}\right]^{\frac{1}{k_i^{(l+1)}}} \tag{26}$$

$$g\left(k_i^{(l+1)}\right) = \frac{1}{k_i^{(l+1)}} + \frac{\sum_{i=1}^{n} f_i\left(v_j;\mu^{(l)}\right) ln(v_j)}{\sum_{i=1}^{n} f_i\left(v_j;\mu^{(l)}\right)} - \frac{\sum_{i=1}^{n} f_i(v_j;\mu^{(l)})(v_j)^{k_i^{(l+1)}} ln(v_j)}{\sum_{i=1}^{n} f_i(v_j;\mu^{(l)})(v_j)^{k_i^{(l+1)}}} = 0 \tag{27}$$

The Newton-Raphson method is applied (Elmahdy, 2017), (Elmahdy, 2015); by making a judicious choice of the initial value of the shape parameter, the value of the local maximum is obtained by successive iterations from Equation (28).

$$k_i^{(l+1)} = k_i^{(l)} - \frac{g\left(k_i^{(l)}\right)}{g'\left(k_i^{(l)}\right)} \tag{28}$$

For the global parameter convergence, the estimation and maximization steps are repeated until the difference between the estimated likelihood of two consecutive iterations is below a certain threshold. The initial values are provided by the Levenberg-Marquardt algorithm (LMA) (Kumar & Sahay, 2018). In MATLAB software, the command "lsqnonlin" allows selecting the LMA algorithm among the least squares methods. The standard value of the threshold is fixed at 10 and can be modified by the command "initdamping". The stopping condition of the algorithm is the same as that of the Expectation-Maximization algorithm. The advantage of this algorithm is that it always finds a solution whatever the initial values given to it. This is why we use it in parallel with the Bayesian method to generate the initial values of the E-M algorithm. The LMA iteratively solves the nonlinear problem of finding the parameters of the mixture model that make the quadratic sum of residuals (SQR), which are the errors due to the estimation of the values of the probabilities of occurrence of wind speed (Marquardt, 1963). The problem of minimizing SQR compared to θ is equivalent to making the SQR expression as minimal as possible according to Equation (29). The value of SQR is expressed by Equation (30).

$$\hat{\mu} = \underset{\mu}{Argmin}\{SQR(\mu)\} \tag{29}$$

$$SQR = \sum_{i=1}^{n}(f_i - \hat{f}_i)^2 \qquad (30)$$

Where $\hat{f}_i$ is a matrix containing the approximate numerical values of the distribution function of the mixture model computed at each wind speed data point. f_i is a matrix containing the observed values of the probabilities of occurrence of wind speeds, and n is the total number of wind speed data. The Equation (31) can be written as:

$$SQR = E'E \qquad (31)$$

With:

$$E_i = f_i - \hat{f}_i \qquad (32)$$

E' is the transpose of the matrix E. Levenberg-Marquardt method depends on the search for the SQR gradient of Equation (30) concerning µ following:

$$\frac{\partial(E' \times E)}{\partial \mu} = -2X'f + 2X'f(\mu) = -2X'E \qquad (33)$$

where µ is the matrix containing the vectors w_i, ki, c_i, and X is the dimension matrix mxn which contains the partial derivatives of f concerning the parameters:

$$X = \frac{\partial f}{\partial \mu} \qquad (34)$$

E is the matrix with size $nx1$ which contains the errors at each point of wind speed data. The vector of the set of parameters that makes it possible to obtain the sum of the minimum possible quadratic residues is then obtained after the combination of the Gauss-Newton method and the conjugate gradient by the general iterative Equation (35) with μ^i the vector of parameters expressed by Equation (36)

$$\mu^{i+1} = \mu^i + (X'.X + \lambda I)^{-1}.X'.E \qquad (35)$$

$$\mu_i = (\omega_i, k_i, c_i, F_0) \qquad (36)$$

Where λ is a scale constant, m is the number of components of the model.

9. Methodology

This section highlights the process for developing the models in our work from mixtures of Weibull and hybrid Weibull distributions whose parameters are estimated by the Expectation-Maximization algorithm.

9.1. Description of the proposed approach

The most suitable wind turbine model which needs to be installed in a wind farm is selected by careful wind energy resource evaluation. An accurate evaluation could be done using the best-fit distribution model. Thus, using inappropriate

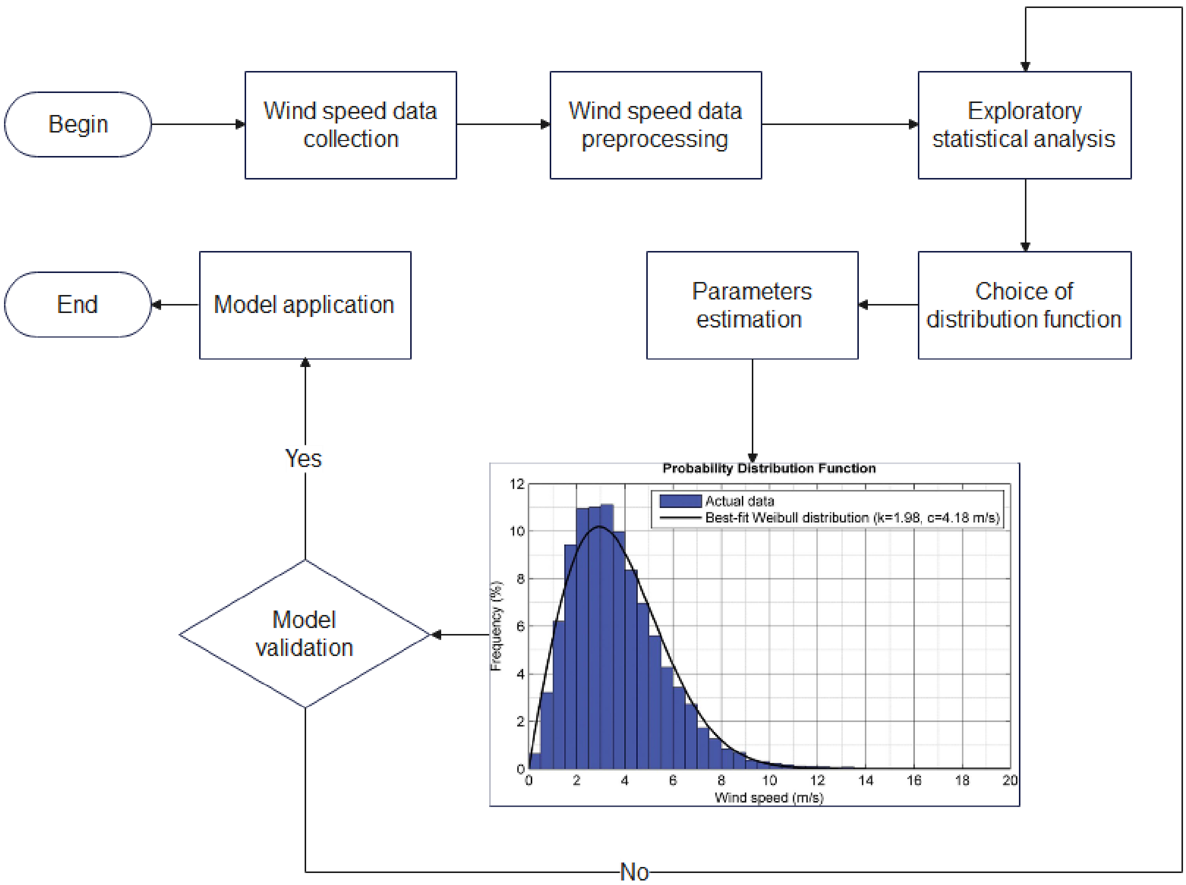


Fig. 1. Methodology adopted for modeling wind speed data

Table 1
Characteristics of the selected sites

Sites	Latitude	Longitude	Altitude (m)	Mean (m/s)	St. dev. (m/s)	Skewness	Kurtosis	Height (m)	Period
Abuja	9.25N	7.00 °E	344	2.43045	1.27036	1.25746	11.03356	10	2012-2022
Accra	5.60N	0.17 °W	69	4.16032	2.21591	0.08801	2.76699	10	2006-2018
Cotonou	6.35N	2.38 °E	9	4.01159	1.81438	-0.12249	2.49218	10	2012-2022
Lome	6.17N	1.25 °E	25	3.52870	2.02964	0.26247	2.33358	10	2012-2022
Tambacounda	13.77N	13.68 °W	50	2.95754	1.64106	1.36276	8.59716	10	2012-2022

distribution models gives an inaccurate estimation of wind turbine capacity and annual energy production which leads to an improper estimation of levelized production cost. Hence, it is important to choose an accurate distribution model which cl osely mimics the wind speed distribution at a particular site. Hence, let us consider the output V as a random variable on a set Ω, taking values v_i with $i \in \{1, 2, ..., n\}$. We define on Ω, a distribution of V which ∀ v_i, we associate the distribution function $f(v_i)$. Fig. 1 shows the methodology adopted for modeling wind speed data. This process follow these steps :

- the wind speed data over a significant period are collected. They come from wind sites where measuring devices are installed on wind turbines;
- the pre-processing of the wind speed data to remove outliers and correct for other contingencies to ensure data quality Before performing statistical analysis. The collected wind data are first filtered to eliminate errors, omissions, gaps, and other non-exploitable values. For wind energy applications, wind speeds above 25 m/s are not exploited, so for this study, these speeds are not considered;
- an exploratory statistical analysis of the data to understand the nature of the distribution and overall behavior of this data is proceeded;
- the distribution law that best describes the behavior of the wind speed of the site studied is choose. In our context, we used the Weibull law, hybrid Weibull, Weibull mixture, and hybrid Weibull mixture to model the wind speed;
- the parameters are fitted to real data using statistical estimation methods, such as EPF, W-EMJ, W-ML, and E-M algorithm. Then, from these data, we calculate the Weibull parameters k and c by the three methods EPF, W-EMJ, and W-ML, as well as those of the mixing model and the hybrid mixing model. The parameters of the mixture model and the mixture hybrid model are estimated by the Bayesian approach using the expectation-maximization algorithm, generating the initial values from the Levenberg-Marquardt algorithm. The parameters estimated by all the mentioned methods will be used to calculate the wind power density;
- Subsequently, it is essential to validate the chosen model by comparing the values predicted by the latter to the actual data. The use of performance criteria such as relative percentage error (RPE), root mean square error (RMSE), and correlation coefficient (R^2) highlights the good agreement between the predicted values and the observed data indicating a good fit;
- finally, the model can be used for various applications, such as resource assessment for wind energy projects, estimation of energy yields, or other wind-related studies.

9.2. Description of the modeling data

Table 1 presents the characteristics of the selected sites. The collected wind data cover the period from January 2012 to December 2022, i.e. a twelve (12) year registration period for all sites except the Accra site where data covers the period from January 2006 to December 2018. The data are recorded daily at one-hour intervals at 10 meters height. At the annual scale, wind data collected over 12 years for the Abuja, Accra, Cotonou, Lome, and Tambacounda sites are used to represent frequency histograms that represent the actual probabilities of wind occurrence.

9.3. Performance criteria

Several statistical indicators, including relative percentage error (RPE), root mean square error (RMSE), and correlation coefficient (R^2) calculated respectively by Equations (37), (38), (39) are used to evaluate the performance of the methods.

$$RPE = \left|\frac{P_w - P_m}{P_m}\right| \times 100 \tag{37}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_{i,w} - f_{i,m}\right)^2} \tag{38}$$

$$R^2 = \frac{\sum_{i=1}^{N}(f_{i,w} - \overline{f_{i,w}})(f_{i,m} - \overline{f_{i,m}})}{\sqrt{\sum_{i=1}^{N}(f_{i,w} - \overline{f_{i,w}})^2 \sum_{i=1}^{N}(f_{i,m} - \overline{f_{i,m}})^2}} \tag{39}$$

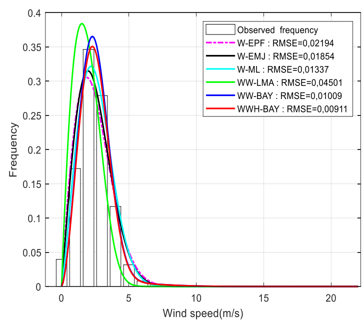
10. Results and discussions

The Table 2 summarizes the parameters estimated by the mentioned methods pour Abuja, Accra, Cotonou, Lome, and Tambacounda. The Analysis of the k and c (m/s) form factor values for each site shows variations according to the methods used. The peak value of k is reached for Cotonou with the ML method. With the EMJ method, on the other hand, Abuja has the lowest c (m/s) value. Furthermore, the k and c (m/s) values observed at the wind farm sites studied show similar trends. However, on some sites there is a slight discrepancy. This is because the shape factor k characterizes the asymmetry of the distribution and the scale factor c (m/s) the dimension of the wind speed. Generally, for all methods, k is in the range 1 to 3, and c (m/s) between 0 and 5. For the Abuja site, the estimated values of the k parameters by EPF, EMJ, and ML are 1.92332, 2.02298, and 2.21170 respectively, while the values of the c (m/s) parameters are 2.73997, 2.74300 and 2.85822. For the Accra site, the k-parameter values estimated by these methods are respectively in the order of 2.06160, 1.98199, and 2.38247, while the c (m/s) parameter values are 4.69648, 4.69359, and 5.01723. At the Cotonou site, the specific variations in the parameters of the Weibull distribution follow the same trend for the different EPF, EMJ, and ML methods (k equal to 2.43719, 2.36714, and 2.57223) and (c (m/s) equal to 4.52393, 4.52638 and 4.61735). The same is true for Lome and Tambacounda, where the k and c (m/s) parameters estimated by EPF, EMJ, and ML have the following values respectively: (1.88456,

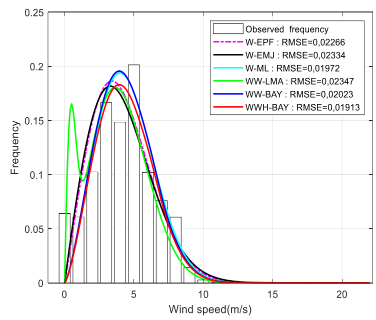
Table 2
Parameters estimated by fitted models

Method	Parameters and indicators values	Abuja	Accra	Cotonou	Lome	Tambacounda
W-EPF	k	1.92332	2.06160	2.43719	1.88456	1.79351
	c (m/s)	2.73997	4.69648	4.52393	3.97553	3.32516
	RMSE	0.02194	0.02266	0.02241	0.01949	0.02035
	R^2	0.97324	0.93629	0.95881	0.96762	0.96860
W-EMJ	k	2.02298	1.98199	2.36714	1.82327	1.89586
	c (m/s)	2.74300	4.69359	4.52638	3.97037	3.33272
	RMSE	0.01854	0.02334	0.02249	0.01869	0.01788
	R^2	0.98084	0.93033	0.95703	0.96872	0.97557
W-ML	k	2.21170	2.38247	2.57223	2.03100	0.02326
	c (m/s)	2.85822	5.01723	4.61735	4.17884	3.43488
	RMSE	0.01337	0.01972	0.02055	0.02004	0.01695
	R^2	0.99008	0.95491	0.96701	0.96494	0.97796
WW-LMA	w	0.69577	0.88585	0.81547	0.52405	0.53894
	c_1 (m/s)	2.46764	4.66468	4.56089	1.95598	2.67169
	c_2 (m/s)	1.30956	0.65927	1.17173	4.87829	2.66792
	k_1	2.53358	2.31051	3.20133	1.24766	1.64290
	k_2	1.84830	1.89783	1.87836	3.95609	2.37055
	RMSE	0.04501	0.02347	0.02464	0.02038	0.02732
	R^2	0.90566	0.92945	0.95139	0.96308	0.95008
WW-BAY	w	0.95462	0.99057	0.12621	0.19754	0.60601
	c_1 (m/s)	3.11698	4.93447	1.62810	1.58985	2.75114
	c_2 (m/s)	2.17732	6.28726	4.99847	4.79200	4.44858
	k_1	2.23477	2.38442	3.08857	3.03324	2.78562
	k_2	3.3957	9.95976	3.30687	2.68474	2.15675
	RMSE	0.01009	0.02023	0.00686	0.01331	0.00817
	R^2	0.99665	0.95381	0.99676	0.98445	0.99525
WWH-BAY	F_0	0.0396	0.0750	0.0219	0.0451	0.0250
	w	0.95462	0.99057	0.12621	0.19754	0.60601
	c_1 (m/s)	2.75683	4.93447	1.62810	1.58985	2.75114
	c_2 (m/s)	4.94110	6.28726	4.99847	4.79200	4.44858
	k_1	2.57782	2.38442	3.08857	3.03324	2.78562
	k_2	1.89848	9.95976	3.30687	2.68474	2.15675
	RMSE	0.00911	0.01913	0.00642	0.01243	0.00791
	R^2	0.99565	0.95381	0.99676	0.98445	0.99525

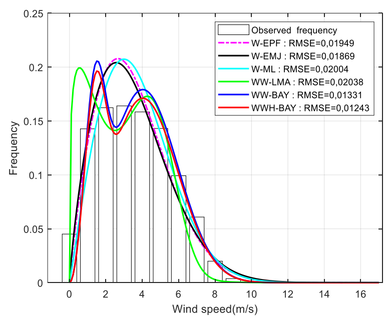
1.82327, and 2.03100 for Lome) and (1. 79351, 1.89586 and 0.02326 for Tambacounda) for k values, and (3.97553, 3.97037 and 4.17884 for Lome) and (3.32516, 3.33272 and 3.43488 for Tambacounda) for c (m/s) values. Indeed, when c (m/s) value is low, the site is less windy; and windy in the opposite case. These c (m/s) values show the presence of several wind regimes



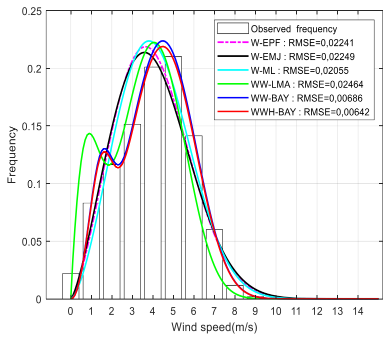
a. Probability distribution function - Abuja



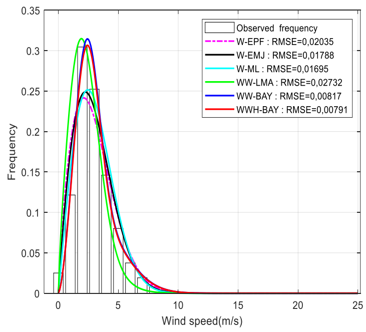
b. Probability distribution function - Accra



c. Probability distribution functions – Lome

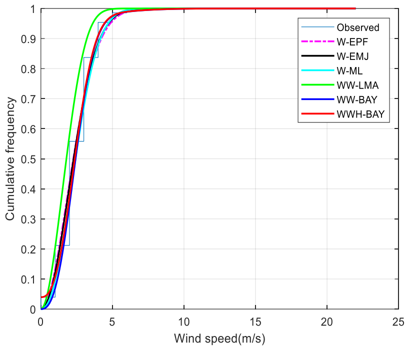


d. Probability distribution function - Cotonou

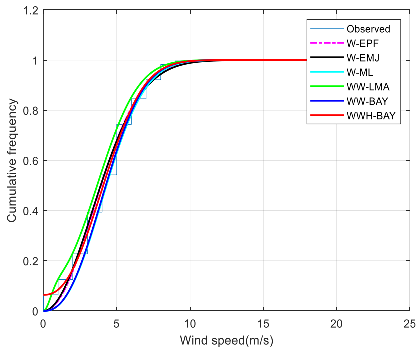


e. Probability distribution function - Tambacounda

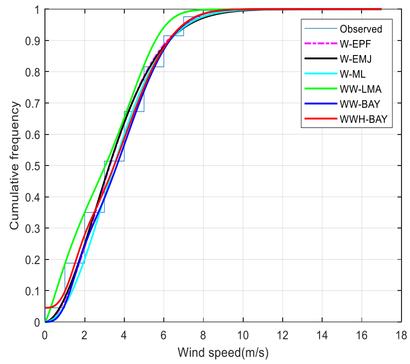
Fig.2. Probability distribution functions for select wind sites



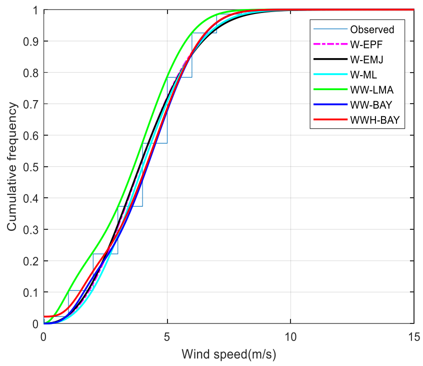
a. Cumulative distribution function - Abuja



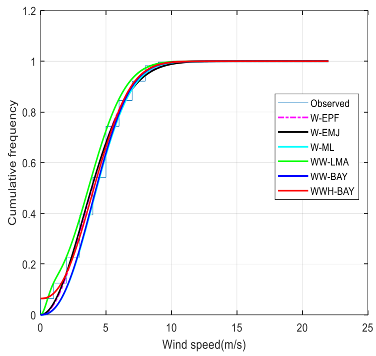
b. Cumulative distribution function - Accra



c. Cumulative distribution functions – Lome



d. . Cumulative distribution function - Cotonou

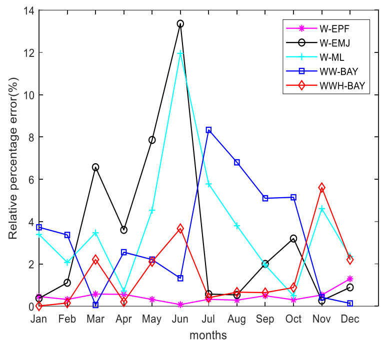


e. Cumulative distribution function - Tambacounda

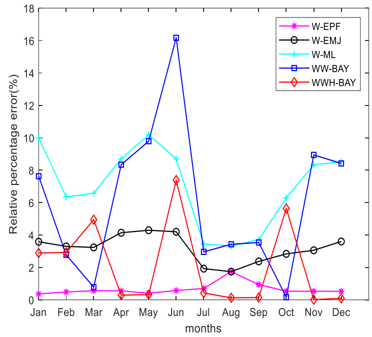
Fig.3. Cumulative distribution functions for wind sites

at these wind farm sites (Abuja, Accra, Cotonou, Lome, and Tambacounda). This led to the use of the WW-BAY and WWH-BAY methods (Table 2) based on the Bayes approach, with parameters estimated by the E-M algorithm whose initial values are given by the Levenberg-Marquardt algorithm (LMA). The RMSE and R^2 values are used to evaluate the performance of each method. The best method can be selected based on a compromise between the highest value of R2 and the lowest value of RMSE. The RMSE results obtained with the WW-LMA model show high values for all sites compared with the other methods. For the EPF method, RMSE values for the different cities (Abuja, Accra, Cotonou, Lome, Tambacounda) vary between 0.01949 and 0.02266. R^2 values for the cities range from 0.93629 to 0.97324. This indicates that the EPF method explains between 93.6% and 97.3% of the variance in the data for each site. For EMJ, RMSE values range from 0.01788 to 0.02334, with R^2 ranging from 93.0% to 98.1%. RMSE values for cities range from 0.01337 to 0.02055 using the ML method, with R^2 values between 95.5% and 99.0%. RMSE values for WW-BAY are generally lower than those of the other methods. They range from 0.00686 to 0.02023. The R^2 values for sites range from 95.4% to 99.7%, and are generally high, indicating good model fit. With the WWH-BAY model, RMSE values for cities range from 0.00642 to 0.01913. This suggests that the predictions obtained with the WWH-BAY method have an average error between these values for each city. The R^2 values are between 0.95381 to 0.99676. These values indicate that the WWH-BAY method explains between 95.4% and 99.7% of the variance in the data for each city. The R^2 values for WWH-BAY are also high. For all sites, WWH-BAY has low RMSEs compared with the other methods. It is followed by WW-BAY. From the above, we can see that WW-BAY and WWH-BAY provide the best fits, with generally lower RMSE values and higher R^2 values, indicating a better model fit to the wind data. The Figs.2. a., b., c., d., e.; and Fig. 3. a., b., c., d., e. show that the WWH-BAY model performs well. In addition, to obtain the best estimate of wind power density, the RPE indicator is used. The lower the RPE indicator, the better the method.

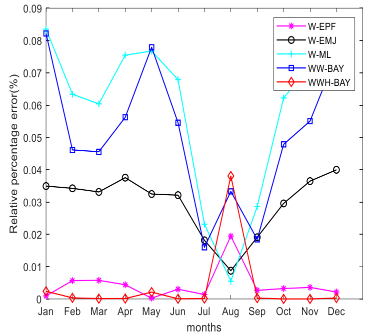
The results presented in Table 3 show that the WWH-BAY model performs best for wind power density estimation at the Cotonou and Lome sites. In contrast, the EPF method is suitable for the Abuja and Accra sites. In addition, the WW-BAY method gives the best performance for the Tabacomda site. This is reflected in the results of fitting the distribution of wind speed data at these different sites on Fig. 4. a., b., c., d., e., and 3.e., which show the variations in the absolute value of the EPR error relative to the calculation of power density using wind distribution functions. Table 3 shows the results of different methods for estimating power density and relative power error (using RPE) for five cities: Abuja, Accra, Cotonou, Lome, and Tambacounda. The methods used are W-EPF, W-EMJ, W-ML, WW-BAY, and WWH-BAY. A full analysis of Fig. 4. a., b., c., d., e., and Table 3 compares the estimated and measured power density for each site according to each method and the relative power error (RPE), reveals the following characteristics: overall, the EPF method provides relatively accurate power density estimates, with EPRs generally close to zero for most sites. The estimated power density values are usually relative to the measured values, indicating good agreement between both. However, the W-EPF method slightly underestimates the power density in a few cases, as observed for Abuja and Lome with negative EPRs. The W-EMJ method shows variable performance across sites. For some sites, such as Abuja and Lome, the power density estimates are quite close to the actual measurements, as shown by the low EPR values. However, for



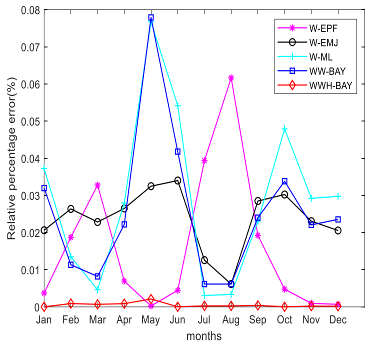
a. Power density errors - Abuja



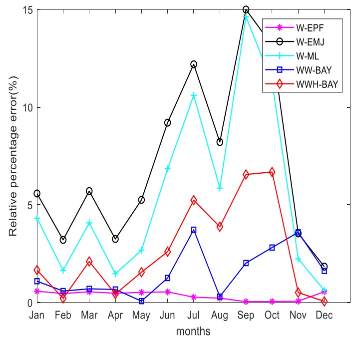
b. Power density errors - Accra



c Power density errors – Lome



d. . Power density errors - Cotonou



e. Power density errors - Tambacounda

Fig.4. Power density errors calculated for s
wind sites

other sites, such as Accra, the estimates show significant error, indicated by high EPR. The W-ML method shows a tendency to overestimate the power density compared to the actual measurements. For most sites, the EPR values are positive, indicating an overestimation of the estimated power density compared to the measurements. Despite this, the differences between the estimates and measurements remain relatively small, suggesting a reasonable approximation of the method. The WW-BAY method has a similar performance to the W-EPF method. The power density estimates are generally close to the actual measurements, with EPRs near zero for most sites. However, some notable differences are observed for specific sites, such as Lome, where the WW-BAY method overestimates the power density. The WWH-BAY method shows comparable results to the W-EPF method. The EPR values are generally close to zero, indicating good agreement between the estimates and the actual measurements. However, there are cases where the WWH-BAY method shows a significant error, as observed for Accra with a high EPR.

11. Conclusion

The distribution of wind speed is an important tool for the design of wind farms, and power generators. In most cases, Weibull distribution is widely used. However, in the case of the multimodal aspect of wind speed distribution, the use of classical Weibull distribution is limited. Thus, Weibull mixture is

Table 3
Parameters estimated by fitted models

Method	Error	Abuja	Accra	Cotonou	Lome	Tambacounda
W-EPF	Power density (W/m^2)	17.48318	81.76899	63.56021	54.68574	34.04155
	RPE (%)	-0.54752	-0.55774	0.31634	-0.51109	-0.37414
W-EMJ	Power density (W/m^2)	16.60532	85.00413	65.00443	56.73312	31.99003
	RPE (%)	-5.54118	3.37662	2.59574	3.21367	-6.37809
W-ML	Power density (W/m^2)	17.27552	88.11041	65.24766	58.47545	32.60194
	RPE (%)	-1.72875	7.15429	6.38346	6.38346	-4.58728
WW-LMA	Power density (W/m^2)	7.60390	64.22049	46.46320	38.36405	16.91939
	RPE (%)	-56.74548	-21.89912	-26.66767	-30.20489	-50.48377
WW-BAY	Power density (W/m^2)	17.96266	84.26982	64.77892	57.56959	34.23510
	RPE (%)	2.18001	2.48361	2.23983	4.73544	0.19232
WWH-BAY	Power density (W/m^2)	17.25066	78.86656	63.36200	54.97263	33.37868
	RPE (%)	-1.87017	-4.08750	0.00351	0.01084	-2.31407
Measured power density (W/m^2)		17.57943	82.22761	63.35978	54.96667	34.16939

used. The purpose of our study is to determine the best model that accurately characterizes the wind potential of five sites in West Africa for estimating using mixture Weibull (WW-BAY) and mixture hybrid Weibull (WWH-BAY) distributions based on the Bayes approach, and the classic Weibull distribution which parameters were estimated by the EPF, EMJ, and ML methods. The results obtained show that the WWH-BAY method performs well the wind speeds distribution than other mentioned distributions. Based on the RPE values which are less than 10%, EPF, WW-BAY, and WWH-BAY give respectively the best estimate of the power density at the Abuja and Accra cites, Tambacounda site, Cotonou, and Lome sites. Therefore, the use of the WWH-BAY model is recommended to characterize the wind potential in West Africa, especially Lome and Cotonou sites. Overall, the use of the WWH-BAY model presents prospects for advanced wind energy planning and development in West Africa and other regions. This study contributes to the establishment of sustainable and adaptable energy systems, thus enhancing resilience.

Acknowledgments

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