Revue des Energies Renouvelables Vol. 18, N°1 (2015) 105 – 125

Statistical analysis of wind speed distribution based on six Weibull Methods for wind power evaluation in Garoua, Cameroon

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(reçu le 6 Octobre 2014 – accepté le 30 Mars 2015)

Abstract - *Wind data analysis and accurate wind energy potential assessment are critical factors for suitable development of wind power application at a given location. This paper explores wind speed distribution to select the two-parameter Weibull methods that provide accurate and efficient estimation of energy output for Wind Energy Conversion Systems (WECS).The dimensionless shape parameter k and the scale parameter C are determined based on measured hourly mean wind speed data in times-series from 2007 to 2012, collected at the Garoua International Airport, main meteorological station, in Garoua, Cameroon. Six numerical methods, namely Empirical Method (EM), Energy Pattern Factor method (EPF), Graphical Method (GM), Maximum Likelihood Method (MLM), Moment Method (MM) and Modified Maximum Likelihood Method (MMLM) are examined to estimate the Weibull parameters. To analyze the efficiency of the methods and to ascertain how closely the measured data follow the Weibull methods, goodness of fit tests were performed using the chi-square test (χ^2), correlation coefficient (R^2), root mean square error (RMSE) and Kolmogorov-Smirnov test (KOL). The results revealed that the EPF followed by the MM were the most accurate and efficient methods for determining the value of C and k to approximate wind speed distribution. The statistical tests rejected the GM as an adequate method and revealed as well that the EM, MLM and MMLM ranked respectively third, fourth and fifth. Furthermore, the potential for wind energy development in Garoua is not fitted for generating electricity and a very fruitful result would be achieved if windmills were installed for producing community water supply, livestock watering, and farm irrigation.*

Résumé - *L'analyse des données du vent et l'estimation du potentiel éolien sont des facteurs déterminant pour le développement des éoliennes. Cet article explore les données horaires de vitesse du vent afin de choisir les méthodes de Weibull à deux paramètres, les plus précises et aptes à évaluer l'énergie produite par les éoliennes. Le facteur adimensionnel de forme k et le facteur d'échelle C sont ainsi déterminés sur la base des données mesurées (2007 à 2012), obtenues auprès de la station météorologique de l'aéroport international de Garoua au Cameroun. Six méthodes numériques, à savoir, la Méthode Empirique (EM), la Méthode du Facteur d'Energie (EPF), la Méthode Graphique (GM), la Méthode du Maximum de Vraisemblance (MLM), la Méthode de Moment (MM) et la Méthode Modifiée du Maximum de Vraisemblance (MMLM) sont ainsi examinées pour calculer les paramètres de Weibull. Afin d'analyser l'efficience des dites méthodes et d'établir la méthode qui se rapproche davantage des données mesurées, les tests de performance du chi-carrée (χ^2), du coefficient de correlation (R^2), de l'erreur moyenne quadratique (RMSE) et de Kolmogorov-Smirnov (KOL) ont été effectués. Les résultats ont révélé que les méthodes EPF et MM sont les plus précises et efficientes pour déterminer les valeurs de C et k. Les tests statistiques ont également révélés que la méthode GM n'est pas appropriée et que les méthodes EM, MLM et MMLM sont respectivement classées troisième, quatrième et cinquième. De plus, the potentiel*

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énergétique éolien dans la localité de Garoua n'est pas approprié pour produire de l'électricité et que des meilleurs résultats pourraient être obtenus si des éoliennes mécaniques étaient installées pour produire de l'eau pour la communauté, l'abreuvage du bétail et l'irrigation des fermes agricoles.

Keywords: Maximum likelihood method - Modified maximum likelihood method - Graphical method - Energy pattern factor method - Empirical method.

1. INTRODUCTION

The rate of energy consumption in Cameroon is rising rapidly and fossil fuels remain the major energy sources that play crucial role in meeting energy demand despite their negative effects on the environment. Although Cameroon is an oil producing Country, high amount of currency is spent to import crude oil to meet energy demand. Recently, the Cameroonian government has taken steps to reduce its dependence on imported oil products, which negatively affects its trade balance.

It is expected that the importance of this economical issue and the environmental pollution problem associated with the use of oil, will boost over time the development of renewable energy resources, which have gained huge magnitude due to their sustainability, inexhaustibility and ecological awareness. More than a decade ago, the government has adopted policies aimed at increasing the use of renewable energy; so far, detailed evaluation of renewable resources is a major concern. Small hydropower is yet to be fully exploited while the maximum utilization of biomass, solar and wind energy resources is not in view.

Among the sources of renewable energy, wind energy is the most common and fastest-growing energy technology in terms of percentage of yearly growth of installed capacity [1]. 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 [2]. According to Rehman *et al.* [3], wind resources are seldom consistent and vary with time of the day, season of the year, height above the ground, type of terrain, and from year to year, hence should be investigated carefully and completely.

Due to the absence of a reliable and accurate cameroonian wind atlas, wind resources evaluation has so far received only limited attention in this country and further studies on the assessment of wind energy are necessary. Until now,a small amount of work is reported in the literature on various aspects of wind energy such as its measurements, conversion, and utilization.

Tchinda *et al.* [4] presented the estimation of mean wind energy available in the far North region of Cameroon. In another study Tchinda *et al.* [5] analysed wind speed and wind energy distributions in the Adamaoua and North region.

It was observed that wind energy potential in the north and far region of Cameroon is not fitted for generating electricity and a very fruitful result would be achieved if windmills were installed for producing community water supply, livestock watering, and farm irrigation.

Kidmo *et al.* [6] performed an assessment of the wind energy for small-scale water pumping in the north region of Cameroon by means of the Weibull Probability Density Function (PDF) with two parameters. The maximum likelihood method (MLM) was used to estimate the dimensionless Weibull shape parameter k, and the Weibull scale parameter C.

The maximum wind power density extracted by the blades as well as the useful average hydraulic power output and the daily water production of a hypothetic windmill were determined in order to forecast applications in the north region of Cameroon such as providing domestic water, watering farm animals and small scale irrigation.

Furthermore, Kidmo *et al.* [7-9] studied the performance assessment of five numerical methods for estimating Weibull distribution parameters for WECS in Maroua, Kousseri, Ngaoundéré, Banyo and Meiganga.

The aim of that analysis was to select between the maximum likelihood method (MLM), the modified maximum likelihood method (MMLM), the energy pattern factor method (EPF), the graphical method (GM) and the empirical method (EM), the most accurate two-parameter Weibull PDF method to represent the wind data collected in each of the above mentioned locality. The results strongly recommended the EPF method as the more accurate estimation of the Weibull parameters in order to reduce uncertainties related to the wind energy output calculation.

Afungchui *et al.* [10] analyzed based on the Weibull distribution, using the graphical method, wind regimes for energy estimation in Bamenda, North West Region of Cameroon. The results of this study suggested, based on the data obtained through the RETScreen software tool provided by CANMET Canada, that Bamenda could be only suitable for the development of mechanical wind power for water pumping. This study must be reinforced by complementary observations on sites to further draw a conclusion.

Wind data analysis and accurate wind energy potential assessment is critical for proper and efficient development of wind power application and is highly site-dependent [11]. As a result, knowledge of the statistical properties of wind speed is essential for predicting the energy output of WECS. For statistical distribution of wind speed data analysis, Weibull PDF function is usually considered as the most qualified function due to its simplicity and high accuracy [12].

A large numbers of studies have been published in scientific literature that proposes the use of two-parameter Weibull PDF methods to describe wind speed frequency distributions. More Recently in 2014, Azad *et al.* [13] presented statistical diagnosis of the best Weibull methods for wind power assessment for agricultural applications. Al Zohbi *et al.* [14] evaluated wind potential of Lebanon using Weibull PDF. Indhumathy *et al.* [15] dealt with the estimation of Weibull parameters for wind speed calculation at Kanyakumari in India.

Petkovic *et al.* [16] performed an appraisal of wind speed distribution prediction by soft computing methodologies. Adaramola *et al.* [17] evaluated the performance of wind turbines for energy generation in Niger Delta, Nigeria.

In 2012, Costa Rocha *et al.* [18] analyzed and compared the performance of seven numerical methods for the assessment of effectiveness in determining the parameters for the Weibull distribution, using wind data collected for Camocim and Paracuru cities in the northeast region of Brazil.

The Weibull PDF has been employed almost unanimously by researchers involved in wind speed analysis and it has also extensively been used in wind power analysis for many decades [19].

According to International Standard IEC 61400-12 and other international recommendations, the two-parameter Weibull probability density function is the most appropriate distribution function for wind speed data as it gives a good fit to the observed wind speed data both at surface and in the upper air [1, 20, 21].

In the present study, six Weibull PDF methods, namely the MML, MMLM, EPF, GM, EM and MM are explored and their performance assessed using the chi-square test (χ^2), correlation coefficient (R^2), root mean square error (RMSE) and Kolmogorov-Smirnov test (KOL) for goodness of fit to precisely rank and acknowledge the methods that are adequate for the specific wind data collected for the district of Garoua.

The aim of this work is to select a method that gives more accurate estimation for the Weibull parameters as to reduce uncertainties related to predicting the wind energy output of WECS.

2. MATERIALS AND METHODS

2.1 Data source

The wind speed data in hourly time-series format over a period of 6 years (2007 - 2012) have been collected and statistically analyzed. The wind speed data were recorded at a height of 10 m, continuously by a cup-generator anemometer at the International Airport of Garoua, main meteorological station.

Table 1 provides geographical coordinates of the Meteorological station in Garoua.

Table 1: Geographical coordinates of the Meteorological station in Garoua

Location	Variable	Value
Garoua	Latitude	09°20' N
	Longitude	13°23' E
	Anemometer height	10 m
	Elevation	242 meters above sea level

2.2 Measured mean wind speed and standard deviation

The monthly mean wind speed V_m and the standard deviation σ of the time-series of measured hourly wind speed data are determined using the {Eq. (1)} and {Eq. (2)}, [12, 16, 22, 23]:

$$v_m = \frac{1}{N}\left(\sum_{i=1}^{N} v_i\right) \tag{1}$$

$$\sigma = \left[\frac{1}{N-1}\sum_{i=1}^{N}(v_i - v_m)^2\right]^{1/2} \tag{2}$$

Where, v_m, mean wind speed, m/s; σ, standard deviation of the observed data, m/s; v_i, hourly wind speed, m/s; N, number of measured hourly wind speed data.

2.3 Measured wind speed probability distributions

In a study, Lysen [24] quoted that to determine frequency distribution of the wind speed, we must first divide the wind speed domain into a number of intervals, mostly of equal width of 1 m/s.

As a result, for a suitable statistical analysis, the wind speed data in time series format were transformed into frequency distribution format. Based on the wind speed classes (bins), the frequency distribution of the measured wind speed was established and shown by the **Table 2**.

Table 2: Wind speed data transformed into frequency distribution format

→Bins Period↓	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-11
January	0.315	0.401	0.199	0.068	0.015	0.002	0.000	-	-	-	-
February	0.309	0.401	0.191	0.067	0.016	0.003	0.000	-	-	-	-
March	0.154	0.359	0.288	0.148	0.043	0.007	0.001	-	-	-	-
April	0.071	0.267	0.313	0.189	0.091	0.042	0.016	0.006	0.003	0.001	0.000
May	0.083	0.308	0.310	0.174	0.081	0.031	0.011	0.002	0.001	-	-
June	0.091	0.314	0.302	0.171	0.075	0.030	0.011	0.004	0.001	0.0000	-
July	0.113	0.362	0.283	0.132	0.067	0.028	0.011	0.003	0.001	0.000	-
August	0.192	0.457	0.226	0.083	0.030	0.009	0.002	0.000	-	-	-
September	0.259	0.481	0.187	0.053	0.015	0.004	0.000	-	-	-	-
October	0.281	0.483	0.151	0.055	0.021	0.007	0.001	0.000	-	-	-
November	0.389	0.420	0.129	0.044	0.014	0.003	0.000	-	-	-	-
December	0.459	0.399	0.115	0.024	0.004	0.000	-	-	-	-	-
Whole Year	0.226	0.389	0.225	0.101	0.039	0.014	0.005	0.001	0.000	0.000	0.000

Wind speed distribution in frequency format

Table 3 provides for the whole year, measured wind speed data arranged in frequency and cumulative distribution format of equal width of 1 m/s. The Weibull PDF methods can be used to estimate the Weibull parameters, given wind speed in either time-series or frequency distribution format. In this process, the wind speeds were grouped into classes (bins), see **Table 3** (the second column).

The mean wind speeds v_i are calculated for each speed class intervals (the third column). The fourth column gives the frequency of occurrence of each speed class (f_i). The fifth column presents the probability of the measured wind speed based on the {Eq. (3)} as given [12, 19]:

$$f(v_i) = \frac{f_i}{\sum_{i=1}^{N} f_i} = \frac{f_i}{N} \tag{3}$$

The mean wind speed and its standard deviation are calculated using the following equations, respectively, as given in,

$$\overline{V} = \frac{\sum_{i=1}^{N} f_i \cdot v_i}{\sum_{i=1}^{N} f_i} = \frac{1}{N}\left[\sum_{i=1}^{N} f_i \cdot v_i\right] \tag{4}$$

$$\sigma = \left[\frac{1}{N-1}\sum_{i=1}^{n} f_i \cdot (v_i - v_m)^2\right]^{1/2} \tag{5}$$

Table 3: Measured Wind speed Data arranged in frequency and cumulative distribution format of equal width of 1 m/s

i	v	v_i	f_i	$f(v_i)$	$f(v)$
1	0-1	0.686	11866	0.226	0.226
2	1-2	1.471	20430	0.389	0..614
3	2-3	2.440	11809	0.225	0.839
4	3-4	3.427	5303	0.101	0.940
5	4-5	4.421	2071	0.039	0.979
6	5-6	5.416	735	0.014	0.993
7	6-7	6.409	243	0.005	0.998
8	7-8	7.393	72	0.001	0.999
9	8-9	8.491	32	0.000	1.000
10	9-10	9.332	6	0.000	1.000
11	10-11	10.467	1	0.000	1.000
			$\sum_{i=1}^{N} f_i = N = 52560$	$\sum_{i=1}^{N} f(v_i) = 1000$	

Table 4 provides for class intervals (bins), monthly mean wind speed. **Table 5** presents monthly mean wind speeds and standard deviations, obtained using data in times-series and frequency distributions formats. A comparison by means of relative error shows no difference for the mean wind speeds while standard deviations values obtained using time-series format are comparatively larger (2.038 to 4.543 %) than the values determined using the frequency distribution format.

Table 4: Mean wind speeds ν_i calculated for each speed class intervals

→Bins Period↓	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-11
January	0.667	1.466	2.420	3.393	4.376	5.337	6.133	-	-	-	-
February	0.681	1.447	2.419	3.399	4.386	5.394	6.411	-	-	-	-
March	0.701	1.490	2.470	3.420	4.380	5.382	6.285	-	-	-	-
April	0.719	1.553	2.480	3.443	4.438	5.442	6.433	7.365	8.402	9.349	10.467
May	0.710	1.542	2.466	3.441	4.427	5.407	6.409	7.438	8.680	-	-
June	0.713	1.539	2.462	3.441	4.427	5.413	6.404	7.410	8.579	9.454	-
July	0.712	1.526	2.442	3.446	4.460	5.443	6.409	7.435	8.482	9.040	-
August	0.701	1.481	2.414	3.425	4.419	5.382	6.461	7.362	-	-	-
September	0.701	1.448	2.409	3.406	4.420	5.403	6.625	-	-	-	-
October	0.697	1.436	2.404	3.430	4.415	5.439	6.353	7.129	-	-	-
November	0.681	1.401	2.413	3.405	4.379	5.377	6.314	-	-	-	-
December	0.658	1.407	2.383	3.386	4.358	5.329	-	-	-	-	-
Whole Year	0.686	1.471	2.440	3.427	4.421	5.416	6.409	7.393	8.491	9.332	10.467

Table 5: Monthly mean wind speeds and standard deviations for time-series and frequency formats

	Time-Series format		**Frequency format**		**Relative error**	
Period	ν_m	σ_{ts}	$\overline{V}$	σ_f	ε_ν	ε_σ
January	1.585	0.920	1.585	0.881	0.000%	4.170%
February	1.588	0.930	1.588	0.893	0.000%	4.078%
March	2.093	1.057	2.093	1.022	0.000%	3.392%
April	2.711	1.385	2.711	1.357	0.000%	2.038%
May	2.511	1.256	2.511	1.225	0.000%	2.474%
June	2.492	1.296	2.192	1.266	0.000%	2.302%
July	2.333	1.287	2.333	1.258	0.000%	2.324%
August	1.840	1.017	1.840	0.981	0.000%	3.559%
September	1.603	0.884	1.603	0.843	0.000%	4.543%
October	1.583	0.949	1.583	0.913	0.000%	3.857%
November	1.395	0.870	1.395	0.832	0.000%	4.379%
December	1.237	0.733	1.237	0.688	0.000%	6.134%
Whole Year	1.915	1.168	1.915	1.136	0.000%	2.704%

2.4 Methods to estimate Weibull parameters

The two-parameter Weibull PDF has been generally used in scientific literature to express the wind speed frequency distribution and to estimate the wind power density. It's is the most appropriate distribution function for wind speed data as it gives a good fit to the observed wind speed data both at surface and in the upper air [1, 20, 21]. Weibull distribution can be characterized by its probability density function $f(\nu)$ and cumulative distribution function $F(\nu)$ as follows [2, 12, 14, 16, 18, 22, 23, 25-29]:

$$F(\nu) = \left(\frac{k}{C}\right).\left(\frac{\nu}{C}\right)^{k-1}.\exp\left[-\left(\frac{\nu}{C}\right)^{k}\right] \tag{6}$$

And $$F(\nu) = 1 - \exp\left[-\left(\frac{\nu}{C} \right)^{k} \right] \qquad (7)$$

Where, $F(\nu)$, probability of observing wind speed ν; ν, wind speed, (m/s); C, Weibull scale parameter, (m/s); k, Weibull shape parameter.

Six numerical methods to estimate the dimensionless shape k, and the shape C, parameters of the Weibull PDF are computed.

2.4.1 Graphical Method

The Graphical method requires that wind speed data be in cumulative frequency distribution format. Time-series data must therefore, first be sorted into bins. In this distribution method, the wind speed data are interpolated by a straight line, using the concept of least squares regression [7-9, 13, 16, 18, 25]. The logarithmic transformation is the foundation of this method. By converting the {Eq. (7)} into logarithmic form, the {Eq. (8)} is obtained:

$$\ln\left[-\ln(1 - F(\nu))\right] = k \times \ln(\nu) - k \times \ln(C) \qquad (8)$$

The Weibull shape and scale parameters are estimated by plotting $\ln(\nu)$ against $\ln\left[-\ln(1 - F(\nu))\right]$ in which a straight line is determined. In order to generate the line of best fit, observations of calms should be omitted from the data. The Weibull shape parameter k is the slope of the line and the y-intercept is the value of the term $-k \times \ln(C)$.

2.4.2 Maximum Likelihood Method

The Maximum Likelihood Estimation method (MLM) is a mathematical expression known as a likelihood function of the wind speed data in time series format. The MLM method was used by Costa Rocha *et al.* [18] quoting Stevens *et al.* [29] in their study for the estimation of parameters of the Weibull wind speed distribution for wind energy utilization purposes. The MLM method is solved through numerical iterations to determine the parameters of the Weibull distribution. The shape factor k and the scale factor C are estimated by the {Eqs. (9)} and {Eqs. (10)}, [7-9, 13, 15, 16, 18, 26, 27, 29]:

$$k = \left[\frac{\sum_{i=1}^{n} \nu_i^k \,.\, \ln(\nu_i)}{\sum_{i=1}^{n} \nu_i^k} - \frac{\sum_{i=1}^{n} \ln(\nu_i)}{n} \right]^{-1} \qquad (9)$$

$$C = \left(\frac{1}{N} \left[\sum_{i=1}^{n} \nu_i^k \right] \right)^{1/k} \qquad (10)$$

Where: n, number of non zero data values; i, measurement interval; ν_i, wind speed measured at the interval i (m/s).

2.4.3 Modified Maximum Likelihood Method

The Modified Maximum Likelihood Estimation method (MMLM) is used only for wind speed data available in the Weibull distribution format. The MMLM method is solved through numerical iterations to determine the parameters of the Weibull distribution [1, 7-9, 13, 15, 16, 18]. The shape factor k and the scale factor C are estimated by the {Eqs. (11)} and {Eqs. (12)}.

$$k = \left[\frac{\sum_{i=1}^{n} \nu_i^k \cdot \ln(\nu_i) \cdot f(\nu_i)}{\sum_{i=1}^{n} \nu_i^k \cdot f(\nu_i)} - \frac{\sum_{i=1}^{n} \ln(\nu_i) \cdot f(\nu_i)}{f(\nu \geq 0)} \right]^{-1} \tag{11}$$

$$C = \left[\frac{\sum_{i=1}^{n} \nu_i^k \cdot f(\nu_i)}{f(\nu \geq 0)} \right]^{-1} \tag{12}$$

Where: $f(\nu_i)$, Weibull frequency with which the wind speed falls within the interval i; $f(\nu \geq 0)$, Probability of wind speed $(\nu \geq 0)$.

2.4.4 Moment Method

The Weibull factors k and C for the Moment Method (MM) are estimated from the mean wind speed v and standard deviation σ of wind data. The MM method is solved through numerical iterations by the following equations [13, 18, 26]:

$$C = \frac{\nu_m}{\Gamma(1 + 1/k)} \tag{13}$$

The standard deviation σ of the observed data is determined using the {Eqs. (14)} and {Eqs. (15)}.

$$\sigma = C \cdot \left[\Gamma(1 + 2/k) - \Gamma^2(1 + 1/k)\right]^{1/2} \tag{14}$$

Where the standard gamma function is given by:

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

The gamma function used by Manwell *et al.* [30] quoting Jamil [31] is given by:

$$\Gamma(x) = (\sqrt{2\pi x}\, (x^{x-1}) \cdot \left(e^{-x}\right) \cdot \left(1 + \frac{1}{12}x + \frac{1}{288}x^2 - \frac{139}{51840}x^3 + \ldots\right) \tag{16}$$

2.4.5 Empirical Method

The empirical method is considered a special case of the moment method, where the Weibull parameters k and C are given by the equations shown below [2, 7-9, 13, 14, 15, 17,18, 23]:

$$k = \left(\sigma / \nu_m\right)^{-1.089} \tag{17}$$

$$C = \frac{\nu_m}{\Gamma(1 + 1/k)} \tag{18}$$

2.4.6 Energy Pattern Factor Method

The energy pattern factor method (EPF) is related to the averaged data of wind speed and is defined by the {Eqs. (19)}, {Eqs. (20)} and {Eqs. (21)}, [7-9, 13-15, 18].

$$E_{pf} = \frac{\left(v^3\right)_m}{\left(v_m\right)^3} = \frac{\left(\frac{1}{n}\sum_{i=1}^{n} v_i^3\right)}{\left(\frac{1}{n}\sum_{i=1}^{n} v_i\right)^3} \tag{19}$$

Where, E_{pf} is the energy pattern factor.

Once the energy pattern factor is calculated by using the {Eq. (19)}, the Weibull shape parameter is estimated from the {Eq. (20)}.

$$k = 1 + \left(3.69 \big/ (E_{pf})^2\right) \tag{20}$$

The Weibull scale parameters is determined using the {Eq. (21)}.

$$C = \frac{v_m}{\Gamma.(1+1/k)} \tag{21}$$

2.5 Performance of the of the two-parameter Weibull PDF methods

In order to evaluate the performance of the six Weibull methods, the following statistical indexes of accuracy were utilized.

1. The root mean square error ($RMSE$) gives the deviation between the predicted and the experimental values. Successful forecasts correspond to low values of $RMSE$, while higher indicate deviations. $RMSE$ should be as close to zero as possible, and it is expressed as [7-9, 13-15,18]:

$$RMSE = \left[\frac{1}{N}.\sum_{i=1}^{N}(y_i - x_i)^2\right]^{1/2} \tag{22}$$

2. The Chi-square test returns the mean square of the deviations between the experimental and the calculated values for the distributions and it is expressed as [13]:

$$\chi^2 = \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{x_i} \tag{23}$$

3. The coefficient of determination R^2 determines the linear relationship between the calculated values from the Weibull distribution and the calculated values from measured data. A higher R^2 represents a better fit using the theoretical or empirical function and the highest value it can get is 1. R^2 is determined by the {Eq. (24)}, [7-9, 13-15, 18]:

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2 - \sum_{i=1}^{N}(y_i - \bar{x}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{24}$$

Where, y_i is the actual data (measured, observed), x_i is the predicted data using the Weibull distribution, $\bar{y}_i$ is the mean value of y_i, N is the number of all observed wind data.

4. The Kolmogorov-Smirnov test for goodness of fit is considered to precisely rank and acknowledge the methods that are adequate for the available wind data. The procedure of the Kolmogorov-Smirnov test applied to a velocity histogram n with intervals, verifies the hypothesis that a data set is represented by a Weibull distribution with known shape and scale parameters. Then, it calculates the cumulative probability combined with the Weibull distribution $F(v)$ and the experimental histogram $F_n(v)$.

Finally, a parameter, that is taken as representative of the Kolmogorov-Smirnov test (KOL), is calculated through the following equation [32]:

$$KOL = Max\left|F(v) - F_n(v)\right| \tag{25}$$

Where, v, identifies the set of velocity to be considered.

In this work, the chosen significance level for KOL has been defined 10% (i.e. the likelihood of the presence of initial rejection is 10 %). Critical parameters for the significance level are given by [32].

$$KOL_{0.10} = 0.8324905 - \frac{0.199103}{\sqrt{n}} = 0.026511 \times KOL + 0.002725911 \times (KOL)^2 \quad (26)$$

The parameter $KOL*$ for the number of n intervals of the wind histograms is given by:

$$KOL* = KOL \times \sqrt{n} \quad (27)$$

If the value of $KOL*$ is greater than the value of the critical parameter $KOL_{0.10}$, then the used method is not adequate for the specific wind data.

2.6 Site specific wind speeds

As the scale and shape parameters have been determined, two meaningful wind speeds for wind energy estimation are very useful to wind energy investors and assessors. These are called the most probable (V_{mp}) and maximum energy carrying ($V_{E\,max}$) wind speeds [1, 2, 17, 21].

The most probable wind speed (V_{mp}) simply provides the most frequently occurring wind speed for a given wind probability distribution. The most probable wind speed can be calculated using the Weibull shape and scale parameters via the following equation [1, 2, 17, 21]:

$$V_{mp} = C \times \left(\frac{k-1}{k}\right)^{1/k} \quad (28)$$

The wind speed carrying maximum energy represents the wind speed that generates the maximum amount of wind energy. $V_{E\,max}$ is expressed as follows [1, 2,17, 21]:

$$V_{E\,max} = C \times \left(\frac{k+2}{k}\right)^{1/k} \quad (29)$$

2.7 Weibull parameters extrapolation

If the wind distribution is desired at some height other than the anemometer level, Justus *et al.* [25] proposed a consistent methodology that can be used to adjust Weibull C and k (values known at one height) to another desired height.

The Weibull distribution values C_{10} and k_{10} determined at 10 meters height above ground level (AGL), ($z_{10} = 10$ meters meters) are adjusted to any desired height z by the relation [2, 12, 14]:

$$C_z = C_{10} \times (z/z_{10})^n \quad (30)$$

$$k_z = \frac{k_{10}}{1 - 0.00881 \ln(z/10)} \quad (31)$$

Where z and z_{10} are in meters and the power law exponent n is given by:

$$n = [0.37 - 0.088 \ln(C_{10}) \quad (32)$$

2.8 Wind power density estimation

The wind resource available at a potential site is most often assessed by calculating the wind power density (WPD). The WPD based on the Weibull PDF can be calculated using expression given as [1, 2, 12, 14, 17]:

$$WPD = p(v) = P(v)/A = \frac{1}{2}\,.\,\rho\,.\,C^3\,.\,\Gamma\left(1+\frac{3}{k}\right) \tag{33}$$

Where, $P(v)$, wind power, W; $p(v)$, wind power density, W/m^2; A, sweep area of the rotor blades, m^2; ρ, air density at the site, (kg/m^3) is often written in a simple form [33]:

$$\rho = \rho_0 - 1.194\times10^{-4}\times H_m \tag{34}$$

Where, H_m, site elevation in meters; the air density value at sea level is ρ_0 = 1.225 kg/m^3; the site elevation is 242 meters, and ρ =1.196 kg/m^3.

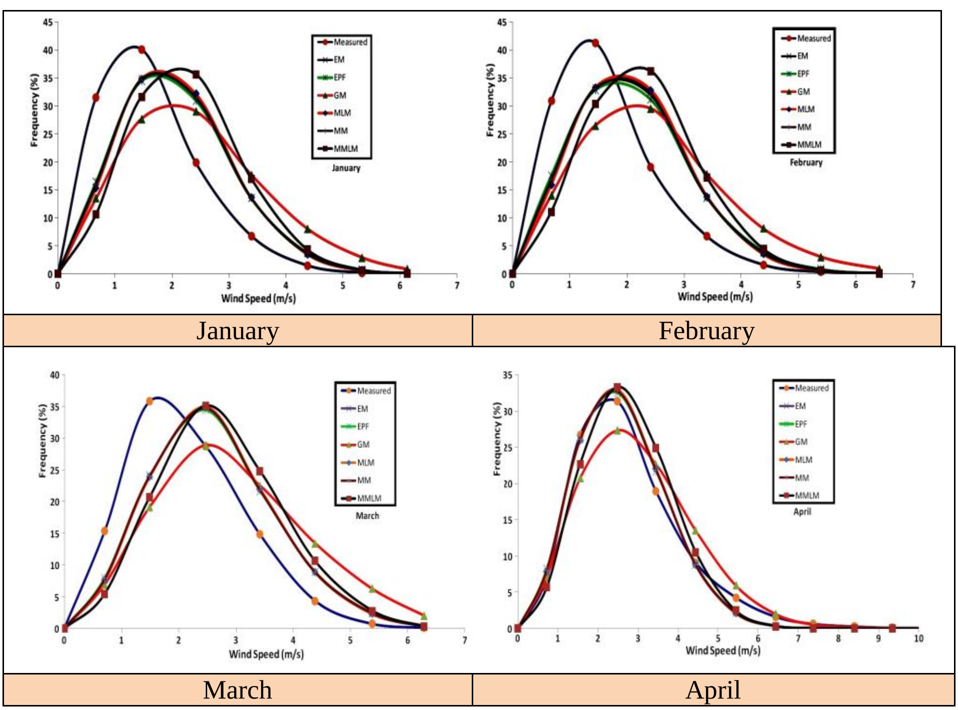
2.9 Wind energy density estimation

Once the WPD has been estimated, the wind energy density (WED) can be obtained just multiplying by the number of hours (T). To get the annual WED, one can multiply WED by 8760 hours to get the wind energy density in kWh/m^2 [1]:

$$WED = p(v)\,.\,T = \frac{P(v)}{A}\,.\,T = \frac{1}{2}\,.\,\rho\,.\,C^3\,.\,\Gamma\left(1+\frac{3}{k}\right).\,T \tag{35}$$

3. RESULTS

The figure 1 shows for each month, the Weibull Frequency plotted against the frequency distribution of measured wind speed. These curves illustrate the Weibull methods that fit best to the measured wind speed data.



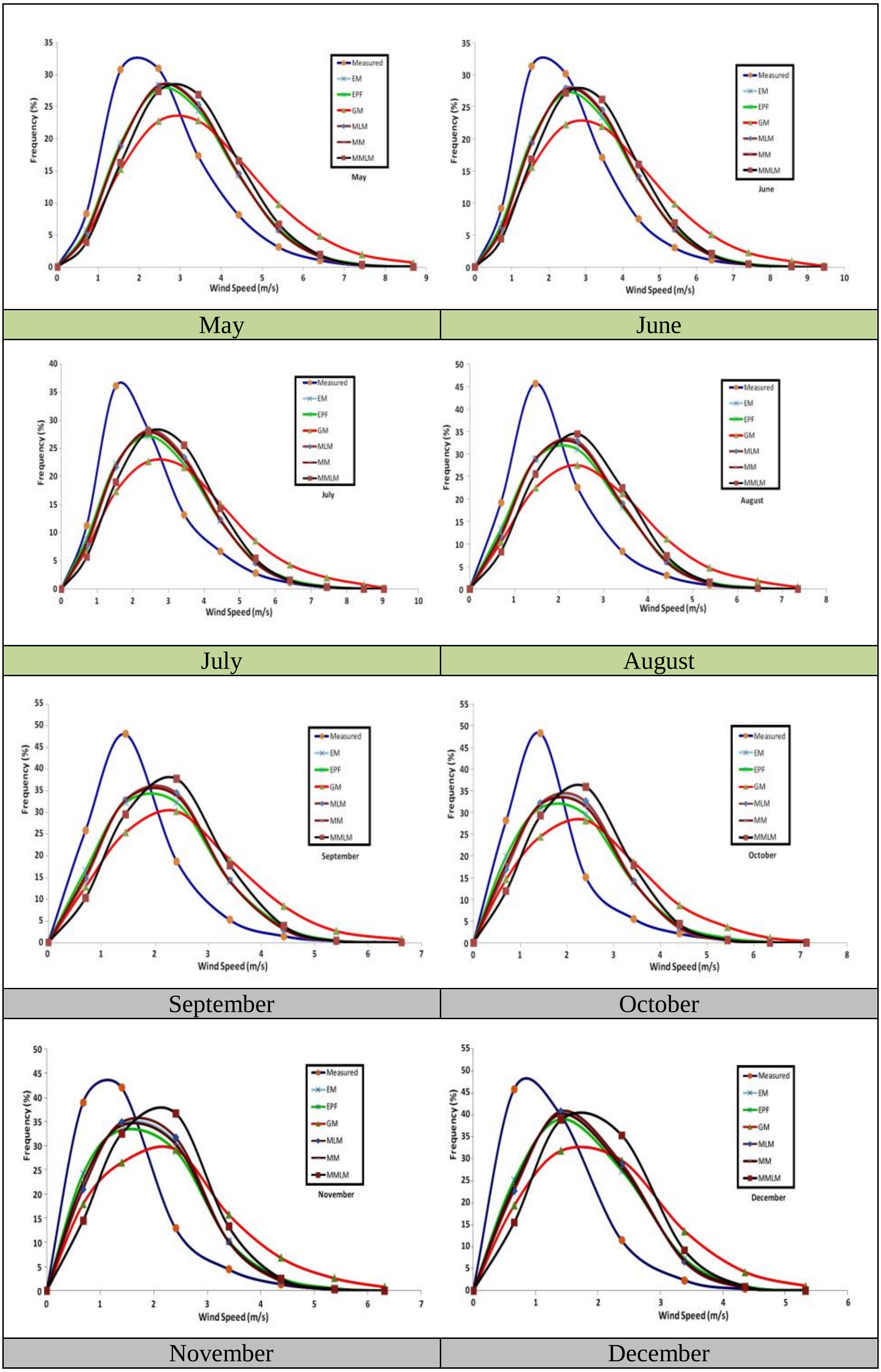


Fig. 1: Weibull Frequency against measured wind speed frequency distribution

For the whole year, **Table 6** provides values for the probability density distribution for the observed wind speed distribution and the forecasted Weibull methods, based on mean wind speeds (third column), calculated for each speed class intervals (column two).

Furthermore, for the whole year, **Table 7** offers values for the cumulative probability density distribution for the observed wind speed distribution and the forecasted Weibull methods, based on mean wind speeds (third column), calculated for each speed class intervals (column two).

Table 6: Probability Density Distribution for the six Weibull methods

i	v	v_i	$f(v_i)$	$f_{EM}(v_i)$	$f_{EPF}(v_i)$	$f_{GM}(v_i)$	$f_{MLM}(v_i)$	$f_{MMLM}(v_i)$	$f_{MM}(v_i)$
1	0-1	0.686	0.226	0.132	0.146	0.113	0.127	0.117	0.136
2	1-2	1.471	0.389	0.275	0.274	0.213	0.274	0.274	0.275
3	2-3	2.440	0.225	0.304	0.290	0.255	0.309	0.320	0.300
4	3-4	3.427	0.101	0.180	0.173	0.191	0.183	0.189	0.178
5	4-5	4.421	0.039	0.076	0.078	0.117	0.076	0.075	0.076
6	5-6	5.416	0.014	0.024	0.028	0.062	0.024	0.021	0.025
7	6-7	6.409	0.005	0.006	0.008	0.029	0.006	0.004	0.007
8	7-8	7.393	0.001	0.001	0.002	0.012	0.001	0.001	0.001
9	8-9	8.491	0.000	0.000	0.000	0.005	0.000	0.000	0.000
10	9-10	9.332	0.000	0.000	0.000	0.001	0.000	0.000	0.000
11	10-11	10.467	0.000	0.000	0.000	0.001	0.000	0.000	0.000

$f(v_i)$	$f_{EM}(v_i)$	$f_{EPF}(v_i)$	$f_{GM}(v_i)$
$\sum_{i=1}^{N} f(v_i) = 1000$	$\sum_{i=1}^{N} f_{EM}(v_i) = 1000$	$\sum_{i=1}^{N} f_{EPF}(v_i) = 1000$	$\sum_{i=1}^{N} f_{GM}(v_i) = 1000$

$f_{MLM}(v_i)$	$f_{MMLM}(v_i)$	$f_{MM}(v_i)$
$\sum_{i=1}^{N} f_{MLM}(v_i) = 1000$	$\sum_{i=1}^{N} f_{MMLM}(v_i) = 1000$	$\sum_{i=1}^{N} f_{MM}(v_i) = 1000$

Table 7: Cumulative Probability Density Distribution for the six Weibull methods

i	v	v_i	$f(v)$	$f_{wEM}(v)$	$f_{wEPF}(v)$	$f_{wGM}(v)$	$f_{wMLM}(v)$	$f_{wMMLM}(v)$	$f_{wMM}(v)$
1	0-1	0.686	0.226	0.132	0.146	0.113	0.127	0.117	0.136
2	1-2	1.471	0.614	0.408	0.420	0.326	0.401	0.391	0.411
3	2-3	2.440	0.839	0.712	0.710	0.581	0.710	0.710	0.711
4	3-4	3.427	0.940	0.892	0.884	0.772	0.893	0.899	0.890
5	4-5	4.421	0.979	0.968	0.961	0.889	0.969	0.974	0.966
6	5-6	5.416	0.993	0.992	0.989	0.951	0.993	0.995	0.992
7	6-7	6.409	0.998	0.998	0.997	0.980	0.999	0.999	0.998
8	7-8	7.393	0.999	1.000	0.999	0.993	1.000	1.000	1.000
9	8-9	8.491	1.000	1.000	1.000	0.998	1.000	1.000	1.000
10	9-10	9.332	1.000	1.000	1.000	0.999	1.000	1.000	1.000
11	10-11	10.467	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 8 gives the prediction accuracy of the Weibull PDF method. The prediction accuracy of the Weibull PDF methods in the estimation of the wind speeds with respect to the actual values, were evaluated based on the chi-square test (χ^2), correlation coefficient (R, root mean square error ($RMSESE$) and Kolmogorov-Smirnov test (KOL).

Table 8: Prediction accuracy of the Weibull PDF methods

January

Weibull method	Weibull parameters		Kolmogorov-Smirnov Test			Statistical Tests		
	Scale C	Scale k	$KOL_{0.10}$	KOL*	KOL0.1-KOL*	RMSE	R^2	χ^2
EM	1.7822	1.8060	0.7517	0.5613	0.1904	0.0659	0.7885	0.2646
EPF	1.7791	1.7476	0.7519	0.5480	0.2039	0.0628	0.7841	0.2386
GM	2.1527	1.6460	0.7494	0.8063	-0.0569	0.0817	0.5330	0.4786
MLM	1.7891	1.8193	0.7516	0.5702	0.1815	0.0671	0.7209	0.2760
MMLM	1.8554	2.1881	0.7503	0.7072	0.0431	0.0898	0.6283	0.5949
MM	1.7810	1.7812	0.7518	0.5557	0.1961	0.0646	0.7751	0.2532

February

Weibull method	Weibull parameters		Kolmogorov-Smirnov Test			Statistical Tests		
	Scale C	Scale k	$KOL_{0.10}$	KOL*	KOL0.1-KOL*	RMSE	R^2	χ^2
EM	1.7850	1.7872	0.7514	0.5969	0.1545	0.0850	0.5786	0.2512
EPF	1.7805	1.7110	0.7516	0.5782	0.1733	0.0801	0.6021	0.2225
GM	2.1584	1.6390	0.7491	0.8403	-0.0912	0.1061	-0.0650	0.4769
MLM	1.7938	1.8112	0.7513	0.6096	0.1417	0.0873	0.5614	0.2672
MMLM	1.8539	2.1371	0.7501	0.7349	0.0158	0.1128	0.4066	0.5197
MM	1.7837	1.7624	0.7515	0.5909	0.1605	0.0834	0.5861	0.2414

March

Weibull method	Weibull parameters		Kolmogorov-Smirnov Test			Statistical Tests		
	Scale C	Scale k	$KOL_{0.10}$	KOL*	KOL0.1-KOL*	RMSE	R^2	χ^2
EM	2.3630	2.0992	0.7521	0.5205	0.2316	0.0670	0.6854	0.2082
EPF	2.3626	2.0600	0.7522	0.5078	0.2445	0.0651	0.6918	0.1959
GM	2.7784	1.9190	0.7507	0.6660	0.0847	0.0868	0.0790	0.4048
MLM	2.3672	2.0944	0.7521	0.5215	0.2306	0.0671	0.6822	0.2092
MMLM	2.4038	2.3392	0.7512	0.6193	0.1319	0.0816	0.6060	0.3414
MM	2.3628	2.0769	0.7522	0.5133	0.2389	0.0659	0.6891	0.2011

April

Weibull method	Weibull parameters		Kolmogorov-Smirnov Test			Statistical Tests		
	Scale C	Scale k	$KOL_{0.10}$	KOL*	KOL0.1-KOL*	RMSE	R^2	χ^2
EM	3.0603	2.0742	0.7679	0.5809	0.1870	0.0457	0.7723	0.1479
EPF	3.0580	1.9765	0.7681	0.5561	0.2120	0.0432	0.7816	0.1307
GM	3.6075	1.9010	0.7657	0.8744	-0.1088	0.0637	0.3150	0.3479
MLM	3.0670	2.0692	0.7679	0.5848	0.1830	0.0459	0.7687	0.1491
MMLM	3.0879	2.1760	0.7675	0.6265	0.1411	0.0498	0.7429	0.1868
MM	3.0599	2.0516	0.7679	0.5753	0.1927	0.0451	0.7747	0.1431

May

Weibull method	Weibull parameters		Kolmogorov-Smirnov Test			Statistical Tests		
	Scale C	Scale k	$KOL_{0.10}$	KOL*	KOL0.1-KOL*	RMSE	R^2	χ^2
EM	2.8353	2.1218	0.7615	0.5283	0.23320	0.0496	0.7210	0.1643
EPF	2.8343	2.0405	0.7616	0.5155	0.2461	0.0472	0.7306	0.1485
GM	3.3215	1.9460	0.7591	0.8156	-0.0565	0.0667	0.1810	0.3666
MLM	2.8410	2.1147	0.7615	0.5318	0.2297	0.0549	0.7176	0.1653
MMLM	2.8640	2.2514	0.7612	0.5713	0.1899	0.0552	0.6801	0.2138
MM	2.8352	2.0998	0.7616	0.5249	0.2366	0.0489	0.7238	0.1596

June

Weibull method	Weibull parameters		Kolmogorov-Smirnov Test			Statistical Tests		
	Scale C	Scale k	$KOL_{0.10}$	KOL*	KOL0.1-KOL*	RMSE	R^2	χ^2
EM	2.8117	2.0332	0.7650	0.5466	0.2184	0.0488	0.7452	0.1634
EPF	2.8090	1.9392	0.7652	0.5304	0.2347	0.0462	0.7562	0.1438
GM	3.3366	1.8590	0.7625	0.8640	-0.1015	0.0669	0.2379	0.3715
MLM	2.8186	2.0323	0.7650	0.5520	0.2129	0.0516	0.7406	0.1658
MMLM	2.8435	2.1609	0.7647	0.5928	0.1718	0.0545	0.7050	0.2213
MM	2.8112	2.0101	0.7651	0.5427	0.2223	0.0482	0.7482	0.1577

July

Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	2.6292	1.9073	0.7649	0.5610	0.2039	0.0592	0.6674	0.1844
EPF	2.6280	1.8115	0.7650	0.5487	0.2163	0.0560	0.6797	0.1660
GM	3.1568	1.7520	0.7622	0.9055	-0.1433	0.0771	0.1097	0.4084
MLM	2.6396	1.9237	0.7648	0.5711	0.1937	0.0602	0.6574	0.1925
MMLM	2.6693	2.0589	0.7642	0.6431	0.1211	0.0666	0.6134	0.2488
MM	2.6281	1.8830	0.7649	0.5580	0.2069	0.0583	0.6709	0.1790

August

Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	2.0731	1.9028	0.7559	0.6775	0.0784	0.0832	0.5389	0.2469
EPF	2.0684	1.7969	0.7562	0.6422	0.1140	0.0791	0.5471	0.2234
GM	2.5198	1.7280	0.7539	0.9057	-0.1518	0.1055	-0.2198	0.5096
MLM	2.0811	1.9192	0.7558	0.6888	0.0670	0.0844	0.5282	0.2562
MMLM	2.1202	2.1394	0.7549	0.7863	-0.0314	0.0969	0.4566	0.3751
MM	2.0722	1.8785	0.7560	0.6695	0.0864	0.0822	0.5412	0.2406

September

Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	1.8067	1.9099	0.7506	0.6850	0.0656	0.0976	0.4751	0.2803
EPF	1.8024	1.7975	0.7508	0.6586	0.0922	0.0927	0.4820	0.2532
GM	2.2093	1.7220	0.7481	0.9432	-0.1951	0.1233	-0.4092	0.5611
MLM	1.8136	1.9262	0.7505	0.6948	0.0557	0.0990	0.4637	0.2902
MMLM	1.8579	2.2141	0.7495	0.7985	-0.0490	0.1176	0.3703	0.4638
MM	1.8060	1.8856	0.7506	0.6794	0.0712	0.0965	0.4769	0.2736

October

Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	1.7771	1.7428	0.7553	0.7510	0.0043	0.0950	0.4512	0.2889
EPF	1.7674	1.6173	0.7556	0.7160	0.0396	0.0898	0.4662	0.2607
GM	2.2380	1.5790	0.7526	1.0539	-0.3013	0.1195	-0.4261	0.5938
MLM	1.7890	1.7887	0.7551	0.7722	-0.0171	0.0979	0.4312	0.3102
MMLM	1.8376	2.0383	0.7541	0.8765	-0.1224	0.1141	0.3322	0.5183
MM	1.7755	1.7181	0.7553	0.7443	0.0110	0.0939	0.4569	0.2820

November

Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	1.5610	1.6697	0.7509	0.6445	0.1064	0.0994	0.4690	0.2827
EPF	1.5518	1.5612	0.7511	0.6243	0.1268	0.0920	0.5117	0.2447
GM	1.9938	1.5100	0.7479	0.9675	-0.2196	0.1262	-0.4655	0.5822
MLM	1.5741	1.7251	0.7508	0.6639	0.0868	0.1043	0.4328	0.3142
MMLM	1.6368	2.0522	0.7497	0.7754	-0.0257	0.1323	0.2478	0.6005
MM	1.5593	1.6452	0.7510	0.6401	0.1108	0.0977	0.4783	0.2733

December

Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	1.3888	1.7649	0.7454	0.5476	0.1978	0.1160	0.4172	0.3436
EPF	1.3838	1.6685	0.7456	0.5259	0.2197	0.1085	0.4551	0.3001
GM	1.7329	1.5860	0.7424	0.8438	-0.1014	0.1435	-0.5144	0.6291
MLM	1.3968	1.7980	0.7452	0.5649	0.1803	0.1195	0.3917	0.3677
MMLM	1.4690	2.2887	0.7432	0.7624	-0.0192	0.1623	0.1458	0.8802
MM	1.3877	1.7401	0.7455	0.5375	0.2080	0.1141	0.4264	0.3319

Whole year									
Weibull Method	Weibull parameters Scale C	Scale k	Kolmogorov-Smirnov Test $KOL_{0.10}$	KOL*	KOL0.1-KOL*	Statistical Tests RMSE	R^2	χ^2
EM	2.1478	1.7115	0.7671	0.6863	0.0808	0.0570	0.7334	0.1917
EPF	2.1389	1.6245	0.7674	0.6455	0.1219	0.059	0.7570	0.1647
GM	2.6682	1.5600	0.7650	0.9556	-0.1905	0.0748	0.2942	0.4278
MLM	2.1595	1.7425	0.7669	0.7083	0.0586	0.0590	0.7181	0.2084
MMLM	2.1678	1.8114	0.7667	0.7420	0.0246	0.0626	0.6957	0.2420
MM	2.1453	1.6866	0.7672	0.6749	0.0923	0.0558	0.7403	0.1831

4. DISCUSSIONS

4.1 Test of Goodness fit

In this work, the prediction accuracy of the Weibull PDF methods in the estimation of the wind speeds with respect to the actual values were evaluated based on the chi-square test (χ^2), correlation coefficient (R^2), root mean square error ($RMSE$) and Kolmogorov-Smirnov test (KOL) for goodness of fit. Based on the results, it can be noted that the statistical tools used offer enough information for the accuracy of individual forecast errors and for the ranking the quality of fit of the six competing Weibull distributions.

Kolmogorov-Smirnov test

The goodness of fit tests summarized in **Table 8**, show that the GM is not adequate for the available wind data and as such is rejected by the Kolmogorov-Smirnov test. The reason for that rejection is that the value of $KOL*$ is greater than the value of the critical parameter $KOL_{0.10}$. Furthermore, the MMLM has proved to be inadequate for the available wind data from August to December. For the Month of October, the MLM is also rejected by the Kolmogorov-Smirnov test. The best estimation method is the EPF because, the difference between $KOL_{0.10}$ and $KOL*$ is higher. As a result, the MM and EM ranked respectively second and third best estimation method.

RMSE test

Successful forecasts correspond to low values of RMSE, while higher indicate deviations. Since $RMSE$ should be as close to zero as possible, it can be seen that for the available data, the results reveal that the best fitting Weibull distribution methods are ranked as follows: the best estimation method is EPF, the MM ranked second, the EM ranked third.

From November to February, the GM and MMLM ranked respectively fifth and sixth while from March to August, the GM and MMLM ranked respectively fifth and sixth.

Chi-square χ^2 test

The method generating the best results is established by considering a low value for the chi-square indicator in each case. Since the chi-square value should be as close to zero as possible, it can be seen that for the available data, the results reveal that the best fitting Weibull distribution methods are ranked as follows: the best estimation method is EPF, the MM ranked second, the EM ranked third.

From November to February, the GM and MMLM ranked respectively fifth and sixth while from March to August, the GM and MMLM ranked respectively fifth and sixth.

Correlation coefficient R^2 test

The best parameters estimation shall disclose the highest value of R^2. The highest value of R^2 is one while the lowest is zero, it can be seen that negative values for the GM were obtained during the months of February, August, September, October, November and December. As a result, it can be concluded that the GM is not adequate for the available data. Furthermore, the results reveal that the EPF is the best fitting Weibull distribution method. The MM ranked second while the EM, MLM and MMLM ranked respectively third, fourth and fifth.

4.2 Weibull parameters C and k

Since the scale and shape parameters have been determined using the EPF as the best fitting Weibull distribution method, the most probable (V_{mp}) and maximum energy carrying ($V_{E\,max}$) wind speeds have been calculated based on the 10 meters height AGL. Consequently, the wind power density (WPD) and the wind energy density (WED) have been evaluated respectively to assess the wind resource available in the district of Garoua. Furthermore, Weibull parameters have been extrapolated at 20 and 30 meters height AGL to as well assess wind resource as shown by **Table 9**.

Table 9: Wind power density and wind energy density at different height above ground level

10 meters height AGL

Period	V_{mp} (m/s)	$V_{E\,max}$ (m/s)	V_m (m/s)	σ (m/s)	WPD (W/m^2)	Daily WED kWh/m^2/d	Monthly WED kWh/m^2/m	Yearly WED kWh/m^2/y
January	1.094	2.753	1.698	0.961	6.127	0.147	4.412	52.941
February	1.066	2.799	1.704	0.982	6.339	0.152	7.564	54.765
March	1.711	3.284	2.224	1.085	11.664	0.280	8.398	100.774
April	2.141	4.356	2.886	1.461	26.492	0.636	19.074	228.890
May	2.038	3.962	2.669	1.313	20.348	0.488	14.651	175.811
June	1.933	4.048	2.655	1.367	21.001	0.504	15.121	181.457
July	1.684	3.956	2.495	1.366	18.687	0.448	13.455	161.457
August	1.316	3.136	1.969	1.086	9.255	0.222	6.663	79.960
September	1.147	2.733	1.715	0.946	6.121	0.147	4.407	52.886
October	0.974	2.907	1.704	1.034	6.784	0.163	4.885	58.616
November	0.806	2.632	1.505	0.942	4.881	0.117	3.514	42.172
December	0.800	2.219	1.329	0.783	3.094	0.074	2.228	26.734
Whole year	1.187	3.505	2.061	1.245	11.935	0.286	8.593	103.120

20 meters height AGL

Period	V_{mp} (m/s)	$V_{E\,max}$ (m/s)	V_m (m/s)	σ (m/s)	WPD (W/m^2)	Daily WED kWh/m^2/d	Monthly WED kWh/m^2/m	Yearly WED kWh/m^2/y
January	1.376	3.419	2.118	1.191	11.797	0.283	8.494	101.926
February	1.340	3.476	2.124	1.218	12.198	0.293	8.782	105.387
March	2.108	4.014	2.726	1.323	21.370	0.513	15.386	184.637
April	2.598	5.238	3.482	1.754	46.275	1.111	33.318	399.817
May	2.483	4.788	3.236	1.584	36.056	0.862	25.961	311.527
June	2.359	4.894	3.220	1.649	37.250	0.894	26.820	321.837
July	2.066	4.800	3.039	1.655	33.527	0.805	24.140	289.677
August	1.638	3.861	2.432	1.334	17.341	0.416	12.485	149.826
September	1.440	3.392	2.137	1.172	11.762	0.282	8.469	101.624
October	1.228	3.611	2.126	1.282	13.060	0.313	9.403	112.838
November	1.025	3.293	1.891	1.178	9.616	0.231	6.924	83.085
December	1.022	2.798	1.682	0.986	6.233	0.150	4.488	53.851
Whole year	1.479	4.303	2.541	1.527	22.189	0.533	15.972	191.715

30 meters height AGL

Period	V_{mp} (m/s)	$V_{E\,max}$ (m/s)	V_m (m/s)	σ (m/s)	WPD (W/m²)	Daily WED kWh/m²/d	Monthly WED kWh/m²/m	Yearly WED kWh/m²/y
January	1.573	3.882	2.409	1.351	17.306	0.415	12.460	149.525
February	1.533	6.946	2.417	1.381	17.889	0.429	12.880	154.557
March	2.382	4.513	3.071	1.485	30.454	0.731	21.927	263.121
April	2.909	5.836	3.887	1.951	64.129	1.539	46.173	554.072
May	2.788	5.349	3.622	1.767	50.388	1.209	36.279	435.350
June	2.650	5.468	3.605	1.841	52.085	1.250	37.501	450.013
July	2.329	5.375	3.410	1.851	47.196	1.133	33.981	407.774
August	1.862	4.360	2.753	1.505	25.038	0.601	18.028	216.332
September	1.645	3.849	2.431	1.329	17.235	0.414	12.409	148.913
October	1.406	4.098	2.419	1.454	19.157	0.460	13.793	165.520
November	1.180	3.755	2.162	1.342	14.298	0.343	10.295	123.538
December	1.180	3.204	1.931	1.129	9.388	0.225	6.760	81.117
Whole year	1.682	4.851	2.872	1.720	31.893	0.765	22.963	275.552

5. CONCLUSIONS

The hourly wind speed data in time-series format for the District of Garoua, Cameroon, have been statistically analyzed, based on the Weibull PDF. The aim was to select the most accurate and efficient methods to ascertain how closely the measured data follow the two-parameter Weibull PDF.

The performance of six Weibull methods were assessed using the chi-square test (χ^2), correlation coefficient (R^2), root mean square error (RMSE) and Kolmogorov-Smirnov test (KOL) goodness of fit to precisely rank and acknowledge the methods that are adequate for the specific wind data, collected in the district of Garoua. Based on the analysis, the most important outcomes of the study can be summarized as follows:

1. Wind speeds are modelled using Weibull probability function. The dimensionless shape parameter k and the scale parameter C (m/s) are shown in **Table 8**;

2. The EPF ranked first, followed by the MM as the most accurate and efficient methods for determining the value of C and k to approximate wind speed distribution. As a result, the EPF is recommended for more accurate estimation of the Weibull parameters in order to reduce uncertainties related to the wind energy output calculation for WECS;

3. Globally, the EM, MLM and MMLM ranked respectively third, fourth and fifth, while the GM proved to be an inadequate method for estimating Weibull parameters;

4. The winds are giving power densities of between (3.094 – 26.492) W/m^2 at 10 m, (6.233 – 46.275) W/m^2 at 20 m and (9.388 –64.129) W/m^2 at 30 m;

5. According to the Pacific Northwest Laboratory (PNL) classification, Garoua falls into class1 [12]. It can therefore be concluded that the potential for wind energy development in Garoua is not fitted for generating electricity and a very fruitful result would be achieved if windmills were installed for producing community water supply, livestock watering, and farm irrigation.

NOMENCLATURE

v_m, Mean wind speed, m/s	σ, Standard deviation, the observed data, m/s
v_i, Hourly wind speed, m/s	v, Hourly wind speed, m/s

$f(v)$, Probability of observing wind speed	$f(v \geq 0)$, Probability of wind speed, $v \geq 0$
N, Number of measured hourly wind speed data v	$\Gamma(x)$, Standard gamma function
R^2, Correlation coefficient	χ^2, Chi-square
E_{pf}, Energy pattern factor	RMSE, Root mean square error
x_i, Predicted data using the Weibull distribution	y_i, Actual data (measured, observed)
$f(v_i)$, Weibull frequency with the wind speed falls within the interval i	z, Mean value of y_i

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