International Journal of Scientific Engineering and Science
Volume 2, Issue 4, pp. 53-62, 2018. ISSN (Online): 2456-7361

How to Use the Temperature Data to Find the Appropriate Site for Best Wind Speed Generation? Applications on Data Obtained from Three Different Cities of Cameroon

Marinette G. Jeutho[1], Fabien Kenmogne[2*], David Yemélé[1]
[1]Laboratoire de Mécanique et de Modélisation des Systèmes Physiques (L2MSP), Faculté des Sciences, Université de Dschang, B.P. 067, Dschang, Cameroon
[1, 2]Lab. of Modelling and Simulation in Engineering, Biomimetics and Prototype, Faculty of Science, University of Yaoundé I, Po Box 812, Yaoundé, Cameroon
* Corresponding author; phone: (+237) 675225326; email: kenfabien@yahoo.fr

Abstract— *In order to prove that temperature data can be used to find the adequate site leading to the best wind energy production, the temperature and wind characteristics are analyzed for three meteorological stations of Cameroon, submitted to different climates: The hot and the cool ones. The data was collected for the period going to 2007 to 2016. Assessment of the wind power potential was carried out using the Weibull distribution parameters, which are evaluated by five numerical techniques: The mean standard deviation method, the moment's method, the energy pattern factor method, the Least squares regression method and the maximum likelihood method (MLM). Results of the study show that the average annual wind speeds at 10 m above ground for Yagoua, Maroua and Bafoussam are 3.1, 3,2 and 1.4 m/s, respectively, leading to the fact that Bafoussam is not suitable for wind energy production at 10 m altitude. Next, we use the data of temperatures for each city and the corresponding wind speed to derive the empirical function governing the dependency of ambient temperature and wind speed, which lead to the fact that temperature data from numerical weather prediction models can replace in-situ wind speed measurements.*

Keywords— *Assessment; Wind Energy; Weibull Distribution; Temperature estimation.*

I. INTRODUCTION

Energy plays a significant role in human and economic development. Demand for energy is growing exponentially while conventional energy resources are limited and their use contributes major proportion to environmental pollution [1].Since more than one century ago, electricity supply has been highly due to the discovery of fossil fuels such as coal and oil. Nowadays the use of fossil fuels is remained in growth and they continue to make up a large part of the global supply chain for electricity. Due to depletion of fossil fuels and looming climate changes, the development of sustainable energy has received considerable attention over the last two decades.

The rising concerns over global warming, environmental pollution, and energy security have increased interest in developing renewable and environmentally friendly energy sources such as wind, solar, hydropower, geothermal, hydrogen, and biomass as the replacements for fossil fuels[1]. Renewable energy resources are sustainable. This means that they can be replaced and will not run out. They are clean and friendly to the environment. Wind energy can provide suitable solutions to the global climate change and energy crisis. The utilization of wind power essentially eliminates emissions of CO_2, SO_2, NO_x and other harmful wastes as in traditional coal-fuel power plants or radioactive wastes in nuclear power plants. By further diversifying the energy supply, wind energy dramatically reduces the dependence on fossil fuels that are subjected to price and supply instability, thus strengthening global energy security. During the recent three decades, tremendous growth in wind power has been seen all over the world.[2]

There are three basic steps to identify and characterize the wind resource in a given region. In general, they are prospecting, validation and optimization. In prospecting, one usually make the identification of potential windy sites within a fairly large region, and generally, this is carried out by meteorologists who depend on various sources of information such as topographical maps, climatological data from meteorological stations, and satellite imageries[3]. A site visit is also conducted at this stage and a representative location for wind measurement is identified. Validation process involves a more detailed level of investigation like wind measurements and data analysis [4-6].

The main objective of this manuscript is to identify the appropriate city of Cameroon where the best intensity of wind power energy can be found, and adequate for wind turbine installation. It is important to mention that in their previous studies M. G. Jeutho et al. [7] estimated the wind potential energy of Bafoussam' city. As a result they found that Bafoussam is a lower wind potential energy area. In the present manuscript, we compare the area of lower temperature to the area of higher temperature, and propose the empirical mathematical relation between temperature and wind speed, leading to the fact that temperature data can be used in place of speed data to choose the appropriate site for wind turbine installation. Thus, the rest of the paper is organized as follow: In Section 2, we present materials and tools for the data

International Journal of Scientific Engineering and Science
Volume 2, Issue 4, pp. 53-62, 2018. ISSN (Online): 2456-7361

analysis, following in Section 3 by the presentation of the main results of the present manuscripts and the providing of some discussions. Finally, concluding remarks are devoted to Section4.

II. Materials and Tools for the Data Analysis

2.1 Wind speed data

The wind and temperature data used in this paper were obtained from NASA meteorological services for three meteorological stations of Cameroon: Maroua, Yagoua and Bafoussam. The velocity measurements of the wind were made at 10 m height, while the geographical coordinates of the selected sites are given in Table 1.

TABLE 1. Geographical coordinates of selected locations.

Station	Longitude	Latitude	Altitude
Yagoua	15°13′58″ Est	10°20′27″Nord	336 m
Maroua	14°18′57″ Est	10°35′27″ Nord	406 m
Bafoussam	10°25′03″ Est	5°28′39″ Nord	1438 m

2.2. Statistical analysis of wind speed variations; Weibull distribution function

The Weibull distribution function is usually used, accepted and recommended in the literature. It proved not only adapted for the description of the statistical properties of the wind but gives a good agreement with the experimental data [5]. The function of Weibull distribution with two parameters for a place at a particular time is given by [5-11]

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

where v (expressed in m/s) is the speed of the wind, while k is an adimensional factor of form which characterizes the frequency distribution and c is the scale factor which has the dimension speed. The determination of k and c called parameters of Weibull leads to the knowing of the distribution of the winds for a given site. In order to find these Weibull distribution's parameters, one usually use one of the following five methods:

2.2.1 Mean standard deviation method or empirical method (MSDM)

One can use the MSDM to estimate the Weibull parameters k and c when the mean wind speed and standard deviations are available [6-7]. In this method, k and c are expressed as:

$$k=\left(\frac{\sigma}{\bar{v}}\right)^{-1.086}, \quad c=\frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{2}$$

where σ shows standard deviation and $\bar{v}$ is the average speed, with

$$\sigma=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(v_i-\bar{v}\right)^2}, \quad \bar{v}=\frac{1}{n}\sum_{i=1}^{n}(v_i) \tag{3}$$

2.2. 2 Method of moment (MOM)

The MOM, well known as the empirical method is the imperative techniques universally used for estimating Weibull shape and scale parameters by averaging wind speed and standard deviation Following this method, k and c can be estimated as

$$k=\left(\frac{0.9874}{\frac{\sigma}{\bar{v}}}\right)^{1.0983}, \quad c=\frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{4}$$

with

$$\bar{v}=\frac{1}{n}\sum_{i=1}^{n}(v_i), \quad \sigma=\sqrt{\Gamma\left(1+\frac{2}{k}\right)-\Gamma^{3}\left(1+\frac{1}{k}\right)} \tag{5}$$

where by $\Gamma(x)$, we mean the Gamma function of x

2.2. 3 Energy pattern factor method (EPFM)

The EPFM is related to the average data of wind speed and is defined by the following equation [9-10]

$$EPF=\frac{1}{\left(\bar{V}\right)^{3}}\sum_{i=1}^{N}\frac{v_i^3}{N}=\frac{\Gamma\left(1+\frac{3}{k}\right)}{\Gamma^{3}\left(1+\frac{1}{k}\right)} \tag{6}$$

Where v_i (espressed in m/s) is the wind speed for the i^{th} observation. N being the total number of wind speed data and $\bar{V}$ is the mean wind speed. The Weibull shape and scale parameters can be calculated by using the following equations:

$$k=1+\frac{3.69}{(EPF)^2}, \quad c=\frac{\bar{V}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{7}$$

2.2.4 Least squares regression method or graphical method (LSRM)

LSRM, also known as a graphical method implemented by plotting a graph in such a way that the wind speed data are interpolated by a straight line. The equation given the probability density function, after transformation through the logarithm function gives the following equation [8, 11-13]:

$$ln\left[-ln\left(1-f(v)\right)\right]=klnv-klnc, \tag{8}$$

which can be fitted using the least square regression y=ax+b with

$$y=ln\left[-ln\left(1-f(v)\right)\right], \quad x=lnv, \quad b=-klnc, \tag{9}$$

and

$$a=k \quad \text{and} \quad c=e^{-\left(\frac{b}{k}\right)} \tag{10}$$

2.2.5 Maximum likelihood method (MLM)

The MLM is solved through numerical iterations to determine the parameters of the Weibull distribution k and c, which are estimated by the following equations [14-15]:

$$k=\left[\left(\frac{\sum_{i=1}^{n}v_i^k ln(v_i)}{\sum_{i=1}^{n}v_i^k}-\frac{\sum_{i=1}^{n}ln(v_i)}{n}\right)\right]^{-1}, \quad c=\left(\frac{1}{n}\sum_{i=1}^{n}v_i^k\right)^{\frac{1}{k}} \tag{11}$$

2.3 Determination of the Degree of Accuracy of the Weibull distribution model results

To estimate the degree of accuracy of the Weibull results, various estimation statistics were employed, These are the coefficient of determination, *COD*, the root mean square error (RMSE) and the Nash-Sutcliffe model coefficient of efficiency (COE). They are mathematically expressed as [15]:

$$COD = X^2 = \frac{\sum_{i=1}^{n}(y_i - y_m)^2 - \sum_{i=1}^{n}(y_{ic} - y_i)^2}{\sum_{i=1}^{n}(y_i - y_m)^2}, \qquad RMSE = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}(y_{ic} - y_i)^2\right]} \tag{12}$$

$$COE = 1 - \frac{\sum_{i=1}^{n}(y_i - y_{ic})^2}{\sum_{i=1}^{n}(y_{ic} - y_m)^2} \tag{13}$$

where y_i is the ith actual data, y_{ic} is the ith Weibull result, y_m is the mean of the actual data and n is the number of observations. It is important to mention that the closer the values of COD and COE are to one, the more accurate the result, while the closer to zero the values of RMSE the better results.

2.4. Statistical Analysis of Maximum Entropy Principle

In order to study the Maximum entropy principle, the probability density function of speed has been introduced in the following form:

$$f(v) = \exp\left(\sum_{j=1}^{M}\alpha_j \ v^j\right) \tag{14}$$

Where α_j are the Lagrangian multipliers, while M is the number of the low order moments used. This density function is obtained by minimizing the Shannon's entropy, the well-known Carla et al principles [4], suggesting the following constraints:

$$\int_0^{\max(v)} f(v)d(v) = 1 \ , \quad \int_0^{\max(v)} vf(v)d(v) = m_i' \ . \tag{15}$$

m_i' being the M-low statistical orders, obtained empirically as $m_i' = \frac{1}{N}\sum_{i=1}^{N} v^i [3]$.

2.5. Effect of ambient temperature on the wind speed predictions

By studying the method to parameterize the physical dependency of temperature and relevant meteorological parameters, Kurtz at al [16] used the following relation to calculate the module temperature T_c:

$$T_c = T_a + I.\exp(-a - bv_f) \ , \ a = 3.4433, \ b = 0.040392 \tag{16}$$

Here T_a and T_c are the ambient and module temperatures, respectively, while I is the in-plane irradiance and v_f the wind speed measured at 10 meters above the ground. As shall be proved in the following section, a similar equation can be used to estimate the wind speed data, just by knowing the temperature data, which can help to select the appropriate site for wind energy, without use the data of speed.

III. Main Results and Discussion

3.1 Preliminary: In situ data

Wind is a natural phenomenon, and is one of the unlimited renewable energy resources which can be a better alternative energy resource in Cameroon. The wind data for Yagoua, Maroua and Bafoussam, not shown here used in this study were obtained from the NASA meteorological services.

3.2 Weibull distribution function analysis

The Weibull distribution parameters have been calculated for daily wind speed data for 2007-2016 for Yagoua, Maroua and Bafoussam. The shape and scale parameters (k and c) for each region are estimated by the five methods mentioned above. As shown in Table2, a comparison of shape parameter (k) and scale parameter (c) reveals that: The values of scale parameters for Yagoua, Maroua and Bafoussam found by MSDM, MOM, EPFM, and MLM are in good agreement; Except LSRM which finds slightly different values of scale parameter range of 0.3. The value of scale parameter is less than 2 for the region of lower temperature and higher than 2 for the region of high temperature, while the LSRM estimating the value of shape parameter is less than measured value of the other methods. For the region of lower temperature (that is Bafoussam), the value of shape parameter is highest than the region of high temperature, Maroua and Yagoua respectively. The comparison of measured and predicted mean wind speeds is presented in Table3, showing that the estimated value of mean wind speeds found by MSDM, MOM, EPFM are identical with measured one. The correlation coefficient between measured and predicted mean wind speeds is given in Table4 in which we can that they are more adequate for the region of high temperature, Maroua and Yagoua respectively, than the region of lower temperature, Bafoussam. Table 5 summarizes the prediction accuracy results for the presented models. The actual data and the theoretical probability distribution function (PDF) generated with the help of shape and scale parameters are plotted for each region in Figure 1, in which we can see that the Weibull shape and scale parameters calculated by using the EPFM show very fine agreement than the other Weibull shape and scale parameters estimated using the other fourth methods.

3.3 Effects of temperature: Basic equation to predict the relationship between wind speed and temperature data

In order to study the relationship between temperatures and wind speed, the temperature data have been also collected, leading by plotting both the wind speed and the temperature versus time as shown in Figures 2 and 3 to the following remarks:

- The Cities having higher temperature, that is Maroua and Garoua respectively have higher wind speed than that of the city of the lower temperature, Bafoussam. Therefore higher the temperatures, higher the wind speeds and lower the temperatures, lower wind speed.
- The plots of speed depend of days is globally the linear function of time, leading by using the mean square regression to the following expression [17]:

$$v = a_0 t + b_0 \ , \ a_0 = \bar{v} - b_0 \bar{t}, \ b_0 = \frac{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)\left(v_i - \bar{v}\right)}{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)^2} \tag{17}$$

Where $\bar{x}$ is the mean value of x (x replacing v or t), with $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$. It is important to mention that this form of mean square linear approximation have been already used by E. Kaplani and S. Kaplanis in [18] for the Thermal modelling

International Journal of Scientific Engineering and Science
Volume 2, Issue 4, pp. 53-62, 2018. ISSN (Online): 2456-7361

and experimental assessment of the dependence of PV module temperature on wind velocity and direction, module orientation and inclination.

- The plots of temperature depend of days give the random variation, meaning that temperature is an arbitrary function of time. In order to find the dependency of temperature and time, we have made different tests and we found, as appeared in Figure3 that the plot of $\sqrt{\left|\ln\left(\frac{T_0}{T}\right)\right|}$ as a function of time leads to a curve which globally appears to be a straight line. By using again the mean square linear regression method, one can find two parameters a_1 and b_1 so that

$$\sqrt{\left|\ln\left(\frac{T_0}{T}\right)\right|} = a_1 t + b_1 ,$$

$$a_1 = \left(\overline{\sqrt{\left|\ln\left(\frac{T_0}{T}\right)\right|}}\right) - b_1 \bar{t} , \qquad (18)$$

$$b_1 = \frac{\sum_{i=1}^{N}\left[\left(\sqrt{\left|\ln\left(\frac{T_0}{T_i}\right)\right|} - \left(\overline{\sqrt{\left|\ln\left(\frac{T_0}{T}\right)\right|}}\right)\right)\left(v_i - \bar{v}\right)\right]}{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)^2}$$

Equations (15) and (16) will be combined to give $\sqrt{\left|\ln\left(\frac{T_0}{T}\right)\right|} = b_1 + \frac{a_1}{a_0}(v - b_0)$, leading to the following empirical equation showing the dependency of speed and temperature:

$$T = T_0 exp\left[\pm\left(b_1 + \frac{a_1}{a_0}(v - b_0)\right)^2\right] \qquad (19)$$

This result is very important since it means that one can check the adequate site for wind energy generation by using either the wind speed or temperature data. Figure 6 shows the annually variation of Weibull, maximum entropies and maximum entropies function of temperature distribution.

3.3. Computed MEP based wind speed distribution and effects of temperature

The Lagrangian parameters of Eq.(14) subjected to constraints (15) are obtained by using the Newton-Raphson iterative method for the monthly distributions, leading to the probability density function plotted in Fig. 4 with the collected data. In order to check the effect of temperature on the wind speed distribution, let us consider here the wind as a stochastic event, meaning that wind is unpredictable and without a stable pattern or order (It has been proved that all natural *events* are *stochastic* phenomenon). Let us now consider that wind is governed by two collective variables, the temperature $\mathbf{T}$, and the wind speed $\mathbf{V}$. When the wind speed part is considered to act alone, the MEP based wind speed distribution is given by Eq.(14), satisfying the constraints (15). When the temperature is taking alone into account, the wind speed probability distribution can be given by the following expression

$$g(v) = \sqrt{\frac{2m^3}{\pi (k_B T)^3}} v^3 exp\left(-\frac{mv^2}{2k_B T}\right) \qquad (20)$$

where m is the effective mass of air, $\mathbf{k_B} = 1.38064852\times10^{-23}\ \mathbf{m}^2\ \mathbf{kg}\ \mathbf{s}^{-2}\ \mathbf{K}^{-1}$ *is the Boltzmann constant. When we consider both the temperature and speed to act together, the wind speed probability distribution can be given by* $\mathbf{f}(\mathbf{v})\times\mathbf{g}(\mathbf{T})$ *, leading to*

$$\rho(v,T) = 4\sqrt{\frac{\beta^3}{\pi T^3}} v^3 exp\left(-\frac{\beta}{T}v^2 - \sum_{j=1}^{M}\alpha_j\ v^j\right) \qquad (21)$$

with $\beta = m/2k_B$. The 3-D plot of this probability distribution is shown in Figure 4, obtained for $\beta = ?????$. From where, it appears that the probability distribution is fairly sensitive to temperature variation.

TABLE 2. The estimated values of Weibull parameters by five numerical methods.

Method	MSDM		MOM		EPFM		LSRM		MLM	
Site	k	c	k	c	k	c	k	c	k	c
Yagoua	2.8660	3.5037	2.8602	3.5040	2.7480	3.5093	2.5923	3.1304	2.8579	3.5100
Maroua	2.7590	3.6011	2.7523	3.6014	2.6563	3.6058	2.5746	3.2494	2.7464	3.6089
Bafoussam	3.5629	1.5739	3.5646	1.5739	3.1426	1.5840	3.0441	1.3719	3.3476	1.5760

IV. General Conclusion

The temperature and the wind characteristics have been analyzed for three meteorological stations, namely: Both Yagoua and Maroua in the Far North Region of Cameroon, and Bafoussam in the West region, these regions being submitted to different climates. The studies have been performed by using five numerical methods (MSDM, MOM, EPFM, LSRM and MLM) for the determination of the Weibull distribution parameters, that is the scale and shape ones, which are used to generate the probability distribution function. From these obvious results, RMSE and X^2 tests are performed giving values in the recommended range suggesting reliability of the methods used for estimating Weibull parameters and consequently a better approximation of measured wind speed data distribution. Next, by plotting both the speed and temperature variations versus the time, we found the function giving the dependency of the temperature and the speed, which is interesting since the site for wind turbines installation can be studied by using either the temperature or the wind speed data. Next, the Maximum entropies function of temperature distribution is fitted to measure wind speed distribution. The agreement between the observed wind speed distributions, maximum entropies distribution and Maximum entropies function of temperature distribution was analyzed by performing statistical tests, such as RMSE and X^2 tests. The tests indicated good agreement between the observed and fitted distribution function.

International Journal of Scientific Engineering and Science
Volume 2, Issue 4, pp. 53-62, 2018.
ISSN (Online): 2456-7361

TABLE 3. The mean wind speed (actual and predicted).

Months	Mean Wind Speed					
	Measured	**MSDM**	**MOM**	**EPFM**	**LSRM**	**MLM**
Yagoua	3.1227	3.1227	3.1227	3.1227	2.7802	3.1280
Maroua	3.2049	3.2049	3.2049	3.2049	2.8853	3.2112
Bafoussam	1.4175	1.4175	1.4175	1.4175	1.2259	1.4147

TABLE 4. The annually R^2 analysis.

R^2	MSDM	MOM	EPFM	LSRM	MLM
Yagoua	0.9907	0.9907	0.9914	0.9934	0.9900
Maroua	0.9916	0.9916	0.9922	0.9937	0.9910
Bafoussam	0.9682	0.9681	0.9741	0.9825	0.9658

TABLE 5. Comparative statistics of the wind speed probability distribution models.

	Weibull distribution			MEP distribution			MEP Function of temperature distribution		
	COD	RSME	X^2	COD	RSME	X^2	COD	RSME	X^2
Bafoussam	0.9288	0.0487	0.7373	0.9982	0.0077	0.0169	0.9985	0.0070	0.0141
Maroua	0.9913	0.0722	0.4906	0.9994	0.0186	0.0311	0.9995	0.0174	0.0274
Yagoua	0.9912	0.0696	0.5118	0.9997	0.0118	0.0135	0.9998	0.0107	0.0111

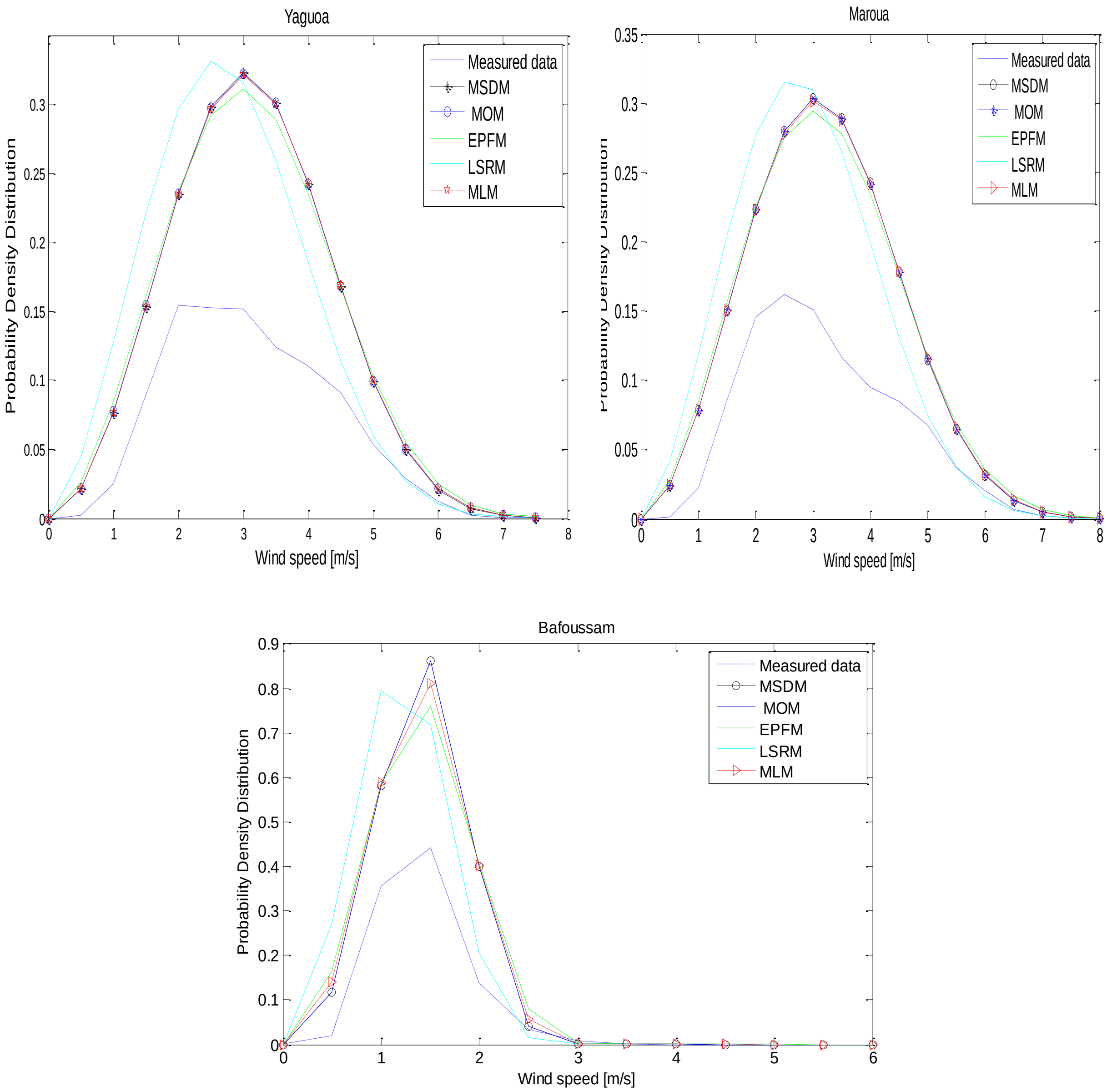


Fig. 1. Plot of PDF of actual and predicted data obtained from five methods MSDM, MoM, EPFM, LSRM, and MLM. (a)Yagoua, (b) Maroua, (c) Bafoussam.

Volume 2, Issue 4, pp. 53-62, 2018.
ISSN (Online): 2456-7361

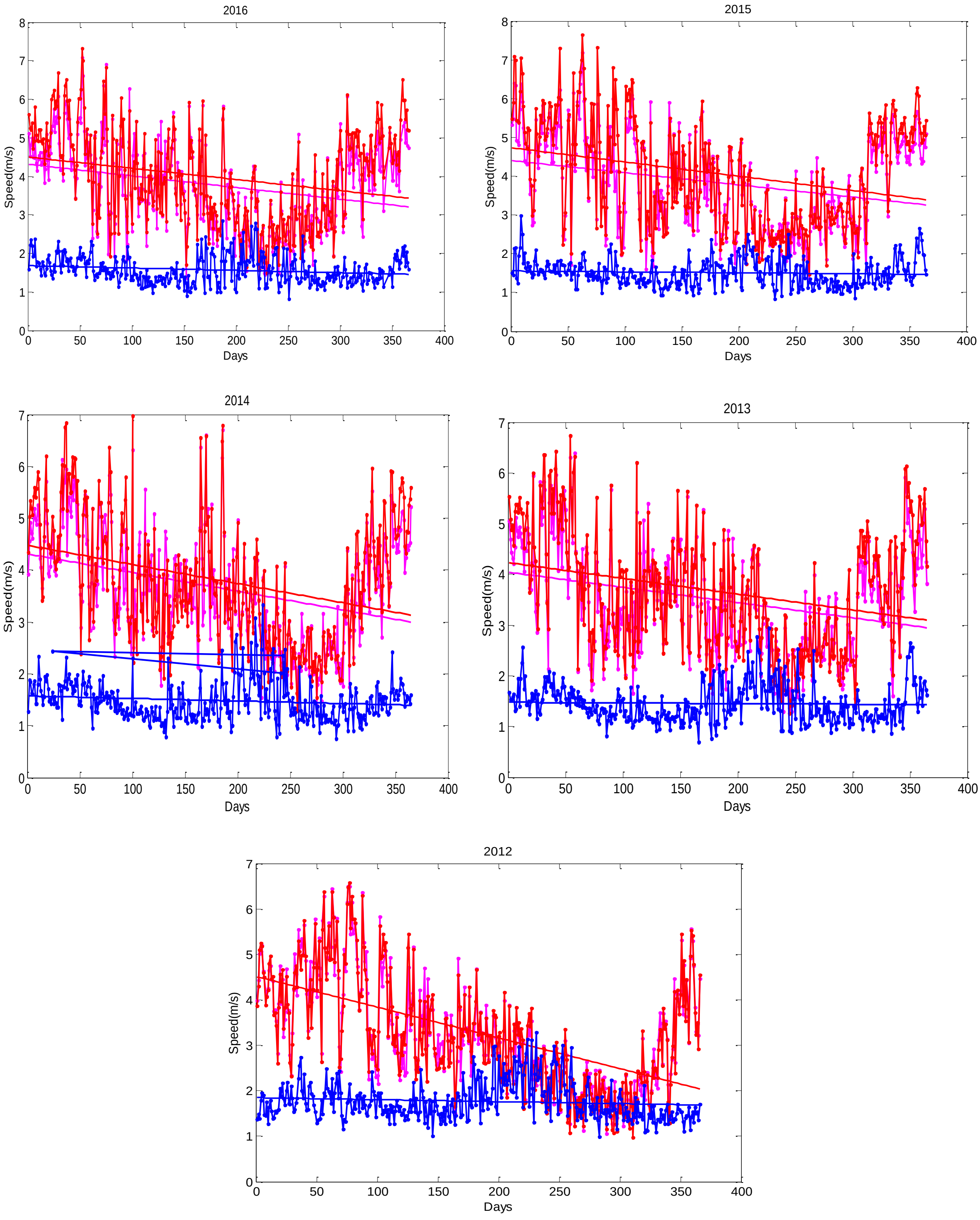
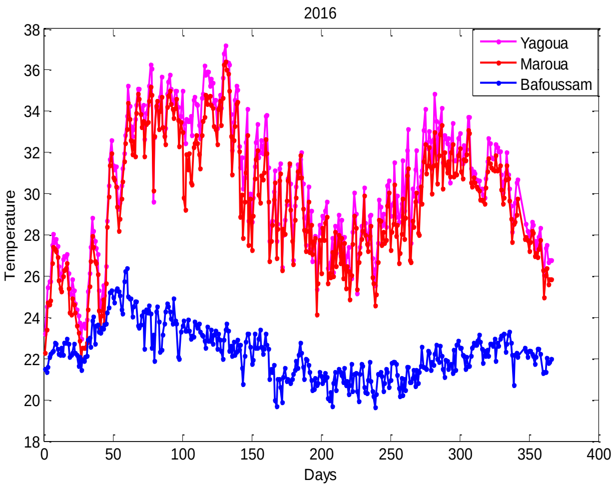
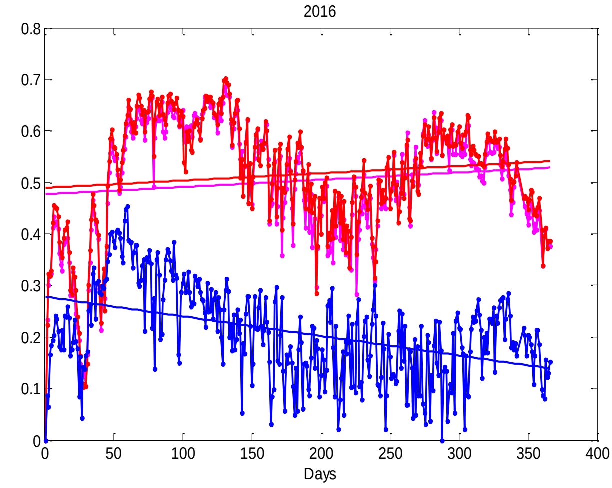


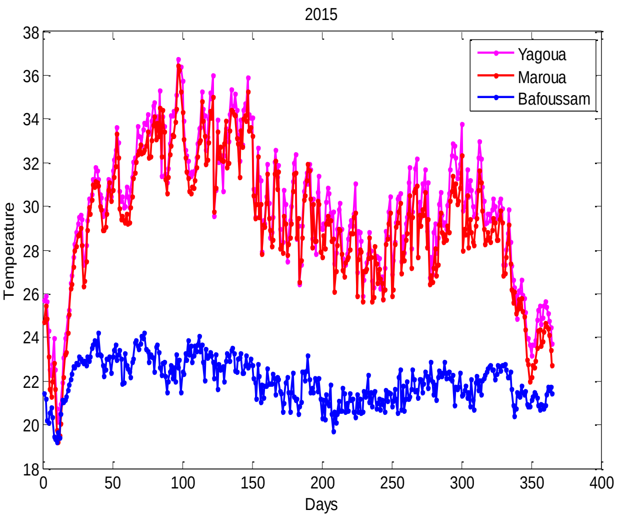
Fig. 2. Speed versus time. The random form is the simply plot, which tend globally to the straight line, while the straight line is its least square linear regression for Bafoussam Yagoua and Maroua cities of Cameroon within the 5-year interval.

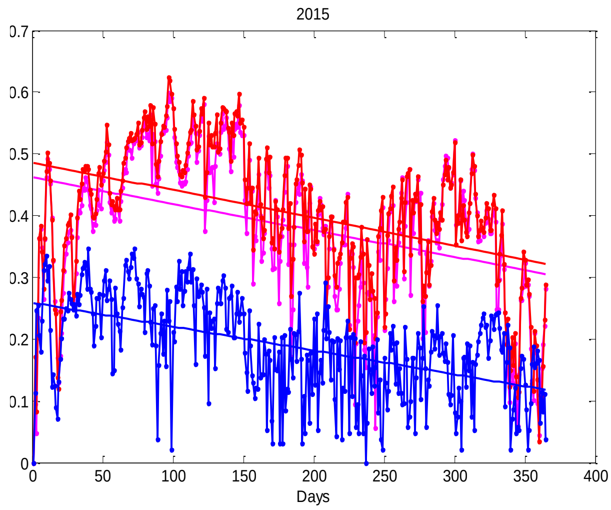
Volume 2, Issue 4, pp. 53-62, 2018.

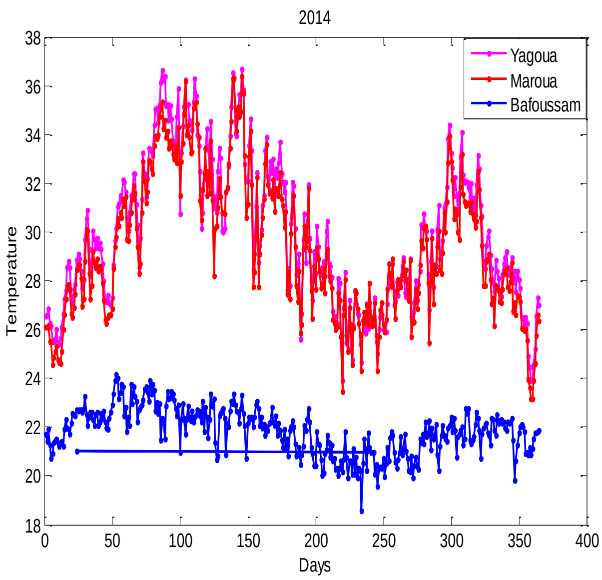
International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

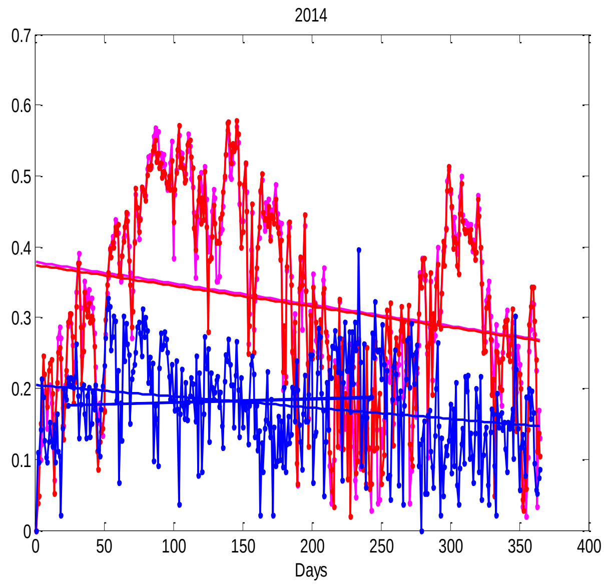












International Journal of Scientific Engineering and Science
Volume 2, Issue 4, pp. 53-62, 2018. ISSN (Online): 2456-7361

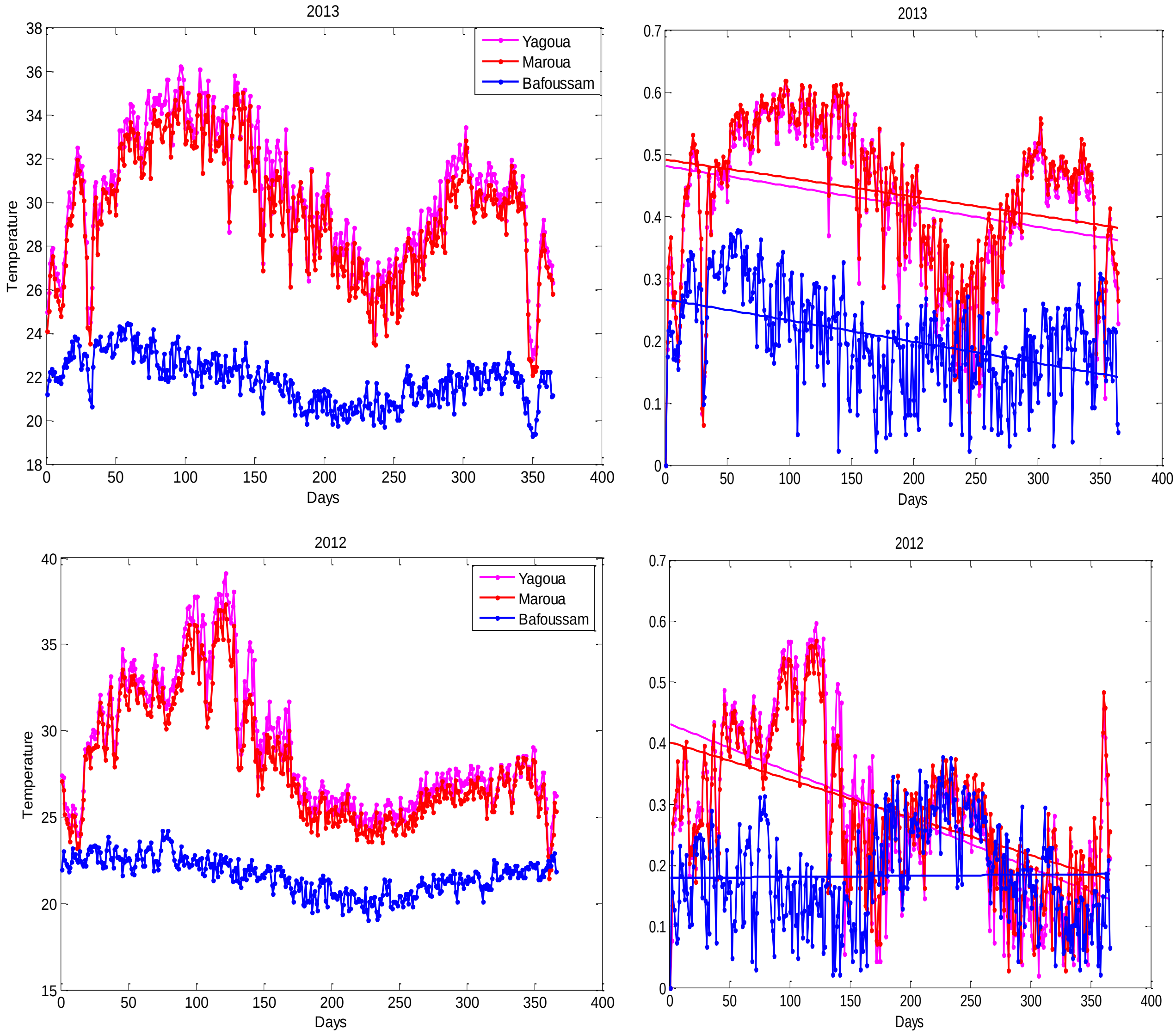
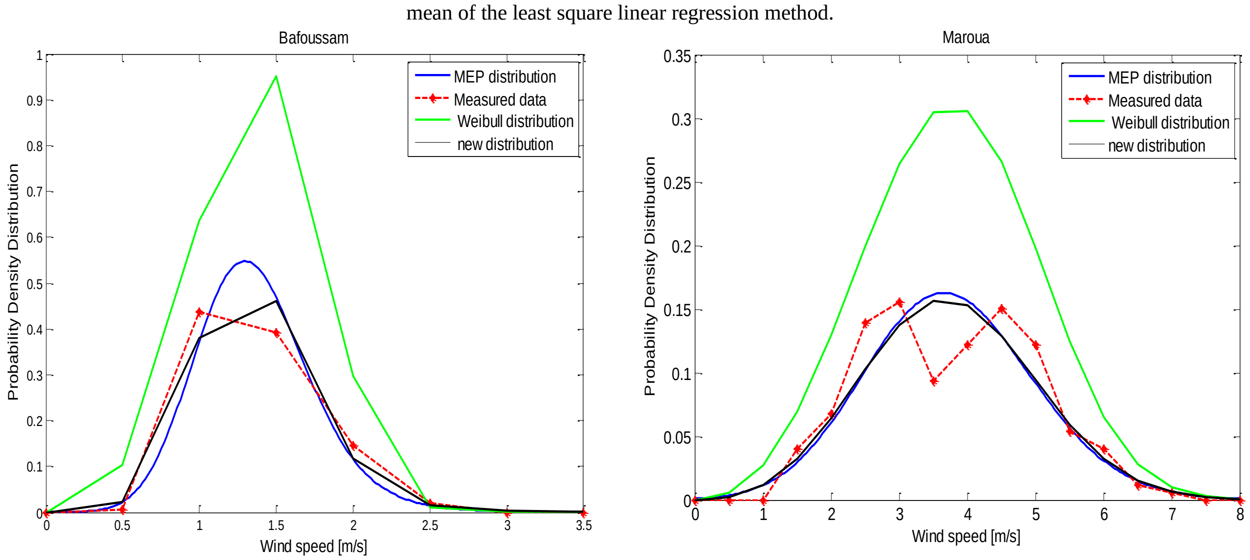


Fig. 3. Left hand side: Temperature versus time, which tends to the straight line for the city of lower temperature (in blue). Otherwise, the form is arbitrary for the cities of higher temperatures (in red and magenta). Right hand side: $\sqrt{\ln\left(\frac{\mathbf{T}_0}{\mathbf{T}}\right)}$ versus time, which tend globally to the straight line, which is approximated by mean of the least square linear regression method.



Volume 2, Issue 4, pp. 53-62, 2018.

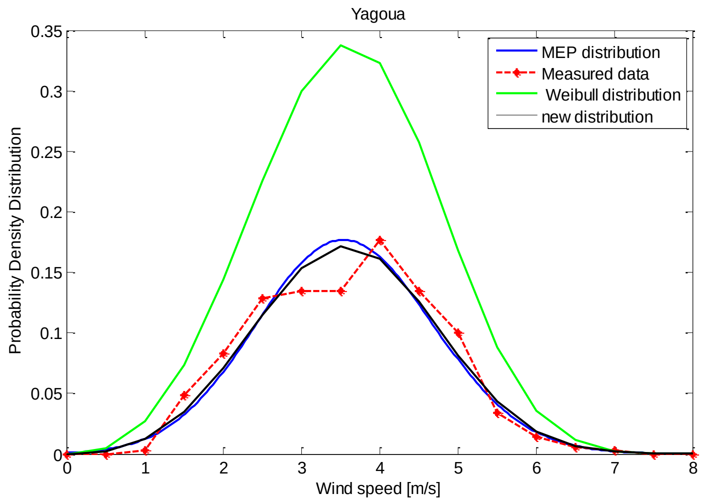


Figure 4: Wind speed frequency distributions for Bafoussam Yagoua and Maroua regions, Cameroon for year 2016

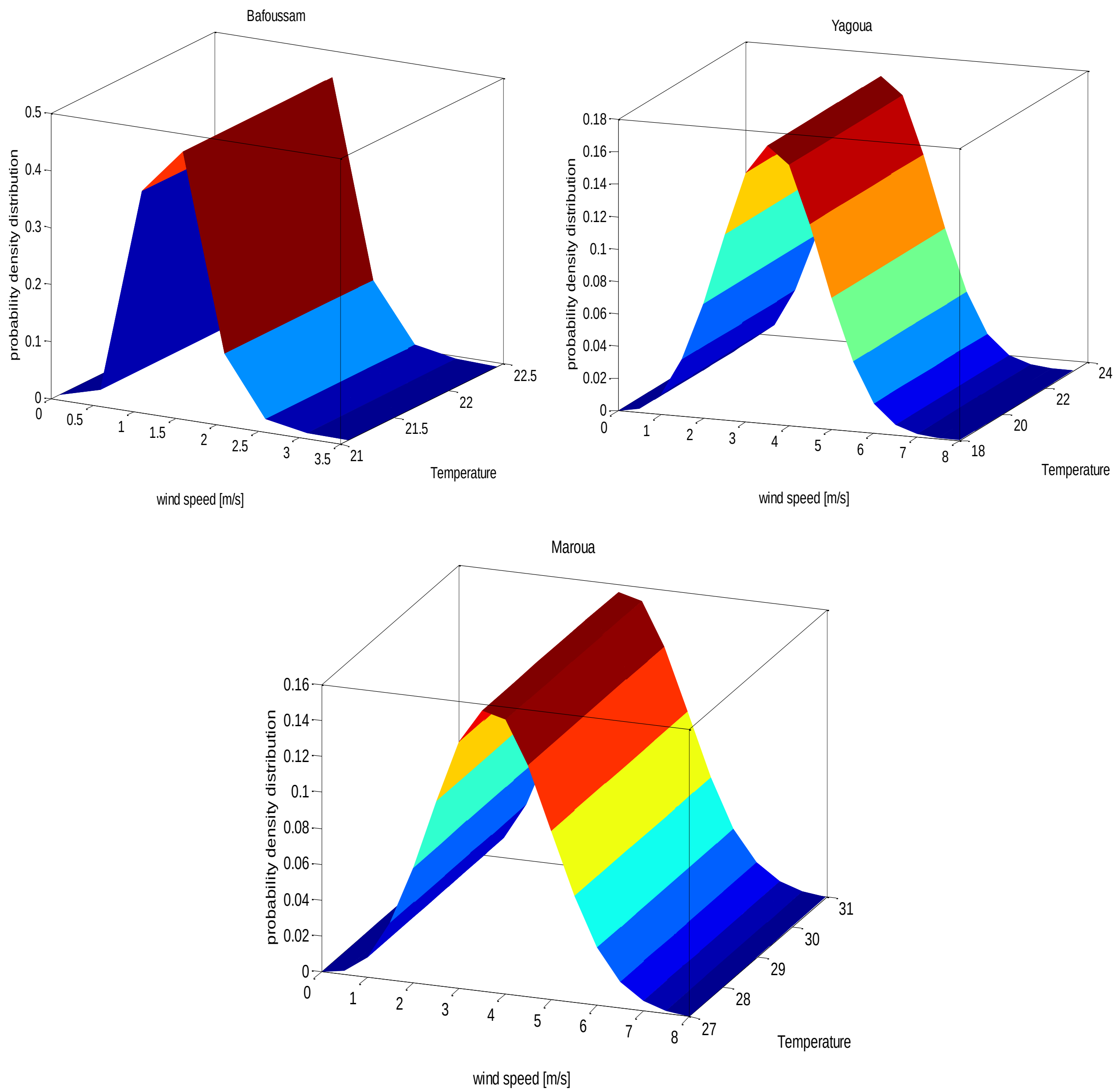


Figure 6: 3-D plot of the MEP distributions versus temperature and wind speed, for Bafoussam Yagoua and Maroua regions, Cameroon for year 2016.

Volume 2, Issue 4, pp. 53-62, 2018. ISSN (Online): 2456-7361

REFERENCES

[1] V. Nelson, *Wind Energy – Renewable Energy and the Environment*, CRC Press, 2009.
[2] P. Gipe, *Wind Energy Comes of Age*, John Wiley & Sons, 1995.
[3] H. Lund, "Renewable energy strategies for sustainable development," *Energy*, vol. 32, issue 6, 2007.
[4] A. K. Azad, M. G. Rasul, and T. Yusaf, "Statistical Diagnosis of the Best Weibull Methods for Wind Power Assessment for Agricultural Applications," *Energies*, vol. 7, pp. 3056-3085, 2014.
[5] M. R. Islama, R, Saidura, and N. A. Rahima, "Assessment of wind energy potentiality at Kudat and Labuan, Malaysia using Weibull distribution function," Energy, vol. 36, issue 2, pp. 985–992, 2011.
[6] T. P. Chang, "Performance comparison of six numerical methods in estimating Weibull parameters for wind energy application," *Applied Energy*, vol. 88, pp. 272–282, 2011.
[7] G. M. Jeutho, F. Kenmogne, and D. Yemélé, "Statistical estimation of mean wind energy available in Western Region of Cameroon: Case of the Bafoussam city," *J. Harmoniz. Res. Eng*., vol. 5, issue 1, pp. 15-27, 2007.
[8] S. A. Ahmet Shata and R. Hanitsch, "Evaluation of wind energy potential and electricity generation on the coast of Mediterranean Sea in Egypt," *Renewable Energy*, vol. 31, pp. 1183 202, 2006.
[9] P. A. Costa Rocha, R. Coelho de Sousa, C. Freitas deAndrade, and M. Vieira da Silva, "Comparison of seven numerical methods for determining Weibull parameters for wind energy generation in the northeast region of Brazil," *Applied Energy*, vol. 89, pp. 395–400, 2012.
[10] E. G. Pavia and J. JO'Brian, "Weibull statistics of wind speed over the ocean," *Journal of Climate and Applied Meteorology*, American Meteorological Society, vol. 25, pp. 1324 1332, 1986.
[11] F. C. Odo and G. U. Akubue, "Comparative Assessment of Three Models for Estimating Weibull Parameters for Wind Energy Applications in a Nigerian Location," *International Journal of Energy Science (IJES)*, vol. 2, issue 1, pp. 22-25, 2012.
[12] Paritosh Bhattacharya, "A study on Weibull distribution for estimating the parameters," *Journal of Applied Quantitative Methods*, vol. 5, issue 2, pp. 234-214, 2010.
[13] N. L. Johnson and S. Kotz, "Continuous univariate distributions," vol. 2. Houghton Mifflin, 1970.
[14] P. A. C. Rocha, R. C. D. Sousa, C. F. D. Andrade, and M. E. V. D. Silva, "Comparison of sevennumerical methods for determining Weibull parameters for wind energy generation in the northeast region of Brazil," *Applied Energy*, vol. 89, pp. 395–400, 2012.
[15] C. F. D. Andrade, H. F. M. Neto, P. A. C. Rocha, M. E. V. D. Silva, "An efficiency comparison of numerical methods for determining Weibull parameters for wind energy applications: A new approach applied to the northeast region of Brazil," *Energy Conversion and Management*, vol. 86, issue 10, pp. 801–808, 2014.
[16] S. Kurtz, K. Whitfield, D. Miller, J. Joyce, J. Wohlgemuth, M. Kempe, et al., "Evaluation of high-temperature exposure of rackmounted photovoltaic modules," in *34th IEEE Photovoltaic Specialists Conference (PVSC)*, pp. 2399-2404, 2009.
[17] F. Reid, "The Mathematician on the Banknote: Carl Friedrich Gauss," *Parabola*, vol. 36, issue 2, pp. 2-9, 2000.
[18] E. Kaplani and S. Kaplanis, "Thermal modelling and experimental assessment of the dependence of PV module temperature on wind velocity and direction, module orientation and inclination," Solar Energy, vol. 107, pp. 443–460, 2014.