Statistical Modelling of Wind Speed Data for Mauritius

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Abstract- This paper focused on the statistical modelling of wind speed data observed at two locations in Mauritius using some standard probability distribution functions (PDF). The objective was to determine the best PDF which can represent the data. The PDFs considered were Weibull, Rayleigh, Lognormal, Gamma, Normal and Frechet. The parameters for each PDF were estimated from the data using the Maximum Likelihood Estimation (MLE) technique. The Chi-Square (C-S), Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D) goodness-of-fit (GOF) tests were utilized to evaluate the effectiveness of the PDFs. For both locations all three GOF tests revealed that the Weibull and Burr distributions fit the wind speed data when the significance level is less than 5 %.

Keywords. Statistical analysis, Probability Density Functions, Wind Speed data, Mauritius, Goodness-of-fit tests.

1. Introduction

Wind energy has been exploited by mankind for more than 2000 years and represents a reliable source of renewable energy. In the present days, the wind energy technologies have reached such a mature level that it is being used as one of the main sources of producing electricity in many countries including Germany, Spain, United States, China and India [1, 2]. According to some recent studies presented by Elahee [3] and Mohee *et al.* [4], it is evident that Mauritius also possesses vast renewable resource potentials, including wind energy, for the production of electricity. Hence, it is worthwhile to make an assessment of the prospective of wind energy for the country. Although there are several initiatives already being undertaken to assess the possible use of wind energy locally, there are still a number of works that remain to be tapped, particularly in the light of recent technological development [5].

A wind energy evaluation involves a consolidated analysis of the possible wind energy resources of a specific location. It starts with comprehending the general wind patterns of the region, and evolves to the gathering and analysis of the wind data [6]. To facilitate the analysis, researchers have relied on long-term wind measurements (more than one year of hourly data) which were statistically modelled using a standard probability density function (PDF) and its corresponding cumulative density function (CDF). This approach, which has been widely employed in the literature, provided the researcher with a simple and comprehensive method to estimate the mean power that can be extracted from the wind.

Most of the research publications on the subject have given particular considerations to the Weibull distribution because it was found to fit a wide collection of wind data. For example, the Weibull PDF has been employed in the analysis of the wind energy potential for different regions in countries such as Tunisia [7], Nigeria [8], Turkey [9, 10], Iran [11], Columbia [12] and coastal areas of Jiwani, Pakistan [13]. However, some authors have noted that, in certain cases, the Weibull distribution failed to represent the wind speed data while another distribution may better fit the data. For instance, Morgan *et al*. [1] have shown that the bimodal Weibull, Kappa, and Wakeby distributions all displayed better approximate of the wind data recorded over a period of 20 years from different ocean buoy stations. Abbas *et al*. [5] performed a comparative study with six standard distributions for the wind speed data in Pakistan. Their results demonstrated that Burr, Lognormal and Gamma distributions modelled the data more accurately than Weibull. Kollu *et al*. [14] compared the accuracy of ten well-known statistical models on wind speed data observed at five weather stations over the west coast of America. The goodness of fit tests utilised concluded that the GEV PDF gave the closest fit to the observed data. Recently Masseran *et al*. [15] have analysed mean hourly wind speed data from 20 stations in East Malaysia with nine different statistical distributions. They found that the Gamma distribution provided the best fit to all the data. It is therefore important to perform a preliminary comparative analysis to identify which distribution better fits the wind data in a particular location. This will give the researcher a better estimate of the wind power at that location.

In the present work the focus was to determine the best statistical distribution for wind speed data collected at two locations in Mauritius. The distributions considered were the Weibull, Rayleigh, Lognormal, Gamma, Normal and Frechet PDFs. The effectiveness of these distributions to fit the data was investigated using three goodness of fit tests, namely, Chi-Square (C-S), Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D).

2. Materials and Methods

2.1. The Study Area and Data Set

The island of Mauritius is situated in the tropical South West Indian Ocean (SWIO) region. It spans around 60 km from north to south and 42 km from east to west. Being of volcanic origin, its topography consists of a central plateau which is about 500 meters above sea level and gradually rising towards the south west where it reaches its highest point at about 700 meters above sea level, as shown in Figure 1. This plateau is surrounded by a chain of mountains and some isolated peaks. Urban areas are mostly concentrated on the central plateau and coastal regions.

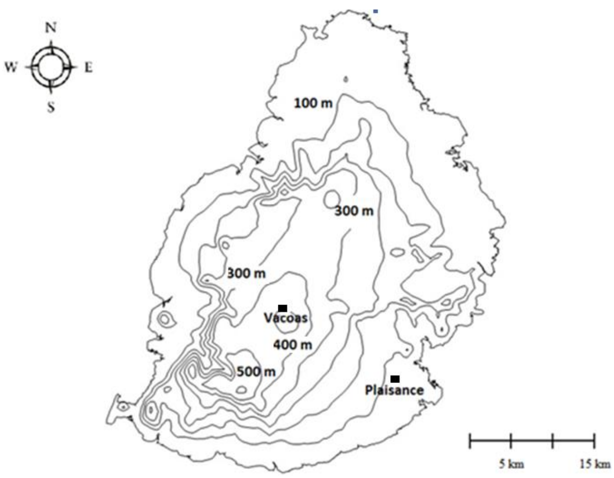
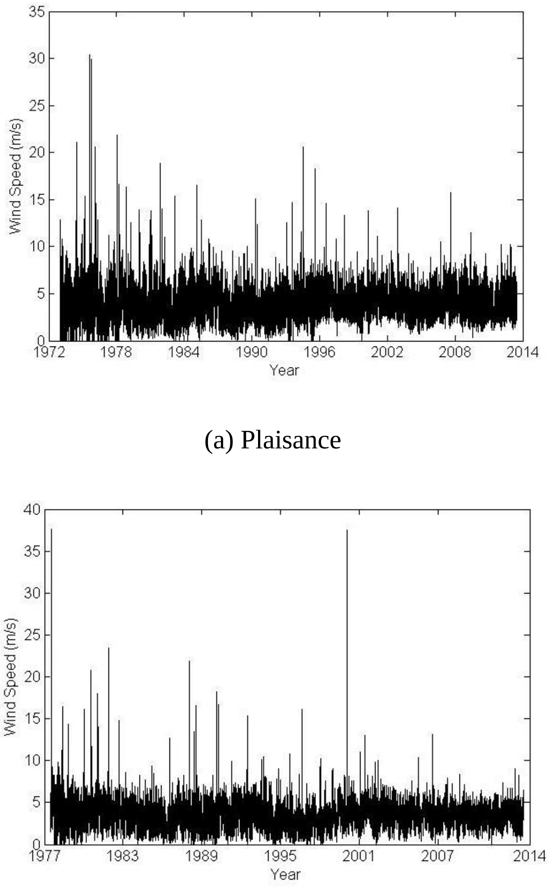


Fig. 1. A map of the island of Mauritius showing the elevation contours and locations of Plaisance and Vacoas.

Due to its geographical location, the island is influenced by large ocean-atmosphere interactions such as the south east trade winds. The two sites selected in this study are Plaisance and Vacoas. Plaisance is located near the South East coast of Mauritius with latitude 20.26 °S, longitude 57.41 °E at an elevation of 57 m above sea level. Vacoas is located on the central plateau with latitude 20.17 °S, longitude 57.29 °E at an elevation of 425 m above sea level.

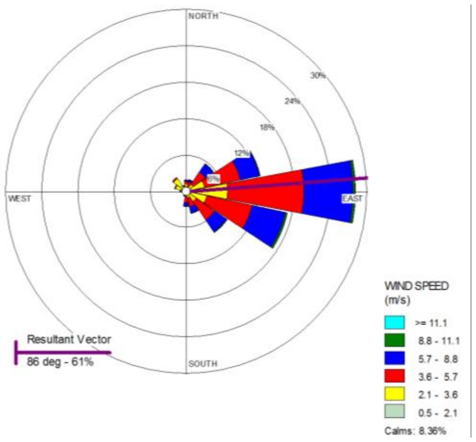
The data used in this study are daily mean wind speeds which were obtained from the Utah Data Climate Centre and the Mauritius Meteorological Services (MMS). Wind speed data obtained for Plaisance were from 1st January 1973 to 30th July 2013, while data for Vacoas were from 1st July 1977 to 30th July 2013. They were measured using cup anemometers placed at a height of 10 m above ground level. The data were checked thoroughly for homogeneity, outliers and missing records before being processed for this study as guided by the AWS (1997) [16] wind resource assessment handbook. Figure 2 shows plots of the observed temporal variations of wind speed data at both Plaisance and Vacoas and Figure 3 displays their corresponding prevailing directions using wind roses. The latter represents the bearing of the wind along the angular direction while the radial axis represents the percentage of occurrences.



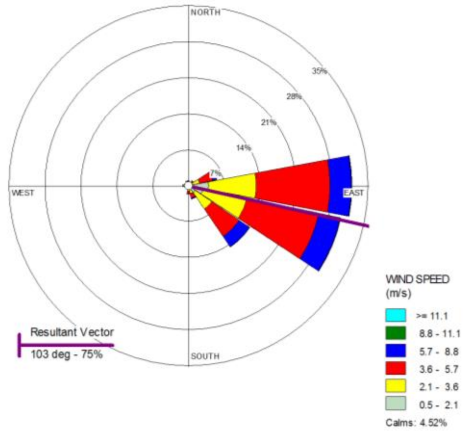
(a) Plaisance

(b) Vacoas

Fig. 2. Wind Speed time series data.



(a) Plaisance



(b) Vacoas

Fig. 3. Wind Roses for observed wind data.

It can be observed from Figure 2, that the wind speeds for both locations vary almost periodically. The sudden peaks correspond to wind gusts. The wind roses demonstrate that the prevailing wind direction was from the south east, although some westerly winds were apparent. The whole dataset for both stations are statistically described in Table 1. It can be seen that the mean value of the wind speed is higher for Plaisance than for Vacoas. The Standard Deviation, which describes by how much the data differ from the mean, is nearly the same for both stations. Skewness is a measure of symmetry. Hence the skewness values indicated that the distributions for both stations are asymmetric. Moreover the excess Kurtosis which indicates the shape of the random variable probability distribution suggested that the data for Vacoas is more peaked compared to the data for Plaisance. Therefore, only standard probability density distribution that correspond to the above statistical characteristics were considered as discussed in the next section

Table 1. Descriptive Statistics of the wind speed data.

Statistics	Estimates (m/s)	
	Plaisance	Vacoas
Sample size (n)	16790	14193
Mean ($\bar{v}$)	4.0507	3.5729
Standard Deviation (σ_m)	1.7906	1.6140
Minimum Value ($v_{\min}$)	0.0714	0.0833
Maximum Value ($v_{\max}$)	30.4	37.6
Skewness	1.2802	2.3123
Excess Kurtosis	9.5069	34.343

2.2. Standard Statistical Distributions

The probability density function (PDF) for the velocity variable *v* and its corresponding cumulative density function (CDF) for each standard distribution considered are listed in table 2.

2.3. Method for Estimating the Parameters

Several methods have been proposed to estimate the parameters of a particular distribution which will make the latter fit the data as close as possible. The suitability of the method depends mostly on the data size. The most accurate and common one is the Maximum Likelihood Estimation (MLE) [19]. MLE was generally preferred in this work as it lowers the mean square errors associated with model parameters estimates.

The MLE of a variable, say x, in a given function $g(x)$ is defined as the value of x that maximizes the likelihood of $g(x)$ or, equivalently, the logarithm of the likelihood of $g(x)$. This reduces the occurrence of an important number of unlikely outcomes for x. Table 3 lists the MLE formulation of each of the distributions presented in Table 2

2.4. Goodness-of-fit (GOF) Tests

GOF tests are techniques used to assess how well a distribution fits a given data. They are used to calculate the deviation between the observed and predicted data from the distribution considered. The decision for accepting or rejecting the PDF depends on the critical value of the test. If it is greater than the computed statistical value of the test, then the null hypothesis is accepted, that is the distribution fits the wind speed data. The critical value is dependent on the specific distribution that is being tested. However, this value alone is not sufficient to confirm the null hypothesis. Another parameter which is also useful for the conclusion of a goodness of fit test is the *p*-value. It is the probability that another sample will be unusual as the current sample given that the fit is appropriate. It is like a “best fit” test of the distribution with data. On comparing the fitting of some distributions to a set of data, the one with the higher *p*-value is likely to be the better fit regardless of the level of significance [20]. The threshold for the *p*-value is 0.5.

The most popular GOF tests are Chi-Square (C-S), Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D). In the following sections, these GOF tests are briefly described and the formulation for their critical and *p*-values are given.

2.4.1. Chi-Square Test

The Chi-Square (C-S) test compares the histogram of the data to the shape of the PDF. It is therefore dependent on binned data (class intervals) and the estimated parameters. The C-S test is valid for data with large sample sizes [21]. The statistical test is initiated by arranging the *n* observations into a set of *k* type intervals as given. The test statistics is given by

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}, \qquad (1)$$

where O_i denotes the observed frequency in the i^{th} class interval and $E_i = np_i$ is the expected frequency in the same class interval, with p_i being the corresponding probability associated with the PDF.

The statistical value is computed from equation (1) and is compared with the critical value $\chi^2_{\alpha,k-s-1}$ where α is the level of significance and $k - s - 1$ is the degrees of freedom, with *k* and *s* representing the number of class intervals and the number of parameters in each distribution respectively. The critical value is obtained from the table of Chi-Square distribution [22].

Table 2. Probability density function (PDF) and cumulative density function (CDF) for each distribution.

Distribution	**PDF ($f(.)$) and CDF ($F(.)$)**
Burr [5]	$f(v;\alpha,k,\beta) = \dfrac{\alpha k v^{\alpha-1}}{\beta^{\alpha}\left(1+\left(\frac{v}{\beta}\right)^{\alpha}\right)^{1+k}}$; $F(v;\alpha,k,\beta) = 1 - \left[1+\left(\frac{v}{\beta}\right)^{\alpha}\right]^{-k}$ α and k are both shape parameters, β: scale parameter
Frechet [18]	$f(v;\alpha,\beta) = \left(\frac{\alpha}{\beta}\right)\left(\frac{\beta}{v}\right)^{\alpha+1}\exp\left(\left[-\left(\frac{\beta}{v}\right)\right]^{\alpha}\right)$; $F(v;\alpha,\beta) = \exp\left\{-\left[\left(\frac{\beta}{v}\right)\right]^{\alpha}\right\}$ α : shape parameter, β: scale parameter
Gamma [14]	$f(v;\alpha,\beta) = \dfrac{1}{\beta^{\alpha}\Gamma(\alpha)} v^{\alpha-1}\exp\left[-\frac{v}{\beta}\right]$; $F(v;\alpha,\beta) = \dfrac{1}{\Gamma(\alpha)}\gamma\left(\alpha,\frac{v}{\beta}\right)$ $\gamma()$:lower incomplete gamma function, α: shape parameter, β: scale parameter, $\Gamma(\alpha)$:Gamma function evaluated at α
Lognormal [1]	$f(v;\mu,\sigma) = \dfrac{1}{\sigma v\sqrt{2\pi}}\exp\left[\dfrac{-(\ln(v)-\mu)^2}{2\sigma^2}\right]$; $F(v;\mu,\sigma) = \dfrac{1}{2} + \dfrac{1}{2} erf\left[\dfrac{\ln(v)-\mu}{\sigma\sqrt{2}}\right]$ erf []=complementary error function, μ: mean, σ: standard deviation
Normal [18]	$f(v;\alpha,\beta) = \dfrac{1}{\beta\sqrt{2\pi}}\exp\dfrac{-(v-\alpha)^2}{2\beta^2}$; $F(v;\alpha,\beta) = \dfrac{1}{\beta\sqrt{2\pi}}\int_{-\infty}^{v}\exp\dfrac{-(v-\alpha)^2}{2\beta^2}dv$ α: shape parameter, β: is the scale parameter
Rayleigh [1]	$f(v,\sigma) = \dfrac{v}{\sigma^2}\exp\left[-\dfrac{v^2}{2\sigma^2}\right]$; $F(v,\sigma) = 1 - \exp\left[-\dfrac{v^2}{2\sigma^2}\right]$ σ : continuous scale parameter
Weibull [14]	$f(v;k,c) = \dfrac{k}{c}\left(\dfrac{v}{c}\right)^{k-1}\exp\left[-\left(\dfrac{v}{c}\right)^{k}\right]$; $F(v;k,c) = 1 - \exp\left[-\left(\dfrac{v}{c}\right)^{k}\right]$ k: shape parameter, c: scale parameter

Table 3. MLE formulation for estimating the parameters of each distribution.

Distribution	MLE formulation
Burr [15]	$\frac{n}{\alpha}+\sum_{i=1}^{n}\ln\left(\frac{v_i}{\beta}\right)=(1+k)\sum_{i=1}^{n}\ln\left(\frac{v_i}{\beta}\right)\left[\left(\frac{\beta}{v_i}\right)^{\alpha}+1\right]^{-1}$, $n=(1+k)\sum_{i=1}^{n}\left[\left(\frac{\beta}{v_i}\right)^{\alpha}+1\right]^{-1}$, $\frac{n}{k}=\sum_{i=1}^{n}\ln\left[\left(\frac{v_i}{\beta}\right)^{\alpha}+1\right]$
Frechet [18]	$\frac{\partial \log l_n(\alpha,\beta)}{\partial\beta}=0$, $\beta=\left(\frac{n}{t}\right)^{\frac{1}{\alpha}}$ where l_n is the Log likelihood and $t=\sum_{i=1}^{n}\left(\frac{1}{v_i}\right)^{\alpha}$
Gamma [15]	$\ln(\alpha)-\varphi(\alpha)=\ln\left[\frac{1}{n}\sum_{i=1}^{n}v_i\right]-\frac{1}{n}\sum_{i=1}^{n}v_i$, $\beta=\frac{\bar{v}}{\alpha}$ where φ is the digamma function
Lognormal [1]	$\sigma=\frac{1}{n}\sum_{i=1}^{n}\ln v_i$, $\mu^2=\frac{1}{n}\sum_{i=1}^{n}(\ln v_i-\sigma)^2$
Normal [18]	$\beta^2=\frac{1}{n}\sum_{i=1}^{n}(v_i-\bar{\alpha})^2$, $\alpha=\frac{1}{n}\sum_{i=1}^{n}v_i$
Rayleigh [15]	$\sigma^2=\sqrt{\frac{1}{2n}\sum_{i=1}^{n}v_i^2}$
Weibull [1, 15]	$\frac{\sum_{i=1}^{n}v_i^k\ln v_i}{\sum_{i=1}^{n}v_i^k}-\frac{1}{k}-\frac{1}{n}\sum_{i=1}^{n}v_i=0$, $c=\left[\frac{1}{n}\left(\sum_{i=1}^{n}v_i^k\right)\right]^{\frac{1}{k}}$

2.4.2. Kolmogorov-Smirnov test

The Kolmogorov-Smirnov (K-S) test is mainly based on the maximum largest absolute deviation between an empirical and a theoretical frequency cumulative distribution [23]. Its sample statistics is formulated as:

$$D=\max\left|F(v)-O(v)\right|, \quad (2)$$

where $O(v)$ is the empirical cumulative frequency distribution evaluated at v and $F(v)$ is the corresponding theoretical cumulative distribution for the PDF considered. The K-S test compared the value obtained from equation (2) with the critical value D_α which is obtained from table of K-S critical values for the specified significance level α and sample size [14].

2.4.3. Anderson-Darling test

The Anderson-Darling (A-D) test is a modification of the K-S test. It compares the fit of an observed cumulative distribution to an expected one, by giving higher weights to the tails as opposed to the K-S test. It is more suitable for sensitive data [24]. In this GOF test, the sample statistics is computed by

$$A^2=-n-\frac{1}{n}\sum_{i=1}^{n}(2i-1)\left[\ln F(v_i)+\ln(1-F(v_{n-i+1}))\right], \quad (3)$$

where $F(v_i)$ is the cumulative distribution function for the PDF.

3. Results and Discussion

3.1. MLE of the Wind Speed Data

Wind speed data of the two stations, Plaisance and Vacoas, were used in the evaluation of different probability distribution functions to assess their suitability. Table 4 shows the fitted parameters for each distribution at each station obtained by using the MLE estimates. Comparison of probability density distributions according to observed data with all the distribution under the investigated sites are illustrated in Figures 4 and 5 for Plaisance and Vacoas respectively. For both stations, Weibull, Rayleigh, Burr and Frechet visually appear to follow the trend of the data, while Rayleigh and Frechet tended to skew to the left. Burr PDF appears to over predict the maximum peak of the data while Weibull seemed to slightly under predict the maximum peak

Table 4. Fitted Parameters of each PDF obtained from their MLE.

Distribution	Parameters	
	Plaisance	**Vacoas**
Burr	α =2.672, k = 13.033, β = 2.7594	α =3.0087, k = 4.0726, β = 6.1324
Frechet	α = 2.2522 , β = 2.7594	α =2.2721, β = 2.5425
Gamma	α = 5.6447, β = 0.7029	α = 5.1413, β = 0.7090
Lognormal	μ = 1.2713, σ = 0.5021	μ = 1.1889, σ = 0.4918
Normal	α = 3.9678, β = 1.6699	α = 1.6077, β = 3.6453
Rayleigh	σ = 3.1151	σ = 2.7454
Weibull	k = 2.544, c = 4.4695	k = 2.5771, c = 4.0811

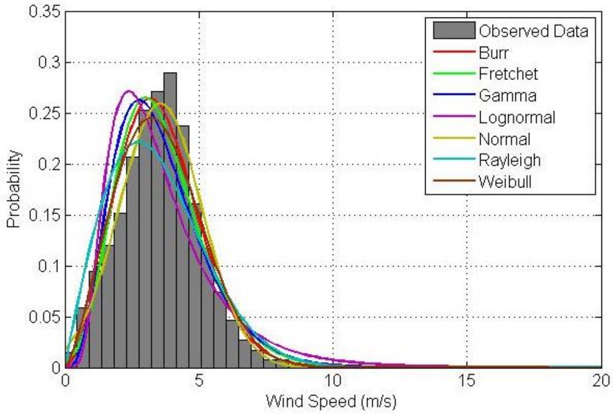


Fig. 4. PDF for Plaisance data.

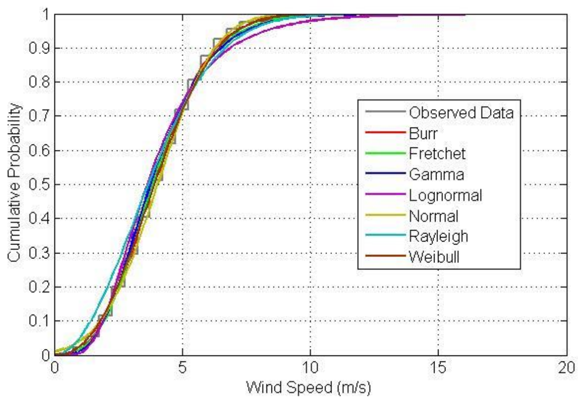


Fig. 6. CDF for Plaisance.

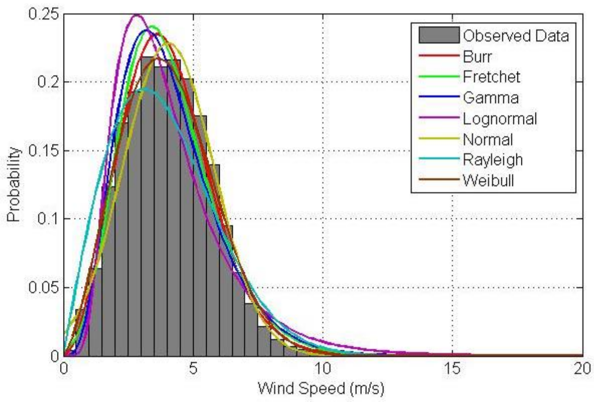


Fig. 5. PDF for Vacoas data.

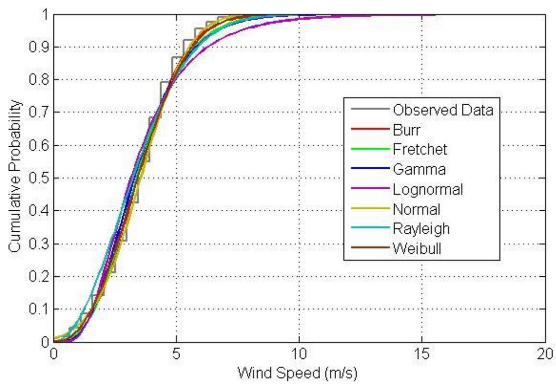


Fig. 7. CDF for Vacoas.

The wind speed cumulative probability distributions obtained from probability density functions (Weibull, Rayleigh, Burr, Frechet, Lognormal, Normal, and Gamma) distribution functions for the investigated sites are shown in Figures 6 and 7. It can be seen from both figures, that Burr and Weibull are closer to the Observed Data. This indicates that these distributions represent better the data compared to the other distributions.

3.2. GOF Tests

The GOF tests statistics given by equations (1), (2) and (3) were applied to the wind speed data for Plaisance and Vacoas. The tests were performed at significance levels 10%, 5%, 2% and 1%. Tables 5 to 10 compare the statistic values of each GOF test with the critical value for the distribution considered. İt can be noted that out of the seven distributions considered, the Weibull and the Burr distributions significantly fit the data when a significance level of less than 5 percent is used.

Table 5. GOF test for Plaisance wind speed data using C-S test.

Distribution	***α***	0.1	0.05	0.02	0.01
	Critical Value	12.02	14.07	16.62	18.48
	Statistics (*p*-value)	**Accept**			
Weibull	15.82 (0.0268)	No	No	Yes	Yes
Burr	13.12 (0.0691)	No	Yes	Yes	Yes
Normal	69.24 (2.1×10^{-12})	No	No	No	No
Gamma	107.43 (0)	No	No	No	No
Rayleigh	245.48 (0)	No	No	No	No
Lognormal	297.06 (0)	No	No	No	No
Frechet	1104.30 (0)	No	No	No	No

Table 6. GOF test for Plaisance wind speed data using K-S test.

Distribution	***α***	0.1	0.05	0.02	0.01
	Critical Value	0.0223	0.0248	0.0277	0.0297
	Statistics (*p*-value)	**Accept**			
Weibull	0.0200 (0.1779)	Yes	Yes	Yes	Yes
Burr	0.0272 (0.0232)	No	No	Yes	Yes
Normal	0.0296 (0.0102)	No	No	No	Yes
Gamma	0.0523 (1.4×10^{-7})	No	No	No	No
Rayleigh	0.0632 (7.1×10^{-11})	No	No	No	No
Lognormal	0.0793 (7.4×10^{-17})	No	No	No	No
Frechet	0.1523 (0)	No	No	No	No

Table 7. GOF test for Plaisance wind speed data using A-D test.

Distribution	***α***	0.1	0.05	0.02	0.01
	Critical Value	1.9286	2.5018	3.2892	3.9074
	Statistics (*p*-value)	**Accept**			
Weibull	1.0424 (-)	Yes	Yes	Yes	Yes
Burr	1.8135 (-)	Yes	Yes	Yes	Yes
Normal	6.3919 (-)	No	No	No	No
Gamma	16.233 (-)	No	No	No	No
Rayleigh	41.691 (-)	No	No	No	No
LogNormal	39.825 (-)	No	No	No	No
Frechet	154.09 (-)	No	No	No	No

Table 8. GOF test for Vacoas wind speed data using C-S test.

Distribution	α	0.1	0.05	0.02	0.01
	Critical Value	12.017	14.067	16.622	18.475
	Statistics (*p*-value)	**Accept**			
Weibull	15.408 (0.0311)	No	No	Yes	Yes
Burr	11.771 (0.1083)	Yes	Yes	Yes	Yes
Normal	63.512 (3×10^{11})	No	No	No	No
Gamma	101.95 (0)	No	No	No	No
Rayleigh	230.36 (0)	No	No	No	No
Lognormal	296.6 (0)	No	No	No	No
Frechet	1010.3 (0)	No	No	No	No

Table 9. GOF test for Vacoas wind speed data using K-S test.

Distribution	α	0.1	0.05	0.02	0.01
	Critical Value	0.02233	0.02479	0.02771	0.02974
	Statistics (*p*-value)	**Accept**			
Weibull	0.01507 (0.49849)	Yes	Yes	Yes	Yes
Burr	0.02342 (0.07334)	No	Yes	Yes	Yes
Normal	0.03309 (0.00274)	No	No	No	No
Gamma	0.04668 (4×10^{-6})	No	No	No	No
Rayleigh	0.06723 (1.8×10^{-12})	No	No	No	No
Lognormal	0.07394 (1×10^{-14})	No	No	No	No
Frechet	0.14465 (0)	No	No	No	No

Table 10. GOF test for Vacoas wind speed data using A-D test.

Distribution	α	0.1	0.05	0.02	0.01
	Critical Value	1.9286	2.5018	3.2892	3.9074
	Statistics (*p*-value)	**Accept**			
Weibull	1.0709 (-)	Yes	Yes	Yes	Yes
Burr	1.7343 (-)	Yes	Yes	Yes	Yes
Normal	6.5114 (-)	No	No	No	No
Gamma	14.099 (-)	No	No	No	No
Rayleigh	41.056 (-)	No	No	No	No
Lognormal	40.63 (-)	No	No	No	No
Frechet	156.46 (-)	No	No	No	No

4. Conclusion

In this paper the C-S, K-S and A-D GOF tests were used to verify which of the seven standard probability distribution considered best fit the wind speed data collected at Plaisance and Vacoas. Although visual comparisons of the standard PDF and CDF curves with the data indicated that the Burr and Weibull distributions better fit the data, these were confirmed by the GOF tests which revealed that these two distributions fit the data when the significance level is less than 5%.

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