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On Some Models for Wind Power Assessment in Yola, Nigeria

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Abstract: Probability distributions are used in the evaluation of wind energy potentials to describe the wind speed characteristics of the chosen location for wind farm establishment. However, the Weibull distribution that is the most chosen by wind energy modelers may likely fail to properly describe the wind speed data of certain locations, or it may not be the best model to describe wind speed when compared to the fitness of other probability distributions. Thus, in this study, four probability distributions are fitted to wind speed data from Yola, Nigeria. They are the Weibull, the exponentiated Weibull, the generalized power Weibull and the exponentiated epsilon distributions; and, all provided good fit to the wind speed dataset. The exponentiated epsilon distribution is new and provided the best fit. These models are compared based on the relative likelihood gain per data point; it is found that there is about 5% gain by the other three probability distributions over the Weibull distribution. Hence all the three distributions can also be used as wind models. The estimated average wind speeds computed using the four models at various hub heights show that wind is sufficiently available to support a wind turbine with a cut-in speed of 3 m/s at hub heights 90 m above ground level. For the exponentiated-epsilon model, average wind speed of 3.68 m/s at hub height of 120 m above ground level can generate 6.11 W/m^2 of electricity; and for a wind turbine of rotor diameter of 128 m with 12,868 m^2 swept area, this amounts to 78.6 kW of electricity supply for a small-scale wind power project. Consequently, Yola holds a good potential for the establishment of a wind farm.

Keywords: Cut-in Wind Speed, Exponentiated-Epsilon Distribution, Likelihood Gain, Turbine Hub Height, Wind Energy, Wind Farm

1. Introduction

The need for energy is increasing globally, particularly with increasing world population and the giant developmental strides by developing economies. For instance, energy consumption grew by 2.9% in 2018, the highest and fastest since 2010's 1.5% [5]. This growth was led by natural gas and renewable energy sources, with wind and solar energy clinching 14.5% [5] while hydro and nuclear energies are included in the renewable energy portfolio. Yet Africa had only managed to contribute 3% of the global total growth, less than 9% of China's alone while Nigeria, with its vast population and economic potential, could not appear on the renewable energy tables. For most developing economies and Nigeria for example, renewable energy sources portend the most realistic hopes for sustainable development. This assertion is, on the one hand due to the fact that fossil fuels are fast depleting with global risk of exhaustion by 2060 [4] while Nigeria's target exhaustion is projected to 2050 with continued extraction [1]. On the other hand, renewable energy sources are freely available, self-replenishing and sustainable, and the cost of harnessing them reduces with use.

Nigeria, like many African countries, is faced with tremendous challenges in meeting the growing needs for energy. The fast-growing population with dwindling investment in energy and other developmental infrastructures has resulted in very low per capita of electricity compared to many other developing economies. Yet, there is abundance of renewable energy resources that can be harnessed to mitigate the energy deficit. The country has the potential of 150,000 terra joule per year that can be generated from average wind speed of 2.0–4.0 m/s and other renewable energy resources [24]. There are many other studies in the literature portraying renewable energy potentials in the country, see for example [23, 14, 20]. Wind resource has been at the fore front in the global renewable energy growth. To successfully harness this resource, it is imperative to characterize its intermittent nature.

2. Wind Speed Modeling

The characterization of wind speed is of great significance in everyday endeavor of man. Its study has practical application in many areas, namely, determination of air quality and the movement of air pollutants [9, 19, 7], estimation of wind load on buildings and other physical objects including humans [27]; prediction of atmospheric or space probe and missile trajectory; and the production of energy from the wind [8, 15, 28, 11]. All these require thorough study of the wind regime. Wind energy production, in particular requires planned study of the intermittent nature of wind speed for proper wind farm siting, and the determination of effective cut-in and cut-out wind speeds for appropriate deployment of efficient wind turbines. For the understanding of this intermittent nature, probability distributions are deployed.

The Weibull distribution is the most preferred and widely used probability distribution for modeling wind speed data. Its tractable nature and flexibility have often presented it the first choice among wind speed modelers and/or wind energy developers. Its moments are explicitly expressed in terms of the parameter estimates of sample wind speeds, and these are used in wind power assessment at proposed sites for wind power generation.

However, many research questions have aroused regarding the dominant role of the Weibull distribution for wind energy assessment [21, 26]. Its validity for application to wind speed modeling is argued and shown not to be the best to properly describe the wind speed characteristics of certain times and locations [8]. Some probability distributions that have also been deployed for assessment of wind speed include generalized extreme value distribution of Gumbel (Type I), Fréchet (Type II) and reverse Weibull (Type III) [6] and mixed Rayleigh-Rice distribution [12]. Other non-Weibull distribution applications are found in [22, 16, 25].

Extended probability distributions do exercise better flexibility to capture the most versatile skewness property than the standard distributions. Although their moments are not easily expressed in explicit forms thus making direct estimations difficult, the existence of high tech computer systems and software makes this challenge less burdensome. Numerical integration capabilities in most of the mathematically oriented computer software, such as MATLAB and R statistical programming language, make the work much easier.

3. The Models

To determine a model to best fit wind speed dataset and provide efficient estimate of potential power in the wind, the best statistical practice is to fit many similar distributions and choose the best by appropriate model selection process. Thus, in this study, the Weibull distribution is compared to three other probability distributions to determine its efficacy in modeling wind speed datasets in Yola, Nigeria. Two extensions of the Weibull distribution namely; the exponentiated Weibull [17] and the generalized power Weibull [18] distributions; and the exponentiated epsilon distribution [10] will be used to model the wind speed dataset. These are given in equations (1) to (4), respectively, below

$$f_X(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta}}, \tag{1}$$

$$f_X(x) = \frac{\beta\theta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta}} \left(1 - e^{-\left(\frac{x}{\alpha}\right)^{\beta}}\right)^{\theta-1}, \tag{2}$$

$$f_X(x) = \frac{\beta\theta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} \left(1 + \left(\frac{x}{\alpha}\right)^{\beta}\right)^{\theta-1} e^{1-\left(1+\left(\frac{x}{\alpha}\right)^{\beta}\right)^{\theta}}, \tag{3}$$

and

$$f_X(x) = \alpha\beta\left(\frac{\theta^2}{\theta^2-x^2}\right)\left(\frac{x+\theta}{\theta-x}\right)^{-\frac{\beta\theta}{2}} \left[1 - \left(\frac{x+\theta}{\theta-x}\right)^{-\frac{\beta\theta}{2}}\right]^{\alpha-1}. \tag{4}$$

To estimate the parameters in each of equations (1) to (4) above, the *fitdistrplus* package of R statistical programming language will be used. The package offers opportunity for different methods of estimation, but in this study the default maximum likelihood method is chosen. For the Weibull distribution in equation (1), its parameters are estimated directly from the package; while to estimate the parameters in the models of equations (2) to (4), their density, distribution and quantile functions will be specified in the *fitdistrplus* package of R statistical programming language.

4. Determination of Model Efficiency

As stated earlier, the Weibull distribution is used in this study as a control model for the determination of the relative efficiency, in terms of likelihood gain per data point, of using the exponentiated Weibull, generalized power Weibull, and exponentiated-epsilon distributions. The gain in likelihood per data point, expressed in percentage, is used for the determination of relative efficiency of the other distributions over the Weibull distribution. A positive gain implies a distribution performed better in providing a good fit to the data while a negative gain implies a loss in likelihood of using the distribution over the Weibull distribution. It is computed by

$$\gamma = \left(\sqrt[n]{\frac{exp(LL_R)}{exp(LL_C)}} - 1\right) \times 100\%, \tag{5}$$

where n is the sample size, LL_R is the log-likelihood function value of the distribution whose relative gain in likelihood per data point is sought and LL_C is the log-likelihood function value of the distribution (in this case the Weibull distribution) against which the relative gain in likelihood per data point of the other distribution (s) is sought.

5. Wind Energy Estimation

From the Wind Energy Conversion (WEC) point of view, the energy in the wind is expressed as a function of a cube of the average wind speed. This is given by

$$P = \frac{1}{2}\rho\bar{V}^3, \tag{6}$$

where ρ is the density of the air with standard value taken as 1.225 kg/m^3, and $\bar{V}$ is the average wind speed. $\bar{V}$ can be estimated directly for the Weibull distribution in equation (1) using the estimated parameter values, given by

$$\bar{V} = \hat{\alpha}\Gamma\left(1 + \frac{1}{\hat{\beta}}\right), \tag{7}$$

where $(\hat{\cdot})$ is the estimated parameter value. For the models in equations (2) to (4), the average wind speed, $\bar{V}$, is computed at the estimated parameter values by

$$\bar{V} = \int_0^\infty x f(x;\, \hat{\omega})dx, \tag{8}$$

where $\hat{\omega}$ is the estimated parameter space, $f(x)$ are as specified in equations (2) to (4) and the upper limit of integration for equation (4) is $\hat{\theta}$. The integral will be evaluated numerically at the estimated parameter values in R.

However, many other components are considered when discussing real power that is derivable from the wind. First, is the swept area, A, indicating radius of space through which the rotor turns. It is determined as the area of a circle with the rotor radius as main input. The second component is called the power coefficient. It is the proportion of the kinetic energy of the wind convertible into mechanical energy that turns the rotor to generate electricity. Theoretically, only 59.3% of the kinetic energy of the wind can be converted by the best wind turbines [3]. And because of some mechanical factors impeding the wind turbines such as frictional force and machine aging, about half of the convertible kinetic energy of the wind is lost. This leaves only 10% - 30% of the power in the wind that is actually converted into electricity [13]. Thus, the power coefficient, C_p, assume values in the range 10 – 30%; and for this application, 20% is used to avoid extreme points. The power that is extractable from the wind is given, for this application, by

$$P_E = \frac{1}{2}\rho A C_p \bar{V}^3, \tag{9}$$

Here we consider $\bar{V}$ as average wind estimated from the models. These are computed at selected heights to depict turbine hub heights for different applications. The heights are 10 m (anemometer height), 30 m, 60 m, 90 m, 120 m and 150 m above ground level. Wind speeds at these selected heights will be extrapolated using the relation given by

$$V_2 = V_1\left(\frac{h_2}{h_1}\right)^{\varphi}, \tag{10}$$

where V_1 is the wind speed at the anemometer height, $h_1 = 10$ m, h_2 is the projected height at which the extrapolated wind speed, V_2, is sought, and φ is the shear exponent taken as 0.3 for small towns with trees and shrubs [2], which is adopted for the Airport in Yola from where the wind speed data were collected.

6. Results

6.1. Extrapolation of Wind Speed

The wind speed data collected at the Yola Airport at anemometer height of 10 m were not sufficient for analysis in order to estimate the extractable power from the wind. Five other heights were selected that could represent different applications and wind speed extrapolated for those heights using the relation in equation (10). The wind speed at 10 m anemometer height, are represented in Figure 1 below.

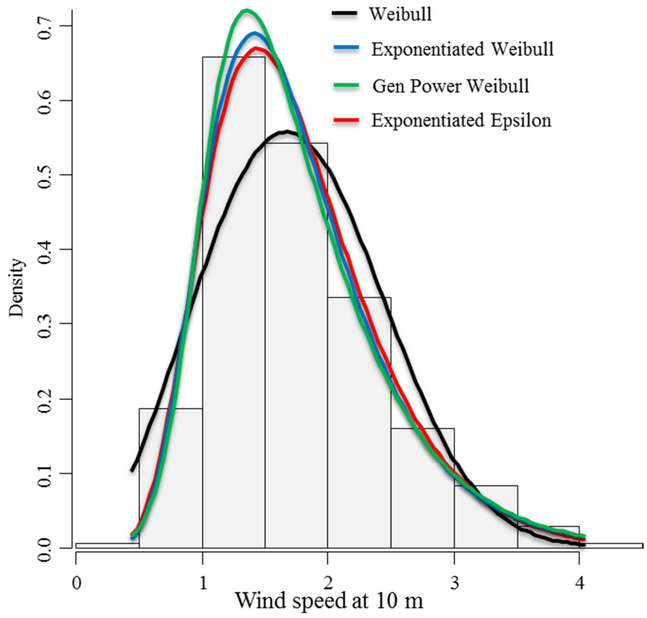

Figure 1. *Plots of the Weibull, Exp-Weibull, G-Power Weibull and Exp-Epsilon distributions for wind speed at 10 m anemometer height.*

6.2. Parameter Estimates and Goodness-of-Fit Test

The estimates of parameters and standard errors of the four models to the wind speed dataset and the Kolmogorov-Smirnov goodness-of-fit test results are presented in Table 1 below.

Table 1. *Parameter Estimates and Goodness-of-fit Test Results.*

Height (m)	Model	Parameter estimates $\hat{\alpha}\ (se)$	$\hat{\beta}\ (se)$	$\hat{\theta}\ (se)$	LL	KS	Remark
10	Wei	1.969 (0.039)	2.766 (0.107)	NA	-363.61	0.0689	Good fit
	Exp-Wei	0.617 (0.234)	1.054 (0.196)	10.880 (6.263)	-344.93	0.0458	‘’
	GP-Wei	1.122 (0.058)	5.813 (0.775)	0.237 (0.044)	-344.49	0.0485	‘’
	Exp-Eps	10.627 (1.814)	1.635 (0.136)	6.086 (1.840)	-344.06	0.0445	‘’
30	Wei	2.738 (0.055)	2.766 (0.107)	NA	-483.91	0.0689	‘’
	Exp-Wei	0.858 (0.330)	1.053 (0.199)	10.886 (6.360)	-465.23	0.0457	‘’
	GP-Wei	1.559 (0.081)	5.816 (0.774)	0.237 (0.044)	-464.79	0.0485	‘’
	Exp-Eps	10.621 (1.813)	1.176 (0.098)	8.462 (2.564)	-464.36	0.0430	‘’
60	Wei	3.371 (0.068)	2.766 (0.107)	NA	-559.81	0.0688	“
	Exp-Wei	1.057 (0.400)	1.054 (0.196)	10.874 (6.250)	-541.13	0.0458	‘’
	GP-Wei	1.920 (0.099)	5.817 (0.775)	0.237 (0.044)	-540.69	0.0485	‘’
	Exp-Eps	10.622 (1.816)	0.955 (0.080)	10.426 (3.177)	-540.26	0.0431	‘’
90	Wei	3.907 (0.076)	2.766 (0.107)	NA	-604.21	0.0689	‘’
	Exp-Wei	1.188 (0.461)	1.051 (0.199)	10.959 (6.452)	-585.53	0.0458	‘’
	GP-Wei	2.168 (0.112)	5.817 (0.775)	0.237 (0.044)	-585.09	0.0485	‘’
	Exp-Eps	10.618 (1.808)	0.846 (0.070)	11.762 (3.534)	-584.66	0.0431	‘’
120	Wei	4.150 (0.083)	2.766 (0.107)	NA	-635.71	0.0589	‘’
	Exp-Wei	1.301 (0.499)	1.054 (0.198)	10.882 (6.349)	-617.03	0.0458	‘’
	GP-Wei	2.363 (0.123)	5.816 (0.778)	0.237 (0.045)	-616.59	0.0486	‘’
	Exp-Eps	10.615 (1.818)	0.776 (0.065)	12.823 (3.902)	-616.16	0.0431	‘’
150	Wei	4.438 (0.089)	2.766 (0.107)	NA	-660.14	0.0689	‘’
	Exp-Wei	1.350 (0.549)	1.039 (0.203)	11.383 (6.969)	-641.47	0.0460	‘’
	GP-Wei	2.527 (0.131)	5.818 (0.777)	0.237 (0.045)	-641.03	0.0486	‘’
	Exp-Eps	10.620 (1.808)	0.726 (0.060)	13.697 (4.113)	-640.59	0.0431	‘’

KS=Kolmogorov-Smirnov, CV=Critical Value, NA=Not Applicable

From Table 1, the goodness-of-fit test results show the computed values of the test statistic are all less than the critical value of 0.0711. These imply that all the distributions significantly fitted the wind speed data of Yola at all heights.

6.3. Percent Gain in Likelihood

The log-likelihood function values in the LL column of Table 1 were substituted in the equation (5) to determine the relative gain in likelihood per data point. The results of 5.25%, 5.38% and 5.50% for the exponentiated Weibull, generalized power Weibull and exponentiated epsilon distributions, respectively, were obtained at each of the heights. These show that all the non-Weibull distributions have gained significantly on the likelihood per data point, over 5%. However, the exponentiated epsilon distribution has gained a little above the exponentiated Weibull and the generalized power Weibull distributions in likelihood per data point.

6.4. Wind Power Estimation

The power in the wind is estimated based on the theoretical capability of 59% and the practical reality of 10 – 30%. Here, a realizable target of 20% is set to avoid extreme points. The average wind speeds ($\bar{V}$) obtained from the models of equations (1) to (4) are given in Table 2 below.

Table 2. *Mean wind speed (m/s) for different models.*

Model	Height (m) 10	30	60	90	120	150
Weibull	1.752	2.437	3.000	3.388	3.694	3.950
Exp-Wei	1.748	2.432	2.994	3.365	3.686	3.942
GP-Wei	1.745	2.424	2.985	3.370	3.674	3.928
Exp-Eps	1.746	2.427	2.989	3.375	3.680	3.934

a. Theoretical power estimate

The theoretical power estimate is the 59% of the kinetic energy of the wind captured by a wind turbine that is convertible to electricity. It is computed by

$$P_T = \frac{1}{2} \times 1.225 \times 0.59\bar{V}^3 \tag{11}$$

The power at 10 m anemometer height is not computed since it is not up to the minimum cut-in wind speed for most commercial turbines in use. The power computed at the projected heights are presented in Table 3.

Table 3. *Theoretical power density (Watts/m^2) computed at the projected heights.*

Model	Height (m) 30	60	90	120	150
Weibull	7.705	14.378	20.712	26.836	32.802
Exp-Wei	5.197	9.702	13.770	18.103	22.131
GP-Wei	5.146	9.611	13.825	17.922	21.899
Exp-Eps	5.165	9.649	13.892	18.010	22.001

b. Realizable power density

As mentioned earlier, mechanical and other factors such as gearbox, bearings and generator also impact significantly on the amount of kinetic energy in the wind that is convertible into electricity. These factors also act to reduce the actual power output from a turbine. Consequently, the power that is realizable falls in the range of 10 – 30%. For this study, 20% is assumed to be realizable to avoid the curse of under estimation or overestimation. Thus, the realizable power density is computed by

$$P_R = \frac{1}{2} \times 1.225 \times 0.2\bar{V}^3 \tag{12}$$

The computed power density at projected height is given in Table 4 below

Table 4. *Realizable power density (Watts/m^2) computed at the projected heights.*

Model	Height (m)				
	30	60	90	120	150
Weibull	2.612	4.874	7.021	9.097	11.119
Exp-Wei	1.762	3.289	4.667	6.137	7.502
GP-Wei	1.744	3.258	4.686	6.075	7.423
Exp-Eps	1.751	3.271	4.709	6.105	7.458

7. Discussion

Observe from Table 4 that the average wind speed at anemometer height (10 m) is not up to the cut-in wind speed required by most turbines. However, the extrapolated wind speeds show that wind resource is available for power generation at height 30 m and above. All the probability distributions fitted the extrapolated wind speeds and the analysis of their likelihood function values relative to the Weibull distribution show that exponentiated Weibull, generalized power Weibull and exponentiated-epsilon distributions fitted the wind speed data with more precision. In the same vein, Morgan et al [16] found that more complex distributions such as the four-parameter Kappa and the five-parameter Wakeby distributions gave much better results compared to the Weibull distribution.

Although the three distributions are better than the Weibull distribution in fitting the wind speed dataset in Yola, the exponentiated epsilon distribution is much better with higher gain in likelihood per data point.

The general results show that there is a potential for wind power generation in Yola. For instance, the average wind speed projected at 120m above ground level based on the exponentiated epsilon distribution is 3.68 m/s. This is sufficient to satisfy the cut-in wind speed requirement of most commercial wind turbines. For a turbine of rotor diameter 128 m with 20% efficiency, offering a swept area of 12,868 m^2, the amount of electric power it can produce is 78.56 kW. Twenty of such turbines in a mini-grid wind farm can generate electricity amounting to 1.57 MW, sufficient to power a village with 1000 homes.

8. Conclusion

The analysis of wind speed at various heights above ground level show that only winds at 30 m above ground level can meet up the cut-in wind speed requirements of most wind turbines. The average speeds of the extrapolated winds based on the distributional assumption show there is ample potential for wind power generation in Yola. A wind farm consisting 20 wind turbines of swept area 12, 868 m^2 and mounted at 120 m above ground level is shown to be capable of generating 1.57 MW of electricity.

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