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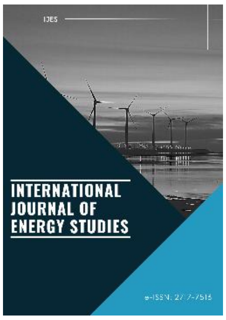

Research Article

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Wind energy estimation in Sabratha and Msallata: A comparison study

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Highlights

- First comparative wind assessment for Sabratha and Msallata identifies "good-to-very good" potential in western Libya.
- Burr and Johnson SB distributions are optimal for modeling seasonal wind speeds in these coastal Libyan sites.
- Sabratha shows superior resource with higher wind power density (up to 390.81 W/m²) compared to Msallata.
- Technical screening reveals Winwind-1MW and ENERCON-E53 turbines as optimal, with capacity factors >40%.
- Study provides site-specific data and turbine recommendations to de-risk future wind projects in the region.

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ABSTRACT

Accurate wind resource assessment is fundamental to developing wind power, a key contributor to a sustainable energy future. This study presents a comparative analysis of the wind potential in Sabratha and Msallata, Libya, using 2017-2018 meteorological data for Msallata and online data for Sabratha, then Wind speed data were processed and fitted to probability distributions using EasyFit software, which identified the Burr and Johnson SB distributions as the best fit, as determined by Kolmogorov-Smirnov and Anderson-Darling tests. Mean monthly wind speed at 10m height was 5–8 m/s for Msallata and 5–11 m/s for Sabratha, corresponding to a wind power density (WPD) of 76.92–289.1 W/m² and 97.08–390.81 W/m², respectively. This classifies both sites as having good-to-very good wind potential. A technical assessment of various wind turbines identified the Winwind-1MW and ENERCON-E53 models as the most efficient, achieving capacity factors exceeding 40%. These results demonstrate a highly productive synergy between the local wind regimes and specific turbine technologies, providing critical insights for future wind energy projects in western Libya.

Keywords: Wind power, Sustainable energy, Wind turbine, Probability distribution

1. INTRODUCTION

Renewable energy resources—including wind, solar, and hydropower—are abundant, inexhaustible, and offer the critical advantage of minimal environmental impact. This stands in stark contrast to fossil fuels, whose emissions drive global warming. Libya faces increasing electricity demand, necessitating a shift from fossil fuels to its abundant renewable resources [3]. The country possesses significant wind energy potential [2], with coastal areas like Sabratha and Msallata being particularly promising. However, detailed resource assessments for these western coastal sites are lacking [4].

This study addresses that gap by performing a comparative analysis of wind resources in Sabratha and Msallata. I analyze monthly, seasonal, and annual wind speed data—collected via a met mast in Msallata and from online sources for Sabratha. The methodology involves: (1) identifying optimal probability distribution functions for wind speed; (2) calculating wind power density across various hub heights to categorize the resource; and (3) conducting a technical evaluation of energy generation using commercial horizontal-axis wind turbines. The findings provide crucial data to guide future wind power development in western Libya.

2. METHODOLOGY

2.1. Site Description and Data Collection

Wind speed data for Msallata were collected from a meteorological mast station at a height of 10 m for the years 2017 and 2018. Data for Sabratha were obtained from weather website for the same period and reference height. The raw data of Msallata was averaged per ten minutes while less daily data were available on weather website for Sabratha. then, these data were processed and analyzed using excel software into monthly, seasonal, and annual summaries. Subsequently, the wind speed data were analyzed with EasyFit software to determine the optimal probability distribution functions of wind speed data at the studied locations.

2.2. Data Analysis and Characterization

The mean wind speed (V_m) and standard deviation (σ_v) were calculated for each dataset (monthly, seasonal, annual) using standard formulas:

$$V_m = \left(\frac{1}{n}\sum_{i=1}^{n} {V_i}^3\right)^{1/3} \tag{1}$$

$$\sigma_v = \sqrt{\frac{\sum_{i=1}^{n}(v_i - v_m)^2}{n}} \tag{2}$$

The standard deviation (σ_v) represents a measure for the variability of wind velocities in a given set of data. Lower values of σ_v indicate the uniformity of the data set.

To estimate the wind speed at a wind turbine hub height, the measured data were extrapolated using the power law which is given by [5,6]:

$$\frac{v}{v_0} = \left(\frac{h}{h_0}\right)^{\alpha} \tag{3}$$

Where v_0 is the wind speed at reference height h_0 , v is the wind speed at the desired height h, α is the shear exponent a function of surface topology and depends on the roughness of the terrain.

The wind power density (WPD) was calculated using equation 4 as mentioned in ref. [7]. which has value given in W/m^2 and depends only on the air density and the wind speed.

$$WPD = \frac{P}{A} = \frac{1}{2}\rho v^3 \tag{4}$$

For simplicity, the mean wind power density (WPD) in W/m^2 can be calculated using Equation (5) [8].

$$WPD = \frac{\bar{P}}{A} = \frac{1}{2}\rho \bar{v}^3 \tag{5}$$

Air density (ρ) was calculated based on average monthly pressure and temperature data [9].

$$\rho = \frac{P_{avg}}{R\,T_{avg}} \tag{6}$$

The standard air density value is 1.225 kg/m^3 at sea level at pressure of 1 atm and a temperature of 15 ^{0}C.

2.3 Wind Power Density and Output Power of Wind Turbines:

Different types of wind turbines have different power output performance curves; so that the model used to describe the performance is also different [10]. The designer of a wind energy project must choose the turbine type optimally matching with the site characteristics to maximize the energy production. The total power of wind turbine can be expressed by equation (7) as in [5]:

$$P = \left\{ \begin{array}{ll} 0 & (v < v_i) \\ P_r \frac{v^n - v_i^n}{v_r^n - v_i^n} & (v_i < v < v_r) \\ 0 & (v > v_o) \end{array} \right\} \tag{7}$$

Where P is electrical power output of a wind turbine, P_r is the rated electrical power, v_i is the cut-in wind velocity, v_r is the rated wind velocity, v_o is the cut-off wind velocity. In practice, the exponent value can take any form such as linear, quadratic, cubic or even higher powers and its combinations. In this paper the author will use quadratic value (i.e. n =2).
The total energy output of wind turbine can be expressed by:

$$E_t = \sum_{i=1}^{N} P \times T \tag{8}$$

Where E_t is the total energy for a period of time T, T=8760 hours for annual energy estimation.
The capacity factor $C.F$ is defined as the ratio of the average power output of a wind turbine over a time period versus the rated electrical power,

$$C.F = \frac{P_{avg}}{P_r} \tag{9}$$

2.4. Probability Distribution Fitting and Selection

To accurately model the wind speed frequency distribution, a robust fitting procedure was implemented using the EasyFit software [13]. A suite of eight candidate distributions gave best fit results compared to observed data: Burr [11], Johnson SB, Generalized Extreme Value [14], Normal, Dagum [16], Beta, Log-Logistic, and Log-Pearson III [12].

Table 1. Probability Distribution Functions Used for Wind Speed Modeling.

Distribution Name	Parameters & Support	Probability Density Function (PDF)	Cumulative Distribution Function (CDF)
Burr (3P)	$k, \alpha > 0$ (shape) $\beta > 0$ (scale) $x > 0$	$f(x) = \frac{\alpha k (x/\beta)^{\alpha-1}}{\beta[1 + (x/\beta)^{\alpha}]^{k+1}}$	$F(x) = 1 - [1 + (x/\beta)^{\alpha}]^{-k}$
Johnson SB	$\gamma, \delta > 0$ (shape) $\lambda > 0$ (scale) $z = (x - \mu)/\lambda$	$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}z(1-z)} \exp\left[-\frac{1}{2}\left(\gamma + \delta \ln\left(\frac{z}{1-z}\right)\right)^2\right]$	$F(x) = \Phi\left(\gamma + \delta \ln\left(\frac{z}{1-z}\right)\right)$ where Φ is the standard normal cumulative distribution function.

Generalized Extreme Value (GEV)	μ (location) $\zeta > 0$ (scale) β (shape)	$f(x) = \zeta^{-1}\exp[-(1-\frac{\beta(x)-\mu}{\zeta})^{1/\beta}](1-\frac{\beta(x)-\mu}{\zeta})^{1/\beta-1}$	$F(x) = \exp[-(1-\frac{\beta(x)-\mu}{\zeta})^{1/\beta}]$
Normal	μ (mean) $\sigma > 0$ (std. dev.) $x \in (-\infty, \infty)$	$f(x) = \frac{1}{\sigma\sqrt{2\pi}}\exp(-\frac{(x-\mu)^2}{2\sigma^2})$	$F(x) = \frac{1}{2}[1+\mathrm{erf}(\frac{x-\mu}{\sigma\sqrt{2}})]$
Dagum	$k, \alpha > 0$ (shape) $\beta > 0$ (scale) $x > 0$	$f(x) = \frac{\alpha k (x/\beta)^{\alpha k-1}}{\beta[1+(x/\beta)^{\alpha}]^{k+1}}$	$F(x) = [1+(x/\beta)^{-\alpha}]^{-k}$
Beta (4P)	$\alpha_1, \alpha_2 >$ 0 (shape) a, b (boundaries) $a \le x \le b$	$f(x) = \frac{(x-a)^{\alpha_1-1}(b-x)^{\alpha_2-1}}{B(\alpha_1,\alpha_2)(b-a)^{\alpha_1+\alpha_2-1}}$ where $B()$ is the Beta function.	$F(x) = I_z(\alpha_1, \alpha_2)$ where I_z is the regularized incomplete beta function.
Log-Logistic (3P)	$\alpha, \beta > 0$ (shape) γ (location) $x > \gamma$	$f(x) = \frac{(\alpha/\beta)((x-\gamma)/\beta)^{\alpha-1}}{[1+((x-\gamma)/\beta)^{\alpha}]^2}$	$F(x) = [1+(\beta/(x-\gamma))^{\alpha}]^{-1}$
Log-Pearson III	$\alpha > 0$ (shape) β (scale) γ (location) $x > 0$	$f(x) = \frac{1}{x\mid\beta\mid\Gamma(\alpha)}[\frac{\ln(x)-\gamma}{\beta}]^{\alpha-1}\exp[-\frac{\ln(x)-\gamma}{\beta}]$	$F(x)$=Γ(α)Γα(βln(x)−γ) Γ (gamma function)

The goodness-of-fit for each distribution was evaluated using two statistical tests:

1- **Kolmogorov-Smirnov (K-S) Test:** Measures the maximum vertical deviation between the empirical and theoretical cumulative distribution functions

$$D = max_{i=1,\ldots,N}\left|CDF(x_i) - \frac{i-1}{N}, \frac{i}{N} - CDF(x_i)\right| \quad (10)$$

A lower test statistic (D) indicates a better fit [15].

2- **Anderson-Darling (A-D) Test:** A more sensitive test that gives more weight to the tails of the distribution (Eq. 21, 22). A lower test statistic (A^2) indicates a better fit.

$$A^2 = -N - S \quad (11)$$

Where:

$$S = \sum_i^N \frac{2i-1}{N}[lnF(Y_i) + \ln(1 - F(Y_{N+1-i}))] \quad (12)$$

Where:

F is the cumulative distribution function, Y_i is the ordered sample value. a better fitted model is indicated by a lower value of AD test [17].

For each dataset (e.g., Sabratha Winter 2017), the distribution with the lowest K-S and A-D statistics was selected as the best model for subsequent WPD calculations.

2.5. Wind Turbine Energy selection

A diverse range of commercially available horizontal-axis wind turbines with different specifications such as rated power, hub height, operating speeds, rotor diameter were selected for the technical assessment. This selection was made to evaluate the performance sensitivity to different turbine designs at the two sites.

Table 2. General Specifications of wind turbines.

Turbine model	cut in speed (m/s)	rated speed (m/s)	cut out speed (m/s)	rotor diameter (m)	Hub height (m)	Rated power (Kw)
ENERCON-E48	3	14	28	48	50	800
ENERCON-E53	2	13	28	53	60	800
VESTAS V47	4	15	25	47	50	660
M.Torres TWT 1.65-82	3.5	13	25	82	71	1650
SUZLON S52	2.7	13	25	52	75	600
WINWIND-1MW	3	12.5	20	60	56,66	1000
Gamesa G80-2MW	4	16	25	80	80	2000

3. RESULTS AND DISCUSSION

3.1. Seasonal and Monthly Wind Speed Characteristics

The annual wind patterns for Msallata and Sabratha are shown in Figures 1 and 2. Msallata exhibits a relatively stable wind regime throughout the year, with peak speeds occurring in the autumn (October). In contrast, Sabratha shows stronger seasonality, with significantly higher wind speeds in the winter and early summer months of 2017, particularly in January and June. The year 2018 was notably calmer in Sabratha, though it still generally outperformed Msallata.

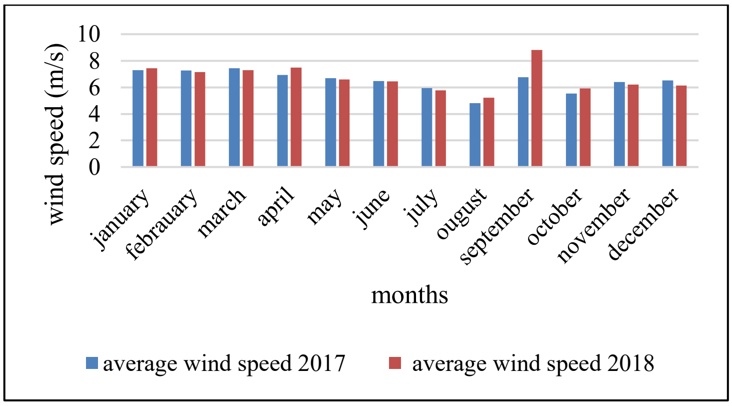

Figure 1. Msallata average wind speeds at 10 m height (2017-2018).

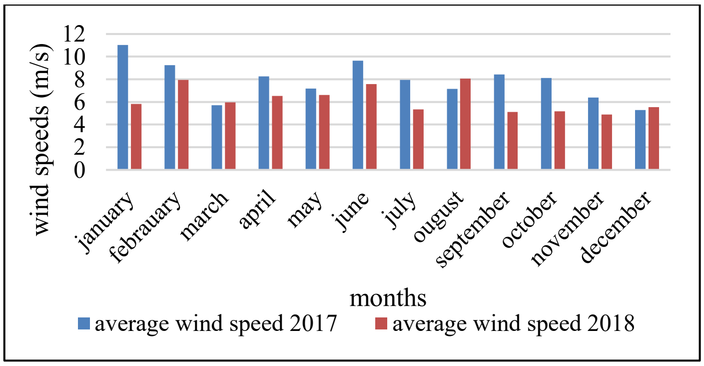

Figure 2. Sabratha average wind speeds at 10 m height (2017-2018).

3.2. Wind Power Density and Energy Potential

The Wind Power Density (WPD) confirms Sabratha's superior energy potential. The average annual WPD was 183.86 W/m² for Msallata and 228 W/m² for Sabratha. According to the U.S. Department of Energy wind resource classification system [1], these values classify both sites as Class 3 (Good), with Sabratha at the higher end of the class range. Sabratha's advantage is particularly evident during the winter months, where its WPD is significantly higher (see Table 3). This consistent, strong winter performance is a key advantage for grid reliability.

Table 3. Monthly Wind Power Density (W/m²) at 10m Height.

Month	Msallata	Sabratha
Jan	157.27	367.03

Feb	244.41	388.56
Mar	228.89	122.01
Apr	245.06	246.92
May	229.46	200.61
Jun	179.45	390.81
Jul	164.54	179.28
Aug	123.14	269.37
Sep	76.92	190.23
Oct	289.10	179.71
Nov	115.19	109.84
Dec	152.84	97.08

3.3. Best-Fit Probability Distributions

A key objective was to identify the optimal probability distribution for modeling wind speed at each site. Eight distributions were tested for each seasonal and annual dataset using the Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D) tests. The best-fit distribution for each period was selected based on achieving the lowest test statistics.

Table 4. Summary of Best-Fit Probability Distributions.

Site	Season	Best-Fit Distribution	Site	Season	Best-Fit Distribution
Msallata	Winter	Dagum & Burr	**Sabratha**	Winter	Burr &Dagum
	Spring	Johnson SB		Spring	Log-Pearson 3
	Summer	Johnson SB & Dagum		Summer	Burr
	Autumn	Beta		Autumn	Burr & Dagum
Annual		Johnson SB	Annual		Burr

Winter: Both locations show a preference for the Burr distribution, indicating significant wind speed variability and potentially high average power densities.

Spring: Msallata's Johnson SB distribution suggests less extreme speeds, while Sabratha's Log-Pearson 3 indicates more variability, leading to higher average speeds and power densities for Sabratha.

Summer: Msallata's Dagum (4P) vs. Sabratha's Burr (4P) suggests Sabratha may experience a broader wind speed range, resulting in higher average power density.

Autumn: Both locations favor distributions that manage moderate variability well, indicating stable wind speeds and moderate power densities.

- The Burr family of distributions (Burr, Burr 4P) demonstrated the most consistent performance across all seasons in Sabratha. For Msallata, the Johnson SB and Burr distributions were most effective.

Summary of Best-Fit Distributions for annual Data in Msallata and Sabratha (2017-2018).

For annual wind speed data of Msallata the Best fit is Johnson SB distribution, Since Johnson SB is suited for handling skewed data, its strong performance suggests it captures the moderate wind speeds typically seen in the whole year well.

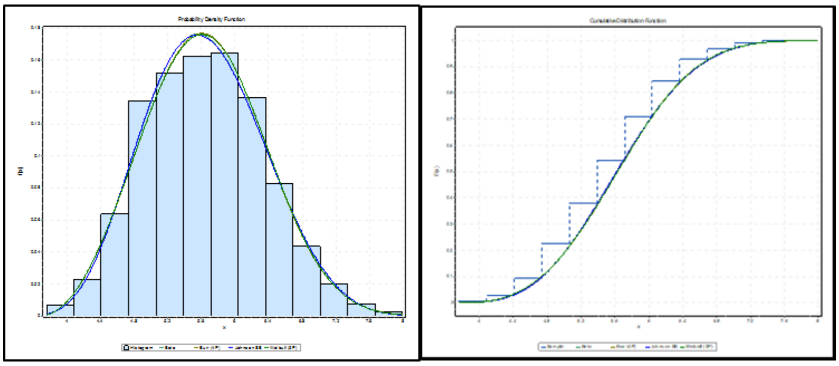

Figure 3. $f(v)$and $F(v)$ results for annual mean wind speed Distributions in Msallata at 10 m height

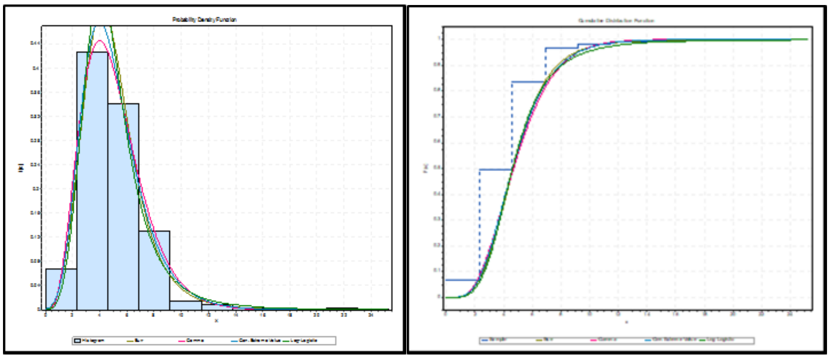

Figure 4. $f(v)$and $F(v)$ results for annual mean wind speed Distributions in Sabratha at 10m height.

For annual wind speed data of Sabratha the best fit is Burr distribution. This indicates consistent fit and reliability in estimating wind speeds across seasons in Sabratha, suggesting stable and possibly moderate average wind speeds, with corresponding power density estimates.

Table 5. Msallata and Sabratha fitting test results of mean annual wind speed distributions at 10m.

Site	Year	Best-Fit Distribution	K-S Statistic	A-D Statistic
Msallata	2017	Johnson SB	0.01774	1.0825
	2018			
Sabratha	2017	Burr	0.03812	15.352
	2018			

3.4. Wind Turbine Energy Production Analysis

A technical evaluation of five commercial wind turbines was conducted to translate the wind resource into projected energy output. The results, presented in Table 6, show that the Winwind-1MW and ENERCON-E53 models are optimally suited for the wind regimes at both sites.

These two turbines significantly outperformed others, achieving capacity factors (CF) of 46% and 41% in Msallata and 53% and 48% in Sabratha, respectively. These exceptionally high CF values confirm a highly productive synergy between the turbines' operational specifications and the sites' characteristic wind speeds.

Table 6. Annual Energy Production and Capacity Factor of Selected Wind Turbines.

Turbine Model	Rated Power (kW)	Msallata		Sabratha	
		AEP (MWh)	CF	AEP (MWh)	CF
Winwind-1MW	1000	4027	0.46	4670	0.53
ENERCON-E53	800	2890	0.41	3400	0.48
SUZLON S52	600	1920	0.37	2300	0.44
ENERCON-E48	800	2350	0.34	2850	0.41
VESTAS V47	660	1650	0.29	1950	0.34

Note: The turbines are ranked by their performance in Sabratha, the superior site.

4. CONCLUSION

This study provides a comprehensive wind resource assessment for Sabratha and Msallata. Sabratha was identified as the superior site, with higher annual wind power density and stronger seasonal performance, particularly in winter. The Burr distribution was the most reliable model for Sabratha's wind speeds, while the Johnson SB distribution was best for Msallata. A techno-economic analysis revealed that the Winwind-1MW and ENERCON-E53 turbines are the most efficient choices, achieving capacity factors exceeding 40%. These findings provide a robust foundation and clear recommendations for the development of wind energy projects in western Libya.

Collectively, these findings offer a robust, data-driven foundation for policymakers and investors. . Prioritizing development in Sabratha, equipped with the recommended turbine models, presents a strategic opportunity for Libya to diversify its energy mix, reduce reliance on fossil fuels, and enhance its energy security. Future work should focus on micro-siting within these regions, detailed grid integration studies, and securing financing to translate this significant potential into operational power plants.

NOMENCLATURE

abbreviations used in the paper.

Symbol	Description	Unit
AEP	Annual Energy Production	kWh
$C.F$	Capacity Factor	–
$f(v)$	Probability density function	–
$F(v)$	Cumulative distribution function	–
$P(v)$	Power output of a turbine	kW
P_r	Rated power of a turbine	kW
V	Wind speed	m/s
v_i	Cut-in wind speed	m/s
v_r	Rated wind speed	m/s
v_o	Cut-out wind speed	m/s
V_m	Mean cubic wind speed	m/s
WPD	Wind Power Density	W/m²
ρ	Air density	kg/m³
α	Wind shear exponent	–

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DECLARATION OF ETHICAL STANDARDS

The author of the paper submitted declares that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Rabee Ahmeed: Conceived and designed the analysis, collected the data, performed the analysis, wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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