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REASSESSING THE ACCURACY OF WEIBULL DISTRIBUTION FOR WIND SPEED MODELING AND ENERGY ASSESSMENT IN LIBYA

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إعادة تقييم دقة توزيع Weibull لنمذجة سرعة الرياح وتقييم الطاقة في ليبيا

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الملخص

تُعد نمذجة سرعة الرياح بدقة متطلبًا أساسيًا لإجراء تقييم موثوق لموارد طاقة الرياح والتخطيط لمشروعات مزارع الرياح. وعلى الرغم من الانتشار الواسع لاستخدام توزيع ويبول في دراسات طاقة الرياح، إلا أن دقته قد تتباين تبعًا للخصائص المناخية للمناطق المختلفة. تهدف هذه الدراسة إلى تقييم مدى ملاءمة توزيع ويبول لتمثيل بيانات سرعة الرياح في ليبيا ومقارنة أدائه بعدد من التوزيعات الاحتمالية البديلة. استند التحليل إلى 7305 قراءة يومية لسرعة الرياح تم الحصول عليها من قاعدة بيانات NASA POWER خلال الفترة 2004–2023 عند ارتفاع مرجعي قدره 50 م فوق سطح البحر، وذلك لخمسة مواقع في ليبيا هي: طرابلس، أجدابيا، الكفرة، أوباري، ودرنة. وتراوحت متوسطات سرعة الرياح بين 6.419 م/ث في طرابلس و7.270 م/ث في درنة. وقد أُجري التحليل الإحصائي باستخدام برنامجي EasyFit وMATLAB، مع تطبيق اختبار كولموغوروف- سميرنوف (K–S) لتقييم جودة المطابقة بين البيانات الفعلية والتوزيعات النظرية. أظهرت النتائج أن توزيع ويبول لم يقدم أفضل تمثيل إحصائي لأي من المواقع المدروسة، في حين أظهرت توزيعات Johnson SB و Dagum (4P) و Burr أداءً إحصائيًا أفضل. كما تراوحت قيم كثافة طاقة الرياح بين 52.57 واط/م² في طرابلس و78.97 واط/م² في درنة، مما يبرز أهمية استخدام التوزيعات الاحتمالية متعددة المعاملات لتحسين دقة تقييم موارد الرياح ودعم التخطيط لمشروعات طاقة الرياح في ليبيا.

الكلمات المفتاحية: كثافة طاقة الرياح، توزيع وايبل، اختبار كولموجروف- سميرنوف، توزيعات الاحتمالات، نمذجة سرعة الرياح.

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ABSTRACT

Accurate wind speed modeling is essential for reliable wind resource assessment and wind farm planning. Although the Weibull distribution is widely used in wind energy studies, its accuracy may vary depending on regional climatic characteristics. This study evaluates the suitability of the Weibull distribution for modeling wind speed data in Libya and compares its performance with several alternative probability distributions. The analysis is based on 7,305 daily wind speed observations obtained from the NASA POWER database for the period 2004–2023 at a reference height of 50 m above Sea level for five locations in Libya: Tripoli, Ajdabiyah, Alkufra, Awbari, and Darnah. The mean wind speeds range from 6.419 m/s in Tripoli to 7.270 m/s in Darnah. Statistical analysis was performed using EasyFit and MATLAB, while the Kolmogorov–Smirnov (K–S) test was applied to evaluate the goodness of fit between observed and theoretical distributions. The results show that the Weibull distribution does not provide the best statistical representation for any of the studied locations. Instead, Johnson SB, Dagum (4P), and Burr distributions demonstrated superior performance. The estimated wind power density ranged from 52.57 W/m² in Tripoli to 78.97 W/m² in Darnah, highlighting the importance of flexible multi-parameter distributions for improving wind resource assessment and supporting more reliable wind farm planning in Libya.

KEYWORDS: Wind power density, Weibull distribution, Kolmogorov–Smirnov test, Probability distributions, Wind speed modeling.

INTRODUCTION

Wind energy has become one of the most promising renewable energy sources worldwide due to its abundance, sustainability, and environmental benefits. As global efforts intensify to transition toward clean energy systems, accurate estimation of wind potential becomes a crucial step in the design and optimization of wind farms. The effectiveness of such estimation largely depends on the accuracy of statistical models used to describe wind speed distributions.

Among these models, the Weibull distribution is the most commonly applied due to its mathematical simplicity and flexibility in fitting diverse wind regimes. It has been widely adopted in studies across Europe, Asia, and Africa to characterize wind speed data and estimate power density. However, recent research indicates that Weibull does not always provide the best statistical representation, especially in regions with complex topography, seasonal variability, or multi-modal wind patterns [1, 2].

In Libya, most previous studies have relied on the Weibull distribution as the default model for wind resource assessment. For instance, Abdusamad [3] applied the Weibull distribution in reliability analysis of Libyan wind systems, while Selimli et al. [4] confirmed its adequacy for energy density estimation in selected Libyan sites. Nevertheless, later investigations (e.g., S. Milad et al. [5]) demonstrated that alternative distributions such as Gamma and Lognormal outperformed Weibull in certain western regions, including Gharyan and Nalut.

Globally, Lo Brano et al. [6] found that the Burr distribution offers higher accuracy in southern Italy, and Soukissian [7] reported that the Johnson SB distribution provides better fitting in Mediterranean conditions. Similar findings by Jung and Schindler [8] showed that Wakeby and Kappa distributions were more suitable for offshore and onshore environments, respectively.

Inaccurate modelling of wind speed distributions can lead to substantial errors in estimating Wind Power Density (WPD), resulting in inefficient design and deployment of wind turbines. Although several alternative distributions such as Gamma, Log-Normal, Burr, Dagum, and Johnson SB have been proposed in recent years, their performance has not been comprehensively evaluated for Libyan conditions. Most local studies have continued to rely exclusively on the Weibull distribution without validating its accuracy against other models. This methodological gap raises concerns about the reliability of current wind energy assessments in Libya. Therefore, this paper aims to reassess the applicability of the Weibull distribution for modelling wind speeds across selected Libyan regions and to compare its performance with alternative statistical models using rigorous goodness-of-fit tests [9].

DATA AND METHODOLOGY

This section outlines the methodology used to achieve the research objectives. The analysis is based on wind speed data collected from five Libyan regions to evaluate the accuracy of the Weibull distribution in representing such data. To accomplish this goal, a comprehensive methodology was implemented, encompassing data collection, analysis using specialized statistical tools and advanced software, and assessing distribution fitness through robust performance metrics.

Figure (1) presents an overview of the proposed methodology. The process is divided into structured steps as shown in the flowchart, starting with data collection and initial analysis, followed by goodness-of-fit testing using the Kolmogorov-Smirnov K-S test, and culminating in the calculation of daily wind power density for each location.

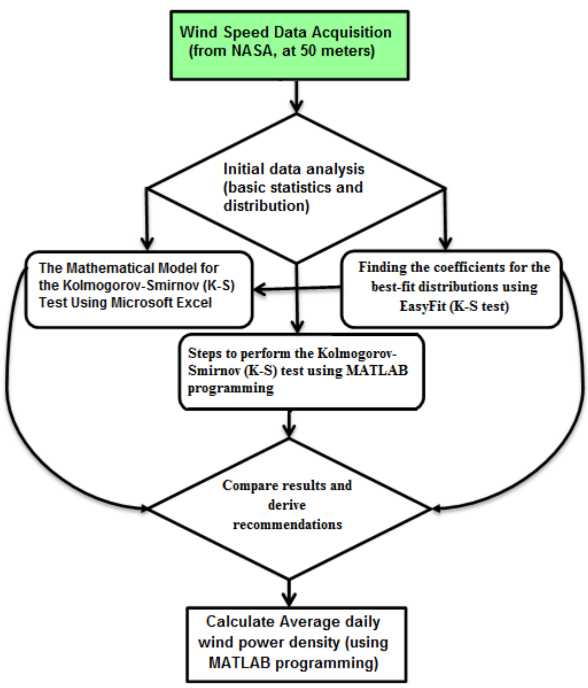

Figure 1: Flowchart of the proposed Methodology.

STUDY SITES AND DATA SOURCE

This study examines five geographically diverse locations in Libya: Tripoli, Ajdabiyah, Alkufra, Awbari, and Darnah. These sites represent coastal, semi-arid, and desert environments, allowing the analysis to capture the country's climatic variations, which significantly influence wind characteristics and energy potential.

Daily wind speed data were collected from the NASA Prediction of Worldwide Energy Resources (POWER) database, covering a continuous 20-year period from 2004 to 2023 at a reference height of 50 meters above Sea level. Each dataset contained more than 7,300 daily records (approximately 20 years × 365 days), ensuring adequate statistical reliability and temporal resolution for long-term wind behavior analysis.

NASA POWER dataset was used because local wind measurements in Libya often suffer from calibration issues, incomplete records, and difficulties in obtaining long-term wind data. In contrast, NASA provides a continuous, validated 20-year dataset, which is more reliable for statistical analysis despite some smoothing of small-scale terrain effects. The selection of study sites is a critical component in the assessment of wind resources, as these sites must adequately represent the diverse geographical and climatic conditions within the study area [10].

In this research, five regions in Libya were chosen to provide a comprehensive evaluation of wind speed distribution across varying terrains. The selection process was based on the need to analyze wind patterns across different altitudes and coastal proximity levels. The selected sites include three coastal locations: Tripoli in the western sector, Darnah in the eastern sector, and Ajdabiyah in the central coastal region. These sites were chosen to investigate the influence of marine factors on wind characteristics. Additionally, two inland sites were selected: Alkufra in the southeastern region and Awbari in the southwestern region, both located more than 1000 kilometers from the nearest coastline. Including these inland sites allows for an analysis of wind behavior in desert and semi-arid environments, highlighting the impact of surface roughness, altitude above sea level, and temperature gradients on wind dynamics.

Figure (2) illustrates the map of Libya with the five selected study locations [11] as follows:

Figure 2: Libya map, with the five selected study locations [11].

WIND SPEED ANALYSIS

A preliminary statistical analysis was conducted to characterize wind behavior at each site. This analysis involved computing key descriptive statistics, including the mean wind speed ($\bar{v}$) and standard deviation (σ), all of which provide essential insights into the central tendency, variability, and overall shape of the wind speed distribution. Histograms and frequency plots were also generated to visually examine the behavior of the data and to identify any departures from normality, such as asymmetry or heavy-tailed patterns. The mean wind speed was calculated using the standard averaging formula, while the standard deviation was computed to quantify the degree of variation in wind speeds relative to the mean. Together, these statistical measures form the foundation for understanding local wind regimes and play a crucial role in guiding the subsequent selection of the most suitable probability distribution models for wind energy analysis [12, 13].

Table (1) displays the mean wind speed ($\bar{v}$), standard deviation (σ) for the selected sites.

Table 1: The statistical results obtained to the mean wind speed and the standard deviation.

REGION	Total sample (n)	mean wind speed (m/s) ($\bar{\upsilon}$)	standard deviation (m/s) (σ)
TRIPOLI	7305	6.419	2.546
AJDABIYAH	7305	6.764	2.292
ALKUFRA	7305	6.687	1.576
AWBARI	7305	7.025	1.874
DARNAH	7305	7.270	2.744

Table (1) presents the descriptive statistics of wind speed for the five locations. The mean wind speed ranges from 6.419 m/s in Tripoli to 7.270 m/s in Darnah, indicating favorable wind conditions, while the standard deviation values show moderate variability, especially in coastal regions influenced by sea–land interactions. The mean wind speed for each location was calculated using equation (1):

$$\bar{\upsilon} = \frac{1}{n}\sum_{i=1}^{n} V_i \tag{1}$$

where (V_i) represents the wind speed for each observation and (n) is the total number of observations. The standard deviation calculated as:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(V_i - \bar{\upsilon}\right)^2} \tag{2}$$

These measures provided an overview of local wind regimes, which later guided the selection of appropriate probability distributions [12]. The statistical parameters derived from equations (1) and (2) provide a basic characterization of the wind regime at each study site and serve as the initial step prior to the probability distribution fitting process.

PROBABILITY DISTRIBUTION FITTING AND KOLMOGOROV-SMIRNOV (K–S) GOODNESS OF FIT EVALUATION

In order to determine the most appropriate statistical model for each site, several probability distributions including Weibull, Lognormal, Dagum (4P), Burr, and Johnson SB were systematically evaluated. The fitting procedure was conducted using EasyFit 5.6 Professional, which estimates the distribution parameters based on the maximum likelihood estimation (MLE) method [14]. To strengthen the robustness, transparency, and reproducibility of the statistical assessment, the Kolmogorov–Smirnov (K–S) goodness-of-fit test was employed to rigorously validate the adequacy of each fitted model. The K–S test is a nonparametric technique that examines the degree of agreement between the empirical cumulative distribution function (ECDF) of the observed wind speed data and the theoretical cumulative distribution function (CDF) of the proposed model. Its sensitivity to deviations in both central tendency and variability makes it particularly effective for assessing wind speed distributions [15].

Accordingly, each candidate distribution (e.g., Weibull, Lognormal, Dagum, Burr, and Johnson SB) was subjected to the following systematic evaluation steps:

DATA PREPRARTION

Wind speed data were obtained from the NASA POWER Data Access Viewer for a continuous 20-year period (January 1, 2004- December 31, 2023) at a height of 50 m above ground level [10].

The use of long-term daily records improves the reliability of the statistical analysis by capturing both seasonal and interannual variability in wind behavior.

EMPIRICAL AND THEORETICAL CDF CALCULATION

The empirical CDF $\left(F_{empirical}\,(v_i)\right)$ was computed for the observed wind speed data using the formula:

$$F_{empirical}\left(V_i\right)=\frac{i}{n} \tag{3}$$

where (i) is the rank of the data point (V_i) in the ordered dataset, and (n) is the total number of observations.

The theoretical CDF ($F_{theoretical}\,(V)$) was calculated for each candidate distribution using its respective probability density function PDF. For instance, the Weibull CDF is given as follows:

$$F_{theoretical}\left(V\right)=1-e^{-\left(\frac{V}{c}\right)^{K}} \tag{4}$$

where (k) is the shape parameter and (c) is the scale parameter [7].

K-S STATISTIC CALCULATION

The K-S statistic (D_n) was determined as the maximum absolute difference between the empirical and theoretical CDFs:

$$D_n = MAX\left|\,F_{emprical}\,\left(V_i\right)-F_{theoretical}\,\left(V\right)\right| \tag{5}$$

This value represents the greatest deviation between the observed data and the fitted distribution.

GOODNESS OF FIT EVALUATION

The computed (D_n)-statistic was compared against the critical value at a significance level of (α_n = 0.05), calculated as:

$$D_{critical} = \frac{1.36}{\sqrt{n}} \tag{6}$$

If $D_n < D_{critical}$, the theoretical distribution was considered an acceptable fit for the observed data [15, 16].

MATHEMATICAL FORMULATION OF WIND POWER DENSITY(WPD)

The kinetic energy of moving air per unit volume is given by:

$$KE = \frac{1}{2}\rho V^2 \tag{7}$$

Where:

KE: is the kinetic energy per unit volume (J/m³),
ρ: is the air density (kg/m³),
V: is the wind speed (m/s).

Since wind energy is captured by a cross-sectional area (A) perpendicular to the wind direction, the power passing through this area can be expressed as:

$$P = \frac{1}{2}\rho A V^3 \tag{8}$$

To obtain wind power density WPD, we consider power per unit area:

$$WPD = \frac{P}{A} = \frac{1}{2}\rho V^3 \tag{9}$$

The integration of the probability density function PDF into the WPD equation is essential to account for the stochastic nature of wind speeds. The general form of WPD, incorporating the PDF, is given by:

$$WPD = \frac{1}{2}\int_{V_{\min}}^{V_{M\max}} \rho V^3 f(V) dV \tag{10}$$

where:

ρ : is the air density (kg/m³),
V : is the wind speed (m/s),
f(V) : is the probability density function of wind speeds,
V_{min} and V_{max} are the minimum and maximum wind speeds considered for power generation [17, 18].

The unit of WPD is watts per square meter (W/m²), which provides a standardized measure for comparing wind energy potential across different locations. Selecting the most suitable probability distribution is crucial, as it directly impacts the accuracy of WPD calculations and, consequently, the decision-making process for wind farm development. By leveraging advanced statistical models and site-specific wind data, stakeholders can optimize energy output and ensure the economic viability of wind energy projects [19].

DISTRIBUTION SELECTION

Among all candidate distributions, the one with the smallest (D_n)-statistic was selected as the best fit for the observed wind speed data. To ensure the robustness and credibility of the analysis, all computed results were subjected to thorough cross-verification using independent statistical procedures. This multi-layer validation enhances confidence in the accuracy of the distributional fitting and adheres to established methodologies commonly applied in wind energy assessment. Such rigorous verification is essential because the choice of distribution has a direct influence on the estimation of wind energy potential, particularly in regions where resource evaluation plays a critical role in energy planning. The mathematical evaluation performed throughout this study served as a foundational element in confirming the reliability of the findings and in selecting the most appropriate probability distribution for each study site [16].

RESULTS AND DISCUSSION

Selecting an appropriate probability distribution is crucial for accurate wind resource assessment. The choice of model affects energy predictions and turbine performance evaluation .The choice of an optimal statistical model directly influences the accuracy of subsequent analyses, including energy yield predictions and turbine performance evaluation. Therefore, robust statistical testing and distribution fitting were employed to ensure that the selected models accurately reflect the real behavior of wind speed at the investigated sites. Following the identification of candidate distributions, key statistical parameters such as shape, scale, and location were extracted to evaluate the suitability of each distribution in modeling the observed wind speed data [10].

Table (2) through Table (6) provide a comprehensive summary of the selected distributions and their corresponding parameter values as determined by the EasyFit software. These tables offer a detailed foundation for interpreting the statistical behavior of the wind speed data across the five study locations: Tripoli, Ajdabiyah, Alkufra, Awbari, and Darnah.

Table (2) presents the Goodness of Fit summary for all study areas and highlights the ranking of each distribution based on the Kolmogorov–Smirnov (K–S) test. For Tripoli site, the Johnson SB distribution ranked first, indicating its superior capability in capturing the statistical characteristics of the local wind speed data.

In contrast, the widely used Weibull distribution ranked 37th, suggesting that it is less representative of the wind regime at this specific location. This discrepancy underscores the distinct nature of the Tripoli dataset and demonstrates the enhanced performance of the Johnson SB distribution in accurately reflecting the underlying wind speed variations. According to the results shown in Table (3) the Dagum (4P) distribution achieved the highest ranking for fitting the wind speed data in Ajdabiyah based on the Kolmogorov–Smirnov (K–S) test.

In contrast, the commonly applied Weibull distribution ranked 28th, indicating a considerably lower level of agreement with the observed data. This outcome underscores the spatial variability in wind speed behavior across different sites and highlights the superior ability of the Dagum (4P) distribution to accurately represent the statistical characteristics specific to the Ajdabiyah location.

According to the results presented in Table (4), the Burr distribution achieved the highest ranking for modeling wind speed data in Alkufra based on the Kolmogorov Smirnov (K–S) test, whereas the Weibull distribution ranked 13th. This outcome underscores the importance of employing multiple statistical models when analyzing wind speed data, as the wind characteristics in this region appear to be more accurately represented by the Burr distribution compared to more conventional models such as the Weibull.

Based on the results shown in Table (5) the Burr distribution attained the highest ranking for modeling wind speed data in Awbari according to the Kolmogorov-Smirnov (K–S) test, while the Weibull distribution ranked 26th. This outcome highlights the necessity of employing statistical models that are well suited to the specific characteristics of local wind regimes, as the Burr distribution demonstrates a stronger capacity to capture the substantial variability observed in the Awbari dataset compared with more traditionally used distributions such as the Weibull.

According to the results presented in Table (6), the Burr (4P) distribution emerged as the best-fitting model for the wind speed data in Darnah based on the Kolmogorov–Smirnov (K–S) test, whereas the Weibull distribution ranked 28th. This ranking underscores the significance of employing advanced statistical models such as the Burr (4P) distribution, which offers substantial flexibility in representing non-symmetric data patterns, making it particularly well-suited for capturing the distinctive wind characteristics observed in regions like Darnah.

To evaluate the statistical significance of the results obtained from the Kolmogorov–Smirnov test, the calculated K–S statistic (D_n) was compared against the critical value at a significance level of ($\alpha_n = 0.05$). The critical value was computed using the formula:

$$D^{\alpha_n}_{Critical,n} = \frac{1.36}{\sqrt{n}} = \frac{1.36}{\sqrt{7305}} = 0.0159 \tag{11}$$

where n: Represents the number of Daily wind speed, which in this case was 7305.

Accordingly, the critical value was determined to be 0.0159. If the calculated value of (D_n)was less than the critical value, the distribution was accepted as a good fit for the wind speed data; otherwise, it was rejected.

Table 2. Goodness of Fit – Summary Distribution models derived for the Tripoli region.

Distribution Function	Kolmogorov Smirnov		Probability Density Function	Cumulative Distribution Function	Parameters
	Statistic	Rank	PDF	CDF	
Johnson SB	0.00939	1	$f(v)=\frac{\delta}{\lambda\left(\sqrt{2\pi}\right)x(1-x)}\times \exp\left(-\frac{1}{2}\left(\gamma+\delta*\ln\left(\frac{x}{1-x}\right)\right)^2\right)$	$f(v)=\phi\left(\gamma+\delta.\ln\left(\frac{x}{1-x}\right)\right)$	γ - continuous shape parameter = 1.9812 δ - continuous shape parameter (δ > 0) = 1.434 λ - continuous scale parameter (λ > 0) = 22.271 ξ - continuous location parameter ≡ 1.4812
Fatigue Life	0.01061	2	$f(v)=\frac{\sqrt{\frac{v}{c}}+\sqrt{\frac{c}{v}}}{2kv}\times\phi\left(\frac{1}{k}\left(\sqrt{\frac{v}{c}}-\sqrt{\frac{c}{v}}\right)\right)$	$f(v)=\phi\left(\frac{1}{k}\left(\sqrt{\frac{v}{c}}-\sqrt{\frac{c}{v}}\right)\right)$	k - continuous shape parameter (k > 0) = 0.39903 c - continuous scale parameter (c > 0) = 5.9454
Weibull	0.07892	37	$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\times\exp\left(-\left(\frac{v}{c}\right)^k\right)$	$f(v)=1-\exp\left(-\left(\frac{v}{c}\right)^k\right)$	k - continuous shape parameter (k > 0) = 3.1758 c - continuous scale parameter (c > 0) = 7.1332

where $x=\frac{v-\zeta}{\lambda}$, ϕ is the PDF of the standard Normal distribution.

Table 3. Goodness of Fit – Summary Distribution models derived for Ajdabiyah region.

Distribution Function	Kolmogorov Smirnov		Probability Density Function	Cumulative Distribution Function	Parameters
	Statistic	Rank	PDF	CDF	
Dagum (4P)	0.00923	1	$f(v)=\frac{\beta .k\left(\frac{v-\gamma}{c}\right)^{\beta k-1}}{c\left(1+\left(\frac{v-\gamma}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=\left(1+\left(\frac{v-\gamma}{c}\right)^{-\beta}\right)^{-k}$	k - continuous shape parameter (k > 0) = 0.459 β - continuous shape parameter (β > 0) = 5.663 c - continuous scale parameter (c > 0) = 6.5814 γ - continuous location parameter ≡ 1.3001
Burr	0.00976	2	$f(v)=\frac{\beta .k\left(\frac{v}{c}\right)^{\beta-1}}{c\left(1+\left(\frac{v}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=1-\left(1+\left(\frac{v}{c}\right)^{\beta}\right)^{-k}$	k - continuous shape parameter (k > 0) = 1.969 β - continuous shape parameter(β> 0) = 4.2404 c- continuous scale parameter (c > 0) = 8.0256
Weibull	0.04407	28	$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}.\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	$f(v)=1-\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	k - continuous shape parameter (k > 0) = 3.6081 c - continuous scale parameter (c > 0) = 7.4813

Table 4. Goodness of Fit – Summary Distribution models derived for Alkufra region.

Distribution Function	Kolmogorov Smirnov		Probability Density Function	Cumulative Distribution Function	Parameters
	Statistic	Rank	PDF	CDF	
Burr	0.0115	1	$f(v)=\frac{\beta k\left(\frac{v}{c}\right)^{\beta-1}}{c\left(1+\left(\frac{v}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=1-\left(1+\left(\frac{v}{c}\right)^{\beta}\right)^{-k}$	k - continuous shape parameter (k > 0) = 6.8555 β - continuous shape parameter (β > 0) = 5.185 c - continuous scale parameter (c > 0) = 10.356
Burr (4P)	0.01153	2	$f(v)=\frac{\beta k\left(\frac{v-\gamma}{c}\right)^{\beta-1}}{c\left(1+\left(\frac{v-\gamma}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=1-\left(1+\left(\frac{v-\gamma}{c}\right)^{\alpha}\right)^{-k}$	k - continuous shape parameter (k > 0) = 7.8228 β - continuous shape parameter (β > 0) =4.9231 c - continuous scale parameter (c > 0) = 10.457 γ - continuous location parameter ≡ 0.26947
Weibull	0.01725	13	$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}.\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	$f(v)=1-\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	k - continuous shape parameter (k > 0) = 4.9597 c - continuous scale parameter (c > 0) = 7.2828

Table 5. Goodness of Fit – Summary Distribution models derived for Awbari region.

Distribution Function	Kolmogorov Smirnov		Probability Density Function	Cumulative Distribution Function	Parameters
	Statistic	Rank	PDF	CDF	
Burr	0.00885	1	$f(v)=\frac{\beta k\left(\frac{v}{c}\right)^{\beta-1}}{c\left(1+\left(\frac{v}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=1-\left(1+\left(\frac{v}{c}\right)^{\beta}\right)^{-k}$	k - continuous shape parameter (k > 0) = 3.1729 β - continuous shape parameter (β > 0) =4.9181 c - continuous scale parameter (c > 0) = 9.293
Burr (4P)	0.00988	2	$f(v)=\frac{\beta k\left(\frac{v-\gamma}{c}\right)^{\beta-1}}{c\left(1+\left(\frac{v-\gamma}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=1-\left(1+\left(\frac{v-\gamma}{c}\right)^{\alpha}\right)^{-k}$	k - continuous shape parameter (k > 0) = 4.9092 β - continuous shape parameter (β > 0) = 3.923 c - continuous scale parameter (c > 0) = 9.5611 γ - continuous location parameter ≡ 1.0542
Weibull	0.0308	26	$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}.\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	$f(v)=1-\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	k - continuous shape parameter (k > 0) = 4.4859 c - continuous scale parameter (c > 0) = 7.6903

Table 6. Goodness of Fit – Summary Distribution models derived for Darnah region.

Distribution Function	Kolmogorov Smirnov		Probability Density Function	Cumulative Distribution Function	Parameters
	Statistic	Rank	PDF	CDF	
Burr (4P)	0.00896	1	$f(v)=\dfrac{\beta k\left(\frac{v-\gamma}{c}\right)^{\beta-1}}{c\left(1+\left(\frac{v-\gamma}{c}\right)^{\beta}\right)^{k+1}}$	$f(v)=1-\left(1+\left(\frac{v-\gamma}{c}\right)^{\alpha}\right)^{-k}$	k - continuous shape parameter (k > 0) = 4.9363 β - continuous shape parameter (β > 0) =2.6466 c - continuous scale parameter (c > 0) = 11.755 γ - continuous location parameter ≡ 1.2262
Generalized Extreme Value	0.01065	2	$f(v)=\frac{1}{c}\exp\left(-(1+kx)^{-1/k}\right).(1+kx)^{-1-1/k}$	$f(v)=\exp\left(-(1+kx)^{-1/k}\right)$	k -continuous shape parameter (k > 0) = -0.08857 c - continuous scale parameter (c > 0) = 2.3722 γ - continuous location parameter ≡ 6.0934
Weibull	0.03886	28	$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}.\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	$f(v)=1-\exp\left(-\left(\frac{v}{c}\right)^{k}\right)$	k - continuous shape parameter (k > 0) = 3.2093 c - continuous scale parameter (c > 0) = 8.0816

This criterion offers a clear and quantitative threshold for evaluating the adequacy of each distribution model. Among all candidate distributions, those exhibiting the lowest K–S statistics were identified as the most appropriate for modeling the observed wind speed data.

Table (7) presents the final outcomes of this validation process, highlighting the accepted and rejected distributions for each of the five study locations. The table serves as a comprehensive summary that distinguishes between statistically suitable distributions and those that failed to meet the acceptance criteria. This step reinforces the methodological rigor of the study by ensuring that only distributions with demonstrable statistical reliability are selected for further analysis and energy estimation.

Table 7: Final Evaluation Results of Probability Distributions Using the K–S Test for Each Study Location (Mathematical model).

Study Location	Distribution Function	K–S Statistic (D_n)	Best-Fitting Distribution (Lowest K–S Statistic)	Distribution Rejected
Tripoli	Johnson SB	0.00960	Johnson SB	Weibull
	Fatigue Life	0.01077		
	Weibull	0.07885		
Ajdabiyah	Dagum (4P)	0.00883	Dagum (4P)	Weibull
	Burr	0.00684		
	Weibull	0.03422		
Alkufra	Burr	0.01125	Burr	Weibull
	Burr (4P)	0.01236		
	Weibull	0.01731		
Awbari	Burr	0.00894	Burr	Weibull
	Burr (4P)	0.01061		
	Weibull	0.03133		
Darnah	Burr (4P)	0.00912	Burr (4P)	Weibull
	Gen. Extreme Value	0.01030		
	Weibull	0.03884		

The results in Table (7) demonstrate clear variability in the performance of statistical distributions across the five study sites, indicating that no single distribution provides a universally superior fit for wind speed data.

This variation in best-fitting distributions across the studied locations can be attributed to regional climatic and geographical differences. Coastal regions such as Tripoli and Darnah experience stronger atmospheric interactions between land and sea, leading to higher variability in wind speeds. Such variability often produces asymmetric wind patterns that are better represented by flexible multi-parameter distributions such as Johnson SB and Burr (4P). In contrast, inland desert regions such as Awbari and Alkufra exhibit relatively more stable wind regimes with lower turbulence levels, making Burr-type distributions more suitable for representing their statistical behavior.

Although the Weibull distribution is commonly used in wind energy studies, the present analysis shows that it does not consistently offer the most accurate representation. Instead, distributions such as Johnson SB, Dagum, and Burr outperform Weibull in several locations, highlighting the necessity of site-specific statistical evaluation to ensure reliable wind speed modeling and accurate energy potential estimation. Table 8 reports the K–S test outcomes for the examined distributions.

Table 8: K–S Test Results for Wind Speed Distributions.

Study Location	Distribution Function	K–S Statistic (D_n)	Distribution is a good fit or is not a good fit for the wind speed data
Tripoli	Johnson SB	0.010054	The Johnson SB distribution is a good fit for the wind speed data (Fail to reject H0).
	Fatigue Life	0.010912	The Fatigue Life distribution is a good fit for the wind speed data (Fail to reject H0).
	Weibull	0.078847	The Weibull distribution is not a good fit for the wind speed data (Reject H1).
Ajdabiyah	Dagum (4P)	0.0093234	The Dagum (4P) distribution is a good fit for the wind speed data (Fail to reject H0).
	Burr	0.0095036	The Burr distribution is a good fit for the wind speed data (Fail to reject H0).
	Weibull	0.044104	The Weibull distribution is not a good fit for the wind speed data (Reject H1).
Alkufra	Burr	0.011392	The Burr distribution is a good fit for the wind speed data (Fail to reject H0).
	Burr (4P)	0.01136	The Burr (4P) distribution is a good fit for the wind speed data (Fail to reject H0).
	Weibull	0.017311	The Weibull distribution is not a good fit for the wind speed data (Reject H1).
Awbari	Burr	0.0089404	The Burr distribution is a good fit for the wind speed data (Fail to reject H0).
	Burr (4P)	0.010743	The Burr (4P) distribution is a good fit for the wind speed data (Fail to reject H0).
	Weibull	0.031335	The Weibull distribution is not a good fit for the wind speed data (Reject H1).
Darnah	Burr (4P)	0.0091224	The Burr (4P) distribution is a good fit for the wind speed data (Fail to reject H0).
	Gen. Extreme Value	0.010296	The Gen. Extreme Value distribution is a good fit for the wind speed data (Fail to reject H0).
	Weibull	0.038836	The Weibull distribution is not a good fit for the wind speed data (Reject H1).

The K–S statistic reflects the maximum deviation between empirical and theoretical cumulative distributions, while the parameter “H” indicates acceptance or rejection of the null hypothesis. The results show that Johnson SB, Dagum, and Burr distributions achieve the lowest K–S values, with additional models such as Fatigue Life, Burr, and General Extreme Value also outperforming Weibull.

These findings reinforce that alternative distributions may more effectively characterize wind speed behavior in the studied regions, challenging the traditional reliance on the Weibull model.

Table (9) presents the final analysis comparing various distributions to identify the most suitable distribution that represents wind speed data in the studied regions.

Table 9: Final Comparison Table.

Region	Best Fit (EasyFit)	Best Fit (Mathematically)	Best Fit (MATLAB)	Weibull Rank
Tripoli	Johnson SB	Johnson SB	Johnson SB	37th
Ajdabiyah	Dagum (4P)	Dagum (4P)	Dagum (4P)	28th
Alkufra	Burr	Burr	Burr	13th
Awbari	Burr	Burr	Burr	26th
Darnah	Burr (4P)	Burr (4P)	Burr (4P)	28th

The graphical representations presented in Figure (3) through Figure (7) illustrate the probability distributions of wind speeds for each of the five Libyan regions under study, confirming the optimal distribution selected for each location.

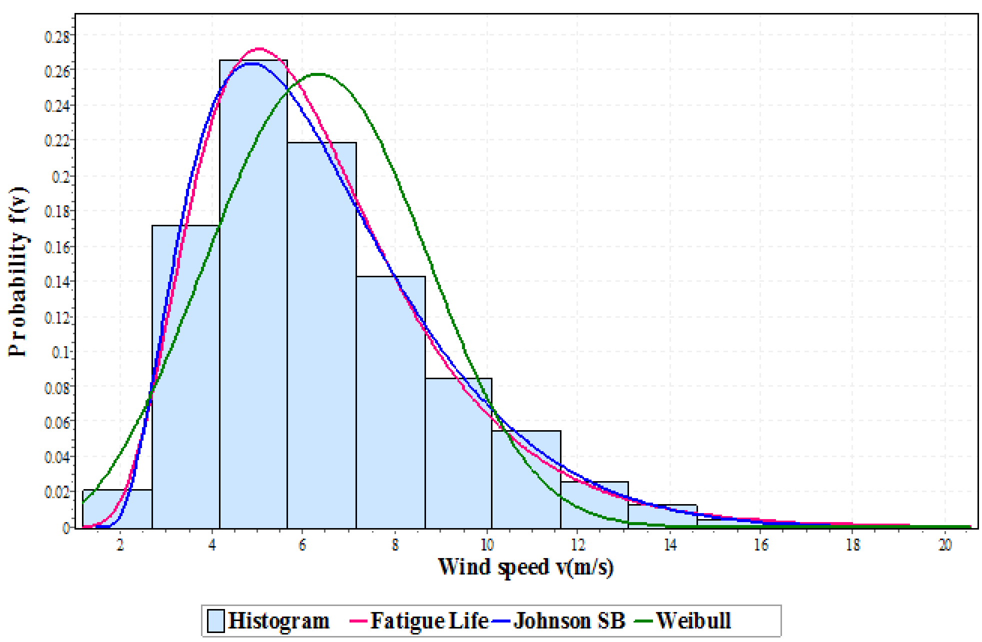

Figure 3: Histogram and Probability Density Function of Tripoli region.

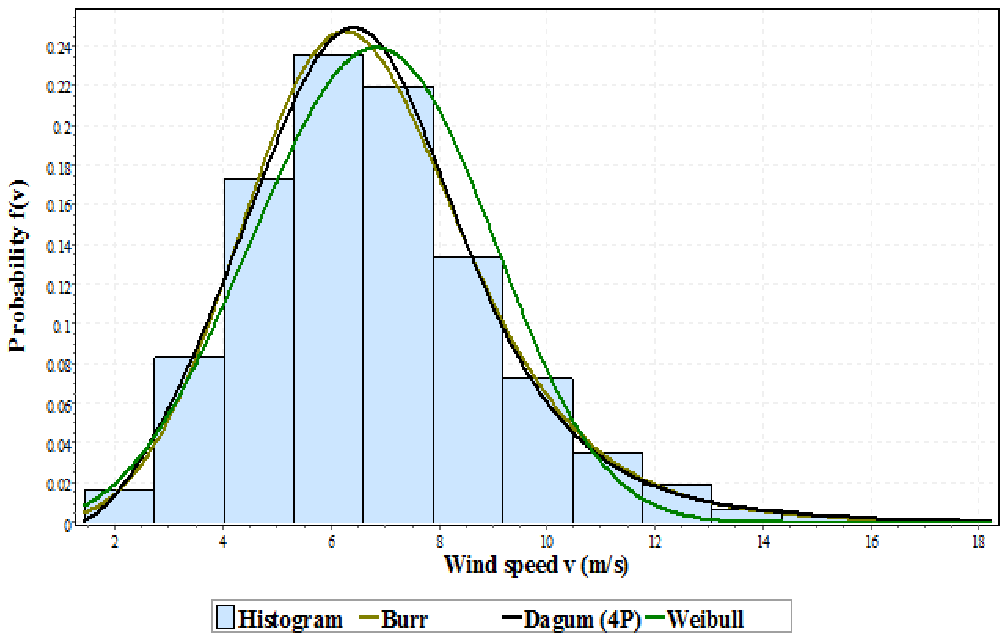

Figure 4: Histogram and Probability Density Function of Ajdabiyah region.

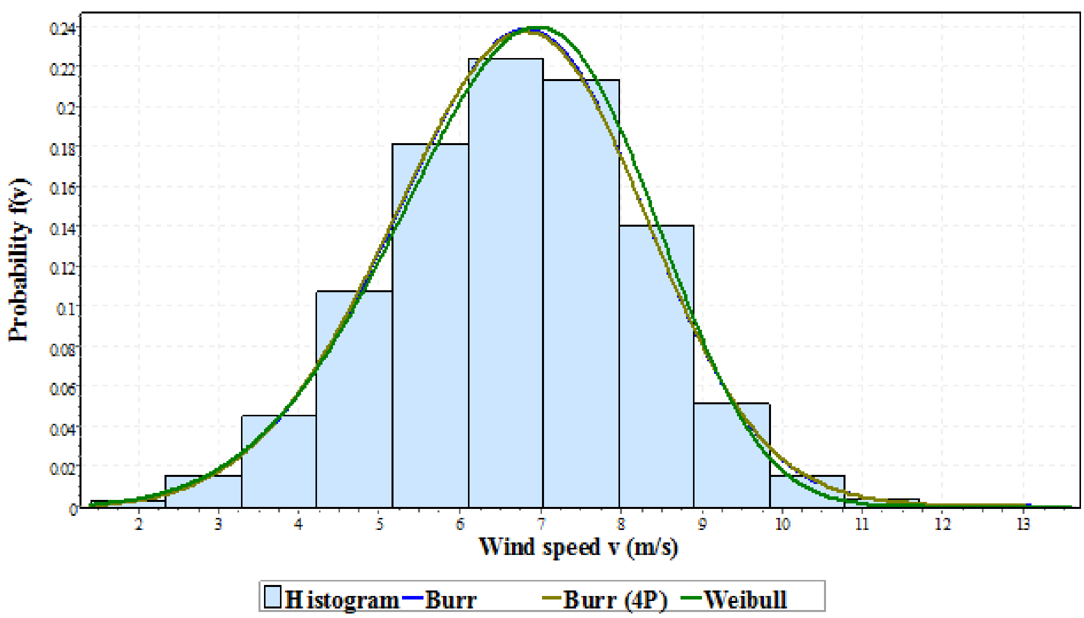

Figure 5: Histogram and Probability Density Function of Alkufra region.

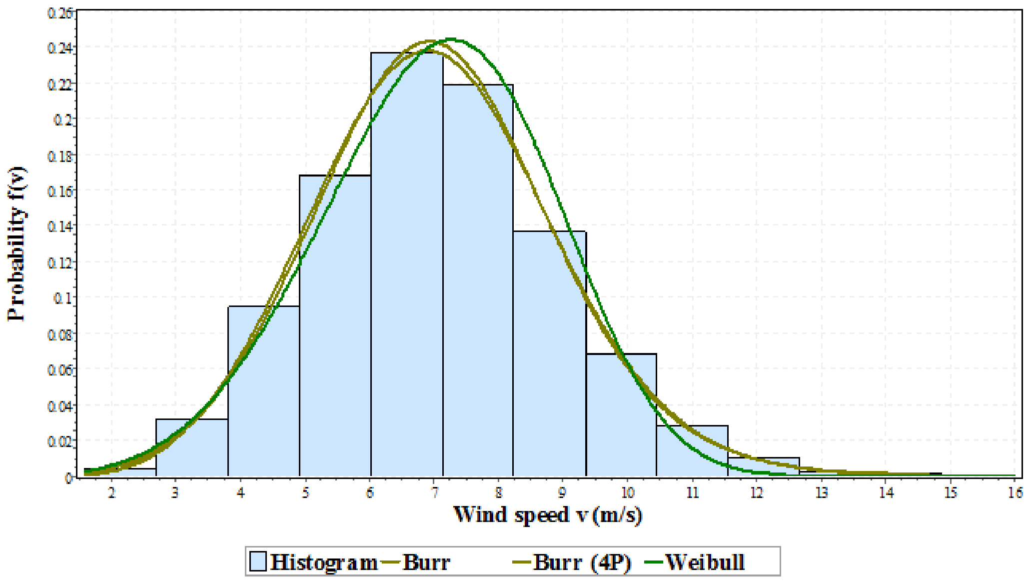

Figure 6: Histogram and Probability Density Function of Awbari region.

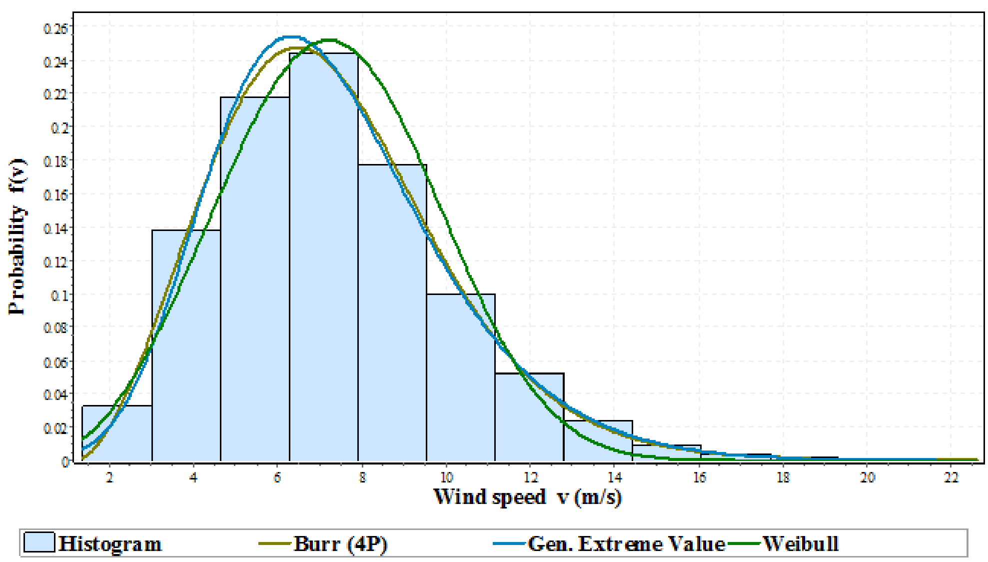

Figure 7: Histogram and Probability Density Function of Darnah region.

In summary, the graphical illustrations presented in Figure (3) through Figure (7) provide compelling visual evidence supporting the selection of alternative distributions over the conventional Weibull model. These findings not only enhance our understanding of wind speed dynamics across diverse terrains but also underscore the significance of employing advanced statistical tools and computational techniques in renewable energy assessments. The consistency between visual and numerical results enhances the overall credibility of the distribution selection process in this study.

Table (10) presents the average daily wind power density calculated using the optimal probability distributions. These values differ from the maximum theoretical WPD values reported in the abstract, which represent the upper energy potential derived from peak wind conditions.

Table 10: Average Daily Wind Power Density WPD **Results.**

Region	Optimal Distribution	Average Daily WPD (W/m²)
Tripoli	Johnson SB	52.57
Ajdabiyah	Dagum (4P)	64.97
Alkufra	Burr	69.08
Awbari	Burr	77.32
Darnah	Burr (4P)	78.97

Figure (8) visually contrasts these regional WPD estimates through comparative histogram representation.

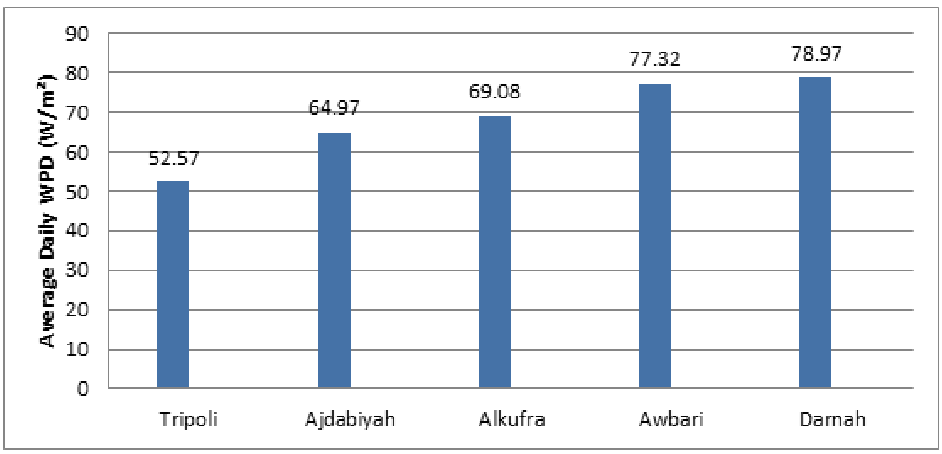

Figure 8: Histogram Average Daily Wind Power Density WPD for the selected regions.

These results highlight the variability in wind energy potential across different regions, underscoring the importance of location-specific assessments. Furthermore, they demonstrate the superiority of alternative distributions in capturing nuanced wind patterns, thus enhancing the reliability of energy predictions. Accurate estimation of wind power density is pivotal in planning and developing wind energy projects. It informs critical decisions regarding site selection, turbine type, and expected energy output. Underestimating WPD might lead to undersized turbines, reducing energy generation potential and financial returns. Conversely, overestimation risks overinvestment in unsuitable locations, resulting in economic losses. By employing advanced statistical models tailored to specific geographical conditions, this research ensures precise WPD evaluations, thereby supporting informed decision-making processes.

Moreover, the findings contribute significantly to the advancement of renewable energy technologies in Libya. The best-fitting distribution at each site depends on local environmental characteristics. Coastal regions (Tripoli, Darnah) favor flexible multi-parameter models (Johnson SB, Burr 4P), semi-arid zones (Ajdabiyah) fit Dagum (4P), and inland deserts (Awbari, Alkufra) match the Burr family due to more stable wind regimes. For unstudied sites, terrain, distance from the coast, and wind variability can guide initial distribution selection before statistical.

They provide a robust framework for assessing wind energy potential across diverse terrains, enabling policymakers and stakeholders to prioritize regions with the highest energy yields. This scientific rigor not only enhances the credibility of wind energy assessments but also fosters sustainable development by optimizing resource utilization and minimizing environmental impact.

CONCLUSION

This study aimed to evaluate the accuracy of the Weibull distribution in modeling wind speed data across five distinct regions in Libya. Using advanced statistical tools such as MATLAB and EasyFit, alongside the Kolmogorov-Smirnov K–S test, a comprehensive assessment was conducted to identify the most suitable probability distribution for each location.

The findings revealed that while the Weibull distribution is widely used and generally acceptable in many cases, it does not always provide the best fit, particularly in areas with complex topographical and climatic conditions. Alternative distributions such as Burr, Dagum (4P), and Johnson SB demonstrated superior performance in capturing the variability of wind speeds.

These results emphasize the importance of adopting a location-specific approach when selecting statistical models for wind energy assessments. The use of inappropriate distributions can lead to misleading estimations of wind power density WPD, which are crucial for evaluating the feasibility of wind energy projects.

Based on the analysis of five locations Tripoli, Ajdabiyah, Alkufra, Awbari, and Darnah the best-fit distributions were identified as follows:

Tripoli: Johnson SB   Darnah: Burr(4P)   Awbari: Burr

Alkufra: Burr   Ajdabiyah: Dagum(4P)

This variation highlights the need to move beyond the conventional reliance on the Weibull model and instead adopt more flexible and regionally adapted statistical frameworks.

DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors did not use generative AI or AI-assisted technologies in the preparation of this manuscript.

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