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Statistical Analysis of Wind Speed Characteristics Using the Weibull Distribution at Selected African Stations

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Abstract: The Weibull distribution (WD) is widely recognized as an effective statistical tool for characterizing wind speed (WS) variability. This study investigates the applicability of the WD to analyze WS data from a selection of African stations, with data spanning from 2000 to 2023, obtained from the Power Data archive in comma- separated values (CSV) format. The analysis aimed to assess the distribution's ability to represent the variations in WS across different regions in Africa. The results reveal significant spatial variability in the Weibull parameters across the selected stations. wind direction patterns were analyzed, with the highest frequency recorded from the east-north-east (ENE) direction, reaching a value of approximately 400 at certain locations. The lowest wind direction frequencies were observed in Abuja, where the predominant directions were north-northwest (NNW) and north (N). The probability distribution of WS demonstrated a considerable range, with Abuja exhibiting the highest values (exceeding 0.5), while Tunis recorded the lowest values (approximately 0.2). The mean WS for each location varied over the year, with Nairobi experiencing the highest recorded mean WS in October (5.72 m/s), accompanied by a standard deviation of 1.22 m/s. In contrast, the lowest mean WS was observed in Luanda during September (1.72 m/s), with a standard deviation of 0.46 m/s. The maximum and minimum wind power density (PDw) recorded across the selected station are ($> 100\ \mathrm{W/m^2}$) and ($> 18\ \mathrm{W/m^2}$). These findings highlight the considerable potential for wind energy across Africa, emphasizing the importance of incorporating wind energy into the region's renewable energy strategy. The results underscore the need for region-specific energy policies and further research to optimize the utilization of wind resources for sustainable development in Africa.

Keywords: Meteorology; Atmospheric; Statistical analysis; Renewable energy; Environmental physics

1 Introduction

Renewable energy research and policymaking have been shown to have an impact on energy generation in the electricity sector. Renewable energy is regarded as one of the energy sources that contribute to the growth and development of any nation on a global scale [1]. Furthermore, research has shown that wind energy is less expensive to generate power than other sources of energy; however, according to literature, the total amount of potential wind energy contributes massively to the development and growth of global electricity demand, which is 20 times the demand [2].

According to the study [3], wind energy in Iraq is divided into three zones; however, 48% of the WS in the country is low, 35% of the annual WS ranges between 3.1 and 4.9 m/s, and 8% of the WS is found to be high in the region. However, WS in Nigeria is lower than in Iran, as reported by the studies [4–6]. This could be because Nigeria is less close to the desert than Iran. According to research, WS is the most important factor in the global generation of wind energy. However, during the energy collection process, wind energy has the potential in any selected station for analysis and explanation of WS data from any meteorological station or satellite data, which is required for the data set's accuracy and accountability. WD is a suitable statistical method for this study because it effectively models WS data, accommodating the variability and skewness typically observed in wind regimes. Its flexibility in representing both light and strong winds makes it ideal for assessing wind energy potential across diverse African stations.

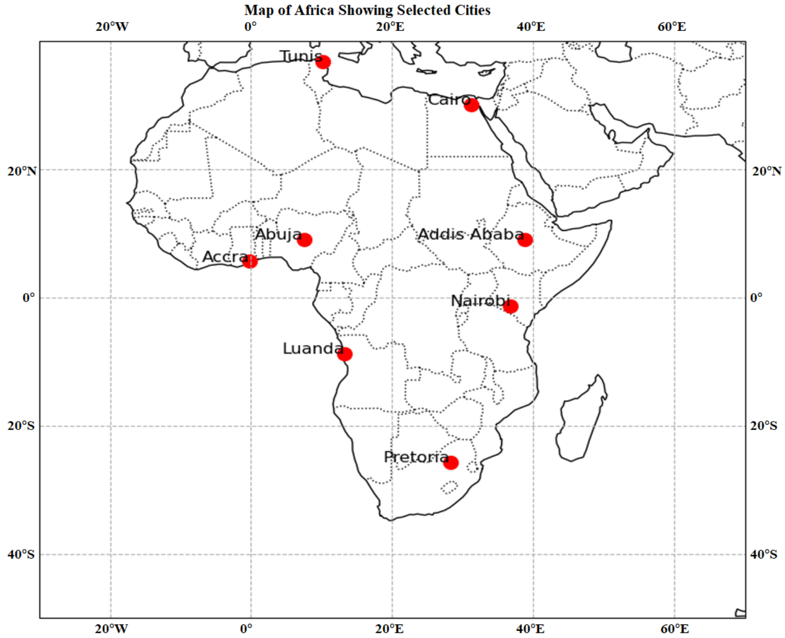

Figure 1. Map of the selected stations used for the study

According to the study [7], WS data is classified as daily, monthly, and yearly. However, in the process of identifying potential wind energy, wind turbines have been known to be a significant factor in determining the efficiency of energy production, which is based on the type of wind, whether daily, monthly, or yearly [8]. As reported by the study [1, 9], wind assessments in various projects may not be satisfactory enough, so adequate analysis using statistical means is required for the implementation of a remarkable assessment of any wind project [9]. Analyzing WS characteristics using the WD for selected African stations provides insights into regional wind patterns, essential for optimizing wind energy projects. This study contributes to the field by filling data gaps, enhancing resource assessment, and supporting sustainable energy solutions tailored to Africa's diverse climatic and topographic conditions. However, the study aims to analyze WS characteristics using the WD to assess energy potential and variability across selected stations. Understanding these patterns is crucial for optimizing wind energy resources, improving renewable energy planning, and addressing climate-related challenges by leveraging wind as a sustainable and environmentally friendly energy source in the selected African stations.

2 Research Methodology

2.1 Process of Data Collection

The WS data values for eight stations were obtained from the power data access viewer (https://power.larc.nasa.gov /data-access-viewer/), of the National Aeronautics and Space Administration (NASA) website repository of power data. The data were downloaded on March 23rd, 2024. Data from 2000 to 2023 were collected as a daily average from January to December of each year in CSV format. The process of data collection followed what was reported by the following authors [10–12] using MERRA-2 data.

2.2 Data Process and Acquisition

This study's data collection and assembly process was based on the daily and monthly average method, which was used to analyze diurnal and seasonal variations. However, the monthly mean of the data was used to accurately represent the seasonal variation of the data based on the data used for the relevant years. The missing data was treated as zero, and it was not included in the analysis process. Furthermore, the data were subjected to the Weibull Probability Distribution Function and the Cumulative Distribution Function using the equations provided below [6, 13].

2.3 Study Location, Coordinate and Elevation

This study's stations are located in African sub-regions, specifically in the west, north, east, and south of Africa. These stations are based on geographical locations that are classified based on their proximity to the ocean, with some stations primarily used for agricultural production. Table 1 and Figure 1 display the station's coordinates and map.

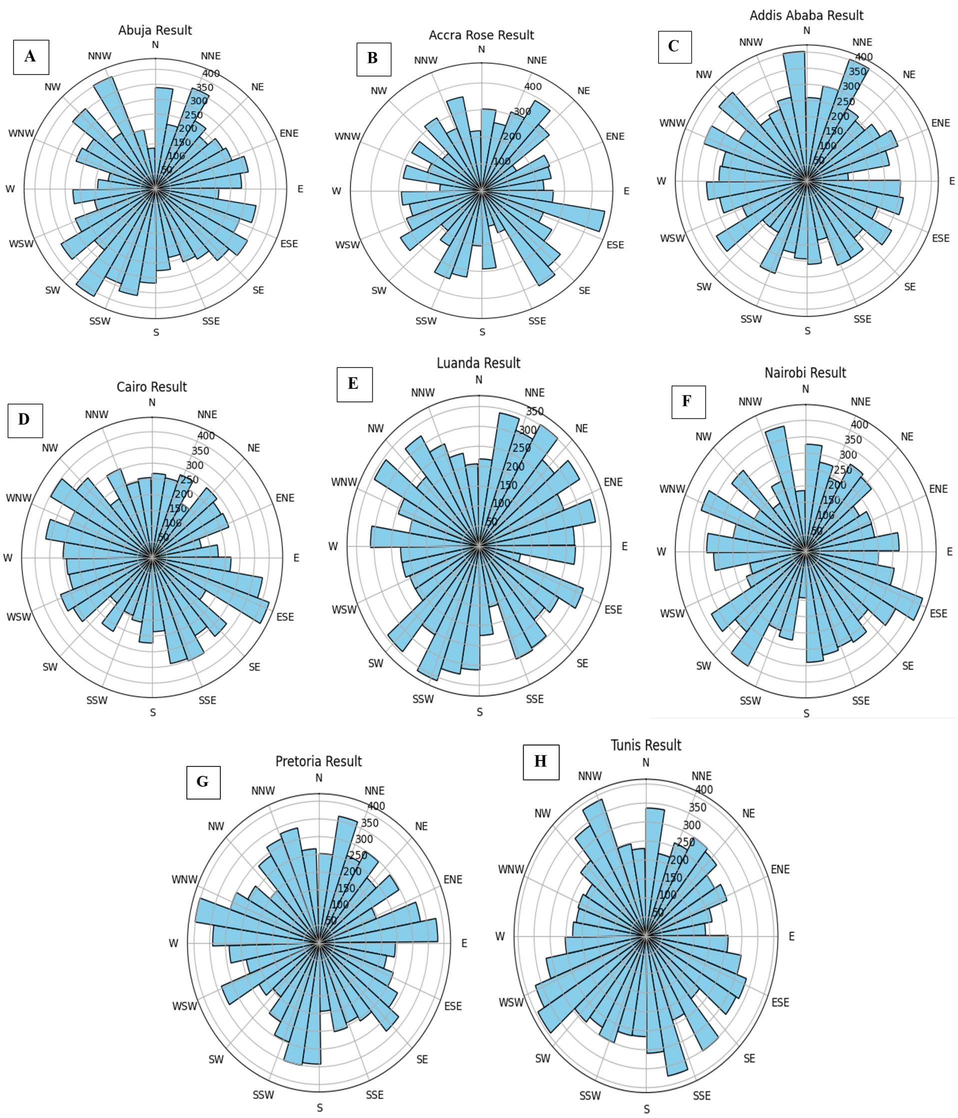

Figure 2. Monthly WS rose of the selected African stations

Table 1. The geographical coordinate and elevation of the selected stations used for the study

Country	Stations	Longitude	Latitude	Altitude (m)	Date Range
Kenya	Nairobi	1.2921°S	36.8219°E	1795	2000 – 2023
Ethiopia	Addis Ababa	9.0129°N	38.7525°E	2355	2000 – 2023
Egypt	Cairo	30.0444°N	31.2357°E	23.0	2000 – 2023
Tunisia	Tunis	36.8065°N	10.1815°E	4.0	2000 – 2023
Nigeria	Abuja	9.0563°N	7.4985°E	360	2000 – 2023
Ghana	Accra	5.5593°N	0.1974°W	61.0	2000 – 2023
South Africa	Pretoria	25.7566°S	28.1914°E	1339	2000 – 2023
Angola	Luanda	8.8157°S	13.2302°E	6.0	2000 – 2023

2.4 Weibull Probability Distribution Function and Cumulative Distribution Function

For this study, the Weibull probability distribution function (WPDF) was used on the WS data collected for the selected stations, which is based on the time interval and uses two parameters as reported by [1, 14].

$$W(x) = \frac{y}{v}\left(\frac{x}{v}\right)^{y-1} \exp\left(-\left(\frac{x}{v}\right)^{y}\right), y > 0; x > 0; v > 0 \tag{1}$$

Where v is known as the scale parameters measured in (m/s), y is the shape parameter. However, research has shown that approximate WD parameters can be obtained using a simple fitting curve procedure. Furthermore, it has been established that the cumulative distribution function (CDF) of WS is an integration of the WPDF. It is also known that the frequency of WS intervals is determined by the WS's cumulative probability function (CPF). According to the study [1, 15], the WD function corresponds to the cumulative probability of WS.

$$W(x) = \int_0^x w(x)dx = 1 - \exp - \left(\frac{x}{v}\right)^y \tag{2}$$

It has been established that the behaviour of WS about its values is determined by the shape of the parameters used to describe the phenomenon. Furthermore, WS is extremely weak in the parameter when y is small. However, the large value of y indicates that the station experienced both very high and low WS. As a result, it has been determined that the WS distribution has the value y = 2. These were reported by the research [1].

2.5 WD by Estimation and Fitting

The WD uses the maximum likelihood method (MLM) in the fitting of the WD of the WS distribution [1, 16]. The equation used for this calculation was based on the iterative form of the Weibull parameter y as shown below.

$$y = \left[\frac{\sum_{j=1}^{M} x_j^y \ln x_j}{\sum_{j=1}^{M} x_i^y} - \frac{\sum_{j=1}^{M} \ln x_i}{M}\right]^{-1} \tag{3}$$

Therefore x_j is known as the WS at the step of j, and M is known as the number of time steps.

The equation below will provide the value of the scale parameter v as shown for the defined parameter shape y:

$$v = \left(\frac{\sum_{j=1}^{M} x_j^k}{M}\right)^{\frac{1}{y}} \tag{4}$$

Therefore, as shown in the equations above, Eqs. (3) and (4) provide the Weibull parameters with the main height of 2 m from the downloaded data, however, since it has been known that the parameters can be actualized from the WS data which followed what was reported by Mahmood et al. [1] as revealed in Eqs. (5)-(7).

$$v_2 = v_2 \left(\frac{r_2}{r_1}\right)^m \tag{5}$$

$$y_2 = y_1 \frac{1 - 0.088 \ln \frac{r_1}{10}}{1 - 0.088 \ln \frac{r_2}{10}} \tag{6}$$

$$n = \frac{0.37 - 0.088 \ln v_1}{1 - 0.088 \ln \frac{r_2}{10}} \tag{7}$$

According to research, wind resource capacity can be determined by wind power density (PD_w), which occurs in specific locations. However, different approaches can be used to estimate PD_w, as reported by the study [1, 17, 18], resulting in the wind monthly or annual power density PD_w per unit of site area based on the Weibull probability density function [1, 12].

$$PD_w = \frac{1}{2}\rho v^3 \Gamma\left(1 + \frac{3}{y}\right) \tag{8}$$

ρ is known as the density as it has the value $\left(\rho = 1.225 \text{ kg/m}^3\right)$ which is the standard atmospheric level at the sea area, where Γ is known as the gamma function [1, 19].

$$\bar{x} = v\Gamma\left(1 + \frac{1}{y}\right) \tag{9}$$

where, $\bar{x}$ is the average WS for each of the stations considered.

Eq. (10) is obtained by substituting the scale factor as shown in Eq. (8) and applying the equation's formula. This was reported by the studies [1, 20].

$$\overline{PD_w} = \frac{\overline{c^3}\rho\Gamma\left(1 + \frac{3}{y}\right)}{2\left[\Gamma\left(1 + \frac{1}{y}\right)\right]^3} \tag{10}$$

As reported by Mahmood et al. [1], research has shown that wind turbines have a discrete height with significant value, which has contributed to the power law t use in the determination of WS as a result of wind turbines in various stations.

$$x_2 = x_1 \left(\frac{r_2}{r_1}\right)^{\alpha} \tag{11}$$

As a result, x_2 represents WS at a height of $r_2(\text{ m})$, while x_1 represents the known WS at the reference height r_1. The variation of the exponential (α) indicates that the atmosphere is stabilized by WS movement in any direction. The constant variable of the WS data is (0.14), which is due to the variation between the two levels of the atmosphere, r_1 and r_2. Higher variation can lead to significant deviations in WS estimation [1].

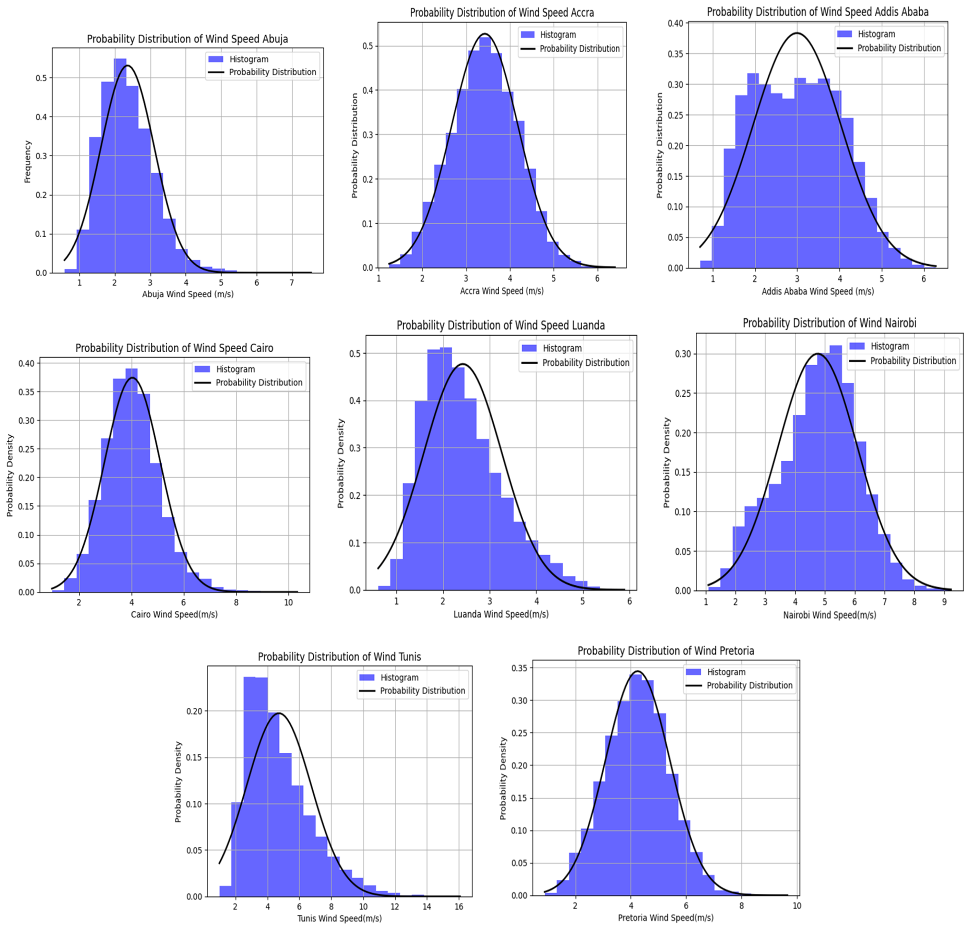

Figure 3. Probability distribution of WS data for selected Africa station

$$\sigma = \sqrt{\frac{\sum_{j=1}^{M} (x_j - \bar{x})^2}{M-1}} \tag{12}$$

According to the study by Mahmood et al. [1], WS turbines have been known to perform in various locations and can be evaluated based on the quantity of the average power output $(U_{e,avg})$ on the capacity factor of the WS. However, the CF is defined as the ratio of the average power output $(U_{e,avg})$ to the electrical power (Prated) of the turbine model used in any research. However, research has shown that the WD parameters, mean power output $(U_{e,avg})$, and capacity factor of a WS turbine can be calculated using the equations below.

$$U_{\text{eavg}} = U_{\text{rated}} \frac{e^{-\left(\frac{x_{in}}{v}\right)^y} - e^{-\left(\frac{x_a}{v}\right)^y}}{\left(\frac{x_a}{v}\right)^y - \left(\frac{x_{in}}{v}\right)^y} - e^{-\left(\frac{x_{out}}{v}\right)^y} \tag{13}$$

$$V_w = \frac{U_{\text{eavg}}}{U_{\text{rated}}} \tag{14}$$

For this study it was observed that the WD has been known to be a widely used model for analyzing WS data, however, it defines two key parameters: The shape parameter (k) and the scale parameter (λ). These parameters provide insights into the variability and magnitude of WS, making the distribution highly applicable in meteorology and wind energy studies. The shape parameter (k) reflects the spread and consistency of WS. A low k value (< 2) indicates highly variable or turbulent wind conditions, while a higher k value (> 2) suggests more consistent WS. This is crucial for understanding the reliability of wind resources in a given location. The scale parameter (λ) represents the characteristic magnitude of WS, closely related to the average WS. Higher λ values indicate windier locations and greater energy potential. Physically, λ corresponds to the WS exceeded approximately 63% of the time. Together, k and λ characterize WS patterns, with regions having high λ and moderate to high k being ideal for wind power generation. The WD thus plays a vital role in assessing wind energy potential by providing a comprehensive understanding of wind behavior in different regions.

The MLM for fitting the WD was computationally intensive and sensitive to outliers or small sample sizes, which could potentially lead to biased parameter estimates. Alternatives include the method of moments (MoM) and least squares regression (LSR), which are simpler but may sacrifice accuracy under certain conditions.

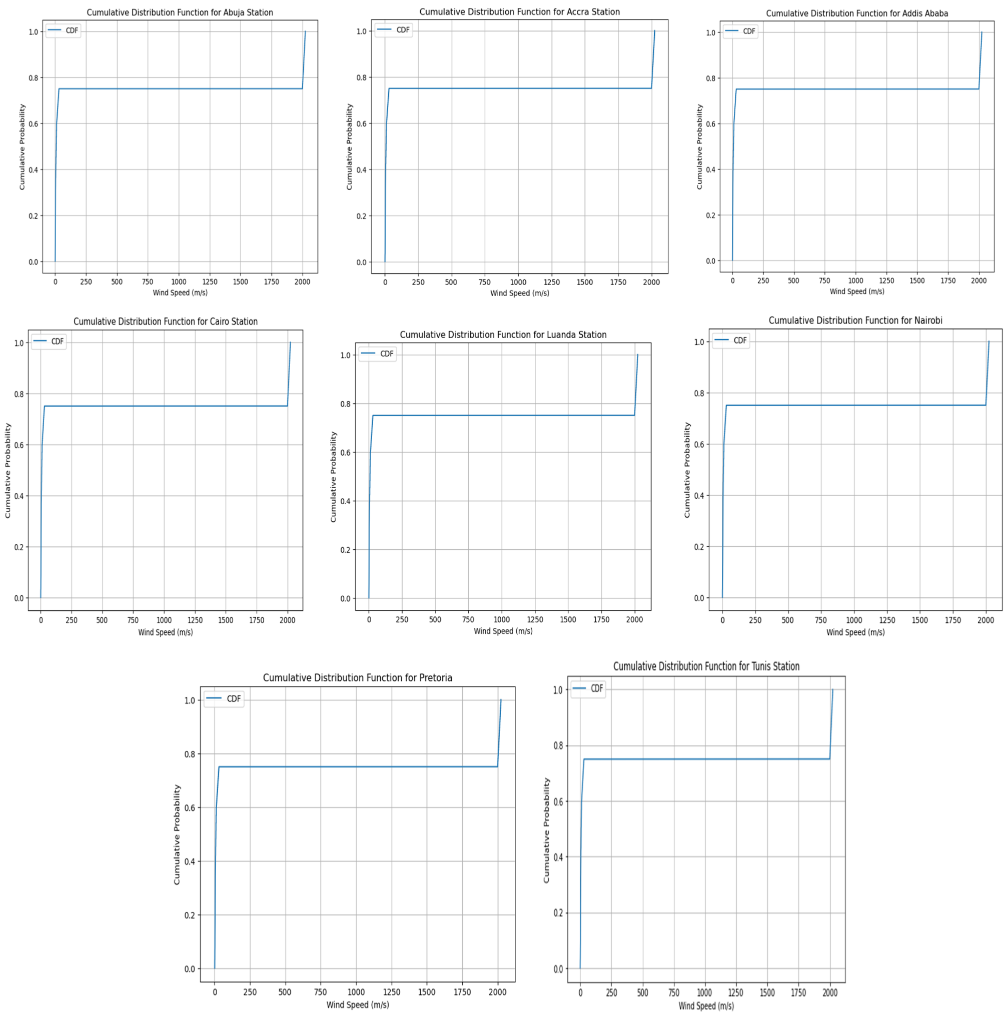

Figure 4. Cumulative probability distribution of WS for selected station

3 Results and Discussion

Table 2 shows the mean and standard deviation for the descriptive statistics analysis of the variability in WS data from the selected stations. The analysis revealed that the maximum WS was observed in Nairobi in October (5.7207 m/s) with a standard deviation of 1.2169 m/s, while the minimum WS was observed in Luanda in September (1.7198 m/s) with a standard deviation of 0.4570 m/s. The results show that the two stations represent the highest and lowest WS in the selected African stations, indicating that the station with the highest WS can generate more energy for the benefit of the country, whereas the station with the lowest WS may generate energy in small quantities. However, the results of other stations demonstrate that energy can be generated if properly harnessed.

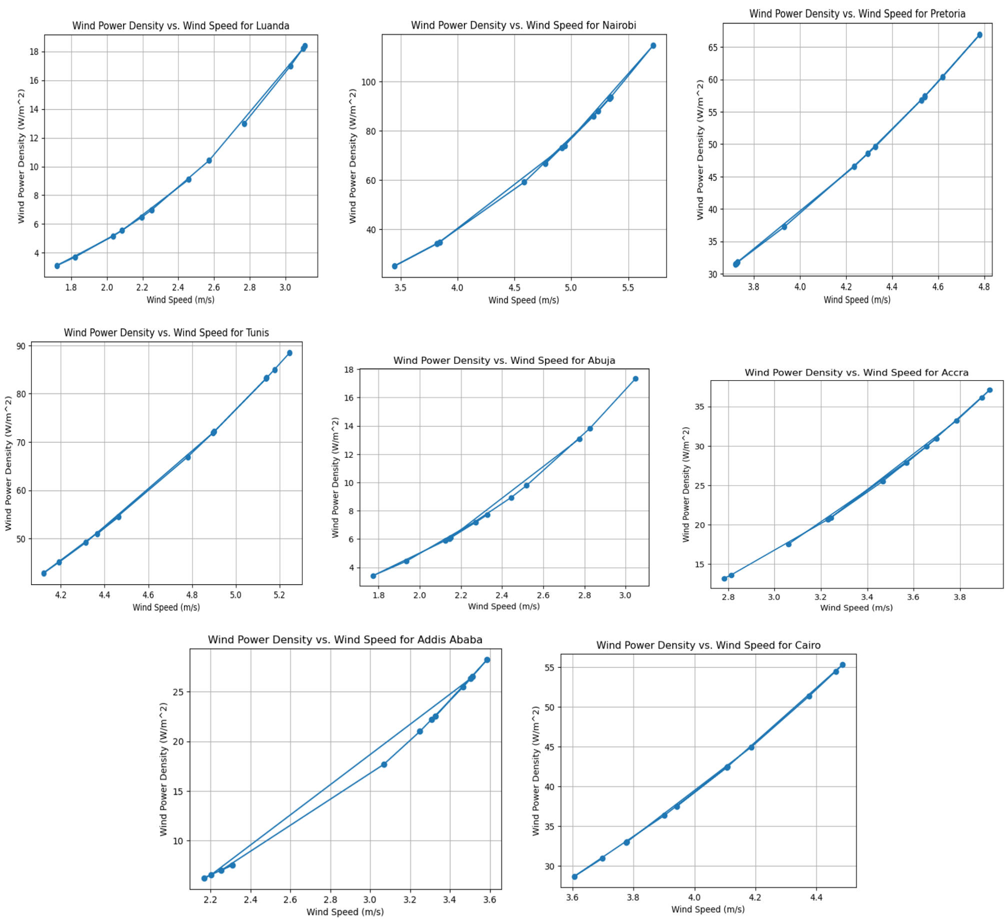

Figure 5. Wind power density against WS for the selected station used

Table 2. The mean and standard deviation of the selected stations used for the analysis

Month	Abuja (m/s)		Accra (m/s)		Addis Ababa (m/s)		Cairo (m/s)		Luanda (m/s)		Nairobi (m/s)		Pretoria (m/s)		Tunis (m/s)	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
January	3.0481	0.9504	3.0601	0.7055	3.3276	0.8893	3.7764	1.3801	2.7673	0.8197	4.7722	0.8553	3.7238	1.1643	5.2473	2.4089
February	2.8258	0.7974	3.5684	0.7487	3.5861	1.0094	3.7780	1.2923	3.0270	0.8579	5.1939	0.9782	3.9320	1.2837	5.1776	2.1301
March	2.5184	0.6513	3.6970	0.6830	3.4655	1.0213	4.1874	1.1793	3.1083	0.8959	5.3371	1.0502	4.2954	1.3458	5.1420	2.2484
April	2.4428	0.5629	3.4656	0.6683	3.2489	1.1726	4.3772	1.0926	3.0979	0.8443	5.2357	1.3538	4.3284	1.2345	4.9016	1.9457
May	2.1507	0.4860	3.2309	0.6484	3.0675	1.0846	4.4635	0.9603	2.5720	0.7182	4.5869	1.3745	4.5426	1.1424	4.7801	1.9598
June	2.1253	0.5276	3.6555	0.6867	2.2543	0.6926	4.4869	0.8179	2.2518	0.6576	3.8217	1.1882	4.7808	1.0039	4.3671	1.6153
July	2.2723	0.5960	3.9279	0.6278	2.3094	0.7655	4.1072	0.7590	2.1939	0.6140	3.4488	1.0167	4.6196	0.8733	4.4647	1.6935
August	2.3286	0.6988	3.8933	0.6046	2.1670	0.7449	3.9413	0.6574	2.0353	0.6200	3.8452	1.2641	4.5272	0.8680	4.1203	1.5746
September	1.9352	0.5734	3.7854	0.6323	2.2022	0.6779	4.1093	0.7519	1.7198	0.4570	4.9419	1.3777	4.5414	0.9724	4.1922	1.6489
October	1.7719	0.4808	3.2420	0.6388	3.5032	0.7098	3.9011	0.8786	1.8224	0.4643	5.7207	1.2169	4.2352	0.9821	4.3147	1.8691
November	2.1439	0.6846	2.8128	0.5624	3.5133	0.7890	3.6049	0.9969	2.0856	0.5618	5.3455	0.9759	3.7185	1.0608	4.8971	2.0861
December	2.7740	0.7380	2.7817	0.6264	3.3085	0.8647	3.6973	1.2747	2.4581	0.6657	4.9203	0.9006	3.7298	1.1503	5.1393	2.3634

The results of the monthly descriptive statistics and WD estimate for WS data in the selected stations, as shown in Table 3, show that the maximum scale parameter was measured in Nairobi (6.2022 m/s) in October, while the minimum scale parameter was measured in Luanda (1.8938 m/s) in September. This shows that Nairobi has a higher WS than other stations. As a result, Luanda has a lower WS than other stations because the scale parameter is set to the lowest value. Table 3 shows that the maximum value of the shape parameter was observed in Accra (6.8696 m/s), while the minimum value was recorded in Tunis (2.3301 m/s), indicating that the two stations have both the maximum and minimum WS values recorded in the selected African stations. As a result, the WS shape parameter indicates that Accra has a higher WS than other stations.

Figure 2 depicts the monthly WS rise direction for the selected African stations. These findings explain the variability of wind direction across all stations studied.

Subgraph (A) of Figure 2 depicts the results of Abuja, which show that the wind speed direction (WSD) of the

Table 3. Monthly distractive statistics and WD estimate for WS data in the selected stations

	Abuja (m/s)		**Accra (m/s)**		**Addis Ababa (m/s)**		**Tunis(m/s)**		**Pretoria (m/s)**		**Cairo (m/s)**		**Luanda (m/s)**		**Nairobi (m/s)**	
Months	y	v	y	v	y	v	y	v	y	v	Y	v	y	v	y	v
Jan.	3.2827	3.3865	4.8250	3.3385	4.2847	3.6591	2.3301	5.9429	3.4872	4.1397	2.8424	4.2353	3.6126	3.0696	6.3196	5.1223
Feb	3.7357	3.1220	5.2737	3.8707	4.1153	3.9569	2.6020	5.8421	3.3226	4.3841	3.0691	4.2244	3.8340	3.3476	5.9886	5.5881
Mar.	3.9478	2.7683	5.9215	3.9796	3.9147	3.8357	2.4222	5.8137	3.3788	4.7761	3.6756	4.6268	3.7732	3.9553	5.7927	5.7579
Apr.	4.6938	2.6657	5.9215	3.9796	3.0874	3.6432	2.6731	5.5240	3.8092	4.7885	4.2151	4.8025	3.9553	3.4176	4.5916	5.7370
May	4.7546	2.3444	5.4980	3.4951	3.1112	3.4363	2.5864	5.3942	4.2742	4.9815	4.8158	4.8500	3.8140	2.8421	3.7952	5.0811
Jun.	4.1657	2.3296	5.9691	3.9375	3.3424	2.5053	2.8479	4.9057	5.2072	5.1825	5.5787	4.8291	3.5940	2.4949	3.4874	4.2498
July	4.0488	2.5005	6.5113	4.1979	3.1842	2.5790	2.7786	5.0225	5.8500	4.9760	5.8218	4.4222	3.8586	2.4237	3.5761	3.8235
Aug.	3.5082	2.5832	6.8696	4.1500	3.0971	2.4260	2.7362	4.6346	4.8852	4.8852	6.2577	4.2205	3.5394	2.2608	3.3351	4.2919
Sept.	3.4962	2.1460	6.2214	4.0521	3.4341	2.4474	2.6671	4.7215	5.2096	4.9310	5.9272	4.4223	3.8097	1.8938	4.1813	5.4400
Oct.	3.7997	1.9545	5.5505	3.5026	5.8917	3.7813	2.4309	4.8752	4.5223	4.6243	4.5458	4.2544	4.0902	2.0021	5.2892	6.2022
Nov.	3.3789	2.3886	5.2608	3.0443	5.1514	3.8189	2.4807	5.5310	3.8618	4.1104	3.8427	3.9801	3.8974	2.2986	6.4569	5.7370
Dec.	4.0959	3.0517	4.6995	3.0311	4.3974	3.6322	2.3243	5.8191	3.5273	4.1422	3.0125	4.1327	3.9448	2.7112	5.9542	5.2906
All Data	3.2417	2.6263	4.9878	3.7271	3.1812	3.3511	2.4743	5.3409	5.3409	4.6817	3.9183	4.4406	3.0620	2.7138	4.0786	5.2497

station has the lowest value at north-north-west (NNW) and north (N) with 100, while the maximum WSD of the station is observed at south-south-west (SSW) and south-west (SW). The results show that the direction of the WS has the highest value above 450, indicating that the station's rose result indicates that the WS may be useful for energy generation.

Subgraph (B) of Figure 2 depicts the results of the Accra wind speed rose (WSR), which show that the minimum WS observed between east-south-east (ESE) and south-east (SE) is less than 200, while the maximum WS observed in the station is between north-east (NE) and east-north-east (ENE), which is 400. The direction of the WS represents the rate at which the wind moves through the station or the volume of wind that can be used for wind energy generation.

Subgraph (C) of Figure 2 depicts the results of Addis Ababa's wind rose; the results show that the minimum WSD was observed between west (W) and west-north-west (WNW), implying that the minimum WSD is observed in the west direction of the station with the value 100. Meanwhile, the maximum WSR of the result was recorded between north-west (NW) and north-north-west (NNW) at 400. The WSD shows that the maximum wind direction is observed around the west direction; however, this indicates that the station's maximum WSD is in the west, which could aid in the installation of wind energy equipment.

Subgraph (D) of Figure 2 depicts the results of Cairo's wind rose, which show that the station's minimum WS is east-northeast (ENE) and east (E). With a value of 100. The maximum WSD of the station is east-south-east (ESE), with a value of 400. However, the station's wind direction revealed that wind energy equipment could be placed to the east of where the wind comes from in the station. Because the WS is strongest in the east, this could aid in energy generation at the station.

Subgraph (E) of Figure 2 depicts the results of the Luanda wind rose; the results show that the minimum WSD was observed between south-south-east (SSE) and south (S), implying that the minimum WSD is observed in the west direction of the station with the value 150. Meanwhile, the maximum WSR of the result was observed at 350 in the south-southwest (SSW). The WSD shows that the maximum wind direction is observed around the west direction; however, this indicates that the station's maximum WSD is in the west, which could aid in the installation of wind energy equipment.

Subgraph (F) of Figure 2 depicts the wind rose of Nairobi, with the minimum WS pointing south (S) and south-south-west (SSW). With a value of less than 100. The maximum WSD of the station is east-south-east (ESE), with a value of 400. However, the station's wind direction revealed that wind energy equipment could be placed to the east of where the wind comes from in the station. Because the WS is strongest in the east, this could aid in energy generation at the station.

Subgraph (G) of Figure 2 depicts the Pretoria results, which show that the WSD of the station has the lowest value at south-west (SW) with 100 and the highest value at west (W) and west-north-west (WNW). The results show that the direction of the WS has the highest value above 450, implying that the station's rose result indicates that the WS could be useful for energy generation in the high wind direction as shown.

Subgraph (H) of Figure 2 depicts the results of the Tunis station, where the WS is distributed across all wind directions; however, the main prevailing wind direction for the station was observed to be north-west (NW) and north-north-west (NNW), with the highest value recorded as 400, while other wind directions had values less than that. Furthermore, it demonstrates that the wind direction in Tunis has a minimum value between east (E) and east-north-east (ENE) with a value greater than 150, indicating that the station is more prevailing in the region due to the direction of the wind; however, the maximum WSD was observed at south-west (SW) and west-south-west (WSW) with a value greater than 400.

Figure 3 revealed the WS data for the selected African stations, which exhibit varying probability distributions. Abuja, Nigeria, has a relatively narrow WS range of 1-7 m/s, with a maximum histogram value of 0.6. Accra, Ghana, and Addis Ababa, Ethiopia, have similar WS ranges of 1-6 m/s, with maximum histogram values of 0.55 and 0.35, respectively. In contrast, Cairo, Egypt, and Tunis, Tunisia, have wider WS ranges of 0.5-10 m/s and 1-16 m/s, respectively. Luanda, Angola, and Pretoria, South Africa, have WS ranges of 0.5-5.9 m/s and 1-9.5 m/s, respectively. The probability distributions for the stations also vary, with Abuja and Accra having more pronounced peaks, indicating a higher likelihood of WS within a specific range. Overall, the data suggest that WS patterns vary significantly across the selected African stations.

Figure 4 demonstrates the use of the MLM, which provides the best fit for the WD of WS across the selected stations. The results, as shown in the graph, show that the frequency distribution falls within different bins of variable for all of the selected stations, indicating that the WS data used for the study are within the range of 0 to 10 m/s for about 10% of the time, 11 to 20 m/s for about 12% of the time, 21 to 30 m/s for 15% of the time, 31 to 40 m/s for 20% of the time, and so on. The results also showed that the Weibull parameters (y, v) as shown in Eqs. (3) and (4), are between 10.55 m/s and 5.56 m/s for all of the selected stations in Figure 4. This demonstrates that the height of the data collected ranges from 5 to 50 meters above the earth's surface for all of the selected stations.

Figure 5 depicts the cumulative distribution of the selected stations, demonstrating that their probability variability follows a nearly identical pattern, with a maximum recorded as 1.0 CDF . The results from all stations considered show that there is a similarity to distinct values, accounting for nearly 90% of the variation in WS. However, more than 90% of the variation in WS indicates that the stations used can generate energy based on the amount of wind received at the station. As a result, each of the stations under consideration may benefit from improved energy production. Figure 5 shows the wind power density (PD_w) for the selected stations. Nairobi has the highest power density ($> 100\mathrm{Wm}^{-2}$) among all stations analyzed. The power density results show that the maximum value recorded in Luanda is $\left(> 18\mathrm{Wm}^{-2}\right)$, and the highest value recorded in Pretoria is $\left(> 65\mathrm{Wm}^{-2}\right)$. Tunis has a power density of $\left(< 90\mathrm{Wm}^{-2}\right)$. The maximum power density recorded in Abuja is $\left(< 18\mathrm{Wm}^{-2}\right)$, while the maximum value recorded in Accra's power variation is $\left(> 35\mathrm{Wm}^{-2}\right)$. As shown in the results, Nairobi has the highest recorded power density, while Abuja has the lowest. This demonstrates that WS in Nairobi has a higher power output than that recorded in other stations; thus, Nairobi is advised to use more wind energy for energy generation and production for national development.

Differences in WS characteristics among stations arise from geographical location (latitude and proximity to oceans or mountains), topography (elevation, terrain roughness, and obstacles like buildings or trees), and local climate conditions (prevailing weather systems, seasonal variations, and temperature gradients). These factors collectively influence wind patterns and intensity.

4 Conclusion

This study analyzed WS for selected African countries using the WD. The research findings show the daily and seasonal variation in WS for the selected stations. The WS profile shows that a high WS was recorded in Nairobi (5.7207 m/s) in October, indicating that the station has the potential to generate more energy than the other stations studied. As a result, the MLM demonstrates that Weibull parameters can be determined based on WS characteristics, which will aid in the generation of energy in high WS locations. The parameter shape of the WS of the selected station reveals a close Rayleigh wave that depicts the behavioural relationship of the WS in the selected stations, which is uniform and regular.

The Weibull shape parameter (k) indicates wind consistency; higher values show steady winds, ideal for energy generation. The scale parameter (c) reflects average WS; larger values signify higher energy potential. Stations with high k and c values are optimal for wind energy, ensuring reliable and efficient power generation.

As a result, the study's findings indicate that the Weibull probability density function and data actualization have good matching curves, resulting in WS variations of less than 50% for the selected stations. As a result, the findings indicate that some of these stations are capable of erecting mini power stations for the use of turbines for electricity production in Africa. Because research has shown that Africa has a problem with electricity generation, it is concluded that the factor of shape scale of the factors used for the generation of electricity, which ranges from 0.4808 to 5.7207 m/s for this period of WS generation for the selected station.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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