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Statistical Trends in Wind Speed for Khulna, Bangladesh: An Analytical Approach

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Abstract
This study aims to examine the characteristics of the speed of wind and evaluate the prospective of wind power in Khulna, Bangladesh, from 2019 to 2023 using numerical methods. The research involves modeling wind speed data with probability density functions, specifically Weibull and the Rayleigh distributions, every month. By determining the parameters of these distributions, the study seeks to assess how wind power varies over time and its potential for energy generation. The insights gained from comparing these distributions are intended to support decision-making in renewable energy planning, infrastructure investment, and resource allocation. The study's relevance lies in its potential to provide valuable information for effectively harnessing wind energy and making informed decisions about renewable energy utilization.

Keywords: *Wind speed data, Rayleigh distribution, Shape factor, Weibull distribution, Wind power.*

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1. Introduction

One relevant quote from the Quran emphasizes the importance of environmental conservation: "And the earth We have spread out, and placed therein firm mountains, and caused to grow therein every kind of beautiful growth." This verse (Qur'an 50:7) highlights the concept of being good stewards of the Earth and refraining from causing harm or pollution to it. Bangladesh, a rapidly developing country, faces increasing energy demands due to its growing population and industrial expansion (Noman et al., 2023). According to recent estimates, the country's energy demand has been rising at an annual rate of 10-12% (Das et al., 2024), with a peak demand of around 14,000 MW recorded in 2023. This rising demand has placed a strain on the country's predominantly fossil fuel-based energy sector, leading to concerns about energy security, economic sustainability, and environmental impact (Habib et al., 2024). Currently, more than 60% of Bangladesh's electricity is generated from natural gas, while renewable energy contributes less than 5% to the national grid (Islam et al., 2022). Given this scenario, the need for sustainable and renewable energy (RE) sources, such as wind power, has become more critical than ever. Regarding the environment, wind power is considered one of the most prominent renewable energy resources due to its environmental benefits. Unlike traditional sources of energy such as fossil fuels, wind power does not produce harmful emissions or pollutants that contribute to air and water pollution or climate change. This makes it a non-polluting energy source that helps in preserving the environment and public health (Zhou et al., 2010). In addition, wind power is also cost-effective over time (Adaramola et al., 2011). While there are initial investment costs associated with setting up wind turbines and related infrastructure, once operational, the ongoing costs for wind power are relatively low compared to traditional forms of energy generation. This makes it an economically viable option for sustainable energy production (Habib et al., 2024). The Weibull probability distribution is commonly used to describe wind variations at a specific site (Keyhani et al., 2010). It provides a statistical model for the distribution of wind speeds, which is essential for understanding the potential for wind power generation at that location. The Weibull distribution allows for an accurate demonstration of the frequency and intensity of different wind speeds at a particular site over a period of time (Akpinar & Akpinar, 2005). This information is crucial for designing efficient wind turbines and predicting energy output from a wind farm. By using this probability distribution model, energy developers, and engineers can better assess the potential performance of wind power systems, optimize turbine design, and make informed decisions about siting new projects based on local wind conditions (Habib, 2022). Overall, utilizing the Weibull probability distribution helps in effectively harnessing wind power resources by providing insights into the variability and strength of winds at specific locations. Wind energy represents a feasible solution to Bangladesh's energy challenges (Jacobson et al., 2018). It is a clean, abundant, and cost-effective source of power that can considerably reduce the reliance on fossil fuels and contribute to the country's transition toward a greener energy portfolio (Habib, 2022). Wind power generates electricity without emitting greenhouse gases, making it an essential component in combating climate transformation and enhancing air quality. Moreover, Bangladesh's geographical location, with its long coastal belt and favorable wind patterns (Mazumder et al., 2019), particularly in regions like Khulna, offers significant potential for wind energy development. Wind energy is not only environmentally advantageous but also economically beneficial. Initial investment costs for wind power infrastructure can be high; however, the long-term operational costs are considerably lower compared to conventional energy sources (Akpinar & Akpinar, 2005). Additionally, wind energy can help expand the country's energy selection, reducing vulnerability to fluctuations in global fossil fuel prices and ensuring a more stable and sustainable energy supply (Adaramola et al., 2011). By harnessing wind energy, Bangladesh can also work towards meeting its renewable energy targets. The remainder of the paper is arranged as follows. A literature review is demonstrated in section 2. Section 3 provides a theoretical analysis. Section 4 represents the results and discussion, and section 4 concludes the study.

2. Literature review

Research on wind power optimization in Bangladesh based on Weibull parameters (shape parameter; k (Noman et al., 2023) and scale parameter; c (Jacobson et al., 2018) is crucial for understanding the potential for wind energy generation in the country. The Weibull distribution allows researchers to analyze and model the variability of wind speeds at different locations, providing valuable insights for optimizing the design and operation of wind turbines (Islam et al., 2022). By evaluating the Weibull parameters in various places in Bangladesh, researchers can acquire a deeper insight of the local wind conditions, which is essential for making informed decisions about implementing and managing wind power projects (Mazumder et al., 2019). This research contributes to maximizing energy output, improving efficiency, and ultimately harnessing Bangladesh's wind resources more effectively (Rashid, Habib, et al., 2018). Furthermore, by utilizing Weibull parameters to assess wind power potential in Bangladesh, researchers can provide valuable data and recommendations that inform sustainable energy development strategies aligned with environmental concerns. This research also supports efforts to address energy needs while promoting cost-effective and non-polluting renewable energy sources (Rashid et al., 2018). Analyzing the wind speed data at a precise location such as Khulna (located at 22° 49' 12.0000'' N and 89° 33' 0.0108'' E.) in Bangladesh provides valuable insights into the potential for wind power generation in that area (Akpinar & Akpinar, 2005; Boeker & Grondelle, 1999). By examining long-term wind data from 2019 to 2023, researchers can derive important information about the consistency and variability of wind speeds, which are essential factors for assessing the feasibility of wind energy projects. Through this analysis, researchers can determine the Weibull parameters (shape parameter k and scale parameter c) for Khulna, allowing for a complete understanding of the neighbouring wind conditions. This information is crucial for optimizing the placement and operation of wind turbines to maximize energy production. Furthermore, by focusing on a specific location like Khulna, this study contributes to a more targeted approach to harnessing wind power in Bangladesh. The results obtained from analyzing long-term wind data can provide valuable inputs for decision-making processes related to renewable energy investments and policies. Overall, this research contributes to advancing our understanding of wind power potential in Bangladesh by providing localized insights through detailed analysis of measured wind speed data over an extended period. Currently, there is no existing research focusing on wind energy systems that utilize wind speed data specifically for Khulna, Bangladesh. This study's primary goal is to determine whether the wind speed data from Khulna is statistically significant for predicting wind energy output. Several studies have applied the Weibull and Rayleigh distributions for wind speed analysis in regions with varying climate conditions and topographies. For instance, studies in Turkey (Akpinar & Akpinar, 2005), Yemen (Algifri, 1998), and Nigeria (Adaramola et al., 2011) have demonstrated these models' effectiveness in estimating wind power potential. In coastal areas, such as the Chittagong coastline in Bangladesh (Mazumder et al., 2019), these distributions have been crucial for identifying viable sites for wind energy. However, literature also indicates challenges, as seen in (Habib, 2022; Jacobson et al., 2018; Zhou et al., 2010), where deviations in local wind characteristics required alternative modeling approaches.

3. Theoretical analysis

3.1 Frequency distribution of wind speed

The probability density distribution of wind speed and its functional forms are key elements in wind-related literature. For a given location over a specific period, the probability distribution of wind speed is commonly fitted using two primary functions: the Weibull distribution and the Rayleigh distribution. The Weibull probability density function is represented as (Akpinar & Akpinar, 2005; Boeker & Grondelle, 1999),

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (1)$$

$f(v)$ is the probability of wind speed v, k is the Weibull shape factor, and c is the scaling parameter of the Weibull distribution.

The function of cumulative probability based on Weibull distribution (Algifri, 1998; Celik, 2004; Ramírez & Carta, 2005) is shown as,

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (2)$$

A special case of the Weibull distribution is the Rayleigh distribution when the shape parameter k is 2. From equation 1, the Rayleigh distribution is expressed as (Akpinar & Akpinar, 2005; Habib, 2022),

$$f(v) = \left(\frac{2v}{c^2}\right)\exp\left[\left(-\frac{v}{c}\right)^k\right] \quad (3)$$

In Weibull distribution, the mean value v_m and the standard deviation σ is computed as (Akpinar & Akpinar, 2005; Habib, 2022),

$$v_m = c\Gamma\left(1 + \frac{1}{k}\right) \quad (4)$$

and

$$\sigma = c\left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)\right]^{0.5} \quad (5)$$

Where Γ( ) is the gamma function.

There are two critical factors in approximating wind energy: the most probable wind speed and the wind speed that carries the maximum energy. The most probable wind speed represents the value that occurs most frequently in the wind speed probability distribution and can be expressed by (Akpinar & Akpinar, 2005; Habib, 2022),

$$v_{MP} = c\left(\frac{k-1}{k}\right)^{1/k} \quad (6)$$

The wind speed conveying maximum energy can be represented as follows (Akpinar & Akpinar, 2005; Habib, 2022),

$$v_{MaxE} = c\left(\frac{k+2}{k}\right)^{1/k} \quad (7)$$

Various methods are used in the literature to evaluate Weibull parameters. The standard deviation method is taken to estimate k and the c.

i. The method of standard deviation

Weibull factors can be calculated from the following equations (Mohammadi & Mostafaeipour, 2013),

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.086} \quad (8)$$

$$c = \frac{v_m}{\Gamma(1 + \frac{1}{k})} \quad (9)$$

The standard deviation method approximates Weibull parameters (shape parameter k and scale parameter c) due to its simplicity, reliability, and straightforward approach. By employing the standard deviation and mean wind speed values from observed data, this method offers an efficient approach, especially for large datasets. The standard deviation method requires less computation and performs well with near-normal wind speed data, as seen in Khulna, Bangladesh than other methods like the maximum likelihood method, graphical method, and method of moments. This choice also supports consistent parameter estimation across a balanced time interval between accuracy and efficiency for assessing wind energy potential.

3.2 Wind speed variation with height

Wind speed varies with height based on the ground. The most common equation for variation of the wind speed considering height is expressed as follows (Akpinar & Akpinar, 2005; Habib, 2022),

$$\frac{v_1}{v_2} = \left(\frac{h_1}{h_2}\right)^p \quad (10)$$

Where v_1 and v_2 are mean of wind speeds at the height of h_1 and h_2. The exponent p relies on several factors such as the stability of the atmosphere, the surface roughness, temperature, and air density.

i. **Atmospheric Stability**: Under stable environments (e.g., during clear nights when the ground cools rapidly), the atmosphere becomes stratified, and vertical air mixing is suppressed, leading to lower wind shear (Celik, 2004). In contrast, under unstable conditions (e.g., during sunny days when the ground heats up), convective air movements enhance mixing, resulting in higher wind shear.

ii. **Surface Roughness**: The nature of the terrain or surface over which the wind blows influences the frictional drag on the wind. For example, smooth surfaces like water bodies or flat plains exhibit lower friction, leading to lower wind shear exponents (typically around 0.10 to 0.14). In contrast, urban areas with tall buildings or forests have higher surface roughness, resulting in higher wind shear exponents (up to 0.4 or more) (Algifri, 1998).

iii. **Temperature and Air Density**: Wind speed at higher altitudes can also be affected by changes in air density due to temperature fluctuations. Warmer air is less dense, which can reduce the drag on wind flow and increase wind speeds at greater heights (Ramírez & Carta, 2005).

The wind speed measurements are taken at a height of 10 meters, and the wind speed variations with height are analyzed using the wind profile power law. Based on the local terrain of Khulna, which consists mainly of flat and coastal land, a moderate value of p = 0.14 is taken, corresponding to typical values for open rural areas.

3.3 Wind power density

Wind power speed through the blade sweep area (A) rises as the cube of its velocity which is shown as,

$$P(v) = \frac{1}{2}\rho A v^3 \qquad (11)$$

where ρ is the average air density (1.225 kg/m^3, according to the average atmospheric pressure from sea level at 15° C), which relies on the altitude, air pressure, and the temperature.

The expected wind power density per unit area for a site, derived from the Weibull probability density function, can be represented for both monthly and annual periods as follows,

$$P_w = \frac{1}{2}\rho c^3 \Gamma\left(1 + \frac{3}{k}\right) \qquad (12)$$

The Weibull scale parameter (m/s) is demonstrated as,

$$c = \frac{v_m}{\Gamma(1 + \frac{1}{k})} \qquad (13)$$

When $k = 2$, Rayleigh power density model can be represented from equation (9) as (Akpinar & Akpinar, 2005; Habib, 2022) ,

$$P_R = \frac{3}{\pi}\rho {v_m}^3 \qquad (14)$$

$P_{m,\ R}$ is the wind power density in terms of probability density distribution that can be found as,

$$P_{m,\ R} = \sum_{j=1}^{n}\left[\frac{1}{2}\rho {v_m}^3 f(v_j)\right] \qquad (15)$$

The error in power density calculations using probability distributions is determined by the following equation (Akpinar & Akpinar, 2005; Habib, n.d.),

$$\text{Error (\%)} = \frac{\mathrm{P_{w,\ R}} - \mathrm{P_{m,\ R}}}{\mathrm{P_{m,\ R}}} \qquad (16)$$

Where $\mathrm{P_{w,\ R}}$ is the average power density achieved from either Rayleigh or Weibull function in error calculation.

The yearly average error in power density, when using the Weibull function, can be determined by the following formula,

$$\text{Error (\%)} = \frac{1}{12}\sum_{i=1}^{12}\frac{\mathrm{P_{w,\ R}} - \mathrm{P_{m,\ R}}}{\mathrm{P_{m,\ R}}} \qquad (17)$$

3.4 The statistical analysis of the distributions

The square of correlation coefficient (R^2), the chi-square (χ^2) and the root mean square error analysis (RMSE) are executed to estimate the performances of Weibull and Rayleigh distributions (Akpinar & Akpinar, 2005; Habib, 2022).

To determine these parameters, use the following equations,

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - z_i)^2 - \sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}(y_i - z_i)^2} \quad (18)$$

The correlation coefficient (R^2) measures the fit between observed and modeled wind speed distributions, with values closer to 1 indicating a better fit.

$$\chi^2 = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{N - n} \quad (19)$$

χ^2 tests the goodness-of-fit by comparing observed and expected frequencies, and lower values suggest a closer match.

$$\text{RMSE} = \left[\frac{1}{\text{N}}\sum_{i=1}^{N}(y_i - x_i)^2\right]^{1/2} \quad (20)$$

where y_i is the ith measured data, z_i is the mean value, x_i is the predicted data with Weibull or Rayleigh distribution, N is the number of the observations and n is the number of constants (Akpinar & Akpinar, 2005; Habib, n.d.). Root Mean Square Error (RMSE) quantifies average deviation, where lower RMSE values indicate higher accuracy in the distribution's prediction. When R^2 is the maximum and RMSE, χ^2 is the minimum then the most probable distribution will be chosen. These statistical measures together provide a robust assessment of distribution performance, necessary for selecting models that best represent wind behavior in Khulna.

4. Results and discussion

The wind speed data from 2019 to 2023 for Khulna, Bangladesh, were analyzed at a height of 10 meters above ground. Using statistical methods, the analyzed wind speeds were processed, and the key findings from this study can be summarized as follows.

Table 1: Monthly average wind speeds and the standard deviation in Khulna, 2019-2023.

Year	2019		2020		2021		2022		2023		Whole year	
Parameter	v_m	σ	v_m	σ	v_m	σ	v_m	σ	v_m	σ	v_m	σ
January	2.333	0.511	2.222	0.722	2.194	0.706	2.639	0.528	2.583	0.722	2.394	0.638
February	2.389	0.867	2.25	0.803	2.611	0.706	2.5	0.833	2.75	0.867	2.5	0.815
March	2.722	0.881	2.639	0.914	3.306	0.833	3.111	0.897	3.25	1.381	3.006	0.981
April	3.556	0.961	3.389	0.867	3.889	0.786	5	1.106	3.361	0.819	3.839	0.908
May	5	0.947	4.139	1.008	4.028	0.833	3.861	0.867	3.528	0.994	4.111	0.93
June	3.972	0.85	4.194	0.914	4.25	0.786	4.722	0.769	4.556	0.769	4.339	0.818
July	4.444	0.85	4.111	0.786	3.889	0.803	3.833	0.881	4.361	0.914	4.128	0.847
August	3.778	0.897	4.083	0.867	3.639	0.642	3.833	0.833	3.333	0.769	3.733	0.802
September	3.222	0.803	3.111	0.753	3.083	0.803	3.111	0.722	3.556	0.914	3.217	0.799
October	2.167	0.528	2.333	0.642	2.417	0.481	2.694	0.672	2.5	0.689	2.422	0.602
November	2.306	0.481	2.278	0.528	2.306	0.369	2.417	0.336	2.222	0.578	2.306	0.458
December	2.306	0.706	2.111	0.786	2.694	0.561	2.444	0.672	2.278	0.528	2.367	0.651
Yearly	3.183	0.773	3.072	0.799	3.192	0.692	3.347	0.76	3.19	0.829	3.197	0.771

The calculated monthly mean wind speeds and standard deviations from the time series data are shown in Table 1. It presents the monthly average wind speeds and their standard deviations for Khulna from 2019 to 2023. The data reveals clear seasonal patterns, with the highest wind speeds consistently recorded during the monsoon months (June and July) and the lowest during the winter months (November and December). These trends align with the typical seasonal weather patterns in Bangladesh, where the southwest monsoon brings stronger winds, while the dry season is characterized by relatively calm conditions.

A more detailed analysis of the trends across the years highlights several key observations:

a. **June and July:** It consistently exhibits the highest average wind speeds, reaching as high as 5.0 m/s in some years. This is attributable to the strong monsoonal flow during these months, which brings higher wind velocities across the coastal regions. The increased wind speeds during this period are favorable for wind energy generation, as higher wind velocities directly contribute to increased power output.
b. **Notable Year-to-Year Variability**: While the general seasonal trends remain consistent, there are fluctuations in the magnitude of wind speeds from year to year. For example, 2022 recorded a particularly high average wind speed in June (4.72 m/s), while in 2023, the wind speed for the same month was lower (3.83 m/s). This variability may be due to differences in monsoonal strength or other meteorological phenomena such as the intensity of low-pressure systems.
c. **Anomalies in Specific Months**: In some cases, there are notable deviations from the expected seasonal pattern. For instance, in April 2022, the average wind speed peaked at 5.0 m/s, which is unusually high for a pre-monsoon month compared to previous years where the wind speeds for April hovered around 3.5–4.0 m/s. This anomaly could be linked to abnormal pre-monsoon storms or localized weather events that temporarily increased wind speeds.
d. **November's Low Wind Speeds**: November consistently shows the lowest average wind speeds across all years, with values ranging from 2.22 m/s to 2.41 m/s. The low wind speeds in November coincide with the post-monsoon period, when the region experiences stable atmospheric conditions and less wind activity. These low wind speeds indicate a period of reduced wind energy potential, which could pose challenges for continuous energy production during this time.
e. **Standard Deviation and Wind Variability**: The standard deviation values across the months provide insights into the variability of wind speeds. For example, the high standard deviation in March 2023 (1.381 m/s) indicates a larger fluctuation in wind speeds during that month, suggesting inconsistent wind patterns. In contrast, months like November show lower standard deviations, indicating more stable but weaker winds.

The analysis indicates that the highest wind speeds are recorded in June in the whole year, while the lowest are observed in November in the whole year. The monthly mean wind speeds for Khulna from 2019 to 2023 are shown in Fig. 1. This figure illustrates that the trend in monthly mean wind speeds across different years is quite consistent. The monthly probability density and cumulative distributions from Khulna's time-series data for the whole year are depicted in Fig. 2 and 3. These figures demonstrate that the curves for both cumulative density and probability density exhibit similar trends in wind speed. The patterns displayed in Fig. 2 and 3 provide clear evidence of seasonal variation in wind energy potential. The concentration of higher wind speeds during the monsoon months offers a prime opportunity for maximizing energy generation. However, the shift toward lower wind speeds during the dry season suggests that wind energy production may be less reliable, requiring supplementary energy sources or energy storage solutions to maintain a stable supply. These interpretations reinforce the importance of seasonal wind speed analysis in planning and optimizing wind energy projects, particularly for ensuring continuous and efficient operation throughout the year. Additionally, Fig. 4 presents the annual probability density distribution and cumulative distribution which exhibits the highest probabilities found at wind speeds around 5 m/s.

The data presents monthly values for the parameters k and c over the years 2019 to 2023, along with their yearly averages in Table 2. The parameter values k and c show notable monthly fluctuations across the years. For instance, the highest values for both parameters are generally observed in months, particularly in June (k) and June (c), indicating increased variability or intensity during the whole year. The yearly averages of the parameters show a general trend of increased values over the years, with some variability. Specifically, the average k values range from 4.316 to 5.258, while the average c values span from 3.374 to 3.645 yearly.

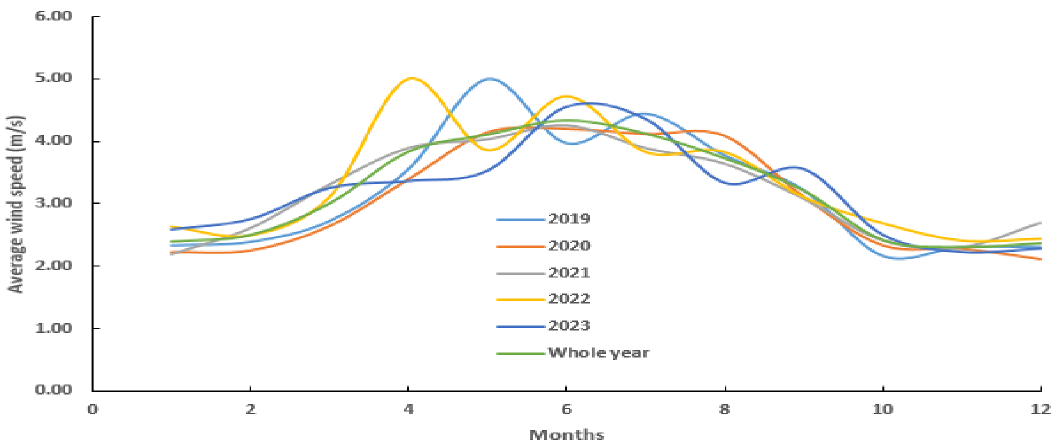

Fig. 1: The monthly wind speed of Khulna 2019-2023.

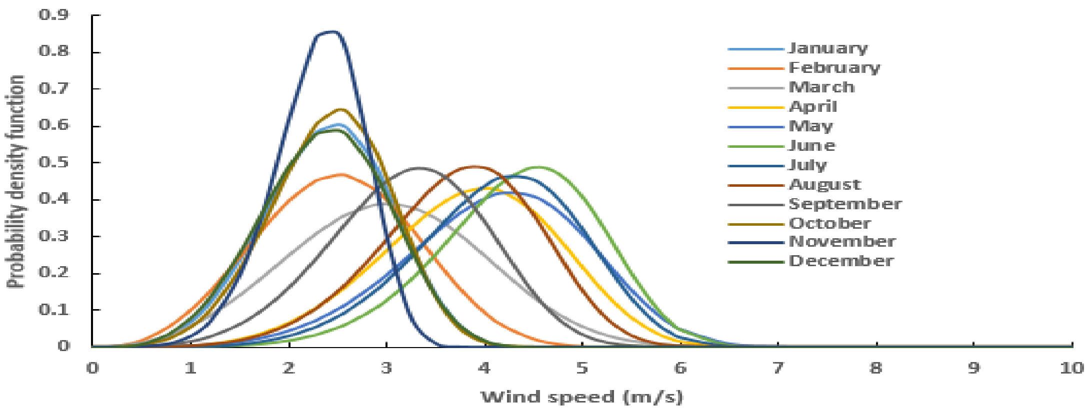

Fig. 2: The monthly wind speed probability distributions resulted from time series data of Khulna for the whole year

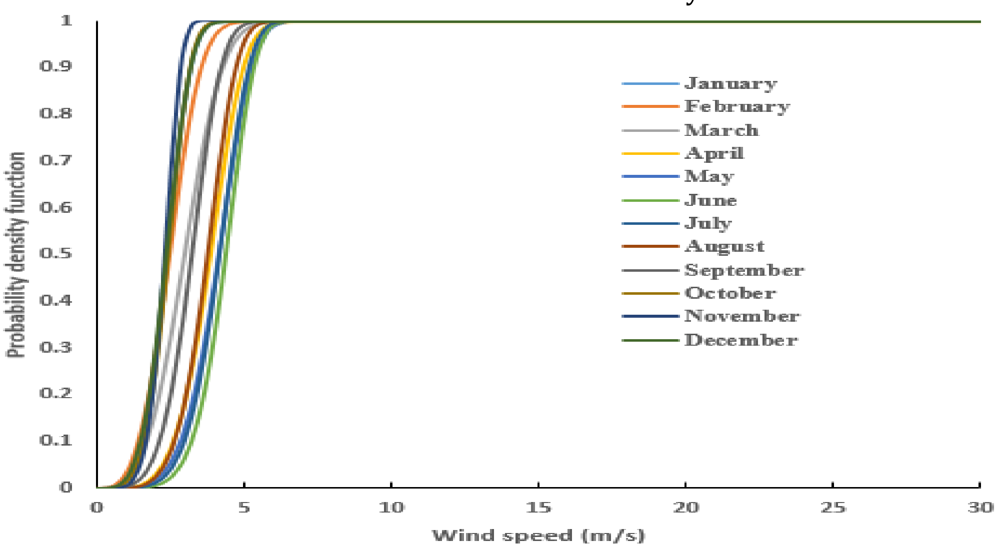

Fig. 3: The distributions of monthly Cumulative probability of wind speed derived from the measured data in Khulna for whole year

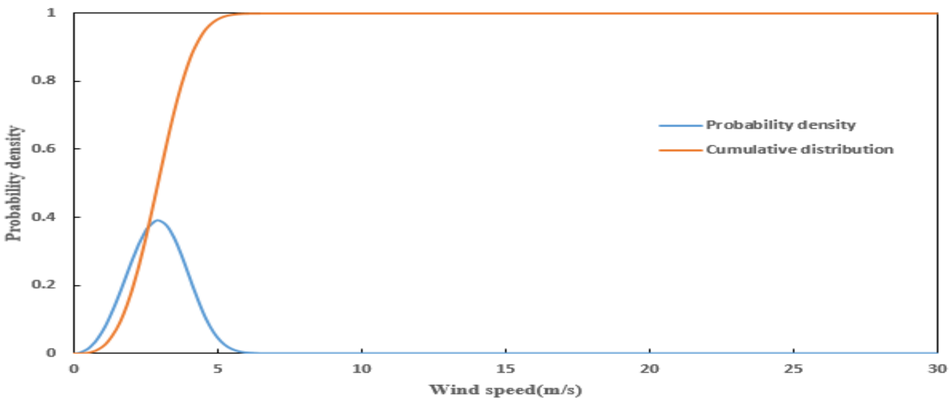

Fig. 4: Yearly wind speed probability density and the cumulative probability distributions, from measured data in Khulna for the whole year.

Table 2: Monthly shape parameter, k, and the scale parameter, c, in Khulna, 2019-2023.

Year	2019		2020		2021		2022		2023		Whole year	
Parameter	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*
January	5.202	2.535	3.389	2.474	3.429	2.442	5.742	2.851	3.991	2.85	4.207	2.634
February	3.008	2.675	3.063	2.517	4.142	2.875	3.297	2.787	3.504	3.056	3.378	2.784
March	3.407	3.03	3.163	2.948	4.466	3.624	3.859	3.439	2.534	3.662	3.373	3.347
April	4.14	3.915	4.397	3.719	5.676	4.205	5.149	5.436	4.631	3.677	4.787	4.192
May	6.091	5.385	4.635	4.528	5.535	4.361	5.066	4.202	3.956	3.895	5.023	4.476
June	5.336	4.31	5.232	4.556	6.251	4.571	7.174	5.042	6.899	4.874	6.125	4.672
July	6.028	4.789	6.029	4.43	5.548	4.21	4.94	4.178	5.458	4.726	5.587	4.467
August	4.765	4.126	5.383	4.428	6.584	3.903	5.245	4.163	4.914	3.634	5.316	4.052
September	4.523	3.53	4.669	3.402	4.312	3.387	4.884	3.393	4.373	3.903	4.539	3.523
October	4.635	2.37	4.063	2.572	5.778	2.61	4.517	2.952	4.054	2.756	4.534	2.653
November	5.49	2.498	4.894	2.484	7.305	2.459	8.519	2.558	4.319	2.441	5.78	2.49
December	3.618	2.558	2.924	2.367	5.496	2.919	4.063	2.694	4.894	2.484	4.065	2.609
Yearly	4.648	3.481	4.316	3.374	5.258	3.467	5.005	3.645	4.322	3.504	4.688	3.495

Fig. 5 illustrates the Weibull and Rayleigh approximate distributions of the actual wind speed probability distribution for whole year. Table 3 provides a comparison of these approximations with actual probability distribution. A distribution provides a good fit to the actual wind speed data by a higher R^2 value, and a lower RMSE in the Table 3. This suggests that the Weibull probability distribution more accurately represents the probability density of wind speeds for the whole year. Table 4 displays the annual Weibull parameters, average wind speed, and wind power density. The average wind speed v_m fluctuated but remained fairly consistent across the years, with 2022 showing the highest mean wind speed. The shape parameter (k) increased over time, indicating a trend towards sharper peaks in wind speed distribution. Power density (P) showed significant variation, with the highest wind energy potential observed in 2022. This suggests that wind energy potential can vary considerably from year to year based on wind conditions. Overall, the data reflects how wind speed characteristics and energy potential evolve annually, influenced by changes in distribution shape and extreme wind speeds. The power density derived from calculated probability density distributions is compared to the values from Weibull and Rayleigh distributions, as illustrated in Fig. 6. The Weibull model predicts lower power densities than the Rayleigh model, especially in months with higher wind speeds. Therefore, the Rayleigh model might provide a more accurate reflection of the actual wind conditions and energy potential during these periods. The error in power densities when using the Weibull and Rayleigh distributions compared to the actual calculated probability distributions is represented in Fig. 7. It is observed that the Weibull model generally exhibits lower error values in predicting power densities compared to Rayleigh model. Specifically, the highest error for the Weibull model is noted in November, while the lowest error is observed in March. Conversely, the Rayleigh model shows its greatest error in November.

Table. 3: Comparison of the wind speed data of the actual probability distributions with the Weibull and Rayleigh approximation for the whole year.

$f(v)$			
Wind speed	Actual data	Weibull Probability density function	Rayleigh Probability density function
1	0.008904584	0.013250862	0.160553287
2	0.15501953	0.159201274	0.319229913
3	0.501070511	0.468566209	0.470746947
4	0.300712105	0.335669401	0.627662596
5	0.033507545	0.023599834	0.784578245
6	0.000693225	3.31066E-05	0.941493894
7	2.66284E-06	9.23681E-11	1.098409543
8	1.89913E-09	2.33976E-20	1.255325192
9	2.51481E-13	1.04207E-35	1.412240841
10	6.18295E-18	6.20355E-59	1.56915649
11	2.82244E-23	1.3649E-92	1.726072139
12	2.39218E-29	1.0358E-139	1.882987788
R^2		0.991602887	0.270083407
RMSE		0.014181907	0.285200001

Potential sources of error in the power density analysis include assumptions about air density, which can vary with temperature and altitude, and the simplification of wind shear effects, which may not capture local terrain influences on wind flow. Additionally, measurement errors in wind speed data and inherent limitations in the Weibull and Rayleigh models may contribute to discrepancies in calculated versus actual power densities. This analysis utilizes both Weibull and Rayleigh distributions to model wind speed data for Khulna, Bangladesh from 2019 to 2023. Both distributions are commonly used in wind energy studies. The Rayleigh distribution offers certain advantages in representing the wind power potential in this specific region. While the Weibull distribution offers greater flexibility and accuracy in wind speed variability, the Rayleigh distribution emerges as a more effective tool for modeling wind power potential in Khulna, particularly during the high wind season. Its simplicity, coupled with its strong performance in estimating wind power density and lower error rates during peak energy months, makes it the preferred distribution for this specific study. These findings highlight the importance of selecting the appropriate distribution model based on the characteristics of the local wind regime and the specific objectives of the analysis. The error analysis (Fig. 7) further supports the preference for the Rayleigh distribution. Although the Weibull distribution generally provides lower error rates for wind speed predictions, the Rayleigh distribution exhibited lower errors when calculating power density during the months with higher energy potential.

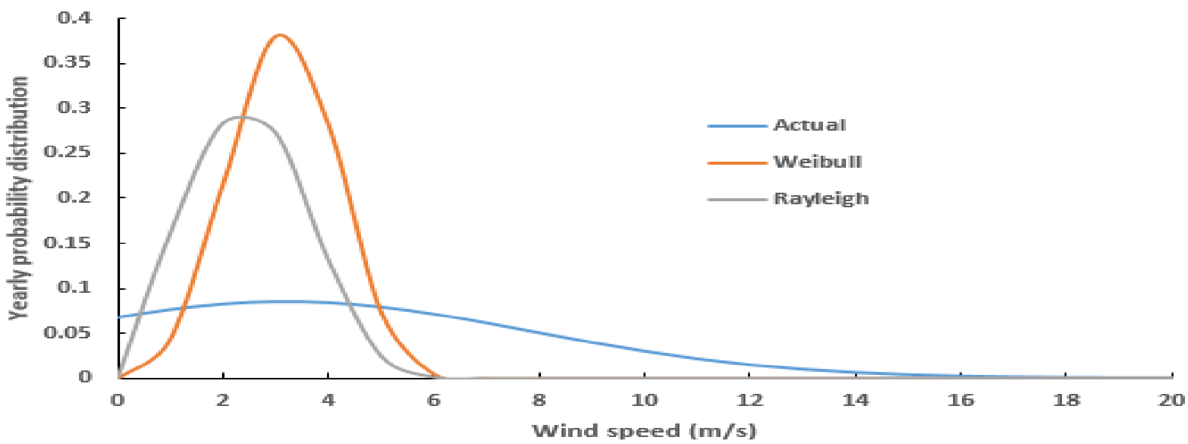

Fig.5: The actual probability distributions of Weibull and the Rayleigh approximations of the wind speeds

Table.4: Yearly wind speed characteristics 2019-2023, Khulna.

Year	v_m (m/s)	K	c (m/s)	v_{MP} (m/s)	v_{MaxE} (m/s)	P (w/m²)
2019	3.18	4.65	3.48	3.304450058	3.759879363	23.24236915
2020	3.07	4.32	3.37	3.174311934	3.685370661	21.35816061
2021	3.19	5.26	3.47	3.330242611	3.685728043	22.72247939
2022	3.35	3.47	5.01	4.537100177	5.70794924	72.98839342
2023	3.19	3.65	4.32	3.958276154	4.873222729	46.37511939

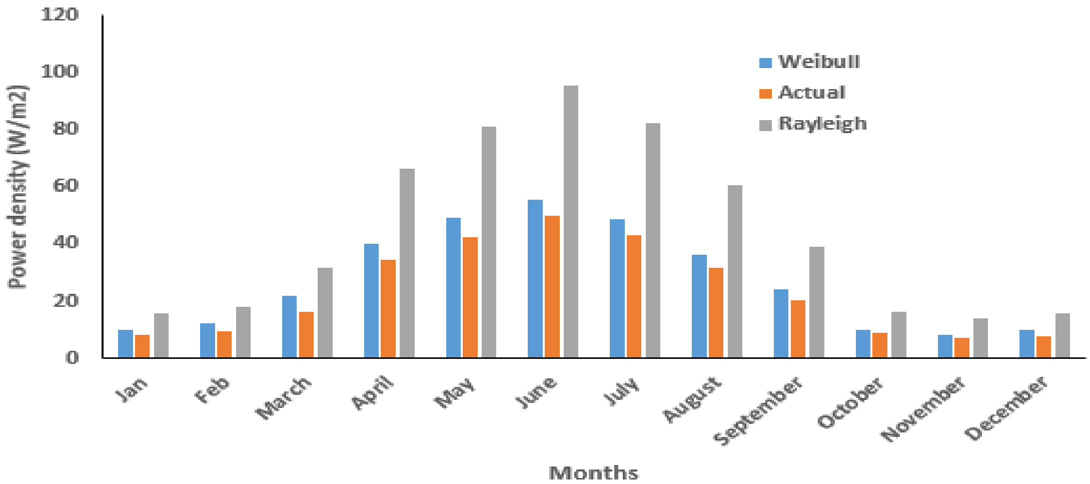

Fig. 6: The wind power density achieved from the actual data versus those obtained from the Weibull and Rayleigh models on the monthly basis

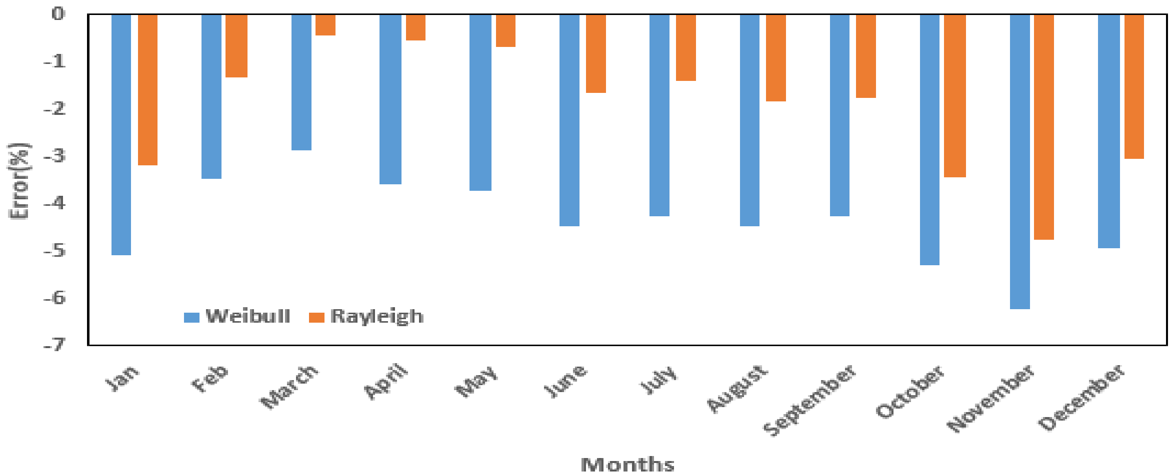

Fig. 7: The error values of the wind power density on monthly basis obtained from the Weibull and Rayleigh models based on the power density obtained from the measured data.

While the Weibull and Rayleigh distributions are widely used in wind data modeling, they have certain limitations. The Weibull distribution may overestimate or underestimate wind speeds, especially in areas with complex wind behavior due to local geographic or atmospheric conditions. The Rayleigh distribution assumes a shape parameter (k = 2), which may not accurately reflect varying wind patterns, particularly in regions where the wind distribution deviates significantly from this assumption. These limitations suggest that while Weibull and Rayleigh's models are practical, specific studies may sometimes require additional statistical models for improved accuracy. The unevenness in wind power density from 2019 to 2023 in Khulna has key implications for energy policy and infrastructure planning. Seasonal fluctuations, with peak wind energy in monsoon months, indicate that wind energy alone can't meet year-round demands, underscoring the need for a diversified energy mix, including solar power and energy storage solutions. Infrastructure investment should prioritize high-density wind areas, particularly during monsoon season, and optimize turbine design for both peak and off-season conditions. Long-term policies should account for changing wind patterns due to climate change, including adaptive, data-driven strategies and investments in grid resilience. Key recommendations include supporting wind-solar hybrid systems, incentivizing energy storage, establishing wind energy zones, and advancing wind energy research to sustain growth and energy security. Furthermore, the infrastructure investment should focus on areas with the highest wind power density, especially during the monsoon season, when the return on investment for wind energy projects would be maximized. Policymakers and investors must consider long-term wind data to identify optimal turbine locations, ensuring that resources are allocated efficiently and that wind farms are situated in regions with consistent and favorable wind patterns. They should develop strategies that are responsive to such variability by incorporating regular monitoring and updating of wind data. This would enable better forecasting of wind energy potential and more informed decisions regarding infrastructure development and energy policy adjustments.

5. Conclusions

The wind characteristics of Khulna from 2019 to 2023 were statistically analyzed to assess wind energy potential. Probability density and power density distributions were derived from wind speed data using Weibull and Rayleigh models. The analysis found that the Rayleigh distribution better represents wind power density in Khulna compared to the Weibull distribution, as indicated by superior R^2 and RMSE values. Additionally, significant variability in wind power density over time highlights the dynamic nature of wind energy potential, emphasizing the need for detailed data analysis to effectively harness this renewable resource. These insights are valuable for decision-making in wind energy projects in Khulna and similar areas. This study offers some key recommendations for stakeholders for optimizing wind energy in the Khulna region. These are

i. **Focusing on monsoon season**: To leverage high wind speeds during monsoon months by optimizing turbine placement and increasing investment in wind farms for maximum returns.
ii. **Adopting hybrid systems**: To counter low wind speeds in the dry season, integrate wind with solar power for year-round energy stability.
iii. **Investing in energy storage**: To use storage solutions (e.g., battery, pumped hydro) to store excess energy from high-wind periods for use during low-wind times, ensuring reliability.
iv. **Enhancing monitoring and forecasting**: Need to implement continuous monitoring and forecasting systems for a better plan for wind energy production and manage grid integration.
v. **Supportive Policies and Incentives**: Government support through tax incentives, feed-in tariffs, and private investment promotion will accelerate sector growth.
vi. **Planning for Climate Resilience**: Designing adaptive wind systems and policies that account for potential climate-induced wind pattern changes, ensuring long-term sustainability.

These recommendations will help to maximize Khulna's wind energy potential, support Bangladesh's sustainable energy goals, and reduce reliance on fossil fuels.

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