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Research Article

Wind speed analysis and its implications for Muktagacha, Mymensingh, Bangladesh

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ABSTRACT

With its distinctive geography and varied climatic conditions, Muktagacha in Mymensingh, Bangladesh, is well-suited for wind energy exploration. This study investigates wind speed characteristics and the potential for generating wind power in the area from 2019 to 2023. The research uses statistical methodologies to develop probability density functions through Weibull and Rayleigh distributions for monthly wind data analysis. The Weibull model provides a more precise estimation of power density, validated by higher R^2 and lower RMSE values. Wind speed data (2019–2023) from Muktagacha, Bangladesh, were analyzed using Weibull and Rayleigh distributions. Model performance was evaluated using R^2, RMSE, and χ^2. The Weibull model provided a better fit for wind speed distributions ($R^2 = 0.998$), while the Rayleigh model estimated higher power densities, especially during high wind months like June. Year 2022 showed the highest wind energy potential, with a power density of 135.66 W/m². The results offer essential insights into wind energy capabilities in Muktagacha, supporting decision-makers and emphasizing the importance of renewable energy in the region.

Introduction

Rain falls from the sky, reviving the lifeless earth and bringing it back to life. This remarkable transformation is a clear sign of natural energy. This highlights the life-giving power of rain and its essential role in sustaining the natural balance, emphasizing the importance of conserving natural resources (Redclift, 2002). The principles derived from this verse advocate for the responsible utilization of the earth's resources and align with promoting renewable energy initiatives (Habib et al., 2024a). The rapid advancements in renewable energy technologies are transforming the global energy landscape, providing valuable insights into technological innovations and emerging trends (Eze et al., 2023). Renewable energy sources, including solar, hydroelectric, geothermal, and wind power, are continually advancing, offering viable solutions to the challenges posed by climate change and sustainable development. These advancements highlight a promising future for renewable energy as it becomes an integral component of global sustainability initiatives (Gielen et al., 2019). Renewable technologies are pivotal in reducing greenhouse gas emissions and provide a comprehensive approach to the evolving clean energy sector. Notable innovations include developments in energy storage systems, innovative grid technologies, and the seamless integration of renewables into existing energy infrastructures. The shift towards renewable energy has significant environmental and public health benefits (Islam et al., 2023). By minimizing air (Aditya et al., 2022) and water pollution associated with fossil fuel use, renewable energy technologies contribute to

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improved air quality and enhanced public health outcomes. This transition aligns with the principles of responsible stewardship of natural resources, as emphasized in various cultural and philosophical texts. Ongoing advancements in renewable energy highlight the potential for a sustainable future where clean energy solutions address global environmental challenges and enhance social well-being. Among renewable energy sources, wind energy stands out due to its abundance, minimal ecological impact, relatively higher efficiency, and capability to generate power even during nighttime (Dyrholm et al., 2023). The wind energy sector is rapidly evolving, driven by innovations such as larger and more efficient wind turbines, advancements in offshore wind farms, and the integration of digital technologies (Giebel and Kariniotakis, 2017). The Weibull probability distribution often models wind patterns at specific locations (Keyhani et al., 2010; Akpinar and Akpinar, 2005; Al-Buhairi, 2006). In Mymensingh, Bangladesh, several studies have been undertaken to optimize wind power generation (Habib, 2022, Jacobson, 2018; Habib et al., 2024b; Rahman et al., 2024; Mazumder et al., 2019; Rashid et al., 2018a), focusing on the shape parameter (k) and scale parameter (c) of the Weibull distribution in their analyses.

Extensive research has explored optimization techniques using deep learning (Wang et al. , 2021; Hong and Rioflorido, 2019; He et al., 2023), data processing strategies (Liu and Chen, 2019), and a strong focus on decision-making processes (Habib et al., 2022). Additionally, numerous studies have examined survey-based methods (Marugan et al., 2018), simulation techniques (Islam et al., 2022a; Rahaman et al., 2015; Noman et al., 2023; Rashid et al., 2018b; Sinha and Chandel, 2015), applications of game theory (Habib, 2019; Habib et al., 2020), and various other related approaches (Yan and Ouyang, 2019; Wang et al., 2019a; Giebel et al., 2017; Wang et al., 2019b; Lipu et al., 2021) worldwide. Physical models, such as Numerical Weather Prediction (NWP) and Weather Research and Forecasting (WRF), often incorporate environmental conditions (Hanifi et al., 2020). These factors include surface roughness, terrain, wake effects, humidity, pressure, and temperature (Zhang et al., 2019; Du et al. 2019). Advanced mathematical models are subsequently applied to forecast wind speed characteristics, using these variables specific to the area. Wind speed data is then utilized to estimate wind power output through the turbine's wind power curve. This forecasting approach does not require training with historical data but relies on physical data inputs. Research has demonstrated that physical prediction models often outperform traditional statistical models in medium-term and long-term wind speed predictions, albeit at the expense of higher computational complexity and resource demands (Yuan et al., 2019). Conversely, statistical models utilize historical data to identify linear and non-linear relationships between weather conditions and power output (Wang et al. 2019). These relationships enable predictions for future power generation. While statistical models are easier to develop and require fewer computational resources than physical ones, they tend to produce less accurate forecasts over longer time horizons.

This study conducts a detailed analysis of wind speed data collected in Muktagacha (24.7660° N, 90.2665° E), Mymensingh, Bangladesh, for the period between 2019 and 2023 (worldweather and bmd.gov.bd), utilizing continuous probability distributions such as Weibull and Rayleigh. The research identifies a critical gap in previous studies, which often overlooked localized data in the analysis of wind energy systems. Consequently, the primary objective of this paper is to statistically analyze the wind speed data to assess the potential for wind energy production in Muktagacha, Mymensingh.

This paper is organized into different subsections, such as Section 2, Section 3, Section 4, and Section 5, which describe the theoretical analysis, results and discussion, machine learning-based model, and conclusion, respectively.

Theoretical analysis

Analysis of wind speed using frequency distribution

The wind speed distribution and its functional form play a pivotal role in wind energy research. Weibull and Rayleigh distributions are commonly employed to model wind speed data for specific locations and periods. The probability density function of the Weibull distribution is mathematically expressed as (Boeker and Grondelle, 1999),

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

Where *f(v)* is the wind speed probability of v, c and k are the scaling parameters and shape factors of the Weibull distribution, respectively.

The cumulative probability function that relies on the Weibull distribution (Ramirez and Carta, 2005; Celik, 2003; Algifri, 1998) can be expressed as follows,

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

The Weibull distribution becomes identical to the Rayleigh distribution when the shape parameter (*k*) equals 2. Thus, the Rayleigh distribution can be expressed from Equation 1 using *k=2* as,

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

The mean value ($_{\mu m}$) and standard deviation (σ) of the Weibull distribution are calculated as,

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

and

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

Where Γ () is the gamma function.

Two key factors, such as wind speed and the direction that carries the maximum energy, are most probable in estimating the wind energy. The most probable wind speed represents the wind speed that occurs most frequently in the distribution of wind probability, which is expressed as follows,

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

The wind speed carrying the maximum energy can be represented as follows,

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

Concerning the Lognormal distribution, parameters: **μ** and **σ** (log-scale mean and standard dev)

$$\sigma_{\log} = \sqrt{\ln\left(1+\left(\frac{sd}{v_m}\right)^2\right)}$$

$$\mu_{\log} = \ln(v_m) - \frac{1}{2}\cdot\sigma_{\log}^2$$

The Gamma Distribution shows Parameters: **α** (shape), **θ** (scale),

$$\alpha = \left(\frac{v_m}{sd}\right)^2$$

$$\theta = \frac{sd^2}{v_m}$$

The literature provides various methods for evaluating the Weibull distribution parameters, including the standard deviation method, graphical method, maximum likelihood method, moment method, energy pattern factor method, and power density method. The standard deviation method is widely regarded as effective for determining the shape parameter (k) and scale parameter (c) values.

Standard deviation method

To calculate the parameters of the Weibull distribution, the following equations can be used,

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

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

Variation of wind speed with height

The value of wind speed changes with the variation of heights above the ground. The widely exploited equation for expressing the wind speed variation with height is,

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

Where v1 and v_2 are average wind speeds for heights h_1 and h_2. The exponent '*p*' value depends on atmospheric stability and surface roughness.

Wind power density

Wind power speed through the blade sweep area (*A*) is expressed in the following equation and is found to rise as the cube of its velocity.

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

Where ρ is the average air density (1.225 kg/m³, based on standard atmospheric conditions at sea level and at a temperature of 15 °C), several constraints, such as altitude, air pressure, and temperature, are constituents of wind power density.

The expected wind power density per unit area for monthly or annual wind data can be found by utilizing the Weibull probability density function as follows,

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

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

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

When $k = 2$, from equation (9), the model of Rayleigh power density can be expressed as,

$$P_R = \frac{3}{\pi}\rho {v_m}^3 \tag{14}$$

$P_{m,\ R}$ is the wind power density for a probability density distribution which can be represented as,

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

Errors that occurred during the calculation of power densities are found by utilizing probability distributions, and the error can be determined by exploiting the following expression,

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

Where $P_{w,\ R}$ is the average power density obtained from the Weibull or Rayleigh distribution.

The yearly average error in the power density, calculated utilizing the Weibull function, is obtained from the following expression,

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

The statistical analysis of the distributions

To obtain the performance of Weibull as well as Rayleigh distributions, the square of the correlation coefficient (R^2), chi-square (χ^2), and root mean square error (RMSE) are used. These parameters are determined utilizing the following expression,

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

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

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

Where y_i, z_i, x_i, N, and n are the ith measured data point, mean value, predicted data utilizing either Weibull or Rayleigh distributions, total number of observations,

and constraints, respectively. Thus, as the value of the R^2 is maximized and the values of RMSE and χ^2 are minimized. The probability distribution that best fits the data is selected using these parameters.

Results and discussion

Wind speed data from Muktagacha, Mymensingh, Bangladesh, collected between 2019 and 2023 at a height of 10 meters, were analyzed using various statistical techniques. A summary of the key findings is presented in Table 1 below:

Table 1. The monthly mean wind speeds and their corresponding standard deviations in Muktagacha between 2019 and 2023.

Years	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	1.75	0.589	2.056	0.817	1.639	0.597	2.167	0.444	2.083	0.5	1.939	0.589
February	2.278	0.981	2.139	0.861	2.111	0.5	2.444	0.569	2.306	0.639	2.256	0.71
March	2.472	1.236	2.278	1.453	2.611	0.819	2.75	0.611	2.778	1.194	2.578	1.063
April	2.806	1.158	2.944	1.156	3.167	0.681	3.75	0.667	2.889	0.792	3.111	0.891
May	3.75	1.044	3.25	1.225	2.806	0.6	3.278	0.569	2.806	0.694	3.178	0.827
June	3.111	1.089	3.472	0.911	3.556	0.594	3.75	0.5	3.694	0.653	3.517	0.749
July	3.722	1.019	3.472	0.839	3.278	0.528	2.694	0.486	3.194	0.625	3.272	0.699
August	3.139	0.931	3.583	0.908	3	0.472	2.917	0.583	3	0.597	3.128	0.698
September	2.806	0.908	2.806	0.931	2.167	0.514	2.5	0.472	2.611	0.694	2.578	0.704
October	2.056	1	2.028	0.725	2.111	0.417	2.083	0.486	2.25	0.528	2.106	0.631
November	1.778	0.667	1.861	0.681	1.861	0.347	1.833	0.389	1.861	0.444	1.839	0.506
December	2.028	0.833	1.889	0.636	2.139	0.486	1.861	0.403	1.667	0.472	1.917	0.566
Yearly	2.641	0.955	2.648	0.928	2.537	0.546	2.669	0.515	2.595	0.653	2.618	0.719

Table 1 (worldweather and bmd.gov.bd) provides the calculated monthly mean wind speeds and their standard deviations. The analysis indicates that the highest wind speeds were recorded in April, while the lowest wind speeds occurred in July. Fig. 1 illustrates the monthly mean wind speeds for Muktagacha from 2019 to 2023, showcasing a consistent wind speed pattern across the years.

Fig. 2 and Fig. 3 depict the monthly probability density and cumulative distributions, respectively, based on Muktagacha's time-series data for the entire year. These distributions demonstrate that both curves exhibit a similar trend in wind speed. Additionally, Fig. 4 presents the annual data's probability density and cumulative distribution, providing a comprehensive view of the wind speed patterns over the year.

Table 2 presents the monthly values of the Weibull parameters k and c from 2019 to 2023, along with their yearly averages. Both parameters display notable fluctuations across the months. For instance, the highest k values are generally observed in July, while the highest c values also occur in July, reflecting increased wind speed intensity or variability during these months. The yearly averages of the parameters reveal a general upward trend over the years, with some variations. Specifically, the average k values range from 3.02 to 5.97, while the average c values vary from 2.754 to 2.96 yearly.

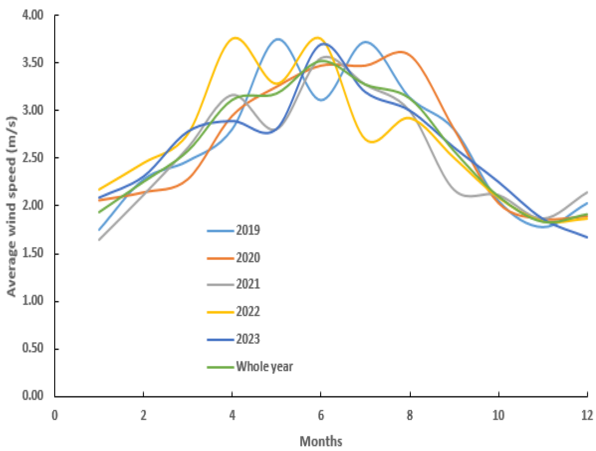

Fig 1. The monthly wind speed of Muktagacha, 2019-2023.

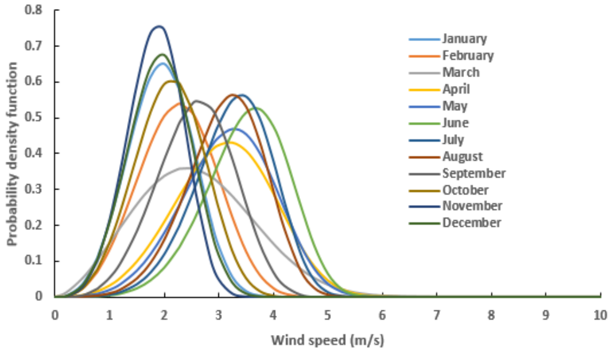

Fig 2. The probability distributions of the monthly wind speeds were based on the time

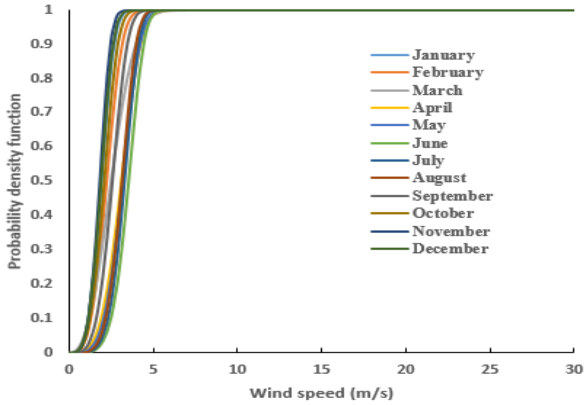

Fig 3. The cumulative probability distributions for the monthly wind speeds over the year are based on data from Muktagacha.

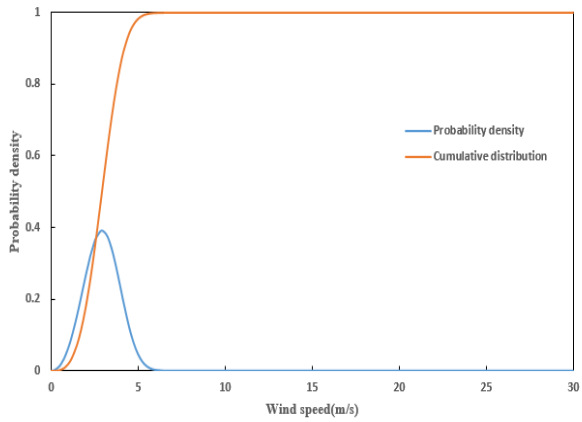

Fig 4. The wind speed probability density and cumulative distributions for the year were derived from the measured data from the Muktagacha.

Table 2. The monthly Weibull shape parameter (k) and scale parameter (c) for Muktagacha during 2019-2023.

Period	2019		2020		2021		2022		2023		Whole year	
Parameter	***k***	***c***	***k***	***c***	***k***	***c***	***k***	***c***	***k***	***c***	***k***	***c***
January	3.263	1.952	2.725	2.311	2.993	1.835	5.587	2.345	4.711	2.277	3.644	2.15
February	2.498	2.567	2.686	2.406	4.779	2.305	4.866	2.667	4.03	2.543	3.509	2.507
March	2.123	2.791	1.63	2.545	3.52	2.901	5.121	2.991	2.501	3.131	2.618	2.902
April	2.614	3.158	2.762	3.308	5.311	3.437	6.526	4.024	4.079	3.184	3.89	3.438
May	4.008	4.137	2.885	3.646	5.339	3.044	6.691	3.512	4.555	3.072	4.316	3.491
June	3.127	3.477	4.276	3.816	6.976	3.802	8.919	3.962	6.569	3.963	5.36	3.815
July	4.081	4.102	4.677	3.796	7.267	3.497	6.422	2.894	5.881	3.447	5.342	3.55
August	3.745	3.476	4.439	3.93	7.448	3.197	5.742	3.152	5.771	3.241	5.095	3.403
September	3.403	3.123	3.315	3.127	4.772	2.366	6.11	2.692	4.214	2.872	4.095	2.84
October	2.187	2.321	3.056	2.269	5.825	2.279	4.857	2.273	4.829	2.455	3.701	2.333
November	2.901	1.994	2.982	2.085	6.193	2.003	5.387	1.988	4.736	2.033	4.065	2.027
December	2.627	2.282	3.261	2.107	4.998	2.33	5.271	2.021	3.934	1.841	3.76	2.122
Yearly	3.02	2.957	3.121	2.96	5.3	2.754	5.97	2.878	4.476	2.844	4.067	2.886

Table 3. Comparison of the year's wind speed data with Weibull and Rayleigh distribution approximations.

Wind speed	Actual data	Probability density function	Rayleigh
1	0.044212788	0.053921653	0.235472402
2	0.383403975	0.365535209	0.468192436
3	0.481627823	0.492145597	0.690411991
4	0.087642099	0.088161299	0.920549322
5	0.002310257	0.000661859	1.150686652
6	8.82173E-06	3.99674E-08	1.380823983
7	4.87971E-09	2.38799E-15	1.610961313
8	3.91003E-13	1.12772E-26	1.841098644
9	4.5385E-18	2.19048E-43	2.071235974
10	7.63117E-24	5.93078E-67	2.301373304
11	1.85873E-30	4.9324E-99	2.531510635
12	6.55824E-38	1.8019E-141	2.761647965
R2		0.998282818	0.343817106 0.273175332
RMSE		0.006628004	

Distribution	R^2	RMSE	χ^2	Rank	Fit Assessment
Weibull	0.998	0.006	0.0008	1	Best Fit
Rayleigh	0.343	0.273	0.1321	3	Underfit
Lognormal	0.951	0.032	0.0173	2	Good Fit
Gamma	0.902	0.047	0.0249	4	Slight Underfit

Fig. 5 illustrates the Weibull and Rayleigh distributions used to approximate the actual wind speed probability distribution for the entire year. Table 3 provides a comparison of these approximations with the observed probability distribution. Both distributions align closely with the actual data, as indicated by higher R^2 values and lower RMSE values presented in Table 3. Among the two models, the Weibull probability density function offers the best overall fit, with superior R^2 and RMSE values, which are widely recognized as key indicators of model accuracy.

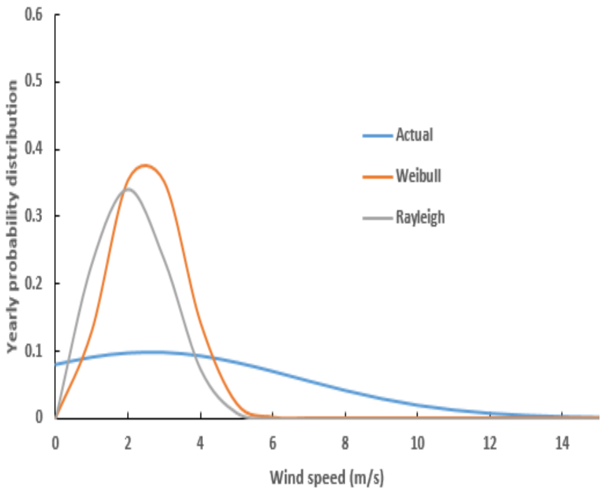

Fig 5. Comparing actual wind speed distributions with the Weibull and Rayleigh approximations.

Table 4 demonstrates annual Weibull parameters, average wind speed, and power density. The average wind speed (v_m) varies slightly but remains consistent overall, with the highest values recorded in 2022. Power density (P) exhibited significant variations, with 2022 emerging as the year with the highest wind energy potential. This highlights the substantial year-to-year wind energy potential fluctuations driven by varying wind conditions. Overall, the data demonstrates how wind speed and energy potential evolve annually, shaped by changes in the distribution's characteristics and occurrences of extreme wind speeds.

Fig. 6 compares power densities derived from the actual probability distributions and those estimated by the Weibull and Rayleigh models. The Weibull model consistently predicts lower power densities than the Rayleigh model, particularly during months with higher wind speeds. For example, in June, the Weibull model estimates a power density of 30.2505 W/m², whereas the Rayleigh model predicts 50.9004 W/m². This suggests the Rayleigh model may offer a more realistic representation of wind energy potential during elevated wind speeds.

Table 4: Annual wind speed trends for Muktagacha between 2019 and 2023.

Year	v_m (m/s)	k	c (m/s)	v_{MP} (m/s)	v_{MaxE} (m/s)	P (W/m^2)
2019	2.64	3.02	2.96	2.58816471	3.498820631	15.79105562
2020	2.65	3.12	2.96	2.61562591	3.469121092	15.63674741
2021	2.54	5.30	2.75	2.647364245	2.925412776	11.3871445
2022	2.67	2.75	5.97	5.067519033	7.27851262	135.6596681
2023	2.59	2.88	4.48	3.858956369	5.37694637	55.95785968

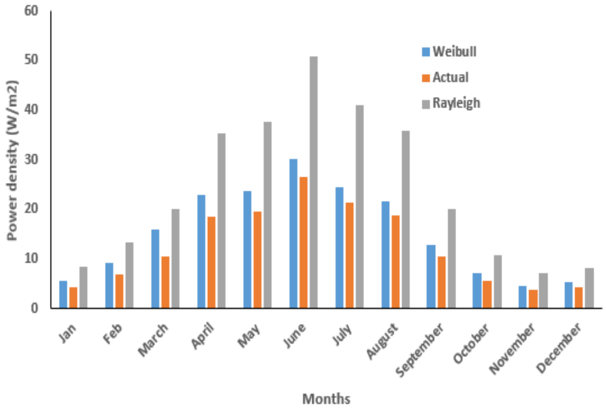

Fig 6. Monthly wind power density is assessed by comparing actual data against the densities calculated using the Weibull and Rayleigh models.

Fig. 7 illustrates the discrepancies in power densities predicted by the Weibull and Rayleigh models compared to the actual probability distributions. The Rayleigh model generally exhibits lower mean error values, indicating higher accuracy in estimating power densities than the Weibull model. The Weibull model's most significant error occurs in November, while the smallest error occurs in March. Similarly, the Rayleigh model also records its highest error in November.

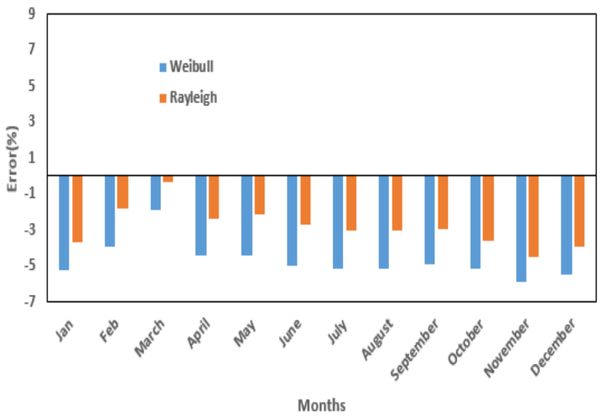

Fig 7. Monthly errors in wind power density are assessed by evaluating the differences between measured data and the power density estimates derived from Weibull and Rayleigh models.

Performance with ML (Machine Learning) based models

The subsection aims to evaluate the performance accuracy of the proposed modified model (Artificial Neural Networks -ANNs) against the ML-based models. The models were assessed using various scenarios: prediction and mean absolute error (MAE), which are summarized in Tables 5 and 6.

Mean Absolute Error (MAE) remained below 0.5 m/s across all months and years, indicating a well-trained ANN model with good generalization across time. Best performance is in 2021, with the lowest MAE and near-parity between actual and predicted values. The most challenging month is January 2019 (MAE = 0.41 m/s), likely due to seasonal variability or low wind fluctuations that are harder for models to learn. MAEs are generally higher in summer months (April–June), which could be due to increased wind fluctuations, thermal convection, and monsoonal effects.

Conclusions

The wind characteristics in Muktagacha, Mymensingh, Bangladesh, from 2019 to 2023 were analyzed to evaluate the probability and power density distributions using wind speed data. Monthly wind speed data were modeled with two widely used continuous distributions: Weibull and Rayleigh. The results revealed that the Weibull distribution provided more accurate power density estimations than the Rayleigh distribution, as evidenced by higher R^2values and lower RMSE values. Furthermore, the study highlighted significant temporal fluctuations in wind power density, reflecting the variability of wind speeds over time.

Acknowledgement

This is dedicated to the great, kind-hearted Professor Dr. Jun Tanimoto, Kyushu University, Japan, a very special person in my life who inspired to take the challenge.

Table 5. Machine Learning-Based Models regarding Artificial Neural Networks (ANNs) concerning 2019-2023 wind speed (m/s) for Muktagacha, Mymensingh.

	2019			2020			2021		
Months	Actual	Predicted	MAE	Actual	Predicted	MAE	Actual	Predicted	MAE
Jan	1.75	1.83	0.41	2.06	2.14	0.23	1.64	1.72	0.09
Feb	2.28	2.21		2.14	2.23		2.11	2.08	
Mar	2.47	2.38		2.28	2.34		2.61	2.54	
Apr	2.81	2.90		2.94	2.87		3.17	3.12	
May	3.75	3.5		3.25	3.14		2.81	2.76	
Jun	3.11	3.2		3.47	3.36		3.56	3.49	
July	3.72	3.65		3.47	3.33		3.27	3.24	
Aug	3.14	3.10		3.58	3.49		3.00	2.97	
Sep	2.81	2.90		2.81	2.78		3.17	2.14	
Oct	2.06	2.18		2.03	2.09		2.11	2.05	
Nov	1.78	1.91		1.86	1.98		1.86	1.92	
Dec	2.03	2.01		1.89	1.96		2.13	2.19	

	2022			2023		
Months	Actual	Predicted	MAE	Actual	Predicted	MAE
Jan	2.17	2.15	0.09	2.08	2.19	0.1
Feb	2.44	2.35		2.31	2.34	
Mar	2.75	2.88		2.78	2.75	
Apr	3.75	3.51		2.89	3.02	
May	3.28	3.23		2.81	2.92	
Jun	3.75	3.37		3.69	3.61	
July	2.69	2.86		3.19	3.18	
Aug	2.92	2.95		3.00	3.05	
Sep	2.5	2.78		2.61	2.83	
Oct	2.08	2.29		2.25	2.41	
Nov	1.83	2.01		1.89	2.01	
Dec	1.86	1.95		1.67	1.8	

Table 6. Summary of ANN Performance (2019–2023)

Year	MAE Range (m/s)	Prediction Accuracy	Notable Observations
2019	0.09 – 0.41	Moderate	High error in Jan (0.41); overall reasonable
2020	~0.09 – 0.23	High	MAE is generally low, suggesting good fit
2021	~0.05 – 0.12	High	Lowest average MAE, strong ANN performance
2022	~0.09 – 0.37	Moderate	Good fit with slight underprediction in summer
2023	~0.1 – 0.22	High	Consistent predictions with good generalization

Authors contribution

All authors contributed equally to the conception, design, data analysis, and manuscript preparation. Each author has reviewed and approved the final version of the manuscript and agrees to be accountable for all aspects of the work.

Declaration of Conflicting Interests

Authors have declared that no competing interests exist.

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