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Integrated Analysis of Wind Speed Dynamics and their Influence on Darjeeling, West Bengal, India

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Abstract: The city of Darjeeling possesses a distinct terrestrial location and diversified climatic conditions which enable an eternal source of wind power generation. The current study focuses on estimating the characteristics of wind speed and potential for wind power generation in Darjeeling, West Bengal, India in recent years between 2019 and 2023. Statistical methodology has been exploited to develop probability density functions by utilizing continuous probability distributions such as Weibull and Rayleigh distributions for monthly analyses of wind data. The Weibull distribution exhibits a relatively precise assessment of power density verified by higher square of the correlation coefficient (R^2), and lower root mean square error (RMSE)values. The outcome of this research provides a critical insight into wind energy potential that serves as a resource for decision-makers and emphasizes the importance of wind energy in Darjeeling district.

Keywords: Wind power; Wind speed; Shape factor; Weibull distribution; Rayleigh distribution

1. Introduction

The Quranic verse of Surah Al-Zumar (39:21): "Do you not see that Allah sends down rain from the sky and gives life thereby to the earth after its lifelessness? Indeed, that is a sign for people who listen." This verse emphasizes the rejuvenating power of rain and its role in sustaining life, underscoring the importance of maintaining natural resources [1].The principle outlined in this verse advocates for the mindful exploitation of resources available in our mother nature and an alignment of advancing the renewable energy initiatives [2].The swift progress in renewable energy technologies is reshaping the global energy landscape and offering important insights into technological developments and trends [3].

Renewable energy resources such as solar, hydroelectric, geothermal energy, and wind continue to evolve as they provide suitable solutions to challenges associated with climate change due to fossil fuel-based energy sources and sustainable developments. Thus, a significant development in power generation from renewable energy sources have been reported. These innovations indicate a brilliant future for renewable energy as it establishes itself as a fundamental element of global sustainability efforts [4].Renewable technologies play a crucial role in lowering greenhouse gas emissions and offer a holistic perspective on the advancing clean energy sector. Key advancements include innovations in storage solutions, smart grids, and the incorporation of renewable energy into existing infrastructure. Moreover, the transition to renewable energy has far-reaching effects on both environmental and public health [5]. By reducing air [6] and water pollution associated with traditional fossil fuels, renewable energy technologies can improve air quality and public health outcomes. This shift aligns with the principles of responsible stewardship of natural resources found in many cultural texts. Continuous advancements in renewable energy underscore the potential for a more sustainable future, where clean energy solutions tackle global environmental challenges while promoting social well-being. Among renewable sources, wind energy has become increasingly popular owing to its abundance, negligible environmental effect, relatively higher efficiency, and ability to generate power even during nighttime hours [7].The wind energy sector is advancing quickly, featuring innovations like larger and more efficient wind turbines, progress in offshore wind farms, and enhancements in digital technology [8]. Wind patterns at typical location are frequently modeled utilizing the Weibull probability distribution[9-11]. In different locations ofWest Bengal, India, numerous studies have been conducted for optimizing the wind power [12-18], by employing the shape parameter (k) as well as scale parameter (c) of the Weibull distribution in their analyses.

A wide range of research’s have delved deeply into optimization techniques using deep learning [19-21], data processing strategies [22], and particularly focused on decision-making processes [23-25]. Furthermore, extensive studies have been conducted on survey-based approaches [26], simulation techniques [27-32], game theory applications [33-35], and various other relevant methods [36-40] across the world.Physical models, like numerical weather prediction (NWP), and the weather researcher forecasting (WRF), normally take environmental conditions into consideration [41]. These factors consist of surface roughness, terrain, wake effect, humidity, pressure and temperature [42-43]. Subsequently, complex mathematical models are exploited to forecastthe characteristics of wind speed using all variables for that specific area followed by the wind speed data are used to predict the wind power with the turbine wind power curve. Thus, this forecasting method does not need to be trained with historical data but requires physical data. Studies have shown physical prediction models to have better performance compared with traditional statistical models in medium-term and long-term wind speed prediction, however, this comes at the cost of being computationally complex, needing more computational resources [44].Unlike physical models, historical data is used with statistical methods to find linear and non-linear relationships between weather and power output [45]. These relationships are used to make predictions for future power outputs. Generally, this method is easy to modelling and requires less computational resources than that of physical models. However, the model produces erroneous results in forecasting with the lager time horizon.

In this paper, an in-depth analysis of wind speed data in Darjeeling district (27.0416° N, 88.2664° E), located in West Bengal, India, between 2019 and 2023 [46-47] have been analyzed using continuous probability distributions such as Weibull and Rayleigh distributions. This paper also found a critical gap exists in previous research, as they did not specifically focus on analyzing wind energy systems using localized data. Thus, the primary goal is to statistically evaluate the wind speed data to estimate the potential for wind energy production in Darjeeling district.

This paper is organized into different subsections such as Section 2, Section 3, and Section 4 whichdescribes theoretical analysis, results and discussion, and conclusion, respectively.

2Theoretical analysis

2.1 Analysis of wind speed using frequency distribution

Both the wind speed distribution and its functional form are essential in wind literature. Typically, Weibull and Rayleigh distributions are used to fit wind speed data for a particular location and for a period. The Weibull probability density function can be represented as [48],

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

Where, *f(v)* is wind speed probability of*v*, c and k are scaling parametershape factor of Weibull distribution, respectively.

Cumulative probability function that relied on Weibull distribution [49-51] can be expressed as follow,

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

Weibull distribution becomes identical to Rayleigh distribution when the shape parameter (k) is equal to 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 (v_m) as well as standard deviation (σ) of Weibull distribution are evaluated utilizing following expression

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

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 $\Gamma()$is the gamma function.

Two key factors such as wind speed and wind speed 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 probabilitywhich is expressedas follows,

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

The wind speed carrying the maximum energy can berepresented as follows,

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

To evaluate the Weibull parameters several methods such as standard deviation method, graphical method, maximum likelihood method, moment method, energy pattern factor method, and power density method are available in literature.Among them the standard deviation method is considered appropriateto determine the values of shape parameter (k), and scale parameter (c).

2.1.1 Standard deviation method

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

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

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

2.2 Variation of wind speed withheight

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,

$$\frac{v_1}{v_2} = (\frac{h_1}{h_2})^p \qquad (10)$$

Where, v_1, and $v_2$are averagewind speeds for a height of h_1, and h_2. The value of exponent 'p' depends on various factors such as atmospheric stability and surface roughness.

2.3 Wind power density

Wind power speed through the blade sweep area (A) is expressed in the following equation and found that itrises as the cube of its velocity,

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

where ρ is average air density (1.225 kg/m^3, based on standard atmospheric conditions at sea level and at temperature of 15°C). Several constraints such as altitude, air pressure, and temperature are constituent 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,

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

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

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

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

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

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

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

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

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

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

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

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

2.4The statistical analysis of the distributions

To obtain the performance of Weibull as well as Rayleigh distributions, 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,

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

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

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

Wherey_i, z_i, x_i, N, and n are ith measured data point, mean value, predicted data utilizingeither Weibull or Rayleigh distributions, total number of observations, and number of constraints, respectively. Thus, as the value of the$R^2$is maximized and the values of RMSE and $\chi^2$are minimized. The probability distribution that best fits the data is selected using these parameters.

3. Results and discussion

The wind speed data from Darjeeling, West Bengal, India, was collected between 2019 and 2023 at a height of 10 meters, were analyzed using various statistical methods. The summary of key findingsis represented in Table 1 as follows:

Table 1: The monthly mean wind speeds and standard deviations in Darjeeling, between 2019and 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	$\boldsymbol{v_m}$	**σ**
January	2.167	0.306	1.528	0.361	1.639	0.45	1.972	0.433	2.278	0.439	1.917	0.398
February	2.083	0.369	1.694	0.375	1.972	0.386	1.861	0.481	2.083	0.458	1.939	0.414
March	2.361	0.353	1.944	0.361	2.139	0.544	2.222	0.528	2.333	0.539	2.2	0.465
April	2	0.333	2.028	0.403	2.361	0.608	1.889	0.625	2.111	0.472	2.078	0.488
May	2.139	0.347	1.694	0.531	1.806	0.386	1.667	0.531	1.944	0.353	1.85	0.429
June	1.667	0.372	1.306	0.319	1.5	0.283	1.306	0.45	1.5	0.297	1.456	0.344
July	1.278	0.361	1.028	0.369	1.167	0.336	1.194	0.531	1.111	0.358	1.156	0.391
August	1.333	0.389	1.222	0.45	1.056	0.369	1.222	0.544	1.056	0.392	1.178	0.429
September	1.222	0.319	1.25	0.369	1.444	0.464	1.389	0.3	1.583	0.439	1.378	0.378
October	1.556	0.347	1.639	0.417	1.778	0.378	1.861	0.414	1.944	0.481	1.756	0.407
November	1.611	0.389	1.917	0.369	1.972	0.383	2.111	0.417	2.111	0.45	1.944	0.402
December	1.694	0.347	1.611	0.417	2.056	0.417	1.944	0.464	2.028	0.464	1.867	0.422
Yearly	1.759	0.353	1.572	0.395	1.741	0.417	1.72	0.476	1.84	0.428	1.726	0.414

The time series data in Table 1 [46-47] presents the calculated monthly mean wind speeds and their standard deviations. The analysis reveals that the highest wind speed was obtained in April, whereas the lowest wind speed was found in Julythroughout the year. Fig. 1 illustrates the monthly mean wind speeds for Darjeeling from 2019 to 2023. Fig. 1 reveals a consistent wind speed pattern over the years.

Fig. 2 and Fig. 3demonstrate monthly probability density and cumulative distributions, respectively based on Darjeeling's time-series data over the whole year. Theprobability density and cumulative distributions illustrate both curves follow a comparable trend in wind speed. Additionally, Fig. 4 illustrates the probability density and cumulative distribution over a yearly data.

The monthly values of the parameters *k* and *c* from 2019 to 2023, along with their yearly averages, are shown in Table 2. Both parameters exhibit significant fluctuations across the months. For example, the highest values for *k* are typically observed in November, and the highest values for *c* occur in March, indicating increased intensity or variability during these months. The yearly averages of the parameters show a general upward trend over the years, with some variation. Specifically, the average values of *k*shift from 4.032 to 5.726, while the average values of *c*change from 1.726 to 2.007.

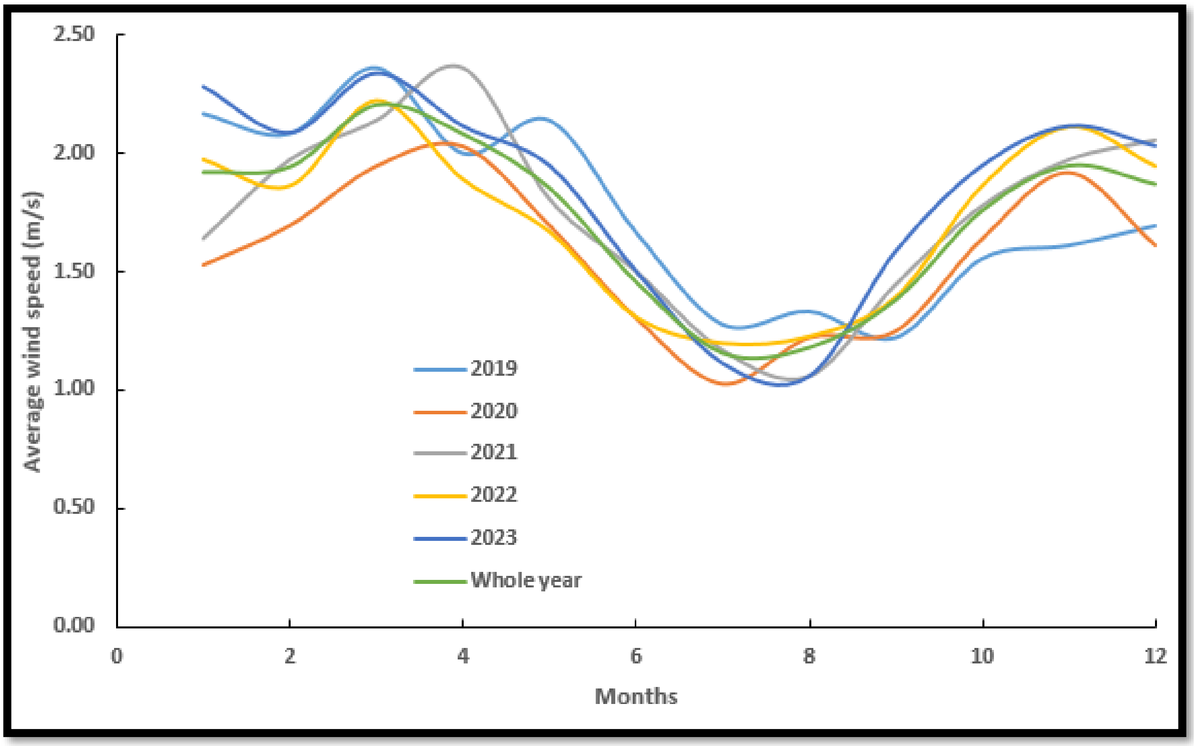

Fig1.Illustrating the Monthly wind speed data in Darjeeling during 2019-2023.

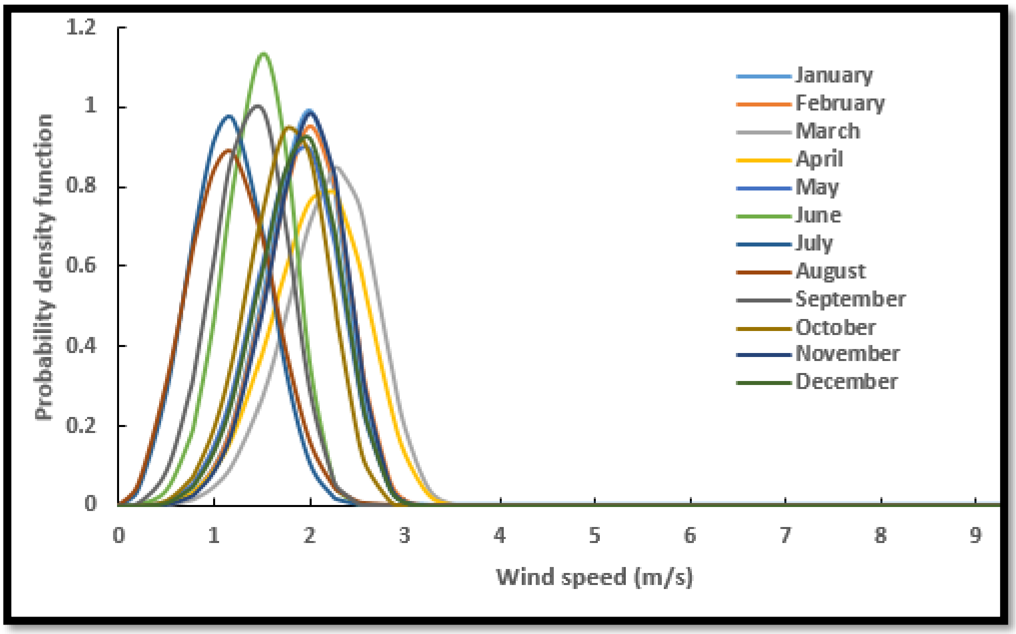

Fig2.Demonstrating the probability distributions of monthly wind speeds based on the time series data.

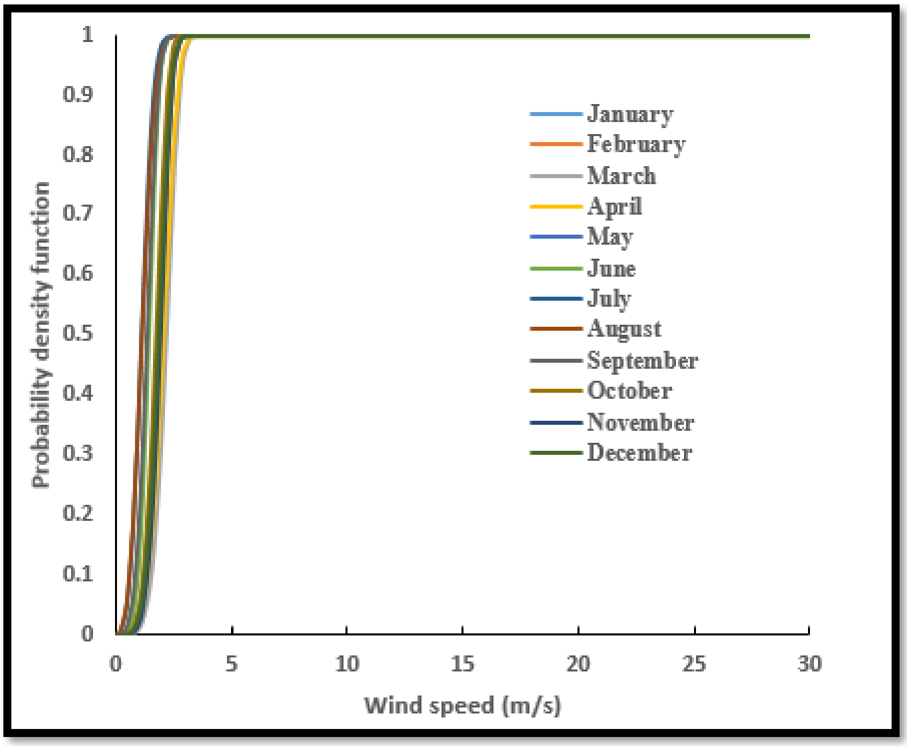

Fig3.Illustrating the cumulative probability distributions for monthly wind speeds over the whole year.

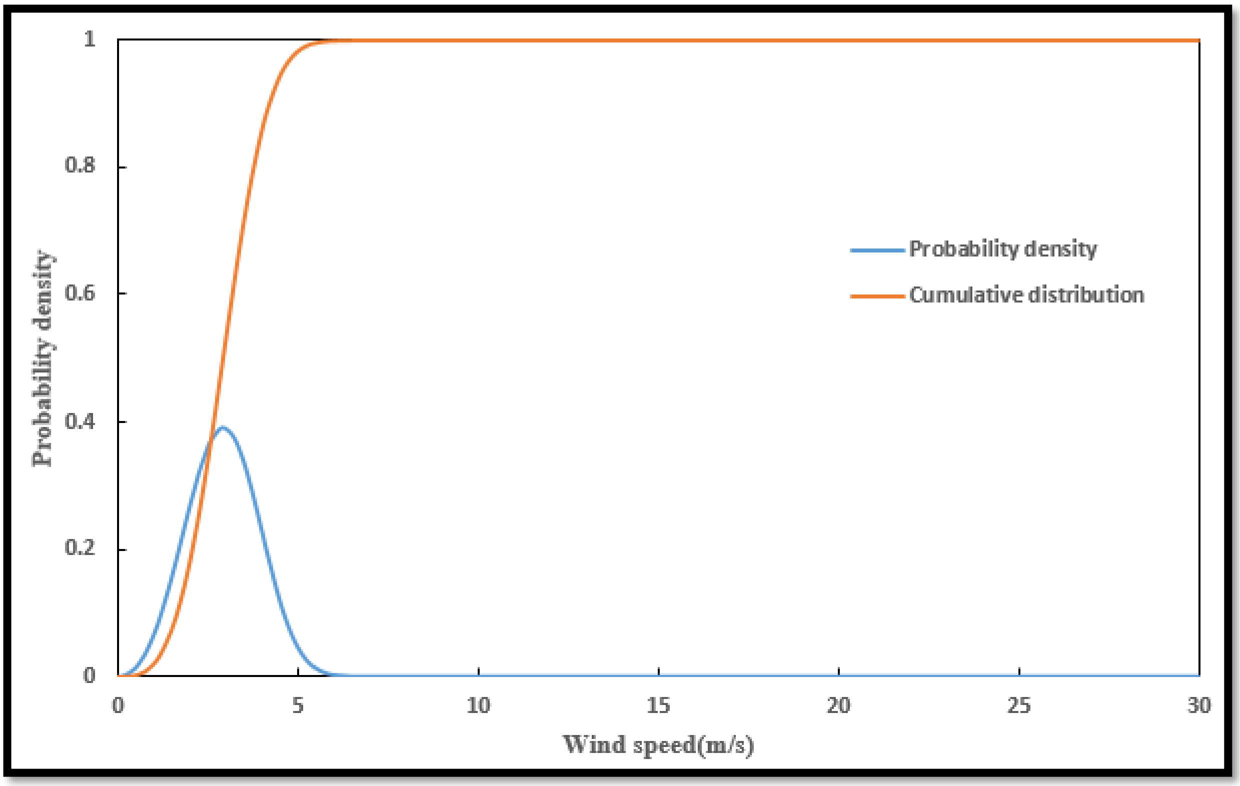

Fig4.Illustrating the wind speed probability density and cumulative distributions for whole year.

Table 2. The monthly Weibull *k* and *c*in Darjeeling 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	8.392	2.295	4.79	1.668	4.07	1.806	5.185	2.144	5.979	2.456	5.516	2.076
February	6.544	2.235	5.144	1.842	5.877	2.128	4.351	2.043	5.178	2.264	5.35	2.103
March	7.882	2.509	6.223	2.092	4.419	2.346	4.765	2.427	4.912	2.544	5.408	2.385
April	7	2.138	5.785	2.19	4.361	2.592	3.324	2.105	5.085	2.297	4.819	2.268
May	7.203	2.283	3.529	1.882	5.34	1.959	3.466	1.853	6.383	2.089	4.884	2.018
June	5.094	1.813	4.613	1.429	6.11	1.615	3.18	1.458	5.801	1.62	4.783	1.589
July	3.945	1.411	3.038	1.15	3.863	1.29	2.414	1.347	3.418	1.236	3.243	1.289
Augus	3.81	1.475	2.9	1.37	3.12	1.18	2.4	1.379	2.93	1.183	2.99	1.319

t	2		6		7		07		5		5	
September	4.294	1.343	3.757	1.384	3.433	1.607	5.282	1.508	4.028	1.746	4.07	1.519
October	5.097	1.692	4.425	1.798	5.376	1.928	5.117	2.024	4.563	2.129	4.888	1.915
November	4.682	1.761	5.977	2.066	5.923	2.127	5.825	2.279	5.358	2.29	5.544	2.105
December	5.593	1.834	4.344	1.769	5.659	2.223	4.741	2.124	4.962	2.209	5.031	2.032
Yearly	5.726	1.901	4.479	1.723	4.719	1.902	4.032	1.897	4.869	2.007	4.715	1.887

Fig. 5 demonstratesWeibull and Rayleigh distributionsfor approximating the actual wind speed probability distribution for the entire year. Table 3 represents a comparison of these approximations with the actual probability distribution. The distribution fits the actual data wellas evidence by the higher R^2 and lower RMSE values as shown in Table 3. The Weibull probability density function model provides the best fit overall, with higher R^2 and lower RMSE, which are generally accepted as the primary indicators of model accuracy.

Table 4 demonstrates annual Weibull parameters, average wind speed, and wind power density. The average wind speed (v_m) varies slightly but remained consistent overall, with the highest values recorded in 2019 and 2023. Power density (P) demonstrated notable fluctuations, with 2023 marking the peak of wind energy potential. This suggests that wind energy potential can fluctuate significantly from one year to another, depending on wind conditions. In general, the data reflects how wind speed and energy potential evolve annually, influenced by changes in distribution shape and extreme wind speeds.

A comparison of power densities obtained from the probability distributions with those from Weibull and Rayleigh models is expressed in Fig. 6. The Weibull model consistently estimates lower power densities than the Rayleigh model, especially during months with higher wind speeds. For instance, in March, the Weibull model estimates a power density of 7.39 W/m^2, while the Rayleigh model predicts 12.46 W/m^2. Thus, the Rayleigh model could provide a more realistic representation of wind energy potential during these times.

Subsequently, Fig. 7 depicts the discrepancy in power densities using the Weibull and Rayleigh distributions against the actual probability distributions. The Rayleigh model tends to have lower mean error values in predicting power densities, indicating its higher accuracy compared to the Weibull model. The largest error for the Weibull model is observed in April, while the smallest occurs in September. On the other hand, the Rayleigh model shows its largest error in April.

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

f(v)			
Wind speed	Actual data	Probability density function	Rayleigh
1	0.206720622	0.224801697	0.55087421
2	0.774594151	0.831991879	1.095309412
3	0.008485394	0.001895201	1.615179344
4	2.71755E-07	3.90281E-14	2.153572458
5	2.54443E-14	9.10659E-42	2.691965573
6	6.96482E-24	4.5363E-100	3.230358688
7	5.57362E-36	2.1618E-208	3.768751802
R2		0.999906758	0.33297409
RMSE		0.022881231	0.293810031

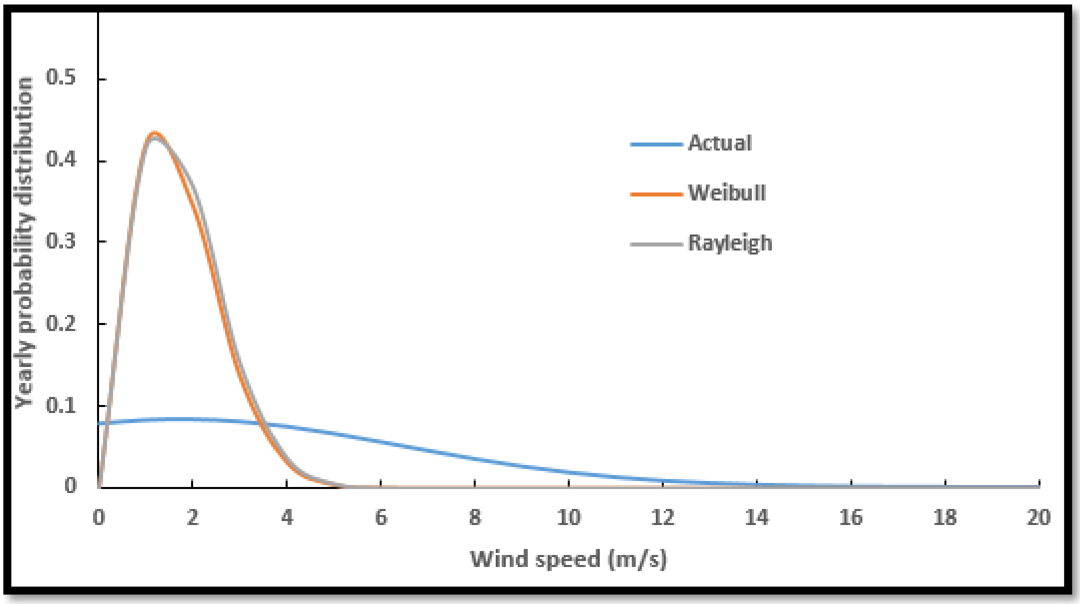

Fig5. Illustrating a comparison between actual wind speed distributions with the Weibull and Rayleigh approximations

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

Year	v_m(m/s)	k	c (m/s)	v_{MP} (m/s)	v_{MaxE} (m/s)	P (W/m²)
2019	1.76	5.73	1.90	1.838601363	2.003403447	3.734941747
2020	1.57	4.48	1.72	1.628319746	1.870796107	2.828924282
2021	1.74	4.72	1.90	1.808630662	2.050177562	3.786256774
2022	1.72	1.90	4.03	2.723957754	5.88209943	56.41313165
2023	1.84	1.90	4.87	3.279819085	7.116497255	99.67568718

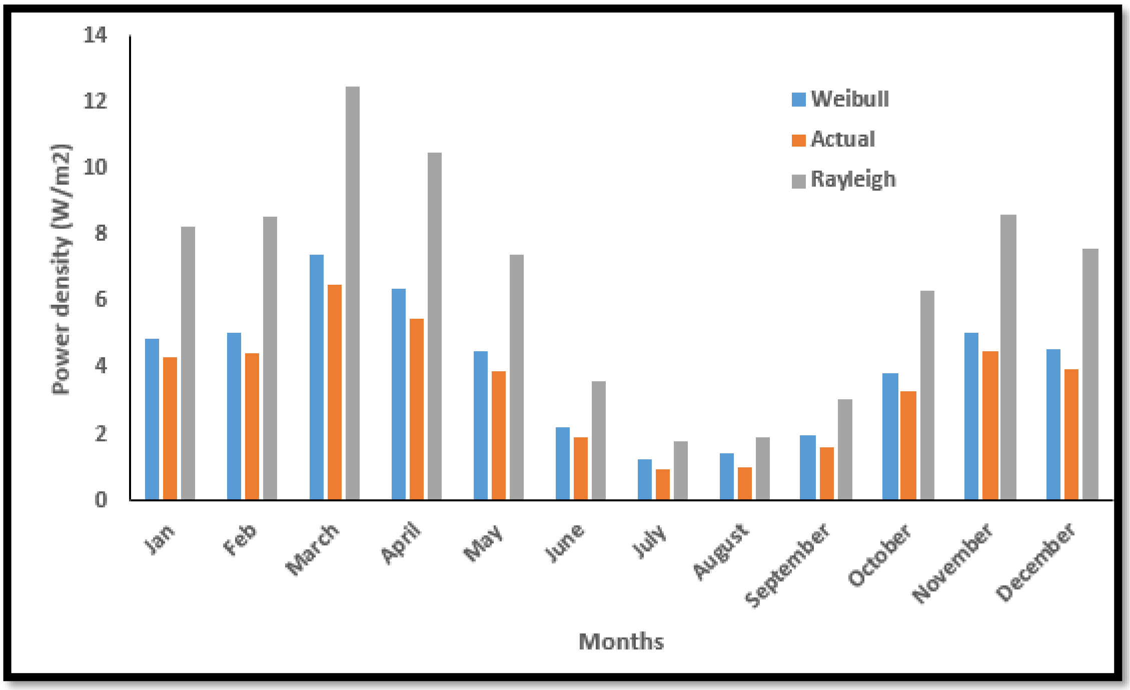

Fig6.Demonstrating monthly wind power density assessed by comparing actual data against the densities calculated using the Weibull and Rayleigh models.

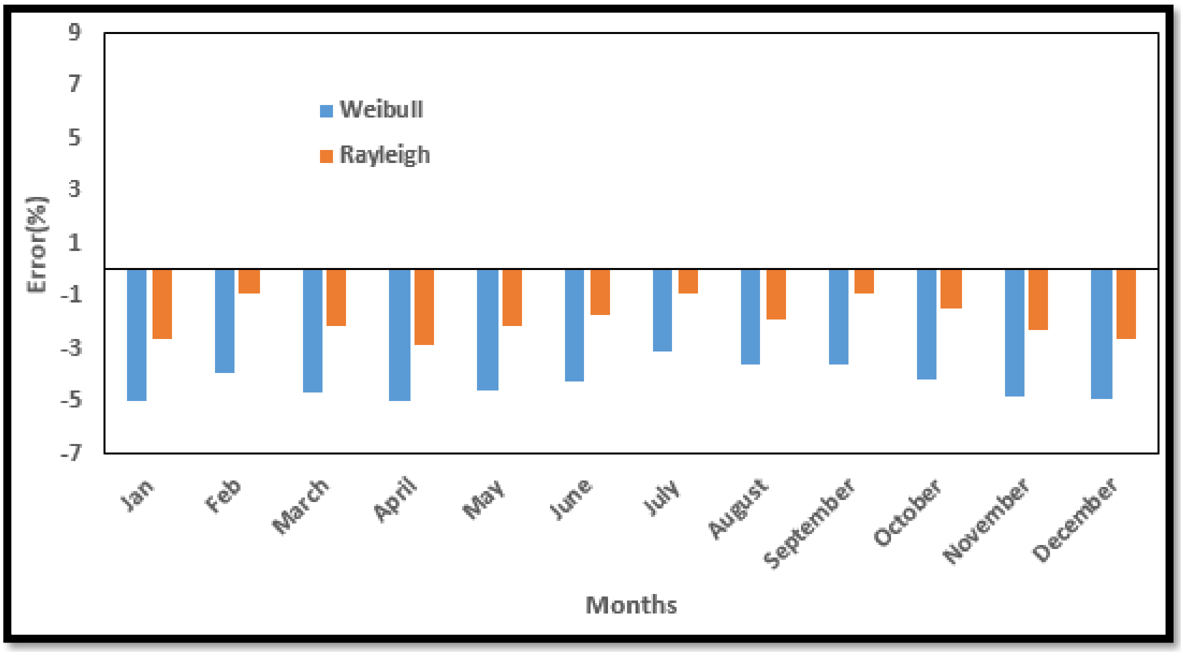

Fig7.Depiction of error values in monthly wind power density are assessed by evaluating the differences between measured data and the power density estimates derived from Weibull and Rayleigh models.

4. Conclusions

The wind characteristics in Darjeeling, West Bengal, India, from 2019 to 2023 were studied for assessment of the probability and power density distributions based on wind speed data. Monthly data were modeled using two prominent Weibull and Rayleigh continuous distributions. The findings exhibitsthe Weibull distribution yielded a relatively accurate determination of power density compared to Rayleigh distribution, supported by higher R^2 values and lower RMSE values. Additionally, the study discloses a considerable temporal fluctuation in wind power density, reflecting the variability in wind speed over time.

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Conflicts of Interest

The authors declare that there is no conflict of interestregarding the publication of this paper.

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