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Holistic Assessment of Wind Speed Behavior and its Effects on Thimphu, Bhutan

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Abstract: This study presents an evaluation of wind speed characteristics and the potential for wind power at Thimphu in Bhutan, over the period from 2019 to 2023. Employing statistical methodologies to develop probability density functions, the study applies Weibull and Rayleigh distributions for monthly analysis. The results provide critical information regarding the region's wind energy capabilities, serving as a resource for decision-makers and highlighting the importance of wind energy in the region.

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

1. Introduction

One important verse from Surah Al-Hadid (57:17): "Know that Allah gives life to the earth after its lifelessness. We have certainly made clear the signs to you that you might give thought". So, this verse emphasizes the significance of natural cycles and phenomena, inviting contemplation of the natural world as a manifestation of divine wisdom and a foundation for sustainable practices [1]. The principles outlined in this verse advocate for the mindful utilization of natural resources, aligning with the objectives of advancing renewable energy initiatives [2].The swift progress in renewable energy technologies is reshaping the global energy landscape and is offering important insights into technological developments and trends [3]. As resources like solar, hydroelectric, wind, and geothermal energy continue to evolve, they present viable solutions to the challenges of climate change and sustainable development. These innovations indicate a bright 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 due to its efficiency, abundance, minimal environmental impact, 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 sites are frequently modeled using the Weibull probability distribution [9-11], which has been widely researched around the world. In Bhutan, numerous studies have concentrated on optimizing wind power in different locations [12-18], employing the shape parameter (k) and scale parameter (c) of the Weibull distribution in their analyses.

A wide range of researchers have delved deeply into optimization techniques in 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]. All of these variables are then used in a complex mathematical model to predict the wind speed for that specific area. This wind speed will then be used to predict the wind power with the turbine wind power curve. Therefore, it can be said 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 model and requires less computational resources than physical models, but the forecasting error increases with a larger time horizon.

This document presents a thorough review of wind speed data from Thimphu (27.4716° N, 89.6386° E), Bhutan, encompassing the years 2019 to 2023 [46-47]. It fills an essential research void, as earlier studies have not specifically analyzed wind energy systems using localized data. The central focus is to statistically assess this data to predict the area's capacity for wind energy generation.

The subsequent sections of the paper are organized as follows: Section 2 addresses the theoretical analysis, Section 3 covers the results and discussion, and Section 4 presents the conclusion.

2. Theoretical analysis

2.1 Frequency distribution of wind speed

The wind speed distributions and their functional forms is essential in wind literature. To fit wind speed data for a specific location and period, the Weibull and Rayleigh distributions are typically used. The Weibull probability density function is represented by [48],

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

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

The cumulative probability function relied on Weibull distribution [49-51] is expressed as follows,

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

With a shape parameter k equal to 2, the Weibull distribution becomes the Rayleigh distribution. The Rayleigh distribution is expressed in Equation 1 as,

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

In Weibull distribution, mean valuev_m and the standard deviation σ is calculatedas,

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

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.

Two key factors in estimating wind energy are most probable wind speed and wind speed that carries the maximum energy. The most probable wind speed represents the wind speed that occurs most frequently in the distribution of wind probability and can be displayed 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,

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

Several methods are used in the literature to evaluate the Weibull parameters. These methods include:1. Standard deviation method, 2. Graphical method, 3. Maximum likelihood method, 4. Moment method, 5. Energy pattern factor method and 6. Power density method. Among these methods, the standard deviation method is considered to determine the values of the shape parameter k and scale parameter c.

2.1.1. Standard deviation method

The following equations can be used to calculate the Weibull parameters,

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

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

2.2. The wind speed variation with the height

The wind speed varies with the height above the ground. The most commonly used equation to express this variation is,

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

Wherev_1 andv_2 are the average of wind speeds at the height of h_1 and h_2. The exponent ρ depends on various factors, including atmospheric stability and surface roughness.

2.3. Wind Power density

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

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

where ρ is average air density (1.225 kg/m³, based on standard atmospheric conditions at sea level and 15°C). This density depends on factors such as altitude, air pressure, and temperature.

Using the Weibull probability density function, the expected wind power density per unit area for monthly or annual wind data can be formulated 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 regarding the probability density distribution that can be shownas,

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

The error in the power densities calculated using the probability distributions can be determined using the following equation,

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

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

The yearly average error in the power density, calculated using the Weibull function, can be obtained from the following equation,

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

2.4. The statistical analysis of the distributions

The performance of the Weibull and Rayleigh distributions is evaluated using the square of the correlation coefficient (R^2), chi-square (χ^2), and root mean square error (RMSE). These parameters can be calculated as follows,

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

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

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

where y_i denotes the ith measured data point, z_i is the mean value, x_i represents the predicted data using Weibull or Rayleigh distributions, N is the total number of observations, and n denotes the number of constants. So, when the values 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.

3. Results and discussion

The wind speed data from Thimphu in Bhutan, collected between 2019 and 2023 at a height of 10 meters, were analyzed using various statistical methods. The key findings from this analysis are summarized as follows:

Table 1: The monthly mean wind speeds and standard deviations in Thimphu, covering the years 2019 to 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	1.639	0.592	1.306	0.458	1.306	1.044	1.5	0.839	1.694	0.744	1.489	0.736
February	1.722	0.769	1.361	1.019	1.361	1.089	1.5	0.617	1.472	0.611	1.483	0.821
March	1.917	1.156	1.389	0.542	1.583	0.883	1.639	0.903	1.5	0.567	1.606	0.81
April	1.556	0.567	1.389	0.681	1.806	0.772	1.583	0.769	1.694	0.692	1.606	0.696
May	1.639	0.864	1.306	0.425	1.25	0.864	1.361	0.997	1.5	0.908	1.411	0.812
June	1.472	0.531	1.056	0.778	1.222	0.956	1.028	0.856	1.444	1.019	1.244	0.828
July	1	0.817	0.861	0.839	0.972	0.819	1.139	0.908	0.944	0.953	0.983	0.867
August	1.167	0.45	1.083	0.928	0.917	0.831	1.194	1.044	0.889	0.864	1.05	0.823
September	0.944	0.778	1.028	0.836	1.194	0.839	1.111	0.817	1.306	1.156	1.117	0.885
October	1.361	0.925	1.361	0.817	1.361	0.817	1.472	0.658	1.361	0.931	1.383	0.829
November	1.278	0.483	1.583	0.758	1.5	0.864	1.778	0.725	1.694	0.975	1.567	0.761
December	1.333	0.908	1.278	0.361	1.583	0.794	1.472	0.944	1.528	0.908	1.439	0.783
Yearly	1.419	0.737	1.25	0.703	1.338	0.881	1.398	0.84	1.419	0.861	1.365	0.804

The calculated monthly mean wind speeds and standard deviations from the time series data are presented in Table 1 [46-47]. The analysis reveals that the highest wind speeds occur in March and April regarding whole year and the minimum wind speeds occur in July. Fig. 1 displays the monthly mean wind speeds for Thimphu from 2019 to 2023, illustrating a consistent trend in wind speeds across different years.

The monthly probability density and cumulative distributions derived from Thimphu, time-series data for the whole year are illustrated in Fig. 2 and 3. These figures show that both the cumulative density and probability density curves follow similar trends in wind speed. Additionally, Fig. 4 displays the yearly probability density distribution and cumulative distribution.

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 April (k)&March (c), indicating increased variability or intensity during this period. 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 1.574to 2.038, while the average c values span from 1.408to 1.602for yearly.

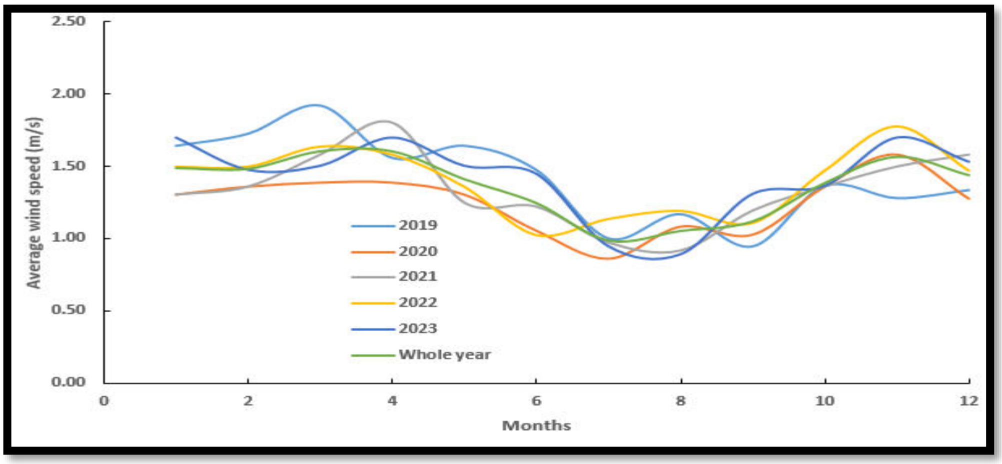

Fig.1: The Monthly wind speed of Thimphu, 2019-2023.

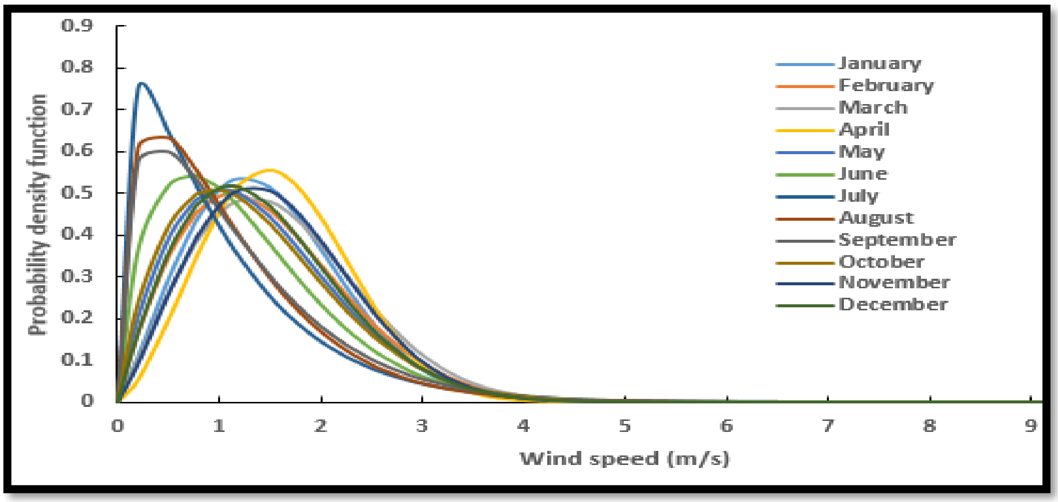

Fig.2: The probability distributions of monthly wind speeds based on the time series data from Thimphu.

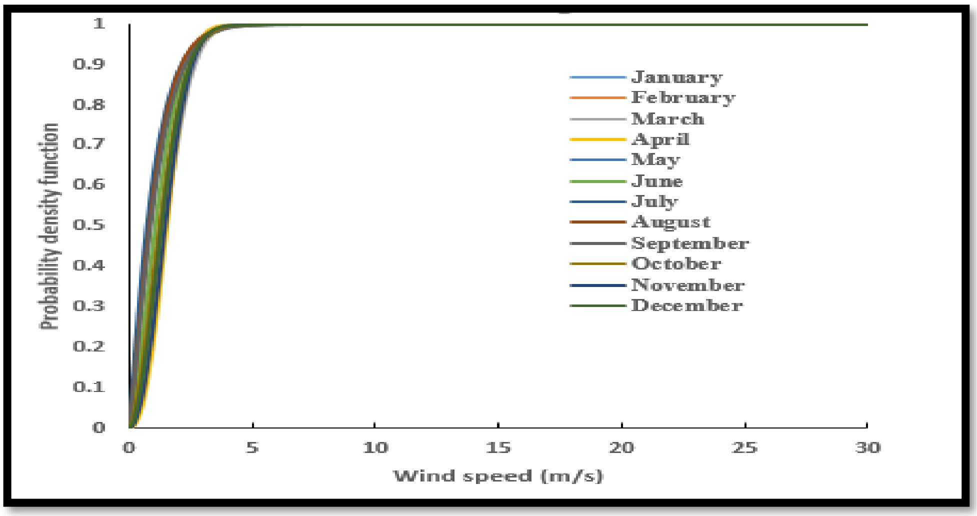

Fig.3: The cumulative probability distributions for monthly wind speeds over the whole year, based on data from Thimphu.

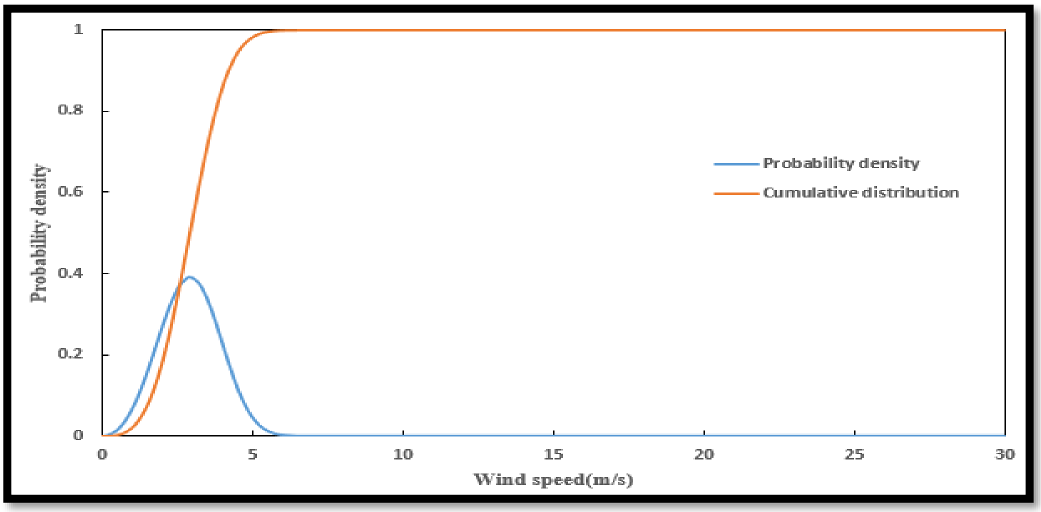

Fig.4: The wind speed probability density and cumulative distributions for whole year, derived from Thimphu measured data.

Table 2. The monthly Weibull shape parameter (k) and scale parameter (c) for Thimphu 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	3.024	1.835	3.117	1.459	1.274	1.408	1.88	1.69	2.443	1.911	2.151	1.681
February	2.399	1.943	1.369	1.488	1.274	1.468	2.626	1.688	2.598	1.658	1.901	1.672
March	1.732	2.151	2.78	1.56	1.885	1.784	1.911	1.847	2.878	1.683	2.102	1.813
April	2.994	1.742	2.17	1.568	2.515	2.035	2.19	1.788	2.646	1.907	2.478	1.81
May	2.005	1.849	3.383	1.454	1.494	1.384	1.402	1.494	1.724	1.683	1.823	1.588
June	3.029	1.648	1.393	1.157	1.306	1.325	1.22	1.097	1.46	1.595	1.557	1.384
July	1.246	1.073	1.029	0.871	1.204	1.034	1.278	1.229	0.991	0.941	1.146	1.032
August	2.814	1.31	1.183	1.147	1.113	0.954	1.157	1.257	1.031	0.9	1.302	1.137
September	1.235	1.011	1.251	1.104	1.468	1.319	1.397	1.219	1.142	1.369	1.287	1.207
October	1.521	1.51	1.742	1.528	1.742	1.528	2.397	1.661	1.511	1.509	1.743	1.553

November	2.874	1.434	2.224	1.788	1.821	1.688	2.649	2	1.822	1.906	2.19	1.769
December	1.517	1.479	3.945	1.411	2.115	1.788	1.619	1.644	1.759	1.716	1.935	1.622
Yearly	2.038	1.602	1.867	1.408	1.574	1.49	1.739	1.569	1.721	1.592	1.776	1.534

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. The distribution provides a good fit to the actual wind speed data, as indicated by a higher R^2 value, and a lower RMSE in the Table 3. The Weibull pdf model is better overall in terms of R^2 and RMSE, which are generally considered more direct indicators of fit quality.

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 2019 and 2023 showing the highest mean wind speed. 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 yearly, 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. For example, the Weibull model estimates the power density in March to be4.61382927 W/m², while the Rayleigh model predicts it to be4.843995247 W/m². 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 Rayleigh model generally shows lower mean error values in predicting power densities compared to Weibull model. This indicates that the Rayleigh distribution is more accurate in modeling the data for the given context. Specifically, the highest error for the Weibull model is noted in July while the lowest error is observed in January. Conversely, the Rayleigh model shows its greatest 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	0.447522385	0.52042268	0.833622176
2	0.363127897	0.286579763	1.657500384
3	0.062800775	0.07245287	2.444204673
4	0.002314893	0.010086646	3.258939563
5	1.81868E-05	0.00083215	4.073674454
6	3.0454E-08	4.2417E-05	4.888409345
7	1.08691E-11	1.37373E-06	5.703144236
8	8.26799E-16	2.88556E-08	6.517879127
9	1.34051E-20	3.99507E-10	7.332614018
10	4.63231E-26	3.69402E-12	8.147348909
11	3.41183E-32	2.30651E-14	8.9620838
12	5.35597E-39	9.81802E-17	9.77681869
R2		0.961540228	0.477482833
RMSE		0.030724986	0.140240344

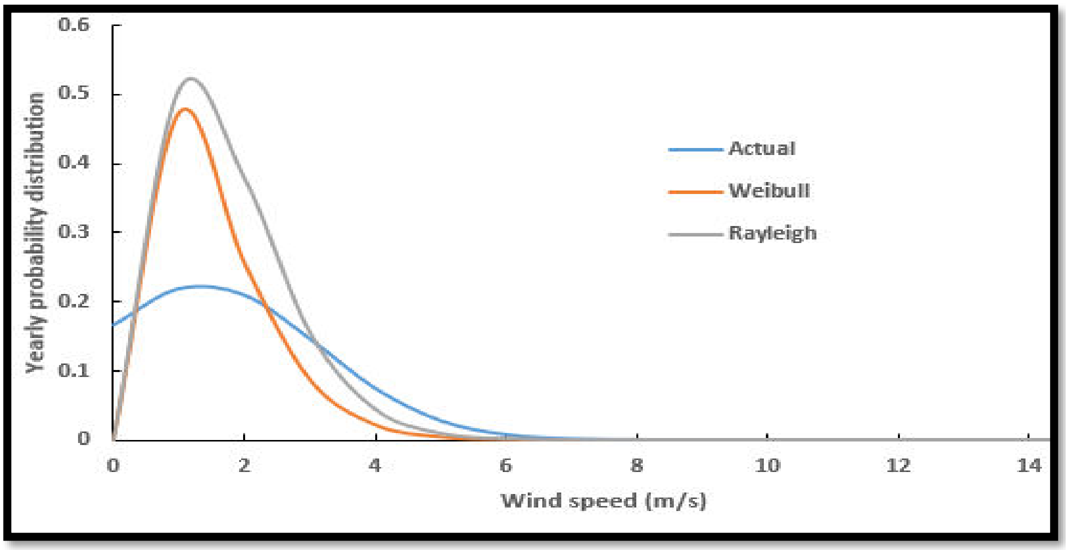

Fig.5: Comparing the actual wind speed distributions with the Weibull and Rayleigh approximations.

Table.4: Annual wind speed trends for Thimphu from 2019 to 2023.

Year	v_m(m/s)	K	c (m/s)	v_{MP} (m/s)	v_{MaxE} (m/s)	P (W/m²)
2019	1.42	2.04	1.60	1.150342797	2.240003319	3.280395406
2020	1.25	1.87	1.41	0.933483754	2.079365344	2.455939206
2021	1.34	1.57	1.49	0.785158828	2.508430297	3.72110557
2022	1.40	1.49	1.74	0.824608849	3.079567081	6.527660918
2023	1.42	1.57	1.72	0.902018656	2.90560704	5.766263749

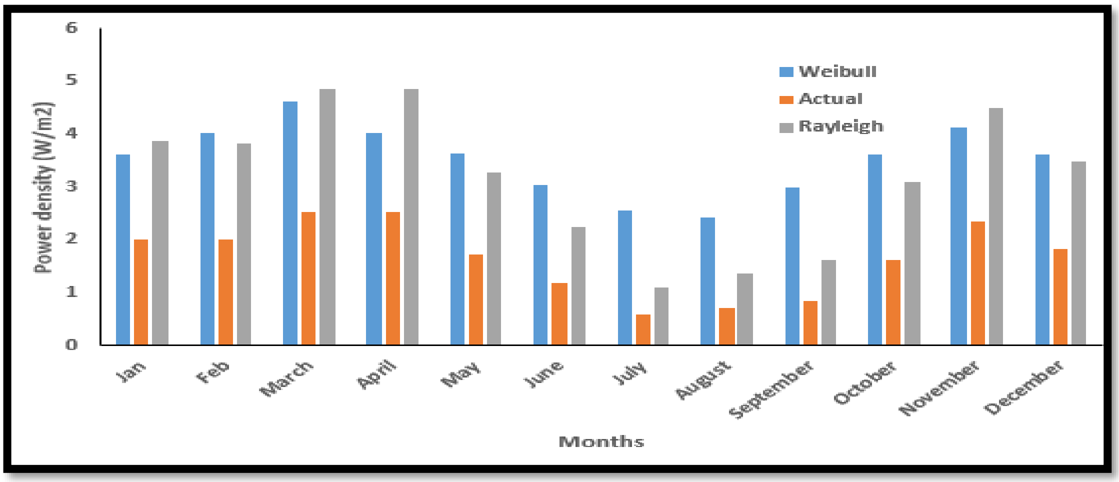

Fig.6: Monthly wind power density is assessed by comparing actual data against the densities calculated using the Weibull and Rayleigh models.

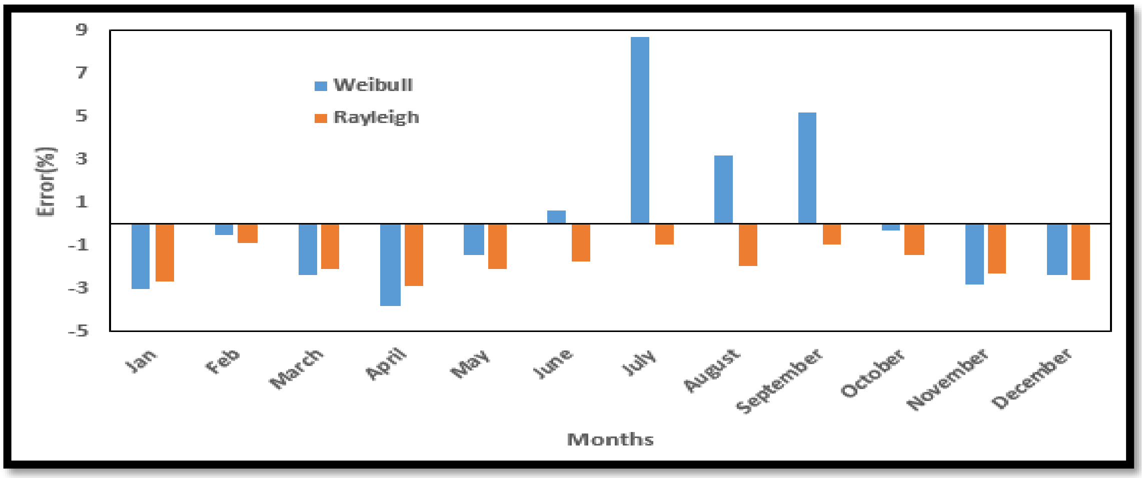

Fig.7: Monthly errors in wind power density are assessed by evaluating the differences between measured data and the power density estimates derived from Weibull and Rayleigh models.

4. Conclusions

The investigation of wind characteristics in Thimphu, Bhutan, from 2019 to 2023 focused on assessing the probability and power density distributions derived from wind speed data. Monthly wind speed data were modeled using Weibull and Rayleigh distributions. The findings indicated that the Weibull distribution generally provides a more accurate representation of power density than the Rayleigh distribution, as evidenced by higher R^2 values and lower RMSE values. Furthermore, the analysis revealed significant temporal variations in wind power density, reflecting fluctuations in wind speed over time.

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