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Seasonal and Altitudinal Wind Energy Potential Assessment at Varying Heights Using Stochastic Modeling Approaches

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***Abstract*—Wind power has emerged as a key renewable energy source globally and is widely used in different regions for their renewable energy needs. To take full advantage of the wind's potential for energy production, wind energy potential assessment is key to turbine placement and achieving the highest energy generation efficiency. The use of wind energy potential has been analyzed at different altitudes (40m to 200m) given the variation of wind pattern and energy production with height. Wind speeds at 40m average 4.85 m/s while they reach 8.02 m/s at 200m, which shows the benefit of higher heights to capture energy. Statistical models, such as Weibull distribution, are used to assess wind potential, while different estimation methods like Maximum Likelihood Estimation (MLE), Least Squares Method (LSM), Method of Moments (MOM) and Energy Pattern Factor Method (EPFM) are applied. The analysis has proved that there is a direct relationship between wind speed and height, that is, as the height increases, the wind speed increases, and the wind speed at 200m was 8.02 m/s in summer while at 40m was 5.89 m/s. The wind speed is maximum during summer season, from June to August, attaining to 8.95 m/s at 200m. The study also uses high-level statistical techniques to improve wind energy evaluations and outlines the benefits of higher elevations for more reliable and productive energy production. It provides some ideas on how to optimize turbine placement to enhance wind energy production.**

***Index Terms*— Weibull distribution, Maximum Likelihood Estimation, Least Squares Method, Method of Moments, Energy Pattern Factor Method.**

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I. INTRODUCTION

WIND energy potential is the potential capacity of a region or country to produce electricity from wind using wind turbines, which depends on the wind speed, number of wind hours per year, and land/offshore resources available. Wind energy is a key technology for the decarbonisation of electricity generation, with more than 1000 gigawatts (GW) of installed wind power worldwide as of 2023, and providing about 6-7% of the world's electricity generation [1]. The top countries are China, with around 370 GW, the United States (135 GW) and Germany (63 GW) [2]. Offshore wind speeds in the North Sea range from 8 to 10 m/s and the U.S. Midwest has an average wind speed of 6 to 8 m/s, which are large wind regions. Coastal locations having wind speed of 4-6m/s in emerging markets like Bangladesh are suitable for small scale or hybrid wind systems. Technological advances and grid integration advances are expected to allow wind energy to reach 20-30% capacity for global electricity demand by 2040 [4].

The Weibull distribution continues to be a cornerstone in wind energy assessments due to its flexibility and simplicity. Its utility as a wind energy resources assessment tool has been demonstrated in Europe by Moulin et al. (2020) [5] and the effects of wind speed variability in areas with higher wind thresholds has been emphasized by López et al. (2022) [6] who concluded that the 3-parameter Weibull distribution was more suited to be used in these areas. Similarly, Jain and Lee (2022) also examined the impact of turbine design optimizations on wind energy generation and identified the factors that contribute to a higher wind energy capture with larger wind turbines with optimized aerodynamic designs [7]. Although widely used, the Weibull distribution has been found to be limited in areas of irregular wind patterns and other distributions have been investigated. Singh and Ghosh (2021) presented a new wind speed analysis method as Champernowne distribution [8]. A comparison indicated that Champernowne distribution is better than two parameters and three parameters Weibull distributions for regions with highly variable wind directions and skewed wind directions. This is supported by the work of Zhou et al. (2022) who tested the performance of the wind forecasting systems using Weibull, Champernowne and

Lognormal distributions in the coastal areas of China, concluding that the Champernowne distribution was the best distribution in wind energy forecasting in the wind characteristics changing variation between seasons [9]. On this premise, Sánchez et al. (2023) suggested the use of hybrid statistical models that combine the Weibull and Champernowne distribution, with the conclusion that these hybrids are more appropriate for forecasting than the two distributions are considered separately, especially when there are areas with windy conditions and complicated wind fields [10]. Apart from these statistical developments, the use of machine learning techniques has started to make a significant impact on wind energy forecasting. Müller et al. (2024) used deep learning algorithms with wind speed along with a Weibull distribution which significantly improved the accuracy of the prediction, especially in areas with non-uniform wind [11]. There are several studies that have examined wind energy potential through statistical modelling, specifically wind speed distribution and estimation of energy. Carta et al. (2019) did a thorough review of wind speed probability distributions adopted in wind energy studies. They focused on the performance of Weibull distribution, as its versatility in modelling wind parameters was found to be good, and that it is widely used for wind energy potential assessment in various geographical regions [12]. In the context of Bangladesh, Hasan et al. (2024) have done a critical analysis of wind energy generation potential of different regions. Their study showed great spatial variability in wind resources, and highlighted the need for statistical techniques to be used in order to assess wind resources accurately. The results also showed that regional climatic conditions are also very important in the determination of wind energy feasibility [13].

In addition, Alanazi et al. (2023) studied the wind energy assessment using the Weibull distribution, with various numerical estimation techniques. They evaluated several parameter estimation methods and found that there was a significant impact in the accuracy of wind energy predictions, depending on the method selected. The results demonstrated the importance of using the appropriate estimation techniques to ensure an appropriate wind resource assessment is carried out [14]. Wind energy forecasting will be further discussed in the future, incorporating a mixture of the statistical and machine learning approach to enhance the forecasting accuracy (Wiklund et al., 2022; Bygrave et al., 2023). From their work, it is evident that real-time data will be vital in energy models for wind energy if they are to generate dynamic energy forecasts that are responsive. [16]. Guevara et al. (2023) and Patel et al. (2023) explored wind energy assessments and the use of remote sensing technologies as more novel methods to accurately measure wind speed in difficult conditions [17, 18]. Furthermore, Tiwari and Verma (2024) discussed the application of hybrid Renewable Energy (RE) Systems, combining wind energy with solar and energy storage technologies for stable and reliable energy in off-grid areas [19]. Thomas et al. (2021) discussed the use of artificial intelligence technologies for wind power improvement in operation and maintenance of wind farms, where the potential of artificial intelligence (AI) systems for minimal down time and increased wind power efficiency is discussed [20]. On the other hand, Li and Zhang (2024) proposed a more scalable forecasting solution for wind power by utilizing AI to provide a more precise forecasting of wind energy potential by analyzing enormous amounts of wind farm data [21].

Assessment of wind energy has improved but there are some gaps in the research. These encompass the need to assess these statistics-based models (like Weibull distribution) with a wider spatial and climatic range. Besides, hybrid approaches that integrate statistical distributions and machine learning methods, such as those using real time data, also need to be explored to improve forecasting accuracy. There is a need to further mitigate the effects of land use and wildlife disruptions to the environment, as well as to make wind energy more economically competitive in less developed countries by enhancing economic models and policies in those nations. The efficiency of the turbines, particularly in low-wind, and cold-wind conditions, and the forecasting of turbine performance over the long term, also require research. Solving these challenges will play a key role in the continued success of wind energy.

The primary objectives of this study are to: investigate wind resource distribution, investigate seasonal variation of wind resources and develop appropriate statistical modelling techniques to improve wind energy prediction. The main contribution of this work are given below:

1. To evaluate wind resources distribution based on wind speed, wind direction and wind intensity at various geographical locations for selection of high wind potential sites for wind energy generation.
2. To analyse seasonal wind variations and comprehend seasonal influence on wind availability and consistency for increased energy production planning.
3. To use statistical modelling techniques (probability distributions, time-series analysis) to simulate and forecast wind behavior to enhance wind energy potential assessments.

The methodology is discussed in section 2, where the use of the Weibull distribution and different parameter estimation techniques used for the wind energy potential assessment are explained. Detailed analysis is given in Section 3 which contains graphs, tables and wind rose diagrams, as well as tables of data from the time series, histogram and tables of results from various heights of installation for Weibull fitting, and a comparison of results for various locations. The findings are summarized and discussed in Section 4, focusing on the effect of height and seasonal variations on wind energy production, and the use of machine learning techniques. Finally, in Section 5, the key lessons learned are summarized and future research opportunities are suggested, including the use of real-time data and optimization of turbine placement to maximize energy extraction.

II. METHODOLOGY

The area of interest for the present study is the Inani beach of the Thana, Ukhia in the district of Cox's Bazar, Chittagong division. The location was chosen based on the following, Different parameters (wind speed, wind direction, altitude etc.) were taken into consideration and the condition (geographic and climatic) that made Inani a suitable location for wind assessment. A map of Inani Beach is provided to aid in the explanation.

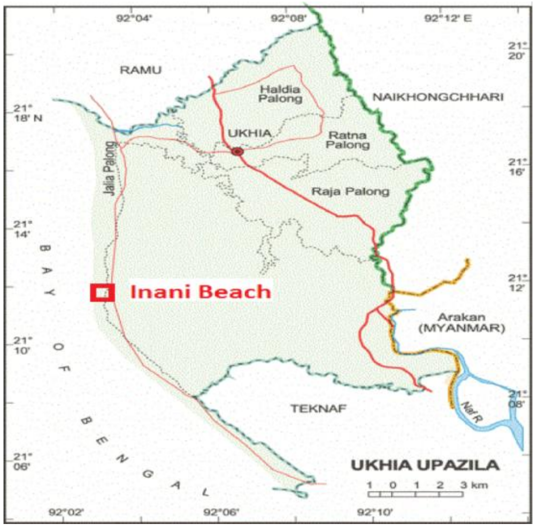


Fig.1: Location map the Inani Beach, Cox's Bazar, Bangladesh

A. *Data Collection from SREDA website*

The data of wind speed, used in this study, were obtained from the database of Sustainable and Renewable Energy Development Authority (SREDA). This data set is one-year wind speed observations. The data were collected at 10 minutes temporal resolution, which is appropriate for detailed wind resource assessment.

B. *Weibull Distribution*

The Weibull distribution is employed as it gives a better representation of the probability density distribution than other statistical functions. Furthermore, after the Weibull distribution parameters have been estimated at a certain height, they can also be estimated at other heights. The two important parameters of the Weibull distribution used are the probability density function f(V) and cumulative distribution function F(V) [22]. The probability density function (pdf) is the probability of the wind speed V occurring, showing the percentage of time when the wind speed will be observed at a particular location [31]. The cumulative distribution function is the probability that the wind speed is less than or equal to a value V. It also has the advantage that it can be used to estimate the length of time the wind speed is below a certain threshold [23].

$$f(V) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^{k}} \qquad (1)$$

The cumulative distribution function is obtained by integrating the probability density function and can be represented by the following equation.

$$F(V) = \int_0^a f(v)\,dV = 1 - e^{-\left(\frac{v}{c}\right)^{k}} \qquad (2)$$

In this case, V is the wind speed, k is the shape parameter (dimensionless) and c is the scale parameter (m/s). The shape parameter (k) expresses the wind potential at a specific site and describes the steepness of the wind speed distribution and the overall windiness of a site under consideration, respectively, with the scale parameter (c).

C. *Method of Moments (MOM)*

The moment approach estimates the Weibull distribution parameters kk and cc by numerical iterations, using the average wind speed and the standard deviation (σ) as follows: (3) and (4) [30]. Both the moment method and graphical method are simple methods because they require little computation. Wang calls the instant approach the most conventional method to get a point estimator, which is suitable for easy operation and low complexity [24].

$$\sigma = c\left[T\left(1+\frac{2}{k}\right) - T^{2}\left(1+\frac{1}{k}\right)\right]^{\frac{1}{2}} \qquad (3)$$

$$k = \left(\frac{0.987}{\frac{\sigma}{v}}\right)^{1.098} \qquad (4)$$

$$c = \left(\frac{v}{T\left(1+\frac{i}{k}\right)}\right) \qquad (5)$$

D. *Energy Pattern Factor Method (EPFM)*

The Energy Pattern Factor Method (EPFM) is used to estimate the shape factor by evaluating the ratio of the total wind energy to the cube of the average wind speed [25]. This approach gives a reliable approach for determining the characteristics of wind distribution, the shape factor calculated by Eq. (6):

$$k = 3\cdot 95EPF^{-0.89} \qquad (6)$$

E. *Maximum Likelihood Estimation (MLE)*

Maximum Likelihood Estimation (MLE) is a statistical technique which aims to obtain the Weibull distribution parameters by maximizing the likelihood function with the observed wind speed data. The method is iterative solution of the nonlinear equations, which is an accurate estimation of the parameters to obtain a good fit for wind speed distribution analysis [26]. The shape parameter (k) and the scale parameter (c) are estimated as follows:

$$k = \sum_{i=1}^{n}\left(\frac{V_i^k \ln V_i}{c^k}\right) - \frac{\sum_{i=1}^{n} \ln V_i}{n} - \frac{1}{k} = 0 \qquad (7)$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} V_i k\right)^{1/k} \qquad (8)$$

F. *Least Squares Method (LSM)*

The LSM is a statistical method of estimating the parameters of the Weibull distribution that minimises the sum of the squared differences between the observed and predicted values. This approach is popular because it is simple and can be used to describe wind speed data in a satisfactory way using the Weibull distribution [27].

$$F(V) = 1 - e^{-\left(V/c\right)^k} \tag{9}$$

G. Proposed framework for wind energy potentiality analysis

The flowchart in fig. 2 shows the step-by-step process of assessing wind energy potential using Weibull distribution analysis. It begins with wind data collection, followed by Probability and cumulative distribution function using Weibull distribution analysis. Weibull parameters are determined by various methods such as EPFM, MLE, LSM, and MOM which are used in wind energy prediction. The results will be evaluated and validated for accuracy and then you will get a final wind potential assessment for the optimum wind farm site selection.

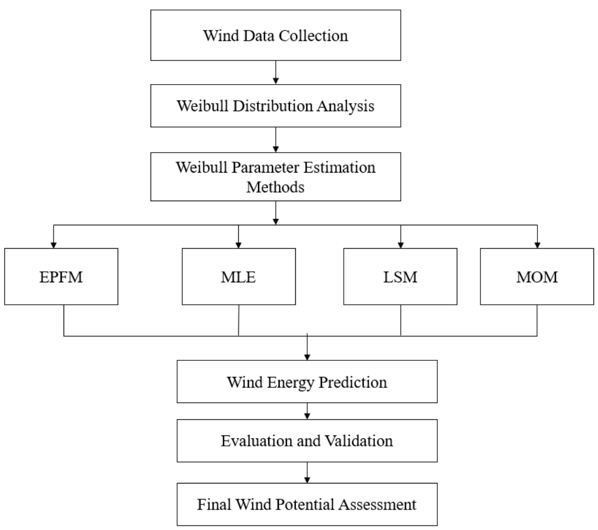


Fig.2. Flowchart of Wind Energy Potential Assessment Methods.

III. RESULTS AND DISUSSION

A. Time-Series Plot of Wind Speeds at Different Heights

Fig. 3 is a wind speed time-series analysis at different heights from 40m to 200m, showing the variations of wind speed at different times. The wind speed is plotted on the y-axis (m/s) and the time steps are plotted on the x-axis. The various colored lines represent winds of varying speeds at height; high variability in winds. There is a strong agreement between the trends in wind speeds of increasing height, with higher wind speeds typically found at higher elevations exceeding 20 m/s. There are instances of strong wind periods, especially in the latter part of the data set, which may indicate influences of the seasons or meteorology. These data reveal that the winds are not continuous and steady, and that this is important for optimizing wind energy production and turbine siting.

B. Histogram of Wind Speeds at Different Heights

Fig. 4 shows the wind speed distribution at different heights: The wind speed distribution at different heights shows the frequency of different wind speeds in the dataset. The x-axis represents wind speed (in meters per second or m/s) and the y-axis represents the number of times the wind speed occurred. The histograms overlap, showing that the wind speeds most frequently occur in the range between 3 and 7 m/s, and then they slowly decrease as the wind speed increases. The distribution is right skewed, indicating that lower wind speeds are more likely, and higher wind speeds are less likely. The curves fitted show that wind speed characteristics vary with height and higher altitudes would have higher wind speed and constant. This analysis is key to wind energy assessments and important in the placement of wind turbines and maximizing power production.

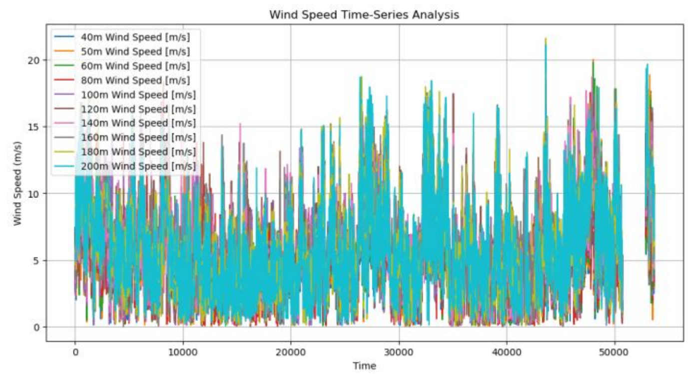


Fig.3. Description of Wind Speed Comparison Over Time

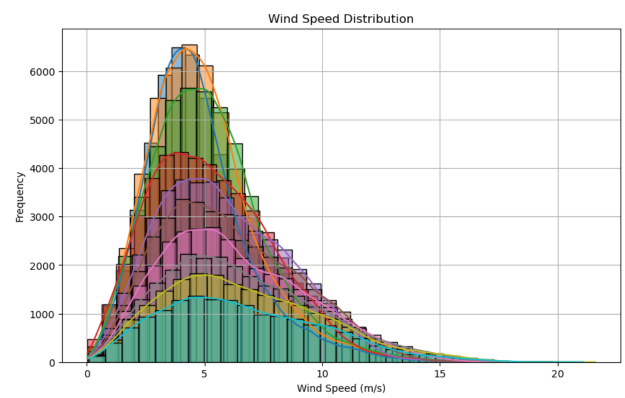


Fig. 4. Description of Wind Speed Comparison Over Time

C. Analysis of Wind Rose

The wind rose analysis is given in fig. 5 which shows that the wind blows mostly from North (N) and SouthEast (SE) direction at all altitudes.There is no general trend for the wind speed to increase with height but higher heights (above 100m) have higher frequencies of high speed winds. The colour-coded segments clearly show the variations in wind speed, with the darker colours representing lower wind speed and the lighter colours representing higher wind speed. The results are in line with the idea of increasing wind power power potential with increasing height above the ground, as the friction losses on the surface decrease with the height, and the higher the elevation, the more advantageous it would be to develop wind power for the best output and power. The variation of wind speed with height is important and the hub height of the wind turbine is of

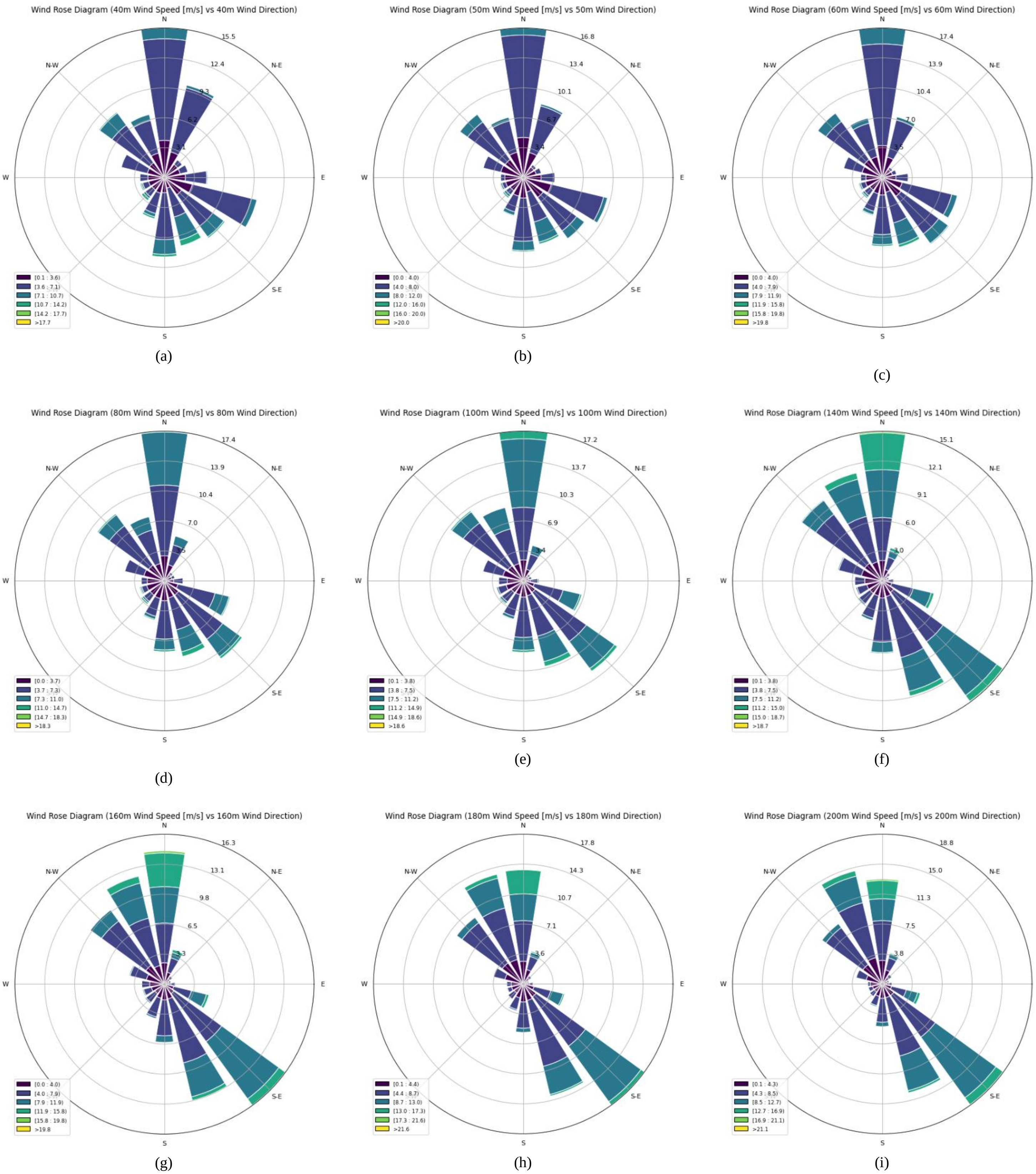


Fig. 5. Wind Rose Diagram Representing Wind Speed and Direction at Different Heights in Inani: (a)40m, (b)50m, (c)60m, (d)80m, (e)100m, (f)140m, (g)160m, (h)180m and (i)200m

great importance to be selected for maximum wind energy conversion efficiency. The data suggest that with a higher elevation (160m or above) more constant and stronger wind resources could be expected, which would increase the energy output. Additionally, these wind roses are very important when assessing a site, as they can help to identify the wind regimes where the wind is consistent and strong, reducing downtime and maximising energy generation. Understanding the wind characteristics at different levels helps to better forecast wind speed and wind growth, and facilitate grid integration for informed wind energy project development.

D. Different Weibull Methods analysis

The wind speed at 40m was plotted using Weibull distribution by using the MLE, LSM, MOM and EPFM methods as illustrated in Fig. 6(a). The curves are fitted to the data to show how each method approximates the wind speed distribution; the real distribution is represented by the blue histogram. Unlike EPFM, all the other models are closer to the observed distribution with MLE, LSM, and MOM underestimating the low wind speeds and overestimating higher wind speeds. The outputs show that MLE, LSM and MOM are more accurate estimates, and are more appropriate for the wind energy evaluation and optimum turbine placement at 40m.

E. Wind Speed Average Trends Over Time

The parameters of the Weibull distribution, shape factor (k), scale factor (c) and power density (W/m2) are shown in Table I.

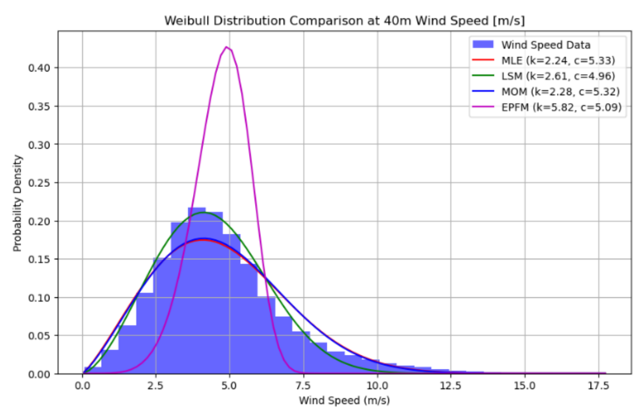
The estimation of wind speeds from 40m to 200m is done by four methods namely MLE, LSM, MOM and EPFM. The scale factor (c) is determined to be larger with the increase of height in each of the two methods implying stronger wind speed at higher heights, whereas the shape factor (k) is found to be fairly constant. The power density also rises significantly, with MLE showing an increase from 110.38 W/m² at 40m to 339.35 W/m² at 200m, LSM from 80.26 W/m² to 353.01 W/m², and MOM from 108.84 W/m² to 336.32 W/m². The values of power density, however, for EPFM start from 71.60 W/m² at 40 m and increase to a maximum of 207.19 W/m² at 200 m. This trend supports the previous conclusions that the potential benefits of wind energy increase with height, taller location wind energy benefits are higher, MLE, LSM, MOM provide better Weibull estimation than EPFM.

F. Wind Speed Analysis

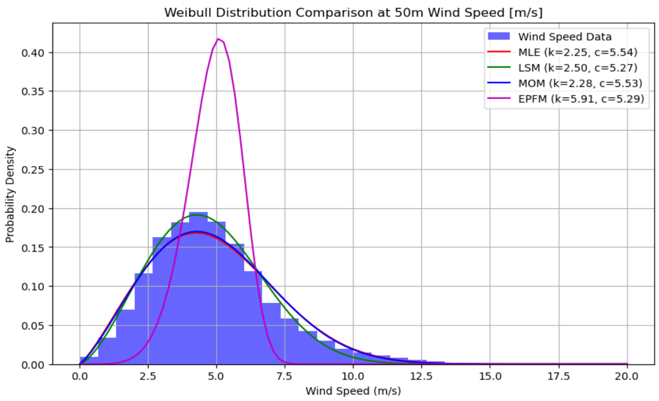
Data on monthly mean wind speed obtained from different heights (40m-200m) are given in Table II. It has a well-defined gradient with wind velocity increasing with height and it demonstrates that the winds are stronger and more enduring at higher altitudes. The wind speed for instance at 40m in January is 4.85 m/s, and at 200m, it's 6.81 m/s. The same applies to each of the months, and it seems that the more one climbs, the more wind power might be available. An analysis of the seasonal variations also showed that the month of June experienced the highest wind speed while the month of July experienced the maximum wind speed and the maximum wind speed was recorded for June at 40m height in 6.46m/s and in July at 200m height in 8.95m/s, indicating that these months are most favorable for wind energy production. On the other hand, April and May also have low wind speed, 40m 3.84 m/s and 200m 5.77 m/s respectively indicating less wind activity during these months. In addition, the wind speed variations for each month are presented, illustrating the potential for monthly differences in wind power generation. In cases like March and August, the wind is moderate, with a gradually increasing trend with the height. The variations show that location is a crucial factor in the deployment of wind turbines, and that higher elevations have more consistent wind speeds, which are good for achieving the best efficiency in wind power generation.

G. Seasonal Wind Speed Analysis

The seasonal average wind speed values for the different heights (from 40m to 200m) are shown in Table III for the purpose of highlighting the seasonal differences that are crucial for wind energy assessment. Summer has the peak wind strength at all elevations ranging from 5.89m/s to 200m to 8.02m/s, which is the best time of the year for wind power generation. Winter comes next, during which the wind speed ranges 4.56 to 6.20 m/s at 40m and 200m, respectively, providing relatively stable wind conditions. The relative wind speeds are lower during Autumn with a range between 4.26 m/s at 40m and 5.26 m/s at 200m and Spring with a range between 4.23 m/s at 40m and 6.73 m/s at 200m, showing moderate wind energy potential. The lightGBM model has the highest AUC score, indicating good classification performance, while both AdaBoost and SVM show comparable results. The SVM model has the lowest score, suggesting that the wind speed increases with height and higher elevation is more suitable for wind power generation, and autumn has the lowest wind speed, which may affect wind energy generation. Fig.10 shows the ROC curve of LightGBM, AdaBoost, SVM, and GRU according to the AUC score. Among the four models, the performance of lightGBM is the best with an AUC of 1.00, followed by GRU (0.99) and SVM (0.99), and AdaBoost has the lowest (0.98). LightGBM achieves high classification accuracy and an AUC of 1.00, which makes it suitable for practical use, such as for health monitoring (on the human body) and stress management systems.



(a)



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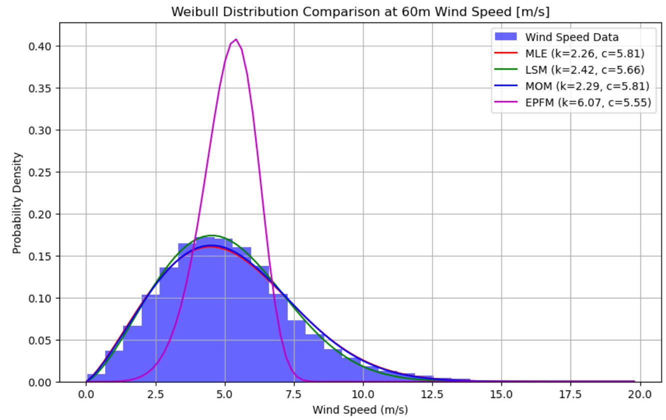
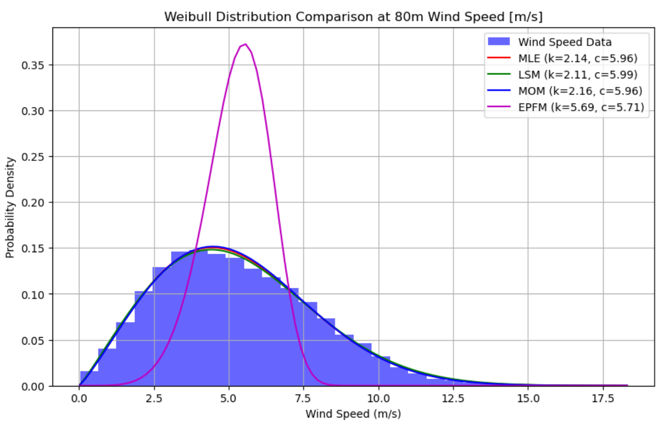


(c)



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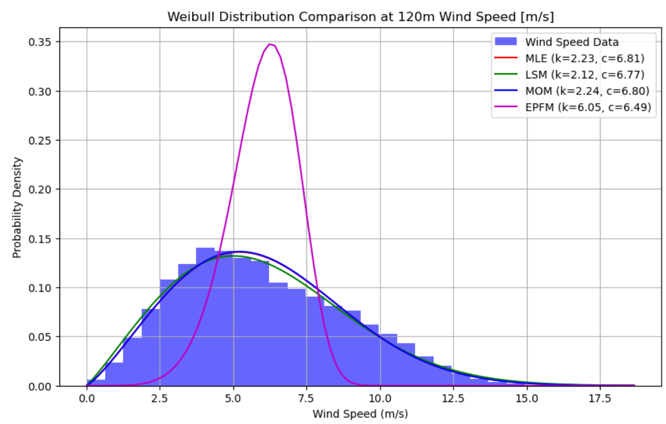

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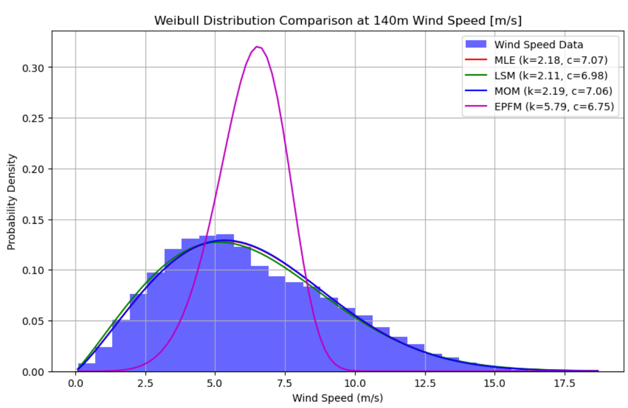

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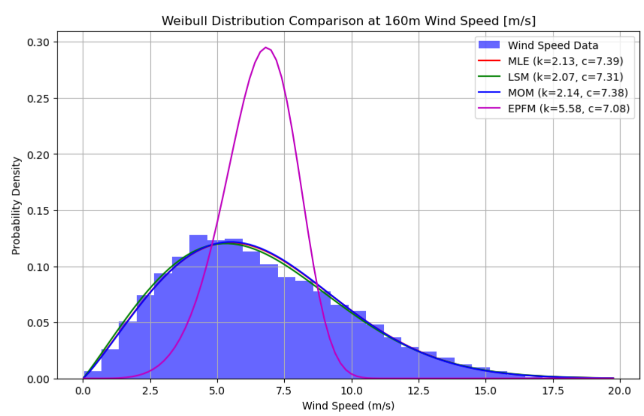

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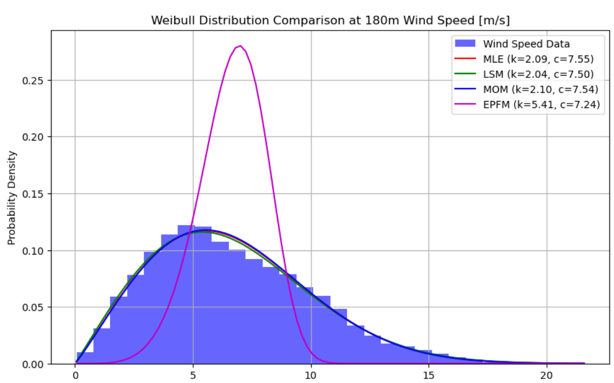

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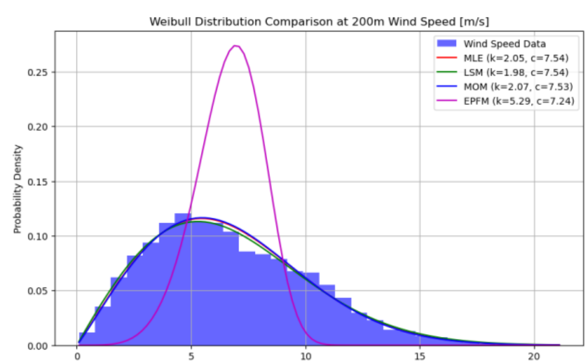

(i)

Fig 5:Weibull Distribution Fits for Wind Speed at Different Heights: (a)40m, (b)50m, (c)60m, (d)80m, (e)100m, (f)140m, (g)160m,(h)180m and (i)200m

TABLE I. WEIBULL DISTRIBUTION PARAMETERS AND POWER DENSITY AT DIFFERENT HEIGHTS USING VARIOUS ESTIMATION METHODS

Method	Height (m)	Shape (k)	Scale (c)	Power Density (W /m²)
MEL	40	2.244629	5.325768	110.379985
	50	2.248117	5.536825	123.870735
	60	2.260910	5.813491	142.716860
	80	2.138262	5.963563	161.680799
	100	2.274473	6.555665	203.662123
	120	2.229707	6.807254	231.780039
	140	2.180086	7.069964	264.742521
	160	2.129114	7.390733	308.973262
	180	2.087694	7.548410	335.347195
	200	2.052965	7.536803	339.348968
LSM	40	2.607032	4.960666	80.258108
	50	2.498151	5.273033	98.992302
	60	2.422356	5.657518	124.842552
	80	2.107255	5.994067	166.425881
	100	2.179507	6.558519	211.393281
	120	2.122251	6.767320	237.909665
	140	2.107388	6.979686	262.746958
	160	2.073229	7.308026	306.382921
	180	2.041421	7.502156	336.593124
	200	1.982049	7.544422	353.011117
MOM	40	2.276059	5.320923	108.837214
	50	2.278041	5.533406	122.318009
	60	2.288828	5.811766	141.188587
	80	2.160540	5.964809	160.266337
	100	2.285471	6.551722	202.511049
	120	2.236347	6.799716	230.436256
	140	2.187988	7.061424	262.947722
	160	2.139879	7.383576	306.647990
	180	2.102492	7.543804	332.475645
	200	2.067959	7.532447	336.324112
EPFM	40	5.817550	5.089331	71.603006
	50	5.911765	5.287870	80.282858
	60	6.065223	5.546266	92.592056
	80	5.687899	5.711033	101.246823
	100	6.282975	6.240249	131.826744
	120	6.047332	6.488867	148.285529
	140	5.792919	6.754116	167.380333
	160	5.579803	7.077203	192.804552
	180	5.414784	7.243691	207.000136
	200	5.293498	7.243146	207.193886

H. *Wind Speed Average Trends Over Time*

The monthly changes in the mean wind speed for the heights of 40 m to 200 m are shown in Fig. 7. Each data point is shown as a colored line, indicating the trends over the 12 months of the year. The wind speed is more variable for the higher elevations than the lower elevations, and tends to be strongest during the middle of the year (mid-June through mid-August) and weakest during the later months. The graph also shows that the wind speed is more dynamic at higher altitudes (e.g., 200 meters) than at lower altitudes, which may suggest differences in atmospheric conditions at different elevations.

A comparative study of the characteristics of the wind speed and power density at four sites: Inani, Sandip, Chandpur and Mymensingh is presented in the Table IV. Inani has the largest range of wind speed (4.27–8.95 m/s) and the maximum recorded wind speed at 200 meter is 8.95 m/s with the highest power density (353.01 W/m²) making it a "Good" site for wind energy development with moderate seasonal wind variation. Sandip has a low wind speed range (4.89 – 5.18 m/s), a max wind speed at 50 mts of 5.18 m/s, moderate power density of 243.20 W/m2 and high seasonal variation and hence a 'Moderate' feasibility grade. Similarly, the wind speed range of Chandpur is 3.08 to 5.91 m/s and the lowest power density is189.45 W/m², also falls under "Moderate" class, and Mymensingh also falls under "Moderate" class with a range of 2.30 to 5.69 m/s and a power density of 256.74 W/m². Like

Sandip, both Chandpur and Mymensingh regions have high seasonal wind variation which may affect the energy output stability. The overall results show that Inani is the most favorable location for wind energy utilization from the four locations evaluated.

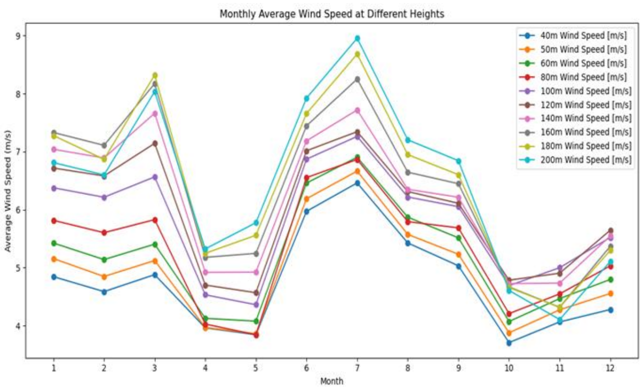

Fig. 7. Monthly Variation in Average Wind Speed at Different Altitudes

stronger and more stable during mid-year months (June-August) with the greatest wind speeds. Data also reveals that wind speeds vary seasonally, with wind speed lowest in the winter (4.56 m/s at 40m) and highest in the summer (6.72 m/s at 120m). The power density is similar, with higher power density at higher altitudes—rising from 110.38W/m² at 40m to 339.35W/m² at 200m—and it continues to benefit from positioning turbines higher. Comparative analysis is conducted between different places like Inani beach, Sandip, Chandpur and Mymensingh for the wind energy potential, wind speed (4.27–8.95 m/s) and power density (353.01 W/m²) and it is found out that Inani beach is the best location for wind energy potential among other location. This qualifies Inani beach as a "Good" wind energy development site, whereas other sites such as Sandip and Chandpur are in a "Moderate" wind energy development zone as their wind speeds and power density are less.

TABLE II. MONTHLY AVERAGE WIND SPEED AT VARIOUS HEIGHTS

Month	Monthly Avg Wind Speed (40m)	Monthly Avg Wind Speed (50m)	Monthly Avg Wind Speed (60m)	Monthly Avg Wind Speed (80m)	Monthly Avg Wind Speed (100m)	Monthly Avg Wind Speed (120m)	Monthly Avg Wind Speed (140m)	Monthly Avg Wind Speed (160m)	Monthly Avg Wind Speed (180m)	Monthly Avg Wind Speed (200m)
1	4.845084	5.156731	5.424739	5.81547	6.377255	6.717597	7.04115	7.330183	7.277442	6.811019
2	4.587776	4.847781	5.139487	5.60316	6.21426	6.581151	6.890812	7.108833	6.867708	6.598635
3	4.879503	5.123025	5.405359	5.82799	6.564758	7.143137	7.663226	8.173501	8.322338	8.034819
4	3.962095	3.970028	4.126423	4.027747	4.532142	4.699947	4.919547	5.177904	5.248238	5.323333
5	3.844218	3.859957	4.078332	3.843594	4.361349	4.568443	4.923411	5.246423	5.558542	5.774507
6	5.971542	6.188625	6.458365	6.552793	6.871045	7.015633	7.186431	7.44537	7.657783	7.923228
7	6.460863	6.664598	6.903745	6.865344	7.262825	7.344002	7.718451	8.251466	8.68113	8.954595
8	5.426218	5.573504	5.870558	5.793911	6.217986	6.311977	6.3513	6.645509	6.948415	7.203849
9	5.032848	5.231699	5.514584	5.686094	6.052189	6.109732	6.214679	6.481023	6.603329	6.844309
10	3.708922	3.877253	4.072545	4.208255	4.690685	4.78414	4.725396	4.667952	4.658013	4.607764
11	4.064851	4.273857	4.466825	4.547313	4.999136	4.904703	4.732423	4.48015	4.317428	4.105982
12	4.278282	4.554668	4.797180	5.031434	5.52169	5.645106	5.545883	5.368557	5.2975	5.107442

TABLE III. SEASONAL AVERAGE WIND SPEED AT VARIOUS HEIGHTS.

Season Name	Seasonal Avg Wind Speed (40m)	Seasonal Avg Wind Speed (50m)	Seasonal Avg Wind Speed (60m)	Seasonal Avg Wind Speed (80m)	Seasonal Avg Wind Speed (100m)	Seasonal Avg Wind Speed (120m)	Seasonal Avg Wind Speed (140m)	Seasonal Avg Wind Speed (160m)	Seasonal Avg Wind Speed (180m)	Seasonal Avg Wind Speed (200m)
Autumn	4.261497	4.452541	4.679927	4.81898	5.288845	5.326777	5.305897	5.306561	5.295941	5.262899
Spring	4.230117	4.317391	4.53535	4.560175	5.152479	5.51197	5.968023	6.473282	6.750067	6.733796
Summer	5.892567	6.077973	6.348461	6.341663	6.727206	6.845853	7.036358	7.409395	7.736127	8.02556
Winter	4.569252	4.852286	5.118925	5.477554	6.043681	6.334436	6.53271	6.678327	6.556317	6.200431

IV. DISCUSSION

Wind energy potential is calculated at the different heights from 40m to 200m, which is reflected in the trend that wind speed rises with height and therefore taller turbines are more effective at wind energy capture. Winds are stronger and more stable at high altitudes, as seen at 40m, with an average speed of 4.85 m/s, and at 200m, average winds of 6.81 m/s, which are

The results also highlight the need for accounting for seasonal variation of the wind for wind energy projects. For instance, energy production is ideal in the summer, and is risky in the autumn and winter months. These results underscore the importance of reliable wind data and advanced statistical analysis, including Weibull distribution modeling, for optimal wind turbine placement and energy generation strategies. In addition, the use of machine learning algorithms can enhance the prediction accuracy, especially in areas with different wind patterns, which can lead to better utilization of wind energy potential throughout the year.

V. Conclusion

This research systematically evaluated the wind energy potential at different heights from 40m to 200m with emphasis on wind speed distribution, power density, and the implications on optimal turbine placement. The key findings indicate that wind speeds tend to rise with elevation and higher elevations, especially those between 180m and 200m, have greater wind intensity and stability, demonstrating the benefits of taller turbines to harness wind energy. The following key findings and contributions summarize the overall findings of the research:

The wind speed increases with height and the wind pattern is stronger and more consistent at the higher elevations. This means that taller turbines, located at higher altitudes, will be able to extract more wind energy, emphasizing the benefits of increasing turbine height for better wind extraction. The wind rose analysis indicates that those higher altitudes have more favorable wind from the North and Southeast with better wind strength and stability, which helps in the placement of the turbine for efficient wind power generation. The wind speed was found to change significantly throughout the year, most favourable conditions were observed during the middle of the year (June, July and August) for wind energy generation.The wind speed range at the Inani Beach is 4.27m/s to 8.95m/s at different heights ranging from 50m to 200m and the power density ranges up to 353.01W/m2. The parameters described above makes Inani beach the most suitable beach among the studied areas due to its larger range of wind speed and high power density. The study of comparative wind potential analysis across the different coastal and non-coastal locations in Bangladesh reveals that, Inani Beach has higher wind speed and wind power density.

Moving forward, more research is needed to enhance the integration of machine learning algorithms with wind energy models to further improve the accuracy of wind forecasting, especially in areas with complex wind patterns. Also, the effect of various turbine designs and configurations at different altitudes could be investigated to improve energy capture efficiency. Real-time operational wind farm data would be used to give more practical insights into optimizing turbine placement and performance by expanding the study.

References

[1] S. A. Singh, P. K. Gupta, M. Rajeshwari, and T. Janumala, "Detection of Stress Using Biosensors," *Mater. Today*, vol. 5, no. 10, pp. 21003–21010, 2021.

[2] L. Ferrari, G. Pasini, and U. Desideri, "Towards a power production from 100% renewables: The Italian situation," SSRN Electronic Journal, 2022.

[3] J. A. Guarienti, A. Kaufmann Almeida, A. Menegati Neto, A. R. de Oliveira Ferreira, J. P. Ottonelli, and I. Kaufmann de Almeida, "Performance analysis of numerical methods for determining Weibull distribution parameters applied to wind speed in Mato Grosso do Sul, Brazil," Sustainable Energy Technologies and Assessments, vol. 42, July 2020.

[4] M. A. Hannan, et al., "Wind energy conversions, controls, and applications: A review for sustainable technologies and directions," 2023.

[5] Moulin, A., et al., "Assessment of Wind Energy Potential Across Europe Using Weibull Distribution," Renewable Energy, vol. 145, pp. 1234–1245, 2020.

[6] López, J., et al., "Enhancing Wind Resource Assessment with Three-Parameter Weibull Distribution," Energy Reports, vol. 8, pp. 567–578, 2022.

[7] Jain, R., and Lee, S., "Impact of Turbine Design Improvements on Wind Energy Output," Journal of Wind Engineering, vol. 46, no. 3, pp. 345–356, 2022.

[8] Singh, A., and Ghosh, P., "Champernowne Distribution: A Novel Approach for Wind Speed Analysis," Applied Energy, vol. 284, pp. 116–125, 2021.

[9] Zhou, L., et al., "Comparative Analysis of Weibull, Champernowne, and Lognormal Distributions for Wind Energy Forecasting in Coastal China," Atmospheric Measurement Techniques, vol. 15, pp. 757–773, 2022.

[10] Sánchez, M., et al., "Hybrid Statistical Models Combining Weibull and Champernowne Distributions for Wind Forecasting," Energy Conversion and Management, vol. 254, pp. 112–121, 2023.

[11] Müller, T., et al., "Deep Learning Algorithms Combined with Weibull Distribution for Enhanced Wind Speed Prediction," Scientific Reports, vol. 14, no. 1, pp. 1–12, 2024.

[12] J. A. Carta, P. Ramírez, and S. Velázquez, "A review of wind speed probability distributions used in wind energy analysis: Case studies in the Canary Islands," Renewable Energy, vol. 28, no. 4, pp. 607–615, Apr. 2019.

[13] M. Hasan, P. Dey, S. Janefar, N. A. Salsabil, I. J. Khan, N.-U.-R. Chowdhury, A. Arefin, and O. Farrok, "A critical analysis of wind energy generation potential in different regions of Bangladesh," Energy Reports, vol. 11, pp. 2152–2173, 2024.

[14] M. A. Alanazi, M. Aloraini, M. Islam, S. Alyahya, and S. Khan, "Wind energy assessment using Weibull distribution with different numerical estimation methods: A case study," Emerging Science Journal, vol. 7, no. 6, Dec. 2023.

[15] Wiklund, J., et al., "Integrated Models Combining Statistical and Machine Learning Approaches for Wind Energy Forecasting," Renewable Energy, vol. 189, pp. 345–356, 2022.

[16] Bygrave, L., et al., "Real-Time Data Integration in Wind Energy Models for Dynamic Forecasting," Energy Systems, vol. 14, no. 2, pp. 123–134, 2023.

[17] Guevara, R., et al., "Integration of Remote Sensing Technologies in Wind Energy Assessments," Remote Sensing of Environment, vol. 276, pp. 112–123, 2023.

[18] Patel, S., et al., "Enhancing Wind Speed Measurements in Challenging Environments Using Remote Sensing," Journal of Atmospheric and Oceanic Technology, vol. 40, no. 5, pp. 789–798, 2023.

[19] Tiwari, A., and Verma, S., "Hybrid Renewable Energy Systems: Integrating Wind and Solar Power with Energy Storage," Renewable Energy, vol. 180, pp. 456–467, 2024.

[20] Thomas, L., et al., "Artificial Intelligence in Optimizing Wind Farm Operation and Maintenance," Applied Energy, vol. 284, pp. 116–125, 2021.

[21] Li, H., and Zhang, X., "Predicting Wind Energy Potential Using AI and Large Datasets from Multiple Wind Farms," Energy AI, vol. 5, pp. 112–123, 2024.

[22] H. R. Ghosh, "Wind speed Weibull distribution and wind energy potential of Chandpur, Bangladesh," Dhaka University Journal of Applied Science and Engineering, vol. 6, no. 2, pp. 99–108, 2022.

[23] M. Hasan, P. Dey, S. Janefar, N. A. Salsabil, I. J. Khan, N.-U.-R. Chowdhury, A. Arefin, and O. Farrok, "A critical analysis of wind energy generation potential in different regions of Bangladesh," Energy Reports, vol. 11, pp. 2152–2173, 2024.

[24] P. E. R. Reyes, R. V. D. Giesen, and M. H. G. Savenije, "Seasonal variability in wind energy potential across Europe," Renewable and Sustainable Energy Reviews, vol. 97, pp. 469-479, 2018.

[25] T. A. Patwary, D. H. Didane, S. Al-Alimi, Y. A. M. Saif, and B. Manshoor, "Assessment of wind power potentials in Chittagong, Bangladesh using Weibull distribution function," Journal of Advanced

Research in Fluid Mechanics and Thermal Sciences, vol. 105, no. 1, pp. 154–165, 2023.

[26] M. Mondal, D. H. Didane, A. H. I. Ali, and B. Manshoor, "Technical assessment of wind energy potentials in Bangladesh," *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, vol. 96, no. 2, pp. 10–21, 2022.

[27] T. Stathopoulos, et al., "Urban wind energy: Some views on potential and challenges," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 179, pp. 146–157, May 2018.

[28] K. D. Islam, T. Theppaya, F. Ali, J. Waewsak, T. Suepa, J. Taweekun, T. Titseesang, and K. Techato, "Wind energy analysis in the coastal region of Bangladesh," Energies, vol. 14, no. 18, pp. 5628, 2021.

[29] M. M. Ahmed, S. K. Das, M. A. Haydar, M. M. H. Bhuiyan, M. I. Ali, and D. Paul, "Study of natural radioactivity and radiological hazard of sand, sediment, and soil samples from Inani Beach, Cox's Bazar, Bangladesh," J. Nucl. Part. Phys., vol. 4, no. 2, pp. 69-78, 2014.

[30] U. Dev, S. Ahmad, M. R. Uddin, M. R. Hazari, M. Kabiruzzaman, M. S. R. Zishan, and K. F. Ahmed, "Day ahead wind energy forecasting in two distinct locations of Bangladesh using deep learning models," in *Proc. 2025 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Feb. 2025, pp. 1–6.

[31] U. Dev, S. Ahmad, M. R. Uddin, R. Dhar, H. Mubarak, M. R. Hazari, S. Mekhilef, M. Seyedmahmoudian, A. Stojcevski, and O. Alshammari, "Short-term wind speed forecasting using different LSTM deep learning," Innovations in Electrical and Electronics Engineering: Proceedings of ICEEE 2024, vol. 2, no. 2, p. 199, 2025.

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