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Accurate prediction functions for turbine-scale wind energy resources from low-elevation measured data for Bangladesh

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ABSTRACT

This paper presents a highly accurate statistical modeling method for selecting prediction functions for turbine-scale wind energy resources in Bangladesh, which are not yet extensively covered in existing literature. The proposed resource modeling encompasses key turbine parameters, including turbine power, energy pattern factors, and wind energy outputs. The study, surveyed by the United Nations (UN), identifies prospective areas in mainland and coastal belt regions with the capacity to support commercial wind energy conversion systems for modeling purposes. As Bangladesh's current meteorological measurement facilities primarily collect low-elevation data (approximately 10 meters), the study employs prediction models and projection laws to estimate energy resources suitable for turbines of low-to-medium ratings (80 meters, less than 1 MW). The time-series probability distribution of available wind resources is analyzed in these potential regions, utilizing wind velocity prediction functions such as Weibull, Rayleigh, and Gumbel distributions. Their performances are compared against established statistical standards. Weibull factors are derived using graphical least squares (GLS) and modified maximum likelihood (MML) methods, and validated against parameter values reported in the literature. To enhance the analysis's coverage and accuracy, the Weibull function is expanded by incorporating the effect of output power ratio into its probability distribution. Wind power density (WPD) trends are confirmed through energy pattern factors, and a portable wind system model is employed to estimate the actual energy output at prospective locations, thereby increasing the comprehensiveness of the energy data modeling process.

Contribution/Originality: This study explores modeling methods of turbine-scale wind energy resources of Bangladesh from low-elevation data, which are not covered in the literature. It aims to assist the planning and development phases of future standalone and grid-connected turbine plants for the country.

1. INTRODUCTION

To ensure that a developing economy with limited natural resources can maintain long-term growth and address environmental concerns simultaneously, it is essential to integrate renewable energy sources into the country's power sector (Sayigh, 1999; Smil, 2016; Sourgens, Baldwin, & Banet, 2024; Wrixon, Rooney, & Palz, 1993). In recent times, consensus has been emerging among experts in the power field that, apart from helping to reduce dependence on carbon-emitting fossil fuels and high-risk nuclear plantations, renewable technologies can also be economically efficient and commercially competitive (International Energy Agency, 2010). This change of attitude validates a notion which has been contested in the past with respect to emerging markets. Among different alternative energy ventures, wind technology has been receiving the power industry's attention in developed countries as a resource that can be harnessed effectively from a business point of view (Shamshad, Bawadi, & Sanusi, 2009). Although the current worldwide installed wind capacity (approaching the range of 1200 GW in 2025 World Wind Energy Association, 2025) is small compared to the production of conventional fuel-driven systems, this sector has experienced average annual growth rates of up to 35% during periods over the last decade (Van Lieshout, 2001; World Wind Energy Association, 2025). A study prepared by the US Department of Energy (DOE) reports that, by the year 2030, wind plants will satisfy about 20% of the electricity demand in the country (Lindenberg, Smith, & O'Dell, 2008). Additionally, a new energy initiative in Greece has identified wind power as the most promising sector for investment based on sensitivity and cost-benefit analyses of its energy generation network (Celik, 2003).

Bangladesh, a South Asian country with LDC (least developed country) status, has many remote regions along its approximately 650 km long coastal belt (bordering the Bay of Bengal) where it is difficult to develop reliable electricity distribution systems on the back of a struggling grid-based power network (Dey, 2006; Islam, Islam, & Alam, 2008). It has a number of offshore islands that are completely dependent on diesel-fueled portable power systems. Under these circumstances, switching from conventional resources to alternative energy is necessary for Bangladesh so that it can reduce its reliance on fossil oil sources and become more independent from foreign imports (currently standing at around 5 million tons of crude oil and refined petroleum imports for the year 2024) (Dhaka Tribune, 2024; Ediger & Kentel, 1999; Standard & Poor's Global, 2024). Despite some efforts by the government to build an infrastructure of renewable systems in remote localities of Bangladesh, the country's existing wind capacity stands at only around 62 MW (Sustainable and Renewable Energy Development Authority (SREDA), 2024). Reported studies attempting to evaluate the country's wind potential have focused on offshore islands in its south as prospective areas for building wind power plants (Abdullah-Al-Mahbub & Islam, 2024; Dey, 2006; Islam et al., 2008). However, an environment study conducted by the United Nations over the last decade has shown that there are also areas located on the country's mainland with reasonable to strong potential for harnessing wind energy (United Nations Environment Programme (UNEP), 2024).

Based on field experience, the assessment of wind resources at potential turbine locations has been receiving increased interest in a number of recent wind power-related studies (Ahmed, Islam, & Masud, 2025; Bivona, Burlon, & Leone, 2003; Celik, 2004; Elfarra, Silini, & Gasaymeh, 2025; Garcia, Torres, Prieto, & De Francisco, 1998; Hasan et al., 2024; Sarkar & Kasperki, 2009; Shaikh, Chowdhury, Sen, & Islam, 2017; Sulaiman et al., 2002; Zaharim, Razali, Abidin, & Sopian, 2009).

Incentives to install small-scale standalone turbines in India have resulted in more than one-third of the plants being installed in areas with insufficient turbine-level wind streams (Daoo, Panchal, Sunny, Sitaraman, & Krishnamoorthy, 1998). In many cases, the reason behind the selection of an unsuitable location for installation and the setting of erroneous ratings and critical speeds was a lack of planning and accurate assessment of wind potential. This underlines the need to build a comprehensive database of wind characteristics (e.g., wind profiles at high altitudes, estimated achievable turbine outputs, site properties) if a country wants to develop its renewable wind power network. Therefore, performing variability analysis of wind streams and examining its relation to production limits in the context of a particular geographical position also assumes importance (García-Bustamante, González-Rouco, Jiménez, Navarro, & Montávez, 2008).

A number of published findings (conducted over different places on the earth) have identified the importance of wind speed probability distribution, site properties (surface roughness, topography), and long-term data analyses to assess the prospects of wind energy development and in the planning phase of a renewable power project (Bechrakis, Deane, & McKeogh, 2004; Caires & Sterl, 2005; Ramírez & Carta, 2006; Roy, 2011). They also emphasize profiling high-elevation wind streams for possible locations that can reduce energy production costs by helping to optimize the design parameters of a commercial turbine. This work aims to address these concerns by devising an accurate modeling approach and assessing the turbine-scale wind potential of Bangladesh based on data collected from a UNadministered survey. Apart from windy coastal areas, potential regions located on the country's mainland are also covered. As most of these locations only have low-elevation weather monitoring stations (~10-12 m), turbine height wind profile models are developed with the help of prediction models and projection laws. Area-dependent time-series analyses of wind speed probability, portable conversion system output, and dependence of production on design speeds are performed using measured data from meteorological facilities. Weibull, Rayleigh, and Gumbel probability functions are utilized in an effort to find a suitable wind frequency distribution model. This study will assist in the assessment of commercial turbine-scale wind resources for the entire shore of the country.

The paper is organized as follows. In Section II, the methodology for collecting national wind data based on a renewable resource assessment survey is described. Section III presents the modeling and estimation process of turbine-scale wind resources for the selected locations. Analyses are provided on wind velocity probability distribution, statistical prediction functions, wind power density, and wind outputs before the findings of the study are summarized in Section IV.

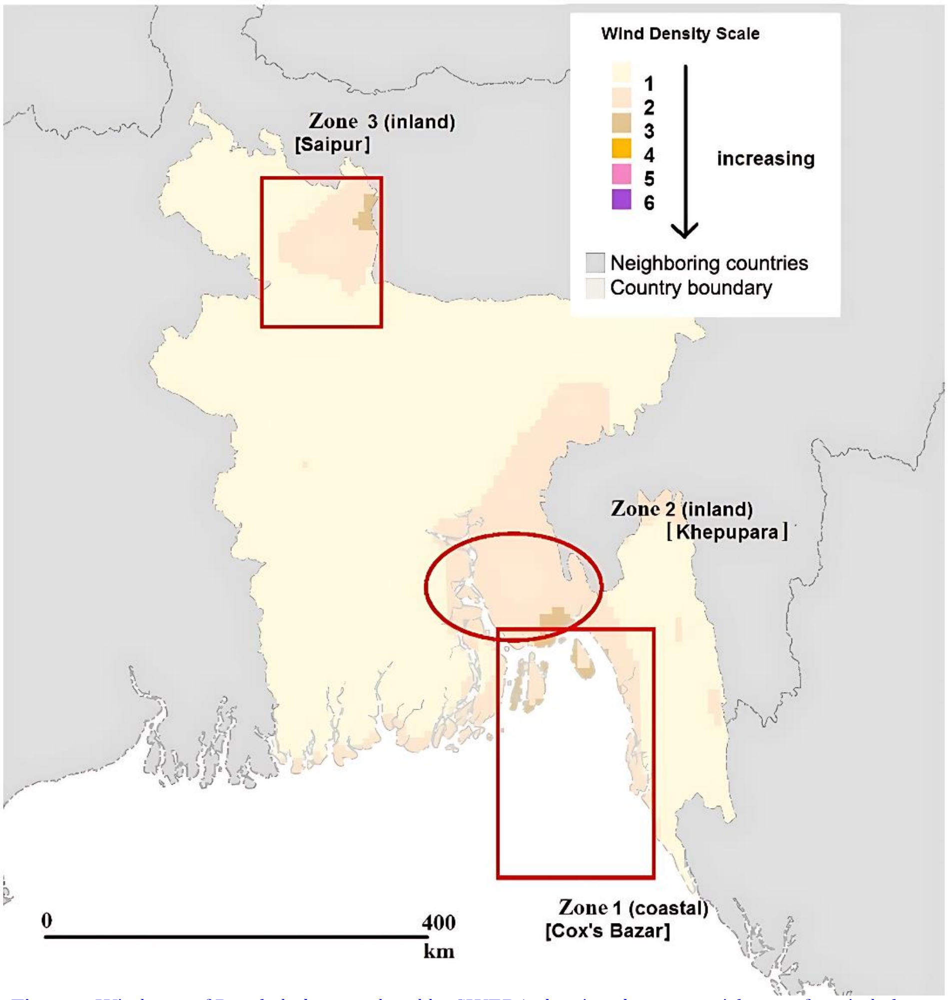
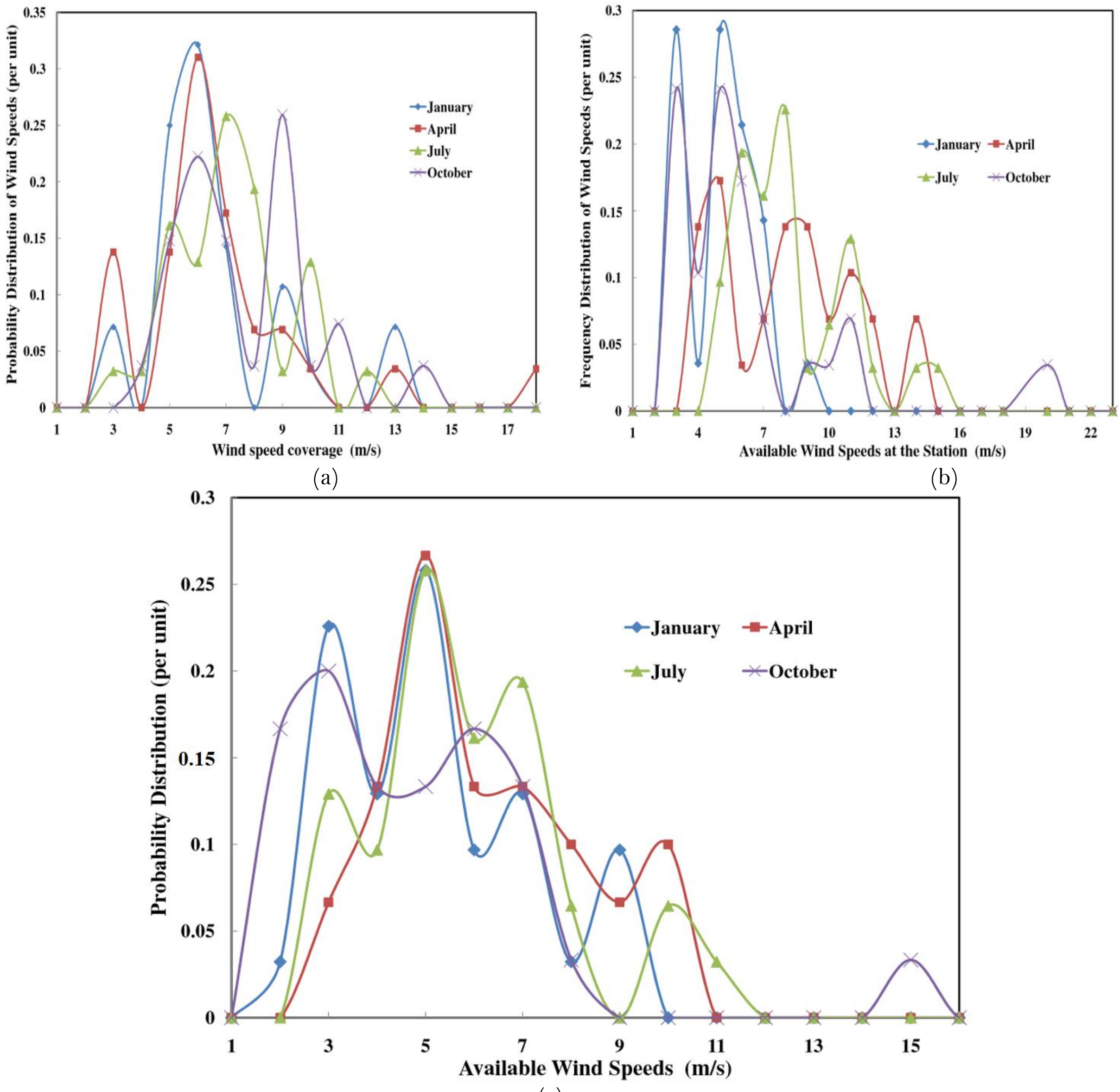


Figure 1. Wind map of Bangladesh as produced by SWERA showing three potential zones for wind plants.

2. METHOD OF WIND DATA SELECTION

As Bangladesh is located on a geographic position bordering the Bay of Bengal, it has a long stretch of southern coastal belt (~650 km) where strong wind forces are available. Published literature on wind resources of Bangladesh has mainly concentrated on offshore islands located along its coastal regions (Abdullah-Al-Mahbub & Islam, 2024; Dey, 2006; Islam et al., 2008). Recently, the United Nations launched an environmental programme (for a wide geographical area) which aimed to document solar and wind power available on the planet under a wind/solar resource assessment program (SWERA) (United Nations Environment Programme (UNEP), 2024). According to the wind map produced by this initiative, Bangladesh has three distinct geographic zones located on its mainland and offshore areas, which have class 2 (or above) wind resources. They can be identified as Zone 1 (the southeastern coastal belt and offshore islands), Zone 2 (a mainland area near the southern seashore), and Zone 3 (an interior landlocked region in the north), as shown on the wind density map of Bangladesh in Figure 1 (Roy, 2011; United Nations Environment Programme (UNEP), 2024). The national meteorological society of Bangladesh has weather monitoring stations in these areas, which collect raw wind data in a periodic fashion using tower-mounted (~10-12 m) anemometers. Three weather stations have been selected in this analysis, one from each of the three zones, to collect measured wind data for the estimation of achievable turbine-scale wind resources in Bangladesh. They are located in Cox's Bazar (Zone 1, 21.4 N 91.9 E), Khepupara (Zone 2, 21.98 N 90.2 E), and Saidpur (Zone 3, 25.8 N 88.9 E). To account for the effect of time-series dependency of wind resources and the annual variation of seasonal profiles, average daily low-elevation data collected over an eight-year period are analyzed in the study.



(a) (b) (c)

Figure 2. Yearly frequency distribution of wind velocity (At an elevation of 80 m) for a) Zone 1, b) Zone 2, and c) Zone 3.

3. RESULTS OF TURBINE-SCALE WIND RESOURCE MODELING

Wind energy assessment can be defined as an integrated analysis of the potential power that can be extracted from wind resources in a particular location (Elmabrouk, 2009). The following subsections present the resource estimation and modeling techniques of turbine-scale wind profiles for Bangladesh in a sequential manner.

3.1. Wind Speed Probability Distribution

Wind power is often categorized as an intermittent source of energy because available wind streams may face a certain degree of seasonal variation for a particular location. During the planning phase of turbine installation and to prepare a schedule of expected power generation, it becomes useful to explore the probability of specific wind levels being sustained at a station during the progression of a year through the seasons. Figure 2(a) presents the probability of Zone 1 achieving wind speeds in the 1-18 m/s range at an elevation of 80 m. During the month of January, the station has a 32.5% chance of crossing the high threshold of 6 m/s. The probability of achieving very strong winds is lower when the speed limit is set to 9 and 13 m/s (11% and 7%, respectively). The likely peak wind speed remains unchanged during the summer months (April), and higher probabilities (26%) exist for stronger winds (7 and 9 m/s) after the half-yearly point (during July and October). The probability curves for Zone 2, as presented in Figure 2(b), indicate a likely maximum profile speed in the 5-8 m/s range. In the later part of the year, the station experiences occasional storm gusts exceeding 14 m/s. Zone 3 delivers the most consistent profiles among the three regions, albeit with a lower range of peak speeds (2-7 m/s), as shown over the seasons in Figure 2(c). To estimate the probability of a particular location achieving a specific wind velocity, monthly wind data are assessed for the last year of the observation period. If N is the number of days in a month when wind data are recorded, n is the number of speed levels, and f_i is the frequency of occurrence for a particular level (v_i), the probability of a location achieving a given wind speed is calculated from Celik (2003).

$$f(v_i) = \frac{f_i}{\sum_{i=1}^{n} f_i} = \frac{f_i}{N}. \qquad (1)$$

As measured wind data are recorded at relatively lower heights (~10 m) in Bangladesh, projection laws will be necessary to estimate available power density at altitudes usually occupied by wind turbines (30-120 m). Base wind power density (WPD, at 10 m) is calculated from raw measured data with an empirical equation which relates power density with average reading and variance of wind data recorded over a sufficiently long period of time (Kainkwa, 2000). If v represents average monthly readings, σ^2 is the variance of the data and ρ is the mean air density for the location, monthly mean wind power (P_{wind}) can be calculated with

$$P_{wind} = \frac{1}{2}\rho(\overline{v}^3 + 3\overline{v}\sigma^2) \qquad (2)$$

For this analysis, 80 m is selected as the height of commercial turbines of low-to-medium rating (0.01-1 MW output), and the projected wind power density at this elevation can be calculated from the wind power law (Peterson & Hennessey Jr, 1978).

$$P_{wind_{80}} = P_{wind_{10}} * (\frac{z_{tur}}{z_{ref}})^{3\psi} \qquad (3)$$

Where ψ is a power law coefficient that depends on atmospheric conditions and the nature of the terrain at the locality. For assumed stability and relatively plain geographic features, ψ is approximated by $\frac{1}{7}$ or 0.143. z_{tur} and z_{ref} are turbine and reference elevations, respectively, which are set at 80 m and 10 m. For these parameters, the wind velocity used in the power law is expressed as

$$v_{tur} = v_{ref} * (\frac{z_{tur}}{z_{ref}})^{\psi} \qquad (4)$$

where v_{tur} is the estimated wind speed at turbine elevation.

3.2. Statistical Prediction Functions

1) Weibull Factors and Weibull Distribution: This analysis employs three different prediction functions to assess the statistical probability of a geographical location experiencing a specific wind force and compares it with the frequency distribution of velocity described by equation (1). The first prediction function is based on the Weibull distribution, which is a continuous probability function typically used to make natural event-related projections. It is particularly useful for the estimation of wind resources, as it has been reported that Weibull functions can closely follow patterns manifested by experimental wind data (Sarkar, Singh, & Mitra, 2011; Zaharim et al., 2009). The cumulative distribution function of the Weibull distribution for a specific wind speed is defined using two control parameters: a scale parameter c (with the same units as velocity) and a shape parameter k (dimensionless).

$$F_w(v) = 1 - exp[-(\frac{v}{c})^k] \quad (5)$$

With the objective of obtaining an estimate of these two parameters, the graphical least squares (GLS) method, which is based on Equation 5, is applied to the data. The cumulative $F_w(v)$ function is approximated with the help of the calculated $f(v_i)$ distribution and Equation 5 is transformed to

$$klog_e(v) - klog_e(c) = log_e\{-log_e(1 - F(v))\}z \quad (6)$$

Now, if $log_e\{-log_e(1 - F(v))\}$ is plotted against $log_e(v)$, and a linear estimation is fitted with the curve following the principle of the least squares method. It will take the form of $ax + b = y$, where the line's slope is proportional to the shape factor (k).

$$k = a \quad (7)$$

In addition, the intercept of the y-axis (b) along with the line's slope can be used to calculate the scale factor (c).

$$c = exp[-(\frac{b}{k})] \quad (8)$$

Table 1. Graphical estimation of Weibull factors (Zone 1).

Wind speed (v_i)	$f(v_i)$ [From eq. (1)]	$F(v_i)$	$log_e(v_i)$	$log_e[-log_e(1-F(v_i))]$
2	0	0	0.693	–
3	0.071	0.071	1.099	-2.602
4	0	0.071	1.386	-2.602
5	0.25	0.321	1.609	-0.947
6	0.321	0.643	1.792	0.029
7	0.143	0.786	1.946	0.432
8	0	0.786	2.079	0.432
9	0.107	0.893	2.197	0.804
10	0.036	0.929	2.303	0.97
11	0	0.929	2.398	0.97
12	0	0.929	2.398	0.97
13	0.071	1	2.485	0.97

A sample estimation process of the two parameters is presented in Table 1 using data measured at the station of Coxs Bazaar (Zone 1) for the month of January. The corresponding $log_e\{-log_e(1- F(v))\}$ versus $ln(v)$ curve is presented in Figure 3, which leads to constants a=2.0293 and b=-3.8064 for a least square fit. This results in a scale factor of c=6.526 m/s and a shape factor of k=2.029 for the period. In the same manner, Weibull factors are calculated for all selected locations, and their monthly distribution is documented in Table 2. It shows a trend of the scale factors being marginally greater than the location's average wind speed (at an altitude of 80 m), and the shape factors residing within the range of 1.39-2.91.

After the calculation of Weibull factors, we proceed to establish the prediction functions and compare their results with the actual wind velocity frequencies in the 1-18 m/s range. It should be noted that the mean and variance of measured wind data may also be calculated from the distribution described by Equation 1, and the expressions will take the form of (Jamil, Parsa, & Majidi, 1995).

$$\overline{v} = \frac{\sum_{i=1}^{n} f_i v_i}{\sum_{i=1}^{n} f_i} = \frac{1}{N}\left[\sum_{i=1}^{n} f_i v_i\right] \tag{9}$$

$$\sigma^2 = \frac{1}{N-1}\left[\sum_{i=1}^{n} f_i (v_i - \overline{v})^2\right]. \tag{10}$$

The first prediction function, derived from the continuous Weibull distribution, uses scale and shape factors calculated with the graphical (GLS) method.

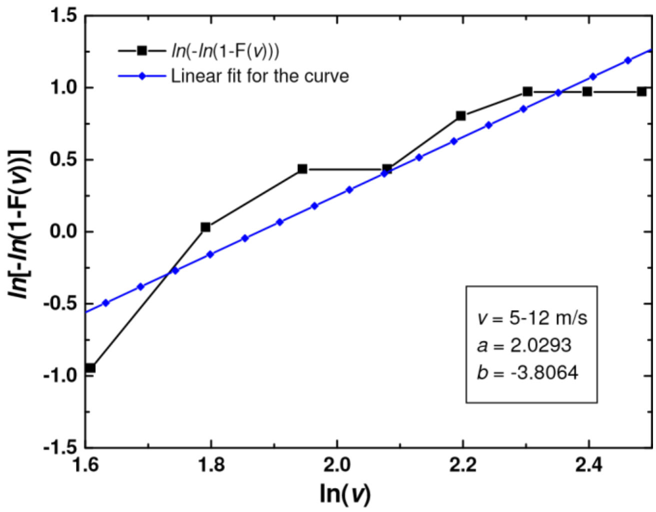


Figure 3. Sample plot of $log(-log(1- F(v)))$ versus $log(v)$ producing a=2.03 and b=-3.81 for graphical estimation of Weibull factors.

Table 2. Weibull factors for the three potential zones.

Month	*k* (Zone 1)	*c* (Zone1), m/s	*k* (Zone 2),	*c* (Zone2), m/s	*k* (Zone 3),	*c* (Zone3), m/s
1	2.029	6.526	2.905	4.996	1.826	4.935
2	1.833	6.151	1.699	6.219	2.039	5.133
3	2.036	6.080	1.729	6.806	1.399	5.713
4	1.619	6.571	2.502	8.471	2.210	6.163
5	1.416	5.559	2.626	6.634	1.915	5.817
6	1.963	6.505	1.805	8.876	1.999	5.201
7	2.685	6.767	2.129	7.821	2.098	5.604
8	1.798	7.111	1.399	9.496	2.490	5.408
9	1.785	6.967	1.706	9.088	2.197	4.596
10	2.594	7.559	1.452	5.834	1.399	4.532
11	2.155	6.857	1.727	5.030	1.482	4.896
12	2.009	6.329	2.799	5.883	1.955	4.047

$$f_w(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right]. \tag{11}$$

This is a distribution of two control parameters with the ability to include an additional location-dependent factor if the station can always sustain a velocity greater than a minimum threshold.

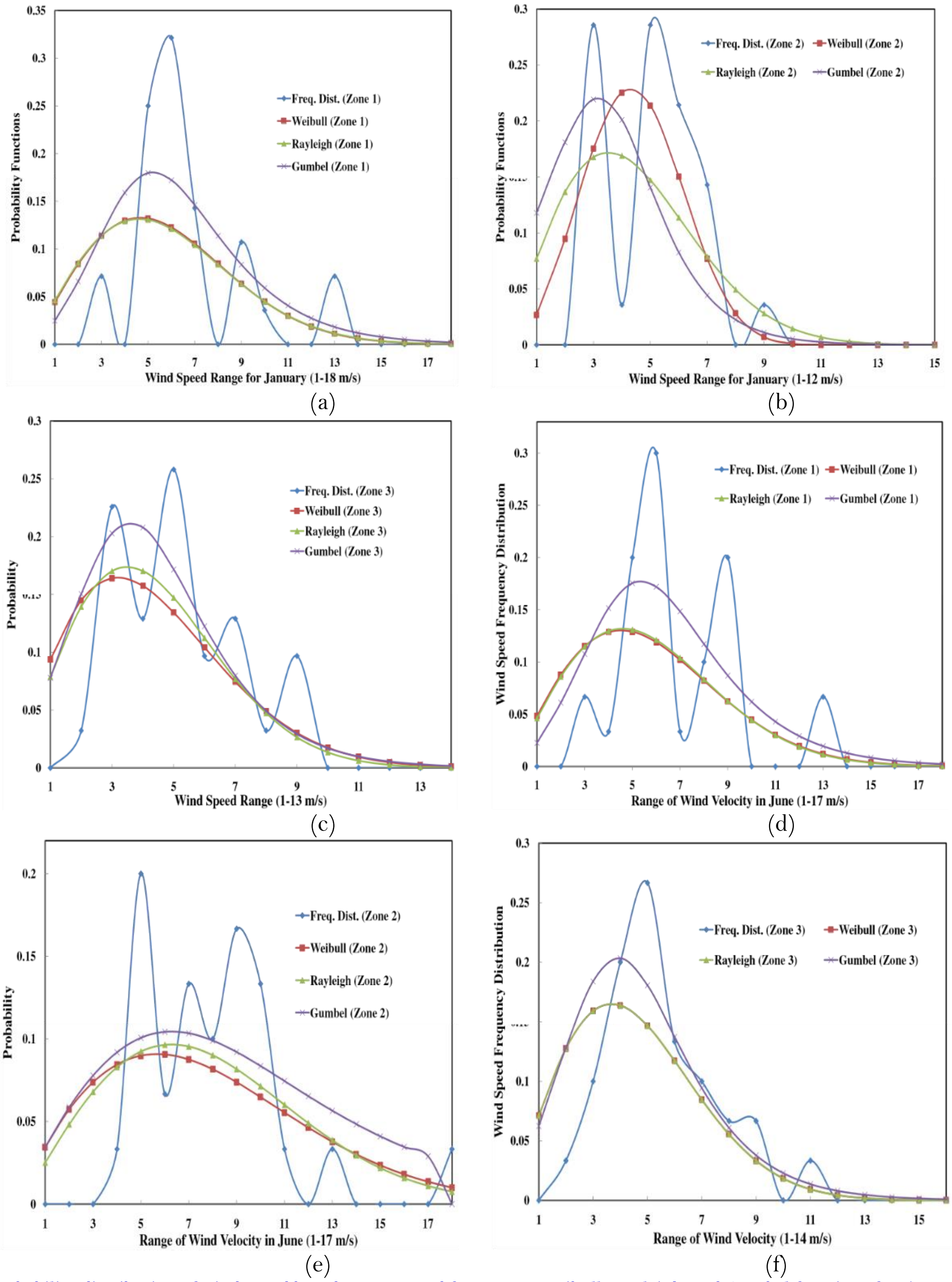


Figure 4. Probability distribution of wind speed based on measured frequency, Weibull, Rayleigh, and Gumbel functions for a) Zone 1, b) Zone 2, c) Zone 3 for the month of January and d) Zone 1, e) Zone 2, f) Zone 3 for the month of June.

2) Rayleigh and Gumbel Probability: The second probability function is based on the Rayleigh distribution, which may be utilized when sufficient measured data are not available to determine the Weibull factors graphically. In this case, the function is defined as a modified version of the Weibull function, and the shape factor assumes a constant value of 2.0 regardless of the geographic features existing at the station (Persaud, Flynn, & Fox, 1999). The third probability function for wind speed is derived from the Gumbel distribution, which is an extreme value distribution suitable for cases when monitoring equipment faces sudden stormy gusts (Gumbel, 1958). It utilizes average reading and standard deviation of measured data as calculated from Equations 9 and 10 and incorporates Euler's constant γ (with a value of 0.5772). The distribution is described by a double exponential function taking the form of

$$f_g(v) = 1 - exp[-exp(-[\gamma + (\frac{\pi}{\sqrt{6}})(\frac{v-\overline{v}}{\sigma})])] \quad (12)$$

To fit with observed wind profiles, the Gumbel distribution is scaled with the shaping factor k' which is defined by

$$k^{/} = \frac{\sigma}{\bar{v}}(\frac{v}{\bar{v}})^{\sigma-1} \qquad (13)$$

The results from the three prediction functions, along with the actual wind speed distribution, are presented for the stations in Figure 4(a)-4(c) and Figure 4(d)-4(f) for the months of January and June, respectively. The general trend of the Rayleigh distribution is to closely follow the Weibull data, except at the Khepupara station (Zone 2), due to random profile fluctuations. The Gumbel data, on the other hand, cover a wider range of velocities compared to the other distributions. The Rayleigh and the Weibull prediction functions for Coxs Bazaar are almost identical in Figure 4(a) and Figure 4(d) because the Weibull shape factors (k) for the concerned months (see Table 2) are 2.03 and 1.96, within 2% of an ideal Rayleigh shape factor (2.0). The situation is not the same for Khepupara (Zone 2) in Figure 4(b) and Figure 4(e), as the Weibull shape factors register values of 2.91 and 1.81 during the same period at this location.

3.3. Comparison between Weibull, Rayleigh, and Gumbel Distributions

Probabilities calculated with Weibull, Rayleigh, and Gumbel functions at a turbine height are compared with the actual frequency distribution of estimated wind speed through the estimation of root mean square errors (RMSE). This parameter helps to evaluate the accuracy of the prediction functions with respect to measured data. If the analysis is performed with n categories of speed, RMSE for a prediction function is defined as

$$RMSE_x = \sqrt{\frac{\sum_{i=1}^{n}[f_x(v_i) - f(v_i)]^2}{n}}, \qquad (14)$$

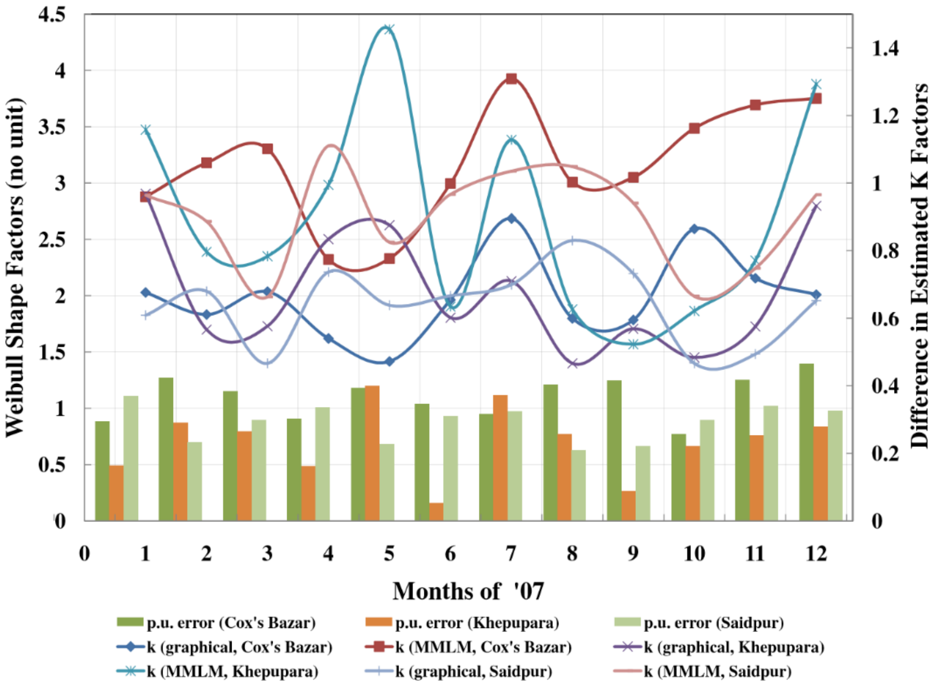


Figure 5. Weibull shape parameters (k) as determined by GLS and MML methods and the per-unit difference between estimated factors.

Where $f(v_i)$ denotes the measured frequency distribution, $f_x(v_i)$ stands for the approximated functions, and Weibull, Rayleigh, or Gumbel distributions are indicated with the subscript x (w,r,g). Table 3 documents the monthly distribution of extracted estimation errors (in percentage) applicable for the three prediction techniques. It is interesting to note that for the station in Zone 1 (Coxs Bazaar), the three techniques produce roughly the same percentage of average error (~6%). For the other two zones, the Gumbel function results in an RMSE which is higher than Weibull and Rayleigh functions. If the overall average RMSE is calculated for the three zones, it takes on values of 5.77%, 5.67%, and 6.09% for Weibull, Rayleigh, and Gumbel probabilities. Hence, if RMSE is considered as the criterion to select a prediction technique for higher elevations, the Weibull distribution appears as the best choice considering it employs a site-dependent shape parameter. The Weibull pattern is also suitable because of its ability to reproduce a significant portion of the frequency spectrum (particularly in the lower range of speed). Moreover, it can be adapted to provide projections of achievable turbine output for a particular location as reported in (Pryor, Schoof, & Barthelmie, 2005).

3.4. Verification of Weibull Factors

As we have decided to employ the Weibull distribution to define the likelihood of a turbine location attaining rated speed, it is necessary to verify the estimation process of Weibull factors (k and c), which ultimately determine the Weibull function. The factors in Table 2 were derived using a graphical technique based on a least squares estimation method. To obtain a secondary estimate of the same factors, a technique based on the modified maximum likelihood method (MMLM) (Fichaux, 2003) is employed for the locations. This approach presents the speed distribution in the format of a function in the frequency domain. The shape parameter (k) is calculated using a recursive expression with repeated iterations, starting from an initial guess value for k.

Table 3. Tabulation of percentage RMSE for the three probability functions.

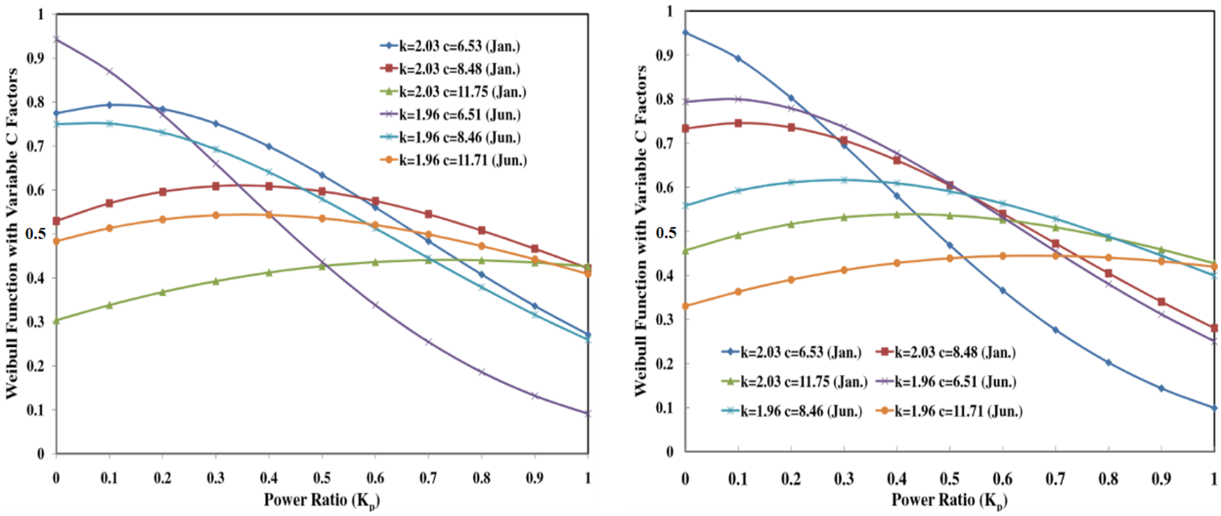
Month	$RMSE_w$ (Zone 1)	$RMSE_r$ (Zone 1)	$RMSE_g$ (Zone 1)	$RMSE_w$ (Zone 2)	$RMSE_r$ (Zone 2)	$RMSE_g$ (Zone 2)	$RMSE_w$ (Zone 3)	$RMSE_r$ (Zone 3)	$RMSE_g$ (Zone 3)
Jan	7.32	7.37	6.62	6.37	7.17	8.42	5.25	4.90	4.87
Feb	6.09	5.82	5.24	5.27	4.71	5.77	4.34	4.37	4.43
Mar	6.45	6.51	5.94	5.60	5.22	7.45	4.70	3.21	10.63
Apr	6.95	6.25	7.37	4.05	4.34	4.92	4.19	4.62	4.53
May	7.49	6.46	6.35	4.48	5.74	6.62	3.07	2.90	3.40
Jun	7.06	7.00	6.33	5.29	5.00	5.27	4.46	4.46	4.03
Jul	5.11	6.13	6.29	5.59	5.80	4.62	4.97	5.17	4.93
Aug	6.95	6.62	5.58	5.42	5.10	0.00	4.64	5.43	6.22
Sep	6.67	6.31	5.05	6.79	6.66	0.00	6.48	6.80	7.33
Oct	5.61	6.40	5.89	6.36	5.27	0.00	4.84	3.47	5.99
Nov	7.23	7.40	7.57	6.21	5.58	5.39	6.52	5.19	5.28
Dec	6.97	6.99	6.75	6.77	7.89	8.65	6.07	5.99	6.47
Average	6.66	6.60	6.25	5.68	5.71	6.35	4.96	4.71	5.67

$$k = [\frac{\sum_{i=1}^{n} {v_i}^k ln(v_i) N(v_i)}{\sum_{i=1}^{n} {v_i}^k N(v_i)} - \frac{\sum_{i=1}^{n} ln(v_i) N(v_i)}{N(v \geq 0)}]^{-1} \quad (15)$$

Here, n is selected on the basis of the available 80 m wind speed at the monitoring station, v_i represents the base wind speed for a particular range, $N(v_i)$ is the frequency with which turbine-scale wind reaches the v_i level, and $N(v \geq 0)$ denotes non-zero data recordings during a particular month. In the next step, the scale parameter (c) is extracted with the help of the calculated shape parameter (k).

$$c = [\frac{1}{N(v \geq 0)} \sum_{i=1}^{n} {v_i}^k]^{\frac{1}{k}} \quad (16)$$

Figure 5 illustrates the two sets of Weibull shape parameters obtained through GLS and MML methods. The MML method produces estimates (1.99-4.36), which are usually higher in magnitude than the projections of the graphical method (1.39-2.91). The same figure also documents the per-unit difference between the two sets, where the average deviation lies within 0.23-0.37 for the three stations. Since Weibull parameters (k) reported for the coastal regions of Bangladesh tend to follow the graphical estimates (Dey, 2006), it can be concluded that the parameters reported in Table 2 will be more suitable for statistical analysis of wind resources in Bangladesh.



(a) (b)

Figure 6. Effect of a variable scale factor when the Weibull function is expressed in terms of power ratio for a) v_{ci}=0.6v_m, v_r=1.5v_m and b) v_{ci}=0.8v_m, v_r=1.9v_m.

3.5. Probability in Terms of Turbine Power

The final step in expanding the Weibull distribution for a turbine location involves expressing the function in terms of turbine output power. This process converts the random variable in the Weibull function, which is wind speed by default, to the energy conversion system's output power. To initiate the transformation, it is required to define the cut-in speed (v_{ci}) and rated speed (v_r) for a wind turbine on the basis of the weighted mean velocity achieved at the location. The rated turbine power (W_{rated}) for the analysis is specified as 500 kW (0.5 MW), which is representative of a medium-scale commercial plant. If real power produced by the turbine is W_r at any time, we may define two extra control parameters (for power and speed) to be included in the modified Weibull function. Firstly, the speed factor k_s is defined as a ratio of the range between rated and cut-in speeds to the limit set by the cut-in speed.

$$k_s = \frac{v_r - v_{ci}}{v_{ci}} \qquad (17)$$

In addition, the power factor k_p is expressed as a ratio of actual output power to rated turbine power.

$$k_p = \frac{W_r}{W_{rated}} \qquad (18)$$

As the period of observation, the months of January and June are selected in Zone 1 (Cox's Bazar) when the Weibull factors $\{k, c\}$ have values of $\{2.029, 6.526\}$ and $\{1.963, 6.505\}$, as obtained from the graphical method. The modified Weibull PDF (probability density function) as a function of turbine output takes the form of (Hetzer, David, & Bhattarai, 2008).

$$f_w(W) = \frac{k k_s v_{ci}}{c_x}\left[\frac{(1+k_s k_p)v_{ci}}{c_x}\right]^{k-1} *\exp\left[-\left\{\frac{(1+k_s k_p)v_{ci}}{c_x}\right\}^{k}\right] \qquad (19)$$

In the analyzed text, the Weibull scale parameter (c_x) is considered a variable to investigate the relationship between factors that define the probability function (k and c) and critical speed ratings for turbine output (v_r and v_{ci}). Figure 6(a) illustrates the modified Weibull probability density function (PDF) plotted against the power factor (k_p) when cut-in and rated speeds are assigned values equal to 60% and 150% of the measured mean velocity. During

January, wind speed PDFs are plotted for k_1= 2.03 and c_x= 6.53 (c_1), 8.48 (= 1.3*c_1), and 11.75 (= 1.8*c_1) m/s. Similarly, during June, when k_2= 1.96, the scale parameter (c_x) assumes a set of values represented by {6.51, 8.46, 11.71} m/s. The findings suggest that smaller values of the c parameter confine the Weibull profile to the spectrum's lower portion, and as the parameter increases in response to stronger wind speeds, a greater segment of the curve shifts to higher power ratios. Therefore, an increase in the scale factor improves the chances of a turbine achieving its rated power, provided it has a suitable shape parameter. Figure 6(b) documents the same set of curves when critical turbine speeds (v_{ci} and v_r) have ratings higher than the previous assignment. The two cases cover the typical range of design speeds [v_{ci} = (0.6~0.8)v_m, v_r = (1.5~1.9)v_m], which will be ultimately determined by the frequency of peak winds available at the location. The figures suggest that when k_2 > 2.0, raising critical speed shifts the Weibull profile to the right of the power ratio scale (as for June when k=1.96). The situation is reversed during January when k=2.03 (>2.0). The modified Weibull functions show a similar trend for the other zones of Bangladesh.

3.6. WPD from Energy Pattern Factors

In the next step of available wind resource assessment, energy pattern factors (K_e) are extracted and used to estimate wind-power densities at turbine axle height. Measured wind data collected at regular intervals and projected at 80 m are used to determine the monthly distribution of K_e factors for a given location. If N is the size of a data set (for a particular month) and v is the mean velocity reading of velocity for that duration, K_e can be defined with the expression.

$$K_e = \frac{1}{N\overline{v}^3}\sum_{i=1}^{N}(v_i)^3 \quad (20)$$

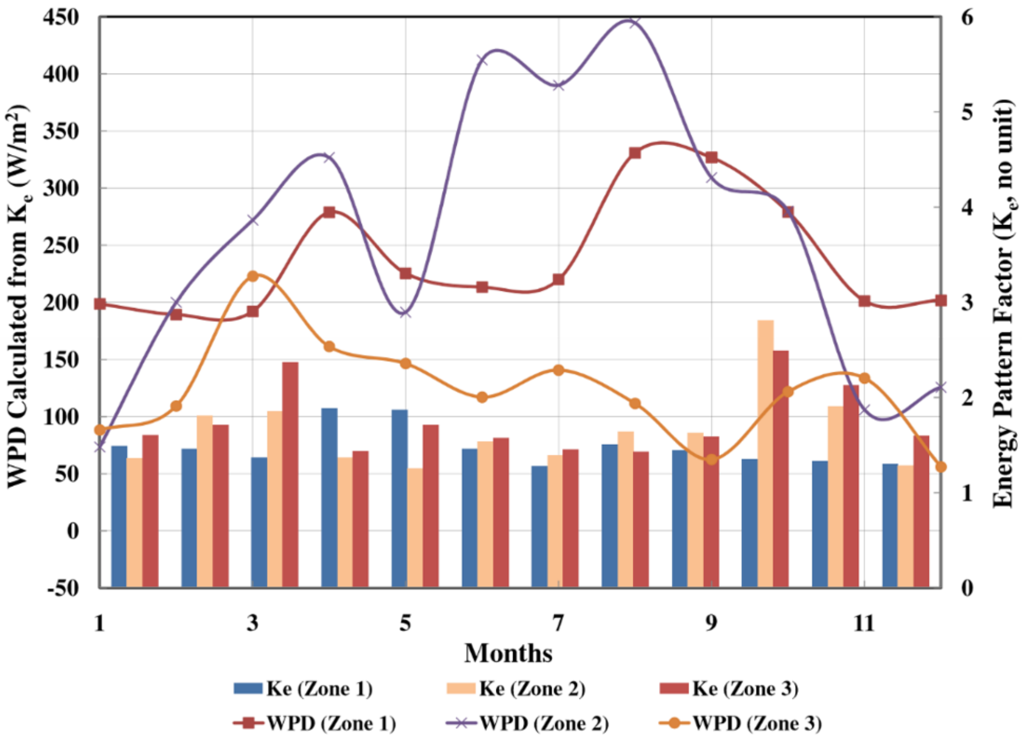


Figure 7. Energy pattern factors for the three zones and corresponding wind power densities.

As K_e is also defined as the ratio of average wind-power-density to WPD calculated from mean wind speed (Dahmouni, Salah, Askri, Kerkeni, & Nasrallah, 2011), it can be used to project turbine-scale WPD with

$$P_{wind_{80}} = \frac{1}{2}K_e\rho\overline{v}^3 \quad (21)$$

Where ρ is the wind density for the selected station (1.225 kg/m^3 for assumed stability). Figure 7 shows the extracted energy pattern factors for the three zones along with the corresponding wind power densities. When projected from K_e factors, WPD readings cover a range of 56-444 watt/m^2. These average estimates follow a similar trend with values calculated directly from wind speed. In contrast, the mean K_e for Cox's Bazar (Zone 1), Khepupara (Zone 2), and Saidpur (Zone 3) are determined as 1.48, 1.65, and 1.76, respectively, suggesting there is no direct correlation between the factor's magnitude and average power density over a long observation period. The overall range of K_e resides within 1.25-2.81 for the country's potential regions.

3.7. Wind Energy Output for Portable Wind Systems

The estimation of actual wind energy output from isolated or grid-connected turbines requires experimental on-site data relating power output of the system (in watts) to available wind velocity at tower height. The absence of empirical power data at the monitoring stations of Bangladesh makes it difficult to model turbine output as a function of wind velocity. In this situation, a power-velocity curve which was reported in (Protogeropoulos, Brinkworth, & Marshall, 1997).

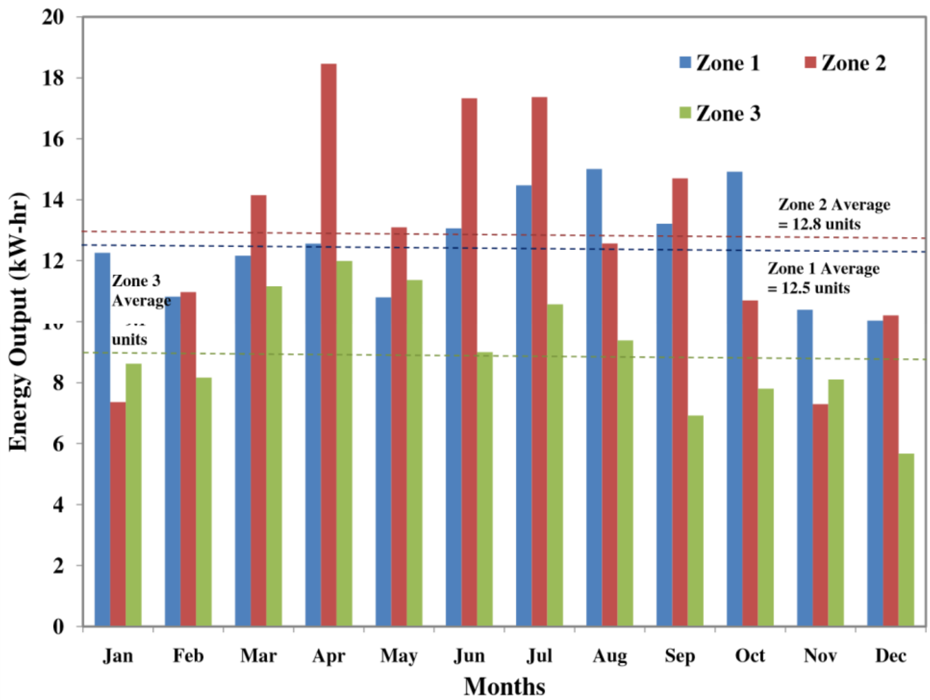


Figure 8. Time-series distribution of wind energy output for a portable wind system.

Celik (2003), for a turbine of 50 W nominal power (swept area 0.65 m^2) is used as a model to calculate estimated wind energy output at the turbine locations. Such a portable system with a small power rating reduces the chance of overestimation in predicted energy output (in kWh or units). These small-scale installations are more expensive in terms of cost efficiency but are useful for autonomous applications and remote locations with no access to the supply grid. According to the empirical system data with a cut-in speed of 1.35 m/s, when the wind velocity at turbine height ranges from 1.4 to 18 m/s, the power output (in watts) can be calculated with Celik (2003).

$$P_{out}(v) = 0.96 - 2.29v + 1.21v^2 - 0.057v^3. \tag{22}$$

The total monthly working period (Δt, in hours) for the turbine is calculated from the number of days when significant streams (greater than cut-in velocity) were recorded at the station. The Weibull distribution is employed for the 1.4-18 m/s range to estimate achievable watt-hours at the location. Finally, energy output (in units) is calculated from the Weibull representative data.

$$E_{out} = \frac{1}{1000}\sum_{i=1}^{n} f_w(v_i)\Delta t P_{out}(v_i) \quad (23)$$

Where $f_w(v_i)\Delta t$ is the working period (in hours) for wind speed v_i and $P_{out}(v_i)$ is the power output generated by this stream. The monthly portable system outputs are presented in a time-series format in Figure 8. The station in Zone 1 is able to generate more than 10 units during every single month of the year. Zone 2 exhibits more variation in the quantity of output, but its peak reaches highs of 17-18 kWh during April, June, and July. On average, the volume of energy production is similar for Zones 1 and 2 (~12.5 kWh), whereas the mean production for Zone 3 is lower (9.1 units).

4. CONCLUSIONS

This study provides an overview of the available potential of commercial wind plants in Bangladesh in the absence of measurement facilities at turbine elevation. Using projection techniques and statistical modeling, wind resources are estimated for a height typically occupied by wind towers of medium power rating (~80 m). Locations that can support standalone or grid-connected turbines are identified based on findings from a United Nations wind/solar resource assessment program. Profiles for the selected areas are established in terms of the energy output of practical systems. Weibull, Rayleigh, and Gumbel probability functions are employed to make predictions about wind speed coverage, and their suitability for different ranges of velocity is determined through performance comparison. Modifications are carried out to improve the scope of the Weibull distribution (probability as a function of speed/power), and Weibull factors are verified against literature data. The aim of this study is to assist in the planning and development phase of future turbine plants for the country.

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