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Introduction

This assignment focuses on the detailed assessment of wind energy resources using real-world wind data collected from Wind Turbine located at Dundalk Institute of Technology for the year 2008. The wind data measurements were recorded at 10-minute intervals over the entire year, providing time-averaged data for a comprehensive evaluation of wind conditions at the site. The analysis involves the evaluation of key wind characteristics, including wind speed, direction, and power output, using various statistical and graphical methods.

The project will cover wind characteristic knowledgeable such as the wind speed variation with height, atmospheric conditions, and turbulence, and explore how these factors influence wind energy potential. Additionally, tools such as the bar, plot, Weibull distribution and wind rose visualizations will be used to analyze wind patterns. The methodology will include calculating the average velocity, the standard deviation of wind speed and estimating the shape and scale factors.

Furthermore, an analysis of the actual and expected energy output will be performed, followed by a comparison of the turbine's capacity factor. Through this approach, a comprehensive understanding of the wind turbine's performance will be developed, helping in the prediction of future energy yields and overall efficiency. This will aid in the evaluation of wind energy potential at the site.

Wind Characteristics

Global and Local Wind Patterns

Wind is generated due to the uneven heating of the Earth's surface by solar radiation, leading to the movement of air masses from high-pressure to low-pressure regions.

The Coriolis effect due to Earth's rotation influences wind direction, causing deflection to the right in the northern hemisphere and to the left in the southern hemisphere. This deflection leads to the formation of atmospheric cells—Hadley, Ferrel, and Polar cells (Figure 1)—that determine global wind patterns.

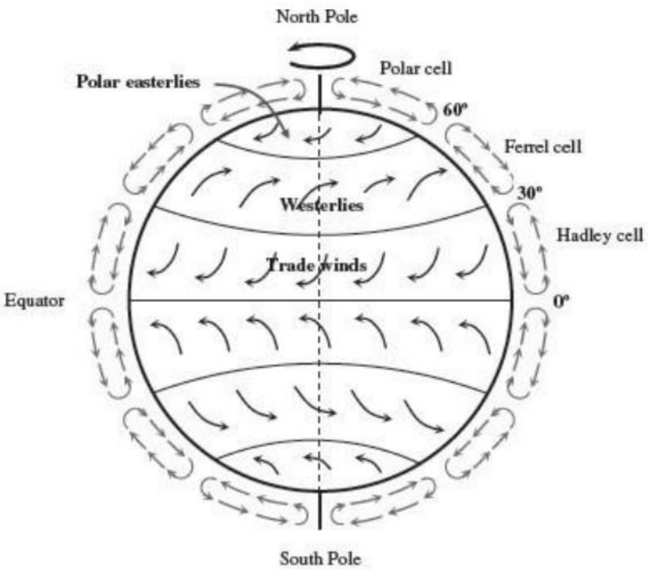

Figure 1 The Formation of Atmospheric Cells

Wind Shear and Local Effects

Wind Shear refers to the change in wind speed with height above the ground. It occurs because wind is slowed down near the surface due to friction with obstacles (trees, buildings, etc.)

Local Effects influence wind speed and direction in specific geographical areas.(such as: Surface Roughness, Topography, Thermal Effects)

Atmospheric

The **atmospheric boundary layer** is the lower part of the atmosphere where wind speeds are influenced by surface friction, with speeds generally increasing with height. **Atmospheric stability** affects how wind behaves; stable conditions restrict vertical movement, while unstable conditions promote turbulence, impacting wind consistency. Additionally, **atmospheric density and pressure** decrease with altitude and are influenced by temperature. Higher air density, which occurs in colder conditions, leads to greater wind energy potential as wind power is directly proportional to air density.

$$\rho = 3.484P/T$$

Equation 1

Wind Speed Variation with Height

Wind speed increases with height due to reduced friction from the Earth's surface. This phenomenon is referred to as wind shear.

There are two key methods to model wind speed variation with height:

The Logarithmic Law, used for theoretical modeling (HOMERPro n.d.).

$$U_z = U_{zr} \frac{ln(\frac{z}{z_0})}{ln(\frac{z_r}{z_0})}$$

Equation 2

Where：

U_z is the wind speed at height z

U_{zr} is the wind speed at reference height

z_0 and z_r is the surface roughness.

The Power Law, a more empirical approach commonly used in the wind energy industry (HOMERPro n.d.).

$$U_z = U_{zr} \left(\frac{z}{z_r}\right)^a$$

Equation 3

Where：

U_z is the wind speed at height z

a is the wind shear exponent (typically a = 1/7)

Turbulence

As wind passes over obstacles, it generates turbulence, leading to fluctuations in both speed and direction. Turbulence reduces the power available in the wind stream and imposes fatigue loads on wind turbines.

Turbulence is random wind speed fluctuations about a mean wind speed. This means that while the overall wind speed may stay around a specific average, there are unpredictable and sudden increases and decreases in the speed.

A gust is a discrete event in a turbulent wind field.

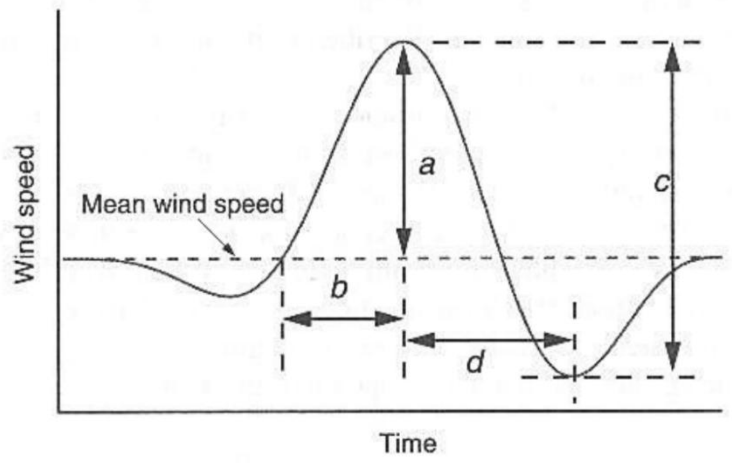

Figure2 Illustration of a discrete gust event

In the plot, we can see how the wind speed varies above and below the mean value, showing how unpredictable turbulence can be. The section marked with the rise (labelled "a") shows a gust event, where the wind speed increases sharply above the mean wind speed for a short time before decreasing again.

Where:

a: Amplitude (The maximum wind speed during the gust).

b: Rise time (The time before the gust begins).

c: Maximum gust variation (The magnitude or difference between the gust peak and mean wind speed).

d: Lapse time (The duration of the gust).

Terrain Effects

The terrain plays a significant role in wind characteristics. Wind flowing over rough or irregular terrain experiences more friction, resulting in lower wind speeds near the surface. Conversely, smooth, flat terrain allows wind to flow with less resistance, increasing wind speeds at lower heights. Topographic features such as mountains and ridges can channel and accelerate wind flow through natural corridors, enhancing wind speeds in these areas, which makes them ideal for wind farm installations. Figure3 illustrates how mountains can funnel wind, resulting in higher wind speeds due to the Venturi effect.

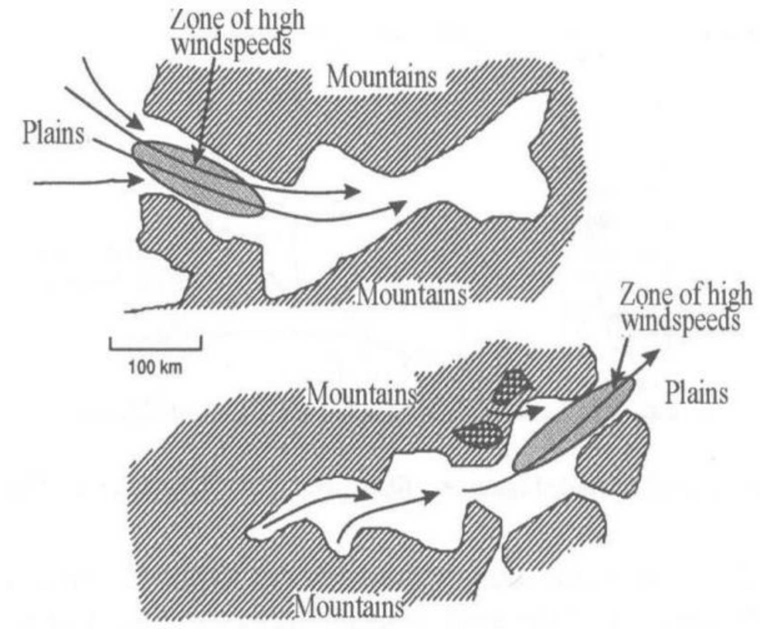

Figure 3 Increased wind speed due to channeling of prevailing winds by mountains

Wind Variation in time.

Wind Resource Assessment and Energy Potential Estimation

Wind Direction Variation:

Wind direction changes on the same timescales as wind speed.

Short-term changes in wind direction affect turbine yaw, potentially increasing gyroscopic loads on the turbine. Figure4 the wind rose shows wind direction distribution. Wind predominantly comes from certain directions (indicated by the largest sectors), and the speed of wind from each direction is color-coded (e.g., blue for higher speeds).

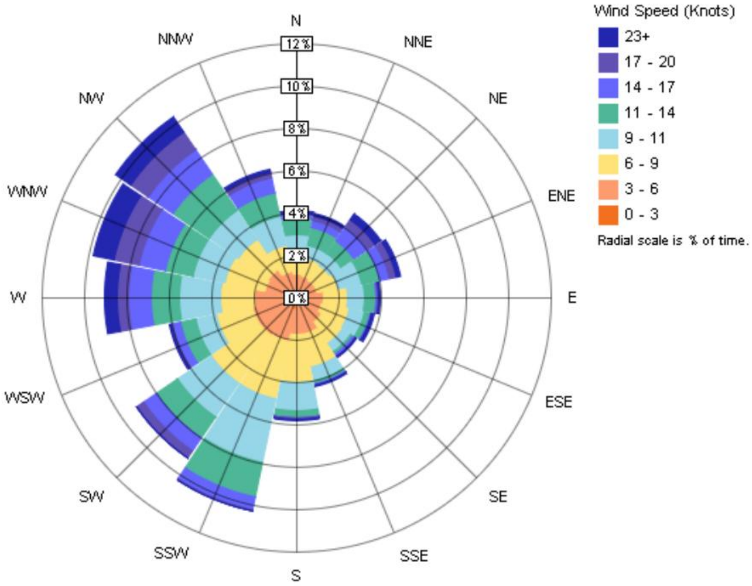

Figure 4 The wind rose

Wind energy is derived from the kinetic energy of moving air, and its conversion into electrical power depends heavily on the wind characteristics at a given location. Understanding these characteristics is critical for evaluating the feasibility of wind energy projects. The wind's behavior is influenced by various atmospheric and geographic factors, such as the Coriolis effect, wind shear, turbulence, terrain, and temporal variations. These factors impact wind speed, direction, and ultimately, the amount of energy that can be harnessed by wind turbines.

Wind Statistics

Turbulence Intensity (I or TI) is defined as the ratio of the standard deviation of wind speed (σU) to the mean wind speed (U). Higher values of I (e.g., 0.3) indicate more turbulence, while lower values (e.g., 0.1) indicate smoother wind conditions.

$$I = \frac{\sigma U}{U}$$

Equation 4

σU measures the variability in wind speed over a time period, typically using **1-second samples over 10 minutes.**

$$\sigma U = \sqrt{\frac{1}{N_s - 1} \sum_{i=1}^{N_s} (u_i - U)^2}$$

Equation 5

Where:

N_s is the number of samples

u_i is the instantaneous wind speed

U is the mean wind speed

Mean Wind Speed (U)
Integrating the instantaneous wind speed u over time:

$$U = \frac{1}{\Delta t} \int_0^{\Delta t} u \, dt$$

Equation 6

Or by taking a numerical average of instantaneous wind speed samples u_i:

$$U = \frac{1}{N_s} \sum_{i=1}^{N_s} u_i$$

Equation 7

Instantaneous Wind Speed (u)
The wind speed at any given moment can be described as the sum of the mean wind speed (U) and the fluctuating component (turbulence) $\tilde{u}$.

$$u = U + \tilde{u}$$

Equation 8

This shows that the actual wind speed fluctuates around the mean due to turbulence.

Wind Turbine Energy Conversion
The section covers several methods for estimating the energy output of wind turbines by analyzing wind data.

Direct Use of Data:

Uses raw wind speed observations, averaging over time intervals.

long-term average wind speed.

$$U = \frac{1}{N} \sum_{i=1}^{N} U_i$$

Equation 9

standard deviation

$$\sigma U = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (U_i - \tilde{U})^2}$$

Equation 10

Average wind power density (P), which is proportional to wind speed cubed (Green Rhino Energy, n.d.-b).

$$P=\frac{1}{2}*\rho*A*U^3$$

Equation 11

where ρ is the air density, A is the area swept by turbine blades, and U is the wind speed.

Method of Bins

This method organizes wind speed data into intervals or "bins" and calculates the turbine's energy output based on the time spent in each wind speed bin.

The wind speed data is divided into N_B bins of width w_j, with m_j as the midpoint of each bin. The occurrences in each bin (f_j) determine the time the wind speed stays in that range.

$$E = \sum_{i=1}^{N_B} f_i P(m_j) w_j$$

Equation 12

Where:

f_i is the frequency of wind speed in each bin,

m_i is the midpoint wind speed of each bin,

$P(m_i)$ is the power output at the midpoint speed,

w_i is the bin width.

Energy Calculation: The average wind turbine power for each bin is multiplied by the time spent in that bin to determine the energy generated. The sum of these gives the total energy output over the period.

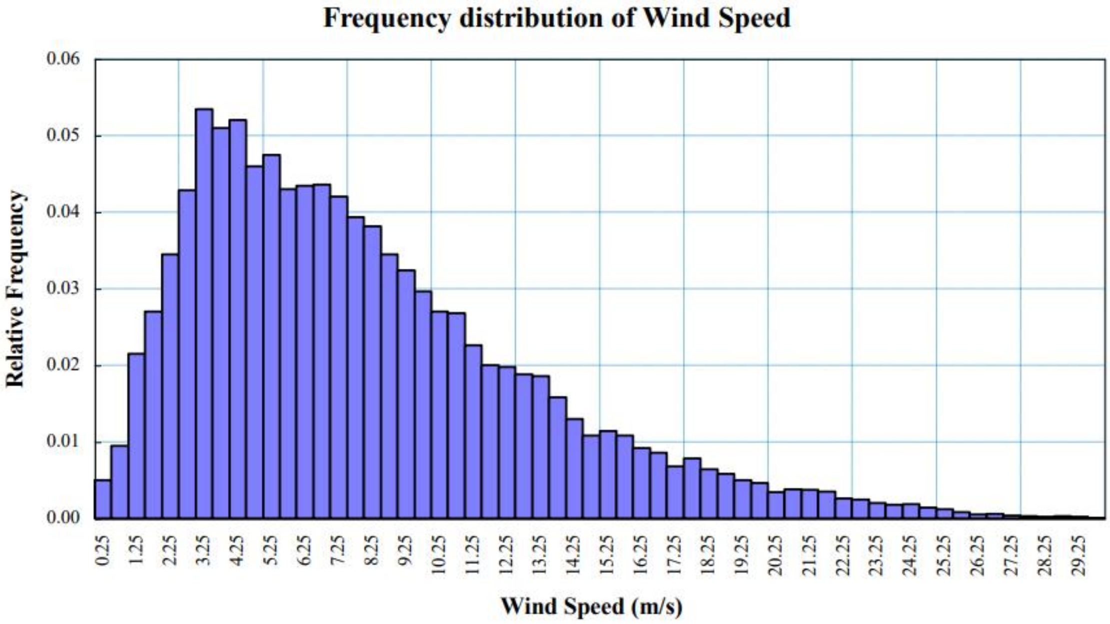

Figure 5 frequency distribution of wind speed

Weibull Distribution for Wind Speed

Wind speed distributions are often modeled using the Weibull distribution, characterized by two parameters: the shape factor (k) and the scale factor (c).

Probability Density Function (PDF) (Green Rhino Energy, n.d.-a).

$$p(U) = \frac{k}{c}(\frac{\mathrm{U}}{c})^{k-1}\mathrm{exp}\,(-(\frac{\mathrm{U}}{c})^{k})$$

Equation 13

Where:

U: The wind speed

k: The shape parameter

c: The scale parameter

Energy Yield: The total energy yield is obtained by multiplying the power curve of the turbine with the probability density function and integrating:

$$\mathrm{E} = 8760 * \int_0^\infty p(U)\mathrm{P(U)dU}$$

Equation 14

Where：

8760 is the total number of hours in a year. It comes from:

8760 = 24 hours/day * 365 days/year

p(U) is the probability density function (PDF) of wind speeds at the turbine site. It describes how often different wind speeds U occur during a given period (e.g., a year).

P(U) is the power curve of the wind turbine, the power curve defines how much power the wind turbine generates at different wind speeds.

dU represents a small increment of wind speed in the integration process.

Duration Curves

Duration curves plot wind speed against the number of hours during which each wind speed is exceeded. These curves can be converted to wind power duration curves using the power equation:

$$P=\frac{1}{2}*\rho*A*U^3$$

The **energy output** is calculated by integrating the wind power duration curve to account for the turbine's power curve features. This approach helps to estimate the turbine's annual energy output.

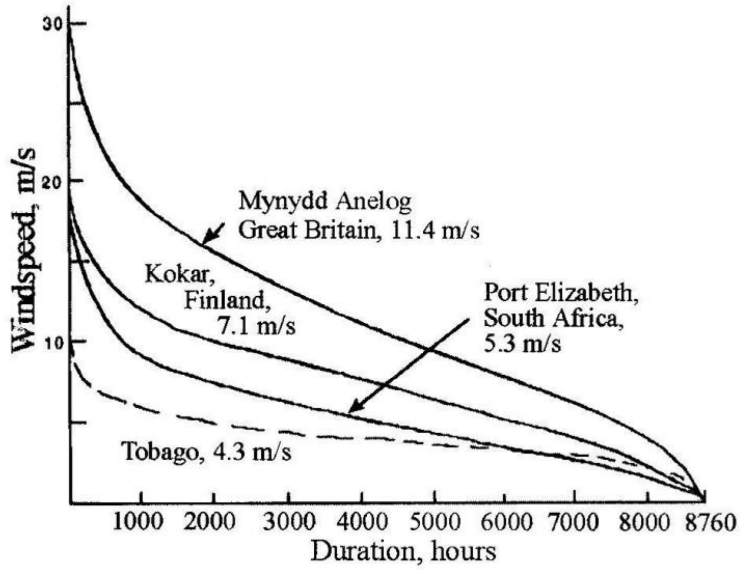

Figure 6 wind speed (m/s) versus duration (hours) over a year (8,760 hours)

Measure-Correlate-Predict (MCP)
This method correlates wind measurements from a site with long-term data from nearby reference stations to predict future wind speeds. This is crucial for long-term energy production forecasting and site assessment.

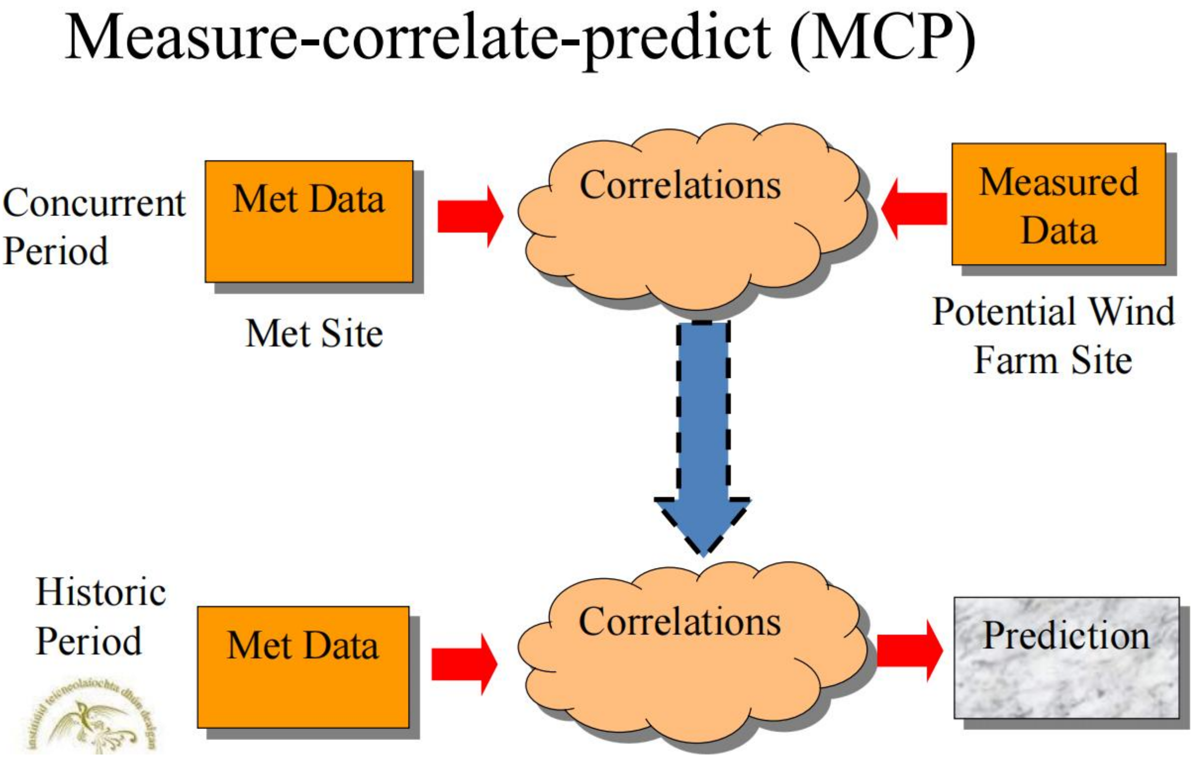

Figure 7 Measure-Correlate-Predict (MCP) process

Figure7 shows that the Measure-Correlate-Predict (MCP) method is used to estimate long-term wind conditions at a potential wind farm site by correlating data from a nearby reference meteorological (Met) site. During the Concurrent Period, wind data is collected at both the Met site and the wind farm site. These datasets are then correlated to establish how the wind characteristics at both sites relate to each other. In the Historic Period, long-term historical data from the Met site is used. The correlations from the concurrent period are applied to this historical data to predict future wind conditions at the potential wind farm site, allowing for accurate energy production estimates without requiring long-term measurements directly at the site. The MCP method helps predict long-term wind behavior at a new wind farm site using existing data from a nearby Met site, enabling cost-effective, informed decisions about energy yield and project feasibility.

Methodology

Function in MALAB Describe

Function in MALAB	Describe	Reference
xlsread()	Read data from an Excel file	(MathWorks, n.d.)
wind_data(:,1)	Extracts the first column from wind_data	
length()	The length of the largest array dimension.	
start:step:end	This creates a vector starting at start, incrementing by step, and ending at end, such as (1:1:n) dividing each element of this vector by n to normalize the values to a range from 1/n to 1.	
plot()	Create 2-D line plots	
mean()	Calculates the arithmetic mean (or average) of the input data.	
std()	Computes the standard deviation of the elements in an array. By default, it normalizes by (N-1), where (N) is the number of observations	
max()	Calculate the maximum value within an array.	
histc()	Count the number of data points that fall into predefined bins	
bar()	Creates bar plots (also known as histograms or bar charts). It is often used to visually display how frequently values occur in different categories (such as wind speeds or power outputs).	
Weibull probability density		

function (PDF)		
Polarhistogram()	Creates a polar histogram for wind direction at various speed ranges	
deg2rad(direction(speed < 25))	Converts wind direction from degrees to radians for plotting. The condition speed < 25 filters data for wind speeds less than 25 m/s.	
hold on	Ensures that multiple plots (for different speed ranges) are displayed on the same figure	
facecolor	Sets different colors for each histogram (red, yellow, green, blue) to represent different wind speed ranges.	
polaraxes	Creates a polar coordinate system	
ThetaDir	This property controls the direction in which the angles are displayed in a polar plot.	
	When set to 'clockwise', the angles on the polar plot increase in a clockwise direction.	
	When set to 'counterclockwise', the angles increase in a counterclockwise direction (this is the default behavior in MATLAB).	
ThetaZeroLocation	This property specifies where the 0-degree angle is located on the polar plot.	
	'top': The 0-degree angle is positioned at the top of the polar plot (12 o'clock position).	
	'right': The 0-degree angle is positioned at the right (3 o'clock position).	

	'bottom': The 0-degree angle is positioned at the bottom (6 o'clock position).	
	'left': The 0-degree angle is positioned at the left (9 o'clock position).	
RTick	The radial tick marks on a polar plot.	

Table 1 Matlab Function Details

Import And Process The Wind Data

```
%%Important wind data input in MALAB

wind_data = xlsread('Wind_data.xls'); % Reads the data from the Excel file named 'Wind_data.xls' and stores it in the variable wind_data.

wind_speed = wind_data(:,1); %wind speed

wind_direction = wind_data(:,3); %wind direction

power = wind_data(:,5); %power generated

n = length(speed); % the number of speed

tm = (1:1:n) ./ n * 12; % Creates a time vector tm that spans from 0 to 12
```

Calculate Wind Statistics

Average Wind Speed

The mean wind speed is a measure of the wind resource. Higher mean wind speeds normally indicate better wind resources (Global Wind Atlas n.d.).

```
v_mean = mean(speed); % mean wind speed
```

The Standard Deviation Of The Wind Velocity

The standard deviation of wind velocity is a measure of how much the wind speeds vary from the average wind speed over a specific period. It provides insight into the variability and consistency of wind speeds at a particular site.

```
%%standard deviation and mean velocity

Stdwind = wind_data(:,2); %standard of the 10 minutes samples

S = std(Stdwind);%stand deviation of dataset
```

```
v_mean = mean(speed); % mean wind speed
v_std = v_mean*S;
```

The shape (k) and scale (c) factors

```
%%shape and scale factor
k = (0.9874/(v_std/v_mean))^1.0983;
c = ((1/n)*sum(speed.^k))^(1/k);
```

Smith et al. (2015) discuss the k formula as follow:

$$k = \left(\frac{0.9874}{\frac{\sigma}{\bar{v}}}\right)^{1.0983}$$

Where:

σ is the standard deviation of wind speed

$\bar{v}$ is the average wind speed

Windpower Plus (n.d.) provides the c formula as follow:

$$c = \left(\frac{1}{N}\sum_{i=1}^{N} {v_i}^k\right)^{\frac{1}{k}}$$

Where:

N is the number of observations

v_i is the average wind speed recorded in time interval i

Calculating the shape and scale factors for a Weibull distribution is crucial for accurately modeling and understanding data behavior, particularly in fields like reliability engineering and wind energy analysis. In wind energy analysis, these factors are used to accurately model wind speed distributions, which helps in estimating energy production potential and optimizing decisions regarding turbine placement and design.

The shape factor (k) determines the form of the Weibull distribution and influences the skewness and variability of the data. It helps identify whether the data represents early variability, constant rate, or stable increase. For example, k < 1 indicates decreasing trends (e.g., early failures), k = 1 represents constant trends, and k > 1 suggests increasing trends, often seen in consistent or stable wind speeds (Wikipedia, 2024).

The scale factor (c) measures the characteristic value of the distribution, affecting how the data is spread along the x-axis. It represents the typical value around which data is centered, helping in understanding the average behavior, such as the characteristic wind speed in energy assessments.

Generate Visualizations

Wind Speed

```
%%plotting wind speed v/s Month
figure()
plot(tm,speed)
xlabel('Time (month)')
ylabel('Wind Speed (m/s)')
title('Wind Speed')
legend('Time')
```

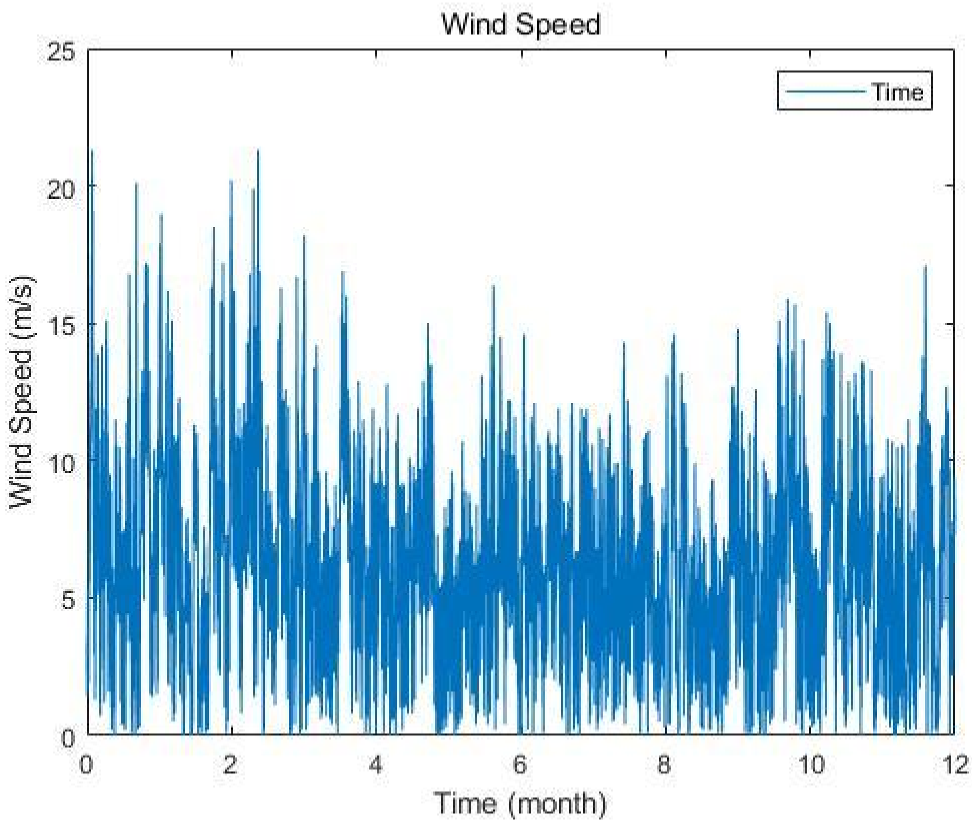

Figure 8 Time vs Wind Speed

Figure8 generates a plot showing how wind speed varies during 12-month period represented by time vector. The x-axis represents the time in months, spanning from 0 to 12 (January to December). The y-axis represents wind speed (m/s). The plot shows how wind speed fluctuates over time throughout the year. There is no clear upward or downward trend, which suggests that are significant fluctuations in wind speed, with peaks reaching up to 20 m/s and wind speeds occasionally dropping close to zero.

Wind Power

```
%%plotting wind power kW Month

figure()

plot(tm,power)

xlabel('Time (month)')

ylabel('Wind Power (kW)')

title('Wind Power')

legend('Time')
```

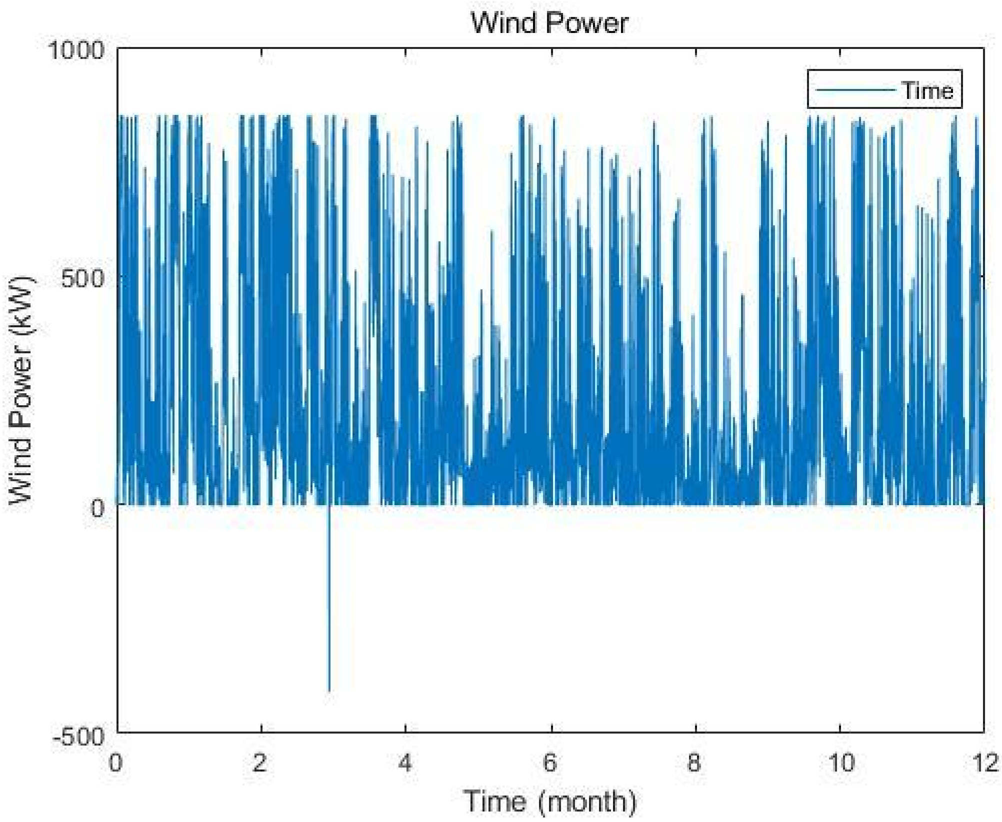

Figure 9 Time vs Wind Power

Figure9 shows the variability of power output from the turbine over the course of 12 months. The power fluctuates significantly, reflecting the changing wind speeds throughout the year. Occasionally, there are periods of zero or negative power, possibly due to turbine downtime or very low wind speeds. The turbine reaches its peak capacity (close to 850 kW) when wind conditions are optimal.

Velocity Bins

```
%%Histogram
%speed
M_speed = max(wind_speed); %max speed

bin_s = (0:1:M_speed);%creates bins that range from 0 to the maximum wind speed in steps of 1 m/s. Each bin will hold the wind speeds that fall within that 1 m/s interval.

v_bin = histc(wind_speed, bin_s); %This line groups the speed data into bins defined by bin_s. The function histc counts the number of values in speed that fall into each bin, resulting in a histogram count stored in v_bin.

figure()

bar(v_bin)% generates a bar chart from the bin counts (v_bin)

xlabel('Wind Speed (m/s)')

ylabel('Frequency (n)')

title('Frequency Distribution of Wind Speed')

legend('Wind Speed')
```

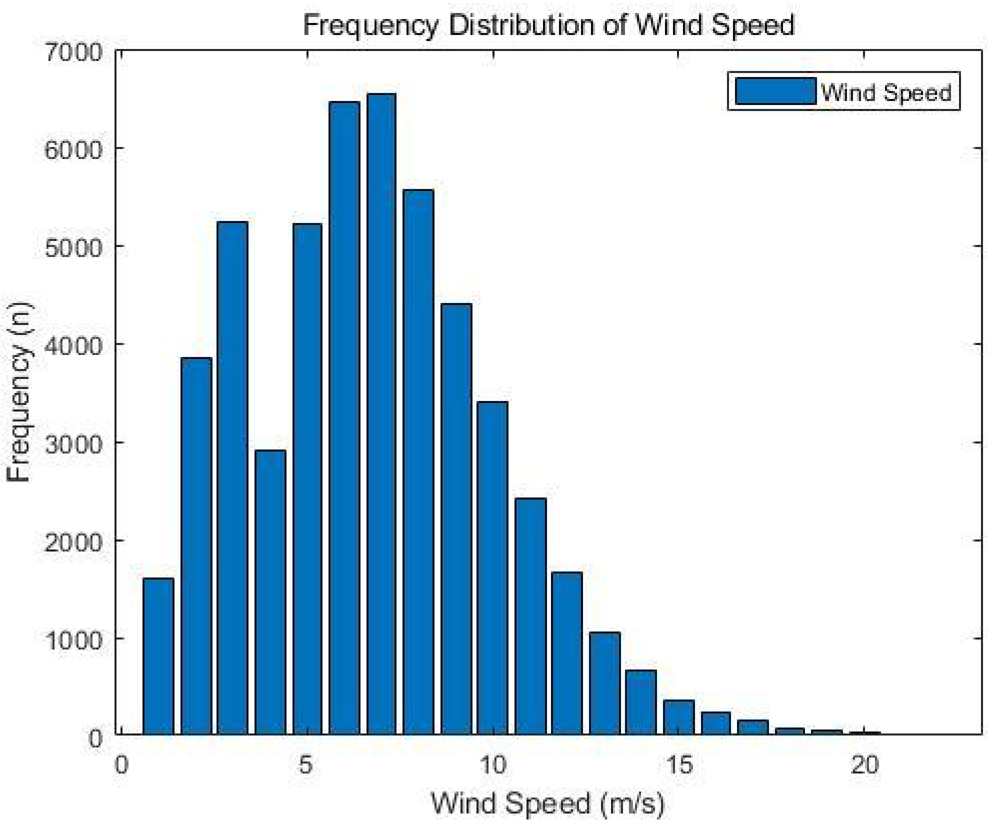

Figure 10 Present the data in speed bins.

The histogram visualizes the distribution of wind speeds,which is crucial for applications like wind energy. The x-axis represents wind speeds (in m/s), and the y-axis represents the frequency of each speed. The peak around 6-7m/s indicates that these wind speeds are the most common at a site, identifying the most common speeds, and understanding the variability in wind speeds. It is with fewer occurrences of very low or very high wind speeds. The distribution is positively skewed (longer tail to the right), indicating that higher wind speeds are less frequent than lower to moderate wind speeds.

Wind Power Bins

The histogram visualizes the distribution of wind speeds,which is crucial for applications like wind energy. The x-axis represents wind speeds (in m/s), and the y-axis represents the frequency of each speed. The peak around 6-7m/s indicates that these wind speeds are the most common at a site, identifying the most common speeds, and understanding the variability in wind speeds. It is with fewer occurrences of very low or very high wind speeds. The distribution is positively skewed (longer tail to the right), indicating that higher wind speeds are less frequent than lower to moderate wind speeds.

```
M_power = max(power); %max power
bin_p = (0:1:M_power);% This creates a vector bin_p that ranges from 0 to M_power in increments of 1. This vector will be used to define the bins for grouping the power data.

p_bin = histc(power, bin_p); % This line groups the power data into bins defined by bin_p. The function histc counts the number of values in power that fall into each bin, resulting in a histogram count stored in p_bin.
figure()
bar(p_bin)% generate bar chart
plot(speed,weibull_dist, '.')
xlabel('Power (kW)')
ylabel('Frequency (n)')
title('Frequency Distribution of Wind Power')
legend('Wind Power')
```

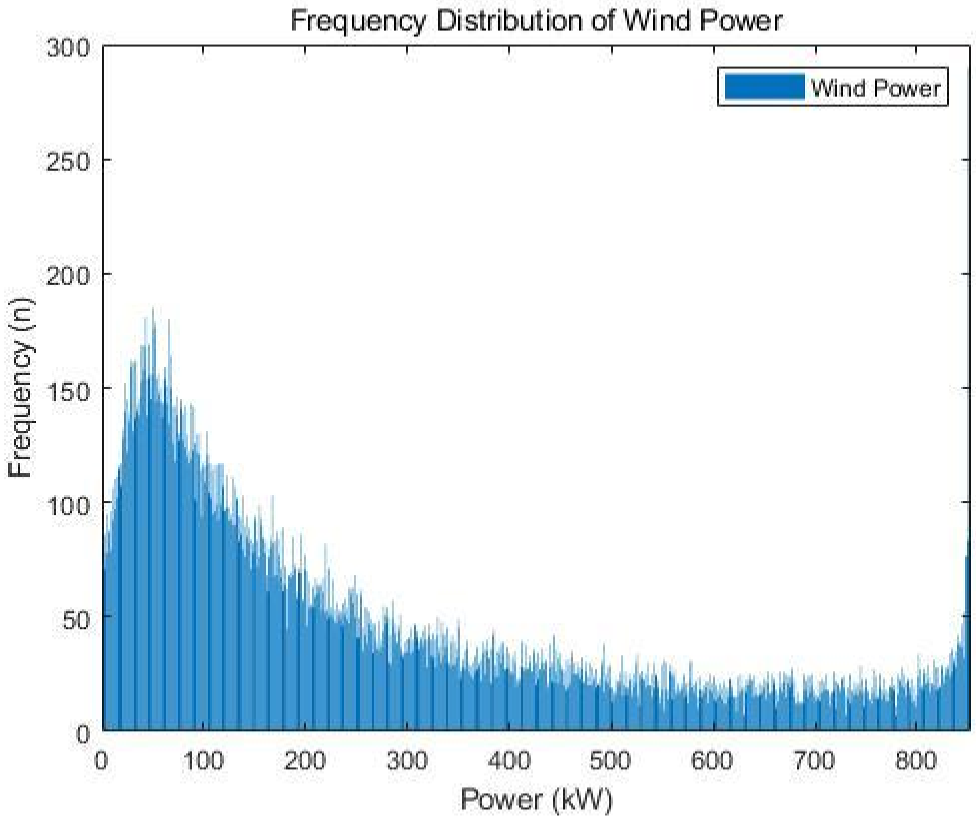

Figure 11 Present the data in the power bins

Figure11 histogram visualizes how often the wind turbine generates different levels of power output over time. The x-axis represents power outputs (kW), it shows a range from 0 to approximately 850 watts, indicating the power generated by the wind turbine, and the y-axis represents the frequency of each power output. Low Power Outputs (0-100 kW) occur most frequently, meaning the turbine often operates in lower wind speed conditions that produce smaller amounts of power. High Power Outputs (400-800 kW) are much less frequent, indicating that strong winds capable of generating the turbine's maximum output are rare. There is a noticeable rise near the turbine's rated capacity of around 850 kW, suggesting occasional high wind events allow for full power generation, but these are not common.

Wind Energy Bins

```
%Energy bins

M_Energy = max(Energy); %max Energy

bin_s3 = (0:1:M_Energy);%bin vector

v_Energy = histc(Energy, bin_s3); %Grouping of energy data into bins

figure()

bar(v_Energy)% generate bar chart
```

```
xlabel('Wind Energy (kWh)')
ylabel('Frequency (n)')
title('Frequency Distribution of Wind Energy')
legend('Wind Energy')
```

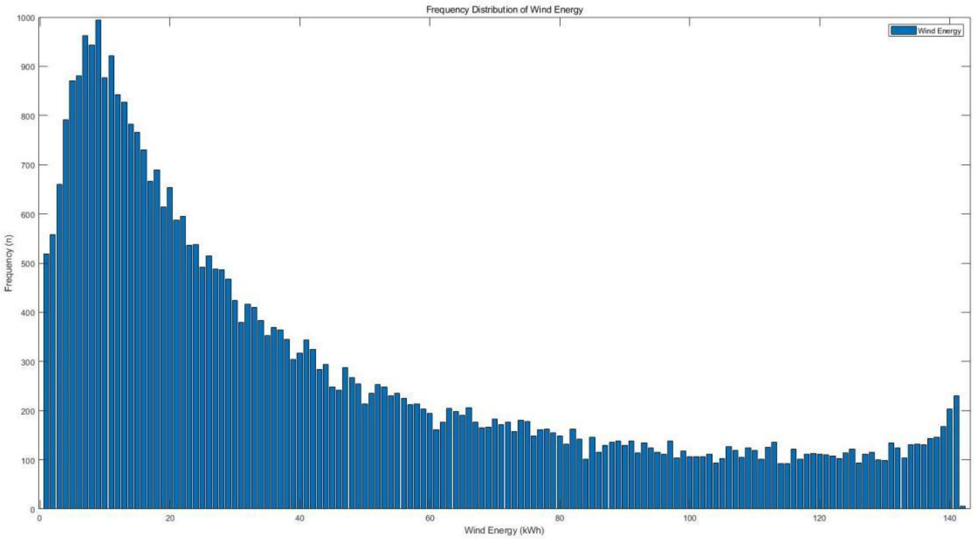

Figure 12 Frequency Distribution of Wind Energy

Figure12 shows that the x-axis is the wind turbine generates energy values in kWh. The range from 0 to 140 kWh indicates that energy outputs are grouped into bins, with each bin representing a small range of energy values. The y-axis represents the frequency of occurrences of energy output within each bin. The peak frequency occurs in the range of 10 to 20 kWh, suggesting that this is the most common energy output from the turbine based on the wind speeds in wind_data file. As expected, the occurrence of higher energy outputs is much rarer, indicating that the turbine doesn't often reach its maximum capacity.

Weibull Distribution

The Weibull distribution is a probability distribution used to model the lifetime or reliability of products, systems, or materials. It was introduced by Wallodi Weibull in 1951. It is characterized by two parameters: the shape parameter, which determines the hazard rate's shape (increasing, decreasing, or constant), and the scale parameter, which determines the location on the time axis. The flexible distribution can capture various failure patterns, making it valuable for reliability analysis. It helps assess and predict the reliability and lifetime of various objects, making it widely used in engineering, finance, healthcare, and other fields (Wallstreetmojo n.d.).

```
%%calculate and visualize the Weibull probability density function (PDF)
for wind speeds
weibull_dist = (k/c)*(speed/c).^(k-1).*exp(-(speed/c).^k);
figure()
plot(speed,weibull_dist, '.')
xlabel('Wind Speed (m/s)')
ylabel('Weibull Distribution')
title('Weibull Distribution vs Speed')
legend('Wind Speed')
```

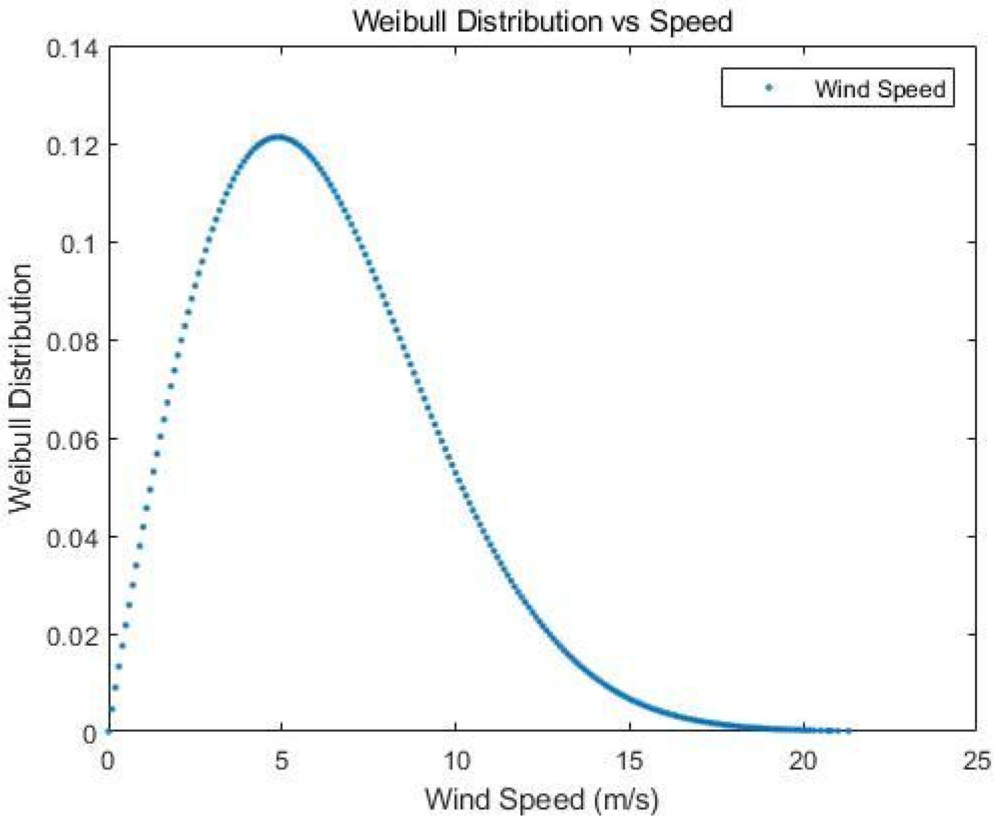

Figure 13 Weibull Distribution vs Speed

Figure14 shows a typical Weibull distribution curve representing wind speeds. On the x-axis, wind speeds range from 0 to 25 m/s, and on the y-axis, the Weibull distribution values represent the probability density function (PDF) of each wind speed. The peak of the curve, between 5-7 m/s, represents the most frequent wind speeds at the site. The curve sharply declines after this peak, indicating that higher wind speeds are less frequent. It approaches zero at around 20 m/s, suggesting that very high wind speeds are rare. This distribution highlights that the majority of wind speeds are in the moderate range (~5-7 m/s). The curve's shape factor (k) influences the curve's width and peak, while the scale factor (c) shifts the distribution to higher or lower wind speeds. This type of analysis is widely used in wind energy assessments and reliability engineering to model distributions.

```
%%calculate and visualize the Weibull probability density function (PDF)
%%for wind speeds bins
weibull_dist = (k/c)*(bin_s/c).^(k-1).*exp(-(bin_s/c).^k);
figure()
plot(bin_s,weibull_dist, '-x')
xlabel('Wind Speed Bins (m/s)')
ylabel('Weibull Distribution')
title('Wind Weibull Distribution of Speed Bins')
legend('Wind Speed Bins')
```

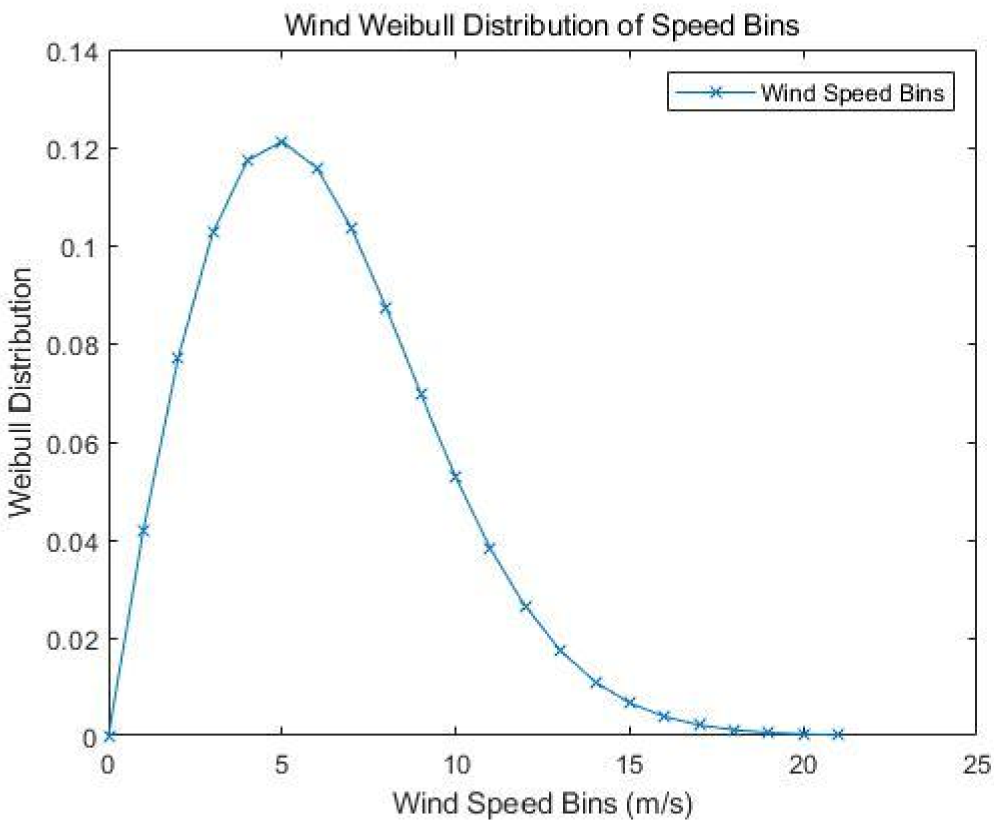

Figure 14 Wind Weibull Distribution of Speed Bins

Figure15 is same as the Figure14 the distribution starts at the origin, rises to a peak around bin_s value 5-7m/s, and then gradually decreases, approaching zero beyond 20. This indicates that the probability density is highest around 5-7m/s. The shape and scale parameters (k) and (c) influence the curve's peak and spread. Higher (k) values make the distribution more peaked, while (c) scales the distribution along the bin_s axis. This type of distribution is often used in reliability engineering and failure analysis to model time-to-failure data or wind speed distributions.

Wind Rose

```
%%wind Rose
figure()
pax = polaraxes;
polarhistogram(deg2rad(direction(speed<25)),60 , 'displayname', '20-25 m/s')
hold on
polarhistogram(deg2rad(direction(speed<20)),60 ,'facecolor','red','displayn
ame', '15-20 m/s')
polarhistogram(deg2rad(direction(speed<15)),60 ,'facecolor','yellow','displ
ayname', '10-15 m/s')
polarhistogram(deg2rad(direction(speed<10)),60 ,'facecolor','green','displa
yname', '5-10 m/s')
polarhistogram(deg2rad(direction(speed<5)),60 ,'facecolor','blue','displayn
ame', '0-5 m/s')

legend('show')
title('wind Rose')

pax.ThetaDir = "clockwise"; % sets direction for displaying angles
clockwise
pax.ThetaZeroLocation = "top"; % fixed angle 0 at the top pf the graph

%Displaying direction
text(deg2rad(0),max(pax.RTick),'N')
text(deg2rad(45),max(pax.RTick),'NE')
text(deg2rad(90),max(pax.RTick),'E')
text(deg2rad(135),max(pax.RTick),'SE')
text(deg2rad(180),max(pax.RTick),'S')
text(deg2rad(225),max(pax.RTick),'SW')
text(deg2rad(270),max(pax.RTick),'W')
text(deg2rad(315),max(pax.RTick),'NW')
```

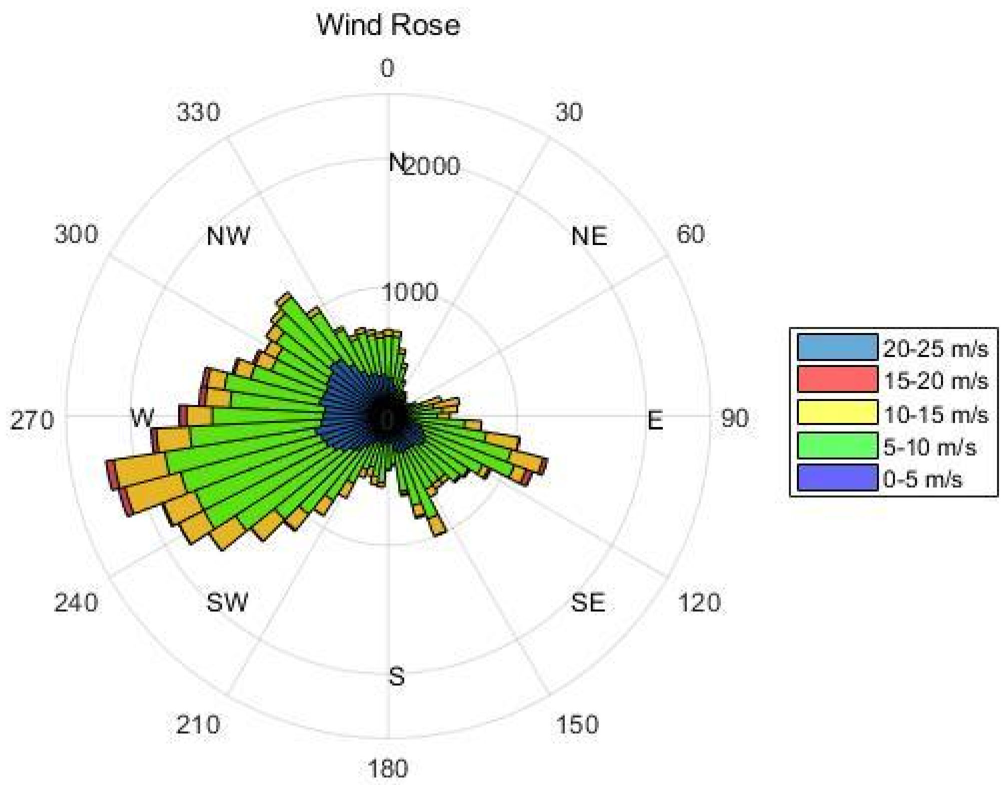

Figure 15 Wind rose

Figure16 provides a clear and detailed visualization of wind characteristics at various speed intervals. The wind blows predominantly from the west (270°) direction, with the 5-10 m/s range being the most frequent. Here's a summary of the findings:

0-5 m/s (Blue): Calmest winds, mostly from the southwest and west.

5-10 m/s (Green): Most common winds, primarily from the west and southwest.

10-15 m/s (Yellow): Less frequent, mainly from the west.

15-25 m/s (Orange/Red): Strongest but least frequent winds, still coming from the west.

This distribution helps in understanding the wind direction and speed patterns, important for turbine placement and energy prediction.

Vestas V52 Power Curve

```
%% Vestas V52 Power Curve
Vestas_V52 = xlsread('VestasV52.xlsx');
power_V52 = Vestas_V52(:,2); %power
bin_s2 = Vestas_V52(:,1); %storing speed data
figure()
plot(bin_s2, power_V52,'g','LineWidth',2)
```

```
title('Vestas V52 Power Curve')

xlabel('Vestas V52 Speed Bins (m/s)')

ylabel('Vestas V52 Wind Power(kW)')
```

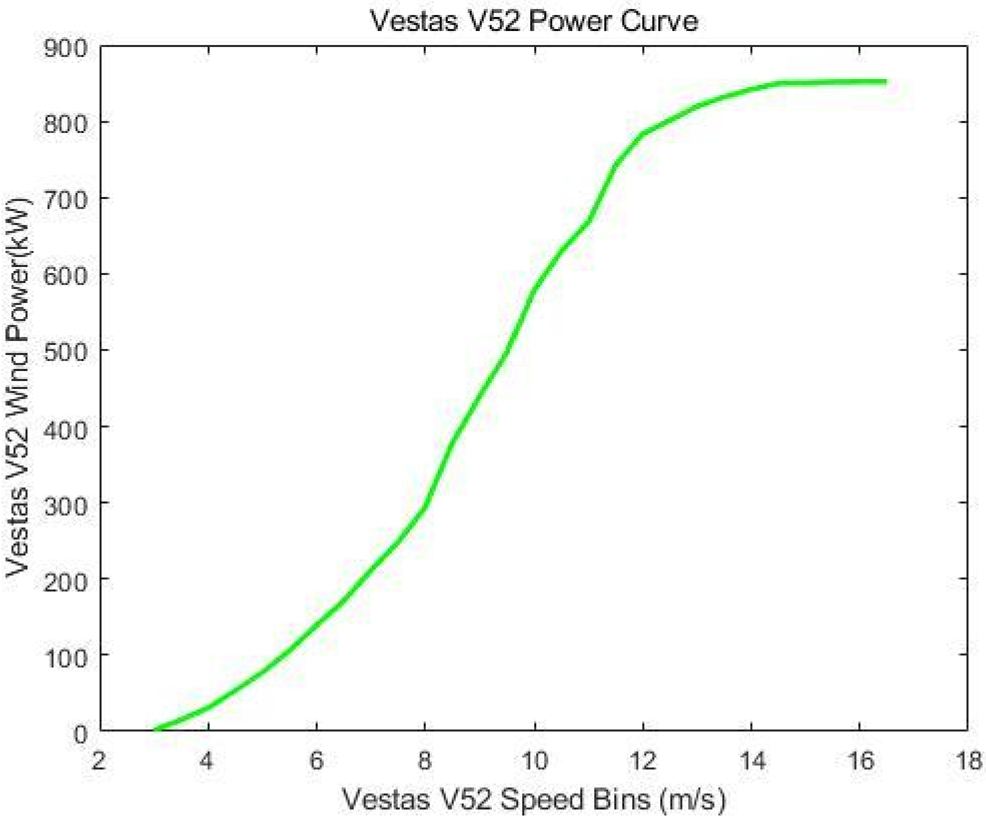

Figure 16 Vestas V52 Power Curve

Figure 17 shows that the Vestas V52 power curve, we can observe from 2 to 6 m/s, the power output starts to rise steadily. 6 to 12 m/s, the turbine generates more power rapidly as wind speed increases. 12 to 15 m/s, the turbine reaches its maximum output of around 850 kW, also known as the rated power. Above 15 m/s, the power output remains constant, as the turbine operates at full capacity. This curve is essential for predicting the energy output based on wind speed data.

Analyze energy output

Annual Actual and Expect Energy Output

```
%%AEO Calculations

Energy = power.*(1/6); % convert the power into energy every 10 minutes

AEO_measured = sum(Energy);

disp(['The actual measured annual energy output is: ',
num2str(AEO_measured), 'kwh']);
```

```
bin_s2 = sort(bin_s2);

v_bin2 = histc(speed, bin_s2); %Grouping of speed data into bins from our
wind turbine power curve

Energy_P1 = power_V52.*v_bin2.*(1/6);  %total expected energy output at
each speed of power curve

AEO_Predicted =  sum(Energy_P1);

disp(['The expect measured annual energy output is: ',
num2str(AEO_Predicted), 'kwh']);
```

Khan Academy (n.d.) mentioned to calculate the energy produced or consumed over time, the formula is:

$$\text{Energy} = \text{power} * \text{time}$$

Equation 15

Expected Annual Energy Output:

$$\text{Expected Energy=Power at each wind speed bin (from the V52 power curve)*} \\ \text{Frequency of wind speeds (binned data)} \times \text{time.}$$

Equation 16

This uses the Vestas V52 power curve to predict the energy output at different wind speeds based on the frequency distribution of the wind speeds (v_bin2).

Comparison:

Measured Energy Output: This reflects the actual energy generated by the turbine over the year, based on the real measured power data.

Expected Energy Output: This is a prediction based on the Vestas V52 power curve and the frequency distribution of wind speeds. It’s an estimate of what the turbine is expected to produce based on theoretical performance under varying wind speeds.

Calculate the Capacity Factor

Quora (n.d.) provides that this is a measure of how often the turbine is producing at or near its rated capacity. It can be calculated or obtained from historical performance data. The capacity factor can be estimated using the formula:

$$\text{Capacity Factor} = \frac{\text{Actual Energy Output}}{\text{Maximum Possible Energy Output}}$$

Equation 17

Where:

Actual Energy Output is the energy produced over a period (in kWh).

Maximum Possible Energy Output is calculated as:

$$\text{Maximum Possible Energy Output} = \text{Rated Power} * \text{Hours in a Year}$$

Equation 18

For a Vestas V52 turbine, Rated power = 850 kW (0.85 MW) (Bauer n.d.)

```
%Capacity factor
cp=[ AEO_measured/(365*24*850)]*100
disp(['The Capacity factor is: ', num2str(cp), '%']);
```

Results and Discuss

Mean Wind Speed	6.1906 m/s	At 6.19 m/s, the site shows a viable wind resource, which is suitable for energy generation in most cases.
The Standard Deviation Of The Wind Velocity	3.2988 m/s	The wind speed variability (3.30 m/s) suggests some fluctuation, which could affect power consistency but remains within a reasonable range for energy production.
Shape (k)	1.9688	It shows a balanced wind speed distribution, which is favorable for steady energy production.
Scale (c)	7.0009	It shows that wind speeds are most concentrated around 7 m/s.
Actual Energy Output	1814449.45kwh	The actual annual energy output of 1,814,449 kWh is closely aligned with the expected output of 1,798,191 kWh, showing that the turbine's performance matches the predictions based on wind speed data. This close alignment reflects the reliability of the wind data analysis and the turbine's
Expect Energy Output	1798191.1333kwh	

		efficiency.
Capacity Factor	24.3681%	It shows the percentage of the turbine's maximum possible output that was achieved. This value is typical for onshore wind turbines, indicating good performance but also the inherent variability of wind conditions (WindEurope n.d.).

Table 2 Wind Statistics Output Results

Table2 shows the data suggests that the wind site offers consistent and efficient wind energy production, with actual performance closely matching expectations based on resource assessment.

Conclusions

Outlines and Findings

This assessment focuses on the detailed analysis of wind characteristics and resource assessment, which are essential components in understanding wind energy generation. By MATLAB, we were able to calculate and visualize important wind data such as the mean wind speed, standard deviation of wind velocity, and the parameters for the Weibull distribution (shape and scale factors). These calculations help us assess the behavior and potential of wind energy at a specific site, providing a comprehensive view of the wind resource available for energy production.

Wind Characteristics:

The average wind speed and standard deviation were calculated to understand the typical wind conditions and their variability over time. Wind energy production depends heavily on both the magnitude and stability of wind speeds.

Using Weibull distribution modeling, we accurately described the probability of various wind speeds occurring, which is essential for predicting long-term energy output.

Weibull Distribution:

The shape (k) and scale (c) factors of the Weibull distribution describe how the wind speed data is distributed. A higher shape factor ($k > 1$) suggests more consistent wind speeds, benefiting energy generation, whereas a lower shape factor indicates greater variability. The scale factor (c) provides the characteristic wind speed around which the wind data is centered.

Applying the Weibull distribution to the site's wind data allowed us to estimate the expected energy output, which was compared to the actual measured data.

Energy Yield and Prediction:

By integrating the Vestas V52 turbine's power curve with the wind speed distribution, we calculated the expected annual energy output. The expected output closely matched the actual measured data, confirming the reliability of our predictions.

The capacity factor, which compares actual energy output with the turbine's theoretical maximum output, was calculated to be 24.38%, indicating typical turbine performance relative to the variability of wind speeds.

Visualization of Wind Data:

The use of velocity bins, energy bins, and power bins helped visualize wind speed distribution and frequency. This provided insights into which wind speeds contributed most to energy production and pinpointed the most frequent wind conditions.

The Weibull probability density function further helped predict energy yield by showing the likelihood of different wind speeds.

Overall, the effectiveness of combining measured wind data with theoretical models such as the Weibull distribution and the Vestas V52 power curve. The close alignment between the expected and actual energy outputs confirms the reliability of these models for predicting future wind energy production. By understanding the frequency distribution of wind speeds, the power curve, and the capacity factor, we can accurately estimate energy generation under various wind conditions.

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