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دراسة مقارنة لتقييم معاملات ويبل تحت تأثير ظروف الاستقرار الجوي

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A comparative Study to evaluate the Weibull Parameters under the influence of atmospheric stability conditions

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الملخص:

تحليل توزيع سرعة الرياح واحتمالية تكرارها على مدار السنة أمر بالغ الأهمية لفهم مصادر الرياح وخصائصها في موقع محدد. هذه الخطوة الأولية والحيوية تساعد في تقدير الطاقة المتاحة وتوجيه اختيار أجهزة توربينات الرياح المناسبة والمعدات ذات الصلة لمزارع الرياح. في هذه الورقة، تم جمع بيانات سرعة الرياح على مدى عام واحد في مدينة المقرون لتقييم معلمتي دالة ويبل (الشكل والمقياس) باستخدام خمس طرق مختلفة: الرسوم البيانية، التجريبية، اللحظات، الاحتمال الأقصى، وعامل نمط الطاقة. تم إجراء هذه الحسابات في ظل ظروف استقرار جوي مختلفة وهي الظروف المستقرة والمحايدة وغير المستقرة. لتقييم دقة هذه الطرق، تم تطبيق ثلاثة تحليلات إحصائية: جذر متوسط مربع الخطأ، ومعامل الارتباط، وخطأ مربع كاي. تختلف دقة حساب معلمات ويبل باختلاف الموسم وظروف الاستقرار الجوي. توضح الطريقة التجريبية دقة فائقة في تقدير معلمات ويبل للظروف المستقرة خلال معظم الفصول، بينما تعمل طريقة الاحتمال الأقصى بشكل جيد للظروف غير المستقرة، وتختلف دقة الظروف المحايدة حسب الموسم. بالنظر إلى الدقة المتفاوتة للطرق المختلفة عبر ظروف ومواسم استقرار الغلاف الجوي المختلفة، فإن الاختيار الدقيق للطرق المناسبة أمر حيوي لتقدير موثوق لمعلمات ويبل وبالتالي تقييم إمكانات طاقة الرياح.

الكلمات الدالة: *دالة ويبل، ظروف الاستقرار الجوي، معاملات الشكل والمقياس.*

Abstract

Analysing the wind speed distribution and the likelihood of its recurrence throughout the year is crucial for understanding the wind sources and their characteristics at a specific site. This initial and vital step assists in estimating the available energy and guides to the selection of suitable wind turbines and related equipment for wind farms. In this paper, wind speed data was collected over a one-year period in Magron city to evaluate the two Weibull parameters (shape and scale) using five different methods: graphical, empirical, moments, maximum likelihood, and energy pattern factor. These calculations were conducted under different atmospheric stability conditions namely stable, neutral, and unstable conditions. To assess the reliability of these methods, three statistical analyses were applied: root mean square error, correlation coefficient, and the Chi-Square Error. The accuracy of calculating Weibull parameters varies with season and atmospheric stability conditions. The empirical method demonstrates superior accuracy in estimating Weibull parameters for stable conditions during most seasons, while the maximum likelihood method performs well for unstable conditions, and the accuracy of neutral conditions varies depending on the season. Considering the varying accuracy of different methods across different atmospheric stability conditions and seasons, careful selection of appropriate methods is vital for reliable estimation of Weibull parameters and therefore, assessment of wind energy potential.

Keywords: *Weibull function, shape and scale Parameters, atmospheric stability conditions.*).

Introduction:

Energy plays a pivotal role in the development of human life, contributing to the progress of civilization and the economy. The current demand for energy is on a significant upswing and is projected to double within the next 20 years. [(1)] Transitionally, fossil fuels like oil, gas, and coal have been the primary sources of energy, but their consumption results in the emission of gases that directly impact the atmosphere, leading to temperature rise and the melting of polar ice, with tangible consequences for human life. Moreover, besides the environmental harm, fossil fuels are finite resources that may be exhausted in the foreseeable future. [(2)]

Addressing these challenges involves an increasing focus on investigating novel, sustainable, and eco-friendly sources of energy. [(3)] This led to substantial efforts and advancements in the search for alternatives to conventional energy sources. Wind energy, in particular, has garnered significant attention and development as a promising renewable and clean energy source, offering a potential solution to our energy needs in the future.

There is a strong relationship between the cube of wind speed and the quantity of energy collected. Therefore, understanding the characteristics of the wind resource is essential for making use of wind energy, installing wind turbines, determining if wind farm projects are financially feasible and refining wind turbine design. It becomes essential to appropriately define the wind speed at a specific location as a result. [(4)]

The evaluation of wind energy involves a comprehensive analysis that has a substantial impact on choices about the construction of wind farms or the installation of wind turbines. The focus of research over the last 20 years has been on developing statistical models that more accurately represent the frequency distribution of wind speeds. [(5)]

This entails determining the parameters of a probability density function that characterizes the distribution of various wind speeds at a certain point. These initiatives are essential to the thorough evaluation of wind resources and the estimation of wind potential at a given site. [6]

A range of probability density functions were used to illustrate wind speed frequency distributions. [7] For assessing wind speed data, the two-parameter Weibull Probability Distribution Function is highly suggested and widely recognized due to its better fit. Because it captures observed probability density distributions more effectively than other statistical functions, it is often employed in wind energy research. [8, 9, 10]

A probability density function that describes the frequency of wind speed and a cumulative distribution that shows the likelihood of reaching a specific wind speed are what define the Weibull distribution. The formula takes two inputs: the dimensionless shape parameter (k), which can be determined in a number of ways, and the scale parameter (c), which is measured in meters per second (m/s). [2]

The two Weibull parameters (shape and scale) can be computed more easily using a number of numerical techniques that have been suggested in the literature. The maximum likelihood method, the modified maximum likelihood approach, the moment method, the energy pattern factor method, the empirical method, and the graphical method are some of these techniques. [7]

Multiple research studies have been employed various statistical analyses to estimate wind velocity distributions.

Maja Celeska et al. [8] examined the power density approach, empirical method, maximum likelihood method, and method of moments in wind energy analysis to determine the Weibull wind speed distribution parameters. Using wind speed data from the northern region of the Republic of Macedonia (August 2012 to March 2015) to evaluate accuracy using statistical analysis, they discovered that the maximum likelihood technique produced the best accurate Weibull distribution for the particular site.

Six numerical techniques were used by Kasra Mohammadi et al. [7] to assess the shape (k) and scale (c) Weibull factors. The purpose of this assessment was to determine the wind power density at four stations in Alberta, Canada, utilizing three years' worth of hourly wind speed data that was collected at a height of 10 meters (January 2012 to December 2014). The study found that the accuracy of wind power density estimates computed using the Weibull function was greatly affected by the use of different techniques to estimate Weibull components. In contrast, the graphical technique performed poorly across all stations. The empirical methods of Justus, Lysen, energy pattern factor, and maximum likelihood showed positive performance. Furthermore, Justus's empirical approach performed somewhat better.

Alhassan Ali Teyabeen et al. [11] used seven numerical techniques to calculate the Weibull parameters for wind speeds measured at 10, 30, and 50 meters above sea level at Zuwara, Libya in 2007. The techniques used were energy pattern factor, graphical, standard deviation, empirical (Justus and Lysen), maximum likelihood, and modified maximum likelihood. According to their results, the maximum likelihood approach had superior accuracy at 10 meters, while the empirical approaches of Justus and Lysen showed the highest accuracy at 30 and 50 meters.

On the other hand, the recorded wind speed histogram at all heights was poorly fitted by the curve using the graphical technique.

On Jeju Island, South Korea, Dongbum Kang et al. [12] used Weibull distribution parameters to analyze wind speed based on real wind speed data collected over a five-year period from nine sites with different topographical circumstances. They contrasted Weibull parameters obtained using six different techniques: maximum likelihood, modified maximum likelihood, graphical, empirical, moment, and energy pattern factor. Four accuracy tests were used in the study to determine the best approach. The results indicated that, whilst the graphical technique exhibited reduced efficacy, the moment method effectively estimated the shape (k) and scale (c) parameters, giving a satisfactory match for Weibull distribution curves for wind speed data. Additionally, the study discovered that the approaches' accuracy ratings stayed true under a variety of topographical circumstances, indicating that no method showed.

In four Indian towns, Syed Rahman and Himadri Chattopadhyay [13] determined the best locations for wind energy generation by calculating the Weibull distribution to describe the wind's speed and type. To determine the Weibull parameters, they used the following five methods: the energy variance technique, the maximum likelihood method, the power density method, the empirical approach, and the method of moment. The findings showed that in the cities of Kolkata and Guwahati, the energy variance approach produced the lowest amount of inaccuracy. The power density approach proved to be the most successful for Imphal city, while the greatest probability strategy offered the best fit in Shillong.

The effectiveness of twelve numerical approaches for figuring out the size and shape parameters of the Weibull distribution function—which is used to calculate the wind power density in two stations across the Republic of Korea—was evaluated by Sangkyun Kang et al. [14]. Alternative maximum likelihood, equivalent energy, graphical, modified energy pattern factor, empirical (Justus and Lysen), energy pattern factor, maximum likelihood, moment, modified maximum likelihood, power density, and standard deviation were among the techniques used. The findings showed that there were significant inaccuracies in the approaches for estimating the distribution of wind speed, including graphical, energy pattern factor, equivalent energy, and alternative maximum probability. On the other hand, the moment and standard deviation techniques, as well as the empirical approaches of Justus and Lysen, showed the highest accuracy in this context.

Using monthly and annual wind speed data from 2011 to 2016, Iqrar Hussain et al. [15] examined the generation of wind power in four coastal locations of Pakistan. Eight numerical techniques were used in the study to estimate the two Weibull parameters: least squares regression, graphical, empirical, wasp algorithm, energy pattern, moment, maximum likelihood, and energy trend. To evaluate how accurate the procedures were, three statistical error tests were used. The results showed that the graphical and energy trend approaches performed poorly at every location under investigation.

Observations from previous studies and a comprehensive review of various researches indicate a notable variation in the accuracy of the methods employed to determine the two Weibull parameters across different sites. This discrepancy highlights the dependency of Weibull parameters on the specific characteristics and wind patterns of each site. It is noteworthy that many studies overlooked the impact of atmospheric stability conditions on the two Weibull parameters.

The primary aim of this paper is to identify the most effective methods for achieving the best fit of Weibull distributions to wind speed data of a specific site. The study examines five numerical methods–graphical, empirical, moments, maximum likelihood, and energy pattern factor methods–utilized for estimating Weibull function parameters (shape and scale). Importantly, the investigation takes into account the influence of atmospheric stability conditions on the accuracy of these methods.

2. Methodology and Theoretical background

To generate wind power, a range of features need to be studied. The most important factor is the wind speed. The wind fluctuates in speed in both space and time. This difference in wind speed is influenced by a number of elements, including topography and wind. As wind speed is considered a random quantity, statistical analytic approaches are employed to handle it. The best methods for describing the random variation in wind speed at a location are the Weibull distribution function and atmospheric stability. [16]

In this study, wind speed data spanning a one-year period (Jan. 2003 to Dec. 2003) was collected from a measurement station installed in Magron city, located on the Mediterranean Sea coast in north western Libya. The site served as a case study, and data was gathered at three different heights (10, 20, and 40 meters a.g.l.). The study estimated the shape (k) and scale (c) parameters of Weibull distribution of the wind speed data using five methods, incorporating considerations for atmospheric stability conditions. The suitability of the parameters was assessed through three statistical analyses: the Root Mean square error (RMSE), the Correlation Coefficient (R^2) and the Chi-Square Error (x^2), as follows.

2.1 The Weibull distribution function

One technique for figuring out the wind speed distribution is to utilize the two parameters in the Weibull distribution function, commonly known as the Probability Density Function (PDF). It is dependent upon the data's statistical analysis. Wind power prediction and pattern analysis both benefit from an understanding of the Weibull distribution. It can provide accurate fits to data on wind speed observations. Mathematically, it is expressed as: [3]

$$f(u) = \frac{k}{c}\left(\frac{u}{c}\right)^{k-1} exp\left(-\left(\frac{u}{c}\right)^{k}\right) \quad (1)$$

Where f(u) is the likelihood or frequency that a certain wind speed will occur. The scale factor, u, and c, have a strong relationship with the mean wind speed. A stronger wind speed is indicated by a larger value of c. The dimensionless form factor, or k, characterizes the distribution's shape and indicates wind stability; the greater k's value, the more stable wind speed. The statistical analysis of the site's observed wind speed data can yield these two parameters.

The histogram is one tool for describing observed wind speed data over time. Each wind speed bin has a width of one meter per second. The wind speeds are separated into these bins. For each wind speed bin, the histogram shows how frequently the wind is blowing. [16]

$$F(u) = 1 - exp\left(-\left(\frac{u}{c}\right)^k\right) \tag{2}$$

2.2 Atmospheric stability

Atmospheric stability is a way to assess how turbulent the vertical movement of air is near the earth's surface. Turbulence promotes mixing and dispersion, so understanding atmospheric stability is crucial for describing the wind patterns in the Atmospheric Boundary Layer. (17)

There are three main categories for classifying atmospheric stability conditions: Neutral, Stable, and Unstable, which depend on factors like heat flux and temperature. Various methods exist to determine and classify these conditions, and one such method is the wind shear coefficient. (18)

2.3 Wind Shear Coefficient

The Wind Shear Coefficient (α) can be calculated at two heights using the power law model, and it can be directly calculated using equation (1)

$$\alpha = \frac{\ln(V_2/V_1)}{\ln(z_2/z_1)} \tag{3}$$

The recorded wind speeds at heights z_1 and z_2, respectively, are represented by the variables V_1 and V_2 in this equation. The vertical distance between the two heights, atmospheric stability, and the terrain of the area all have an impact on the wind shear coefficient (α). (19) It is used to categorize the state of atmospheric stability. The requirements for each atmospheric stability regime as they are used in the literature are listed in Table (1). (20)

Table1: Stability classification based on wind shear exponent.

Stability Class	Wind shear exponent, α
Strongly stable	$\alpha > 0.3$
Stable	$0.2 < \alpha < 0.3$
Neutral	$0.1 < \alpha < 0.2$
Unstable	$0.0 < \alpha < 0.1$
Strongly unstable	$\alpha < 0.0$

2.4 Methods of Estimating the Two Weibull Parameters

Various methods can be employed to determine the Weibull distribution parameters, c and k, based on the available wind data. In this study, five methods were utilized: the graphical method (GM), empirical method (EM), method of moments (MOM), maximum likelihood method (ML), and energy pattern factor method (EPF). These methods were employed to calculate the parameters and identify the most accurate estimation for the Weibull parameters in Magron city.

2.4.1 Graphical Method (GM)

The graphical method (GM) involves organizing wind speed data in a cumulative frequency distribution format by grouping it into bins. By applying a double natural logarithm transformation to Equation 2, and then Equation 3 is produced, which represents a straight line:

$$ln[-ln(1 - F(u))] = kln(u) - kln(c) \tag{4}$$

The c and k parameters are calculated by plotting the ln(u) on x axis against ln(−ln(1−F(u))) on y axis, resulting in a straight line. The slope of the line corresponds to k, while the y− intercept represents (−k ln c), and therefore, c can be calculated. [7]

2.4.2 Empirical Method (EM)

In the empirical method (EM), the k and c parameters are estimated using the average wind speed $(\bar{u})$ and standard deviation (σ) of wind speed data. Equations 4 and 5 are used for the calculation: [21]

$$k = (\sigma/\bar{u})^{-1.089} \tag{5}$$

$$c = \bar{u}/\Gamma(1 + 1/k) \tag{6}$$

Here, Γ is the gamma function.

2.4.3 Method of Moments (MOM)

The method of moments (MOM) is a commonly used approach to estimate the c and k parameters. It relies on the mean wind speed and standard deviation of wind data. The c parameter is calculated using equation (5), while the k parameter is determined using Equation (6) [21]

$$k = \left(\frac{0.9874}{\frac{\sigma}{\bar{u}}}\right)^{1.0983} \tag{7}$$

2.4.4 Maximum Likelihood Method (ML)

The maximum likelihood method (ML) involves numerical iteration to calculate the c and k parameters when wind speed data is in time series format. The following equations are utilized: [22]

$$k = \left\{\frac{\sum_{i=1}^{n} u_i^k \ln(u_i)}{\sum_{i=1}^{n} u_i^k} - \frac{\sum_{i=1}^{n} \ln(u_i)}{n}\right\}^{-1} \tag{8}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} u_i^k\right)^{\frac{1}{k}} \tag{9}$$

Here, u_i represents the wind speed at *i–th* point and *n* is the number of nonzero wind speed data.

2.4.5 Energy pattern factor method (EPF)

The energy pattern factor method (EPF) relies on average wind speed data and provides a straightforward implementation without complex computations. The k parameter is estimated using the following equation: [9]

$$k = 1 + \left\{\frac{3.69}{(E_{pf})^2}\right\} \tag{10}$$

Where E_{pf} is the energy pattern factor obtained numerically from the equation:

$$E_{pf} = \frac{\frac{1}{n}\sum_{i=1}^{n} u_i^3}{\left(\frac{1}{n}\sum_{i=1}^{n} u_i\right)^3} = \frac{\overline{u^3}}{\bar{u}^3} \tag{11}$$

Here, $\overline{u^3}$ represents the mean of the cube of wind speed, and $\bar{u}^3$ represents the cube of the mean speed.

Once the energy pattern factor is calculated, the c parameter is estimated as follows: [23]

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} \bar{u}_i^k\right)^{1/k} \tag{12}$$

2.5 Statistical Error Analysis (Goodness of Fit)

In order to assess the performance and evaluate the most suitable method for estimating the five Weibull distribution parameters, the study conducted a statistical error analysis using three measures: root mean square error (RMSE), correlation coefficient (R^2), and chi–square tests (x^2).

2.5.1 The Root Mean Square Error (RMSE)

The RMSE quantifies the deviation between the probability value calculated from Weibull distribution and the actual wind speed values. A smaller RMSE value indicates a better fit. It is calculated using the following formula: [2]

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2\right]^{1/2} \tag{13}$$

Where, y_i represents the actual wind speed probability value, x_i is the probability value calculated from Weibull distribution, and N is the number of observations.

2.5.2 The Correlation Coefficient (R^2)

The correlation coefficient determines the linear relationship between the calculated values from the Weibull distribution and the values received from the measured data. Its value ranges from 0 to 1, with 1 indicating a perfect fit. The correlation coefficient is determined using the following equation: [23]

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - z_i)^2 - \sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(y_i - z_i)^2} \tag{14}$$

Where, z represents the mean value of actual data.

2.5.3 The Chi–Square Tests (χ^2)

The chi–square test assesses the deviations between the actual data values and the values calculated from the Weibull distribution function. It is calculated using the following formula: [24]

$$\chi^2 = \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{x_i} \tag{15}$$

Here, yi represents the actual data value, xi is the value calculated from the Weibull distribution, and N represents the number of observations.

3. Results and Discussion

The methodology involved in this study focuses on analysing wind speeds in Magron city, situated on the coast of the Mediterranean Sea in north western Libya. The average wind speeds for three different heights above ground level (10, 20 and 40m) were utilized.

This research utilized five different methods, mentioned above, to determine the values of shape and scale parameters for the Weibull distribution function under various atmospheric stability conditions. The suitability of these parameters was assessed by conducting three statistical analyses. To assess the effect of the atmospheric stability conditions on the Weibull parameters, the study employed seasonally averaged wind speed data. Table (1) was used to classify the conditions based on the wind shear coefficient, which was calculated using equation (3). The shape and scale parameters for the Weibull distribution function were then calculated using equations (4) to (12) through the five different methods.

Looking at Table (2), the Weibull parameter estimates of ('k' and 'c') are provided for each level of atmospheric stability conditions, along with the methods of estimation of these parameters (GM, EM, MOM, ML, and EPF). For the summer season, the values of 'k' range from approximately 3.07 to 4.52, while 'c' ranges from 6.92 m/s to 8.15 m/s. These values indicate the shape and scale of the Weibull distribution for each atmospheric stability condition during the summer.

A similar pattern was observed in the autumn season with three classes of atmospheric stability conditions. The parameter estimates of 'k' range from approximately 3.24 to 4.17, and 'c' range from 6.92 m/s to 9.15 m/s. It could be noticed that the autumn season experiences similar levels of atmospheric stability conditions as summer but with some variations in the Weibull parameters values.

The table also provides data for the winter and spring seasons. These seasons exhibit a similar pattern of atmospheric stability conditions levels and corresponding Weibull parameter estimates. The values for 'k' range from approximately 3.33 to 4.18, while 'c' range from 5.84 m/s to 8.08 m/s.

Comparing the different methods of estimation within each season, we can observe some variations in the Weibull parameters' estimates. However, it is important to note that the magnitude of these variations is relatively small, indicating that the estimation methods yield consistent results overall.

In conclusion, to select the most accurate parameters for all seasons and atmospheric stability conditions, additional analysis was conducted using the root means square error (RMSE), correlation coefficient, and the chi-square test. These metrics serve to evaluate the goodness-of-fit and reliability of the estimation methods. A higher correlation coefficient indicates a stronger linear relationship between the estimated parameters and the observed data, suggesting a more accurate fit. Conversely, lower values of RMSE and the chi-square test indicate better agreement between the estimated parameters and the actual values, reflecting greater accuracy. By considering the highest correlation coefficient along with the lowest values of RMSE and the chi-square test, we can identify the estimation method consistently exhibiting the best performance across all seasons and atmospheric stability conditions. The comprehensive evaluation aids in selecting the most reliable method for estimating atmospheric stability conditions and provide more confidence in the obtained results.

Table2: Seasonal estimated Weibull parameters at different atmospheric stability conditions.

Season		Summer						Autumn					
ASC		Stable		Neutral.		Unstable		Stable		Neutral.		Unstable	
Weibull Parameters		k	c	k	c	k	c	k	c	k	c	k	c
Method of Estimation	GM	4.52	4.17	3.07	7.08	3.02	8.15	5.17	4.80	4.00	5.46	3.51	7.66
	EM	4.33	4.20	3.49	7.03	3.27	8.13	4.82	4.83	4.04	5.47	3.34	7.73
	MoM	4.35	4.20	3.49	7.03	3.27	8.13	4.84	4.83	4.05	5.47	3.34	7.73
	ML	4.05	4.20	3.70	7.01	3.47	8.12	4.45	4.84	4.08	5.47	3.37	7.75
	EPF	3.53	4.13	3.24	6.92	3.11	8.03	3.69	4.75	3.45	5.38	3.08	7.66

Season		Winter						Spring					
ASC		Stable		Neutral.		Unstable		Stable		Neutral.		Unstable	
Weibull Parameters		k	c	k	c	k	c	k	c	k	c	k	c
Method of Estimation	GM	4.18	5.85	3.99	7.53	3.66	6.95	4.65	5.32	3.76	8.08	5.35	7.23
	EM	3.87	5.91	4.00	7.53	3.56	7.00	4.03	5.42	3.47	8.16	5.16	7.26
	MoM	3.87	5.91	4.01	7.53	3.56	7.00	4.04	5.42	3.47	8.16	5.18	7.25
	ML	3.69	5.92	4.01	7.53	3.62	7.01	3.56	5.43	3.37	8.17	4.92	7.26
	EPF	3.33	5.84	3.43	7.41	3.22	6.91	3.34	5.38	3.12	8.09	3.81	7.10

Table3: Statistical error analysis values for summer at different ASCs.

ASC		Stable atmospheric condition			Neutral atmospheric condition			Unstable atmospheric condition		
Statistical Analysis		RMSE	R^2	χ^2	RMSE	R^2	χ^2	RMSE	R^2	χ^2
Method of Estimation	GM	0.55938	0.93144	0.31406	**0.56950**	**0.98371**	**0.32734**	**0.58855**	**0.98702**	**0.34740**
	EM	**0.55376**	0.93787	**0.30778**	0.57827	0.97497	0.33750	0.59473	0.98329	0.35474
	MoM	0.55389	0.93753	0.30792	0.57829	0.97495	0.33752	0.59468	0.98332	0.35468
	ML	0.55426	0.94531	0.30834	0.58191	0.97027	0.34175	0.59836	0.97990	0.35908
	EPF	0.57044	**0.95461**	0.32660	0.59001	0.98072	0.35134	0.60200	0.98612	0.36346

Table 3. Illustrates the statistical analysis of the summer at different atmospheric stability conditions. Based on the provided data, for the stable condition, the EPF method tends to perform the best with the highest R^2 values of 0.95461, indicating a better fit to the data compared to other methods. However, the EPF method also has a slightly higher RMSE value of 0.57044, indicating a slightly higher average difference between predicted and actual values. If we consider the two factors (RMSE and X^2), the EP method has the values 0.55376 and 0.30778, respectively. These are the smallest values among all the methods indicating a better fit to the data. Therefore, the EP method is selected as the best-fit method for stable atmospheric conditions. On the other hand, the graphical method tends to give the highest R^2 and smaller values of RMSE and X^2 for both neutral and unstable conditions, which represents the best-fit in these conditions.

For the autumn season, the results are shown in table 4. It demonstrates that the empirical method produces highly accurate outcomes under stable and neutral conditions. Specifically, for stable conditions, the smallest values of RMSE and X^2 are 0.55666 and 0.31072, respectively. Similarly, for the neutral conditions, the empirical method yields the smallest values of RMSE (0.56999) and X^2 (0.32737). Conversely, in unstable conditions, the maximum likelihood method emerges as the most effective, yielding the best values of RMSE (0.57474) and X^2 (0.33129). In summary, the empirical method proves robust for stable and neutral conditions.

Table 4: Statistical error analysis values for autumn at different ASCs.

ASC		Stable atmospheric condition			Neutral atmospheric condition			Unstable atmospheric condition		
Statistical Analysis		RMSE	R^2	χ^2	RMSE	R^2	χ^2	RMSE	R^2	χ^2
Method of Estimation	GM	0.56465	0.93183	0.31971	0.57101	0.97108	0.32855	0.58416	0.98578	0.34224
	EM	**0.55666**	0.94154	**0.31072**	**0.56999**	0.97043	**0.32737**	0.57588	0.98779	0.33261
	MoM	0.55688	0.94108	0.31097	0.57013	0.97029	0.32753	0.57587	0.98780	0.33259
	ML	0.55672	0.94955	0.31080	0.57014	0.96986	0.32754	**0.57474**	0.98740	**0.33129**
	EPF	0.57779	**0.95844**	0.33476	0.58251	**0.97803**	0.34191	0.58073	**0.99030**	0.33824

Table 5 summarizes statistical analysis errors between the five methods in winter. The table reveals that the maximum likelihood method consistently delivers accurate results in both stable and unstable conditions. In stable conditions, the method achieves RMSE and X^2 values of 0.55930 and 0.31372, respectively. In unstable conditions, it achieves the smallest RMSE (0.57140) and X^2 of (0.32914) values. On the other hand, for neutral conditions, the empirical methods remains the most effective, with RMSE and X^2 values of 0.57100 and 0.32726, respectively. In summary, the maximum likelihood method excels in stable and unstable conditions, while the empirical method continues to be optimal for neutral conditions.

Table 5: Statistical error analysis values for winter at different ASCs.

ASC		Stable atmospheric condition			Neutral atmospheric condition			Unstable atmospheric condition		
Statistical Analysis		RMSE	R^2	χ^2	RMSE	R^2	χ^2	RMSE	R^2	χ^2
Method of Estimation	GM	0.56866	0.94394	0.32431	0.57101	0.96667	0.32727	0.57862	0.98273	0.33751
	EM	0.55984	0.95336	0.31432	**0.57100**	0.96641	**0.32726**	0.57204	0.98455	0.32987
	MoM	0.55990	0.95323	0.31439	0.57111	0.96626	0.32739	0.57207	0.98453	0.32990
	ML	**0.55930**	0.95706	**0.31372**	0.57133	0.96611	0.32764	**0.57140**	0.98393	**0.32914**
	EPF	0.57088	**0.96018**	0.32685	0.58441	**0.97595**	0.34282	0.57973	**0.98691**	0.33879

Table 6. Presents the results of statistical analysis obtained for the five methods of obtaining Weibull parameters in Spring, where it is shown that the maximum likelihood method is the best method in estimating the Weibull parameters for neutral and unstable conditions, while for stable condition, the empirical method is ranked first.

Table 6: Statistical error analysis values for spring at different ASCs.

ASC		Stable atmospheric condition			Neutral atmospheric condition			Unstable atmospheric condition		
Statistical Analysis		RMSE	R^2	χ^2	RMSE	R^2	χ^2	RMSE	R^2	χ^2
Method of Estimation	GM	0.55436	0.87737	0.30840	0.56686	0.95640	0.32280	0.56605	0.95258	0.32176
	EM	**0.53818**	0.90348	**0.29065**	0.55915	0.96476	0.31407	0.56114	0.95656	0.31621
	MoM	0.53822	0.90324	0.29070	0.55916	0.96475	0.31408	0.56144	0.95608	0.31655
	ML	0.54109	0.91557	0.29381	**0.55833**	0.96684	**0.31315**	**0.56105**	0.96089	**0.31611**
	EPF	0.55095	**0.91666**	0.30462	0.56655	**0.96893**	0.32244	0.58614	**0.97500**	0.34500

Table 7 displays the results and statistical analysis of Weibull parameters under various atmospheric stability conditions for the yearly mean wind speed. The maximum likelihood method proves to be the optimal fitting approach for stable and neutral conditions, with an RMSE of 0.55096 and X^2 of 0.30442 for stable conditions, and the smallest values of RMSE (0.55982) and X^2 (0.31529) for neutral conditions. Conversely, the graphical method yields the most accurate results for unstable conditions, with RMSE of 0.57316 and X^2 of 0.32996.

In conclusion, the maximum likelihood method excels in stable and neutral conditions, while the graphical method stands out for unstable conditions.

Table 7: Yearly Weibull parameters and statistical analysis at different ASCs.

Stable atmospheric condition		Weibull Parameters		Statistical Analysis		
		k	c	RMSE	R^2	χ^2
Method of Estimation	GM	7.43	5.13	0.56643	0.94827	0.32176
	EM	7.06	5.18	0.55283	0.95761	0.30650
	MoM	7.12	5.17	0.55339	0.95672	0.30712
	ML	6.16	5.19	**0.55096**	0.96878	**0.30442**
	EPF	4.14	5.05	0.59160	**0.97857**	0.35099
Neutral atmospheric condition		**Weibull Parameters**		**Statistical Analysis**		
		k	c	RMSE	R^2	χ^2
Method of Estimation	GM	7.12	6.40	0.57067	0.96845	0.32762
	EM	6.87	6.44	0.56221	0.97184	0.31798
	MoM	6.93	6.44	0.56285	0.97121	0.31871
	ML	6.44	6.45	**0.55982**	0.97647	**0.31529**

	EPF	4.13	6.28	0.59549	**0.994584**	0.35674
Unstable atmospheric condition		Weibull Parameters		Statistical Analysis		
		k	c	RMSE	R^2	χ^2
Method of Estimation	GM	8.30	7.34	**0.57316**	0.93623	**0.32996**
	EM	8.47	7.34	0.57429	0.93371	0.33126
	MoM	8.56	7.33	0.57548	0.93251	0.33264
	ML	8.77	7.33	0.57701	0.92927	0.33441
	EPF	4.31	7.13	0.61249	**0.99282**	0.37679

The scale and shape parameters have been determined for each atmospheric stability condition using the accurate fitting method to plot the histogram of the actual frequency distribution of diurnal wind speed for mean yearly wind speed with the Weibull distribution function (PDF), which is illustrated in Figure 1.

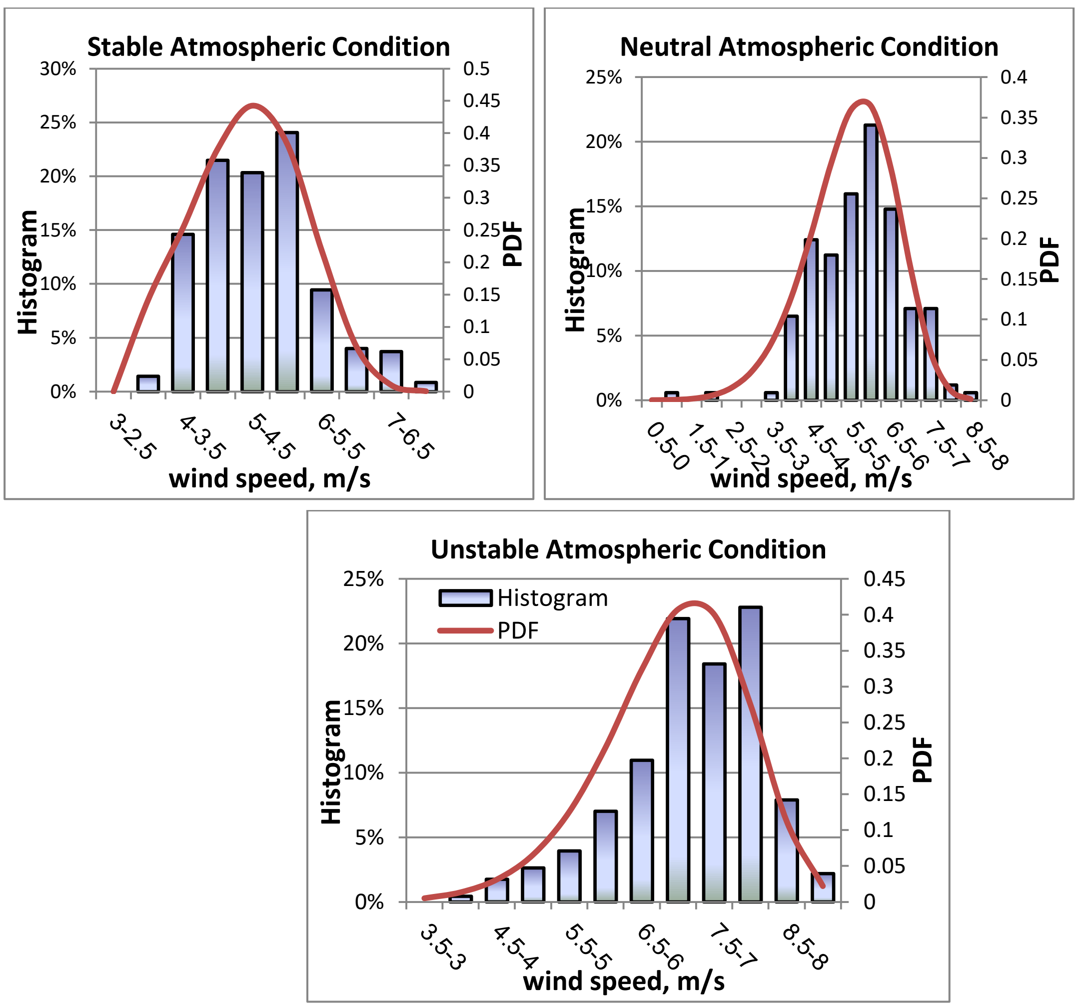

Figure 1: the yearly histogram with the PDF for stable, neutral, and unstable conditions

4. Conclusion

According to the presented results, the five different methods that were mentioned in section 2 to calculate the shape (k) and scale (c) factors of the Weibull distribution function, the following conclusions can be drawn from this paper.

1- Analysing the seasonal averaged wind speed data using the five proposed methods under different atmospheric stability conditions reveals that the empirical method yields the most precise results for stable condition across most seasons. The maximum likelihood method performs best under unstable conditions, while for neutral conditions; different methods show the highest accuracy depending on the season. This suggests that the choice of method should be tailored to specific atmospheric stability conditions when calculating Weibull distribution parameters.

2- Examining the yearly averaged wind speed data using the five methods indicates that the maximum likelihood method provides accurate results for stable and neutral conditions, followed by the graphical method for unstable condition. The other methods show comparatively lower accuracy. Therefore, it is strongly recommended to utilize the maximum likelihood and graphical methods as the most effective models for calculating the yearly Weibull distribution parameters for this site.

In summary, the accuracy of the methods for calculating the two Weibull distribution parameters varies depending on the season and atmospheric stability conditions, as demonstrated by the results obtained in this study.

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