Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi

Pamukkale University Journal of Engineering Sciences

# Statistical analysis of wind energy potential for bartın province: Weibull distribution approach

## Bartın ili için rüzgâr enerjisi potansiyelinin istatistiksel analizi: Weibull dağılımı yaklaşımı

*Beytullah Erdoğan[1], Abdulsamed Güneş[2*], arda Karaoğlu[3]*

[1]Mechanical Engineering, Faculty of Engineering, Zonguldak Bulent Ecevit University, Zonguldak, Türkiye.
beytullah.erdogan@beun.edu.tr

[2]Department of Electricity and Energy, EOSB Vocational School, Fırat University, Elazığ, Türkiye.
abdulsamedgunes@gmail.com

[3]Mechanical Engineering, Faculty of Engineering, Zonguldak Bulent Ecevit University, Zonguldak, Türkiye.
c_lark_85@hotmail.com

Received/Geliş Tarihi: 08.07.2025 Revision/Düzeltme Tarihi: 13.10.2025 doi: 10.65206/pajes.63833
Accepted/Kabul Tarihi: 15.10.2025 Research Article/Araştırma Makalesi

**Abstract**

*Our study aimed to investigate the wind potential of Bartın, one of Türkiye's northernmost provinces. To determine this potential, we analyzed the region's wind power density and wind speed parameters. 3561 hourly wind speed data obtained from the stations of the General Directorate of Meteorology between the years 2015-2024 were used in the analyses. The obtained data were evaluated to examine the annual, seasonal, and monthly distributions of wind speed. In the actual data collected, the highest wind speed was measured as 1.5645 m/s and the lowest as 0.3345 m/s. Based on the Weibull analysis, the highest average wind speed was determined to be 1.2712 m/s in 2024, and the highest power density corresponding to this average wind speed was 1.6453 W/m². The obtained data were evaluated in order to examine the annual, seasonal and monthly distributions of wind speed. Weibull distribution function, which is frequently preferred in the literature and known to provide reliable results, was used for statistical modeling of wind speeds. The shape (k) and scale (c) parameters of the Weibull distribution were determined by the least squares method; the suitability of the model was statistically verified by the coefficient of determination ($R^2$), root mean square error (RMSE) and chi-square ($\chi^2$) tests. The analyses show that the wind data of Bartın province can be successfully represented by the Weibull distribution. The findings shed light on the feasibility of wind energy-based investments in Bartın and provide a solid data basis for new studies in this field. It is also anticipated that they may contribute to the planning of sustainable energy policies at the regional level.*

**Keywords:** Wind energy, statistical wind analysis, Weibull distribution, Bartın

**Öz**

*Bu çalışmada, Türkiye'nin en kuzeyinde yer alan Karadeniz Bölgesi'nin Bartın ilindeki rüzgâr enerjisi potansiyelinin belirlenmesine yönelik olarak, rüzgâr hızı ve güç yoğunluğu parametrelerinin istatistiksel analizi gerçekleştirilmiştir. Analizlerde 2015-2024 yılları arasında Meteoroloji Genel Müdürlüğü istasyonlarının saatlik olarak aldığı 3561 adet rüzgâr hızı verileri kullanılmıştır. Elde edilen veriler, rüzgâr hızının yıllık, mevsimlik ve aylık dağılımlarını incelemek amacıyla değerlendirilmiştir. Toplanan gerçek verilerde rüzgar hızı en yüksek 1.5645 m/s, en düşük 0.3345 m/s olarak ölçülmüştür. Weibull analizi sonucunda en yüksek ortalama rüzgar hızı 2024 yılında 1,2712 m/s, bu ortalama rüzgar hızına karşılık gelen en yüksek güç yoğunluğu ise 1,6453 W/m² olarak tespit edilmiştir. Rüzgâr hızlarının istatistiksel modellemesi için literatürde sıklıkla tercih edilen ve güvenilir sonuçlar sunduğu bilinen Weibull dağılım fonksiyonu kullanılmıştır. Weibull dağılımının şekil (k) ve ölçek (c) parametreleri, en küçük kareler yöntemiyle belirlenmiş; modelin uygunluğu ise belirleme katsayısı ($R^2$), kök ortalama kare hata (RMSE) ve ki-kare ($\chi^2$) testleri ile istatistiksel olarak doğrulanmıştır. Yapılan analizler, Bartın ilinin rüzgâr verilerinin Weibull dağılımı ile başarılı biçimde temsil edilebildiğini göstermektedir. Elde edilen bulgular, Bartın'da rüzgâr enerjisi temelli yatırımların fizibilitesine ışık tutmakta olup, bu alanda yapılacak yeni çalışmalar için sağlam bir veri temeli sunmaktadır. Ayrıca, sürdürülebilir enerji politikalarının bölgesel düzeyde planlanmasında da katkı sağlayabileceği öngörülmektedir.*

**Anahtar kelimeler:** Rüzgâr enerjisi, istatistiksel rüzgâr analizi, Weibull dağılımı, Bartın

## 1 Introduction

To effectively utilize wind energy potential, accurate and detailed analysis of regional wind potential is crucial. Local wind speed measurements and statistical assessments, in particular, play a critical role in planning energy investments and determining turbine placement strategies. In this regard, wind potential analyses conducted in various regions of Turkey contribute to the development of the country's renewable energy map. Data obtained from wind data measurement stations in various regions and city centers have been used to classify wind speeds in these regions according to their probabilistic properties and to be used in scientific studies [1]. Low-frequency strong wind speeds (LOSWS) have attracted significant attention in the statistical modeling of wind speed and power density parameters in determining wind energy potential [2]. Thanks to the advancement of experimental equipment and theoretical calculation methods for wind energy analysis, areas with high wind potential can be identified and interpreted using highly accurate time-series data. [3],[5]. In one study, a hot-wire anemometer was also used to determine the vertical wind profile near the ground in adjacent buildings. [6]. Takemi et al. used LES to investigate the wind potential in what they consider to be a large-scale district in Kyoto [7].

*Corresponding author/Yazışılan Yazar

Although it is now easier to obtain higher quality and more comprehensive data than before, effective statistical tools are still important for PLWE studies. Using a specific distribution function to evaluate the probabilistic properties of wind speed can simplify the analysis. He developed a statistical model based on beta distribution to estimate probability distribution functions (PDFs) in wind speed studies and validated its performance in various cases [8],[9]. He analyzed the wind environment around an isolated building using a Gaussian distribution and found that this distribution was more suitable for velocity components than wind speed. While the Gaussian distribution is applicable in many cases, the symmetric bell-shaped distribution is not ideal for modeling oblique PDFs.

A study conducted using a Gaussian distribution to analyze wind potential at a building located in an isolated site unaffected by external environmental conditions found that velocity components were more suitable than wind speed. While the Gaussian distribution is applicable in most studies, the symmetric bell-shaped distribution is not considered suitable for modeling oblique PDFs. [10].

In the study conducted by Demirkol et al., where the LSTM method was used and a strong estimation performance was shown, reliable inferences were made for wind energy estimation [11]. In the study where the 2W2W defined mixed Weibull distribution was evaluated to provide more accurate results for unimodal and bimodal PDFs, it was stated that the 2W2W method gave better results in estimating strong wind speeds (LOSWS) lower than 2W at most points. [12].

Considering the important role of the location parameter in the three-parameter (3-P) Weibull model and its rare application in wind turbines, this study performed the reliability analysis of wind turbine subassemblies based on field data fitted to the 3-P Weibull distribution model by means of maximum likelihood estimation (MLE) [13]. Maximum Likelihood Estimation (MLE), Graphical Method (GM) and Method of Moments (MM) methods were used with the weibull analysis of wind data obtained from 318 cities by Huo et al. As a result, it was stated that wind input information can be used as basic information in the evaluation of weibull distribution patterns and climate potential [14]. Among similar methods, there are studies in which the standard deviation method gives better results than others [15]. As a result of the two-parameter weibull modeling of wind turbines located in Okorobo town, Nigeria, it was determined that the annual cumulative 145.13 W/m$^2$ was in high agreement with the actual measured data at 10 m height [16]. Similarly, in the study conducted in Taza province of Morocco where the wind energy potential was determined with the Weibull distribution, it was stated that the 104/3.4 wind turbine model was the most suitable for all areas [17]. In the study where the Metropolis-Hastings algorithm was used and the standard deviations were less than 0.0193 and 0.0244 m/s, respectively, the discrepancies between the estimated and actual wind speeds were found to be less than 0.089 m/s [18]. In the study conducted by Rüstemli et al., wind direction, wind speed, temperature, relative humidity and air pressure data were taken at 5-second intervals for a year and the wind energy potential was analyzed with the Weibull distribution, and it was investigated whether the region was suitable for wind energy [19].

Among renewable energy sources, wind energy has reached a remarkable position thanks to both the technical advantages provided by technological advances and the decrease in investment costs over time. Wind occurs as a result of air currents resulting from temperature and pressure differences in the atmosphere, and these currents contain a significant amount of kinetic energy. Various studies in the literature reveal that the total kinetic wind energy available in the atmosphere is approximately 190 x $10^9$ kW, and approximately 3 x $10^9$ kW of this can be technically evaluated for energy production purposes [20]. In addition, approximately 2% of the total solar energy reaching the earth is converted into wind energy. This rate is far above the amount of energy needed worldwide and clearly demonstrates how important a source wind energy is in terms of sustainability. However, in order to effectively benefit from wind energy, regional wind regimes must be analyzed and estimated correctly. The fact that wind speed varies over time necessitates its modeling with statistical methods. In this regard, probability distributions such as Weibull, Rayleigh, Gamma and Log-Normal are used in modeling wind speed distributions [21]. Particularly, the two-parameter Weibull distribution is one of the most widely used methods in wind energy modeling due to the flexibility of its parametric structure, its high level of compliance with wind data and its ability to reflect the energy potential in detail [22]. Thanks to the shape (k) and scale (c) parameters of the Weibull distribution, the statistical properties of the wind speed can be determined precisely. The accuracy of these parameters is evaluated with various statistical tests (e.g. Kolmogorov-Smirnov, Anderson-Darling, $\chi^2$). In addition, goodness-of-fit measures such as coefficient of determination ($R^2$) and root mean square error (RMSE) are also used to test the reliability of the model [23]. Thanks to these analyzes, the regional wind energy potential is reliably revealed and the basis for energy production planning is formed. In recent years, studies on the evaluation of wind energy potential have gained momentum in Turkey. Measurements made especially in high altitude areas on the coastline and inland regions show that the country has a significant wind energy potential [24]. In the analyses carried out to evaluate this potential, Weibull and Rayleigh distributions are generally preferred, and energy production capacity, turbine location and cost feasibility are evaluated based on the measured data [25 ,26].

The primary objective of this study is to statistically assess the wind energy potential in mountainous regions at an altitude of approximately 20 m in the Amasra district of Bartın province. Located in the Black Sea Region of Türkiye, Bartın, with its geographical structure, coastline, and valleys, is a potential region with diverse wind regimes. Therefore, determining the region's wind energy capacity will significantly contribute to both meeting local energy needs and achieving sustainable development goals. The data used in the study were obtained from hourly average wind speeds measured at meteorological stations established in Bartın province by the Turkish State Meteorological Service between 2015 and 2024. Using the provided data, the required data for the analyses, such as the Weibull method functions, cumulative distribution function, mean wind speeds in the region, standard deviation, maximum wind speed in the region, and wind power density, were calculated. The success level of the model was evaluated with fit criteria such as $R^2$, RMSE and $\chi^2$. In addition to these studies, the least squares method was used to detect data in the Weibull distribution in estimating the specified model parameters [27]. This study presents an up-to-date, detailed and long-term analysis that evaluates the wind energy potential specific to the Bartın province in the Black Sea Region of Turkey. While many studies on wind energy in the literature are conducted at a national or more general regional scale, this research contributes to the determination of the energy potential at the local level by focusing only on the Bartın province. In addition, the originality of the study is further increased by the comprehensive statistical analyses performed based on hourly measurement data in a wide time period covering the years 2015-2024. In this context, the study not only presents the annual, seasonal and monthly distributions of wind speed data, but also reinforces the reliability of the data by verifying a statistically reliable model such as the Weibull distribution with different performance criteria. This approach allows for more accurate planning of region-specific energy projects, while also providing a new perspective for the evaluation of sustainable energy resources in the Bartın province and makes a significant contribution to local wind energy studies in the literature.

## 2 Materials and Methods

In this study, wind speed data obtained from automatic meteorological observation stations operating under the General Directorate of Meteorology (MGM) of the Republic of Turkey were used in order to statistically evaluate the wind energy potential of Bartın province. The analyses were based on the average wind speed data recorded hourly from a height of 10 meters in Bartın province for the period between 2015 and 2024 [28]. Missing, erroneous or inconsistent measurements in the raw data set were subjected to data cleaning and pre-processing processes before the analysis; only reliable and consistent data were evaluated within the scope of the analysis.

In order to model the frequency distribution of wind speeds, the two-parameter Weibull distribution function was preferred. This distribution function is frequently used in wind energy analyses due to its ability to flexibly represent the statistical changes in wind speeds [29]. The shape (k) and scale (c) parameters of the Weibull distribution were calculated according to the formulas specified in the relevant literature; the accuracy and reliability of the model were tested with both visual and numerical methods. Weibull probability graph was used within the scope of visual evaluation; Kolmogorov-Smirnov test was applied as a numerical suitability test. The least squares method was adopted in estimating the Weibull distribution parameters, and the technical details regarding the application of this method were explained using the relevant literature sources. As a result of the analyses, it was revealed to what extent the Weibull distribution represented the wind speed data of Bartın province, and the annual wind energy production potential of the region was calculated.

The general expression of the two-parameter Weibull probability function used in determining wind speed is given in Eq. 1.

$$fw(V) = \left(\frac{k}{c}\right) * \left(\frac{V}{c}\right)^{k-1} * \exp\left(-\left(\frac{V}{c}\right)^{k}\right) \quad (1)$$

The expression c used as the scale parameter in the Weibull analysis also has a reference value in wind data. The Weibull cumulative distribution function is determined by Eq.2.

$$Fw(V) = 1 - \exp\left(-\left(\frac{V}{c}\right)^{k}\right) \quad (2)$$

The Weibull cumulative distribution function gives the probability of the wind speed being less than or equal to a certain value ν. The k (shape parameter), c (scale parameter) formulas used in trying to find the Weibull probability density and Weibull cumulative distribution functions are given in Eq. 3 and Eq. 4.

$$k = \left(\frac{\sigma}{Vm}\right)^{-1{,}086} \quad (3)$$

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

The average wind speed of the studied region and the standard deviation of this value are calculated using Eq. 5 and Eq. 6, respectively.

$$Vm = c * \Gamma\left(1 + \frac{1}{k}\right) \quad (5)$$

$$\sigma = \sqrt{\left(c^2 * \left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)\right]\right)} \quad (6)$$

Based on the Weibull distribution, the wind speed with the largest frequency is calculated from Eq. 7.

$$Vmod = c * \left(1 - \frac{1}{k}\right)^{\frac{1}{k}} \quad (7)$$

Eq. 8 given below is used when calculating maximum wind speed.

$$Vmax,e = c * \left(\frac{k+2}{k}\right)^{\frac{1}{k}} \quad (8)$$

Eq. 9 is used to determine the average wind power density for a region.

$$Pm = \int_0^\infty P(V) * f(V)dv \quad (9)$$

The average power density for the Weibull distribution is obtained from Eq. 10 as follows.

$$Pw = \left(\frac{1}{2}\right) * \rho * c^3 * \Gamma\left(1 + \frac{3}{k}\right) \quad (10)$$

Statistical analysis criteria frequently used in interpretations are determined as Eq. 11, Eq. 12 and Eq. 13 and their calculations are given below.

$$R^2 = \left[\sum_{i=1}^{N}(yi - zi)^2 - \sum_{i=1}^{N}(xi - yi)^2\right] / \sum_{i=1}^{N}(yi - zi)^2 \quad (11)$$

$$\chi^2 = \left[\sum_{i=1}^{N}(yi - xi)^2\right] / (N - n) \quad (12)$$

$$RMSE = \sqrt{\left[\left(\frac{1}{N}\right) * \sum_{i=1}^{N}(yi - xi)^2\right]} \quad (13)$$

Here, yi is the real data, xi is the data estimated by the Weibull distribution analysis, zi is the mean value of yi's, N is the number of observations, n is the number of parameters in the Weibull distribution. Of these criteria, all except $R^2$ determine the best distribution according to their smallest values. $R^2$ can range from 0 to 1 as an expression of the model's predictive power. As this value approaches 1, it indicates increased predictive power for the given study. Weibull least squares method (LSM) was preferred for parameter estimation because of its ease of calculation compared to other methods (especially MLE), its ability to make stable predictions in suitable data situations, and its ease of visualization [30, 31, 32].

## 3 Findings and Discussion

The frequency distributions of hourly wind speed data between 2015 and 2024 are presented in detail in Table 1. In this context, the observational frequency distributions created using the wind speed data measured for each year and the theoretical frequency values calculated using the two-parameter Weibull distribution function were comparatively evaluated. Wind speed data were categorized into specific speed classes, and wind frequencies corresponding to each speed range were determined. According to the measurement results, 1489 data points were recorded in the 0–1 m/s range, while no measurements were made in the 13–14 m/s range. Measurements were made by recording data for approximately one hour per day. A total of 3561 hours of wind speed data were analyzed. According to the obtained data, it was determined that the highest probability density occurred in the 1–2 m/s range.

The performance criteria used in the analyses include statistical validation criteria including the observational values ($y_i$), the theoretical values estimated by the Weibull distribution ($x_i$), the mean of the observational values ($z_i$), the number of observations (N) and the number of parameters of the distribution function (n). These criteria include the coefficient of determination ($R^2$), root mean square error (RMSE) and chi-square ($\chi^2$) tests, and for all criteria except $R^2$, lower values indicate that the model fits the real data better. The $R^2$ value is a criterion reflecting the explanatory power of the model, and varies between 0 and 1, and the value approaching 1 indicates the high predictive power of the model. As a result of the comparisons made, it was seen that the Weibull distribution successfully represented the wind speed data of Bartın province.



Table 1. Wind speed frequency distributions.

| No | Vi<br>Wind Speed Range | Vm,j<br>Wind Speed Range | fi<br>Number of Wind Speeds Measured | fA(vi)<br>Probability frequency | Fa(vi)<br>Cumulative frequency | fw(vi)<br>Weibull Probability |
|---|---|---|---|---|---|---|
| 1 | 0 − 1 | 0.5 | 1489 | 0.204379562 | 0.412807663 | 0.5202 |
| 2 | 1 − 2 | 1.5 | 1955 | 0.748175182 | 0.966777929 | 0.4927 |
| 3 | 2 − 3 | 2.5 | 104 | 0.04379562 | 0.996350343 | 0.0115 |
| 4 | 3 − 4 | 3.5 | 11 | 0.003649635 | 0.999451302 | 5.56388E-06 |
| 5 | 4 − 5 | 4.5 | 1 | 0 | 0.999726027 | 3.38589E-11 |
| 6 | 5 − 6 | 5.5 | 1 | 0 | 1 | 1.60644E-18 |
| 7 | 6 − 7 | 6.5 | 0 | 0 | 1 | 3.80572E-28 |
| 8 | 7 − 8 | 7.5 | 0 | 0 | 1 | 2.9811E-40 |
| 9 | 8 − 9 | 8.5 | 0 | 0 | 1 | 5.26144E-55 |
| 10 | 9 − 10 | 9.5 | 0 | 0 | 1 | 1.46071E-72 |
| 11 | 10 − 11 | 10.5 | 0 | 0 | 1 | 4.54613E-93 |
| 12 | 11 − 12 | 11.5 | 0 | 0 | 1 | 1.1506E-116 |
| 13 | 12 − 13 | 12.5 | 0 | 0 | 1 | 1.7444E-143 |
| 14 | 13 − 14 | 13.5 | 0 | 0 | 1 | 1.183E-173 |



The data presented in Table 1 show the statistical distribution of wind speed measurements belonging to the examined region in detail. In this direction, the Vi parameter represents the wind speed ranges created to provide the classification of wind speeds measured in a certain time period. The Vm,j value calculated for each range is obtained by taking the arithmetic average of the lower and upper limits of the relevant speed range and shows the average wind speed corresponding to that range. fi indicates the number of data observed in each wind speed range, i.e. how many measurements were made in that range.

The fA(Vi) value calculated based on the relevant frequency information is the probability density function (PDF) showing the probability of occurrence of each wind speed range. In contrast, FA(Vi) is defined as the cumulative distribution

function (CDF) expressing the cumulative sum of all probabilities up to a certain wind speed value. fw(Vi) represents the Weibull probability density function values calculated for each wind speed range. The Weibull distribution is a widely used parametric method in the assessment of wind energy potential and provides high accuracy results in the statistical modeling of wind speeds.

With the help of these parameters, the distribution characteristics of the wind speed data belonging to the region were analyzed in detail and the obtained results were used in the evaluations for determining the potential wind energy. The graphical representations of the fA(Vi), FA(Vi) and fw(Vi) functions calculated based on the relevant wind speed ranges and fi values are presented in Figure 1.

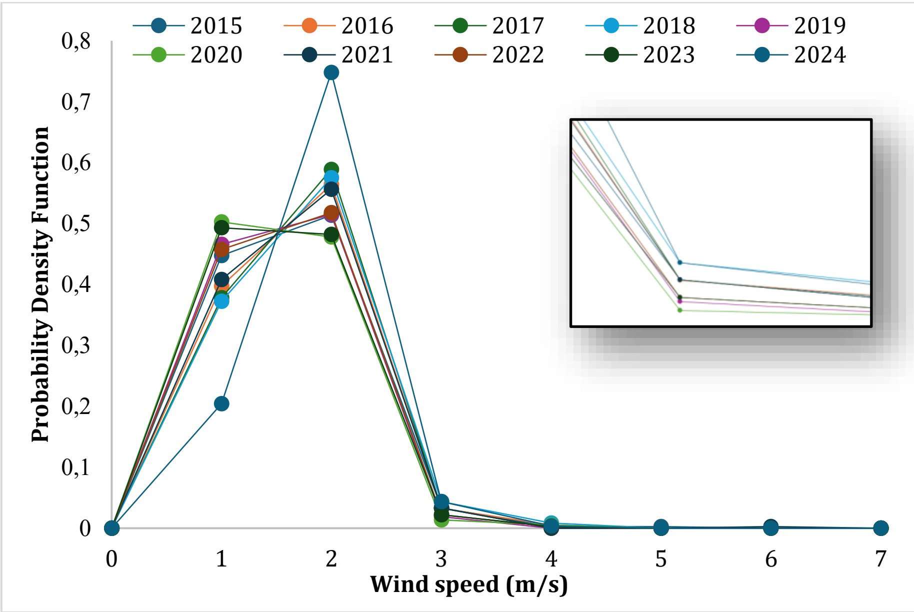


Figure 1. Variation of probability density function with wind speed

Figure 1 presents the probability density functions of wind speeds measured in Bartın province between 2015 and 2024. It is observed that wind speeds are concentrated around 2 m/s for all years, indicating that the dominant wind speed in the region is at low levels. The year 2021 draws attention by exhibiting a significantly higher probability density in the 2 m/s range compared to other years; this situation shows that the wind blew more frequently and steadily at this speed that year. The probability densities for speeds of 3 m/s and above are quite low, indicating that high-speed wind events in the region occur rarely. On the other hand, the absence of major differences between years reveals that the long-term wind regime of Bartın province has a stable structure. These findings show that the wind energy potential of the region, although limited, can be evaluated with turbine technologies that are sensitive to low speeds.

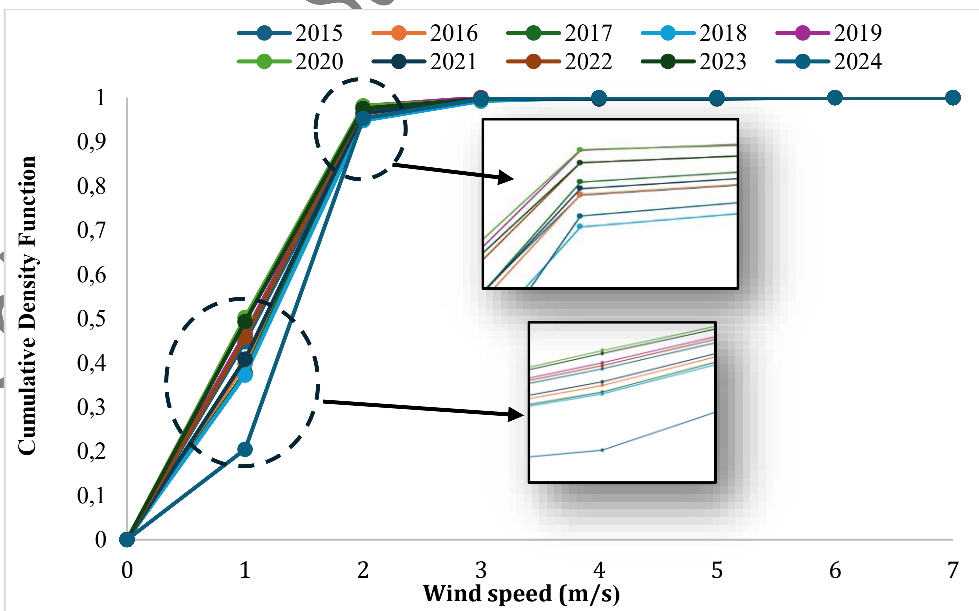


Figure 2. Variation of cumulative density function with wind speed

Figure 2 presents the cumulative probability distribution (CDF) for wind speeds measured in Bartın province between 2015 and 2024, and compares the probabilities of wind occurrence up to certain speed values. According to the results obtained, the cumulative density rate of wind speeds up to 2 m/s exceeds 90% for most years, which reveals that wind blows largely at low speeds in the region. In particular, the years 2015 and 2024 draw attention by deviating from other years in the range of 1–2 m/s, and it is understood that wind speeds are observed at lower frequencies during these periods. The details shown in the expanded areas reveal that there are small but significant differences between the years in low speeds (0–2 m/s) and transition to medium speeds (3–4 m/s). When the general trend is examined, it is understood that wind speeds in Bartın province are largely concentrated below 3 m/s, and therefore the region can be evaluated in the low-speed wind class. This finding points to the need for optimising wind power plants to be built in the region with turbines that can operate at low starting speeds.

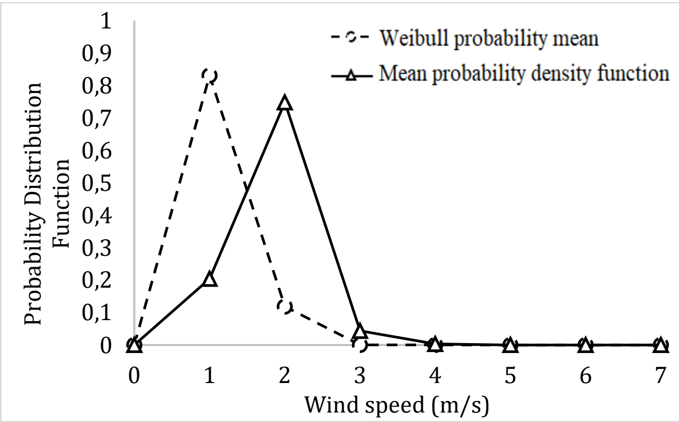


Figure 3. Variation of PDF and CDF probability density functions with wind speed

The graph compares the average probability density estimated by the observational mean of wind speed data for Bartın province with the average probability density estimated by the Weibull distribution applied to these data. The Weibull probability distribution, shown in blue, gives the highest value in the range of 1–2 m/s and exhibits a distinct peak in the range of 0–1 m/s. In contrast, the observational probability density function, shown in orange, gives the peak in the range of 2–3 m/s. This situation reveals that the Weibull distribution predicts higher probability compared to the observational data, especially at low speeds, but that the real data occurs with higher probabilities at speeds above 2 m/s. This difference shows that the Weibull model is sufficient to represent a region where low-speed winds are dominant, but it does not fully overlap with the observational data in some speed ranges. Although the Weibull distribution is generally successful in capturing the general trend of wind speeds, it can be said that the model may need certain corrections when microclimatic factors specific to the region are taken into account.



Table 2. The shape parameter (k) and scale parameter (c) values according to the Weibull distribution

| Months | Parameters | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| January | k | 2.0381 | 1.9772 | 2.5621 | 1.6431 | 2.7774 | 1.6239 | 1.8901 | 1.6344 | 1.7872 | 1.9490 |
| | c | 0.9248 | 0.7278 | 1.0646 | 1.1756 | 0.9712 | 0.6125 | 0.8541 | 0.9516 | 0.6019 | 1.2078 |
| February | k | 1.2532 | 1.8636 | 2.3406 | 3.1595 | 2.3918 | 0.7868 | 3.3003 | 3.0180 | 1.9671 | 2.7789 |
| | c | 1.2853 | 0.8699 | 1.1326 | 1.2090 | 1.2651 | 0.2917 | 1.0869 | 0.9076 | 0.9709 | 1.1350 |
| March | k | 4.3012 | 2.1970 | 4.9327 | 3.6338 | 3.0507 | 1.2627 | 3.3626 | 2.9191 | 2.5890 | 4.0502 |
| | c | 1.2227 | 1.3805 | 1.2834 | 1.2702 | 1.4186 | 0.9373 | 1.3401 | 1.3020 | 1.0788 | 1.2590 |
| April | k | 2.7452 | 4.2201 | 6.1792 | 4.8850 | 7.1462 | 2.9206 | 3.7460 | 3.5591 | 4.4005 | 5.0363 |
| | c | 1.4348 | 1.2685 | 1.3344 | 1.3960 | 1.2245 | 1.5659 | 1.2291 | 1.3584 | 1.3788 | 1.3572 |
| May | k | 3.3233 | 4.7976 | 4.4880 | 4.0458 | 5.7996 | 4.1617 | 4.8841 | 7.1292 | 7.2389 | 3.8445 |
| | c | 1.3299 | 1.2643 | 1.4707 | 1.4191 | 1.0765 | 1.1469 | 1.2982 | 1.3333 | 1.2186 | 1.4731 |
| June | k | 3.6601 | 5.1070 | 7.5596 | 6.2737 | 4.8290 | 5.4211 | 8.2524 | 5.1801 | 8.3861 | 4.4230 |
| | c | 1.1974 | 1.4323 | 1.3204 | 1.5807 | 1.2041 | 1.2503 | 1.2547 | 1.3550 | 1.2219 | 1.6783 |
| July | k | 4.8621 | 7.0917 | 5.5174 | 6.2564 | 6.6865 | 6.6451 | 6.8901 | 7.4047 | 6.0414 | 6.7096 |
| | c | 1.4111 | 1.5921 | 1.6385 | 1.3934 | 1.4069 | 1.3762 | 1.2804 | 1.3513 | 1.2200 | 1.5449 |
| August | k | 4.9554 | 6.4497 | 5.9876 | 5.1788 | 7.4148 | 6.2559 | 4.1701 | 5.9910 | 6.2232 | 4.6940 |
| | c | 1.4693 | 1.4823 | 1.4884 | 1.7005 | 1.3994 | 1.3703 | 1.2853 | 1.2310 | 1.1764 | 1.6256 |
| September | k | 4.5753 | 4.8926 | 3.3263 | 4.4655 | 3.0975 | 3.9339 | 1.4639 | 2.9553 | 4,1775 | 7.3888 |
| | c | 1.1787 | 1.2795 | 1.1961 | 1.3411 | 1.1182 | 1.2074 | 1.4025 | 1.0608 | 1.2619 | 1.2437 |
| October | k | 2.3081 | 2.8175 | 2.3515 | 2.6926 | 4.3782 | 2.1738 | 3.8565 | 3.4848 | 3.6894 | * |
| | c | 1.0231 | 1.1771 | 1.0629 | 0.8090 | 0.7258 | 0.7540 | 0.8916 | 0.8356 | 0.7043 | * |
| | k | 2.6482 | 1.7783 | 2.1390 | 1.9124 | 1.5881 | 3.0942 | 1.6597 | 2.6872 | 1.0999 | * |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| November | c | 0.7652 | 0.9890 | 0.8582 | 1.1234 | 0.4050 | 0.8275 | 0.8913 | 0.6711 | 0.9534 | * |
| December | k | 1.7052 | 1.7805 | 2.4532 | 2.4750 | 1.5109 | 5.8811 | 1.7505 | 1.5926 | 1.3277 | * |
| | c | 0.7268 | 0.9752 | 0.6874 | 0.9710 | 0.6366 | 0.7275 | 0.9091 | 0.6761 | 0.7575 | * |

* Data are taken until September 2024

According to the assessments made between 2015 and 2024, wind energy potential shows seasonal and annual fluctuations. The fact that the k (shape) and c (scale) parameters are generally high in the summer months (especially June–August) indicates that wind speeds are more stable and strong, and therefore the most efficient periods for energy production are the summer months. On the other hand, in the winter months (January, February, December), more variable and lower wind speeds are noted with values of $k < 2$ and $c < 1.2$. While the years 2017–2019 generally carry high potential, decreases were observed in some months after 2020. These data reveal the importance of seasonal and annual analyzes in wind energy investments.



Table 3. Monthly mean wind speed and standard deviation values according to Weibull distribution

| Months | Parameters | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| January | Vm | 0.8194 | 0.6452 | 0.9452 | 1.0516 | 0.8645 | 0.5484 | 0.7581 | 0.8516 | 0.5355 | 1.0710 |
| | σ | 0.4253 | 0.3444 | 0.3974 | 0.6657 | 0.3375 | 0.3509 | 0.4218 | 0.5417 | 0.3137 | 0.5793 |
| February | Vm | 1.1964 | 0.7724 | 1.0036 | 1.0821 | 1.1214 | 0.3345 | 0.9750 | 0.8107 | 0.8607 | 1.0103 |
| | σ | 0.9719 | 0.4354 | 0.4586 | 0.3752 | 0.5024 | 0.4171 | 0.3247 | 0.2932 | 0.4616 | 0.3942 |
| March | Vm | 1.1129 | 1.2226 | 1.1774 | 1.1452 | 1.2677 | 0.8710 | 1.2032 | 1.1613 | 0.9581 | 1.1419 |
| | σ | 0.2904 | 0.5923 | 0.2709 | 0.3490 | 0.4539 | 0.7026 | 0.3939 | 0.4331 | 0.3990 | 0.3150 |
| April | Vm | 1.2767 | 1.1533 | 1.2400 | 1.2800 | 1.1467 | 1.3967 | 1.1100 | 1.2233 | 1.2567 | 1.2467 |
| | σ | 0.5038 | 0.3063 | 0.2318 | 0.2971 | 0.1875 | 0.5206 | 0.3290 | 0.3801 | 0.3211 | 0.2813 |
| May | Vm | 1.1933 | 1.1581 | 1.3419 | 1.2871 | 0.9968 | 1.0419 | 1.1903 | 1.2484 | 1.1419 | 1.3323 |
| | σ | 0.3949 | 0.2733 | 0.3368 | 0.3554 | 0.1975 | 0.2803 | 0.2763 | 0.2046 | 0.1845 | 0.3855 |
| June | Vm | 1.0800 | 1.3167 | 1.2400 | 1.4700 | 1.1033 | 1.1533 | 1.1833 | 1.2467 | 1.1533 | 1.5300 |
| | σ | 0.3270 | 0.2934 | 0.1925 | 0.2710 | 0.2588 | 0.2432 | 0.1695 | 0.2741 | 0.1628 | 0.3891 |
| July | Vm | 1.2935 | 1.4903 | 1.5129 | 1.3290 | 1.3129 | 1.2839 | 1.1968 | 1.2677 | 1.1323 | 1.4419 |
| | σ | 0.3015 | 0.2454 | 0.3139 | 0.1507 | 0.2282 | 0.2245 | 0.2024 | 0.2006 | 0.2161 | 0.2499 |
| August | Vm | 1.3484 | 1.3806 | 1.3806 | 1.5645 | 1.3129 | 1.2742 | 1.1677 | 1.1419 | 1.0935 | 1.4871 |
| | σ | 0.3089 | 0.2481 | 0.2657 | 0.3441 | 0.2075 | 0.2355 | 0.3136 | 0.2196 | 0.2031 | 0.3581 |
| September | Vm | 1.0767 | 1.1733 | 1.0733 | 1.2233 | 1.0000 | 1.0933 | 1.2700 | 0.9467 | 1.1467 | 1.1667 |
| | σ | 0.2654 | 0.2719 | 0.3549 | 0.3084 | 0.3531 | 0.3098 | 0.8941 | 0.3490 | 0.3074 | 0.1850 |
| October | Vm | 0.9065 | 1.0484 | 0.9419 | 0.7194 | 0.6613 | 0.6677 | 0.8065 | 0.7516 | 0.6355 | * |
| | σ | 0.4196 | 0.4039 | 0.4286 | 0.2890 | 0.1698 | 0.3267 | 0.2327 | 0.2381 | 0.1910 | * |
| November | Vm | 0.6800 | 0.8800 | 0.7600 | 0.9967 | 0.3633 | 0.7400 | 0.7967 | 0.5967 | 0.9200 | * |
| | σ | 0.2774 | 0.5179 | 0.3774 | 0.5486 | 0.2373 | 0.2615 | 0.4997 | 0.2401 | 0.8428 | * |
| December | Vm | 0.6484 | 0.8677 | 0.6097 | 0.8613 | 0.5742 | 0.6742 | 0.8097 | 0.6065 | 0.6968 | * |
| | σ | 0.3967 | 0.5101 | 0.2668 | 0.3739 | 0.3926 | 0.1319 | 0.4835 | 0.3951 | 0.5367 | * |



* Data are taken until September 2024.

According to the monthly wind speed analysis between 2015 and 2024, a significant seasonality is observed in the annual cycle of wind speeds. The average wind speed (Vm) values increase in the summer months (especially June–August), indicating periods when the potential for wind energy production is high. The relatively low standard deviation (σ) values in the same period indicate that the fluctuations in wind speed are limited and the wind is stable. On the other hand, Vm values are generally lower in winter and early spring, and σ values tend to increase in some years. This situation reveals the need for seasonal optimization in wind energy production.

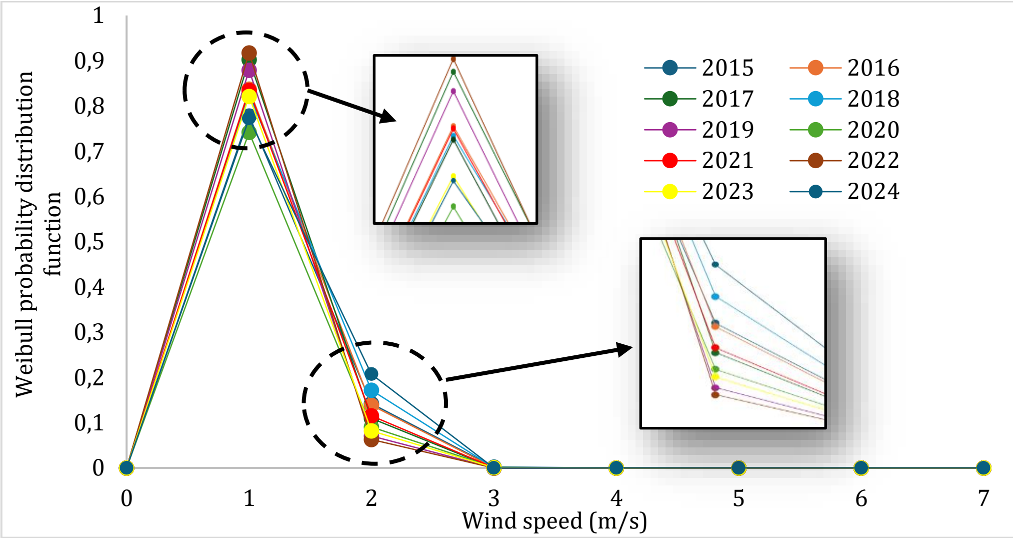


Figure 4. Change graph of calculated Weibull probability distribution functions according to wind speed

Figure 4 shows the modeling of wind speed data between 2015 and 2024 with the Weibull probability distribution function. In all years, the highest probability value is concentrated in the range of 1–2 m/s. Especially in 2023 and 2024, a decrease is observed in probability values around 2 m/s compared to other years. This shows that low wind speeds have been relatively decreasing in recent years.

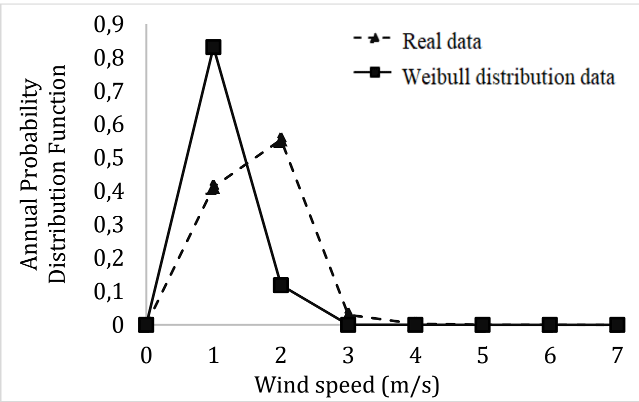


Figure 5. Variation of annual probability distribution functions with wind speed

The annual wind speed probability distribution is shown in Figure 5 in comparison with the real data and the Weibull distribution. The real data (triangle marked, dashed line) and the Weibull distribution (square marked, solid line) are generally similar in the range of 0–3 m/s. Especially at 1 m/s wind speed, the Weibull distribution estimates the probability as approximately 0.85, at which point a high agreement is observed with the real data. However, at 2 m/s speed, the Weibull distribution estimates a lower probability compared to the real data. At speeds of 3 m/s and above, both distributions show low probabilities. In general, the Weibull distribution satisfactorily represents the real data at low speeds.

Table 4. $R^2$, RMSE and χ2 values according to Weibull distribution

| Years | $R^2$ | RMSE | χ2 |
|---|---|---|---|
| 2015 | 0.9964 | 0.0062 | 3.95989E-05 |
| 2016 | 0.9957 | 0.0036 | 1.33526E-05 |
| 2017 | 0.9932 | 0.0018 | 3.29215E-06 |
| 2018 | 0.9976 | 0.0039 | 1.56591E-05 |
| 2019 | 0.9904 | 0.0094 | 9.13512E-05 |
| 2020 | 0.9931 | 0.0136 | 0.000192041 |
| 2021 | 0.9942 | 0.0083 | 7.08272E-05 |
| 2022 | 0.9885 | 0.0078 | 6.26993E-05 |
| 2023 | 0.9918 | 0.0100 | 0.00010367 |
| 2024 | 0.9994 | 0.0055 | 3.22224E-05 |

The high $R^2$ values obtained in the Weibull-based wind speed model (0.9885–0.9994 between 2015 and 2024) demonstrate a strong model fit. However, extremely high $R^2$ values observed in some years (e.g., 0.9994 in 2024) should be interpreted with caution, as they may indicate the possibility of overfitting in the literatüre [33, 34]. However, this risk is significantly reduced by the low results of other error measures such as RMSE and χ2 (e.g., RMSE = 0.0018, χ2 = 3.29×10−6 in 2017). However, applying methods such as cross-validation or test-data splitting to assess the generalizability of the model is recommended for further studies to support the robustness of the fit.

The fit of the Weibull distribution to the annual wind speed data was evaluated with $R^2$, RMSE and $\chi^2$ statistics. The $R^2$ values for all years ranged between 0.9885 and 0.9994, indicating that the distribution represents the data with high accuracy. Especially the $R^2$ value for 2024 (0.9994) reveals that the modeling was quite successful. The RMSE and $\chi^2$ values were generally low, reaching minimum values in 2017 (RMSE: 0.0018; $\chi^2$:

$3.29\times10^{-6}$), indicating that the model provided the highest precision for that year. In general, the Weibull distribution successfully modeled the wind speed data statistically in all years.

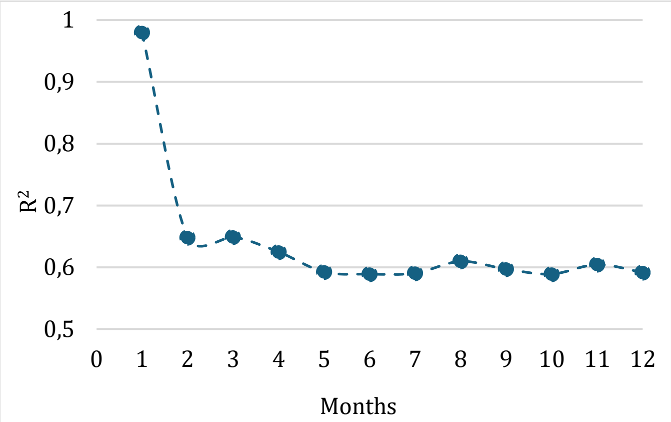


Figure 6. Monthly $R^2$ variation of Weibull probability distribution function

Figure 6 evaluates the fit of the Weibull distribution to monthly wind speed data using the $R^2$ statistic. The fit of the model is quite high in January, with the $R^2$ value approaching approximately 1; this shows that the Weibull distribution represents the data almost perfectly for this month. In other months, the $R^2$ values are relatively lower, but generally in the range of 0.6–0.7. This shows that the fit of the model is moderate for the rest of the year, and the explanatory power of the Weibull distribution decreases, especially in the summer months. Similar levels of $R^2$ values are seen in all months except January, suggesting that seasonal effects may create differences in model performance.

Table 5. Weibull distribution parameters of the calculated data

| Year | k | c (m/s) | Vm (m/s) | σ (m/s) | Vmod (m/s) | Vmax (m/s) | Pw (W/m²) |
|---|---|---|---|---|---|---|---|
| 2015 | 2.2601 | 1.1870 | 1.0514 | 0.4962 | 0.9166 | 4.50 | 1.2151 |
| 2016 | 2.5689 | 1.2318 | 1.0937 | 0.4588 | 1.0167 | 3.30 | 1.2398 |
| 2017 | 2.8609 | 1.2380 | 1.1033 | 0.4191 | 1.0652 | 2.60 | 1.1871 |
| 2018 | 2.8265 | 1.3105 | 1.1674 | 0.4484 | 1.1230 | 3.40 | 1.4166 |
| 2019 | 2.4532 | 1.1013 | 0.9767 | 0.4275 | 0.8896 | 2.60 | 0.9128 |
| 2020 | 2.0230 | 1.0435 | 0.9246 | 0.4833 | 0.7449 | 3.50 | 0.9142 |
| 2021 | 2.4211 | 1.1717 | 1.0389 | 0.4602 | 0.9403 | 5.60 | 1.1095 |
| 2022 | 2.5843 | 1.1137 | 0.9890 | 0.4126 | 0.9216 | 3.00 | 0.9130 |
| 2023 | 2.2679 | 1.0838 | 0.9600 | 0.4517 | 0.8387 | 3.70 | 0.9223 |
| 2024 | 3.4606 | 1.4136 | 1.2712 | 0.4053 | 1.2810 | 3.20 | 1.6453 |

When the data between 2015 and 2024 are examined, the annual average wind speeds (c) and the power density (Pw), which represents the kinetic energy of the wind, show a fluctuating course over the years. In 2020, the average wind speed and Vm values regressed to the lowest level, and this situation was reflected in Pw as a decrease. On the other hand,

a significant increase was observed in all parameters in 2024, and especially the power density reached the highest level periodically with 1.6453 W/m². This increase indicates that the wind-based energy potential was the highest in that year. In general, statistical parameters show that there is a slight increase in wind speed over the years.

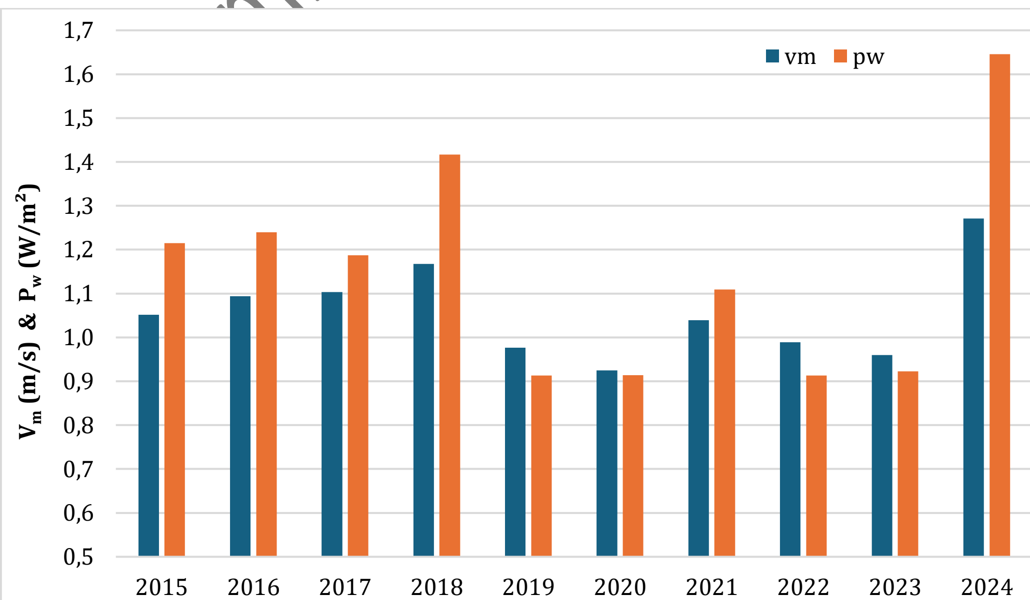


Figure 7. Display of wind power density and wind speed values calculated according to the Weibull distribution

In Figure 7, the annual changes in the parameters vm (average wind speed) and pw (wind power) for the period 2015–2024 are presented comparatively. When the general trend is examined, it is seen that the pw values are mostly above the vm values. The difference between the two parameters became apparent especially in 2018 and 2024. While both parameters decreased in 2019 and 2020, both values reached their highest levels in the observed period as of 2024. This shows that there was a significant increase in the performance of the relevant system in 2024.

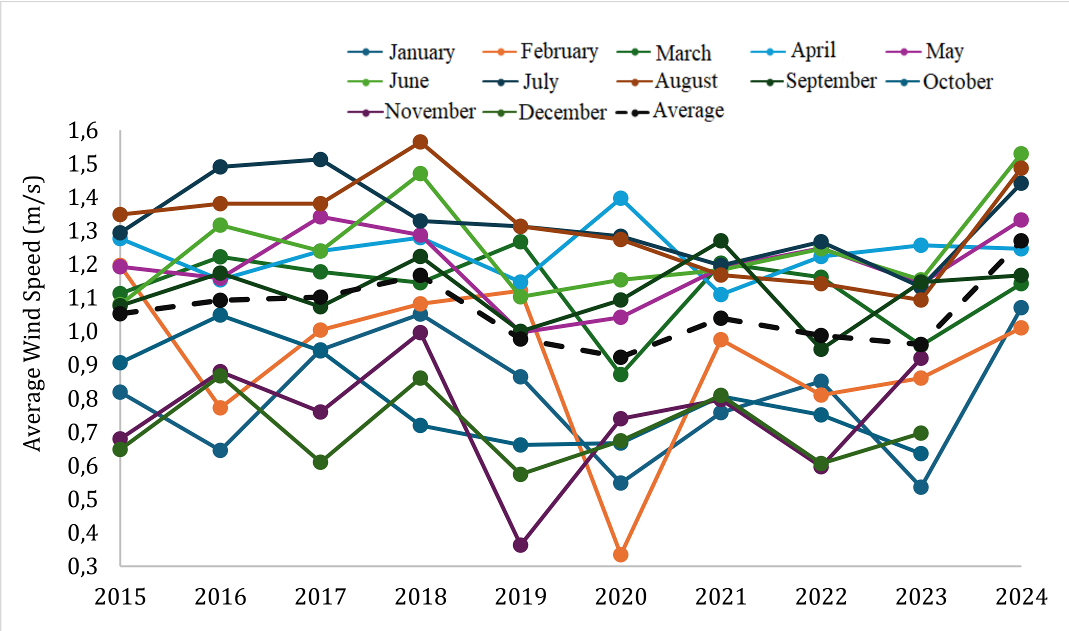


Figure 8. Changes in monthly average wind speed values over the years

According to annual data, it is observed that the highest average wind speeds in Bartın province generally occur in the summer months, especially in June, July and August. In this direction, the data dated August 2018 and June 2024 stand out with the high wind speeds recorded. This feature of the summer months shows that they offer high efficiency potential in terms of wind energy production for the region.

On the other hand, it has been determined that the lowest wind speeds are mostly recorded in the winter months, especially in December, January and February. In fact, it is seen that the average wind speeds decreased to approximately 0.35–0.4 m/s in the data of November 2019 and February 2020; this indicates that wind energy production may be seriously limited in these periods.

The year 2020 brings to the agenda the possibility of being an unusual year in terms of climate due to the observation of low wind speeds in many months. On the other hand, high wind speeds were recorded in many months throughout 2024, indicating that the wind energy potential of the year is quite high. In addition, it is observed that the average wind speeds recorded in the same month fluctuate significantly between years during the analyzed period. For example, while January had a relatively high average wind speed in 2016, this speed decreased to minimum levels in the same month in 2023. This situation reveals that the wind regime in Bartın exhibits significant volatility on an annual basis.

## 4 Conclusions and Recommendations

In our study, wind power density and wind speed distribution parameters for Bartın province were calculated using wind data measured between 2015 and 2024. These data were interpreted and analyzed statistically. Within the scope of this analysis, Weibull distribution was preferred in modeling wind speeds and the accuracy of the model was evaluated with $R^2$, RMSE and $\chi^2$ statistics. According to the results obtained, the lowest wind speed on a monthly basis was measured as 0.3345 m/s in February 2020, and the highest value was measured as 1.5645 m/s in August 2018. In the annual analysis based on the Weibull distribution, the lowest average wind speed was calculated as 0.9246 m/s in 2020 and the lowest power density was calculated as 0.9128 W/m$^2$ in 2019. By interpreting the data obtained as a result of the study, the highest average wind speed was determined as 1.2712 m/s in 2024, and the highest power density corresponding to this average wind speed was determined as 1.6453 W/m$^2$. The modeling results of the Weibull distribution give high $R^2$, low RMSE and acceptable $\chi^2$ values for all years, revealing that this distribution is a suitable model for the study region. Indeed, the literature study presented in the introduction indicates that the results obtained by using the Weibull distribution are more accurate than other methods. Furthermore, the wind speeds in the experimental data from the literature studies are very close to the wind speeds in our data. Consequently, the obtained data are consistent with the values in the literature study.

According to the findings, the fact that the monthly and annual average wind power densities in Bartın province are below 100

W/m² indicates that this region is not sufficient to provide electrical energy directly to the grid with wind energy systems [35]. However, it can be said that it offers a suitable potential for rural applications with low power requirements or areas where there is no grid connection. On the other hand, the fact that the daily and monthly average wind speeds are largely below 2 m/s reveals that the region has limited efficiency in terms of wind energy production.

## 5 Author Contributions

Author 1 handled the conceptualization and draft design of the article, the literature review, and the writing of the article. Author 2 evaluated the resulting draft and results, procured the necessary materials for the experimental study, and conducted the analyses. Author 3 completed the final review and formalization of the article's content.

## 6 Ethical Approval and Conflict of Interest

The article does not require ethics committee approval. There is no conflict of interest with any person or institution.

## 7 References


[1] Willemsen E, Wisse J. A. "Design for wind comfort in The Netherlands: Procedures, criteria and open research issues. *Journal of Wind Engineering and Industrial*". *Aerodynamics*, *95*(9-11),1541-1550, 2007..

[2] Ikegaya N, Ikeda Y, Hagishima A, Tanimoto J. "Evaluation of rare velocity at a pedestrian level due to turbulence in a neutrally stable shear flow over simplified urban arrays". *Journal of Wind Engineering and Industrial Aerodynamics*, *171*,137-147, 2017.

[3] Wang W, Ikegaya N, Okaze T. "Comparing Weibull distribution method and Gram–Charlier series method within the context of estimating low-occurrence strong wind speed of idealized building cases". *Journal of Wind Engineering and Industrial Aerodynamics*, *236*, 105401, 2023.

[4] Blocken B. "50 years of computational wind engineering: past, present and future". *Journal of Wind Engineering and Industrial Aerodynamics*, *129*, 69-102, 2014.

[5] Blocken B, Stathopoulos T, Van Beec J. "Pedestrian-level wind conditions around buildings: Review of wind-tunnel and CFD techniques and their accuracy for wind comfort assessment". *Building and Environment*, *100*, 50-81, 2016.

[6] Takadate Y, Okuda Y. "Wind Tunnel Study on Wind Speeds near the Ground with Roughness Blocks". *Advanced Experimental Mechanics*, *7*, 162-167, 2022.

[7] Takemi T, Yoshida T, Horiguchi M, Vanderbauwhede W. (2020). "Large-Eddy-simulation analysis of airflows and strong wind hazards in urban areas". *Urban Climate*, *32*, 100625.

[8] Efthimiou G C, Hertwig D, Andronopoulos S, Bartzis J G, Coceal O. "A statistical model for the prediction of wind-speed probabilities in the atmospheric surface layer. *Boundary-Layer Meteorology*, *163*, 179-201, 2017.

[9] Efthimiou GC, Kuma P, Giannissi, SG, Feiz AA, Andronopoulos S. "Prediction of the wind speed probabilities in the atmospheric surface layer". *Renewable energy*, *132*, 921-930, 2019.

[10] Ikegaya N, Kawaminami T, Okaze T, Hagishima A. "Evaluation of exceeding wind speed at a pedestrian level around a 1: 1: 2 isolated block model". *Journal of Wind Engineering and Industrial Aerodynamics*, *201*, 104193, 2020.

[11] Demirkol Z, Dayi F., Erdoğdu A, Yanik A, Benek A. "A Techno-Economic Analysis of Power Generation in Wind Power Plants Through Deep Learning: A Case Study of Türkiye". *Energies*, *18*(10), 2632, 2025.

[12] Wang W, Gao Y, Ikegaya N. "Approximating wind speed probability distributions around a building by mixture weibull distribution with the methods of moments and L-moments". *Journal of Wind Engineering and Industrial Aerodynamics*, *257*, 106001, 2025.

[13] Han F, Li X, Qi S, Wang W, Shi W. "Reliability analysis of wind turbine subassemblies based on the 3-P Weibull model via an ergodic artificial bee colony algorithm". *Probabilistic Engineering Mechanics*, *73*, 103476, 2023.

[14] Huo X, Yang L, Li D, H. "Determining Weibull distribution patterns for wind conditions in building energy-efficient design across the different thermal design zones in China". *Energy*, *304*, 132013, 2024.

[15] Basumatary H, Sreevalsan E, Sasi KK. "Weibull parameter estimation—A comparison of different methods". *Wind Engineering*, *29*(3), 309-315, 2005.

[16] Ukoima KN, Okoro OI, Akuru UB, Davidson IE. "Determination of the Weibull parameters and wind power potential: A case of Okorobo-Ile town, Rivers state, Nigeria". *Wind Energy and Engineering Research*, *2*, 100006, 2024.

[17] El Kihel B, Elyamani NK, Chillali A. "Wind energy potential assessment using the Weibull distribution method for future energy self-sufficiency". *Scientific African*, *26*, e02482, 2024.

[18] Wang L, Liu R, Zeng W, Zhang L, Peng H, Calautit JK, Li X. "Revealing the theoretical wind potential of the Qinghai-Tibet Plateau: A novel Bayesian Monte-Carlo framework for the Weibull bivariate distribution". *Energy Conversion and Management*, *325*, 119375, 2025.

[19] Rüstemli S, Güntas O, Şahin G, Koç A, Van Sark W, Doğan SŞ. "Wind power plant site selection problem solution using GIS and resource assessment and analysis of wind energy potential by estimating Weibull distribution function for sustainable energy production: The case of Bitlis/Turkey". *Energy Strategy Reviews*, *56*, 101552, 2024.

[20] Can ÖF. "Numerical investigation of wind resistance and heat island formation in buildings of different configurations". *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 30(6), 729-736, 2024.

[21] Celik AN. "A statistical analysis of wind power density based on the Weibull and Rayleigh models at the southern region of Turkey". *Renewable Energy*, 29(4), 593-604, 2004.

[22] Akdağ SA, Dinler A. "A new method to estimate Weibull parameters for wind energy applications". *Energy Conversion and Management*, 50(7), 1761–1766, 2009.

[23] Seguro JV, Lambert TW. "Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis". *Journal of Wind Engineering and Industrial Aerodynamics,* 85(1), 75-84, 2004.

[24] T.C. Meteoroloji Genel Müdürlüğü (MGM). "Bartın Meteorolojik Gözlem Verileri (2015–2024)''

https://www.mgm.gov.tr/sondurum/guncel-haritalar.aspx (04.05.2025)

[25] Bilgili M, Yasar A, Simsek E. "Offshore wind power development in Europe and its comparison with onshore counterpart". *Renewable and Sustainable Energy Reviews*, *15*(2),905-915, 2011.

[26] Gungor A, Gokcek M, Uçar H, Arabacı E, Akyüz A. "Analysis of wind energy potential and Weibull parameter estimation methods: a case study from Turkey". *International Journal of Environmental Science and Technology*, 17(2), 1011-1020, 2020.

[27] Akpınar EK, Balpetek N. "Statistical analysis of wind energy potential of Elazığ province according to Weibull and Rayleigh distributions". *Journal of the Faculty of Engineering and Architecture of Gazi University*, *34*(1), 569-580, 2019.

[28] T.C. Meteoroloji Genel Müdürlüğü (MGM). "Otomatik Meteoroloji Gözlem İstasyonları (OMGİ) Veritabanı: 2015–2024 Yılları Arası Rüzgâr Verileri" https://www.mgm.gov.tr/sondurum/radar.aspx (04.05.2025)

[29] Gong Z, Fang P, Wang Z, Li X, Wang Z, Meng F. "Pyrolysis characteristics and products distribution of haematococcus pluvialis microalgae and its extraction residue". *Renewable Energy*, *146*, 2134-2141, 2020.

[30] Justus, C. G., Hargraves, W. R., Mikhail, A., & Graber, D. (1978). Methods for Estimating Wind Speed Frequency Distributions. Journal of Applied Meteorology, 17(3), 350–353. https://doi.org/10.1175/1520-0450(1978)017<0350:mfewsf>2.0.co;2

[31] Seguro, J. V., & Lambert, T. W. (2000). Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis. Journal of Wind Engineering and Industrial Aerodynamics, 85(1), 75–84. https://doi.org/10.1016/s0167-6105(99)00122-1

[32] YILMAZ, A., KARA, M., & AYDOĞDU, H. (2020). A study on comparisons of Bayesian and classical parameter estimation methods for the two-parameter Weibull distribution. Communications Faculty Of Science University of Ankara Series A1Mathematics and Statistics, 576–602. https://doi.org/10.31801/cfsuasmas.606890

[33] Yılmaz, E., Kara, D., & Aydoğdu, N. (2020). A study on comparisons of Bayesian and classical parameter estimation methods for the two-parameter Weibull distribution. Communications Faculty of Sciences University of Ankara Series A1: Mathematics and Statistics, 69(2), 848–865. https://doi.org/10.31801/cfsuasmas.606890

[34] Erişoğlu, M., Aras, S., & Yıldızay, H. (2020). Optimum method for determining Weibull distribution parameters used in wind energy estimation. Pakistan Journal of Statistics and Operation Research, 16(2), 345–356. https://pjsor.com/pjsor/article/view/3456

[35] Celik, A. N. (2003). Assessing the suitability of wind speed probabilty distribution functions based on wind power density. Renewable Energy, 28(10), 1563-1574.