

ANNUAL ENERGY PRODUCTION ESTIMATION OF A WIND TURBINE WITH WIND CONDITION IN VIETNAM

Hoang Trung Kien^{1,*}, Ngo Gia Khai¹

DOI: <https://doi.org/10.57001/huih5804.2026.002>

ABSTRACT

This study calculates the annual wind energy production of a wind farm located in Huong Linh, Quang Tri, Vietnam. An analytical method, utilizing a wind speed probability distribution function, is employed based on statistical wind data collected from the site. Various techniques including Maximum Likelihood Estimation, Method of Moments, and the Power Density Method are used and compared to determine the shape factors of the Weibull function. The estimated energy yield, based on an idealized power curve, closely aligns with the yield obtained using the measured power curve, showing only about a 4% difference. This indicates a fast yet accurate approach for estimating wind energy during the preliminary phase of wind project development.

Keywords: Annual Energy Production, Weibull distribution, wind energy.

¹University of Science and Technology of Hanoi, Vietnam Academy of Science and Technology, Vietnam

*Email: hoang-trung.kien@usth.edu.vn

Received: 15/10/2025

Revised: 14/01/2026

Accepted: 28/01/2026

1. INTRODUCTION

In recent decades, global demand for electricity has significantly increased due to industrial expansion, urbanization, and rapid technological advancements. This rising demand has raised concerns about climate change and the depletion of fossil fuel reserves, making it urgent to shift toward cleaner and more sustainable energy sources. Among these, wind energy emerges as a particularly promising solution because of its abundance, minimal environmental pollution, low operating costs, and scalability [1]. According to the Global Wind Energy Council (GWEC), the total installed wind power capacity reached over 1,023 GW globally by the end of 2024, with continuous growth expected in the coming years [2].

Vietnam has significant potential for wind energy, especially in its coastal and highland areas, where wind speeds are consistent and strong. The Power Development Plan VIII (PDP8) sets ambitious targets for both onshore and offshore wind power. To encourage investment, the government has implemented feed-in tariffs and other incentives [3]. However, there are still practical challenges that remain, including issues related to accurate site selection, investment risks, and estimating energy yield.

A crucial aspect of project planning in wind energy is accurately estimating annual energy production (AEP). To achieve a precise estimate of this energy output, several factors must be considered, including wind speed availability, turbine performance, the wake effect at the site, electrical losses, and other local environmental conditions [4]. Various studies have focused on AEP estimation. For instance, the authors in [4] explored methods for accounting for losses due to the unavailability of wind turbines and cables within wind farms, as well as wind energy curtailments in networks. Additionally, Mohammad et al. [5] proposed a new method that takes into account the impact of air temperature measurements during the operation of wind turbines. A novel Monte Carlo approach was also discussed in [6], which simulates wind speed for AEP estimation. The results indicate that this method provides a more realistic estimate of AEP compared to the Weibull estimate. While the Weibull distribution function is a popular tool for AEP estimation due to its efficiency and straightforward implementation, there is a notable lack of research on the influence of different approaches used to determine the shape parameter, which is one of the two critical parameters of the Weibull function.

This research focuses on modeling wind speed distributions and calculating key statistical parameters

for a wind farm located in Huong Linh, Quang Tri. Three different approaches will be employed and compared to determine the shape parameter of the Weibull distribution. The AEP of a wind turbine will be assessed using statistical wind data along with the performance characteristics of a selected turbine. We will compare both the ideal and realistic power curves in the AEP estimation. The structure of the article is organized as follows: Section 2 elaborates on the characteristics of the wind data and the methodologies used to determine the critical parameters of the Weibull distribution function. Section 3 presents the AEP estimation based on both the ideal and measured power curves of the turbine. The main results are discussed in Section 4, followed by the conclusion.

2. WIND DATA CHARACTERISTIC

2.1. Wind data

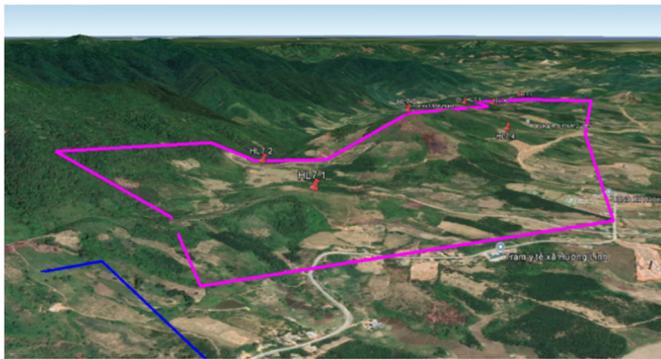


Figure 1. Huong Linh 7 wind farm, Quang Tri

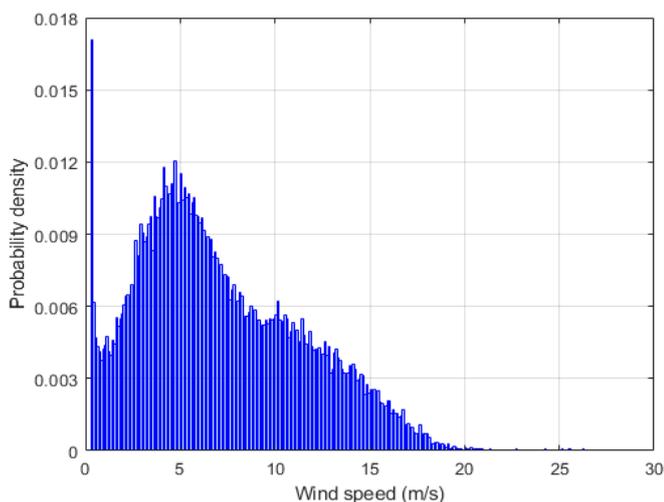


Figure 2. Probability density of the 10-minute wind speed data

The wind speed data used in this study was collected from the Huong Linh 7 wind power plant located in Quang Tri province, within Vietnam's central coastal zone, as illustrated in Fig. 1. The site's proximity to the coast and its channeled terrain significantly influences

wind behavior, resulting in strong, steady, and directionally consistent flows driven by monsoonal patterns and sea breezes. Wind measurements were recorded using the NRG Systems SymphoniePRO data acquisition system at a height of 100 meters, which is close to the turbine hub height; details will be presented in Section 3. This height aligns with the data collection point, helping to avoid extrapolation for wind speeds at altitudes different from the measured one. The dataset covers a continuous period of one year, from January 1, 2020, to December 31, 2020. While a one-year dataset is generally sufficient for academic studies and preliminary project assessments, it may not fully capture long-term wind variability due to interannual fluctuations caused by seasonal anomalies, large-scale climate cycles, or localized meteorological patterns. In this study, the analysis is limited to a single year of wind speed data primarily because the dataset is proprietary and not publicly available. The probability density of the wind speed data is shown in Fig. 2, indicating that the wind speed distribution is concentrated more in the low-speed region, with a mean wind speed of 7.15m/s.

2.2. Weibull distribution function

The Weibull distribution, expressed by (1), is a widely used statistical model for representing wind speed frequency distributions due to its flexibility and reliability in capturing a range of wind behaviors [7, 8].

$$f(v) = \frac{k}{A} \left(\frac{v}{A}\right)^{k-1} e^{-(v/A)^k} \quad (1)$$

where v is the wind speed, k and A are shape and scale parameters, respectively.

A higher value of k indicates less variability and a more symmetrical distribution, while a lower k signifies greater variability and skewness. Theoretical values often assume $k \approx 2$ for typical wind regimes, especially when wind speed measurements are not available. Higher values of A suggest stronger prevailing wind speeds, which generally lead to greater wind energy potential. In this study, three different techniques are used to enhance the reliability of determining the parameters k and A : Maximum Likelihood Estimation (MLE), Method of Moments (MoM), and Power Density Method (PDM). These techniques are widely used in wind data analysis. Among them, the PDM is more effective for low altitude wind data but is less reliable at higher altitudes. On the other hand, the MoM and MLE methods demonstrate greater efficiency with reduced error rates and can be applied at any altitude [9]. Due to the different

mechanisms involved, the resultant Weibull functions will vary, ultimately affecting the AEP estimate.

The MLE method has been widely used for estimating the parameters of Weibull distribution function [9]. By this method, the shape and scale parameters are estimated through numerical iterations as (2).

$$\begin{cases} k = \left(\frac{\sum_{i=1}^n v_i^k \ln(v_i)}{\sum_{i=1}^n v_i^k} - \frac{\sum_{i=1}^n \ln(v_i)}{n} \right) \\ A = \left(\frac{\sum_{i=1}^n (v_i)^k}{n} \right)^{\frac{1}{k}} \end{cases} \quad (2)$$

The MoM method [9] estimates parameters by matching the first two statistical moments - the sample mean μ and variance σ^2 - to their theoretical expressions under the Weibull distribution. The shape parameter k is determined by solving (3):

$$\frac{\Gamma\left(1 + \frac{2}{k}\right) - \left[\Gamma\left(1 + \frac{1}{k}\right)\right]^2}{\left[\Gamma\left(1 + \frac{1}{k}\right)\right]^2} = \frac{\sigma^2}{\mu^2} \quad (3)$$

The PDM method [9] estimates parameters based on the energy pattern factor (EPF), defined as the ratio between the mean of the cubed wind speeds and the cube of the mean wind speed as (4).

$$E_{pf} = \frac{\frac{1}{n} \sum_{i=1}^n v_i^3}{\left(\frac{1}{n} \sum_{i=1}^n v_i\right)^3} \quad (4)$$

From this, the shape parameter k is estimated using an empirical equation (5).

$$k = 1 + \frac{3.69}{E_{pf}^2} \quad (5)$$

The scale parameter A is then derived by (6).

$$A = \frac{\bar{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \quad (6)$$

where Γ is gamma function. The gamma function of a variable x is defined by (7) [10].

$$\Gamma(x) = \int_0^{\infty} t^{x-1} e^{-t} dt \quad (7)$$

3. ANNUAL ENERGY PRODUCTION ESTIMATION

3.1. Wind turbine

In this study, the wind energy converter selected for evaluation is the Enercon E-138 EP3 E2, a modern, high-performance wind turbine designed for utility-scale renewable power generation. It is a horizontal-axis, upwind-facing wind turbine equipped with three blades

and a variable-speed rotor system. The turbine integrates a pitch control mechanism that allows active adjustment of blade angles to optimize aerodynamic efficiency under varying wind conditions. Its gearless direct-drive synchronous generator ensures high energy conversion efficiency and reduced mechanical complexity. The turbine has a rated power output of 4200kW and is mounted on a tubular steel tower with a hub height of 111 meters, which is close to the measurement point of the wind speed. The detailed specifications of the turbine are summarized in Table 1.

Table 1. Enercon E-138 EP3 E2 wind turbine specification

Category	Specification
Turbine type	Horizontal-axis, upwind, variable-speed
Rated power	4200kW
Rotor diameter	138.25m
Hub height	111m
Cut-in wind speed	2.5m/s
Cut-out wind speed	28.0m/s
Generator type	Direct-drive synchronous generator

3.2. AEP estimation

The estimation of AEP is significantly influenced by the characteristics of wind speed, which can be modeled using the Weibull function, as well as the power curve of the turbine. In this analysis, we will compare two different power curves and utilize three variations of the Weibull function. Fig. 3 and Fig. 4 illustrate the idealized and measured power curves, along with the corresponding power coefficients. The idealized power curve, shown in Fig. 3, presents a simplified representation of turbine performance based on the assumptions of optimal aerodynamic operation and perfect control systems throughout the turbine's operational range. In the range between the cut-in wind speed of 2.5m/s and the rated wind speed, 10.8m/s, the turbine operates under conditions where the power output increases in proportion to the cube of the wind speed, as expressed by (8). During this phase, the power coefficient (C_p) is maintained at a constant value of 0.47, which is close to the maximum achievable in practical turbine designs. Once the wind speed exceeds the rated threshold, the turbine enters a regulation zone extending up to the cut-out speed of 28m/s. In this zone, power output is intentionally capped at the rated value of 4200kW to prevent overloading the mechanical and electrical components of the system.

$$P(v) = \frac{1}{2} \rho A C_p(v) v^3 \tag{8}$$

where ρ is the air density.

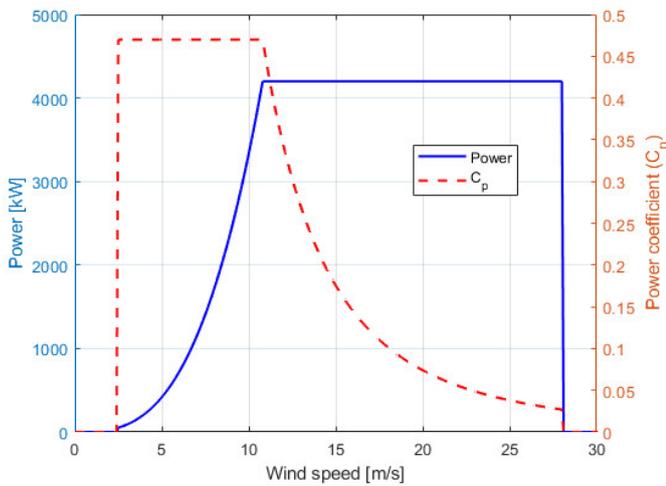


Figure 3. Idealized power curve and power coefficient according to the wind speed

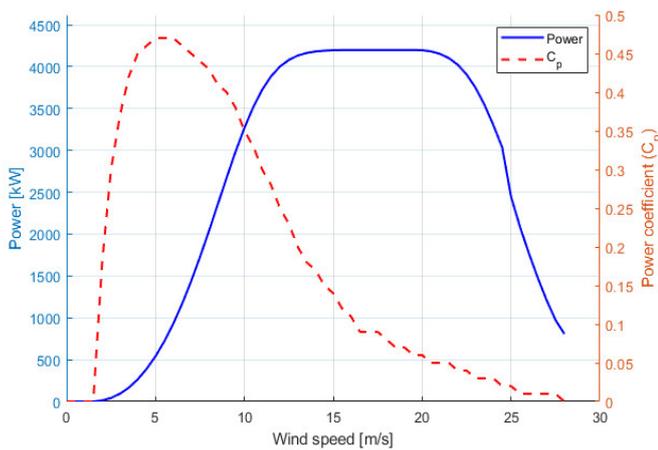


Figure 4. Measured power curve and power coefficient according to the wind speed

In the measured case, the turbine power output is taken directly from manufacturer-provided data. This dataset includes discrete wind speeds from 0 to 28m/s. The shape of the measurement curve (shown in Fig. 4) reflects more realistic turbine behavior under actual operating conditions, capturing the effects of aerodynamic losses, control limitations, and mechanical inefficiencies. Power output increases with wind speed up to the rated level, but unlike the ideal curve, it does not remain constant afterward; instead, it gradually declines as wind speed continues to rise. This smoother transition and downward slope beyond the rated wind speed indicate the influence of practical design constraints and control strategies that limit power capture at higher wind speeds. Since the data only covers

specific wind speed values, linear interpolation is used to estimate the power output for wind speeds that fall between two recorded points.

The comparison between the idealized and measured power curve is shown in Fig. 5. As seen, in the lower wind speed region, the idealized curve is lower than the data provided by the manufacturer, meaning that wind energy production in the lower speed region should be higher for the measured case.

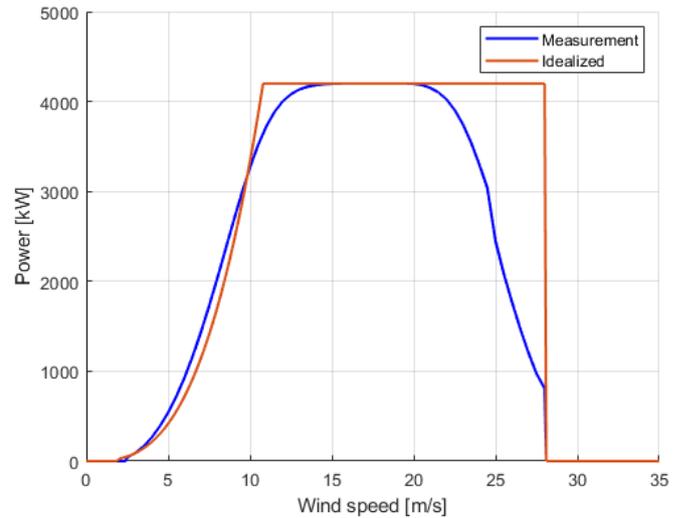


Figure 5. Idealized and measured power curves

The AEP is calculated by integrating the product of the turbine’s power output $P(v)$ and the Weibull PDF $f(v)$, multiplied by the number of hours in a year and the system efficiency. The general expression used for both cases can be expressed by (9):

$$AEP = \eta \cdot 8760 \cdot \int_{v_{min}}^{v_{max}} P(v) \cdot f(v) dv \tag{9}$$

where 8760 is the number of hours in a year, η is the overall system efficiency, which is assumed to be 0.81, a representative value for conventional wind energy conversion systems [11].

4. RESULTS AND DISCUSSION

The resultant shape and scale parameters from the three methods are summarized in Table 2. The corresponding Weibull functions are displayed in Fig. 6 alongside the wind speed measurements. As shown in Fig. 5, although each method approximates the empirical distribution reasonably well, minor deviations are present - particularly in the tail regions where extreme wind speeds occur less frequently but significantly influence energy output. Among the three approaches, the distribution produced by the MLE method seems to

be closer to the empirical data. Its curve more accurately traces the observed values not only around the modal wind speed but also across the lower and upper extremes, resulting in a better overall fit.

Table 2. Weibull parameters using different methods

Parameter	MLE	MoM	PDM
k	1.689	1.721	1.757
A	7.992	8.021	8.031

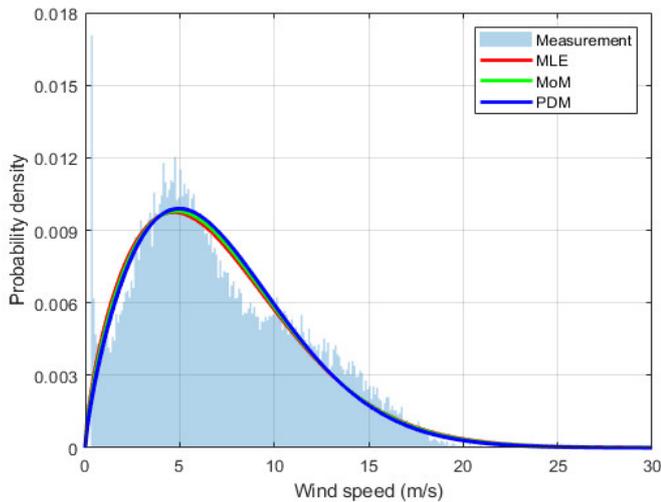


Figure 6. Weibull distribution functions obtained by various methods

The shape parameter k was consistently estimated to be around 1.8 across all methods. This lower k value indicates a broader and more skewed wind speed profile, suggesting that the site experiences a wide range of wind speeds rather than a narrow band clustered around the mean. This type of distribution implies more frequent occurrences of both low and high wind speeds, which introduces increased variability in turbine performance. This variability is particularly important near threshold operating points such as cut-in and cut-out speeds, where small differences in wind speed can lead to significant changes in power output. The scale parameter A was estimated at approximately 8 m/s using all three methods. This value reflects moderate prevailing wind conditions typical of many inland regions in Vietnam. The consistency of A values across all methods reinforces the reliability of the wind speed characterization at this location and supports the robustness of subsequent performance modelling. While none of the Weibull curves perfectly replicate the observed wind speed distribution, especially near the central peak, as seen in Fig. 6. This divergence is expected due to the limitations of the two-parameter Weibull model. Real-world wind data often show irregularities caused by diurnal effects, turbulence,

or seasonal shifts, leading to small-scale fluctuations that a smooth, continuous distribution cannot capture. Consequently, discrepancies between the fitted curves and the empirical histogram are inherent across all methods.

The estimation of AEP was conducted using three different methods and two cases of power curves, as summarized in Table 3. Overall, the estimates are closely aligned. Regarding the power curve, due to higher power in the low wind speed region, where the probability of wind speed is high, the AEP estimates for the measured power curve are a bit higher (about 4%). This discrepancy suggests the error estimation when manufacturing data is unavailable. Additionally, despite the differences in shape and scale parameters produced by the three methods, the AEP estimates generated using the corresponding Weibull function show slight variations, amounting to less than a 1% difference.

Table 3. AEP estimate by different methods [MWh]

	MLE	MoM	PDM
Idealized power curve	13851	13925	13953
Measured power curve	14406	14495	14540
Ratio (measured/idealized) [%]	104.01	104.09	104.21

5. CONCLUSION

This paper presented an analysis aimed at characterizing the wind speed for a wind farm located in Huong Linh, Quang Tri province. Various algorithms were applied to determine the shape parameters, with the Maximum Likelihood Estimation demonstrating slightly better performance compared to the Method of Moments and the Power Density Method. The analysis also indicates a close match in the estimation of Annual Energy Production based on both the measured and idealized power curves, although results obtained with the measured power curve yields 4% higher energy. These findings suggest the need for calibration during the preliminary phase of a wind energy project for more accurate energy estimations.

REFERENCES

[1]. R. Asghar, M. J. Anwar, H. Wadood, H. Saleem, N. Rasul and Z. Ullah., "Promising Features of Wind Energy: A Glance Overview," in *2023 4th International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, Sukkur, Pakistan, pp. 1-6, 2023.

- [2]. GWEC's Global Wind Report 2024, (n.d.)
- [3]. Decision No. 500/QĐ-TTg dated May 15, 2023 Approving the National Power Development Master Plan for the 2021-2030 period, with a vision toward 2050.
- [4]. Muhammad Ali, Julija Matevosyan, J.V. Milanović., "Probabilistic assessment of wind farm annual energy production," *Electric Power Systems Research*, 89, 70-79, 2012.
- [5]. Mohammad Al-Khayat, Majed AL-Rasheedi., "A new method for estimating the annual energy production of wind turbines in hot environments," *Renewable and Sustainable Energy Reviews*, 195, 114343, 2024.
- [6]. Hrafnkelsson B., Oddsson GV., Unnthorsson R. A., "Method for Estimating Annual Energy Production Using Monte Carlo Wind Speed Simulation," *Energies*, 9, 4, 2016.
- [7]. Lencastre Pedro, Anis Yazidi, Pedro G. Lind., "Modeling Wind-Speed Statistics beyond the Weibull Distribution," *Energies*, 17, 11, 2024.
- [8]. Vladimir A. Katic, SrDan Milicevic, Sulaiman Milad, "The wind-speed analysis using probability distribution function for winds in Serbia," in *12th International Conference on Electrical, Electronics and Computer Engineering*, Cacak, 2025.
- [9]. A. K. Azad, M. G. Rasul, T. Yusaf, "Statistical diagnosis of the best weibull methods for wind power assessment for agricultural applications," *Energies*, 7, 5, 3056-3085, 2014.
- [10]. A. A. Teyabeen, "Statistical analysis of wind speed data," in *The Sixth International Renewable Energy Congress, Sousse, Tunisia*, 1-6, 2015.
- [11]. Iain Allan Dinwoodie, David McMillan, "Operational strategies for offshore wind turbines to mitigate failure rate uncertainty on operational costs and revenue," *IET Renewable Power Generation*, 08, 359-366, 2014.