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A Study on Determining the Output Power of Wind Energy Generation Considering Uncertainty in Input Power Forecasting

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ABSTRACT

This paper presents a method for determining the output power of a wind power generation system under wind speed uncertainty. Hourly wind data collected in Hawaii, USA, is statistically modeled using four probability distribution functions: Weibull, Rayleigh, Log-normal, and Gamma. The distribution parameters are estimated via the Maximum Likelihood Estimation (MLE) method and subsequently applied to a Doubly-Fed Induction Generator (DFIG) model in MATLAB/Simulink to simulate power output variations based on probabilistically modeled wind speed. The fit quality of each distribution is assessed by calculating the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), in comparison to the empirical histogram. The results indicate that the two-parameter Weibull distribution best fits the measured data (MAE = 0.00708, RMSE = 0.0097, R^2 = 0.93), followed by the Gamma distribution. In contrast, the Rayleigh and Log-normal distributions exhibit significant deviations. When the Weibull parameters are applied to the DFIG model, the simulated weekly power output ranges from 0.96 MW to 1.37 MW, clearly illustrating the nonlinear relationship between wind speed and output power. The proposed approach thus provides a rigorous quantitative framework that links the probabilistic characteristics of wind to the actual power output range, thereby enhancing reliability in operational planning and mitigating risks in modern power systems.

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1. Introduction

Wind power converts the wind's kinetic energy into electrical energy via turbines. However, wind speed is strongly dependent on the prevailing meteorological state, so forecasts inherently contain uncertainty; in parallel, measurement and sampling errors contaminate model inputs and propagate to errors in power estimation. These constitute the two primary sources of uncertainty in wind power forecasting [1], [2], [3]. Fluctuations in wind speed and direction severely degrade the accuracy of estimating a wind turbine's output power. Specifically, because output power is proportional to the cube of wind speed, even a small error in wind speed can cause a large error in the estimated power [4], [5]. Moreover, variability in wind direction makes the inflow across the turbine non-uniform, reduces the rotor's effective wind-capture area, and lowers actual power relative to the ideal value predicted by the model [6].

Recent studies on wind power forecasting increasingly consider probability density function (PDF) modeling as a tool for quantifying uncertainty. The Weibull distribution is often recognized for its good fit in the body of the data and ease of parameter estimation; however, it is less reliable in the tail regions [7]. The Rayleigh distribution, requiring only a single parameter, enables rapid computation for potential assessment but is prone to inaccuracies when the data exhibit multimodal behavior or positive skewness [8]. The statistical post-processing approach, which utilizes a Log-normal distribution, reduces underdispersion and provides a more flexible confidence interval. However, it tends to be biased toward low wind speeds and must often be replaced by a truncated normal distribution under changing conditions [9]. A hybrid model combining the Gamma distribution with the Generalized Pareto distribution effectively captures both regular and extreme wind events, improving the continuous ranked probability score (CRPS) by approximately 10%. However, this approach requires complex inference procedures and extensive extreme value data [10]. A multi-distribution framework incorporating Gaussian, Beta, Gamma, and Laplace distributions enhances the confidence interval coverage, yet lacks a consistent rule for selecting or blending distributions under site-specific conditions [11].

A range of additional studies continues to explore probability distribution functions (PDFs) to reduce uncertainty in wind power estimation. Research in [12] compared various PDFs and even proposed a bimodal Weibull mixture to better represent multimodal wind data and reduce estimation bias compared to the standard Weibull distribution. However, this approach is complex and requires manual parameter adjustment. The study in [13] derived empirical formulas relating the shape and scale parameters of the Weibull distribution to mean wind speed and power density, enabling quick energy estimation. They also identified meteorological stations where the Weibull model poorly fits the data and suggested the use of the Pearson distribution, though their analysis was based on a limited dataset. The review presented in [14] emphasized the importance of selecting distributions based on local terrain and climatic conditions, but remained at a conceptual level without providing a quantitative selection framework. The investigation reported in [15] compared five distributions across four stations and confirmed the superior goodness-of-fit of the Weibull distribution. They proposed a selection procedure based on histogram features, but only utilized short-term datasets, which may not capture long-term variability. The analysis in [16] demonstrated that the two-parameter Weibull distribution, estimated using Maximum Likelihood Estimation (MLE), accurately models power density in Alacatı and illustrated a practical method for assessing economic wind potential. However, the analysis overlooked the heavy-tail behavior, leading to an underestimation of risk under extreme wind conditions. Another study in [17] proposed the use of an inverse Weibull distribution to capture heavier right tails, thus addressing the underestimation of high wind speeds, though the study was limited to wind speed analysis without translating results into power output or accounting for real-time uncertainty. The evaluation in [18] compared the Weibull and Rayleigh distributions in estimating power density, concluding that while Rayleigh is useful for preliminary assessments, it lacks accuracy under skewed data conditions and does not address error propagation into power forecasting.

However, the aforementioned studies lack a systematic comparison of different probability distributions applied to the same long-term wind power time series. They also fail to directly link wind speed uncertainty to the turbine power curve, resulting in error quantification that remains limited to wind speed rather than modeling power output uncertainty. This paper presents a comparative analysis of the goodness-of-fit between several commonly used and highly flexible probability distributions—such as Weibull, Rayleigh, Gamma, and Log-normal—against empirical wind data. The distribution parameters are estimated using the Maximum Likelihood Estimation (MLE) method to accurately capture the statistical characteristics of wind speed. Evaluation metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), are employed to identify the most suitable probability distribution for the specific site dataset. The output power of the wind energy conversion system is simulated using a Doubly-Fed Induction Generator (DFIG) wind turbine model.

2. Methodology

In modern power systems, particularly with the increasing penetration of renewable energy sources such as wind power, quantifying wind speed uncertainty is an essential step toward enhancing operational efficiency and ensuring grid reliability. Wind speed fluctuates not only over time but is also strongly influenced by climatic conditions and topographical features, leading to significant variability in power generation output. Accurately characterizing the statistical properties of wind speed enables the development of more precise forecasting models and risk analysis frameworks, thereby supporting generation optimization and mitigating technical risks.

In this study, a probabilistic modeling approach is employed to characterize the wind speed distribution at the selected site. Commonly used distributions such as Weibull, Rayleigh, Log-normal, and Gamma are selected for modeling purposes. By estimating parameters from empirical data, the probability density functions (PDFs) are fitted to the actual wind speed distribution and evaluated using three quantitative metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The distribution with the best fit is selected as the statistical representative of wind characteristics and serves as the input for simulating the power output of a Doubly-Fed Induction Generator (DFIG) wind turbine. The overall workflow is illustrated in Figure 1.

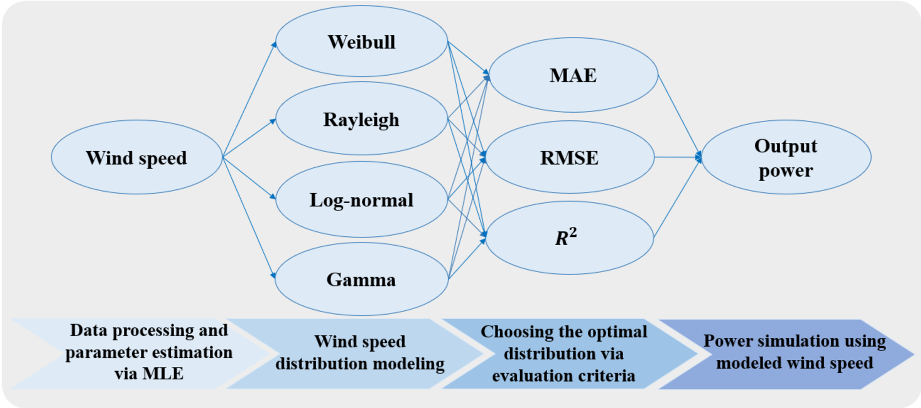

Figure 1. *Process Flow Diagram.*

2.1. Probability Distributions

In the field of wind energy, probability distributions play a vital role in accurately modeling wind speed characteristics to optimize energy conversion systems. They provide the mathematical framework necessary to determine wind power density, estimate the available electrical energy output, and assess the performance of wind turbines. The selection and application of appropriate wind speed probability distribution functions are critically important for minimizing uncertainty in energy yield forecasting, thereby supporting efficient wind farm design and system operation planning [12], [14], [19].

2.1.1. Weibull Probability Distribution

The two-parameter Weibull distribution is the most commonly used form, allowing for the characterization of wind speed patterns at the study site. The probability density function (PDF) of the Weibull distribution is mathematically expressed as follows[16], [20], [21].

$$f(v;k,c)=\left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1}e^{-\left(\frac{v}{c}\right)^{k}},v>0,k>0,c>0 \tag{1}$$

where v is the wind speed, k is the shape parameter, and c is the scale parameter.

The parameters of the Weibull distribution are estimated using the Maximum Likelihood Estimation (MLE) method [22], where the parameters k and c can be determined from the solution of the following system of equations [23]:

$$k=\left(\frac{\sum_{i=1}^{n}v_i^k\ln v_i}{\sum_{i=1}^{n}v_i^k}-\frac{1}{n}\sum_{i=1}^{n}\ln v_i\right)^{-1},c=\left(\frac{1}{n}\sum_{i=1}^{n}v_i^k\right)^{1/k} \tag{2}$$

where v_i is the wind speed at time point i, and n is the count of data points with non-zero wind speeds.

2.1.2. Rayleigh Probability Distribution

The Rayleigh distribution is a special case of the Weibull distribution when the shape parameter is a constant value k = 2. The mathematical expression is defined as follows [8], [18].

$$f\left(v\right)=\frac{\pi v}{2v_m^2}e^{\left[-\frac{\pi}{4}\left(\frac{v}{v_m}\right)^2\right]},v>0 \tag{3}$$

where v_m is the mean wind speed.

Using a similar approach to the Weibull distribution, the parameter c of the Rayleigh distribution can be calculated using the following equation:

$$c=\sqrt{\frac{1}{2n}\sum_{i=1}^{n}v_i^2} \tag{4}$$

2.1.3. Log-normal Probability Distribution

The Log-normal distribution models a random variable whose logarithm follows a normal distribution. It is particularly suitable for wind data analysis where the data exhibit linear-logarithmic skewness. The probability density function (PDF) of the Log-normal distribution is expressed as follows [24]:

$$f\left(v\right)=\frac{1}{v_i\sigma\sqrt{2\pi}}e^{\left(-\frac{(\ln v-\mu)^2}{2\sigma^2}\right)},v>0,\mu\in R,\sigma>0 \tag{5}$$

where μ is the mean of the natural logarithm of wind speed values v_i, and σ is the standard deviation of the natural logarithm. These parameters are determined using the following equations:

$$\mu=\frac{1}{n}\sum_{i=1}^{n}\ln v_i\ ,\ \sigma^2=\frac{1}{n}\sum_{i=1}^{n}\left(\ln v_i-\frac{1}{n}\sum_{i=1}^{n}\ln v_i\right)^2 \tag{6}$$

2.1.4. Gamma Probability Distribution

The probability density function (PDF) of the Gamma distribution is defined as follows [12], [24]:

$$f\left(v\right)=\frac{1}{\Gamma(\alpha)\beta^{\alpha}}v^{\alpha-1}e^{\left(-\frac{v}{\beta}\right)},v>0,\alpha>0,\beta>0 \tag{7}$$

where α is the shape parameter, β is the scale parameter, and $\Gamma(\cdot)$ is the gamma function. This distribution is used to normalize the probability density function such that the area under the Gamma PDF curve is equal to 1. To estimate the parameters α and β from the empirical dataset $\{v_1, v_2, \ldots, v_n\}$, the Maximum Likelihood Estimation (MLE) method is applied. The estimation equations are expressed as:

$$\log\alpha-\psi\left(\alpha\right)=\log\left(\bar{v}\right)-\frac{1}{n}\sum_{i=1}^{n}\log v_i,\beta=\frac{\bar{v}}{\alpha} \tag{8}$$

where $\psi\left(\alpha\right)=\frac{d}{d\alpha}\ln\Gamma\left(\alpha\right)$ is the digamma function, and $\bar{v}$ is the mean wind speed.

2.2. Evaluation Methodology

Evaluating the goodness-of-fit between probability distributions and actual wind speed data is an indispensable step to ensure the reliability and real-world applicability of the research outcomes. The evaluation employs three statistical indicators: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Each metric reflects a different aspect of the

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model's performance. These indices are calculated based on the deviation between measured wind speed values or their statistical means and those estimated by the fitted probability distributions [25], [26], [27]. MAE represents the average magnitude of the absolute errors between the observed and predicted values; the lower the MAE, the more accurate the model. RMSE, by squaring the deviations before averaging, penalizes larger errors more heavily, thus being more sensitive to outliers than MAE. A smaller RMSE indicates a better fit. Finally, R^2 indicates the proportion of the variance in the observed data that is explained by the model. R^2 values range from 0 to 1, where $R^2 = 1$ signifies a perfect fit, and $R^2 = 0$ indicates that the model does not improve prediction compared to the mean.

3. Results

This section presents the simulation results to evaluate the goodness-of-fit of several probabilistic models in characterizing the statistical behavior of wind speed in the Hawaii region, USA. The dataset consists of hourly average wind speed measurements over a monthly period, collected from the National Renewable Energy Laboratory (NREL) [28]. The wind power system is simulated using a Doubly-Fed Induction Generator (DFIG) model, as illustrated in Figure 2 [29].

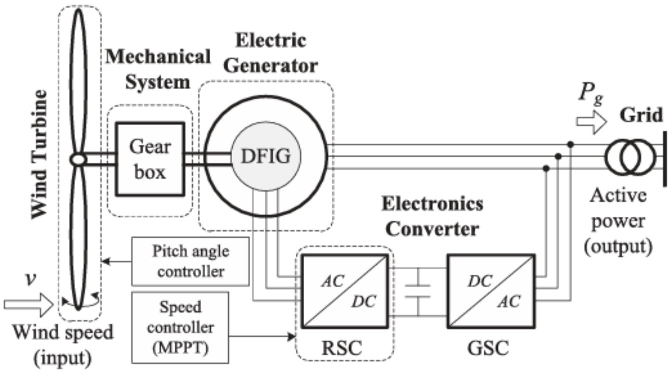

Figure 2. *General schematic of a DFIG-based wind turbine* [29].

Figure 3 presents the simulation model of a wind power generation system utilizing a DFIG generator in the Simulink environment. The system consists of a wind turbine, gearbox, DFIG generator, RSC–GSC converter system, and associated PI controllers. This model enables the analysis of dynamic response and wind power characteristics under varying wind conditions.

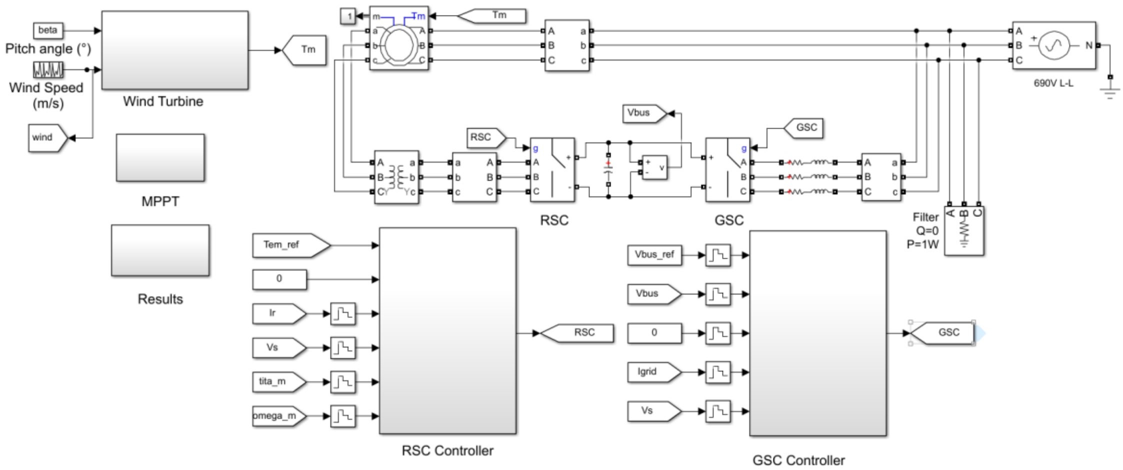

Figure 3. *Wind turbine model structure in MATLAB & Simulink.*

Four probability distributions selected for this study include Weibull, Rayleigh, Gamma, and Log-normal, which are widely used in wind data modeling due to their flexibility and proven statistical effectiveness in previous research. The characteristic parameters of each distribution are estimated using the Maximum Likelihood Estimation (MLE) method, based on equations (2), (4), (6), and (8), and are summarized in Table 1.

The visual representation of the probability density functions (PDFs) corresponding to each model is shown in Figure 4, along with the empirical histogram. While the Weibull and Gamma models closely match the actual distribution, particularly at the peak and on the left slope, Rayleigh exhibits limited accuracy due to its fixed shape parameter structure, and the Log-normal distribution shows a right-skewed profile with a wide spread that does not accurately capture the central characteristics of the wind dataset at the study site. These differences demonstrate the varying suitability of each model in representing the actual probabilistic structure of wind speed data.

Table 1. *Results of parameter estimation for probability distributions.*

Distribution	Shape Parameter	Scale Parameter
Weibull	2.1901	8.5665
Rayleigh	2	5.9622
Log–normal	0.6543	-
Gamma	3.2648	2.3316

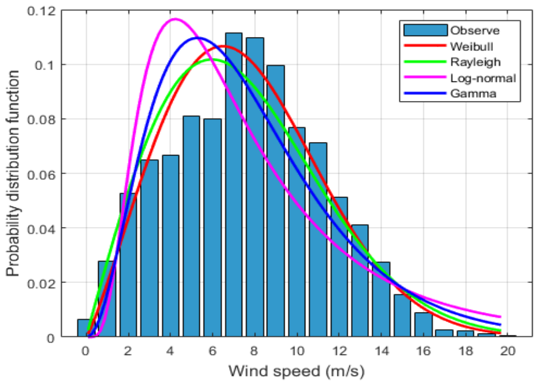

Figure 4. *Comparison of the observed wind speed frequency distribution with the Weibull, Rayleigh, Log-normal, and Gamma distributions.*

To evaluate performance quantitatively, three statistical metrics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2), are employed to compare the models. The results are summarized in Table 2. The Weibull distribution demonstrates superior performance with MAE = 0.007522, RMSE = 0.009330, and R^2 = 0.914555, indicating high capability in accurately and consistently modeling wind speed. The Gamma distribution achieves R^2 = 0.857223, but its relatively large absolute errors suggest that while it fits the overall trend, it is less effective at capturing extreme values. The Rayleigh model, constrained by its fixed shape parameter, yields lower accuracy R^2 = 0.849910, and the Log-normal distribution exhibits the poorest performance R^2 = 0.607377, confirming a significant mismatch with the statistical characteristics of the local wind dataset.

Table 2. *Evaluation index values of probability distributions.*

Evaluation Index	Weibull	Rayleigh	Log–normal	Gamma
MAE	0.00708	0.00883	0.01949	0.01324
RMSE	0.00971	0.01144	0.02379	0.01631
R^2	0.93025	0.90329	0.58154	0.80345

Figure 5 projects the distribution fits into the hourly time domain over a week, enabling a direct comparison of the rhythm and amplitude of the wind-speed series across the four models. Based on the reported performance metrics, the Weibull trajectory is expected to track the data most closely (low MAE/RMSE, high R^2), thus exhibiting minimal systematic bias. Gamma ranks second: it captures the overall trend but shows spurious oscillations near the extremes. Rayleigh, constrained by its fixed shape

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parameter, lacks flexibility and reduces overall accuracy (underfitting). In contrast, the Log-normal distribution exhibits pronounced right-skewness, leading to the weakest performance relative to the statistical characteristics of the local dataset.

Figure 6 presents the daily-averaged wind speed over a seven-day horizon for four distribution models. Overall, the Weibull case exhibits the largest variation amplitude and clearly reproduces two

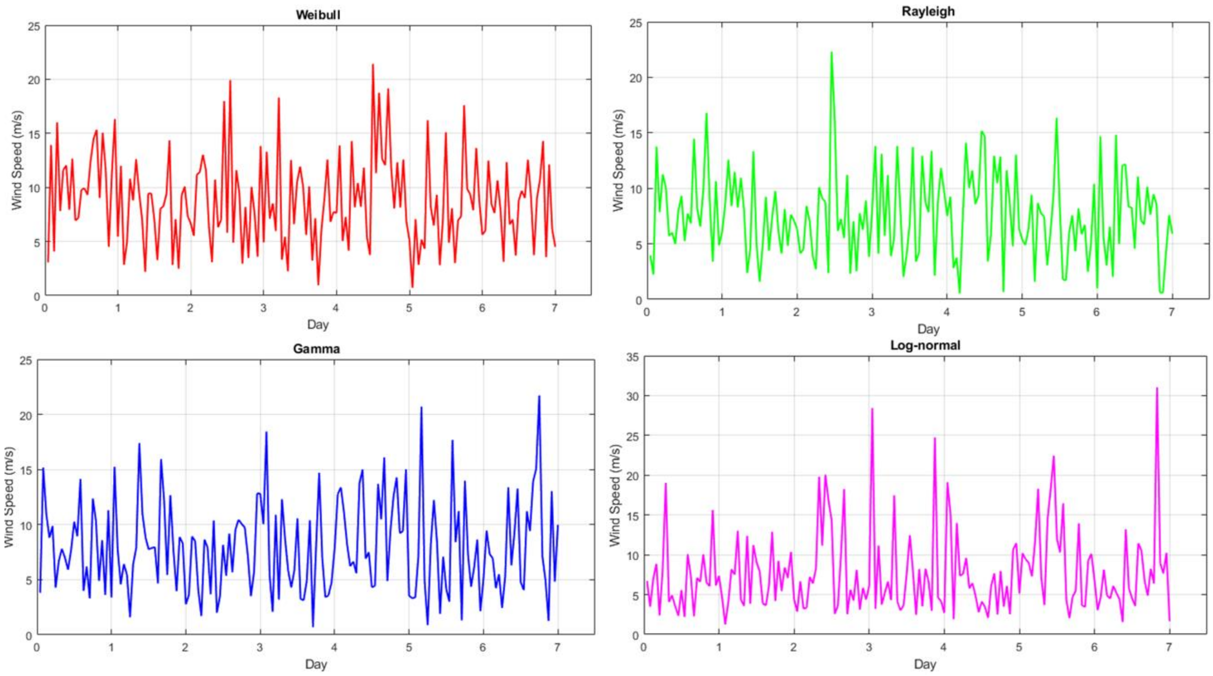

Figure 5. *Simulated wind speed by hour of the week of four probability distributions.*

extremes, with very high peaks on day 1 and day 5 at approximately 10.5 m/s. The Gamma model tracks the underlying trend stably, matching the day-5 peak at 9.8 m/s while avoiding over-amplification of extremes—appropriate when stability is prioritized. The Rayleigh model yields a low-amplitude, flattened trajectory that generally lies below the others and markedly underestimates on day 6 at about 6.3 m/s, indicating underfitting under large variability. The Log-normal model oscillates primarily around 7–7.5 m/s but shows a local spike on day 6 at 9.8 m/s, consistent with its heavy right tail that tends to inflate high-wind episodes. Consequently, Weibull and Gamma tend to provide more credible day-to-day power estimates, whereas Rayleigh risks underestimating available energy and Log-normal is prone to overshoot on extreme-wind days.

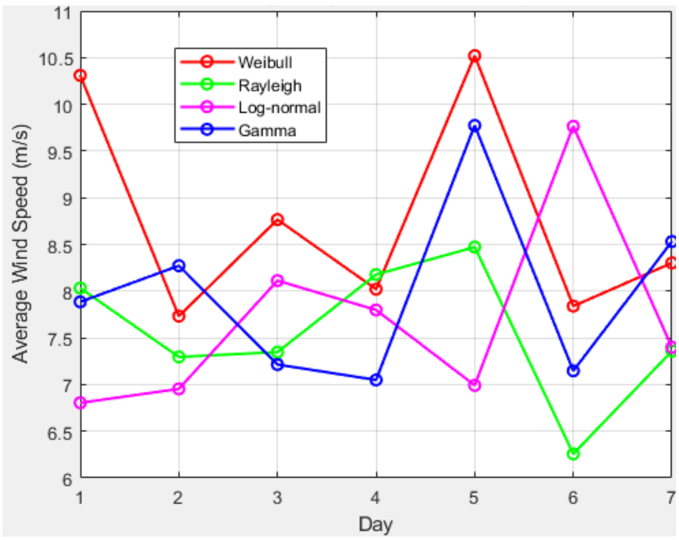

Figure 6. *Average simulated wind speed.*

The wind turbine's daily average output power, with inputs being wind speeds simulated by the probabilistic models, is shown in detail in Figure 7. Weibull clearly dominates in both level and amplitude, with pronounced maxima of approximately 1.4 MW on day 6 and 1.30 MW on day 2. Gamma is stable and follows the trend, oscillating within 0.68–1.00 MW, consistent with a heavy right-tail characteristic and therefore susceptible to local overshoot under strong-wind conditions. Rayleigh is the lowest and flattest, spanning 0.45–0.80 MW and dropping markedly on day 7 to about 0.55 MW, indicating an underfitting tendency and underestimation of available energy.

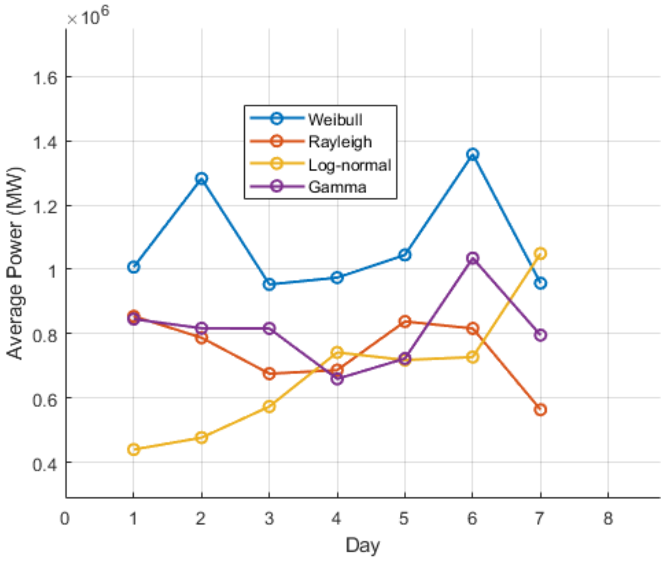

Figure 7. *Wind turbine output power according to probability distributions*.

The Weibull distribution is the most suitable for this dataset, as its evaluation metrics (low MAE, low RMSE, and high R^2) outperform the other three distributions, and its daily-mean profile closely follows the actual temporal variability, capturing both high-wind and low-wind days. When transformed into electrical power, the Weibull-based results remain stable and physically consistent, whereas Rayleigh yields a flattened response, Log-normal tends to exaggerate extremes, and Gamma, while reasonably competitive, still exhibits mismatch in the tail region.

4. Discussions

The analysis results show that the two-parameter Weibull distribution more accurately represents the wind characteristics at the measurement site than the other models. The MAE and RMSE are the lowest, while the R^2 is the highest. The Gamma distribution ranks second due to its bias in the peak and tail regions, while the Rayleigh and Log-normal distributions exhibit more pronounced errors in these regions. When the Weibull parameters are introduced into the DFIG wind turbine model, the calculated output power series fluctuates weekly between 0.95 MW and 1.36 MW with small amplitude variations, but these fluctuations reflect the non-linear sensitivity between wind speed variations and output power. This phenomenon shows that even small percentage changes in wind speed can lead to noticeable changes in actual output power.

The advantage of the Weibull distribution aligns with the classical findings in [13] and [23] regarding its superior ability to fit unimodal wind data. However, the present study advances one step further by directly coupling the probabilistic wind speed distribution with the DFIG wind turbine model, an approach rarely adopted in earlier works that typically stopped at mere wind speed characterization. The divergence from the preference for the Log-normal distribution reported in study [9] can be explained by the nearly symmetric coastal wind patterns in Hawaii, which reduce the skewness that the Log-normal distribution attempts to capture.

The poor performance of the Rayleigh distribution, despite its frequent recommendation for preliminary wind data analysis due to its fixed shape parameter $k = 2$, lacks the flexibility required to represent multi-modal wind regimes in the study area. In contrast, the Log-normal distribution tends to overestimate the tail region because its probability density function assumes an exponential growth pattern at high wind speeds, a phenomenon that does not manifest in the observed coastal wind time series with moderate variability.

This paper establishes a three-step process, including parameter estimation for four distribution functions based on the maximum likelihood of long-term wind speed series; rigorous statistical testing using MAE, RMSE, and R^2 indices to eliminate overfitting; and simulation of wind power output using a DFIG-based wind turbine model. The simulation results allow for the identification of optimal operating strategies to avoid excessive backup generation, which leads to unnecessary losses or power shortages. This supports the assessment of factors related to power fluctuations and power quality as wind power penetration continues to increase, supporting risk warning systems for automatic adaptive control, thereby improving power reliability without investing in large-scale energy storage systems.

However, the turbine model employs an idealized power curve and does not account for electromechanical losses, power curtailment, or control limits, which may lead to an overestimation of performance. The dataset only covers a single coastal location and a relatively short observation period, making it unsuitable to generalize the applicability of the Weibull distribution across different terrains or seasonal cycles.

To develop the current proposal, future research should simultaneously focus on expanding the data set and refining the analysis method. First, testing four probability distributions, Weibull, Rayleigh, log-normal and Gamma, on long-term wind sequences in diverse climates will enable the selection of more appropriate distribution models for specific site conditions. Power curve models should move away from ideal assumptions and fully incorporate electromechanical losses and tailwind effects into practical turbine control strategies, allowing probability-based power ranges to better reflect actual operating conditions. Finally, probabilistic power forecasts should be linked to decision making for economic and technical planning, reserve allocation and storage sizing. Advanced data-driven approaches, such as machine learning-based positioning tools or high-resolution spatial wind density mapping, combined with practical operational insights, can further enhance the accuracy and applicability of the proposed methodology in real-world scenarios.

5. Conclusions

Simulation results indicate that the two-parameter Weibull distribution is the most suitable model for characterizing the wind speed profile in the Hawaii region, showing good agreement in both qualitative and quantitative aspects (R^2 = 0.93025, MAE = 0.00708, RMSE = 0.00971). The output power simulation based on the DFIG wind turbine model using the simulated wind speed data using the Weibull probability distribution also gives superior results with the curved distributions (0.95 – 1.36 MW). The Gamma distribution also demonstrated a reasonably good fit, though it was less accurate in high wind speed ranges. In contrast, Rayleigh and log-normal distributions exhibited significant deviations from the measured data, producing results inconsistent with prior research findings. However, despite its performance, the Weibull distribution model should not be considered universally applicable. As previously reported, the suitability of a probability distribution largely depends on site-specific conditions such as topography, climate, and temporal characteristics of the wind speed series at each location. Therefore, model selection should adopt a flexible approach, supported by experimental validation in each region. Furthermore, the power curve models employed in this study were developed based on idealized assumptions, neglecting the impacts of real-world operational factors such as electrical losses, turbine power limitations, and control strategies. These omissions can compromise the accuracy of model applications under practical operating conditions, particularly as modern power systems demand increasingly high levels of reliability and optimization. This research highlights the need for further development of probabilistic models combined with energy analysis to improve forecasting quality and operational decision-making. The obtained results provide valuable references for selecting suitable probability models, enhancing forecasting accuracy, and supporting practical decision-making in dynamic wind energy scenarios.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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