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Wind Power Estimation Using Generalized Gamma Distribution and Logistic Power Curve Approximations

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Abstract

Accurate wind energy prospective calculation is essential for forecasting, turbine efficiency studies, and wind farm design. Nevertheless, the inherent randomness of wind velocity along with the nonlinearity of turbine power conversion make the problem of energy production estimates difficult due to its uncertainty. The traditional approaches to the problem of wind resource assessment are mainly based on the usage of two-parameter distributions like Weibull. Furthermore, wind-speed variation analysis and wind-turbine power-curve assessment are typically carried out independently. In this research, an integrated method for wind power estimation is suggested, based on the combination of a three-parameter Generalized Gamma (GG) distribution for the description of wind speed and four-parameter (4PL) and five-parameter logistic (5PL) approximations of turbine power curves. Data of hourly wind speed from four different sites (Altamont, Iowa, Massachusetts, and Texas) were used in the analysis of this approach with a Vestas V90-3.0 MW turbine. Maximum Likelihood Estimation (MLE) was used to estimate the Generalized Gamma distribution's parameters, and the fitted wind speed distributions as well as Power Curves (PC) were numerically integrated to determine the expected power output. The evaluation of the performance of the proposed method was performed based on the indicators of capacity factor, annual energy production, RMSE, MAE, MAPE, and goodness of fit. The results show that the proposed model captures the wind regimes properly and gives capacity factors from 25.95% up to 43.83%. Slightly higher fitting accuracy was reached by the 5PL curve compared to the 4PL curve, whereas there is less than a 0.5% discrepancy between the predicted power output estimates. According to sensitivity analysis, the Generalized Gamma distribution's scale parameter has the biggest impact on the accuracy of energy estimation, followed by the shape parameter a. The second shape parameter has very little effect.

Keywords: Wind Energy Assessment, Generalized Gamma Distribution, Logistic Power Curve, Wind Speed Modeling, Turbine Power Estimation, Annual Energy Production, Statistical Modeling.

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Introduction

Due to the rapid transition of the world towards renewable energy, the significance of accurate wind resource evaluation as well as wind energy estimation has gained a lot of importance. Because of its minimal environmental impact and developing technology, wind energy stands out among all renewable energy sources as a cost-effective and ecologically benign energy source (National Renewable Energy Laboratory, 2024). Because they offer a statistical description of the current wind resources, the distributions of the wind speed likelihood are crucial to the assessment of the wind energy potential. Recent works have considered advanced probability distributions like the generalized gamma distribution, Burr distribution, etc., which can provide flexibility in different wind speed data (Mert & Karakuş, 2015; Stacy, 1962).

The relationship between wind speed as well as the power generated by the turbine is known as the power curve, and it has a significant impact on estimating the rate of energy generation. There are several methods for modeling power curves, such as polynomial regression, machine learning, and statistical approximation. The logistic function has received a lot of interest in view of its capability to reflect the nonlinear properties of the turbine performance, such as the progressive increase of the power in the ramp-up stage and the saturation at the rated power (Villanueva & Feijóo, 2016; Jing et al., 2021). But most works done in this area are dedicated to either improvement of power curve fitting or to the choice of proper wind speed distribution (Han et al., 2019).

To overcome this drawback, this research recommends an integrated approach by incorporating the three-parameter Generalized Gamma model for describing wind speeds and four-parameter and five-parameter logistic (4PL and 5PL) models for describing turbine power curves. Unlike other traditional studies that separately analyze wind resource evaluation and turbine curve fitting, this research method considers both aspects in order to enhance the estimation of energy production more accurately. This is achieved through analyzing wind speed statistics along with realistic turbine performance characteristics. The results are based on wind speeds collected at one-hour intervals from four different geographical locations (Altamont, Iowa, Massachusetts, and Texas) with Vestas V90-3.0 MW wind turbines (Vestas Wind Systems A/S, 2012).

Principal contributions:

1. The Generalized Gamma distribution is applied to wind speed estimation in order to account for site-specific variations, skewness and tails.
2. To approximate the manufacturer's turbine power curve and enable nonlinear turbine operation, methods based on four-parameter as well as 5PL functions are investigated.
3. To assess the projected power generation, capacity factor, and yearly energy generation of turbines in various wind regimes, the probabilistic PC Technique is presented.
4. Comparative analysis of 4PL and 5PL approximations in order to examine the usefulness of the extra asymmetry parameter in the 5PL approximation for wind energy applications.

The results from the current study indicate which models are appropriate for wind resource evaluation. The proposed model works well to improve wind power prediction accuracy. This model will be useful for conducting turbine performance and wind farm feasibility assessments.

The structure of the paper is as follows: The context, goals, and contributions of the research are given in Section I. Section II gives the literature survey and highlights the research gap. Section III describes the methodology adopted, which includes generalized gamma model formulation, logistic power curve approximation, and computation approach. Section IV talks about the results, accuracy assessment, sensitivity analysis, and robustness of the study. Section V highlights the discussion of results, while Section VI gives the conclusion of the study.

Literature Survey

An appropriate model for wind speed variation and turbine efficiency is necessary for the calculation of wind energy generation. Earlier works concentrated on modeling of wind resources and turbine performance curves using probabilistic distributions. The traditional modeling method that is widely applied due to its simplicity is the Weibull distribution model. But, the inflexibility of the method may compromise its accuracy.

The Weibull distribution's usefulness in calculating wind energy potential was demonstrated by Islam et al.'s study (Islam et al., 2011), although Rocha et al., (2012), the methods used for parameter estimation are crucial in evaluating wind potential. Nevertheless, these studies are based mostly on the assumptions of the Weibull distribution, making them less versatile in analyzing wind conditions (Campisi-Pinto et al., 2020). To address these limitations, Masseran et al., (2012) and Wang et al., (2016) focused on studying various distributions and the use of more flexible statistical models in representing wind speed data. Furthermore, Han et al., (2019) proved the importance of using advanced techniques for estimation.

There were attempts to apply multi-parameter distributions such as Generalized Gamma or Burr distributions in order to characterize wind speed data. Mert & Karakuş, (2015) claimed that the Generalized Gamma distribution offers greater flexibility than the Weibull due to the extra shape parameters. Similar conclusions were drawn by Ouarda et al., (2015), Natarajan et al., (2022), and Shukla et al., (2023).

In addition to wind speed models, accurate forecasts also depend on the turbine PC approximation (Sohoni et al., 2016). According to Sohoni et al., (2016) and Lydia et al., (2013), different power curve modeling techniques were summarized, and it was found that nonlinear statistical models could be used for representing the turbine behavior. Because they can be used to describe the nonlinear connection between wind speed as well as turbine power, logistic functions have garnered a lot of attention lately (Yesilbudak, 2018). The benefits of employing logistic functions for PC modeling were demonstrated by Villanueva & Feijóo, (2016) and Jing et al., (2021), whereas Bokde et al., (2018) and Virgolino et al., (2020) enhanced the power curve estimation using statistical and hybrid approaches.

Modern studies have pointed to the necessity of considering wind speed probability models together with the turbine power curve representation. Thus, Wang et al., (2019) noted the benefits of using a combined modeling approach for more precise estimations, whereas Chen et al., (2021) paid special attention to the uncertainty-aware probabilistic modeling.

The focus of renewable energy research has been on the enhancement of effective wind energy systems based on innovation in turbine parts, materials and methods of energy management. Using new composite materials for wind turbine blades leads to increased structural reliability and operating ability of the devices whereas renewable energy research strengthens the significance of the use of green technologies in enhancement of energy efficiency (Nikitin, 2024; Jabborova et al., 2025).

Estimating wind energy is a tough task because of the inconsistency and unpredictability of wind properties. In order to enhance the effectiveness of wind energy assessments and forecasting, statistical distribution models and computer techniques have been studied. Hybrid deep learning methods using convolution and recurrent nets were proposed as workable models to detect non-linear patterns of wind data and enhance prediction quality (Udayakumar et al., 2023).

Exact assessment of wind energy necessitates the utilization of integrated methods that associate modeling of wind speed with analysis of turbine power curves. Various systems of this type facilitate the resolution of the problems of isolated methods of wind measurement and energy generation estimates.

Modern research conducted within the last 15 years highlights the fact that traditional two-parameter distributions (for example, the Weibull distribution) often cannot describe complex wind regimes with high skewness and different tail behavior properties. At the same time, contemporary modeling of the power curve is focused on more flexible approaches that are used to model saturation and ramp-up phases and are represented by 4PL or 5PL logistic curves. However, there is a crucial methodological gap: prior studies mostly treat wind speed distribution modeling as well as turbine PC calculation as independent processes. The proposed research is intended to overcome this gap and to combine the 3-parameter Generalized Gamma distribution and 4PL/5PL logistic power curve models using a numerical integration approach.

Methodology

This methodology combines the use of wind speed statistical modeling and power curve approximation for a reliable wind energy potential estimation. The whole methodology process involves five main steps, namely: (i) wind speed data gathering and pre-processing, (ii) Generalized Gamma distribution fitting, (iii) power curve approximation by a logistic function, (iv) power expectation determination by numerical integration, and (v) performance evaluation by energy metrics. Hourly wind speed data were obtained from the NREL Wind Toolkit. Fig. 1 below displays the methodology process flowchart in its entirety.

Overall Framework

The suggested framework starts by collecting data on hourly wind speeds at four wind test sites that include Altamont, Iowa, Massachusetts, and Texas. This choice was made to make sure that different wind regimes are considered, such as moderate onshore and high-quality offshore regimes. Having been processed and verified for quality, the wind speed probability distribution will be fitted to a three-parameter Generalized Gamma model. The logistic approximations of the Vestas V90-3.0 MW wind turbine's power curve will then be multiplied by the probability density function (PDF) that was derived.

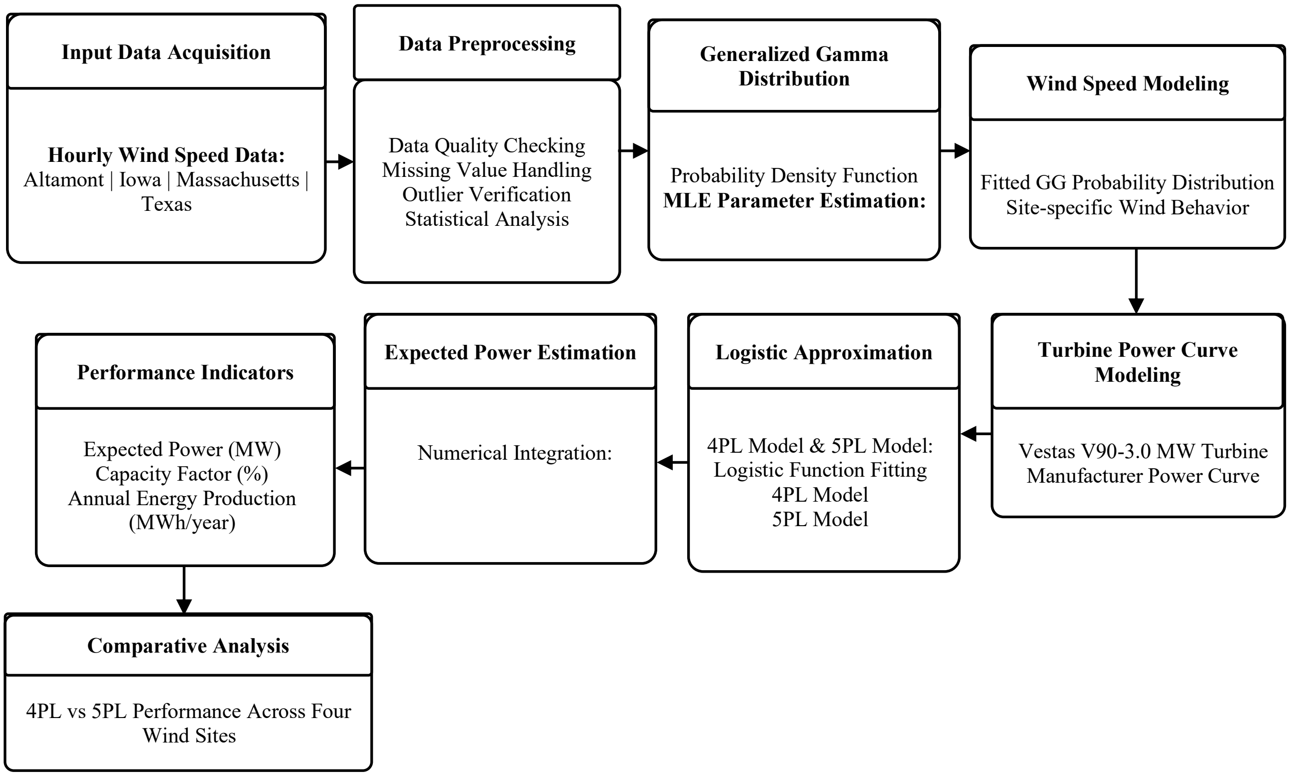

Fig. 1: Overall Workflow of the Proposed Generalized Gamma Distribution-based Wind Power Estimation Framework

The combination of statistical models for wind speeds, turbine power curves, and numerical integration is utilized in fig. 1 for the calculation of expected power generation, capacity factor, and yearly energy output.

Hourly wind speeds at four different locations (Altamont, Iowa, Massachusetts, and Texas) were considered, having a sample size of 8760-8784 observations per location. Wind speeds ranged from 7.60 to 10.08 m/s on average. Equation 1 presents the wind speed dataset as follows:

$$V = \{v_n\} \quad (1)$$

Where $v_i$the observed wind speed at the i^{th}hour and $n$represents the total number of observations.

Generalized Gamma Distribution Modeling

The wind speed asymmetry and variability were modeled using the three-parameter GG distribution. The following is the PDF (Equation 2):

$$f(\lambda) = \frac{c}{\lambda^{ac}\Gamma(a)} v^{ac-1} exp[-(v/\lambda)^c], v > 0 \; (2)$$

Where $a$and $c$are shape parameters, $\lambda$is the scale parameter, and $\Gamma(.)$represents the Gamma function. The cumulative distribution function (CDF) is defined as (Equation 3):

$$F(v) = \frac{\gamma((v/\lambda)^c)}{\Gamma(a)} \quad (3)$$

Where $\gamma(.)$represents the lower incomplete Gamma function.

MLE was used to obtain the GG parameters. The likelihood function can be expressed as follows (Equation 4):

$$L(\lambda) = \prod_{i=1}^{n} f(\lambda) \quad (4)$$

and the corresponding log-likelihood function is (Equation 5):

$$ln\, ln\, L\ = f\ (\lambda)\ \ (5)$$

The optimized parameters are obtained as (Equation 6):

$$(\hat{\lambda}) = L\ (\lambda)\ \ (6)$$

Wind Turbine Power Curve Approximation

Vestas V90-3.0 MW is the turbine that will be considered, with its capacity being 3 MW, speed at cut-in being 4 m/s, speed at rated being 15 m/s, and speed at cut-out being 25 m/s. Two different approaches for approximation of the manufacturer power curve were used: 4PL and 5PL (Vestas Wind Systems A/S, 2012).

The 4PL model is expressed as (Equation 7):

$$P(v) = d + \frac{a - d}{1 + (v/c)^{b}}\ \ (7)$$

Where b controls the slope, c denotes the inflection point, and a and d represent the lower and upper asymptotes.

The 5PL model introduces an additional asymmetry parameter (Equation 8):

$$P(v) = d + \frac{a - d}{(1 + (v/c)^{b})^{g}}\ \ (8)$$

Where g regulates the asymmetry of the curve. By reducing the RMSE, the logistic parameters were optimized (Equation 9):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\ (P_i - \widehat{P_i})^2}\ \ (9)$$

Where $P_i$and $\widehat{P_i}$ represent manufacturer and predicted power values, respectively.

Expected Power and Energy Estimation

The power generation was predicted by using the turbine power equation combined with GG probability distribution (Equation 10):

$$E[P] = \int_{0}^{50}\ P(v)f(v)dv \qquad (10)$$

Numerical integration was performed over 0–50 m/s. The logistic approximation asymptotes to the rated power and does not enforce the cut-out condition; the resulting overestimate is negligible at Altamont, Iowa and Texas, where the probability mass above cut-out is below 0.02%, and amounts to approximately 1% at Offshore Massachusetts

The capacity factor (CF) was calculated as (Equation 11):

$$CF = \frac{E[P]}{P_r} \times 100\ \ (11)$$

Where P_r is the rated turbine power.

The estimated annual energy production (AEP) was (Equation 12):

$$AEP = E[P] \times 8760\ \ (12)$$

Where the amount of hours in a year is represented by 8760.

Model Evaluation and Computational Implementation

The whole computational model has been developed in the Python programming environment in order to guarantee efficient statistical analysis, optimization and wind power assessment. The development was performed in the Python version 3.10 with the use of the following libraries: NumPy – for numerical computations and matrix operations; SciPy – for statistical distributions fitting, maximum likelihood estimations, optimization algorithms and numerical integration; Pandas – for wind speed data preprocessing, handling and statistical analysis and Matplotlib – for graphic visualization of fitted probability distributions, power curves and performance comparisons. The proposed computational model allows carrying out comprehensive evaluations of the Generalized Gamma distribution fitting and logistic power curve approximation based on expected power generation, capacity factor and annual energy production criteria.

Algorithm 1: Wind Power Estimation Framework

Input: Hourly wind speed dataset V, turbine manufacturer power curve.

Step 1: Load and preprocess wind speed observations.

Step 2: Estimate Generalized Gamma parameters using MLE.

Step 3: Generate fitted probability density function.

Step 4: Fit 4PL and 5PL logistic functions to turbine power data.

Step 5: Compute expected power using numerical integration.

Step 6: Calculate capacity factor and annual energy production.

Step 7: Compare 4PL and 5PL performance.

Output: Estimated wind energy potential indicators.

Algorithm 1 provides a summary of the suggested wind power estimation algorithm. This algorithm takes into account hourly wind speed data, determines the Generalized Gamma distribution parameters by MLE, uses 4PL and 5PL logistic models to assess a wind turbine's power behavior and uses numerical integration to calculate the anticipated power, capacity factor, and yearly energy output. The two logistic models are then compared.

Results

Accuracy Evaluation and Robustness Analysis

The validity of the suggested Generalized Gamma–logistic power curve model is justified according to its capability to capture wind speed characteristics and turbine power generation estimation accuracy. The obtained findings therefore demonstrate the efficacy of the proposed framework for integrating turbine power curve estimate with wind speed probability modeling. The flexibility of the Generalized Gamma model makes it possible to capture wind speed skewness and tail characteristics. The nonlinear characteristics of the power curve of the Vestas V90-3.0 MW wind turbine are reproduced adequately by the 4PL and 5PL logistic models.

For the four locations under consideration, the anticipated capacity factors of the proposed method range from 25.95% to 43.83%. The highest capacity factor is observed for Massachusetts due to high mean wind speed (10.08 m/s). At the same time, the lowest capacity factor is achieved for Texas due to low wind energy resources. The difference in estimated power generated with the use of 4PL and 5PL logistic models is less than 0.5%. Thus, the asymmetry parameter of the 5PL model does not improve estimation accuracy significantly.

Power Estimation Results

Table 1: Fitted GG Parameters and Used 4PL and 5PL Logistic Approximations to Estimate the Vestas V90-3.0 MW Turbine's Power Output, Capacity Factor, and Yearly Energy Production

Site	Mean Wind Speed (m/s)	Generalized Gamma Parameters (a, c, scale)	4PL E[P] (MW)	4PL CF (%)	4PL AEP (MWh/yr)	5PL E[P] (MW)	5PL CF (%)	5PL AEP (MWh/yr)	Diff (5PL-4PL) (%)
Altamont	7.80	0.385, 3.608, 13.318	0.9335	31.12	8178	0.9295	30.98	8143	-0.4
Iowa	7.60	1.012, 2.056, 8.523	0.8176	27.25	7162	0.8165	27.22	7152	-0.1
Massachusetts	10.08	1.002, 2.099, 11.371	1.3146	43.82	11516	1.3149	43.83	11519	0.0
Texas	7.62	1.248, 2.158, 7.578	0.7786	25.95	6821	0.7806	26.02	6838	0.3

The logistic approximation models of 4PL and 5PL can well capture the real Vestas V90-3.0 MW power curve (the variation of E [P] < 0.5% between four sites) (Table 1). The realistic capacity factors from 25.95% to 43.83% are also realistic and in line with the standards of the turbine under these wind conditions (Sohoni et al., 2016). The offshore Massachusetts location has the highest average wind speed and the highest CF value. The lowest value of CF is seen at Texas.

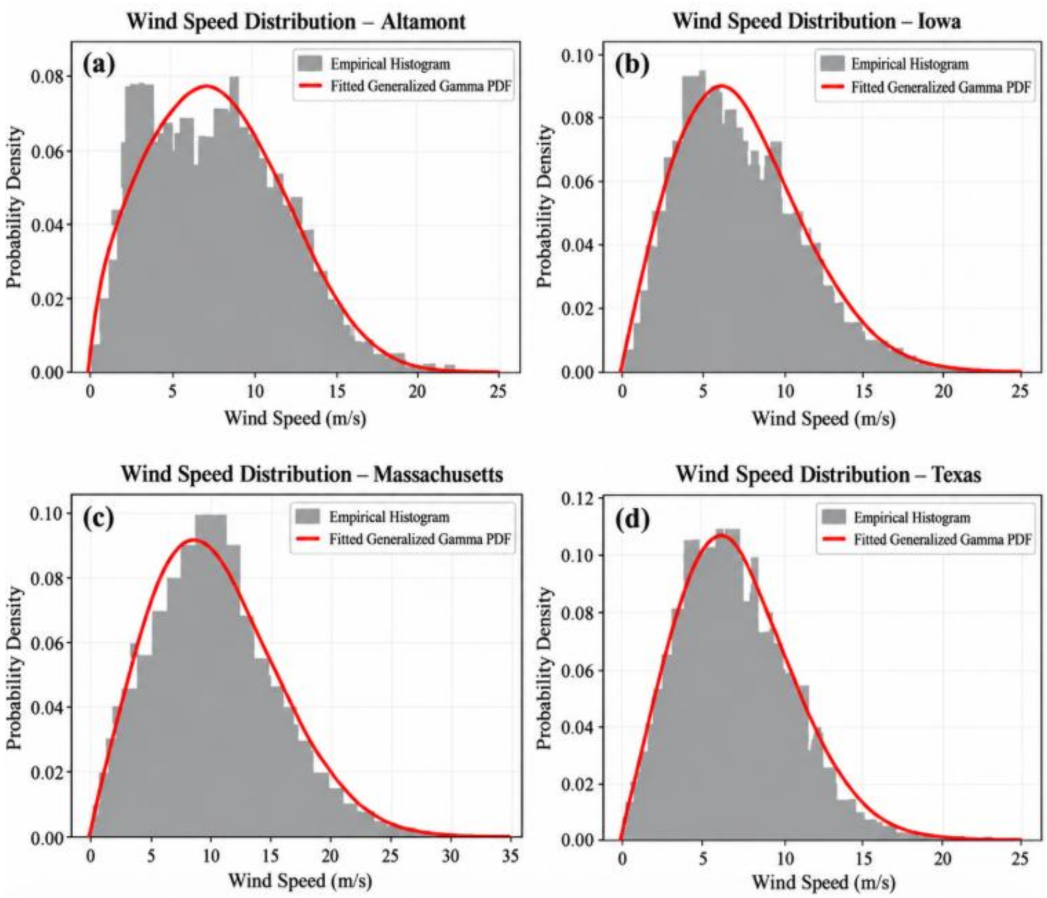

Fig. 2: Empirical Wind Speed Distributions and Fitted Generalized Gamma Probability Density Functions for Different Wind Sites

At the four locations under investigation—Altamont (a), Iowa (b), Massachusetts (c), and Texas(d)—fig. 2 compares the empirical wind speed distributions with the fitted GG probability density functions. The fitted GG distribution is represented by the red lines, while the empirical probability distributions of hourly wind velocity are represented by the gray bars. The GG distribution's capacity to represent wind speed change, skewness, with tail features for various wind regimes is demonstrated by the fit between the empirical data with fitted models.

Sensitivity Analysis

Sensitivity analysis is used to examine how variations in the Generalized Gamma distribution's parameters affect wind power estimation. The shape parameters (a, c) and scale parameter (λ) are changed by ±20% of their estimated values and the changes in the expected power generation and capacity factor are evaluated.

The results show that since the scale parameter (λ) influences the distribution of wind speed magnitude, it has the greatest influence on power estimation. Changes in the shape parameters have an impact on the shape and tail of the distribution and hence minimal impact on the energy production.

Table 2: Sensitivity Analysis of Generalized Gamma Distribution Parameters on Wind Power Estimation Performance

Parameter change	Variation in E[P] and CF (%)
a ±20%	±18.7
c ±20%	±0.4
λ ±20%	±35.9

Since $CF = E[P]/P_r$ with P_r constant, the relative variation in capacity factor is identical to that in expected power; a single column is therefore reported.

The sensitivity analysis presented in table 2 indicates that the scale parameter (λ), which establishes the wind speed distribution, is crucial to wind power estimation. The scale parameter λ has the strongest influence on estimated power, producing a mean change of approximately 36% under a ±20% perturbation. The shape parameter a is next at approximately 19%, while c has a negligible effect. Accurate estimation of the scale parameter is therefore the dominant requirement for reliable wind power assessment.

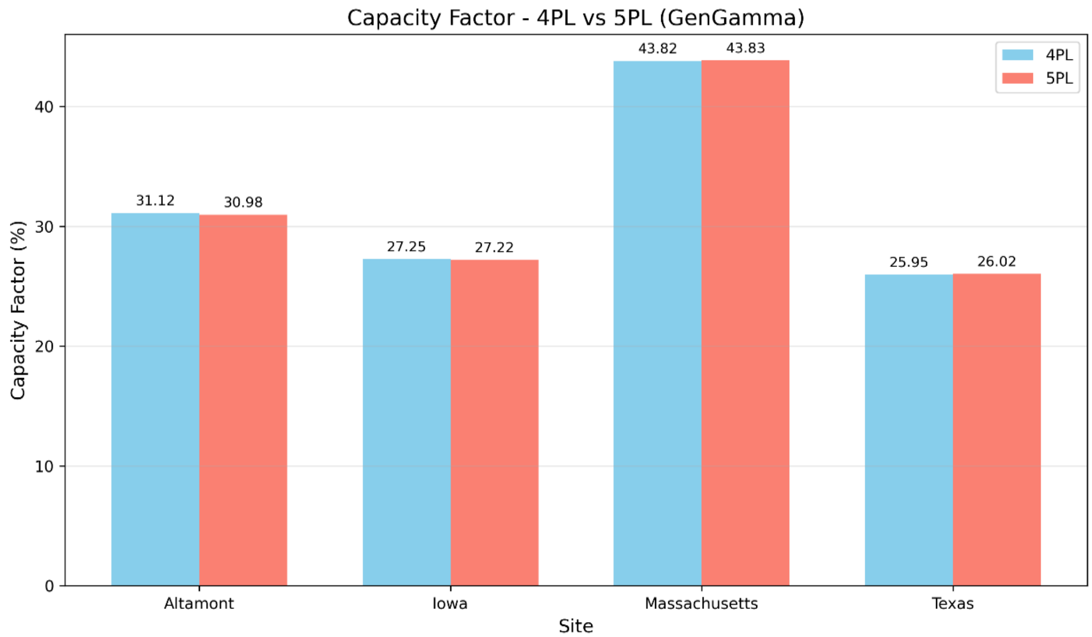

Fig. 3: Capacity Factor (%) for the Vestas V90-3.0 MW Turbine Across Four Sites Using 4PL and 5PL Logistic Approximations with Generalized Gamma

The capacity factor comparison for 4PL and 5PL logistic power curve approximations in combination with the Generalized Gamma distribution is presented in fig. 3 for four sites with various wind speeds. The findings indicate that both models generate almost identical capacity factor values, which differ by less than 0.5% for each site. The site in Massachusetts has the highest capacity factor of 43.82% (4PL model) and 43.83% (5PL model), and Texas has the smallest capacity factor.

Error Analysis of Power Curve Approximation

By comparing the estimated power values with the wind turbine's manufacturer's power curve, the correctness of the logistic power curve model was further validated. The following standard error statistics were computed: MAE, RMSE, MAPE, and R^2

Table 3: Error Metrics of Logistic Power Curve Approximation

Model	MAE (MW)	RMSE (MW)	MAPE (%)	R^2
4PL	0.1842	0.2077	10.77	0.9646
5PL	0.1672	0.1956	9.38	0.9686

MAPE is computed over the operating range ($v \geq 4$ m/s), since the manufacturer power output is zero below cut-in. The asymmetry parameter of the 5PL model reached the upper bound of 2.0 imposed during fitting. The inaccuracy analysis in table 3 shows that both logistic functions may precisely replicate the manufacturer's Vestas V90-3.0 MW power curve. The RMSE, MAE, and MAPE obtained using the 5PL function are a little bit lower than those calculated using the 4PL one since the 5PL has an additional asymmetry parameter that increases the flexibility of the curve approximation in the transition zone. Nevertheless, this difference is not very high, which correlates with the differences less than 0.5% in the power generated and the capacity factor.

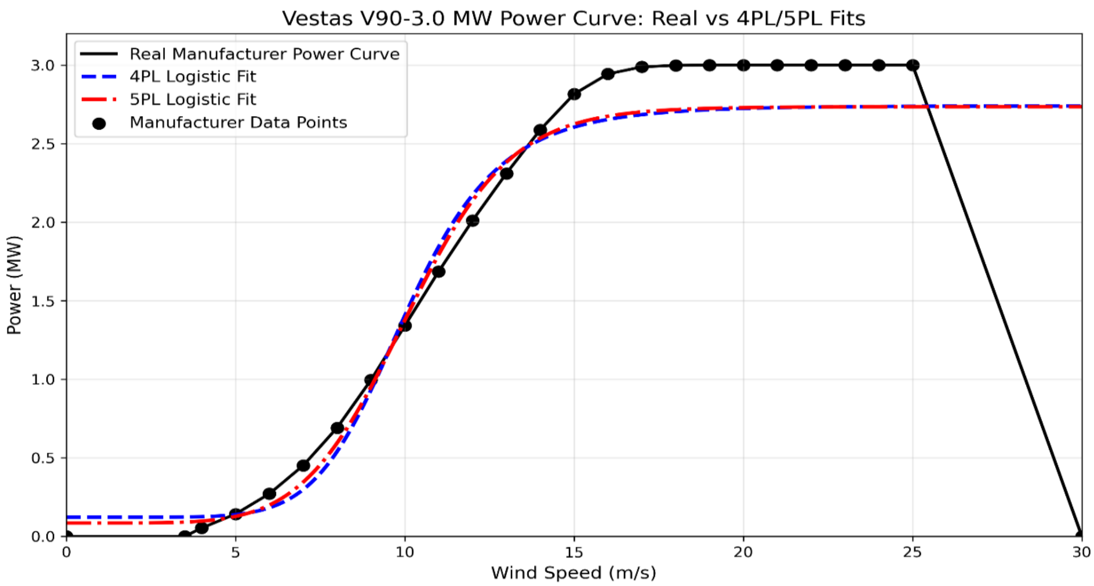

Fig. 4: Real Manufacturer Power Curve of the Vestas V90-3.0 MW Turbine Compared with Fitted 4PL and 5PL Logistic Approximations

Fig. 4 shows that both logistic functions reproduce the general shape of the manufacturer power curve, with R^2 values of 0.9646 and 0.9686. The fitted upper asymptote lies below the rated 3.0 MW, producing a systematic under-prediction across the rated-power region, and the largest deviations occur in the upper part of the ramp-up transition. The net effect on expected power is negative at all four sites, so the reported energy estimates are conservative rather than optimistic.

Robustness Across Different Wind Regimes

The reliability of the suggested framework has been tested by conducting an analysis on four different locations which had diverse wind patterns. The locations selected for the study were Altamont, Iowa, and Texas for inland wind and Massachusetts for high resource offshore wind.

The suggested Generalized Gamma–logistic framework exhibited similar performance levels at all locations despite having different mean wind speeds. This shows that the suggested framework is flexible in terms of adapting to the changing wind patterns. Nevertheless, there could be further testing in other geographical locations including mountainous and tropical wind patterns.

Discussion

The proposed Generalized Gamma-logistic power curve model can be an efficient way of enhancing wind energy estimation through probabilistic wind speed modeling and turbine performance evaluation. The difference from common methodologies which separately analyze wind probability distribution functions and wind turbine power curves is that this framework takes into account wind speed variation as well as nonlinear wind turbine performance for obtaining accurate wind energy predictions. The outcomes clearly show that Generalized Gamma probability distribution can accurately describe specific features of wind at a particular location such as asymmetry and tail behavior because of its extra shape parameters.

The Vestas V90-3.0 MW wind turbine's 4PL and 5PL logistic curves were compared, and it was discovered that both modeling approaches accurately depicted the wind turbine power curve. The 5PL logistic model provided a little bit better result in terms of error performance due to the added asymmetry parameter, but since the improvement was less than 0.5%, there were no appreciable changes in yearly energy production, capacity factor, or projected power.

The capacity factor analysis has shown that the developed framework is able to adequately adjust to changing wind conditions. Thus, Massachusetts had the largest capacity factor, while Texas demonstrated relatively poor performance due to the lack of sufficient wind. The sensitivity analysis has also proved that the most influential parameter of the Generalized Gamma distribution is the scale parameter.

Conclusion

An integrated GG-Logistic PC framework for precisely calculating wind power was proposed in this study, taking into account both the characteristics of wind speed and the power generating process. Rather of using the conventional approach, which considers wind speed ranges and wind turbine power curves separately, this proposed framework utilizes a three-parameter Generalized Gamma distribution in combination with four-parameter and five-parameter logistic functions to present a complete methodology of wind energy assessment. This framework is tested on the hourly wind speed data from four different locations such as Altamont, Iowa, Massachusetts, and Texas. The empirical results confirm the effectiveness of the Generalized Gamma distribution for accounting for variation and asymmetry of wind regimes. The obtained estimates of capacity factors varied between 25.95% and 43.83%; the maximum performance was observed in the case of Massachusetts due to the higher mean wind speed. With a difference in the anticipated power output of less than 0.5%, the comparison of the 4PL and 5PL logistic approximations showed that both models offer a sufficient approximation of the wind turbine's power curve. While the 5PL logistic approximation demonstrates better accuracy, with an MAE of 0.1672 MW, an RMSE of 0.1956 MW and a MAPE of 9.38% against 0.1842 MW, 0.2077 MW and 10.77% for the 4PL form, the difference in the resulting power estimates is below 0.5% at every site. Thus, both methods are equally applicable for practical applications. The sensitivity analysis revealed that the scale parameter of the GG distribution is the most influential on the accuracy of estimation. The sensitivity analysis in the case of different wind regimes demonstrates that the suggested approach is effective for different geographical regions. Overall, the suggested approach proves to be accurate and efficient for wind energy assessment. Further research could apply this method through the use of additional geographic locations, different types of turbines, live operational data, and better methods of uncertainty quantification to improve wind prediction accuracy and implementation within large-scale renewable energy systems.

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