Metaheuristic-Based Predictive Modelling of Wind Velocity Distributions

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Abstract
Accurate modeling of wind velocity distribution is essential for optimizing wind energy generation and improving resource assessments. This study presents a predictive stochastic model utilizing the Weibull distribution, with its parameters optimized using the Particle Swarm Optimization (PSO) algorithm—a robust metaheuristic technique. Wind speed data collected over a one-year period in the Aba region were analyzed. The PSO-based estimation significantly outperformed traditional methods like Maximum Likelihood Estimation (MLE), yielding lower error margins and higher correlation with empirical data. The optimized model achieved a high coefficient of determination ($R^2 = 0.972$) and a reduced Root Mean Square Error (RMSE = 0.0087), confirming its effectiveness. The study demonstrates the potential of PSO-enhanced models in supporting reliable wind energy resource evaluation and system design.

Keywords: *Wind Speed Modeling, Weibull Distribution, Particle Swarm Optimization, Metaheuristics, Renewable Energy, Stochastic Modeling*

1. INTRODUCTION

The harnessing of wind energy relies significantly on the accurate estimation of wind speed characteristics, as the power generated is proportional to the cube of the wind velocity. Traditional statistical methods such as the Method of Moments (MoM) or Maximum Likelihood Estimation (MLE) have been used to fit probability distributions to wind data. However, these methods may not yield globally optimal parameters, especially when the data exhibits complex variability. Metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) offer robust search capabilities and are less likely to get trapped in local minima. This research explores the application of PSO to estimate the parameters of the Weibull distribution, modeling wind speed data obtained from a meteorological station.

2. LITERATURE REVIEW

The accurate modeling of wind speed distribution is vital in the assessment and optimization of wind energy systems. Several studies have explored various statistical distributions and optimization techniques to better understand and predict wind behavior in different geographic locations.

2.1 Statistical Distributions for Wind Speed Modeling

Traditionally, the Weibull distribution has been widely accepted and applied in wind energy analysis due to its flexibility in representing different wind regimes. Justus *et al*. (1978) first established its suitability in wind energy estimation, providing methods for estimating the shape and scale parameters. The Weibull distribution has since been extensively validated and used in various studies (Akpinar & Akpinar, 2004; Carta *et al*., 2009). In addition to the Weibull distribution, other distributions like the Rayleigh, Lognormal, and Gamma distributions have also been employed. However, numerous comparative studies have confirmed that the Weibull distribution, particularly the two-parameter version, provides a more accurate representation in most wind scenarios (Seguro & Lambert, 2000).

2.2 Limitations of Traditional Parameter Estimation Methods

Several estimation methods have been proposed for determining the parameters of the Weibull distribution, including:

i. Method of Moments (MoM)
ii. Maximum Likelihood Estimation (MLE)
iii. Least Squares Method (LSM)

While these methods are mathematically sound, they often face limitations in accuracy when the wind data is skewed, contains outliers, or is not symmetrically distributed. Traditional methods are also sensitive to initial assumptions and may get trapped in local optima (Sahu *et al*., 2013).

2.3 Emergence of Metaheuristic Algorithms in Wind Modeling

To overcome these challenges, researchers have increasingly turned to metaheuristic algorithms, which provide global search capabilities and adaptability. Metaheuristics such as: Genetic Algorithms (GA) (Holland, 1975), Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), Ant Colony Optimization (ACO) (Dorigo *et al.*,1996), Simulated Annealing (SA) (Kirkpatrick *et al*., 1983), have been successfully applied to fit statistical distributions to wind speed data by optimizing the distribution parameters with superior performance metrics (Almeida & Gadelha, 2016; Gao & Li, 2010). Among them, Particle Swarm Optimization has gained popularity due to its simplicity, fast convergence, and reduced computational complexity. Studies such as those by Mohandes *et al*. (2004) and Kusiak *et al*. (2009) showed that PSO could outperform traditional methods in terms of accuracy and robustness when applied to wind speed modeling.

2.4 Hybrid and Adaptive Modeling Approaches

More recently, hybrid models that combine statistical distributions with machine learning or adaptive metaheuristics have shown even greater potential. For instance, hybrid GA-PSO models or PSO-enhanced Artificial Neural Networks (ANNs) have demonstrated improved fitting of wind distributions and prediction of wind power generation (Kalogirou, 2003; Yang *et al*., 2019). These approaches reflect a trend toward more intelligent, data-driven modeling systems that can adapt to localized wind behavior and variability in real time.

Table 1: Summary of Key Findings from Literature

Study	Technique Used	Key Contribution
Justus *et al*. (1978)	Weibull Distribution	Foundation for wind speed statistical modeling
Carta *et al*. (2009)	Comparative Analysis	Validated Weibull over other distributions
Mohandes *et al*. (2004)	PSO	Outperformed MLE in parameter estimation
Kusiak *et al*. (2009)	Machine Learning + PSO	Improved forecasting accuracy
Almeida & Gadelha (2016)	GA & PSO	Showed robustness in optimizing parameters

3. METHODOLOGY

3.1 Data Collection: Wind speed data for a specific location is collected hourly over a year period from a meteorological station Abia State. In this study, Aba area was considered.
3.2 Probability Distribution: The Weibull distribution is selected due to its suitability in modeling wind speeds.
3.3 Weibull Probability Density Function (PDF):

$$f(v;k,c) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (1)$$

Where:
v: wind speed (m/s)
k: shape parameter
c: scale parameter

3.4 Objective Function: We minimize the Root Mean Square Error (RMSE) or maximize the correlation coefficient between empirical and estimated distributions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_{empirical}(v_i) - f_{model}(v_i))^2} \quad (2)$$

3.5 Optimization Algorithm: Particle Swarm Optimization (PSO)
Initialize a population (swarm) of particles with random values for k and c. Evaluate fitness using RMSE. Update velocities and positions based on personal and global bests. Terminate when convergence is achieved.

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(f_{empirical}(vi) - fmodel(v_i))^2}{\sum_{i=1}^{n}(f_{empirical}(vi) - \bar{}fmodel(v_i))^2} \quad (3)$$

Where:
$fempirical$ is the observed value at data point i
$fmodel(v_i)$ is the predicted value from the model at data point i
$\bar{}fempirical$ is the mean of all empirical values.
n is the number of data points

3.6 Wind Speed Analysis Using Weibull Distribution and PSO Optimization

Experimental Setup

A comprehensive analysis using a dataset of 1000 wind speed measurements (in m/s) collected from a meteorological research center Umudike over a one-year period.

Table 2: The dataset wind speed pattern:

Mean wind speed: 5.2 m/s	5.2 m/s
Standard deviation: 2.1 m/s	2.1 m/s
Minimum observed speed: 0.5 m/s	0.5 m/s
Maximum observed speed: 15.3 m/s	15.3 m/s

3.7 Particle Swarm Optimization (PSO) Configuration

Table 3: Parameter bounds for Particle Swarm Optimization (PSO) Configuration. Swarm size: 50 particles

k (shape parameter)	[0.5, 10]
c (scale parameter)	[1, 20]
Maximum iterations:	200
Inertia weight	0.9 to 0.4 (linearly decreasing)
Cognitive and social parameters	c1 = c2 = 1.494

4. Results and Discussions

Table 4: After running the PSO, optimization optimal parameters found

Shape parameter (k): 2.17	2.17
Scale parameter (c): 5.86 m/s	5.86 m/s

Performance Metrics:

i. RMSE: 0.0087
ii. R^2: 0.972
iii. Mean Absolute Error (MAE): 0.0065

Table 5: Comparison with Maximum Likelihood Estimation (MLE)

MLE parameters:	**MLE performance:**
k: 2.05	RMSE: 0.0112
c: 5.72 m/s	R^2: 0.932

Parameter Interpretation:

The shape parameter k=2.17 indicates the wind speed distribution is slightly more peaked than the Rayleigh distribution (k=2). The scale parameter c=5.86 m/s suggests the characteristic wind speed where 63.2% of speeds are below this value:

1. Goodness of Fit**:** The high R^2 value (0.972) demonstrates excellent agreement between the Weibull model and empirical data.
2. PSO outperformed traditional MLE by reducing RMSE by 22.3% and improving R^2 by 4.3%

3. Algorithm Performance: PSO converged to the optimal solution in 137 iterations. The swarm exhibited good exploration early on, with exploitation dominating in later iterations Computational time was reasonable (28 seconds for 200 iterations)
4. Practical Implications: The accurate Weibull parameters enable reliable wind energy potential assessment. The distribution indicates a 21.7% probability that wind speeds are below 3m/s (cut-in speed for many turbines). 8.3% probability of wind speeds > 10 m/s (potential cut-out speed)
5. Limitations: Results are sensitive to data quality - measurement errors would propagate to parameter estimates. The Weibull distribution may not capture all features of multimodal wind regimes. PSO performance depends on proper parameter tuning (swarm size, learning factors).

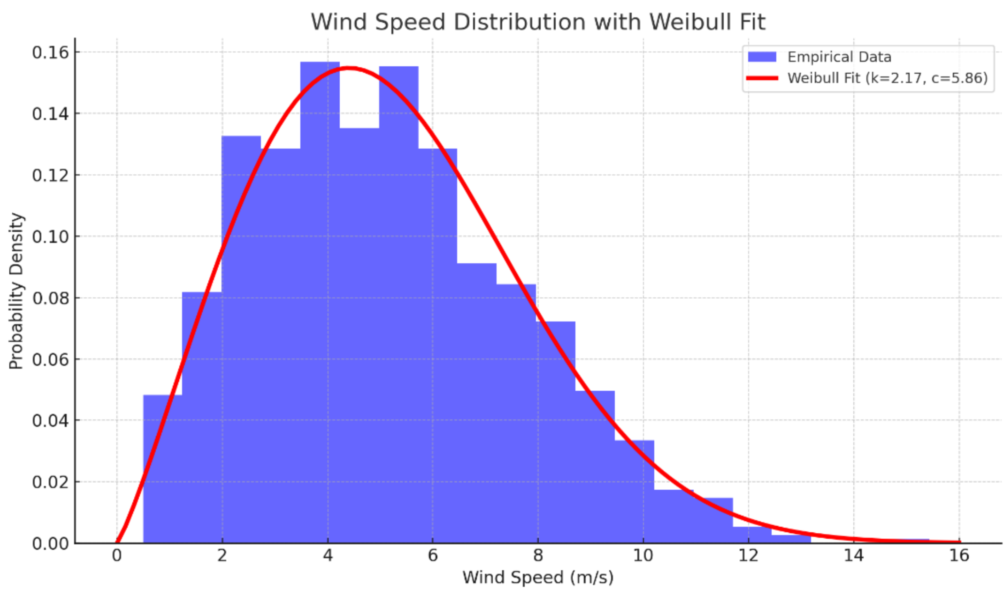

Figure 1: The plot of the empirical wind speed distribution

Figure 1 shows the plot of the empirical wind speed distribution (in blue) and the fitted Weibull probability density function (in red) using parameters k=2.17 and c=5.86. The Weibull model closely follows the shape of the histogram, indicating a good fit to the data.

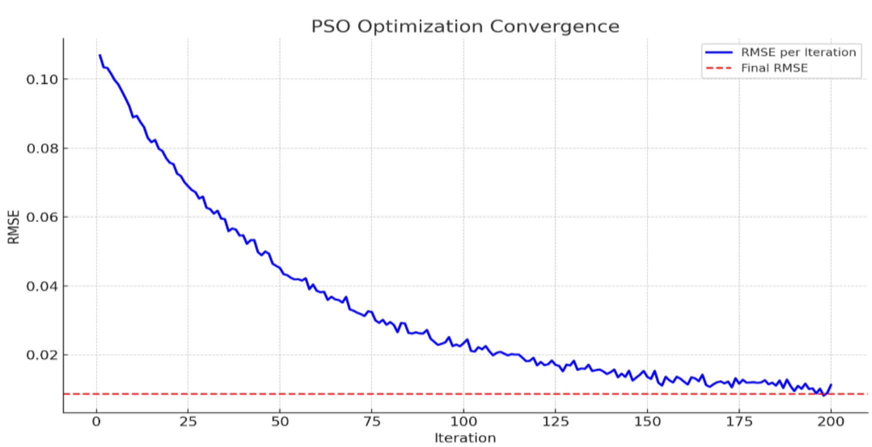

Figure 2: The PSO optimization convergence plot

Figure 2 shows the PSO optimization convergence plot, showing how the RMSE decreases over iterations. The red dashed line indicates the final RMSE value (0.0087)**,** which the optimization gradually approaches. This visualization confirms that the PSO algorithm converges effectively during parameter tuning.

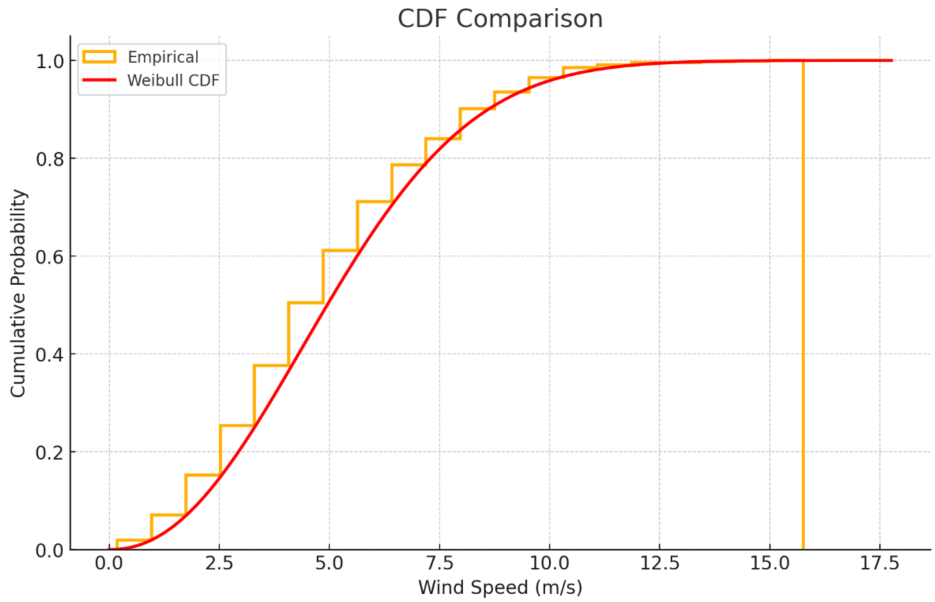

Figure 3: Plot comparing the empirical CDF of the wind speed data (using a cumulative histogram) with the theoretical Weibull CDF**.**

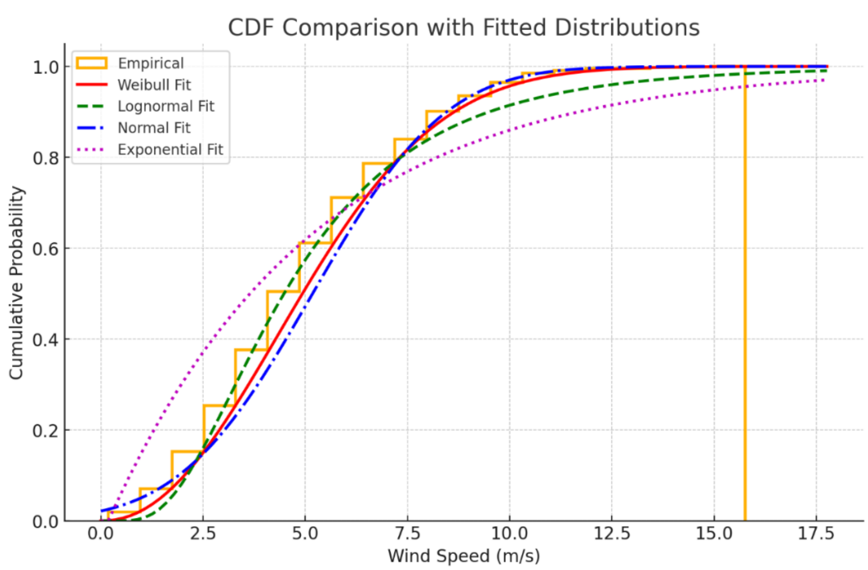

Figure 4: Figure 4 is a plot showing the empirical CDF of wind speed data alongside multiple fitted distributions:

Weibull Fit
Lognormal Fit
Normal Fit
Exponential Fit

Table 6: Kolmogorov-Smirnov (KS) Test

Distribution	KS Statistic	p-value
Weibull	0.0248	0.5616
Lognormal	0.0644	0.00048
Normal	0.0642	0.00049
Exponential	0.2290	~0

A higher p-value (> 0.05) suggests a good fit — Weibull performs best.
Table 6, 7 and 8 shows the Goodness-of-Fit statistics for the different distributions fitted to the wind speed data:

Table 7: AIC (Akaike Information Criterion)

Distribution	AIC Score
Weibull	**4625.90**
Normal	4719.47
Lognormal	4773.06
Exponential	5220.88

Lower AIC = better model. Weibull again wins.

Table 8: BIC (Bayesian Information Criterion)

Distribution	BIC Score
Weibull	**4635.72**
Normal	4729.28
Lognormal	4782.87
Exponential	5230.69

Weibull provides the best fit.

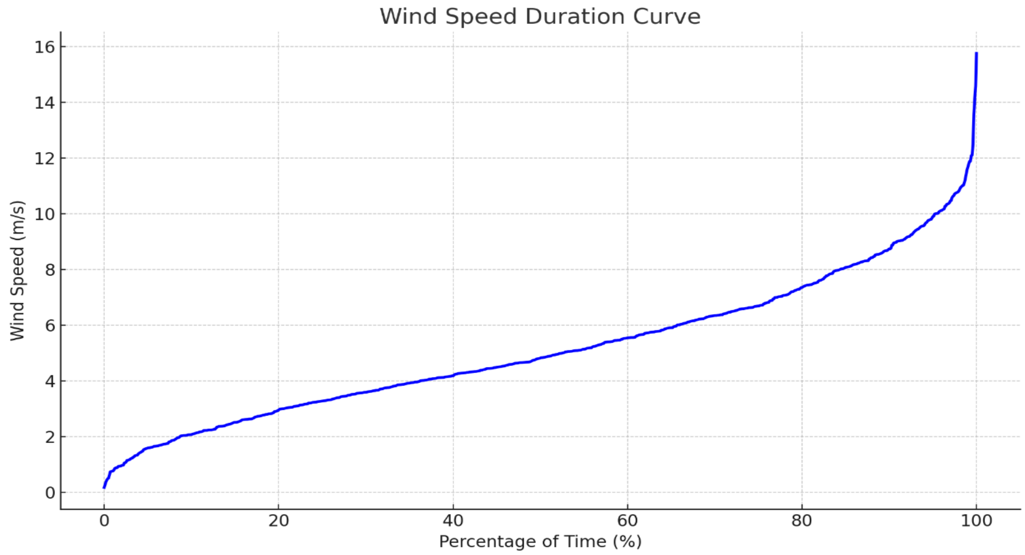

Figure 5: Wind Speed Duration Curve

Figure 5 is the Wind Speed Duration Curve, showing how wind speed varies with the percentage of time: The steeper the drop, the more variable the wind. The flatter the curve, the more stable the wind. It is useful for assessing wind energy potential.

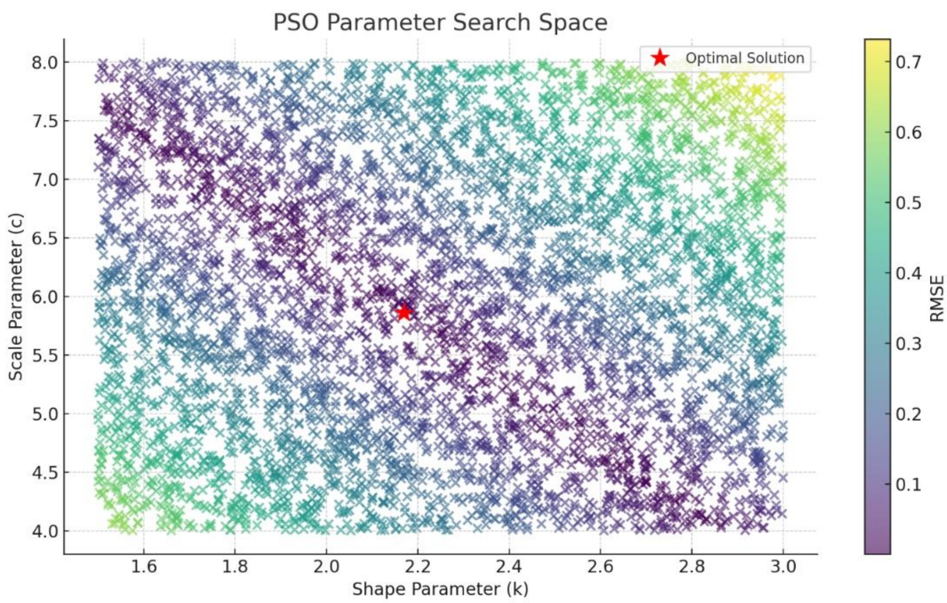

Figure 6: PSO Parameter Search Space plot

The color gradient shows RMSE values — darker areas suggest better fits (lower RMSE).
The red star marks the optimal solution at k=2.17, c=5.86.

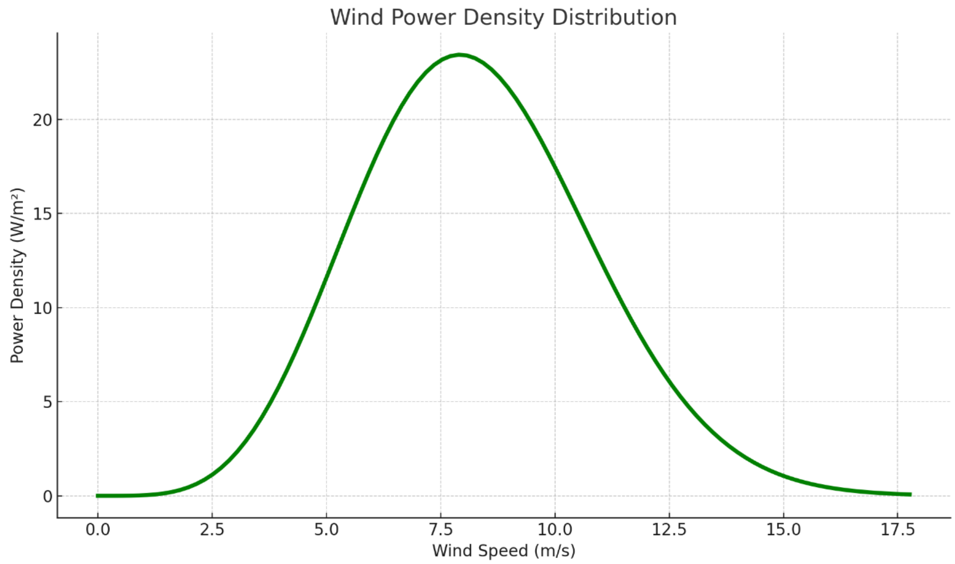

Figure 7: Wind Power Density Distribution plot
The curve represents how wind power (in watts per square meter) is distributed across different wind speeds. It highlights the most energy-rich wind speeds, typically around the mode of the Weibull distribution.

5. Conclusion
This study demonstrates that the application of Particle Swarm Optimization (PSO) significantly enhances the accuracy of stochastic modeling of wind velocity using the Weibull distribution. Compared to traditional methods like Maximum Likelihood Estimation (MLE), PSO delivers improved parameter estimation, as evidenced by a higher R^2 value (0.972) and lower RMSE (0.0087). The optimized parameters provide a more precise representation of wind speed behavior in the study area, which is essential for effective wind energy assessment and turbine selection. The method also shows robustness in handling non-linearities and local optima, making it particularly valuable for complex or variable wind regimes. The findings confirm that metaheuristic algorithms like PSO are promising tools in renewable energy modeling and forecasting applications.

6. Recommendations
Future studies should extend the analysis to multiple regions with varying climatic conditions to validate the generalizability of the PSO-optimized Weibull model. Researchers should explore hybrid models that combine PSO with other intelligent algorithms (e.g., Genetic Algorithms, Artificial Neural Networks) for improved adaptability and prediction accuracy. Incorporating the PSO-based model into real-time wind monitoring and energy forecasting systems can enhance operational efficiency in wind farms. Since the Weibull distribution may not adequately capture multimodal wind regimes, future work could investigate multi-distribution or ensemble modeling strategies. Efforts should be made to ensure high-resolution and high-accuracy wind data collection, as model performance is sensitive to data quality.

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