Indonesian Journal of Electrical Engineering and Computer Science
Vol. 41, No. 1, January 2026, pp. 180~190
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v41.i1.pp180-190

Enhancing wind energy prediction accuracy with a hybrid Weibull distribution and ANN model: a case study across ten locations in Java Island, Indonesia

Silvy Rahmah Fithri[1,2], Nurry Widya Hesty[1], Rudi P. Wijayanto[1], Bono Pranoto[3,4], Prima Trie Wijaya[1], Akhmad Faqih[2], Wisnu Ananta Kusuma[5], Agus Nurrohim[1], Agus Sugiyono[1], Yudiartono[1]

[1]Research Center for Conversion and Conservation Energy - National Research and Innovation Agency, Jakarta, Indonesia
[2]Applied Climatology Study Program-Department of Geophysics and Meteorology-IPB University, Bogor, Indonesia
[3]Natural Resources and Environmental Management Science (NREMS)-IPB University, Bogor, Indonesia
[4]Research Center for Limnology and Water Resources - National Research and Innovation Agency, Jakarta, Indonesia
[5]Department of Computer Science – IPB University, Bogor, Indonesia

Article Info

Article history:

Received Aug 27, 2025
Revised Dec 10, 2025
Accepted Dec 13, 2025

Keywords:

Artificial neural network
Hybrid approach
Renewable energy
Weibull parameters
Wind speed prediction

ABSTRACT

Accurate wind speed forecasting is essential for optimizing renewable energy (RE) systems, especially in coastal and island regions with high variability. This study proposes a hybrid predictive model that combines Weibull distribution parameters with artificial neural networks (ANN) to enhance forecasting accuracy. Using ten years of hourly NASA POWER data from 10 locations across Java Island, 24 scenarios were tested with varying combinations of Weibull and meteorological variables. Results demonstrate that incorporating both Weibull shape (k) and scale (c) parameters significantly improves performance, with the best configuration (Scenario 1) achieving a MAPE of 0.44% in Garut. Excluding one or both parameters sharply reduced accuracy, with errors rising up to 35.12%. Beyond technical accuracy, the findings emphasize the practical relevance of Weibull-informed ANN models for energy planning. Reliable forecasts support better wind resource assessment, grid integration, and investment decisions, reducing uncertainties that often hinder wind power deployment. By providing accurate and stable predictions across diverse locations, this approach offers policymakers and planners a robust tool to accelerate RE development and meet national energy targets.

Corresponding Author:

Prima Trie Wijaya
Research Center for Conversion and Conservation Energy
National Research and Innovation Agency
Building 720, BJ Habibie Science and Technology Area, South Tangerang 15314, Indonesia
Email: prim002@brin.go.id or prima3ewijaya@gmail.com

1. INTRODUCTION

Indonesia holds substantial renewable energy (RE) potential, yet its RE share reached only 15% in 2023, falling short of the 23% target set for 2025 [1]. This gap highlights the need to accelerate RE deployment, with wind energy offering significant promise despite its inherent intermittency and unpredictable variability. Reliable wind speed forecasting is crucial for maximizing the efficiency of wind energy production, enhancing grid integration, supporting energy trading, and anticipating extreme events [2], [3]. Despite advances in wind energy technology, existing models remain insufficiently precise for effective energy management, particularly under Indonesia's diverse and variable wind conditions.

The Weibull distribution is widely recognized as a robust method for wind speed prediction and wind power density estimation. Defined by the shape (k) and scale (c) parameters, it effectively captures wind speed variability beyond conventional meteorological variables, enabling more accurate assessments of energy potential [4]-[6]. Both two-and three-parameter Weibull models have been applied to improve wind resource evaluation and optimize energy generation strategies [7], [8]. Comparative studies further confirm its superiority over other distributions, such as Rayleigh, making Weibull the preferred standard for wind energy assessment under diverse climatic conditions [9], [10].

While the Weibull distribution remains the foundation, advanced data-driven methods such as artificial neural networks (ANNs) are increasingly being used to improve forecast accuracy under complex wind conditions. ANNs can capture nonlinear relationships, learn from historical data of weather variables, and provide more reliable short- to medium-term forecasts compared to traditional models, thereby supporting real-time energy management and grid stability [11], [12]. Previous studies, including those [13]-[15], demonstrated that Weibull parameters significantly improve ANN-based wind prediction. However, no study has systematically examined the effect of each Weibull parameter (k and c) on prediction accuracy, either individually or combined with other meteorological variables. Moreover, earlier approaches were limited to non-varied input scenarios and did not explore ANN sensitivity in depth.

To address these gaps, this study proposes a hybrid forecasting method that integrates the statistical robustness of the Weibull distribution with the adaptive learning of ANN. The Weibull parameters (k and c) represent wind speed variability, while ANN captures nonlinear temporal patterns, resulting in higher accuracy and broader generalizability than purely statistical or machine learning models. Using ten years of hourly wind data from 10 locations across Java Island and surrounding islands, monthly Weibull parameter time series are incorporated into the ANN across 24 forecasting scenarios. This design allows seasonal variability and temporal dynamics—often neglected in previous work—to be systematically evaluated, providing detailed insights into how Weibull parameters enhance prediction accuracy.

Furthermore, this approach advances hybrid forecasting research, which has increasingly integrated clustering, fuzzy inference, signal decomposition, and deep learning to reduce uncertainty and capture nonlinear dynamics [16]-[19]. Building on these advances, this study contributes by systematically assessing the role of shape (k) and scale (c) parameters in strengthening ANN-based forecasting, thereby supporting more accurate wind energy planning and deployment in Indonesia's coastal and island regions.

2. METHOD

2.1. Dataset

The data for this study were sourced from the NASA Langley Research Center (LaRC) prediction of worldwide energy resource (POWER) Project, funded by NASA's Earth Science/Applied Science Program (https://power.larc.nasa.gov/data-access-viewer/). The study focused on 10 locations across Java Island and nearby small islands, with coordinates listed in Table 1 and shown in Figure 1. These locations were chosen to provide a comprehensive view of wind dynamics across the region.

The dataset comprises a 10-year hourly time series (2013–2022) of wind speed and direction (10 m), air temperature, relative humidity, and surface pressure, totaling 87,648 records. These parameters were used in the hybrid prediction model to capture seasonal patterns, long-term trends, and variability. The methodology includes data preprocessing, Weibull parameter estimation, scenario design, data mining, and error analysis, as summarized in Figure 2.

Table 1. Research locations

Location	Lat	Long
Pandeglang	-6.86	105.54
Sukabumi	-7.22	106.52
Garut	-7.57	107.88
Baron	-8.13	110.54
Cirebon	-6.76	108.65
Situbondo	-7.81	114.44
Banyuwangi	-8.09	114.39
Sebira Island	-5.2	106.46
Gili Ketapang Island	-7.68	113.25
Bawean Island	-5.78	112.65

2.2. Preprocessing data and Weibull parameters

This process generated monthly values of Weibull parameters k and c, as well as wind speed, wind direction, temperature, surface pressure, and humidity for the entire ten-year period. Additionally, the software produced a monthly diurnal profile of wind speed, revealing cyclical patterns throughout each day of each month. These analyses offer a comprehensive view of the wind dynamics at the study sites over the decade.

For Weibull parameter calculation, we employed the maximum likelihood method (MLM) to estimate the Weibull distribution parameters: the parameter k and c. The advantages of the MLM method include its computational efficiency and fast convergence due to the absence of complex calculations [20], its ability to provide parameter estimates that closely fit the observed data distribution [21], and its asymptotic efficiency, making it suitable for large datasets [22]. The MLM estimates the shape parameter (k) and scale parameter (c) using the following formulas:

$$\text{Shape parameter, } k = \frac{1}{n}\sum_{i=1}^{i} \ln \frac{Xi}{c} \quad (1)$$

$$\text{Scale parameter, } c = \left(\frac{1}{n}\sum_{i=1}^{n} X_i^k\right)^{\frac{1}{k}} \quad (2)$$

It should be noted that because the equations for estimating k and c are interdependent, the MLM employs an iterative procedure. An initial guess for k is made, followed by the calculation of c. The values are then updated iteratively until convergence is achieved. This process ensures accurate and stable estimation of the Weibull parameters.

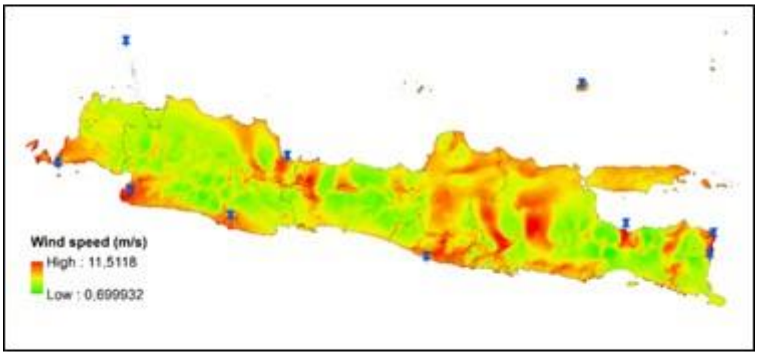

Figure 1. Research location and wind speed distribution at 100 meters above ground level (Source: Global Wind Atlas)

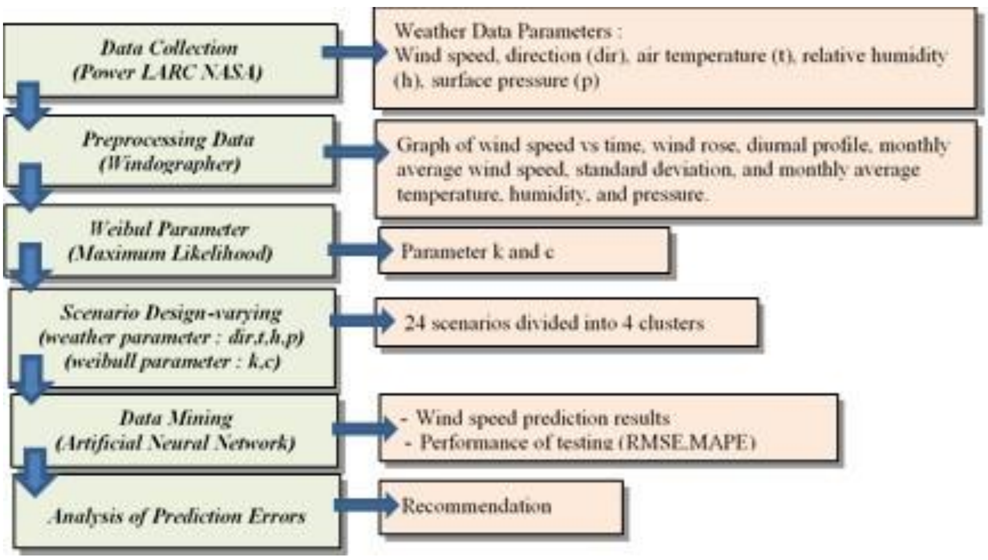

Figure 2. Flow diagram of research methodology

2.3. Scenarios and prediction model

In testing this prediction model, the input parameters involve Weibull parameters as well as environmental parameters (temperature t, humidity h, pressure p, and wind direction dir). A total of six parameters will be assessed in this test. To further understand the role of Weibull parameters in improving the accuracy of the prediction model, this research determines 24 scenarios, which are grouped into four clusters as shown in Table 2.

Table 2. Prediction model testing scenarios with Weibull and environmental parameter variations

Cluster	Scenario	Parameter input	Purposes
I	Sce 1	k, c, t, h, p, dir	Analyzing the extent to which the presence of Weibull parameters (k and c) impacts the performance of the prediction model, both independently and in combination with other environmental parameters
	Sce 2	k, c, t, h, p	
	Sce 3	k, c, t	
	Sce 4	k, c, h	
	Sce 5	k, c, p	
	Sce 6	k, c, dir	
	Sce 7	k, c	
II	Sce 8	c, t, h, p, dir	Assess the influence of each Weibull parameter (k and c) separately, and evaluate the model performance when only "c" as scale Weibull parameter is included in the prediction
	Sce 9	c, t, h, p	
	Sce 10	c, t	
	Sce 11	c, h	
	Sce 12	c, p	
	Sce 13	c, dir	
	Sce 14	c	
III	Sce 15	k, t, h, p, dir	Assess the influence of each Weibull parameter (k and c) separately, and evaluate the model performance when only "k" as shape Weibull parameter is included in the prediction
	Sce 16	k, t, h, p	
	Sce 17	k, t	
	Sce 18	k, h	
	Sce 19	k, p	
	Sce 20	k, dir	
	Sce 21	k	
IV	Sce 22	t, h, p, dir	Identifying the influence of environmental parameters (without k and c) on the prediction model, evaluating model performance in the absence of Weibull parameters.
	Sce 23	t, h, p	
	Sce 24	dir	

The study proposes a hybrid model, combining the strengths of each approach. The proposed hybrid model is a machine learning-based integration of Weibull and neural network parameters. Each model is expected to contribute unique advantages to wind speed forecasting. The overall design of the study is depicted in Figure 3.

In this study, we limited the ANN inputs to meteorological parameters (t, h, p, dir) and Weibull parameters (k, c) to isolate the effect of Weibull distribution characteristics on prediction accuracy. Higher-level descriptors such as diurnal pattern strength, monthly averages, and autocorrelation coefficients were not included, as they are statistical derivatives of the wind speed series and could introduce redundancy or bias into the training process. Nevertheless, these variables remain valuable, and their integration into ANN frameworks is recommended for future studies to further enhance the robustness of wind speed forecasting models.

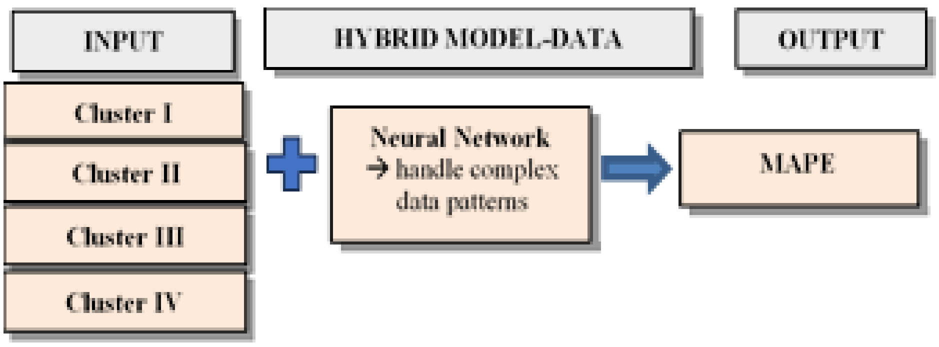

Figure 3. Grand design proposed integrated model

2.4. ANN architecture and error analysis

The ANN learning algorithm was employed in this study using wind speed and environmental parameters as inputs, with the software platform (RapidMiner) used for implementation. From the monthly dataset, 70% of data points were used for training and 30% for testing, with performance validated through 10-fold cross-validation. The ANN architecture as shown in Figure 4 consisted of an input layer with nodes corresponding to the number of parameters, two hidden layers (size=2) with a linear activation function, and a single output node. Model parameters were set to 200 training cycles, a learning rate of 0.01, momentum of 0.9, and an error epsilon of 1.0E-4 to ensure stable convergence and avoid local minima.

It should be noted that the original hourly dataset was aggregated into a monthly series. Weibull parameters (k and c) were computed monthly, while meteorological parameters were averaged every month. Therefore, each input to the ANN corresponds to one month, and the ANN output layer produces one predicted wind speed value per month. For the 10-year dataset, this yields a total of 120 predicted monthly values.

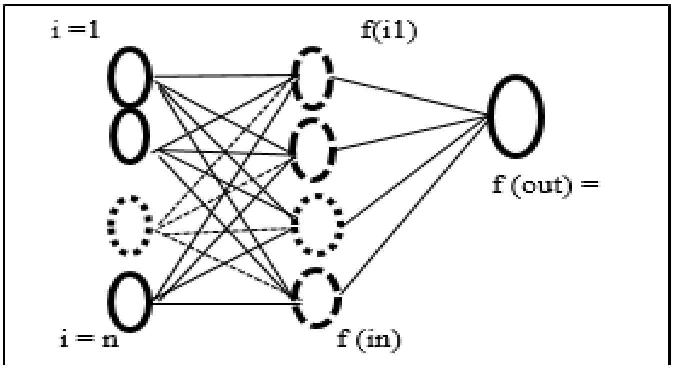

Figure 4. Architecture of the ANN for all scenarios

Model performance was evaluated using two error metrics: root mean square error (RMSE) and mean absolute percentage error (MAPE). RMSE (3) measures the average deviation between predicted and actual values, providing insight into the magnitude of prediction errors. MAPE (4) expresses the average absolute percentage difference between predicted and actual values, offering a readily interpretable measure of forecasting accuracy. Its widespread use stems from its relative ease of understanding compared to other metrics.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Ai-Fi}{Ai}\right| x\ 100\% \quad (4)$$

3. RESULTS AND DISCUSSION

This study explores the impact of Weibull distribution parameters integrated into the ANN model to predict wind speed. Predictions are based on Weibull parameters and weather variables, as explained in subsection 2.3. The 24 prediction scenarios are grouped into four clusters (I–IV) based on input combinations. Model accuracy is evaluated using MAPE values at 10 locations across three regions: the South Coast of Java, the North Coast of Java, and small islands. Table 3 presents the MAPE values for these scenarios.

The analysis results are discussed per cluster, outlining the key insights and trends found in each scenario configuration, namely:

Cluster I (Scenario 1–7)

- Cluster I shows the best performance (MAPE 0.369–1.311%), with Scenario 1—using all variables—achieving notably low errors in several sites such as Pandeglang (0.608%), Sukabumi (0.508%), Baron (0.449%), Sebira Island (0.521%), and Gili Ketapang (0.847%).
- Key insight: the integration of both Weibull parameters (k and c) with weather variables leads to significantly improved accuracy across diverse geographical locations. This confirms that combining these parameters optimizes the wind speed prediction model’s performance.

- Exception: in Garut, Scenario 6 achieves slightly better accuracy, while in Banyuwangi, Scenario 7 outperforms others, higher than other southern coastal areas. This variation is likely due to coastal dynamics, also present in Banyuwangi, which is influenced by monsoon winds and upwelling currents in the strait between Java and Bali. These factors complicate predictions and lead to higher MAPE values [23], [24].

Table 3. Results of model prediction error evaluation at ten (10) different study locations

Cluster	Scenario	Input	MAPE (%)									
			South Coast of Jawa					North Coast of Jawa		Small Island North of Jawa		
			Pandeglang	Sukabumi	Garut	Baron	Banyuwangi	Cirebon	Situbondo	Sebira Island	Gili Ketapang Island	Bawean Island
I	Sce 1	k, c, t, h, p,dir	0.61	0.51	0.44	0.45	1.31	1.10	1.31	0.52	0.85	1.15
	Sce 2	k,c,t,h,p	0.66	0.59	0.50	0.62	1.46	1.07	1.46	0.56	1.23	0.82
	Sce 3	k,c,t	0.70	0.67	0.40	0.48	1.46	1.17	1.46	0.57	1.36	0.96
	Sce 4	k,c,h	0.71	0.56	0.48	0.49	1.61	1.20	1.61	0.61	1.29	0.93
	Sce 5	k,c,p	0.71	0.60	0.42	0.51	1.49	1.16	1.49	0.61	1.44	0.98
	Sce 6	k, c, dir	0.66	0.56	0.37	0.50	1.55	1.13	1.55	0.60	1.12	0.90
	Sce 7	k,c	0.72	0.60	0.44	0.50	1.15	1.21	1.15	0.62	0.89	1.13
II	Sce 8	c,t,h,p,dir	1.00	1.00	0.61	0.92	1.36	1.32	1.36	0.89	0.98	1.27
	Sce 9	c,t,h,p	0.95	1.18	0.56	0.66	1.43	1.17	1.43	0.78	1.25	1.26
	Sce 10	c,t	1.23	1.27	0.58	0.66	1.61	1.18	1.61	0.80	1.40	1.30
	Sce 11	c,h	1.22	1.28	0.68	0.68	1.53	1.21	1.53	0.73	1.39	1.49
	Sce 12	c,p	0.94	1.15	0.60	0.82	1.35	1.27	1.35	0.81	1.09	1.54
	Sce 13	c, dir	1.20	1.22	0.65	0.70	1.37	1.22	1.37	0.66	1.15	1.33
	Sce 14	c	1.18	1.21	0.50	0.68	1.44	1.43	1.44	0.76	1.14	1.82
III	Sce 15	k,t,h,p,dir	10.04	10.17	8.75	7.32	10.17	10.36	10.17	9.51	8.96	11.97
	Sce 16	k,t,h,p	11.98	10.51	9.37	9.53	10.14	11.48	10.14	8.36	8.94	13.04
	Sce 17	k,t	12.04	10.31	9.96	11.14	10.53	11.91	10.53	9.15	12.59	13.90
	Sce 18	k,h	11.01	11.08	12.30	10.03	10.98	13.47	10.98	9.90	10.39	11.98
	Sce 19	k,p	10.69	11.86	10.52	11.58	11.20	14.71	11.20	10.77	14.63	16.03
	Sce 20	k, dir	11.33	10.07	11.43	10.96	10.77	12.93	10.77	9.76	12.54	13.92
	Sce 21	k	14.26	13.64	12.95	12.71	11.29	12.00	11.29	10.30	13.98	21.00
IV	Sce 22	t, h, p, dir	16.67	13.37	10.61	7.95	10.53	11.29	10.53	11.74	13.11	26.10
	Sce 23	t, h, p	19.07	14.59	11.60	10.95	11.11	14.27	11.11	13.44	14.68	24.58
	Sce 24	Dir	23.08	21.71	18.84	16.61	19.76	25.93	19.76	15.13	21.21	35.12

Cluster II (Scenario 8–14)
- Cluster II loses accuracy when the Weibull shape parameter k is removed and only the scale parameter c is retained, as shown in Table 3 by higher MAPE values of 0.56 %–1.43 % for Scenarios 8–9. Including wind direction in Scenario 8 partly offsets this drop, improving predictions at some sites such as Sukabumi (1.003 %) and Gili Ketapang Island (0.979 %).
- Key insight: while the absence of the shape parameter reduces accuracy, wind direction still contributes positively to the model's performance in specific locations. However, Scenario 9 (which excludes wind direction) still performs well at locations like Pandeglang (0.946%) and Cirebon (1.170%), suggesting that weather variables other than wind direction can still be effective.
- Trend: despite good results in certain locations, the absence of the shape parameter results in lower overall consistency, highlighting the importance of both Weibull parameters for reliable, high-accuracy predictions.

Cluster III (Scenario 15–21)
- Cluster III, using only the Weibull shape parameter (k) with specific weather variables, shows poor performance, with MAPE values ranging from 7.32% to 14.71%, as presented in Table 3. Scenario 15, which includes wind direction, gives the best performance in Pandeglang (10.042%), Garut (8.745%), and Baron (7.325%).
- Key insight: the elimination of the Weibull scale parameter (c) results in a marked reduction in accuracy. Even the best scenario in this cluster still produces higher MAPE values than those in Cluster I and Cluster II, indicating that the scale parameter (c) plays a crucial role in improving prediction accuracy.
- Trend: This cluster clearly demonstrates the importance of both Weibull parameters in enhancing the model's ability to predict wind speed accurately across varied conditions.

Cluster IV (Scenario 22–24)
- Cluster IV relies solely on weather variables, with Scenario 24 (using only wind direction) showing the poorest performance in Table 3, with MAPE values reaching 35.12% in Bawean Island.
- Key insight: the drastic performance drop in Cluster IV shows that wind direction alone is inadequate for accurate wind speed prediction. Without Weibull parameters, particularly the scale parameter, the model fails to capture wind speed distribution, resulting in high errors.
- Trend: Bawean Island performs poorly in Scenario 24, underscoring the limitation of using only wind direction and the necessity of Weibull parameters, while local factors such as wind conditions, topography, and environment also strongly influence model effectiveness [25].

The heatmap in Table 4 shows performance degradation from Cluster I to IV, underscoring the importance of Weibull parameters. Cluster I performs best, while Cluster II shows moderate accuracy. Cluster III drops significantly, and Cluster IV performs worst, particularly in Bawean (MAPE 28.6%). Weibull parameters (*k* and *c*) are thus essential for accurate predictions, especially in complex wind regimes. Wind direction adds value in Cluster II but cannot substitute Weibull parameters. Nonetheless, Cluster II remains suitable for simpler models in stable wind conditions.

The findings of this study are consistent with previous works by Tian and Wei [16] and Tang *et al.* [17], yet demonstrate slightly improved MAPE values using 10 years of hourly data. Notably, Scenario 22 without Weibull parameters (*k* and *c*) yielded a lower MAPE (7.95%) compared to Kadhem *et al.* [15] (16.4–20.3%), whereas Scenario 24, relying solely on wind direction, resulted in the highest MAPE (35.12%). These results further emphasize the critical role of Weibull parameters and meteorological variables in enhancing prediction accuracy.

Table 4. Heatmap of average MAPE by location and cluster

Location	Cluster					
	I	II	III	IV		
Banyuwangi	1.43	1.44	10.73	13.8		
Baron	0.51	0.73	10.47	11.84	-25	
Bawean Island	0.98	1.43	14.55	28.6		
Cirebon	1.15	1.26	12.41	17.16		MAPE (%)
Garut	0.44	0.6	10.75	13.68	-15	
Gili Ketapang Island	1.17	1.2	11.72	16.33		
Pandeglang	0.68	1.1	11.62	19.61		
Sebira Island	0.58	0.78	9.68	13.44	-5	
Situbondo	1.43	1.44	10.73	13.8		
Sukabumi	0.58	1.19	11.09	16.56		

4. CONCLUSION

This study demonstrates that integrating Weibull parameters with weather variables significantly improves wind speed prediction accuracy. Cluster I, which uses both Weibull parameters (k and c), provides the best results, emphasizing the importance of these parameters for regions with complex wind dynamics. The findings show that Weibull parameters enhance prediction accuracy, which can be further refined through hyperparameter tuning, advanced architectures, and larger datasets for greater model robustness.

For utilities and planners, integrating Weibull distribution with high-frequency wind speed measurements (such as those taken every 5 or 10 minutes) can further improve prediction accuracy by providing more granular data. Additionally, applying models like autoregressive integrated moving average (ARIMA), long short-term memory (LSTM,) and gated recurrent unit (GRU) for longer-term forecasting (predicting wind speeds over extended periods such as days or weeks) will help in more effective planning and optimization of wind energy resources. While this study relies on satellite data, which may be less accurate in complex terrains, future research should incorporate ground-based observations and geospatial artificial intelligence (AI) to enhance the reliability and precision of the model's predictions.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to NASA LaRC POWER for providing the time series weather data used in this study. We also extend our sincere appreciation to all co-authors for their valuable contributions to this manuscript.

FUNDING INFORMATION

This research is part of an independent study required to complete a Master's program, supported by a Degree by Research scholarship from the National Research and Innovation Agency (BRIN). The research funds are self-funded by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRedit) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Silvy Rahmah Fithri	✓	✓			✓	✓	✓	✓	✓	✓		✓		
Nurry Widya Hesty	✓	✓	✓	✓	✓	✓			✓	✓				
Rudi P. Wijayanto			✓		✓				✓	✓				
Bono Pranoto						✓					✓			
Prima Trie Wijaya							✓	✓			✓		✓	
Akhmad Faqih				✓								✓		
Wisnu Ananta Kusuma		✓										✓		
Agus Nurrohim										✓				
Agus Sugiyono										✓				
Yudiartono													✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The Authors state that there is no conflict of interest

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [Prima Trie Wijaya] on request.

REFERENCES

[1] Dirjen EBTKE, "Ministry of energy and mineral resources, directorate general of new and renewable energy and energy conservation (DG EBTKE), "[Performance Report of DG EBTKE 2022] (in Indonesian: *Laporan Kinerja Ditjen EBTKE 2022*) ," Jakarta: 2023.

[2] M. H. Shams, H. Niaz, B. Hashemi, J. Jay Liu, P. Siano, and A. Anvari-Moghaddam, "Artificial intelligence-based prediction and analysis of the oversupply of wind and solar energy in power systems," *Energy Conversion and Management*, vol. 250, p. 114892, Dec. 2021, doi: 10.1016/j.enconman.2021.114892.

[3] M. Ibrahim, A. Alsheikh, Q. Al-Hindawi, S. Al-Dahidi, and H. ElMoaqet, "Short-time wind speed forecast using artificial learning-based algorithms," *Computational Intelligence and Neuroscience*, vol. 2020, pp. 1–15, Apr. 2020, doi: 10.1155/2020/8439719.

[4] M. G. M. Khan and M. R. Ahmed, "Bayesian method for estimating Weibull parameters for wind resource assessment in the Equatorial region: a comparison between two-parameter and three-parameter Weibull distributions," Jan. 2022, doi: 10.21203/rs.3.rs-504670/v2.

[5] M. G. M. Khan and M. R. Ahmed, "Bayesian method for estimating Weibull parameters for wind resource assessment in a tropical region: a comparison between two-parameter and three-parameter Weibull distributions," *Wind Energy Science*, vol. 8, no. 8, pp. 1277–1298, Aug. 2023, doi: 10.5194/wes-8-1277-2023.

[6] F. S. dos Santos, K. K. F. do Nascimento, J. da Silva Jale, S. F. A. Xavier, and T. A. E. Ferreira, "Brazilian wind energy generation potential using mixtures of Weibull distributions," *Renewable and Sustainable Energy Reviews*, vol. 189, p. 113990, Jan. 2024, doi: 10.1016/j.rser.2023.113990.

[7] M. A. Baseer, J. P. Meyer, S. Rehman, and M. M. Alam, "Wind power characteristics of seven data collection sites in Jubail, Saudi Arabia using Weibull parameters," *Renewable Energy*, vol. 102, pp. 35–49, Mar. 2017, doi: 10.1016/j.renene.2016.10.040.

[8] S. Wang, J. Wang, H. Lu, and W. Zhao, "A novel combined model for wind speed prediction – Combination of linear model, shallow neural networks, and deep learning approaches," *Energy*, vol. 234, p. 121275, Nov. 2021, doi: 10.1016/j.energy.2021.121275.

[9] J. A. Carta, P. Ramírez, and S. Velázquez, "A review of wind speed probability distributions used in wind energy analysis," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 5, pp. 933–955, Jun. 2009, doi: 10.1016/j.rser.2008.05.005.

[10] N. Shirzadi, F. Nasiri, R. P. Menon, P. Monsalvete, A. Kaifel, and U. Eicker, "Smart urban wind power forecasting: integrating weibull distribution, recurrent neural networks, and numerical weather prediction," *Energies*, vol. 16, no. 17, p. 6208, Aug. 2023, doi: 10.3390/en16176208.

[11] C. Barış, C. Yanarateş, and A. Altan, "A robust chaos-inspired artificial intelligence model for dealing with nonlinear dynamics in wind speed forecasting," *PeerJ Computer Science*, vol. 10, p. e2393, Oct. 2024, doi: 10.7717/peerj-cs.2393.

[12] H. Halidah, N. Hesty, P. Aji, Ifanda, D. Amelia, and K. Akhmad, "Short-Term wind forecasting with weather data using deep learning - case study in Baron Techno Park," *Evergreen*, vol. 10, no. 3, pp. 1753–1761, Sep. 2023, doi: 10.5109/7151724.

[13] A. A. Majid, "Accurate and efficient forecasted wind energy using selected temporal metrological variables and wind direction," *Energy Conversion and Management: X*, vol. 16, p. 100286, Dec. 2022, doi: 10.1016/j.ecmx.2022.100286.

[14] A. A. Majid, "Accuracy of wind speed forecasting based on joint probability prediction of the parameters of the Weibull probability density function," *Frontiers in Energy Research*, vol. 11, Sep. 2023, doi: 10.3389/fenrg.2023.1194010.

[15] A. A. Kadhem, N. Wahab, I. Aris, J. Jasni, and A. Abdalla, "Advanced wind speed prediction model based on a combination of weibull distribution and an artificial neural network," *Energies*, vol. 10, no. 11, p. 1744, Oct. 2017, doi: 10.3390/en10111744.

[16] Z. Tian and D. Wei, "A hybrid wind speed forecasting model with two-stage data processing based on adaptive neuro-fuzzy inference systems and deep learning algorithms," *Earth Science Informatics*, vol. 18, no. 1, Jan. 2025, doi: 10.1007/s12145-024-01528-8.

[17] Y. Tang, K. Yang, S. Zhang, and Z. Zhang, "Wind power forecasting: a hybrid forecasting model and multi-task learning-based framework," *Energy*, vol. 278, p. 127864, Sep. 2023, doi: 10.1016/j.energy.2023.127864.

[18] T. Bashir, H. Wang, M. Tahir, and Y. Zhang, "Wind and solar power forecasting based on hybrid CNN-ABiLSTM, CNN-transformer-MLP models," *Renewable Energy*, vol. 239, p. 122055, Feb. 2025, doi: 10.1016/j.renene.2024.122055.

[19] I. Tyass, T. Khalili, M. Rafik, B. Abdelouahed, A. Raihani, and K. Mansouri, "Wind speed prediction based on statistical and deep learning models," *International Journal of Renewable Energy Development*, vol. 12, no. 2, pp. 288–299, Jan. 2023, doi: 10.14710/ijred.2023.48672.

[20] R. Wang, W. Li, and B. Bagen, "Development of wind speed forecasting model based on the weibull probability distribution," in *2011 International Conference on Computer Distributed Control and Intelligent Environmental Monitoring*, Feb. 2011, pp. 2062–2065, doi: 10.1109/cdciem.2011.333.

[21] G. Chunlin, M. Zhou, P. Xin, and Y. Xiaoyan, "Research on the combined forecasting method of wind speed," in *2017 China International Electrical and Energy Conference (CIEEC)*, Oct. 2017, pp. 194–198, doi: 10.1109/cieec.2017.8388445.

[22] A. Bensoussan and A. Brouste, "Cox–Ingersoll–Ross model for wind speed modeling and forecasting," *Wind Energy*, vol. 19, no. 7, pp. 1355–1365, Aug. 2015, doi: 10.1002/we.1896.

[23] K. Ondara and S. "Husrin characteristics of breaking waves and analysis of sediment transport in Teluk Kendari," J*urnal Ilmu Dan Teknologi Kelautan Tropis*, vol. 9, pp. 585–96, 2018, doi: 10.29244/jitkt.v9i2.19293.

[24] Siswanto and Suratno, "Seasonal pattern of wind induced upwelling over Java-Bali sea waters and surrounding area," *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, vol. 5, no. 1, Sep. 2010, doi: 10.30536/j.ijreses.2008.v5.a1228.

[25] Z. Hidayah, H. Wirayuhanto, Z. R. Norma Sari, and M. K. Wardhani, "Modelling sea surface currents in the eastern coast of Bawean Island, East Java," *IOP Conference Series: Earth and Environmental Science*, vol. 925, no. 1, p. 12006, Nov. 2021, doi: 10.1088/1755-1315/925/1/012006.

BIOGRAPHIES OF AUTHORS

Silvy Rahmah Fithri is a young expert engineer at the Research Center for Energy Conversion Technology, National Research and Innovation Agency (BRIN), Indonesia. He is currently pursuing a Master's degree in applied science at the Department of Geophysics and Meteorology, IPB University. His thesis research focuses on bias correction of GFS wind speed data using hybrid machine learning approaches with AWS observations in Java Island, supporting the advancement of wind energy utilization. He has contributed to the development of renewable energy potential maps for wind, solar, and micro-hydro resources, which form an integral part of Indonesia's National Energy General Plan (RUEN) under the Ministry of Energy and Mineral Resources. He has also produced patents and copyrights and has been involved in the development of wind energy forecasting applications for optimizing wind power plant operations. She can be contacted at email: silv010@brin.go.id.

Nurry Widya Hesty is a senior researcher at the Research Center for Energy Conversion Technology, National Research and Innovation Agency (BRIN), Indonesia. She earned her Master's degree in earth sciences from the Bandung Institute of Technology (ITB) and focuses her research on renewable energy, particularly wind energy. Her work applies computational modeling to evaluate national wind energy potential and contributes to the development of wind, solar, and micro-hydro energy potential maps, which are integral to Indonesia's National Energy General Plan (RUEN) under the Ministry of Energy and Mineral Resources. She is also actively engaged in supporting the transition toward Net Zero Emission (NZE) and has produced several patents and copyrights, officially registered with the Directorate General of Intellectual Property, Ministry of Law and Human Rights of the Republic of Indonesia. She can be contacted at email: nurr010@brin.go.id.

Rudi P. Wijayanto is a young expert engineer at the Research Center for Energy Conversion Technology, National Research and Innovation Agency (BRIN), Indonesia. He earned his Doctoral degree from Kanazawa University, Japan, with a research focus on the development and performance analysis of vertical axis wind turbines (O-VAWT) under shear flow conditions through both experimental studies and computational fluid dynamics (CFD). In addition, he has contributed to the development of Savonius turbine concepts for waste air energy recovery, demonstrating the potential application of renewable energy in industrial and urban sectors. His recent research focuses on the development of wind energy forecasting applications to optimize load management in wind power plants. His contributions strengthen innovation in sustainable wind energy technology in Indonesia. He can be contacted at email: rudi014@brin.go.id.

Bono Pranoto is a senior researcher (*Peneliti Ahli Madya*) at the Research Center for Limnology and Water Resources, National Research and Innovation Agency (BRIN), Indonesia. He earned his Doctoral degree in natural resource and environmental management, specializing in renewable energy and environment. His research focuses on the sustainability of renewable energy, covering resource potential, power generation technologies, and their environmental implications. He holds 14 patents and 29 copyrights, officially granted and registered by the Directorate General of Intellectual Property, Ministry of Law and Human Rights of the Republic of Indonesia. His research interests include renewable energy resource assessment, mapping, and environmental sustainability of renewable power plants. He can be contacted at email: bono.pranoto@brin.go.id.

Prima Trie Wijaya is a young expert engineer at the Research Center for Energy Conversion Technology, National Research and Innovation Agency (BRIN), Indonesia. He earned his Bachelor's degree in information systems from Gunadarma University and his Master's degree in computer science from IPB University. He has served as a civil servant since 2014, beginning his career at the Agency for the Assessment and Application of Technology (BPPT) before continuing at BRIN following the merger of several Indonesian government research institutions. He has produced a number of scientific publications, patents, and copyrights, which are officially registered at the Directorate General of Intellectual Property, Ministry of Law and Human Rights of the Republic of Indonesia. His research interests focus on renewable energy, computational modeling, and the application of machine learning for sustainable energy systems. He can be contacted at email: prim002@brin.go.id or prima3ewijaya@gmail.com.

Akhmad Faqih is an associate professor at the Department of Geophysics and Meteorology and currently serves as the Vice Dean for Academic, Student Affairs, and Alumni at the Faculty of Mathematics and Natural Sciences, IPB University, Indonesia. He earned his Doctoral degree from the University of Southern Queensland, Australia, and has extensive research experience in climate change, tropical climate variability, and climate and extreme weather prediction. His recent work focuses on the integration of IoT and machine learning through the Automatic Weather Station (AWS) Community network to support adaptive agriculture in Indonesia. He is an active member of professional organizations such as the American Geophysical Union (AGU), American Meteorological Society (AMS), INSAM, and PERHIMPI, and has previously been involved with ARC NESS and AMOS in Australia. He can be contacted at email: akhmadfa@apps.ipb.ac.id.

Wisnu Ananta Kusuma is an associate professor (*Lektor Kepala*) in the Computer Science Study Program, Faculty of Mathematics and Natural Sciences, IPB University, Indonesia. He earned his Bachelor's and Master's degrees from the Bandung Institute of Technology (ITB) and his Doctor of engineering degree from the Tokyo Institute of Technology, Japan. His research interests include bioinformatics, high-performance computing (HPC), network pharmacology, and artificial intelligence for life sciences. He is actively leading research in bioinformatics, the development of predictive systems for traditional herbal medicine (*jamu*), and genomic analysis for plant breeding. In addition, he serves as a Core Scientist at the HPC Laboratory, IPB University. He can be contacted at email: ananta@apps.ipb.ac.id.

Agus Nurrohim is a principal researcher at the Research Center for Energy Conversion and Conservation, National Research and Innovation Agency (BRIN), Indonesia. He earned his Doctoral degree in modeling and management of environmental dynamics. His research interests encompass energy conservation, renewable energy, sustainable energy systems, and environmental studies. He has published widely in international journals and holds several patents and copyrights in the energy field. His current research focuses on renewable energy and the future of Indonesia's power systems, including studies on wind energy potential in Sumba, net zero emissions scenarios in the Java–Madura–Bali region, rooftop solar systems for electric vehicle charging stations, and agrivoltaic development. He can be contacted at email: agus.nurrohim@brin.go.id.

Agus Sugiyono received his B.E. degree in electrical engineering from Bandung Institute of Technology, Indonesia, and the M.Eng. degree in industrial administration from Tokyo University of Science, Japan. Presently he is working as an associate researcher at the National Research and Innovation Agency (BRIN), Indonesia. He has more than 20 journal and conference publications. His research interests include energy planning, energy modeling, and energy economics. He can be contacted at email: agus.sugiyono@brin.go.id.

Yudiartono is an engineering specialist and associate expert in energy planning at Indonesia's National Research and Innovation Agency. He has a Master's degree in energy planning, and his research focuses on sustainability-oriented energy modeling and long-term planning at regional and national levels. He can be contacted at email: yudi004@brin.go.id.