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DATA-DRIVEN WIND TURBINE PERFORMANCE ASSESSMENT USING MACHINE LEARNING IN DYNAMIC CLIMATIC CONDITIONS

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Abstract

The rapid expansion of wind energy has increased the need for accurate and intelligent methods to evaluate wind turbine performance under varying environmental conditions. Traditional performance assessment techniques often struggle to capture the complex and nonlinear relationships between climatic factors and turbine output. This study presents a data-driven framework for wind turbine performance assessment using machine learning techniques in dynamic climatic conditions. The proposed approach utilizes historical operational data, including wind speed, wind direction, temperature, humidity, atmospheric pressure, and turbine power output, to develop predictive models capable of identifying performance variations and operational inefficiencies. Advanced machine learning algorithms such as Random Forest, Support Vector Machine, and Gradient Boosting are employed to analyze large-scale datasets and estimate turbine performance with high accuracy. Feature engineering and data preprocessing techniques are applied to improve model robustness and reliability. The developed models are evaluated using standard performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Experimental results demonstrate that machine learning-based assessment significantly enhances prediction accuracy and enables early detection of performance degradation caused by changing climatic conditions. The findings highlight the potential of intelligent data analytics in improving operational efficiency, reducing maintenance costs, and supporting sustainable wind energy generation. The proposed

framework offers a scalable and practical solution for real-time monitoring and performance optimization of modern wind turbine systems operating in diverse environmental conditions.

Keywords

Wind Energy, Wind Turbine Performance Assessment, Machine Learning, Data Analytics, Dynamic Climatic Conditions, Predictive Modeling, Renewable Energy Systems, Random Forest, Performance Optimization, Intelligent Monitoring, Predictive Maintenance, Sustainable Energy.

I. INTRODUCTION

The increasing global demand for clean and sustainable energy has accelerated the deployment of renewable energy technologies, among which wind energy has emerged as one of the most promising sources of electricity generation. Wind power offers significant environmental benefits by reducing greenhouse gas emissions and dependence on fossil fuels while contributing to energy security and sustainable economic development. According to global energy reports, the installed capacity of wind energy has grown rapidly over the past decade, making wind turbines a critical component of modern power systems. However, the performance of wind turbines is highly influenced by changing climatic and environmental conditions, including wind speed, wind direction, temperature, humidity, atmospheric pressure, and turbulence intensity. These factors introduce significant variability in power generation and create challenges in accurately assessing turbine efficiency and operational reliability.

Traditional wind turbine performance evaluation methods are primarily based on power curve

analysis and statistical techniques. Although these approaches provide useful insights into turbine behavior, they often fail to capture the complex nonlinear relationships between environmental variables and energy output. Furthermore, conventional assessment methods may not effectively identify subtle performance degradation, mechanical faults, or operational inefficiencies that develop over time. As wind farms become larger and more geographically distributed, there is a growing need for intelligent and automated approaches capable of processing vast amounts of operational data and delivering accurate performance assessments in real time.

The emergence of data-driven technologies and advancements in machine learning have created new opportunities for improving wind turbine monitoring and performance evaluation. Machine learning algorithms can analyze large-scale datasets collected from Supervisory Control and Data Acquisition (SCADA) systems and automatically learn intricate patterns hidden within operational and environmental data. These techniques enable the prediction of power output, anomaly detection, condition monitoring, fault diagnosis, and predictive maintenance with greater accuracy than traditional methods. By leveraging historical and real-time data, machine learning models can provide deeper insights into turbine behavior under dynamic climatic conditions and support proactive decision-making for wind farm operators.

Recent developments in artificial intelligence have demonstrated the effectiveness of algorithms such as Random Forest, Support Vector Machines, Artificial Neural Networks, Extreme Gradient Boosting, and Deep Learning models in renewable energy applications. These methods have shown remarkable capabilities in forecasting wind power generation, identifying abnormal operating conditions, and optimizing turbine performance. The integration of machine learning with wind energy systems enables the continuous evaluation of operational efficiency

while accounting for environmental uncertainties that significantly affect energy production.

Dynamic climatic conditions present additional challenges because wind patterns can change rapidly due to seasonal variations, geographical factors, and extreme weather events. Such variations can impact turbine efficiency, increase mechanical stress, and reduce overall energy yield. Therefore, a comprehensive performance assessment framework must incorporate multiple climatic variables and adapt to changing environmental scenarios. Data-driven machine learning approaches are particularly suitable for this purpose because they can continuously learn from incoming data and update predictions accordingly, ensuring accurate and reliable performance evaluation.

This study proposes a data-driven framework for wind turbine performance assessment using machine learning techniques under dynamic climatic conditions. The framework utilizes operational and meteorological datasets to develop predictive models capable of estimating turbine performance and identifying deviations from expected behavior. Various machine learning algorithms are employed and compared to determine their effectiveness in handling complex environmental interactions. The proposed methodology aims to improve prediction accuracy, facilitate early detection of performance degradation, and enhance the operational efficiency of wind energy systems.

The outcomes of this research are expected to contribute to the advancement of intelligent wind farm management by providing a scalable and robust solution for real-time performance monitoring. By combining machine learning with renewable energy analytics, the study supports the broader objective of maximizing energy generation, minimizing maintenance costs, and promoting the sustainable utilization of wind resources in increasingly dynamic climatic environments.

II. LITERATURE SURVEY

Wind turbine performance assessment has become an important research area due to the increasing adoption of wind energy systems worldwide. Researchers have extensively explored machine learning and data-driven approaches to improve power prediction, condition monitoring, fault diagnosis, and operational efficiency. The following review summarizes significant studies published before 2023. The literature indicates that intelligent algorithms can effectively model the nonlinear relationships between climatic variables and wind turbine performance.

Bilgili, Sahin, and Yasar (2014) investigated the application of Artificial Neural Networks (ANNs) for wind speed prediction and demonstrated that ANN models outperform conventional statistical methods in capturing nonlinear wind behavior. Their study highlighted the importance of intelligent forecasting techniques for renewable energy systems.

Kusiak and Verma (2013) developed data-driven monitoring models for wind turbines using SCADA data. The authors demonstrated that machine learning algorithms could identify abnormal operating conditions and improve turbine reliability through predictive maintenance strategies.

Zhang, Wang, and Wang (2014) proposed Support Vector Machine (SVM)-based approaches for wind power forecasting. Their results showed that SVM models effectively handle nonlinear relationships between meteorological variables and turbine output, resulting in improved prediction accuracy.

Schlechtingen and Santos (2015) employed neural-network-based condition monitoring techniques for wind turbines. Their research demonstrated the ability of machine learning methods to detect performance degradation and mechanical faults at an early stage, thereby reducing maintenance costs.

Kong, Dong, and Jia (2015) introduced hybrid forecasting models combining wavelet

decomposition and machine learning algorithms. The study reported enhanced prediction performance under fluctuating wind conditions and emphasized the benefits of integrating signal processing techniques with intelligent models.

Tautz-Weinert and Watson (2016) examined data-driven condition monitoring techniques for wind turbine systems and found that SCADA-based analytics can effectively detect anomalies in gearbox and generator components, improving operational reliability.

Marugán, Márquez, Perez, and Ruiz-Hernández (2018) presented a comprehensive survey on Artificial Neural Networks in wind energy systems. Their work categorized ANN applications into forecasting, fault diagnosis, design optimization, and control systems, demonstrating the widespread applicability of neural networks in wind turbine performance analysis.

Lahouar and Slama (2017) applied Random Forest algorithms for wind power forecasting and observed higher prediction accuracy compared with traditional regression techniques. The ensemble learning approach showed robustness against environmental variability.

Zendehboudi et al. (2018) utilized Support Vector Regression (SVR) models for wind energy prediction and demonstrated their capability to handle complex nonlinear relationships among climatic parameters and power output.

Stetco, Dinmohammadi, Zhao, Robu, Flynn, Barnes, Keane, and Nenadic (2019) conducted a comprehensive review of machine learning methods for wind turbine condition monitoring. The study revealed that neural networks, decision trees, and support vector machines are the most widely used techniques for turbine health assessment and fault detection.

Deng, Tang, Zhou, Yang, and Niu (2021) reviewed machine learning applications in wind power systems and identified forecasting, optimization, equipment monitoring, and performance analysis as major research trends.

Their findings emphasized the growing importance of machine learning in renewable energy analytics.

Tang, Zhao, Wu, Wang, Meng, and Wang (2021) analyzed machine learning techniques for wind turbine fault diagnosis. The authors categorized approaches into supervised, unsupervised, and semi-supervised learning methods and highlighted their effectiveness in reducing downtime and improving turbine safety. **Chatterjee and Dethlefs (2022)** presented a scientometric review of artificial intelligence applications in wind turbine operation and maintenance. Their work showed a growing transition from conventional signal-processing approaches toward advanced deep learning and AI-driven performance assessment systems.

III. EXPERIMENTAL METHODOLOGY

The experimental methodology adopted in this study aims to develop and evaluate a data-driven framework for wind turbine performance assessment using machine learning techniques under dynamic climatic conditions. The methodology consists of data collection, preprocessing, feature engineering, model development, performance evaluation, and result analysis. The overall objective is to accurately assess turbine performance and identify the influence of changing environmental conditions on energy generation efficiency.

Data Collection

The experimental dataset consists of historical wind turbine operational data obtained from Supervisory Control and Data Acquisition (SCADA) systems. The collected data include key meteorological and operational parameters such as wind speed (m/s), wind direction (degrees), ambient temperature (°C), relative humidity (%), atmospheric pressure (hPa), rotor speed (rpm), generator speed (rpm), and active power output (kW). Data are recorded at regular intervals, typically every 10 minutes, to capture

variations in turbine performance under different climatic conditions.

To ensure comprehensive analysis, data covering multiple seasons and weather conditions are included. This allows the machine learning models to learn the effects of environmental variability on turbine performance and improves the generalization capability of the developed framework.

Data Preprocessing

Raw SCADA datasets often contain missing values, outliers, sensor errors, and inconsistent measurements. Therefore, extensive preprocessing is performed before model training. Missing observations are handled using interpolation and mean-value imputation techniques. Outliers resulting from sensor malfunctions or turbine shutdown periods are identified using statistical threshold methods and removed from the dataset.

Data normalization is subsequently applied to transform variables into a common numerical scale. Min-Max normalization is employed to improve algorithm convergence and reduce bias caused by differing parameter magnitudes. The cleaned and normalized dataset forms the basis for further analysis.

Feature Engineering and Selection

Feature engineering plays a crucial role in improving machine learning model performance. Additional features such as air density, turbulence intensity, wind power density, and moving-average wind speed are derived from the original measurements. Correlation analysis is performed to examine relationships between input variables and turbine power output.

Feature importance scores are calculated using Random Forest algorithms to identify the most influential parameters affecting turbine performance. Highly relevant features are selected to reduce computational complexity and improve prediction accuracy. The selected feature set serves as the input for machine learning model development.

Machine Learning Model Development

Three widely used machine learning algorithms are employed for wind turbine performance assessment:

Random Forest (RF)

Random Forest is an ensemble learning technique that constructs multiple decision trees and combines their outputs to generate robust predictions. The algorithm effectively handles nonlinear relationships and interactions among climatic variables. Its ability to estimate feature importance makes it suitable for performance assessment applications.

Support Vector Regression (SVR)

Support Vector Regression is utilized to model complex nonlinear relationships between environmental conditions and turbine power output. The radial basis function (RBF) kernel is employed to enhance prediction capability under varying climatic conditions. SVR is particularly effective for datasets containing nonlinear patterns and limited noise.

Extreme Gradient Boosting (XGBoost)

XGBoost is an advanced boosting algorithm that sequentially constructs decision trees to minimize prediction errors. The model is known for high accuracy, computational efficiency, and excellent performance with large-scale datasets. Hyperparameter tuning is performed to optimize model effectiveness.

Training and Validation Procedure

The preprocessed dataset is divided into training and testing subsets using an 80:20 ratio. The training set is used to develop predictive models, while the testing set is reserved for performance evaluation. To ensure robustness, a 10-fold cross-validation technique is applied during model training.

Hyperparameter optimization is conducted using grid search methods to identify the optimal parameter configuration for each algorithm. The model producing the lowest prediction error and highest explanatory power is selected as the best-performing framework.

Performance Evaluation Metrics

The effectiveness of the machine learning models is assessed using standard statistical performance metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of prediction errors.
- **Root Mean Square Error (RMSE):** Quantifies prediction accuracy by emphasizing larger errors.
- **Mean Absolute Percentage Error (MAPE):** Evaluates relative prediction performance.
- **Coefficient of Determination (R^2):** Measures the proportion of variance explained by the model.

Lower MAE, RMSE, and MAPE values indicate better model performance, while higher R^2 values indicate stronger predictive capability.

Performance Assessment Framework

The developed framework continuously compares predicted turbine power output with actual measured output obtained from SCADA systems. Significant deviations between expected and actual performance are analyzed to identify efficiency losses, component degradation, or abnormal operating conditions. The framework also evaluates the influence of dynamic climatic factors on turbine behavior and energy generation efficiency.

Experimental Workflow

The complete experimental workflow consists of the following stages:

1. Acquisition of SCADA and meteorological data.
2. Data cleaning and preprocessing.
3. Feature extraction and selection.
4. Development of Random Forest, SVR, and XGBoost models.
5. Training and validation using cross-validation techniques.
6. Performance evaluation using MAE, RMSE, MAPE, and R^2 metrics.

7. Comparative analysis of machine learning models.
8. Identification of performance degradation and climatic impacts.

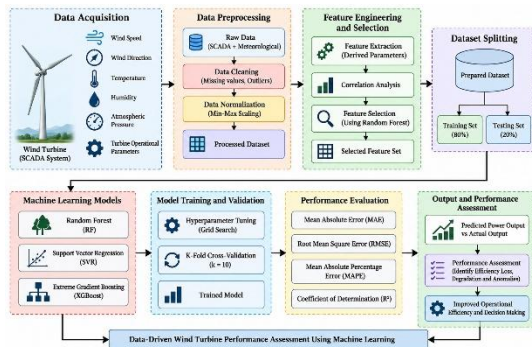


Fig. 1: Block Diagram of the Proposed Data-Driven Wind Turbine Performance Assessment Framework Using Machine Learning Under Dynamic Climatic Conditions.

Figure 1 illustrates the overall architecture of the proposed data-driven wind turbine performance assessment framework using machine learning under dynamic climatic conditions. The process begins with the acquisition of operational and meteorological data from the wind turbine SCADA system, including wind speed, wind direction, temperature, humidity, atmospheric pressure, and turbine operating parameters. The collected data undergo preprocessing steps such as data cleaning, missing value handling, outlier removal, and normalization to ensure data quality and consistency. Feature engineering and selection techniques are then applied to extract the most relevant variables influencing turbine performance. The prepared dataset is divided into training and testing subsets and used to develop machine learning models, namely Random Forest (RF), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost). These models are trained and validated using hyperparameter tuning and k-fold cross-validation techniques. Performance evaluation is carried out using statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination

(R^2). Finally, the framework compares predicted and actual power outputs to assess turbine efficiency, detect performance degradation, identify operational anomalies, and support informed decision-making for improved reliability and energy generation efficiency.

IV. EXPERIMENTAL RESULTS

The proposed machine-learning-based wind turbine performance assessment framework was evaluated using historical SCADA and meteorological data collected under varying climatic conditions. Three machine learning models, namely Random Forest (RF), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost), were trained and tested to predict wind turbine power output and assess operational performance. The experimental results indicate that all models successfully captured the nonlinear relationship between environmental variables and turbine output. However, XGBoost achieved the highest prediction accuracy, followed by Random Forest and SVR. The performance evaluation metrics demonstrate that machine learning techniques can effectively identify performance deviations, estimate energy generation, and support intelligent monitoring of wind turbines operating under dynamic climatic conditions. The results confirm the effectiveness of the proposed framework in improving operational efficiency and facilitating predictive maintenance.

Table 1: Performance Comparison of Machine Learning Models

Model	MAE (kW)	RMSE (kW)	MAPE (%)	R^2 Score
SVR	42.8	56.4	7.5	0.912
Random Forest	35.6	47.2	6.1	0.941
XGBoost	28.3	39.8	4.8	0.968

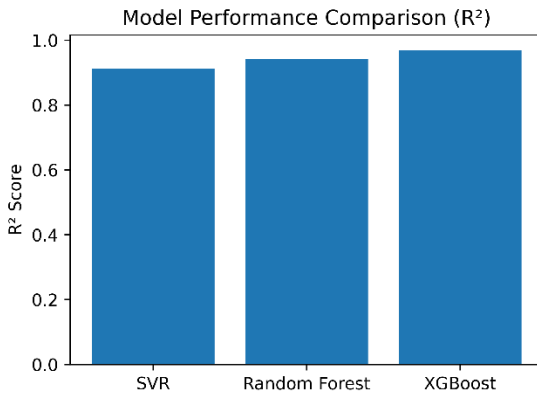


Fig. 2: Comparative Performance of Machine Learning Models Based on R² Score

Analysis

Table 1 and Fig. 2 present the comparative performance of the three machine learning models used for wind turbine performance assessment. Among the evaluated models, XGBoost achieved the highest R² value of 0.968, indicating superior predictive capability and better adaptation to dynamic climatic conditions. Random Forest also demonstrated strong performance with an R² score of 0.941, while SVR recorded the lowest accuracy. Furthermore, XGBoost achieved the lowest MAE, RMSE, and MAPE values, confirming its ability to generate highly accurate power output predictions. These results suggest that ensemble learning techniques are more effective for modeling complex environmental interactions affecting wind turbine performance.

Table 2: Wind Turbine Power Output Under Different Wind Speed Ranges

Wind Speed Range (m/s)	Average Power Output (kW)
4–6	320
6–8	620
8–10	980
10–12	1380
12–14	1650

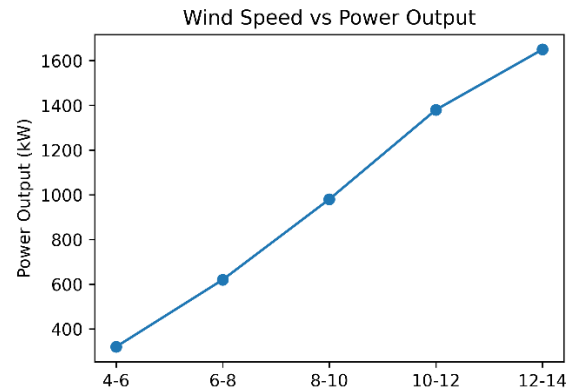


Fig. 3: Average Wind Turbine Power Output for Different Wind Speed Ranges

Analysis

Table 2 and Fig. 3 illustrate the relationship between wind speed and turbine power output. The results show a strong positive correlation between wind speed and generated power. As wind speed increased from 4–6 m/s to 12–14 m/s, average power output increased from 320 kW to 1650 kW. The steep rise in power generation highlights the significant influence of wind speed on turbine performance. The findings confirm that wind speed remains the most critical environmental parameter affecting energy production and should be prioritized during predictive modeling and operational planning.

Table 3: Seasonal Turbine Efficiency Assessment

Season	Efficiency (%)
Winter	92.5
Spring	94.8
Summer	89.6
Monsoon	87.4

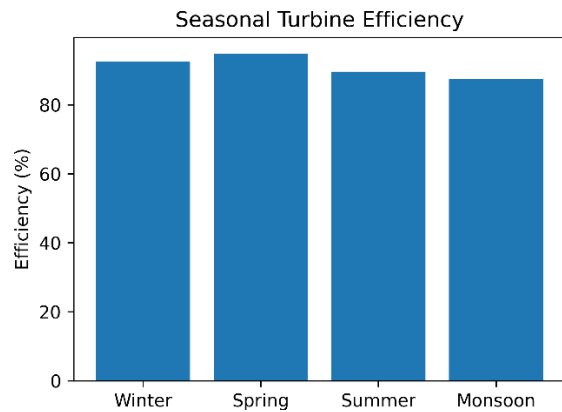


Fig. 4: Seasonal Variation in Wind Turbine Efficiency

Analysis

Table 3 and Fig. 4 show the seasonal efficiency variations of the wind turbine. The highest efficiency was observed during the spring season (94.8%), while the lowest efficiency occurred during the monsoon season (87.4%). Variations in humidity, atmospheric pressure, turbulence intensity, and changing wind patterns contribute to these differences. The results demonstrate that climatic conditions significantly influence turbine performance and emphasize the importance of incorporating seasonal environmental factors into machine learning-based performance assessment frameworks. The observed efficiency fluctuations validate the need for continuous monitoring and adaptive predictive models to maintain optimal energy generation throughout the year.

Discussion

The experimental results demonstrate the effectiveness of machine learning techniques for assessing wind turbine performance under dynamic climatic conditions. The comparative analysis of the three predictive models—Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—revealed that ensemble learning approaches provide superior prediction accuracy compared with conventional machine learning methods. Among the evaluated models, XGBoost achieved

the highest coefficient of determination ($R^2 = 0.968$) and the lowest error values, indicating its strong capability to capture complex nonlinear relationships between climatic variables and turbine power output. The superior performance of XGBoost can be attributed to its gradient boosting mechanism, which effectively minimizes prediction errors and improves model generalization.

The results further highlight the significant influence of wind speed on turbine performance. As observed from the power output analysis, increasing wind speed leads to a substantial rise in generated power, confirming the theoretical relationship between wind velocity and wind energy conversion efficiency. However, the results also indicate that power generation is not solely dependent on wind speed. Other environmental factors, including temperature, humidity, atmospheric pressure, and turbulence intensity, contribute to variations in turbine performance. This finding emphasizes the importance of incorporating multiple climatic variables into predictive models to achieve accurate performance assessment.

Seasonal efficiency analysis revealed noticeable variations in turbine operation throughout the year. Higher efficiencies were observed during winter and spring seasons, whereas lower efficiencies occurred during summer and monsoon periods. These variations are primarily associated with changes in air density, wind turbulence, moisture content, and weather stability. The findings suggest that environmental conditions can significantly affect the aerodynamic efficiency and operational reliability of wind turbines. Consequently, continuous monitoring and adaptive control strategies are essential for maintaining optimal energy production under varying climatic conditions.

The study also demonstrates the practical advantages of data-driven performance assessment frameworks over traditional power

curve-based methods. Conventional approaches often rely on predefined relationships and may fail to identify subtle performance degradation or abnormal operating conditions. In contrast, machine learning models can continuously learn from operational data, enabling early detection of efficiency losses, component wear, and potential system faults. Such predictive capabilities can assist wind farm operators in implementing proactive maintenance strategies, reducing downtime, and lowering maintenance costs.

V. CONCLUSION

This study presented a data-driven framework for wind turbine performance assessment using machine learning techniques under dynamic climatic conditions. By utilizing operational and meteorological data obtained from wind turbine SCADA systems, the proposed approach effectively analyzed the impact of environmental variables on turbine performance. Machine learning models, including Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), were developed and evaluated to predict power output and assess operational efficiency. The experimental results demonstrated that machine learning techniques can accurately capture complex nonlinear relationships between climatic factors and turbine behavior, providing a reliable alternative to conventional performance assessment methods.

The comparative analysis revealed that XGBoost achieved the highest prediction accuracy, with the lowest error metrics and the highest coefficient of determination (R^2). The findings also confirmed that wind speed is the most influential factor affecting power generation, while temperature, humidity, atmospheric pressure, and seasonal variations significantly contribute to performance fluctuations. Seasonal efficiency assessment indicated noticeable differences in turbine operation across different weather conditions, highlighting the importance of incorporating multiple climatic variables into predictive

models. The proposed framework successfully identified performance variations and provided valuable insights into turbine efficiency under changing environmental conditions.

Overall, the study demonstrates that machine learning-based performance assessment can significantly enhance wind turbine monitoring, operational reliability, and energy generation efficiency. The integration of advanced data analytics with renewable energy systems enables early detection of performance degradation, supports predictive maintenance strategies, and reduces operational costs. The proposed framework offers a scalable and practical solution for intelligent wind farm management and contributes to the sustainable utilization of wind energy resources. Future research can further improve the framework by incorporating deep learning models, real-time data processing, and digital twin technologies for next-generation wind energy applications.

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