

Review

A Comprehensive Review of Wind Power Prediction Based on Machine Learning: Models, Applications, and Challenges

Zongxu Liu ¹, Hui Guo ¹, Yingshuai Zhang ¹ and Zongliang Zuo ^{2,*} 

¹ Henan Jiuyu Enpai Power Technology Co., Ltd., Zhengzhou 450001, China; 15939044335@163.com (Z.L.); guohuijiuyu@126.com (H.G.); 13939005561@139.com (Y.Z.)

² School of Environmental and Municipal Engineering, Qingdao University of Technology, No. 777, Jiaolingjiang East Rd., Qingdao 266520, China

* Correspondence: zuozongliangneu@163.com

Abstract: Wind power prediction is essential for ensuring the stability and efficient operation of modern power systems, particularly as renewable energy integration continues to expand. This paper presents a comprehensive review of machine learning techniques applied to wind power prediction, emphasizing their advantages over traditional physical and statistical models. Machine learning methods, especially deep learning approaches such as Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and ensemble learning techniques like XGBoost, excel in addressing the non-linearity and complexity of wind power data. The review also explores critical aspects such as data preprocessing, feature selection strategies, and model optimization techniques, which significantly enhance prediction accuracy and robustness. Challenges such as data acquisition difficulties, complex terrain influences, and sensor quality issues are examined in depth, with proposed solutions discussed. Additionally, the paper highlights future research directions, including the potential of multi-model fusion, emerging deep learning technologies like Transformers, and the integration of smart sensors and IoT technologies to develop intelligent, automated, and reliable prediction systems. By addressing existing challenges and leveraging advanced machine learning techniques, this work provides valuable insights into the current state of wind power prediction research and offers strategic guidance for enhancing the applicability and reliability of prediction models in practical scenarios.



Academic Editor: Ahmed Abu-Siada

Received: 27 November 2024

Revised: 10 January 2025

Accepted: 13 January 2025

Published: 15 January 2025

Citation: Liu, Z.; Guo, H.; Zhang, Y.; Zuo, Z. A Comprehensive Review of Wind Power Prediction Based on Machine Learning: Models, Applications, and Challenges. *Energies* **2025**, *18*, 350. <https://doi.org/10.3390/en18020350>

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1. Introduction

Wind power, as an important renewable energy source, has seen widespread application and development globally in recent years. With increasing attention to environmental protection and sustainable development, the installed capacity of wind power continues to grow [1–6]. Against this backdrop, how to effectively predict wind power to ensure the safe and stable operation of the power system has become one of the core issues in the field of wind energy.

1.1. Background and Significance of Wind Power Generation

Wind power generation is a clean and renewable energy source that, compared to traditional fossil fuel power generation, has significant advantages in reducing greenhouse gas emissions and environmental pollution. Many countries are committed to promoting

the development of the wind power industry through policies and technological means to address climate change and energy security issues. The global installed capacity of wind power has seen remarkable growth over the past two decades, becoming an important part of energy diversification and carbon emission reduction. However, the uncontrollability and intermittency of wind power also bring challenges to grid scheduling and power balance, which raises higher requirements for wind power prediction.

1.2. Importance and Challenges of Wind Power Prediction

The accuracy of wind power prediction is critical for the safe and stable operation of the power system. Due to the intermittency and randomness of wind energy, fluctuations in wind power greatly affect grid scheduling and load balancing. Inaccurate wind power predictions can lead to frequency fluctuations in the power system, increased demand for backup power, and even stability issues in the grid. Wind power prediction is typically divided into short-term, ultra-short-term, and long-term forecasts, with different time scales applied in power market trading, scheduling plans, and real-time control. However, due to the complexity of factors such as wind speed and meteorological conditions, wind power prediction faces challenges such as incomplete data and insufficient prediction accuracy.

1.3. Potential of Machine Learning in Wind Power Prediction

In recent years, with the improvement in computational power and the increased availability of data, machine learning has gained widespread attention for its application in wind power prediction. Compared to traditional physical and statistical models, machine learning is better suited to handle the nonlinear and complex issues of wind power data. For example, deep learning models such as Long Short-Term Memory (LSTM) networks have shown outstanding performance in time-series forecasting, effectively capturing long-term dependencies in wind speed and power variations. Additionally, ensemble learning models like Random Forest and Extreme Gradient Boosting (XGBoost) have been widely used for wind power prediction, demonstrating excellent generalization ability and predictive accuracy. By combining different machine learning models, researchers are working to build more accurate and robust wind power prediction systems to improve the reliability and economy of the power system.

1.4. Research Goals and Structure of This Paper

This paper aims to review current machine learning-based wind power prediction techniques, explore the applications of different machine learning models in wind power prediction, as well as their advantages and disadvantages, and analyze future research directions. First, the Section 2 will introduce commonly used machine learning methods in wind power prediction. The Section 3 will delve into the specific applications of different machine learning models in wind power prediction, including short-term prediction, ultra-short-term prediction, and spatial transferability. The Section 4 will discuss the performance comparison of these models and optimization techniques. The Section 5 will highlight the importance of feature selection and data preprocessing in wind power prediction. The Section 6 will address the challenges in wind power prediction and future research directions. Finally, the Section 7 will summarize the key findings of this paper and offer suggestions for future research.

2. Overview of Machine Learning Methods for Wind Power Prediction

2.1. Introduction to Traditional Wind Power Prediction Methods

There are two main methods for wind power forecasting: one is based on wind speed prediction, and the other directly predicts the output power. The wind speed-based

prediction first performs short-term wind speed forecasting, and then the wind power output is predicted using the wind power curve, as shown in Formula (1).

$$P = 0.5\rho Av^3C_p \quad (1)$$

where P is the output power of the wind turbine in watts (W); ρ is the air density in kilograms per cubic meter (kg/m^3); A is the swept area of the wind turbine in square meters (m^2); v is the wind speed in meters per second (m/s); and C_p is the coefficient of performance (C_p), which is dimensionless. It represents the efficiency with which the wind turbine converts wind energy into mechanical energy. The theoretical maximum value is around 0.59 (the Betz limit), but in practice, the C_p value is typically lower.

Traditionally, the process of wind power prediction by direct prediction involves several key stages. The first stage, data preprocessing, involves cleaning the dataset by removing duplicate entries and handling missing values. In the second stage, attribute selection and exploratory data analysis are conducted to identify the most relevant features for the prediction models. The third stage focuses on the development of machine learning (ML) models and their performance evaluation.

Figure 1 illustrates the current classification of wind power forecasting models. Traditional wind power prediction methods mainly include physical models and statistical models. Physical models are based on numerical weather prediction technology to simulate the impact of wind speed and meteorological conditions on wind power output. These models take into account physical factors such as wind speed, air temperature, and air pressure and perform precise modeling using computational fluid dynamics [1]. However, physical models are computationally complex, sensitive to initial conditions, and require substantial computational resources [7].

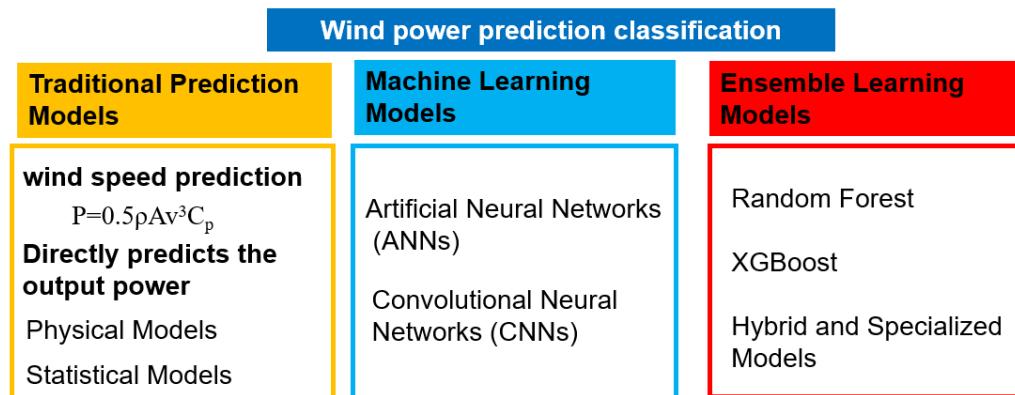


Figure 1. Wind power prediction classification.

Statistical models, on the other hand, establish mathematical relationships between input and output by analyzing historical wind speed and power data, such as autoregressive moving average models and support vector machines [7,8]. These models do not require detailed physical information but have certain limitations in handling the nonlinearity and complexity of the data [1].

2.2. Advantages of Machine Learning

Compared with traditional physical and statistical models, machine learning and deep learning methods have significant advantages in wind power prediction. Machine learning models can automatically learn the complex nonlinear relationship between wind speed and power from a large amount of historical data, avoiding excessive reliance on physical processes [9–12]. In addition, deep learning models such as Convolutional Neural Networks

(CNNs) and Long Short-Term Memory Networks (LSTMs) can handle high-dimensional data and time series, demonstrating strong feature extraction capabilities [10]. Machine learning methods not only improve prediction accuracy but also enhance model robustness and reduce biases of individual models through ensemble learning [6]. Moreover, machine learning methods can be combined with physical models to form physically guided hybrid models, further improving prediction performance [7].

2.3. Introduction to Common Machine Learning Models

This section introduces several commonly used machine learning models for wind power prediction. To address the issues of comprehensiveness and parallel structure, the models are categorized into broader types based on their methodologies and use cases.

2.3.1. Neural Network Models

Artificial Neural Networks (ANNs)

Artificial Neural Networks are among the earliest machine learning models used in wind power prediction. By simulating the working mechanism of neurons in the human brain, ANNs can learn complex input–output relationships [1]. ANNs are suitable for handling nonlinear and multidimensional data but perform poorly when dealing with long-term dependencies and are prone to overfitting issues [13].

Long Short-Term Memory Networks (LSTMs)

The Long Short-Term Memory Network is a type of Recurrent Neural Network (RNN) that effectively captures long-term dependencies in time series data [10,14]. By introducing forget, input, and output gates, LSTMs solve the gradient vanishing problem in traditional RNNs during long sequence training. LSTMs are widely applied in wind power prediction, especially for ultra-short-term and short-term forecasts [10,15].

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks are initially used for image processing but have also gradually been applied in wind power prediction [1]. CNNs can automatically extract local features from data, making them particularly suitable for input data with spatial correlations. In wind power prediction, CNNs are often combined with other models, such as LSTMs, to improve prediction accuracy.

2.3.2. Ensemble Learning Models

Random Forest

Random Forest is an ensemble learning model that constructs multiple decision trees and combines their output results to improve prediction stability and accuracy [7]. Random Forest performs well in handling nonlinear relationships and high-dimensional data and has strong anti-overfitting capabilities [1]. In wind power prediction, Random Forest is often used to handle historical wind speed and meteorological data for short-term and medium-term predictions [16].

XGBoost

XGBoost is an ensemble model based on gradient boosting that improves the model's predictive ability by weighted combinations of multiple weak classifiers. XGBoost has shown high accuracy and robustness in wind power prediction, particularly in dealing with large data sets and complex features. Other ensemble models, such as Gradient Boosting (GB) and Bagging, are also widely used in wind power prediction to enhance overall predictive performance by integrating multiple weak models [14].

2.3.3. Hybrid and Specialized Models

Hybrid models that combine different machine learning methods have been increasingly adopted in wind power prediction. For example, CNN-LSTM models leverage the spatial feature extraction capabilities of CNNs and the temporal modeling strengths of LSTMs, offering improved accuracy for wind power forecasting. Similarly, models combining traditional statistical approaches with machine learning methods are used for specific tasks such as outlier detection or feature engineering.

2.3.4. GRU Models vs. LSTM

To alleviate the complexity of LSTM units, Gated Recurrent Units (GRUs) were introduced. GRUs are a variant of Recurrent Neural Networks (RNNs). The predictive performance of LSTM and GRU models is shown in Table 1. GRUs have fewer trainable parameters compared to LSTMs, resulting in faster training times. They incorporate gating mechanisms to address the vanishing gradient problem, making them more suitable for handling long sequences. By utilizing a single-cell state to maintain long-term memory and filtering information through gating mechanisms, GRUs achieve better control over long-term dependencies.

Table 1. Demonstration of LSTM and GRU model prediction performance.

Authors	Dataset Stride	Models
Ying et al. [17]	1 h	BiLSTM
Zhang et al. [18]	5 min	BiTCN-BiLSTM
Xiang et al. [19]	15 min	SATCN-LSTM
Han et al. [20]	10 min	VMD-LSTM
Hu et al. [21]	10 min	CEEMDAN-LSTM-TCN
Yue et al. [22]	15 min	CNN-LSTM
Xiao et al. [23]	15 min	WPCA-PSO-GRU
Meng et al. [24]	15 min	EEMD-BA-RGRU
Liu et al. [25]	15 min	Bayesian-BiGRU

In practice, the choice between LSTM and GRU layers depends on the specific task, dataset size, and computational resources available. Both layers have been widely used in various natural language processing tasks and have shown impressive results.

Generally, GRUs outperform LSTM networks on low-complexity sequences, while on high-complexity sequences, LSTMs perform better. GRUs are much simpler and require less computational power, so they can be used to form deeper networks. However, LSTMs are more powerful as they have more gates, but they require more computational resources.

In conclusion, the key difference between RNNs, LSTMs, and GRUs is the way they handle memory and dependencies between time steps. RNNs remember information from previous inputs but may struggle with long-term dependencies. LSTMs effectively store and access long-term dependencies using a special type of memory cell and gates. GRUs balance complexity and performance, often as effective as LSTMs but with faster training times.

3. Feature Selection and Data Preprocessing in Wind Power Prediction

3.1. Data Preprocessing Methods

Data preprocessing is a crucial step in ensuring the accuracy and reliability of wind power prediction models. Wind power data are often impacted by sensor faults, commu-

nication errors, and extreme weather conditions, leading to missing values, noise, and outliers that can negatively affect model performance. To address missing values, techniques like interpolation (e.g., linear or spline interpolation) estimate gaps using adjacent data, while extensive or unrepresentative missing data may be removed entirely. Outliers, which often result from extreme events or hardware errors, are detected using methods like boxplots, Z-score tests, or advanced machine learning-based anomaly detection. These approaches identify and remove anomalous data points that deviate significantly from normal patterns, ensuring dataset integrity and consistency. By effectively cleaning and preparing the data, preprocessing minimizes biases, enhances the model's ability to identify meaningful patterns, and improves prediction accuracy. This foundational step is essential for developing reliable wind power forecasting models that optimize grid integration, improve operational efficiency, and support energy market decisions [26].

To reduce noise interference and improve the quality of wind power data, digital filters are widely used as an essential preprocessing technique. Noise in wind power data, often caused by environmental fluctuations, sensor inaccuracies, or communication errors, can obscure meaningful patterns and degrade predictive model performance. The Savitzky–Golay filter is a commonly used smoothing filter that effectively reduces noise while preserving critical local features. Unlike simple moving average filters that may oversimplify data, the Savitzky–Golay filter performs polynomial fitting within a sliding window, replacing each central point with the value derived from the polynomial. This method smooths the data without excessively blurring important peaks and troughs, which are vital for accurate wind power predictions. Its adjustable window size and polynomial degree offer flexibility, allowing it to balance noise reduction and feature preservation according to specific data characteristics. By applying such filters, the preprocessing stage ensures cleaner and more reliable datasets, enabling predictive models to focus on meaningful patterns and deliver more accurate and robust forecasts [27]. Studies have shown that the Savitzky–Golay filter performs well in preprocessing wind speed and wind power data, effectively improving the accuracy and stability of prediction models [27].

3.2. Impact of Feature Selection on Model Performance

Feature selection is a crucial step in enhancing the performance of wind power prediction models by identifying and retaining the most relevant features from a potentially large dataset. Wind power data often includes diverse input variables such as wind speed, direction, temperature, pressure, and turbine operational data. While these features contribute to predictive capabilities, including irrelevant or redundant features can increase model complexity, lead to overfitting, and degrade accuracy. Feature selection addresses these challenges by isolating the most significant features, reducing model complexity, and improving computational efficiency and interpretability. Common methods include variable importance-based selection, such as using Random Forest to rank features based on their contribution to reducing impurity, and Recursive Feature Elimination (RFE), which iteratively removes less significant features to optimize model performance. By focusing on the most predictive variables, feature selection enhances model generalization, minimizes overfitting, and provides insights into the key factors driving wind power generation, making it an essential step for developing accurate, efficient, and reliable prediction models [28]. Using these methods, key features such as wind speed, wind direction, temperature, and air pressure, which have significant impacts on wind power, can be identified.

Wind power data exhibit significant temporal dependency and periodic characteristics, so it is essential to extract and analyze time-series features before modeling. Fourier transform or wavelet transform can be used to extract periodic components from the data, providing richer temporal features for the model [29]. In addition, lag embedding is also

commonly used to extract the influence of historical data on current predictions to enhance the time-series learning capability of the model.

4. Specific Applications of Machine Learning Models in Wind Power Prediction

4.1. Short-Term and Ultra-Short-Term Wind Power Prediction

4.1.1. Applications and Performance Comparison of Short-Term Prediction Models

Classification of wind power prediction based on time scale is shown in Table 2. Based on the time scale, wind power forecasting can be divided into ultra-short-term forecasting, short-term forecasting, medium-term forecasting, and long-term forecasting. Table 2 summarizes the application scenarios of various forecasting methods. This paper focuses on short-term and ultra-short-term forecasting, as these two categories represent future development trends and hold significant importance.

Table 2. Classification of wind power prediction based on time scale.

Classification	Prediction Time Range	Application
Ultra-short-term	Within 30 min	Real-time scheduling and operation of the power grid, as well as the real-time operation and control of wind farms.
Short-term	30 min to several hours	Day-ahead transactions in the electricity market, along with the daily operation and scheduling of the power grid.
Mid-term	A few days to a few months	Medium-term transactions in the electricity market, as well as equipment maintenance planning and medium-term generation planning for the power grid.
Long-term	A few years	Site selection for wind farms, along with long-term planning and construction of the power grid.

Short-term wind power prediction is pivotal for power system scheduling and maintaining grid stability. Recent studies reveal that combining traditional models with advanced machine learning methods significantly enhances prediction accuracy [30]. For instance, Malakouti [13] demonstrated that CNN-LSTM models outperform conventional methods like Random Forest and Support Vector Regression (SVR) by reducing prediction errors. A comparison of predicted and actual power outputs over a year underscores the ability of CNN-LSTM models to closely track real-time power variations, thereby mitigating grid integration challenges posed by wind energy's variability. This advancement highlights the model's critical role in balancing prediction accuracy against computational efficiency.

4.1.2. Sparse Modeling and Probabilistic Prediction in Ultra-Short-Term Forecasting

Ultra-short-term wind power prediction is essential for real-time grid operations. Innovative techniques, such as noise-intensified data augmentation, enhance the robustness of predictive models by improving their stability and generalization capabilities [31,32]. Zhang [15] explored the application of inferential statistics and dynamic machine learning models like LSTM, revealing their superior accuracy in capturing temporal patterns over short time frames. The result illustrates the advantages of dynamic models over static benchmarks, emphasizing the importance of high-quality datasets and robust training methods for achieving reliable predictions under ultra-short time constraints.

4.2. Spatial Transferability and Wind Power Prediction at Different Locations

4.2.1. Spatial Transferable Wind Power Prediction Models

To address the operational diversity of wind farms, spatially transferable models have been developed by integrating probabilistic machine learning with geospatial features [33]. These models effectively predict power output across varied geographic conditions. A comparative analysis demonstrates that machine learning models aligned closely with observed data while significantly reducing computational overhead. This approach is particularly valuable for real-time decision-making and dynamic operations in geographically diverse wind energy systems.

4.2.2. Multi-Location Prediction Models and Adaptability

Integrating CNNs and LSTMs facilitates accurate wind power predictions across multiple locations by leveraging their respective strengths in spatial and temporal data analysis. These hybrid frameworks generalize effectively across sites with different climatic and topographical characteristics. This adaptability ensures robust performance, making these models indispensable for global renewable energy applications. Furthermore, this modeling approach enhances grid integration by accommodating diverse environmental variables, ultimately supporting sustainable energy solutions.

4.3. Wind Power Prediction on Low-Cost Devices

4.3.1. Implementation on Low-Cost Hardware

The deployment of lightweight machine learning models on devices like Raspberry Pi demonstrates the feasibility of cost-effective wind power prediction in resource-constrained environments. Techniques such as pruning unnecessary network layers, optimizing model parameters, and using pre-trained architectures enable efficient predictions despite limited computational resources. These advancements pave the way for scalable, decentralized predictive systems that reduce latency and dependency on centralized infrastructure.

Low-cost devices like Raspberry Pi have been used to deploy lightweight machine learning models for wind power prediction. Studies have shown that despite limited computational resources, efficient wind power prediction can still be achieved by appropriately optimizing model structures and parameters. The use of low-cost devices, such as Raspberry Pi, for deploying lightweight machine learning models has opened new possibilities for cost-effective wind power prediction [13]. These compact and affordable devices, known for their portability and energy efficiency, provide a practical platform for implementing machine learning models, especially in remote or resource-constrained settings. By optimizing the structure and parameters of these models, researchers have demonstrated that accurate wind power prediction can still be achieved despite the limited computational capabilities of such devices.

For instance, techniques such as pruning unnecessary layers in neural networks, reducing the complexity of algorithms, and leveraging simpler yet effective machine learning methods have been explored to ensure compatibility with low-resource hardware. Additionally, efficient parameter tuning and the use of pre-trained models help maintain prediction accuracy while minimizing computational load.

This approach is particularly valuable for small-scale wind farms or developing regions where high-end computing infrastructure may not be feasible. By enabling real-time processing and on-site prediction, these lightweight models on Raspberry Pi not only reduce dependency on centralized computational facilities but also decrease latency in decision-making processes. Moreover, the low cost of these devices makes them highly scalable, allowing widespread deployment and greater accessibility to advanced predictive analytics in the renewable energy sector. This innovation demonstrates the potential

of combining edge computing with machine learning to create sustainable and efficient solutions for wind power forecasting.

4.3.2. Practical Applications and Technical Challenges of Low-Cost Platforms

Low-cost computing platforms, such as Raspberry Pi and similar devices, provide a budget-friendly and energy-efficient solution for deploying machine learning models. However, they are often constrained by limited computational power, reduced memory capacity, and lower processing speeds compared to high-performance computing systems. These limitations pose significant challenges, particularly for resource-intensive tasks like wind power prediction, which involves handling large datasets, complex algorithms, and real-time computations.

To overcome these challenges, researchers have developed optimization strategies aimed at improving the efficiency of machine learning models without compromising their predictive performance. One such approach is feature selection, which involves identifying and retaining only the most relevant features from the input data. By reducing the dimensionality of the data, feature selection decreases the computational load, allowing the model to process data more quickly and efficiently while minimizing memory usage. This technique not only enhances the model's speed but also helps prevent overfitting, leading to better generalization.

Another effective method is model pruning, which systematically removes unnecessary or redundant components of a neural network, such as nodes, connections, or entire layers. By simplifying the model structure, pruning significantly reduces the computational burden and memory requirements while maintaining a high level of accuracy. Techniques like weight pruning, where insignificant weights in the network are removed, or structured pruning, which eliminates entire filters or layers, are commonly employed to streamline models for deployment on low-resource devices.

These optimization methods are complemented by other strategies, such as quantization, which reduces the precision of computations (e.g., using 8-bit integers instead of 32-bit floating points) to save processing power and memory. Additionally, efficient algorithms and lightweight architectures, such as MobileNet or TinyML frameworks, are specifically designed for deployment on low-cost platforms.

By implementing these techniques, low-cost devices can effectively perform wind power prediction tasks despite their inherent resource limitations. These advancements enable the practical application of machine learning in real-world settings, particularly in remote or under-resourced areas, expanding the accessibility and impact of predictive analytics in renewable energy management.

4.4. Wind Power Prediction Under Special Conditions

4.4.1. Wake Effects and Yaw Control

Under yaw control conditions, the wake effect significantly affects the power output of wind farms. A literature study proposed a wind farm control strategy based on modifier adaptation, which improves overall wind farm performance by adjusting yaw settings [26,34]. He [34] introduces a machine learning-based approach for predicting fatigue loads and power output of wind turbines under yaw control. Using Support Vector Regression (SVR), the method incorporates wake effects and yaw misalignment to achieve accurate and efficient predictions. The proposed model demonstrates superior accuracy and robustness compared to traditional methods, offering insights for optimizing yaw control to maximize power output and mitigate structural fatigue in wind farms. The proposed fatigue and power prediction method aims to efficiently and accurately predict the structural performance of WTs under active yaw control. The proposed framework

is able to improve the fatigue loads and power prediction accuracy in the applications of active yaw control.

4.4.2. Prediction Under Climate Change and Complex Meteorological Conditions

Wind power prediction is inherently complex, and the challenges are further magnified under the influence of climate change and intricate meteorological conditions. Factors such as shifting weather patterns, increased frequency of extreme weather events, and the variability of wind resources make accurate forecasting a demanding task [30]. Addressing these challenges requires innovative approaches that integrate advanced modeling techniques with domain knowledge.

One promising solution involves the combination of grey models with machine learning techniques. Grey models, known for their strength in modeling systems with limited or uncertain data, are particularly useful in capturing the underlying trends and uncertainties in wind power data. When integrated with machine learning, which excels in handling large datasets and uncovering complex relationships, this hybrid approach provides a powerful tool for improving prediction accuracy. Machine learning algorithms can complement grey models by processing extensive meteorological data and refining predictions based on nonlinear and dynamic relationships. This synergy allows for better adaptation to changing weather conditions and enhances the robustness of wind power forecasting.

Meteorological characterization further plays a critical role in improving wind power prediction. Machine learning models can process high-dimensional meteorological data, such as wind speed, direction, temperature, and pressure, to establish intricate patterns and correlations. This enables more precise modeling of wind behavior and power output, even under variable and evolving climatic conditions. For instance, models like LSTM (Long Short-Term Memory) or CNNs (Convolutional Neural Networks) are particularly effective in capturing temporal and spatial dependencies in meteorological data, which are essential for accurate wind power forecasting [35].

In addition to addressing general forecasting challenges, specialized issues such as icing detection and prediction for wind turbines have also been studied using machine learning [36]. Icing on turbine blades can significantly reduce efficiency and lead to mechanical failures, making early detection and mitigation critical. By analyzing multivariate sensor data, machine learning algorithms can identify patterns indicative of icing conditions and predict their onset. This proactive approach enables operators to take timely action, such as blade heating or operational adjustments, minimizing downtime and maintenance costs while ensuring consistent power generation.

By integrating grey models, leveraging machine learning for meteorological characterization, and addressing specific challenges like icing, these advancements collectively offer a comprehensive strategy for overcoming the complexities of wind power prediction. They contribute to more reliable and efficient renewable energy systems, which are essential for sustainable development in the face of climate change.

5. Performance Comparison and Optimization of Machine Learning Models

5.1. Performance Evaluation Metrics for Common Models

The evaluation of wind power prediction models is critical for assessing their effectiveness and reliability in real-world applications. Typically, the performance of these models is measured using standard metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R² coefficient. These metrics provide quantitative insights into the accuracy and robustness of the predictions, offering a basis for comparison between different models and approaches. By relying on these evaluation metrics, researchers and practitioners can

objectively assess and refine wind power prediction models, ensuring their readiness for deployment in diverse and dynamic operational environments. The performance of wind power prediction models is usually evaluated using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R^2 coefficient. For example, in short-term wind power prediction using SCADA system data, the XGBoost regression model demonstrates excellent performance in terms of MSE and R^2 , indicating high prediction accuracy [37].

Mean Squared Error (MSE): This metric calculates the average of the squared differences between predicted and actual values. It emphasizes larger errors due to squaring, making it particularly sensitive to outliers. In the context of wind power prediction, MSE is widely used because it penalizes large deviations, which is critical for ensuring the reliability of power generation forecasts. However, its sensitivity to outliers can sometimes overemphasize rare extreme events.

Mean Absolute Error (MAE): Unlike MSE, MAE focuses on the absolute differences between predictions and actual values, providing a more straightforward measure of average error magnitude. MAE is less influenced by extreme errors, making it a useful complement to MSE for evaluating model performance. In wind power prediction, MAE is particularly suitable for assessing the general accuracy of models without over-penalizing occasional large deviations. The combination of MSE and MAE allows for a comprehensive evaluation of both overall model performance and the impact of outliers on prediction accuracy.

R^2 coefficient (Coefficient of Determination): This metric measures how well the predictions explain the variability in the actual data. An R^2 value close to 1 indicates that the model accounts for most of the variance in the target variable, signifying high predictive power. The R^2 coefficient is used to measure the goodness of fit of the model, while the reliability of the prediction interval is used to evaluate the stability and generalization ability of the model under different conditions. For instance, the CNN-LSTM-based method shows a good R^2 value in short-term wind power prediction, indicating that its prediction interval is highly reliable [13,38].

For instance, in short-term wind power prediction using data from SCADA (Supervisory Control and Data Acquisition) systems, advanced machine learning models such as XGBoost regression have been shown to excel in performance. SCADA systems provide high-frequency data on turbine operations, including wind speed, power output, and other critical parameters, which serve as rich input for predictive models.

The XGBoost model, a gradient boosting algorithm, is particularly well-suited for this application due to its ability to handle large datasets, manage missing data, and prevent overfitting through regularization. In comparative studies, XGBoost demonstrates superior performance with low MSE values, indicating minimal prediction errors, and high R^2 values, reflecting its capacity to capture the underlying trends and relationships in the data. These results highlight the model's potential for delivering precise and reliable short-term forecasts, which are essential for optimizing wind farm operations, balancing grid load, and reducing reliance on non-renewable energy sources.

Hao [38] examined the impact of turbulence intensity on ultra-short-term wind power and speed forecasts using machine learning models. The framework applies four machine learning algorithms (Linear Regression, Back Propagation Neural Networks, Reduced-Error Pruning Tree, and Random Forest) and evaluates their performance through rigorous statistical tests. This research emphasizes a structured approach to exploring whether turbulence significantly influences prediction accuracy.

The results reveal that including turbulence intensity does not statistically enhance prediction accuracy for ultra-short-term wind forecasts in most cases. This finding suggests that turbulence's stochastic nature might limit its utility as a predictive feature in the short term. However, it is noted that turbulence may still affect wind speed predictions more

than power forecasts, hinting at complex interactions between meteorological variables. The study underscores the need for careful variable selection in forecasting models to balance computational efficiency and prediction performance.

5.2. Model Optimization Techniques

5.2.1. Parameter Optimization and Algorithm Selection (e.g., Particle Swarm Optimization, Fruit Fly Algorithm)

To enhance the performance of wind power prediction models, parameter optimization methods such as Particle Swarm Optimization (PSO) and the Fruit Fly Algorithm have been widely applied. These methods aim to fine-tune key model parameters, enabling more accurate wind power forecasts and improving the overall reliability and performance of the models. PSO is a nature-inspired algorithm that mimics the social behavior of bird flocks or fish schools. In PSO, each “particle” represents a potential solution that adjusts its position dynamically based on its own experience and the best position found by the swarm, iterating until it converges to an optimal parameter set. This method is particularly effective in optimizing hyperparameters for complex machine learning models, such as neural networks or support vector machines, including learning rates and weights, thereby reducing prediction errors and enhancing model accuracy.

On the other hand, the Fruit Fly Algorithm mimics the foraging behavior of fruit flies, leveraging their keen sense of smell and vision to locate food sources. In the context of prediction model optimization, the algorithm evaluates parameters using an objective function, such as minimizing prediction errors, and iteratively adjusts them to identify the optimal solution [33]. Like PSO, the Fruit Fly Algorithm is appreciated for its simplicity, efficiency, and robustness, making it especially suitable for applications with limited computational resources.

The significant advantages of these methods lie in their efficiency, adaptability, and robustness. They can not only converge quickly to optimal solutions but also effectively handle the high-dimensional and nonlinear characteristics of wind power data, adapting to different data features from various wind farms. Through these optimization techniques, models can achieve significantly lower prediction errors and higher accuracy for both short-term and long-term wind power forecasting. This, in turn, provides reliable support for grid scheduling, wind farm management, and energy market operations. The application of these methods underscores that parameter optimization is a critical step in enhancing wind power prediction model performance and plays a vital role in the efficient utilization of renewable energy.

5.2.2. Application of Ensemble Learning Methods and Hybrid Models

Ensemble learning methods, such as XGBoost and Random Forest, along with hybrid models like CNN-LSTM, have demonstrated exceptional performance in wind power prediction by leveraging the strengths of multiple models [13,16]. Ensemble methods operate by combining the predictions of several base models to create a more accurate and reliable overall prediction. For instance, Random Forest aggregates the predictions of multiple decision trees, reducing the risk of overfitting and enhancing generalization, while XGBoost employs gradient boosting to optimize model performance by iteratively improving upon prediction errors.

Hybrid models like CNN-LSTM take a different approach by integrating two complementary architectures to address the complexities of wind power data. Convolutional Neural Networks (CNNs) are particularly effective at capturing spatial patterns and relationships in the input data, such as meteorological variables or turbine sensor readings, while Long Short-Term Memory (LSTM) networks excel at modeling temporal dependencies and long-term trends. By combining these two methods, CNN-LSTM models

are capable of handling both spatial and temporal dynamics in wind power prediction, resulting in higher accuracy and adaptability to varying conditions.

The key advantage of these approaches lies in their ability to enhance both the accuracy and robustness of predictions. Ensemble learning reduces the impact of errors from individual models by integrating diverse perspectives, while hybrid models leverage complementary capabilities to address different aspects of the prediction task. These methods are particularly effective in handling the inherent variability and uncertainty of wind power data, ensuring more reliable forecasts for both short-term and long-term applications. As such, ensemble and hybrid approaches have become indispensable tools in advancing the field of wind power prediction and optimizing renewable energy integration into the grid.

Yao [39] presented an integrated machine learning and statistical approach for wind power interval forecasting, addressing the nonlinear and time-varying characteristics of wind speed and error distributions as shown in Table 3 [39]. By evaluating six regression methods, the study highlights LSTM as the most effective for improving forecast accuracy and uncertainty quantification. This approach provides valuable support for optimizing wind power integration into the grid. As illustrated, the prediction intervals given by all five nonlinear machine learning algorithms perfectly contain the true values of wind power.

Table 3. Prediction errors of different methods.

Regression Methods	MAPE
Linear regression	12.81
Multilayer perceptron	12.32
LSTM	8.10
Lazy IBK	10.46
Decision table	15.10
Regression tree	11.26

6. Application Challenges and Future Research Directions in Wind Power Prediction

6.1. Common Challenges of Machine Learning Models in Wind Power Prediction

6.1.1. Data Acquisition and Sensor Quality Issues

In wind power prediction, data acquisition and sensor quality are important factors that affect model performance. Sensor faults, data loss, and measurement errors in wind farms can negatively impact the training and testing of prediction models. Especially under complex meteorological conditions, the quality of sensor data may decline, which, in turn, reduces the accuracy of model predictions. Therefore, ensuring high data quality and completeness is a key issue that needs to be addressed.

6.1.2. Impact of Wind Farm Layout and Complex Terrain on Prediction

The layout of wind farms and terrain characteristics significantly affect the distribution of wind speed and wind power output. Complex terrain, such as mountainous and hilly areas, can increase wind turbulence, making wind power prediction more difficult. In addition, the layout of wind turbines within a wind farm affects wake effects, leading to interference among different turbines. Therefore, under conditions of complex terrain and internal wind farm layout, how to build more accurate prediction models is an important challenge.

6.2. Future Research Directions

6.2.1. Application of Multi-Model Fusion and Emerging Deep Learning Technologies

Future research on wind power prediction is expected to increasingly focus on the integration of multi-model fusion techniques and emerging deep learning technologies to achieve higher accuracy and robustness. Multi-model fusion combines the strengths of different models, leveraging their unique capabilities to enhance overall prediction performance. For instance, hybrid models like CNN-LSTM demonstrate the potential of capturing both spatial and temporal features of wind speed changes. The CNN excels at extracting spatial patterns from input data such as wind speed, direction, and meteorological variables, while the LSTM network effectively models temporal dependencies, enabling the hybrid model to comprehensively address the complex dynamics of wind power data. Additionally, emerging deep learning technologies, such as Transformer architectures, offer significant promise for advancing wind power prediction. Transformers, known for their success in natural language processing and time-series forecasting, can handle long-range dependencies in data and adapt effectively to complex, multivariate input features. By applying self-attention mechanisms, Transformers can focus on the most relevant parts of the input data, improving the model's ability to capture subtle patterns and correlations. These advancements provide exciting opportunities for future research to develop more accurate, robust, and adaptable wind power prediction models, addressing the increasing demands for reliable renewable energy integration.

6.2.2. Integration with Energy Storage Systems and Grid Management

The inherent variability of wind power presents significant challenges to the stable operation of power grids, making its effective integration a critical area for future research. To address this, future studies can focus on the deep integration of wind power prediction with energy storage systems and advanced grid management strategies to improve the scheduling and utilization of renewable energy. For instance, combining accurate wind power forecasting with battery energy storage systems (BESSs) offers a promising solution for mitigating fluctuations in wind power output. By storing excess power during periods of high wind generation and releasing it during low-generation periods, BESS can effectively smooth out variability, enhancing the reliability and stability of the power system. Additionally, integrating wind power prediction with smart grid management systems can further optimize power transmission and distribution. Advanced grid management technologies that leverage real-time forecasting data can dynamically adjust power flows, balance supply and demand, and reduce the risks of instability caused by wind power fluctuations. This holistic approach not only ensures a more stable and efficient power grid but also facilitates the large-scale adoption of wind energy, contributing to the broader goal of transitioning to sustainable energy systems.

6.2.3. Prospects of Smart Sensors and IoT in Wind Power Prediction

The advancement of IoT technology has opened up broad application prospects for smart sensors in wind power prediction, offering significant potential to improve the accuracy and efficiency of forecasting systems. Smart sensors can continuously monitor multiple meteorological variables, such as wind speed, wind direction, temperature, and air pressure, providing real-time and high-resolution data critical for wind power prediction. By leveraging IoT networks, these sensors can transmit data directly to centralized or distributed prediction systems, ensuring a seamless flow of up-to-date information. This integration enhances the real-time nature and accuracy of prediction models, enabling them to better capture the dynamic and complex patterns of wind behavior. Future research can delve deeper into the design and implementation of IoT-enabled intelligent predic-

tion systems, where smart sensors form the backbone of a fully automated and adaptive framework. These systems could address various challenges in wind power prediction, such as handling large-scale and geographically dispersed datasets, adapting to rapidly changing weather conditions, and improving response times for grid management. By combining smart sensors with IoT and advanced analytics, researchers and practitioners can build more intelligent, scalable, and reliable wind power prediction solutions, ultimately supporting the broader integration of renewable energy into the power grid.

7. Conclusions

7.1. Key Findings and Summary

This paper reviewed the application of machine learning in wind power prediction and its related methods, including the limitations of traditional physical and statistical models, as well as the advantages of machine learning and deep learning methods in wind power prediction. Through the comparison of various machine learning models and analysis of application scenarios, it is evident that machine learning, especially deep learning methods, has significant advantages in dealing with the nonlinearity and complexity of wind power. The literature presented various data preprocessing methods, feature selection strategies, and model optimization techniques, all of which are crucial for improving the accuracy and robustness of wind power prediction. Additionally, challenges such as data acquisition, complex terrain, and sensor quality in wind power prediction were discussed in detail, and corresponding solutions were proposed.

7.2. Prospects of Machine Learning in Wind Power Prediction

With the improvement of computing power and the continuous enrichment of data collection methods, the application prospects of machine learning in wind power prediction are very promising. Multi-model fusion, emerging deep learning methods (such as Transformer), and the integration of smart sensors are expected to significantly improve the accuracy and robustness of wind power prediction in the future. Moreover, the deep integration of machine learning with energy storage systems and power grid management systems will further enhance the stability of wind farm operations and the reliability of power systems. The combination of smart sensors and IoT technology also provides new development directions for the automation and intelligence of wind power prediction systems.

7.3. Recommendations for Future Work in Wind Power Prediction Using Machine Learning

To further advance research in wind power prediction, future work can be strengthened in the following areas: First, greater emphasis should be placed on studying emerging deep learning technologies and exploring their potential applications in wind power prediction, particularly the use of models like Transformer and Graph Neural Networks. Second, attention should be given to the application of multi-model fusion and ensemble learning methods to enhance prediction accuracy and robustness by integrating the strengths of different models. Additionally, the collaborative optimization of wind power prediction with energy storage systems and deep integration with grid management systems should be key focus areas for future research. Finally, the combination of smart sensors and IoT technology can provide more real-time and high-quality data, offering comprehensive support for wind power prediction, which should also become an important direction for future research.

Author Contributions: Conceptualization, Z.Z. and Z.L.; methodology, Z.L.; resources, H.G. and Y.Z.; data curation, Z.Z.; writing—original draft preparation, Z.L. and Z.Z.; writing—review and editing, H.G. and Y.Z.; supervision, Z.Z.; project administration, H.G.; funding acquisition, Z.Z. All authors have read and agreed to the published version of the manuscript.

Funding: The study was funded by the Open Project of Key Laboratory of Industrial Fluid Energy Conservation and Pollution Control, Ministry of Education (NO. CK-2024-0034), and Henan Jiuyu Enpai Electric Power Technology Co., Ltd. Science and Technology Project (2024-KJ-07).

Conflicts of Interest: Authors Zongxu Liu, Hui Guo and Yingshuai Zhang were employed by the company Henan Jiuyu Enpai Power Technology Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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