International Journal of Network Dynamics and Intelligence

Article

Analysis and Prospect of Wind Power Forecasting Methods from Multiple Perspectives

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Received: 31 July 2025
Accepted: 13 September 2025
Published: 21 November 2025

Abstract: As one of the typical clean energy sources, the power prediction of wind power is crucial for power system scheduling, stability maintenance, and market trading. However, due to the intermittency and uncertainty of wind energy, wind power prediction faces many challenges. This paper overviews the basic concepts and application scenarios of wind power prediction, and systematically analyzes the methods that currently exist for wind power forecasting. Furthermore, this paper summarizes the key factors which affect the prediction accuracy, such as wind speed variations, unit characteristics, meteorological data quality, and geographic environment. In addition, this paper also introduces the commonly used error and reliability assessment metrics. Finally, the future research direction of wind power prediction is discussed the references for research in related fields are also provided.

Keywords: wind power forecasting; power system scheduling; intermittency and uncertainty; prediction accuracy; assessment metrics

1. Introduction

Due to its eco-friendliness and zero-carbon emission nature, the renewable power generation has gained considerable research attention from both academic and industrial areas. Wind energy, with its advantages of being clean, renewable and resource-rich, has played an increasingly important role in the power industry and therefore gained much research enthusiasms [1]. However, the inherent stochasticity and fluctuation in wind power [2,3] poses serious challenges to the stable operation of power systems, and the wind power forecasting (WPF) technology seems an effective way to ensure the safe operation of the power grid and further promote the consumption of wind power.

From the perspectives of methodologies, the mainstream WPF methods include the physics-based, statistics-based and artificial-intelligence-based (AI) ones [4]. Specifically, for the physics-based method, it mainly uses the physical characteristics of wind farms to predict the power generation, and such a method is highly generalized and interpretable, see [5–7] for some representative works. For the statistics-based method, it performs exceptionally well when there is a sufficient amount of wind power data available [8–10]. As for the AI-based methods, it owns unique merits in capturing the features of data and handling the complex data [11–13].

From the view of time scale, the ultra-short-term forecasting mainly focuses on application scenario of real-time control, while medium-term and long-term forecasting serves the scenarios of power trading and scheduling [14]. In [15], a dynamic matching and online modeling strategy for ultra-short-term wind energy prediction has been proposed, which improves the prediction accuracy and meets the requirements of grid timeliness. In Ref. [16], a deep-learning-based ultra-short-term wind energy prediction method has been developed which adapts the event-triggered real-time model predictive control (MPC) strategy to regulate the ocean pumped storage system in a real time manner to cope with the uncertainty of wind and wave energy.

From the perspective of data output style, the forecasting with probabilistic approach has gradually replaced the traditional point-wise-based one by quantifying uncertainty [17]. This shift allows for more accurate predictions, providing not only the most likely outcome but also the interval of possible outcomes and their associated probabilities [18,19]. This approach is particularly beneficial in complex systems since the dynamics are usually difficult to represent precisely.

This paper reviews wind power prediction techniques, and the corresponding framework is shown in Figure 1. Section 2 introduces the fundamental concepts of wind power prediction. In Section 3, a detailed discussion of the methods utilized for WPF is presented. Section 4 reviews the factors which influence the accuracy of wind power predictions. Section 5 outlines the evaluation metrics commonly used in assessing the performance of wind power forecasts. In Section 6, the emerging trends and future research directions in the field is explored. Finally, Section 7 offers the conclusion of the paper.

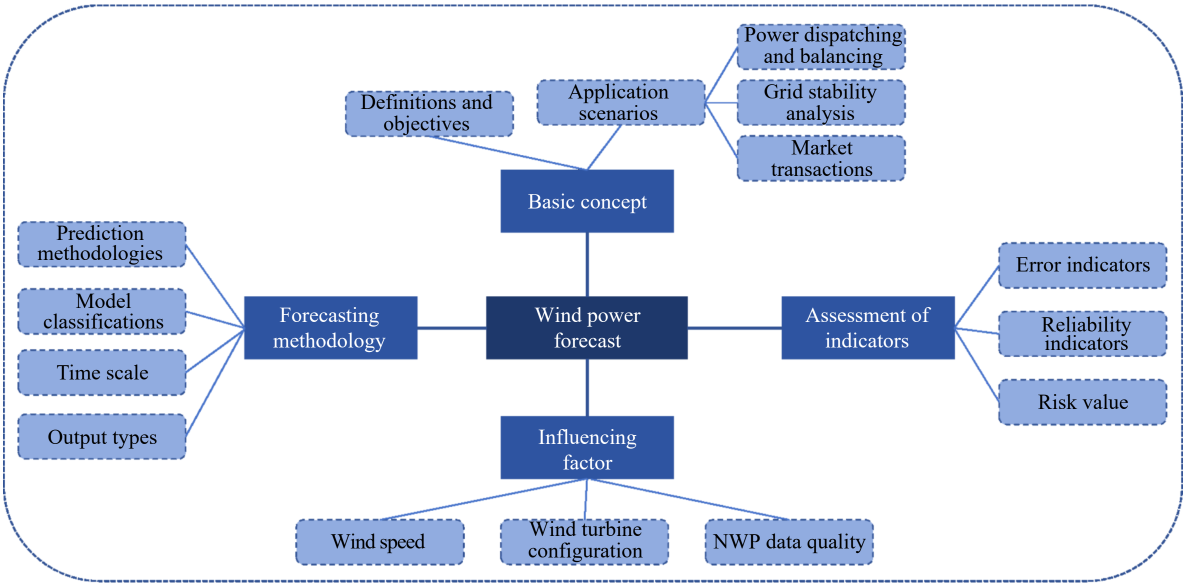

Figure 1. Overview of wind power forecasts from different perspectives.

2. Basic Concepts of WPF

WPF refers to the process of predicting the expected power generation of wind turbines or wind farms over a specific time horizon. Accurate and timely prediction of wind power plays an important role in modern power systems (which poses higher demand on the coordination among power generation units, power grid, load and even energy storage).

As grid-connected wind power capacity continues to grow, the WPF is now widely used in power system dispatch and operation. To be specific:

● Dispatching and balancing. When a large amount of wind power is connected [20], its randomness and fast changes make dispatch more difficult. The accurate forecasting results make it easier for the power generation planing, power generation unit selection, backup resources arrangement and renewable energy consumption [21,22].

● Stability analysis. The intermittent nature of wind power may cause fluctuations in voltage, frequency and power flow, and further affect the stability of the grid. WPF makes it easier to identify possible risks of power fluctuations in advance and helps to improve the response capability of the grid [23,24].

● Market transaction. In a market-based power system, wind power operators must use forecast results to upload generation plans and participate in competitive bidding [25]. Accurate WPF helps operators improve contract fulfillment and avoid market risks by using storage or signing service contracts in advance [26].

3. Wind Power Prediction Methods

The selection and optimization of prediction methods directly affect the accuracy of the prediction results. Therefore, fruitful forecasting approaches have been proposed. In this section, the mainstream methods of WPF and their features are systematically reviewed from four aspects, namely, the ways of prediction, model classifications, time scale and output types.

3.1. Prediction Methodologies

So far, there are two kinds of prediction styles, namely, the direct one and the indirect one, have appeared in literature. The main idea of the direct one uses historical power and meteorological data to predict wind power through statistical or physical models. For instance, in Ref. [27–29], the direct mapping relationships between input variables and wind power output have been established with the aid of advanced algorithms and models.

As for the indirect prediction method, it usually predicts wind power output by combining factors such as equipment performance, operating status, and load characteristics of the wind farm. For example, in [30–32], the wind speed data are converted into power output by resorting to the wind turbine's power curve.

In addition to the above two mentioned methods, hybrid approaches have also gained attention in recent years, see e.g. [33,34] for some examples. These methods integrates meteorological data with equipment-specific parameters, such as turbine efficiency or operational status, to improve forecasting.

3.2. Classification of Predictive Models

1) Physical model: For the physics-based model, it mainly uses physical principles such as aerodynamics and thermodynamics to predict wind power generation. Specifically, the prediction of wind power is realized by deeply analyzing the geographic information (such as topography, roughness and/or distribution of obstacles), meteorological conditions (wind speed, wind direction, air temperature and/or air pressure), and the characteristics of wind turbines.

Common physical models include power curve model, numerical weather prediction (NWP) model and computational-fluid-dynamics (CFD) based wind field model, see e.g. [35–38] for some representative works. For instance, in Ref. [39], a transfer coefficient method which can significantly reduce the computation time without sacrificing the accuracy of the prediction has been proposed to improve the efficiency of wind farm power prediction. In Ref. [40], the importance of physical dependencies in the simplification process has been emphasized by simplifying the mathematical equations of the physical model to predict the electricity production of wind farms. In Ref. [41], a CFD model-based wind power prediction method has been developed which utilizes numerical weather forecast data for short-term wind power prediction with high accuracy and low computation time.

Although the physics-based model owns significant advantages in meeting the demands for new wind farms due to the light reliance on the historical data, the shortcomings also need to pay attention. For example, the model calculation process involves a large number of complex numerical solutions, and such a process may face high computational burden and long computation time.

2) Data-driven model: Till now, the data-driven-based approach has gradually emerged as a hot area for research and application in WPF due to its unique advantages in extracting patterns from historical data and handling the complex variation. In addition, the data-driven method owns strong adaptive and learning ability [42,43]. Taking the neural network model in machine learning algorithm as an example, through repeated training of massive historical data, the model can automatically learn the law of wind power change under different meteorological conditions, see e.g. [44–49] for some representative works.

In terms of prediction accuracy, data-driven schemes also perform well in dealing with the non-linear and non-smooth characteristics of wind power. For example, the support vector machine (SVM) model is able to map nonlinear problems in low-dimensional space to high-dimensional space through kernel functions, thus realizing effective classification and regression of complex data distributions, and capturing the nonlinear characteristics of power changes more accurately in wind power prediction [50]. Moreover, with the development of deep learning techniques (e.g. recurrent neural network (RNN), long short-term memory network (LSTM) and gated recurrent units (GRU)), the long-term dependencies in time series data can be better handled, see [51–56] for some examples. For instance, a hybrid regression model based on wind speed-power curves, Optuna optimization and LightGBM has been proposed in [53] to improve the accuracy of wind power prediction. In Ref. [55], a CNN-Transformer-Autoregressive (CTAR) model has been developed to capture the short-and long-term patterns of variation in wind power data, in which the effects of factors such as temperature and barometric pressure on wind power have also been considered.

3) Hybrid model: The intermittent, fluctuating and stochastic nature of wind energy makes the physical or data-driven model face many limitations in predicting wind power. Therefore, hybrid approach which combines physical model and data-driven model become an effective way to improve the accuracy and reliability of wind power prediction.

In Ref. [57], an ultra-short-term wind power generation prediction method combining data-driven and physically-driven models has been proposed to switch the prediction model by wind speed fluctuation characteristics, which can significantly improve the prediction accuracy and is especially suitable for the time period with large wind speed fluctuations. In Ref. [58], a LSTM-based method for forecasting ultra-short-term wind power generation has been developed, in which the historical wind speed, wind power and weather forecasting data are considered. In [59], a model which combines physical processes and machine learning has been proposed for predicting wind turbine output power under wake effects.

Hybrid models combine the strengths of different single models to overcome the limitations of single models in predicting complex wind conditions. This makes the prediction results not only more accurate, but also more stable and reliable in responding to sudden weather changes. It provides more accurate and stable prediction results, which are crucial for the safe, stable, and economical operation of the power grid.

3.3. Time Scale of Forecasting

WPF is usually categorized into ultra-short-term forecasting, short-term forecasting, medium-term forecasting, and long-term forecasting according to the time scales. Forecasting methods with different time scales are suitable for different application scenarios and have their own advantages and limitations, see Figure 2 for more details. To be specific:

- Ultra-short-term forecasts generally refer to forecast of wind power in the next 0-4 hours with a time resolution of 15 minutes, and such a framework can be used in the real-time dispatch of the power grid. For example, representative works in Ref. [60–63] focus on the ultra-short-term wind power prediction where different innovative models are utilized to address the stochastic and volatility issues of wind power.
- Short-term wind power forecasts usually refer to wind power forecast in the next few hours to days, and such a forecasting framework can be used in the power market trading. For example, in Ref. [64], a hybrid wind energy prediction model combining a temporal fusion transformer (TFT) and theoretical power curve modeling was proposed. By integrating manufacturer specifications, numerical weather forecast data, and physical information equations, the accuracy of wind energy prediction was significantly improved. In Ref. [65], a high-accuracy hybrid method for short-term wind power prediction has been proposed. In Ref. [66], a short-term wind energy prediction model combining the empirical modal decomposition method and optimized BiLSTM was proposed. The RIME algorithm was used to improve prediction accuracy and reduce computational requirements.
- Medium-term forecasts typically involve wind power forecasts in the next 3 days to 1 week, which can be used in the maintenance scheduling. Its prediction method mostly integrates NWP medium-term data and long-time historical data, and is realized with the help of trend analysis and statistical modeling. It should be noted that the prediction accuracy will be reduced due to the increase of prediction time and the intensification of meteorological conditions uncertainty e.g. [67–70].
- Long-term forecasting is the prediction of wind power more than 1 week in the future, which can be used in the power system planning, long-term planning of wind farms, the power layout of the power system, and the formulation of energy policies. For example, in Ref. [71], the current state of research on medium- and long-term wind energy forecasting was reviewed, and the application of innovative hybrid forecasting models in wind energy forecasting was emphasized. In Ref. [72], the Hiformer method was proposed, which combines signal decomposition and meteorological feature extraction to significantly improve the accuracy of long-term wind energy prediction and reduce computation time. In Ref. [73], a long-term prediction method for wind power based on adaptive wavelet neural network has been designed, which significantly improves the prediction accuracy and outperforms the traditional persistence prediction method by using NWP system.

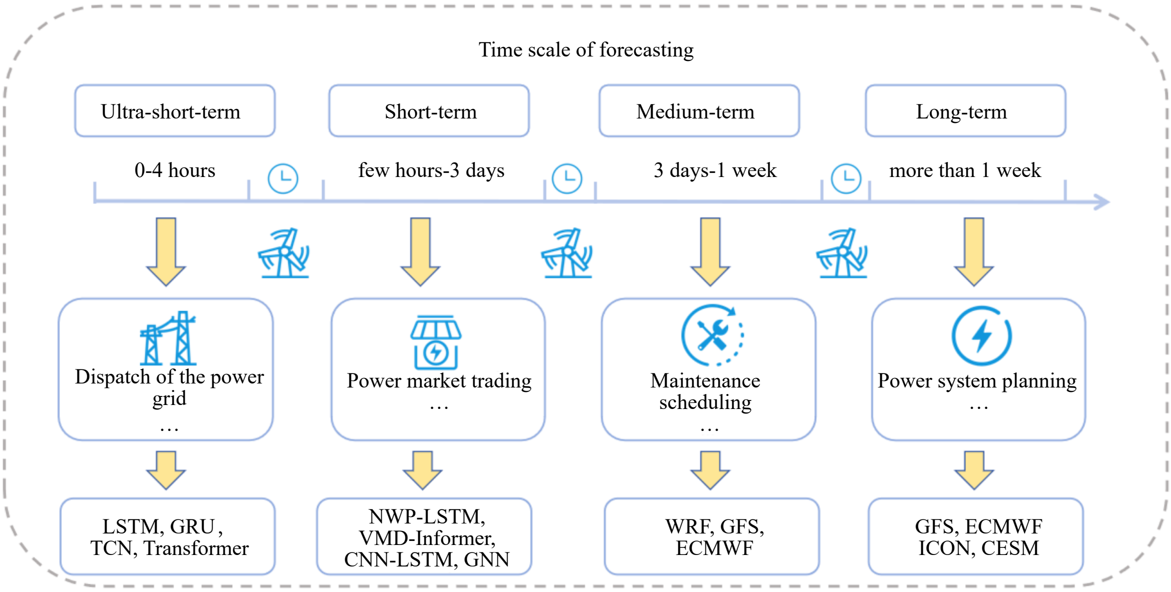

Figure 2. Scope and application scenarios of wind power prediction on different time scales.

3.4. Predicted Output Types

In the process of wind power prediction, the output of the prediction model can be classified into two main categories, i.e. the point prediction and the probabilistic prediction. These two output styles have different value types and application scenarios.

1) Point-based prediction: Point-based forecast is one of the most common types of forecast which is designed to predict a specific wind power value with a time stamp. From the perspective of prediction methods, numerous machine learning and deep learning algorithms have been applied in point prediction tasks, see e.g. [74–77] for some examples. Since wind power is often affected by a variety of complex uncertainties like random fluctuations in wind speed, changes in wind direction, and complex terrain and geomorphology, the single point prediction value cannot reveal the degree of uncertainty in the prediction results. Moreover, in practice, decisions based only on point predictions can lead to increased risk in power system operation due to actual power deviations from predicted values.

Point prediction provides a single most probable value, which is mainly used for routine grid dispatching and planning because it is simple and straightforward, making it easy to arrange power generation.

2) Probabilistic-based prediction: Unlike the point-based forecast style, probabilistic-based forecast provides the probability distribution of future wind power in different value intervals, and such a framework comprehensively considers the uncertainty information of the forecast results. For instance, in Ref. [78], the LSTM-WPRE-PF model was proposed, which combines wind energy slope events to improve the accuracy and reliability of daily wind energy probability forecasts. In Ref. [79], a new multi-model combination (MMC) approach has been designed to improve the probabilistic prediction performance of wind power by combining the advantages of different prediction models. In Ref. [80], a wind farm cluster power output probability prediction model combining Moran-Graph networks and hybrid decomposition methods was proposed, significantly improving prediction accuracy and coverage probability.

Probabilistic prediction provides a range of possible outcomes and their probabilities, and is mainly used for risk management and market decision-making, such as determining how much backup power is needed or how to quote prices, because it can quantify the risks associated with uncertainty.

The application of probabilistic prediction results in power systems is of great importance. However, probabilistic prediction also faces some challenges such as high computational complexity, strict requirements on data quality and model assumptions.

4. Factors Affecting Wind Power Prediction

In this section, factors which affect WPF accuracy are introduced from multiple perspectives (e.g. wind speed, wind turbine configuration and NWP data quality).

4.1. Wind Speed

In WPF, the dynamic variability of wind speed caused by factors such as atmospheric turbulence and thermal gradients constitutes the predominant source of prediction inaccuracies.

To reduce measurement uncertainties in wind speed variability, advanced decomposition techniques like the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) combined with the refined composite multiscale fuzzy entropy (RCMFE) frameworks effectively isolate multi-scale wind components [81], while hidden markov models (HMM) reduce input uncertainties, see e.g. [82].

However, isolated decomposition remains insufficient in addressing the problems of nonlinear dynamics. To be specific, non-linear dynamics such as turbulence, wake interactions, and sudden wind ramps adversely affect prediction accuracy through complex energy transfer mechanisms. To address these problems, hybrid solutions which combine deep learning and Gaussian wake modeling are developed to capture spatiotemporal patterns, see e.g. [83–85]. Wavelet packet decomposition (WPD) and ramp detection algorithms further enhance wind speed data preprocessing robustness, see e.g. [86,87].

Besides single-variable optimization, the non-linear wind-speed-to-power mapping can also be refined with attention mechanisms [88]. As for the multivariate interaction issue, it can be resolved via bidirectional gated recurrent unit (BiGRU) networks and the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) decomposition, see e.g. [89].

4.2. Wind Turbine Configuration

The configurations of wind turbine such as spatial layout, equipment heterogeneity, subsystem dynamics, and environmental adaptability often cause significantly impacts on the WPF accuracy.

The spatial arrangement of turbines directly affects wake effects and power coupling. In the early stage, the single-turbine prediction models often ignored wake interference between units, and thus the error is accumulated. In contrast, a "N encoder-1 decoder" multi-channel fusion group forecasting seq2seq architecture has been developed in Ref. [90], and it considers the spatial correlation between turbines, improving the accuracy of wind speed and power prediction. Similarly, in Ref. [91], a wind-turbine cluster power-forecasting model has been proposed based on density-based spatial clustering and an enhanced hunter-prey optimization algorithm.

The equipment heterogeneity also makes the WPF complex, especially in wind farms with mixed direct-drive and doubly-fed turbines. In Ref. [92], such an issue is addressed by assigning multi-dimensional random vectors to each turbine and using space embedding to create representative vectors. This enables a single model to account for individual turbine characteristics. In Ref. [93], an improved fuzzy C-means clustering algorithm has been designed to classify turbines with similar power output traits and select representative power curves.

Subsystem dynamics play a critical role in forecasting accuracy, as their configurations influence performance through component-specific behaviors. For instance, a spatial-temporal graph convolutional network (STGCN)-based method that processes wind turbine data by explicitly accounting for subsystem dynamics and their interconnections has been proposed in Ref. [94]. Similarly, in Ref. [95], a BWO-BiLSTM-ATT hybrid framework has been developed where the Bidirectional LSTM (BiLSTM) network captures bidirectional temporal dependencies to model system dynamics effectively.

Environmental adaptability is another key factor in WPF. For example, a hybrid WT–PSO–NARMAX model which combines wavelet transforms, particle swarm optimization, and nonlinear autoregressive methods has been developed in Ref. [96] to handle chaotic meteorological and SCADA data, thereby improving accuracy under varying environmental conditions. In Ref. [97], it has been further advanced with the FCM–WOA–ELM–GMM model, which employs Gaussian mixture models (GMM) to estimate prediction confidence intervals across diverse climates and time scales.

4.3. NWP Data Quality

Accurate and high-quality NWP data is crucial for reliable WPF. To enhance the quality of NWP data, various methods have been proposed. These include NWP data correction, fusion and integration, quality assessment and selection, and forecasting model optimization.

In terms of NWP data correction, several techniques have been developed. In Ref. [98], a wind speed error correction model based on ResNet-GRU has been proposed, and this model effectively corrects forecasting results across different heights. In Ref. [99], a hybrid model has been developed for long-term WPF. It corrects NWP wind speed data and uses multi-scale deep learning regression to exclude redundant NWP data.

The fusion of NWP data with other sources has attracted significant research attention. For instance, ref. [100] has integrated LiDAR and SCADA data with deep learning algorithms to develop a high-accuracy 3-hour WPF model. Similarly, ref. [101] has enhanced forecasting performance by incorporating weather research and forecasting (WRF) model features into artificial neural networks.

To ensure reliable NWP inputs, researchers have developed advanced selection strategies. Ref. [102] has proposed an interpretable base model selection strategy using elastic net regression and Shapley additive explanations. Meanwhile, ref. [103] has combined inputs from three distinct NWP sources while implementing dynamic weighting based on recent forecast errors.

Recent studies have focused on optimizing models to leverage NWP data quality. Ref. [104] has systematically compared hyperparameter optimization techniques for deep learning applications. Additionally, Ref. [105] has introduced a novel data enhancement framework to improve historical dataset completeness and resolution.

The influencing factors do not act independently; they interact with each other and jointly cause dramatic changes in wind power. For example, wind speed, temperature, and air pressure jointly determine air density, which in turn affects power generation. If the model ignores this coupling relationship, it will produce huge prediction errors in complex weather conditions.

5. Assessment of Indicator Categories

5.1. Evaluation Metrics for WPF

Accurately assessing the performance of wind power prediction is of key significance in optimizing the prediction model and ensuring the stable operation of the power system. The assessment indicators reflect the degree of fit between the prediction results and the actual values in different aspects, and thus provide a quantitative basis for the improvement and selection of prediction methods.

Common assessment metrics are mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2) [106], as given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{1}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100, \tag{2}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}, \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \tag{5}$$

In these formulas, $\hat{y}_i$ is the predictive value, y_i is the actual value, and n is the number of predictive data.

5.2. Reliability Indices and Value at Risk

In addition to the commonly used error metrics, reliability metrics are also an important part of WPF. Reliability metrics are commonly used to assess the stability and robustness of prediction results, reflecting the performance of predictive models in different contexts. Common reliability indicators include standard deviation (SD) and bias of the predicted values, etc., which are calculated by the formula:

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{6}$$

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i). \tag{7}$$

In addition, the Risk Value (RV) of wind power prediction is also an important metric to assess the performance of the model. The value-at-risk reflects the potential loss due to errors in WPF and is usually measured by calculating the probability of exceeding a certain error threshold, which is calculated as follows:

$$Risk = P(|y_i - \hat{y}_i| > \epsilon). \tag{8}$$

where ϵ is the set error threshold. P denotes the probability that the error exceeds this threshold. By introducing a value-at-risk, it is possible to provide a quantitative assessment of the uncertainty in WPF, which in turn helps decision makers to make a trade-off between forecast accuracy and risk management.

6. Future Development Trends and Research Directions

The future development trends of WPF will focus more on the integration of deep learning, artificial intelligence, and big data technologies. By merging large-scale meteorological data, historical generation data and geographical factors, the accuracy of prediction will be improved.

As climate change and the complexity of wind farm layouts increase, the combination of physical models and data-driven models will become the mainstream approach. In addition, multi-model integration methods and the application of reinforcement learning will enhance the adaptability and optimization of WPF systems and improve their predictive capabilities in various environments. Meanwhile, the development of uncertainty analysis techniques will make prediction results more reliable, providing more precise decision support for grid scheduling. Through the fusion of these technologies, WPF will not only improve prediction accuracy but also enhance the operational efficiency and stability of the power grid.

7. Conclusion

Wind power prediction has become a key technology for enhancing grid integration capacity and ensuring power system stability. In this paper, we have systematically studied the fundamental concepts and application scenarios of WPF. Our research has comprehensively analyzed technological advancements and challenges across multiple aspects, including prediction methods, influencing factors, evaluation metrics, and future development trends. We have classified wind power prediction methods according to methodology, modeling principles, application scenarios, and result characterization perspectives.

The field of wind power prediction has reached a stage that demands interdisciplinary innovation, and it has been recognized the need to simultaneously optimize prediction accuracy, reliability, and computational efficiency to better support power system stability and operational reliability in the future.

Author Contributions: Jie Liu: Investigation, Writing - original draft. **Bogang Qu:** Supervision, Project administration, Funding acquisition, Writing - review & editing, **Enming Wu:** Investigation. **Nan Li:** Visualization. **Zuxian Wang:** Formal analysis. **Daogang Peng*:** Conceptualization, Supervision.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grant 62303301, Grant 62373241, and the Shanghai Pujiang Program of China under Grant 23PJD040.

Data Availability Statement: This study does not involve the generation, collection, or analysis of empirical datasets. As it focuses on theoretical analysis, conceptual framework construction, and literature review, no raw data, processed data, or supplementary datasets were produced or used during the research process.

Conflicts of Interest: The authors declare no conflict of interest.

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Citation: Liu, J.; Qu, B.; Wu, E.; *et al*. Analysis and Prospect of Wind Power Forecasting Methods from Multiple Perspectives. *International Journal of Network Dynamics and Intelligence*. 2025, 4(4), 100024. doi: 10.53941/ijndi.2025.100024