KAPITEL 1 / *CHAPTER 1* [1]

MULTI-TIME-SCALE WIND POWER PREDICTION MODELS: A REVIEW

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Introduction

Energy forms the foundational material support for human survival and societal advancement. Since the onset of the First Industrial Revolution, the development of human society has been largely driven by fossil fuel-based energy systems. However, fossil energy sources—primarily coal, oil, and natural gas—not only represent finite and depleting resources but are also major contributors to global carbon emissions. As a result, the intensifying threat of climate change is posing increasing risks to human well-being and environmental stability. In response, countries across the globe have proposed 'zero carbon' or carbon neutrality targets, underscoring a growing international consensus around the urgency of transitioning to renewable energy sources.

Accurate forecasting of wind power is vital to mitigate these challenges. It enables grid operators to optimize generation schedules, enhance dispatch efficiency, and maintain overall system reliability. Accordingly, a growing body of research has focused on developing predictive tools and strategic frameworks for better integration of wind energy. Recent advancements have explored various aspects, including system-level coordination scheduling, flexible dispatch in multi-energy systems, scenario planning using machine learning, and data-driven two-stage scheduling approaches. These efforts underscore the importance of coupling renewable energy development with advanced storage and transmission technologies, such as liquid hydrogen superconducting transmission. Additionally, studies have proposed the optimal configuration of hybrid energy storage systems and emergency control coordination strategies to improve grid resilience and manage the volatility inherent in renewable-dominated power networks [1].

Despite the substantial increase in wind power deployment, its inherent

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intermittency and unpredictability remain primary constraints on the secure and stable operation of electrical grids. As wind power penetration deepens, the complexity of ensuring grid stability correspondingly increases. Therefore, it is imperative for grid management entities to formulate generation and dispatch strategies grounded in reliable wind condition forecasts. Wind power prediction thus plays a decisive role in determining both the accuracy of electricity supply and the robustness of system operations.

1.1. Modeling approaches classification

The core focus of wind power prediction research lies in forecasting both wind speed and wind power output. Given the approximate cubic relationship between wind speed and power output, wind speed forecasts can serve as a proxy for power generation estimates. However, this indirect approach is constrained by the variability in turbine operating conditions, which can introduce substantial prediction errors. Consequently, recent studies have increasingly favored direct wind power forecasting approaches. These approaches can be classified based on several dimensions: prediction time scale, spatial resolution, input data types, and model characteristics. Furthermore, evaluation metrics used to assess forecasting performance vary across studies, adding to the methodological diversity of this field [2].

Temporal Classification: The prediction horizon—or lead time—plays a critical role in determining forecast accuracy. Generally, a shorter lead time is associated with higher predictive accuracy. Forecasting timeframes are typically categorized into ultra-short-term (0–4 hours), short-term (0–72 hours), and medium- to long-term (ranging from weeks to months). Each serves distinct operational needs: ultra-short-term forecasts are vital for power control, real-time grid scheduling, and intra-wind farm dispatch, whereas short-term forecasts support unit commitment decisions and electricity market operations. Medium- and long-term forecasts are used for strategic applications, such as wind farm planning and maintenance scheduling. However, due to the inherent unpredictability of atmospheric systems over extended periods, the

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majority of current research focuses on improving ultra-short- and short-term forecasting capabilities [3].

Spatial Classification: Wind power prediction is also categorized by spatial scale—ranging from individual turbines to entire wind farms and even regional clusters of farms. For small-scale installations comprising a few turbines, predictions at the individual turbine level are necessary for operational control and self-regulation. In contrast, for larger wind farms, aggregate power output forecasts are more relevant for grid integration and dispatch planning. Regional wind power predictions, which encompass multiple wind farms, are particularly important for broader grid management and regional energy balance assessments. To enhance prediction accuracy across all spatial scales, supplementary data inputs—such as turbine operational status, precise wind farm locations, and neighboring wind farms’ numerical weather prediction (NWP) data and output—are increasingly being incorporated into forecasting models [4].

Input Data Types: Input datasets used in wind power forecasting can be broadly divided into two categories: (1) those containing only wind power-related data and (2) those integrating both wind power and NWP information. The nature and quality of input data fundamentally limit the upper bounds of predictive accuracy. Historical datasets of wind speed, power output, and meteorological conditions are the most readily available and are sufficient for very short-term forecasting. However, due to the dynamic nature of atmospheric processes, models relying solely on historical data lack robustness over longer time horizons.

The inclusion of NWP data—produced by meteorological agencies using atmospheric equations and numerical methods—has significantly improved forecasting accuracy, particularly for short-term horizons. Nonetheless, NWP data typically have coarse spatial granularity, which can reduce prediction precision at the turbine or local wind farm level. Therefore, incorporating high-resolution and context-specific inputs (e.g., turbine status and micro-location weather patterns) is critical for improving the granularity and reliability of wind power predictions.

Model Characteristics: Wind power forecasting models can be broadly classified into two categories: physical models and statistical models.

- **Physical Models** are the earliest form of wind forecasting methods. They predict wind power by solving equations derived from fluid dynamics and atmospheric physics, accounting for turbine-specific parameters and geographical conditions. These models integrate NWP data, turbine configurations, and site-specific factors to simulate the conversion of wind speed into electrical power. However, the infrequent updates and lower temporal resolution of NWP data, along with the computational demands of physical models, render them less suitable for short- and medium-term forecasting. Nonetheless, physical models are particularly valuable for new wind farms that lack sufficient historical operational data [9].
- **Statistical Models** rely predominantly on historical data and are typically simpler and more computationally efficient than physical models. They utilize observed wind speed, wind power output, and NWP forecasts to identify patterns and correlations, drawing from established mathematical and statistical theories. With the accumulation of operational data, statistical models can achieve high levels of accuracy, provided appropriate methodologies are employed to extract meaningful features from complex datasets. Consequently, statistical models continue to represent a key area of research in the advancement of wind power prediction techniques [4].

Statistical Modeling Approaches: Statistical methods include traditional statistical models, machine learning algorithms, and hybrid modeling strategies.

- **Traditional Statistical Models**—such as the persistence method and autoregressive models like ARMA—forecast future values based on historical trends. While the persistence model, which uses current conditions as forecasts, is sometimes effective for ultra-short-term predictions, it lacks adaptability for longer timeframes. ARMA models, though simple to construct, are often inadequate in dynamic environments characterized by gusty winds or shifting weather patterns [7].
- **Machine Learning Models** outperform traditional approaches by offering

greater flexibility and learning capacity. These include classic algorithms such as support vector machines (SVMs), k-nearest neighbors with fuzzy logic, logistic regression, and random forest (RF) models. A significant advancement in this area is the adoption of **deep learning**, which is now integral to wind speed and power forecasting. These models are typically categorized into:

- *Spatial Models*, such as convolutional neural networks (CNNs) and deep belief networks (DBNs), which are adept at identifying spatial dependencies within gridded meteorological data.
- *Temporal Models*, such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and gated recurrent units (GRUs), which excel in processing sequential data. While RNNs can suffer from vanishing gradients, LSTMs and GRUs offer improved long-term dependency learning and computational efficiency.

Hybrid Models and Optimization Techniques: Given the inherent complexity of wind energy systems and the multifactorial influences on wind behavior—particularly during extreme weather events—single-model approaches often fall short. **Hybrid forecasting models** have thus emerged as a vital research direction. These models combine the strengths of various methods to enhance predictive accuracy [8].

Hybrid models are typically classified into two categories:

- **Weighted Ensemble Forecasting** involves combining multiple model outputs using weighted averages. This method can employ fixed weights, optimized through error-minimization functions, or dynamic weighting schemes that adapt in real time to changing conditions.
- **Fusion-Based Forecasting** enhances model accuracy through optimization of both inputs and internal parameters. Techniques such as wavelet transform (WT) and empirical mode decomposition (EMD) are used to stabilize non-stationary time series data. Additionally, data mining methods like rough set theory and principal component analysis help reduce dimensionality without sacrificing information richness. For model training and optimization, metaheuristic algorithms such as genetic algorithms and firefly algorithms are used to

overcome local optima and fine-tune model parameters. Furthermore, **error correction models** refine initial predictions by learning from forecast residuals [10].

This layered, multi-stage approach—integrating input preprocessing, model optimization, and output correction—has become increasingly prominent in the pursuit of more accurate and resilient wind power forecasting systems.

1.2. Ultra-short-term models for wind power predictions

This section provides a comprehensive review of the literature concerning ultra-short-term forecasting of wind speed and wind power. The focus is on methods developed to address the challenges of predicting wind energy output over very short lead times (typically ranging from a few minutes to several hours). The reviewed studies are categorized primarily based on the type of forecasting models employed. Additionally, key attributes such as input data types, evaluation metrics, and spatial scales used in the analyses are summarized. Input data used in these forecasting models generally fall into two categories: those containing only wind power data and those that incorporate both wind power data and meteorological variables.

Traditional statistical models have played a foundational role in ultra-short-term wind power forecasting due to their effectiveness in analyzing historical patterns and extracting data features. These models primarily rely on classical time series techniques to generate forecasts based on observed trends and statistical relationships in historical data. Among these, autoregressive models and their extensions have been widely utilized [4].

- **Autoregressive Integrated Moving Average (ARIMA) Models**

The ARIMA model is a cornerstone of time series forecasting, particularly effective in handling non-stationary data. The autoregressive (AR) component captures the relationship between the current value of a time series and its preceding values, while the moving average (MA) component accounts for past forecast errors to adjust future predictions. The integrated (I) component involves differencing the data to

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achieve stationarity, making the ARIMA model suitable for real-world wind data, which often exhibit non-stationary characteristics. The general ARIMA model is denoted as ARIMA(p, d, q), where: **p** represents the number of autoregressive terms, **d** is the degree of differencing required to achieve stationarity, **q** refers to the number of lagged forecast errors in the prediction equation.

In ultra-short-term forecasting applications, ARIMA and its variants have been used to model both wind speed and power outputs. For example, some studies decompose wind speed into horizontal and vertical components, modeling them individually using ARMA techniques and subsequently integrating the results to derive overall wind direction and speed forecasts. Other approaches apply dual ARMA models in a multi-class forecasting framework. This involves using a logistic classification model to segment data into distinct regimes, followed by separate ARMA-based predictors tailored to each class [5].

- **Extensions and Hybrid Approaches**

The Seasonal ARIMA (SARIMA) model extends ARIMA by incorporating seasonality, making it particularly useful for time series with recurring patterns. SARIMA has been effectively integrated with probabilistic methods such as Markov Chain Monte Carlo (MCMC) to estimate both short-term wind fluctuations and persistent wind conditions. These hybrid methods have demonstrated that SARIMA, while maintaining computational simplicity and forecasting speed, can still deliver a high degree of predictive accuracy when tuned properly. Such combinations enhance the robustness of forecasts, particularly under fluctuating atmospheric conditions that typify ultra-short-term horizons [6].

- **Long Short-Term Memory (LSTM) Networks**

Long Short-Term Memory (LSTM) networks represent a significant improvement over traditional recurrent neural networks (RNNs) by addressing their limitations in capturing long-term dependencies due to vanishing or exploding gradients. LSTMs incorporate gating mechanisms—specifically, the input gate, forget gate, and output gate—that regulate the flow of information into and out of a memory cell. This gated architecture enables the network to retain relevant information over long sequences and discard irrelevant inputs, making it particularly effective for time series forecasting tasks [7].

1.3. Short-term models for wind power predictions

This section provides a comprehensive overview of the literature addressing short-term wind speed and wind power forecasting, with an emphasis on the unique challenges associated with this forecasting horizon. The reviewed literature is categorized based on the types of models employed, while also summarizing the input data types, evaluation metrics, and spatial scales considered in each study. Input data for short-term forecasting are typically divided into two main categories: one comprising solely wind power information, and the other combining wind power data with meteorological observations or numerical weather predictions. In the domain of short-term wind power prediction, a considerable volume of research has focused on the application of traditional statistical models. These earlier studies laid a foundational basis for more advanced forecasting methodologies and significantly contributed to the technical evolution of predictive models in this field. The techniques used in short-term prediction closely mirror those applied in ultra-short-term forecasting; therefore, only key studies and applications are summarized below.

- **Support Vector Machine (SVM)**

Support vector machines (SVMs) are also widely adopted in short-term wind power forecasting, often as part of hybrid model frameworks. For instance, SVMs have been combined with ARIMA to enhance predictive accuracy. A notable variant, the least squares support vector machine (LSSVM), simplifies the optimization process by converting inequality constraints into equality constraints and minimizing squared errors. This modification results in computational efficiency and faster model execution, making LSSVM particularly suitable for large-scale and real-time wind forecasting tasks. When paired with techniques like phase space reconstruction and Markov chains, LSSVMs show strong predictive performance [5].

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- **Artificial Neural Networks (ANN)**

Artificial Neural Networks (ANNs) are widely utilized in short-term wind power forecasting due to their capacity for nonlinear modeling, self-adaptation, and learning. Research has employed ANN to analyze both temporal and spatial aspects of wind speed variations. While ANNs are advantageous for their flexibility, ongoing studies aim to further enhance their efficiency and stability in wind forecasting applications [11].

- **Backpropagation Neural Network (BP)**

Backpropagation (BP) networks, a subset of ANN architectures, are commonly used to model complex relationships between meteorological variables and power output. These networks operate by propagating errors backward through layers during training to refine predictions. A standard BP network comprises an input layer, one or more hidden layers, and an output layer, through which it generates forecast results. Although BP networks may not achieve state-of-the-art performance compared to more recent deep learning methods, they remain valuable for their simplicity, transparency, and ease of implementation, making them suitable for baseline comparisons and educational use in wind power prediction modeling [9].

1.4. Mid and Long-term models for wind power predictions

Modern distribution networks are undergoing a profound transformation. Historically designed as radial structures for unidirectional power flow—from centralized generation sources to medium and low-voltage consumers—they are now evolving into active networks due to the growing integration of distributed energy resources (DERs). One of the most significant contributors to this shift is the proliferation of photovoltaic (PV) installations, which introduces both opportunities and challenges, particularly concerning the variability and intermittency of solar generation.

Accurate forecasting of mid- to long-term wind power generation plays a pivotal role in enhancing power system planning, optimizing dispatch strategies, improving operational management, and increasing the effective utilization of renewable energy within the power grid. These forecasting capabilities are essential to achieving large-scale coordination, mutual aid, and complementary dispatching among various renewable energy sources. However, unlike short-term forecasting, mid- to long-term prediction introduces significant challenges due to several inherent limitations—such as the reduced reliability of meteorological forecasts over extended horizons, scarcity of long-term historical power generation data, and the more complex, nonlinear nature of wind power behavior over prolonged periods.

Given the fundamental differences between short-term and mid- to long-term forecasting contexts, conventional short-term techniques are not directly transferable. Moreover, traditional statistical models often fall short in meeting the accuracy demands of mid- to long-term predictions due to their limited capacity to handle highly dynamic and uncertain environments. As a result, there remains a pressing need for more effective and adaptable forecasting methodologies tailored to the unique characteristics of this temporal scale.

To address these challenges, recent research has explored the application of advanced machine learning models and hybrid frameworks. These approaches aim to improve predictive performance by integrating data-driven techniques with ensemble learning strategies.

In recent years, machine learning (ML) models have emerged as a robust and versatile approach for mid- to long-term wind power forecasting. Traditional models such as k-nearest neighbors (KNN) and artificial neural networks (ANNs), as well as deep learning variants, have been extensively utilized due to their capacity to model nonlinearities and to generalize from limited data.

These models are particularly effective in learning complex mappings between input features—such as high-altitude and surface wind speed observations—and output variables like power generation. For instance, ANNs have been employed to establish correlations between wind speeds at various altitudes and to transform environmental parameters into energy output estimations. Likewise, KNN algorithms have been used to identify and weight similar historical wind patterns to infer future wind dynamics

[7].

The choice of machine learning technique often hinges on factors such as the volume and quality of available data, the computational resources at hand, and the level of complexity inherent in the wind behavior at the targeted geographical location. While deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) generally yield superior predictive accuracy, they demand considerable data and computational power. In contrast, traditional ML models offer interpretability and efficiency, making them suitable for scenarios with constrained resources.

Overall, the growing adoption of ML-based models has substantially advanced the field of mid- to long-term wind forecasting. These models contribute significantly to the stability and flexibility of power systems by offering improved forecast precision, ultimately supporting the broader integration of wind energy and the progression toward sustainable energy infrastructure.

To further enhance forecast accuracy and reliability, hybrid models that integrate traditional statistical methods with machine learning or deep learning techniques have gained increasing attention. These composite frameworks aim to capitalize on the complementary strengths of different models—such as the interpretability of statistical models and the high representational capacity of neural networks [8].

In summary, the weighted combination model represents a sophisticated solution for mid- to long-term wind power forecasting. Its ability to adapt dynamically and integrate heterogeneous model outputs makes it an essential tool for improving forecast quality in complex, uncertain environments. The implementation of such hybrid models is instrumental in ensuring the stable and efficient operation of wind energy systems over extended time frames, thereby supporting strategic planning and policy development for renewable energy integration.

Conclusion

The global commitment to achieving carbon neutrality has accelerated transformative advancements in renewable energy systems, positioning wind energy as a foundational pillar of sustainable power generation. As the integration of wind power into modern energy systems intensifies, the demand for accurate, high-resolution, and rapid-response forecasting models has become increasingly critical. These predictive capabilities are indispensable for ensuring power grid reliability, optimizing operational decision-making, and enhancing the overall economic viability of renewable energy deployment.

This review has undertaken a comprehensive synthesis of the methodological progression in wind power forecasting, with a focus on the interdependence between forecasting time horizons—ranging from ultra-short-term to mid- and long-term scales—and their corresponding modeling strategies. By systematically classifying wind speed and power prediction methodologies and examining their structural and temporal characteristics, this work proposes an integrated taxonomy that aligns theoretical advancements with practical engineering imperatives.

Beyond consolidating the current state of knowledge, this review advocates for the future development of forecasting frameworks that strike a balance between predictive accuracy, computational efficiency, and model interpretability. Such systems should be designed not only to meet technical performance benchmarks but also to integrate seamlessly into institutional planning and operational processes within the broader context of the global energy transition. Addressing these multifaceted demands will be essential to unlocking the full potential of wind energy and supporting a resilient, low-carbon power grid.