Innovative Approaches to Wind Power Forecasting: A Comprehensive Review

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Abstract

Accurate wind power forecasting is essential for the seamless integration of wind energy into modern power systems, yet it remains a challenging task due to the inherent variability of wind, complex atmospheric dynamics, and the influence of local terrain. Traditional forecasting models often struggle to capture these complexities, particularly for short-term and intra-hour predictions. Machine learning (ML) methodologies have emerged as transformative tools for addressing these challenges. By leveraging large datasets and advanced algorithms, ML models can identify intricate patterns and significantly enhance prediction accuracy. Techniques such as deep learning, ensemble methods, and hybrid approaches integrate weather data with historical power output to improve spatial and temporal resolutions. Despite their promise, challenges like data quality, model interpretability, and computational demands require further research to fully optimize ML applications in wind power forecasting. The global transition toward smart grids, driven by the increasing penetration of renewable energy sources (RES), underscores the importance of reliable forecasting. Wind energy, as a key RES, plays a pivotal role in reducing greenhouse gas emissions and mitigating global warming. However, the stochastic nature of wind energy complicates power system analysis and management. Accurate forecasting is critical for enhancing power system security, supporting sustainability, and facilitating economic transactions in energy markets. This review examines ML-based methodologies for wind power forecasting, categorizing them into supervised, unsupervised, semi-supervised, and reinforcement learning techniques. It highlights their adaptability, scalability, and real-time capabilities while addressing challenges posed by noisy data, dynamic system behaviors, and complex grid configurations. Hybrid and ensemble models, in particular, demonstrate exceptional potential in overcoming these challenges. By identifying research gaps and emerging trends, this study provides strategic insights into developing innovative ML-driven forecasting methods, supporting effective grid management in an energy ecosystem increasingly dominated by RES.

Keyword: Wind power forecasting; Machine learning; Renewable energy; Smart grids; Hybrid models; Sustainability

1. Introduction

The Integrating wind energy into modern power grids poses substantial challenges due to its intermittent and unpredictable nature [1][2]. The variability of wind can disrupt grid stability, complicate load balancing, and necessitate costly reserve capacities to manage fluctuations. Furthermore, the decentralized and remote locations of wind farms often strain transmission infrastructure, requiring advanced grid management strategies to ensure reliable operation. The rising global demand for energy, coupled with the finite nature of fossil fuel reserves, has driven a significant shift towards RES [3][4]. Among these, wind energy stands out as an abundant, clean, and sustainable resource. However, the generation of wind power is highly dependent on geographical and meteorological conditions, introducing complexity and uncertainty to its integration into power systems. Accurate wind power forecasting is crucial to addressing these challenges. By predicting wind energy output with high precision across various time horizons, forecasting enables the safe and stable operation of power grids [5]. It facilitates effective scheduling, dispatching, and resource allocation while minimizing disruptions caused by wind variability. Considering the inherent volatility and randomness of wind, this study explores the potential of artificial intelligence (AI)-based approaches for wind power forecasting[6][7][8]. AI offers transformative solutions to overcome the complexities of wind energy integration[9][10]. By leveraging AI-driven forecasting models, grid operators can achieve more accurate predictions of wind energy output, enabling better operational planning [11]. Moreover, AI enhances real-time grid optimization through advanced energy management systems, dynamic demand-response mechanisms, and predictive maintenance for wind turbines and associated infrastructure [12][13][14]. These innovations help mitigate variability and support the seamless incorporation of wind energy into the combined operation of plant [15]. Addressing these issues will enable the full realization of AI's potential in driving a sustainable and reliable energy ecosystem dominated by renewable sources like wind energy. Forecasting methods broadly fall into three categories:

- **Physical Approach:** Considers meteorological and geographical factors, such as humidity, surface roughness, temperature, terrain quality, and hub height.
- **Statistical Approach:** Identifies relationships between input and output variables using historical data.
- **Hybrid Method:** Combines physical and statistical approaches, leveraging their respective strengths to improve accuracy.

2. Forecasting Issues

Real-time forecasting in dynamic grid environments is a pivotal challenge for the effective integration of renewable energy sources like wind. The unpredictability of wind patterns, influenced by rapidly changing meteorological conditions, poses difficulties in aligning power generation with fluctuating demand. In dynamic grid environments, where load profiles and generation sources are constantly shifting, the stakes for accurate real-time forecasts are even higher [16]. The Fig. shows the different forecasting issues in power systems and these are described as given in Figure 1.

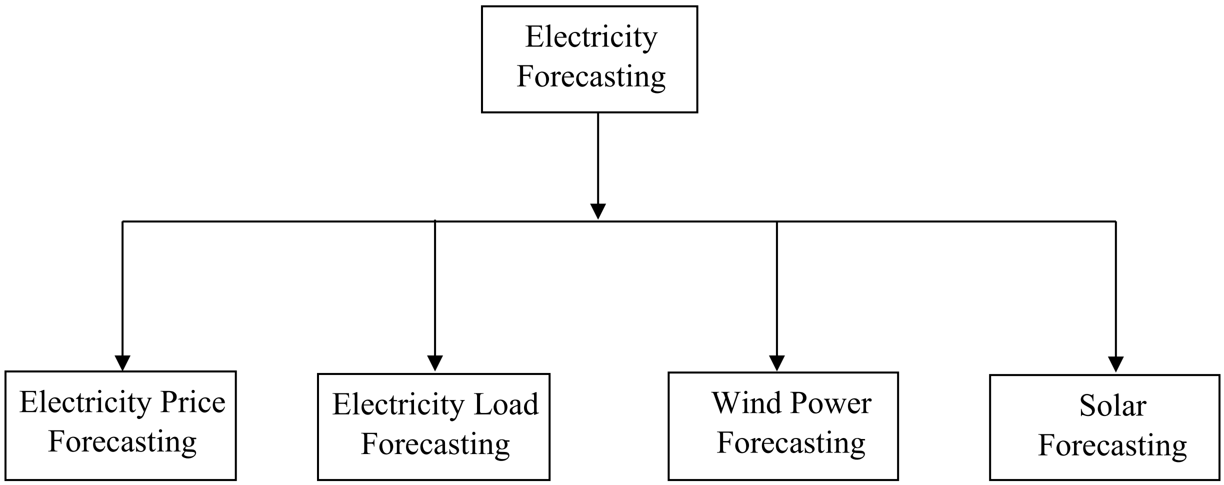

Figure 1 Different forecasting issues in power systems

Several forecasting challenges arise in power systems, as illustrated in Figure 1. These include electricity load forecasting, electricity price forecasting, wind power forecasting, and solar forecasting. Each presents unique complexities:

- **Electricity Load Forecasting:** Predicting future load demands over different time scales, ranging from hourly to yearly, to optimize grid operations.
- **Electricity Price Forecasting:** Estimating future electricity prices, closely tied to load predictions, to maximize market efficiency and profitability [17].
- **Wind Power Forecasting:** Addressing the inherent uncertainty of wind velocity to enhance the integration and efficiency of wind energy in power grids. Accurate forecasting reduces system balancing costs and improves planning [18].
- **Solar Forecasting:** Predicting solar radiation for optimal operation and management of solar power plants using intra-hour, intra-day, and day-ahead perspectives [19].

Key challenges in AI-driven wind power forecasting include:

Wind power forecasting is inherently stochastic due to the unpredictable nature of wind, which varies in speed, direction, and turbulence[14]. Accurately predicting these fluctuations is challenging, often resulting in large discrepancies between forecasts and actual production, particularly over short time frames. This unpredictability, along with rapid changes in electricity demand and weather conditions, leads to market price fluctuations, introducing risks for both energy producers and consumers, especially in deregulated markets[20]. Furthermore, forecasting consumer energy demand is complicated by factors like weather, economic activity, and social behavior. As the grid incorporates more renewable energy sources, including wind and solar, these stochastic fluctuations make balancing supply and demand increasingly difficult, as traditional power plants cannot adjust as quickly to these rapid changes [21].

- **Temporal and Spatial Variability:** Rapid changes in wind speeds complicate accurate, real-time predictions.
- **Grid Balancing:** Unreliable forecasts can disrupt frequency and voltage stability, requiring costly balancing measures.
- **Data Latency:** Delays in data transmission impact the accuracy and timeliness of forecasts.
- **Integration of Distributed Energy Resources (DER):** Coordinating distributed energy sources with wind generation adds complexity to grid management.

AI-based methodologies offer significant promise in overcoming these challenges. Techniques such as deep reinforcement learning, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) are particularly effective in processing large, high-frequency datasets to capture non-linear dependencies in wind patterns [22][23]. AI models can also incorporate real-time grid data, weather forecasts, and historical performance to dynamically adjust predictions. Moreover, AI-powered energy management systems can support automated decision-making, such as activating demand-response programs, optimizing battery storage utilization, or curtailing generation to prevent overload. These systems enable a proactive approach to grid management, ensuring stability even amidst the variability of wind energy. Despite these advancements, the practical implementation of AI in real-time forecasting faces challenges such as the need for robust data pipelines, the high computational requirements of advanced models, and the need for interpretability to build trust among grid operators. Addressing these hurdles will be critical for the successful deployment of real-time forecasting solutions in dynamic grid environments.

3. Need of Wind Power Forecasting in Power Systems

AI-driven real-time wind power forecasting plays a transformative role in market strategies and decision-making within dynamic energy systems. By providing accurate and timely predictions, it empowers stakeholders to make informed decisions that optimize operations, enhance profitability, and ensure grid stability. Wind power forecasting is crucial for:

- Managing the variability of wind energy.
- Aligning electricity production with demand.
- Facilitating grid operators in planning and decision-making.
- Optimizing the design and location of future wind power plants.

- Improving grid reliability and operational efficiency under variable conditions.
- Supporting contract negotiations and market strategies between suppliers and customers.
- Enhancing bidding strategies for power suppliers and consumption plans for end-users.

4. Challenges in Wind Energy (Power) Forecasting Approaches

Integrating wind energy into modern grids is essential for a sustainable future, but it presents significant difficulties due to its intermittent and unpredictable nature [24]. These challenges are compounded by non-linear and stochastic behaviors, which can impact both forecasting and grid stability. AI has emerged as a critical tool to address these complexities, improving forecasting accuracy, optimizing grid management, and supporting decision-making in market environments. Forecasting approaches face various challenges due to the non-linear and dynamic nature of wind power generation [25][26]. The key methods include:

- **Physical Approach:** Relies on meteorological factors and numerical weather predictions (NWP) but struggles with short-term accuracy.
- **Statistical Approach:** Utilizes historical data to identify correlations but is limited in capturing non-linear dynamics.
- **Hybrid Approach:** Combine physical and statistical techniques, improving forecasting accuracy by leveraging strengths from both.

Recent advancements highlight the integration of AI and big data technologies. For instance:

Zhao *et al*. (2022) [27] Explored the role of big data and AI in wind power forecasting, emphasizing advancements in feature engineering, deep learning, and hybrid techniques. In particular, the speed of the wind, meteorological information, and imagery from satellite data are among the several forms of data that are identified and utilized in AI-based wind energy forecast studies. Moreover, to potential problems, including processing massive amounts of data and enhancing accuracy with cutting-edge AI approaches, the report emphasized the expansion of analysis on this subject, especially after 2018. Furthermore, it emphasized frontier breakthroughs and study topics in wind power forecasting, such as feature engineering, machine learning, deep learning, data cleaning, large data processing, and hybrid forecasting techniques.

Lagos *et al*., (2022) [28] Reviewed wind power forecasting methods, focusing on prediction timeframes, probabilistic models, and integration into distributed power systems and microgrids. Resulting in the discovery of several groups of connected articles. Each cluster is represented by a cluster that is connected to shared references or content. The clusters encompass a broad variety of subjects related to wind power forecasting, including statistical models, ANN, NWP, and hybrid models. The use of probabilistic prediction and the incorporation of wind power into distributed power plants and micro-grids are emphasized. Specifics on the data sources and performance assessment indicators for the models used for forecasting are also included in the conclusion.

5. Input Variables for Wind Forecasting

The highly uncertain nature of wind originates from the variability and unpredictability of its derivatives, significantly impacting the reliability of power systems. Improved forecast reliability directly correlates with reduced operational costs of wind power integration into the grid. This relationship highlights that large-scale wind power adoption can lead to substantial cost savings for wind farm operators while enhancing overall system efficiency. Despite these advantages, wind power forecasting remains a challenging task due to the inherently stochastic nature of wind. Wind speed time series exhibit unique characteristics, including high volatility, non-linearity, non-stationary behavior, and significant complexity. The selection of input variables is crucial for the accuracy of wind power forecasting models. The effectiveness of these models depends on the integration of relevant variables and their historical behaviors. Input variable selection can be broadly categorized into two types:

- **Exogenous Variables:** Include external factors such as weather conditions or market data that influence wind power dynamics.

- **Non-Exogenous Variables:** Focus solely on intrinsic wind power characteristics without external dependencies.

Noman *et al.* (2021) [29] highlighted the difficulty in forecasting wind speed because of its erratic and non-stationary characteristics, particularly when considering the integration of wind power into the electrical grid. The investigated system uses a selection of features and transferred learning methods to present the multistep short-term speed of the wind forecasting system. It assessed the effectiveness of several models, such as the persistent approach, shallow neural networks, and methods for transfer learning. The results highlighted that the nonlinear auto-regressive exogenous (NARX) model achieved reduced mean absolute error (MAE) and root mean square error (RMSE) in wind speed prediction when compared to other techniques. The influence of input selection of variables is also covered, which also offers a thorough analysis of the forecast outcomes. The overall goal of the project is to increase wind speed forecast accuracy to facilitate improved wind power integration into the electrical grid.

Zulkifly *et al.* (2021) [30] provided a system of rankings to assess how well ML models predict grid-connected photovoltaic systems' (GCPVs) production in Malaysia. Four ML models are used in their study: decision trees, linear regression (LR), gaussian process regression (GPR), and support vector machines (SVM). Mean Absolute Deviation (MAD), Mean Absolute Error (MAE), calculation time, Root Mean Squared Error (RMSE), and coefficient of determination (R^2) are among the assessment metrics that are employed. The method does not include other practical methods since it relies on high-resolution ground-based observations of PV system power production and meteorological information. The amount of computing power needed for every model is not taken into account in their study; this change is based on the size and complexity of the dataset.

6. Forecasting Models

Physical Models (Numerical Weather Prediction - NWP): Physical models incorporate atmospheric physics to predict wind behavior.

Haupt *et al.* (2020) [31] highlighted the creation of the Kuwait Renewable Energy Prediction System (KREPS), which forecasts the output of energy from renewable sources with an emphasis on solar and wind power through the integration of AI techniques with physical models. The system forecasts wind and solar power generation using measurements, atmospheric physics, and AI techniques. The Analog Ensemble (AnEn) is used to provide probabilistic predictions and quantify unpredictability, while ML techniques like StatCast-Wind and StatCast-Solar are utilized for short-range forecasting. The design of the KREPS display, which enables users to examine and interact with power prediction products as well as historical forecasts and observations, is also covered. The findings highlight that AI techniques improved sustainable energy forecasting accuracy and offered useful decision assistance for end users.

Guo *et al*. (2022) [32] explained that the use of wind energy is becoming more and more important, and reliable wind power forecast models are necessary to keep the electricity grid stable. It draws attention to the many classifications and techniques of wind energy forecasting, with a particular emphasis on the application of AI models, especially for short-term forecasting. It also highlighted how physical elements, such as the wake effect in wind farms, affect the accuracy of wind power predictions. It presented a wake-effect-aware neural network system with physics inspiration to increase the precision of short-term wind energy forecasts.

Statistical Models (Time Series Analysis): Statistical models analyze historical data to detect patterns and trends.

Jiang *et al*. (2021) [33] explored the difficulties in predicting wind speed and the limits of several forecasting techniques, including AI, statistical, numerical modeling, and spatial correlations. In addition to introducing the idea of combined models for forecasting, it suggested a unique combination approach for forecasting wind speed shortly. The four components of the suggested system are interval forecasting, point forecasting, system assessment, and optimum sub-model selection. The construction of an integrated forecast model, the best sub-model selection, and interval predictions are only a few of their study's achievements that are highlighted. Finally, an analysis of the suggested system and its possible uses in power systems is included.

Kim and Hur (2020) [34] highlighted the significance of forecasting wind power in light of the growing worldwide capacity for energy from renewable sources, of which wind energy is a significant component. It described various strategies for wind power forecasting, such as statistical models, physical models, and their combinations. Presented a short-term wind power forecasting model that makes use of spatial modeling to increase the accuracy of the wind speed forecast data. It mixed several statistical techniques, including autoregressive integrated moving averages with exogenous variables (ARIMAX), SVR, and Monte Carlo simulation (MCS). The suggested model was validated through an investigation on a turbine farm located on Jeju Island, which showed an increase in accuracy through the use of an ensemble forecasting technique. To tackle the issue of intermittent power fluctuations, it seeks to allow dependable electrical grid operation and the incorporation of renewable energy sources.

Combined (Physical + Statistical) Models: Combined models leverage the strengths of both statistical and physical methodologies.

Duan *et al.* (2022) [35] explained the creation of an innovative hybrid model for forecasting wind output in the short term. To get around the drawbacks of linear weighting combinations and increase accuracy in forecasting and stability, this model makes use of a decomposition technique, a nonlinear weighted combination, and two deep learning models (LSTM and PSO-DBN). Variational mode decomposition (VMD) is used by the model to break down the original wind energy series and extract local characteristics. LSTM and PSO-DBN are then used to build sub-series models for prediction. A hybrid forecasting model is produced by combining these models using a nonlinear weighting combining method based on PSO-DBN. Wind velocity information from a Chinese wind farm is used to validate the accuracy of the model and show how successful it is in comparison to other available techniques.

Tian *et al.* (2021) [36] explained the difficulties caused by wind power's erratic and intermittent nature, which might jeopardize the stability of the electrical energy supply. Their study suggests a unique decomposition-based wind speed forecasting model as a solution to this problem. The model separates historical data on wind speeds into stable variables with various frequencies using variational modal decomposition. After that, an echo phase system is used to forecast each component, and its parameters are optimized using an enhanced whale optimization method. Combining the forecasts from every part yields the final forecast. The model outperforms other innovative forecasting algorithms in terms of precision and capacity to capture fluctuations in wind speed when verified using actual data on wind speeds.

6.1 Wind Power Forecasting: Techniques and Advancements

Wind power forecasting has evolved significantly, employing a range of techniques to address the complexities of predicting this stochastic and highly volatile resource. Traditional statistical approaches, such as ARIMA and linear regression, provide foundational insights but often struggle in dynamic scenarios. Physical models based on NWP offer detailed forecasts but are computationally intensive and data-dependent. Machine learning (ML) and hybrid techniques have emerged as powerful tools, handling non-linear, non-stationary, and volatile time series data with superior accuracy.

Suárez-Cetrulo *et al.* (2022) [37] tackled the challenges of minute-by-minute wind power forecasting for energy markets. They proposed a novel method that accounted for turbine degradation and curtailing, using ML algorithms to evaluate predictability and assess wind-power relationships. Boosting ensembles demonstrated superior runtime efficiency, making them a cost-effective choice for day-ahead wind output forecasting. Table 1 shows the reviews by various authors about the State of Art for wind power Forecasting

Table 1 Review of wind power Forecasting

Author & Year	Aim	Technique Used	Advantage	Limitation

Zhao *et al*. (2022) [27]	Identify the data types used and analyze the big data and AI applied in WPFs.	AI techniques and big data analysis	Increased effectiveness and precision of forecasts	Handling big data sets
Lagos *et al*. (2022) [28]	Describe the models used to anticipate wind energy, with an emphasis on forecast uncertainty.	Statistical, ANN, NWP, and hybrid models	Emphasize different forecasting techniques and uncertainty considerations.	There is a narrow emphasis on particular prediction horizons.
Noman *et al*. (2021) [29]	Create a model for predicting short-term wind speed and assess its effectiveness.	Methods of transfer learning, shallow neural networks, and persistence	Greater accuracy in predictions, reduced MAE, and RMSE	Constrained with short-term forecasting
Zulkifly *et al*. (2021) [30]	Examine AI methods to predict the output of GCPV systems.	Decision Tree, SVM, GPR, and Linear Regression	Use of high-resolution data and thorough evaluation metrics	Does not include their study of computing resources.
Haupt *et al*. (2020) [31]	Create a forecasting tool for energy from renewable sources, with an emphasis on solar and wind energy.	Analog Ensemble, StatCast-Wind, and StatCast-Solar	Improved forecasting precision and probabilistic forecasts	Restricted to predicting during a brief period.
Guo *et al*. (2022) [32]	Examine the significance of WPF and present a neural network with physics influences.	Neural network with physics inspiration	Improved accuracy of short-term wind power forecasts	Limiting focus on near-term forecasting
Jiang *et al*. (2021) [33]	Provide a combination forecasting model and assess its efficacy for predicting wind speed.	Integrated prediction model	Choosing the best sub-model and interval prediction	inadequate mention of practical implementation
Kim and Hur (2020) [34]	Provide a short-term forecast of the wind power model and use an ensemble technique to evaluate it.	MCS, SVR, and ARIMAX	Higher precision with ensemble forecasting	Minimal focus is paid to long-term projections.
Duan *et al*. (2022) [35]	Create a hybrid model and assess its efficacy for projecting wind power in the short term.	VMD, PSO-DBN, and LSTM	Increased stability and precision	Confined to making short-term forecasts
Tian *et al*. (2021) [36]	Provide a model for forecasting wind speed based on decomposition and assess its capabilities.	Echo state network, variational mode decomposition	Increased precision and recording of changes in wind speed	Constrained to forecasting wind speeds.
Suárez-Cetrulo *et al*. (2022) [37]	Create a method to forecast high-frequency wind power and assess it with ML.	Boosting ensembles	More accurate prediction at a lower cost than competing ML methods	Restricted to forecasting one day ahead of time.

6.2 State of Art for Wind Power Forecast

Chai *et al* (2023) [38] focused on the model's framework and price factors while analyzing 62 literature parts on energy price forecasting (EPF) from 2012 to 2022. The significance of performance evaluation is emphasized, along with the use of data preparation and model development to increase accuracy. The purpose of the document is to offer information to market users and decision-makers regarding electricity.

Malhan and Mittal (2022) [39] offered a unique ensemble forecast methodology for long-term hydro and wind energy generation projection. In the initial phase, the model combines ARIMA and Bi-LSTM prediction; in its second stage, it employs diligent searching algorithms to find seasonal trends. The model is appropriate for forecasts made a year in advance, as evidenced by the low rate of errors for medium- to long-term projections in the data. The model's goal is to assist with strategic planning in power networks with significant penetration of energy from renewable sources. Table 2 shows the reviews by various authors about the State of the art for Wind Power Forecast

Table 2 Review of Wind Power Forecast

Author & Year	Aim	Technique Used	Advantage	Limitation
Chai *et al.* (2023) [38]	Examine forecasting power prices, with a focus on model optimization.	Different models for predicting	Insights for decision-makers and participants in the market	This only includes projecting power prices
Malhan and Mittal (2022) [39]	The current ensemble forecasting system to estimate wind and hydropower over the long term	Diligent Search Algorithm, Bi-LSTM, and ARIMA	Minimum mistake rates for projections that are mid- to long-term	Only able to make long-term forecasts

6.3 Key Techniques and Methodologies

- **Input Variables & Their Selection Techniques**

Singh *et al* (2021) [40] have outlined the five best practices for robust regression ML-extra tree regression, random forest (RF), decision-tree, gradient boosting machine (GBM), and kNN that are employed to boost the precision of short-term wind energy generation projections in Turkish wind farms located in the country's westward. Drawing polar diagrams enables one to investigate how input variables, such as wind direction, and speed, influence the creation of wind energy. The results show that a technique employing GBM learning performs better in estimating.

Mujeeb *et al* (2019) [41] have mentioned a two-phase DL method. Wavelet Packet Transform (WPT) was developed in the first phase to break down the previous wind power signals. Several external inputs, including calendar variables and Numerical Weather Prediction. Efficient Deep Convolution Neural Network (EDCNN), a novel prediction model, was used in the second stage for calculating wind energy. The Maine windmill ISO NE, USA massive data set was employed to evaluate the performance of the recommended predictive method.

- **Physical (NWP) Models**

Zhang *et al* (2020) [42] have built a Seq2Seq wind power output prediction model by fusing a multivariate time series clustering approach with a DL network. As inputs, historical wind data from actual wind farms and NWP data were used. The feature vectors were projected into the K-means method using the dimension reduction technique t-SNE, and further clustering of the inputs into distinct groups was achieved by employing diminished dimension. The predicted model exceeded other available forecasting techniques, according to the data.

Zhang *et al* (2019) [43] have provided background value optimization to estimate wind speed. Following this, fractional-order grey system models of varying orders were built. To lower the uncertainty, two NWP outputs, such as ECMWF and GRAPES-MESO, have been included in the prediction model. To fit the wind speed power scatter operation data, the support vector regression model was developed. The outcomes demonstrate that the prediction accuracy was increased by the presented grey combination strategy.

- **Statistical Models**

Ibrahim *et al* (2021) [44] highlighted how the tested dataset's forecasting ability is enhanced by the adaptive dynamic particle swarm algorithm combined with a guided whale optimization technique, which modifies the LSTM classification method's parameters. For feature selection, this method was used. RF, k-NN, LSTM, Average ensemble, and NN are used to compare the outcomes of this scenario. An examination of several tests, such as ANOVA and Wilcoxon's rank-sum tests, was conducted statistically to verify the algorithm's correctness.

- **Hybrid (Physical + Statistical) Models**

Donadio *et al* (2021) [45] have created two hybrid ANN and NWP models for forecasting wind power in extremely complicated terrain. The temporal resolution of the produced models is finely tuned. The initial model predicts each wind turbine's energy output precisely. The second version uses a fitted power curve to anticipate wind speed first, then converts it to power. Four normalized error measurements are used to assess the performance of various models. Python was used to automate tasks.

Devi *et al* (2020) [46] have started using a hybrid forecasting model to anticipate wind power to enhance prediction performance. The subseries data that is recovered using ensemble empirical mode decomposition (EEMD) was forecasted using an upgraded LSTM-enhanced forget-gate network (LSTM-EFG) model. The experimental findings demonstrate that the aforementioned forecasting model outperforms conventional forecasting models and functions as an operational tool for the management of wind power facilities.

Table 3 Research Gaps from the Preceding Works

Author's names and citations	Methods used	Advantages	Disadvantages
Singh *et al* (2021) [40]	ML (Extra Tree Regression, RF, Decision Tree, GBM, kNN)	Boosts wind energy predictions	High Complexity
Mujeeb *et al* (2019) [41]	Two-phase DL (WPT, EDCNN)	Handle higher-level computational tasks	Expensive
Zhang *et al* (2020) [42]	Seq2Seq	Exceeds other prior techniques	Inability to retain longer sequences
Zhang *et al* (2019) [43]	Fractional-Order Grey System, Support Vector Regression	Increased Prediction Accuracy	Limited availability of tools

Ibrahim *et al* (2021) [5]	Adapti ve Dynamic Particle Swarm + Guided Whale Optimization	Easy implementation	Slow Convergence
Khosravi et al (2018) [52]	SVR-RBF	Suitable for complex data patterns	Struggle with noisy data
Donadio *et al* (2021) [45]	Hybrid ANN and NWP models	Precise output for wind power predictions	Potential complexity
Devi *et al* (2020) [46]	EEMD for subseries data recovery and LSTM-EFG model for forecasting.	Enhanced wind power predictions	Faces implementation Struggle

6.4 Input Data Pre-processing

Santhosh *et al* (2019) [47] have suggested a novel, strong hybrid DL approach that preprocesses the raw data to improve prediction accuracy. Ensemble empirical mode decomposition, the most efficient signal decomposition method, was employed for preprocessing. Four constrained Boltzmann machines were assembled to create the Deep Boltzmann Machine model. To determine the time series' outcome, the anticipated outcomes are assessed. These algorithms produced more accurate findings.

López et al (2018) [48] have created the ESN using an LSTM design that blends the features of the two networks. This method was used as a target for the input signal, to extract characteristics automatically as the autoencoder approach; subsequently, a quantile regression was used to obtain a robust estimate of the expected target. These two layers are particularly important to the training process of this network: the output and hidden layers. The experimental findings demonstrate that the proposed strategy performs better across all global measures compared to the WPPT model.

Table 4 Reviews of Various authors on wind power predictions

Author's name and citations	**Methods used**	**Advantages**	**Disadvantages**
Santhosh *et al* (2019) [47]	Ensemble Empirical Mode Decomposition, DBM	Less human interaction	Complexity in Feature Extraction
López et al (2018) [48]	Quantile regression, autoencoder, and LSTM	Automatic feature extraction	Complexity in the training process

6.5 Wind Power Estimation Techniques

Demolli *et al* (2019) [49] have created ML methods that rely on daily wind speed data. The daily mean wind speed values were constructed using the hourly wind speed data, and the daily total wind power was estimated using the daily wind speed and standard deviation The findings demonstrated the viability of the RF, SVR, and xG Boost, SVR algorithms in long-term daily total wind power forecasting. These algorithms offer high power efficiency in unidentified geographic areas. RF is the most effective algorithm and provides acceptable outcomes.

Mujeeb et al (2019) [41] have mentioned a two-phase DL method. Wavelet Packet Transform (WPT) was developed in the first phase to break down the previous wind power signals. Several external inputs, including calendar variables and Numerical Weather Prediction.

Efficient Deep Convolution Neural Network (EDCNN), a novel prediction model, was used in the second stage for calculating wind energy. The Maine windmill ISO NE, USA massive data set was employed to evaluate the performance of the recommended predictive method.

- **Statistical Models**

Statistical models are widely used for wind power forecasting due to their ability to analyze historical data and identify patterns between input variables (e.g., wind speed, direction) and output (power generation). Techniques such as autoregressive integrated moving average (ARIMA), regression analysis, and support vector machines (SVM) are commonly employed. These models are effective for short- to medium-term forecasts and are computationally efficient [50].

Yin *et al* (2021) [51] have proposed a revolutionary two, three, one step wind power forecasting method called SHD-CSO-ELM (Secondary Hybrid Decomposition-Crisscross Optimization Algorithm-Extreme Learning Machine). The original wind power time series was sliced down using a novel secondary decomposition technique developed during the data pre-processing stage. The original time series was reduced into many intrinsic mode functions using the empirical mode decomposition method. The given method attained good efficacy.

Yildiz *et al* (2021) [52] have recommended using the two-step DL approach to anticipate wind power. The process of extracting features based on variational mode decomposition and converting them into images is covered in the first phase. Next, wind power was forecasted using an enhanced residual-based deep CNN. A dataset comprising wind power, wind direction, and meteorological wind speed was used. These variables are intimately connected. A wind farm in Turkey provided the combined dataset.

- **Traditional Models**

Duan *et al* (2021) [53] have started developing a reliable short-term hybrid wind power forecasting model using an LSTM neural network, which combines Sample Entropy and an improved variational mode decomposition. Next, to create a unique, robust hybrid model for wind power forecasting, the MCC was also used to replace the MSE in the traditional LSTM network. Lastly, to test the efficacy, four experiments were carried out utilizing actual data from two wind farms in China at various sampling intervals.

Heydari *et al* (2019) [54] have started using the Group Method of Data Handling Neural Network, Pareto analysis, and the modified Fruit Fly Optimization Algorithm to estimate wind speed. Furthermore, compared to the other models, this one performs better and has an acceptable error rate. The microgrid located on the island of Favignana in southern Italy has been subjected to the examination of renewable energy forecast. The findings indicate that this model performs well over a range of confidence levels.

- **Linear or Time Series (TS) Models**

Santamaría-Bonfil et al (2016) [55] have created a hybrid approach for wind speed forecasting that is based on Support Vector Regression. Time series of univariate wind speed were used to train this model. A genetic algorithm was used to adjust the parameters. Additionally, the time series stationary transformation was assessed. The approach yielded more accurate findings, according to the results.

Wang *et al* (2018) [56] have announced the creation of a new hybrid model for forecasting wind speed in the short term. This model includes adaptive noise, an enhanced complementary ensemble empirical mode decomposition, and an extreme learning machine with an autoregressive integrated moving average. This research also presents the findings from a comparative analysis of time series data pretreatment and postprocessing. This approach performs well enough.

Table 5 Several Reviews by various authors on wind power forecasting

Author's names and citations	**Methods used**	**Advantages**	**Disadvantages**
Demolli *et al* (2019) [49]	ML (RF, SVR, xG Boost)	Viability in long-term	Tuning of hyperparameters
Mujeeb *et al* (2019) [50]	Two-phase DL (WPT, EDCNN)	Handle higher-level computational tasks	Lack of interpretability
Yin *et al* (2021) [51]	SHD-CSO-ELM	Improves Stability	Requires more resources
Yildiz *et al* (2021) [52]	Variational Mode Decomposition, Enhanced CNN	Weight Sharing	Data Dependency
Duan *et al* (2021) [53]	LSTM, improved variational mode decomposition, Sample Entropy, MCC	Robust hybrid model	Dependency on data quality
Heydari *et al* (2019) [54]	Pareto analysis, Group Method of Data Handling Neural Network, modified Fruit Fly Optimization Algorithm	Better performance	Sensitivity to hyperparameter tuning
Santamaría-Bonfil *et al* (2016) [55]	Genetic algorithm, Support Vector Regression	Hybrid approach	Parameter tuning challenges

6.6 Artificial Intelligence (Ai) Models

Aly (2020) [57] has reported on extremely precise hybrid DL clustered models for predicting wind speed and power utilizing various AI systems. In this study, several combinations of Recurrent Fourier Series (FS), ANN, Wavelet (WNN), and Kalman Filter (RKF) are employed. Tests and proposals are made for twelve distinct hybrid vehicles. The K-fold cross-validation approach was used to validate this work utilizing several unseen data sets. All other models are not as good as the hybrid clustered model of RKF and WNN.

Lin and Liu (2020) [58] have implemented a DL neural network with a 1-s sample rate to forecast wind power using a very high-frequency SCADA database. The physical operation of offshore wind turbines served as the basis for the engineering of the input characteristics, and Pearson product-moment correlation coefficients were used to further examine the relationships between them. The results of the simulation show that the projected method can forecast wind power with high accuracy while lowering computing time and cost.

6.7 Probabilistic or Interval Forecasting

Zhou *et al* (2019) [59] have developed the K-Means-LSTM network model and the nonparametric kernel density estimation model for wind power spot prediction. To create a new LSTM sub-prediction model, the K-Means clustering technique groups wind power effect variables into multiple clusters. The mean integrated squared error criteria were used to optimize the bandwidth. Based on simulation findings, the suggested model has improved prediction accuracy, and the bandwidth optimization model has more narrow prediction intervals with higher interval coverage rates.

6.8 Comparison of Computation Time

Chen *et al* (2018) [60] have suggested a new technique based on EO, SVRM, and LSTMs called Ensem LSTM. This technique uses a nonlinear learning ensemble for DL time series prediction. The implicit information of wind speed time series is used and explored by a cluster of LSTMs with different neurons and hidden layers. The fine-turning top layer provided the final ensemble forecast for wind speed. It is capable of more accurate predictions.

Jiao *et al* (2018) [61] have announced the creation of a novel forecasting technique using the BP algorithm and stacked auto-encoders. Initially, the features are extracted from the reference data sequence using a three-layered SAE. The BP method was used to adjust the network's weights following the addition of one output layer to the stacked autoencoders. The PSO was implemented to obtain the optimal network design. The experimental findings demonstrate that this strategy produces more consistent and effective performance for short-term wind power forecasting. Under various time steps, the accuracy improvement is, on average, 12% higher.

6.9 Methods of Wind Power Forecasting

Wang *et al* (2020) [62] have unveiled a hybrid approach to calculating wind power that employs Bayesian model averaging and Ensemble Learning (BMA-EL). To generate different training subsets, SOM clustering, and K-fold cross-validation are implemented. To develop the system, these learning subsets are exported into three fundamental learners: RBFNN, BPNN, and SVM. With more precision and security, this approach can forecast wind power production under different scientific circumstances.

- **Deterministic or Point Forecasting**

Fu *et al* (2018) [63] have offered a hybrid model for 10-min wind speed forecasting that is based on an LS-SVM model and uses an altered version of the Cuckoo Search method to improve forecasting model parameters. When compared to the other four models, it can produce meaningful predicting results. The suggested hybrid model also shows the least variations in MAPE values at each forecasting point, suggesting that it can increase wind speed forecasting accuracy. It might increase the use of renewable energy sources and be used for wind farm dispatch.

Hu *et al* (2020) [64] have established a stacked hierarchy of reservoirs (Deep ESN) by integrating the DL framework into the fundamental echo state network to estimate energy consumption and wind power output. To verify the correctness and dependability of the provided model, two comparison instances and an expanded application are examined. These examples demonstrate how this model works better than the current ones. Furthermore, Deep ESN exhibits significant gains in terms of mean absolute error, root mean square error, and other metrics when compared to the echo state network.

- **Probabilistic or Interval Forecasting**

Hossain *et al* (2021) [23] have started using a DL model to increase the accuracy of the forecast for extremely short-term wind power output at Australia's Bodangora wind farm, which is situated in New South Wales. It was made up of gated recurrent unit (GRU) layers, convolutional layers, and a fully connected neural network. The 5-minute interval data sets from the wind farm are utilized. Another set of data from Australia's Capital wind farm was utilized to assess the effectiveness even more. It is noted that in both data sets, this model performs better.

Table 6 Various reviews by authors regarding wind power predictions

Author's names and citations	**Methods used**	**Advantages**	**Disadvantages**
Chen *et al* (2018) [60]	Ensemble LSTM	Improved forecasting accuracy	Evaluation against benchmark models for generalization and robustness
Jiao *et al* (2018) [61]	BP Algorithm, Stacked Auto-Encoders	Applicable to various data types	Consume more memory resources
Wang *et al* (2020) [62]	Hybrid (BMA-EL, RBFNN, BPNN, SVM)	More precision and security	Has memory limitations
Fu *et al* (2018) [63]	LS-SVM	Improved wind speed forecast accuracy	Complexity in hybrid methods

7. Forecast Techniques and Methodologies

The numerous debates and important problems in wind power forecasting research are essential to improving the precision and dependability of these forecasting systems. The choice and optimization of input variables for various forecasting models is a major topic of study. Numerous research works emphasize how crucial it is to choose pertinent input factors such as wind direction, speed, calendar variables, and NWP data. Predictive models for wind energy generation that combine statistical and physical methods have demonstrated the potential for increasing forecast accuracy. To further improve prediction accuracy, there are still difficulties in determining the best combination of input variables and improving preprocessing methods. A key issue for discussion is to assess the estimation speeds and scalability of different approaches for predicting wind power. The goal is to develop models that are efficient in the delivery of accurate forecasts, especially in real-time applications where rapid judgment is crucial. Researchers are currently tackling scalability difficulties with wind power forecasting systems to render them more accurate and beneficial for broader adoption in renewable energy management systems. Scalability issues are particularly challenging when dealing with large datasets and intricate modeling techniques.

- **Basic Theory of Models Used**

Advanced AI and ML algorithms as well as conventional statistical models are among the array of models utilized in wind power forecasting research. For prediction purposes, statistical models such as SVR, RBFNN, and GRNN use statistical analysis of past data together with mathematical correlations. In wind speed and power data, these models frequently excel at identifying linear or nonlinear trends. Conversely, AI and ML models like CNN, FFNN, and DL architectures like LSTM networks use sophisticated algorithms to learn from data, extract features, and provide predictions. To attain both accuracy and computing efficiency in wind power forecasting applications, hybrid models that combine the characteristics of statistical and AI/ML approaches are also widely used.

- **Benchmark Models**

Niu *et al* (2020) [65] have improved forecasting methods by introducing a new sequence-to-sequence model that uses the Attention-based Gated Recurrent Unit (AGRU). By using GRU block activations that are hidden, it embeds the responsibility of connecting several forecasting processes. To further determine which input variables are most crucial, an attention mechanism was created as a feature selection technique. Their results are compared with other benchmarks for wind power forecasting to verify the efficacy of the AGRU model.

Zameer *et al* (2017) [66] have introduced the GP-based ensemble regressor for wind power prediction. The actual power and the anticipated power produced by this model nearly match. The outcomes show that in comparison to individual regresses, the ensemble regressor performed admirably. Five distinct farms situated across Europe provided the data that was used to test various models. Wind farms located around the globe may utilize the technique shown here to forecast and train their wind generation.

- **Feed Forward Neural Networks (FFNN)**

Liu et al (2021) [67] have presented the wind speed forecasting system that uses the Data Area Division (DAD) technique with the DL neural network model. Three modules make up the system: predicting, preparing, and extraction modules. Good results for short-term wind speed forecasts are shown by numerical simulation results. For short-term wind power forecasting in the Hokkaido region, the system's prediction deviation is less than 6% year-round, according to the examination of wind power impact indicators. This has significant practical implications.

Al-Janabi *et al* (2020) [68] have proposed a model for producing electricity from wind termed multi-objectives renewable energy generation (MORE-G). There are five fundamental phases to this concept. To produce the energy, another model known as DCapsNet, a multilayer neural network, was created. The MORE-G is distinguished by its ability to reduce material prices, upgrade the Ministry of Electricity's control, and handle one of the actual issues.

➢ Elman Recurrent Neural Network (ERNN)

Liu *et al* (2018) [69] have made public a novel hybrid wind speed prediction model that was created by combining the empirical wavelet transform, the Elman neural network, and the long-short memory network. Within the suggested hybrid EWTLSTM-Elman model, the Elman and LSTM neural networks are utilized to forecast the high-frequency and low-frequency sublayers, respectively, while the EWT was utilized to break down the raw wind speed data into many sub-layers. Excellent multi-step forecasting results are obtained using the suggested framework.

Tian *et al* (2018) [70] have introduced a new multi-objective satin bowerbird optimizer method and a new data preprocessing technique based on the hybrid Elman neural network model and data preprocessing strategy. Multiple forecasting instances based on eight wind speed datasets are presented to validate the system's forecasting efficacy. The findings show that the supplied system has superior predicting accuracy and stability.

➢ Linear Neural Networks with Time Delay (LNNTD)

Yuan *et al* (2017) [71] have created a hybrid model that combines a fractionally integrated moving average with a least squares SVM. Initially, the wind power series' long memory properties were identified using the autocorrelation function analysis. The linear components of the wind power series were then predicted using the autoregressive fractionally integrated moving average model. Lastly, by combining the forecast outcomes, the wind power prediction was generated. The findings show that the supplied hybrid model has a greater accuracy when compared to other models.

Peng *et al* (2017) [72] have created a hybrid model to address the nonlinearity of wind speed time series. This two-stage decomposition approach combines the Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise and Variational Mode Decomposition. After that, an extreme learning machine was combined with an upgraded AdaBoost-RT algorithm. The suggested model is contrasted with non-denoising techniques. The study's findings suggest that the hybrid model that was suggested produces more accurate forecasts.

Table 7 Research Gaps from Published Works

Author's names and citations	**Methods used**	**Advantages**	**Disadvantages**
Niu *et al* (2020) [65]	Attention-based GRU, Feature Selection	Better spatial information	Hard to parallelize
Zameer *et al* (2017) [66]	Genetic Programming-based Ensemble Regressor	Admirable performance	Dependency of hyperparameters tuning
Liu *et al* (2021) [67]	DAD	Good short-term wind forecasting results	Limited information
Al-Janabi *et al* (2020) [68]	MORE-G model, DCapsNet	Reduced material prices	Potential scalability challenges

Liu *et al* (2018) [69]	Empirical Wavelet Transform, Elman NN, LSTM	Better multi-step forecasting outcomes	Complexity of hybrid model

- **General Regression Neural Network (GRNN)**

Naik *et al* (2018) [73] have announced the development of an effective, non-iterative hybrid Kernel Ridge Regression and Empirical Mode Decomposition model for predicting wind speed and power with a substantial degree of accuracy in the short term. In that order, the EMD-KRR model was put to the test for three hours, ten minutes, one hour, and thirty minutes. Using the wind power data from three actual wind farms, the performance measures of the provided model validate its accuracy and efficacy in generating a forecast when compared to all other prediction models.

Harrou *et al* (2019) [74] have embraced the decision tree bagging ensembles technique for forecasting wind power. It can combine many techniques and lower the total error. Four established prediction techniques have been compared to the wind power prediction performance of bagged trees. The prediction quality of the investigated approaches is demonstrated using real measurements taken from an actual wind turbine every 10 minutes. The bagged trees regression technique achieved the highest prediction performance, according to the results.

- **FFNN Parameters Optimization by Genetic Algorithms**

Shahid *et al* (2021) [75] have announced that they have discovered an innovative way to estimate wind power for seven wind farm datasets across Europe using genetic long short-term memory. By making use of the genetic algorithms bioinspired architecture, it controls the number of neurons and window size of LSTM layers. Comparing GLSTM to current methods, the improvement in wind power estimates ranges from 6% to 30% on average.

Santamaría-Bonfil *et al* (2016) [55] have created a hybrid approach for wind speed forecasting that is based on Support Vector Regression. Time series of univariate wind speed were used to train this model. A genetic algorithm was used to adjust the parameters. Additionally, the time series stationary transformation was assessed. The approach yielded more accurate findings, according to the results.

- **Particle Swarm Optimization-Based Neural Networks**

Khosravi *et al* (2018) [76] have declared three kinds of ML algorithms to forecast wind power, direction, and speed. A layered feed-forward neural network served as the basis for the initial model. Radial basis function SVR is the second model. PSO optimization was used for the third model ANFIS. The SVR-RBF model compares well with the other two models when comparing the statistical indices for the actual and projected data.

- **Concept of Single and Multiple Step-ahead Wind Power Forecasting**

Mahmoud *et al* (2018) [77] have created a wind power-generating device called a self-adaptive evolutionary extreme learning machine. The self-adaptive differential evolution optimization approach was used in SAEELM to optimize the output weight matrix in a single hidden layer extreme learning machine. A variety of case studies utilizing actual Australian wind farms have been compiled. Through comparison with other models, this strategy achieved a high level of effectiveness.

Wang *et al* (2020) [78] have presented a novel hybrid Laguerre neural network and singular spectrum analysis-based wind power forecasting technique. Initially, the wind power series was examined using single-spectrum analysis. The Laguerre neural network was then developed. The wind farm in Xinjiang, China, was the subject of an investigation of this methodology. Results from prediction performance showed that the suggested model is more accurate.

- **Wavelet Transform**

Nascimento *et al* (2023) [79] have presented a unique transformer-based DNN architecture combined with wavelet transform for multivariate time series forecasting, utilizing several meteorological data as input for wind speed predictions for the next six hours. Statistical measures were used to assess the predicted performance results in addition to training and making conclusions. Also, results demonstrated that predicted efficiency was improved by combining the transformer model with wavelet decomposition.

- **Data Used and Pre-processing**

Zhang *et al* (2019) [80] have created a short-term wind speed prediction model based on an online sequential outlier resilient extreme learning machine and hybrid mode decomposition technique. HMD thoroughly dissected the wind speed throughout the data pre-processing phase. The experiment findings demonstrate that this strategy was a successful means of wind speed prediction. The crisscross algorithm was used to optimize the hidden layers and input weights.

8. Discussion and Key Issues

- Identifying relevant input variables is challenging. Too many can lead to overfitting, while too few may cause underfitting, missing essential wind patterns.
- Increasing the number of turbines and regions raises computational load, which can cause delays in real-time processing, reducing prediction effectiveness.
- Real-time decision-making needs fast processing and accurate predictions. AI must balance prediction speed with accuracy, especially given wind volatility and market fluctuations.
- High computational costs for AI models make them expensive, especially for smaller operators, and can strain infrastructure, causing delays.
- Data quality and consistency are crucial for effective AI training. Inconsistent data can lead to biased models and inaccurate forecasts, harming grid stability and market performance.

- AI models must remain adaptable to diverse wind environments. Over-specialized models may require frequent retraining to handle evolving conditions.

9. Future Directions in Ai-Driven Wind Energy Integration

As the demand for clean, renewable energy sources like wind power grows, the future of AI-driven wind energy integration lies in embracing emerging technologies that can further enhance forecasting accuracy, grid adaptability, and overall efficiency. Several key technological advancements—such as quantum computing, federated learning, and edge AI—are poised to play a transformative role in overcoming the challenges of integrating wind energy into modern grids. Furthermore, improving grid adaptability to accommodate high levels of renewable energy is crucial to achieving a sustainable and resilient energy future.

i. **Quantum Computing:** Quantum algorithms can process data faster, improving forecasting and optimization for wind energy. This could speed up decision-making, enhance grid operations, and optimize market bidding strategies.

ii. **Federated Learning:** This allows wind farms to collaborate on forecasting models without sharing sensitive data, improving accuracy and generalizing predictions across regions.

iii. **Edge AI:** By processing data locally, edge AI allows real-time decision-making on wind farms and grids, improving response times and operational efficiency, especially in decentralized energy systems.

iv. **Grid Adaptability:** AI will help manage renewable energy fluctuations through dynamic grid management, energy storage optimization, and demand response, ensuring stability and efficiency as renewable energy sources like wind increase.

v. **Digital Twins:** Virtual models of wind farms and grids will simulate operations, helping operators optimize strategies, predict maintenance needs, and improve grid management before real-world implementation.

The future of AI-driven wind energy integration is promising, with advancements in quantum computing, federated learning, and edge AI. These technologies will improve wind power forecasts, enhance grid adaptability, and support real-time decision-making. As AI evolves, it will optimize energy storage, grid operations, and renewable integration, accelerating the transition to a sustainable, renewable-powered future.

10. Limitations of Literature Review

The review emphasizes short-term forecasting, with limited focus on medium- and long-term models essential for strategic planning.

i. Emerging and niche methodologies developed in recent years may not be comprehensively covered.
ii. A lack of standardized evaluation metrics across studies complicates direct comparison of forecasting models.
iii. Geographical bias exists, as most studies focus on specific regions, limiting global generalizability.
iv. Practical scalability and real-world deployment of the reviewed models are not deeply analyzed.
v. Computational efficiency, including training times and resource demands, is insufficiently addressed.
vi. The socio-economic impacts and cost-benefit analyses of forecasting models are not discussed.
vii. Data constraints, such as challenges in handling noisy or incomplete data, are overlooked.
viii. Advances in emerging technologies like quantum computing and optimization are excluded.
ix. Integration of wind forecasting with other renewable energy sources is not explored.

These limitations highlight potential areas for enhancing future research in wind power forecasting.

11. Conclusion

This review comprehensively examines the state-of-the-art techniques in wind power forecasting, highlighting the evolution and application of statistical, machine learning (ML), and artificial intelligence (AI) models. Hybrid approaches combining these methodologies demonstrate significant promise in improving prediction accuracy and addressing the inherent complexities of wind data. The discussion underscores the importance of optimizing input variables, improving preprocessing techniques, and enhancing model scalability for real-world applications. Despite notable advancements, challenges remain, including the need for standardized evaluation metrics, better handling of large and noisy datasets, and addressing scalability for broader adoption. Future research should focus on integrating forecasting models with other renewable energy sources, exploring the socio-economic impacts of wind forecasting, and leveraging emerging technologies like quantum computing. The insights presented in this review provide a foundation for developing more robust and efficient forecasting systems, contributing to the broader goal of sustainable energy management and optimizing the utilization of wind resources. Wind power predictions are critical for the integration of renewable energy sources into the electrical grid and ensuring grid stability. However, wind power's erratic and intermittent nature presents significant forecasting challenges. Traditional methods relying on statistical analysis and meteorological models often fall short in delivering accurate predictions. AI techniques, including ML and deep learning (DL) algorithms, have shown potential for improving the accuracy of wind power projections across different time scales. However, limitations in data availability, technological capabilities, and the complexity of wind turbine systems pose persistent difficulties. Factors such as demand pattern fluctuations, the influence of distributed energy resources (DER), data accuracy and accessibility, and policy and regulatory ambiguities further complicate load forecasting within the current electrical system. Moreover, price forecasters in the global wholesale power market face challenges such as the influence of renewable energy sources, market structure, data restrictions, market design, and regulations. Integration with grid operations, data unpredictability, variability, intermittency, and the need for precise geographical and temporal forecasts are critical aspects influencing wind power forecasting (WPF). Errors inherent in statistical techniques or meteorological models also impact the precision of wind power projections. In conclusion, addressing these multifaceted challenges requires continued innovation, interdisciplinary collaboration, and investment in advanced forecasting technologies. By doing so, the field can achieve more accurate, scalable, and actionable wind power forecasts, thereby supporting the transition to a more sustainable and resilient energy future.

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