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**Review Article**

# A comprehensive review on traditional and cutting-edge approaches for wind speed/power forecasting

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## ABSTRACT

Wind forecasting is essential for improving the effectivness of wind energy in overall power system. İt helps in the areas like improving stability of grid , energy planning and to support the effective market operation. This paper is an attempt to examine traditional as well as advanced forecasting methods, from the classical statistical approaches to modern data-driven and hybrid techniques. The traditional techniques including time-series analysis as well as the numerical weather prediction (NWP) techniques are quite good but are incapable of capturing the complexity and variation patterns of wind pattern. While the cutting-edge techniques, including the machine learning & deep learning have helped to increase the forecasting accuracy, hybrid models, have given increasingly promising results as they offer a balance between the high accuracy and computational requirements by merging the traditional and modern approaches used for wind speed and/power forecasting. This study shows the significant value achieved by hybrid approachs, reporting Root Mean Square Error (RMSE) values of 0.1089 m/s for statistical approach, 0.02 m/s for intelligent approaches, and 0.0096 m/s for hybrid approaches. Using a real-world wind dataset, the performance of several widely used forecasting models is evaluated and compared. This study provide an symmetrical analysis of advantages and disadvantages of various forecasting approaches across different time scale & weather condition. It also elaborates persistent challenges, e.g., limited data availability and the requirement for better model interpretability as well as real-time adaptability. The review concludes that although data-driven and hybrid models currently achieve the best performance, additional research is needed to enhance interpretability and data integration. This research improve reviews on wind forecasting, highlighting latest developments and practical uses. İt also provide helpful guide for researchers and idustry experts to understand present & future opportunities in the field.

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## INTRODUCTION

Several organizations are moving toward the production of renewable energy in the current energy scenario. The sustainable energy sources enhance the reliability and reduce the carbon impact of power systems [1,2]. Wind energy is one of the most effective renewable energy sources. However, because of its intrinsic variability and intermittent nature, integrating it into modern power networks is extremely difficult [3]. The need to switch to alternative energy sources is further highlighted by the rising price of crude oil. Wind power continues to be one of the most appealing renewable options because of its great efficiency and low emissions. The installed wind power capacity in India is shown in Figure 1.

Forecasting of wind speed and power is essential for many tasks in the wind energy sector and for the general functioning of the power system [4]. For those involved in the electrical market, such as energy dealers and wind farm operators, forecasting is crucial. Operators to schedule maintenance and improve turbine performance use predictions of wind speed and power. They can reduce unplanned outages and related expenses by scheduling maintenance during times of low wind by predicting wind conditions [5]. When market-related decisions need to be taken under uncertain circumstances, accurate forecasting is also helpful.

Moreover, the long-term planning for wind farms and further extension of transmission lines is supported by wind and/or power forecasts. Accurate wind forecasting is also helpful to reduce the gap between planned and actually generated power, thus reducing the financial risk of contributors to the energy market. In brief, wind forecasting is very much essential for using the wind energy efficiently, smooth integration of grid, market operations, planning of maintenance schedules, infrastructure development along with maintaining system reliability.

Following are the major benefits of precise wind speed and/or power forecasting :

- Wind speed and/or power forecasting helps in improving/maintaining the system balance, avoid the outages, and ensuring steady performance of grid.
- It supports the optimal operation of turbine and reduces the operating costs.
- It also contributes to the economic dispatch, unit commitment along with power system decision-making process. [6].
- It also helps to improve the weather measurement technique and design. Due to this weather and energy, forecasting can be enhanced.
- More accurate wind forecasting helps in improving the utilization of renewable energy, lowers emissions and thus contributes to cleaner air.
- Higher accuracy of prediction results in better turbine protection, maintenance scheduling and to reduce disruptions when extreme weather conditions occur.
- Accurate forecasting improves reliance on renewable energy, lowering emissions and contributing to cleaner air.

The forecasting of wind depends on various weather parameters such as direction, humidity, temperature, speed, and pressure. The traditional and cutting-edge approaches are typically used to obtain precise forecasting, as shown in Figure 2.

Traditional approaches include the persistence method, physical method, and statistical method. Cutting-edge approaches, such as machine learning and artificial intelligence techniques, and hybrid techniques. Traditional approaches are stable, interpretable, and simple, while cutting-edge approaches improve accuracy, adaptability, data

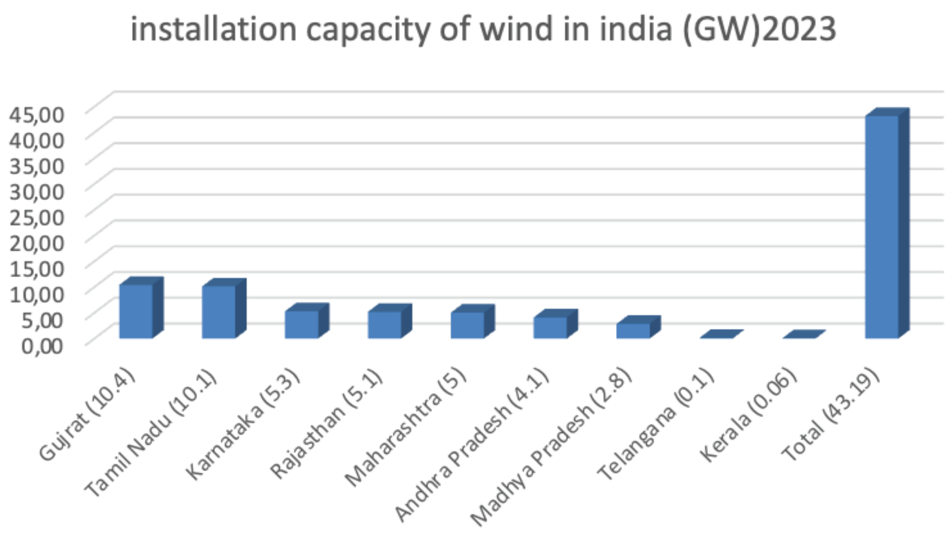


**Figure 1.** Installation capacity of wind power.

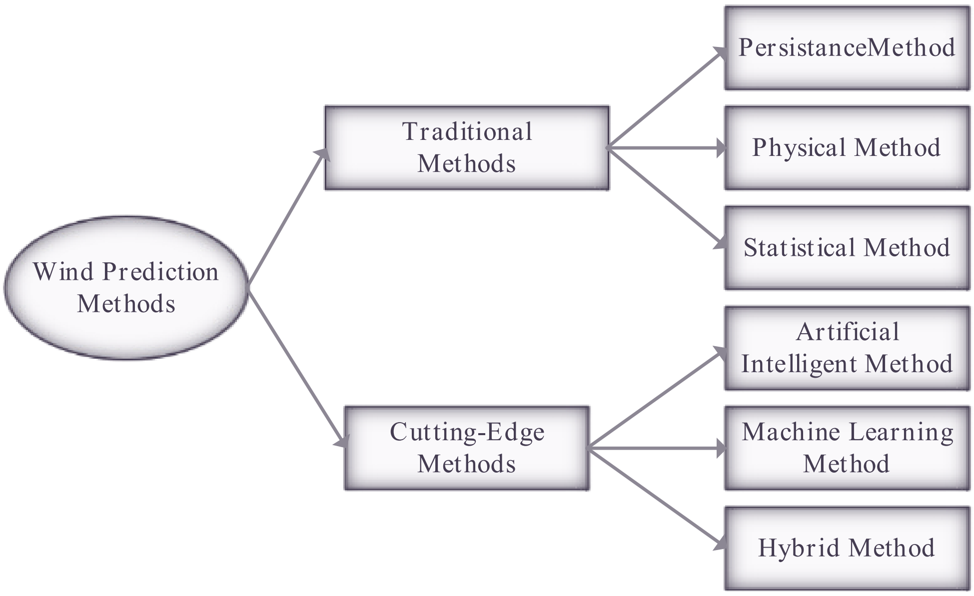


**Figure 2.** Classification of wind speed/power prediction methods.

integration, and uncertainty handling. Both approaches have their significance and can be complementary, providing a range of tools and techniques for wind speed/ power forecasting that can be tailored to specific needs and requirements. Other classifications of wind forecasting schemes are (i) weather-based forecasting and (ii) time-series-based forecasting approaches [7]. For weather-based forecasting models, the accuracy of wind forecasts is heavily dependent on the morphology of the terrain at the location of the wind turbines. On the other hand, Statistical methods anticipate future values only based on historical wind speed readings [8].

**Research Gaps and Novelty**

Many previous researches have been done on wind speed and wind power forecasting, which are extensive and cover a wide range of methods like traditional methods, deep learning and data-driven methos, and hybrid methods. This review paper differentiates itself from previous works by providing a technically rigorous analysis of traditional as well as state-of-the-art forecasting methods, resulting in the following core contributions:

- This paper comparess the traditional and modern approaches using multiple metrics, while previous researches rely on individual models. The evaluation of predictive/forecasting model is done on the basis of factors such as scalability, accuracy of forecasting, computational complexity as well as suitability across changing forecasting horizons.
- This review presents a complete examination of recent developments, including future hybrid architectures and novel learning techniques such as ensemble-based and deep reinforcement based frameworks, covered minimally in present academic discourse.
- This paper examines the real-world models , focuses on geographical issues, considers grid integration, and the explores the need for support during real-life conditions.
- The work identifies the main research gap and gives future direction for further improvement by making use of IoT sensors in case of high-resolution data along with a transparent model for improving accuracy.

Main goals of this paper are as follows::

- To provide an intensive review of prior research on wind speed/power prediction techniques.
- Identification of gaps, unresolved questions, and/or areas requiring further investigation.
- To evaluate traditional, machine learning, and hybrid approaches across multiple performance metrics, proficiency, precision, and applicability for forecasting of wind, and evaluation of the latest hybrid machine learning algorithms.
- A discussion on the working of models in real-life conditions or applications.
- To make contributions in advancing knowledge in field of wind speed and/power prediction/forecasting.

The review provides guidance on forecasting methodologies which enable grid operators to adjust with variability of wind power with higher precision, thus supporting more stable as well as reliable grid operation. This paper may help the wind farm operators to choose the best models for forecasting/prediction so as to improve the performance of turbines and to reduce the unwanted mechanical stress. By using cutting-edge techniques, wind farms will get highly efficient wind power/energy. The participants of market can easily manage the varitions in generation of wind by knowledge of strength, and limitations of different forecasting techniques discussed in this review.

The review is also helpful to scholars in highlighting research gaps, providing opportunities alongwith new ideas for development of novel models with innovative ideas. Moreover, this work is helpful to improve the efficiency and accuracy of prediction/forecasting techniques. This review also provides motivation to engineers to create more reliable as well as accurate prediction/forecasting systems. Its findings can help to develop standards and best practices for incorporating wind energy into the present grid infrastructure, ensuring that the most appropriate forecasting technologies are used. This study analyzes the forecasting results in several climate conditions, helping planners prepare for climate-driven shifts in wind behaviors and thereby supporting the maintenance of long-term wind energy viability.

## CLASSIFICATION OF WIND SPEED/POWER PREDICTION METHODS

Wind prediction methods can be classified into several categories based on their approach, complexity, and data sources, and these categories are discussed below:

### Traditional Approaches

The time series and statistical methods are involove in traditional approach for wind forecasting and these approaches are briefly discussed in Table 1.

### Persistence Methods

Persistence is the humblest approach to predicting the wind. Persistence forecasting is a basic and straightforward method used in wind speed/power forecasting. It relies on the assumption that the future wind conditions will be similar to the most recent past conditions. In some incredibly short periods of predictions (a few minutes to hours) [9], this simpler approach is even more reliable than a Numerical Weather Prediction model. The model's precision falls dramatically as the prediction lead time increases.

On a functional level, the most recent available wind power measurements, as provided by the SCADA system [10], should be used. Persistence forecasting offers simplicity and real-time applicability; it has limitations in capturing changing wind conditions, incorporating external factors, and providing accurate forecasts beyond short time intervals. Every forecast technique should be measured compared to the standard of the classic persistence approach to evaluate how much better it may be than persistence-derived forecasts [11].

### Physical Methods

In [12], various weather based models, and complex atmospheric models are used for wind forecasting. Obstacle shelter, local surface roughness and fluctuations, wind farm layouts, orography influences, within wind farms, increasing local wind velocity, speed up or down, and wind turbine power curves are among the factors taken into account in these models. For downscaling, the physical method employs a meso or micro-scale model that interpolates these wind speed projections to the level of wind producers [13].

Figure 3 shows the forecasted wind speed and power generated by the NWP model. Different NWP models are utilized in a model chain with varied hierarchical levels [14]. Meteorological observations made by meteorologists, weather monitoring stations, satellites, and other sources around the world serve as the model chain's starting point [15]. Long-term wind speed predictions are better served by NWP (Numerical Weather Prediction) techniques and have been found to save up to 20% in fossil fuel. Some researchers related to the NWP technique for wind prediction are given in Table 2.

**Table 1.** Classification of traditional models for wind forecasting

| Category | Method | Description |
|---|---|---|
| Persistence methods | 'Persistence method' | Assumes that future wind conditions will be similar to the most recent past conditions. |
| | 'Climatology method' | Uses long-term historical data to predict future wind patterns. |
| Physical methods | 'Numerical weather prediction (NWP) models' | Utilizes complex mathematical models based on atmospheric physics to simulate and predict wind behavior. |
| | 'Computational fluid dynamics (CFD) models' | Uses numerical analysis and algorithms to solve and analyze problems involving fluid flows, applied to wind behavior around structures and terrains. |
| | 'Mesoscale models' | Focuses on atmospheric processes at the mesoscale (1-1000 km) to predict wind patterns over larger regions. |
| Statistical methods | 'Time series analysis' | Analyzes historical wind data to identify patterns and forecast future values. |
| | 'Regression analysis' | Identifies relationships between wind speed and other variables (e.g., temperature, pressure) to make predictions. |
| | 'ARIMA models' | Auto-Regressive Integrated Moving Average models for capturing temporal dependencies in wind data. |

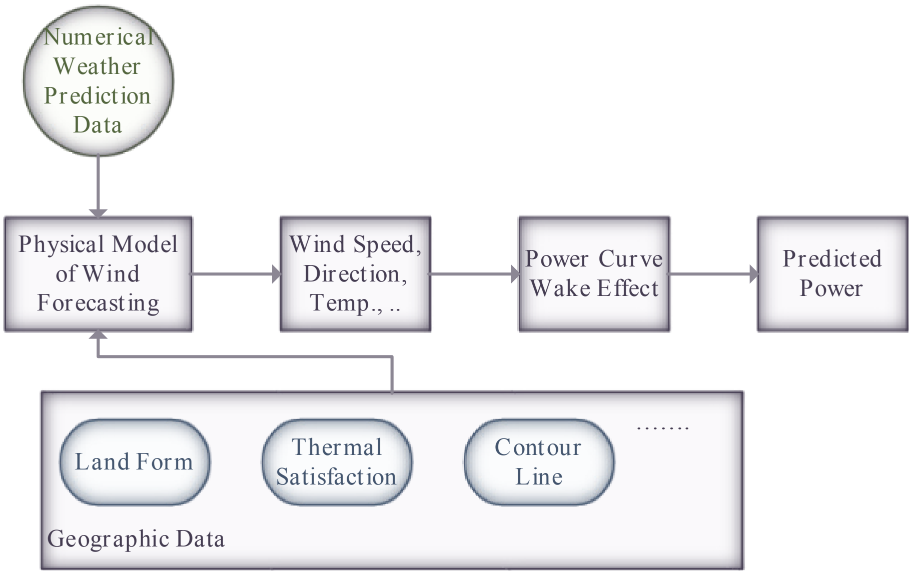


**Figure 3.** Physical model.

**Table 2.** Physical method for wind speed/power prediction

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Al-Yahyai et al. (2011) [16] | "Nested ensemble NWP approach for wind energy assessment" | NWP | RMSE=1.753 |
| Marcos Lima et al. (2017) [17] | "A meteorological statistic model for short-term wind power forecasting" | NWP, Kalman filtering | RMSE= 1.6513 |
| Saini and Ahuja (2019) [18] | "A research on wind power forecasting techniques" | NWP | Not determined |
| Liu et al. (2022) [19] | "Numerical weather prediction enhanced wind power forecasting: Rank ensemble and probabilistic fluctuation awareness" | NWP | $RMSE_4$=13.39% $RMSE_{16}$=18.89% |

Physical approaches are being used to improve the NWP approach in the direction of achieving precise weather forecasts [20]. In [21], it is reported that the physical approaches require a lot of computation, and they are displayed on supercomputers. The physical methods need weather parameters for precise forecasting [22]. Physical systems improve the final output (wind prediction) utilizing the unprocessed information from Numerical Weather Prediction, depending on the physics of the sub-atmospheric boundary layer [23].

### Statistical Methods

Statistical modeling techniques are widely used in wind speed/power forecasting to capture the relationships and patterns in historical data. These techniques employ statistical principles and methods to analyze past observations and generate forecasts. The correlation between online average power data and other variables is examined using statistical methods. Statistical models are easier to develop and maintain than other models. The drawback of this strategy is that the forecast inaccuracy rises as the forecast period rises [11]. The following are the details of various statistical models for wind speed/power forecasting:

Regression analysıs models ınclude the following:

#### Linear Regression

Simple linear regression models the relationship between a dependent variable (e.g., wind speed) and a single independent variable (e.g., temperature). Multiple linear regression models extend simple linear regression by including multiple independent variables to predict the dependent variable.

#### Non-Linear Regression

It models relationships that cannot be adequately described with linear models. Techniques include polynomial regression and other forms of regression that can handle more complex relationships between variables.

Time Series Analysis and ARIMA Models include the following:

#### Moving Averages

- **Simple moving average (SMA)**

Computes the arithmetic mean of a fixed window of previous data points, providing a smoothed representation of the time series.

- **Weighted moving average (WMA)**

Follows the same principle as SMA but assigns varying weights to the observations within the window, with more emphasis typically placed on recent values.

**Exponential Smoothing**

- **Simple exponential smoothing (SES)**

Applies exponentially decreasing weights to historical observations, giving the strongest influence to the most recent data. It is most suitable for time series without evident trends or seasonal patterns.

- **Holt's linear trend method**

Extends SES by incorporating a trend component in addition to the level, enabling improved forecasting for data exhibiting a linear trend but lacking seasonality.

- **Holt–Winters method**

Builds upon Holt's approach by adding a seasonal component, making it appropriate for time series that simultaneously exhibit trend and seasonality.

**ARMA (Autoregressive Moving Average) Models**

It combine autoregressive (AR) and moving average (MA) processes to represent a time series using both its lagged values and historical error terms [24]. These models capture short-term temporal dependencies as well as the effects of past disturbances. Four general modeling strategies are commonly adopted:

1. **Component-wise decomposition:** Wind speed is separated into lateral and longitudinal components and modeled independently.
2. **Dual ARMA modeling:** Separate ARMA models are used for wind speed and wind direction, and the results are combined for forecasting.
3. **Vector auto-regression (VAR):** A multivariate framework is used to forecast multiple interrelated wind characteristics simultaneously.
4. **Reduced VAR models:** A simplified VAR structure is implemented to reduce computational complexity while maintaining prediction capability.

The ARMA model order is defined by both AR and MA orders, indicating how many past values and past errors are included in the model.

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

ARIMA models extend ARMA by introducing a differencing step to enforce stationarity—meaning that the mean and variance of the series remain constant over time. An ARIMA model is defined by three parameters:

- **Autoregressive (AR) component**

Represents the relationship between the current value and several lagged observations. AR models assume the time series can be expressed as a linear combination of its historical values plus random noise [25]. They are effective for modeling short-term structure, trends, and serial correlations. Because wind speed exhibits sequential dependence and inherent variability, ARMA and ARIMA frameworks are often well-suited for its prediction.

- **Integrated (I) component**

Applies differencing to the raw data to remove trends or other non-stationary behavior, making the series more suitable for modeling.

- **Moving average (MA) component**

This component uses the effect of past forecast/prediction errors values on the present value. MA models represent the present values as a linear combination of previous ones. The model's order helps to determine how many lagged error values are considered.

**State-Space Models**

State-space models help to represent the underlying process in terms of combination of unobserved-states and observations. They help in providing more flexibility to capture complex relationships and these can help to handle different data patternsThese models include Kalman filter aswell as Bayesian models. Statistical modeling techniques provide a solid framework for analyzing and forecasting wind speed/power data. The choice of the appropriate model depends on the characteristics of the data, the presence of trends or seasonal patterns, and the desired forecasting horizon. These techniques have been widely employed in practice and form the foundation for more advanced and hybrid models used in wind speed/power forecasting. Literature work on wind forecasting using statistical methods has been done by some researchers. The AR, ARMA, ARIMA, Bayesian approach, and grey forecasts are all statistical approaches. These approaches can be utilized to tackle difficulties in fields such as engineering, economics, and science disciplines that include a large amount of data and interdependent explanations. For wind speed prediction, [26] proposed a combination of two models, i.e., ARMA and wavelet transform. The low-frequency characteristics of the entire wind speed are extracted using the wavelet transform. In [27], an Auto Regression Integrated Moving Average approach outperforms the BPNN (back propagation neural network) in forecasting short-term intermissions. In [28], a Bayesian methodology has been proposed to describe the wind resource and estimate one-hour-ahead wind speeds. The modeling outcome has shown that the Bayesian approach can be operative for the prediction of wind speed and power.

For predicting short-term fluctuations in wind power, an approach that depends on a Markov-switching auto-regressive (AR) approach with a time-varying coefficient was developed in [29]. The approach has the advantage of being simple to use in calculating full predictive densities. In [30], the authors propose an autoregressive conditional heteroscedastic (ARCH) model. In [31], the hourly average wind speed is predicted using the autoregressive moving average and the persistence model. Authors in [32] have examined the use of an auto-regressive integrated moving average approach for time-series forecasting using wind speed observations. For short-term forecasts, the ARIMA model has been demonstrated to outperform the ANN model [33]. In [34], three different samples of wind speed data are used to test the validity of the ARIMA model that is being proposed. Given that the hour-ahead forecast takes no more than five minutes to compile, the proven prediction inaccuracy of less than 16% is quite an accomplishment. In [35], Time series analysis, ARIMA, and Ordinary Least Squares (OLS) multiple regression have been used to predict wind speeds. In [36], Non-stationary annual wind speed data are analyzed using the Fractional Autoregressive Moving Average (FARIMA) Model. A comparison has been conducted between the F-ARIMA model and the Persistence and ARIMA models in [37], and it has been found that the F-ARIMA model is superior at capturing the long-term and short-term properties of time-series observations. In [38], Wind Speed Forecasting Based on Second Order Blind Identification (SOBI) and Autoregressive (AR) Model has resulted in higher accuracy compared with direct forecasting. In [39], short-term wind power forecasts based on ARX models have been shown to give better accuracy in forecasting. Some researchers related to the statistical techniques for wind prediction are given in Table 3.

Wind is a stochastic variable, it is difficult to anticipate due to its non-stationary and nonlinear features [45]. Statistical weather forecasting models have also outperformed numerical weather forecasting models [46]. The above literature survey helps to identify the strengths and limitations of statistical methods as listed in Table 4.

**Table 3.** Statistical Methods for Wind Speed/Power Prediction

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Li et al. (2022) [40] | "A Wind Speed Correction Method Based on Modified Hidden Markov Model for Enhancing Wind Power Forecast. | Markov | RMSE = 3.093<br>MAE = 2.451 |
| Wang et al. (2020) [41] | "Forecasted Scenarios of Regional Wind Farms Based on Regular Vine Copulas" | KDE, R-vine | RMSE = 0.1089<br>MAE = 0.075 |
| Mararakanye et al. (2022) [42] | Incorporating Spatial and Temporal Correlations to Improve Aggregation of Decentralized Day-Ahead Wind Power Forecasts" | KNN, KDE | MAE = 3.18;<br>RMSE = 4.63; R2 = 0.94 |
| Yu et al. (2020) [43] | Probabilistic Prediction of Regional Wind Power Based on Spatio-temporal Quintile Regression. | SQR | RMSE = 16.62%;<br>MAE = 11.23% |
| Dong et al. (2022) [44] | "Power Prediction Based on Multi-class Autoregressive Moving Average Model with Logistic Function" | ARMA | RMSE = 127.10<br>MAPE = 1.25% |

**Table 4.** Strengths and limitations of statistical methods

| Parameters | Strengths | Limitations |
|---|---|---|
| Data availability | Statistical models can work with readily available historical wind data. | Less Accuracy with data sparsity |
| Simplicity | Implementation is simple and easy | Difficult to capture complex nonlinear data. |
| Interpretability | Results are interpretable, aiding in understanding the factors affecting wind speed. | May not observe all relevant weather variables. |
| Computational speed | Less computational power required | Its prediction accuracy is low for highly dynamic and nonlinear wind patterns. |
| Adaptability | Use for short-term and long-term wind predictions. | It may not easily identify extreme events and rapid wind variability. |
| Assumption flexibility | Flexibility in choosing the appropriate statistical distribution (e.g., normal, Weibull) for wind data. | Assumptions about the data distribution may not always hold. |
| Forecast updates | It can be updated with new data easily, making it suitable for real-time applications. | Less accuracy in clamite changing regions. |
| Noise handling | Easily handle noisy data | Low performance in highly non-linear wind condition |
| Historical patterns | Use for long-term wind speed patterns and trends. | May not account for sudden shifts or local microclimatic influences. |
| Risk assessment | Provides a foundation for risk assessment and resource allocation. | It may not be suitable for critical applications requiring high precision. |
| Model transparency | Transparency in model structure and parameters makes it accessible to a wider audience. | Lack of robustness in situations where statistical assumptions are violated. |

## CUTTING-EDGE APPROACHES

The cutting-edge approaches use advanced approaches and data for more accurate wind forecasting. Table 5. Shows the classification of cutting-edge approaches for wind forecasting.

### Machine Learning and AI Methods

Machine learning methods can determine intricate nonlinear correlations and patterns in wind speed/power data that conventional statistical models may not capture. This can lead to improved forecasting accuracy, especially for long-term and nonlinear predictions. Machine learning algorithms can adapt and learn from new data [47]. Machine learning algorithms can automatically select relevant features from a large set of potential predictors. This helps in identifying the most important factors influencing wind speed/power, eliminating irrelevant features, and reducing model complexity[48].

The machine learning approaches used for the prediction of solar radiation [49], wind potential [50], and short-term traffic flow [51]. And handle large data with complex computation. Machine learning approaches give highly accurate outcomes for wind forecasting at various time scale intervals from from single turbine to entire wind farm [52,53]. RBF (Radial basis function) outperforms both linear and nonlinear functions in neural networks, and it is best suited for the prediction of wind speed [54,55]. Genetic algorithms (GA) which are algorithms based on evolution thus expressing individual qualities through genetics [56]. Approximate reasoning is possible using fuzzy sets and fuzzy logic. Fuzzy logic is a field of study that depends on generalization and CI (computational intelligence) principles. The fuzzy simulation outperformed the persistent technique in predicting wind speed as of 30 minutes-2 hrs. ahead. In [57], various neural networks are used to predict wind speed such as Long Short-Term Memory (LSTM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Convolutional LSTM (ConvLSTM) hybrid model. These algorithms can capture temporal dependencies and long-term patterns in wind speed/power data, making them effective for predicting future values. In [58], a grouped strategy has been provided for predicting wind power 10 minutes ahead of time. A persistence approach, a BPNN (Back Propagation Neural Network), and an RBFNN (Radial Basis Function Neural Network) are combined in the suggested method. Table 6. Provide insights into the underlying algorithms used in machine learning-based forecasting models. It includes the classification of machine learning algorithms in four broad classes, i.e., supervised learning, unsupervised learning, deep learning, and ensemble methods. Further sub-classification of each category, along with a brief description of the applications of each algorithm, is also given.

Table 7 and Table 8 respectively summarize the state-of-the-art contributions from various researchers in the field of machine learning and deep learning methods for wind prediction.

Wind forecasting is done utilizing an upgraded form of EMD (EEMD), complementary ensemble EMD (CEEMD), and complete ensemble EMD with adaptive noise (CEEMD) in [105] (CEEMDAN). Even though EMD looked to beat many conventional approaches (Persistence & ARMA), the authors state that there seemed to be a problem with approach mixing [106], in which different IMFs contain signals in the same frequency range.

### Hybrid Methods

In recent years, attention has switched to hybrid forecasting systems, i.e. combination of two or more two or more prediction methods and then aggregating them as shown in Figure 4 [107]. Machine learning techniques can be combined with traditional statistical models to create hybrid models.

Combining an autoregressive integrated moving average (ARIMA) model with machine learning algorithms can improve forecasting accuracy by incorporating both statistical properties and complex patterns in the data. Hybrid methods such as ANN-ARIMA [108], PSO-ANFIS [109], and WT-NN (Wavelet transform Neural Network) [110]. For a short period of wind power prediction in Portugal, an

**Table 5.** Classification of cutting-edge approaches

| Category | Approaches | Detail |
|---|---|---|
| Machine Learning & AI approaches | ‘Supervised Learning’ | Prediction is based on labeled data by using random foreast, regression, aupport vector machine, and decision trees. |
| | ‘Unsupervised Learning’ | Prediction is based on unlabeled data and identify pattern using clustring. |
| | ‘Deep Learning, | For complex sequence prediction various neural networks are used like CNN (Convolutional neural network), RNN ( recurrent neural networks), and LSTM (long short-term memory) networks |
| | ‘Ensemble Methods’ | Enhance prediction accuracy by combining multiple algorithms. |
| Hybrid approaches | ‘Combination Techniques’ | Enhance the accuracy by combination of two approaches |

**Table 6.** Algorithms for machine learning-based models

| Algorithm category | Algorithm | Detail | Application |
|---|---|---|---|
| Supervised learning | 'Linear Regression' | İt provide relationship between a dependent variable and a single independent variable. | Appropriate for linear relationships between variables. |
| | 'Decision Trees' | leverages decision rules constructed from variables to divide data into branches. | Analyzes interactions and non-linear correlations between features. |
| | 'Random Forests' | A number of decision trees that have been trained on variable subsets of characteristics and data. | Avoids overfitting in comparison to single trees and offers reliable forecasts. |
| | 'Support Vector Machines (SVM)' | Evaluates which hyperplane best matches the data for regression or divides the data into several classes. | Appropriate for complicated interactions and high-dimensional spaces. |
| | 'K-Nearest Neighbors (KNN)' | Forecasting based on the k-nearest training examples in the feature space. | Easy to use and efficient for low-noise brief datasets. |
| Unsupervised learning | 'K-Means Clustering' | Partitions data into k clusters based on feature similarity. | Finds trends and clusters in wind data. |
| | 'Hierarchical Clustering' | Uses divisive techniques to create a hierarchy of clusters. | Recognizes the relation between wind speed patterns and data structure. |
| Deep learning | 'Artificial Neural Networks (ANN)' | Layers of interconnected neurons acquire the ability to map inputs to outputs. | Identifies intricate, non-linear interactions; processing and huge quantities of data are needed. |
| | 'Recurrent Neural Networks (RNN)' | RNN retains memories through connections that form a temporal sequence. | Suitable for anticipating time series based on historical trends. |
| | Long Short-Term Memory (LSTM) Networks | An distinctive kind of RNN with long-term dependency learning capabilities. | Useful in identifying long-term patterns and trends in time series forecasting. |
| | Convolutional Neural Networks (CNN) | Although it may be used to 1D time series, this neural network is mainly used for image recognition. | Captures local patterns and trends in wind data. |
| Ensemble methods | Bagging (Bootstrap Aggregating) | Increases accuracy and stability by averaging predictions from several models trained on various subsets. | Reduce variation and overfitting for better predictions. |
| | Boosting | Sequentially trains models, focusing on the errors of previous models. | Enhance the forecasting accuracy by reducing bias and variance. |

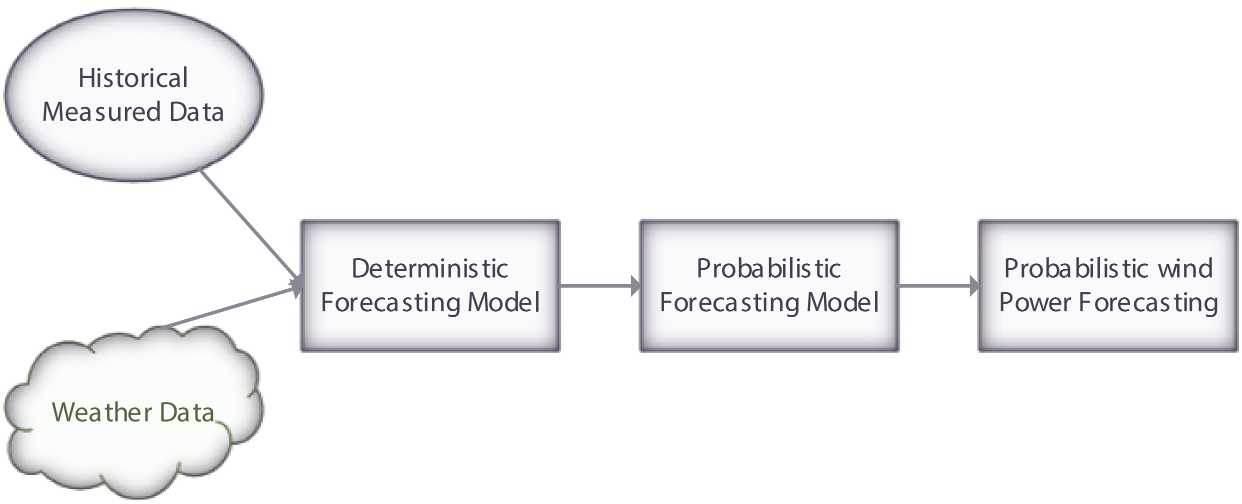


**Figure 4.** Hybrid model.

**Table 7.** Machine Learning Methods for Wind Speed/Power Prediction

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Jyothi et al. (2016) [59] | "Very-short-term wind power forecasting through Adaptive wavelet neural network" | WNN, ANN, ANFIS | MSE = 0.25<br>RMSE = 0.367 |
| Xu and Mao (2016) [60] | "Short-term wind power forecasting based on elman neural network with particle swarm optimization" | ENN, PSO | ERMS = 16.55% |
| Catalão et al. (2009) [61] | "An artificial neural network approach for short-term wind power forecasting in Portugal" | ANN | RMSE = 0.0362 |
| Mabel et al. (2008) [62] | "Analysis of wind power generation and prediction using ANN: A case study" | ANN | RMSE = 0.0806 |
| Singh et.al. (2007) [63] | "Wind power estimation using artificial neural network" | ANN, Kalman filtering | Not determined |
| Marugán et al. (2018) [64] | "A survey of artificial neural network in wind energy systems" | ANN | more than 80% of accuracy |
| Sharma et al. (2018) [65] | "A review of wind power and wind speed forecasting" | ANN | RMSE = 2.849 (1 hr) |
| Sideratos et al. (2012) [66] | "Probabilistic wind power forecasting using radial basis function neural networks" | RBFNN | -- |
| Ramadevi and Bingi (2022) [67] | "Chaotic time series forecasting approaches using machine learning techniques: A review" | Machine learning | Not determined |
| Zhou et al. (2022) [68] | "Performance ımprovement of very short-term prediction intervals for regional wind power based on composite conditional nonlinear quantile regression" | WMTSM and conditional<br>LP (CLP) | Both MAE and RMSE of less than 10% |
| Lee et al. (2020) [69] | "Wind power prediction using ensemble learning-based models" | Ensemble learning models (GRF, RF, XGB) | R2 = 98.9;<br>RMSE = 50.36;<br>MAE = 23.63 |
| Tu et al. (2020) [70] | "Short term wind power prediction based on data regression and enhanced support vector machine" | EBSO and LSSVM | MAE (m/s): 0.723<br>RMSE (m/s): 0.932 |
| Tan et al. (2020) [71] | "Ultra-Short-Term Wind Power Prediction by Salp Swarm Algorithm-Based Optimizing Extreme Learning Machine" | SSA-ELM | MAPE = 1.2677<br>RMSE = 0.2576 |
| Huang et al. (2023) [72] | "Priori-guided and data-driven hybrid model for wind power forecasting" | Priori-guided and data-driven hybrid model | MAE = 0.0861,<br>RMSE = 0.1262,<br>R2 = 0.8333,<br>AR = 87.38% |
| Wang et al. (2023) [73] | "A hybrid intelligent framework for forecasting short-term hourly wind speed based on machine learning" | Intelligent hybrid model | MAPE = 2.62 and<br>RMSE = 0.14 |
| Pombo et al. (2022) [74] | "Assessing stacked physics-informed machine learning models for co-located wind–solar power forecasting" | Stacked physics-informed machine learning model | RMSE = 5% and<br>R2 = 0.95 |
| Moayyed et al. (2022) [75] | "A Cyber-Secure generalized supermodel for wind power forecasting based on deep federated learning and image processing. Energy Convers" | Cyber-secure generalized supermodel | RMSE = 0.02,<br>MAE = 0.007<br>MAPE = 0.60 |
| Liu et al. (2023) [76] | "An online transfer learning model for wind turbine power prediction based on spatial feature construction and system-wide update" | Online transfer learning model | MAE = 84.837<br>RMSE = 134.837 |
| Nascimento et al. (2023) [77] | A transformer-based deep neural network with wavelet transform for forecasting wind speed and wind energy" | Discrete wavelet<br>transform | 100 m RMSE [m/s] = 0.383<br>150 m RMSE [m/s] = 0.368<br>120 m RMSE [m/s] = 0.375 |
| Sobolewski et al. (2023) [78] | "Gradient boosting-based approach for short- and medium-term wind turbine output power prediction" | Goddard earth observing system model | RMSE [kW] = 76.18 |
| Yu et al. (2023) [79] | Research on Hierarchical Control Strategy of ESS in Distribution Based on GA-SVR Wind Power Forecasting. | SVR | RMSE/MW = 14.7435 |
| Wang et al. (2023) [80] | "Short-Term Wind Power Prediction by an Extreme Learning Machine Based on an Improved Hunter–Prey Optimization Algorithm" | Improved hunter-prey optimization (IHPO algorithm-based extreme learning machine (ELM) | RMSE (kW) = 50.55 |

**Table 8.** Deep learning method for wind speed/power prediction

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Lin et al. (2020) [81] | "Wind power prediction based on high-frequency SCADA data along with isolation forest and deep learning neural networks" | "Deep Learning Neural Network (DLNN) & SCADA" | MSE = 0.0032 |
| Ahuja and Saini (2023) [82] | "Recurrent Neural Network for Chaotic Wind Speed Time Series Prediction" | RNN | RMSE = 0.2497 |
| Wang and Li (2023) [83] | "Wind speed interval prediction based on multidimensional time series of Convolutional Neural Networks" | CNN | RMSE1 = 0.2805<br>RMSE2 = 0.3021<br>RMSE3 = 0.2838 |
| Mert (2021) [84] | "Agnostic deep neural network approach to the estimation of hydrogen production for solar-powered systems" | "Agonistic Deep learning neural network" | RMSE = 0.0703 |
| Hu et al. (2020) [85] | "Very Short-Term Spatial and Temporal Wind Power Forecasting: A Deep Learning Approach". | "A convolution-based spatial–temporal wind power predictor (CSTWPP)" | MASE = 190.02<br>RMSE = 7.49 |
| Dong et al. (2022) [86] | "Spatio-temporal Convolutional Network Based Power Forecasting of Multiple Wind Farms" | "The spatiotemporal convolutional network (STCN) with a directed graph convolutional structure" | MAEs = 3.17%<br>RMSEs = 2.88%, |
| Jalai et al. (2022) [87] | "New Hybrid Deep Neural Architectural Search-Based Ensemble Reinforcement Learning Strategy forWind Power Forecasting" | "Adeep-optimized convolutional LSTM-based ensemble reinforcement learning strategy (DOCLER)" | RMSE = 7.1322%<br>MAE = 4.6713% |
| Sun and Zhao (2020) [88] | "Short-Term Wind Power Forecasting Based on VMD Decomposition, ConvLSTM Networks and Error Analysis" | "A variational mode decomposition (VMD) and convolutional long short-term memory network (Conv LSTM) model" | MRE(KW) = 0.016<br>MAE(KW) = 792<br>MSE(KW) = 568,305<br>RMSE(KW) = 1252.32 |
| Miao et al. (2021) [89] | "Ultra-Short-Term Prediction of Wind Power Based on Sample Similarity Analysis" | "The CNN-MLSTMs-T Model" | RMSE = 0.1998;<br>MAE = 0.1523 |
| Liao and Yang (2022) [90] | "Wind GMMN: Scenario Forecasting for Wind Power Using Generative Moment Matching Networks" | "Generative moment matching network (GMMN)" | RMSE = 127.10;<br>MAE = 0.6855 MW |
| Huang (2022) [91] | "Wind Power Generation Forecast Based on Multi-Step Informer Network" | "Multi-step informer network (MSIN)" | Multi-step informer Network (MSIN) improves forecast accuracy by 29% compared with the informer network for RMSE |
| Wu and Jiang (2022) [92] | "Short-TermWind Power Prediction Based on Data Decomposition and Combined Deep Neural Network" | "Long short-term memory neural network (LSTM) with the improved particle swarm optimization algorithm (IPSO)" | MAE = 2.92668;<br>RMSE = 3.59604 |
| Yu, et al. (2022) [93] | "Short-term wind power prediction for regional wind farms based on spatial-temporal characteristic distribution. Renew" | "Spatiotemporally multiple clustering and I–CNN-BILSTM deep learning network." | MAE = 18.64,<br>RMSE = 28.45 |
| Liu et al. (2023) [94] | "A unified multi-step wind speed forecasting framework based on numerical weather prediction grids and wind farm monitoring data" | "The unified forecast based on STC-DPN And The single-site error correction of TCN-LSTM" | MAE = 2.071,<br>RMSE = 2.431, |
| Hossain et al. (2021) [95] | "Very short-term forecasting of wind power generation using hybrid deep learning model" | "Hybrid deep learning model" | MAE = 1.59,<br>RMSE = 3.73<br>and MAPE = 8.13. |
| Garg and Krishnamurthi (2023) [96] | "A CNN encoder decoder LSTM model for sustainable wind power predictive analytics" | "CNN-ED-LSTM model" | MSE = 0.0102<br>MAPE = 46.24<br>MAE = 0.0623<br>RMSE = 0.1012 |

**Table 8.** Deep learning method for wind speed/power prediction (continued)

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Zhang et al. (2021) [97] | "Power prediction of a wind farm cluster based on spatiotemporal correlations" | "Long short-term memory (LSTM) neural network" | RMSE (MW) = 0.94<br>MAE (MW) = 0.67<br>MAPE (%) = 49.71 |
| Zhang et al. (2020) [98] | "Short-term wind power forecasting approach based on Seq2Seq model using NWP data" | "Seq2Seq model" | RMSE = 129.3<br>MAE = 81.1 |
| Lliao et al. (2022) [99] | "Short-term power prediction for renewable energy using hybrid graph convolutional network and long short-term memory approach" | "Long short-term memory (LSTM)" | RMSE (MW) = 1.27<br>MAE (MW) = 0.90 |
| Tian et al. (2022) [100] | "Developing a wind power forecasting system based on deep learning with attention mechanism" | "A deep learning model (gated recurrent unit, GRU)" | RMSE = 111.9766 |
| Yildiz et al. (2021) [101] | "An improved residual-based convolutional neural network for very short-term wind power forecasting" | "Residual CNN-based deep forecasting method" | 1-h ahead.<br>RMSE = 0.9947 |
| Liu et al. (2023) [102] | "Short-term wind power forecasting based on feature analysis and error correction" | "Bidirectional long short-term memory network (BiLSTM)" | RMSE/MW = 1.0822 |
| Wang et al. (2023) [103] | "Artificial intelligent power forecasting for wind farm based on multi-source data fusion" | "The encoder-decoder framework is constructed with LSTM as the basic Unit" | RMSE = 0.1243 |
| Xiao et al. (2023) [104] | "Wind power short-term forecasting method based on LSTM and multiple error correction" | LSTM | RMSE (%) = 10.23 |

NNWT technique that depends on the integration of ANN and WT (wavelet transform) has been proposed, which has proven to be both new and effective. Its MAPE outperforms persistence, ARIMA, and NN techniques with an average value of 6.97 percent and a calculation time of less than 10 seconds. Wavelet- SVM (Support vector machine) optimized by GA (genetic algorithm) [111], Kalman filter-ANN (KF+ANN) [112], WT- SVM-GA (Wavelet-Support vector machine) optimized by genetic algorithm & EMD+SVM (Support vector machine with empirical mode decomposition) [113] are some work reported in this literature. To build a unique grouped simulation for wind speed forecast, authors in [114] have proposed combining EMD with feature selection. Hybrid forecasting approaches have lately become popular due to their extra benefits over traditional single forecasting methods. Candenas and Rivera established a wind forecasting model that is based on ARIMA-ANN [115] with a fixed prediction horizon. For the prediction of multi-step wind speed, a hybrid approach that includes WDT (wavelet decomposition transform), an exciting learning machine, and adjustment for extremes methodology is proposed in [116]. Li et al. proposed a mixed technique that depends on continuous and flexible weight for predicting short periods of wind speeds [117]. In [118] to identify oscillations brought on by nearby wind generators and send the necessary inputs to modeling, a novel short-period wind forecasting approach is being deployed. In [119], an attribute selection model depending upon a k-means cluster, and an MLPNN (multi-layer perceptron neural network) were created to forecast short periods of wind speed. For a short period wind speed prediction, correlation-based DWT, LSSVM, and GARCH. The contributions to the LSSVR (Least Squares Support Vector Regression) wind speed forecasts are evaluated using correlation coefficients among different sub-series introduced by [120]. State-of-the-art hybrid models for wind prediction are detailed in Table 9.

In [142], authors have proposed and validated an improved BFGS (Broyden-Fletcher-Goldfarb-Shanno) neural network (using four wind speed datasets) and wavelet transform-signal processing method for short periods of wind speed forecasts. After wavelet decomposition, correlation coefficients are calculated for each sub-series to identify their comparative relevance. In this study [143], the hybrid model possesses a more accurate forecasting ability than the other models, and the level of accuracy of the hybrid model is different from that of the GRNN, BPNN, LSSVM, CS-BPNN, WOA-LSSVM, EMD-WOA-LSSVM, and EEMD-WOA-LSSVM. In this study, a system that combines NWP and hybrid wind forecasting ANN models is proposed. This hybrid forecasting approach is beneficial in improving the perception of wind power in China [144]. In [145], two grouped models for wind power and speed prediction: ARIMA-ANN & ARIMA-SVM have been proposed. This research systematically and comprehensively analyzes the use of the suggested hybrid models. In [146], authors have employed a new hybrid wind speed forecast approach that is dependent on a BPNN and the knowledge of using periodic exponential forecasting adjustment to remove seasonal impacts from authentic wind speed

**Table 9.** Hybrid method for wind speed/power prediction

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Hong et al. (2019) [121] | "Hybrid deep learning-based neural network for 24-h ahead wind power forecasting" | CNN-MFNN, CNN- RBFNN, CNN- RBFNN-DGF | RMSE of Winter = 375.2369<br>RMSE of Spring = 352.2999<br>RMSE of Summer = 221.3698<br>RMSE of Autumn = 194.2075 |
| Foley et al. (2012) [122] | "Current methods and advances in the forecasting of wind power generation" | NWP, statistical, machine learning | Not Described |
| Shetty et al. (2016) [123] | "Optimized radial basis function neural network model for wind power prediction" | RBFNN, FCM, PSO-FCM, Extreme Learning Machine | MSE = 0.0034 at no. of center 60 model 1 |
| Peng et al. (2013) [124] | "A hybrid strategy of short-term wind power prediction" | ANN+ Physical | MAE = 757.25 (KW)<br>NRMSE = 2.01% |
| Wang et al. (2018) [125] | "A novel hybrid forecasting system of wind speed based on a newly developed multi-objective sine cosine algorithm (MOSCA)" | CEEMD- MOSCA- WNN | RMSE1 = 0.078693<br>RMSE2 = 0.118740<br>RMSE3 = 0.192665<br>RMSE4 = 0.143523 |
| Saini and Ahuja (2017) [126] | "Wind speed prediction using wavelet transform and artificial neural network" | ANN, WT | RMSE = 0.1576 |
| Saini and Ahuja (2019) [127] | "Wind speed prediction using wavelet transform and GA trained artificial neural network" | ANN, WT, GA | |
| Duan et al. (2022) [128] | "A combined short-term wind speed forecasting model based on CNN–RNN and linear regression optimization considering error" | CNN-RNN | RMSE1 = 0.1172<br>RMSE2 = 0.1017<br>RMSE3 = 0.2104<br>RMSE4 = 0.1876 |
| Zhang et al. (2022) [97] | "A comprehensive wind speed prediction system based on Monte Carlo and artificial intelligence algorithms" | AI | RMSE = 0.5794 |
| Zou et al. (2022) [129] | "Forecasting of short-term load using the MFF-SAM-GCN model" | "A multi-feature fusion self-attention mechanism graph convolutional network (MFF-SAM-GCN) forecasting model" | RMSE = 0.0284<br>SMAPE = 9.453%<br>MBE = 0.025<br>R2 = 0.989 |
| Aisyah et al. (2022) [130] | "Exploratory Weather Data analysis for electricity load forecasting using svm and grnn, case study in Bali, Indonesia" | GRNN, SVM | The GRNN model gives the CC value of 0.956, RMSE of 28.82 The SVR model gives a CC value of 0.965 and an RMSE of 44.40. |
| Zhao et al. (2023) [131] | "Hybrid VMD-CNN-GRU-based model for short-term forecasting of wind power considering spatio-temporal features" | VMD-CNN-GRU | RMSE = 1.5651,<br>MAE = 0.8161,<br>MAPE = 11.62%,<br>and R2 = 0.9964. |
| Che et al. (2023) [132] | "Ultra-short-term probabilistic wind power forecasting with spatial-temporal multi-scale features and K-FSDW based weight" | I-CNN-BILSTM | MAPE (%) = 4.86,<br>MAE = 18.64,<br>and RMSE = 28.45. |
| Hu et al. (2021) [133] | "Hybrid forecasting method for wind power integrating spatial correlation and corrected numerical weather prediction" | "The hybrid forecasting method based on the corrected NWP data and the SC" | RMSE = 1.238,<br>MAPE = 0.325,<br>MAE = 0.7002 |
| Wen et al. (2022) [134] | "A new hybrid model for power forecasting of a wind farm using spatial–temporal correlations" | "KHC algorithm for clustering, components extraction and selection with SVD, and building SVR forecast model" | MAE = 0.273<br>RMSE = 0.343 |
| Hu et al. (2021) [135] | "An improved deep belief network based hybrid forecasting method for wind power" | "GBRBM-DBN consists of the PCA, NWP, and SC for wind power Forecasting" | RMSE = 2.6018,<br>MAPE = 0.2859,<br>MAE = 2.3857 |

**Table 9.** Hybrid method for wind speed/power prediction (continued)

| Authors | Title | Techniques | Accuracy |
|---|---|---|---|
| Gu et al. (2023) [136] | "Short-term wind power forecasting and uncertainty analysis based on FCM–WOA–ELM–GMM" | FCM-WOA-ELM-GMM Model | MAE = 3.8%, RMSE = 5.24% |
| Al-Duais and Al-Sharpi (2023) [137] | "A unique Markov chain Monte Carlo method for forecasting wind power utilizing time series model" | "Seasonal autoregressive integrated moving average (SARIMA) model" | RMSE = 13.09 MAPE = 1.03 |
| Yan et al. (2022) [138] | "Uncovering wind power forecasting uncertainty sources and their propagation through the whole modeling chain. renew. sustain" | "Historical wind climate model and physical model" | RMSE = 13% MAE = 20.7% |
| Xiong et al. (2022) [139] | "Short-term wind power forecasting based on Attention mechanism and deep learning" | "AMC-LSTM hybrid model" | MSE = 0.8951 MAE = 0.0505 RMSE = 0.0946 |
| Zhang et al. (2023) [140] | "Deterministic and probabilistic prediction of wind power based on a hybrid intelligent model" | "XGBoost, Tree, SVR, and BPNN methods" | RMSE = 1.8313 |
| Wu et al. (2024) [142] | "Interpretable wind speed forecasting with metrological feature exploring and two-stage decomposition" | IEEMD-EWT-JADE-TFT | RMSE = 0.1063 |

information. The outcomes of the tests have revealed that the proposed strategy outperformed a single BPNN.

In [147], authors employed a hybrid method depending on the integration of ANN and WT for a short period of wind energy forecasting in Portugal. Using the wavelet approach, the wind power series is decomposed into a set of effective constituent sequences. Results of the tests indicate that the proposed hybrid approach for predicting wind production has a proportion of promise. Hybrid models' main purpose is to integrate the advantages of each model to attain global forecasting performance [148]. In [149], forecasting the average daily wind speed using a predicting scheme based on discrete wavelet transform (DWT) associated with Artificial Neural Networks (ANN ) is proposed, and the results show that, when using ANN for prediction, the db4 wavelet with a 5-level decomposition is the most appropriate wavelet for wind speed forecasting in the three considered regions. Also, the proposed scheme exhibits high precision and accuracy for one-day-ahead wind speed forecasting in terms of RMSE and MAPE. In [150], authors have employed a grouped intellectual model termed an ANFIS (Adaptive Neural Fuzzy Inference System) that combines two AI approaches, Fuzzy Logic, and ANN, to estimate wind constraint and energy production shortly. In [151], depending on wavelet and classical time series analysis approaches, a new short-period prediction algorithm is employed. An adaptive neuro-fuzzy inference system (ANFIS) is utilized in [152] to anticipate wind direction 2.5 minutes ahead, taking into account both direction & speed. In this study, artificial intelligence techniques, such as the ANN algorithm, are utilized to anticipate wind power [153]. To predict wind power, four alternative approaches were applied. It has been discovered that the Genetic algorithm outperforms the other models when it comes to training data sets.

In [154], three approaches for predicting wind speed are proposed. Which hybrid models proposed, such as Wavelet packet-BFGS (Broyden–Fletcher–Goldfarb–Shanno), have been demonstrated to be superior to Wavelet packet-ARIMA-BFGS. Second, Wavelet packet-BFGS has been discovered to be superior to Wavelet-BFGS. In [155], four different models for the prediction of wind power are presented. The two learning algorithms, the backpropagation algorithm and the genetic algorithm, along with a combination of these models, are used for the prediction of wind power. The genetic algorithm performs better for both the training data sets than the other models. In [156], the system consists of two main parts: a point prediction module based on a nonlinear combination and an interval prediction module based on fuzzy clustering. It is of great significance to explore the predictability and modeling of wind speed comprehensively. Unlike previous works, the authors have implemented a BP neural network using MOEA/D (Multi-objective evolutionary algorithm based on decomposition) optimization as a novel nonlinear combination mechanism to derive final prediction results, which enhances the accuracy of point prediction and improves final prediction accuracy. Wind speed predictions in a short period utilizing mathematical models that include ANN and Hybrid time-series models are given in [157].

The back propagation neural network (BPNN) algorithm is integrated with GA and PSO in [158] to create an integrated prediction model for short-period wind farms. The output power is calculated using climatic data gathered by a WSN (wireless sensor network), which is then sent into the BP neural network as an input variable. In [159], BPNN is a basic prediction method, and the proposed prediction method is validated by the output power prediction of a real wind farm. A support vector machine (SVM) is chosen as another basic prediction method to test the versatility of the proposed improved prediction method. The results show that the proposed wind power prediction method can improve the prediction accuracy by about 8%.

In [160], the SARIMA-EEMD-LSTM hybrid prediction model is used to forecast wind speed time series at 15-, 30-, and 60-minute intervals. Thus, hybrid methods can effectively forecast wind speed/power wind power generation fluctuations must be anticipated by power system operators to control grid operations and plan rotating backup power [161]. Authors in [162] have utilized a fusion of neural networks and fuzzy logic approaches to precisely estimate the production of a wind farm. A self-organised map that categorises the input data into distinct groups is used.

It is found that there is a significant improvement in prediction accuracy achieved through hybrid models, with Root Mean Square Error values of 0.1089 m/sec for statistical methods from Table 3, 0.02 m/sec for intelligent methods from Table 7, and 0.0096 m/sec for hybrid approaches from Table 9.

### Organization of Wind Prediction According to time Scale Horizons

Methodologies based on prediction period may be classified as extremely short-period predicting, short-term predicting, long-term predicting, and long-term predicting. Wind prediction organization based on time scale is discussed below:

- Very Short-Term (Seconds to Minutes):

The significance of these predictions lies in their necessity for jobs that demand accuracy in real-time or near-real-time scenarios. The applications of the technology encompass a range of areas, including wind energy production control, wind gust prediction, and emergency response in the context of severe weather occurrences.

- Short-Term (Minutes to Hours):

This wind forecasting is used in various sectors like managing transportation, power system management, wind farm operation, traffic systems, and several outdoor activities.

- Medium-Term (Hours to Days):

This forecasting is important for various sectors that depend on weather conditions, such as scheduling for generation, several-day span forecasting planning, construction market operation, etc.

- Long-Term (Days to Weeks):

These forecasts are employed in various sectors such as large-scale infrastructure planning, assessing climate change impacts, and choosing the best site for wind farm installation.

- Seasonal (Months to Seasons):

The seasonal wind forecasting is used in various fields, including agriculture, energy infrastructure investment, and long-range climate projections.

- Climate (Years to Decades):

The significance of climate-scale wind predictions is to enhance our comprehension of long-term wind patterns and their potential impacts on regional and global climate systems. The applications of the research encompass climate analysis, the formulation of policies, and the creation of measures for adaptation. Table 10 gives a classification of state-of-the-art work on the basis of forecasting horizons.

### Comparison of Traditional and Cutting-Edge Approaches

Based on findings from numerous research studies, a comparison of the traditional and cutting-edge approaches

**Table 10.** Classification of the review works based on the forecasting time scale

| Time Scale | Reviewed Work | Time Resolution |
|---|---|---|
| Ultra Short-term | [88,89] | 5 min |
| | [73,78,81,83,88,94,101,105,137] | 10 min |
| | [80,88,92,93,95,96,98,106,146] | 15 min |
| | [49,88,90,142] | 30 min |
| Short term | [76,77,80-82,91,99,102,104,134-136,139,142-144] | 1 h |
| | [77,89,136,139,142] | 2 h |
| | [77,89,136,139,142] | 3 h |
| | [77,136,139,141,142] | 4 h |
| | [77,139,141,142] | 6 h |
| | [77,139,141] | 12 h |
| | [45-47,77,93,97,136,138,140,141] | 24 h |
| | [74,75,91,141] | 48 h |
| Medium-term | [142] | 72 h–1 week |

**Table 11.** Comparison between traditional and Cutting-Edge approaches

| Metric | Traditional approaches | Machine learning approaches | Hybrid approaches |
|---|---|---|---|
| Accuracy | Average | High | Very high |
| Computational efficiency | It requires low computational resources, so effeciency is high. | It requires significant computational resources, so the effeciency is average. | It depends on the complexity of the hybrid model, so the effeciency is low. |
| Ease of ımplementation | Easy to implement | Complex to implement and often considered a “black box.” | İt involves integrating multiple models, which increases complexity. |
| Data requirements | Work with small datsets | İt requires large, high-quality datasets | It requires substantial data and preprocessing, especially when integrating different models. |
| Scalability | Easily scalable on standard hardware. | Scalable but requires specialized infrastructure like GPUs. | Low to moderate; scaling depends on the integration of traditional and machine learning components. |
| Energy consumption | Low | High | Very high |
| Interpretability | High; models are generally easy to understand and explain. | Low; often difficult to interpret the inner workings of the model. | Low to moderate; interpretability depends on the combination of methods used. |
| Applicability to short-term forecasting | High | High | Very high. |
| Applicability to medium-term forecasting | Average | High | Very high |
| Applicability to long-term forecasting | Low | High | High |

on the basis of accuracy, resources, robustness, and data requirements etc. is given in Table 11.

From Table 11, it can be inferred that although Traditional methods offer ease of use and interpretability, they are often sufficient for short-term forecasts. The Cutting-edge approaches provide significant improvements in accuracy and adaptability, especially for complex, nonlinear wind forecasting problems. They are better suited for environments with rapidly changing conditions and where higher computational resources are available. It is equally important to consider the Practical implications of different forecasting techniques in real-world applications. Table 12 represents the implications of different forecasting techniques, particularly in terms of their adaptability to different geographical contexts and real-time operational needs.

**Process of Wind Speed/Power Forecasting**

The procedure for training and validation of wind data for both techniques, such as traditional & cutting-edge approaches, is shown in Figure 5. Many steps of wind forecasting that are represented in Figure 5 were discussed in the previous section. The various types of data pre-processing and advanced techniques reported in this study are used to improve the performance of wind forecasting. The most important among these are:

- **Data Cleaning:** Addressing missing observations through methods such as imputation and eliminating outliers to ensure dataset consistency and accuracy. This reduces systematic errors and increases model robustness.
- **Standarization:** It is applied to input variables on a comparable scale, there by enhance the stability, training, and overall efficiency.
- **Feature Extraction:** It is the process of choosing and transforming essential features from primary data, to enhance models performance such as derived indicators, lag based features etc.
- **Time Series Decomposition:** By applying decomposition, the time series is divided into seasonal, tendency, and remaining components. After decomposition, each can be trained separately, and then the results outcomes more precise.
- **Dimensionality Reduction:** PCA (Principal Component Analysis) can be used to increase generalization, computing complexity, and dimensionality reduction.

These steps help to improve the data quality , prediction accuracy, decrease noise, and thus help to produce more reliable as well as stable predictions. Moreover, standard evaluation metrics that can be used for identifying

**Table 12.** Practical implications of different forecasting techniques

| Forecasting technique | Adaptability to geographical contexts | Real-time operational needs |
|---|---|---|
| 'Statistical methods' | Average adaptability | Low computational demand, suitable for short-term forecasts but less effective in dynamic weather conditions. |
| 'Physical models' | High adaptability across diverse regions | High computational resources required; effective for medium to long-term forecasts but slower in real-time. |
| 'Machine learning' | High adaptability, especially when trained on region-specific data, can handle complex, non-linear relationships. | Requires substantial computational resources and real-time data input; performance improves with data availability. |
| 'Hybrid models' | Enhanced adaptability by leveraging the strengths of multiple methods; flexible across various terrains and climates. | Balances computational demand and accuracy; effective in both short-term and long-term forecasting, with real-time application potential. |
| 'Ensemble methods' | Highly adaptable, as they aggregate diverse models to improve overall accuracy across different regions. | Moderate to high computational demand; offers improved reliability in real-time operations due to averaging out model errors. |

the accuracy and use of wind prediction/forecasting models by having a comparison of predicted and actual values. Common metrics include:

**MSE**: It stands for mean square error (MSE), which is commonly used in wind forecasting, but is an underutilized method. If the MSE indicates a higher value, then the model's performance is low, and vice versa. This method can be used where unexpected data may offer perceptive information about the issue. MSE is calculated by Eqn 1.

$$\text{MSE}=\frac{1}{x}\sum_{i=1}^{x}(Y_i-X_i)^2 \tag{1}$$

**RMSE:** The root mean square error (RMSE) refers to the square root of the mean squared error (MSE). The introduction occurs when the magnitude of the error is equivalent to the magnitude of the objective. It is calculated by Eq. 2.

$$\text{RMSE}=\sqrt{\frac{1}{x}\sum_{i=1}^{x}(Y_i-X_i)^2} \tag{2}$$

RMSE penalizes larger errors more heavily than MAE due to the squaring of errors. It is helpful for analyzing the variance of errors because it gives a measure of the standard deviation of prediction errors. Better model performance is shown by lower RMSE values; 0 is the optimal score.

**MAE:** The average of the absolute variations between the expected and predicted values is known as the mean absolute error, or MAE. The average gives equal weight to each individual difference. Compared to the MSE, this statistic is less affected by outliers. The MAE is determined by:

$$\text{MAE}=\frac{1}{x}\sum_{i=1}^{x}|Y_i-X_i| \tag{3}$$

A precise, comprehensible indicator of prediction accuracy is offered by MAE. Because it does not need squaring the errors, it is less affected by outliers than RMSE.Lower MAE values indicate better model performance, with 0 being the ideal score (perfect predictions).

**MAPE:** Mean Absolute Percentage Error (MAPE) is a commonly used statistical measure for evaluating the accuracy of forecasting or prediction models. It is widely used in various areas, i.e., data analytics, statistics, and economics, and it demonstrates average error as a percentage of the actual value.

$$\text{MAPE}=\frac{1}{x}\sum_{i=1}^{x}\frac{|y_i-x_i|}{|y_i|}*100\% \tag{4}$$

If the MAPE indicates a lower value, then the model's performance is highly accurate & vice versa. The MAPE is sensitive when actual values are close to zero, which may outcomes in division by zero error.

**R2**: It demonstrates the total variance percentage of data that can be analyzed by the model performance. It gives a measure of predicted values matched to the actual outcomes.

$$R^2=1-\sum_{i=1}^{x}\frac{|y_i-x_i|}{y_i-x_i|} \tag{5}$$

Traditional forecasting techniques are typically evaluated using metrics such as RMSE, MAE, and occasionally MAPE. Such methods focus on capturing temporal dependencies and recurring cycles in wind speed or power data, using error measures that reflect deviations from historical averages. While the cutting-edge approaches are evaluated by using RMSE, MAE, MAPE, and R2 metrics. And enhance the performance of these approaches by adjusting model sturucture, hyper parameters.

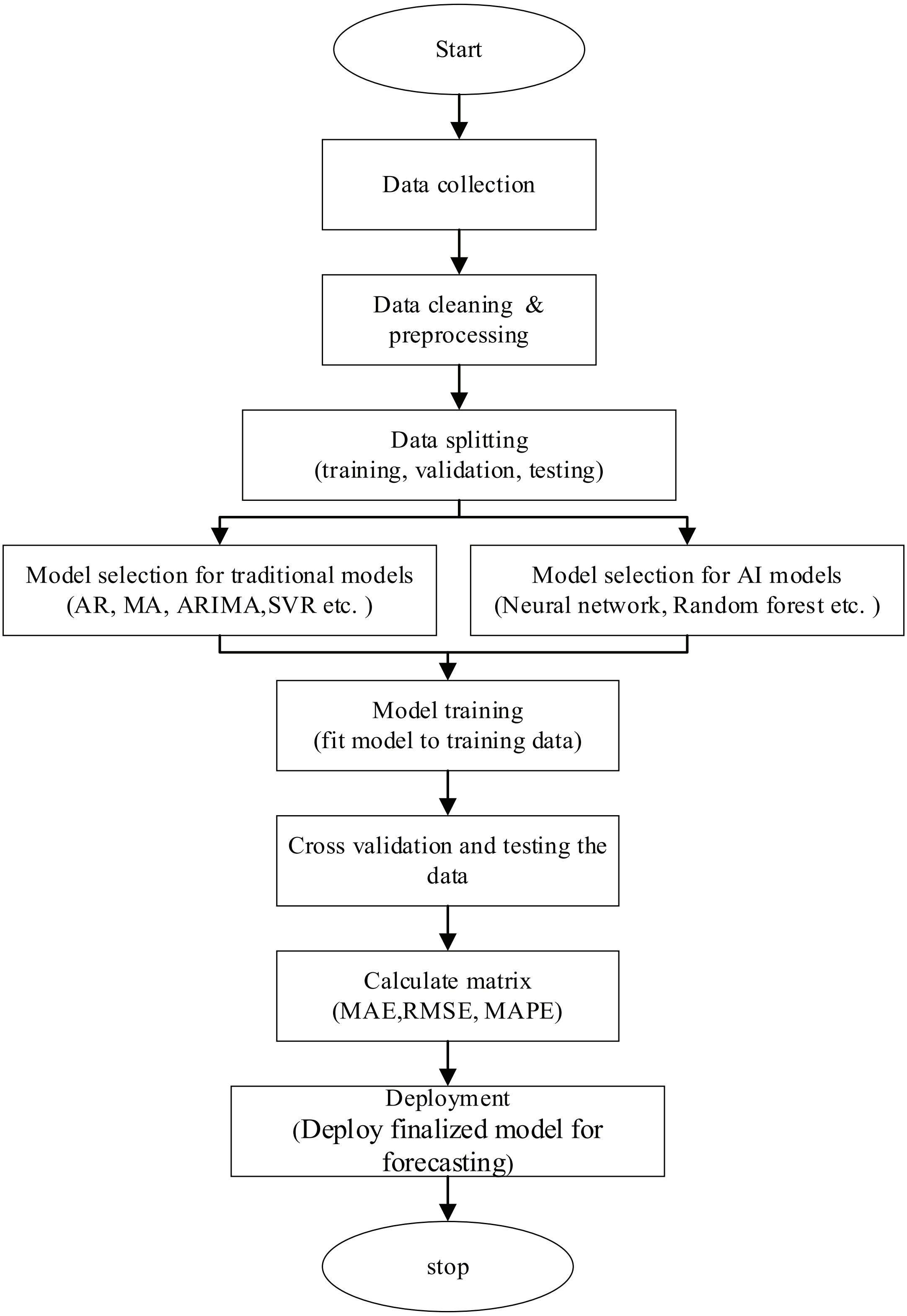


**Figure 5.** Flow chart of models training and validation.

## Numerical Case Study

In this section, some popular Wind speed forecasting models are compared using a real-world dataset.

## Data Description

The wind speed data is collected from open websites (https://maps.nrel.gov/wind-prospector/). The dataset was collected from March 1st, 2023 to May 2023 with a time resolution of 1 hour. The first 70% of the data points were used as training samples, and the remaining 30 % of the data points were used as test data.

**Experimental Setting**

The models compared in the case studies can be divided into four groups: traditional benchmark models, machine learning models, deep learning models, and hybrid deep models. Six traditional benchmark models were selected, namely AR, MA, ARMA, ARIMA, SARIMA, and GARCH. The Machine Learning and deep Learning models used were ANN, RNN, and hybrid CNN-RNN models. In hybrid models, CNN was used to extract features, which were then fed into the other deep models to make wind speed forecasts.

## RESULTS AND DISCUSSION

The wind speed forecasting results of different models are presented in Table 13. It can be seen that the hybrid intelligent model shows the best performance. This phenomenon shows that nonlinear models characterize the fluctuations of WS/WP more accurately and are more suitable than linear models for WS/WP forecasting. In order to measure the forecasting performance of different models, four forecasting error indicators were used: mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (SMAPE). Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are used to give more weight to only larger errors, while MAE is used to give equal weightage to all types of errors, and SMAPE is used to assessi percentage-based errors only, thus making them suitable for different perspectives. ARMA model included in traditional statistical approaches shows superior performance with values of RMSE, SMAPE, MAE, and MSE respectively as 1.6622, 0.1178, 1.3537, and 2.7632, respectively. Due to temporal dependencies, this model is efficient for wind predictions & is also more accurate for forecasting short-term data as compared to otherer statistical models.

There are some neural network models which are more advanced, e.g., Recurrent Neural Networks (RNN) models, mainly used to improve the forecasting accuracy. The RNN model has better performance than basic ANN models with values of RMSE, SMAPE, MAE, and MSE as 1.3935, 0.0924, 1.0382, and 1.9420, respectively as reported in literature. Main qualities of a RNN includes retaining the information from previous time steps. This model is helpful for wind speed forecasting that has influence on future patterns. In contrast, traditional ANN model(s) lack these qualities, thus their ability to captue (fully) the time-dependent structure (in the data) is limited. CNNs have shown superior performance for wind prediction/forecasting with RMSE, SMAPE, MAE, and MSE values of 1.6622, 0.1178, 1.3537, and 2.7632, respectively. To further improve forecasting/prediction accuracy in the future, hybrid CNN-RNN models are used to extract the spatial features and capture temporal dependencies at the same time. The CNN-RNN approach is found to be effective for forecasting of wind speed, thus showcasing more reliable and accurate forecasting as compared to simple neural networks models. These models have helped to achieve RMSE, SMAPE, MAE, and MSE values of 0.9641, 0.0648, 0.7235, and 0.9295, respectively which is far better than basic ANN & RNN models.

This study surveys various wind-forecasting techniques, which include traditional, machine learning based, and. It has evaluated short-term and long-term forecasting models for different time scales and location (s). Table 13 is showcasing a comparison of various models' performance,showing that the use of machine learning based model can decrease the error by 30% in comparison to traditional approach, while the use of hybrid approach helps to further enhance the accuracy, i.e., reduces error. The prior survey(s) in this field only focused on general challenges such as quality & availability of data along with improvement in forecasting accuracy. This study further outlines future directions of research, e.g., using the Internet of Things (IoT) for the purpose of real-time forecasting and development of various adaptive models considering changes in climate.

**Table 13.** Comparison between all models' performance

| Techniques | Metrics | MSE | MAE | RMSE | SMAPE |
|---|---|---|---|---|---|
| Conventional statistical models | AR | 2.7640 | 1.3522 | 1.6625 | 0.1177 |
| | MA | 2.7715 | 1.3571 | 1.6647 | 0.1180 |
| | ARMA | 2.7632 | 1.3537 | 1.6622 | 0.1178 |
| | ARIMA | 3.2792 | 1.5569 | 1.8108 | 0.1178 |
| | SARIMA | 2.9123 | 1.4178 | 1.7065 | 0.1219 |
| | GARCH | 4.8473 | 1.5793 | 2.2016 | 0.1629 |
| Intelligence models | ANN | 1.9951 | 1.0848 | 1.4124 | 0.0969 |
| | RNN | 1.9420 | 1.0382 | 1.3935 | 0.0924 |
| Hybrid model | **CNN-RNN** | **0.9295** | **0.7235** | **0.9641** | **0.0648** |

## CONCLUSION

Area of wind forecasting covers a wide range of traditional as well as cutting-edge approaches. Traditional approaches have been utilized since many years, and have been proven to be reliable in many applications. These approaches are generally simple, interpretable, and requiring fewer computational resources. These include the methods like persistence models, numerical weather prediction (NWP), etc. and have formed the foundation of wind forecasting inspite of having some limitations like less accuracy, and difficulty in handling sophisticated non-linear patterns.

Cutting-edge approaches use data processing techniques. These techniques easily deal with challenges of dealing with high-dimensional data and composite forecasting. These techniques are capable of providing high accuracy and flexibility alongwith managing variable climate conditions. Hybrid models, integrating multiple forecasting methodologies with use of diverse data source(s), are likely to dominate the future of wind prediction. Accurate forecasting is in fact critical for optimizing the generation of renewable energy, efficiently managing the operations of power grid, and supporting the development of a sustainable energy system. This paper reviews the current research and highlights the future directions to increase the accuracy of wind forecasting and is of great help for researchers and practitioners.

### Challenges & Future Directions

Data collection and data availability are main concerns strongly related with wind forecasting challenges and future directions. Major obstacles in this field are as follows:

1. **Data sparstiy:** Wind time series data is not available for some time intervals and sometimes for some geographical location. This issue poses challenge in analyzing the model performance.
2. **Data resolution:** Low-resolution data (wind) reduces forecast accuracy for short-term predictions which requires high-frequency information. There may be requirement of recording of Wind measurements at varying temporal intervals (e.g., hourly or every 15 minutes).
3. **Data quality and calibration:** Small errors may lead to a big mistake in prediction produced by sensor miscalibration of sensor and/or equipment malfunction. Therefore, regular cheking and device maintaince are essential.
4. **Missing data:** Missed datasets are very common Due to sensor failures and/or other technical issues, problem of missing data becomes common. For reliable forecasting, it becomes essential to handle missing data values.
5. **Spatial variability:** Due to topography and local geography, Wind speed variation is observed over short distances. Recording this variability becomes challenging in absence of time-grained spatial data.

**Table 14.** Research Gaps In Future Research Directions of Wind Speed/Power Prediction

| Underexplored Field | Research Gap | Future Research Directions |
|---|---|---|
| Integration of IoT technologies for real-time data acquisition | Limited use of IoT devices in capturing high-resolution, real-time environmental data. | Develop and deploy IoT networks for continuous data collection to improve forecasting accuracy and responsiveness. |
| Use of machine learning which are interpretable | Most machine learning models are complex and lack transparency, making them hard to interpret. | Focus on developing explainable AI techniques that offer transparency while maintaining prediction accuracy. |
| Long-term wind power forecasting | Existing models primarily focus on short-term forecasting; long-term predictions remain less accurate. | Research into hybrid models combining machine learning and climate models to improve long-term forecasts. |
| Extreme weather event prediction | Poor accuracy in forecasting wind speed/power during extreme weather conditions like storms or hurricanes. | Develop specialized models that can accurately predict wind patterns under extreme conditions, incorporating climate change factors. |
| Geographical and terrain variability | Inadequate adaptation of forecasting models to complex terrains and diverse geographic regions. | Create region-specific models that account for local topography and microclimates, leveraging high-resolution geographic data. |
| Energy storage integration | Insufficient research on integrating wind forecasting with energy storage management systems. | Explore real-time integration of forecasting models with energy storage solutions to optimize grid stability and energy use. |
| Social and environmental impact assessment | Limited consideration of the socio-environmental impacts of wind power forecasting and deployment. | Conduct interdisciplinary research assessing the social and environmental implications of wind forecasting technologies. |

6. **Temporal variability:** It includes random fluctuations, rapid as well as seasonal change in wind data, making accurate wind forecasting difficult.
7. **Long-Term trends and climate change:** Nature of wind data is stochastic, nonlinear, and non-stationary. Which makes it necessary to provide high-quality data (over a long period of time) for accurate forecasting.
8. **Data consistency:** Variations in datasets caused by Changes in location of station and/or sensor, and methods of measurement can make datasets variable and must be avoided to ensure high prediction accuracy.
9. **Data privacy and access:** Due to proprietary concerns, it becomes difficult to get the historical wind data.
10. **Data integration:** Merging of datasets from various sources is generally seen in prediction which is also challenging.

In the current era, although wind forecasting has improved a lot by using various modern approaches, yet further improvement is necessary for increasing the forecasting reliability. Future research work should focus on development of the best methods which helps to balance the forecasting accuracy and computational efficiency. It is necessary that data from actual wind farms needs to be validated model-wise, while considering wind farm observations and various atmospheric conditions incorporated via simulation studies. Table 14 highlights the unexplored fields, research gaps and directions for future work in the area of wind speed and/power forecasting.

In conclusion, however previous reviews have established a base to understand various wind forecasting methods, this paper is an extension of that work and provides a comprehensive, quantitative as well as a prospective evaluation. For improving the wind speed and power prediction, this paper helps to identify the gaps in literature and is providing useful insights. It covers methodologies for improvements, discusses theoretical concerns, points out real-world applications while strengthening the present knowledge. It is providing the researchers, business professionals, and all other stakeholders with a solid foundation for the purpose of enhancing the wind energy forecasting tools.

## AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

## DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

## CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## ETHICS

There are no ethical issues with the publication of this manuscript.

## STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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