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Review article

A review of short-term wind power generation forecasting methods in recent technological trends

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ABSTRACT

Climate change and the escalating demand for energy are among the most pressing global challenges of our era. Renewable energy sources, such as wind energy, are considered a viable solution to these issues. However, the integration of renewable energy sources into electric power systems also presents operational challenges, particularly in terms of uncertainty. In order to mitigate this uncertainty, it is crucial to improve the accuracy of generation forecasting methods for wind energy. This review explores various wind power forecasting methods, categorizing them by factors such as time frame, and model structure. Special attention is given to short-term forecasting, crucial for the day-ahead electricity market. This study traces the evolution of wind power forecasting, from early statistical approaches to the integration of numerical weather prediction, machine learning, neural networks, and advanced techniques. Its aim is to provide valuable insights into wind power forecasting methods for stakeholders, including grid operators, traders, and wind farm operators. This review serves as a vital resource for researchers and industry professionals navigating the dynamic field of wind power forecasting, contributing to effective renewable energy resource management in a rapidly evolving energy sector.

1. Introduction

As the world enters the second quarter of the 21st century, the utilization of clean and renewable energy sources has become increasingly imperative due to the growing environmental consciousness of societies and advancements in science and technology. The demand for electricity is continually rising on a global scale, and wind energy, being a clean and renewable energy source, is considered to be a viable solution to this escalating demand. Effective wind power forecasting plays a pivotal role in seamlessly integrating wind energy into the power grid. As wind generation continues to expand, precise forecasts are indispensable for managing this variable resource efficiently. The use of wind energy is on

Abbreviations: AE, Auto-Encoder; AI, Artificial İntelligence; AMC, Attention-Based Multi-Component; ANFIS, Adaptive Network Based Fuzzy İnference System; ANN, Artificial Neural Networks; AR, Auto Regressive; ARCH, Autoregressive Conditional Heteroscedasticity; ARIMA, Auto-Regressive İntegrated Moving Average; ARMA, Auto-Regressive Moving Average; BP, Back Propagation; CEEMDAN, Complete Ensemble Empirical Mode Decomposition With Adaptive Noise; CNN, Convolutional Neural Network; ConvLSTM, Convolutional Long Short Memory Network; DBN, Deep Belief Network; DL, Deep Learning; DWT, Discrete Wavelet Transform; ELM, Extreme Learning Machine; ENCSA, Enhanced Crow Search Algorithm; EXMS, Experimental Steps; FWNN, Fuzzy Wavelet Neural Network; GA, Genetic Algorithm; GMM, Gaussian Mixture Model; GPR, Gaussian Process Regression; GRU, Gated Recurrent Unit; HKLSSVM, Hybrid-Kernel Least-Squares Support Vector Machine; IOWA, Induced Ordered Weighted Average; IVMD, Improved extre Mode Decomposition; LSSVM, Least Squares Support Vector Machine; LSTM, Long Short-Term Memory; MA, Moving Average; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MKRPINN, Multi Kernel Ridge Pseudo Inverse Neural Network; MLP, Multi-Layer Perceptron; MMMD, Multiscale Mathematical Morphological Decompositio; MSE, Mean Square Error; MWNN, Morlet Wavelet Neural Network; NLP, Natural Language Processing; NN, Neural Network; NSGA, Non-Dominated Sorting Genetic Algorithm; NWP, Numerical Weather Prediction; PCC, Pearson'S Correlation Coefficient; PSAF, Parametric Sine Activation Function; PSO, Particle Swarm Optimization; PSR, Phase Space Reconstruction; RBF, Radial Basis Function; RMSE, Root Mean Square Error; RNN, Recurrent Neural Network; RWT, Repeated Wavelet Transform; SARIMA, Seasonal Autoregressive Integrated Moving Average; SE, Sample Entropy; SMLDAE, Stacked Multilevel-Denoising Autoencoder; SOM, Self-Organizing Map; SRNN, Stacked Recurrent Neural Network; SVM, Support Vector Machine; SWD, Swarm Decomposition; TOB, Transparent Open Box; TSA, Time Series Analysis; VAPWCA, Vaporization And Precipitation Based Water Cycle Algorithm; VAR, Vector Autoregressive; VARTA, Vector-Autoregressive-To-Anything; VMD, Variational Mode Decomposition; WDLSSVM, Wavelet-Decomposition Least-Squares Support Vector Machine; WPE, Weighted Permutation Entropy; WSCFS, Wind Speed Combined Forecasting System; WT, Wavelet Transform.

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the rise globally, as seen in Table 1, which illustrates the size of installed wind power by region and globally for the years 2013 and 2022. As of 2022, Asia had the highest installed power at 425.485 MW, with North America experiencing the largest increase, with an approximate thirteen-fold increase in a decade. The total installed power of wind energy worldwide has also seen a threefold increase over the past decade, totalling 898.856 MW (IRENA, 2023). However, the integration of renewable energy sources into power systems also presents operational challenges, particularly in terms of uncertainty (Hdidouan and Staffell, 2017; Cradden et al., 2012). The inherent uncertainty of renewable energy sources, coupled with the effects of climate change, poses a risk to the stability of the power system and requires new measures to mitigate this risk (Niu et al., 2022). One such measure is to improve the accuracy of generation forecasting methods for wind energy, thus reducing uncertainty (Tawn and Browell, 2022).

Methods for forecasting wind energy production can be classified in various ways. It is possible to classify them based on the time frame of the forecasts, the structure of the forecasting model, the predicted physical value, and the input-output data used (Tawn and Browell, 2022; Meka et al., 2021a). The most commonly used approach in the literature is to categorize forecasting methods based on the time frame. These categories include ultra-short-term, short-term, medium-term, and long-term forecasts (Zhang et al., 2017a; Monteiro et al., 2009). In this study, particular emphasis is placed on short-term forecasts, specifically those made between 4 hours and 72 hours in advance. Short-term forecasts cover time horizons ranging from the very short-term to between 48 and 72 hours. These forecasts are typically limited to a 48-hour time horizon. This time frame is particularly important for trading in the day-ahead electricity market. The timing for bid submissions can vary by country, therefore the time horizon may also vary (Monteiro et al., 2009). Short-term forecasting is of critical importance for balancing supply and demand in the day-ahead electricity market. The short-term power forecast, significantly impacts the predictive accuracy and reliability of the system.

Understanding the complexity of wind power generation necessitates an examination of the diverse factors influencing it. Meteorological conditions, geographical settings, and turbine technology significantly impact the efficiency and output of wind power systems.

Table 2 categorizes various factors influencing wind energy production into three main groups: Positive Effects, Negative Effects, and Other Important Factors. Each category is populated with factors identified across multiple studies focusing on wind energy generation. The table aims to consolidate these factors to provide a comprehensive overview of elements that can either enhance or inhibit wind energy production efficiency, as well as those that play a significant role in planning and operational strategies (Burke and O'Malley, 2011; El-Ahmar et al., 2017; Zhao et al., 2013; Papież et al., 2019).

The earliest conceptualizations of short-term forecasting in the academic literature emerged in the 1970s, but significant progress in this field did not occur until the study conducted by Notis and colleagues in 1980. Throughout the 1980s, various studies utilized statistical time series analysis methods, but it wasn't until the 1990s that the numerical weather prediction (NWP) method gained prominence. In the early 2000s, the use of machine learning (ML) and neural networks in forecasting became prominent (Costa et al., 2008). In the first decade of the 2000s, autoregressive forecasting methods were developed and the focus of studies shifted towards these methods. In the following decade, various other methods such as Auto-Regressive İntegrated Moving Average (ARIMA), Auto-Regressive Moving Average (ARMA), Variational Mode Decomposition (VDM), Extreme Learning Machine (ELM), Support Vector Machine (SVM), and Artificial Neural Networks (ANN) were explored in the literature (Chen et al., 2022). As depicted in Fig. 1, the 'Wind Energy Forecasting Timeline' illustrates the history of wind energy forecasting. A plethora of models were examined individually and hybrid approaches were employed, with evaluations of the advantages and disadvantages of each method. This study aims to provide researchers with a comprehensive review of various methods by presenting a synthesis of the available literature with technological advances and evaluating the strengths and limitations of the methods. It aims to empower stakeholders, including grid system operators, electricity traders, and wind farm operators, with the knowledge needed to make informed decisions regarding efficient energy storage management and microgrid scheduling. Despite the challenges posed by the stochastic and intermittent nature of wind speeds, accurate and reliable forecasting can mitigate risks associated with grid integration and facilitate effective energy trading across all levels of the transmission

Table 1
Distribution of wind energy installed power by regions (IRENA, 2023).

Regions	2013 (MW)	2016 (MW)	2019 (MW)	2022 (MW)
World	300052	467013	622780	898856
Africa	1742	3831	5529	7687
Asia	99542	184143	257669	425485
C America +Carib	754	1481	1949	2101
Eurasia	2775	5801	7783	13712
Europe	118170	155727	196110	240285
Middle East	122	423	775	1053
N America	70122	97526	123597	163470
Oceania	3895	5066	8625	11522
S America	2930	13013	20742	33541

Table 2
Factors Influencing Wind Energy Production (Burke and O'Malley, 2011; El-Ahmar et al., 2017; Zhao et al., 2013; Papież et al., 2019).

Factor Category	Factors	Descriptions
Positive Effects	Abundant wind resources, renewable energy policy, energy mix, offshore wind power utilisation, wind speed, rotor swept area, tower height	These factors directly enhance wind energy production and improve efficiency and generation capacity.
Negative Effects	High price of wind power, lack of key technologies, heavy repayment and tax burden, minimum system inertia constraints, grid congestion, load balancing requirements, obstacles to wind flow	These factors hinder or complicate wind energy production, increase costs, and limit technological advancement.
Other Important Factors	System demand profile and fuel price uncertainties, policy support and regulatory instruments might negatively impact, air density, air pressure and temperature	These factors indirectly influence wind energy production and are crucial for planning and strategy formulation.

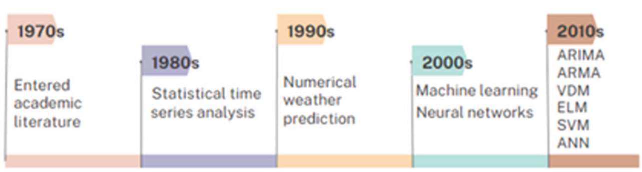

Fig. 1. Wind Energy Forecasting Timeline.

and distribution network.

In this article, we will examine short-term wind energy forecasting methods. This review comprehensively examines the development and technological advancements of short-term wind energy forecasting methods, contributing to the enhancement of energy management strategies. Our study focuses on critically important ultra short-term and up to 72-hour short-term forecasts for day-ahead electricity markets. In addition to traditional methods, we detail our potential to increase forecast accuracy through innovative hybrid models that incorporate advanced technologies such as ML and ANN. These models combine the advantages of both physical and statistical forecasting techniques, outperforming individual methods. Moreover, incorporating the latest advancements, our updated classification system of wind energy forecasting methods enables researchers and practitioners to better understand and apply current technologies. However, our study also identifies significant gaps, particularly the need for models that can quickly adapt to different geographical conditions and the dynamics of weather variables. These gaps present significant research opportunities and open new avenues for further improvement of forecasting models. The introduction introduces the subject's importance and summarizes the article's structure. Section 2 presents a classification of these forecasting techniques. Chapter 3 provides a detailed analysis to provide a deeper understanding of the methods. Section 4 discusses the results and implications of the study, while Section 5 summarizes key implications and suggests potential future research directions

2. Classification of forecasting methods

Although the classification of wind energy forecasting techniques according to time has been approached in many ways in the literature, it will generally be correct to examine them in 4 parts. These are: ultra-short-term forecasting, short-term forecasting, medium-term forecasting and long-term forecasting methods. Ultra-short-term forecasts are expressed in minutes, short-term forecasts in hours, medium-term forecasts in days, and long-term forecasts in weeks, months and even years. Fig. 2 in this article shows a time classification of commonly used forecasting methods and provides examples of its usefulness (Chen and Folly, 2018).

Forecasting methods are divided into two main categories. These are physical and statistical methods (Tascikaraoglu and Uzunoglu, 2014; Landberg, 1999). However, when these methods are used alone, their prediction accuracy is low. In order to improve the accuracy of forecasts, hybrid methods have been developed by combining physical and statistical methods. When examining the studies in the literature, it is observed that hybrid methods tend to have higher accuracy compared to individual methods. Therefore, it is important to evaluate and classify forecasting methods to include physical, statistical, and hybrid models (Hanifi et al., 2020; Yang et al., 2021). Fig. 3 illustrates the classification of commonly used forecasting methods in the literature based on their approaches.

Table 3 provides a detailed comparison of these methods, highlighting their descriptions, advantages, and disadvantages. This comparative analysis serves as a guide for selecting the most appropriate forecasting technique based on specific needs and constraints in the context of wind power management.

3. Forecasting methods

3.1. Physical forecasting methods

Among physical models, the NWP method stands out as the most widely employed approach. In NWP, real-time atmospheric data like wind direction, wind speed, barometric pressure, and humidity are harnessed to make forecasts. NWP has proven particularly effective in producing accurate results for long-term wind predictions and is extensively employed in the management of large-scale wind facilities. Its precision is especially vital within the context of wind energy forecasting, as it plays a fundamental role (Meka et al., 2021b). It's worth

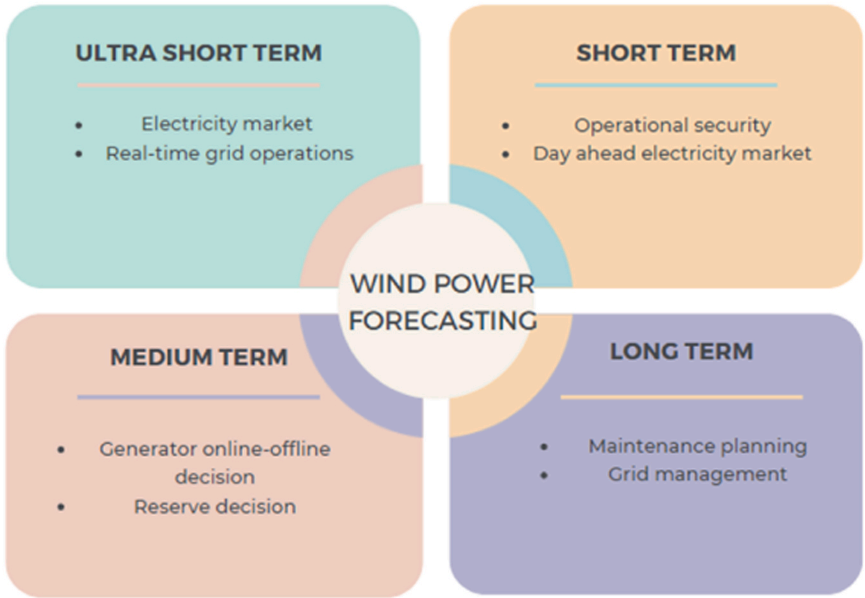

Fig. 2. Time-scale classification for wind forecasting.

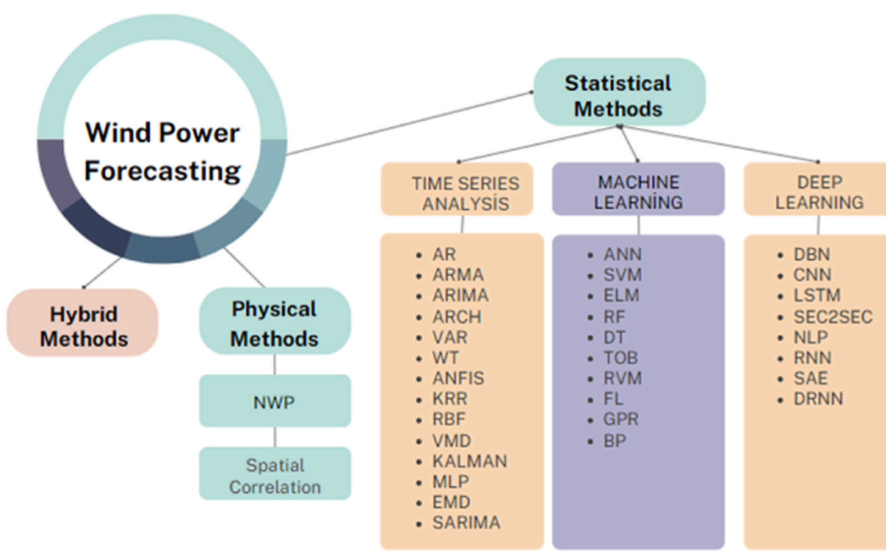

Fig. 3. Classification of Forecasting Methods.

noting that this method forms the cornerstone of literature studies. However, a key drawback to this method lies in its substantial computational time, leading to associated error rates (Li et al., 2020a). Another physical approach to wind prediction is the spatial correlation method, which leverages spatial correlations between wind speeds at different locations (Zhang et al., 2020a). This approach utilizes wind speed time series from the predicted points and nearby areas, taking into account the spatial relationship of wind speeds in different fields to predict wind speed (Lei et al., 2009a; Yang et al., 2005).

Considering that wind energy production is dependent on meteorological data such as wind speed, direction, and intensity, it becomes imperative to utilize certain data for making forecasts regarding the future. These meteorological data are derived, in fact, from a predictive methodology known as NWP. It is accurate to assert that NWP serves as a fundamental cornerstone in the initial stages of wind forecasting (Yang and Kleissl, 2023).

Zang and colleagues introduced a forecasting model that amalgamates multivariate time series clustering with deep learning. By harnessing input data from NWP and historical wind farm data, their sequence-to-sequence neural network-based model outperformed conventional methods, such as deep belief networks and random forests (Zhang et al., 2020a).

Wang et al. developed a deep belief network (DBN) model for wind energy forecasting using NWP data. Their DBN model achieved an accuracy surpassing 44 %, outperforming traditional Backpropagation Neural Network (BP) and Morlet Wavelet Neural Network (MWNN) methods (Wang et al., 2018).

Khazaei et al. proposed a hybrid forecasting approach with three stages: wind direction, wind speed, and wind energy forecasting. This method demonstrated robust performance, including outlier detection, wavelet transformation for time series decomposition, effective feature selection, and forecasting using a Multi-Layered Perceptron (MLP) neural network (Khazaei et al., 2022).

Eseye and colleagues introduced a two-stage hierarchical genetic algorithm-trained hybrid artificial neural network (GA-ANN) for short-term wind power forecasting. This approach improved forecasting

Table 3
Comparative Overview of Wind Energy Forecasting Methods.

Methods	Description	Advantages	Disadvantages
Physical Methods	Use real-time atmospheric data to make predictions.	High accuracy in long-term forecasts. Effective in managing large-scale wind facilities.	High computational requirements. Slow response times and high error rates.
Statistical Methods	Use historical data-based models (such as AR, MA, ARIMA) to predict wind speed and power.	Quick and effective for short-term forecasts. Low computational cost.	Limited in modeling non-linear relationships. Performance degrades with high-noise data.
Hybrid Methods	Combine the strengths of physical and statistical methods to create more complex models	Broad applicability using different data types and structures. High accuracy and reliable predictions.	Model complexity and high training requirements. Implementation and maintenance costs.

accuracy, integrating meteorological parameters from NWP in the first stage and modelling wind speed and power relationships in the second stage (Eseye et al., 2017).

Dong et al. aimed to enhance input data precision for wind forecasting through a multi-stage procedure, including data pre-processing, a hybrid neural network, and error analysis. The model utilized a stacked multi-level denoising auto encoder (SMLDAE) for data pre-processing, a hybrid model incorporating neural network-based multi-scale mathematical morphological decomposition (MMMD), and stacked noise removal auto encoders, k-means clustering, and error analysis via a long short-term memory (LSTM) network. This model demonstrated accurate wind forecasting at both a broad geographical level and for individual farms (Dong et al., 2021).

He and colleagues presented a model for short-term wind energy forecasting relying on NWP analysis. The model selected various factors from NWP multi-variable data using the minimum redundancy-maximum relevance (mRMR) algorithm, classified weather models into different categories based on extracted features, and applied Convolutional Neural Networks (CNN) and LSTM under diverse weather conditions. The combination of these models using the Induced Order Weighted Average (IOWA) operator showed superior forecasting accuracy compared to existing methods (He et al., 2022).

Indeed, studies (Zhang et al., 2020a; Wang et al., 2018; Khazaei et al., 2022; Eseye et al., 2017; Dong et al., 2021; He et al., 2022; Piotrowski et al., 2019; Higashiyama et al., 2018) collectively emphasize the significance of integrating NWP data into wind power generation forecasting. They highlight the limitations of relying solely on NWP for short-term wind power forecasting and demonstrate that combining NWP with other techniques, such as neural networks, ML, and statistical analysis, can enhance the precision of wind power forecasts (Zhao et al., 2016).

3.2. Statistical forecasting methods

Statistical forecasting methods can be broadly classified into three major categories: time series analysis, ML, and deep learning. These methods are widely used in wind energy forecasting. Its most important advantage has been shown to be effective in processing high-dimensional and nonlinear data. Studies using statistical forecasting methods are shown with reference numbers in Table 4.

3.2.1. Time series analysis

Using time series analysis tools to forecast wind energy production is important as it can help predict short-term power. In the context of time series analysis, the AR model combines previous variables with current variables, while the Moving Average model takes into account errors that have occurred in the past. ARMA model is created by integrating two components. ARIMA models can be created by changing the original value of the time series (González-Sopeña et al., 2021; Makridakis et al., 2018).

AR time series analysis, first introduced by Jenkins and Box in 1976, is a fundamental component of time series analysis. It forms the basis of many various time series techniques (Duran et al., 2007).

In the field of short-term wind power forecasting, AR models are utilized to predict future wind speeds and power output based on historical data. These models are particularly effective due to their ability to model the time-dependent structure of wind data. The general approach involves estimating the future value of the time series as a function of its past values. The mathematical formulation of an AR model, detailed below, leverages past data points to forecast future trends, making it invaluable for operational planning and grid management in wind energy production (González-Sopeña et al., 2021; Duran et al., 2007).

$$X_t = C + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t \quad (1)$$

Where X_t is the value at time t, c is a constant, $\varnothing_i$ are the coefficients of the model for each of the p previous terms, and ϵ_t represents the noise or error term.

By applying this formulation, AR models can capture the autocorrelations within the wind speed data, thus providing a reliable basis for accurate short-term predictions (Duran et al., 2007).

ARMA models are used to predict wind power and speed fluctuations and have high accuracy. However, in large data sets, the reliability of prediction approaches decreases, which poses a problem due to data fluctuations (Cao et al., 2013; Milligan et al., 2003). In a study by Korprasertsak, researchers compared the performance of different forecasting models such as ANN, GP, and ARMA. Researchers have demonstrated that the ANN model performs well in terms of predictive ability. It was also more versatile than other models despite its computational requirements (Korprasertsak and Leephakpreeda, 2019).

ARIMA models are used to predict wind energy production based on statistical analysis method. They make predictions using previous time series values. ARIMA models are powerful tools for analyzing the linear structures in time series data. They stand out for their ability to model trends and seasonality in non-stationary data. However, their limitations

Table 4
Statistical Forecasting Methods in Reviewed Studies.

	Time Series														Machine Learning										Deep Learning					
	AR	ARIMA	ARMA	WT	ANFIS	KRR	RBF	VAR	VMD	ARCH	KALMAN FILTER	MLP	EMD	SARIMA	SVM	ELM	ANN	WNN	RANDOM FOREST	TOB	RVM	FL	GPR	BP	LSTM	CNN	DBN	SEQ2SEQ	NLP	RNN
Zhang[22]																												√		
Wang[26]																											√			
Khazaei[27]							√					√																		
Eseye[28]																	√													
Dong[29]																									√					
He[30]																									√	√				
Piotrowski[31]												√					√													
Higashiyama[32]																										√				
Duran[36]	√																													
Cao[37]			√																											
Milligan[38]			√																											
Zhang[42]				√										√											√					
Singh[43]		√		√																										
Liu[44]														√																
Lv[47]		√								√																				
Koivisto[51]								√																						
Kalman[55]											√																			
Cassola[56]											√																			
Carolin[63]																	√													
Ansari[64]																	√													
Kariniotakis[65]		√															√													
Bhushan[66]																	√													
Sideratos[69]																						√								
Kariniotakis[70]																	√					√								
Ding[75]															√															
Li[76]															√															
Ji[77]															√															
Sun[79]																			√						√					
Yu[84]						√									√	√	√													
Sun[85]				√																										
Gu[86]																									√					
Lu[87]																									√	√				
Zhang[88]				√																	√			√						
Wood[89]																				√										
Du[90]													√					√												
Jinhua[91]																					√									
Naik[92]									√				√																	
Qu[93]																													√	
Liu[94]																														√
Xiong[95]																									√	√				
Toubeau[96]							√																		√					
Zhang[97]																								√	√					
Duan[98]																									√					
Cevik[99]					√								√		√		√													
Li[100]																√														
Ahmad[101]																							√							
Liu[102]					√		√								√									√						
Qin[103]																									√	√				
Dadkhah[104]							√										√													
Duan[106]									√																√		√			
Xing[107]																		√												
Viet[108]																	√								√					
Sun[109]									√																					
Kumar[110]																									√	√				
Zheng[112]																								√						
Singh[113]																	√													
Weidong[114]																	√							√						
Sun[115]									√																√					

become apparent in capturing the complex and non-linear characteristics of natural processes like wind speed. Their sensitivity to noise and inability to rapidly respond to unexpected events can pose specific challenges in wind energy forecasting (Hodge et al., 2011; Lei et al., 2009b).

In a study conducted by Zhang and colleagues, a new hybrid model combining DWT, SARIMA and Deep Learning techniques was proposed. The model showed high performance in tests, demonstrating the superiority of complex models of time series analysis in predicting wind power. Researchers tested the accuracy of the model by predicting wind power for a wind turbine in Scotland (Zhang et al., 2022).

Aasim and colleagues analyzed the errors produced by different time series when using ARIMA and WT models to predict wind speeds. They then developed a new model using the Iterated Wavelet Transform approach, which managed to provide high accuracy in predicting wind speeds. They tested the RWT-ARIMA model by comparing it with other time series models over different time periods. They found that it outperformed other models in predicting wind speeds (Singh and Mohapatra, 2019).

In a study by Liu and colleagues, researchers presented a SARIMA model that can predict wind speeds in Scotland. The model was compared with LSTM and Gated Recurrent Unit algorithms developed using deep learning. Test results of the SARIMA model revealed that the model can accurately predict future delays of time series data and offshore wind speeds (Liu et al., 2021a).

Autoregressive Conditional Heteroscedasticity (ARCH) models are used to model random fluctuations in time series data. It takes into account changes in certain periods (Gao et al., 2009; Wang et al., 2012). The conditional variance of the series depends on the previous values. The heteroscedasticity function may exhibit long-term autocorrelation (Lv and Yue, 2011).

In a study by Peng et al., wavelet analysis was used to separate wind speed series into approximate and detailed series. Using the ARIMA model for each component, the effect of heteroscedasticity on the series was taken into account and the ARIMA-ARCH model was established. Wind speed values were estimated by summing the estimated approximate and detailed values. This method was applied to estimate and verify actual wind speed data; this indicates improved accuracy in wind speed estimation (Lv and Yue, 2011).

Vector Autoregressive (VAR) models are based on the linear relationship between two or more-time series, extending the univariate autoregressive model to utilize multiple variables (Ghofrani and Alolayan, 2018; Jiang et al., 2021). They find wide application in power systems operations, including multi-site wind energy forecasting, wind speed forecasting, electricity price forecasting, and load forecasting (He et al., 2015).

Koivisto et al. proposed a Vector Autoregressive-Time-Varying-All (VARTA) process that incorporates temporal cross-correlation to model wind speeds at multiple locations. The model considers the likelihood of high or low wind speeds occurring simultaneously or sequentially in many locations, taking into account temporal and spatial dependencies. The performance of the model was evaluated using measurements from 21 locations in Finland and provided insights into power systems analyses, risk assessment and network planning, particularly for systems with significant wind energy capacity (Koivisto et al., 2016).

The Kalman filter is a second-order linear forecasting method using statistical noise and errors in the dataset to estimate variables, representing data trends based on probability distribution analysis (Aly, 2022). It provides an efficient computational solution to the least squares method, adapting easily to observation changes, requiring minimal background information, and exhibiting low computational costs (Heinermann and Kramer, 2016; Louka et al., 2008a).

In 1960, a paper by Kalman revealed a method for solving the discrete-data linear filtering issue. Due to the advancements in computing, the paper became a subject of numerous studies and applications in wind power. The Kalman filter is a computational method that can be utilized for forecasting the state of a process. It can also perform various other functions such as predicting the past, present, and future conditions (Kalman, 1960).

Cassola et al. employed the Kalman filter to determine the optimal configuration for wind speed and wind power forecasting. The method was evaluated retrospectively using a 2-year wind speed dataset from an NWP model and two anemometric stations in Italy. The results indicated that this methodology significantly improved forecasting, particularly for short-term predictions, compared to direct wind speed model output (Cassola and Burlando, 2012).

3.2.2. *Machine learning*

ML fundamentally transforms the approach to short-term wind energy forecasting by leveraging patterns hidden within historical data to predict future events. Originating from the fields of pattern recognition and artificial intelligence, ML has evolved to utilize statistical, probabilistic, and optimization techniques that enable models to improve iteratively as they are exposed to more data. Unlike traditional models that manually specify the entire model structure based on physical equations, ML algorithms autonomously identify the most significant features from the data, learning complex mappings from inputs to outputs. This capability is particularly useful in wind power forecasting, where ML techniques such as regression trees, neural networks, and SVM are employed to anticipate wind speeds and power generation more accurately than conventional methods. ML, as a progressive step beyond conventional statistical forecasting, is grounded in its adaptability and learning from data—a fundamental shift from rule-based to data-driven analysis. It excels by leveraging computational algorithms to discern complex patterns, leading to more nuanced and dynamic predictions of wind power generation (Demolli et al., 2019; Louka et al., 2008b).

ANNs are computational models that are inspired by the human brain. They consist of input, output, and hidden layers, where data processing takes place within the hidden layer. The most widely used types of ANNs are multilayer perceptrons (MLPs) and radial basis function (RBF) networks (Alabi et al., 2022; Sewsynker-Sukai et al., 2017; Ferrero Bermejo et al., 2019). ANNs offer advantages such as their ability to model complex non-linear relationships, adapt and learn from new data, process multiple inputs in parallel, and maintain functionality even with damaged components. However, they are often seen as "black box" models due to their lack of interpretability, are prone to overfitting, which necessitates the use of regularization techniques, can be computationally complex to train, especially for large datasets, and demand substantial labelled training data for effective learning, making them sensitive to data quality and quantity (Medina and Ajenjo, 2020).

$$\hat{y} = v_0 + \sum_{j=1}^{NH} v_J \cdot g\left(w_j^T x^i\right). \tag{2}$$

Where x^i is the input vector x, w_j is the weight vector, NH are the weights for the output node, g represent the hidden node in terms of a function, and $\hat{y}$ is the network output (Alabi et al., 2022).

Fig. 4 representation of an ANN structure is illustrated in the diagram, where nodes X1 through Xn in the input layer are fully connected to a series of hidden layers H1 through Hn, which in turn are linked to the output layer nodes Y1 through Yn, demonstrating the flow of information through the network.

In the field of wind energy forecasting, ML techniques mark a significant departure from traditional forecasting methods. Unlike AR models that rely on historical data to predict future trends based on linear assumptions, ML methodologies, especially ANN, are excellent at capturing the nonlinearity and complexity inherent in wind models. The power of ML lies in its data-driven nature, which allows models to reveal complex relationships within data without being limited to predefined equations. This adaptability is crucial in handling the variable and stochastic characteristics of wind speed and direction (Sewsynker-Sukai et al., 2017; Medina and Ajenjo, 2020).

Mabel and colleagues collected field data from seven wind farms over a 3-year period and used it to analyse and forecast electricity production from wind farms. They proposed a model developed using ANN network methodology. The model takes into account input wind speed, relative humidity and energy output variables. Modelling was done using the MATLAB program. The accuracy of the model was evaluated by comparing it with real values in wind power plants and it was found to provide high accuracy (Carolin Mabel and Fernandez, 2008).

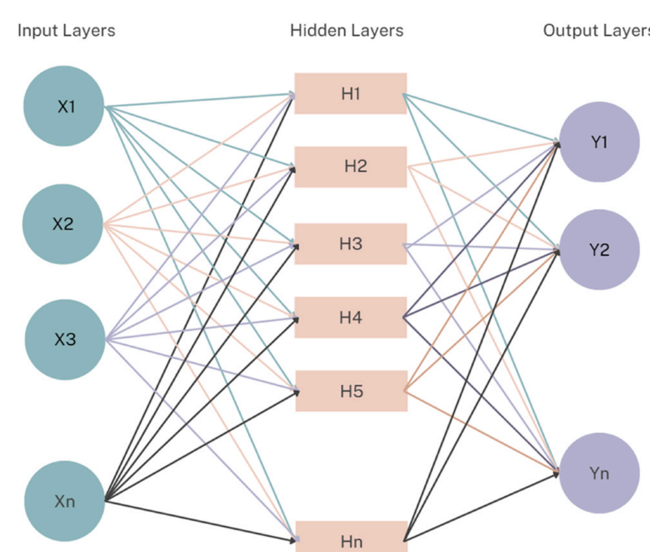

Fig. 4. Artificial Neural Network (ANN) structure.

Ansari and colleagues used wind data to predict power generation for 3 different types of wind turbines with different characteristics using MATLAB. They compared the forecasting with actual data and achieved an accuracy of over 80 % (Ansari et al., 2021).

Nair and colleagues used ANN, ARIMA and a hybrid method, which is a combination of both, in three different regions in India. The input data for the proposed model is wind speed at 1 hour intervals for 3 years. To evaluate the accuracy of the model, numerical error evaluation methods such as MAPE, MSE and MAE were used. The results showed that the error rate of the hybrid model was smaller than that of the ANN and ARIMA model separately (Kariniotakis et al., 2024).

Sahay and colleagues used various ANN algorithms using MATLAB to predict short-term wind speed. Hourly historical data on wind direction and wind speed are the data used for forecasting. Simulation results have shown that it is possible to make accurate wind speed forecasting with a small error (Bhushan Sahay and Srivastava, 2018).

The concept of fuzzy logic is a method used when modeling a complex system is difficult. It can be used to solve problems involving incomplete information and uncertainty (Zendehboudi et al., 2018).

Fuzzy logic methods are also used in wind energy forecasting systems, such as those developed by Zhang and colleagues in 2017 (Zhang et al., 2017b).

Sideratos and colleagues used a statistical method using artificial intelligence techniques to estimate wind energy. This method uses historical data and estimates of wind direction and speed. The salient aspect of the approach is that it also estimates the quality of meteorological forecasts created after a preliminary analysis. The researchers' method was able to predict wind energy levels 48 hours in advance and provide useful forecasts for wind energy (Sideratos and Hatziargyriou, 2007).

Kariniotakis and colleagues developed models using fuzzy logic and recurrent high-dimensional neural networks to predict the power of a wind farm. The models have been tested using various wind energy time series and have been shown to outperform traditional models (Kariniotakis et al., 1996).

The SVM algorithm was first proposed by Vapnik and Cortes in 1995. It is a ML method based on statistical learning and structural risk minimization theory. SVM method is frequently used as a forecasting method. The purpose of this method is to transform input spaces into high-dimensional spaces through nonlinear mapping (Cortes and Vapnik, 1995; Chapelle et al., 2002; Tinoco et al., 2014). The SVM method is a more efficient alternative to neural networks due to its ability to overcome overfitting and local minimal (Ghoushchi et al., 2021).

SVM models are widely used in wind and solar energy forecasting. They are extremely sensitive and can handle complex relationships. Unfortunately, SVM models have some drawbacks due to their limitations in terms of interpretability and hyperparameter selection. They also tend to have difficulty capturing temporal dependencies in data (Zendehboudi et al., 2018).

Min Ding and colleagues proposed a time series method that considers various factors affecting wind energy forecasting using hybrid kernel least squares support vector machine (HKLSSVM). The researchers compared the proposed framework with wavelet and empirical mode decomposition models. The comparison results showed that the proposed model has better performance than the comparison models (Ding et al., 2021).

Ling Li and colleagues proposed a hybrid model that combines SVM and improved bat algorithm. The proposed model has demonstrated superior forecasting performance compared to other models such as backpropagation neural network and Gaussian process regression (Li et al., 2020b).

Ji and colleagues utilized a chaotic analysis-based approach for forecasting wind energy. It includes a time series analysis and a phase space reconstruction procedure. They first calculated the Lyapunov exponent for the level of chaos in the data.The researchers then analyzed the time series data collected from nearby wind farms using two different multidimensional regression models. They found that the proposed framework performed better than the classic LSSVM model when it came to stability and accuracy (Ji et al., 2022).

Random forest is a versatile ML algorithm that combines multiple weak decision trees through voting or averaging to obtain the final outcome, making the result more robust. It is an ensemble method that uses an algorithm called bagging to combine many decision trees (Lahouar and Ben Hadj Slama, 2017).

Sun and colleagues proposed a hybrid model that consists of secondary decomposition, pre-prediction, and error analysis which is able to better capture wind energy variability while ensuring prediction stability in their study. The random forest algorithm is used to identify the regular trend of wind power, while the combination of K-means and LSTM enhances the comprehensive ability for the analysis of irregular components (Sun et al., 2021a).

3.2.3. Deep learning

Deep learning-based models are an extension of ML methods that involve several hidden layers. Three main types of deep learning that are frequently used in literature include stacked autoencoders, deep belief networks, and deep recurrent neural networks (Wang et al., 2019).

Deep learning encompasses several key techniques, including Stacked Autoencoders (SAE), Deep Boltzmann Machines (DBM), and Convolutional Neural Networks (CNN). SAE, in particular, comprises an unsupervised learning component that utilizes autoencoders as its fundamental building blocks, along with a logistic regression layer for data fitting (Hu et al., 2016). The primary objective of SAE is to acquire a dimensionality reduction representation of the input data. Deep learning techniques, including CNNs, RNNs, and LSTM networks, offer unique advantages in modeling the temporal and spatial complexities of wind data. CNNs excel at capturing spatial features and local dependencies in wind speed patterns, while RNNs and LSTMs are effective in capturing temporal dependencies and long-range correlations. By leveraging these strengths, deep learning models can provide accurate and robust predictions of wind speed behavior across various spatial and temporal scales (Wang et al., 2019; Hu et al., 2016).

The researchers utilized the DBM and SAE models as their models. The former is a generative model that features numerous hidden Boolean units. Its main objective is to find a desirable distribution of the input units to the outputs. In contrast to other neural networks, both DBM and SAE utilize training processes to address the local minima issue (Hinton, 2009).

The training process for DBM and SAE involves two phases. The first is focused on establishing favorable initial values, while the latter involves tuning the network's performance (Wang et al., 2016).

3.3. Hybrid methods

Hybrid methods refer to techniques that integrate physical and statistical methods to improve model performance. These methods leverage the strengths of each individual model and combine them to achieve higher accuracy than existing approaches. A review of the literature reveals that a significant proportion of proposed methods are of the hybrid methods.

Lean Yu and colleagues introduced an innovative forecasting model that employs a rolling decomposition-reconstruction-ensemble approach, focusing on complexity features, to enhance the accuracy of short-term wind energy predictions. Their model outperformed benchmark models like AI, ELM, SVR, and ANN in empirical evaluations, demonstrating its effectiveness in short-term wind energy forecasting (Yu et al., 2022).

Gaiping Sun and colleagues developed a hybrid short-term wind energy forecasting method that combines clustering and a wavelet-based neural network. This methodology aims to identify similar wind speed patterns using clustering, Euclidean Distance, and Cosine Angle measurements. Results indicated improved forecasting accuracy compared to other models (Sun et al., 2018).

Bo Gu and colleagues proposed a short-term power generation forecasting approach utilizing LSTM, a recurrent neural network known for its effectiveness in time series prediction. Their results showed superior forecasting accuracy for 4-hour, 24-hour, and 72-hour forecasts compared to BP neural network, Particle Swarm Optimization (PSO), and the hybrid PSO-BP model (Gu et al., 2021).

Peng Lu and colleagues utilized historical wind power and basic meteorological data to develop a forecasting model based on a combination of CNN and LSTM. They introduced an integrated forecasting framework that includes the selection of key meteorological factors, data decomposition, integrated model construction, and optimization strategy. Their CNN-LSTM model effectively predicts day-ahead wind power, enhancing forecasting accuracy and reliability (Lu et al., 2022).

Jinhua Zhang and colleagues propose a combined forecasting model that employs a fusion strategy involving BP, Wavelet, and Relevance Vector Machine (RVM). This hybrid approach seeks to enhance the accuracy of individual results obtained from each method. Their study results demonstrate that this combined system outperforms the separate outcomes of each method (Zhang et al., 2020b).

David A. Wood highlights the unique capability of the Transparent Box Algorithm to identify distinctive relationships among multiple input variables across the entire dataset. This characteristic sets it apart from most ML algorithms, as it considers relationships within the dataset. This feature enhances forecasting methods by leveraging these input variable relationships (Wood, 2020).

Pei Du and colleagues introduce a hybrid model designed to improve forecasting accuracy. Their approach begins with full ensemble empirical mode decomposition to remove noise and extract primary data features. Subsequently, an optimized improved wavelet neural network is employed to produce highly accurate and stable forecasts. Comparative assessments against four case studies and 18 comparison models reveal that the hybrid model yields lower average absolute percentage error (Du et al., 2019).

Zhang et al. utilize SVM, Wavelet, and RBF to estimate and compare power generation in three wind farms. Simulation results indicate that the SVM method exhibits higher accuracy and efficiency (Jinhua et al., 2019).

Naik et al. It proposes a new hybrid technique based on Multi-Core Regularized Pseudo-Inverse Neural Network (MKRPINN), optimized using Evaporation and Precipitation Based Water Cycle Optimization Algorithm (VAPWCA). Comparative evaluations against various models show the superiority of the Variable Mode Decomposition based wind energy forecasting model VAPWCA-VMD-MKRPINN based on performance metrics such as RMSE, MAPE, MAE and CC2 (Naik et al., 2018).

Kai Qu et al. apply the Transformer model, commonly used in natural language processing (NLP), to wind energy forecasting. This novel approach accurately extracts correlation levels between multiple wind farms and provides precise wind power forecasts, outperforming other methods in case studies (Qu et al., 2022).

Xin Liu et al. introduced an SRNN with a parametric sine activation function (PSAF) algorithm for adaptive wind energy forecasting. They designed a nonlinear difference equation model for SRNN-PSAF with adjustable parameters, conducting sensitivity analysis on forecasting accuracy. The model was applied to NERL wind data and compared to SVR, ANN, RNN, LSTM, and GRU, demonstrating superior performance (Liu et al., 2021b).

Xiong and team proposed AMC-LSTM, a hybrid model incorporating CNN and LSTM, for short-term wind forecasting using real wind turbine data. This model effectively integrates multi-scale features and improves forecasting performance (Xiong et al., 2022).

Toubeau et al. aimed to enhance forecasting accuracy by utilizing LSTM to capture complex temporal wind power dynamics. Their Belgian case study showed that optimal recalibration significantly improved forecasting reliability, reducing system balancing costs (Toubeau et al., 2021).

Zhang et al. employed a deep learning network based on LSTM for wind turbine power prediction and used a Gaussian mixture model (GMM) to analyze error distributions. LSTM outperformed other methods in terms of accuracy and convergence speed (Zhang et al., 2019).

Duan et al. proposed a robust hybrid wind energy forecasting model based on LSTM, incorporating Correntropy-enhanced Variational Mode Decomposition (IVMD) and Sample Entropy (SE). Experiments with real data from two Chinese wind farms demonstrated the method's effectiveness over traditional approaches (Duan et al., 2021).

Cevik and colleagues introduced a three-stage wind energy forecasting method. They predicted wind speed, wind direction, and wind power in the first stage using ANFIS, ANN, and SVR with preprocessing methods EMD and Stationary Wavelet Decomposition (SWD). The multistage model achieved effective wind energy prediction, with MAE values of 0.333, 0.294, and 0.278 in each stage, respectively, compared to real data (Cevik et al., 2019).

Ling-Ling Li and colleagues introduced the Enhanced Cuckoo Search Algorithm Optimization-Extreme Learning Machine (ENCSA-ELM) model for highly accurate short-term wind power prediction. The ENCSA-ELM model demonstrated superior performance compared to existing wind energy forecasting methods, traditional ML models, and other ELM-optimized algorithms. It achieved RMSE and MAPE values below 20 % and 4 %, respectively (Li et al., 2021).

Ahmad et al. utilized a Gaussian GPR framework for forecasting solar, wind, and short-term energy. It performed well at two temporal resolutions. The four experimental steps were conducted with different forecasting methods and parameters. The researchers were able to use the GPR model to predict power in the data (Ahmad et al., 2021).

Liu et al. presented a novel hybrid methodology for short-term wind energy forecasting, incorporating ANFIS, BPNN, RBFNN, and LSSVM as individual forecasting models. They applied a data pre-processing method based on Pearson correlation coefficient (PCC) to select appropriate inputs for the models, demonstrating its improvement over previous methods. The hybrid methodology significantly improved accuracy compared to individual models (Liu et al., 2017).

Qin et al. proposed a two-stage forecasting method, with the first stage involving the development of four DNN models to learn data characteristics. In the second stage, they investigated model extrapolation using different methods while considering overfitting. Results from three wind farms indicated that the single input-multiple output structure model outperformed existing models in the literature (Qin et al., 2021).

Dadkhah et al. incorporated wind speed and wind direction, less commonly used factors in forecasting, into the dataset, along with additional climate factors. Despite the noise introduced, the importance of these factors in the forecasting method was highlighted. They proposed a neural network-based approach using Kohonen's self-organizing maps (SOM) for clustering and RBF for classification to achieve accurate power output forecasting in an energy plant, considering six variables (Dadkhah et al., 2018).

Ding et al. introduced a correction model for NWP wind speed errors in short-term wind energy forecasting, based on bidirectional recurrent unit neural networks. The model extracts the standard deviation of NWP wind speed errors, reorganizes the NWP wind speed series according to weight time series, and employs bidirectional recurrent unit neural networks to correct errors using NWP wind speed and input features. Their proposed model outperforms in short-term forecasting, surpassing medium and long-term forecasts (Ding et al., 2019).

Jiandong et al. developed a hybrid forecasting model that combines decomposition, nonlinear weighted combination, and two deep learning models to enhance the accuracy and stability of wind energy forecasting. They decomposed the wind energy series using the VMD technique, employed LSTM and PSO-DBN for subseries forecasting, and integrated these models using a PSO-DBN-based nonlinear weighted combination. Their method demonstrated superior effectiveness compared to existing approaches using 10-minute wind speed data from a Chinese wind farm (Duan et al., 2022).

Ghoushchi et al. utilized an extended fuzzy wavelet neural network (FWNN) for power output prediction in a wind farm, incorporating weather and energy plant parameters. They employed a hybrid learning algorithm, a combination of PSO and Gradient Descent, for optimal parameter tuning in the extended FWNN method. This approach exhibited higher efficiency and sensitivity for short-term wind energy forecasting compared to traditional methods (Ghoushchi et al., 2021).

Xing et al. presented a novel forecasting methodology, the Wind Speed Prediction and Forecasting System (WSCFS), which combines data pre-processing, model selection, point and interval prediction, and advanced optimization techniques. The WSCFS model, based on fuzzy knowledge granulation and optimal model selection, integrates deep learning, neural networks, and multi objective optimization. Experimental results indicated its superior accuracy in point and interval predictions compared to tested models (Xing et al., 2022).

Viet et al. proposed a wind energy generation prediction method that incorporates the policies of the Vietnamese government regarding planned wind energy development. The model was trained on historical data from 2015 to 2017 and tested using hourly weather forecast data from a specific wind farm, demonstrating its effectiveness and recommending its use (Viet et al., 2018).

Sun et al. introduced a novel wind energy forecasting model, combining VMD and LSTM techniques. This hybrid model significantly improved forecasting accuracy (Sun et al., 2021b).

Kumar and colleagues advocated the use of an ensemble of models to enhance forecasting accuracy. Their hybrid model leveraged the strengths of four ML algorithms: CNN, LSTM, LightGBM, and XGBoost. Evaluation using real wind farm data in India showed that the proposed model outperformed individual models for various months (Kumar et al., 2020).

Maurya and Goswami emphasized the importance of Multi-Variate Time Series Forecasting (MTFS) in wind power forecasting. They applied Complex Empirical Mode Decomposition (CEEMDAN), Adaptive Noise techniques, and an Attention-based approach to reduce noise and select effective features. A Genetic Algorithm optimized hyper parameters, and their approach outperformed non-attention-based models in terms of RMSE and MAE scores (Maurya and Goswami, 2022).

Zheng and colleagues developed a deep neural network (DNN) method for offshore wind energy forecasting, incorporating clustering analysis to handle input data uncertainty. Compared to BPNN and WNN methods, their proposed method achieved a 40 % higher forecasting accuracy (Zheng et al., 2018).

Singh and colleagues presented ANN-based approaches for predicting wind speed and power in India using data from multiple sources. Direct wind power forecasting resulted in lower error compared to a two-step approach involving wind speed forecasting (Singh et al., 2016).

Weidong and colleagues compared three genetic neural network (NN) techniques for wind speed and power generation prediction, finding that Genetic Algorithm BP was more effective and accurate than Standard BP and Momentum BP (Weidong et al., 2010).

Sun and Zhao proposed a unified model for short-term wind energy forecasting, incorporating Variable Mode Decomposition (VMD), ConvLSTM, and error analysis. This model demonstrated high performance in capturing spatial and temporal features (Sun and Zhao, 2020).

Jeyakumar and associates suggested Markov chain-based models for short-term wind energy forecasting, including first and second-degree models with seasonal variations. Evaluation metrics revealed high accuracy, with second-degree models performing particularly well in both high and low wind regimes (Jeyakumar et al., 2021).

4. Discussion

In Sections 2 and 3, it has diligently examined and classified a plethora of methodologies commonly employed in the wind energy forecasting literature. Each of these methods, brimming with its own set of strengths and vulnerabilities, inherently caters to distinct forecasting scenarios. As it is delved into the nuanced discussions surrounding these methodologies, it becomes evident that they stand as indispensable tools in the pursuit of accurate wind energy predictions.

One prominent category of wind energy forecasting methods revolves around physical modelling, particularly the meticulous characterization of wind turbines and wind farms by refining NWP data through downscaling. These methods shine most brilliantly in the context of medium and long-term wind energy forecasting. Their prowess lies in their capacity to elucidate the intricate physical dynamics at play. However, this precision comes at a price, demanding substantial computational resources and entailing intricate computational complexity.

A contrasting, yet equally vital, realm of forecasting methods encompasses statistical techniques, prominently exemplified by ML and ANNs. These methodologies emerge as stalwarts in the arena of short-term forecasting and serve as the bedrock upon which numerous forecasting studies are built. The hallmark of ML algorithms lies in their knack for uncovering complex, non-linear relationships in data and their adaptability to evolving conditions.

- SVM, a supervised learning model, forges forecasts based on kernel functions and adheres to the principle of structural risk minimization. Notably, SVM exhibits the capability to model non-linear decision boundaries, rendering it invaluable for intricate forecasting scenarios.
- Both Decision Tree and Random Forest methods find application in solving classification and regression problems. In particular, Random Forest employs ensemble learning, harnessing the collective intelligence of multiple decision trees for augmented accuracy and reliability in forecasting. In the domain of short-term predictions, Random Forest often outpaces SVM in terms of precision.
- Modelled after the human brain, ANNs serve as a formidable tool for modelling complex systems, deftly managing vast datasets, unravelling intricate non-linear relationships, and adapting to dynamic environmental shifts. They find utility in both classification and regression tasks, yet, akin to their ML counterparts, ANNs necessitate substantial data volumes for training and substantial computational resources.

While these ML methodologies proffer a panoply of advantages, it is imperative to acknowledge their inherent limitations. The voracious appetite for computational resources, especially conspicuous in the case of SVMs, can elongate the model calibration process, leading to protracted training periods. Moreover, the inability of Random Forest models to extrapolate predictions beyond the confines of training data limits their applicability in certain contexts. Additionally, the presence of noise in input data can obfuscate the accuracy of forecasts generated by these models. Furthermore, ANNs, too, beckon powerful hardware and extensive training durations.

Within the domain of wind energy forecasting, deep learning methodologies, characterized by their multi-layered architecture, stand out as a beacon of innovation. These advanced models often incorporate specialized neurons, including convolutional neurons and recurrent neurons, enabling the execution of complex operations and the facilitation of multiple activations. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) emerge as stalwarts in the deep learning domain, complemented by models such as Deep Belief Networks (DBNs), Autoencoders (AEs), and Long Short-Term Memory networks (LSTMs). Deep learning's hallmark advantage resides in its unrivalled capacity to adeptly process substantial volumes of data, culminating in exceptionally precise predictions. Nevertheless, the realm of deep learning does not remain devoid of its own set of constraints, including a voracious appetite for extensive training data, interpretational challenges in output generation, and an insatiable demand for high-performance hardware.

This comprehensive discussion underscores the multifaceted nature of wind energy forecasting methodologies. The synergistic interplay of physical, statistical, and deep learning approaches empowers forecasters to navigate the complexities of wind energy prediction across diverse temporal horizons. As the field continues to evolve, it becomes increasingly clear that the holistic integration of these methodologies, along with ongoing research to address their inherent limitations, holds the key to enhancing the accuracy and reliability of wind energy forecasts, thereby propelling us closer to a sustainable and resilient energy landscape.

5. Conclusion

In the realm of renewable energy generation, accurate forecasting of wind power plays a pivotal role in ensuring the effective management of power grids, facilitating electricity market operations, and optimizing energy storage strategies. The dependable prediction of energy production from renewable sources, particularly wind, is indispensable for maintaining grid stability and making informed decisions in long-term planning. However, it is in the domain of short-term forecasting, especially for the day-ahead electricity market, where the demand for precise wind power generation forecasts becomes most pronounced.

The review thoroughly examined the different forecasting techniques for wind power generation that are in existence. It revealed their disadvantages and advantages. The advantages of using hybrid models include enhanced accuracy in short-term forecasts, improved integration of renewable energy into power grids, and better resource management and planning. These benefits contribute to a more reliable and efficient energy production process. However, the disadvantages of these models are high computational requirements, complexity in implementation and maintenance, and sensitivity to data quality and availability. These findings underscore the importance of selecting appropriate forecasting methods based on specific requirements and constraints, emphasizing the need for a balanced approach that considers the advantages and disadvantages of the various techniques. It also noted that the technological advancements that have occurred in the field have greatly affected their design. The field of wind power has shifted toward utilizing advanced deep learning methods, which are capable of handling intricate patterns in the data generated by the turbines.

One notable trend that has emerged is the prevalence of hybrid forecasting methods, which amalgamate various techniques to harness their collective strengths and mitigate individual weaknesses. The empirical evidence suggests that these hybrid approaches often yield more accurate predictions compared to their standalone counterparts. This underscores the importance of synergy among different forecasting methodologies, as it enables forecasters to exploit the complementary nature of diverse techniques.

However, it is essential to acknowledge the existing limitations in the body of research. A majority of the reviewed studies have predominantly focused on single, relatively stable, and land-based wind facilities. Consequently, there exists a significant research gap pertaining to offshore wind farms, wind farms situated in complex terrains, and studies capable of extrapolating accurate predictions for larger geographical areas from limited-scale data.

In conclusion, the pursuit of advancing short-term wind power generation forecasting is not only an academic endeavour but also a practical necessity in the ongoing transition toward sustainable energy systems. As future research endeavours continue to bridge these knowledge gaps and refine existing methodologies, the collective pursuit of precise wind power forecasts will undoubtedly contribute to the resilience and efficiency of modern power grids and foster the integration of renewable energy sources into our energy landscape.

CRediT authorship contribution statement

Bülent Oral: Supervision. **Ezgi Arslan Tuncar:** Writing – review & editing, Writing – original draft. **Şafak Sağlam:** Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Safak Saglam reports financial support was provided by Marmara University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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