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Review

A Review of Modern Wind Power Generation Forecasting Technologies

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Abstract: The prediction of wind power output is part of the basic work of power grid dispatching and energy distribution. At present, the output power prediction is mainly obtained by fitting and regressing the historical data. The medium- and long-term power prediction results exhibit large deviations due to the uncertainty of wind power generation. In order to meet the demand for accessing large-scale wind power into the electricity grid and to further improve the accuracy of short-term wind power prediction, it is necessary to develop models for accurate and precise short-term wind power prediction based on advanced algorithms for studying the output power of a wind power generation system. This paper summarizes the contribution of the current advanced wind power forecasting technology and delineates the key advantages and disadvantages of various wind power forecasting models. These models have different forecasting capabilities, update the weights of each model in real time, improve the comprehensive forecasting capability of the model, and have good application prospects in wind power generation forecasting. Furthermore, the case studies and examples in the literature for accurately predicting ultra-short-term and short-term wind power generation with uncertainty and randomness are reviewed and analyzed. Finally, we present prospects for future studies that can serve as useful directions for other researchers planning to conduct similar experiments and investigations.

Keywords: predictive models; weather research and forecasting (WRF); uncertainty; wind forecasting; ultra short term and short term; wind power generation

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Citation: Tsai, W.-C.; Hong, C.-M.; Tu, C.-S.; Lin, W.-M.; Chen, C.-H. A Review of Modern Wind Power Generation Forecasting Technologies. *Sustainability* **2023**, *15*, 10757. https://doi.org/10.3390/su151410757

Academic Editor: Mohamed A. Mohamed

Received: 24 April 2023
Revised: 1 July 2023
Accepted: 2 July 2023
Published: 8 July 2023

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1. Introduction

Of the various sources of renewable energy, wind energy is one of the main types and is growing in use. Worldwide, wind energy reserves are very abundant, and the annual energy that can be developed is about 5.3×10^7 GWh. The wind power industry is mature, and the methods for renewable energy generation are easy to apply. Wind energy will account for 6% of global power generation by the end of 2020, with an installed capacity of 743 GW [1]. However, compared with traditional power sources, wind power generation is affected by weather and the adjacent terrain environment and is extremely unstable, random, intermittent, and inflexible. Various factors such as wind speed, wind direction, temperature, humidity, atmospheric pressure, and altitude will affect wind power generation. These variables are also interrelated, leading to large fluctuations in wind power, which ultimately makes it difficult to achieve satisfactory results in wind power forecasting. Wind power prediction involves applying state-of-the-art algorithms to the field of wind power generation so that wind power generation can be better connected to the electricity grid, and key technologies have developed rapidly. In the study of wind power forecasting, wind power has volatility and discontinuity due to the instability of the wind itself, which will cause serious difficulties in the scheduling optimization of wind power generation by the electricity grid. Therefore, many efforts and methods have been introduced to solve the wind forecasting problem. Wind power forecasting can be divided into physical methods, statistical methods, artificial intelligence (AI)-based methods, and deep learning-based methods. Of these methods, the artificial intelligence method can be adaptive and self-learning (e.g., BNN, knowledge graph) in various industries [2–4], smart grids [5–7], and railway transportation [8], so it is suitable for dealing with the dynamic, nonlinear, and complex characteristics of wind power. Accurate short-term forecasting of wind power is of great significance for alleviating the pressure of power system peak voltage and frequency regulation and wind power connected to the electricity grid.

In order to further improve the accuracy of short-term wind power forecasting, kernel density estimation is used to estimate the probability density function of the random variables required for predictive models to avoid the density leakage problem estimated for probabilistic wind power forecasting (WPF) of a region at both the wind farm and regional levels [9–11]. Quantile regression (QR) approximates the conditional probability distribution of a random variable by quantiles. Numerical weather prediction (NWP) data are often used as explanatory variables. Various QR models have been developed for WPPF, such as quantile passive–aggressive regression [12], regression curve fitting by WRF, and wind farm parameterization (WFP), as well as quantile regression neural network (QRNN) for regional wind power forecasting (RWPF) [13,14]. In recent years, spatiotemporal forecasting models have been increasingly researched due to their success in improving forecasting accuracy [13]. Given the use of data from different farms and sites to improve the performance of predictive models, spatiotemporal forecasting methods require large amounts of data, which in turn require advanced methods to address the high dimensionality of such situations. A convolution operation to capture the spatial–temporal correlation between neighboring wind farms was based on the novel spatial–temporal wind power predictor (CSTWPP) [15] and a spatiotemporal convolutional network (STCN), each developed separately [16]. New ANN model predictive control-based models [14,17–22] have been developed and offered for wind power prediction in microgrid applications and use air density and wind speed as input parameters.

The main advantage of ensemble models is their diversity, which allows for providing a set of multiple forecasts of the same quantity based on different estimates of initial atmospheric conditions in the WPPF, and ensemble approaches such as the CEEMDAN-IBA-GPR model [23], multi-feature fusion/self-attention mechanism/graph convolutional network (MFF-SAM-GCN), weighted multivariate time series motifs (WMTSM), and conditional LP (CLP) have been combined with adaptive boundary quantiles (ABQs), wavelet neural network (WNN) trained by the five algorithms [24–27], data preprocessing (EMD and ICEEMDAN) with parameter optimization [28], and enhanced bee swarm optimization (EBSO) to perform parameter optimization for least squares support vector machine [29] toward probabilistic wind power forecasting, taking full advantage of the most recent information and leveraging the strengths of multiple forecasting models. More recently developed are machine learning methods, which are powerful training algorithms based on artificial intelligence (i.e., neural networks). Due to their high computational intelligence and accuracy, such methods have been widely used in the past few years to improve the accuracy and performance of traditional WPPF models. The machine learning-based wind speed predictions for k-NN and conditional KDE, Adaboost-PSO-ELM, and enhanced bee swarm optimization (EBSO), to perform parameter optimization for least squares support vector machine (LSSVM) [11,26–28,30,31] models, were proposed to identify meaningful training data to reduce the volume of modeling data and improve the computing efficiency. They have good generalization ability and robustness and can provide more accurate wind power forecasting [32–44]. In order to comprehensively understand the research trends in short-term wind power prediction technology in the past three years and further develop the direction of future wind power prediction models, constructive suggestions were provided for short-term wind power prediction, in order to better understand and improve the use of AI methods as well as the correlation between the time resolution and the operation level of the prediction model. This paper further collected 62 papers on the power fluctuation and randomness in the prediction of wind power, as well as the possible errors and omissions in the original data, which were analyzed by different methods and achieved good results. In the reviewed works, deep learning is a machine learning concept that provides superior computation performance and flexibility by directly learning the best possible features of raw time series data; for example, the authors of proposed novel data-driven models based on the concepts of deep learning-based convolutional-long short term memory (CLSTM), mutual information, evolutionary algorithms, neural architectural search procedures, and ensemble-based deep reinforcement learning (RL) strategies [45–73]. The intention of hybrid model forecasting methods [20,74–99] is to combine different forecasting models to increase the accuracy and precision of forecasts, with their main advantage being that they combine the advantages of each model used to provide the best forecast output. The advantage of statistical-analysis-based approaches is that it can minimize the prediction error of the output probability when there is sufficient historical data. By training and adjusting the model, appropriate outputs can also be provided for input data that are not in the training set [100–114]. Other statistical analysis methods, such as five-minute-ahead wind power forecasts in terms of point forecast skill scores and calibration, 1% point analysis RL-based ESS operation strategy, empirical dynamic modeling (EDM)-based probabilistic forecast, etc., were introduced to improve the accuracy of ultra-short-term and short-term wind power forecasts and provide a more reliable basis for wind power grid integration.

To date, several review papers have examined wind power prediction. Wang et al. [115] gave an overview of wind power forecasting based on short-term and long-term methods. However, hybrid methods for AI-based wind forecasting have not been studied in detail. A survey by Hanifi et al. [116] was mainly conducted on physical, statistical, and hybrid methods to predict wind power generation. However, the authors explored some AI neural network methods for predicting wind power forecasts, although critical issues and challenges were not explicitly explored. Dhiman and Deb [117] delivered wind speed and wind force forecasting techniques, although deep learning algorithmic methods and their implementation are not covered. Lu, P. [118] proposed a classification of wind power forecasts based on different horizons. Nevertheless, the survey of hybrid AI methods and their implementation and limitations were not discussed in detail. Bazionis, I.K., et al. [119] reviewed wind power generation forecasts using various parametric and nonparametric approaches. A classification of wind forecasting methods is given according to timescales, forecasting models, and output data. Hybrid machine learning and deep learning methods have not been fully studied. Furthermore, implementation factors, optimization integration, and hybridization, which are critical issues for hybrid machine learning and deep learning methods, were not outlined. Lipu, M. S. Hossain, et al. [120] presented an in-depth investigation of wind power forecasting using artificial intelligence-based hybrid forecasting approaches. Furthermore, various combinations of hybrid AI methods, influencing factors, issues, limitations, and recommendations for achieving wind power forecasting are presented.

In the paper, we did a lot of review work for the proposed paper. In the initial search for this paper, a total of 317 papers were reviewed and identified using Google Scholar, MDPI, IEEE Xplore, Engineering Village, and the Web of Science. Relevant 151 articles were identified based on second-review keywords, title, abstract, article content, and the journal's main subject of interest. The final 106 papers were selected and analyzed based on reviewing the impact factor, review process, citation, exploration of issues and challenges, and future studies. Based on the temporal resolution, the number of AI methods used in the model, and the accuracy of the model, the performance level of short-term wind power prediction models is evaluated for the reviewed works, recommending prediction models with better performance. In order to meet the needs of large-scale wind power grid integration and further improve the accuracy of short-term wind power forecasting, it is necessary to develop a short-term wind power forecasting model based on advanced hybrid AI algorithms to accomplish accurate, robust, and efficient wind power forecasting. This was achieved through the following process:

1. This paper begins by summarizing the time resolution, model type, accuracy, and parameters of current advanced wind power forecasting technologies and determines the classifications, advantages and disadvantages, and contributions of the various wind power forecasting models.

2. These models have different predictive capabilities, and the weights of each model are updated in real time to improve the comprehensive predictive capabilities of the models, which have good application prospects in wind power forecasting.

3. Case studies and examples in the literature of accurate ultra-short-term and short-term wind power forecasting predictions with uncertainty and stochasticity are reviewed and analyzed.

Finally, the conclusion is drawn, and existing issues in the methodologies are outlined. Future research directions are presented.

2. Review of Research Status

European and American countries, such as Denmark, the United States, and Spain, have developed relatively early in terms of studying wind power generation, and many advanced results have been obtained as the basis for the maturation of research on wind power forecasting systems [121,122]. Based on meteorological information, they have built a relatively complete wind power forecasting system with the NWP system as the core. Prediktor is a prediction system developed by Denmark's Risø DTU National Laboratory for Sustainable Energy and put into use in 1994 [123]. Denmark is in a leading position in the development of wind power forecasting. For example, the WPPT forecasting system uses a combination of adaptive least squares and exponential forgetting algorithms (least squares and exponential forgetting algorithms), which can provide forecasts ranging from 0.5 to 36 h [124]. The Zephyr forecasting software developed by the Risø DTU National Laboratory is very popular in Denmark. It combines physical models with adaptive least squares and exponential forgetting algorithms to provide forecasts from 0 to 9 h and 36 to 48 h [125]. It uses a physical model and considers the impact of wind turbine wakes. By combining statistical methods with physical methods, the eWind system developed by American Truewind Company adopts a combination of physical and statistical forecasting methods that can upload real-time information and online in-depth analysis and has the ability to accurately predict the next 48 h [126]. The WPMS forecasting system developed in Germany is the most widely used forecasting software at present [127]. The system is combined with a neural network on the basis of NWP forecasting and further improves the forecasting accuracy of wind power. In Germany, ISET has developed the forecasting system AWPT [128], which was put into operation in 2001 and uses the method of combining NWP and neural networks mainly in 1- to 8-h forecasting. The following year, the University of Oldenburg in Germany developed the Previento system, which added typical physical models to the prediction system and could accurately obtain 2-day prediction results [129]. The Siperolico forecasting software developed by Carlos III University in Spain, HIRPOM [130] in Ireland, and the LocalPred model of the Renewable Energy Operation Centre (CORE) in Spain use both statistical and physical models [131]. The ANEMOS project has a total of 23 institutions from 7 countries, including Ireland, France, and Spain, participating in the research and development that can predict the wind power of large-scale offshore and land wind farms. Multiple NWP models are used in the ANEMOS project, so the local meteorological department is required to provide numerical weather prediction data [132]. After processing, physical and statistical methods are used to make predictions, whose accuracy can reach about 10%.

Different prediction algorithms are selected for prediction according to differences in regions, weather, and climate types. In addition to using physical methods for prediction, the system can perform statistical analysis of historical wind power data, further improving the accuracy of the prediction. In November 2008, the WPFS system was developed by

China [133]. After a series of successful test experiments, the system became the first mature wind power forecasting system in China. The system can effectively predict short-term wind power within three days and ultra-short-term wind power within four hours. The wind power generation forecasting systems currently used around the world are summarized as shown in Table 1.

Table 1. Wind power generation forecasting systems around the world.

Name of Forecasting System	R&D Institutions	Methods
Prediktor	Danish National Laboratory	Physical methods
SIPREÓLICO	University of Carlos III, Madrid, Spain	Physical methods
HIRPOM	University College Cork, Ireland	Physical methods
Previnto	University of Oldenburg, Germany	Physical methods
WPFS Ver 1.0 system	China Electric Power Research Institute	Physical methods/Meta-heuristic
WPPT	Copenhagen University, Denmark	Statistical methods
AWPPS	MINES ParisTech	Statistical methods, Fuzzy ANN
RAL	Appleton Laboratory, Rutherford, UK	Statistical methods
GH Forecaster	Garrad Hassan, UK	Statistical methods
WPMS	Germany-ISET	Statistical methods, ANN
Zephry	Risø National Laboratory	Statistical/Physical methods
LocalPred-RegioPred	Spanish National Energy Center	Statistical/Physical methods
ANEMOS	23 scientific research institutions in 7 EU countries	Statistical/Physical methods
eWind	True Wind USA, Inc.	Statistical/Physical methods
WEPROG	University College Cork, Ireland	Statistical/Physical methods

2.1. Reviews for Technologies and Applications

In recent years, relevant scholars have conducted theoretical research and practical simulation. The prediction type of wind speed has different definitions according to the length of the cycle, and different researchers have different classifications as shown in Table 2, mainly including ultra-short-term, short-term, medium-term, and long-term prediction.

Table 2. Classification of the review works based on the forecasting time scale.

Time Resolution	Reviewed Works	Forecasting Time Scale
1 min	[22,29]	Ultra short term
5 min	[15,16,29,61,101,103]	Ultra short term
10 min	[15,28,30,36,37,43,55,63,64,70,72,81,95–97,103,107,112,113]	Ultra short term
15 min	[12,15,20,21,23,30,38,42,52,53,56,57,59,60,71,74,88,93,98–100,103,108,110,114]	Ultra short term
30 min	[15,16,26,30,45,47,59,74,83,90,103–105,108]	Ultra short term
1 h	[14,16,18,24,27,30,33,35,38–41,44,46,48–51,54,59,62,65–67,69,74–77,80,83,86,90,91,94,102,106,108,111]	Short term
2 h	[16,25,30,35,59,80,83,86,90,94]	Short term
3 h	[16,30,35,59,79,80,83,86,90,94]	Short term
4 h	[25,30,35,59,78–80,83,86,89,90]	Short term
6 h	[35,86,89,90]	Short term
12 h	[35,86,89]	Short term
24 h	[9–11,17,29,35,53,58,79,80,82,84,85,87,89,92]	Short term
48 h	[31,32,46,89]	Short term
72 h–1 week	[13,29,34,89]	Medium term
1 month–years	[19]	Long term

Long-term forecasting based on “month” and “year” is mainly used in the design of wind farm operation plans and the evaluation of wind power resources for the planning of wind farms. The medium-term forecast is usually used to predict the sampling points in the next few days, or “week”, and is mainly used for troubleshooting and maintenance of wind power equipment in the power grid. Short-term and ultra-short-term forecasting is based on “hour” or “minute”, which is mainly used to adjust the reserve capacity of the power system and economic dispatching to reduce the instability of the system caused by wind power connected to the electricity grid, so as to conduct effective grid dispatching. According to different modeling methods, wind power generation forecasting can be divided into physical methods, statistical methods, artificial intelligence methods, and deep learning methods. Depending on the different prediction objects, it can be divided into indirect corresponding wind speed prediction and direct corresponding power prediction, as shown in Figure 1. According to the forecasting model, wind power forecasting can be divided into direct forecasting and indirect forecasting. Direct prediction refers to the establishment of a corresponding mathematical model based on the historical wind power time series of the wind farm to predict future wind power [134].

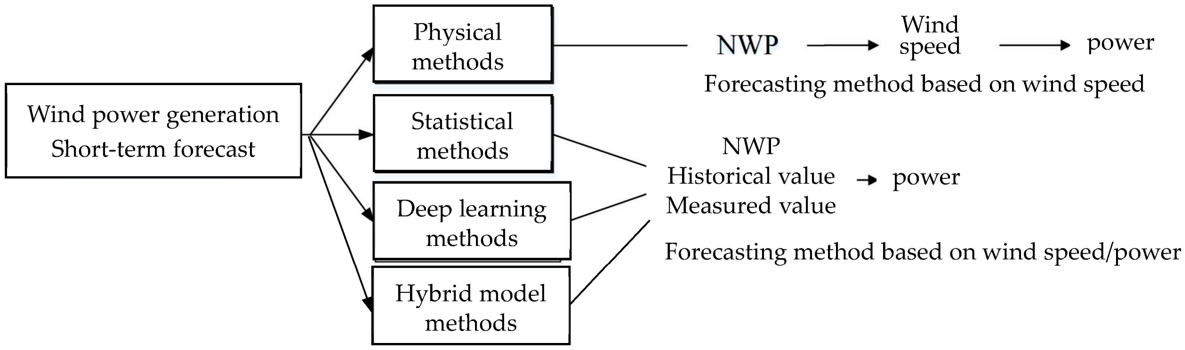

Figure 1. Short-term wind power generation forecast.

According to the prediction principles, wind power prediction can be divided into physical methods, statistical analysis methods, artificial intelligence methods, methods based on deep learning, and combined prediction models. In physical methods, the relatively rough forecast value output by the numerical weather forecast system is analyzed for making predictions based on the physical information around the wind farm and meteorological information such as weather and temperature. The advantage of physical methods is the lack of requirements for supporting historical wind farm power data. The disadvantage is that they are very sensitive to initial parameters, such as terrain description information. Inaccuracies in the initial parameters will cause large prediction errors. Statistical analysis requires a large amount of history of wind power or wind speed for statistical analysis, such as using Markov chains [12,15,135], regression analysis [29,30,34,41,113,114,136], Kalman filtering [137], and ARMA [105,138] models to find the laws contained in historical data for prediction. The advantage of the statistical method is that, under the premise of sufficient historical data, the forecast error can be minimized in theory and the forecast accuracy is high, but the disadvantage is that a large amount of historical data is required for support. The deep learning method is an emerging prediction method that can use artificial intelligence to establish an accurate model describing the nonlinear relationship between input and output. It can predict the essence of wind energy, thereby improving the prediction accuracy. Common methods include neural networks [139], wavelet analysis [98,140], and support vector machines [133,138,139,141]. Hybrid predictive models of artificial intelligence methods are becoming increasingly popular, not only increasing the complexity of algorithms but also enhancing the forecasting of wind power generation. Typically, hybrid predictive models are designed by combining two or three deep learning techniques or optimization algorithms with AI methods. This addresses the aforementioned shortcomings of a single predictive model by finding optimal features, hyperparameters, and training algorithms. The review focuses on wind power generation forecasting for time resolution and the model type, accuracy, and parameters.

2.2. Problem

In order to use physical models for calculation or statistical methods for simulation, the wind speed and wind direction of the wind farm over a short period of time in the future must be predicted. These are the highly relevant meteorological parameters for wind power to predict the ultra-short-term or short-term performance of the wind farm in the future. The output power provides a basis for the power sector to execute power generation scheduling, modeling, and expansion planning. The fluctuation of the wind is relatively large, and there are often jumps in time that cause a high probability of random uncertainty.

As the capacity of newly installed and operated wind turbines continues to grow, they will occupy an increasing proportion of the electrical grid. However, the penetration power of wind power generation cannot exceed its maximum value. If exceeded, the wind turbine units connected to the power grid will pose a huge threat to the grid, making the power system unable to perform normal, stable, and safe operations. In order to solve the above problems, it is necessary to scientifically predict the power output of wind farms according to the changing trend of wind, wind speed, and wind direction so as to improve the controllability of wind power generation. If the output power of wind power generation can be more accurately predicted through parameters such as wind change trends, wind speed, and wind direction, then the predicted data will be uploaded to the power dispatching center. The power dispatch center can scientifically and efficiently control power generation and distribution based on these data. Reasonable arrangements can fundamentally reduce the impact of wind power generation on the electrical grid and greatly increase the grid connection rate of wind power generation. Accurate wind power prediction solves the problem of grid connection and reduces the operating cost of wind farms. Therefore, wind power prediction technology has attracted the global attention of wind power fields, scholars, enterprises, and departments and is of great significance to the development of wind power.

Most prediction systems combine physical and statistical concepts, and their accuracy is limited by the numerical weather prediction model (NWP). When the forecast time exceeds 6 h, the numerical weather prediction (NWP) should reduce the temporal and spatial scale of the wind field to convert the local wind speed into electrical energy and then estimate the power of the entire region for a single wind field. The prediction error is about 10–15% of the root mean square error (RMSE) for the capacity of the whole wind farm. However, with the increasing capacity of wind turbines, the requirements for the accuracy of wind power generation prediction will be stricter. The traditional math equation for calculating power generation cannot directly reflect the rapid change in wind speed, and there is always a great error between the calculated value and the actual value.

2.3. Comparative Study of the Reviewed WPPF Models and Methodologies

In the past decade, research on wind power generation prediction has become increasingly popular. Most models use numerical weather prediction (NWP) and on-site measurement data (SCADA) as the basis, read the data from monitoring points, and then use the obtained wind speed and output data to predict wind power. However, due to the confidentiality of data sources, most prediction models rarely have a complete theoretical basis and historical data; therefore, the research is limited to a single site and region. A single prediction may result in higher forecast accuracy. Once considering multiple regions or large-scale spatial prediction at scattered meteorological stations, the results must be questionable. In addition to the increase in offshore wind turbines and the large amount of investment in private wind farms, persuading private wind farms to provide substantial wind turbine information (wind power generation, operating conditions, etc.) is a major challenge. Therefore, it is necessary to devote efforts to the prediction of large spatial scales. In this paper, the contribution of the current advanced wind power forecasting technology is summarized, outlining the distinct advantages and disadvantages of the various wind power forecasting models. These forecasting models have different forecasting capabilities, update the weights of each model in real time, improve the comprehensive forecasting capability of the model, and have good application prospects in wind power load forecasting. Finally, this paper remarks on the contributions, advantages, disadvantages, and approaches of the reviewed works in terms of wind power forecasting. In previous wind power prediction studies, most researchers used past meteorological data for evaluation. However, we were able to obtain more data, such as satellite data, future meteorological data, etc., due to the advanced information techniques. In the surveyed literature, it was found that more than 50% of the literature on wind power prediction used more input data than previous studies without optimal feature-based data preprocessing. Meanwhile, the prediction structure methods used are becoming increasingly complex, resulting in longer computation times. Some papers in the review literature also propose to preprocess historical wind data to reduce training times, thereby achieving effective data screening and improving the accuracy of wind power prediction.

This section classifies and explains different hybrid methods obtained from the reviewed works on wind power prediction based on artificial intelligence, including neural networks, machine learning, optimization algorithms, deep learning, hybrid predictive models combining two or three deep learning techniques or optimization algorithms, and statistical analysis methods.

A. Neural Network (NN)-based approaches

AI, or neural networks (NNs), have demonstrated excellent self-learning ability, high accuracy, and robustness when predicting wind power. This section classifies various neural network approaches for wind power forecasting, including the Elman neural network (ELM), the feedforward neural network (FNN), the back-propagation neural network (BPNN), the radial basis function (RBF) neural network, the extreme learning machine, the improved deep mixture density network model, and Poisson resampling. Neural networks (NNs) have the strength to address highly nonlinear and complex wind power problems. However, AI or neural networks (NNs) have some shortcomings; for instance, they have a local minimum trap, overfitting issues, a less general performance, and a slow convergence speed. A summary of neural network (NN)-based approaches for wind power forecasting in the reviewed works is presented in Table 3.

Table 3. Summary of Neural Networks (NNs)-based approaches for wind power forecasting.

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[14]	A quantile regression neural network (QRNN) for regional wind power forecasting (RWPF)	Enhancing the abilities of nonlinear mapping and dealing with massive data	NMAE: DQR:9.086; QRNN:9.479 SBL:13.451; IFPA:13.967 NRMSE: DQR:10.917; QRNN:10.227 SBL:14.185; IFPA:14.538	-To verify the model validation for the four-season test.
[17]	Improved deep mixture density network model	Wind speed, wind direction, wind vector, wind power	NRMSE = 0.138	-To avoid the problem of the curse of dimensionality when the number of wind farms increases -To further consider spatial and temporal information.
[18]	New artificial neural network (ANN) models	Wind speed, wind direction, wind power output	(MARE) = 7.5%; R_j = 5.4% (mean value of the Pearson correlation coefficient)	To improve the performance of the new model for the long-term forecasting of wind power
[19]	A fuzzy logic approach and ANN	Wind speed, air density	RMSE = 1.04%; MAD = 0.91% MSE = 1.05%	Wind power prediction technique with integration to the grid would be analyzed for considering load scheduling and demand side management.
[20]	An ensemble neural forecast (ENFF) with three neural predictors 1.ELM 2. FNN 3.RBF	Wind speed, meteorological	Errors around 0.6 m/s	Planning framework and operation strategy are developed for the storage providing virtual inertia support (VIS) in a low inertia power system.
[21]	Day-ahead numerical weather prediction (NWP) with neural network	The persistence method with BP three rolling prediction effect	The model accuracy improved by 7.61% and the RMSE reduced by 8.76%	Generalization and robustness of the BP neural network model will be the focus of future research.
[22]	-A classification model with the output wind power. -Use of Poisson re-sampling	The random forest with Poisson re-sampling and setting the parameters by oneself	Mean square error (MSE) GBRT: 0.224; MLP: 0.117 Random forest with Bootstrap sampling: 0.111 Random forest with Poisson re-sampling: 0.096	To improve the accuracy and speed of prediction for the characteristics of big data in wind power by parallel modeling of the prediction algorithm.

Table 3. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[23]	Dual-meta pool method	Wind farm power	MAE = 2.42, RMSE = 2.67 and MAPE = 0.12.	The prediction accuracy can be improved by using multi-source data.
[24]	Gated recurrent unit (GRU) network combined with ensemble empirical mode decomposition(EEMD)	Wind speed (m/s) Wind power (kW) Wind direction	RMSE(MW) = 0.2949	To apply it to the wind power prediction of offshore wind farms.

B. Machine-learning (ML)-based approaches

Machine-learning-based methods are emerging prediction methods that can establish accurate models to describe nonlinear relationships, predict the essence of wind energy, and improve prediction accuracy. The use of machine learning techniques with optimization algorithms is very effective for day-ahead wind speed prediction. A machine learning strategy may effectively reduce computing time through a data regression algorithm. Due to the variable nature of wind speed and its relationship with meteorological variables, it is possible to study the accuracy of integrating physical forecasting methods into machine learning models. Additionally, higher accuracy and better generalization ability are achieved with machine-learning wind power prediction models. However, it is difficult to select effective data feature values to evaluate the error of wind speed prediction due to the significant changes in wind speed data. Machine learning (ML)-based approaches for wind power forecasting in the reviewed works are summarized as shown in Table 4.

Table 4. Summary of Machine-learning (ML)-based approaches for wind power forecasting.

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[25]	Weighted multivariate time series motifs (WMTSM) and conditional LP (CLP) combined with the adaptive boundary quantiles (ABQs)	Wind speed, wind power	Both MAE and RMSE of less than 10%	The advanced method of dynamic analysis, which can accurately describe the characteristics of wind power time series.
[26]	Ensemble learning models (GRF, RF, XGB)	Wind power, wind speed, gearbox bearing temperatures	R^2 = 98.9; RMSE = 50.36; MAE = 23.63	To consider spatio-temporal dependence, which is not considered in ensemble learning models and machine learning models, for improving prediction quality
[27]	-Wavelet neural network (WNN) trained by ISCA, ELM, RBF, MLP, and PSO. -The best performing models are the WNN trained by ICSA and ELM-based NN models.	Selecting parameters by using particle swarm optimization	The average nRMSE for WNN trained by ISCA and ELM are 5.4059% and 6.925%; The average nMAE for WNN trained by ISCA and ELM are 4.2893% and 5.4787%.	To improve for large errors due to time by using five hybrid NN algorithms for short-term prediction of wind power.
[28]	Enhanced bee swarm optimization (EBSO) to perform the parameter optimization for least squares support vector machine (LSSVM)	Picking parameters for LSSVM by enhanced bee swarm optimization (EBSO)	DR-SVM VMED(m/s): 6.895 MAE (m/s): 0.723 RMSE(m/s): 0.932 MAPE(%): 11.87 CPU time(s): 148.15	To calculate errors using nMAE and nRMSE.
[29]	The state of the art of wind speed and power forecasting models for wind turbines located in different segments of power systems	Data preprocessing (EMD and ICEEMDAN) and parameter optimization	No description	To investigate whether the correction of the obtained forecast values can significantly reduce the error caused by the forecast models within the postprocessing data techniques in hybrid models.

Table 4. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[30]	The Adaboost-PSO-ELM method	Wind speed, wind direction, wind power	MAPE = 0.0372; NBE = 0.4621 RMBE = 0.2950; R^2 = 0.9857	-To consider reconstructing the training samples; -To select specific indicators as training samples for short-term wind power prediction to further improve prediction performance based on numerical weather forecast (NWP) data.
[31]	Salp swarm algorithms–extreme learning machine (SSA-ELM)	Wind speed, wind direction, temperature, atmospheric pressure, and other data are sampled every 10 min	MAPE = 1.2677 RMSE = 0.2576	-To avoid the over-fitting phenomenon of the ELM and improve its generalization ability.
[32]	Priori-guided and data-driven hybrid model	Wind speed, wind direction, and wind power	MAE = 0.0861, RMSE = 0.1262, R^2 = 0.8333, AR = 87.38%	-The online learning approach; -To apply wind power forecasting to turbine control or economic dispatch to facilitate the better operation of the wind turbines connected to the power grid.
[33]	Intelligent hybrid prediction framework	Wind speed	MAPE = 2.62 and RMSE = 0.14	The more efficient and advanced methods in the prediction sub-models may be beneficial to further improve the performance of the proposed framework.
[34]	ELM-based quantile regression model	Historical data on wind power	Reliability and skill score are reduced by 10% to 33%.	- Improving structures of NNs and adjusting network parameters; -The quantiles provided by the proposed method can enclose actual wind power output data more accurately.
[35]	Stacked physics-informed machine learning model	Ambient temperature, humidity, wind speed, wind direction, irradiance, and atmospheric pressure	RMSE = 5% and R^2 = 0.95	Future work involves the employment of new and unexplored ML methods striving for deeper learning.
[36]	Cyber-secure generalized supermodel	Wind speed, temperature, humidity, radiation	RMSE = 0.02, MAE = 0.007 MAPE = 0.60 R^2 = 0.84	-Sensitivity analysis of the correlation between input and output variables; -Users and operators of power grids can make the best decision in selecting input data to achieve maximum forecasting accuracy.
[37]	Online transfer learning model	Active power, wind speed, wind direction, vane position, and temperature	PA = 0.934 MAE = 84.837 RMSE = 134.837	-Improve the prediction accuracy of the proposed online transfer learning method; -Advanced neural networks can be used to replace the ConvLSTM neural network.
[38]	Discrete wavelet transform	Wind speed, wind direction, air temperature, air humidity, and air pressure.	Anemometric height 100 m RMSE [m/s] = 0.383 150 m RMSE [m/s] = 0.368 120 m RMSE [m/s] = 0.375	-The proposed transformer model, integrated with wavelet transform, can be applied to other multivariate time series forecasting tasks.
[39]	Improved kernel density estimation (IKDE)	wind speed, wind direction, and wind power of the wind farm, and numerical weather prediction (NWP) data.	Mean skill score=-0.527	-The effect of outliers for our forecasting model shall be addressed in future research.
[40]	Goddard earth observing system model	Wind speed (m/s) Wind power (kW) Wind direction	RMSE [kW] = 76.18	To incorporate the uncertainty of GEOS FP weather forecasts against MERRA-2 reanalysis into data set to be used for output power prediction for each hour of the time horizon ahead.
[41]	Support vector regression (SVR)	Wind speed (m/s) Wind power (kW)	RMSE/MW = 14.7435	-To reduce the number of charging and discharging cycles of hybrid energy storage devices; -To prolong the operation life of the system, and improve the overall performance of the system.

Table 4. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[42]	Gradient-boosting machine (GBM)	Wind speed (m/s) Wind power (KW)	NMAE = 5.15%	To expand the periods of the test set for various months and seasons of wind-power forecasting.
[43]	Improved hunter-prey optimization (IHPO) algorithm-based extreme learning machine (ELM)	Data from the SCADA systems Wind speed (m/s) Wind power (kW)	RMSE(kW) = 50.55	To improve the prediction accuracy for wind power.
[44]	Kernel extreme learning machine (KELM)	Wind data	Reliability performance parameter P (%) = 90.92	To explore the relevance of the implications for BRICS countries.

C. Deep-learning-based approaches

In recent years, machine learning algorithms have been widely introduced to the field of wind power prediction, and a large number of researchers have proven that ANNs are prone to overfitting during training. This is manifested by the small error when training samples are substituted into the model, but when testing samples are applied to the model, the error suddenly increases, and the generalization ability is insufficient. Based on this, a deep neural network is proposed that has at least three network layers. Through the structure of a multilayer perceptron with multiple hidden layers, the deeper features are mined, and the unsupervised training and supervised learning fine-tuning methods are combined to further improve the accuracy of classification or prediction and avoid the phenomenon where shallow ANNs easily fall into local optimal values. Deep learning methods include the deep belief network, convolutional neural network, recurrent neural network, and long short-term memory network. Many reviewed papers attempted to use the convolutional neural network (CNN) to process unstable wind power data and use its efficient data feature extraction ability to improve the running speed. They used the unique time memory characteristics of long short-term memory (LSTM) to predict short-term wind power. Due to the fact that the direct prediction method uses a set of constant parameters to predict short-term wind power, it is impossible to accurately describe the power variation pattern. In order to improve the accuracy of short-term wind power prediction, recent works used a rolling prediction method, where various parameters change depending on the wind farm data and each rolling energy follows the instantaneous wind power variation pattern. Finally, wind power rolling prediction models based on the CNN-LSTM were established, and experimental verification and a comparative analysis were conducted. Table 5 summarizes the hybrid wind power prediction methods based on deep learning in the reviewed works.

Table 5. Summary of Deep-learning (DL)-based approaches for wind power forecasting.

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[15]	A convolution-based spatial–temporal wind power predictor (CSTWPP)	Historical wind power	MASE = 190.02 RMSE = 7.49	CSTWPP model is essentially a multi-task model, predicting all the wind farms' future power at the same time.
[16]	The spatiotemporal convolutional network (STCN) with a directed graph convolutional structure.	-Historical power data -STCN parameters selected by oneself	MAEs = 3.17% RMSEs = 2.88%,	A wind power forecasting framework will be investigated to ensure data security for multiple wind farms.
[45]	A deep optimized convolutional LSTM-based ensemble reinforcement learning strategy (DOCLER)	Wind power	RMSE = 7.1322% MAE = 4.6713%	Optimization of grid integration issues.
[46]	A variational mode decomposition (VMD) and convolutional long short-term memory network (Conv LSTM) model	Wind power	MRE(KW) = 0.016 MAE(KW) = 792 MSE(KW) = 1,568,305.38 RMSE(KW) = 1252.32	Other intelligent algorithms to optimize the proposed model are studied.

Table 5. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[47]	A multi-source and temporal attention network (MSTAN)	Wind speed, pressure, temperature, humidity, and wind direction	NRMSE = 0.154 NMAE = 0.110	-Novel spatial attention or spatial feature extraction modules should be merged into MSTAN; -The applicability of MSTAN at other time resolutions should be verified.
[48]	Two-dimensional convolution neural network trained by improved accidental floater PSO	Fine-tuning the weights of TDCNN by proposed AFPSO	MAPE:3.76 NMAE:2.46 NRMSE:3.12	Using AFPSO algorithms will lead to a longer modeling time.
[49]	Deep neural network: LSTM method (best); MLP (second best) while using SVR, KNNR, and physical model with an expert correction	More LSTM parameters and setting these parameters by oneself	GBT, RF, PHYS(v1&v2)→ KNNR, MLP, LSTM with additional expert SS:0.5925; nMAE[%]:11.3055; nRMSE:0.1618; nMBE:0.0146	The proposed ensemble methods are also applicable to short-term generation forecasting for other renewable energy sources (RES). -Input data requires pre-processing to extract features to solve long running time due to too much input data.
[50]	-Optimizing the hyperparameters of the LSTM network by the modified PSO algorithm -A PSO_LSTM model	Selecting parameters by PSO	MPSO_ATT_LSTM MAPE: 4.6%; MAE: 211.5 kW Device capacity > 20,000 kW	It is required to avoid overfitting in optimization algorithms and modeling. Therefore, training data and test data are usually required to be evaluated together.
[51]	Advanced deep learning techniques Encoder–Decoder LSTM	Setting parameters by oneself	Annual and monthly errors	Additional meteorological and site determination factors such as the amount of rain, azimuth for solar irradiation, wind direction, etc. for windspeed forecasting could be considered.
[52]	The CNN-MLSTMs-T Model	Wind power	RMSE = 0.1998; MAE = 0.1523	The combination of the sample similarity analysis idea and other hybrid models will be our future research focus.
[53]	Generative moment matching network (GMMN)	Historical wind power	PINAW = 8.66 MW; PICP = 84% RMSE = 127.10; MAE = 0.6855 MW	The WindGMMN can be extended to the robust optimization of distribution networks.
[54]	Bidirectional long short-term memory (Bi-LSTM)	Manual adjustment layers	Error can be divided into training, test, and validation errors	New optimization algorithms or the integration of multiple optimization algorithms will be investigated to optimize the forecasting model.
[55]	Multi-step informer network (MSIN)	Manual selection of parameters	Multi-step informer network (MSIN) improves forecast accuracy by 29% compared with the informer network for RMSE	To consider the non-trivial correlations of meteorological variables without relying on single historical data in forecasting.
[56]	Long short-term memory neural network (LSTM) with the improved particle swarm optimization algorithm (IPSO)	Determining the LSTM and DENSE layers, the number of neurons	VMD-CNN-IPSO-LSTM MAE:2.92668; RMSE:3.59604 MAPE:0.20147; adj-R^2:0.96639	To examine a multi-step decomposition model for feature extraction through different neural networks, such as graph convolutional neural networks for implicit mining.
[57]	Spatiotemporally multiple clustering and I–CNN-BILSTM deep learning network.	Historical power and meteorological data	MAPE(%) = 4.86, MAE = 18.64, abd RMSE = 28.45.	The uncertain power prediction of multiple wind farms with spatio-temporal coupling in extreme weather.
[58]	1.The model input data organization framework 2.The unified forecast based on STC-DPN 3.The single site error correction of TCN-LSTM.	Wind speed, wind direction	MAE = 2.071, RMSE = 2.431, COR = 0.568	To apply the strategies and models proposed to more research fields, such as wind power forecast or wind turbine fault early warning.

Table 5. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[59]	Temporal inception convolutional network (TICN) wind speed interval prediction model	Wind speed	PICP = 0.994 PINAW = 0.087	It may have a better effect on some short-term prediction occasions.
[60]	Hybrid deep learning model	Wind speed, air temperature, and air pressure	MAE = 1.59, RMSE = 3.73 and MAPE = 8.13.	-To tune the parameters of the model using advanced optimization algorithms. -To reduce computation time and provide more accurate results.
[61]	Multi-Task GCN (MTGCN)	Temperature, humidity, weather, historical wind power	PICP = 0.9634, PINAW = 0.0363, CWC = 0.2178	To utilize advanced ML techniques such as transformer to further improve wind power forecasting performance.
[62]	CNN-ED-LSTM model	Air temperature, pressure, wind direction, wind power	MSE = 0.0102 MAPE = 46.24 MAE = 0.0623 RMSE = 0.1012	-To improve the accuracy of the CNN-ED-LSTM model in WPPA, hyperparametric optimization strategies using intelligent algorithms to efficiently enhance DL models to obtain optimal values of hyperparameters.
[63]	Long short-term memory (LSTM) neural network	Actual historical data	RMSE (MW) = 0.94 MAE (MW) = 0.67 MAPE (%) = 49.71	To extend to the power prediction derived from wind over a large area.
[64]	Seq2Seq model	The historical wind speed, wind direction, and total power output of 24 wind turbines with a 10-min resolution	RMSE = 129.3 MAE = 81.1	To implement an adaptively sized time window on the input variables based on cross-correlation analysis
[65]	Long short-term memory (LSTM)	Actual historical data	RMSE(MW) = 1.27 MAE(MW) = 0.90	A good starting point can range from 1×10 without the time of day and numerical weather prediction information -Easily be incorporated in the extension work.
[66]	Deep learning	Historical data on measured weather and numerical weather predictions (NWPs)	NRMSE = 0.16 MAPE = 0.15	Using historical weather measurements as input allows the prediction model to compensate for the errors in weather predictions
[67]	Gated reference unit (GRU)	Ambient temperature, direction of the wind flow, speed of the wind, and wind power generated from the wind turbine.	Mean Square Error = 0.130	The GRU network is better suited to extract extremely non-linear and complex data from an input data set in real time to boost wind speed prediction.
[68]	A deep learning model (gated recurrent unit, GRU)	Meteorological wind speed, wind direction, and wind power data	RMSE = 111.9766	To implement multistep wind power forecasting based on deep learning.
[69]	Residual CNN-based deep forecasting method.	Meteorological wind speed, wind direction, and wind power data	1-h ahead. RMSE = 0.9947	To examine in detail different decomposition approaches
[70]	Bidirectional long short-term memory network (BiLSTM)	Numerical weather prediction (NWP) Wind speed Wind direction Temperature	RMSE/MW = 1.0822	-To develop probability forecasting based on single point forecasting in order to realize the quantitative description of wind energy uncertainty; -To better serve the multi-aspect optimization decisions of the power system.
[71]	The Encoder–Decoder framework is constructed with LSTM as the basic unit	Wind direction Wind speed (m/s) Wind power (kW)	RMSE = 0.1243	To significantly affect the performance of such data-driven forecasting methods. These remain our further research questions.

Table 5. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[72]	Long short-term memory (LSTM) network using an improved Adam optimizer with loss shrinkage (LsAdam)	Data from the SCADA systems Wind speed (m/s) Wind power (kW)	Train set MSE($\times 10^{-3}$) = 3.5961 Test set MSE($\times 10^{-3}$) = 2.1628	The trained model will have better performance since the learning rate is iteratively tuned with past loss-changing information.
[73]	Long short-term memory (LSTM)	Temperature, humidity, pressure, wind power,	RMSE(%) = 10.23	To improve the prediction accuracy for wind power

D. Hybrid predictive model approaches

Hybrid predictive models combine two or three deep learning techniques or include optimization algorithms. By combining multiple algorithms with some strategies, the prediction accuracy of wind power can improve to achieve the desired effect. Generally speaking, hybrid predictive models can be divided into two categories. The first category combines several different modeling algorithms with different weight values to predict wind power. For the same wind power dataset, each single algorithm will obtain different forecasting results. Some algorithms have better prediction performances, and some algorithms have lower prediction accuracies. Therefore, each algorithm involved in forecasting is given a certain weight value, and then the algorithms are combined to predict the wind power data. In the second category, one or several processing algorithms are added at a certain stage of the complete prediction model. These hybrid models are distinguished based on different processing steps. The first method preprocesses the input wind power dataset, for example, by using the wavelet decomposition algorithm to decompose the wind power sequence, which can reduce noise. The second method uses optimization algorithms to find the best hyperparameters in the prediction process. The third method adds processing algorithms to the predicted errors after the prediction. The fourth method introduces different processing algorithms in two or three stages of the prediction process simultaneously. A summary of the hybrid model approaches for wind power forecasting in the reviewed works is given in Table 6.

Table 6. Summary of hybrid model approaches for wind power forecasting.

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[20]	An ensemble neural forecast framework (ENFF) with three neural predictors for wind speed forecasting below. Elman neural network (ELM) Feedforward neural network (FNN) Radial basis function (RBF) neural network	Wind speed, meteorological	Errors around 0.6 m/s	Planning framework and operation strategy are developed for the storage providing virtual inertia support (VIS) in a low-inertia power system.
[74]	The CEEMDAN-IBA-GPR model	Historical wind power data	Stand deviation = 10.42	Optimal dispatching of isolated or grid-connected MG considerations of economic cost, net pollutant emission, and operational security objectives will be the focus of future work.
[75]	A multi-feature fusion self-attention mechanism graph convolutional network (MFF-SAM-GCN) forecasting model	Hyperparameter optimization of the predictive model by Bayesian optimization (BO)	RMSE of the proposed (MFF-SAM- GCN) model is 0.0284, while the SMAPE is 9.453%, the MBE is 0.025, and R^2 is 0.989.	New optimization algorithms or the integration of multiple optimization algorithms will be investigated to optimize the forecasting model.

Table 6. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[76]	The WD-IGFCM-LSTMS model for the accuracy of short-term wind power forecasting (WPF) approach	The best parameters determined by the IGWO algorithm	Case A: NMAE 10.32%; NRMSE 14.59% CR: 85.41%; QR: 91.53% Case B: NMAE 10.18%; NRMSE 13.52% CR: 86.48%; QR: 91.53%	-The forecasting accuracy for short-term WPF can be improved by correcting NWP data; -The possibility of extending the wave-oriented approach to NWP data correction will be further done.
[77]	Generalized regression neural network (GRNN) and support vector machine (SVM)	Turning GRNN and SVM parameters by oneself	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.	A new technique for feature selection is needed to design electricity load forecasting for this type of area, which is connected to multiple electricity grid systems.
[78]	The WPD-VMD-SSA-IGWO-KELM model	Wind speed	NMAE = 11.2% MAPE = 4.2%	-The suitable length of the train set is variable when wind power significantly changed. -The error sequence can be used to correct the prediction.
[79]	Variational mode Decomposition (VMD) and Random forest (RF)	NWP data containing 24 meteorological factors and wind power trend component data.	NRMSE(%) = 11.421 NMAE(%) = 8.152	The implicit law of wind power sequence in frequency and time domain.
[80]	Hybrid VMD-CNN-GRU-based model	Wind power, wind speed, wind direction, temperature, pressure, air density and humidity.	RMSE = 1.5651, MAE = 0.8161, MAPE = 11.62%, and R2 = 0.9964.	The impact assessment and cost-benefit analysis should be performed in future work.
[81]	Spatiotemporally multiple clustering and I-CNN-BILSTM deep learning network.	Historical power and meteorological data	MAPE (%) = 4.86, MAE = 18.64, abd RMSE = 28.45.	The subsequent research will focus on the uncertain power prediction of multiple wind farms with spatio-temporal coupling in extreme weather.
[82]	The hybrid forecasting method based on the corrected NWP data and the SC.	Temperature, humidity, wind direction, wind speed.	RMSE = 1.238, MAPE = 0.325, MAE = 0.7002	To introduce advanced artificial intelligence and machine learning methods to assist the automatic scene division of the complex input data.
[83]	MMMD-K-means-SDAE-LSTM model	Wind speed, wind direction, wind power data	NMAE = 6.43, NRMSE = 9.59	-The operating costs of the model for computational time and hardware costs are higher than those of a simple forecasting model. -The time horizon for effective forecasts is short (30 min to 24 h).
[84]	LSTM-WPRE model	Wind speed, wind direction, air temperature, relative humidity, and pressure	MAPE = 0.094, rRMSE = 0.112	-The overall running time should decrease; -The proposed model should be suitable for newly installed wind farms.
[85]	Outlier detection, decomposition of time series, effective feature selection, and prediction of each time series decomposed.	Wind direction, wind speed, or wind power	NRMSE = 0.1020 NMAE = 0.0803	The economic, technical, and environmental benefits achieved from high-accuracy wind power forecasting.
[86]	KHC algorithm for clustering, components extraction and selection with SVD, and building SVR forecast model.	Wind power, wind direction, wind speed, temperature, pressure, and density	MAE = 0.273 RMSE = 0.343	With the increasing number of wind turbines a more efficient and effective measurement of similarity of weather patterns between different wind turbines.
[87]	GBRBM-DBN consists of the PCA, NWP, and SC for wind power forecasting.	Wind direction, wind speed, rainfall, temperature, surface sensible heat, air pressure, and air density	RMSE = 2.6018, MAPE = 0.2859, MAE = 2.3857	The utilization of the adaptive learning step technique further improves system accuracy.

Table 6. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[88]	ST-GWO-MSVM model	Wind power	NMAE = 3.3221, NRMSE = 4.64875, FB = 0.0029, DA = 0.8342	To improve the performance of ST-GWO-MSVM.
[89]	FCM-WOA-ELM-GMM Model	Wind speed, wind direction, air pressure, temperature, and humidity	MAE = 3.8%, RMSE = 5.24%	To improve the calculation accuracy of the probability density distribution of wind power forecasting errors.
[90]	Seasonal Autoregressive Integrated Moving Average (SARIMA) model	Historical wind velocity	RMSE = 13.09 MAPE = 1.03	If the time series is non-stationary, the study needs to use differencing or de-trending techniques to make it stationary before applying the AR method.
[91]	Historical wind climate model and Physical model	Wind speed and weather data	RMSE = 13% MAE = 20.7%	These span the areas of resource assessment, wind power forecasting, and validation, as well as market instruments.
[92]	Hybrid prediction method	Wind power and direction	MAPE = 16.87% MAE = 27.1% CI = 0.968	The region's correlations between different renewable energy systems on the performance of the prediction model.
[93]	Multi-modal Multi-task Spatiotemporal Attention Network (M2STAN) model	Wind direction, wind speed, temperature, atmospheric pressure, and air density	RMSE = 6.27% MAE = 4.01%	To explore efficient and reliable machine learning hyperparameter optimization methods.
[94]	AMC-LSTM hybrid model	Historical wind power, torsion angle, wind speed, impeller speed, temperature, generator speed, wind direction	MSE(e^{-2}) = 0.8951 MAE = 0.0505 RMSE = 0.0946	-To integrate multi-scale extended features -To improve short-term wind power prediction accuracy.
[95]	Gaussian mixed clustering-Deep neural network probabilistic forecasting (GMC-DeepNN-PF)	Wind direction, wind speed, wind power	RMSE(MW) = 56.6893 MAPE(%) = 4.839 MAE(MW) = 42.0201	-To expand wind direction and time properties for improving the accuracy of WPF.
[96]	Self-attention temporal convolutional network Long-short term memory (SATCN-LSTM)	Wind speed, air density, wind direction, temperature, and surface pressure.	RMSE = 0.680	No description
[97]	Multiple stacked bi-directional long and short-term memory (Bi-LSTM) networks	Wind direction Wind speed (m/s) Wind power (kW)	RMSE($\times 10^{-2}$) = 6.47473	To develop more efficient and accurate prediction methods for wind power prediction by exploiting adaptive denoising.
[98]	The Proposed Hybrid Intelligence Model XGBoost, Tree, SVR, and BPNN methods	Converting wind data to wavelet information	RMSE = 1.8313	The proposed hybrid model will be of great attraction and practical application in power systems.
[99]	Long short-term memory (LSTM)	Wind speed (m/s) Wind power (kW)	RMSE = 2.63109	-To use a multi-step decomposition model; -The sub-sequence obtained from the decomposition is passed through different neural networks for feature extraction.

E. Statistical-analysis-based approaches

The statistical analysis prediction model establishes the nonlinear functional relationships among various input meteorological data and output parameters (wind farm output power value) in the historical data through one or more algorithms. According to this model, NWP and other information are used as inputs to predict the future output power of the wind farm. The advantage of statistical prediction is that it can minimize the prediction error of the output probability when there is sufficient historical data. By training and adjusting the model, appropriate outputs can also be provided for input data that are not in the training set. The disadvantage of statistical methods is that they rely heavily on raw historical data. Table 7 demonstrates a summary of statistical analysis-based approaches for wind power forecasting in the reviewed works.

Table 7. Summary of statistical analysis-based approaches for wind power forecasting.

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[9]	Modified hidden Markov model	Wind speed, wind direction, wind power	RMSE = 3.093 MAE = 2.451	The error transfer mechanism from wind speed forecast (WSF) to wind power forecast (WPF) are of great interest for the improvement of WPF.
[10]	Distance-weighted kernel density estimation (KDE) and regular vine (R-vine) copula	Wind power output, wind speed	RMSE = 0.1089 MAE = 0.075	As computing becomes faster and less expensive, the task of achieving enough scenarios will become easier in the future.
[11]	The k-NN and conditional KDE models	Historical wind power	MAE = 3.18; RMSE = 4.63; R^2 = 0.94	More work needs to be done in terms of bandwidth selection for high-dimensional datasets in KDE based approaches.
[12]	A quantile passive–aggressive regression (QPAR) model for online convex optimization problems	Wind power	Pinball loss (PBL) = 13.3 Average coverage error (ACE) = 4.86%, Winkler score (WKS) = 78.71 and Continuous ranked probability score (CRPS) = 26.21	Addressing this missing data problem is necessary for the actual implementation of these methods.
[13]	Spatiotemporal quantile regression (SQR)	Wind power data	RMSE = 16.62%; MAE = 11.23%	To enhance predictive effects and computational efficiency for wind power prediction.
[100]	Higher-order multivariate Markov chain (HMMC)	Wind power; PV power, Heat index	NRMSE = 2.59	-The HI index was utilized as an additional meteorological variable. -The dynamic update of the model parameters was applied to the wind power forecast.
[101]	Five minute-ahead wind power forecasts in terms of point forecast skill scores and calibration	To deduce the value of kernel methods for parameter adjustment	The error value is represented by a picture rather than a simple number.	Future work will focus on extending this approach to other variables, e.g., temperature, wind speed, wind direction; additional forecast horizons; investigation of other kernel machines; and development of other adaptive models.
[104]	Empirical dynamic modeling (EDM)-based probabilistic forecast	Historical wind turbine power	CRPS (%) = 5.12	The real-time WTP measurements are added to the reconstructed state space during the forecast process.
[105]	Multi-class autoregressive moving average (ARMA)	Historical wind power	RMSE = 127.10 MAPE = 1.25%	-To improve the interpretability of the combined models for further accuracy enhancement; -To incorporate the spatial correlation features into the classification and prediction.
[106]	Renewable energy is directly distributed to power dispatch	Incorporating renewable energy into the power flow	With an increase in power by 1.6 times, there is a decrease in energy of RES by 15-19.	-To generalize the model and evaluate the model accuracy
[107]	Weather research and forecasting model.	Wind power, wind speed, atmospheric and density	MAE = 15% (summer) and MAE = 26% (winter)	To improve large variance in winter model output.
[108]	WRF forecasting model; CCMP satellite data	Wind power, wind speed,	WRF model: RMSE = 1.68 to 2.85 m/s CCMP satellite data: RMSE = 1.79 to 2.89 m/s	To focus on the effects of the sea breeze across the region studied, the prediction of these conditions, and their impact on wind farm power generation.
[109]	Transformer	Wind power and NWP data	8-step ahead RMSE = 7.51 16-step ahead RMSE = 10.88	To further explore machine learning strategies for small sample data, such as data augmentation and transfer learning.

Table 7. *Cont.*

Ref	Model Type	Parameters Used	Accuracy	Future Studies
[110]	SVR with RBF kernel	Number of wind turbines Installed capacity (MW) Manufacturer type Hub height of tower/s (m) Cut-in/Cut-out wind speed (m/s) Rated wind speed (m/s) Swept area of a wind turbine (m^2)	RMSE = 8.3404(Spring) RMSE = 6.6873(Summer)	To reduce computation time to enable the use of a smaller subset with 5-day data or even less.
[111]	ACE in the dynamic-indirect GP (DYINGP) mode	Wind speed (m/s) Wind power (kW) Wind direction	NRMSE = 3.66	The coefficients could be controlled with state-of-the-art algorithms due to the covariance functions being very important in the GP results.
[112]	Secondary evolutionary generative adversarial networks (SEGAN) and dual-dimension attention mechanism (DDAM) assisted bidirectional gate recurrent unit (BiGRU)	Wind speed (m/s) Wind power (kW) Wind direction	RMSE = 119.645 (kW) MAE = 83.179 (kW) MAPE = 0.354%	-To consider the combination of the proposed SEGAN-DDAM-BiGRU with transfer learning. -To better address the wind power prediction problem without sufficient historical data available.
[113]	Support vector regression (SVR)	Wind data	RMSE (kW) = 66.26	To be used as a reference for grid power generation planning and power system economic dispatch.
[114]	Support vector regression (SVR)	Wind power data Meteorological data	RMSE(MW) = 373	The reanalysis data used in this paper may not fully represent the real data in practical applications, which affects the actual prediction of future wind power.

3. State-of-the-Art Approaches for Short-Term Wind Power Forecasting

The prediction effects of different predictive models have their own advantages and disadvantages. The hybrid prediction method involves optimizing and combining the results of the data processing of different models according to a specific strategy so as to obtain better wind power prediction results and ultimately achieve the purpose of improving the accuracy of wind power prediction. In the final analysis, the combined forecasting method is used to optimize the forecasting results, and as long as the time series scale of the power forecasting output corresponds to the combined forecasting of the model, there is no limit to the relevant algorithms used for each forecast. At present, due to the large amount of data that can be provided by wind farm numerical weather prediction (NWP), combining NWP information to improve the accuracy of wind power forecasting has become the main research direction in hybrid wind power forecasting. Statistical methods were used to predict wind power generation in the past and achieved the purpose of predicting wind power generation through wind speed prediction. Due to a large amount of historical data, we currently use the analysis and selection of data features to reduce the training sample space and improve the extraction of more useful data from the database, thereby reducing the amount of data, shortening the running time, and obtaining good prediction results. Then, a wind power generation model is established based on support vector machines as a predictive method suitable for nonlinear regression analysis. Its internal parameters will affect the accuracy of the regression analysis. Therefore, the bee colony algorithm is used to better solve the parameter values. In order to reduce the prediction error, we aim to minimize the error and use the bee colony optimization algorithm to solve the parameter setting problem of the support vector machine, which not only increases the integrity of the prediction model but also improves the prediction accuracy. We use meteorological observation stations for long-term recording and monitoring to obtain relevant wind speed and power generation data, and data regression technology is used to preprocess the input data to remove parameters that reduce the predicted value, thereby reducing network input parameters.

The work described in this paper is shown in Figure 2, and the short-term wind power forecasting model is discussed in depth. The latest approaches to short-term wind power forecasting in the past three years are reviewed to provide an important reference in wind power grid integration. In order to improve the accuracy of wind power forecasting, this paper gives a detailed overview of the contributions, advantages, and disadvantages of various delivered wind power forecasting models and future research. These advanced forecasting methods can be roughly classified into kernel density estimation, quantile regression methods (QR), artificial intelligence/neural networks (NN), ensemble methods, spatiotemporal forecasting, machine learning, deep learning, hybrid model forecasting, and other statistical analysis methods. These proposed novel short-term wind power forecasting models provide very useful information for power system operation and control with high renewable energy penetration.

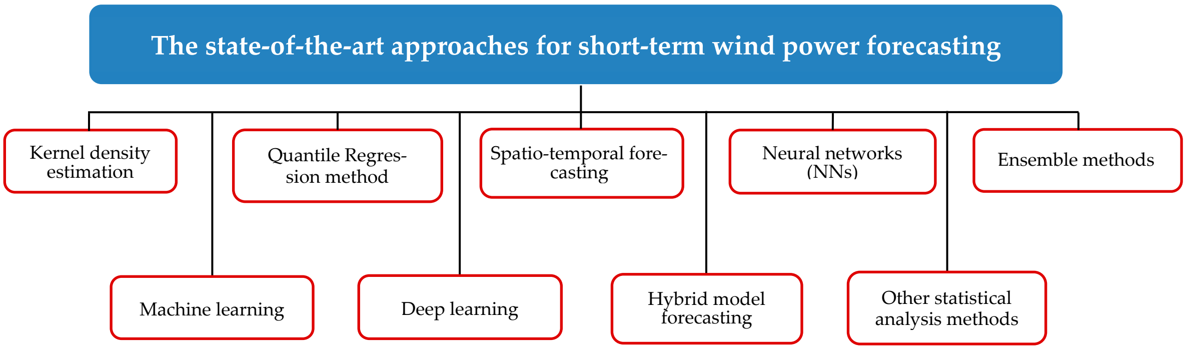

Figure 2. Classification of the state-of-the-art approaches for short-term wind power forecasting.

In recent years, various research institutions and scholars have adopted different state-of-the-art approaches to improve the problems of power fluctuation and randomness in wind power forecasting, as well as possible errors and omissions in the original data. Certain advancements have been made, but there are still some issues that need to be urgently solved. First of all, in the future, the sample space can be further expanded, and the dimension of data samples can be increased to predict wind data diversity. According to the wind power data with different characteristics, the prediction model is further optimized to increase its applicability. Secondly, according to the characteristics of the existing hybrid model, the parameter optimization method is further improved to ensure that the prediction model has high prediction accuracy at different time sampling rates, making it suitable for different prediction occasions.

4. Scientific Contributions, Advantages, and Disadvantages of Reviewed Works

In the process of predicting wind power, each prediction model has its own advantages and disadvantages. Due to the research limitations, it is difficult to achieve high-precision predictions or different types of predictions with a single prediction model. With the continuous increase in wind power grid connection capacity and the increase in wind power penetration power, the Department of power system dispatch has implemented increasingly high requirements for the scheduling and prediction accuracy of wind power. Based on this, establishing a combined prediction model for wind power prediction by integrating the advantages of various prediction models is of great significance for improving the accuracy of wind power prediction. By predicting wind power, it can effectively reduce the operating costs of wind farms, enhance the advantages of wind power participation in the grid connection, and improve the impact on the power system during large-scale grid connections of wind power. Therefore, conducting research on wind power prediction based on artificial intelligence algorithms and optimizing prediction models has practical value in engineering for improving the accuracy of wind power prediction and the reliability of grid connection scheduling.

Artificial intelligence methods are widely applied to improve the efficiency of renewable energy systems. In Section 2, different hybrid methods for wind power prediction based on artificial intelligence are classified and explained, including the neural network, machine learning, algorithm optimization, deep learning, hybrid model, and statistical analysis prediction methods, as shown in Figure 2. This work reviews comprehensive wind power prediction methods based on artificial intelligence and its models by assessing their contributions, advantages and disadvantages, performance, error analysis, and future work, as shown in Tables 3–7. The implementation and influencing factors are clearly discussed, including data preparation, feature selection, accuracy, and verification, as well as an exploration of the key issues and challenges associated with hybrid wind power prediction methods based on artificial intelligence. This section compares the performance and error analysis of five classifications of prediction methods. Three papers with good wind power prediction results and two or three papers for which the prediction results need to be improved were selected from every prediction model classification for analysis and comments. We provide selective future suggestions and directions for further improving the accuracy of wind power hybrid prediction methods based on artificial intelligence.

4.1. Neural Network (NN)-Based Approach

Akhtar, I., et al. [19] developed a fuzzy logic approach and an ANN model for the prediction of wind power outputs. The root mean square error (RMSE) of the proposed fuzzy logic approach with neural networks (NNs) was calculated to be 1.04% and obtained excellent results compared with other neural network (NN)-based approaches. The proposed models can be employed for the estimation of wind speed and wind power generation for any location in the world for which there is complete information, while it is difficult to estimate wind power during the summer period in which wind speed is very low. The wind power forecasting technique with integration into the grid will be analyzed to consider load scheduling and demand-side management in future research.

Medina, S. V., and Ajenjo, U. P. [18] studied the efficiency and stability of ANN models by varying the number of prior 1 h periods. Improvements in the model performance, efficiency, and stability of ANN-based WPF models were studied. However, the suggested hybrid technique with a MARE of 7.5% achieved worse forecasting results than other methods due to the disadvantages of the ANN Model in the short-term prediction of wind power generation.

Sun, Y. et al. [21] proposed a day-ahead numerical weather prediction (NWP) model with a neural network. The hybrid approach combining the neural network and persistence method used the NWP information and time windows to improve the low forecasting accuracy. The RMSE (%) of the hybrid technique was computed to be 8.76%, and disappointing results were obtained. The relevance of the day-ahead method is doubted due to the great change in the wind. The setting of neural network parameters is a big issue.

4.2. Machine Learning (ML)-Based Approaches

An, G. et al. [30] proposed the Adaboost-PSO-ELM method for wind power prediction. This model has good generalization ability and robustness, providing a more reliable basis for power grid dispatch. The MAPE estimation of the proposed technique was computed to be 0.0372. The obtained results show higher accuracy and better generalization ability with the Adaboost-PSO-ELM wind power prediction model. The disadvantage of this method is that the training samples are selected based on experience. It is considered that the reconstruction of training samples and the selection of specific indicators as training samples for short-term wind power prediction could be used to further improve the prediction performance based on numerical weather forecast (NWP) data.

Moayyed, H. et al. [36] studied the cybersecurity of wind power forecasting and the robustness of the proposed forecasting models under exposure to a False Data Injection

Attack (FDIA). The proposed model computed an RMSE of 0.02, an MAE of 0.07, and a MAPE of 0.60, indicating better wind power forecast accuracy than that of other methods, as shown in Table 2. The accurate performance and high generalizability of the cyber-resilient global supermodel in forecasting wind power in various regions were shown. When predicting wind power generation in a large area, poor internet connectivity can cause the optimization of the local parity model to fail, and the server model can have difficulty converging. A sensitivity analysis of the correlation between input and output variables was presented so that the users and operators of power grids can make the best decision when selecting input data to achieve maximum forecasting accuracy.

Liu, L., et al. [37] introduced a novel online transfer learning method for automatic system-wide updates. To improve forecasting accuracy, this work proposes a novel online transfer learning model that can achieve system-wide updating and rapid forecasting. The result indicated that this technique delivered unsatisfactory wind power forecasting results compared with the other existing strategies, having an RMSE of 134.837 and an MAE of 84.837. Although the methods of multisource data processing and the structure of the prediction model have been improved, there is still significant room for improvement. The advanced neural network can be used to replace the ConvLSTM neural network and improve the prediction accuracy of the proposed online transfer learning method.

Liao, S. et al. [44] suggested the mutual information coefficient (MIC) and supported vector regression. The reanalysis data from ERA5 provide more meteorological information for the framework. However, the RMSE (MW) of the proposed SVR-based approach accounted for 373, showing a large error for wind power forecasting. In this paper, by adopting the ERA5 reanalysis dataset as the input, a short-term wind power prediction framework was proposed by combining the light gradient boosting machine (LightGBM), the mutual information coefficient (MIC), and nonparametric regression. The results in this paper may underestimate the error. The used reanalysis data may not fully represent the real data in practical applications, which affects the actual prediction of future wind power.

4.3. Deep-Learning-Based Approaches

Xiong, B., et al. [94] suggested that the hybrid methods effectively alleviate the intermittent and volatile characteristics of wind and significantly improve the prediction accuracy. The suggested hybrid technique, with an MAE of 0.0505 and an RMSE of 0.0946, achieved better forecast results than the other conventional models. The proposed AMC-LSTM hybrid model is capable of integrating multiscale extended features and providing better performance for short-term wind power forecasting. From the above-mentioned information, we know that the redundancy of the long-term trend information in the original time series data and the differences in the importance of input features are important factors that lead to poor prediction performance. Future research directions include the integration of multiscale extended features and the improvement of short-term wind power prediction accuracy.

Yu, G.Z. et al. [57] proposed an I–CNNBILSTM hybrid neural network with an improved attention mechanism, which uses the point CNN to extract the spatial features of multiple WPFs with point cloud distributions and establishes the BILSTM to learn the temporal features. The proposed technique was found to be excellent with respect to execution performance and accuracy. The mean absolute percent error (MAPE) (%) of the proposed approach was 4.86%. The local and global spatiotemporal correlation information of the clusters was deeply mined to improve the prediction accuracy and model the training speed. However, the processing capacity of complex power fluctuations under extreme weather conditions, such as typhoons, is insufficient. Subsequent research will focus on the uncertain power prediction of multiple wind farms with spatiotemporal coupling in extreme weather.

Liu, Xingdou, et al. [58] suggested an STC-DPN unified forecast model with good versatility. An independent TCN-LSTM hybrid model was used for single site error correction. The VMD was also used for noise reduction in the wind speed monitoring sequence and to extract the high-frequency components of the NWP wind speed for error correction. The proposed model delivered the best wind power prediction accuracy in comparison to other methods in terms of MAE (2.071) and RMSE (2.431). The proposed method has good versatility and is suitable for wind speed forecasting in complex wind farm terrain, such as hills, without being affected by the arrangement of wind turbines. The forecast error of physical methods in the first few hours is too large due to the lack of accuracy in the modeling data, but it can be robust for longer-term forecasts. The proposed strategies and models will be applied to more research fields, such as wind power forecasting or wind turbine fault early warnings.

Zhang, J. et al. [63] developed a long short-term memory (LSTM) neural network, in which the key characteristics are extracted using a convolutional neural network (CNN), and a long short-term memory (LSTM) neural network is used to establish the mapping relationship between key characteristics and power generation. The results illustrated a lower forecasting accuracy, indicating an MAE of 0.67 MW, an RMSE of 0.94 MW, and a MAPE of 49.71%. The correlation modeling method considered the influences of wind speed, wind direction, and temperature on the output power of wind farm clusters using waveform similarity, trend consistencies, and monotony correlation characteristics. It affects the element values of the spatiotemporal correlation characteristic matrix, which, in turn, affects the extracted spatiotemporal correlation characteristics. Further investigations could extend to power predictions derived from wind over a large area.

4.4. Hybrid Predictive Model Approaches

Zou, Y. et al. [24] conducted a Bi-LSTM network and a 1D-CNN with a parallel connection to form a multifeature fusion (MFF) framework, which can extract the spatiotemporal correlation features of the load data. The eigenvalue can be found to reduce the data. The results presented a higher forecasting accuracy with an RMSE of 0.0284 and an R^2 value of 0.989, enhancing the feature extraction capability of the 1D-CNN network through a self-attention mechanism. More LSTM parameter settings need to be adjusted, indicating a deficiency in this model. New optimization algorithms or the integration of multiple optimization algorithms will be investigated to optimize the forecasting model.

Cui, Yang, et al. [84] proposed an LSTM-WPRE model to forecast day-ahead WPREs and wind power generation with a time resolution of 15 min. The assessment outcomes revealed that the technique delivered high accuracy, with a MAPE of 0.094. The LSTM-WPRE model performed better than all of the benchmarking methods based on various evaluation metrics assessed over four typical months. The drawback of the LSTM-WPRE is its relatively longer execution time. The overall running time should decrease. The proposed model should be suitable for newly installed wind farms in further research works.

Yan, J., et al. [91] developed a state-of-the-art hybrid model with uncertainty quantification through the modeling chain of wind and wind power forecasting to improve the certainty and reliability of the forecasts. The RMSE and MAE of the proposed model were estimated to be 13% and 20.7%, respectively. In order to ensure the improvement of the data quality, it is necessary to clean the data samples before model training. Future studies could span the areas of resource assessment, wind power forecasting, and validation, as well as market instruments.

Zheng, J.Q., et al. [92] proposed a hybrid framework to forecast multiple forms of energy generation. The framework consists of an A-LSTM layer that captures the nonlinear temporal characteristics of the weather conditions and power generation, a CNN layer that mines the correlations of multiple energy sources, and a linear layer that considers the linear temporal characteristics of each energy source. The recommended hybrid CNN model showed unsatisfactory accuracy in short-term wind power predictions with several deep learning frameworks, with an RMSE and MAE of 27.1% and a MAPE of 16.87%, respectively. The accuracy of the prediction models should be improved in further studies.

4.5. Statistical-Analysis-Based Approaches

Wang, Z. et al. [10] introduced the distance-weighted kernel density estimation (KDE) and regular vine (R-vine) copula. The model is more accurate and flexible than the Gaussian copula model. The prediction outcomes demonstrated that wind power prediction with the novel techniques was superior to that with other forecasting strategies, achieving RMSE and MAE values of 0.1089 and 0.075, respectively. Abundant bivariate copula functions are available to make the model more accurate. Nevertheless, it needs a complex structure and has a large hardware requirement. As computing becomes faster and less expensive, the task of achieving enough scenarios will become easier in the future.

Yu, Y. et al. [13] proposed a spatiotemporal quantile regression (SQR) model, which is a new nonparametric probabilistic prediction method. The values of the RMSE and MAE were estimated to be 16.62% and 11.23%, respectively, indicating the low accuracy of regional wind power probabilistic prediction. It is difficult to generalize the prediction model. Additionally, a complex, nonlinear, and high-dimensional structure is required for the proposed model. Future work can be carried out by enhancing the predictive accuracy and computational efficiency of wind power prediction.

Dong, Y. et al. [105] suggested the multiclass autoregressive moving average (ARMA) model, which has a lower training complexity, ensuring a higher prediction accuracy compared with traditional models. The results revealed that the proposed approach delivered the best results of the statistical analysis-based models, with a MAPE of 1.25%. The seasonality and randomness of wind power are considered with moderate model complexity to effectively guarantee the convergence speed and efficiency of the training process. If the input data are nonstationary, meaning that the proposed data preprocessing fails, the proposed model may not be able to obtain accurate prediction results. The spatial correlation features can be incorporated into the classification and prediction for further accuracy enhancement.

Meng, A.B. et al. [112] proposed a novel prediction model to address the few-shot learning problem of wind power prediction in newly built wind farms based on secondary evolutionary generative adversarial networks (SEGAN) and the dual-dimension attention mechanism (DDAM)-assisted bidirectional gate recurrent unit (BiGRU). The proposed hybrid approach acquired RMSE, MAE, and MAPE values of 119.645 (kW), 83.179 (kW), and 0.354 (%), respectively, in comparison to the FFBPNN method. The proposed hybrid method assures higher accuracy in short-term wind power prediction. In the near future, the proposed SEGAN-DDAM-BiGRU can be considered with transfer learning to better address the wind power prediction problem when sufficient historical data are not available.

Feroz, R.M.A., et al. [107] suggested the weather research and forecasting (WRF) model integrated with the wind farm parameterization (WFP) scheme for the wind speed and power forecasting of a utility-scale, onshore wind farm situated in complex terrain. The proposed model demonstrated unsatisfactory forecasting results, achieving an average MAE of 15% (summer) and an MAE of 26% (winter), respectively. The WRF model exhibited lower accuracy during the winter season, with high RMSE values for wind speed and high NMAE values for the power output of individual turbines. The large variance in the model output for winter can be improved in future work.

4.6. Evaluation of Prediction Method Levels and Research Limitations

Figure 3 shows the evaluation structure of wind power forecasting. In the process of short-term wind power prediction, the last prediction result is simply regarded as the true historical power value. Therefore, the prediction model with a long time resolution is prone to error accumulation, and the reliability of the prediction will gradually decrease. Selective transmission of the encoding information from the last moment to the next prediction preserves the dependency of information in multi-step prediction while also alleviating the phenomenon of error accumulation and slowing down performance degradation. In summary, the methods based on multi-source information proposed in this paper evaluated the reviewed short-term wind power prediction models using various error indicators at different time resolutions.

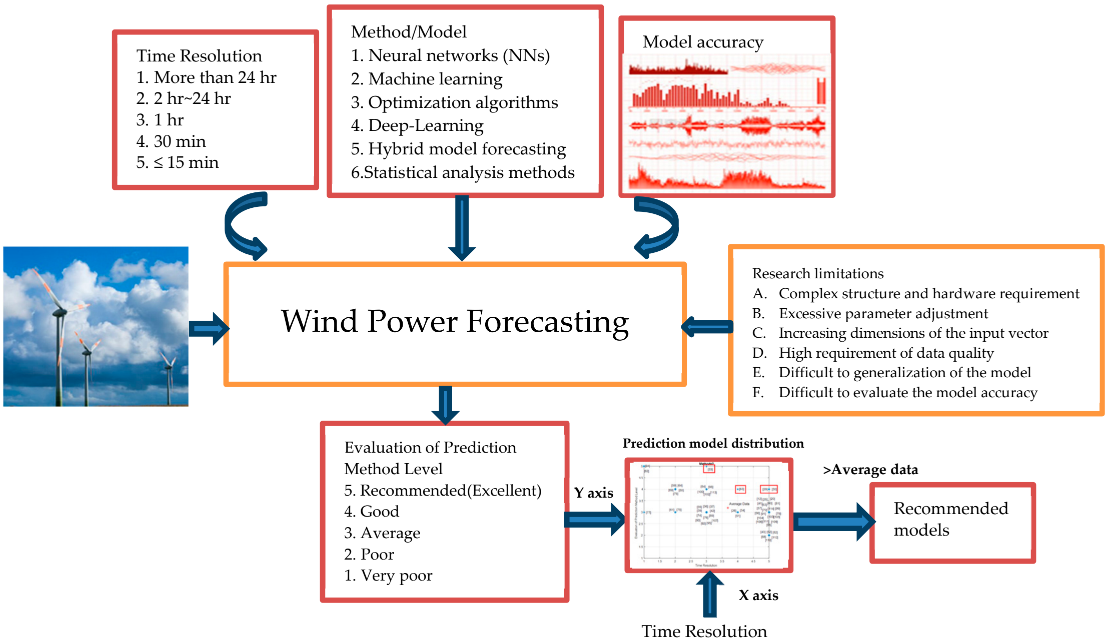

Figure 3. The evaluation structure of wind power forecasting.

To demonstrate the predictive effectiveness of this proposed method, the AI methods, time resolution, and prediction accuracy of each prediction model in the reviewed papers were evaluated using the prediction method level, and the research limitations of each prediction model were analyzed as shown in Table 8. At the same time, the wind power prediction models of 1–3 AI methods proposed in this paper are analyzed for the prediction results of the wind farms under study. In the distribution diagrams of evaluation indicators for short-term wind power prediction models, as shown in Figures 4–6, benchmark algorithm models that are significantly superior to the average value are selected, and the excellent wind power prediction models are recommended to provide useful directions for other researchers planning to conduct similar experiments and investigations. They can effectively track the real power trend, be close to the real trend, and have certain engineering practicalities.

Table 8. Summary of prediction method level and research limitations for wind power forecasting.

Ref	Methods/Models	Time Resolution	Accuracy	Prediction Method Level	Research Limitations
[9]	6	24 h	RMSE = 3.093 MAE = 2.451	3	A
[10]	6	24 h	RMSE = 0.1089 MAE = 0.075	4	A
[11]	2,3,6	24 h	MAE = 3.18; RMSE = 4.63; R^2 = 0.94	4	A,C
[12]	4,6	15 min	Pinball loss (PBL) = 13.3 Average coverage error (ACE) = 4.86%, Winkler score (WKS) = 78.71 and Continuous ranked probability score (CRPS) = 26.21	3	A,C
[13]	6	72 h–1 week	RMSE = 16.62%; MAE = 11.23%	5	A,E
[14]	1	1 h	NMAE: DQR:9.086; QRNN:9.479 SBL:13.451; IFPA:13.967 NRMSE: DQR:10.917; QRNN:10.227 SBL:14.185; IFPA:14.538	3	B,E

Table 8. *Cont.*

Ref	Methods/Models	Time Resolution	Accuracy	Prediction Method Level	Research Limitations
[15]	4	15 min	MASE = 190.02 RMSE = 7.49	3	A,E
[16]	4	5 min~1 h	MAEs = 3.17% RMSEs = 2.88%,	3	B,F
[17]	1	24 h	NRMSE = 0.138	4	A,B
[18]	1	1 h	Mean absolute relative error (MARE) = 7.5%; Rj = 5.4% (mean value of the Pearson correlation coefficient)	3	C,F
[19]	1	1 month-years	RMSE = 1.04%; MAD = 0.91% MSE = 1.05%	5	C,D,E
[20]	1,2	15 min	Errors around 0.6 m/s	3	E,F
[21]	1	15 min	The model accuracy improved by 7.61% and the RMSE reduced by 8.76%	3	B,D,F
[22]	1	1 min	Mean square error (MSE) GBRT: 0.224; MLP: 0.117 Random forest with Bootstrap sampling: 0.111 Random forest with Poisson re-sampling: 0.096	2	A,F
[74]	5	15 min~1 h	Stand deviation = 10.42	3	A
[75]	5	1 hr	RMSE of proposed (MFF-SAM- GCN) model is 0.0284, while the SMAPE is 9.453%, the MBE is 0.025, and R2 is 0.989.	3	B,E
[25]	5	2 h, 4 h	Both MAE and RMSE of less than 10%	3	C,D,F
[26]	2,3	30 min	R2 = 98.9; RMSE = 50.36; MAE = 23.63	3	C,E
[27]	1,2,3	1 h	The average nRMSE for WNN trained by ISCA, ELM, RBF, MLP, WNN trained by PSO are 5.4059%, 6.925%, 10.294%, 12.407%, and 17.038%. The average nMAE for WNN trained by ISCA, ELM, RBF, MLP, and WNN trained by PSO, are 4.2893%, 5.4787%, 8.2527%, 9.5773%, and 13.4847%.	3	D,E,F
[28]	2,3	10 min	DR-SVM VMED(m/s): 6.895 MAE (m/s): 0.723 RMSE(m/s): 0.932 MAPE(%): 11.87 CPU time(s): 148.15	3	D,F
[29]	2,3	1~5 min, 24 h, 72 h–1 week	No description	4	A,B
[30]	2,3	10~30 min, 1–4 h	MAPE = 0.0372; NBE = 0.4621 RMBE = 0.2950; R2 = 0.9857	4	D
[31]	2,3	48 h	MAPE = 1.2677 RMSE = 0.2576	5	A
[45]	4	30 min	RMSE = 7.1322% MAE = 4.6713%	3	A,B
[46]	4,2	1 h,48 h	MRE(KW) = 0.016 MAE(KW) = 792 MSE(KW) = 1,568,305.38 RMSE(KW) = 1252.32	5	C,D
[47]	4,2	30 min	NRMSE = 0.154 NMAE = 0.110	3	A,C
[48]	4,3	1 h	Average error of four seasons MAPE:3.76 NMAE:2.46 NRMSE:3.12	3	C,D

Table 8. *Cont.*

Ref	Methods/Models	Time Resolution	Accuracy	Prediction Method Level	Research Limitations
[76]	4,5	1 h	Case A: NMAE 10.32%; NRMSE 14.59% CR: 85.41%; QR: 91.53% Case B: NMAE 10.18%; NRMSE 13.52% CR: 86.48%; QR: 91.53%	3	A,B
[49]	4,6	1 h	INT_OUT_EXT[GBT, RF, PHYS(v1&v2)→KNNR, MLP, LSTM] with additional expert SS:0.5925; nMAE[%]:11.3055 nRMSE:0.1618; nMBE:0.0146	3	A,C,D
[50]	4,3,2	1 h	MPSO_ATT_LSTM MAPE: 4.6%; MAE: 211.5 kW Device capacity > 20,000 kW	3	A,B,F
[51]	4,2	1 h	Annual and monthly errors	3	D,F
[52]	4,1,2	15 min	RMSE = 0.1998; MAE = 0.1523	3	C,E
[53]	4,1	15 min	PINAW = 8.66 MW; PICP = 84% RMSE = 127.10; MAE = 0.6855 MW	3	E,F
[54]	4,2	1 h	Error can be divided into training, test, and validation errors	3	A,F
[55]	4,2	10 min	Multi-step informer network (MSIN) improves forecast accuracy by 29% compared with the informer network for RMSE	2	C,D
[56]	4,2,3	15 min	VMD-CNN-IPSO-LSTM MAE:2.92668; RMSE:3.59604 MAPE:0.20147; adj-R2:0.96639	3	A,B
[77]	5	1 h	The GRNN model gives a CC value of 0.956, an RMSE of 28.82, and the SVR model gives a C value of 0.965 and RMSE value of 44.40.	3	C,F
[78]	5	4 h	NMAE = 11.2% MAPE = 4.2%	3	A,E
[100]	6	15 min	NRMSE = 2.59	3	A,C
[101]	6	5 min	The error value is represented by a picture rather than a simple number.	2	D,F
[102]	6	1 h	1% point analysis gap to the optimal solution, which requires complete information, including future values	3	C,D
[103]	6	5~15 min	No description	2	C,D,F
[104]	2,6	30-min	CRPS (%) = 5.12	3	F
[105]	4,6	15 min	RMSE = 127.10 MAPE = 1.25%	2	C,E
[106]	6	1 h	With an increase in power by 1.6 times, there is a decrease in the energy of RES by 15–19.	3	E,F
[79]	5	3 h~24 h	NRMSE(%) = 11.421 NMAE(%) = 8.152	4	C,E
[80]	5	1 h~24 h	RMSE = 1.5651, MAE = 0.8161, MAPE = 11.62%, and R2 = 0.9964.	4	E
[57]	1,4	15 min	MAPE (%) = 4.86, MAE = 18.64, RMSE = 28.45.	3	C,D,F
[81]	1,3	10-min	RMSE = 0.0921, MAPE = 0.0081, MAE = 0.0706 PICP = 0.982, PINAW = 0.025, CPIA = 0.973 APL = 0.0267, CRPS = 0.053	3	D,F
[82]	5	24 h	RMSE = 1.238, MAPE = 0.325, MAE = 0.7002	5	D
[58]	1,2	24 h	MAE = 2.071, RMSE = 2.431, COR = 0.568	4	A,C
[23]	1,4	15 min	MAE = 2.42, RMSE = 2.67 and MAPE = 0.12.	3	D,E

Table 8. *Cont.*

Ref	Methods/Models	Time Resolution	Accuracy	Prediction Method Level	Research Limitations
[59]	4,5	0.25 h~4 h	PICP = 0.994 PINAW = 0.087	3	B,C
[32]	2,5	48-h	MAE = 0.0861, RMSE = 0.1262, R2 = 0.8333, AR = 87.38%	5	C,D
[83]	5,1	30 min to 24 h	NMAE = 6.43, NRMSE = 9.59	4	A
[84]	5,4	24-h	MAPE = 0.094, rRMSE = 0.112	4	A
[60]	4	15 min	MAE = 1.59, RMSE = 3.73 and MAPE = 8.13.	3	A,C
[85]	5	24 h	NRMSE = 0.1020 NMAE = 0.0803	4	C,D
[86]	5	1 h~12 h	MAE = 0.273 RMSE = 0.343	4	E
[107]	6	10 min	MAE = 15% (summer) and MAE = 26% (winter)	3	D,F
[87]	5,4	24 h	RMSE = 2.6018, MAPE = 0.2859, MAE = 2.3857	4	C,E
[88]	5,3	15 min	NMAE = 3.3221, NRMSE = 4.64875,FB = 0.0029, DA = 0.8342	3	A,E
[61]	4	5 min	PICP = 0.9634, PINAW = 0.0363, CWC = 0.2178	2	A,B
[89]	5	4 h~72 h	MAE = 3.8%, RMSE = 5.24%	5	E
[90]	5	30 min ~ 6 h 1~7 days	RMSE = 13.09 MAPE = 1.03	3	E,F
[91]	5,6	1 h	RMSE = 13% MAE = 20.7%	3	A,D
[92]	5,4	24 h	MAPE = 16.87% MAE = 27.1% CI = 0.968	3	A,B
[33]	5,2	1 h	MAPE = 2.62 and RMSE = 0.14	3	C,F
[34]	4,3	1 week	reliability and skill score are reduced by 10% to 33%.	3	F
[35]	5,2	1~24 h	RMSE = 5% and R2 = 0.95	4	A
[93]	5,4	15 min	RMSE = 6.27% MAE = 4.01%	3	A,C
[94]	5,4	1~3 h	MSE(e-2) = 0.8951 MAE = 0.0505 RMSE = 0.0946	4	C,E
[36]	1,4	10 min	RMSE = 0.02 MAE = 0.007 MAPE = 0.60 R2 = 0.84	3	C,D
[37]	1,4	10 min	PA = 0.934 MAE = 84.837 RMSE = 134.837	2	A,C
[95]	5,4	10 min	RMSE(MW) = 56.6893 MAPE(%) = 4.839 MAE(MW) = 42.0201	3	A,B
[62]	4,1	1 h	MSE = 0.0102 MAPE = 46.24 MAE = 0.0623 RMSE = 0.1012	4	A,F
[63]	6,1	10 min	RMSE (MW) = 0.94 MAE (MW) = 0.67 MAPE (%) = 49.71	3	C,E

Table 8. *Cont.*

Ref	Methods/Models	Time Resolution	Accuracy	Prediction Method Level	Research Limitations
[38]	2,4	Anemometric height	Anemometric height 100 m RMSE [m/s] = 0.383 150 m RMSE [m/s] = 0.368 120 m RMSE [m/s] = 0.375	3	A
[108]	6	1 h	WRF: RMSE = 1.68 to 2.85 m/s CCMP: RMSE = 1.79 to 2.89 m/s;	4	D
[64]	4,6	10 min.	RMSE = 129.3 MAE = 81.1	2	B
[65]	2,1	1 h	RMSE(MW) = 1.27 MAE(MW) = 0.90	3	A
[66]	4,2	1 h	NRMSE = 0.16 MAPE = 0.15	3	C,E
[96]	5,2	10 min	RMSE = 0.680	3	A,B
[39]	3,2	1 h	Mean skill score = −0.527	3	A
[67]	2,4,5	1 h	MSE = 0.130	3	A,C
[68]	4,3,2	-No description -Establishing wind power curves for wind turbines	RMSE = 111.9766	2	E,F
[69]	1,4	1 h	1-h ahead. RMSE = 0.9947	3	B,C
[97]	1,2,5	10 min	RMSE($\times10^{-2}$) = 6.47473	3	A
[109]	3,6,2	-No time unit written	8-step ahead RMSE = 7.51 16-step ahead RMSE = 10.88	2	E
[24]	1,3	1 h	RMSE (MW) = 0.2949	4	A
[110]	6,3	15 min	Spring RMSE = 8.3404 Summer RMSE = 6.6873	3	A,D
[111]	4,6	1 h	NRMSE = 3.66	4	A
[112]	4,1,6	10 min	RMSE = 119.645 (kW)	3	A,B
[40]	2,6	1 h	RMSE(kW) = 76.18	4	C,D
[70]	2,5	10 min	RMSE(MW) = 1.0822	3	A,B
[98]	5,4	15-min	RMSE = 1.8313	3	A
[71]	4,1	15 min	RMSE = 0.1243	3	C,D
[72]	4,2	10 min	-Train set MSE ($\times10^{-3}$) = 3.5961 -Test set MSE ($\times10^{-3}$) = 2.1628	3	B
[41]	3,2	1 h	RMSE(MW) = 14.7435	3	F
[73]	2,3	-No description -Establishment of wind turbine power capacity	RMSE (%) = 10.23	2	A,B
[42]	3,2	15 min	NMAE = 5.15%	3	C,D
[43]	2,3	10 min	RMSE (kW) = 50.55	2	A,B
[99]	5,3	15 min	RMSE = 2.63109	3	A,B
[113]	3,6	10 min	RMSE (kW) = 66.26	2	B,D
[44]	3,2	1 h	Reliability performance parameter P (%) = 90.92	4	E,F
[114]	2,3	15 min	RMSE(MW) = 373	3	C,D,F

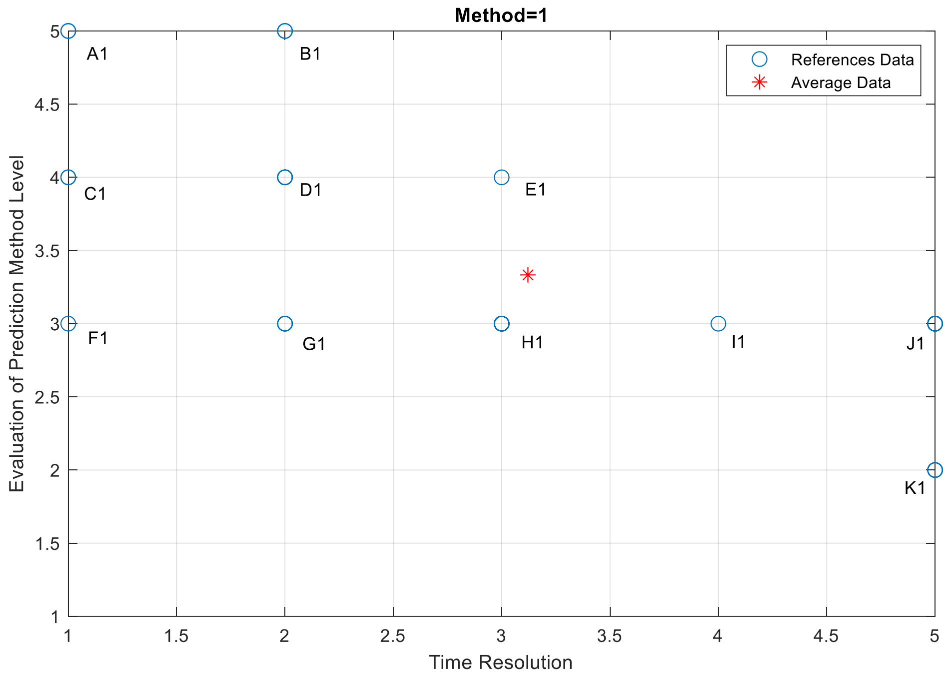

Figure 4. Distribution diagram for time resolution and prediction method level using an AI method (Methods of 1) for modelling wind power prediction.

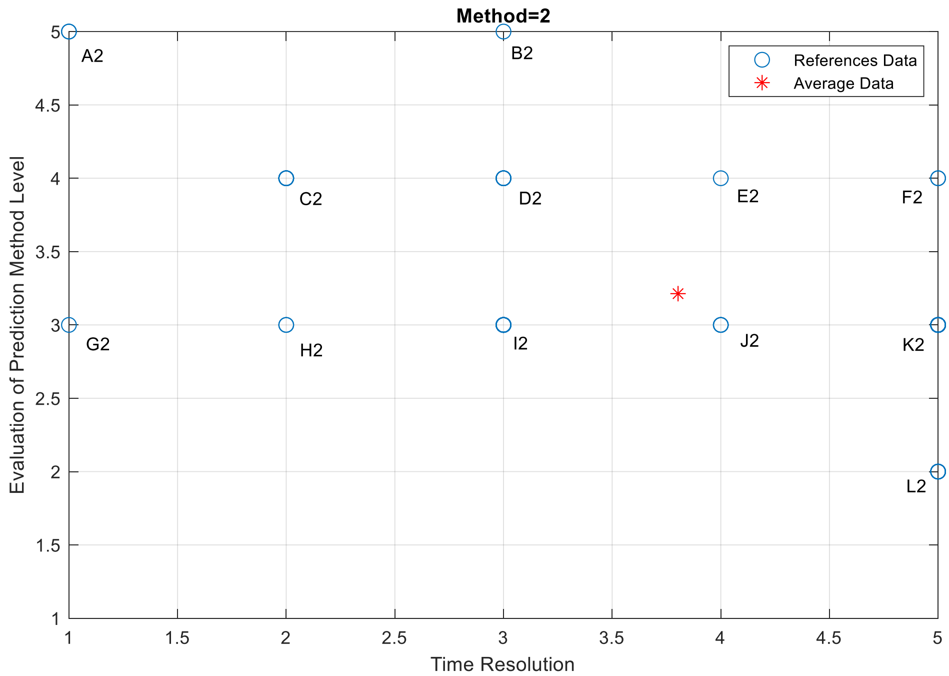

Figure 5. Distribution diagram for time resolution and prediction method level using two AI methods (Methods of 2) for modelling wind power prediction.

In order to enable other researchers planning to conduct similar experiments and investigations in wind power prediction to have a clear understanding of the correlation and impact of AI method types and time resolution on evaluating the level of wind power prediction models, and to provide useful guidance in the paper. The distribution regions between the time resolution and prediction method level of the reviewed paper prediction models are shown in Table 9, and the best wind power prediction model under current research conditions was quickly determined in 106 references.

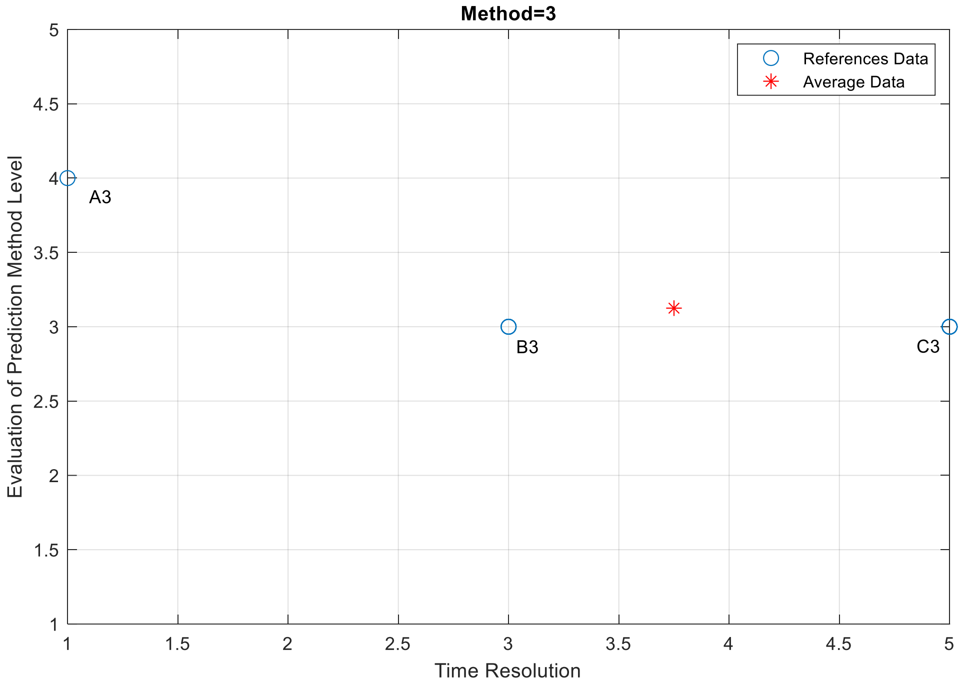

Figure 6. Distribution diagram for time resolution and prediction method level using three AI methods (Methods of 3) for modelling wind power prediction.

Table 9. Distribution region between time resolution and prediction method level for models of reviewed works.

Methods	Distribution Region	Reviewed Works	Distribution Region	Reviewed Works
1	A1	[13,19]	G1	[25,77,90]
	B1	[82,89]	H1	[14,18,75,77,100,106]
	C1	[10,17]	I1	[45]
	D1	[79,80,85,86]	J1	[15,16,21,60,74,107]
	E1	[108]	K1	[22,61,101,103]
	F1	[9]		
2	A2	[31,32]	G2	[34]
	B2	[46]	H2	[59,92]
	C2	[35,58,84,87,94]	I2	[33,39,48,49,51,54,65,66,76,91] [41,69]
	D2	[24,40,44,62,111]	J2	[26,47,104]
	E2	[83]	K2	[12,20,23,28,36,42,53,57,63,70–72,81,88,93,95,96,98,99,110,114]
	F2	[29,30]	L2	[37,43,55,64,105,113]
3	A3	[11]	References [29,30,46,83] using two methods as shown in Figure 5 are even better than the average value of Method 2, which is worth recommending for future studies of wind power prediction models. References [38,68,73,109] are eliminated due to a lack of time resolution and a non-wind power prediction model.	
	B3	[27,50,67]		
	C3	[52,56,97,112]		

4.7. Evaluation of Excellent Wind Power Prediction Models

There are a total of 33 reviewed papers in Figure 4, with their average values falling at Time Resolution = 3.12 and Prediction Method Level = 3.33; in Figure 5, there are a total of 63 reviewed works whose average values fall at Time Resolution = 3.80 and Prediction Method Level = 3.21; and there are a total of 10 reviewed papers in Figure 6, with an average of Time Resolution = 3.75 and Prediction Method Level = 3.13. It can be seen that the current prediction is mainly based on a 1-h prediction, with a recommendation level of around 3 from Figures 4–6. However, the distribution diagram of Method 2 in Figure 4 shows that Time Resolution and Prediction Method Level are better than Method 1 and Method 3. It has been the main research trend in wind power prediction models in recent years. Among these 106 references, References [29,30,46,83] using two methods as shown in Figure 5 are even better than the average value of Method 2, which is worth recommending for future studies of wind power prediction models. References [38,68,73,109] as shown in Figure 6 can be eliminated due to a lack of time resolution and a non-wind power prediction model.

5. Future Studies and Development

Various advanced wind power forecasting methods have been developed over the past few years to help plan and use wind power as efficiently as possible. These methods are used for experiments, and relevant results have been obtained for solving the issues of power fluctuation and randomness in wind power forecasting and the possible errors and omissions of the original data. Based on the latest advances in artificial intelligence, machine learning, and deep learning methods, this paper conducts a comparative analysis in terms of time resolution, parameters used, accuracy, and research limitations and reviews the contributions to the development, advantages, and disadvantages of the latest hybrid wind power forecasting models. However, there are still some issues that need to be improved. The following are the main aspects that can be further studied:

(1) In terms of wind speed prediction, the current study only selects a walrus station for research based on historical data. However, wind speeds are necessarily different in different regions. The geographical environment, weather, or climate-related factors (wind direction, humidity, etc.) where the weather station is located are not included in the forecast. Studying the influence of the physical environment will definitely improve the accuracy of wind speed prediction; in addition, the time period is also a factor affecting the prediction. The impact of different time solutions on the forecast results is explored, and they may even be incorporated into the future meteorological data of the meteorological bureau as an input factor, thereby improving the forecast accuracy.

(2) In terms of wind power modeling, wind power generation models will perform differently in different regions. The same wind speed corresponds to different wind field settings, setting directions, and even the structure of wind turbines (generator speed, blade angle, etc.), resulting in differences in power generation. Most studies only build relationships between wind speed and wind power. If the influence of the wind turbine itself can be further considered, the power generation model will be more complete.

(3) In terms of wind power forecasting, weather forecasts are selected in combination with data characteristics, and wind power generation is indirectly predicted using power generation models. We wonder if it is possible to directly sample power generation and effectively find its own characteristics for prediction, which requires further development; in addition, according to the characteristics of different wind fields, more suitable functions for identification and even other artificial intelligence methods such as neural networks or deep learning methods may be applied for prediction [142–146]. Whether adaptability can improve prediction accuracy is also a very important issue.

(4) The present forecasting methods for short-term wind power of wind farms generally only consider the data of normal wind speed and normal operation of wind turbines, and it is difficult to achieve high accuracy for short-term wind power when the wind speed drops. Therefore, it will be of practical significance to consider short-term wind power forecasting under the actual operation scenarios of wind farms.

(5) WRF based on other initialization times and longer ahead-time. The error transfer mechanism from wind speed forecasting (WSF) to wind power forecasting (WPF) is applied for the improvement of WPF. The forecasting accuracy of short-term WPF is enhanced by correcting NWP data. Various data preprocessing methods for a WPG system model have been investigated, such as singular value decomposition, from the system perspective [147,148]. Real-

time WTP measurements are added to the reconstructed state space during the forecasting process, making the forecast more flexible.

(6) The accuracy and speed of prediction of the characteristics of big data in wind power are improved by parallel modeling of the prediction algorithm. Next, the spatial correlation features are incorporated into the classification and prediction, and the feasibility of the model is verified using different datasets, with the development of new or the integration of multiple optimization algorithms [149–151] for use in the forecasting model to improve the interpretability of the combined models for further enhancement of accuracy.

(7) Wind power generation is very important for dispatching and regulation of the power system when connected to the grid. Due to the influence of the change in wind power generation on the voltage and frequency of the power system at any time, based on the basic view of a large-scale or decentralized wind power system combined with pumped-storage power stations, adjustable biomass power stations, or energy storage battery systems, wind power can be stably transmitted to improve the flexibility of power dispatching.

(8) Robust optimization of the grid integration issues of wind power and distribution networks is applied using WindGMMN. A wind power prediction technique with integration into the electricity grid should consider load scheduling, demand-side management, etc. In addition, optimal dispatching of isolated or grid-connected MG considering economic cost, net pollutant emission, and operational security objectives will be the focus of future research work.

6. Conclusions

Wind energy is inexhaustible. Wind power generation can effectively reduce the consumption of energy resources and has good development prospects. However, uncontrollable factors such as wind intermittency and random fluctuation represent great challenges. Large-scale grid-connected wind power will inevitably affect the stability of the power system, so accurately predicting wind power generation is an urgent matter. The accuracy of wind power generation prediction depends on the way in which the prediction model is built, which in turn affects the accuracy of weather prediction. In the face of the advent of big data, the limited use of effective data can allow us to reduce resource consumption. Therefore, in this paper, many state-of-the-art predictive models of wind power generation based on artificial intelligence (AI)-based and deep learning-based algorithms were reviewed. Among the many artificial intelligence methods, support vector machines with good results when processing nonlinear features were selected for regression analysis as they can not only effectively analyze data but can also improve prediction accuracy. This paper mainly expounds on the research background and significance of papers published in recent years. Secondly, the status of this research is explained from a global perspective. Next, the research content of the reviewed literature is described. Finally, conclusions are drawn, and prospects for future research are presented.

This review evaluates the latest studies on international wind power forecasting models over the past three years, categorizing them according to the time resolution, model type, and forecasting principle and comparing them in terms of their wind power forecasting errors and evaluation indicators. Key recent research efforts [9–114], published between 2020 and 2023, are reviewed. Most of these works aim to cover the field of ultra-short-term and short-term wind power forecasting, which has grown significantly in the past few years. Second, this paper reviews recent advances in AI-based wind hybrid methods published from 2020 to the present, highlighting their contributions to model development and their advantages and disadvantages. Furthermore, these advanced algorithmic hybrid models are classified, compared, and analyzed accordingly in terms of temporal resolution, parameters used, accuracy, and study limitations. Therefore, the research reviewed in this work covers state-of-the-art algorithms and recent advances in wind power forecasting. The contributions to this review article are as follows:

This review (a) focuses on ultra-short-term and short-term forecasting models; (b) evaluates the state-of-the-art algorithms in WPPF; (c) evaluates the accuracy, advantages, and disadvantages of various novel hybrid models; (d) explores existing challenges and issues such as wind data diversity, algorithm structure, implementation, hyperparameter tuning, optimization ensemble problems, and AI hybrid problems; and (e) describes the development of efficient AI-based hybrid ultra-short-term and short-term wind power forecasting methods and future possibilities. It provides future research directions and presents the challenges of the existing wind power forecasting methods, and addressing these challenges is the focus of the further development of AI-based wind power hybrid models, including focusing on improving the accuracy of existing models, improving spatiotemporal forecasting models, effectively utilizing deep learning models, and improving the selection and analysis of input data. A total of 33 reviewed papers (Methods of 1) have proposed a short-term wind power prediction model based on an AI method, which outperforms computer operation efficiency and results in a long calculation time. Based on this defect, there are 63 reviewed papers (Methods of 2) that use two AI-based methods to make short-term wind power predictions. The results obtained in each step are used in the next step of prediction to reduce the error accumulation problem caused by parameters. This has been the main trend in prediction models in recent years. However, the problem of past poor computer performance resulting in long computing times is solved due to the future of parallel, fast computing on computers. Although there are currently only eight reviewed papers on Method 3, all of the latest papers adopt short-term wind power prediction with three AI methods. As long as the AI algorithms can break through existing research limitations, parallel and fast computing by computers will solve the current shortcomings, and it will become mainstream research for short-term wind power prediction models in the future. More innovative ideas for future research on wind power prediction are expressed as follows:

(A) To preprocess the input data to identify data characteristics to make the data more distinctive or minimize data dimensions to reduce computational time.

(B) Model structure and hyperparameter optimization, such as core functions or modeling parameters, can be achieved by optimizing parameter adjustments, which can effectively improve the accuracy of the model in training and testing and also avoid excessive matching during training.

(C) There are parallel operations in the model structure, which often combines various modeling methods for parallel modeling and uses different weight ratios to adjust prediction accuracy. These methods have a complex structure and too many parameter adjustments for each method, resulting in a long calculation time that should be improved in future works.

(D) The prediction models for wind power can be established using cross-validation combined with grid search to improve their accuracy and reliability. In the case of cross-validation, many parameters need to be manually specified or optimized using algorithms. The adjustment process is called hyperparameter tuning. Therefore, the grid search method will preset several hyperparameter combinations for the model, and each group of hyperparameters will be evaluated through cross-validation, and the optimal parameter combination will be selected to establish the new model.

(E) Input signals are first classified and features extracted using feature engineering. Then, a tree classifier method is used to rank features from high to low in importance, eliminating low-ranked features, and defining high discriminative feature values from several feature parameters before incorporating them into intelligent diagnostic model operations.

Author Contributions: W.-C.T., writing—original draft preparation, review, and preparation of the revised version. C.-M.H. contributed to the project administration, modeling investigation, methodology, and preparation of the original draft of the manuscript. C.-S.T., the modeling investigation, conceptualization, and application of methodology. W.-M.L., supervision, and project administration. C.-H.C., verified the prediction results. All authors have read and agreed to the published version of the manuscript.

Funding: The project was funded by the Natural Science Foundation of Xiamen, China (project No. 3502Z20227325).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are contained within the article.

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

Abbreviations

ANN	Artificial Neural Network
BNN	Backpropagation Neural Network
QR	Quantile Regression
NWP	Numerical Weather Prediction
WPF	Wind Power Forecasting
WPPF	Wind Power Probabilistic Forecasting
WSF	Wind Speed Forecasting
WRF	Weather Research and Forecasting
WPG	Wind Power Generation
WFP	Wind Farm Parameterization
RWPF	Regional Wind Power Forecasting
QRNN	Quantile Regression Neural Network
CSTWPP	Convolutional Spatial-temporal Wind Power Predictor
STCN	Spatio-temporal Convolutional Network
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
IBA	Improved Backfill Algorithm
GPR	Gaussian Process Regression
MFF-SAM-GCN	Multi-Feature Fusion/Self-Attention Mechanism/Graph Convolutional Network
WMTSM	Weighted Multivariate Time Series Motifs
CLP	Conditional Linear Programming
ABQs	Adaptive Boundary Quantiles
WNN	Wavelet Neural Network
EMD	Empirical Mode Decomposition
EBSO	Enhanced Bee Swarm Optimization
LSTM	Long-Short Term Memory
CLSTM	Convolutional-Long Short Term Memory
DOCLER	Deep Optimized Convolutional LSTM-Based Ensemble Reinforcement Learning
SVM	Support Vector Machine
DR-SVM	Distributionally-Robust Support Vector Machines
SOM	Self-Organizing Map
k-NN	k-Nearest Neighbors
KNNR	K-Nearest Neighbour Based Routing Protocol
KDE	Kernel Density Estimation
ELM	Extreme Learning Machine
KELM	Kernel Based Extreme Learning Machine
Adaboost	Adaptive Boosting
PSO	Particle Swarm Optimization
LSSVM	Least Squares Support Vector Machine
GMMN	Generative Moment Matching Network
WindGMMN	Wind Power Using Generative Moment Matching Networks
MSIN	Multi-Step Informer Network
WPD	Wavelet Packet Decomposition
VMD	Variational Mode Decomposition
SSA	Salp Swarm Algorithms/Singular Spectrum Analysis
IGWO	Improved Grey Wolf Optimization
GRNN	Generalized Regression Neural Network
SVR	Support Vector Regression
HMMC	Higher-Order Multivariate Markov Chain

MSTAN	Multi-Source and Temporal Attention Network
ARMA	Auto-Regression Moving Average
ARIMA	Autoregressive Integrated Moving Average
MRE	Mean Relative Error
MAE	Mean Absolute Error
MBE	Mean Bias Error
RMSE	Root Mean Squared Error
MAPE	Mean Absolute Percent Error
nMBE	Normalized Mean Bias Error
nRMSE	Normalized Root Mean Squared Error
R^2	Coefficient of Determination
MG	Microgrid

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