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Artificial Intelligence in Wind Speed Forecasting: A Review

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Abstract: Wind energy production has had accelerated growth in recent years, reaching an annual increase of 17% in 2021. Wind speed plays a crucial role in the stability required for power grid operation. However, wind intermittency makes accurate forecasting a complicated process. Implementing new technologies has allowed the development of hybrid models and techniques, improving wind speed forecasting accuracy. Additionally, statistical and artificial intelligence methods, especially artificial neural networks, have been applied to enhance the results. However, there is a concern about identifying the main factors influencing the forecasting process and providing a basis for estimation with artificial neural network models. This paper reviews and classifies the forecasting models used in recent years according to the input model type, the pre-processing and post-processing technique, the artificial neural network model, the prediction horizon, the steps ahead number, and the evaluation metric. The research results indicate that artificial neural network (ANN)-based models can provide accurate wind forecasting and essential information about the specific location of potential wind use for a power plant by understanding the future wind speed values.

Keywords: wind speed forecasting; artificial neural networks; artificial intelligence; ensemble prediction

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1. Introduction

The electricity sector's efficient operation directly influences social and economic development. Therefore, the electricity supply for the population must be maintained and guaranteed. After the industrial revolution, fossil fuels supplied the growing energy required for production; consequently, atmospheric pollution increased. According to the World Meteorological Organization (WMO), in 2021, CO_2 emissions rose compared to previous years [1,2]. As the principal cause of pollution comes from producing electrical energy, other alternatives have been explored to generate it through renewable energy sources.

The development of clean, energy-efficient technology is essential to solving complex environmental problems [3]. Accordingly, wind power generation has increased considerably [4], and many studies on its integration have been published [5,6]. The 93.6 GW of new installations in 2021 brings global cumulative wind power capacity to 837 GW, with year-over-year growth of 12%, and there were over 50 GW of new installations in 2019 [7], as seen in Figure 1. In Mexico, installed capacity has also increased (Figure 2), demonstrating wind energy's importance in social, economic, and environmental future development. In addition, there is a need to install wind power three times faster over the next decade to avoid the worst impacts of climate change [8]. However, the integration of large-scale wind energy presents problems in modern systems due to the randomness and volatility of processes. Hence, wind energy forecasting is of vital importance [9].

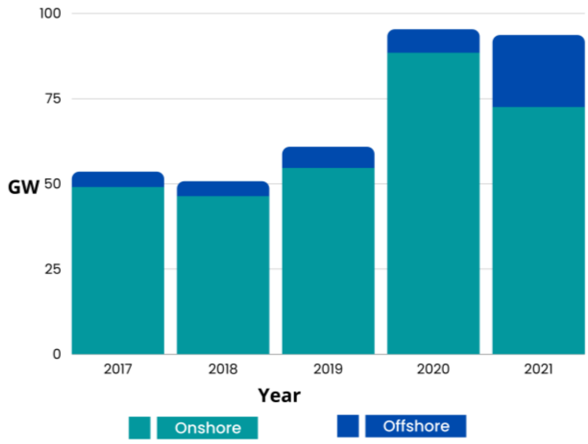

Figure 1. Growth of wind power capacity over the last decade by region. Source: [7].

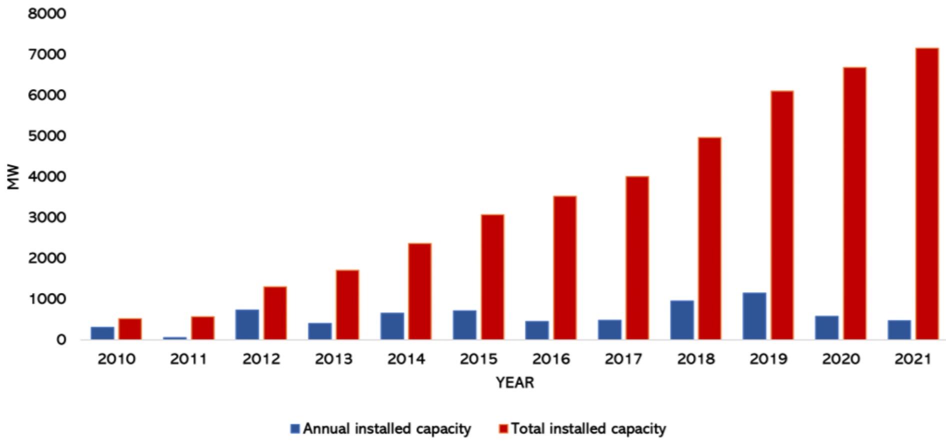

Figure 2. Evolution of installed wind capacity in Mexico. Source: [10].

Several techniques have been implemented to achieve this objective, allowing different factors prediction, such as wind speed. Consequently, several systems have been developed to take advantage of the wind [11]. However, integrating wind energy is not an easy source of electricity because of its nonlinear climate behavior [12]. Therefore, forecasting wind energy techniques is one of the most vital options for reducing the negative impact of wind energy volatility [13].

Wind energy randomness and volatility have presented challenges to the power grid, and the connected amount of wind energy causes difficulties in network distribution. Artificial intelligence has been used for a long time to predict variables in the most diverse applications, such as water desalination, transportation [14,15], and certainly for wind speed forecasting.

Accurate wind prediction is essential in solving these problems [16]. The most common wind speed forecasting methods are the persistence method, with a physical approach (numerical time predictors), and statistical methods such as Autoregressive with Exogenous Input (ARX), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), the ANN, Adaptive Linear Element Network (ADALINE), Feed-forward Neural Network (FNN), Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), and Radial Basis Function (RBF) [17]. Recently, machine learning algorithms (MLA) such as spatial correlation, Fuzzy Logic (FL), and Ensemble prediction have been combined with ANN in the prediction process, creating a new alternative with the hybrid models to improve the precision of wind speed forecasting [18]. On the other hand, models such as Autoregressive Moving Average (AR), ARMA, ARIMA, ARX-Type, and Fractional-Autoregressive Integrated Moving Average (f-ARIMA) [19] require prior mathematical model knowledge and are often used for long-term predictions. Moreover, they must be linear, and their implementation is relatively simple and establishes reliable intervals. For this reason, it is essential to analyze the type of time series to choose the appropriate model.

On the other hand, models based on ANN can work with nonlinear models that do not require prior knowledge of a mathematical model. Also, some hybrid models use time series for artificial intelligence to predict wind speed. These models are helpful because they provide essential information on how to use the wind potential of a specific location for a possible wind power plant by understanding future wind speed values [20]. In addition, these models have an adaptability of inline measurements and fault tolerance. Therefore, using a significant amount of data in the time series is recommended to train the network and obtain better results in wind forecasting.

In 2021, several studies were conducted where the short-term wind is predicted, with up to 96 h extension, and have shown good precision in wind prediction [21–24]. Many researchers have chosen to use neural networks for wind behavior prediction. The ADALINE model was used in [17–19] to predict wind speed with a short-term forecast horizon. Pousinho et al. [25] used Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict short-term wind speed. It is a forwarding network class with multiple adaptive layers suitable for nonlinear predictions. In [26–31], hybrid models are proposed, integrating ANFIS to forecast wind speed in the short term. Furthermore, other methods based on MLP with a short-term prediction, such as MLP-Convolutional Neural Network (CNN) [32], IIR (Infinite Impulse Response)-MLP [33], and Self-Organizing Maps (SOM)-MLP [34], were proposed. The RBF model was used in [30–33] to predict short-term wind speed with high precision. The short-term wind speed was predicted with acceptable accuracy using the CNN model [35,36] and the Elman Neural network (ENN) model [37,38]. In recent years, the ADALINE model has been discontinued because although it has a higher convergence, a high time delay is observed in the training process. Thus, models such as CNN, MLP, and ENN have been chosen in recent years. Although the ADALINE model has a higher convergence, it is delayed in the training process.

Another technique used is the Deep Neural Network (DNN) model, which is the most promising technique, and has been used for some studies on wind prediction. For example, Qin et al. [39] predict wind energy, power, and wind load signals using the Long Short-term Memory (LSTM) model. Hu et al. combined deep learning and transferred learning for a newly created wind farm [40]. An hourly prediction was carried out by including LSTM in a hybrid model as an alternative to improve wind speed forecasting. In addition, Variational Mode Decomposition (VMD) is used as a pre-processing technique, with favorable results [41]. Finally, Ensemble Empirical Mode Decomposition (EEMD) pre-processing is used for historical wind data, along with LSTM as the predictive model [42].

On the other hand, P. Lu et al. (2021) reviewed metaheuristic methods, including algorithms based on evolution, physics, humans, swarms, and hybrid methods for wind energy prediction [9].

The variety of these studies in recent years demonstrates the importance of neural networks. Figure 3 shows a classification of the most-used techniques in wind prediction, their advantages, and their disadvantages.

This study reviews various methods for predicting wind speed using ANN, allowing the decision maker to define the most appropriate conditions for a wind system to obtain a reliable forecast of wind speed, which is essential for a safe and efficient wind power generation system.

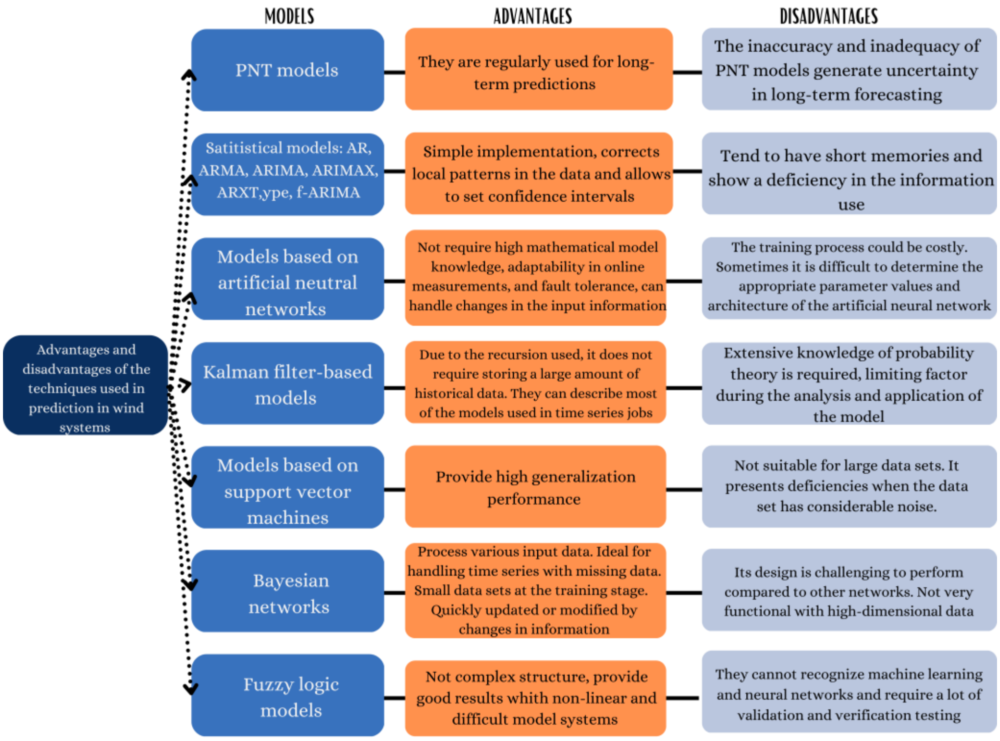

Figure 3. Classification of models used in wind forecasting, advantages, and disadvantages.

2. Methods

This paper presents exhaustive classification of articles published in recent years on wind speed time series forecasting. First, articles from indexed journals and some relevant papers published in conferences were selected. Then, they were identified and classified according to the type of data input model, pre-processing and post-processing techniques, ANN architecture model, forecasting horizon, steps number per dataset, and evaluation metrics. Based on the literature review, a methodology for forecasting wind speed using ANN was designed and developed. Figure 4 shows the general methodology used to carry out this research.

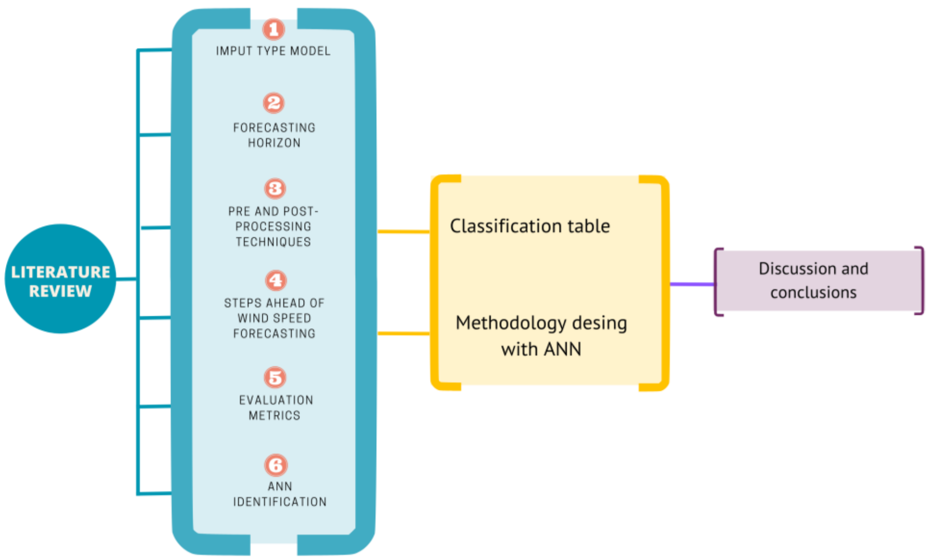

Figure 4. Methodology Flow Chart.

A total of 110 articles with different models used for forecasting wind systems were analyzed, of which 91 were selected due to specific information on the factors considered as essential, namely input type model, pre-processing and post-processing techniques, ANN models, forecasting horizon, number of steps ahead, and evaluation metrics.

2.1. Type of Model Input

The variable input choice is essential to build the prediction model based on the methodological approach. For example, the input variables on physical models contain meteorological information such as pressure, temperature, and orography ([43,44]). In contrast, for a parametric or statistical model, the historical data is used as the input of the forecast model. Table 1 shows the classification of research papers that used physical input-type and statistical input-type models and their main characteristics.

Table 1. Characteristics of type of model input.

Type of Input	References	Principal Characteristics
Statistical	[21,22,24–26,33,35,36,40,45–66]	Wind forecasting from historical data series allows a model construction and the estimation of its parameters, establishing links between the present and the past and obtaining acceptable wind forecasting results with data stability. They have been used and evaluated satisfactorily in ARIMA, ARMAX, and ANN models and applied in the electricity market to estimate energy prices, establish buying and selling strategies, and plan and design wind farms.
Physical	[30,34,67–80]	Typically, the values of meteorological variables are obtained from a numerical weather forecasting model and power generation records from the Supervisory Control and Data Acquisition (SCADA) system. When using this type of input, the researcher must understand fundamental principles such as atmospheric motion, data sources, quality, and the ability to interpret, validate, and verify the data. This type of input can be used in the electricity market and in the design and maintenance of wind farms.

2.2. Ensemble Prediction: Pre- and Post-Processing Techniques

In addition to the persistence method and the statistical approach, new techniques have been developed known as ensemble prediction, which allows model hybridization to obtain better decisions than any base predictor and improves forecasting accuracy.

There are two types of ensemble methods: competitive and cooperative. Competitive strategies consist of training different predictors individually with the same or different data sets (but with other parameters), performing an average, and obtaining a final prediction. They comprise two categories: data diversity (Bagging, Spatial Correlation, Two-Model Competitive, and AdaBootst) and parameter diversity (Ensemble Filter Kalman (EFK), Multi-Scheme, and Ensemble Predictor).

The cooperative set forecast consists of dividing the data set and choosing a predictor for each division. The final prediction is then obtained by summing all the base predictors' results, including the preprocessing [81–83] (Complex Value, Empirical Mode Decomposition (EMD), and Wavelet Decomposition (WD)) and post-processing (Multi-Stage, Support Vector Regression (SVR) support vector classification, and ARIMA-Computational Intelligence (CI)) [82].

Pre-processing divides the input data set and trains each separately with the matching predictor. The final prediction is obtained by summing the outputs. The most popular technique is WD, which allows decomposing of data into several sub-series based on selecting a mother wavelet to predict with greater precision [26].

Post-processing uses forecasting series time consecutively by more than one predictor. The most used combination is the ARIMA model with a Computational Intelligence (CI) model because it is suitable for predicting linear series models.

Based on the literature review, a diagram of the modeling process is shown in Figure 5 to facilitate the visualization of the wind speed forecasting process with ANN. Simultaneously, the pre- and post-processing techniques and the optimization algorithms most commonly used by the researchers of the reviewed articles were added.

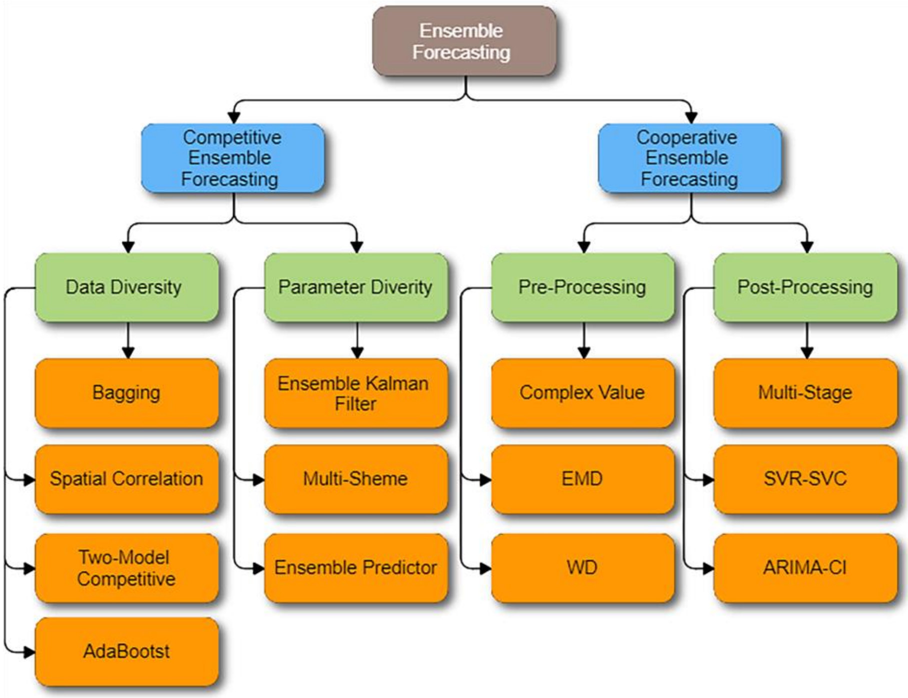

Figure 5. Ensemble prediction classification.

The Wavelet Transform (WT) converts a wind speed data sequence into constitutive series, offering more helpful information and allowing stationarity. Therefore, it will enable high precision of the wind speed prediction [26]. On the other hand, the Wavelet Threshold Denoising (WTD) smooths the wind speed data sequence to capture the main characteristics of the variation trend itself. Thus, the training model shows high-precision data prediction [31]. Another technique is the Principal Component Analysis (PCA), which can reduce the data size and the model training complexity [84]. However, the exact choice of WT is not an easy task, requires analysis of the time series, and involves a compromise between the degree of fit and the degree of localization.

On the other hand, the EMD extracts the WD multiple resolution advantages, overcoming the difficulty of determining the decomposition scale and the Wavelet base. This characteristic makes it suitable for non-stationary and nonlinear sequences [85]. Furthermore, EMD can perform time-frequency analysis while remaining in the time domain. The components are easier to analyze when they are on the same time scale as the original time series. By using EMD, it is possible to remove specific relevant components, such as noise, and reconstruct the signal. Moreover, relevant components can be extracted for further analysis. An advantage of the EMD over the Wavelet is that it recursively removes different resolutions from the series data without filters.

In this way, the original series is fragmented and is finally forecasted separately, creating a hybrid prediction. Unlike this technique, Wavelet Method (WM) is used to section the original time wind speed series into different sub-series to predict each one separately. Moreover, Bayesian Clustering by Dynamics (BCD) is a technique based on unsupervised learning and divides the input training data into subsets without prior knowledge of the classification criteria [86]. Furthermore, the Fifth-Generation Mesoscale Model (MM5) is used for regional predictions and analysis of atmospheric behavior. The main advantage of this model is that it allows the relationship between different areas [87].

In addition, Singular Spectrum Analysis (SSA) solves the problems that other approaches cannot. For example, EMD can present an issue in the nodes, and EEMD cannot completely neutralize the added white noise. Finally, VMD is a pre-processing technique that separates signals into independent, adaptive, quasi-orthogonal nodes [35].

Table 2 presents the references of the works that used some of the pre- and post-processing techniques described in this section in the wind speed forecasting process.

Table 2. Pre- and post-processing techniques used in the wind forecasting process.

Pre-Processing Techniques	References
ARIMA	[50,57,61,88]
ARIMA-KF	[89]
SARIMA	[90]
B.C.D.	[69]
E.M.D.	[38,42,47,62,78,91–95]
EEMD	[95,96]
FEEMD	[37]
SVM based in EMD.	[97]
MM5	[71]
SD	[75]
S.V.R.	[98]
S.S.A.	[99–101]
V.M.D.	[35,41,102]
Wavelet	[30]
WD.	[26,48,67,103]
WM.	[59]
WPD	[104]
WTD	[31]
WT.	[28,46,77,105–107]
E.W.T.	[108,109]
Post-processing techniques	
BMA	[60]
CSA-NNAM	[109]
Statistical	[110]

2.3. Prediction Horizon

The prediction model's classification is based on the time horizon, which varies according to the author between ultra-short-term (from seconds to 30 min), short -term (from 30 min to 6 h), medium-term (from 6 h to 1 day), and long-term (up to 24 h) horizons, which is very risky [11]. There is another classification with only three categories: short-term (8 h ahead), medium-term (1 day ahead), and long-term (more than one day ahead) horizons [72].

2.4. Multi-Step Ahead Forecast

Using a time series during the wind forecasting process makes it possible to know one step ahead of data. However, in some situations, it is desired to predict more than one step forward, which is possible using multi-step prediction: training data to forecast three-time steps ahead or predicting the value of "t", and then that value can calculate the next step (t + 1), repeating this process as needed.

2.5. Regression Metrics

It is crucial to select a metric to evaluate the prediction model performance. Sometimes, the same conclusion may not be reached using two metrics; thus, it is advisable to use more than one to ensure accurate results.

The mean square error (*MSE*) is the simplest but least-used technique in wind forecasting. This statistic's higher value indicates poorer performance and can be helpful when unexpected values could provide elements of interest according to the problem treated. Therefore, both very high and low *MSE* values must be treated carefully. *MSE* is given by:

$$MSE = \frac{1}{N} \sum_{I=1}^{N} (y_i - \hat{y}_i)^2 \tag{1}$$

Root means square error (*RMSE*) represents the square root of *MSE*. It is introduced when the error scale is equal to the objective scale. *RMSE* is given by:

$$RMSE = \sqrt{\frac{1}{N} \sum_{I=1}^{N} (y_i - \hat{y}_i)^2} \tag{2}$$

Mean absolute error (*MAE*) is calculated as an average of absolute differences between the expected and predicted values. All individual differences are weighted equally in the average. This metric is not as sensitive to outliers as the *MSE MAE* is given by:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{3}$$

Mean absolute percentage error (*MAPE*) is fundamental in time series:

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{4}$$

where y_i is the expected or actual result, $\hat{y}_i$ is the model-predicted value, and N is the data number.

Tables 3–5 show the literature analysis according to the time horizon: short-term, ultra-short-term, and long-term horizons, respectively.

Table 3. Studies carried out with a short-term prediction horizon.

Ref.	Step Number	Evaluation Criteria	Ref.	Step Number	Evaluation Criteria	Ref.	Step Number	Evaluation Criteria
[50]	NE	MAPE	[92]	1, 2 & 3	MAPE	[99]	3	MAPE
[33]	12	MSE	[105]	1, 2 & 3.	RMSE	[97]	1	MAPE
[51]	1	MAE	[103]	1	RMSE	[104]	1, 3 & 5	MAPE
[69]	1	RMSE	[88]	1, 3, 5, 7 & 9	RMSE	[66]	1	RMSE
[52]	NE	RMSE	[65]	1, 2 & 3	MAPE	[62]	1	MAPE
[53]	1	MAPE	[111]	1	MAPE	[77]	NE	MAPE
[54]	NE	RMSE	[106]	Multi-step	MAPE	[94]	1	MAPE
[70]	1	MAPE	[34]	1	RMSE	[41]	1–24	MAPE
[55]	2	MAPE	[112]	1	MAPE	[30]	1	MAPE
[71]	1	MAPE	[113]	1 & 5	MAPE	[78]	4	NMAE
[56]	1	MAE	[76]	1	RMSE	[42]	1	MAPE
[57]	1	RMSE	[114]	1	MAPE	[96]	1, 2 & 3	MAPE
[72]	1	MAE	[38]	1	MAPE	[31]	1, 2 & 3	MAPE
[58]	3, 5 & 10	MAPE	[107]	1	MAPE	[102]	1, 2, 4 & 6	MAPE
[59]	multi	MAPE	[115]	1	MAPE	[32]	1	RMSE
[73]	NE	MAPE	[93]	1, 3 & 5	MAPE	[116]	1	MAPE
[60]	1	MAPE	[117]	1	RMSE	[101]	1–6	MAPE
[26]	1	RMSE	[37]	1, 2 & 3	MAPE	[100]	1	MAPE
[50]	1	MAPE	[108]	1, 2 & 3	MAPE	[95]	1	MAPE
[33]	1	MAPE	[109]	1, 2 & 3	MAPE	[22]	1	RMSE MAE
[51]	1	MAPE	[28]	1	MAPE	[21]	1	MAE MAPE RMSE
[69]	1, 2 & 3	MAPE	[118]	1	MAPE	[63]	1	RMSE
[52]	1	MAPE	[29]	1	RMSE			

Table 4. Studies carried out with an ultra-short-term prediction horizon.

Ref.	Step Number	Evaluation Criteria
[45]	-	MAPE
[46]	1	MAPE
[110]	1	MAPE
[119]	1	MAPE
[120]	1	RMSE
[121]	1	RMSE
[79]	1	MAPE
[80]	1, 2 & 3.	MAPE
[40]	1	MAPE
[36]	Multi-step	-
[35]	1 & multi-step	MAPE
[47]	1	MAE
[67]	-	MAPE
[68]	-	RMSE
[48]	1, 2 & 3	MAPE RMSE
[49]	1	MAE CV-RMSE
[24]	1	RMSE & MAE

Note: NE = Does Not Specify.

Table 5. Studies carried out with a long-term prediction horizon.

Ref.	Step Number	Evaluation Criteria
[90]	NE	MAPE
[91]	Multi-step	MAPE
[98]	1	MAPE
[89]	1	RMSE
[122]	1	RMSE & MAE

Note: NE = Does Not Specify.

It can be seen that 69 studies opted for short-term models, 17 used an ultra-short-term model, and five used the long-term model. In addition, the number of steps ahead in each paper is also specified. Hence, 27 articles made multi-step ahead forecasting, and 73 opted for one-step ahead forecasting. The last column shows the metric used to evaluate the predictive model. Most authors chose to calculate the MAPE to assess wind speed forecasting.

The short-term horizon is the most used due to the objective of the forecast. Generally, the wind forecast in the ultra-short or short-term horizons has numerous applications, such as estimating the events of high or low power, turbine control, integration of operations in the network, energy dispatch, and management of the energy market the following day. Also, ultra-short-term and short-term predictions guarantee a smaller margin of error than medium- and long-term predictions. Even with technological advances, medium- and long-term wind forecasting is inaccurate because of wind variability and meteorological chaos, representing a challenge for future research. However, there may be exceptions where some medium- and long-term predictions provide acceptable results due to the application or objective of the study.

2.6. Prediction Model Type

Statistical or parametric methods are estimated using statistical techniques on historical data such as regression models, dynamic modeling with parameter estimation, and time series prediction. Neural networks are used in methods based on artificial intelligence, analyzed in this work. Methods based on neural networks do not require a physical-mathematical model. Still, essential parameters are needed, such as the type of architecture, the inputs, network layers, or the number of neurons [123,124]. Hybrid methods combine statistical and artificial intelligence-based models to improve prediction precision, leveraging individual models to improve wind speed accuracy. Therefore, hybrid models are a trend in the production process. The main architectures that compose the hybrid and computational intelligence models found during the classification process are described below. Subsequently, Table 6 shows the proposed models based on the classification of the type of forecasting model (statistical, computational intelligence, and hybrid) as well as the forecasting objective (wind power (WP), wind speed (WS), and wind energy (EE)) for each of the reviewed articles.

2.7. Architectures of Artificial Neural Networks

The significant difference between the ADALINE, Perceptron and Least Mean Square (LMS) is the learning rules employed by ADALINE. It was first used for signal processing and then applied to prediction problems. ADALINE uses a linear transfer function in which outputs can take any value, minimize the mean square error by using the LMS learning rule, and move decision boundaries as far from training patterns as possible, which is a critical advantage. Therefore, using this model only to solve linearly separable problems is recommended.

Table 6. Model Forecast Type Classification.

Model Proposed Type	Reference	Prediction Objective	Proposed Model
Statistical model	[45]	WS	SES
	[54]	WS.	f-ARIMA
Computational intelligence model	[121]	WS	BSBM
	[79]	WS	LRNN
	[36]	WP	CNN
	[53]	EE	ANN
	[55]	WS	ANN
	[56]	WS	ADALINE BP RBF
	[60]	WS	BMA ADALINE BP RBF
	[25]	EE	ANFIS
	[72]	WP	ETA-model
	[64]	WS	Univariate-RNN Multivariate-RNN
	[112]	WS	BP.
	[76]	WS	PCA
	[118]	WS	BP RBF ANFIS
	[22]	WP	LSTM
	[122]	WP	MLA

Table 6. *Cont.*

Model Proposed Type	Reference	Prediction Objective	Proposed Model
Hybrid Model	[46]	EE	WT-ANN
	[110]	WV	ANN-MC
	[119]	WS	CPBR-NWP
	[120]	EE	FT-ANN
	[80]	WS	GRA-LSSVM-RBF
	[40]	WS	SHL-DNN
	[35]	WS	VMD-CNN
	[47]	WS	EKW
	[67]	WP	WD-NILA-WRF
	[68]	EE	CPCC-based short-term WPF
	[48]	WS	WD-APSOACO-BP
	[49]	WP	LSTNet TPA-LSTM DA-RNN
	[24]	WP	SSA-DELM
	[33]	WS	IRR-MLP
	[51]	WS	ANGMDH
	[69]	EE	BCD-RVS
	[52]	WS	FL-ANN
	[70]	EE	SGP
	[71]	WS	MM5-ANN
	[57]	WS	ARIMA-ANN
	[58]	WS & WP	MFNN
	[59]	WS & EE	WM-ITSM
	[73]	EE	Ridgelet-NN-DE
	[26]	EE	WT-PSO-ANFIS
	[74]	WS	HIFM
	[27]	EE	EPSO-ANFIS
	[75]	WS	SD-BP SD-RBF
	[61]	WS	ARIMA-Kalman ARIMA-ANN
	[92]	WS	EMD-ANN
	[105]	EE	WT-SVM
	[103]	EE	WD-AWNN
	[88]	WS & EE	ARIMA-ANN ARIMA-SVM
	[65]	WS	WP-BFGS-WP ARIMA-BFGS WM-BFGS
	[111]	EE	ICA-ANN PSO-ANN GA-ANN
	[106]	WS	WT-SAM-RBF
	[34]	WS	SOM-MLP
	[113]	WS	SVR-UKF
	[114]	WS	IS-PSO-BP
	[38]	WS	EMD-ENN
	[107]	WS	WT-GA-SVM
	[115]	EE	ICA-ANN
	[93]	WS	EMD-RARIMA
	[117]	WS	MCM
	[37]	WS	WPD-FEEMD-ELM
	[108]	WS	EWT-GPR-ELM-SVM-LSSVM
	[109]	WS	EWT-CSA-LSSVM
	[28]	EE	MI-WT-EPSO-ANFIS

Table 6. *Cont.*

Model Proposed Type	Reference	Prediction Objective	Proposed Model
	[29]	WS	ANN-RBF ANFIS AN-GA ANN-PSO
	[99]	WS	BP-SSA-PSO-SA
	[97]	WS	DSF-ANN DSF-SVM
	[104]	WS	WPD-CSO-ANN
	[66]	WS	MOGA-MLP-ANN
	[62]	WS	EMD-GRNN-FOA
	[77]	WS	WT-RF-KELM-GA
	[94]	WS	Chi^2-Entropy-EF-EW-FTS
	[41]	EE	R-VMD-LSTM D-CVM-LSTM
	[30]	EE	Wavelet-PSO-ANFIS
	[78]	WP	EMD-PE-LSSVM-GSA
	[42]	WS	EMD-GPR-LSTM
	[96]	WS	EEMD-SVM-CSOA
	[31]	WS	WTD-RNN-ANFIS
	[102]	WS	VMD-BSA-RELM
	[32]	WS	MLP-CNN
	[116]	WS	Weibull-ANN
	[101]	WS	SSA-PLS-PSO-BCF
	[100]	WS	SSA-APSO-BP SSA-ACO-BP SSA-APSOACO-BP
	[95]	WS	EMD-ARIMA-RF EMD-ARIMA-BP EMD-ARIMA-SVM EMD-ARIMA-ELM EEMD-SVM-CNN
	[21]	WS	BiLSTM-DBN-IEC
	[63]	WS	Persistence-Model Regressive-Model Neural-Network- Model Fuzzy -Model
	[90]	WS	SARIMA-LSSVM
	[91]	WS	EMD-FNN
	[98]	WS	SVR-ERNN
	[89]	WS	KF-ANN

On the other hand, ANFIS combines ANN and fuzzy algorithms. The ANN can self-learn, an essential feature for the diffuse system to adjust automatically to the problem. Moreover, data transformation or normalization can be optional; it is possible to build models from input-output data, reducing the modeling time. In addition, it does not have synaptic weights and takes the scheme and architecture of a diffuse inference system to adjust the parameters. However, it presents some problems: knowledge is not acquired automatically during the learning process. It is complicated to define the rules when many variables are involved, and it over-trains when an extensive data set is used. In addition, it is computationally complex if the inputs are increased because of the impossibility of learning and adjusting by themselves. For difficult situations, the prediction error can be significant [26–31]. Nevertheless, ANFIS has shown promising results in short-term forecasting. Although it has proven to be better than statistical methods in predicting wind, combining it with another model is suggested to obtain better results.

Another Perceptron generalization is the MLP; Perceptron has a single input neurons layer and one output, and a set of intermediate layers or hidden layers between the input and output layers forms the MLP. The MLP is an ANN of multiple layers: an input layer, at least one hidden layer, and one output layer. It can solve a large number of problems that are not linearly separable. An MLP can be partially or fully connected and has been incorporated into hybrid models for wind forecasting with a short-term prediction horizon [32–34]. The resulting prediction was considered stable and reliable. MLP is more flexible than linear models; therefore, linear relationships are treated more appropriately. The resulting forecast was found to be stable and reliable. MLP is more flexible than linear models; therefore, linear relationships are cautiously treated a.

Unfortunately, MLP has a high computational cost, shows deficiencies with reduced samples, can stagnate in local minimums, presents excessive adjustment in some cases, and it is impossible to determine the number of input values. Nevertheless, MLPs are the most-requested models to solve prediction problems in different areas and have great precision in the wind speed prediction process. It is advisable to use MLP when no pretreatment of the time series is desired; the model alone provides good results. However, some authors propose a hybrid model to investigate its implications and compare results.

CNN has also been used to predict wind speed and is a feed-forward network, similar to MLPs; but in CNN, not all neurons join with each of the following layers, only with a subgroup. Its main advantage is the particular task performed for each network section's function; therefore, it significantly reduces the number of hidden layers. As a result, training is usually faster than in MLP networks.

It is ideal for multiple-step predictions because it avoids cumulative errors in wind speed prediction. In addition, the CNN can extract useful local features at the input through the convolution operation, effectively reducing the burden of neural network training and requiring smaller weights, allowing faster convergence. Unfortunately, it does not guarantee the overall minimum and may incur overlearning. For example, [32,35,36] used CNN to predict wind speed with a short-term horizon, obtaining acceptable results in all cases.

The ENN was proposed in 1990 [125]. It contains additional recurring layers compared to feed-forward ANNs. ENN is known as a simple recurrent network, representing the improvement of feed-forward networks due to feedback between the immediate contiguous layers. Simple feedback allows networks to rapidly memorize previous events, which affect subsequent weight updates at each network layer. Furthermore, the self-connection of the neurons in the recurrent layers makes the ENN sensitive to the time series inputs and efficient in signal modeling.

Furthermore, RNN does not have a layered structure; instead, it uses arbitrary connections between neurons. Moreover, RNN can include cycles, creating temporality and promoting memory in the network. Unlike ENNs, RNN has feedback paths between elements and carries out the information exchange between neurons more complexly than feed-forward networks. Due to its characteristics and the chosen training algorithm, it propagates the information forward in time, which is equivalent to predicting situations.

However, the RBF model has three layers: an input layer, a single hidden layer, and an output layer. The fundamental difference between MLP and RBF is the hidden layer's neurons. The MLP model computes a weighted input sum and applies a function like the sigmoid. The RBF model calculates the Euclidean distance between the vector's synaptic weights and input and applies the radial-type function to the computed distance [126]. RBF was also used in ultra-short-term wind speed prediction [75,80,106,118], with accurate results. One of RBF's difficulties is the sensitivity to the parameters' determination, affecting the prediction precision considerably. However, it guarantees local optimum and faster convergence because it only adjusts the weights for the radial bases linearly and does not adjust the parameters like Backpropagation (BP). Besides, the radial basis function weights are determined by the least squares method.

2.8. Architectures Based on Deep Learning

The deep learning concept has the advantage over ANNs by eliminating the optimum local problem in the objective function. The success of DNN is due to a large hidden number of drives, a better learning algorithm, and a more efficient process to initialize parameters. Although DNN is the most promising technique in speech recognition, automatic translation, and facial recognition, some studies using this model have focused on wind prediction. For example, in [40], deep learning and transfer learning were combined for a newly created wind farm. In [39], the LSTM model was used to predict wind energy signals, power, and wind load signals. Zhang et al. [22] performed a short-term wind energy forecast based on the improved LSTM model.

LSTM is a DNN and presents reliable predictions with high precision. The LSTM unit contains a cell, input, output, and forgetting gate. The cell function is to remember values in arbitrary time intervals, while the function of the gates is to regulate the flow of information in the cell. The hourly prediction is achieved by including LSTM in a hybrid model as an alternative to improve wind speed prediction [41]. Moreover, in [42], LSTM was used for a short-term estimate. The advantages of the LSTM are numerous: it memorizes in the short term for an extended period, avoids the complexity of training an RNN and effectively overfitting even working with an extensive set of data, achieves more accurate predictions than traditional neural networks, converges faster compared to conventional neural networks, discovers and extracts the abstract features and high-level structures' hidden data, forming the wind speed sequence. These advantages make LSTM attractive for use in combination with others, providing highly accurate results.

Figures 6–14 show the fundamental structures of artificial neural networks.

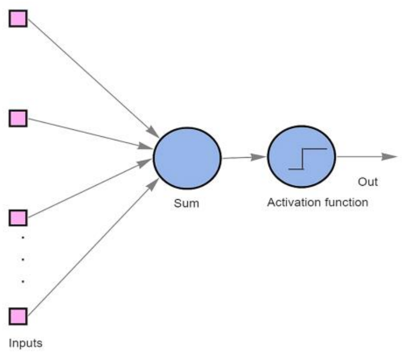

Figure 6. Perceptron model.

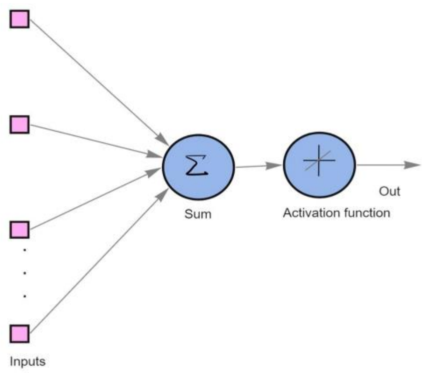

Figure 7. Adaptive Linear Element (ADALINE) model.

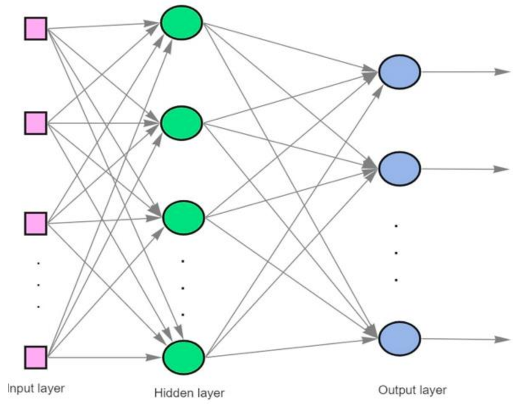

Figure 8. Multiple Adaptive Linear Element (MADALINE) model.

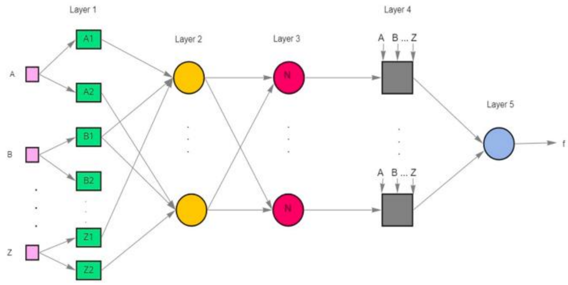

Figure 9. ANFIS model.

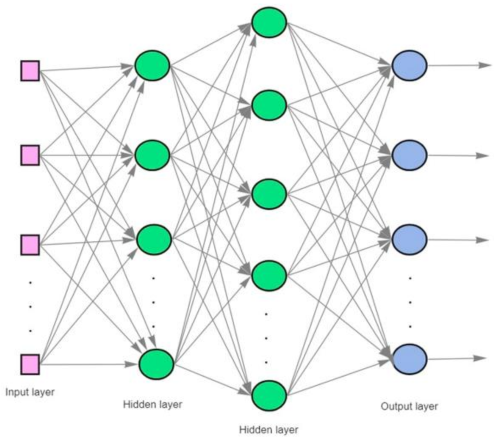

Figure 10. MLP model.

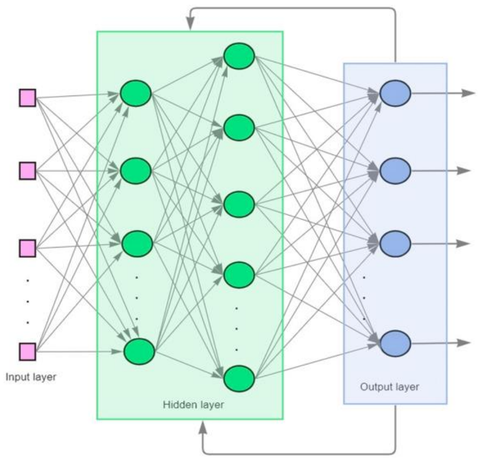

Figure 11. RNN model.

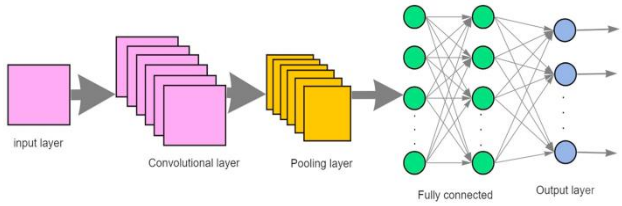

Figure 12. CNN model.

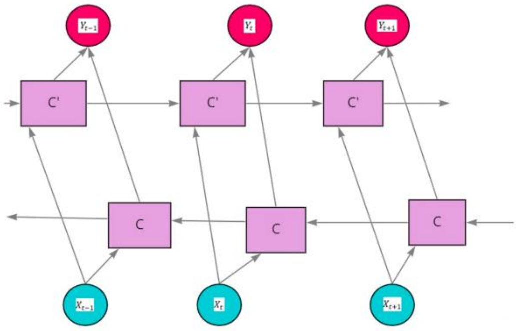

Figure 13. Bidirectional LSTM model.

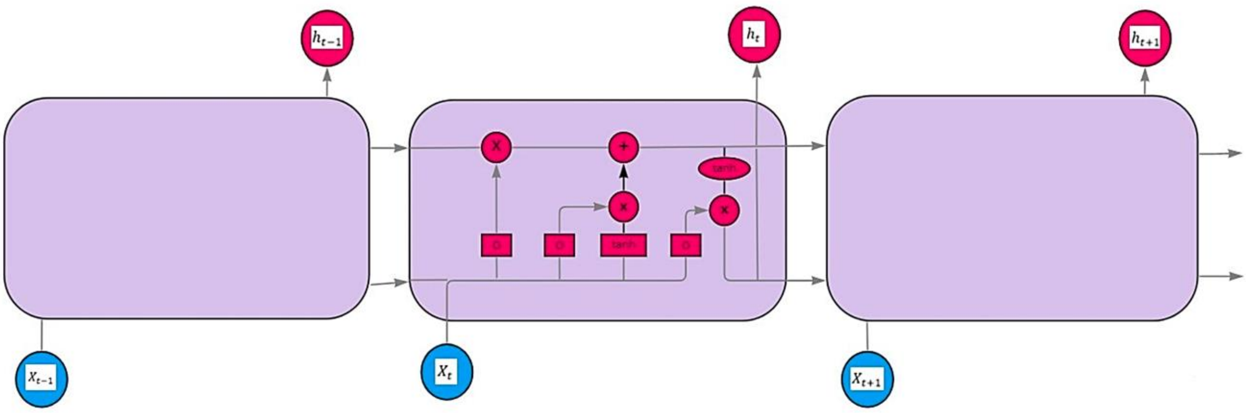

Figure 14. LSTM general structure.

2.9. Learning Algorithms

The learning algorithm is essential for the network to learn and perform well. Literature shows that BP and SVM are widely used during the prediction process.

2.9.1. BP

The ANN of BP is also a modern technique. It is a gradient calculation algorithm used for training ANN. After applying an input pattern to the network as a stimulus, it propagates from the input to the output layer until obtaining a result. The result is compared to the desired output; the error is calculated and propagated to the input [127]. Many studies have chosen BP for the wind speed prediction process, as in [56,60,112,118]. In [48,75,95,99,100,114], model hybridization is used: Secondary Decomposition Algorithm (SDA)-BP, Input Parameters Selection (IS)-Particle Swarm Algorithm (PS0)-BP, BP-SSA-PSO-Simulated Annealing (SA), WD, a modified adaptive particle swarm optimization-based algorithm (APSOACO)-BP, SSA-APSO-BP Y ARIMA-BP, respectively. The prediction result in all cases was satisfactory and showed reliable results. The advantage of using BP is the ability to self-adapt the neurons' weights in the intermediate layers to learn the relationship between a set of input patterns and their outputs. On the other hand, it can sometimes present errors in local minimums and slowness convergence, and there is a possibility of overlearning and not reaching the global minimum.

2.9.2. SVM

SVM is a general learning method developed from statistical learning theory. SVM converts a nonlinear separable problem in the sample space into a linear problem in the Hilbert space [107]. Like ANN and other algorithms, the performance of SVM depends directly on the input and its parameters. It has an excellent capacity to adjust nonlinear behaviors based on historical data. It is characterized by using the "Kernel Trick" technique for linear to nonlinear problems and shows unique advantages in treating reduced samples. SVM is usually combined with pre-processing methods such as (EMD or WT) to obtain better accuracy of wind speed. It can overcome data modification. However, this model is commonly sensitive to parameter selection. Accurate results are obtained in pattern recognition and classification problems.

In [63], wavelet transformation applied in three predictive methods was studied: the neural network, diffuse and stochastic, and six wavelet families. The results showed significant improvements when using the wavelet filter. In [88], two hybrid models, ARIMA-ANN and ARIMA SVM, are proposed; in both cases, the results were viable to estimate wind speed as wind power generation in the short term. However, it was shown that these models are not always the best for prediction horizons. In [128], two models are combined: the integrated Autoregressive Integrated Moving Average with Exogenous Input (ARIMAX) and ANN inputs, incorporating linear and nonlinear characteristics. The model relates pressure, temperature, and precipitation to wind speed, providing high accuracy and efficiency in time series monthly and hourly averages. Moreover, in [105], the WT technique pre-processes historical wind speed data and SVM as a predictive model with short-term results.

On the other hand, the WT technique was used in a hybrid model to pre-process wind speed data and a Genetic Algorithm (GA) to adjust the SVM parameters. A study of an eolic park in North China showed that the proposed model exceeds the prediction accuracy of other models. Furthermore, Least-Square Support Vector Machine (LSSVM) is considered a variant of SVM, employing equality constraints rather than inequalities. LSSVM adequately performs because its algorithms are efficient on nonlinear problems and show high computing velocity in nonlinear situations. However, its predictions are inaccurate due to the complexity of short-term wind velocities series. For this reason, its application on hybrid models in the prediction process is more common [78,90,108,109].

2.10. Methodology for Wind Prediction with ANN

Figure 15 shows a modeling methodology diagram for wind prediction with artificial neural networks, pre- and post-processing techniques, and optimization algorithms. This methodology is proposed by the authors of this work based on the literature review.

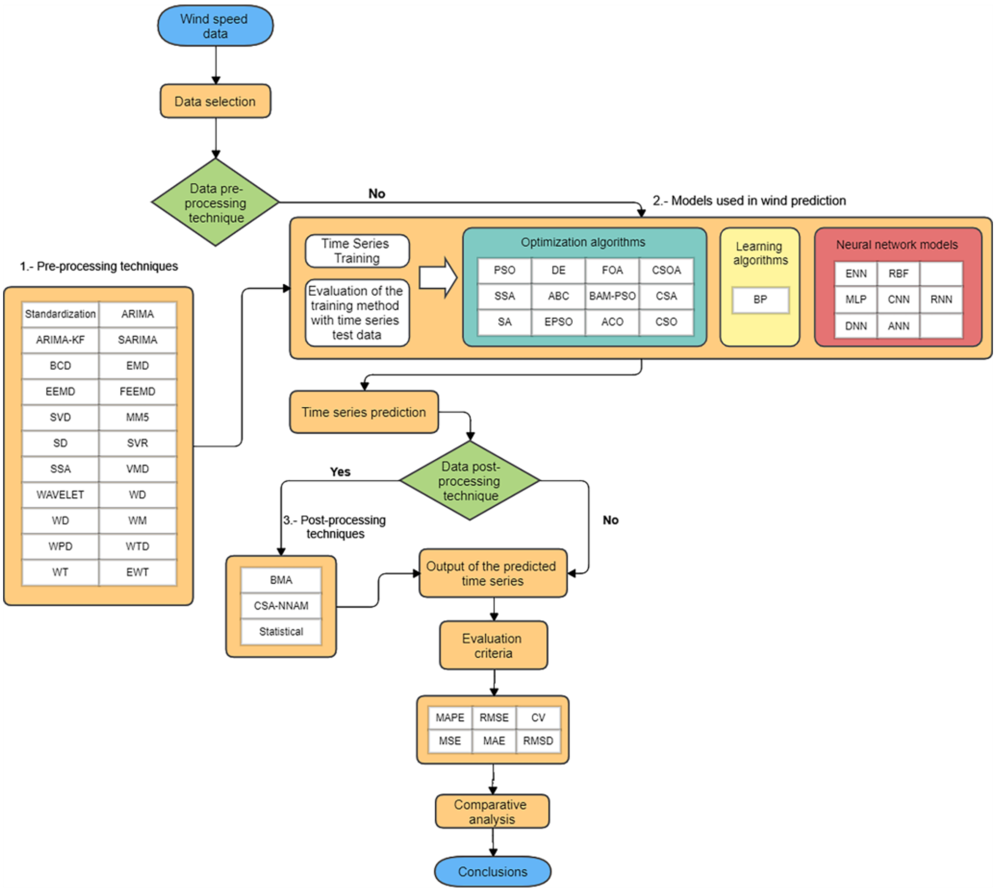

Figure 15. Diagram of the modeling process in wind prediction.

3. Discussion

Figure 16 shows that the short-term forecasting horizon is the most used in the wind speed forecasting process. In Figure 17, 90% of the authors chose not to use post-processing techniques, while Figure 18 shows that 63% decided to use a pre-processing method for the time series before forecasting. There is an abundant variety in the evaluation metrics (Figure 19). However, the review identifies that MAPE and RMSE are the most recurrent in the evaluation and comparison of predictive models, with 61% and 23%, respectively. Almost 80% of the works by researchers tend to use hybrid models in the forecasting process, leaving behind purely statistical methods (Figure 20). Although there is a tendency to perform multi-step ahead forecasting, there is evidence that for now, more than half still perform one-step ahead forecasting (Figure 21) and choose to use time series in the forecasting process instead of physical input data, although this may change depending on the application area (Figure 22).

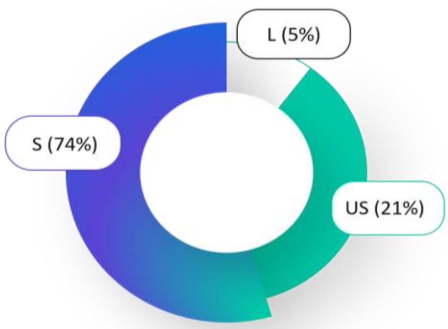

Figure 16. Classification by prediction horizon.

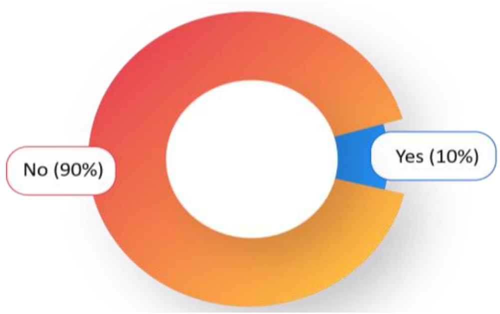

Figure 17. Classification by post-processing techniques.

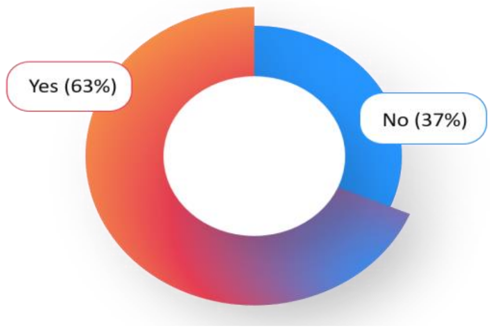

Figure 18. Classification by pre-processing techniques.

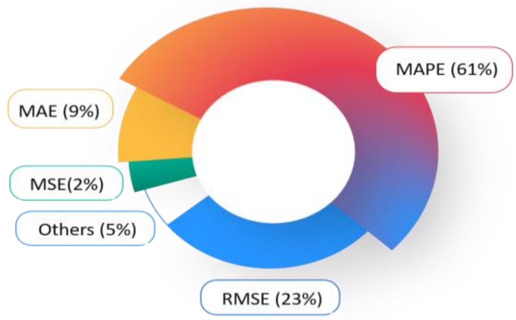

Figure 19. Classification by types of errors.

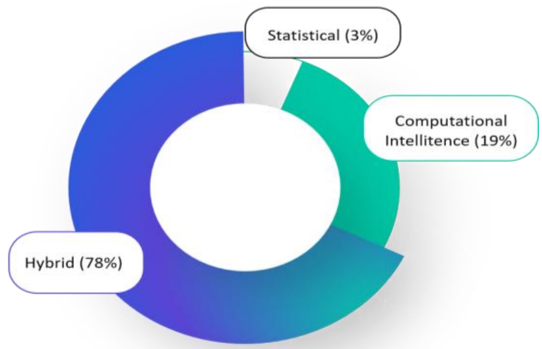

Figure 20. Classification by type of proposed model.

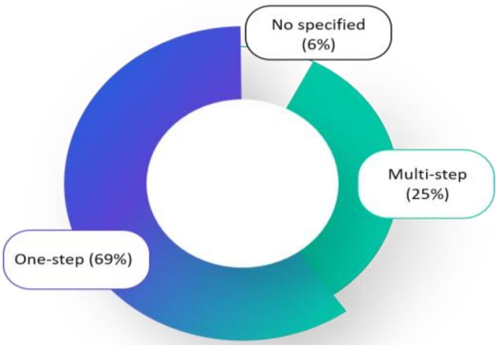

Figure 21. Classification by steps ahead.

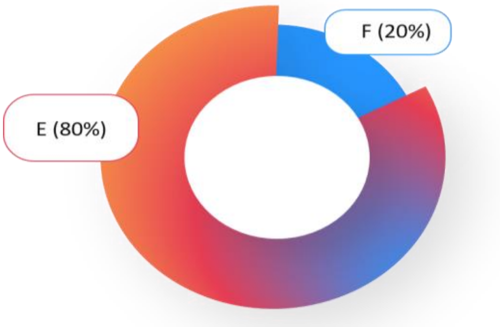

Figure 22. Classification by input data type.

The need to generate a solid and reliable forecasting model is ongoing because the neural network models' accuracy depends on the training algorithm and its parameters, especially the data used for each forecast. So far, no neural network model outperforms others universally, but it is possible to know the accuracy offered by the different techniques based on valuation metrics.

More than one neural network model is recommended when forecasting wind speed since it significantly affects forecasting accuracy. Pre-processing techniques such as WM can be used, in which a sequence of data is decomposed into several sub-series. WM is used to analyze signals by decomposition into several frequencies; under this concept, more methods are obtained with variations, improving the base model. Regarding post-processing, an option to achieve a more reliable result in forecasting accuracy than BMA is to provide a single model based on the prediction of wind speed with different neural network models, which provides a more reliable result. With the use of post-processing techniques, forecasting accuracy can be improved, and thus the integration of wind energy into the power grid is benefited, which minimizes the risks due to forecasting errors.

As seen in Table 6, some researchers have opted to train the neural network model with evolutionary algorithms such as PSO since there is empirical evidence that an algorithm is a helpful tool for optimization. In addition, PSO techniques are less computationally expensive for a specific artificial neural network topology size. EPSO, for example, is also a valuable tool for parameter optimization in training a neural network; however, this algorithm incorporates a selection procedure and self-adaptation for the parameters concerning the original PSO algorithm, and these additional features can make a difference in terms of convergence.

Ensemble techniques in wind speed forecasting have shown promising results. Generally, the final forecasting result is calculated by a weighting or averaging procedure, which is better than the individual prediction of each model. In addition, these techniques can reduce the forecasting error of a single model through sub-model competitions.

Regarding forecasting time, short-term prediction is most used by researchers due to the objectives: to fine-tune the operation, guarantee the system's security, optimize the use of resources, guarantee the energy required by the demand, and ensure the supply. However, during the literature review, it was detected that generally, wind forecasting in the ultra-short or short term has numerous applications, among which the following stand out: knowing the high- or low-power events for turbine control, integration of operations in the network, energy dispatch, and management of the following day's energy market.

Ultra-short-term and short-term forecasting guarantee a lower margin of error than medium- and long-term forecasting. Even with technological advances, medium- and long-term wind forecasting are inaccurate due to wind variability and meteorological chaos, which represents a challenge for researchers. Medium- and long-term forecasting can provide acceptable results depending on the application or of the study, but the literature shows that the best option is still ultra-short or short-term forecasting. Another significant challenge is establishing the metrics to evaluate the model to reduce inconsistency. For example, the choice of the neural model may not be the same if more than one evaluation criterion is used.

As wind power generation increases worldwide, forecasting will not cease to be essential. Without it, the integration of wind power into the electric power system will be affected; wind speed forecasting is the most critical factor, however, obtaining a reliable forecast remains a challenge due to the intermittency of wind.

4. Conclusions

- Wind power could solve many environmental problems due to high energy demands. A determining factor for this clean energy is wind speed forecasting; consequently, there is a growing need to generate a reliable model to estimate this information. Many neural network models applied to this problem differ depending on the training algorithm and its parameters; therefore, knowledge of their principles and differences can help decide the convenience of their use.
- The wind speed forecasting accuracy varies because it depends on training with different parameters such as learning rate or additional inputs. Hence, it is essential to choose factors appropriately; also, the ensemble techniques can reduce the prediction error through sub-model competition. On the other hand, post-processing provides a more reliable result in prediction accuracy.
- The combination of neural models with optimization algorithms improves the wind speed forecasting accuracy, even more so if techniques for noise removal are used since they can model the volatility of wind speed data.
- For the prediction time, the most-used horizon is the short-term horizon due to the objective of the forecast: fine-tune the operation, ensure the system safety, optimize the use of resources, guarantee the energy required by the demand, and ensure the supply.
- Another challenge is selecting the metric to evaluate the model depending on variables and data characteristics to avoid inconsistency when comparing the models.
- ANNs can model linear and nonlinear functions with arbitrary shapes, accurately forecasting wind energy based on historical data. Neural network models outperform the persistence model. Knowledge is automatically acquired during the learning process, even though it cannot be extracted from the network and does not require prior knowledge of the wind data model.
- Using ensemble techniques, model hybridization, or parameter adjustment, reliable results can be obtained, allowing the best use of the wind and thus avoiding certain problems during the wind power generation process.

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Abbreviations

Acronym/Initial	Model
ADALINE	Adaptive Linear Element Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANGMDH	Abductive network based on the group method of data handling
ANN	Artificial Neural Network
APSOACO	A modified adaptive particle swarm optimization algorithm-based ant colony optimization algorithm
APSO	A modified adaptive particle swarm optimization
AR	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Input
ARMA	Autoregressive Moving Average
A.R.X.	Autoregressive with Exogenous Input
AWNN	Adaptive Wavelet Neural Network
B.C.D.	Bayesian Clustering by dynamics
B.C.F.	Combined algorithm Based on Bat, Cuckoo search, and Firefly algorithm.
BFGS	Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton Back Propagation
BiLSTM	BiLSTM
B.M.A.	Bayesian Model Averaging
BP.	Backpropagation
B.S.A.	Backtracking Search
BSBM	Bayesian structural break model
CC	Correlation Coefficient
CI	Computational Intelligence
Chi2	Chi-square
CNN	Convolutional Neural Network
CPCC	Clustering Pre-calculated
CPSR	Chaos Phase Space Reconstruction
C.S.A.	Coupled Simulated Annealing
C.S.O.	Crisscross Optimization
CSOA	Optimized by the Cuckoo Search Algorithm
CV	Coefficient of Variation
DA	Dual-Stage Attention
DBN	Deep Belief network
DE	Differential Evolution Algorithm Deep Extreme Learning Machine
D.N.N.	Deep Neural Network
D.S.F.	Decomposition Selection Forecasting
ED.	Empirical Distribution
EEMD	Ensemble Empirical Mode Decomposition
EF.	Forecasting Effectiveness
EFK	Ensemble Filter Kalman
EKMOABC	Evolutionary Knowledge Multi-Objective Artificial Bee Colony
E.K.W.	Ensemble empirical mode decomposition-Kernel-based fuzzy c-means-Wavelet neural network
E.L.M.	Extreme Learning Machine
E.M.D.	Empirical Mode Decomposition
E.N.N.	Elman Neural Network
EPDF	Empirical Probability Distribution Function
EPSO	Evolutionary Particle Swarm Optimization
ERNN	Elman Recurrent Neural Network

EW	Equal Width
E.W.T.	Empirical Wavelet Transform
f-ARIMA	Fractional-Regressive Integ. Mov Avr
FEEMD	Fast Ensemble Empirical Mode Decomposition
FL	Fuzzy Logic
F.N.N.	Feed-forward Neural Network
FMSE	Forecast Mean Square Error
F.O.A.	Fruit Fly Optimization Algorithm
FT	Physical strategy
F.T.S.	Fuzzy Time Series Algorithm
GA.	Genetic Algorithm
GPR	Gaussian process Regression
G.R.A.	Grey relational analysis
GRNN	General Regression Neural Network
G.S.A.	Gravitational Search Algorithm
HIFM	Hybrid Iterative Forecast Method
I.C.A.	Imperialistic Competitive Algorithm
I.E.C.	Improved Error Correction
I.I.R.	Infinite Impulse Response
IS.	Input Parameters Selection
ITSM	Improved Time Series Method
KELM	Kernel-Based Extreme Learning Machine
KF	Kalman Filter
LMS	Least Mean Square
LRNN	Layer Recurrent Neural Network
LSSVM	Least-Square Support Vector Machine
LSTM	Long Short-Term Memory
LSTNet	Long- and Short-Term Time-Series Network
MADALINE	Multiple Adaptive Linear Element
MLA	Machine Learning Algorithms
MLP	Multilayer Perceptron
MAD	Mean absolute difference
M.A.E.	Mean absolute error
MAPE	Mean Absolute Percentage Error
MC	Markov Chain
MD	Mean difference
ME	Mean Error
MFNN	Multilayer Feed-forward Neural Network
MI	Mutual Information
MM5	Fifth-Generation Mesoscale Model
MOGA	Multi-objective Genetic Algorithm
MSE	Mean Square Error
NFF	Feed-forward Neural Network
NILA	Niche Immune Lion Algorithm
NMAE	Normalized Mean Absolute Error
NNAM	Neural Network Assembling Module
NWP	Numerical Weather Prediction
PCA	Principal Component Analysis
PE	Permutation Entropy
PLS	Partial Least Square
PSO	Particle Swarm Algorithm
RARIMA	Recursive Autoregressive Integrated Moving Average
RBF	Radial Basis Function
RELM	Regularized Extreme Learning Machine
RF.	Random Forests
RidgeletNN	Ridgelet Neural Network
RMS	Root mean square

RMSD	Root mean square difference
RMSE	Root mean square difference
RNN	Recurrent Neural Network
SA.	Simulated Annealing
SAM	Seasonal Adjustment method
SARIMA	Seasonal Auto-Regression Integrated Moving Average
SDA	Secondary Decomposition Algorithm
SES	Single Exponential Smoothing Method
SGP	Combination of the Kalman Filter and Arma model
S.H.L.	Shared-Hidden-Layer
SIA	Seasonal Index Adjustment
SM.	Simulation Method
SOM	Self-Organizing Maps
SSA	Singular Spectrum Analysis
SVM	Support Vector Machine
SVR	Support vectro regression
TPA	Temporal Pattern Attention
UKF	Unscented Kalman Filter
V.M.D.	Variational Mode Decomposition
WD.	Wavelet Decomposition
WF.	Wavelet Filter
WM	Wavelet method
WNN	Red Neuronal Wavelet
WP.	Wavelet Packet
WPD	Wavelet Packet Decomposition
WPF	Wind-Power-Forecasting
WRF	Weighted Random Forest
WT.	Wavelet Transform
WTD	Wavelet Threshold Denoising
B.C.D.	Bayesian clustering by dynamics

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