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Review

State-of-the-Art Using Bibliometric Analysis of Wind-Speed and -Power Forecasting Methods Applied in Power Systems

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Abstract: The integration of wind energy into power systems has intensified as a result of the urgency for global energy transition. This requires more accurate forecasting techniques that can capture the variability of the wind resource to achieve better operative performance of power systems. This paper presents an exhaustive review of the state-of-the-art of wind-speed and -power forecasting models for wind turbines located in different segments of power systems, i.e., in large wind farms, distributed generation, microgrids, and micro-wind turbines installed in residences and buildings. This review covers forecasting models based on statistical and physical, artificial intelligence, and hybrid methods, with deterministic or probabilistic approaches. The literature review is carried out through a bibliometric analysis using VOSviewer and Pajek software. A discussion of the results is carried out, taking as the main approach the forecast time horizon of the models to identify their applications. The trends indicate a predominance of hybrid forecast models for the analysis of power systems, especially for those with high penetration of wind power. Finally, it is determined that most of the papers analyzed belong to the very short-term horizon, which indicates that the interest of researchers is in this time horizon.

Keywords: wind speed forecasting; wind power forecasting; distributed generation; microgrid; urban; residential

Citation: Lagos, A.; Caicedo, J.E.; Coria, G.; Quete, A.R.; Martínez, M.; Suvire, G.; Riquelme, J. State-of-the-Art Using Bibliometric Analysis of Wind-Speed and -Power Forecasting Methods Applied in Power Systems. *Energies* **2022**, *15*, 6545. https://doi.org/10.3390/en15186545

Received: 26 July 2022
Accepted: 2 September 2022
Published: 7 September 2022

1. Introduction

Wind energy represents an unlimited source of electrical energy production since it is environmentally friendly and has emerged as an alternative energy source to reduce dependence on fossil fuels. In recent years, its use has intensified, mainly due to a reduction in installation costs. According to the International Renewable Energy Agency (IRENA), until 2021, wind energy represented 27.9% of the global installed capacity worldwide, with 25.1% installed on land and 1.8% installed in marine areas [1]. The year 2020 was the best in history for the global wind industry, with a 53% annual growth in installed capacity, representing 93 GW of new installations; this increased the total installed wind capacity to 743 GW. It is expected that by 2025, more than 469 GW of new onshore and offshore wind capacity will be installed, that is, almost 94 GW per year of new wind generation installations [2].

Although wind power has several advantages over other types of renewable generation, the high intermittency and randomness of wind speeds make wind generation forecasting challenging. This intermittence and randomness introduce numerous complications to the electrical power system; among them is the reduction in the reliability and stability of the system, which translates into deviations from the optimal load dispatch, especially when wind energy is integrated into traditional grid systems. Generating wind energy locally not only displaces conventional-type energy, but it also contributes to the reduction in peaks, provides auxiliary network support, and increases the quality of the electrical supply [3].

Today, the use of wind power has diversified, in part, due to the constant growth in demand and the more active role of consumers. In addition to being integrated on a large scale through wind farms, there has been important development in wind turbines connected to distribution systems and microgrids, as well as small wind turbines mounted on the rooftops of buildings and houses.

As a result of the above, there has been a lot of interest in researching the topic, and various state-of-the-art articles on wind energy forecasting have been published. A pioneering work is [4]; this paper was published in the year 2003, and in addition to providing an extensive review about the forecast methods included in a timeframe of minutes to days, it serves as a knowledge base on wind generation forecasts. In this work, the author classified the models based on time series and neural networks as forecast models of a few hours (10 min–1 h), where the error obtained in relation to the persistence method was compared to measure its performance. For applications that involve a longer forecast period, such as scheduling activities and dispatch optimization for operation or electricity market purposes, the author emphasizes papers with models based on Numerical Weather Prediction (NWP) since these tend to exceed the time-series approaches after a certain period. They emphasize that many of the forecast errors come from the model. Solutions through ensembles of models or the combination of various NWPs with different input data are proposed to improve wind energy forecasts. In 2011, an update of [4] was published in [5] which included new forecasting models based on time series, neural networks, and finally, NWP-based models; this included references whose forecasting objective is to scale the forecasting model for a certain area, which is useful when it comes to the installation of a turbine or wind farm in a given location. More recently, as a result of the accelerated development of data science and machine learning, [6]—in addition to being considered a basic contribution to the understanding of wind energy production—provides the state-of-the-art of wind power forecasting, focusing on the fundamental formula of wind energy production in data science:

$$f_t(y) = \int_x f_t(y|x)\, f_t(x) dx \tag{1}$$

where $f(.)$ represents the probability density function and denotes the time variation in the function, $f_t(y)$ represents the stochastic aspect of power output y, $f_t(x)$ represents the distribution of wind and other environmental variables, x represents the wind and environmental conditions that determine the production of wind energy from the wind turbine, and $f_t(y|x)$ represents a conditional density function to characterize the conditional distribution as a result of wind intermittency. Chapters 1–3 deal with the modeling of the function that gives rise to the analysis of methods of predicting the temporal and spatiotemporal wind speed in the case of studying one or several turbines located in several places. Additionally, starting in Chapter 4, power-response modeling is discussed, as is how it can be used to evaluate the performance of wind turbines. Finally, from Chapter 8, the reliability of a turbine is analyzed and the load response of a turbine under various wind conditions is evaluated. On the other hand, in [7], Ahmadi et al., identifies the structures of the forecast models that are used in the prediction of wind power, wind speed, power and wind speed (simultaneously), and finally, wind speed and direction, based on very short-, short-, medium-, and long-term horizons. Emphasis is placed on hybrid forecasting structures, in which data preprocessing models, parameter optimization, post processing, and hybrid models are based on the combination of components in series (analyses of data sequentially) or parallel (the structure of the model makes use of raw data). In addition, Wang et al., in [8] analyzes wind-speed and -power forecasting from a Deep Learning standpoint, including hybrid models based on stacking (considering the characteristics of one or more models that are then combined) and weight (the combination of models is optimized by means of an algorithm). Emphasis is placed on the stages of data preprocessing, feature extraction, and complex nonlinear relationships between models. In [9], Alkhayat et al., also discusses forecasting methods based on Deep Learning, but incorporates solar energy forecasting. As in [8], they discuss the data preprocessing methods, but separate the forecast models based on the deterministic or probabilistic approach together with the evaluation and comparison metrics used between the models. Ahmad et al., in [10], conducted a review based on publications that deal with demand forecasting models and renewable energies, including wind energy, aimed at predicting the consumption of buildings, public services, the private sector, and government, among others. The articles reviewed correspond to forecast models based on Artificial Intelligence (AI), encompassing the categories of machine learning, combined or ensemble models, and artificial neural networks for the four forecast intervals reported in the scientific literature. On the other hand, and as a result of the incorporation of wind energy to the grid, in [11], Quan et al. studied the associated uncertainty through prediction intervals based on computational intelligence techniques applied to smart grids. Wind uncertainty is approached from two points of view: traditional (parametric) methods and direct (non-parametric) methods. In addition, the applications and methods of incorporating uncertainty into wind forecasting are analyzed through stochastic models, fuzzy logic models, and robust optimization as part of the decision-making process that quantifies the variability and intermittency of incorporating the wind resource into power systems.

Therefore, considering the analyses of the papers presented above, this review is aimed at establishing the different forecast models that are used to predict the wind speed and power that are part of electrical systems, i.e., large wind farms, distributed generation, microgrids, and small turbines installed at the residential level and in buildings. It establishes differentiation of the predominant models in each of these segments, an approach that has not been covered in the literature so far. This review covers statistical, physical, AI-based, and hybrid forecasting methods with a deterministic or probabilistic approach. In addition, as a novel way of presenting this analysis of the state-of-the-art, the papers analyzed have been compiled through a bibliometric analysis carried out using the VOSviewer and Pajek software, through which citation networks are built that allow us to establish links or correlations between items. A discussion of the results based on the forecast horizon of the models is presented, with the aim of establishing their usefulness and the applications in which the forecast models can be used when wind energy is integrated into power systems. Four forecast horizons were established for this purpose: very short-, short-, medium-, and long-term. Likewise, data tables are included for the data sets. Additionally, application area, forecast method, uncertainty, and validation models are detailed in this review with the aim of giving greater clarity to the reader when choosing a forecast model for a given area and the capacity of wind turbines.

The document is organized as follows: Section 1 describes the methodology used for the systematic literature review. Section 2 details the taxonomy established to analyze wind forecast models. Section 3 includes the results obtained from the bibliometric analysis explained in Section 1. Section 4 presents a discussion of the findings and trends found in the wind forecast models. Finally, Section 5 presents the conclusions of this work.

1.1. Methodology for the Systematic Literature Review

There are two ways to predict the behavior of wind power. The first involves predicting wind power based on historical data, while the second is derived from wind speed prediction to quantify the wind resource, and then, derive the power forecast using the wind turbine power curve. Taking as a reference what was described above, and considering that most of the articles are oriented toward forecasting wind speed or wind power, in this study, we decided to focus the search strategy on using both approaches.

The PRISMA procedure [12] was used to synthesize and facilitate the understanding of the methodology used in this literature review. Figure 1 shows a summary of the stages that make up the PRISMA statement: identification, screening, eligibility, and inclusion.

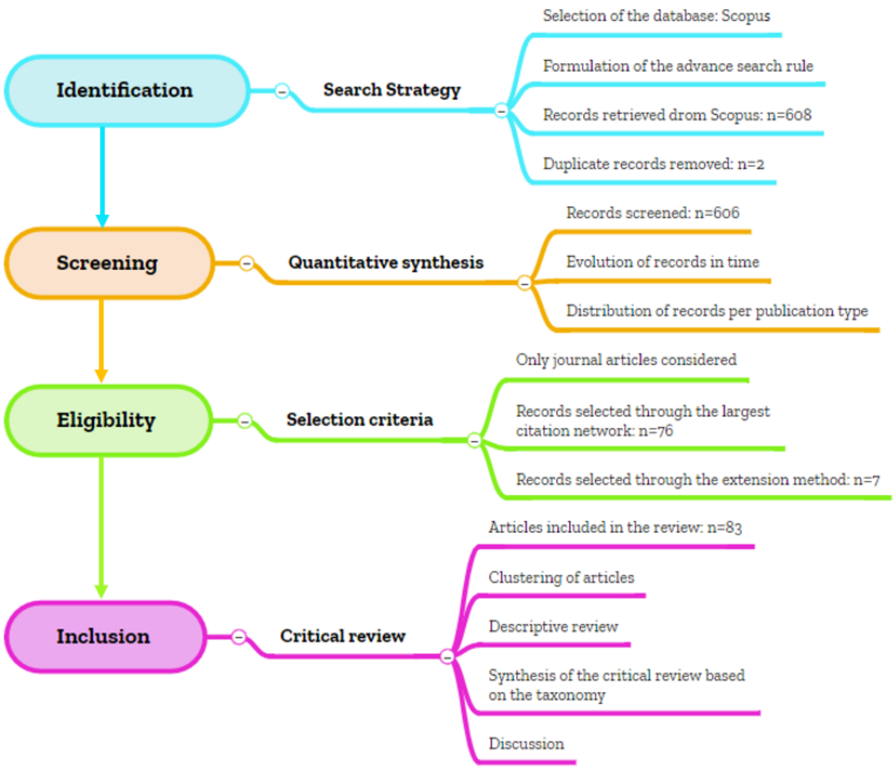

Figure 1. Stages of the systematic literature review.

1.1.1. Identification—Search Strategy

The identification stage includes the search for articles about the topic in question. For this purpose, an advanced search rule was proposed and applied in the Scopus citation database. Considering that our subject of study is the "Forecast of wind speed and power in power systems", the advanced search rule used in Scopus was divided into three main sets of terms:

1. "Forecasting" terms: This set included synonyms that the authors use to refer to the term forecast, and the words derived from it. In the case of the Scopus citation database, to find words that derive from one another, the (*) symbol was used at the end of each word. For example: "forecast*" searches for terms such as forecasting, forecast, etc.
2. "Wind" terms: This set described our forecast objective, e.g., wind power, OR wind energy, OR wind speed, OR wind direction were some of the terms used by the authors to refer to the subject.
3. "Distributed generation", "Electrical network" and "Urban" terms: These sets included associated or related terms that have power systems of the urban area implicit within their definitions.

The search rule is summarized as follows: the "Forecasting" and "Wind" set were linked by the symbol "W/1". This symbol is used to find terms that are separated by a word, regardless of the order, or if the union of both terms does not have a word in between, for example, "forecast of wind energy", "forecasting wind energy" or "wind energy forecasting". Then, these two sets were joined using the logical operators OR, A, B, C, and D, in Figure 2. On the other hand, the "Distributed generation", "Electrical network", and "Urban" sets of terms were joined by logical operators OR, E, F, G, and H, to finally join D and H, through the logical operator AND, and I, as shown in Figure 2.

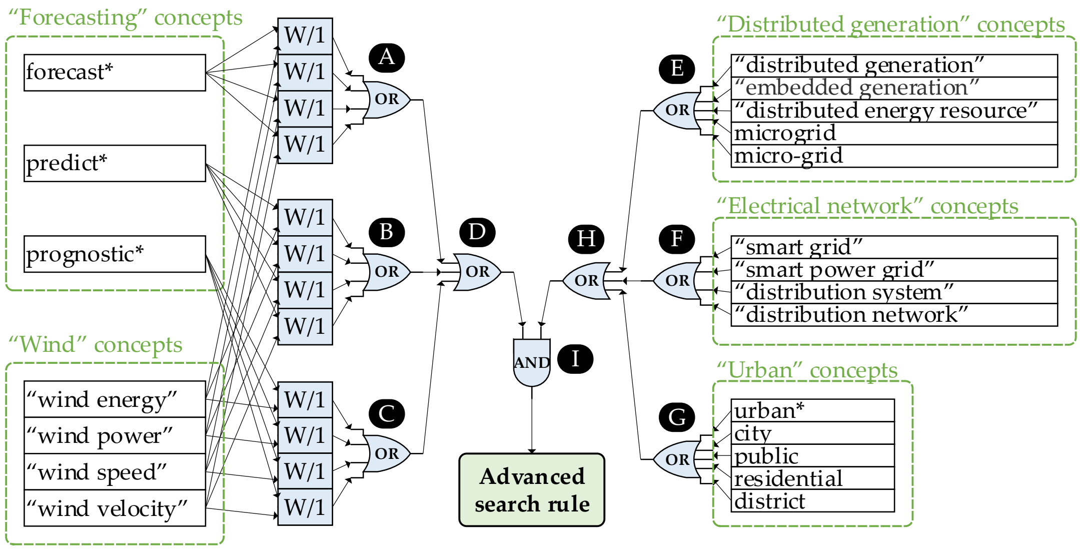

Figure 2. Advanced search rule.

A total of 608 articles were found through the advanced search shown in Figure 2. Two repeated records were excluded, obtaining a total of 606 articles related to the forecast of wind speed and power in power systems and urban areas.

1.1.2. Screening—Quantitative Synthesis

The 606 publications found include conference papers, journal articles, and book chapters, among others. Figure 3 illustrates the distribution of publications per year and type. This figure shows, on one hand, the temporal evolution of publications where a positive trend is observed, demonstrating that the forecast of wind speed and power continues to be a relevant and novel research topic, with about 90 publications in 2021. It should be noted that only 28 publications appear in 2022 because the search rule was applied on 11 April 2022. Moreover, articles before 2003 were also found using the search rule, but only the last 20 years are shown for improved visualization. On the other hand, Figure 3 shows the percentage according to the type of publication.

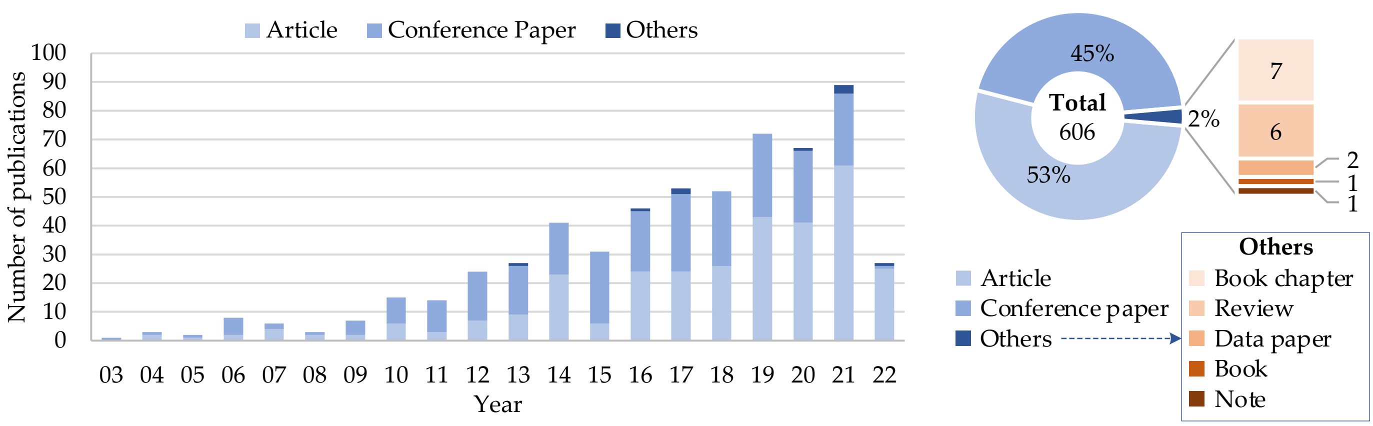

Figure 3. Number of publications related to wind power and speed forecasting. Temporal evolution of publications by type from 2003 to 2022, and percentage according to type of publication.

1.1.3. Eligibility—Selection Criteria

As the first criterion to select the publications for the critical literature review, only journal articles were considered because this type of publication implies a rigorous process of peer review, guaranteeing high reliability of the published information. Therefore, publications for further processing were first limited to 319 records which corresponded to journal articles.

Once the number of articles obtained by the advanced search was limited to 319 journal articles, citation networks were built using VOSviewer and Pajek for display. VOSviewer is a software tool that allows the building of bibliometric networks, connecting elements by co-authorship, co-occurrence, citation, and keywords, and grouping articles in clusters. The clustering is carried out using an algorithm based on the weighting of the connections, and this grouping allows the identification of clusters of articles that have topics in common [13,14].

Citation networks are used in this review to identify relevant literature because they allow us to find patterns and relationships and provide a wide overview of research topics and their evolution. A citation network illustrates the bibliographic relationship between articles and is usually visualized as a graph. Articles are represented as vertices and citations between articles are represented by directed arcs.

The largest citation network from the 319 journal articles was built using VOSviewer, resulting in 76 connected articles. Then, an extension method based on the concepts of co-citation and bibliographic coupling [15] was used to include articles relevant to the topic that could be missed by the search rule. Seven additional journal articles were included in the citation network using the extension method.

1.1.4. Inclusion—Critical Review

The resulting 83 journal articles in the citation network were distributed into 15 clusters using VOSviewer. Figure 4 shows the citation network obtained in Pajek for improved visualization, organized chronologically and distributed by cluster. The critical literature review in this paper was then carried out based on the citation network, whereby the articles that make up each cluster were reviewed and analyzed, and a taxonomy and synthesis were derived. Figure 4 also shows the references corresponding to each cluster. It is worth noting that literature from before 2004 on the topic was also found using the search rule, but the critical review is oriented toward the selection criteria described in Section 1.1.3. Therefore, the resulting citation network comprises a limited set of publications starting from 2004.

On the one hand, the citation network of Figure 4 was used to identify relevant articles on wind-speed and -power forecasting. To that end, articles are depicted in the citation network as vertices whose size depends on the number of article links, i.e., the number of times that the article has cited others and has been cited by other articles in the network. Thus, links in the citation network were used to measure the influence and relevance of articles on the research topic, and those articles with more links appear with a larger size. Table 1 shows a summary of the previously described correlations by cluster, together with other important aspects obtained from the citation network of Figure 4. The importance of those publications in the body of knowledge is analyzed in the descriptive review of Section 3. On the other hand, the citation network also presents the bibliographic relationship, i.e., the direct citations represented with directed arcs (from the citing article to the cited one), between articles, and hence, the evolution of research lines can be identified. This evolution of research lines is also analyzed in Section 3.

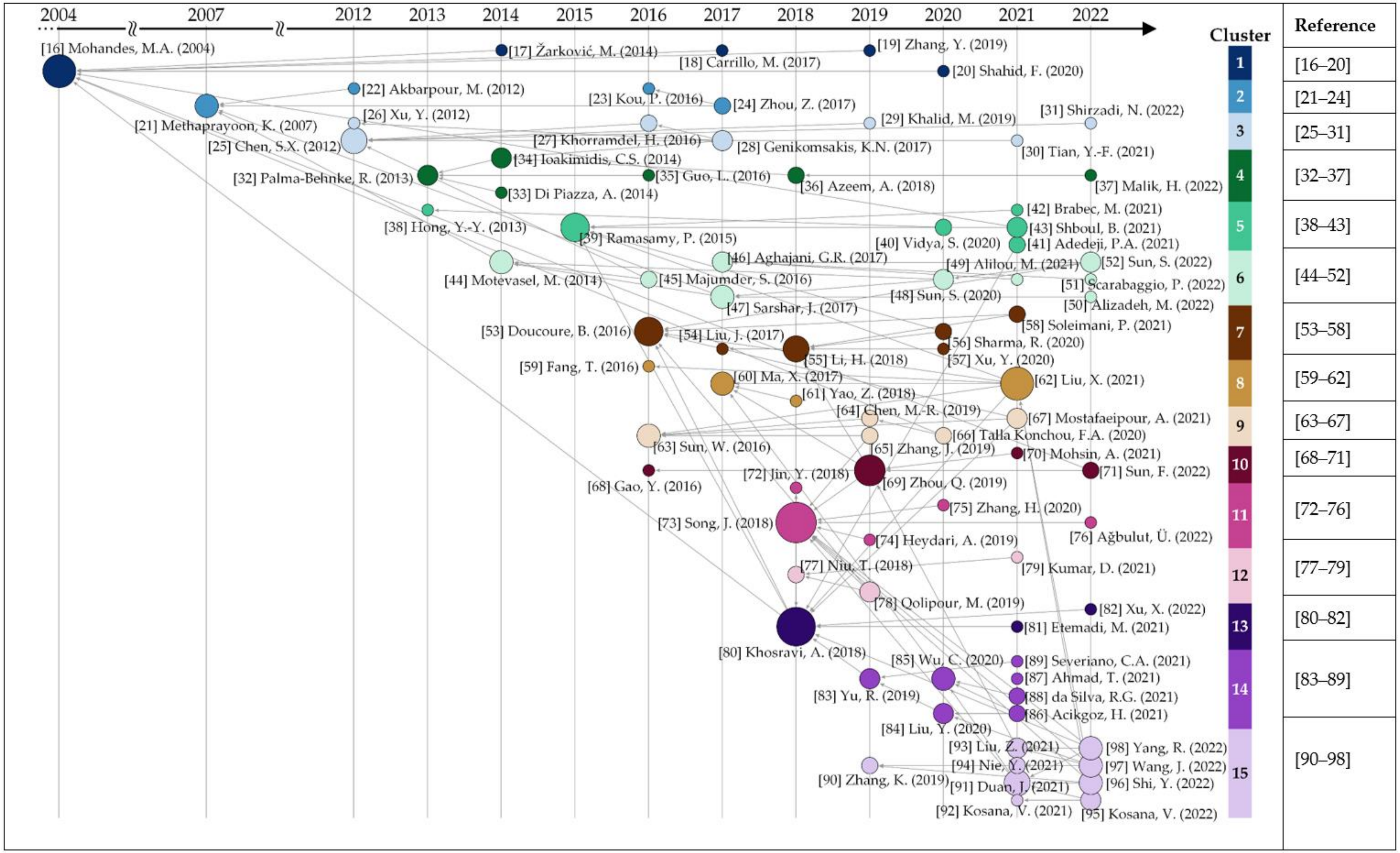

Figure 4. A journal article citation network for the topic "Forecast of wind speed and power applied in power system", organized chronologically and distributed by cluster with the respective references [16–98].

Table 1. Summary of article citation network by cluster show in Figure 4.

Cluster	Number of Articles	Most-Cited Article/Number of Citations	Oldest Article/Year	Newest Article/Year	Most Linked Articles/Citing Articles/Referenced Articles
1	5	[16]/593	[16]/2004	[20]/2020	[16]/[17–20,43,66,71,80]/–
2	4	[21]/205	[21]/2007	[24]/2017	[21]/[22,24,44,47]/–
3	7	[25]/664	[25]/2012	[31]/2022	[25]/[27,29–31,45]/–
4	6	[32]/544	[32]/2013	[37]/2022	[32]/[33–35]/–
5	6	[39]/108	[38]/2013	[43]/2021	[39]/[40,42,43,56,62,80]/–
6	9	[44]/170	[44]/2014	[52]/2022	[44]/[45,47,48]/[21]
7	6	[53]/178	[53]/2016	[58]/2021	[53]/[52,58,62,67,78,80]/–
8	4	[60]/137	[59]/2016	[62]/2021	[62]/[95,96]/[39,53,59,60,63,80]
9	5	[65]/105	[63]/2016	[67]/2021	[63]/[62,64,65,67]/–
10	4	[69]/53	[68]/2016	[71]/2022	[69]/[70,71,93]/[55,60,68,73]
11	5	[73]/132	[72]/2018	[76]/2022	[73]/[65,69,74–76,78,91,96–98]/[72,80]
12	3	[77]/76	[77]/2018	[79]/2021	[78]/–/[53,73,77]
13	3	[80]/113	[80]/2018	[82]/2022	[80]/[41,62,67,73,81–83,98]/[16,39,53]
14	7	[85]/79	[83]/2019	[89]/2021	[85]/[86,88,91]/[60]
15	9	[91]/43	[90]/2019	[98]/2022	[91]/[95,96,98]/[62,91,92]

Furthermore, Figure 4 also depicts the distribution of clusters. The clustering was automatically carried out in VOSViewer using an algorithm based on the weighting of the connections, and this grouping allowed the identification of clusters of articles that have topics in common [13,14]. The clustering algorithm is a modularity-based technique that measures the association strength of vertices (articles) based on links (direct citations) and shared references (bibliographic coupling) and citing articles (co-citations). Thereby, clusters were established with groups of articles with high association strengths. The clusters were then analyzed, as shown in Section 3, highlighting topics in common in the corresponding articles.

2. Taxonomy of Wind Power and Wind Speed

In this article, we use the taxonomy described in Figure 5 to classify wind speed and wind power forecasts. The used approaches refer to the time horizon, forecast methods, forecast objective, and whether to consider forecast uncertainty. Figure 5 details each approach of the proposed taxonomy.

2.1. Time Horizon

Depending on the time horizon, wind forecast models are classified as very short-term (a few seconds to 4 h ahead), short-term (4 to 24 h ahead), medium-term (1 to 7 days ahead), and long-term (1 week, months, years), as observed in Figure 6 [7].

2.1.1. Physical Models

Physical models or NWP are mathematical models that attempt to simulate the dynamic behavior of the atmosphere. They analyze meteorological variables such as pressure, density, and temperature to forecast wind speed. They require large computational efforts due to their complex calculation processes, which makes them unsuitable for short-term wind speed forecasts [90].

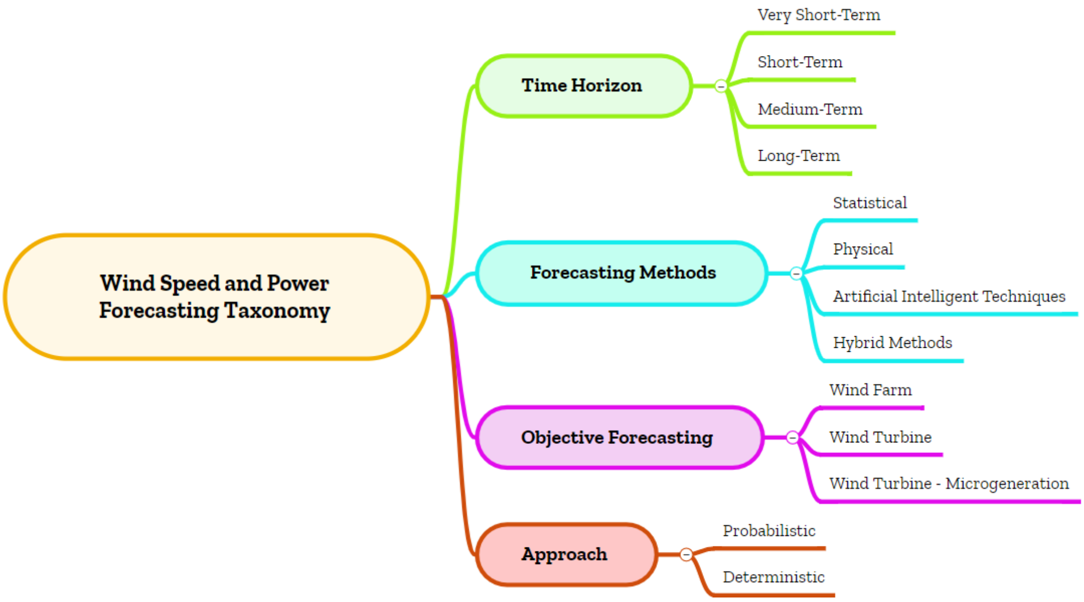

Figure 5. Wind-speed and -power forecasting taxonomy.

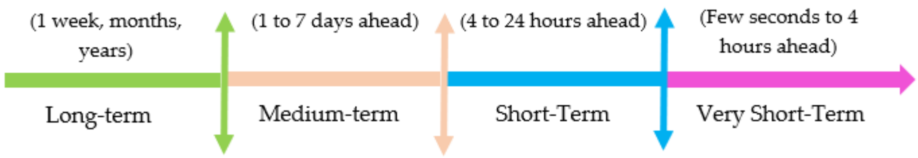

Figure 6. Classification of forecasting models according to their time horizon.

2.1.2. Statistical Models

Statistical models seek to establish a linear relationship between input and output variables, are easy to apply, and have better computational performance compared to physical models. They are models based on time series and have been widely used in short- and very short-term forecasts. The most common statistical models include Regression Analysis, the Persistence Model [71], Exponential Smoothing (ES) [90], the Moving Average, the Autoregressive Integrated Moving Average (ARIMA) [55,71,90], the Autoregressive Moving Average (ARMA) [55], and Generalized Autoregressive Conditional Heteroscedasticity (GARCH), among others.

2.1.3. Artificial Intelligence-Based Models

In recent years, AI has gained increased popularity due to its increasing efficiency in sensory processing and higher-level reasoning [99]. Starting from the beginning of the fifth generation of computers, researchers have been trying to mimic the effectiveness and robustness of the human brain due to its high capacity to handle huge amounts of information and store it in a hierarchy for future use [99], that is, AI includes any computational technique that mimics human behavior [100]. AI allows the capturing of the non-linear characteristics of time series and compared to statistical models, can achieve more accurate predictions in the short term. AI methods can be classified into five categories [100]: learning methods, statistical methods, search methods and optimization theory, game theory, and decision-making algorithms (see Figure 7).

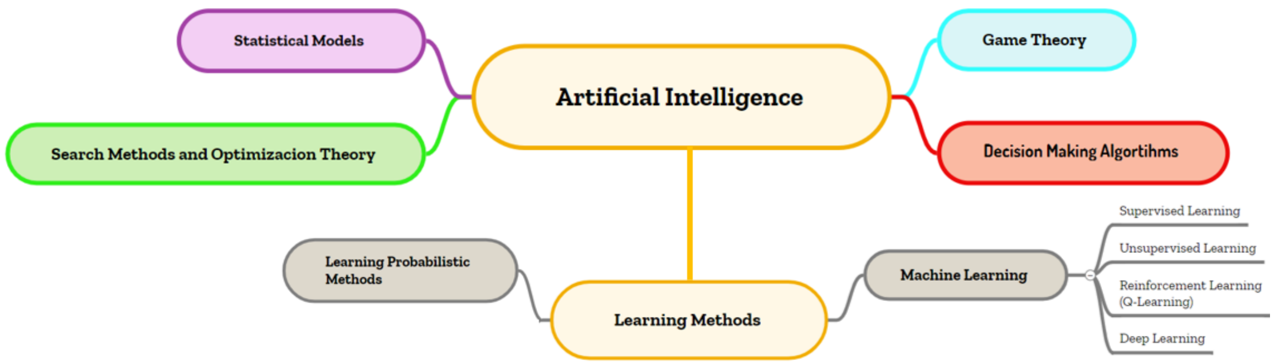

Figure 7. Classification of forecasting methods based on AI.

Many AI forecasting models are within Machine Learning (ML). ML can learn massive amounts of historical or synthetic data without human intervention, for example: Artificial Neural Networks (ANN), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Long Short-Term Memory (LSTM) among others. In more recent development, we find models based on Deep Neural Networks (DNN). Deep Learning (DL)- based DNNs allow modeling of the relationship between complex nonlinear systems, allowing raw data to be developed from the first layer to the last layer for feature extraction [100].

2.1.4. Hybrid Models

A hybrid model is the combination of two or more individual forecast models whose results tend to be more accurate and efficient in terms of computational effort or error. The main idea of hybrid models is to combine the advantages that characterize each of the forecast models, while counteracting the disadvantages and limitations of the models that can negatively affect forecast accuracy. These are classified into hybrid forecasting methods based on data preprocessing, parameter optimization, and data postprocessing. As the name implies, preprocessing methods take care of filtering and extracting outliers found in data sets before they are used in forecast models. Hybrid methods based on parameter optimization are responsible for choosing the parameters that best fit the forecast methods. Finally, hybrid methods based on data postprocessing deal with analyzing the errors coming from the predicted values. These methods are usually used when no preprocessing is performed on the dataset to be used.

2.2. Objective Forecasting

A wind energy forecasts are aimed at obtaining the generation profiles of different types of wind turbines. Its capacity (MW) and model vary according to the place where the wind turbines are planned to be installed. At present, the integration of wind energy in electrical energy systems can be achieved in various ways, either by installing large wind farms connected to the main transmission network, on a smaller scale in the form of Distributed Generation (DG) or as part of a Microgrid (MG). In addition, within the DG and the MGs, we find wind turbines installed in homes, urban areas, or buildings at a micro-generation level.

DG units are defined as small-scale generating units installed in distribution systems near load centers [101]. MGs are defined as a small power system (several MW or less in scale) with distributed generators with optional capacity storage, autonomous load centers, and the ability to operate while connected or isolated from the electrical grid [102]. Chilean regulation establishes distributed generation as generation systems that have installed power of less than 300 kW [103], while in Colombia, the Energy and Gas Regulatory Commission (GREG) limits the connection of small-scale self-generators to a capacity of less than or equal to 1MW, and large-scale to a capacity between 1 MW and 5 MW [104]. Regarding wind generation, the IEC 61400-2-2013 standard [105] classifies all wind turbines with a swept area of less than 200 m^2 as small wind turbines. Therefore, depending on the area and capacity of the wind turbine and where it is located, three groups of turbine to which wind energy forecasts are applied have been identified: wind farms, wind turbines located in GD or MG, and finally, wind turbines installed in residential and urban areas, identified as microturbines.

Wind Power Model

In general, the power output of a wind turbine is affected by factors such as wind speed and direction, the position and size of the turbine, the dynamic performance of the generator, and the load distribution between parallel turbines. Two power curve models have been identified throughout the literature review; in the case of (2), the relationship between power and wind speed is approximately linear [44,46,47,49–51]:

$$P_{wind} = \begin{cases} 0 & v_{wind} < v_{ci} \\ P_R \frac{(Vwind - Vci)}{(Vr - Vci)} & v_{ci} \leq v_{wind} < v_r \\ P_R & v_r \leq v_{wind} < v_{co} \\ 0 & v_{wind} > v_{co} \end{cases} \tag{2}$$

where v_{ci}, v_r, v_{co}, and v_{wind} are the cut-in speed, rated speed, cut-off speed, and actual speed of the wind turbine, respectively, and P_R is the rated power of the turbine. If the wind speed is less than the cut-in wind, the speed cannot overcome system friction and the power output is equal to zero. Once the cut-in wind expires, the wind power increases as the current wind speed increases and reaches the nominal value of the wind speed. Then, if the current speed exceeds the nominal speed, the output power remains equal to the nominal power of the machine for safety reasons until the cut-off speed is reached, where finally, the turbine is turned off. In (3), power wind P_{wind} depends on the wind speed (v), the turbine rotor area (A), the air density (ρ), and the rotor power coefficient (C_P).

$$P_{wind} = \frac{1}{2} A C_P \rho v^3, \tag{3}$$

2.3. Uncertainty

Wind forecast models can also be classified depending on whether or not they consider the uncertainty of their forecast. Having raised the above, we can say that the models are classified as deterministic and probabilistic. Deterministic models result in a point output value and cannot quantify the prediction error of their models. In contrast, probabilistic models are responsible for predicting a prediction interval in which the actual value of the forecast is found. Forecasting by interval allows an estimation of the level of uncertainty in order to quantify the potential risks to obtain more information in the planning of the electrical system [97].

3. Bibliometric Analysis Results

3.1. Cluster 1

This cluster is composed of five papers, [16–20], written in the period 2004–2020. Reference [16] is the most-cited article with 593 citations and is the oldest reference (2004) in the whole citation network. In addition, this reference is also related to articles belonging to clusters 5, 9, 10, and 13. Mohandes et al., in [16], propose an algorithm for mean daily wind speed prediction, on the basis of SVM. The data for training and testing the algorithm comprise mean daily wind speed, stored for 12 years between 1970 and 1982, and were acquired in Madina city in Saudi Arabia. The results of the SVM approach were compared regarding those obtained using a Multi-Layer Perceptron (MLP)-ANN. The Estimated Root Mean Square Error (RMSE) of the wind speed forecasting for the 100 days ahead was lower for the proposed SVM. Therefore, such an approach is considered as a tool for long-term wind speed forecasting.

The next reference in the cluster is [17]. In 2014, Žarković et al. proposed a methodology aimed at the assessment of the distributed generation impacts of wind (i.e., power losses, voltage sags, and voltage total harmonic distortion) on distribution networks. For wind speed estimation, the methodology was developed on the basis of an ANN (one input layer, two hidden layers, and one output layer), and uncertainties affecting input data were modeled using fuzzy set theory. Subsequently, the wind power was calculated by means of (3).

The estimated wind power was used to run power flows to assess the network performance. It was concluded that wind-distributed generation can help to improve voltage regulation and to reduce active power losses, but it can also increase voltage harmonic distortion. It is noted that no planning horizon is reported by the authors, since the methodology is oriented toward planning the expansion of distribution networks, but not toward the operation of these.

Carrillo et al., in [18], present a hybrid approach for wind power forecasting in the short-term, oriented to wind farms. The approach is based on an Extreme Learning Machine (ELM), which is a variant of ANNs characterized by a fast-learning process and Ant Colony Optimization (ACO); it aims to find the optimal path into the ELM, to connect inputs and outputs. The hybrid approach was tested for two different wind farms, i.e., 36.7 MW (22 turbines) and 30 MW (18 turbines), in Zamora and Galicia (Spain), respectively. The coefficient of determination, R^2, was used to measure the performance of the results, achieving a mean value of approximately R^2 = 0.6.

In [19], the authors propose a hybrid approach for wind speed prediction, which uses Variational Mode Decomposition (VMD) to extract different fluctuation characteristics from the historical wind speed time series. Then, an LSTM-ANN and the ARMA model are used to predict the main part and the rest fluctuation part, respectively. Finally, the prediction is completed by adding randomly generated residual series using the Kernel Density Estimation (KDE). To decrease the prediction errors, the approach optimizes the wind speed ramp (i.e., the rate of change in wind speed over a short period of time exceeding a predefined threshold value) using Particle Swarm Optimization (PSO). To test the approach, measurements for 17 and 34 h, each 10 and 20 min, respectively, were employed. Therefore, the approach is classified as one-day-ahead wind speed forecasting. As expected, lower errors are obtained using the complete hybrid approach, i.e., using all the components—PSO, LSTM-ANN, ARMA, and KDE—and using a 10 min sample interval.

Finally, in [20], a hybrid forecast model integrating Wavelet Neural and Long Short-Term Memory (WN-LSTM) was proposed to predict the wind speed of seven wind farms located in Europe. The Sigmoidal activation function was replaced by four basic wavelet transfer functions in LSTM layers, namely, Morelet, Ricker, Shannon, and Gaussian wavelet. The results showed that the WN-LSTM technique presented better results with respect to wavelet sigmoidal function. However, the calculation time and the validation test score favored the standard sigmoid model.

3.2. Cluster 2

This cluster is composed of four papers, [21–24], written in the period 2007-2017; reference [21] is the most-cited with 205 citations. In addition, this reference is also related to articles belonging to cluster 6. In [21], the authors develop a short-term (day ahead) wind power generation forecast for a wind farm, to be integrated into Unit Commitment (UC) scheduling. The wind forecast model is based on ANN with a forecast time step of 10 min. This article looks at five different ANN network structures and evaluates the performance of each using MAPE. The ANN model that uses a single measurement of wind speed and the latest wind power yields the best performance. Finally, to account for wind generation forecast uncertainty in generation planning, the authors estimate that the wind power forecast error has a normal distribution and calculate the mean value and standard deviation of the sampling sequence.

In [22] the authors use PSO to find an optimum operation plan for an MG the next day. In this MG, there is a wind turbine of 200 kW, and the uncertainty in the prediction of the wind speed to produce energy is considered in the plan operation. In this work, a wind forecast is assumed (it is not calculated) and the uncertainty is modeled in the same way as in [21], assuming a mean value and standard deviation of the wind forecast error.

In [23] a hierarchical stochastic control scheme for the coordination of Plug-in Electric Vehicle (PEV) charging and wind power in an MG is presented, where the time horizon of the control scheme is 12 h with a time step of 15 min. The MG has one wind turbine, and the main feature of the control scheme is that it incorporates the non-Gaussian uncertainty of wind power. For this, the authors adopt the sparse online warped Gaussian process, which is an online probabilistic wind power forecasting technique that can provide non-Gaussian predictive distributions. The wind data used in the simulations are sourced from an actual wind farm, which is in Inner Mongolia, China.

Finally, as in [22], in [21–24], the optimal operation of an MG with wind penetration is studied. To obtain the wind generation profiles, a short-term forecast algorithm based on Deep Learning is used by combining stacked auto-encoders; these are the Back Propagation (BP) algorithm and the Genetic Algorithm (GA). The stacked auto-encoders are configurated with three hidden layers in the pre-training process to extract the characteristics from the training sequence and the BP algorithm to calculate the weights of the overall neural network in the ne-tuning process. Then, a GA is adopted to optimize the neuron number of the hidden layers and the learning rate of the auto-encoders. Real data from wind turbines, belonging to a local MG in Hebei Province, China, are employed to perform the training and forecasting processes. Data samples from one year of active power are used. The simulations validated the proposed algorithm and demonstrated how it affects the prediction error (uncertainty) in the energy management. Furthermore, the performance of the proposed algorithm was better than the BP and SVM conventional algorithms.

3.3. Cluster 3

This cluster is composed of seven papers, [25–31], written in the period 2012–2022; reference [25] is the most-cited with 664 citations and is the oldest reference in the cluster. In this document, a method is proposed to determine the optimal sizing of an energy storage system in an isolated MG and a grid-connected MG. The problem involves the restrictions of UC and the spinning reserve, as well as the uncertainty introduced by wind and solar generation. To solve this problem, an objective function is proposed that reduces the total cost of supply in the case of the isolated MG and that maximizes the total benefit for the MG connected to the network. In the case of the grid-connected MG, the benefit of increasing the investment in a storage system is to increase the market benefit; meanwhile, for the isolated MG, its optimum is found through the commitment of the UC cost and the total cost of the battery storage system. The method is tested using forecast profiles with a horizon of one-day and hourly discretization. In the case of wind energy forecasts, these are obtained through time series of wind speed that are then transformed into power through (2). The results indicate an RMSE of 13% when compared with the real wind power.

Additionally, in 2012, in [26], the authors developed a real-time intelligent framework for the Dynamic Security Assessment (DSA) of power systems with high penetration of wind energy, considering Soft Computing (SC) technologies. This methodology consisted of four interactive modules: real-time DSA, wind and load forecasting, database generation, and model updating. In the case of the wind energy and load-demand forecast (W&LF), this consisted of two stages. In an offline stage, many Operating Points (OP) were made that covered a wide operating region; consequently, medium-term forecasts were made (for example, daily). The second stage consisted of an online stage, where short-term (e.g., minute-by-minute) forecasts were made to accommodate rapidly fluctuating wind speeds. For wind power generation forecasting, the wind speed was first predicted, and then, the generation of the wind farm was calculated. For this, the model based on the Weibull PDF was used. The forecast error for the wind speed half an hour ahead was 7.8% in terms of MAPE. The simulation results demonstrated the high efficiency and precision of the proposed method.

The next reference in the cluster is [27]. In 2016, Khorramdel et al. proposed a UC problem based on cost–benefit analysis and the Here-and-Now (HN) approach for the optimal sizing of Battery Banks (BB) in MGs with wind generation. To solve this problem, PSO was used to minimize total cost and maximize total benefit. As in [26], the Weibull distribution was used to represent the probability distribution of the wind speed, and the RMSE error was considered to analyze the daily wind energy forecast. The simulation results showed that the best BB sizes and distributed generation scheduling were different when wind power accessibility was considered by applying the HN approach to the proposed probabilistic UC problem. In turn, it was shown how wind energy and other DGs with different availability affected the best size of the BBs in each mode of operation.

In [28], a short-term wind power forecast model based on ANN clustering is developed, which uses statistical feature parameters in the input vector. In addition, an improved algorithm that fits the ANN output with the Probability Lower Misclassification (PLM) method is proposed. The impact of energy management decisions on the performance of an MG, consisting of a residential building (three wind turbines and a storage unit) under different short-term wind energy forecasting techniques, is also examined. Finally, Monte Carlo simulation is used to evaluate the impact of such management decisions on the MG, with the aim of reducing the building's electricity cost by optimizing the electrical exchanges with the grid and the energy stored in the BB. The results indicate that with the proposed PLM adjustment method, there are significant benefits for the MG in terms of forecast accuracy. Three scenarios are considered based on different wind energy forecasts, and the MAPE is calculated for each of these scenarios; an MAPE between 13.8% and 26.62% is observed, which shows improvements when the proposed forecast method is used.

In 2019, [29], a real-time forecast model of the cost and operating income of a wind generation MG with an associated Battery Energy Storage System (BESS) was proposed. For this, an economic dispatch scheme was formulated to sell energy to the electricity grid through an energy market. In this sense, wind energy and energy price forecasts were incorporated, which were necessary to determine the revenues and operating profits of the wind-generation MG. For wind power forecasting at hourly intervals, a new intelligent forecasting model based on a generalized neural network strategy called a Functional Network (FN) was employed. From the analysis of the RMSE, it was observed that the developed FN forecast model offered greater accuracy compared to the ANN and persistence forecasting models, both for wind energy and for the price of energy. In turn, the economic analysis revealed that the accuracy of the forecasts through the proposed model improved the daily income and the operating profit of the MG.

Additionally, Tian et al. [30] present a model to determine the optimal size, location, and technology for an electrical energy storage system considering uncertainties in renewable resources. For this, a hybrid system composed of wind turbines and fuel cells is studied. The proposed method is based on a Two-Stage Stochastic Search (TSSS) model to model the impact of uncertainty in the energy generated by wind generation resources, by considering the forecast error of wind energy as the main stochastic parameter in storage system planning. This wind energy forecast is made using the stochastic integer linear programming model presented in [25]. Finally, the studied problem is converted into an optimization problem and the Shark Smell Optimization (SSO) algorithm is used.

Finally, in [31], an economic dispatch model is developed for a 72-h horizon applied to an urban MG. The urban MG includes wind turbines, battery storage, and the components of the electrical grid. A new hybrid forecast model based on the Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM is proposed to obtain the demand and wind speed profiles of the MG. SARIMA is integrated into the LSTM model as an independent variable to increase the LSTM ability to interpret future trends and seasonality. The model is compared with the SARIMA and LSTM models to measure its performance. In general, the metrics indicate that the use of the hybrid model reduces the error of the

SARIMA and LSTM models by 10.5% and 16.6%, respectively. However, it is unable to correctly capture the trend and fluctuations for the 72-h forecast, although it generally performs better than the previous two individual models.

3.4. Cluster 4

This cluster is composed of six papers, [32–37], written in the period 2013-2022; reference [32] is the most-cited with 544 citations. In this document, the authors deal with the Energy Management System (EMS) for an MG located in the north of Chile. The EMS is based on the solution of mixed-integer optimization problems, considering rolling-horizon planning. Inputs for optimization are provided by forecasting models, one of which is specifically focused on two-days-ahead wind power forecasting for two 2.5 kW wind turbines. In the EMS proposed methodology, three blocks are related to wind power forecasting; one stores historical data, the second acquires weather forecast data, and the third includes the wind generator model. Therefore, the approach is based on phenomenological models with updated data. First the authors forecast the wind speed using a global forecast system based on NWP for the bounded conditions of a Weather Research and Forecast (WRF) model, [106], which uses a comprehensive description of the atmospheric physics, including cloud parameterization, land surface models, atmosphere–ocean coupling, and broad radiation models. The NWP model is employed to determine the wind speed border conditions that the WRF model employed as an initial condition. Lastly, the WRF model results are calibrated through statistical methods for a 12- or 48-h-ahead forecast. Once the wind speed is predicted, a linearized model of the wind turbine profile given by the manufacturer is used to compute the wind power generation.

In [33], the authors realize the importance of forecasting methods of climate time series for both smart grids and MGs (as was considered in the previous paper [32]). However, in this reference, the research is focused on the application of dynamic recurrent ANNs to predict the daily wind speed. The analyzed ANNs are the Focused Time-Delay Neural Network (FTDNN) and the Nonlinear Autoregressive Network with Exogenous Inputs (NARX), the main advantage of which is their capability to learn dynamic or time-series relationships. Once the wind speed is predicted, the results are applied to a turbine model, to estimate the power profile to be employed for energy management and planning purposes in smart grids. However, the study is not conducted for a specific wind turbine, but the generalized expression (2) is used. To evaluate the approach performance, the normalized RMSE and the Coefficient of Variation (CV) of the RMSE are employed. Three FTDNN architectures, which have different numbers of neurons in the hidden layer, are compared. The best architecture (ANN 1-5-1, with a time delay equal to 4 days) yields the following errors: nRMSEt = 0.124, nRMSEr = 0.139, CV(RMSE)t = 0.338, and CV(RMSE)r = 0.401, where subindex t represents the training phase and r the recalling phase. In addition, the errors obtained in the NARX network for the parallel configuration (ANN 2-3-1, with a time delay of 2 days) are: nRMSEt = 0.1002, nRMSEf = 0.3869, CV(RMSE)t = 0.1444, and CV(RMSE)f = 0.4153, where subindex f represents the forecasting. The authors conclude that NARX exhibits the best forecasting performance.

In parallel with [33], in [34] (also in 2014) the authors state the importance of daily wind speed forecasting for EMS operation in a residence in an urban context. Some of the listed components of the house MG managed by the EMS are a micro-wind turbine, a photovoltaic panel, a PEV equipped with a battery pack, a smart meter, a dish washing machine, and an air-conditioning system. After some considerations regarding MG management, the paper focuses on wind speed forecasting using a multilayer feedforward Back Propagation Neural Network (BPNN). The proposed BPNN has a two-node input layer (wind speed and direction), two hidden layers with 12 and 16 nodes, respectively, and an eight-node output layer, each one corresponding to a class of dimensionless parameter of the horizontal wind velocity:

$$v^* = \frac{v}{U_{\text{inf}}}, \tag{4}$$

where, $U_{\inf}$ is the wind speed obtained from a global forecasting station, and v is the wind velocity in the wind turbine location. Relevant issues were previously identified as influencing factors for electricity generation using micro-wind turbines; these include the presence obstacles such as buildings, mountains, and trees in residential areas. These obstacles affect the wind flow, by reducing its speed and producing turbulence, and, consequently, v^* can range between 0 and 1. In such a framework, the BPNN-based model employs the global forecast system predictions on wind direction and speed to detect patterns of wind behavior in the location considered, to procure a stochastic hourly distribution of the wind speed for the next day.

In 2016, Guo et al. [35] continued to research EMS for MGs, specifically for an MG with a 2 MW wind turbine, aimed at the operation of a sea water desalination system. As in [32], the authors proposed a real-time rolling-horizon EMS, but this time, based on a one-hour-ahead wind speed forecast. In the reference, there are few details regarding the used approach for wind speed forecasting, but it is stated that a BPNN algorithm is implemented. It is mentioned that the Genetic Algorithm is used to optimize the initial weights and thresholds of BPNN to reduce the training time. The structure of the BPNN is six nodes for the input layer (i.e., data every ten minutes, for one hour), ten for the hidden layer, and one for the output layer. With this approach, the authors estimate the mean hourly wind speed with a 10 min interval, and they report that the maximum forecast error is 18%, but lower than 10% most of the time. The performance of the proposed EMS is tested using a real-time digital simulator system.

In [36], Azeem et al., propose an ANN based method for long-term wind speed forecasting. Two distinct techniques for forecasting the monthly wind speed of 168 different Indian cities are implemented: the kNN algorithm and MLP. There are 13 input variables used in the approach, i.e., relative humidity, elevation, longitude, latitude, atmospheric pressure, solar radiation, earth and air temperature, cooling and heating degree-days, cooling and heating design temperature, and earth temperature amplitude. It was found that kNN gives better results than the MLP model, with wind speed forecasting accuracies of 99.1% and 94.1%, respectively.

Finally, reference [37], published in 2022, is the last paper in the cluster. The authors propose an approach based on an ANN for one- to three-days-ahead wind speed forecasting. The approach is developed using a dataset in the period 2015–2017 in Nainital city in India. The selected ANN is based in an MLP-BPNN, for which the input data are pre-processed to reduce the database for training. The minimum and maximum reported MAPEs are 1.59% and 10.3% for different days in a year.

3.5. Cluster 5

Cluster 5 comprises six papers, [38–43], written in the period 2013–2021. Most papers in the cluster are related to wind speed forecasting, and ANNs are the dominant technique for this task. Moreover, [38] appears to be the most relevant reference of Cluster 5 in the citation network of Figure 4 in terms of links, with a total of six.

Describing the cluster in chronological order, in [38], Hong et al. develop a method to forecast wind speed and power one hour ahead based on the integration of the correlation coefficient and Empirical Mode Decomposition (EMD) in the preprocessing stage, and a BPNN as forecasting tool. The method uses wind-speed and -power time series as inputs and first decomposes these time series in Intrinsic Mode Function (IMF) through the EMD. Then, the proper number of inputs is determined according to the correlation coefficients and a BPNN is trained for each of the obtained IMFs. Finally, the outputs of all the trained BPNNs are added to obtain the forecasted wind speed and power. The method is validated using measurements of wind speed and power, measured at a wind turbine in Taiwan, and a comparison is made using the ARIMA and persistence methods, showing good performance in accuracy and computation burden.

Similarly, in [39], Ramasamy et al. present a method to forecast wind speed using an ANN. As the most relevant paper in cluster 5 according to the links, the method uses data on temperature, air pressure, solar radiation, and altitude to predict wind speed in locations in the mountainous region of India where wind speed measurements are not available. For this purpose, a 10-minute averaged measured time series of the meteorological variables and wind speed is used to train the ANN. Then, the model is used to forecast the power generated by a micro-turbine to analyze the wind potential of the studied locations. The results of the ANN are validated against the wind speed measurements.

In the same line of research, Vidya et al. [40] proposes long-term wind forecasting based on EMD, tabu search, and General Regression Neural Network (GRNN). Some similarities are observed in this study compared with the preceding methods of [38,39], e.g., the use of EMD and ANN, hence the links seen in Figure 4. The difference in the method proposed in [40] lies in the use of the tabu search algorithm to optimize the hyperparameters of the GRNN and the forecasting horizon, i.e., long-term (one-month ahead). This method also uses meteorological variables such as atmospheric pressure, temperature, and humidity as inputs to predict wind speed and is applied to 47 cities in India.

Other works in Cluster 5 that use ANN models are [41,43]. In [41], Adedeji et al. integrate an ANN with a Fuzzy Inference System (FIS) to conform an Adaptive Network-Based Fuzzy Inference System (ANFIS) model, and optimization of the hyperparameters of the model is achieved using GA and PSO. The model is trained and tested to predict wind speed 10 min ahead in Rhodes, South Africa, and the prediction is used to estimate the power generation of three wind turbines. The results show better performance using PSO than using GA for parameter optimization. On the other hand, in [43], Shboul et al. implemented a BPNN to predict hourly solar radiation and wind speed simultaneously. In this case, meteorological variables were used to train the BPNN, and the obtained predictions included the global horizontal, direct normal, diffuse horizontal irradiation, and wind speed and direction. The model was validated with solar radiation and wind measurements, showing reduced errors.

Finally, Cluster 5 includes [42], where Brabec et al. formulated a numerical model to forecast wind speed one day ahead. This method is the only one in Cluster 5 based on physical and statistical forecasting models. The method proposed the use of statistical generalized additive models to analyze the sensitivity of the input meteorological variables and improve the behavior of a physical NWP model. The model was applied to meteorological and wind speed data from different locations in Romania and a statistical analysis of the seasonal RMSE was performed, showing that the combination of physical and statistical models facilitates the advantages of both approaches, yielding a more accurate performance.

3.6. Cluster 6

This cluster is made up of nine articles [44–52] that were written in the period 2014-2022. The most-cited and oldest reference corresponds to [44], with 170 citations. Most of the articles deal with the management of different types of MGs in which wind energy production is introduced as an uncertainty factor. For example, in [44], an Expert Energy Management System (EEMS) was proposed with the aim of obtaining the optimal operation of a wind turbine and other Distributed Energy Resources (DER) integrated into the Interconnected MG. To obtain wind speed forecasts for a 20 kW capacity wind turbine, the authors used a three-layer ANN fed historical hourly data, which were then compared to actual measured wind speed values. Finally, to reduce the risk of the uncertain forecast, the concept of confidence intervals was used, whereby the reliable capacity of wind generation was calculated by subtracting the forecast of wind generation obtained by means of (2) from the calculated error.

In [45], a profit maximization methodology is proposed for multiple wind energy producers that participate in the distribution market through a hybrid system, the latter being made up of a wind turbine and a battery. A maximization objective function is proposed with three approaches: participating in the electricity market the next day to maximize benefits, bringing benefits by providing auxiliary services in terms of loss reduction and voltage deviation, and finally, providing a reserve in the face of uncertainty of wind generation. Regarding the wind energy forecast, it is assumed that all producers have their own wind generation forecast with dispatch priority, and the uncertainty of the error follows a standard normal Probability Density Function (PDF).

In 2017, in reference [46], Aghajani et al. proposed a short-term probabilistic management system in an MG that integrates wind energy. The authors used a stochastic approach to obtain the generation profiles of the wind turbines. They developed the Rayleigh PDF to calculate the wind speed and then used (2) to obtain the relationship between the power output of the wind turbine and the wind speed.

In [47], an ANN was also used to perform wind power forecasting; however, unlike in [44], the authors introduced Wavelet Neural Network (WNN)-based data preprocessing to increase accuracy. WNN classifies wind speed data into short-term and long-term categories, which helps ANNs to learn the correlation between different times and different "live times" more clearly. To deal with uncertainty, an Adaptive Probabilistic Concept of Confidence Interval (APCCI) was proposed. APCCI modifies the probabilistic concept of confidence intervals and uses an adaptation using the fuzzy system.

In 2020, in [48], an EEMS that considers a probabilistic forecasting of wind energy for the optimal dispatch of a grid-connected MG was studied. To obtain the probabilistic wind energy forecast (interval forecast), a hybrid model, based on the decomposition of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), and Gaussian Process Regression (GPR) adjusted by the Improved Bat Algorithm (IBA), was introduced, that is, CEEMDAN-IBA-GPR. The model was divided into three modules: (1) it used CEEMDAN to break down the historical data of wind power into IMF and a residual; (2) IBA was developed to adjust the hyperparameters in the GPR model, preventing it from overfitting or underfitting in the training process; and (3) once the GPR was trained, it performed the probabilistic wind energy forecasts, which were used for MG optimization.

Then, in 2021, in reference [49], a Demand Side Management (DSM) method was developed in smart homes with the aim of determining the optimal operating hours of the appliances and the DERs that make up the home, respecting the restrictions of the network and the smart home. The smart grid integrated wind generation and PEVs as energy production/consumer units. To obtain the wind power schedule of the wind turbines, a stochastic approach was used. As in [44], the Rayleigh PDF was used to calculate the wind speed, and later, (2) was used to obtain the relationship between the output power of the microturbine and the wind speed.

In 2022, in [50], Alizadeh Bidgoli at el. proposed a two-stage management system for four MGs connected in the distribution network. In the first stage, a short-term forecast model for wind speed, solar irradiation, and load demand was proposed. The second stage consisted of optimizing the generated profiles using a game theory approach. The proposed prediction model combined an ANN and the Rough Neuron Water Cycle (RNWC) algorithm, called the Deep Learning Artificial Neural Network (DLANN). DLANNs predict parameters with a certain degree of uncertainty. The neuron weighting of the ANN was performed using the BP gradient descent method. To overcome local optimization problems involving the use of BP, a combined BP and WC method using Rough Neurons (RNs), i.e., RNWC, was introduced. WC is inspired by nature, by the process of the water cycle and how rivers and streams flow to the sea in the real world [107]. RN contributes by establishing a lower limit neuron and another limit neuron. The combination is designed in such a way that the limit neuron deals only with the random and unpredictable part of the applied signal. Such architecture effectively reduces the search space of the respective constituent neurons based on certain and uncertain behaviors. This splitting results in an improved error convergence rate in neural network back propagation, along with improved parameter approximation during the network learning process [108].

In [51] a distributed DSM is proposed, composed of an intelligent network, multiple users (traditional and active users), and a wind turbine. Three forecasting approaches are used to deal with wind energy uncertainty. In the first place, the Weibull distribution function is used to calculate the wind speed through historical data, and it is assumed that its parameters vary depending on the location and the period of the year in which the turbine is located. The second strategy is built from wind speed forecasts obtained from weather stations using a PDF to calculate wind power, which reflects the non-linear relationship between wind speed and wind power. The forecast error is assumed to follow a normal distribution, in which its parameters vary according to an instability index. The instability index is calculated by evaluating the error made by forecasts in different time horizons. It refers to the location, the geography of the farm, the meteorological conditions, and especially the uncertainty related to the wind speed and the forecast horizon, which strongly influence the wind speed prediction. Finally, a strategy called Composite Distribution that uses the logarithmic method is considered. It is integrated from the PDFs of strategies one and two, with weights assigned equally. The composite distribution corrects for overestimates in the forecast PDF that occur when the uncertainty is considerably high.

Lastly, in reference [52], a probabilistic wind energy interval forecasting approach is proposed to perform wind power scheduling in an MG. The method combines a deterministic forecast together with the Adaptive Concept of Confidence Interval (ACCI). The deterministic model combines CEEMDAN, the Chaotic and Sinusoidal Mapping Bat Algorithm (CSBA), and Least Squares Support Vector Regression (LSSVM) to obtain the hourly wind power profile of the turbine, while ACCI is used to calculate the forecast uncertainty with an appropriate confidence interval and, thus, avoid an energy forecast overestimation error. The success of LSSVM depends on the input data, the Kernel function used, and its parameters, which is why CEEMDAN is introduced. CEEMDAN takes care of decomposing the wind energy series into a few IMFs and a residual component with lower amplitude and stability, thus alleviating the regression difficulties of LSSVM. On the other hand, CSBA is used to avoid local optimum problems while tuning the Kernel parameters in LSSVM. Once CBSA-LSSVM is trained, the wind energy forecasts are obtained 24 h in advance. Finally, to determine the confidence interval for the forecast error distribution, it is first necessary to determine the significance value (α), since a small value of α can cause an excessive underestimation of wind energy, while a large value leads to unreliable programming. To address this problem, an FIS is needed from which an adequate level of confidence is obtained for α, and then, the upper and lower forecast errors will be obtained according to the non-parametric probability distribution functions of the error of the wind energy.

3.7. Cluster 7

Cluster 7 is composed of six papers, [53–58], written in the period 2016–2021. Most papers in the cluster are related to very short- and short-term wind speed forecasting with hybrid models. In addition, [53] is the most relevant article of Cluster 7 in the network with six links, followed by [55] with five links. However, within Cluster 7, [56] represents the dominant article with four links, whereas [57] only accounts for one link within the cluster.

In [53], Doucoure et al. performed hourly wind speed forecasting using a hybrid method based on Multiresolution Analysis (MRA) and an adaptive WNN. The method also used predictability analysis based on the Hurst coefficient to reduce the inputs to the adaptive WNN, resulting in an efficient algorithm with simplified computational complexity without a reduction in accuracy. The tests were conducted in wind speed time series recorded in Trois-Rivieres, Canada, and the results were compared with the Persistence Model, where the proposed method showed lower RMSE values.

Another hybrid method was proposed in [54], where Liu et al. introduced the combination of three individual forecasting models using ANFIS for the very short-term (15 min) prediction of wind power. The Pearson's correlation coefficient was also applied for selecting suitable inputs for the individual models. These individual forecasting models include a BPNN, Radial Basis Function (RBF), and LSSVM. The three models were used to predict the power generated by wind turbines based on wind speed, wind direction, and temperature simulations and the final output forecast was obtained through the ANFIS. The three models were included because BPNN outperforms the other models in spring and summer seasons, whereas RBF and LSSVM outperform in the fall and winter seasons, respectively. Thus, an accurate forecast was obtained during the whole year.

In [55], Li et al. also presented a hybrid model for very short-term (10 min) wind speed forecasting. The method was also based on the combination of three hybrid models using a modified Support Vector Machine Regression (SVR). First, wind speed time series were decomposed in IMF using EMD. Then, a BPNN and an Elman Neural Network (ENN) were used to solve the nonlinear component of the wind speed time series, whereas the ARIMA model was used to solve the linear component of the time-series forecasting. The Bat Algorithm (BA) was used to optimize the hyperparameters of both ANN and, thus, improve the forecasting accuracy. The proposed model was tested on wind speed time series from Penglai, China showing a more accurate performance than the implemented benchmarking models.

In [56], Sharma et al. performed very short-term (one-minute-ahead) wind speed forecasting. To that end, the authors proposed a hybrid model based on EMD and the Pearson's correlation coefficient to obtain the most suitable IMF to train a modified fuzzy Q learning model. This modified fuzzy Q learning model is based on reinforcement learning and, therefore, it is a self-learning predictor and operates in an unsupervised mode. The model was tested with wind speed data from 10 cities in India and compared with the SVR and kNN techniques, demonstrating higher accuracy.

Another hybrid model for very short-term wind forecasting was proposed in [57], whereby Xu et al. implemented 3, 9, and 15-min-ahead time-series predictions. The hybrid model included Empirical Wavelet Transform (EWT) for the preprocessing of time series, and an ELM for forecasting. The main novelty of the method was the use of a high-performance distributed computing strategy in Apache Spark to operate in parallel with the big data used for wind speed forecasting. Its performance was then evaluated on wind speed big data from Xinjiang, China, and different scenarios were formulated using various benchmarking models and strategies with no computing parallelization. The results showed that the proposed distributed computing framework offered satisfactory accuracy in multistep wind speed predictions with improved computation speed.

Finally, in [58], Soleimani and Emami also proposed very short-term forecasting, i.e., 10-min-ahead predictions, but in this case, for wind direction. Wind direction was highlighted in this study as another important variable to better exploit the wind energy resource by finding the best position for wind turbines. Moreover, the presented method was based on the Autoregressive Fractionally Integrated Moving Average (ARFIMA), which is a statistical approach. The ARFIMA is a time-series model that generalized ARIMA and is useful for representing time series with long-term memory, i.e., the data present a stationary behavior. Therefore, the authors of [106] first verified the stationary behavior of wind direction time series, and then, the parameters of the ARFIMA model were obtained. The model was applied in two cities of Iran and was validated with wind direction measurements, demonstrating good accuracy levels and simple operation.

3.8. Cluster 8

This cluster is composed of four papers, [59–62], written in the period 2016–2021; references [59,60] are the most-cited with 126 and 137 citations, respectively. In addition, these references are also related to articles belonging to clusters 5, 10, 13, and 14.

In [59], the authors propose two models to forecast the heat demand for district heating systems that can also be applied to wind forecasting. In fact, [62] takes these developments as a basis. The first model consists of a simple regression model in which hourly external temperature and wind speed predict the heat demand. The other model is the SARIMA model with a combination of exogenous variables, used to consider the historical heat consumption data and weather factors as dependent variables. The two types of heat-demand forecasting models were assessed based on hourly weather data (external temperature and wind speed) and hourly heat consumption data. Additionally, the combination of the SARIMA model and linear regression can be utilized to forecast heat demand for the short time horizon. Nevertheless, a lot of historical data are needed to adjust the model, and continuity of the historical data is also required.

The authors of [60] propose the combination of a denoising method with a Dynamic Fuzzy Neural Network (DFNN) to address wind speed forecasting in one step and multiple steps. Singular Spectrum analysis (SSa) optimized by Brainstorm Optimization (BSO) is applied to preprocess the wind speed data, and a generalized DFNN is utilized to perform the forecasting. The results of the hybrid model proposed are compared with other well-known forecasting models and models optimized by other metaheuristics, obtaining the best performance.

In [61], a hybrid model is developed for very short-term multi-step wind speed forecasting (10 min time step), which basically includes three modules. The data preprocessing module where the Wavelet De-noising (WD) technique is employed, the optimization module that uses a PSO modified adaptive algorithm-based ACO algorithm, and the hybrid nonlinear forecasting module which uses a BPNN algorithm. The PSO adaptive algorithm-based ACO algorithm is used to optimize the initial weights and thresholds of the BPNN algorithm. Finally, in [62], a SARIMA model is proposed to introduce the seasonal-term to very short-term forecasting of hourly wind speeds in the coastal/offshore area of Scotland. The predictive results obtained from the model proposed are compared with those of the Gated Recurrent Unit (GRU) and LSTM neural networks.

3.9. Cluster 9

This cluster is composed of five papers, [63–67], written in the period 2016-2021. Paper [63] is cited by articles [64,65,67] within the cluster and it is related to Cluster 8. Paper [66] cites paper [64] and it is related to cluster 5. Papers [64,65,67] are not related to other papers in the citation network.

Paper [63] proposes a hybrid model which combines Fast Ensemble Empirical Model Decomposition (FEEMD) with Regularized Extreme Learning Machine (RELM). This model simultaneously considers the characteristics of short-term and mid-term wind speed. To verify the developed models, short-term wind speed data and monthly data in a wind farm in Hebei province, China, are used for model construction and testing. To validate the effectiveness of the proposed method, EMD and Wavelet Transform (WT) for wind speed decomposition, and ELM, RBF, BPNN. and ARIMA for the forecasting algorithm, are used as contrasts. The simulation test results show that the built model is effective, efficient, and practicable.

In 2019, in [64], the authors proposed a two-layer nonlinear forecasting method called EEL-ELM to predict wind speed. The first layer was called EEL and was made up of ELM, ENN, and LSTM. EEL combined the advantages of ELM's computational speed, ENN's generalization performance, and LSTM's predictability. Meanwhile, the second layer was in charge of exploring the non-linear relationship of the individual forecasting methods with the final results through the ELM technique. In summary, to obtain the wind speed forecasts we must first make speed predictions using each of the models that make up the first layer, and then, these forecasts go to the second layer where ELM is used to overcome the weakness of the method and improve the forecast accuracy and stability. The effectiveness of the model was verified by making predictions of the wind speed at intervals of 10 min and 1 h. In the case of 10 min, an MAE of 0.43625 m/s and an MAPE of 6.70068% were obtained, and in the case of 1 h, the results were 1.30250 m/s and 34.63476%, respectively. In general, the results of both simulations were favorable and presented the least error.

Additionally, in 2019, Zhang et al. [65], used LSTM as a wind power forecast model together with a Gaussian Mixture Model (GMM) to analyze the error distribution of power forecasts. The model was validated by predicting power forecasts from three wind turbines at 15 min intervals. The performance metrics showed an RMSE of 12.10%, 6.37%, and

31.29% for turbines 1, 2, and 3. Another aspect that was evaluated was the computational effort; LSTM obtained the second highest execution time when predicting the wind power of turbine 1, and first place for the rest of the turbines with respect to the RBF, WT, Deep Belief Network (DBN), BP, and ELMAN models. In conclusion, LSTM can provide more accurate forecasts due to its complex structure, but it greatly affects execution times. Finally, the authors used the Mixture Density Neural networks (MDN) and the Relevance Vector Machine (RVM) to check the effectiveness of GMM and the evaluation of uncertainty, obtaining the best performance of the three.

In paper [66], the authors investigated the profile of the wind speed in the west region of Cameroon. Two well-known ANNs, MLP and NARX, were used to model the wind speed profile. Moreover, the influence of input variables (weather data) and internal parameters (transfer functions, neurons of the hidden layer, and delay) was studied during the validation. The correlation of MLP with NARX, the forecast and metering wind speed for training, validation, testing, and whole data sets was calculated. It was determined that the MLP model had a higher correlation than the NARX model.

Finally, in [67], the authors proposed three hybrid algorithms for the prediction of wind speed behavior: the genetic neural network hybrid algorithm (NN-GA), simulated annealing neural network hybrid algorithm (NN-SA), and shuffled frog-leaping neural network hybrid algorithm (NN-SFLA). The AI methods were compared to the Moving Average method. The results indicated that artificial intelligence-based predictions had significant superiority compared to the Moving Average. Moreover, the results showed that NN-SFLA was more suitable than other hybrid algorithms for the prediction of wind speed behavior in the study area.

3.10. Cluster 10

This cluster is composed of four papers, [68–71], written in the period 2016–2022; reference [69] is the most-cited with 53 citations. In addition, these references are also related to articles belonging to clusters 7, 8, 9, 11, and 15.

In [68], a hybrid forecasting approach was proposed, which consisted of data preprocessing whit SSa, a BPNN for advancing the accuracy of short-term wind speed forecasting, and a Firefly Algorithm (FA) to optimize the parameters of the BPNN to find the optimal weights and thresholds of the whole network. The horizon of forecasting was one to six steps with time spans of 10, 30, and 60 min. The data used were the wind speed in 2011 from Peng Lai, located in the Shandong Province in China.

In [69], a wind speed forecasting system is developed, which includes four modules. The first module is data analysis using an improved box-plot. The second module is a selection strategy with a novel criterion between: BPNN, WNN, GRNN, and AN-FIS. The special criterion is calculated from the MAPE and RMSE. The third module optimizes the parameters of the selected forecasting model, with a GA to search the global optimum, and then, a PSO to enhance the local search. Finally, in the fourth model, an evaluation is performed using a Taylor diagram to judge the authenticity of the forecasting results of each model.

The authors of [70] used a Bayesian Neural Network (BNN) for forecasting medium- and short-term wind speed on different time horizons (from 6 to 72 h ahead). The MAPE and Normalized Mean Absolute Error criterion were utilized to compare the results of BNN and the Least Absolute Shrinkage (LAS) and Selection Operator (SO) (LASSO). The results show that BNN outperformed exceptionally well and attained good accuracy.

Finally, in [71] the authors propose a hybrid wind speed prediction model with multivariate input and multi-step output capability. The model synthesizes linear time-series regression (such as ARIMA) using a nonlinear machine learning algorithm (such as feedforward neural network (FNN)). The input neurons of the hybrid model are determined by the number of lag observations in ARIMA, and by correlated meteorological features (wind direction, air pressure, etc.). The output neurons are further derived based on the forecasting horizon. The hybrid model simultaneously generates multiple speed prediction data corresponding to different time intervals, varying from 1 to 24 h ahead. The hybrid model is trained, validated, and tested using 1.73 million hourly meteorological records from three cities. The hybrid model proposed outperforms the Persistence Model, ARIMA and univariate neural network models in 3-to-24 h-ahead prediction.

3.11. Cluster 11

This cluster is composed of five papers, [72–76], written in the period 2018-2022. Paper [73] is the one with the highest number of citations within the cluster (132). Moreover, Paper [73] is related to clusters 9, 10, 13, 14, and 15. Papers [72,74–76] only cite paper [73] in a general way, to mention that it uses a method to forecast wind speed.

Jin et al. [72] proposes a complete wind energy conversion model to convert wind fluctuation into electric power fluctuation on a wind farm. The model considers both the spatial effects and the overall effect of all the pitch angle controllers of the wind turbines inside the farm. The paper presents a theoretical derivation of the frequency-domain equivalent modeling method. The proposed modeling method obtains the equivalent model of the complete wind energy conversion process, considering the wind speed before entering the wind farm as the only input signal and obtaining the total power of the wind farm as the only output signal. The equivalent modeling method uses a discrete transfer function for representing both the wind energy conversion process, in addition to all the spatial effects of a wind farm, and a compensation factor to calculate the compensation wind speed of the original incoming wind speed. A simplified frequency-domain equivalent model of the complete wind energy conversion process of a wind farm is also proposed. The effectiveness of the proposed frequency-domain equivalent model is validated by field measurements of an actual wind farm. An example demonstrating the use of the proposed model in hours (around 24 h) for wind power forecast is presented.

Song et al. [73] develop a model to forecast short-term wind speed combining a data preprocessing technique (Improved CEEMD) with Adaptive Noise (ICEEMDAN), an advanced optimization algorithm, No Negative Constraint Theory (NNCT), and forecasting algorithms such as back BPNN, ENN, WNN, and GRNN. The proposed model is useful for enhancing the operation efficiency and increasing the economic benefits of wind power generation systems. Three different experiments are conducted to evaluate the forecasting accuracy of the proposed combined model: (i) Comparison with other ICEEMDAN-based models: ICEEMDAN-BPNN, ICEEMDAN-ENN, ICEEMDAN-WNN, and ICEEMDAN-GRNN; (ii) comparison with models using different data preprocessing methods: EMD, CEEMDAN, and SSa; and (iii) comparison with classic individual models: BP, ENN, WNN, GRNN, ARIMA, and AR. The experimental results demonstrate that the forecasting performance of the developed model is evidently superior to all the other compared models.

In [74], the authors proposed a novel prediction interval model, consisting of several sections, to predict short-term wind speed and solar irradiation and to investigate the energy consumption of MGs. The WT method and a new hybrid feature selection method (NNMFOA) were considered as data preprocessing models. The modified multi-objective fruit fly optimization algorithm (MOMFOA) was used to optimize the objective functions of the prediction interval. The Group Method of Data Handling (GMDH) neural network was used to predict the future values of wind and solar irradiation. The renewables prediction and the energy consumption analysis were applied to the Favignana island MG. The proposed model (the Group Method of Data Handling neural network and modified fruit fly optimization algorithm—GMDHMFOA) was evaluated by indices such as RMSE, MAE, and MAPE, and compared with other methods such as NN-GA, NN-PSO, NN-ACO, and NN-FOA. The results showed that the proposed model had an acceptable error and better performance than the other ones commonly used to predict wind speed and solar irradiation and in predicting energy consumption than other already-existing methods.

In [75] a prediction system integrating an advanced data preprocessing strategy, a novel optimization model, and multiple prediction algorithms was developed. The preprocessing strategy uses the Variable Mode Decomposition (VMD) technique together with an advanced optimization model, the Nondominated Neighbor Immune Algorithm (NNIA). The optimization model utilized the fuzzy c-means clustering (FCM) algorithm and the NNIA optimization algorithm. The core forecasting algorithms involved in the combination system were ARIMA, BPNN, GRNN, and Bidirectional Long Short-Term Memory (BiLSTM). The proposed model was compared with other Weight-Adaptive Combined Denoising (WACD)-Based Models (WACD-ARIMA, WACD-BPNN, WACD-GRNN, and WACD-BILSTM) with different data preprocessing technologies (EMD, Complete Ensemble Empirical Mode Decomposition (CEEMD), SSa, and VMD), and with traditional forecasting models, including: ARIMA, BPNN, ELMNN, GRNN, and ELMAN. The results indicated that, in terms of the forecasting capability and stability, the proposed system was better than the compared models.

Finally, the authors of [76] propose a novel model, Variance-Sensitive Exponential Smoothing (VSES), to forecast the very short-term wind speed in the determination of the wind energy potential of a region. The proposed model is compared with three stochastic models. These three stochastic models are Optimized Simple Exponential Smoothing (O-SES), Pantazopoulos and Pappis (P-P), estimation using the Trigg and Leach method (T-L). From the results, it is noticed that the VSES model proposed gives competitive and satisfying results with the stochastic models frequently used in the literature. It is concluded that the model proposed can be applied to determine the wind energy potential of the regions, and effectively employed in intraday markets, especially to forecast wind speed in the very short term.

3.12. Cluster 12

This cluster is composed of three papers, [77–79], published in the period 2018–2021. The most-cited paper is [77], which has 76 citations. In [77], a hybrid approach for wind speed forecasting was proposed using an ANN optimized by a modified BA with a cognition strategy. To improve the forecast performance of the BPNN, SSa was applied to remove high-frequency noise and select significant features from the raw wind speed series. In addition, the Kruskal–Wallis (K-W) test was applied to detect differences in the experimental data to avoid repetitive experiments. Meanwhile, the BP weights and thresholds were optimized using a WGBA algorithm (i.e., a version of the BA modified algorithm that combines an inertial weight factor (W) and a genetic mutation operator (G)). Considering the accuracy and elapsed time, the proposed hybrid model was clearly more efficient, faster, and more accurate than the other reference models, which provides greater accuracy and stability in wind speed prediction. This was demonstrated by comparing the MAE, MAPE, and RMSE errors of the proposed model with those obtained by applying five forecast models. Consequently, the proposed forecast model not only could achieve outstanding forecast accuracy, but is also suitable for application in wind farms.

Additionally, Qolipour et al. in [78] developed a hybrid algorithm to predict the behavior of wind speed, obtaining predictions of changes in speed for 24 h. The proposed algorithm is called Grey ELM, and it combines an ELM algorithm and the Grey systems theory. To predict changes in wind speed over 24 h, the average speed over a 10-year period was processed. These data were converted into eight variables using the Grey system, and then, reprocessed using the ELM algorithm. The wind speed prediction error values, R^2 and MSE, were 0.99376 and 0.000987, respectively, representing better performance than the traditional ELM algorithm, which had R^2 and MSE values of 0.98075 and 0.00720, respectively. Finally, the efficiency of the proposed algorithm, together with the efficiency of the hybrid algorithms NN+SFLA, NN+SA, and NN+GA, through the measurement of the metrics RMSE, MSE, MAPE, and R^2, allowed the authors to determine that the proposed hybrid algorithm had better performance and better wind speed prediction.

Finally, in reference [79], Kumar et al. analyzed the load-frequency control based on the prediction of wind and solar generation with the aim of studying the MG control in the presence of intermittent renewable generation and dynamic load demand. For this, they implemented a multi-step sequence forecast model based on LSTM-RNN to predict wind speed, that is, the model trains, predicts, and updates the states of the RNN in the LSTM memory cells to obtain more accurate forecasts, while being fed back actual observed wind speed values. The performance metrics indicated that it obtained the lowest RMSE (0.17) compared to other prediction models.

3.13. Cluster 13

This cluster is made up of three papers, [80–82], published in the period 2018–2022. The most-cited and oldest reference corresponds to [80], with a total of 113 citations. The cluster covers the study of wind-speed and -power forecasting in wind farms, except for reference [82], where wind speed prediction is used to determine railway running speed.

In [80], seven forecast models based on ML to predict the wind speed at intervals of 5, 10, 15, and 30 min from historical data were proposed. The models included the Multi-Layer Feed-Forward Neural Network (MLFFNN), SVR, FIS, ANFIS, GMDH-type neural network, ANFIS optimized with PSO algorithm (ANFIS-PSO), and ANFIS optimized with GA (ANFIS-GA). GMDH was introduced as a predictor for time-series data for the first time, where the model used mathematical functions to derive complex nonlinear relationships between input and output data sets. In addition to GMDH, the authors implemented three types of ANFIS models: ANFIS-FCM, ANFIS-SC, and ANFIS-GP. ANFIS-FCM uses fuzzy c-means clustering to generate an FIS structure, ANFIS-SC creates a Sugeno-like FIS structure through subtractive clustering, and finally, ANFIS-GP generates an FIS using data grid partitioning. The performance of each model was calculated to predict the wind speed of a wind farm located in Brazil and through which it was determined which models perform better with respect to the forecast interval used. The MLFFNN model obtained the best results in each of the time intervals with RMSEs of 0.0120, 0.0388, 0.11164, and 0.4129 for the intervals of 5, 10, 15, and 30 min, respectively.

Then, in [81], in 2021, Etemadi et al. proposed a probabilistic forecast model based on the interval concept to obtain the wind speed/power. The method uses Lower and Upper Bound Estimation (LUBE) to find the optimal forecast intervals. It also combines two prediction indices called the Prediction Interval Width (PIW) and Prediction Interval Coverage (PIC) to form a fuzzy multi-objective equation, where PIC is defined as the percentage of estimated samples that are within the prediction interval, while PIW is used to measure the quality of the interval, that is, the information contained within the interval. Finally, the authors proposed an improved optimization method based on Social Spider Optimization (SSO), MSSO, to tune the model parameters. The modifications include the addition of Levy flight and the introduction of random spiders using genetic mutation operators to reduce the risk of entering optima and avoid premature convergence. The model tests indicated a PIC of 93.65 and a PIW of 23.66 for MSSO. In addition, it was found that the use of the multi-objective fuzzy framework satisfies each of the prediction indices by reliably forecasting the wind speed.

Finally, in the year 2022, in reference [82], a forecast model based on LSTM and the Convolutional Neural Network (CNN) was developed for very short-term wind speed prediction around high-speed rail lines. The wind speed can change from moment to moment, and the driver must receive this information before the train crosses any area with gales in order to adjust its running speed considering the wind speed. LSTM-CNN combines the ability of LSTM to make use of changing information over a period of time, along with the drill-down ability of CNN to find features in the data. The performance of the model was compared with the LSTM and CNN models, and the LSTM-CNN prediction model was found to have the smallest error, with RMSEs of 0.387, 0.405, and 0.421 and MAEs of 0.487, 0.547, and 0.593 for the intervals of 1, 5, and 10 min.

3.14. Cluster 14

This cluster is composed of seven papers, [83–89], written in the period 2019–2021; reference [85] the most-cited with 79 citations. Yu et al., in [83], propose a Spatio-Temporal Feature (STF) in the form of a multichannel image that expresses the process of spatio-temporal variation in the airflow. In this work, a CNN is used to predict wind energy based on said STF, called the E2E model, allowing the prediction of wind energy from many turbines in parallel. Compared with wind speed or power series, STF involves factors such as wind speed, wind direction, and air density, which greatly expands the ability to express wind-related information and the accuracy of wind power prediction. To test the validity of the method proposed in this work, the MSE and calculation times are compared with those obtained using the SVR and kNN methods. In this case, the MSE is reduced by between 24.37% and 49.83%, and the time for training both of the models is shortened more than 150 times.

In [84] the authors propose an advanced DL network with a probabilistic approach to forecast the wind speed in a grid space. The Variational Bayesian Space-Time Neural Network (STNN-VB) considers the STFs of the wind speed that derive from the location of the turbines in a grid space and that express the process of temporal and spatial variation in the airflow. STNN combines the GRU and CNN models to address spatial and temporal correlations. Although GRU is suitable for predicting sequence data, spatial correlations are not considered by the model. To solve this problem, ConvGRU is used by using the convolution process for each transition from input to state, as from state to state. Subsequently, 3D CNN is used to extract the features of the ConvGRU layer and reduce the dimensionality between layers considering that the dimensions of the hidden layers must be equal at each time step and that the dimensions of the input data are equal. In short, STNN is the module in charge of forecasting the spatio-temporal prediction of wind speed. Subsequently, to calculate the uncertainty of the forecast, the Bayes rule is used. Bayes calculates the posterior distribution of the model parameters where variational inference is applied to approximate the true posterior distribution. To verify the performance of the proposed model, STNN-VB, forecasting models, including the Persistence (PR) model, Lasso Regression (LR), ANN, LSTM, CNN, GPR, and Hidden Markov Model (HMM), are developed for comparison.

In 2020, [85], a novel hybrid forecasting model was proposed based on the CEEMD, the ELM, and Multi-Objective Gray Wolf Optimization (MOGWO). In this model, CEEMD partitions the original wind speed sequence into a set of IMFs, and then, the MOGWO algorithm is applied to optimize the initial ELM weights and thresholds, thus obtaining better forecast performance and accuracy. The results showed that the proposed hybrid system transcended the other simple and traditional models, and achieved high precision and great stability, yielding the best values for MAE, RMSE, and MAPE. The average MAPE values obtained for the proposed model varied between 1.87% and 2.84%, while for other models, such as ELM and MOGWO-ELM they were between 6.23% and 6.03%, respectively.

Additionally, Acikgoz et al. [86] propose an efficient wind speed forecasting network built from three-channel attention (CA) modules within a densely connected CNN structure (WSFNet), i.e., WSFNet with dense connections and CA (DCA). The proposed approach uses a powerful and efficient forecasting capability that is enhanced by preprocessing the time-series decomposition. In preprocessing, VMD is used to provide effective preprocessing and improve forecasting ability. Four metrics were selected to assess the model's performance, that is, RMSE, the Correlation Coefficient (R), MAE, and Symmetric Mean Absolute Percentage Error (SMAPE). The results obtained for R, RMSE, MAE and SMAPE were 0.9705, 0.7383, 0.5826, and 0.0466, respectively. This indicates that the proposed method achieved competitive performance and high precision for short time horizons. The proposed model also provides a novel and robust approach to wind speed forecasting problems.

In [87], Ahmad et al. presented a forecasting model based on ML with a stochastic approach, which was proposed to forecast load profiles and wind and solar generation simultaneously in the short and medium term. The model is fed by different sets of input variables and different time horizons. It uses GPR with four experimental steps for its configuration, where each experimental step consists of a fit and prediction method. Fit methods are used to calculate the weights/parameters of the training data, while prediction methods are used to measure the weights of the data sets to obtain accurate predictions. In turn, the fitting and prediction methods use four forecasting methods and seven Kernel covariance methods. In which the Kernel covariance in GPR is used to express the similarity between the input and output variables. To optimize the hyperparameters of GPR, the squared exponential Kernel function is used, which reduces the cross-validation loss five times through the use of the automatic optimization function. The models used to compare and validate GPR results are Levenberge Marquardt BPNN (LM-BPNN), Bayesian Regularized BPNN (BR-BPNN), and the conjugate Scale Gradient BPNN (SCG-BPNN).

Simultaneously with [86] in the cluster, in [88], the authors propose a model hybrid of learning combining full CEEMD and Stacking Ensemble Learning (STACK) based on ML algorithms to forecast wind energy from a turbine in a wind farm. STACK uses two levels or layers. The layer zero forecasting methods are kNN, Partial Least Squares Regression (PLS), Ridge Regression (RIDGE) and SVR. Layer zero forecasts are used to train layer one and obtain the final prediction using Cubist regression. In this way, the use of decomposition ensemble learning methods for very short-term forecasts (30 min) several steps ahead is evaluated. The developed models overcome the CEEMD, STACK, and single models at all forecast horizons, with efficiency improvement ranging from 0.06% and 97.53%. In fact, the decomposition ensemble learning model is an efficient and accurate model for wind power forecasting.

Finally, in [89], a new solar and wind energy forecasting model called evolving multivariate fuzzy time series (e-MVFTS) is proposed, which combines a Fuzzy Time Series (FTS) technique and an evolving data clustering method based on Typicality and Eccentricity Data Analytics (TEDA). This method considers scenarios of uncertainty and, consequently, a dynamic and adaptive forecast model. The proposed evolutionary FTS model allows you to continuously evolve your knowledge base by creating new rules and removing or adapting current rules according to the transmitted data. The main innovation of the proposed model lies in providing an adaptive spatio-temporal forecasting method. The good results in terms of precision and computational cost in the different experiments allow the use of the e-MVFTS model in the forecast of renewable energy systems.

3.15. Cluster 15

This cluster focuses on the study of hybrid forecast models applied in wind farms in the very short and short term. It is made up of nine articles [90–98], with the most-cited being [91] with 43 citations. It is the most recent cluster of all and contains articles that were published in the period 2019-2022, with [90] being the oldest of them all. In this paper, Zhang et al. proposes a combined forecast model that uses two linear and four nonlinear algorithms to predict wind speed. The linear algorithms used are Exponential Smoothing (ES) and ARIMA, and the non-linear ones BPNN, GRNN, WNN, and ENN. The main objective was to capture the volatility, intermittency, and randomness of time series using linear and nonlinear prediction models. A mixed optimization algorithm based on the Artificial Fish Swarm Algorithm (AFSA) and ACO (AFSA-ACO) was also proposed to determine the optimal weight of each model. The ACO optimization algorithm has strong global exploration and exploitation capabilities. Additionally, its speed of convergence is fast in early optimization. However, it has limitations in the subsequent optimization process, that is, its speed of convergence and accuracy decrease. The AFSA-ACO algorithm prevents the algorithm from falling into local optimization and stagnation while accelerating convergence.

In 2021, in [91], a hybrid forecast model was proposed to predict wind speed based on data decomposition, prediction, and error correction. The ICEEMDAN signal decomposition technique was used in the decomposition module to convert non-linear, non-seasonal wind speed data into a series of relatively simple subseries. The prediction was performed using BP, LSTM, and GRU to obtain the wind speed forecasts and forecast errors. Subsequently, the error is decomposed with the ICEEMDAN method and the ARIMA model was used to determine the sequence and prediction of the error forecast. Finally, the final forecast wind speed was obtained by adding the previously forecast wind speed and the forecast error. The performance of the model was evaluated in a wind farm in the Ningxia Hui Autonomous Region in China. Predictions were made using the BP, LSTM, and GRU models before and after data preprocessing, and finally, including the ARIMA model for error correction. In general, all the forecast models increased their performance by including the error correction module; however, the results show that the performance of the GRU is best before and after the error correction, with an MAPE of 17.657% for the GRU, 5.58% for ICEEMDAN-GRU, and 3.1% for ICEEMDAN-GRU-ICEEMDAN-ARIMA

Additionally, in 2021, Kosana et al. [92] proposed a hybrid forecasting model based on two main components: feature coding and dimensionality reduction using the LSTM automatic encoder, and forecasting using the convolutional LSTM, i.e., a Unidimensional Convolutional Neural Network (1D-CNN). The LSTM auto encoder is used to encode the input wind speed data with the best possible precision and small dimensions. The CNN then performs the extraction of the optimal features from the coded data that are used in the LSTM model for wind speed forecasting. The evaluation metrics showed the smallest error compared to other models, with an MAPE of 10.96%, an RMSE of 76.04%, an MAE of 50.65%, an MSE of 82.45, and an R^2 of 93.64%. This approach reduced the computational load and led to a significant reduction in prediction errors thanks to the use of automatic encoders.

In reference [93], an ensemble hybrid forecast model was developed to predict wind speed. The model decomposes the wind speed data series into subseries using Variational Mode Decomposition (VDM), which has greater robustness and avoids modal and residual aliasing. The decomposed series are forecast using seven forecast sub-models (ARIMA, BP, ELM, ENN, ANFIS, GMDH, and LSSVM); then, the best model is chosen using a "sub-model selection strategy". This strategy consists of measuring the Comprehensive Evaluation Index (CEI) that is built by measuring the performance of the sub-models, that is, the MAE, MAPE, RMSE, and the Standard Deviation of Error (SDE). Once the optimal sub-model for each subseries has been determined, a Multi-Objective Mayfly Algorithm (MOMA) searches for the optimal weight coefficients. Finally, the authors calculated the uncertainty of the results obtained by calculating the prediction intervals of the forecast. They used four distribution functions to determine which function best fits (Extreme Value, Logistic, Rician, and Weibull). Additionally, the Mayfly algorithm (MA) and the Maximum Likelihood Estimation (MLE) were used to calculate the best parameters of the statistical distribution.

Finally, in last reference from 2021, [94], the wind speed is predicted together with the forecast intervals simultaneously, that is, a bi-forecast system is proposed that combines the punctual forecast and the forecast by probability intervals. The model starts with ICEEMDAN data preprocessing, and a combined model that integrates BP, ELM, and BiLSTM. The optimal weight combination strategy is determined by a Multi-Objective Multi-Verse Optimization algorithm (MOMVO) through which the forecast results and forecast intervals are obtained. In the proposed framework of interval forecasting, assumptions with regard to the distribution and models are not required; therefore, the proposed interval construction is very efficient when the interval data have abnormal values.

In 2022, in [95], ICEEMDAN was also used to remove noise in the wind speed data. However, unlike [91,94], it used an automatic encoder based on Unidimensional- Recurrent Neural Network (1D-RNN). 1D-RNN is used to extract the most dominant and optimal features from the noise-free data where they are encoded. In the next stage, a BiLSTM decoder decodes the data to finally forecast the wind speed.

In [96], a prediction method based on Clockwork Recurrent Neural Networks (CWRNN) to perform marine wind speed predictions was proposed. Unlike onshore wind power, offshore wind power presents different challenges. The main challenge is the lack of historical wind speed data in offshore areas, while the second challenge is that of random, intermittent, and chaotic characteristics, which causes strong non-linearity in the wind speed time series. To address these challenges, the authors proposed the use of CWRNN as a forecast model considering that it can divide its hidden layers into *n* parts with an independent clock speed; this allows it to handle long-term and short-term information in each part of the forecast much faster than a simple RNN. The method was tested at three different sites to verify the generalizability of the model. The first two sites were located offshore and the third was located on land. The results obtained show that CWRNN obtained good results in both cases. The MAPE, MAE, RMSE, and R^2 obtained at site 1 located offshore were 6.7873, 0.4572, 0.6566, and 0.8310, while for site 3 located on land, values of 5.0672, 0.3843, 0.6446, and 0.9480 were obtained, respectively.

In reference [97], a quantile regression bi-directional long short-term network (QrBiLSTM) was developed. QrBiLSTM is used to generate wind speed prediction intervals. It combines quantile regression with bidirectional data processing, providing the ability to effectively learn the hidden correlations between data before and after the time step in a time series while including uncertainty modeling. An improved multi-objective swarm algorithm (IMOTa) is proposed, i.e., an enhancement to the tunicate swarm algorithm (TSa), that includes a multi-objective approach (MOJ), an elite oppositional learning approach (EOLA), and the exponential function step approach (EFSA). The MOJ model generates in the optimization algorithm multiple objective functions, thus improving the optimization results. The EOLA model improves the speed of convergence of the algorithm, and the EFSA model improves the robustness and optimization. The method proposed is compared with the QrLASso, QrLStm, Qr convolution neural network (QrCNn), QrGRu, Gaussian process regression (GPr), Bayesian regression model (BLGM), and the proposed QrBiLStm.

In paper [98], the authors proposed a hybrid method called the Improved Corrected Multi-Predictor Deep Q Decomposition Ensemble Model (ICMPDQDEM) for wind speed forecasting. The ICMPDQDEM is based on DL and reinforcement learning. The method includes a data decomposition module, a reinforcement learning set, and an Improved Error Correction (IEC) technique. It uses EWT to decompose and reconstruct the wind speed series. Once the decomposition is complete, predictions are made through three DL models (the BiLSTM, GRU, and Deep Belief Network (DBN)) that provide a more robust learning capacity. These models are integrated into the ensemble module by means of the Q-learning algorithm. Q-learning determines the combination of weights by establishing a reward-and-punishment strategy, thus obtaining the EWT-Q-GRU-BiLSTM-DBN reinforcement learning ensemble model. In the error correction module, Wavelet Packet Decomposition (WPT) and the Outlier-Robust Extreme Learning Machine (ORELM) are combined to predict the errors.

4. Discussion

The forecast horizon defines the usefulness of each model, that is, a forecast model is useful, or not, for developing activities related to the operation and planning of electrical systems depending on the forecast horizon adopted. Due to the above, the discussion of the results of this article is aimed at establishing the utility or contribution that the implementation of each model can provide in the electrical power system.

According to the reviewed literature, the most-used taxonomy to classify forecasting models by time horizon consists of very short term, short term, medium term, and long term. These categories are not standardized, and the forecast intervals often vary from author to author. Some authors limit these definitions to shorter time horizons, such as up to one week [53,109], or longer time horizons that may include one or more years [56,76]. That said, it is important to clarify that in this article, the classification established by [7] is followed to include a forecast interval that covers the activities of long-term programming. Furthermore, of the 83 articles analyzed in this review, 80 were categorized according to their prognostic horizon and 3 were excluded because their prognostic interval was not specified [81,89,92]. For this, Table 2 shows a summary of the applications in which this type of model is used, with their respective references.

Table 2. Applications of wind forecast models by time horizon.

Category	Scale of Forecast Horizon	Application	References
Very short term	A few seconds to 4 h ahead	• Faster adjustments to turbine settings • Unit commitment decisions • Scheduling of economic dispatch • Real-time operations • Stable operation of the electricity market • Contributes to guaranteeing the reliability, security, and stability of the system such as frequency regulation and the programming of secondary and tertiary reserves	[17,18,20,24,29,32,35,38,41,43,53–61,63,64,68,69,71,75–77,79,80,82–88,90,91,93–98]
Short term	4 to 24 h ahead	• References for the economic programming of dispatch load • Stable operation of electricity markets, including the sale of energy by prosumers • Unit commitment decisions • Reserve allocation plan (day-ahead) • Online adjustments for each wind turbine • Energy management	[19,20,22–28,30,32,34,37,39,42,44–52,62,69–72,78,86]
Medium term	1 to 7 days ahead	• Maintenance planning • Production planning • Electricity trading	[19–21,31,32,37,59,65,66,70,73]
Long term	1 week, months, years	• Planning of major maintenance of the wind power plant • Design and installation of wind farms, through the estimation of performance and the selection of the optimal size of the wind turbine at a particular site • Calculation of annual generation capacity	[16,20,33,36,40,59,63,67,74]

4.1. Very Short Term

In general, very short-term wind forecast models are used to obtain wind power profiles that allow faster adjustments to the wind turbine and to assess the volatility and intermittency of the resource to ensure successful integration into the grid.

A total of 44 articles were categorized within this time horizon. Table 1, reported in the link provided in the Supplementary Materials, offers more details regarding the articles cited in this category, the cluster to which they belong, their taxonomy (Figure 5), and details about the input variables of the model, sampling times, data set used, country of precedence, and finally, the models used to validate each of the proposed models. From the analysis of Table 1 in the Supplementary Materials, below, some discussions are pyt forward in this regard.

Of the 44 referenced articles, 70.5% correspond to the wind speed forecast and 18.2% to the wind power forecast, with a lower percentage being the forecast of wind speed and power, the forecast of wind and solar power, the forecast of wind speed and solar radiation simultaneously, and finally the "Others" category. This category is made up of articles correlated with the topic, but that do not use a forecast model that predicts wind speed or power, which is why they have been omitted from the quantitative analysis that is carried out later. Figure 8a shows the percentage distribution according to the forecast objective mentioned above.

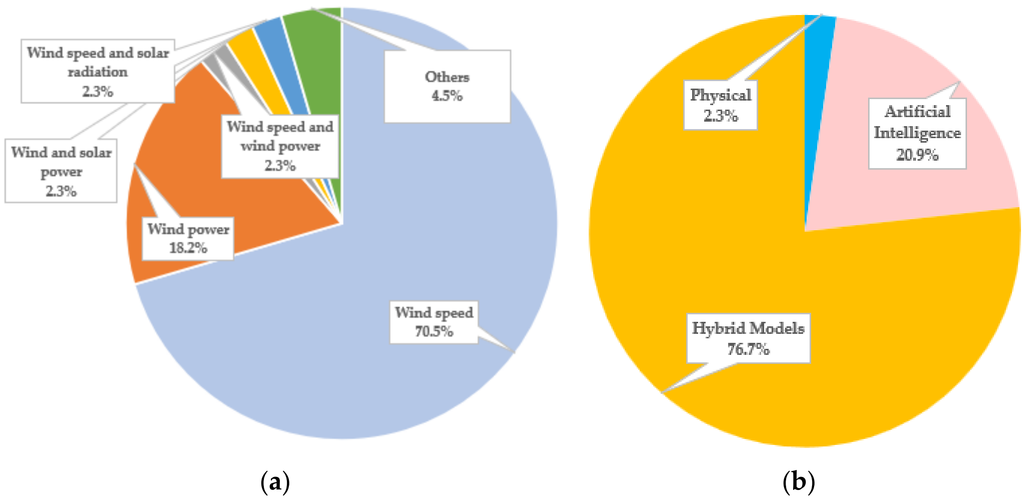

Figure 8. (**a**) Percentage distribution of the forecast objective of the very short-term models. (**b**) Percentage distribution of very short-term forecasting methods.

4.2. Short Term

This category is made up of 31 articles. The classified references are detailed in Table 2 with their respective applications. In addition, Table 2, reported in the link provided in the Supplementary Materials, offers further details regarding each of the categorized articles. The references with more than one time horizon and that qualify as very short and short-term models are [20,24,32,69,71,86], and these have been excluded from Table 2 of the provided in the Supplementary Materials considering that they are repeated and have been previously detailed in Table 1 of said Supplementary Materials. From Table 2, provided in the Supplementary Materials, it is observed that the prediction objective is mainly concentrated in the wind speed forecast, with a percentage of 64.5%. The second and third places are occupied by the wind power forecast and the wind-speed and -power forecasts with percentages of 32.3% and 3.2%, respectively (see Figure 9a).

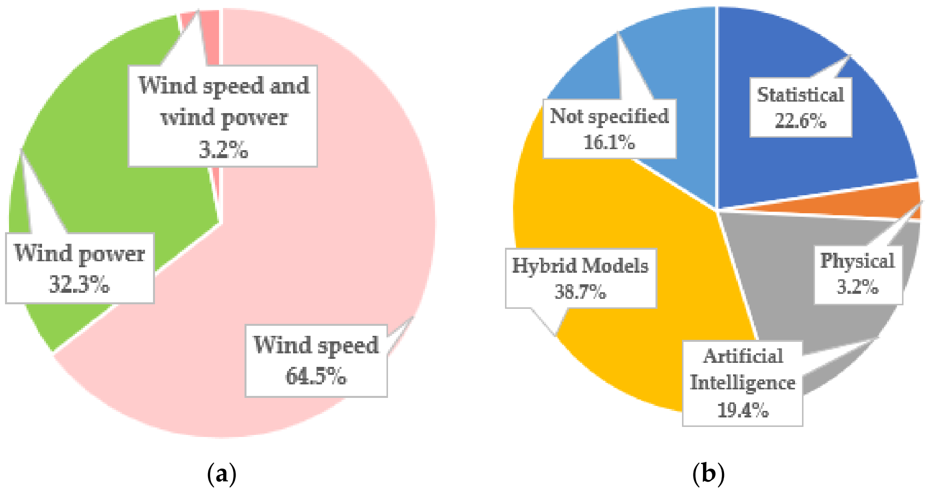

Figure 9. (**a**) Percentage distribution of the forecast objective of short-term models. (**b**) Percentage distribution of short-term forecasting methods.

Regarding the most-used forecasting methods, 38.7% correspond to hybrid models, 22.6% to statistical models, 19.4% to AI-based models, and finally, 3.2% to physical models (Figure 9b). Compared to the very short-term horizon, statistical forecasting methods are still relevant, although their use could also mean a reduction in the accuracy of the forecasts. In addition, 16.1% of the reviewed articles do not indicate the forecast method used; however, they use wind-speed and -power forecast models for different purposes. Unlike very short-term forecasts, whose field of application is mainly directed to the management of wind farms, short-term forecast models have a greater application in areas related to energy management at distribution, MGs, and low-voltage smart grids that have a lower penetration of wind energy; this can be seen reflected in Table 2 provided in the Supplementary Materials. Finally, 74.2% of the models have a deterministic approach and 25.8% probabilistic.

4.3. Medium Term

The medium-term models include a total of 11 articles, as seen in Table 3, reported in the link provided in the Supplementary Materials. The references that qualify as very short-term [20,32,59] and short-term [19,20,32,37,70] models have been excluded from Table 3 provided in the Supplementary Materials, since they have already been previously detailed in Tables 1 and 2 of said Supplementary Materials.

With respect to the prediction objective, the wind speed forecast continues to predominate with percentages of 54.5% and 36.4% for the wind power forecast (Figure 10a). Like the very short-term horizon, the "Others" category refers to articles whose forecast objective is not wind speed or power forecast, but for which the subject studied is highly correlated with the subject of study. These articles have been omitted for the quantitative analysis below. The references of the articles that make up this category are shown in Table 2 with their respective applications. The most-used forecasting methods are still hybrid, with percentages of 50.0% and 40.0% for AI-based models and 10.0% for physical models (Figure 10b). Statistical models have zero participation in these types of forecast. The deterministic approach predominates with a percentage of 80.0% versus a probabilistic percentage that corresponds to 20.0% acceptance.

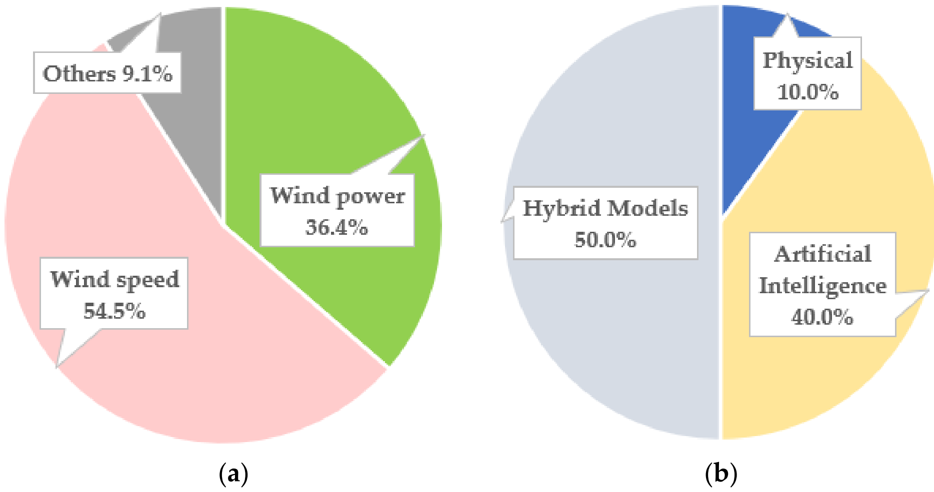

Figure 10. (**a**) Percentage distribution of the forecast objective of medium-term models. (**b**) Percentage distribution of medium-term forecasting methods.

4.4. Long-Term

A total of nine articles were established in this category. The references with more than one time horizon and that classify within the very short-term models are [20,59,63], the short-term models are [20], and finally, the medium-term ones are [20,59]. These articles, as in previous cases, have been omitted from Table 4, reported in the link provided in the Supplementary Materials, considering that they have been previously detailed. As in the other horizons, the domain of the wind speed forecast continues to be evident with a percentage of 66.7%, followed at a lower percentage by the wind power forecast and the forecast of speed and solar irradiation, with percentages of 11.1% (Figure 11a). The "Others" category is made up of one article and has been omitted from further analysis. The references and applications of the long-term models are shown in Table 2.

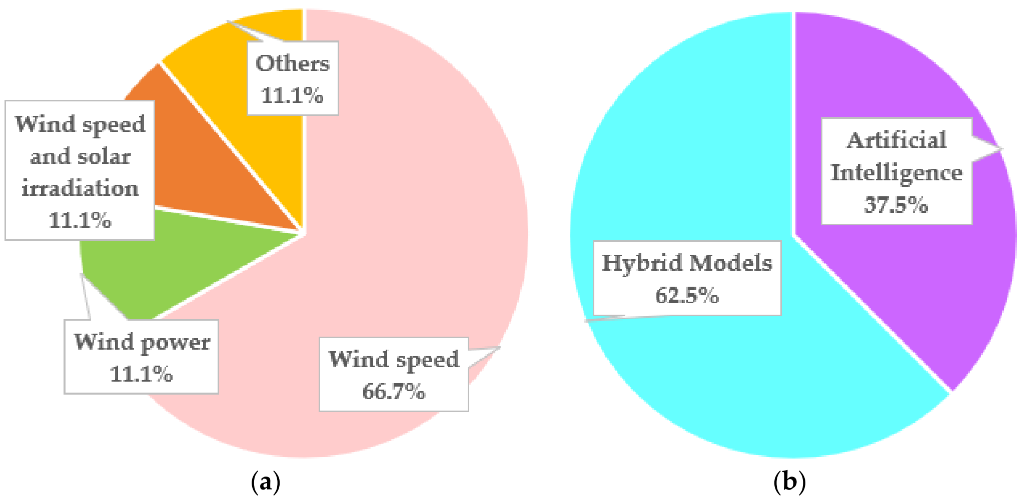

Figure 11. (**a**) Percentage distribution of the forecast objective of long-term models. (**b**) Percentage distribution of long-term forecasting methods.

It is observed that the trends indicate a predominance of hybrid forecasting methods and forecasting techniques based on artificial intelligence, with acceptance percentages of 62.5% and 37.5%, respectively. The physical and statistical prediction models have a null percentage of participation for this type of forecast (Figure 11b). Regarding the consideration of the error or uncertainty of the forecast, only 12.5% of the models have a probabilistic approach versus 87.5% of the deterministic models.

In summary, it can be concluded that trends lean towards wind speed forecasting through hybrid forecasting methods, with a deterministic approach at all time horizons. Most of the articles reviewed in this analysis were categorized as very short-term models, with 46.2% belonging to the rest of the forecast horizons. This indicates that there is a greater interest on the part of the scientific community in reducing the uncertainty attributed to wind generation, which mainly integrates traditional generation systems.

4.5. General Discussions

4.5.1. Calculation Time

The predominant models for wind generation forecasting are hybrid models, which offer high precision; however, their high complexity can interfere with the required calculation times. This is where statistical models gain strength, and, despite not offering high precision, can be functional due to their simplicity and rapid execution. Few authors include the computational effort required by the models when they run the validation tests [20,41,53,57,63,64,83,85,90,98]; however, this factor can have a significant influence when executing a forecast model for a specific task.

4.5.2. Model Efficiency

The efficiency of the models is usually measured through so-called "performance metrics", the most common being the the Mean Square Error (MSE), [55], Mean Absolute Error (MAE) [86], Mean Absolute Percentage Error (MAPE) [88], and the Root Mean Square Error (RMSE) [41]. The mathematical expressions of the mentioned performance metrics are shown in Table 3 below, where $\hat{y}$ represents the results obtained from the forecast, y the actual data, and n the number of actual data.

Table 3. Performance metrics used to evaluate forecasting models.

Indicator	Equation
MSE	$\frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^{2}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y-\hat{y}\rvert$
MAPE	$\left(\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y-\hat{y}}{y}\right\rvert\right)*100$
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^{2}}$

However, the measurement of the efficiency of forecast models is not standardized, and the authors use performance metrics in a non-homogeneous way when verifying the validity of the model. Other frequent metrics that have been detected in the analysis of the state-of-the-art are: the Coefficient of Determination (R2) [96], Symmetrical MAPE (SMAPE) [86], Explained Variance (EV) [20], Median Absolute Error Regression (MAER) [20], Index Agreement (IA) [94], Average Error (AE) [85], Bias2 which reflects the stability and precision of the model [76], and Standard Deviation Error (SDE) [93]. In addition to performance metrics, some authors incorporate statistical tests to check the efficiency of the models. Some of the statistical tests observed in this literature review are: the Score tests, [20], the Friedman, Friedman Aligned, and Quade tests [56], the bias-variance statistics framework [68], and the Diebold–Mariano (DM) [88].

Finally, the performance metrics most used to evaluate probabilistic forecast intervals correspond to Forecasting Interval Coverage Probability (FICP) and Forecasting Interval Normalized Average Width (FINAW) [93,94,97]. The mathematical expressions are detailed below in Table 4, where U_i and L_i represents the upper and lower limits of the forecast interval, N represents the number of testing sets, $y_{\max}$ and $y_{\min}$ are the maximum and minimum values of the targets in the forecast, and g_i is the value number contained in the forecast interval.

Table 4. Performance metrics used to evaluate forecast intervals.

Indicator	Equation
FINAW	$\frac{1}{N}\sum_{i=1}^{N}\frac{U_i-L_i}{y_{\max}-y_{\min}}*100\%$
FICP	$\frac{1}{N}\sum_{i=1}^{N}g_i*100\%$

4.5.3. Data Sets

The data set determines the input variables of each model; therefore, several aspects must be considered when making the predictions: the meteorological conditions of the area, the topography, and the number of data neceSSary to make the prediction. A data set belonging to a geographical area with great climatic variability or topography that is difficult to access has a negative impact on wind generation predictions, since its predictions are more difficult than other data sets. This is very important when validating the model. Of the articles reviewed in this document, it is observed that the most frequently used data sets come from countries such as China, the United States, India, and Spain. Figure 12 shows the percentage distribution by country. The "Others" category is made up of countries whose percentage of frequency is low compared to the rest of the countries, and 15.66% of the articles do not specify the origin of the data used.

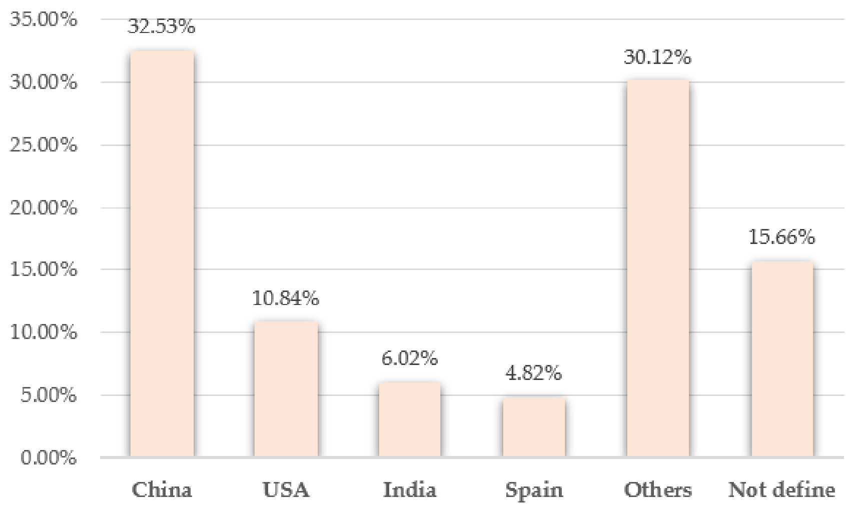

Figure 12. Percentage distribution of countries with data sets most used to evaluate forecast models.

4.5.4. Forecast Scenarios

Evaluating the forecast models in different scenarios, different data sets, or different seasons of the year provides greater robustness to the proposed models. Many studies propose this approach to validate and generalize the application of their forecast models in different places and conditions [20,32,38,39,56].

5. Conclusions

The penetration of wind energy into electrical energy systems has led to the reduction in pollution observed in recent decades. However, this generation source presents randomness associated with the forecasts of the primary resource that they use for the generation of electricity. In this context, the accuracy obtained in these forecasts contributes to the optimal management of electrical networks. Based on the aforementioned, this document presents a review of the literature based on the bibliometric analysis of wind-speed and -power forecasts. The publications were analyzed and synthesized by cluster. Most of the works analyze the wind speed or power forecasts of large-generation wind farms and, secondly, the forecast models applied in distribution networks in the form of distributed generation or within a microgrid. The studies found that are aimed at predicting the behavior of wind microturbines installed in residential and urban areas are scarce.

On the other hand, it is observed that hybrid forecasting methods are the most-used regardless of their forecast horizon. Individual forecasting algorithms have been replaced by mixed algorithms combining mostly AI-based and statistical methods. The most frequent combination in this type of forecasting corresponds to data preprocessing and parameter optimization. EMD and ICEEMDAN stand out as data preprocessing techniques; however, with respect to parameter optimizers, a specific trend cannot be established.

In relation to the forecast horizon, it is observed that most of the articles analyzed focus on the study of forecast models with a time frame of less than 4 h ahead. The prediction of wind speed and wind power with a minute horizon contributes mainly to the analysis of safety and stability in the operation of electrical systems. These tools allow reasonable adjustments to be made to the planning of the generation reserve, which avoids the overestimation of the mentioned reserve and contributes to reducing the impact of voltage fluctuations on the equipment connected to the network.

From the articles analyzed in this document, various research opportunities are identified. In the case of very short-term and short-term forecast models, there is the possibility of studying the accuracy of integrating physical forecasting methods within hybrid models as a result of the changing nature of wind speed and its relationship with meteorological variables. Additionally, within the postprocessing data techniques in hybrid models, there is the opportunity to investigate whether the correction of the forecast values obtained could significantly reduce the error caused by the forecast models.

Finally, as a result of the constant growth of distributed generation in smart grids, research opportunities are identified; these would allow researchers to predict the wind behavior of microturbines installed in urban and residential areas where the turbulence and morphology of the area contribute to determining the impact of wind energy production. The aforementioned aspects indicate that wind-speed and -power forecasts continue to be a developing research topic, as a result of current technological advances and the modernization of electrical networks.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en15186545/s1, Supplementary Materials of State of Art Using Bibliometric Analysis of Wind Speed and Power Forecasting Methods Applied in Power Systems.

Author Contributions: Conceptualization, A.L., G.C. and A.R.Q.; methodology, A.L. and J.E.C.; formal analysis, A.L., J.E.C. and A.R.Q.; investigation, A.L., J.E.C., G.C., A.R.Q., M.M. and G.S.; writing—original draft preparation, A.L., J.E.C., G.C., A.R.Q., M.M. and G.S.; writing—review and editing, A.L., G.C., A.R.Q. and J.R.; supervision, J.R.; project administration, A.R.Q. and J.R.; funding acquisition, J.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This work was supported, in part, by DAAD, CONICET, and CYTED (through the network 718RT0564) and by the CERVERA program for Outstanding Research Centers (CER-20191019). In addition, the research was funded under grant PDTS 2020-2022 of UNSJ and SECITI, and under project PYC20 RE 078 USE of Junta de Andalucía.

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

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