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Review

Wind power generation: A review and a research agenda

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A B S T R A C T

The use of renewable energy resources, especially wind power, is receiving strong attention from governments and private institutions, since it is considered one of the best and most competitive alternative energy sources in the current energy transition that many countries around the world are adopting. Wind power also plays an important role by reducing greenhouse gas emissions and thus attenuating global warming. Another contribution of wind power generation is that it allows countries to diversify their energy mix, which is especially important in countries where hydropower is a large component. The expansion of wind power generation requires a robust understanding of its variability and thus how to reduce uncertainties associated with wind power output. Technical approaches such as simulation and forecasting provide better information to support the decision-making process. This paper provides an overview of how the analysis of wind speed/energy has evolved over the last 30 years for decision-making processes. For this, we employed an innovative and reproducible literature review approach called Systematic Literature Network Analysis (SLNA). The SLNA was performed considering 145 selected articles from peer-reviewed journals and through them it was possible to identify the most representative approaches and future trends. Through this analysis, we identified that in the past 10 years, studies have focused on the use of Measure-Correlate-Predict (MCP) models, first using linear models and then improving them by applying density or kernel functions, as well as studies with alternative techniques, like neural networks or other hybrid models. An important finding is that most of the methods aim to assess wind power generation potential of target sites, and, in recent years the most used approaches are MCP and artificial neural network methods.

Contents

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Abbreviations

ANNs	artificial neural networks
ARIMA	autoregressive integrated moving-average
ARMA	autoregressive moving-average
BNs	bayesian networks
BW	bivariate weibull
CNA	citation network analysis
CRMSE	centered root mean squared error
CRO-SL	coral reefs optimization with substrate layer
CRPS	continuous ranked probability score
GCS	global citation scores
HAR	hammerstein auto-regressive
IIR-MLP	infinite impulse response multilayer perceptron
IPCC	intergovernmental panel on climate change
LAF-MLN	local activation feedback multilayer network
LCS	local citation scores
LR	literature review
MAE	mean absolute error
MAPE	mean absolute percentage error
MBE	mean bias error
MCAE	mean circular absolute error
MCP	measure-correlate-predict
ME	mean error
MPE	margin percentual error
MRE	mean relative error
MSE	mean squared error
NMAE	normalized mean absolute error
NRMSE	normalized root mean squared error
NWP	numerical weather prediction
PHEVs	plug-in hybrid electric vehicles
RAE	relative absolute error
RME	root mean error
RMSE	root mean squared error
RNN	recurrent neural network
RQs	research questions
RRSE	root relative square error
RTSS	real-time software simulator
SLNA	systematic literature network analysis
SLR	systematic literature review
SMAPE	mean absolute percentage error
TGARCH	threshold generalized autoregressive conditional heteroscedastic
TVARMA	time-varying threshold autoregressive moving average
twCRPS	threshold-weighted continuous ranked probability score
VARTA	vector-autoregressive-to-anything
WAsP	wind atlas analysis and application program
WoS	web of science

1. Introduction

The world is passing through a progressive energy transition. Recently Germany and other European countries, along with countries outside Europe such as China, India, USA, Brazil and Canada, have made a serious effort to reduce their dependence on fossil fuels, moving away from the hydrocarbon platform and setting up a renewable energy platform (Hossain, 2015). Promoting renewable energy resource incorporation, in particular wind power, in the electricity mix, is one of the strategies used to achieve this goal and mitigate greenhouse gas emissions (González et al., 2017; Ramadan, 2017; Sovacool, 2016). According to the Intergovernmental Panel on Climate Change (IPCC), global warming is a reality and human activities are responsible for causing approximate warming of 1.0 °C above pre-industrial levels, a figure that is likely to reach 1.5 °C between 2030 and 2052 (Masson-Delmotte et al., 2018). To cope with the environmental challenges posed by global warming, energy generation from renewable sources should be increased as a precautionary measure, not only for energy security, but also to foster a healthier environment (Ramadan, 2017).

Wind is considered an attractive energy resource because it is renewable, clean, socially justifiable, economically competitive and environmentally friendly (Burton et al., 2011). Therefore, the outlook is for increasing participation on wind power in the future, up to at least 18% of global power by 2050 according to the International Energy Agency (IEA, 2013). The Global Wind Energy Council indicated that in 2017 the cumulative total was 11% greater than the 2016 year-end total of 487 GW, and the global production remained above 50 GW in 2017. Furthermore, according to the Global Wind Energy Council, “Beyond the statistics, wind power is becoming a fully commercialized, unsubsidized technology; successfully competing in the marketplace against heavily subsidized fossil and nuclear incumbents” (GWEC, 2018). Among the countries that are promoting wind as a renewable energy resource are 30 countries with more than 1 GW of installed capacity and nine countries with more than 10 GW, including China, USA, Germany, India, Spain, UK, France, Brazil and Canada (GWEC, 2018).

The fluctuating nature of wind, despite the high penetration of wind energy, poses several challenges when integrating wind power into the electric grid, since high costs can be involved for construction of wind farms as well as prior and ongoing assessment studies. Contrary to conventional energy sources, wind speed varies both spatially and temporally, generating fluctuations in wind energy output (Fernández-González et al., 2018). Weather variables such as wind direction, temperature, pressure and humidity, among others, influence wind power production (Sharifian et al., 2018). Hence, to integrate wind power into the electric grid requires estimates, at least, of future wind speed values (Ammar et al., 2018). The development of new techniques to improve understanding of these variables, through simulation, forecasting, distribution curve fitting, filtering and modeling, allows making better decisions about expansion of the wind sector and better management of the electricity system. Additionally, accurate estimation of wind speed can improve the safety, reliability and profitability of the operation of wind farms (Staid et al., 2015). This involves understanding the wind regime of a specific region, to enable more accurate forecasting of future values based on past ones.

The future values of wind power generation comprehend three different time horizons: short, medium and long-term. Short-term forecasts are mainly useful for operational purposes (i.e., economic load dispatch planning, load increase/decrease decisions), while medium-term forecasts aim to increase operational security of day-ahead electricity markets and corroborate online/offline decisions. Finally, long-term forecasts provide information for power system risk assessment and also to identify potential for wind power generation in specific areas, providing valuable data for energy planners (Soman et al., 2010).

On the other hand, in countries like Brazil, even though wind power capacity is growing (González et al., 2017), promoted mainly by incentives for renewable energy sources, the current electric dispatch model still does not consider wind energy output endogenously. So, defining mechanisms to introduce wind power into the hydro-thermal dispatch model requires reliable estimation of wind power to support the development of scenarios and policies considering the migration from the current dispatch model to a hydro-thermal-wind dispatch model. In this context, this paper describes an innovative approach to determine future trends and understand the current state of the art of wind power generation models. The focus of this study is on future wind speed/power trends for medium and long-term, since both horizons could be considered into the aggregate planning, while short-term is mainly used for operational purposes. To achieve the proposed goal, we examine the following research questions (RQs):

- RQ1: What are the current methods and models used in the field of wind power generation?
- RQ2: Which type of analysis do these models involve?
- RQ3: How have these methods evolved over time?
- RQ4: What are the main variables and performance measures considered?
- RQ5: What are the trends for the future?
- RQ6: What are the limitations of current research solutions?

Regarding wind energy, several reviews have focused on different topics, such as development of wind power resources and technologies (Cherubini et al., 2015; Herbert et al., 2007; Ma and Lu, 2011; Sherif et al., 2005), wind speed or wind power forecasting (Foley et al., 2012; Lei et al., 2009; Okumus and Dinler, 2016; Qian et al., 2016; Soman et al., 2010; Y. Zhang et al., 2014; Zhao et al., 2011), and wind resource assessment (Carta et al., 2013; Murthy and Rahi, 2017; Wen et al., 2009). Although providing valuable information, none of them present a scientific framework considering Systematic Literature Network Analysis (SLNA), the core innovation of this study. SLNA combines two research techniques: systematic literature review (SLR) and citation network analysis (CNA), and it offers an additional way to carry out SLR, allowing both qualitative and quantitative analyses. Research areas such as supply chain risk management, smart factories and occupational health and safety issues have employed the same method (Colicchia and Strozzi, 2012; Fan et al., 2014; Maçaira et al., 2018; Strozzi et al., 2017). Hence, the novelty of this study is the use of those two scientific tools to understand the current state of the art of wind energy generation for decision-making processes and an overview of ongoing and future trends.

The paper is organized into five sections, starting with this introduction. Section 2 describes the research method used to identify, select and evaluate the most relevant articles (from indexed journals) on wind power forecasting, along with a brief description of SLR and CNA techniques and bibliometric analysis. Section 3 presents the SLR and CNA results. Section 4 discuss about the main findings. Finally, Section 5 presents our concluding remarks.

2. Research methodology

The SLNA method, proposed by Colicchia and Strozzi (2012), combines the benefits of SLR and CNA. According to the authors, SLNA has advantages over the traditional systematic review process, allowing analyzing the most representative studies in a more rigorous, scientific and objective way. SLR mainly describes, summarizes, evaluates and clarifies the literature related to a selected area, but does not offer any specific comparison to determine the nature of these studies (i.e., the knowledge structure that allows creating the bases of a research field) (Colicchia and Strozzi, 2012; Denyer and Tranfield, 2009; Fan et al., 2014). CNA's main purpose is to identify research domains, using summaries, obtained during the SLN, to reveal the research field's evolution and to map paradigm changes and ruptures (Colicchia and Strozzi, 2012; Fan et al., 2014; Hummon and Dereian, 1989), offering a dynamic perspective to literature review.

Through SLR it is possible to identify answers for the research questions, presented in Section 1. In turn, CNA offers a deeper understanding of the research field's cognitive structure and how knowledge has evolved in a specific research area, giving a prospective view to the subject. It enables recognizing the most relevant papers in a field and those that have most contributed to knowledge, which are defined by networks delineated through main path analysis. Therefore, the SLR and CNA methods are complementary, combining qualitative with quantitative analysis. Applying both methods provides high-quality results and enables researchers to identify gaps and future trends in a research area. To strengthen the quantitative analysis, other networks such as co-citation and co-word networks, can also be applied (Zhao and Strotmann, 2015).

Co-citation analysis measures the frequency of jointly cited documents, allowing researchers to identify and ascertain the importance of outstanding scholars in different disciplines (i.e., to identify authors that have received peer-recognition indicated by citation patterns) (Small, 1973). A similar network is built by co-word analysis, which involves study of the co-occurrence of words in a text, using two or more representative words found together in the articles' keywords or abstracts, for instance. Those networks can detect existing clusters or research lines in a certain field, where the joint occurrence of words represents the concepts contained in the text in cases where two or more representative words appear together (Callon et al., 1991). With the co-citation and co-words techniques it is possible to generate maps to visualize researchers' influences and the knowledge structure, complementing the SLNA process.

The SLNA approach follows the structure in which SLR is responsible for the qualitative analysis and CNA for the quantitative analysis, using part of the SLR results. SLNA includes the following steps: *(i)* formulate the study question(s); and *(ii)* apply SLR, which encompasses search, selection and evaluation of articles. Then the remaining papers pass through the CNA, which is composed of: *(iii)* definition of the citation network obtained via the main path analysis (determining the research field's evolution), and *(iv)* analysis of the results of SLNA. The following sub-sections present a more thorough description of the SLR and CNA methods.

2.1. Systematic literature review – SLR

A literature review (LR) serves to analyze, understand and summarize the literature about a specific subject in an integrated way, visualizing new frameworks, approaches and future perspectives (Torraco, 2005). Considering this, SLR can be understood as a specific framework (approach) to execute a literature review. In this respect, Grant and Booth (2009) and Petticrew and Roberts (2006) identified different LR types: critical mapping or systematic mapping, meta-analysis, mixed studies, overview, meta-synthesis, rapid, scoping, state-of-the-art, systematic, systematized, umbrella, narrative, conceptual, realistic and expert.

Usually, reviews are not necessarily rigorous or explicit in their methods or procedures, but unlike narrative or descriptive reviews, SLR is performed in a scientific and transparent way (Tranfield et al., 2003), through a replicable and updateable process. Systematic reviews are objective and systematic, eliminating duplicated and unnecessary studies. According to Reim et al. (2015), "previous researchers have argued that using such an approach to review literature can ensure that bias (i.e., systematic error) is limited, chance effects are reduced and the legitimacy of data analysis is enhanced" in all aspects of the review process. In this sense, it is "less of a discussion of the literature and more of a scientific tool" (Petticrew and Roberts, 2006). Studies using this technique were first published in medical science (Glasziou et al., 2000; O'Connor et al., 2008; Stroup et al., 2000), but nowadays it is also applied in areas such as management (Colicchia and Strozzi, 2012; Denyer and Tranfield, 2009; Thomé et al., 2012; Tranfield et al., 2003) and engineering (Kitchenham, 2004; Rasool et al., 2015) and time series (Maçaira et al., 2018).

SLR uses a standard procedure in order to address and answer the RQs. This standard procedure is divided into three phases, to identify, select and review scientific articles associated with the research area of interest. Those three main phases are presented in Fig. 1.

The first phase includes definition of the scientific databases to be searched as well as keywords and search queries. In addition, the first paper exclusion criterion is implemented in this phase. In this study, Scopus and Web of Science (WoS) were the search engines chosen. Although these two platforms provide information from different sources (journals, conference proceedings, abstracts and books), the study only focuses on papers published in peer-reviewed scientific journals. With the search engines defined, the next task consists of defining keywords and queries to find the relevant articles. Here these were defined by all six authors during a brainstorming process, considering the main subject (wind power or wind energy), the approach used (e.g., forecasting, simulation, etc.) and time horizon considered (e.g., short, medium or long-term). Table 1 presents the 18 keywords selected which were used for each search engine (Scopus and WoS) until December 2018. Table 2 contains the two queries (one for each of the scientific databases).

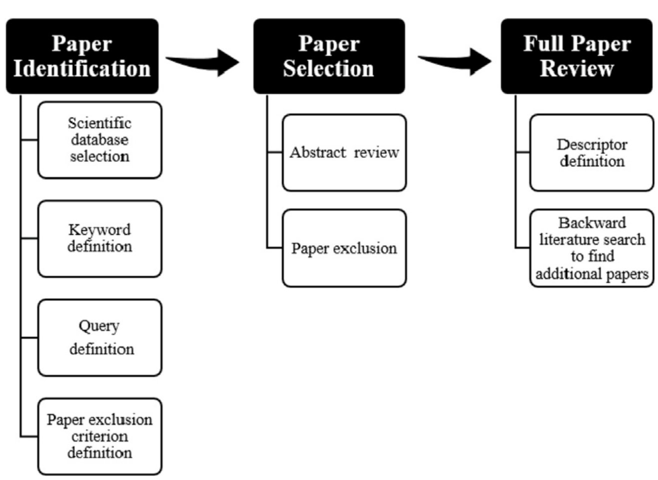

Fig. 1. Paper selection scheme.

The last step of the first phase intends to filter the articles considering specific exclusion criteria. According to Rasool et al. (2015), "the inclusion and exclusion criteria are applied for selecting relevant essential studies to answer the RQ. Inclusion and exclusion criteria are boundaries that are used to include relevant studies and filter irrelevant studies which are extracted through search queries." Therefore, only articles from journals written in English were considered and double-counting was eliminated.

Other exclusion criteria were:

- Articles not related to the subject or research area: here only articles strictly related to wind power forecasting/simulation should remain in the database.
- Forecasting horizon studied: according to Zhao et al. (2011) and Foley et al. (2012), wind power forecasting is classified considering different time scales: short-term (ranging from 1 h to 72 h ahead), medium-term (ranging from 72 h to 7 days ahead) and long-term (ranging from 1 week to 1 year or more ahead). In this study, only medium and long-term were considered, so articles that study short-term future values were excluded, since this horizon is basically focused on the operation management and the spot market, thus excluding the aggregated planning.

The second phase entails reading the abstracts and selecting the papers, so abstracts were read by four authors, who independently determined whether to reject or accept the article for full reading. According to Esteves et al. (2015) "if an article receives more acceptances than rejections, it is accepted for full reading, and vice-versa. If the number of acceptances and rejections matches, the researchers have to decide together how to classify the paper." Convergence level between the four researchers' evaluation was estimated through an intercoder reliability rate called Cohen's kappa (Cohen, 1968). The last phase involves reading the entire articles. During this reading, additional relevant papers could be identified in the reference sections. This full reading aims to extract (collect) detailed information about the studies, to synthetize the most relevant aspects and characteristics. Hence, a descriptor database was conceived to be fed during the full reading. Table 3 contains the information gathered for the descriptor database. The purpose is to summarize each article's main aspects, including retrieved information from the scientific database, grouped as general information and characteristics collected during the reading process. In order to answer the research questions, it is necessary to define both data and model characteristics. Initially, the input and output variables used during the processes are identified. The modeling process can use one or more input variables, such as wind speed and other climate variables like direction and humidity, or even use wind power as an output variable. The models' type, purpose, forecast horizon and evaluation metrics are also identified (Table 3) because the application varies according with the modeling goals.

2.2. Citation network analysis – CNA

As already mentioned, CNA is used to identify knowledge evolution over time and to determine present and future trends in a certain research area, enabling the understanding and mapping of knowledge ruptures and paradigm shifts (Colicchia and Strozzi, 2012; Fan et al., 2014; Hummon and Dereian, 1989). It is also a useful tool to classify relevant topics and research gaps. Hence, it provides a foundation and paths for future studies because it

Table 1
Keywords selected.

	Wind related keywords	Approach related keywords	Horizon related keywords
Inclusion	Wind speed, wind power, wind energy, wind production, wind output.	Forecast, forecasting. Prediction, predicting. Simulate, simulation, simulating.	Medium-term, medium-range. Long-term, long-range.
Exclusion	–	–	Short-term, short-range.

Table 2
Queries considered.

Web of Science	Scopus
TS = ("wind speed"	(TITLE-ABS-KEY("wind speed") OR
OR "wind power"	TITLE-ABS-KEY("wind power") OR
OR "wind energy"	TITLE-ABS-KEY("wind energy") OR
OR "wind production"	TITLE-ABS-KEY("wind production") OR
OR "wind output")	TITLE-ABS-KEY("wind output"))
AND TS = (forecast OR forecasting	AND (TITLE-ABS-KEY("forecast") OR
OR prediction OR predicting	TITLE-ABS-KEY("forecasting") OR
OR simulation OR simulating	TITLE-ABS-KEY("prediction") OR
OR simulate)	TITLE-ABS-KEY("predicting") OR
AND TS = ("medium term" OR "medium range"	TITLE-ABS-KEY("simulate") OR
OR "long term" OR "long range")	TITLE-ABS-KEY("simulation") OR
NOT TI = ("short term" OR "short range")	TITLE-ABS-KEY("simulating"))
	AND (TITLE-ABS-KEY("medium term") OR
	TITLE-ABS-KEY("medium range") OR
	TITLE-ABS-KEY("long term") OR
	TITLE-ABS-KEY("long range"))
	AND NOT (TITLE("short term") OR
	TITLE("short range"))

Table 3
Descriptor database.

General Information	Data Characteristics	Modeling Characteristics
– Authors	– Time series type: wind power, wind speed, direction, temperature, humidity	– Purpose: forecasting, simulation, distribution fitting, etc.
– Article's title	– Time series input: wind speed, wind power, direction, climatological variables, etc.	– Model types: statistical, computational intelligence, physical or hybrid models
– Journal	– Time series output: wind speed, wind power, direction, climatological variables, etc.	– Forecast horizon: number of steps ahead that might depend on the data frequency
– Year	– Data frequency: minutes, hours, days, months or years	– Forecast type: single-step or multi-step
– Number of citations	– Time series length: total observations	– Evaluation Metrics: MAE, MSE, MAPE, R2, etc.
– Keywords	– Region: Africa, Asia, Europe, North America, South America, Central America	– Simulation length
	– Country analyzed	

determines promising research subjects. CNA was first applied by Garfield et al. (1964), followed by Garner (1967), who presented graph theory applications specifically for citation network analysis. To determine a research domain's main path, two significant advances were achieved by proposing to use three different indexes to compute the transversal weights in a citation network (Hummon et al., 1990; Hummon and Dereian, 1989; Hummon and Doreian, 1990).

A citation network is conceived for illustration, representing studies published or authors associated with a field of research through a network, containing nodes and arrows. Its nodes represent papers and its arrows the existing links between them. Thus, the arrows indicate the knowledge flow, indicating from which paper the knowledge and information came that made a new contribution. The citation network uses information from a citation matrix, formulated based on the articles' references. This square matrix contains only papers chosen for full reading during the SLR process. If one article cites another article in the matrix, a value "1" is assigned, representing a citation relationship between them; otherwise the value "0" is attributed (Colicchia et al., 2017).

Through CNA it is possible to rank articles through two different approaches: based on papers 'number of citations' or 'closeness centrality' (De Nooy et al., 2018; Colicchia and Strozzi, 2012; Hummon and Dereian, 1989), representing an article's global citation score (GCS) and local citation score (LCS), respectively. In other words, the LCS denotes the number of times that an article is cited inside the current dataset, while the GCS corresponds to the number of times that the article was cited. A high LCS means that a paper is relevant in the research field, whereas a high GCS indicates the paper is considered important by the academic field worldwide. The closeness centrality identifies the papers, in the network, cited by highly cited papers, indicating how an article is located among the analyzed papers, considering the fewest possible connections (Knoke and Yang, 2008), therefore quantifying the relevance of articles' contribution.

2.2.1. Main path analysis

Main path analysis provides a dynamic perspective to network analysis. This technique determines the most prominent articles of a research area, spotlighting seminal ones that are still considered core references for further works (Lucio-Arias and Leydesdorff, 2008). To define a citation network's main path, a normalized transversal weight needs to be estimated for each article, to calculate the number of times that a connection between articles was established in a citation network. This is a proportion between of all source paths and sink nodes (De Nooy et al., 2018; Fan et al., 2014; Colicchia and Strozzi, 2012). In this sense, each node represents a specific article and the citation data are represented by the links among nodes (which could be sources or sinks). According to De Nooy et al. (2018), a source is defined as a node that does not cite others, while a sink is a node that is not cited by others. Hence, both nodes are, respectively, the starting and ending points of a citation network.

The normalized transversal weights are estimated using the search path count (SPC) method, considering each source vertex and selecting at each iteration the arcs with the highest weight, until the sink node is reached. After obtaining all the normalized weights, all the arcs with transversal weight lower than a certain cut-off value are removed from the citation network, leaving only the most relevant ones (De Nooy et al., 2018; Colicchia and Strozzi, 2012). There are different programs to build the citation network and main path, and in this study Pajek software is the one used (Batagelj and Mrvar, 1998).

2.2.2. Bibliometric analysis: Co-Word and Co-Citation

In bibliometric analysis, co-word analysis (also known as co-occurrence) identifies the conceptual structure and the main subjects of a field, allowing analyzing and tracking a research field's evolution along consecutive time periods (Callon et al., 1983). According to Coulter et al. (1998), co-word analysis reduces a space of keywords to a set of network graphs that effectively illustrate the associations between them. Research themes are identified by counting the number of documents in which the two keywords appear together. Co-citation analyzes the intellectual structure of a scientific research field (Small, 1973), indicating the connection between authors regarding the same topic. In other words, two articles are co-cited when they are jointly cited in one or more subsequent articles. This process is performed by counting the number of documents that contain the quoted one in their reference list (Zhao and Strotmann, 2015).

Here the co-word analysis was performed with the SciMAT software (Cobo et al., 2012), whereas the co-citation analysis employed two different programs: BibExcel to obtain the co-citation matrix (Persson et al., 2009) and Pajek to generate the co-citation network. Other programs can be used for the same purpose, such as UCINET (Borgatti et al., 2002), VOSViewer (van Eck and Waltman, 2010) and the Bibliometrix package of R (Aria and Cuccurullo, 2017).

3. Results

3.1. SLR results

3.1.1. General analysis

From the queries in the Scopus and WoS databases, 2825 articles were found (1667 articles in Scopus and 1158 in WoS). Of this total, 616 were removed from the database as duplicated articles, 716 were not published in indexed journals and 81 were not written in English. Those were the initial exclusion criteria applied. More than a half of the documents found through these two search engines were not considered for abstract reading, and at least 26% were conference proceedings, which is an exclusion criterion. Fig. 2 presents the results described above.

During the abstract reading process, most of the 1412 articles were rejected because they were outside the scope, having no relation with the research questions, leaving only 219 articles for full reading. Also, during the full reading, 76 articles were classified as out of scope. The intercoder index calculated for the articles' selection process (Cohen's kappa coefficient) presented a high level of agreement between the researchers (0.936). With the results of the selection, both SLR and CNA can be performed. Fig. 3 depicts the exclusion process.

Fig. 4 presents the publication evolution in the last 33 years, where it can be observed that wind energy studies started growing considerably after 2010, although there was a decrease in 2016 and 2017, before reaching a peak in 2018, with 24 articles published.

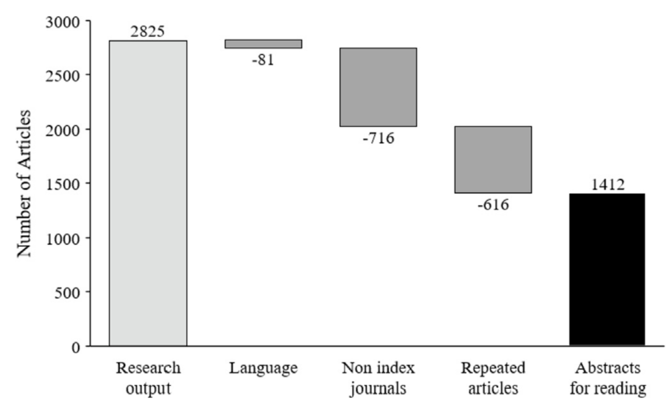

Fig. 2. Abstract selection.

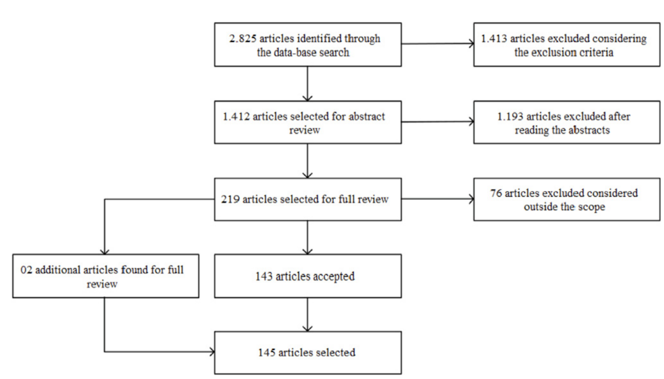

Fig. 3. Article selection process.

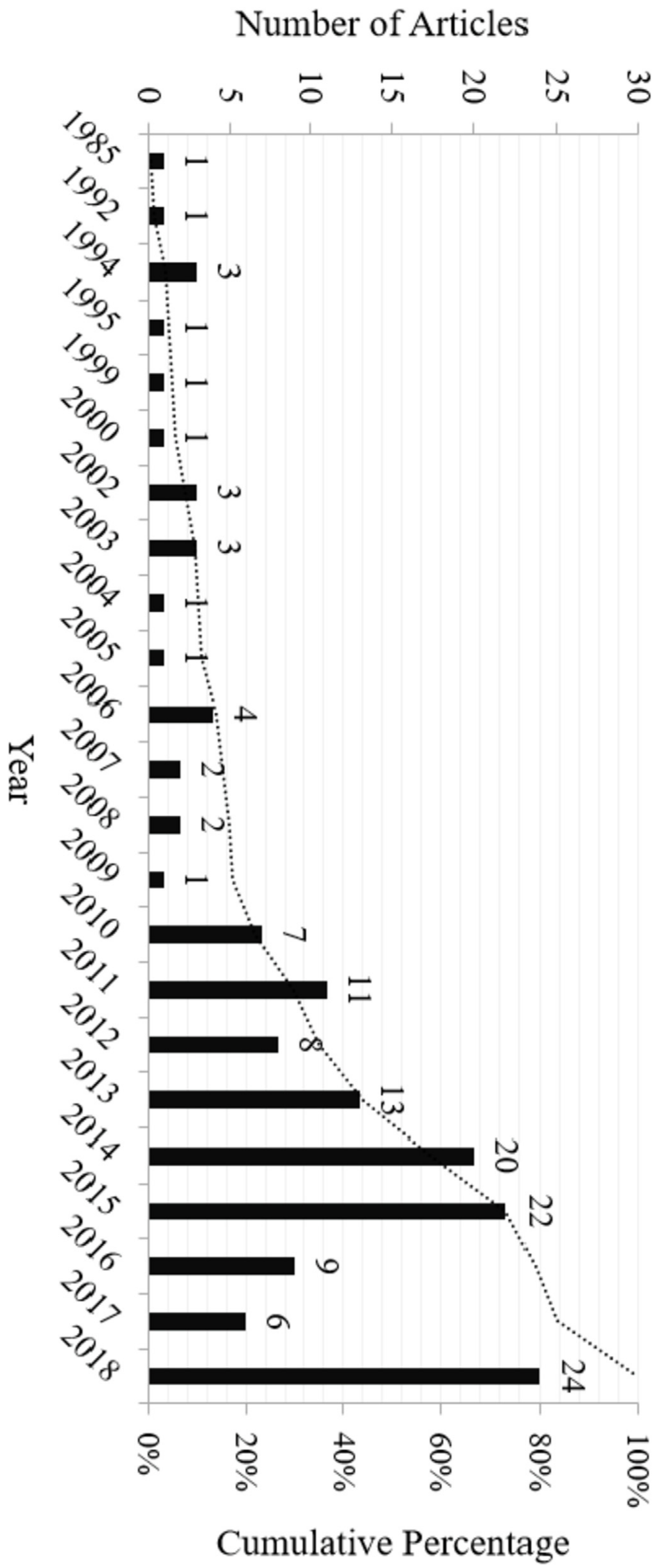

Fig. 4. Article publication evolution.

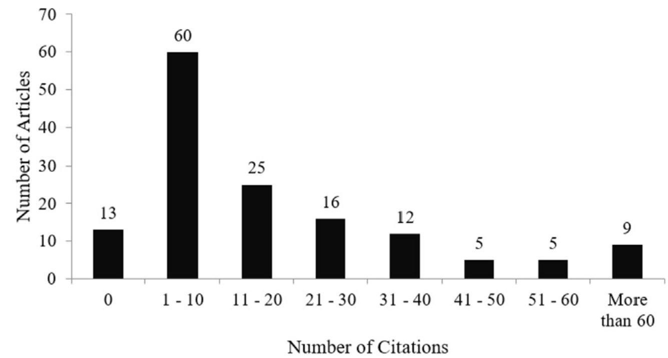

Fig. 5. Citation frequency.

From 2010 until 2018, a total of 120 articles were published (83% of the studies) and the remaining were published before 2010. This represents an average of 12 articles published per year.

From Fig. 5, it is possible to conclude that most of the articles published (whose results were obtained from the search engine - Scopus and WoS - until December 2018) have at least one citation, as only 9% do not have any citation, 41% have between 1 and 10 citations, 18% have between 11 and 20 citations and 32% have more than 21 citations. The most cited articles use forecasting and simulation techniques to address issues about power system operations, planning for connection or disconnection of wind turbines or even wind power potential. The five articles with the highest citation numbers are:

(i) Barbounis et al. (2006): This paper presents wind speed and wind power forecasting considering meteorological data using hourly information. These forecasts are used to schedule connection and disconnection of conventional generators and wind turbines to achieve low spinning reserve and optimal operating cost. The models used were three local recurrent neural networks: infinite impulse response multilayer perceptron (IIR-MLP), local activation feedback multilayer network (LAF-MLN) and diagonal recurrent neural network (RNN).

(ii) Nichita et al. (2002): The authors propose two modeling procedures for wind speed simulation to be used in real-time wind turbine simulators, where wind power systems involve high performance wind turbine simulators. This study uses simulators with a general structure, i.e., any type of servomotor, and includes a real-time software simulator (RTSS), which implements a mathematical model of the wind turbine and contains the wind speed generator.

(iii) Bilgili et al. (2007): This paper uses artificial neural networks (ANNs) to predict wind speed of any target station using neighboring measuring stations. The purpose of the article is to show that this method can be applied to forecast wind speeds for any location around sampled measuring stations, located in the eastern Mediterranean region of Turkey. This procedure has the same purpose as all the measure-correlate-predict (MCP) methods, whose objective is to predict wind speed for a specific target station, considering neighbor stations, providing a wind resource assessment.

(iv) Hill et al. (2012): The article sheds light on wind power's impact on future power systems by modeling diurnal and seasonal effects explicitly, and also considers the correlation of wind speed between geographical locations. This is done by applying autoregressive moving-average (ARMA) models to forecast univariate and multivariate time series, for use to synthesize wind speed and thus wind power time series with the correct seasonal, diurnal, and spatial diversity characteristics.

(v) Liu et al. (2012): The authors develop a two-stage stochastic unit commitment model to study the impacts of plug-in

Table 4
Number of articles by journal and citation.

Journal	Number of Articles	Number of citations
Renewable Energy	25	622
Wind Energy	10	177
Applied Energy	8	165
IEEE Transactions on Sustainable Energy	5	226
Energy	5	131
Journal of Wind Engineering and Industrial Aerodynamics	5	109
Energy Conversion and Management	4	82
Energies	4	23
IEEE Transactions on Energy Conversion	3	596
Energy Policy	3	121

hybrid electric vehicles (PHEVs) on power system operations and scheduling, considering wind power volatility and intermittency. The proposed model also addresses ancillary services provided by vehicle-to-grid techniques. This work uses a combination of quantile regression and Monte Carlo simulation to produce several wind power scenarios, and then both forecasts and historical wind power generation are considered to calculate a quantile regression to be incorporated into the stochastic unit commitment model.

Regarding the publication source scope, the articles considered in this study were published in 69 different journals. The 10 journals with the largest number of articles published are presented in Table 4, and they were obtained from the search engine (Scopus and WoS) until December 2018. These journals are responsible for 50% of all the articles analyzed in this study and two of them have 35 articles (*Renewable Energy* and *Wind Energy*). The remaining 57 journals have one or two articles published in the field. This analysis enables researchers to identify the most relevant journals in this field.

When it comes to number of citations among those 10 journals, *Renewable Energy* followed by *IEEE Transactions on Energy Conversion* and *IEEE Transactions on Sustainable Energy* are the ones with highest number of citations. It is also interesting to mention that one of the most cited articles (Bilgili et al., 2007) – 191 citations, was published in *Renewable Energy* and that 10 of the 25 articles published in *Renewable Energy* studied issues associated with wind resource assessment (Argüeso and Businger, 2018; Deo et al., 2018; Ritter et al., 2015; Vanvyve et al., 2015; Weekes et al., 2015; Weekes and Tomlin, 2014a, 2014b; Bilgili et al., 2007; Manwell et al., 2002).

Most of the articles (around 80%) selected were written by researchers from developed countries like the United States, Spain, England and Germany, along with China. Europe has the highest number of articles published (46%) and also articles written by researchers from several countries studying wind power issues in collaboration. Asia and USA also have considerable proportions (23% and 10%, respectively). Those numbers can be explained by the fact that Europe concentrates most of the countries that introduced wind power in their electricity mix, and China and the USA are the countries that are promoting the largest investments in this renewable energy source (GWEC, 2017). Nevertheless, as a result of the increasing investments on wind energy, researches from developing countries (like Turkey, South Africa, Iran, Brazil, Mexico and India) presented a significant growth in their publications, especially in the last decade.

Fig. 6 contains the research collaboration between countries, whose results were obtained from the search engine (Scopus and WoS) until December 2018, and in which the circle's size represents the proportion of each country's participation. Notice that the number of publications by country is directly related with countries with highest installed wind power capacity as well as amount of investments in wind power generation (GWEC, 2017).

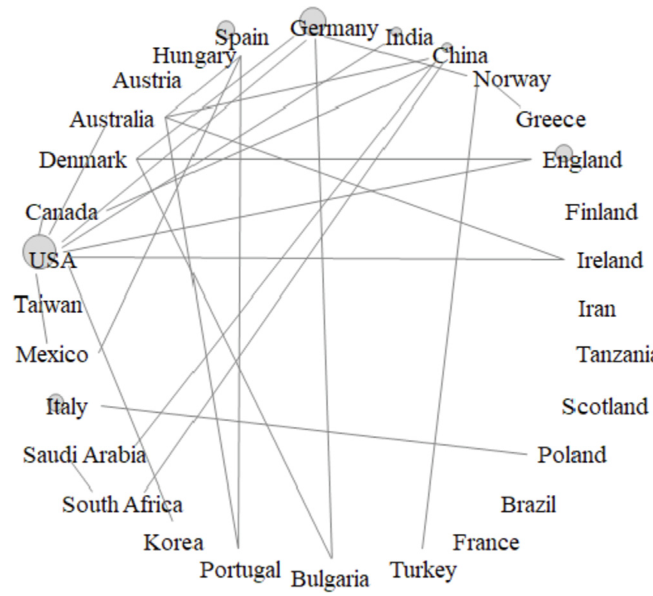

Fig. 6. Countries of collaborative networks.

3.1.2. Analysis of descriptors: approach and techniques

The descriptors presented in Table 3 shed light on the technical issues studied in the articles to improve medium and long-term wind power forecasting. Despite the existence of several approaches to make those forecasts (ranging from physical approaches to statistical and computational intelligence models), most of the articles still apply statistical models (54%) or hybrid models (a combination of these three models; 20%). Physical and computational intelligence models are studied in 14% and 17% of the articles analyzed, respectively (Fig. 7).

Fig. 8 contains a timeline considering the four approaches'

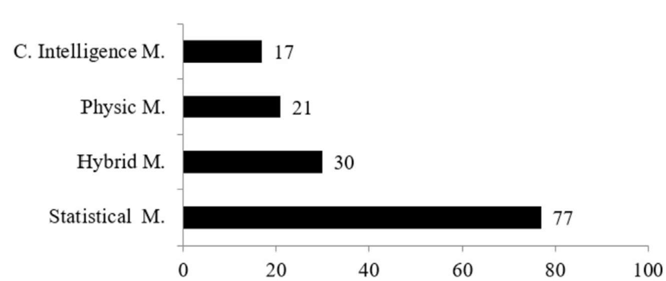

Fig. 7. Articles' composition by approach.

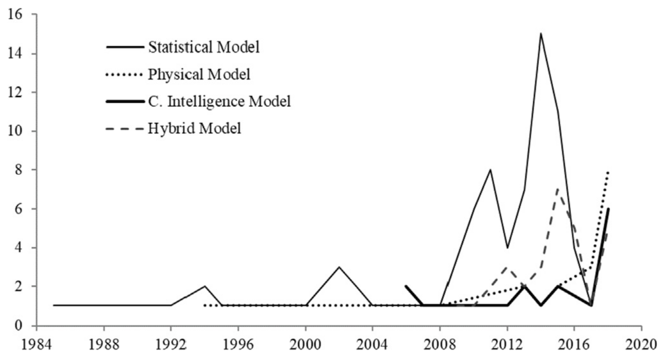

Fig. 8. Use of approaches with time.

usage. The oldest article considered in this analysis (Cheng and Chiu, 1985) uses a statistical approach, which continues to be used nowadays, but also show the emergence of other approaches, like the physical during the nineties and computational intelligence and hybrid models in the last decade. From Fig. 8, it is possible to observe that hybrid models together with innovative statistical models are being studied more actively than other approaches and can be consolidated as the emerging approach of this decade. Although computational intelligence models are employed steadily, their use is usually associated with other models such as statistical or physical models.

The approaches mentioned above can be used for different purposes, such as filtering, forecasting, simulation, distribution fitting, modeling and estimation. From Fig. 9, it is possible to notice that forecasting (39%), simulation (26%), distribution fitting (15%) and modeling (10%) are the main objectives of the articles studied. Table 5 presents a more detailed perspective by author of these techniques. Among the most cited articles are Barbounis et al. (2006), Bilgili et al. (2007), Barbounis and Theocharis (2006), applying forecasting techniques. The other two most cited articles use simulation techniques: Nichita et al. (2002) and Liu et al. (2012). A common feature on these techniques (and even estimation procedures) is the MCP model, used to assess wind power potential.

In distribution fitting, Hill et al. (2012) use univariate and multivariate autoregressive models to understand wind power generation influences on the electric power system, considering diurnal and seasonal effects, as well as the correlation between wind speed and geographical location. Oh et al. (2012) also use distribution fitting to assess wind power potential in an offshore wind farm in Korea. To do so, long-term wind power generation potential is estimated using MCP techniques and the Weibull distribution probability density function to calculate the energy density and estimate energy production. The studies that perform forecasting use a single step (8% of the studies), multiple steps

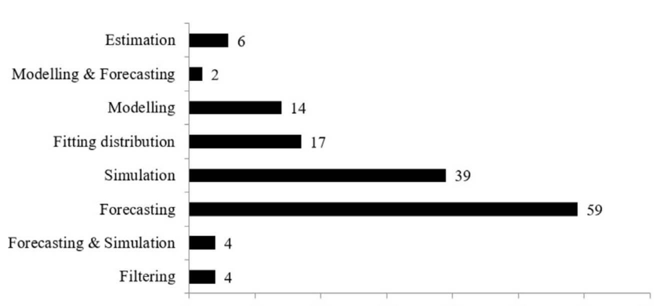

Fig. 9. Articles' composition by technical application.

(29%) or do not report the aspect (63%).

3.1.3. Descriptors analysis: variables, data frequency and evaluation metrics

In this subsection the forecasting procedures' main characteristics are studied. Table 6 is composed by the input and output variables, which correspond to the rows and columns in the table. This table represents the relationship between input and output variables considered in the articles analyzed. Wind speed is presented as an input or output variable in 60% of the articles. Notice that wind speed input variable plays an important role in wind power generation, especially because it has direct influence on power curve forecasting, as well as integrated power system operation and operational aspects of wind farms (Burton et al., 2011; Hill et al., 2012). Most of the models using wind speed as input and output variable apply MCP (Bilgili et al., 2007; Dinler, 2013; Gass et al., 2011; Manwell et al., 2002; Oh et al., 2012; Romo et al., 2011; Weekes et al., 2015; Weekes and Tomlin, 2014a) or the Weibull distribution (distribution fitting technique) (Kelly et al., 2014; Milne, 1992; Monahan et al., 2011; Rashmi et al., 2016). In some cases, when using wind speed as input variable, the output provided by the model is wind power forecasting (Boehme and Wallace, 2008; Jung, 2016; Jung et al., 2013) or the combination of both variables (Kennedy and Rogers, 2003; Muñoz et al., 2011; Pinson and Madsen, 2012; Ritter et al., 2015). Some articles consider other meteorological data together with wind speed as input variables (Agrawal and Sandhu, 2016; Chen and Tran, 2015; Díaz et al., 2018; J. Liu et al., 2018; Sharifian et al., 2018; Tiriolo et al., 2015), implying the use of multivariate models and a more complex approach. For instance, wind speed and wind direction are used together to forecast/simulate wind speed, since including direction as input variable improves the model's performance (Barbounis et al., 2006; Bossavy et al., 2013; Carta and Velázquez, 2011; Ettoumi et al., 2003; Takeyama et al., 2018; Wang et al., 2018). Other studies consider wind power as input and output variables (Burke et al., 2014; Dabernig et al., 2015; Hoeltgebaum et al., 2018; Huh and Lee, 2014; Liu et al., 2012; MacCormack et al., 2010), but in some other cases, first wind speed is forecasted and then wind power generation is estimated as the model output (Barbounis and Theocharis, 2006; Bossavy et al., 2013; Labati et al., 2018; Olaofe, 2014; Sharifian et al., 2018; Weekes and Tomlin, 2014b). A few studies use load and maximum wind speed as input and output variables (Jin et al., 2014; Natarajan et al., 2008; Sapuan et al., 2011; Staid et al., 2015).

Although most studies use hourly data (49%), some of them use lower frequencies such as 10, 20 and 30 min (17%). As can be seen in Table 7, other studies also use daily (14%), monthly (10%) and annual data. Some studies indicate annual frequency (2%) or do not mention frequency (8%).

Table 8 presents the evaluation metrics and accuracy measures used to analyze the modeling results and the model fit. The most used accuracy measures are MAE (Azad et al., 2014; Barbounis et al., 2006; Carta et al., 2011; Celik and Kolhe, 2013; Deo et al., 2018; Lerch and Thorarinsdottir, 2013; J. Wang et al., 2015), RMSE (Barbounis et al., 2006; Bossavy et al., 2013; Hill et al., 2012; McQueen and Watson, 2006; Ritter et al., 2015; Sharifian et al., 2018; J. Zhang et al., 2014), MAPE (Bilgili et al., 2007; Velázquez et al., 2011a; W. Wang et al., 2015; Weekes and Tomlin, 2014b; Yu et al., 2013), MSE (Erto et al., 2010; Jamil and Zeeshan, 2018; Jung, 2016; Kritharas and Watson, 2010; Olaofe, 2014; C. Y. Zhang et al., 2015), R^2 (Chang et al., 2015; Dinler, 2013; Hassan et al., 2011; Hossain et al., 2018; Xia et al., 1999; Yari and Farsani, 2015), and mean error (ME) (Cradden et al., 2017; Kritharas and Watson, 2010; Penchah et al., 2017; Standen et al., 2017). Especially in probabilistic forecasts, the error metrics used are CRPS and twCRPS (Baran and

Table 5
Articles divided by approach and technical application.

Approaches	Techniques	Researchers
Statistical	Estimation	Schindler and Jung (2018)
	Filtering	Alam et al. (2014), Njau (1994a), Deidda et al. (2000)
	Distribution fitting	Oh et al. (2012), Torrielli et al. (2013), Jung et al. (2013), Monahan et al. (2011), Muñoz et al. (2011), Beyer and Nottebaum (1995), Tsekouras and Koutsoyiannis (2014), Akyuz et al. (2013), Milne (1992), Jung (2016), Gong et al. (2014), Kelly et al. (2014), Hassan et al. (2011), Natarajan et al. (2008), Yari and Farsani (2015)
	Forecasting	Hill et al. (2012), Pinson and Madsen (2012), Carta and Velázquez (2011), Lerch and Thorarinsdottir (2013), Yu et al. (2013), Baran and Lerch (2015), Manwell et al. (2002), Huh and Lee (2014), Junk et al. (2015), Marinelli et al. (2015), Gryning et al. (2014), Hasani-Marzooni and Hosseini (2011), Guo et al. (2010), Weekes and Tomlin (2014a), Torrielli et al. (2014), Dinler (2013), Gutiérrez et al. (2013), Ziel et al. (2016), Hussain et al. (2004), Y. Liu et al. (2018), Weekes et al. (2015), Sapuan et al. (2011), Staid et al. (2015), Kritharas and Watson (2010), Suryawanshi and Ghosh (2015), Ali et al. (2018)
	Forecasting & Simulation	Callaway (2010), Caporin and Preś (2012), Koivisto et al. (2016), Hoeltgebaum et al. (2018)
	Modeling	Ettoumi et al. (2003), Xia et al. (1999), Weekes and Tomlin (2014b), J. Zhang et al. (2014), Villanueva and Feijóo (2016), Erto et al. (2010), Ling and Lublertlop (2015), Little et al. (2018)
	Simulation	Nichita et al. (2002), McPherson and Karney (2014), MacCormack et al. (2010), Moriarty et al. (2002), de Lucena et al. (2010), Nogueira et al. (2014), Maatallah et al. (2015), Kennedy and Rogers (2003), Jin et al. (2014), Gass et al. (2011), Torrielli et al. (2011), Cheng and Chiu (1985), McKague et al. (2005), Evans and Clausen (2015), Cheng and Chiu (1994), Koivisto et al. (2015), Koivisto et al. (2017), Askari et al. (2014), Burke et al. (2014), Ekström et al. (2018)
Physical	Filtering	Azorin-Molina et al. (2014)
	Forecasting	Roulston et al. (2003), Pereira et al. (2013), McQueen and Watson (2006), Njau (1994b), Tiriolo et al. (2015), Standen et al. (2017)
	Modeling	Lavagnini et al. (2006), Vanvyve et al. (2015), Whale et al. (2013), Olauson (2018)
	Simulation	Boehme and Wallace (2008), Hsu et al. (2007), Cradden et al. (2017), Soukissian et al. (2017), Argüeso and Businger (2018), Fernández-González et al. (2018), MacLeod et al. (2018), Pryor et al. (2018), Takeyama et al. (2018), Wang et al. (2018)
Computational Intelligence	Estimation	Celik and Kolhe (2013), Díaz et al. (2018)
	Forecasting	Barbounis et al. (2006), Bilgili et al. (2007), Barbounis and Theocharis (2006), C. Y. Zhang et al. (2015), Jung and Kwon (2013), Carta et al. (2011), Olaofe (2014), Deo et al. (2018), Wang and Wang (2017), Ammar et al. (2018), Hossain et al. (2018), Jamil and Zeeshan (2018), Qolipour et al. (2018)
	Modeling & Forecasting	W. Wang et al. (2015)
	Modeling	Barszcz et al. (2012)
Hybrid	Estimation	Carta et al. (2013), Ritter et al. (2015), Salcedo-Sanz et al. (2018)
	Distribution fitting	Chávez-Arroyo et al. (2015), Rashmi et al. (2016)
	Forecasting	Azad et al. (2014), Bossavy et al. (2013), Sun and Liu (2016), Romo et al. (2011), Vaccaro et al. (2012), Sharifian et al. (2018), Lynch et al. (2014), Baran and Lerch (2016), Z. Zhang et al. (2015), Agrawal and Sandhu (2016), Labati et al. (2018), Dabernig et al. (2015), Dunstan et al. (2016), Camelo et al. (2018)
	Modeling & Forecasting	J. Wang et al. (2015)
	Modeling	Velázquez et al. (2011b)
	Simulation	Liu et al. (2012), Nolan et al. (2012), Burlando et al. (2009), Chang et al. (2015), Nolan et al. (2014), Deepthi and Deo (2010), Penchah et al. (2017), J. Liu et al. (2018), Chen and Tran (2015)

Table 6
Relationship between input and output variables.

Input\Output Variables	Load	Wind Speed	Wind Speed and Direction	Wind Speed and Temperature	Wind Power	Wind Speed and Wind Power	Wind Speed and Meteorological Variables	Maximum Wind Speed
Load	1							
Load and Wind Power	1							
Wind Speed and Direction		8	6		3	3		
Wind Speed and Temperature		1		1				
Wind Speed		74			5	8		
Wind Speed and Wind Power					4	4		
Wind Speed and Pressure		2						
Maximum Wind Speed								2
Wind Power					6			
Wind Power and Irradiation		1						
Wind Speed and Meteorological Variables	1	6			5		3	

Lerch, 2016, 2015; Lerch and Thorarinsdottir, 2013; Staid et al., 2015). Less used but still common measures are correlation coefficient (Romo et al., 2011; Soukissian et al., 2017; Velázquez et al., 2011a) and Weibull scale with shape factor (Romo et al., 2011). Additionally, other recent measures considered are NMAE, NRMSE (Pinson and Madsen, 2012), NMSE (Barbounis and Theocharis, 2006), RRSE (Carta et al., 2013, 2011; Carta and Velázquez, 2011), CRMSE (Vanvyve et al., 2015), RAE (Carta et al., 2011), MPE (J. Wang et al., 2015), MRE (Guo et al., 2010), MBE (Weekes and Tomlin, 2014b), and RME, MCAE and SMAPE (Soukissian et al., 2017).

The analysis of the SLR results provides a holistic insight into the different approaches, techniques and models used for wind power forecasting, giving a broad view of the best journals that address the matter, models, variables and data to be considered (and their frequency) as well as the evaluation metrics. SLR encompasses qualitative analysis, while in the next subsection a static and dynamic analysis is performed through the CNA and main path analysis.

Table 7
Data frequency.

Data Frequency	Researchers
<1 Hour	Nichita et al. (2002), Roulston et al. (2003), Pinson and Madsen (2012), Moriarty et al. (2002), Sun and Liu (2016), Torrielli et al. (2013), Torrielli et al. (2011), Barszcz et al. (2012), Junk et al. (2015), Ritter et al. (2015), Gryning et al. (2014), Olaofe (2014), Torrielli et al. (2014), Whale et al. (2013), Chang et al. (2015), Gong et al. (2014), Ziel et al. (2016), Baran and Lerch (2016), Staid et al. (2015), Penchah et al. (2017), Natarajan et al. (2008), Agrawal and Sandhu (2016), Dunstan et al. (2016), Pryor et al. (2018), Takeyama et al. (2018)
Hourly	Barbounis et al. (2006), Hill et al. (2012), Liu et al. (2012), Barbounis and Theocharis (2006), Azad et al. (2014), Bossavy et al. (2013), Ettoumi et al. (2003), Carta et al. (2013), MacCormack et al. (2010), Oh et al. (2012), Carta and Velázquez (2011), Nogueira et al. (2014), Maatallah et al. (2015) Jung and Kwon (2013), Carta et al. (2011), Monahan et al. (2011), Celik and Kolhe (2013), Jung et al. (2013), Jin et al. (2014), Lerch and Thorarinsdottir (2013), Muñoz et al. (2011), Vanvyve et al. (2015), Romo et al. (2011), Callaway (2010), Gass et al. (2011), Manwell et al. (2002), Velázquez et al. (2011a), Marinelli et al. (2015), Boehme and Wallace (2008), Burlando et al. (2009), Weekes and Tomlin (2014b), Cheng and Chiu (1985), Vaccaro et al. (2012), Beyer and Nottebaum (1995), Dinler (2013), Gutiérrez et al. (2013), Njau (1994a), Weekes and Tomlin (2014a), Akyuz et al. (2013), Koivisto et al. (2016), J. Zhang et al. (2014), Sharifian et al. (2018), Hussain et al. (2004), Y. Liu et al. (2018), Cheng and Chiu (1994), Weekes et al. (2015), Cradden et al. (2017), Díaz et al. (2018), Hassan et al. (2011), Milne (1992), Tiriolo et al. (2015), Soukissian et al. (2017), J. Liu et al. (2018), Erto et al. (2010), Kritharas and Watson (2010), Koivisto et al. (2017), Fernández-González et al. (2018), Askari et al. (2014), Rashmi et al. (2016), Standen et al. (2017), Argüeso and Businger (2018), Burke et al. (2014), Deidda et al. (2000), MacLeod et al. (2018), Schindler and Jung (2018), Ling and Lublertlop (2015), Ali et al. (2018), Ekström et al. (2018), Little et al. (2018), Olauson (2018), Wang et al. (2018)
Daily	J. Wang et al. (2015), C. Y. Zhang et al. (2015), W. Wang et al. (2015), Yu et al. (2013), Baran and Lerch (2015), Tsekouras and Koutsoyiannis (2014), Caporin and Preś (2012), Guo et al. (2010), Alam et al. (2014), Jung (2016), McKague et al. (2005), Hsu et al. (2007), Deepthi and Deo (2010), Chávez-Arroyo et al. (2015), Sapuan et al. (2011), Suryawanshi and Ghosh (2015), Yari and Farsani (2015), Z. Zhang et al. (2015), Chen and Tran (2015), Wang and Wang (2017), Qolipour et al. (2018)
Monthly	Bilgili et al. (2007), Azorin-Molina et al. (2014), Kennedy and Rogers (2003), Nolan et al. (2012), Xia et al. (1999), Nolan et al. (2014), Njau (1994b), Lynch et al. (2014), Deo et al. (2018), Camelo et al. (2018), Salcedo-Sanz et al. (2018), Ammar et al. (2018), Hoeltgebaum et al. (2018), Hossain et al. (2018), Jamil and Zeeshan (2018)
Annually	McPherson and Karney (2014), Huh and Lee (2014), Pereira et al. (2013)
Others	de Lucena et al. (2010), Lavagnini et al. (2006), Hasani-Marzooni and Hosseini (2011), McQueen and Watson (2006), Evans and Clausen (2015), Kelly et al. (2014), Koivisto et al. (2015), Villanueva and Feijóo (2016), Labati et al. (2018), Dabernig et al. (2015)

Table 8
Summary of the most used accuracy measurements.

Metric	Nº
MAE	36
RMSE	30
MAPE	15
MSE	11
R^2	11
Bias/ME	10
CRPS	5
Correlation coefficient	4
MBE	3
RRSE	3
twCRPS	3
Standard deviation	3
Coverage	2
Weibull scale factor	2

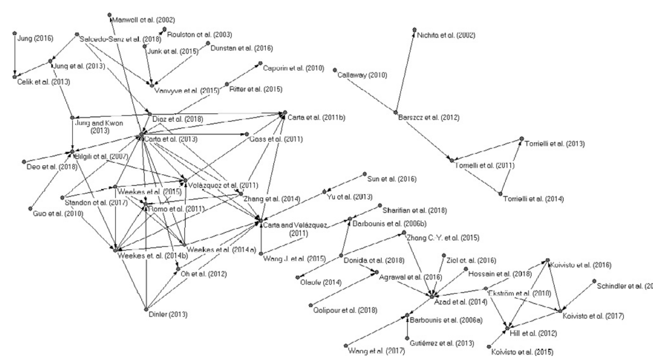
Fig. 10. Citation network.

3.2. CNA results

To perform citation network analysis, the 145 selected articles were organized with the UCINET software and then to the Pajek software, where all the citation network analysis and main path analysis were conducted. In the next subsections both results are discussed.

3.2.1. Citation network – static perspective

In a citation network, each of the articles is represented by a network node and is linked to others by arcs, which are obtained through the citation data. Fig. 10 presents the citation network for the articles with more than two or three connections of the 145 articles analyzed. Fig. 10 shows that the following articles correspond to central nodes in the citation network: Bilgili et al. (2007), Carta et al. (2011), Carta and Velázquez (2011), Velázquez et al. (2011b), Romo et al. (2011), (Hill et al., 2012), Carta et al. (2013), Weekes and Tomlin (2014a) and Azad et al. (2014). Those articles can be characterized as central nodes because they are connected with a large number of nodes in the citation network.

Table 9 presents the most cited articles ranked by the local citation scores (LCS) and the articles with the highest closeness centrality index, respectively. LCS and closeness centrality have a positive relationship, so some articles widely cited also have a high closeness centrality index. As can be seen in Table 10, five of the articles with the highest LCS (Table 9) are also among the articles with largest closeness centrality (Bilgili et al., 2007; Carta et al., 2013, 2011; Carta and Velázquez, 2011; Velázquez et al., 2011a).

3.2.2. Main path analysis – dynamic perspective

In main path analysis, the most prominent articles during a certain time period are identified, setting up the backbone for medium and long-term wind power forecasting research. This analysis provides a dynamic feature to the study, revealing research area's evolution over time. The main path network is derived from the citation network, as mentioned in 2.2.1, and is obtained using the transversal weight frequency as can be seen in Table 11. The main path cutoff value is 0.042 because around 90% of the nodes have traversal weights lower than this value. After applying the cutoff value, only 17 nodes (articles) remain in the network, all of them published between 2002 and 2018.

Fig. 11 show the main path derived from the analysis. Since the

Table 9
Top 10 articles with highest LCS.

Rank	Article's author	Source	Number of Citations	
			LCS	GCS
1	Carta and Velázquez (2011)	Energy	7	35
2	Velázquez et al. (2011a)	Applied Energy	7	22
3	Bilgili et al. (2007)	Renewable Energy	6	151
4	Carta et al. (2013)	Renewable and Sustainable Energy Reviews	6	40
5	Azad et al. (2014)	IEEE Transactions on Sustainable Energy	5	53
6	Carta et al. (2011)	Energy Conversion and Management	5	26
7	Weekes and Tomlin (2014b)	Renewable Energy	4	14
8	Hill et al. (2012)	IEEE Transactions on Sustainable Energy	3	71
9	Barbounis and Theocharis (2006)	Neurocomputing	3	65
10	Barbounis et al. (2006)	IEEE Transactions on Energy Conversion	2	218

Table 10
Top 10 articles with highest closeness centrality.

Rank	Article's author	Source	Centrality
1	Carta et al. (2013)	Renewable and Sustainable Energy Reviews	0.4138
2	Standen et al. (2017)	Wind Energy	0.3517
3	Carta et al. (2011)	Energy Conversion and Management	0.3448
4	Weekes et al. (2015)	Renewable Energy	0.2552
5	Velázquez et al. (2011a)	Applied Energy	0.2483
6	Salcedo-Sanz et al. (2018)	Applied Energy	0.2207
7	Díaz et al. (2018)	Applied Energy	0.2069
8	Carta and Velázquez (2011)	Energy	0.2069
9	Bilgili et al. (2007)	Renewable Energy	0.1517
10	Weekes and Tomlin (2014a)	Renewable Energy	0.1310

Table 11
Traversal weight frequency.

Intervals	Absolut Frequency	% Frequency	% Accumulated Frequency
0.0000–0.0069	106	73.1034	73.1034
0.0069–0.0521	24	16.5517	89.6552
0.0521–0.0973	3	2.0690	91.7241
0.0973–0.1425	3	2.0690	93.7931
0.1425–0.1877	1	0.6897	94.4828
0.1877–0.2330	3	2.0690	96.5517
0.2330–0.2782	2	1.3793	97.9310
0.2782–0.3234	0	0.0000	97.9310
0.3234–0.3686	2	1.3793	99.3103
0.3686–0.4138	1	0.6897	100.0000

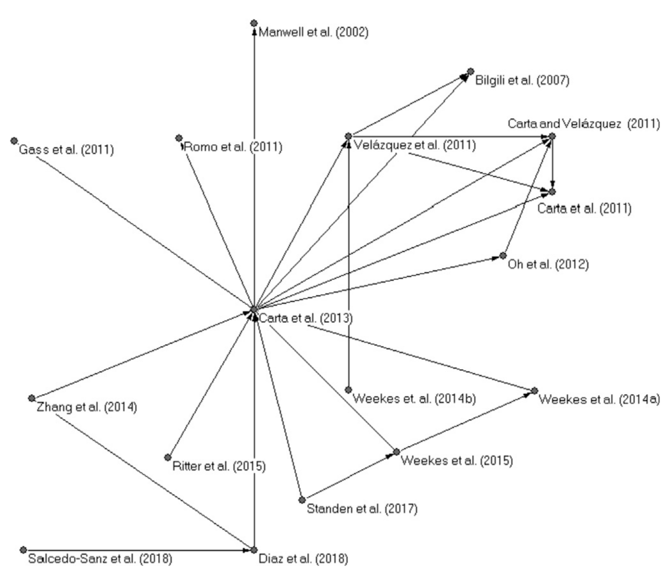

Fig. 11. Main path network.

closeness centrality and the main path have an intrinsic association in all the top 10 articles with the highest closeness centrality, these papers are included in the main path, corroborating the results from the main path analysis. Through a detailed analysis of the 17 articles, we noted that medium and long-term studies have focused on four central topics: MCP methods that consider linear relationships (Gass et al., 2011; Manwell et al., 2002; Oh et al., 2012; Weekes et al., 2015; Weekes and Tomlin, 2014b; J. Zhang et al., 2014), probabilistic MCP methods (Carta and Velázquez, 2011; Romo et al., 2011; Weekes and Tomlin, 2014a), artificial neural networks and Bayesian networks (Bilgili et al., 2007; Carta et al., 2011; Carta and Velázquez, 2011; Díaz et al., 2018; Velázquez et al., 2011a) and alternative techniques to MCP (Ritter et al., 2015; Salcedo-Sanz et al., 2018; Standen et al., 2017).

The main path begins with Manwell et al. (2002), using linear regression and the variance ratio method to determine the potential for installing offshore wind power generation projects. The study is followed by Bilgili et al. (2007), who applied artificial neural networks (ANNs) to forecast the mean monthly wind speed of target stations using data from neighboring stations (called reference stations). Through the monthly wind speed forecast, the wind power potential is estimated. Velázquez et al. (2011a) used similar method to estimate wind power costs of certain sites, but also compared the results of the ANN method with those obtained through the linear MCP method. Four other articles were published in 2011 investigating wind power forecasting issues. Carta published two studies that year. In the first, Carta and Velázquez (2011) estimated wind speed at candidate sites using probability density functions (considering information from a reference site) and compared it with estimates reached considering the variance ratio method, joint probability density distributions and the Weibull scale method. In the second study, Carta et al. (2011) also estimated long-term mean wind speed for candidate sites, but now applying probabilistic Bayesian networks (BNs), using multiple reference stations (with extended historical wind speed and wind direction data) and compared it with the results from two MCP models. Gass et al. (2011) and Romo et al. (2011) also studied wind speed for certain sites considering reference sites. Gass et al. (2011) used the MCP method and variance ratio to generate those estimates for a potential wind power generation site located in Austria, incorporating its risks in a statistical simulation model. Romo et al. (2011) formalized a systematic analysis of MCP methods' statistical fundamentals and conceived three new models: one based on a nonlinear regression and two derived from conditional probability density functions (kernel methods). Those three models were then compared with a simple linear regression and the variance ratio method. All comparisons were carried out considering synthetic wind speed time series of two different sites, simulating the prospective and the reference site. Unlike the other studies so far, Oh et al. (2012) carried out assessments of wind power potential in a southwestern area of the Korean Peninsula using MCP techniques. Carta et al. (2013) aggregated and presented all the MCP methods conceived so far, making a connection between old and new methodological proposals.

Between 2014 and 2015, Weeks published three studies estimating wind power generation potential for different sites in the United Kingdom using different MCP methods. In the first one, the potential was estimated for 22 UK sites with a MCP approach based on onsite wind speed measurements for only three months, comparing the results of three regression-based techniques (Weekes and Tomlin, 2014b). The second study was developed for the same 22 UK sites, comparing a MCP approach based on a bivariate Weibull (BW) probability distribution and standard (linear) regression MCP techniques (Weekes and Tomlin, 2014a). The last study implemented linear MCP algorithms to estimate the wind power resource of 37 UK sites, using an operational forecast model (UK4) as a source of historical reference data and compared the results with data from nearby meteorological stations. The results indicated that UK4 is highly competitive and also showed that it systematically improved MCP predictions at coastal sites due to better representation of local diurnal effects (Weekes et al., 2015).

Zhang et al. (2014) developed a hybrid MCP strategy to assess long-term wind resource variations at a wind farm site. For this, they tested five MCP methods: (*i*) linear regression; (*ii*) variance ratio; (*iii*) Weibull scale; (*iv*) artificial neural networks; and (*v*) support vector regression. Those methods were combined considering a set of metrics to analyze their statistical performance and a set of metrics to evaluate wind speed distribution in the long-term. The results showed that the many-to-one correlation in the hybrid approach could provide a more reliable prediction of onsite wind speed variations than those provided by the one-to-one correlations. Ritter et al. (2015) proposed a new approach to assess the local wind power generation potential, applying meteorological reanalysis data to obtain long-term low-scale wind speed data at specific turbine locations and hub heights, and thus determine the relation between wind data and energy production via a five-parameter logistic function with actual high-frequency energy production data. Standen et al. (2017) presented a method for deriving site-specific wind climatological information from numerical weather prediction (NWP) model data and demonstrated how this can provide a useful alternative to the traditional MCP techniques. From a general perspective, it can be observed that the conceptual structure of the main path is formed by the articles that use MCP or similar approaches to assess wind resource potential for one or more candidate sites. In an attempt to improve their analysis, Díaz et al. (2018) applied various models (artificial neural network, support vector machine for regression and random forest) based on MCP, incorporating air density in the MCP model as an additional covariable for long-term wind turbine power output estimation and considered both wind turbines with blade pitch control and stall-regulated wind turbines. The last study in the main path is the one published by Salcedo-Sanz et al. (2018), using a novel meta-heuristic algorithm, known as the Coral Reefs Optimization with Substrate Layer (CRO-SL), which is hybridized with the analog method as the wind power reconstruction method to identify the most representative points for the wind field. The method is tested to estimate monthly average wind power fields in Europe, from reanalysis data (ERA-Interim reanalysis).

Fig. 12 presents the co-citation network based on the references of the 145 selected articles. This network captures the co-citation relationships between 23 articles with the highest number of citations. Bilgili et al. (2007), Velázquez et al. (2011b), Carta et al. (2011), Carta et al. (2013) and Weekes and Tomlin (2014a) again integrated the co-citation core studies. It also can be noticed that two of the biggest citation clusters are led by Putman (1948), Justus et al. (1979), Koeppl (1982), García-Rojo (2004), Rogers et al. (2005), Öztopal (2006), Sreevalsan et al. (2007) and Velázquez et al. (2011b). Therefore, below we present a brief overview of these studies.

Putman (1948) is the study contained in the co-citation network. It presents a detailed analysis of wind behavior and characteristics. The study also presents parameters and designs for large wind turbines and estimates wind speed at specific sites using simultaneous measurements of the wind speed at the target site and at a neighbor reference sites with a long history of wind data measurements.

Usually short-term data provide the only available information for many sites of interest. In this case, several models have been proposed to estimate long-term wind speed. These models can be classified into two groups: methods that use simultaneous measurements of the wind speed for the target site and for only one reference site (Clive, 2008; Daniels and Schroeder, 1988; García-Rojo, 2004; Justus et al., 1979; Koeppl, 1982; Putman, 1948; Sreevalsan et al., 2007), and methods that use simultaneous measurements of the wind speed for the target site and several nearby references sites (Bechrakis et al., 2004; Carta et al., 2011; Öztopal, 2006; Velázquez et al., 2011b). As stated by Carta et al. (2013), these methods can also be grouped according to the functions used to relate long-term and short-term wind speed data. Rogers et al. (2005), for instance, compared four MCP algorithms, using the following models: linear regression, two-dimensional lineal regression, binning method and variance ratio. Weekes and Tomlin (2014a), besides linear regression alone, used linear regression with Gaussian scatter and variance ratio regression. Sreevalsan et al. (2007) applied MCP methods to assess the potential for a wind power site considering a linear fit using fast Fourier transform

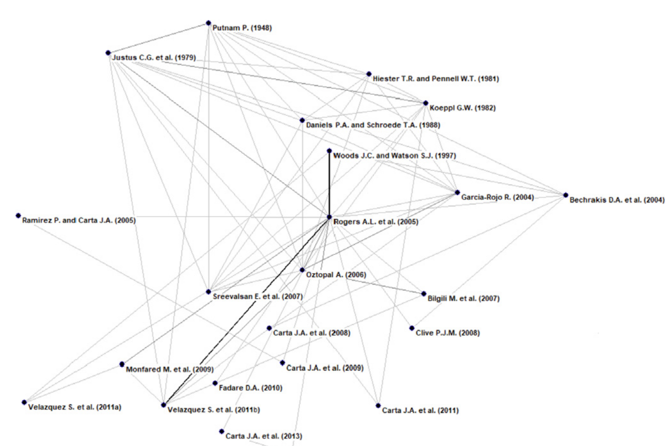

Fig. 12. Co-citation network.

instead of regression analysis. Justus et al. (1979) employed spatial cross-correlations instead of MCP methods for a candidate site evaluation. On the other hand, Woods and Watson (1997) proposed a new matrix method for MCP that relates short- and long-term data. Artificial neural networks (ANNs) are the most common nonlinear relationship used in MCP methods (Bechrakis et al., 2004; Bilgili et al., 2007; Fadare, 2010; Öztopal, 2006; Velázquez et al., 2011b, 2011a), but a study conducted by Monfared et al. (2009) proposed a new approach based on a combination of fuzzy logic and artificial neural networks to predict wind speed. At sites where wind speeds are Weibull distributed, Clive (2008) analyzed and demonstrated analytically that linear relationships do not hold.

Probability relationship is another important grouping, in which one of the biggest citation network clusters includes García-Rojo (2004), who proposed a joint probability distribution approach to estimate long-term wind patterns. On the other hand, Carta et al. (2008) provided a joint probability density function that includes not only wind speed, but also direction for wind power potential and generation analysis. A complementary analysis of the wind speed probability distributions used in wind power potential estimations was carried out by Carta et al. (2009). The method proposed in Carta et al. (2011) is based on probabilistic Bayesian networks (BNs) to estimate the long-term mean wind speed histogram. An important advantage of this approach is that it can be used for sites where few measurements are available. Another study followed a similar path, estimating the parameters of the Weibull wind speed probability density distribution and its standard errors to analyze whether or not data sampling interval influences the estimation (Ramírez and Carta, 2005).

3.2.3. Co-word analysis

When a co-word analysis is carried out, the aim is to identify the conceptual structure and the main concepts related to wind power. To generate a deeper co-word analysis, the selected articles were split into four consecutive periods: 1985–2000, 2001–2006, 2007–2014 and 2015–2018. The SciMAT software (Cobo et al., 2012) was used to perform the co-word analysis. The articles' keywords were exported from the Scopus and WoS databases so the thematic clusters could be identified (Table 12).

As can be seen in Table 12, the keywords are classified into core and secondary words. The former are those with at least two co-occurrences of keywords and the latter are those with a single co-occurrence. Additionally, the number of keywords per period is shown in Fig. 13, as well as the keywords that reappeared in the following periods and those that did not.

The first period in the overlapping map (1985–2000) starts with 13 keywords, rising to 27, 111 and 97 in the next three periods. This growth indicates that wind power research areas passed through a diversification process. It is also interesting to observe the keyword changes and maintenance during the period. From the first to the second period, only 38% remained (8 keywords), while from the second to the third period, 85% remained (23 keywords) and from the third to the fourth period 81% remained (79 keywords). The large number of keywords introduced in the third period (88) can be explained by the intensive growth of scientific interest in wind power during the period. It is also important to mention that wind power forecasting research was quite new, so those increments in keywords and themes are logical.

Fig. 14 clearly illustrates what was mentioned above. In this figure, the solid lines indicate that the connected clusters share a main association between thematic clusters, while the dotted lines mean associations regarding other aspects that are not the main themes. Besides this, the ball sizes represent the number of keywords associated with each cluster. In the first period all the thematic clusters have a homogenous distribution, meaning that extreme-wind-speed, forecasting and stochastic analysis have almost the same amount of keywords connected to them. In the second period there is some diversification, so wind energy, long-term and system are the thematic clusters with the highest number of keywords. For the third period, the thematic "model" is the one with the highest number of keywords and is followed by wind-resource-assessment and forecasting. Finally, for the fourth period, wind energy, energy and artificial neural networks are the most prominent thematic clusters. Concerning the solid and dotted lines, from the second to the third period the thematic model and simulation are both partially correlated with the thematic model. From the third to the fourth period, the same thematic model disappears and becomes partially associated with MCP and Energy.

From 1985–2000 to 2001–2006, the thematic clusters are reorganized as follows: extreme wind speed splits into simulation with long-term; the theme stochastic analysis migrates to long-term. The thematic cluster forecasting disappears, and three others are created: wind energy, system and modeling. From 2001–2006 to 2007–2014, almost all the thematic clusters change into two new clusters. For instance, the wind energy cluster splits into model and wind resource assessment, having a stronger association with the last theme. The same happens with the simulation theme. In the period 2007–2014, the core themes are wind resource assessment and model. Both themes are completely related. The model thematic cluster gathers a group of studies focused on MCP methods, which in the last period is a cluster itself, emphasizing its importance. In these studies, MCP appeared several times as a central issue for wind power forecasting/assessment. Also, as already seen in the main path, 2015–2018 is the period when the most representative studies are concentrated and artificial neural networks (ANNs) and MCP are the core research fields.

Besides the studies mentioned in the previous sections, there are other recent studies that deserve comment. In the thematic cluster artificial neural networks, J. Wang et al. (2015) used hybrid models containing recurrent neural networks to forecast medium-term wind speed; Maatallah et al. (2015) proposed a new recursive wind speed forecasting method named the Hammerstein Auto-Regressive (HAR) model and compared its performance with ANN and autoregressive integrated moving-average (ARIMA) models; and Agrawal and Sandhu (2016) applied ANNs to figure out the most influential parameters affecting wind forecasting. Regarding the wind energy cluster, Ritter et al. (2015), Marinelli et al. (2015) and Ziel et al. (2016) analyzed either wind power generation potential assessment or generation itself through different techniques, such as regional models, multivariate seasonal time-varying threshold autoregressive moving average (TVARMA) and threshold generalized autoregressive conditional heteroscedastic (TGARCH) models or even through an assessment index. In the energy cluster, Koivisto et al. (2016) analyzed the effect of wind power generation on the electric power systems using a Vector-Autoregressive-To-Anything (VARTA) process with a time-dependent intercept, modeling wind speeds in multiple locations. This wind speed simulation method provided a risk assessment for the power system. The recent expansion of wind power generation around the world and the growing interest in this energy source were the main incentives to the progress made in this area during the last 10 years.

4. Discussion

This study applied a rigorous and reproducible SLNA methodology related to wind power production that aims to answer six research questions formulated at the introduction. Table 13 summarizes the outputs obtained for each one of the Research Questions (RQs) drawn in the Introduction.

Table 12
Number of keywords by thematic cluster and period.

Period	Thematic cluster	Number of Keywords			Core with up to 80% citations	References for the Core Keywords with up to 80% citations
		Core	Secondary	Total		
1985–2000	Extreme-wind-speed	6	0	6	1	Cheng and Chiu (1994)
	Forecasting	1	0	1	1	Deidda et al. (2000)
	Stochastic	14	0	14	1	Xia et al. (1999)
	Subtotal	**21**	**0**	**21**	**3**	
2001–2006	Simulation	158	163	321	1	Nichita et al. (2002)
	Wind-energy	26	43	69	2	Manwell et al. (2002), McQueen and Watson (2006)
	Long-term	51	0	51	1	Ettoumi et al. (2003)
	System	241	0	241	2	Barbounis et al. (2006); Barbounis and Theocharis (2006)
	Modeling	26	204	230	1	Lavagnini et al. (2006)
	Subtotal	**502**	**410**	**912**	**7**	
2007–2014	Model	214	388	602	8	Carta and Velázquez (2011), Carta et al. (2013), Torrielli et al. (2013), Jung et al. (2013) Nolan et al. (2012), Velázquez et al. (2011a), Carta et al. (2011), Burlando et al. (2009)
	System	158	592	750	5	Bossavy et al. (2013), MacCormack et al. (2010), McPherson and Karney (2014), Jin et al. (2014), Hasani-Marzooni and Hosseini (2011)
	Wind-resource-assessment	168	649	817	7	Carta et al. (2013), Jung and Kwon (2013), Jung et al. (2013), Nolan et al. (2012), (Gass et al. (2011), Yu et al. (2013), Weekes and Tomlin (2014b)
	Forecasting	120	131	251	5	Azad et al. (2014), Torrielli et al. (2013), Lerch and Thorarinsdottir (2013), Callaway (2010), Caporin and Preś (2012)
	Weibull	62	428	490	3	Celik and Kolhe (2013), Nolan et al. (2012), Gryning et al. (2014)
	Subtotal	**722**	**2188**	**2910**	**28**	
2015–2018	Time-series	31	14	45	2	J. Wang et al. (2015), (C. Y. Zhang et al. (2015)
	Artificial-neural-networks	60	54	114	3	J. Wang et al. (2015), Maatallah et al. (2015), Sun and Liu (2016)
	Measure-correlate-predict	5	24	29	1	Weekes et al. (2015)
	Energy	27	45	72	3	Ritter et al. (2015), Koivisto et al. (2016), Chávez-Arroyo et al. (2015)
	Wind-energy	36	77	113	4	Ritter et al. (2015), C. Y. Zhang et al. (2015), Marinelli et al. (2015), Ziel et al. (2016)
	Subtotal	**159**	**214**	**373**	**13**	
Total		**1404**	**2812**	**4216**	**51**	

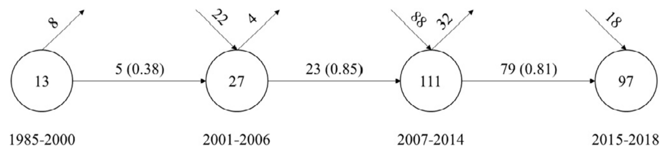

Fig. 13. Keyword maps.

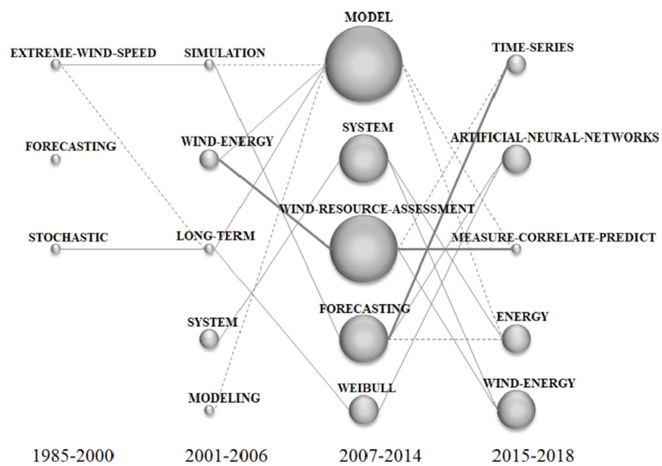

Fig. 14. Thematic network evolution.

The first was: "What are the current methods and models used in the field of wind power generation?" When applying citation analysis, it was found that the oldest article considered corresponds to Cheng and Chiu (1985) which uses a statistical approach and, up to now, continues to be the most prominent one. It has also been responsible for the emergence of other ones, like the physical, during the 90's, and computational intelligence and hybrid models in the last decade. The results from the citation analysis indicate that 54% of the articles analyzed belong to statistical models, 17% to physical, 14% to computational intelligence and 20% to hybrid models. According to the frequency they appeared, the most used for these approaches cover a large number of models, such as the Box-Jenkins family, Neural Networks, Generalized Linear Regression, NWP models, Weibull distribution adjusts with joint probability density functions, Markov Chains, quantile regression and WAsP. Nonetheless, they are also applied to other purposes, including simulation and modeling wind behavior, estimating wind power generation potential or even fitting distributions of the wind energy resource. Notice that statistical models are the ones that were most developed over time when compared to physical models and computational intelligence, being hybrid models the most recent. On the other hand, the last three approaches are those receiving more attention in the last two years.

Similarly, it was used citation analysis to answer the second question: "Which type of analysis do these models involve?" The results indicate that the core of the articles is centralized on forecasting (43%), simulation (28%), distribution fitting (12%), modeling (10%) and some studies are spread out between estimation and filtering, 4% and 3% respectively. A common feature on these techniques (and even estimation procedures) is the Measure-Correlate-Predict (MCP) model, used to assess wind power potential. It was found that the most cited articles use forecasting and simulation techniques to address issues about power system operations, planning for connection or disconnection of wind turbines or even wind power potential.

The third research question is related to: "How have these methods evolved over time?". When implementing citation network analysis (CNA) were obtained the central nodes in the citation network: Bilgili et al. (2007), Carta and Velázquez (2011), Carta et al. (2011), Velázquez et al. (2011b), Romo et al. (2011), Hill et al. (2012), Carta et al. (2013), Weekes and Tomlin (2014a) and Azad et al. (2014). These works are considered as central nodes because they are connected to a large number of nodes in the citation network. Thus, the main path analysis provided the most prominent articles constituting the backbone for medium and long-term wind power generation research. The evolution of these studies indicates that they have focused on four central topics: MCP methods, that consider linear relationships, probabilistic MCP, Artificial Neural Networks and Bayesian Networks and alternative techniques to MCP methods to assess wind power potential. It is possible to observe that over the last 15 years, the most studied tools to forecast and access wind power generation have been MCP methods, which comprise Linear Regression and Variance Ratio techniques. The use of Weibull distribution, joint probability density functions or kernel techniques were analyzed and tested, aiming to provide more accurate results and better understanding of the problems studied. Also, Artificial Neural Networks and Bayesian Networks were considered to capture the nonlinear relationship among the variables and were usually studied to generate more precise long-run wind speed forecasts (for specific

Table 13
Main answers to the Research Questions (RQs).

RQ	Analyses	Main answers
1	Citation	The most used methods are: statistical, hybrid, physical and computational intelligence.
2	Citation	The analysis done by these methods comprehends forecasting, simulation, distribution fitting, modeling, filtering and estimation.
3	Citation	The core publications indicate that MCP methods, to assess wind power potential, has evolved through models that consider linear relationships, probabilistic MCP, Artificial Neural Networks and Bayesian Networks and alternative techniques to MCP.
4	Citation	The main variables are: wind speed and meteorological variables, such as direction, temperature, pressure and irradiation. Similarly, the main accuracy measures are: MAE, RMSE, MAPE, MSE, R^2, Mean Error (ME).
5	Citation Network and Co-word	It is expected that MCP methods, which are combined in hybrid models, have a part of more intensive research focused on applications using computational intelligence methods.
6	Citation Network and Co-citation	The main limitation of MCP methods is related to the lack of historical wind speed data for most of the candidate sites.

targeted sites).

To complement this evolution, co-word analysis allowed to identify the conceptual structure and the main concepts related to wind power, splitting the articles into four consecutive periods: 1985–2000, 2001–2006, 2007–2014 and 2015–2018. It was observed that there was a growth in the thematic clusters which indicates that wind power research areas passed through a diversification process. The thematic cluster gathers a group of studies focused on models that refer to wind-resource-assessment which make use of Artificial Neural Networks and MCP methods. Notice that those thematic are the core research fields for the most recent period (2015–2018), confirming the findings in the main path analysis.

Concerning the fourth research question: "What are the main variables and performance measures considered?", according to the citation analysis, there are several variables used in the field of wind energy considered as input variables, and most studies use hourly data frequency. This include wind speed and meteorological variables, such as direction, temperature, pressure, irradiation among others less used. Nonetheless, based on the number of papers, wind speed implemented as input and output variable represents 60%. Also, wind speed and wind direction variables are used together to forecast/simulate themselves, since including the second improves the performance, according to: (Barbounis et al., 2006; Bossavy et al., 2013; Carta and Velázquez, 2011; Ettoumi et al., 2003; Takeyama et al., 2018; Wang et al., 2018). In some other cases, wind speed is first used to forecast and, then, the future values of this predicted variables are employed to estimate wind power generation. The obtained forecasts and simulations are evaluated through the most used accuracy measures: MAE, RMSE, MAPE, MSE, R^2, Mean Error (ME). In probabilistic forecasts, the error metrics most used are CRPS and twCRPS.

The fifth research question: "What are the trends for the future?", was addressed based on the growing expansion of wind power generation around the world and the increasing interest in this renewable energy source. The developed countries, like USA, Spain, England and Germany, along with China, whose studies represent 80%, at least, of the number of publications, offer a positive outlook of expansion growing of wind power generation around the world, because of the large investments made by these countries to this renewable energy source. As such, it is expected that the developing countries will reach the same level of investment in the field of wind energy of the developed countries implying an expected increase of the number of researches and publications.

Based on the research directions obtained from the CNA, wind resource assessment (on certain target sites using data from reference sites) to estimate wind power generation potential continue being highly explored, probably by applying MCP methods, which are now often combined in hybrid models as part of more intensive research focused on applications using computational intelligence methods.

Finally, concerning the sixth research question: "What are the limitations of current research solutions?", it was also possible to observe that the main bottleneck related to the use of those methods is the lack of historical wind speed data for most of the candidate sites. To overcome this drawback, NWP models and the use of climatological information are gaining more space, mainly due to the costs associated with making new measurements. Although statistical models have been widely used in the last decade, hybrid ones present a promising alternative, especially considering the increasing power of computational intelligence techniques and also the use of physical models to improve data availability.

5. Conclusions and final remarks

Wind power generation is a subject that has been widely analyzed in the last 20 years and much attention has been given by researchers around the world to short-run forecasting and related issues, leaving a gap especially in review studies and analysis focused on medium- and long-term forecasting. This is what the present article addresses, through SLNA and bibliometric analysis. One hundred and forty-five articles selected from the Scopus and WoS databases were analyzed using the SLNA approach. Through the articles, the six research questions proposed in the introduction were answered considering different approaches and, now, the most important observations and conclusions are summed up.

By applying SLNA, it was possible to identify the most relevant studies in the field of wind energy generation, and the most prominent journals and researchers. This study allows to find the main techniques and approaches, and which currently have high prospective to being developed. Additionally, it was possible to recognize which is the knowledge backbone and who are the scholars associated to these works, and also the most outstanding countries. Furthermore, the analysis of the publication lead to identification of the main variables, the data frequency and evaluation metrics that provide a complete understanding of the thematic evolution.

This study has some limitations due to in the choice of search parameters (keywords and exclusion criteria) and the fact of restricting the search to only two databases. So, this work could be extended, as future work, to use additional databases such as JSTOR and ProQuest. Similarly, expand the study to theses, dissertations and conference articles can enrich the analysis and lead to the inclusion of new methods and applications yet to be published in peer-reviewed journals, reducing the risk of publication bias associated with peer-reviewed literature. The analysis of wind power production in the short-term as well as incorporating studies that consider other renewable sources such as photovoltaic generation are other key topics that can be considered.

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