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Review

Advanced neural network and hybrid models for wind power forecasting: a comprehensive global review

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A B S T R A C T

Neural Network Algorithms (NNAs), modeled after the workings of biological neurons, are increasingly utilized in areas like data mining and robotics to address complex challenges in artificial intelligence (AI). This research will undertake a systematic review based on advanced neural networks and hybrid models for wind power forecasting. Using the Scopus database, a methodical search, acquisition, and filtering procedure was utilized to find pertinent publication documents; VOSviewer software was utilized to analyze trends. The emphasis on improving prediction accuracy and stability in wind power forecasting through the application of cutting-edge machine learning techniques and hybrid models is a prominent feature that unites the literature. Furthermore, attention is being paid to resolving issues pertaining to the production of wind energy, such as wind power fluctuation management, grid integration problems, wind speed prediction, and turbine health monitoring. A rising trend involves multi-dimensional, multi-step forecasting and incorporating factors like weather data and spatial-temporal features to enhance reliability. This paper contributes by exploring the integration of optimization techniques with neural networks, investigating hybrid models to improve wind power predictions, assessing LSTM-based approaches in forecasting, and suggesting directions for future research.

1. Introduction

Today, Neural Network Algorithms (NNAs) are computational models inspired by biological neural networks designed to process information and solve complex AI problems [1]. These algorithms have gained prominence in various fields, including robotics [2], and data mining [3]. NNAs are crucial for their ability to learn from data, adapt to new information, and make predictions [4]. Recent advancements in deep learning have further enhanced their capabilities, particularly in computer vision, speech processing, and IoT applications [5]. The effectiveness of NNAs depends on selecting appropriate architectures and training algorithms. Ongoing research focuses on developing innovative topologies, optimization methods, and applications in quantum computing and differential equations [6]. As NNAs continue to evolve, they offer powerful tools for handling high-dimensional data and automating feature extraction processes [7]. Furthermore, in engineering and construction, NNAs are used for structural analysis, materials optimization, energy efficiency forecasting, and smart city technologies [8]. They excel in pattern recognition tasks like character and handwriting recognition [9, 10]. In business, NNAs are employed for hedge fund analytics, marketing segmentation, and fraud detection [11]. Unsupervised NNAs, such as autoencoders and self-organizing maps, are particularly useful in exploratory data analysis, biomedical imaging, and financial applications when labeled datasets are unavailable [12]. In healthcare, NNAs can predict disease severity, as demonstrated in epidermolysis bullosa simplex, with 78% accuracy [13]. NNAs are also applied in system identification, vehicle control, quantum chemistry, and natural resource management [14]. Their ability to simulate nonlinear phenomena and identify hidden patterns in large databases makes them valuable tools across various industries. In this work, the discussion will be narrowed specifically to its application for wind power generation. Wind power generation is a rapidly growing renewable energy source with significant potential for addressing global energy demands and environmental concerns [15]. It offers numerous advantages, including low carbon emissions, resource conservation, and flexible applications [16]. The development of wind energy technology has been dramatic since the 1980s, with many countries setting ambitious targets for its implementation [17]. Key aspects of wind power systems include importance analysis for identifying critical components [18], integration with smart grids and storage systems [19], and advanced control strategies for efficient operation [20]. However, challenges remain, such as technological limitations, environmental impacts, and grid integration issues [21]. Despite these obstacles, wind power is expected to play an increasingly important role in the global energy landscape, driven by ongoing research, technological advancements, and supportive government policies [22]. Neural networks have emerged as powerful tools for improving wind power efficiency and forecasting. They have been applied to turbine control, wind farm optimization, and blade design [23]. Various machine learning approaches, including artificial neural networks (ANNs), recurrent neural networks, support vector machines, and extreme learning machines, have shown promising results in wind power forecasting [24]. Multilayer perceptron structures with Purelin and Sigmoid activation functions are commonly used [25]. Recent advancements include combining ANNs with dependability models to enhance short-term production estimation. Time-series methods, fuzzy logic, and hybrid models have also been explored [26]. The integration of physical, statistical, and hybrid methods has improved forecasting accuracy across different time horizons [27]. Overall, neural network applications in wind power forecasting have increased significantly, offering improved accuracy compared to individual methods [28]. In summary of the key oversions from the previous related literature analyzed above, neural networks have emerged as powerful tools for enhancing wind power efficiency and forecasting. It is evidence that they have been effectively applied to turbine control, wind farm optimization, and blade design.

Various machine learning approaches, including artificial neural networks (ANNs), recurrent neural networks, support vector machines, and extreme learning machines, have shown promising results in wind power forecasting. Commonly used structures include multilayer perceptrons with Purelin and Sigmoid activation functions. Recent advancements involve combining ANNs with dependability models to improve short-term production estimation. Additionally, time-series methods, fuzzy logic, and hybrid models have been explored, leading to better forecasting accuracy. The integration of physical, statistical, and hybrid methods has further improved accuracy across different time horizons. Overall, the application of neural networks in wind power forecasting has significantly increased, offering enhanced accuracy compared to individual methods. However, there is a notable gap in the literature regarding a comprehensive review of neural network algorithms in wind power generation. Thus, the aim of this work is to conduct a systematic review of the applications of neural network algorithms in wind power generation, focusing on key contributions, among others, such as:

- Reviewing the applications of LSTM models in wind power generation, highlighting their effectiveness in improving long-term forecasting accuracy.
- Exploring the use of short-term memory-based models
- Examining the integration of various optimization techniques with neural network models to enhance the accuracy and reliability of wind power forecasts.
- Analyzing different neural network methodologies applied to time series data in wind farms, focusing on their predictive capabilities.
- Investigating the combination of hybrid models and machine learning techniques to improve the prediction of wind speed and power output.
- Detailing various algorithms and neural network models specifically designed for predicting wind energy, and their performance in different scenarios.
- Reviewing the application of neural network models in accurately predicting wind speed and power output, emphasizing recent advancements.
- Proposal for possible future work directions will be discussed.

The remaining part of the paper is organized as follows: Section 2 introduces the relevant theory of similar or related work explored or completed, while Section 3 explores the methods or processes utilized to search, retrieve, collect, and analyze relevant information and documents on the different search engines and software. Section 4 consists of analyzed literature papers, and Section 5, summarizes the analyzed literature papers' observations. Section 5 interprets and discusses results, while Section 6 discusses the results under network and overlay visualization. Section 7, suggests and recommends proposals for future research, and Section 8 summarizes the main conclusions of this work.

2. Wind energy systems

To combat climate change and achieve a sustainable energy future, offshore wind energy is becoming more and more important. Real-time performance monitoring and predictive maintenance are now possible thanks to the revolution in industrial systems brought about by advances in data-driven and machine-learning technologies. For fault detection and operational optimization, accurate wind turbine models are essential. Notwithstanding, there are obstacles, including wind direction, speed, power generation, and performance statistics [29]. Since wind energy doesn't produce pollution like hydropower or coal does, it is an essential alternative energy source. Its potential regions remain unidentified, and the variability of wind speed impacts its generation capacity. Statistics on the availability of wind energy are essential for inventory preparation. The generation of wind energy capacity is predicted using soft computing techniques, such as weather and historical data modeling. Artificial intelligence techniques such as neural networks and fuzzy logic have been used by researchers to develop energy estimation and prediction methods that are more accurate and efficient than conventional statistical methods [30]. The economic, social, political, and environmental aspects of renewable resources are the main subjects of research, with wind energy receiving special challenges for the operation of the electrical network. With a variety of storage technologies available, energy storage systems in conjunction with wind power can improve grid-connection capability [31]. In the past, researchers have proposed various statistical approaches related to wind power, wind speed, and energy prediction [32]. The Artificial Neural Network structure comprises three layers: input, hidden, and output. The input layer receives network inputs, the hidden layer processes information, and the output layer provides network response. The number of neurons in the input layer equals the number of inputs, while the number of neurons in the output layer corresponds to the number of outputs, see Figure 1, where X_1, X_2 are the input functions (wind speed, temperature etc) W_{ij} is the signal weight, and f is an activation function [33].

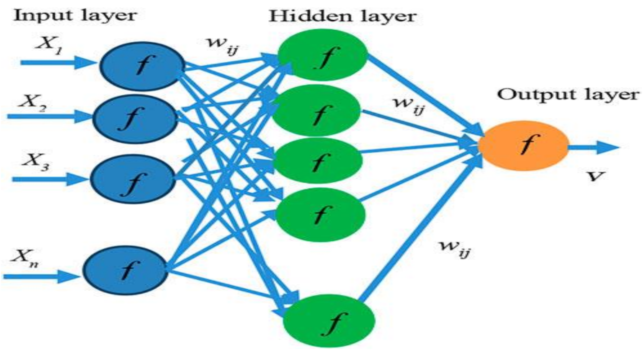

Figure 1. Artificial neural network structure

Artificial Neural Network activation functions map inputs and hidden layers, advancing the node output from one layer to the following and introducing irregularities into the network's modeling abilities. A neuron's functional form is determined by its activation function; for example, a linear activation function multiplies the neuron's value by the learned weight [34]. The activation function is expressed as:

$$f = \frac{1}{1+\exp(x)} \tag{1}$$

A set of 'i' synapses with weight W_i that are supplied by a signal X_i can have either a positive or a negative weight; a negative weight inhibits the sum of the junction's output, while a positive weight has a remarkable impact [35], signal weight is expressed as:

$$W = W_{ij} + \Delta W_{ij} \tag{2}$$

The wind system's power production fluctuates depending on a few factors, including air density and rotor blade area, but it changes more dramatically in response to wind speed. Air density, blade area, and wind speed all affect the wind energy system's output power. The wind power distribution equation for a certain wind turbine can be calculated by utilizing its power curve. The wind speed distribution function at an area is determined by the mean wind speed. One can calculate the mean power density (mean power available) per unit of surface. Getting power from the wind, considering Betz's law, realistic values, and wind turbine factors like Cut-In and Cut-Out wind speed, rated speed, and rated power can all be used in this procedure [36]. One helpful tool for simulating the operation of a wind turbine is its power curve. It displays the power output at a given wind speed. Figure 2 displays a typical power curve for a pitch-regulated wind turbine. The lowest speed at which there is no power output is known as the cut-in speed. Power grows quickly in the second zone, which is between the rated speed and the cut-in. The output in the third region doesn't change until the cut-off speed is reached. After this, the turbine is turned off to shield its internal parts from strong winds [37]. Therefore, accurate wind speed and power forecasting are crucial for reducing wind power fluctuations in system dispatch planning. Deep learning-based models are increasingly being considered due to their ability to handle complex nonlinear problems. However, scheduling, management, and optimization remain the main challenges for high penetration of renewable energy sources like wind power [38].

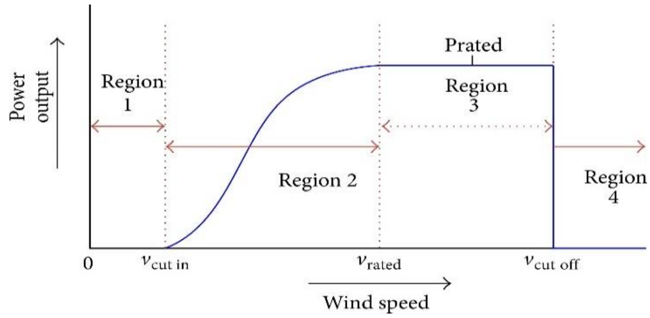

Figure 2. Wind turbine power curve model

The following depicts the equation: Where:P_w is the power extracted from the wind source in watts (W), ρ is the density of air in $\left(\frac{Kg}{m^3}\right)$, A is the area of blades of a rotor in (m^2), and v is the speed of wind in $(\frac{m}{s})$ [39].

$$P_w = 0.5\rho A v^3 \tag{3}$$

3. Methodology

The PRISMA approach was employed to systematically identify and refine the focus on the intersection of neural networks and wind power generation using the SCOPUS database. This comprehensive method followed the four key stages of PRISMA: Identification, Screening, Eligibility, and Inclusion.

3.1 Identification

The SCOPUS database was selected as the primary source for downloading relevant information. The process began by accessing the SCOPUS database and configuring the search parameters. Initially, the "Article title, Abstract, and Keywords" option was chosen from the dropdown menu in the search box. Keywords "Neural Network" AND "Wind Power Generation" were entered, ensuring that the search would return documents containing both phrases exactly as specified. This search yielded an initial result of 811 documents.

3.2 Screening

To refine the search results, several filters were systematically applied. First, the results were sorted by relevance, ensuring that the most pertinent documents appeared at the top. Then, the publication year range was set from 2019 to 2023, reducing the document count to 435. To narrow the focus further, the subject area was limited to Engineering, which brought the count down to 285 documents. Document type was then filtered to include only articles, resulting in 169 documents. The language filter was set to English, reducing the count to 158 documents. Finally, the year range was further restricted to 2021–2023 to ensure the most recent information, leaving 110 documents. Table 1 is an overview of inclusions and exclusions considered in this study.

3.3 Eligibility

In the eligibility phase, the relevant papers were selected and exported for detailed analysis. All documents were highlighted, and the CSV format was chosen for export, successfully exporting 234 documents. This file was saved under a new folder on the desktop as the master file, which was preserved without any editing. A copy of this file, named "SCOPUS documents," was created for editing and analysis purposes.

Table 1. Inclusions and exclusions

Item No.	Description	Criteria	
		Inclusion	Exclusion
1	Database	Scopus	Other databases
2	Publication period	2021-2023	Documents published in 2020 and before.
3	Document type	Articles	book chapters, books, notes, letters, editorials reviews, conferences.
4	Subject area	Engineering	Energy, Mathematics, Physical, life, social, health and humanities sciences
5	Language	English	All other languages
6	File Type	CSV	RIS, BibTex, plain text, etc. (please list all as I showed you)
7 8	Design keywords	"Neural Network" AND "Wind Power Generation"	All documents outside specified used keywords

3.4 Inclusions

The next step involved a thorough review of the data. The SCOPUS documents Excel file was opened, and the abstracts in column R were reviewed to assess the relevance of each document. To facilitate this process, three new columns (S, T, and U) were created. Column S was used to identify the aim, objective, or purpose of each document, the problems addressed, and the methods or techniques used. Column T listed all variables used as inputs and outputs in each document, while Column U identified the type of forecasting (short-term, medium-term, or long-term) if applicable. Documents that were deemed irrelevant were highlighted in red and subsequently deleted from both the SCOPUS documents file and the SCOPUS master file, ensuring consistency between the two files. Initially, both files contained 110 documents, but after removing non-relevant entries, the count was reduced to 64 documents.

3.5 Analysis using VOSviwer

For deeper analysis, VOSviewer software was downloaded and installed. The software was used to identify research gaps (network visualization) and current trending field patterns (overlay visualization). The process began by selecting the option to create a map based on bibliographic data, specifically choosing the Scopus CSV file for upload. Co-occurrence analysis was performed, focusing on all keywords with a full counting method. A threshold of a minimum of five occurrences was set, resulting in 22 keywords meeting the criteria. The resulting map highlighted key topics and trends within the research area. The map was saved and exported for further analysis. Clusters identified in the map were copied to an Excel spreadsheet, where they were edited and analyzed. This detailed analysis helped to identify current trends and gaps in the research on neural networks and wind power generation.

4. Literature review results analysis

4.1 Long short term forecasting

Hong et al. [40] developed a mixed classical-quantum model that predicts wind speeds forecast for twenty-four hours ahead using a long term short term memory and a quantum network model to address the issue of power planning uncertainty of renewable energy by power companies in different countries, including South Korea, Taiwan, China, and Philippines. In Switzerland, Basel, Sun et al. [41] established a wind energy forecasting system using 2 stage attention and a short long term memory system. The approach significantly increased forecast accuracy while reducing the variable nature of climatic circumstances. With a focus on a wind farm in Hunan Province, Wang et al. [42] explored a wind energy forecasting model that made use of a long-term short-term memory system and incorporated Gaussian mutation technique and erratic sequence for enhanced stability and search performance. Using statistically learned methods, Ahmad T and Zhang D [43] improved feature reliability and performance across Belgian, Distribution System Operators (DSO)-Connected, and Elia sites by using an in-depth sequence to sequence; long term short term memory regression approach for accurate wind energy projection. They employed the week ahead prediction.

4.2 Short term memory based forecasting

Anushalini T and Sri Revathi B [44] identified a deep learning model appropriate for wind power forecasting with the aim to correctly predict power produced per hour using wind speed, air temperature, pressure, and air direction as inputs and power produced as output. Cheng L et al. [45] explored a novel spatial temporal approach using an enhanced neural system for short-term forecasting of wind energy to address the issue of fluctuating. In Australia, Hossain et al. [46], in the Boco Rock Wind plant, used a combined model of deep learning to precisely forecast wind power production in intervals of five and ten minutes. In Australia, to accurately predict wind power production. Hossain et al. [47] explored a deep hybrid learning model to accurately enhance a short-term wind power prediction at the Bodangora Wind plant. An et al. [48] analyzed data provided by three organizations to predict accurately wind power using a short-term model that entailed a diverse wind velocity combination. Li et al. [49] explored a short-term adjustable graph network model based on temporospatial to accurately predict wind power. Sopena et al. [50] presented a comparative analysis of up to thirty minutes ahead of the short-term prediction of wind energy utilizing a collection of artificial models based on neural systems and the primary decomposition techniques from a wind plant in Ireland. In Ireland, Gonzalez et al. [51] presented a researched short-term wind energy prediction system that utilized a spiked neural system that was tailored to the processing capabilities of Intel's Loihi.

4.3 Optimization techniques and neural network models for wind power forecasting

To precisely forecast wind power values, Tarek et al. [52] proposed a novel optimization method based on swarm particle optimization and fractal stochastic search to enhance long-term short memory network parameters. Wu et al. [53] proposed a technique model to enhance the factors of Long-short term memory using particle swarm adjustment and erratic fractal to forecast precise values of wind power. Becanin et al. [54] proposed a forecasting energy method that utilizes long short-term memory and gated recurrent units to address the issue of managing the grid power, which also explored an improved algorithm of swarm intelligence. Grace R.K, and Manimegalai R [55] integrated a novel model that entails grey wolf optimization and back propagation neural system to predict wind speed; wavelet transform to divide wind speed into an in-depth band. To accomplish precise and effective power forecasting. Zhang et al. [56] suggested a wind energy forecasting system that used a logistic chaotic atom seek optimized enhanced back propagation neural system. Huang et al. [57] developed an ideal ensemble approach in Taiwan's Changhua for an hourly prediction of wind energy one day ahead of time. Three steps made up the suggested optimum ensemble approach. In order to forecast wind speed in Northwest China, Zhu L and Hu W [58] suggested a technique method that processed wind speed data by combining an optimized variational modal breakdown method with an optimized depth belief neural network. Wang et al. [59] introduced a deep neural system to anticipate wind energy production, and it suggested a storage hydrogen wind-pumped storage combination that employs deep learning as well as intelligent optimization.

4.4 Neural network approaches for predictive time series in wind farms

In China's Xinjiang wind farm, Ai et al. [59] explored the use of neural networks with erratic attribute analysis to create a predictive time series system. The wind farm data was analyzed using an integrated prediction approach, which improved the precision of predictions. To deal with the unpredictable and resolved nature of wind plants in local energy forecasting, a unique multiple-purpose optimal continuous neural system with time pattern awareness was explored by Chen et al. [60]. Qu et al. [61] explored multidimensional power time series, intrinsic mode signals, and convolutional neural systems which are combined with bidirectional long short-term memory and attention mechanisms to estimate wind energy in a wind farm located in Liaoning Province, China. To estimate wind speed in the short term, Chen et al. [63] explored a mixed approach that combined neural networks, time-varying restrictions, modal degradation, permutation entropy, adaptive noise, neuro-fuzzy inference, packet data analysis, and an enhanced monarch butterfly optimization method. Drawing inspiration from the remarkable capabilities of deep neural systems in machine vision, Liu et al. [64] provided a novel method for forecasting short-term wind energy by utilizing the machine learning system to analyze time series pictures.

4.5 Hybrid models and machine learning techniques for wind speed and power prediction

In Canada, Saskatchewan, Abbasipour et al. [65] addressed the issue of wind speed prediction using a twenty-four-hour ahead hybrid model of neural network that entailed 5 algorithms of networks. Xiong et al. [66] worked on a hybrid design prediction system built on descent and meta-heuristic planning to accurately predict wind power and lessen computing load. Hong Y and Santos J [67] suggested a unique hybrid model that combines period and latent long-term, short-term memory improved by optimizing particle swarms to forecast a day wind speed. In Italy, Finamore et al. [68] explored a hybrid wind power prediction model that used an organized framework method that grouped weather data and then used the Person's scrutiny method to locate key elements in each group. Peng et al. [69] proposed a 1 step-ahead power prediction method using a hybrid long-term short-term memory and a convolutional deep learning method. Shah et al. [70] explored a hybrid prediction model that entails ripple transform and swarm particle optimization to address the issue of stability in wind power generation integration. In Indonesia, Barus and Dalimi [71] presented an extensive hybrid machine learning solution that integrated a seasonal moving average on daily hourly operational reserves with specific neural system variables. Long-term short-term memory produced the most precise results. Wang et al. [72] developed a combined innovative forecasting technique consisting of data preprocessing and combination strategy to accurately predict wind speeds for power generation. In this paper, Xiao et al. [73] explored a hybrid model with optimized hyperparameters gated recurrent unit neural network model and feature-weighted principal component analysis, which lessened the effects of unpredictability, noisy data, and instability in wind energy production.

4.6 Hybrid and neuro-fuzzy models for enhanced wind power prediction

In Singapore, Abdullah and Hassan [74] used a neuro-fuzzy short-term hybrid forecast over a twenty-four-hour ahead model to improve the wind power generation prediction, and the results showed 94% accuracy. Roy et al. [75] forecasted 1 hour ahead wind speed accuracy using a synthetic neural network model that compares the input to output data and maps it out, and uses a changeable neuro-fuzzy system to precisely estimate grid power reference for the forecasted hour period. In this paper, Xu et al. [76] presented a reiterative neuro fuzzy hammerstein approach-based projective control system for wind turbines, which addressed the issue of regulating power output.

4.7 Algorithms and neural network models for wind energy prediction

Peiris et al. [77] created an artificial neural system algorithm to predict the amount of wind energy generated at Sri Lanka's operational Pawan Danawi wind farm. The algorithm utilized the produced wind energy as a dependent factor and wind direction, wind speed, and local temperature as independent factors. Xiong et al. [78] suggested and explored a multiple-view deep learning network architecture to estimate wind energy using a wide range of information, including wind speed, wind direction, and wind power. Chen and Han [79] advanced to balance and stabilize the accuracy and wind speed control by using a control method of reward adaptive that entailed controlling the pitch angle and torque of the generator in different conditions. Xia et al. [80] explored and enhanced a stacked gated recurrent unit neural network. They used it to predict the production of wind energy and electrical load in both single and multiple-variable scenarios. To improve calculations and uncover hidden features, Liu et al. [81] presented a novel deep and transfer learning framework that developed efficient data-driven wind energy forecasting algorithms for wind turbines. Liu et al. [82] explored a sophisticated forecasting technique that allowed for both precise and accurate wind power estimates using a standard differential equation system with attention support paired with a long-term short-term memory system. In Montreal, Shirzandi et al. [83], due to the erratic behavior of wind power production, developed a forecasting model of 48 hours ahead using arithmetic weather forecasting, comparing wind speed inputs and output power generation. A synthetic neural network architecture for wind energy prediction was examined in detail by Huang et al. [84] using just historical wind speed and wind energy production statistics for a half hour ahead from a Wind plant in southeast Australia. Gu et al. [85] used collected wind speed information from Chuanshan Port Area, Ningbo-Zhoushan Port, and developed an improved Wavelet Neural Network wind speed prediction model. In Northwest China, Qu et al. [86] investigated the high association properties of wind farm groups and learned their spatial features using a spatial-temporal deep learning system. Ozbek et al. [87] explored a machine intelligence method for precise prediction of wind speeds in Turkey's Marmara and Mediterranean regions. It does this by predicting short-term wind speed data 1 hour ahead of time using neural networks and the Adaptive Neuro Fuzzy Inference System. An algorithm for projecting the production of wind energy, both probabilistic and predictable, as well as related methods, were explored by Wu et al. [88]. Wind speed from Taiwan's Central Weather Bureau was used. Sun et al. [89] to address wind power fluctuations on the grid. They explored a hybrid model of regulating disturbance with an inverter on the grid side. For wind energy projections in the Netherlands and Germany, Wahdany et al. [90] explored a neural network topology that directly considered changing energy system conditions to optimize system costs.

4.8 Neural network models for wind speed and power prediction

Li et al. [91] used eight models to accurately predict wind speeds. Results showed that the convolutional neural model performed better. Song Y et al. [92] presented a method used to precisely forecast wind power using convolutional graphs and convolutional neural systems, mixing spatiotemporal features. Wang et al. [93] created a comprehensive multiple variates mix short-term forecasting of wind speeds system. It consisted of sophisticated feature selection techniques and angle prediction models built on convolutional neural systems. In this research, Nguyen et al. [94] proposed a layered temporal convolutional system method to handle the multi-step forward prediction and increase the reliability of short-term wind energy predictions. This technique tackles the problem of depending on long-term memory. In Japan, Sari et al. [95] explored deep learning that is based on a wind model of one-hour ahead prediction with the intention of establishing a precise prediction model that is made of 3-dimensional neural network convolutional and long-short-term deep convolutional memory.

4.9 Stability and predictability in renewable energy systems enhancement

Alzain and Liu [96] undertook to resolve the issue of uncertainty stability of voltage in the system caused by renewable loads by exploring a model that extracts data between sources using a deep kernel emulator. To tackle the issue of turbine power imbalance causing frequency deviations, Sun et al. [97] explored the use of a load frequency control as a secondary measure for power systems. In Denmark and the Netherlands, Yu T and Yang R [98] explored a wind prediction method to address the wind generation issue by implementing a changeable model that retrieves wind data from different meteorological sources. In this paper, Memmel et al. [99] proposed a selection method of n-1 to address the issue of congestion on the grid. To overcome blade health issues through an additional task and data enhancement neural systems, an independently overseen approach method was presented by Sun et al. [100]. Zhang et al. [101] used wind speed prediction and wind power simulations as its two main elements, developed a system of management for windfarms. To improve renewable system dependability, Tan et al. [102] presented an hour-ahead wind power production forecasting model that used wind speeds as input data. Wang et al. [103] explored a model free adaptable fifteen seconds ahead wind predicting controller to pitch-varying systems, including speed disruption suppression to address variations in wind output.

5. Literature review analysis observations

The literature provided presents a comprehensive overview of various methodologies and models employed for wind power forecasting across different regions globally. One key noticeable aspect throughout the literature is the emphasis on enhancing prediction accuracy and stability in wind power forecasting through the utilization of advanced machine learning techniques and hybrid models. These techniques include deep learning architectures such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), and their combinations with optimization algorithms like particle swarm optimization and fractal stochastic search. Additionally, there is a focus on addressing specific challenges related to wind energy production, such as wind speed prediction, wind power fluctuation management, grid integration issues, and turbine health monitoring. Moreover, there is a notable trend towards incorporating multi-dimensional and multi-step forecasting methods, as well as considering various environmental factors such as weather data and spatial-temporal features to improve forecasting reliability. The literature highlights the significance of accurate wind power forecasting for optimizing energy system operations, enhancing grid stability, and facilitating the integration of renewable energy sources into the power grid.

6. Trends analysis

6.1 Network visualization

The tables below represent the network visualization or gaps within this topic. The table consists of keywords, namely clusters, links, total link strength, and occurrences as headings. They are categorized according to clusters, which range from clusters 1 to 5. Table 2 is the combination of clusters 1 and 2, where cluster 1 consists of 16 keywords, and long short-term memory has a higher number of 243 total link strength, indicating a higher association and relation strength for the keyword. This normally indicates that the higher the total link strength, the higher the occurrence for the keyword, and this is observable from Table 2. Cluster 2 consists of 14 keywords, and electric load dispatching has a higher number of 89 total link strengths, which indicates that there is a higher association and relation strength for the keyword. This normally indicates that the higher the total link strength, the higher the occurrence for the keyword, and this is observable from Table 2 below.

Table 3 represents clusters 3, 4, and 5, and in cluster 3, it can be observed that it consists of 9 keywords. Wind Power has a higher number of 487 total link strength, which indicates that there is a higher association and relation strength on the keyword. This normally indicates that the higher the total link strength, the higher the occurrence for the keyword, which is observable from the table below. Cluster 4, it can be observed that it consists of 8 keywords. Wind power generation has a higher number of 214 total link strengths, which indicates that there is a higher association and relation strength on the keyword. This normally indicates that the higher the total link strength, the higher the occurrence for the keyword, and this is observable from Table 3. Cluster 5, it can be observed that it consists of 5 keywords. Particle swarm optimization (pso) has a higher number of 128 total link strengths, which indicates that there is a higher association and relation strength on the keyword. This normally indicates that the higher the total link strength, the higher the occurrence for the keyword, which is observable from Table 3.

Table 2. Keywords with links, total link strength, occurrences based on application of neural network regression algorithms in wind power generation

Keywords	cluster	Links	Total link strength	Occurrences
Cluster 1 - Red				
long short-term memory	1	50	243	24
wind speed	1	49	185	17
mean square error	1	45	133	12
learning systems	1	43	112	11
deep learning	1	45	111	12
wind speed forecasting	1	38	98	9
convolution	1	38	90	9
machine learning	1	39	84	7
errors	1	44	83	7
stochastic systems	1	32	72	8
machine-learning	1	34	69	6
learning algorithms	1	35	62	5
multilayer neural networks	1	36	60	5
deep neural networks	1	32	59	7
time series	1	28	56	6
convolutional neural networks	1	29	52	5
Cluster 2 - Green				
Keywords	cluster	Links	Total link strength	Occurrences
electric load dispatching	2	36	89	9
brain	2	37	77	7
electric utilities	2	35	61	7
energy utilization	2	24	61	7
neural-networks	2	48	61	15
optimization	2	36	61	8
power generation	2	49	61	26
recurrent neural networks	2	30	61	7
weather forecasting	2	51	61	40
wind farm	2	37	61	10
wind power forecasting	2	40	61	12
wind power prediction	2	27	61	5
wind power predictions	2	36	61	9
algorithm	2	34	54	5

Table 3. Keywords with links, total link strength, occurrences based on application of neural network regression algorithms in wind power generation

Keywords	cluster	Links	Total link strength	Occurrences
Cluster 3 - Blue				
wind power	3	51	487	56
electric power generation	3	51	311	36
forecasting	3	47	122	12
wind	3	35	86	11
electric power transmission networks	3	39	72	8
speed	3	32	70	8
fuzzy inference	3	30	57	6
fuzzy neural networks	3	30	57	6
fuzzy systems	3	28	50	5
Cluster 4 - Yellow				
Keywords	cluster	Links	Total link strength	Occurrences
wind power generation	4	49	214	25
artificial neural network	4	47	128	13
neural networks	4	35	92	11
predictive models	4	39	79	8
wind turbines	4	34	70	9
short term prediction	4	32	57	5
short-term prediction	4	32	57	5
wind forecasting	4	25	50	5
CLUSTER 5 - PURPLE				
Keywords	cluster	Links	Total link strength	Occurrences
particle swarm optimization (pso)	5	43	128	12
particle swarm	5	40	92	8
swarm optimization	5	36	81	7
particle swarm optimization	5	33	63	5
meteorology	5	27	55	5

Figure 3 is a Network visualization, which consists of different colors that represent a gap between the different research topics. The bigger the circle means that much research has been done on that topic, and the smaller the circle means less work or research has been done on that topic and needs further research. The lines between the topics show how the topics are related to each other; the more lines you will have between two topics, the more strength exists between them, and the closer the topics are, the more relationships can be observed between the topics. The graph has five different colors, which are clustered accordingly, namely, Cluster number 1 is indicated in red. It can be observed that long short-term memory has a bigger circle, meaning more research has been done on the topic, with machine learning having a smaller circle, indicating less research work being completed on the topic. Cluster number 2 is indicated in green. It can be observed that weather forecasting as well as power generation have bigger circles, meaning more research has been done on those topics, with algorithm and optimization having smaller circles, indicating less research work being completed on the topics. Cluster number 3 is indicated in blue. It can be observed that wind power as well as electric power generation have bigger circles, meaning more research has been done on those topics, with fuzzy inference and fuzzy systems having smaller circles indicating less research work being completed on the topics. Cluster number 4 is indicated in yellow. It can be observed that wind power generation, as well as artificial neural networks, has bigger circles, meaning more research has been done on those topics, with wind turbines and neural networks having smaller circles, indicating less research work being completed on the topics. Cluster number 5 is indicated in purple. It can be observed that particle swarm optimization (pso) has a bigger circle, meaning more research has been done on the topic, and meteorology has a smaller circle, indicating less research work is being completed on the topic.

6.2 Overlay visualization results

Figure 4 illustrates an overlay visualizing which represents a research trend on the topics. It shows the most recently researched topics and areas by using different colors. The periods have been averaged as depicted on the scale; it starts from 2021.8; this means that 2021 is the year, and the .8 represents month 8; this follows the same trend for the other periods. From 2021.8 to 2022.0, it shows that the investigation has been more on speed, wind, etc., and moving towards 2022.0 to 2022.2, the trends were more into learning systems and errors, then by 2022.2 to 2022.4, the investigation was more based on weather foresting and wind power. From around 2022.4 to 2022.6, the focus was more on particle swarm optimization artificial neural networks. The research topic for the above graph shows the yellow color that from the year period of 2022.6 coming towards 2022.8, the researched topics have been under Power generation, which has a bigger circle representing that much research has been explored on the subject and also a few topics namely, electric load dispatching, algorithm, neural networks having smaller circles representing less researched or explored topics for the future.

7. Future proposal recommendation

Owing to the wind's sudden changes in density, speed, and other important factors, the following topics are recommendations that still need to be thoroughly researched to guarantee consistent generation and a larger role for this source in the electrical power framework.

- Examine how learning algorithms like convolutional neural networks (CNNs) and multilayer neural networks can be combined to increase the accuracy of wind power prediction time series forecasting.
- Create innovative wind power prediction algorithms by combining knowledge from cutting-edge machine learning techniques and conventional forecasting methods.

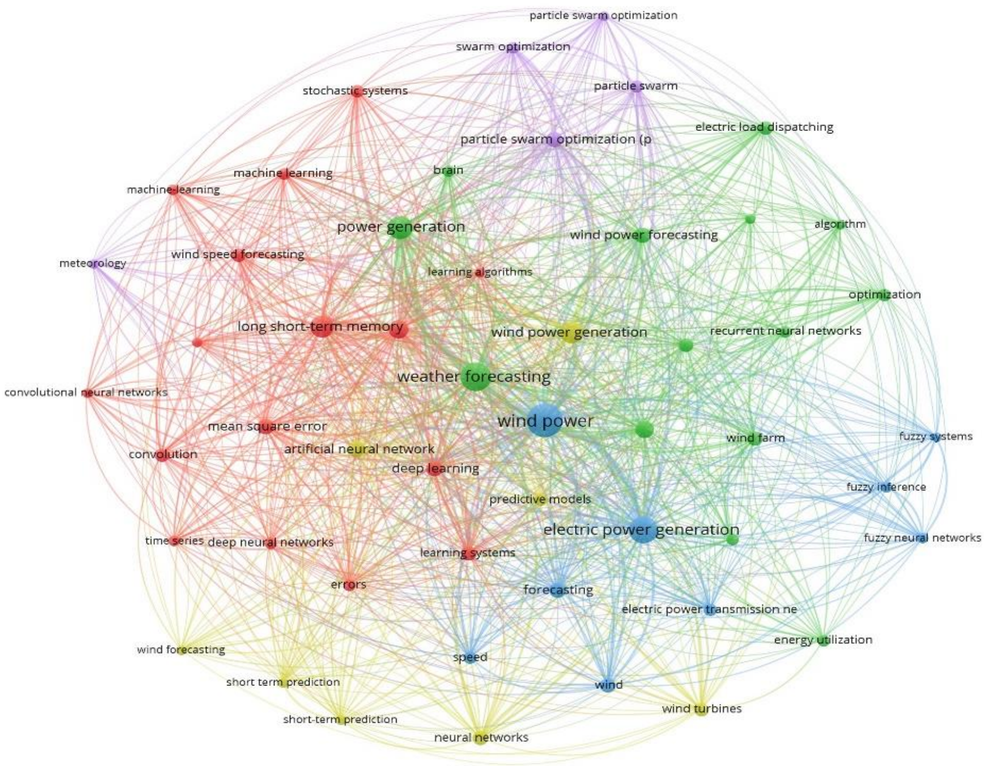

Figure 3. Network visualization based on the application of neural network regression algorithms in wind power generation

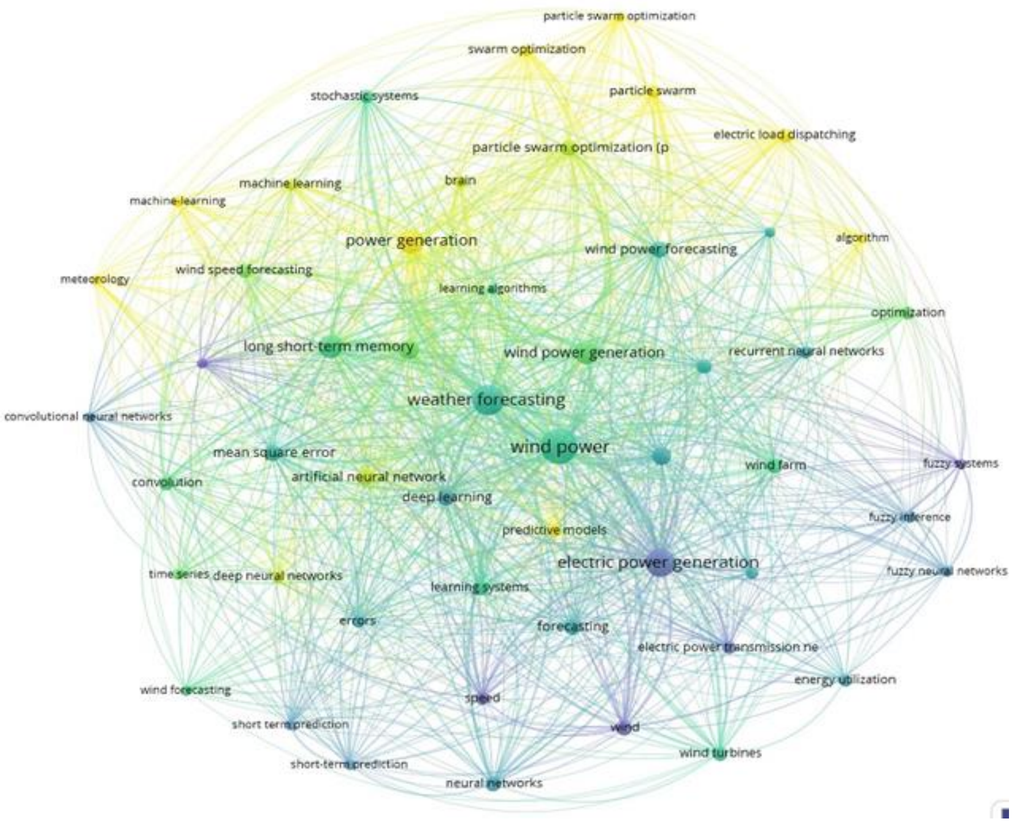

Figure 4. Overlay visualization based on application of neural network regression algorithms in wind power generation

- Investigate how to incorporate fuzzy neural networks and fuzzy inference systems into wind power prediction models to address imprecision and uncertainty in meteorological data.
- By utilizing particle swarm optimization algorithms and incorporating knowledge from meteorology research, create sophisticated short-term prediction models for wind forecasting.
- Create optimization frameworks that improve the accuracy and dependability of short-term wind power predictions by fusing meteorological data with particle swarm optimization techniques.

8. Conclusion

This research undertook a systematic review based on the advanced neural network and hybrid models for wind power forecasting. Using the Scopus database, a methodical search, acquisition, and filtering procedure was utilized to find pertinent publication documents; VOSviewer software was employed to analyze trends. Numerous studies demonstrate the critical role that precise wind power forecasting plays in improving grid stability, accelerating the integration of renewable energy sources into the grid, and optimizing the performance of the energy system. By applying sophisticated machine learning algorithms and hybrid models, wind power forecasting can be made more accurate and stable. Deep learning techniques involve the use of various designs, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and gated recurrent units (GRUs), along with optimization algorithms like particle swarm optimization and fractal stochastic search. In addition to analyzing the integration of optimization techniques with neural networks and offering a thorough review of LSTM and short-term memory-based models in wind power generation, this paper contributed by examining hybrid models that can enhance predictions of wind speed and power output. Along with outlining the effectiveness of different neural network approaches and algorithms used in wind energy forecasting, it also provided recommendations for future research directions.

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Ethical issue
The authors are aware of and comply with best practices in publication ethics, specifically concerning authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere in any language.

Data availability statement
Data sharing does not apply to this article as no datasets were generated or analyzed during the current study.

Conflict of interest
The authors declare no potential conflict of interest.

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