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REVIEW

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Unlocking the potential: A review of artificial intelligence applications in wind energy

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Abstract

This paper presents a comprehensive review of the most recent papers and research trends in the fields of wind energy and artificial intelligence. Our study aims to guide future research by identifying the potential application and research areas of artificial intelligence and machine learning techniques in the wind energy sector and the knowledge gaps in this field. Artificial intelligence techniques offer significant benefits and advantages in many sub-areas, such as increasing the efficiency of wind energy facilities, estimating energy production, optimizing operation and maintenance, providing security and control, data analysis, and management. Our research focuses on studies indexed in the Web of Science library on wind energy between 2000 and 2023 using sub-branches of artificial intelligence techniques such as artificial neural networks, other machine learning methods, data mining, fuzzy logic, meta-heuristics, and statistical methods. In this way, current methods and techniques in the literature are examined to produce more efficient, sustainable, and reliable wind energy, and the findings are discussed for future studies. This comprehensive evaluation is designed to be helpful to academics and specialists interested in acquiring a current and broad perspective on the types of uses of artificial intelligence in wind energy and seeking what research subjects are needed in this field.

KEYWORDS
artificial intelligence, artificial neural network, machine learning, meta-heuristic algorithms, renewable energy, wind energy, wind turbine

1 | OVERVIEW OF WIND ENERGY AND ARTIFICIAL INTELLIGENCE

Renewable energy sources are assuming an increasingly vital role in energy production today. There is a growing need for sustainable energy solutions to combat climate change and provide alternatives to the limited resources of fossil fuels (Shah et al., 2021). The world's installed wind power capacity increased significantly annually between 2001 and 2022. In 2001, the global installed wind power capacity was only 23.6 gigawatts (GW), but by 2022 this figure had increased by over 3700% to 906 GW (Statista, 2023). As a result, wind energy stands out as a clean, renewable, and unlimited energy source, and the installed capacity is increasing daily. Wind energy has worldwide potential and minimal adverse environmental impacts (Fitch, 2015). Therefore, wind power plants are recognized as one of the cornerstones of a sustainable energy future.

While possessing substantial potential as a clean and renewable resource, wind energy encounters several challenges. The ever-changing nature of wind and fluctuations in energy production can pose challenges to the effective deployment of wind power plants (Hovgaard et al., 2015). Uncertainties may arise in energy production as wind speed and direction constantly change (Wohland et al., 2019). This can complicate the assurance of a reliable energy supply and lead to stability problems in energy grids. Furthermore, the high cost of wind power generation presents an additional challenge. The installation costs of wind power plants are quite high, impeding initial investment (Ragheb, 2017; Tagliapietra et al., 2019). Similarly, the maintenance and repair of wind turbines is time and resource-consuming (Mishnaevsky & Thomsen, 2020). This can raise costs and complicate the financing of wind energy projects. In addition, while wind power plants can generate more electricity with strong wind, production can drop or stop altogether when there is insufficient wind. These fluctuations create uncertainty in the energy supply and threaten the electricity grid's stability. If the electricity generated is not fed directly into the grid, there can be energy crises in the case of underproduction and energy waste in the case of overproduction (Özdemir et al., 2022; Özdemir & Dörterler, 2022). Therefore, maintaining a balance between energy production and energy consumption is important (Bilici et al., 2023; Bilici & Özdemir, 2023). Artificial intelligence (AI) technologies can come into play to overcome these challenges. AI can be used to predict fluctuations in wind power generation and optimize energy production. Data analysis and algorithms can monitor and predict variables such as wind speed and direction, thus reducing the effects of fluctuations in energy production. AI-enabled systems can also optimize wind turbines' maintenance and repair processes and reduce costs. Furthermore, using AI technologies in the wind energy sector can increase efficiency in energy production and reduce reliability issues. This could encourage more widespread use of wind energy resources and contribute to a sustainable energy transition.

AI refers to the ability of computer systems to mimic human intelligence to perform complex tasks. For example, according to the European Commission, AI refers to systems that exhibit intelligent behaviour by analysing their environment and acting autonomously to achieve specific goals (Garcia Marquez & Peinado Gonzalo, 2021). A study analysing the research articles published on AI over time stated that approximately 60,000 articles have been published annually in the last five years (Tobin et al., 2019). While there has been a growth of 2.3% in all research, this growth has been 12.9% in AI (Tobin et al., 2019). This significant increase can be attributed to technical advances that enable the use of AI techniques in computing technologies and the availability of AI for various applications such as problem-solving, optimization, data analysis, image recognition, and text processing. In wind power generation, AI offers the potential to optimize wind power generation using complex algorithms and data analysis (Lee & He, 2021). Implementing such technology can lead to more efficient and stable energy production.

Many organizations and researchers are exploring the potential advantages of using AI in the wind energy sector. For example, optimizing wind turbines for power generation is achieved using AI algorithms (Zubova & Rudykh, 2019). By analysing wind speed, direction, and other environmental parameters, AI can adjust the position and angle of wind turbines, thereby increasing energy efficiency. Additionally, AI has great potential in predicting wind power generation. AI systems can predict future energy production by analysing many factors, such as weather data, wind patterns, and turbine performance. Making such predictions provides significant advantages in energy management and consumption planning (Maldonado-Correa et al., 2021).

The integration of AI and wind energy offers potential benefits not only in energy production but also in energy management (Liu, Sun, et al., 2019). AI systems can optimize the management of energy storage systems by predicting energy demand and consumption. This capability enables more efficient and sustainable use of energy resources.

In conclusion, integrating AI technology into the wind energy sector has significant potential for sustainable energy production. AI allows wind energy generation and management to be more efficient, and energy demand and consumption forecasts can be optimized. This application of AI is a significant step towards meeting future energy needs and ensuring environmental sustainability. Researchers continue to explore this potential by using AI in the wind energy sector. Considering the increase in the number of articles in this field over the years, it is seen that this problem is still up to date.

2 | REVIEW METHODOLOGY

In our research, we analysed the number of publications on AI applications on wind energy from 1992 to mid-2023, according to Web of Science (WOS) data. Figure 1 shows that many publications in this field emerged in the early 2000s and have steadily increased (WOS, 2023).

When Figure 1 is analysed, there is an exponential growth in the number of publications from 2000 to 2022. While there were only a few papers in this index category in 2000, the relationship between wind energy and AI has grown in strength and importance among researchers in recent years. While the highest publication volume in this field, with 298, was seen in 2022, the number of publications reached 122 in the half of 2023. It is possible that future research will further deepen the synergy between wind energy and artificial intelligence, and the number of publications will increase. This growth could be the result of the need for sustainable solutions in the energy sector (Taghizadeh-Hesary & Yoshino, 2020) the need for efficient use of renewable energy resources (Sinsel et al., 2020), and the need for optimizing energy production processes (Ammari et al., 2022). Furthermore, with the development of AI technologies, significant progress has been made in areas such as increasing the performance of wind energy systems and improving maintenance processes (Garcia Marquez & Peinado Gonzalo, 2021). Figure 2 represents the countries where research using AI approaches in wind energy research has been published (WOS, 2023). These data reflect the contributions of different countries in this field and global diversity.

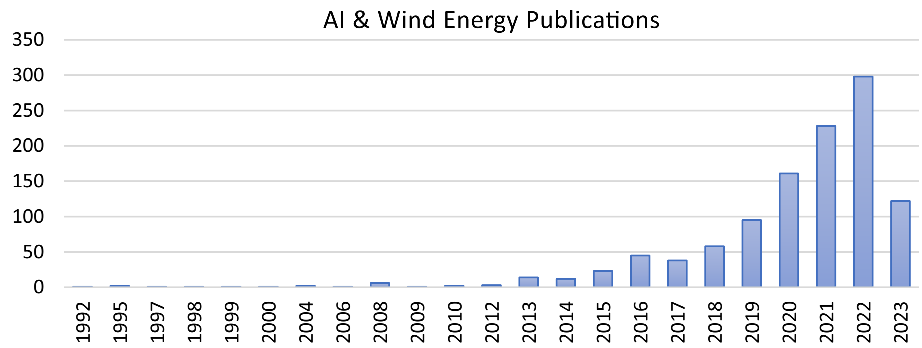

FIGURE 1 Publications on artificial intelligence and wind energy (1992–2023).

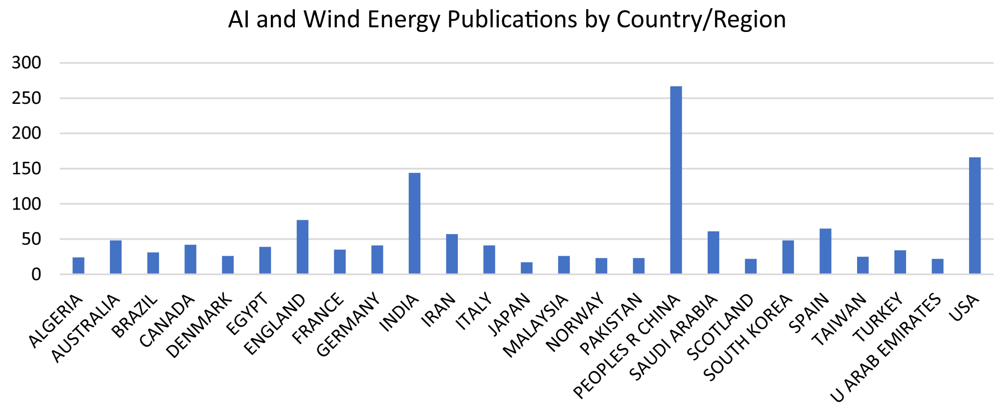

FIGURE 2 Artificial intelligence and wind energy publications by country.

Figure 2 shows that research is concentrated in G20 countries. Accordingly, China, which has the highest number of publications, has invested heavily in research areas that examine the relationship between wind energy and artificial intelligence (Shen et al., 2019). This country's leadership and technological advances in the wind energy sector play an important role in the global renewable energy transition. China is followed by developed countries such as India and the USA. India's wind energy and artificial intelligence publications demonstrate the country's commitment to providing innovative solutions and accelerating the transition to sustainable energy (Satpute & Kumar, 2021). The USA stands out as a country actively researching and developing advanced technologies in this field. In addition to China, India, and the USA, G20 countries such as Australia, Canada, France, Germany, Italy, Saudi Arabia, and South Korea also have many wind energy and AI publications. Furthermore, a notable volume of research in the realm of wind energy and AI has been undertaken in non-G20 countries like Spain, Denmark, Egypt, Iran, Malaysia, Norway, Pakistan, Scotland, Taiwan, and the United Arab Emirates. These data show that studies investigating the relationship between wind energy and AI have aroused great interest globally, and many countries have made significant contributions to this field. As a result, the relationship between wind energy and artificial intelligence has aroused great interest in recent years due to the successful solutions produced using artificial intelligence methods for wind energy problems. Research in this field addresses important issues such as more efficient use of renewable energy resources and improving the performance of wind energy systems. In realizing these studies, various financial support systems are of great importance. Figure 3 shows the financial support organizations that support wind energy and AI research (WOS, 2023).

The National Natural Science Foundation of China (NSFC) is the Chinese organization with the most publication number. NSFC's financial support for research in this field contributes to China's leading position in wind energy and AI. Other crucial financial support systems include the European Commission, the National Science Foundation (NSF), the United States Department of Energy (DOE), UK Research Innovation (UKRI), and the Spanish Government. These systems support wind energy and AI research and are making significant progress in this field. These support organizations help advance wind energy and AI research and develop innovative solutions. Overall, this data shows that financing wind energy and AI research is an important issue globally and that various countries are making significant investments in this area. These financial support systems encourage future research and allow further development of synergies between wind energy and AI.

Wind energy stands out as an environmentally friendly energy production method that has an important place among sustainable energy sources. AI is a technology that has gained tremendous momentum in many sectors in recent years and offers solutions in different fields. Figure 4 presents the leading wind energy topics covered by AI at the intersection of these two fields (WOS, 2023).

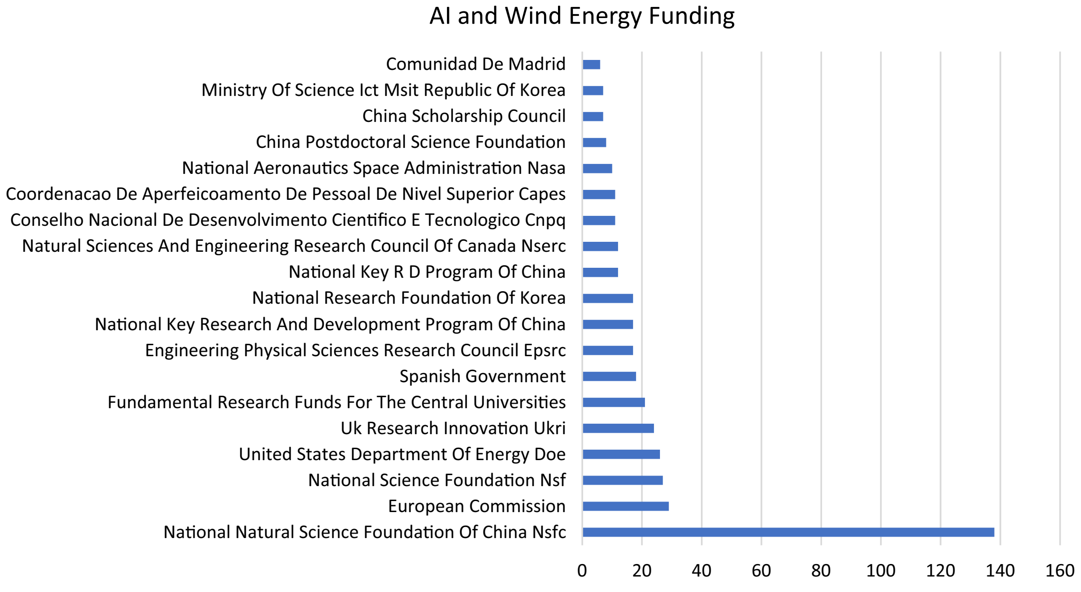

FIGURE 3 Number of artificial intelligence and wind energy related publications funded by sponsors.

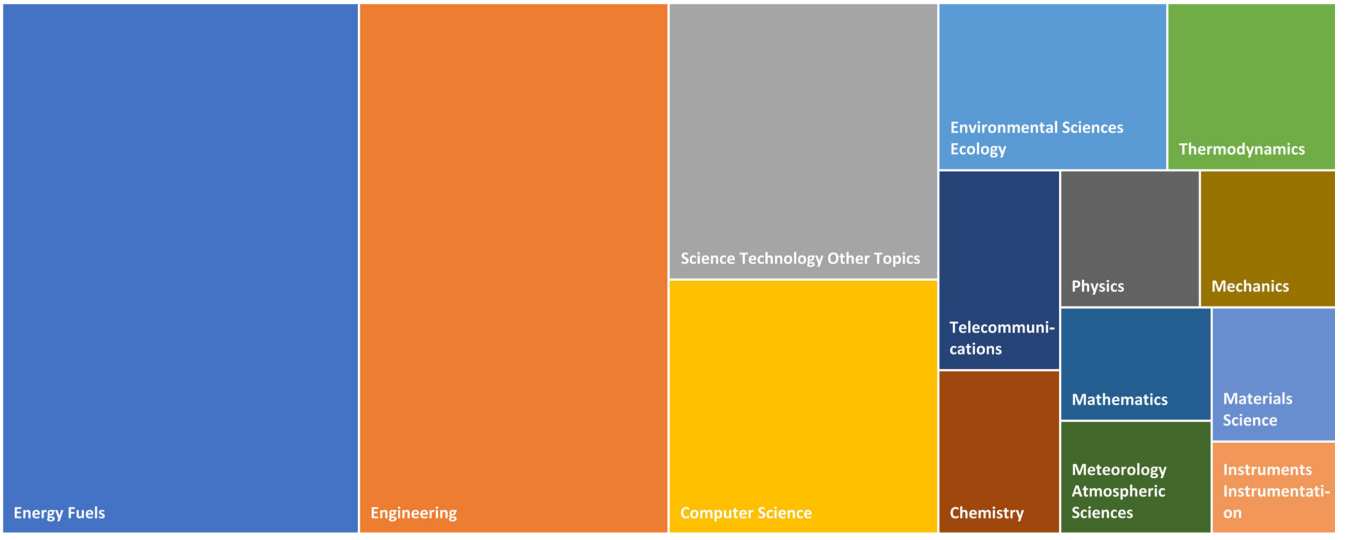

FIGURE 4 Interdisciplinary distribution of wind energy and artificial intelligence research.

The treemap chart visualizes the areas in which AI and wind energy research are focused. These areas help identify the distribution of research topics and which disciplines contribute more to this work. The largest field is Energy Fuels, representing 42,563% of total publications. This result shows the significance of energy fuels in wind energy and AI research, specifically focusing on studies to improve the performance and efficiency of wind energy systems. Engineering also has a large proportion (36.918%), demonstrating that wind energy and AI research are concentrated in engineering. In this field, wind turbine design (Hernandez-Estrada et al., 2021), power electronics (Zhao et al., 2020), control systems (Gao & Liu, 2021), and data analytics (Xiang et al., 2021). The other researches are carried out on topics such as Science, Technology Other Topics (16.756%), Computer Science (15.412%), and Environmental Sciences Ecology (8.602%), which also play an important role in wind energy and AI research. These fields focus on studies covering energy production, environmental impacts, and technological developments within a broader disciplinary framework. The treemap chart shows that wind energy and AI research require a multidisciplinary approach and that different disciplines work together in this field. This diversity increases the potential for innovative solutions and significantly contributes to the energy sector and a sustainable future. Figure 5 shows the distribution of research publications by publication type (WOS, 2023).

Figure 5 shows that the most common document type is 'Article', representing approximately 85% of total publications. This indicates that the vast majority of research in the field of wind energy and AI is published in the form of articles. 'Review Article' (10.212%) is the second most common document type. Publications of this type provided a summarizing approach, such as reviewing the literature on wind energy and AI and

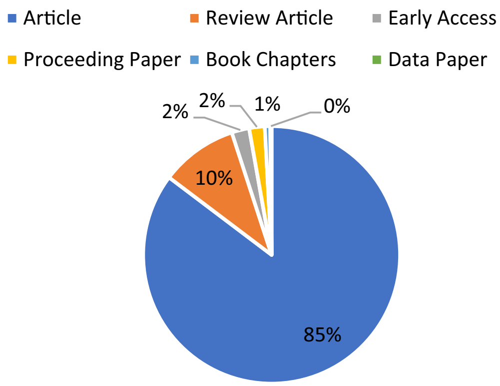

FIGURE 5 Wind energy and artificial intelligence research: Document type distribution.

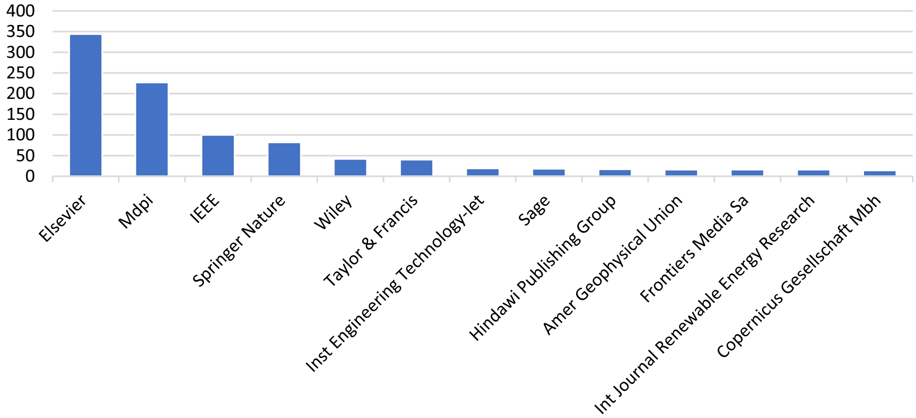

FIGURE 6 Publishers in wind energy and artificial intelligence research: Distribution of publications.

analysing and summarizing existing studies. Other document types have smaller proportions, such as Early Access (2.328%), Proceeding Paper (2.060%), Book Chapters (0.571%), and Data Paper (0.143%). Figure 6 shows the publishers by which wind energy and AI research is published (WOS, 2023). The mentioned publishers have a significant impact on disseminating research and knowledge within the realm of wind energy and AI.

The publisher with the most publications is 'Elsevier', representing 30.838% of total publications. These publications aim to share the latest developments and innovations in the sector. Mdpi (20.331%) is the second most common publisher and is recognized as an essential publisher in wind energy and AI. IEEE (8.982%) is ranked third. Other important publishers include Springer Nature (7.406%), Wiley (3.800%), Taylor & Francis (3.610%) and Inst Engineering Technology-IET (1.708%).

Wind energy is becoming increasingly important as a clean and sustainable energy source. However, advanced techniques are needed to improve the efficiency of wind power plants, reduce maintenance costs, and increase their reliability. In this context, the potential applications of AI and machine learning techniques in the wind energy sector have become a significant focus of interest. These technologies can be used in many areas of wind energy facilities, such as data analysis, prediction models, and operation and maintenance optimization. AI and machine learning algorithms can extract meaningful information from large data sets (Aydemir & Arslan, 2023) and improve the performance of wind power plants.

In this review article, we aim to examine the studies in wind energy and AI, how these two disciplines are combined, and to identify the potential of AI in the wind energy sector and the topics needed in this field. In our study, the Web of Science library was used as a reference, and a total of 1456 publications were searched using the keywords we identified (WOS, 2023). Our search index and keywords are as follows: TI = ((wind energy and artificial intelli*) or (machine learning and wind energy) or (ai and wind energy)) OR AK = ((wind energy and artificial intelli*) or (machine learning and wind energy) or (ai and wind energy)) OR AB = ((wind energy and artificial intelli*) or (machine learning and wind energy) or (ai and wind energy)). Among these publications, 360 proceedings were excluded because they were short and had narrow content, eight book chapters were omitted because they focused on a specific sub-topic, three editorial materials were eliminated because they did not have scientific research content, and 2 data articles were disregarded because they were not suitable for the research objectives of this review article. The 1116 publications to be classified were analysed using the Systematic Literature Review research methodology to examine the relationship between wind energy and artificial intelligence. The specified methodology aims to synthesize the existing literature in a field and write a contribution-oriented review (Kraus et al., 2020). In the rest of the article, we will provide more detailed information about the analysis and results of these publications.

The main innovations of this paper are summarized as follows:

1. A comprehensive review: This paper is a comprehensive review that systematically examines the relationship between wind energy and AI/machine learning. By examining existing publications in the literature, this paper addresses a diverse array of topics, effectively bridging knowledge gaps and contributing to existing research in wind energy and AI/machine learning.
2. Review of current developments in related fields: The paper reviews the most recent studies and research trends in wind energy and AI. This approach aims to provide readers with the latest innovations and advancements in the industry, providing inspiration for future research.
3. Review of potential application areas: The paper provides an in-depth review of the potential applications of AI and machine learning techniques in the wind energy sector and focuses on topics such as data analysis, predictive models, optimization techniques, and safety and control systems. This emphasizes the potential of these technologies to improve the overall performance of wind power plants.
4. Identification of knowledge gaps: The paper guides future research by identifying knowledge gaps in the literature. This identification will help academic and industrial researchers to obtain a guiding resource for new projects and studies.

In Table 1 compares current review articles published in the literature in 2022 and 2023 in the field of artificial intelligence and wind energy with our study. This comparison was made according to criteria such as mentioning the application areas of artificial intelligence in wind energy, explaining the data used in the literature, providing information about the number of citations, and giving information about the use of subcategories of artificial intelligence in wind energy.

Table 1 shows that the most recent studies in the literature generally focus on artificial neural networks (ANN) but need to provide more information on other AI methods. In addition, it is also seen that more information and interpretation is needed in terms of application areas (fault detection, fault prevention, optimization, etc.) and number of citations in recent reviews. This study examines in detail for which purpose all AI methods are used in wind energy.

This paper is structured into the following sections: Section 3 presents the significant works in this area, focusing on the essential research work on ANN. Section 4 analyses machine learning techniques in detail. Sections 5 and 6 discuss data mining and fuzzy logic based methods, respectively. Section 7 analyses the application of metaheuristic techniques in the wind energy sector. Section 8 will focus on statistical-based techniques and their applications in wind energy and AI. The Discussion and Conclusion section emphasizes the importance of making meaningful decisions from data in wind energy facilities. Finally, the main conclusions and recommendations of this paper are presented.

3 | ARTIFICIAL NEURAL NETWORKS METHODS

ANN has attracted attention for its data analysis and prediction capabilities, which have great potential in the wind energy sector. ANN can optimize, predict, and control wind power generation using essential parameters such as wind speed, direction, and power (Garcia Marquez & Peinado Gonzalo, 2021). By increasing the efficiency of wind power plants, this technology accelerates the energy sector's transformation and contributes to a sustainable future. This section examines how ANN is used in wind energy-related studies.

The fault detection studies using ANN in wind energy can be specified as follows: Offshore wind speed, wave, and alignment prediction (Sacie et al., 2022), thermal uplift prediction in wind-solar tower systems (Rushdi et al., 2021), improving lidar turbulence estimates for wind energy (Newman & Clifton, 2017), fault detection in an urban wind energy system (Kwok & Hu, 2023), modelling of clean energy wind power systems using unified power quality conditioner (UPQC) (Reddy & Manohar, 2017), AI-based prediction and analysis of wind and solar energy surplus

TABLE 1 Comparisons with other review articles in the literature.

Articles	Application areas	Data type	Number of citations	ANN	Machine learning	Data mining	Metaheuristics	Fuzzy logic	Statistical methods
(Zhao et al., 2022)	X	X		X					X
(Farrar et al., 2023)		X		X	X	X			
(Garcia Marquez & Peinado Gonzalo, 2021)	X	X		X		X		X	X
(Valdivia-Bautista et al., 2023)		X		X	X			X	X
Current Study	X	X	X	X	X	X	X	X	X

in power systems (Shams et al., 2021), wind-driven seawater reverse osmosis (SWRO) desalination prototype with and without batteries (Cabrera et al., 2018), accurate and efficient wind energy prediction using meteorological variables and wind direction (Majid, 2022), AI techniques in smart grid and renewable energy systems (Bose, 2017), using the ANN for doubly-fed induction generator converters (DFIG) based wind energy conversion systems (Sami et al., 2022; Srinivasan & Jagatheeswari, 2023), wind turbine angular speed estimation using video mining and convolutional neural network (CNN) network (Bahaghighat et al., 2020), damage detection of jacket-type offshore wind turbine platforms using Siamese ANN (Baquerizo et al., 2022), motion detection from video footage of wind energy equipment (Li & Kamruzzaman, 2022).

The works following this section focus more on predicting wind energy using ANNs. Researchers have conducted forecasting studies on wind energy (Kosovic et al., 2020; Özen & Deniz, 2022), and hydrogen production from wind energy (Javaid et al., 2022). Another study proposed a network named M2STAN (multi-modal multi-task spatiotemporal attention network) for multi-location ultra-short-term wind energy forecasting (Wang & He, 2022). In addition to studies such as long- and short-term wind speed forecasting (Ak et al., 2015; Azad et al., 2014; Fazelpour et al., 2016; Kulkarni et al., 2019; Shivam et al., 2020), and wind power generation forecasting with hybrid and ensemble methods (Piotrowski et al., 2021), a literature review on wind energy forecasting with neural networks was also conducted (Manero et al., 2018).

Some different studies with neural networks are as follows: Using autocoders for short-term wind energy forecasting (Jiao et al., 2018), probabilistic wind energy forecasting based on a spike-based neural network (Wang et al., 2020), developing a multi-target wind speed forecasting model with stacked sparse autocoder and adaptive decomposition-based error correction (Liu & Chen, 2019), short-term wind turbine power forecasting with long short-term memory (LSTM) (Zhang et al., 2019), combining autocoder and particle swarm optimization (PSO) algorithm with extreme learning machine for short-term wind energy forecasting (El Bourakadi et al., 2022).

In addition to forecasting studies in different fields, there are also modelling studies using ANN in wind energy. Modelling offshore hybrid wind-wave energy systems (Dehghan Manshadi et al., 2022) and modelling wind energy potential in different regions (Daş et al., 2021) are examples of modelling studies using ANN. Optimization studies in wind energy using ANN can be listed as follows: Using ANN to optimize wind turbine siting (Higgins & Stathopoulos, 2021), optimizing the operation of wind, solar, and photovoltaic (PV) energy systems with and without energy storage (Abualigah et al., 2022), design and optimization of DFIGs for smart grid (Behara & Saha, 2022), designing an optimal flow concentrator for vertical axis wind turbines using genetic algorithm (GA) and ANN (Svorcan et al., 2021), development of a smart energy management system for microgrid (Chaouachi et al., 2012), calculation of power profiles for an Airborne Wind Energy system based on large-scale wind data (Malz et al., 2020), use of ANN to optimize the estimation of wind energy resources and sizing of energy storage in the power grid (Odero et al., 2022). ANN is also used to determine the optimal operating reserves to increase the penetration of wind power in the power grid (Barus & Dalimi, 2021), and to design the optimal active and reactive power control scheme for networked permanent magnet synchronous generator (PMSG) wind turbines (Mahmoud et al., 2018), to solve the real-time alternating current (AC) optimal power flow problem (Zhou et al., 2021), to optimize the layout of an offshore wind farm (Yang & Deng, 2023).

Using ANN in wind energy is a promising effective, and efficient energy production approach. In the studies reviewed in this section, neural networks have been used in critical areas such as wind speed prediction, turbine control, and energy production optimization. Through the utilization of ANN, a more sustainable and efficient future in the wind energy sector is predicted. In recent years, the number of layers in deep learning models has significantly increased the success rates of ANN. Deep learning is capable of learning more complex and abstract patterns using neural network structures with more layers and parameters (Wu et al., 2021). This capability has enabled neural networks in the wind energy field to perform essential tasks such as prediction, control, and optimization more effectively. The references in this chapter are classified based on the used algorithms, their application areas, the number of citations of each reference, and the data set in Table 2.

Table 2 illustrates the extensive utilization of artificial neural networks (ANN) in the forecasting domain within wind energy research. Predicting future long and short-term wind speeds by using wind speed data is a popular field of study. Besides that, ANN has been used in optimization studies in many areas, such as energy generation, storage, and distribution. Other areas where the ANN technique is used relatively less are hybrid methods. The majority of AI studies in the field of wind energy have been conducted using the ANN method. Table 3 shows the total number of citations for various ANN applications.

Table 3 presents citation data for various applications of ANN in wind energy. The forecasting application stands out prominently with 1742 citations, making it the most cited and researched application. Fault detection follows it with 854 citations, and condition monitoring has 548 citations. Decision making and optimization also play essential roles, with 461 and 471 citations, respectively. On the other hand, the areas of modelling, maintenance, planning and scheduling received fewer citations. The table shows that artificial neural networks are used extensively in the wind energy field, especially in specific applications such as forecasting and fault detection, and more research is being done in these areas.

4 | MACHINE LEARNING METHODS

Maximizing the potential of wind energy as a sustainable and clean source necessitates the efficient operation of wind turbines and the reduction of energy production fluctuations. Machine learning methods have become an area of great interest and successful results in the wind energy sector. In this section, machine learning methods used in wind energy are analysed.

TABLE 2 ANN applications.

Application	Algorithm	Data/variables	References	Number of citations
Fault detection	ANN	Numerical	(Majid, 2022)	5
			(Reddy & Manohar, 2017)	4
			(Rushdi et al., 2021)	18
		Simulated data	(Sami et al., 2022)	13
			(Liu, Gao, et al., 2022)	12
			(Bose, 2017)	206
			(Dumnic et al., 2015)	8
		Hourly data of power plants, power exchange, and demand	(Shams et al., 2021)	34
		Wind speed data	(Khatib et al., 2020)	6
		Temperature, wind speed, panel orientation	(Abdellatif et al., 2022)	2
		Vibration data	(Lalik & Wątorek, 2021)	8
		Triboelectric sensor output data, weather parameters	(Shrestha et al., 2022)	4
		Video data	(Bahaghighat et al., 2020)	15
			(Li & Kamruzzaman, 2022)	1
		Supervisory control and data acquisition (SCADA)	(Bangalore & Patriksson, 2018)	111
			(Brandão et al., 2010)	18
			(Brandão et al., 2015)	20
			(Brandão et al., 2015)	6
			(Corley et al., 2021)	19
			(Nithya et al., 2017)	16
			(Optis & Perr-Sauer, 2019)	73
			(Reddy et al., 2019)	111
			(S. Zhou et al., 2018)	1
		Vibration (accelerometer measurements)	(Baquerizo et al., 2022)	7
		Lidar data	(Newman & Clifton, 2017)	24
		Synthetic data	(Yang et al., 2019)	82
	ANN-Adaptive neuro fuzzy inference system (ANFIS)	Solar irradiance, wind speed, ambient air temperature	(Gopi et al., 2023)	30
Fault diagnosis	ANN	Vibration analysis, thermography	(Barbosa et al., 2023)	7
		Vibration	(Lu et al., 2019)	19
			(Xiao et al., 2022)	3
	ANN	Slewing bearing life-cycle test dataset	(Pan et al., 2022)	5
	ANN-PSO	Vibration	(Hu et al., 2019)	48

TABLE 2 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
Fault prediction	ANN-GA	Vibration	(Jiang et al., 2012)	N/A
Fault prevention	ANN	Wind speed, active power demand	(Chojaa et al., 2023)	21
Forecasting	ANN	Airfoil geometry	(Campobasso et al., 2020)	16
		Wind speed and power	(Kosovic et al., 2020)	56
		Wind speed	(Azad et al., 2014)	250
			(Fazelpour et al., 2016)	80
			(Kulkarni et al., 2019)	33
			(Liu & Chen, 2019)	87
			(Shivam et al., 2020)	26
		Meteorological data	(Alghamdi, 2022)	5
			(Huynh et al., 2020)	28
			(Jallal et al., 2020)	23
			(Tao et al., 2023)	5
			(Zhang et al., 2019)	280
		Wind speed data, power generation data	(Lipu et al., 2021)	41
		Wind speed and direction	(Wang & He, 2022)	23
		Wind speed, temperature, humidity, and pressure	(Piotrowski et al., 2021)	13
		Wind speed, energy production, solar irradiance	(Rahman et al., 2021)	84
		Time series	(de Mattos Neto et al., 2021)	35
		ERA5 reanalysis data	(Özen & Deniz, 2022)	1
		Wind power data	(Jiao et al., 2018)	131
			(Li et al., 2019)	48
			(Wang et al., 2020)	51
		Historical wind power data, load demand data, and other numerical data	(Abbasipour et al., 2021)	11
			(An et al., 2021)	44
			(Cenek et al., 2018)	18
			(Jamii et al., 2022)	13
			(Pombo, Rincón, et al., 2022)	10
			(Sun & Liu, 2016)	115
	ANN-Hybrid models	Wind speed, air temperature, humidity, and pressure.	(Barbosa de Alencar et al., 2017)	143
	ANN-Meta-heuristic	Wind speed data, solar radiation data	(Alghamdi et al., 2023)	37
	ANN-Meta-heuristic	Time series data	(Lin & Zhang, 2021)	19
	ANN-Meta-heuristic-Fuzzy logic-Data mining-Statistical methods-Bayesian analysis	Solar radiation data	(Chaudhary et al., 2021)	2

(Continues)

TABLE 2 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
	ANN-Support vector machine (SVM)-Adaptive neuro-fuzzy inference system (ANFIS)	Climacteric and energy data	(Baptista et al., 2020)	14
Modelling	ANN	Wind speed data, meteorological data, power generation data	(Prasad et al., 2020)	15
Decision making	ANN	Numerical weather prediction (NWP), observational data, historical data	(McGovern et al., 2017)	368
		SCADA data	(Lu et al., 2018)	73
			(Rodríguez-López et al., 2018)	9
	ANN-Kalman filter	Wind speed	(Hur, 2019)	11
Planning and scheduling	ANN-Bayesian networks	Fault data, statistical methods	(Sinha & Steel, 2015)	13
	ANN-AI model	Bearing fault progression	(Herp et al., 2019)	12
Condition monitoring	ANN	Vibration	(Koukoura et al., 2019)	9
		SCADA data	(Bangalore et al., 2017)	133
			(Yan, Li, et al., 2015)	10
		Gearbox data	(Bangalore & Tjernberg, 2015)	373
		Rotor speed, temperature	(Mazidi et al., 2017)	23
Control	ANN	Wind speed data	(Fidan et al., 2019)	1
			(Rodríguez et al., 2020)	64
	ANN-Meta-heuristic	Power system data	(Veerasamy et al., 2020)	101
False alarm detection	ANN-Fuzzy logic	Vibration	(Marugán et al., 2019)	87
Maintenance	ANN-Data mining	Power generation	(Zhan et al., 2019)	25
	ANN-Meta-heuristic	Gearbox temperature, gearbox data	(Peng et al., 2012)	7
Optimization	ANN	Wind speed data	(Higgins & Stathopoulos, 2021)	30
			(Mahmoud et al., 2016)	27
			(Xin et al., 2022)	3
		Wind speed, solar irradiance, and other meteorological variables	(Haupt et al., 2020)	32
		Solar radiation, wind speed, load changes, demand response, and energy storage system	(Aly et al., 2021)	13
		Historical demand, weather, and solar energy generation data	(Borghini et al., 2021)	18
		Wind power capacity and utilization rate	(Wang & Qiao, 2021)	1
		Wind and photovoltaic data	(Breesam, 2021)	5
		Real power loss and voltage profile	(Chandrasekaran et al., 2021)	29
		Solar and wind power productions data	(Iliadis et al., 2021)	33
		Historical wind power data	(Dhiman et al., 2021)	12

TABLE 2 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
		Meteorological data	(Guo et al., 2022)	N/A
			(Okonkwo et al., 2022)	22
		Flywheel data	(Mir & Senroy, 2018)	17
	ANN-Meta-heuristic	Numerical data	(Luo et al., 2021)	68
			(Svorcan et al., 2021)	7
		Energy consumption data	(Yuce et al., 2016)	154
Review	ANN	N/A	(Behara & Saha, 2022)	12
			(Ferrero Bermejo et al., 2019)	175
			(Manero et al., 2018)	30

TABLE 3 ANN applications and total number of citations.

ANN applications	Total number of citations
Fault detection	854
Fault diagnosis	82
Fault prevention	21
Forecasting	1742
Modelling	15
Decision making	461
Planning and scheduling	25
Condition monitoring	548
Control	166
False alarm detection	87
Maintenance	32
Optimization	471

In the literature, studies using machine learning methods in the field of wind energy are as follows: Using machine learning algorithms to estimate the energy production value of wind turbines (Aksoy & Selbaş, 2021; Blachnik et al., 2023; da Silva et al., 2021; Ma & Zhai, 2019; Piotrowski et al., 2022; Singh et al., 2021), developing a protocol for wind energy management using machine learning and game theory (Khabbouchi et al., 2023), using the Internet of Things (Aydemir & Arslan, 2021) and machine learning models for proactive maintenance of wind turbines (Selvaraj & Selvaraj, 2022). IoT applications are also used in wind power plants and smart grids. Since wind farms are usually installed in remote areas with high winds, IoT is used for instant data collection, analysis, and real-time decision-making from these remote areas. IoT applications in wind power plants have significant benefits such as wireless data collection and real-time monitoring, early fault detection, prevention of extended downtime, reduction of maintenance costs, and facilitation of real-time decision making (Adekanbi, 2021). Other studies using machine learning methods in the field of wind energy are as follows: Developing a machine learning application to examine the relationship between solar and wind energy production, coal consumption, gross domestic product, and carbon dioxide (CO_2) emissions (Magazzino et al., 2021), estimating hub height wind speed with machine learning (Liu, Ma, et al., 2023; Yu & Vautard, 2022), the use of quantile regression forests to probabilistically predict wind turbine icing-related generation losses (Molinder et al., 2020), the use of ensemble learning and power curves to detect anomalies in wind turbines (Moreno et al., 2020), and the use of gradient boosting regression tree algorithms to predict short-term wind power outputs (Park et al., 2023).

Furthermore, other wind energy studies using machine learning can be listed as follows: Prediction of wind energy ramp events using hybrid machine learning regression techniques and reanalysis data (Cornejo-Bueno et al., 2017), wind speed assessment using Sentinel family satellite imagery and machine learning methods (Nezhad et al., 2021), development of a hybrid wind power prediction model with XGBoost (Phan et al., 2021), wind power forecasting with meteorological characterization (Sasser et al., 2022), planning of wave-wind offshore energy devices (Masoumi, 2021), forecasting short-term offshore wind speed (Dokur et al., 2022), modelling wind turbine site suitability (Petrov & Wessling, 2015), mapping spatial suitability for wind energy systems (Sachit et al., 2022), Predicting wind turbine power output based on SCADA system data (Singh & Rizwan, 2022), using K-Means algorithm to discover SCADA data from wind turbines (Rodriguez et al., 2023), using k-nearest neighbour (KNN) to predict short-term wind power (Mahaseth et al., 2022), using SVM to manage renewable energy resources (Issa et al., 2022), using machine learning and CNN-LSTM approaches to predict wind power generation (Malakouti et al., 2022), using thermal modelling and machine learning to detect faults in wind turbine gears (Corley et al., 2021). These studies are AI studies in wind energy, including machine learning methods other than ANN. Table 4 summarizes the studies in this section, categorizing them according to the algorithms they use, their application areas, the data they consider, and their total number of citations.

As seen in Table 4, one or more hybridized machine learning methods have been frequently used in wind energy studies. Although these methods are primarily used for prediction, different machine-learning techniques are used in many areas, such as fault detection, fault prevention, decision-making, and optimization. Many machine learning methods such as KNN, SVM, KELM, and XGBoost have been used in areas such as the prediction of energy to be produced, long and short-term wind speed prediction, and detection and prevention of physical faults related to wind turbines. Table 5 shows the total number of citations for various Machine Learning applications.

Table 5 shows the number of citations for machine learning applications in wind energy. According to the table, the most cited areas are forecasting with 1126 citations, followed by optimization with 429 citations and fault detection with 425 citations. Forecasting studies are crucial in predicting the future efficiency and energy production of wind power plants. Optimization applications have been frequently studied to increase the efficiency of existing systems. Fault diagnosis applications, which rank fourth with 222 citations, have been used to increase the operational efficiency of wind turbines and minimize unexpected failures. Additionally, areas such as fault prediction modelling, condition monitoring, and decision making have also received significant citations. The results indicate that artificial intelligence techniques are widely accepted in the wind energy sector and have a significant impact, particularly in forecasting, optimization, and fault detection. However, it is worth noting that control, fault prevention and planning and scheduling received relatively few citations. This may suggest that these topics are still under development or that there are gaps in the literature.

5 | DATA MINING

Data mining is an important AI tool used in wind energy, such as preventing errors in wind turbines and wind farms, maintenance of turbines, and detection of faults. Some of the studies using data mining in wind energy can be listed as follows: The use of data mining methods to detect faults in wind farms by monitoring wind speed (Tran et al., 2020), developing a data-driven methodology for predictive maintenance of wind turbines (Garan et al., 2022), using cluster analysis to predict wind turbine generator failure (Turnbull et al., 2019), creating a holistic data set from meteorology, wind, and solar energy data (Pombo, Gehrke, et al., 2022), and data-driven modelling for offshore wind turbines (Janssens et al., 2016). Studies have been carried out using these methods for more efficient operation of wind energy systems. Table 6 presents the algorithms used in data mining and the number of citations they have received, categorized by applications and data considered.

Table 6 summarizes the characteristics of the studies carried out using the data mining method in wind energy. Although data mining methods find utility across various application domains, their prevalent utilization centres on condition monitoring and fault detection. Studies have been conducted in areas of application such as turbine and generator failures, as well as in forecasting, using data mining methods. These studies made use of data from sources including wind speed measurements, vibration sensors, accelerometers, and SCADA systems. Table 7 presents citation data for various applications of Data Mining in wind energy.

Table 7 presents citation data for data mining applications. Fault diagnosis has the highest number of citations, with 478, followed by fault detection and fault prediction, with 160 and 168 citations, respectively. Data mining is also utilized in areas such as maintenance and forecasting, but these studies have received fewer citations. In conclusion, data mining is extensively used in areas such as fault diagnosis, fault detection, and fault prediction, and these studies are highly cited.

6 | FUZZY LOGIC

Fuzzy logic is a mathematical approach for modelling and controlling uncertain systems (Ergün et al., n.d.; Liu & Li, 2005; Nguyen & Sugeno, 2012). While traditional logic is based on specific values, such as true or false, fuzzy logic uses fuzzy sets and fuzzy values to express uncertainty (Alfaro García et al., 2015; Altun et al., 2018; Zadeh, 1983). Fuzzy logic methods are widely used, especially in areas such as integrating control systems into wind energy systems.

Wind energy studies using fuzzy logic can be listed as follows: Using fuzzy logic to integrate fractional order control with DFIG based wind energy system (Ullah et al., 2020), using fuzzy logic to maximize the power efficiency of wind turbines (Ayenew & Berhanu, 2022). Using fuzzy

TABLE 4 Machine learning applications.

Application	Algorithm	Data/variables	References	Number of citations
Control	Machine learning-Genetic algorithm	Floating offshore wind turbine data	(Kane, 2020)	15
Condition monitoring	Medium tree-Bagged trees-Logistic regression kernel	Vibration	(Granados et al., 2023)	1
	Extreme learning machine algorithm-Bonferroni interval method	SCADA data	(Qian et al., 2018)	54
	Ordered weighted averaging operator	Wind speed, turbine rotational speed, and power output	(Chehaidia et al., 2020)	12
Decision making	XGBoost	Wind speed and air density	(Phan et al., 2021)	29
	Decision tree	Wind speed	(Mansour et al., 2021)	9
	Random forest-Support vector machine (SVM)-Multi-layer perceptron	Wind speed, solar irradiance, population density, and so forth	(Sachit et al., 2022)	8
	Cost-oriented machine learning	Wind speed, wind direction, and power output data	(Zhao et al., 2021)	32
Fault detection	Machine learning	Time series data	(Cabrera et al., 2018)	62
			(Ozcanli et al., 2020)	129
			(Şerban & Lytras, 2020)	139
	Linear regression (LR)-SVM-Gaussian process regression-ANN	Wind speed, wave height, and misalignment	(Sacie et al., 2022)	10
	Machine learning	Wind speed, rotor speed, stator voltage, stator current, active power, reactive power	(Srinivasan & Jagatheeswari, 2023)	3
	Weighted k-nearest neighbours-Decision tree-SVM-Random forest-Rotation forest	Wind speed, wind direction, timestamp	(Moreno et al., 2020)	20
	LR-ANN-Support vector regression-Reduced-error pruning tree	Numerical weather prediction data	(Chen et al., 2022)	4
	Supervised machine learning	Wind speed data	(Darwish & Al-Quraan, 2023)	10
	Semi-supervised fuzzy pattern matching	Stator harmonic currents	(Rouabah et al., 2022)	13
	Machine learning	Sensor data	(Bicocchi et al., 2019)	6
	SVM-ANN-Gradient boosted trees	Meteorological data	(Shield & Houston, 2022)	8
	Decision trees	Numerical data	(Saha et al., 2022)	1
	Multilayer perceptron-Naive Bayes-Linear SVM-XGBoosts-Random forest-Decision tree	Vibration signals	(Arockia Dhanraj et al., 2022)	4
	Machine learning-Supervised learning	Simulated data	(Gonzalez-Jimenez et al., 2021)	13
			(Srinivasan & Jagatheeswari, 2023)	3
Fault diagnosis	CNN-LSTM	Wind speed	(Park et al., 2022)	N/A
	Random forest	Overhead transmission line data	(Sobhy et al., 2021)	7
	Machine learning-Radial basis functions networks	Vibration	(Dervilis et al., 2014)	181
	Machine learning-Hilbert–Huang transforms	Gear Fault, bearing fault, looseness fault	(J.-H. Zhong et al., 2018)	34

(Continues)

TABLE 4 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
Fault prediction	Machine learning	Laser scans, erosion analysis	(Cappugi et al., 2021)	32
	Machine learning-LSTM	Testing time, wind flow speed, drag force, bibration	(Dehghan Manshadi et al., 2021)	50
	Machine learning-Regression algorithms-ELM	Real-world data	(Cornejo-Bueno et al., 2017)	25
Fault prevention	Machine learning-Teaching learning-based optimization	Wind speed	(Routray et al., 2021)	11
Forecasting	Machine learning-Random forest-Decision tree	Windspeed, power, wind direction Angle, rtr_rpm, pitch angle, generation, wheel hub temperature, ambient temperature, tower bottom ambient temperature, failure time	(Malakouti, 2023)	12
	Machine learning	Wind speed and solar energy	(Galindo Padilha et al., 2022)	3
			(Javaid et al., 2022)	14
	Machine learning	Wind speed	(Cocchi et al., 2018)	22
			(Dokur et al., 2022)	37
			(Liu, Ma, et al., 2023)	19
			(Malakouti et al., 2022)	31
			(Paula et al., 2020)	28
			(Shang et al., 2022)	30
			(Treiber et al., 2016)	66
			(Yu & Vautard, 2022)	8
			(Zameer et al., 2015)	59
			(Zulu et al., 2023)	13
	Machine learning	Meteorological data	(Baquero et al., 2022)	2
			(Gangwar et al., 2020)	36
			(Kim & Kim, 2023)	2
			(Park et al., 2020)	43
			(Sasser et al., 2022)	31
			(Vaccaro et al., 2012)	27
			(Zjavka, 2022)	1
	Machine learning	Wind speed, wind direction, Air temperature, humidity, pressure, and so forth	(Blachnik et al., 2023)	1
			(Hafeez et al., 2020)	27
	Machine learning-MLP-ELM	Wind speed	(Ak et al., 2015)	182
	Machine learning	Time series	(da Silva et al., 2021)	130
			(Mahaseth et al., 2022)	3
			(Park et al., 2023)	6
			(Park et al., 2021)	2
			(Tharani et al., 2020)	10
			(Ye et al., 2019)	19
	Machine learning-Deep residual networks (DRN)	SCADA data	(Li, 2022)	52

TABLE 4 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
	Machine learning-Autoregressive integrated moving average (ARIMA)	Wind speed	(Liu et al., 2021)	200
	Machine learning-PSO	Wind speed	(El Bourakadi et al., 2022)	10
Modelling	Machine learning-LSTM	Wind speed, wave height, wave period, water depth, seabed slope, current speed	(Dehghan Manshadi et al., 2022)	7
	Machine learning	Wind speed data	(Hanoon et al., 2022; Liu, Yan, et al., 2022)	7
	Machine learning	Meteorological data	(Nourani et al., 2019)	52
			(Yeganeh-Bakhtiary et al., 2022)	22
	Machine learning-Random forest	Geological data	(Friedland et al., 2021)	11
	Machine learning-Decisiton tree-Random forest	Wind speed	(Daş et al., 2021)	N/A
	Machine learning-Regression	Wind velocity, system load, solar irradiation	(Queen et al., 2021)	10
	Machine learning-K means-KNN	Wind turbine power curve data	(Kouissi et al., 2022)	1
	Machine learning-CNN	Numerical data	(Zhang et al., 2021)	27
	Machine learning-Gradient boosting-Random forest	Historical building energy data	(Li et al., 2023)	4
Optimization	Supervised machine learning	Wind speed and direction data	(Krömer et al., 2016)	9
	Machine learning-SVM-LSTM	Wind speed data	(Shabbir et al., 2022)	9
	Machine learning	Time series	(Gupta et al., 2021)	14
			(Lawal et al., 2021)	26
			(Magazzino et al., 2021)	244
			(Pombo, Bindner, et al., 2022)	8
	Machine learning-Regression algorithms	Wind speed	(Salah et al., 2022)	12
	Machine learning wake model	Wind speed data, turbine characteristics data, layout constraints data	(Yang & Deng, 2023)	6
	Machine learning	Real-time	(Sathishkumar & Karthikeyan, 2020)	4
	Machine learning-Support vector regression (SVR)-SVM	Wind power data	(Khabbouchi et al., 2023)	7
	Machine learning-SVR	Wind speed, wind direction, and the power output	(Fischetti & Fraccaro, 2019)	54
	Machine learning-Maximum entropy method (Maxent)	Wind speed, elevation, slope, land cover, distance of infrastructure and settlements, population density	(Petrov & Wessling, 2015)	20
	Machine learning-Probabilistic learning on manifold (PLoM)	Wind speed and direction	(Almeida & Rochinha, 2023)	5
	Machine Learning-SVM	Wind speed, solar irradiance, load demand	(Issa et al., 2022)	N/A
	Machine learning-Support vector data description (SVDD)	Landowners, prices, wind speed and turbulence data, the terrain data	(Reddy, 2021)	5
	Machine learning-LSTM	Power output data, weather data	(Shibl et al., 2023)	3
	Machine learning-KELM-Meta-heuristic	Historical wind power data	(Zhou et al., 2022)	3

(Continues)

TABLE 4 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
Planning and scheduling	Machine learning-SVR	Electric vehicle data	(Jiang et al., 2022)	9
	Machine learning-K-means clustering	Oceanic data	(Masoumi, 2021)	16
Review	Machine learning	N/A	(Abualigah et al., 2022)	71
			(Mabina et al., 2021)	15
			(Tayal, 2017)	26

TABLE 5 Machine learning applications and total number of citations.

Machine learning applications	Total number of citations
Control	15
Condition monitoring	67
Decision making	78
Fault detection	425
Fault diagnosis	222
Fault prediction	107
Fault prevention	11
Forecasting	1126
Modelling	141
Optimization	429
Planning and scheduling	25

logic to fuzzy field oriented control (FFOC) and direct power control (DPC) for wind turbines based on PMSG (Salime et al., 2023), using adaptive neuro-fuzzy logic to control load frequency in the presence of energy storage devices (Jood et al., 2022), use of optimized type 2 fuzzy logic to control frequency in multi-area power systems (Shakibjoo et al., 2021), use of adaptive neuro-fuzzy logic to control grid-connected DFIG based wind energy systems (Shihabudheen et al., 2018). A hybrid approach based on relief algorithm and fuzzy reinforcement learning to predict wind speed (Malik & Yadav, 2021), using fuzzy TOPSIS and fuzzy COPRAS to perform multi-criteria decision-making for hybrid wind farms (Dhiman & Deb, 2020), using extreme learning machine and fuzzy control-based multi-agent system for smart energy management (El Bourakadi et al., 2018). The studies in this section are summarized in Table 8.

As seen in Table 8, Fuzzy Logic methods are mainly used in optimization, condition monitoring, and decision-making applications in wind energy. Utilizing a hybrid structure, fuzzy logic methods are integrated with diverse AI techniques such as ANN. In condition monitoring applications, SCADA data is generally used, but in other application areas, various data such as vibration, turbine data, and wind speed data have been used. In Fuzzy Logic studies, the prevalence of employing DFIG generators is notable compared to other AI techniques. Table 9 presents citation data for various applications of Fuzzy Logic in wind energy.

Based on the citation data, condition monitoring has the highest number of citations, with 565, followed by decision making, with 251 citations. Fault detection, fault prediction, and false alarm detection have 40, 42, and 87 citations respectively. While Fuzzy Logic has been applied in other domains, such as control, modelling, and forecasting, these domains have received fewer citations. Fuzzy Logic has been extensively used, particularly in dondition monitoring and decision making.

7 | META-HEURISTIC

Optimization is a method used to increase the efficiency of a system or process, to make the best use of resources, and to maximize targeted results (Atila et al., 2020; Dörterler et al., 2019). Wind energy has significant potential as a sustainable and environmentally friendly energy source. The use of AI and optimization techniques in this field offers new opportunities to improve the efficiency and performance of wind power plants.

TABLE 6 Data mining applications.

Application	Algorithm	Data/variables	References	Number of citations
Condition monitoring	Data mining	Numerical weather prediction data, wind turbine data, and site data	(Phillips et al., 2022)	1
		Vibration data	(Turnbull et al., 2019)	12
		Power curve data from three offshore wind turbines	(Janssens et al., 2016)	69
Fault detection	Data mining	Wind speed data	(Tran et al., 2020)	11
		Vibration data	(Joshuva & Sugumaran, 2018)	21
		Accelerometer data	(Vidal et al., 2020)	26
		Mixing plant data	(Jove et al., 2020)	48
	Data mining-ANN	SCADA data	(Bi et al., 2017)	54
Fault diagnosis	Data mining	Direct sensor signals, constructed variables from prior knowledge	(Zhang et al., 2018)	478
Fault prediction	Data mining	Wind speed data	(Mohammadi et al., 2015)	94
	Data mining-ANN	Vibration	(Elasha et al., 2019)	74
Forecasting	Data mining	Meteorological data, wind and solar PV power data	(Pombo, Gehrke, et al., 2022)	8
	Data mining-ANN	Sensor data, maintenance time data, data aggregation	(Yeh et al., 2019)	44
Maintenance	Data mining	Turbine operational status, environmental conditions, maintenance activities	(Garan et al., 2022)	17
	Data mining-ANN	Power generation	(Zhan et al., 2019)	25
Optimization	Data mining	Wind power production data, day-ahead market prices, balancing market prices, upward and downward regulation prices	(Munoz et al., 2020)	32

TABLE 7 Data mining applications and total number of citations.

Data mining applications	Total number of citations
Condition monitoring	82
Fault detection	160
Fault diagnosis	478
Fault prediction	168
Forecasting	52
Maintenance	42
Optimization	32

In this section, the studies on optimization methods applied in the field of wind energy are mentioned; the studies can be listed as follows: Development of a new meta-heuristic method for wind energy and multi-objective optimal power flow (Khamees et al., 2021), development of Harmony Search method for grid integration of wind farm (Keshta et al., 2016), optimization of radial flow wind turbines for urban wind energy (Acarer et al., 2020), use of GA and PSO for sizing hybrid energy systems (Torres-Madroñero et al., 2020), use of GA based fuzzy controller model for improving the dynamic performance of a self-adaptive induction generator (Attia et al., 2012), using ant colony optimization for size optimization of a hybrid photovoltaic-wind energy system (Fetanat & Khorasaninejad, 2015), proposing a machine learning assisted Grey Wolf approach for energy management strategy (Behzadi & Sadrizadeh, 2023). Use of Grey Wolf algorithm to provide an optimal scheduling program for a renewable energy-based building (Huang et al., 2022), optimized prediction of dynamic response of floating offshore wind turbines (Chen et al., 2021), development of Chimpanzee Algorithm to optimize short-term wind speed prediction (Sun & Wang, 2023), derivative-free optimization for feature engineering and prediction in renewable energy (Han et al., 2021), optimal sizing of wind-driven SWRO plants (Carta & Cabrera, 2021), development of Gravitational Search Algorithm with Moth Swarm Algorithm for optimal power flow considering wind power (Shilaja & Arunprasath, 2019), use of evolutionary algorithms for short-term wind power forecasting (Jursa & Rohrig, 2008). Through the

TABLE 8 Fuzzy logic applications.

Application	Algorithm	Data/variables	References	Number of citations
Condition monitoring	ANFIS	SCADA data	(Schlechtingen & Santos, 2014)	165
			(Schlechtingen et al., 2013)	355
	Fuzzy logic	SCADA data	(Liu, Chen, et al., 2023)	N/A
	Fuzzy logic-ANN	SCADA data	(Cross & Ma, 2015)	45
Control	Fuzzy logic	Wind turbine data	(Shihabudheen et al., 2018)	33
Decision making	Fuzzy logic	Wind turbine data	(Dhiman & Deb, 2020)	116
		Pollutant emissions, economic	(Shayeghi & Hashemi, 2015)	33
	Fuzzy logic-Meta-heuristic	Costs	(Mao et al., 2019)	7
		Costs, reliability	(Zhong et al., 2019)	95
Fault detection	Fuzzy logic	Simulated data	(Salime et al., 2023)	5
			(Ullah et al., 2020)	35
Fault diagnosis	Fuzzy logic-ANN	System dynamics, noise	(Simani & Castaldi, 2019)	18
Fault prediction	Fuzzy logic-ANN	Temperature	(Alves et al., 2017)	42
False alarm detection	Fuzzy logic-ANN	Vibration	(Marugán et al., 2019)	87
Forecasting	Fuzzy logic	Time series data	(Cuadra et al., 2016)	83
Modelling	Fuzzy logic	Weather data	(El Bourakadi et al., 2018)	18
	Fuzzy logic-Monte Carlo methods	Economic data	(Liu, Yang, et al., 2019)	16
Optimization	Fuzzy logic	Wind speed data, output power data	(Ayenew & Berhanu, 2022)	2
		Numerical	(Jood et al., 2022)	N/A
		Simulated data	(Shakibjoo et al., 2021)	38
		Time series data	(Malik & Yadav, 2021)	42

TABLE 9 Fuzzy logic applications and total number of citations.

Fuzzy logic applications	Total number of citations
Condition monitoring	565
Control	33
Decision making	251
Fault detection	40
Fault diagnosis	18
Fault prediction	42
False alarm detection	87
Forecasting	83
Modelling	34
Optimization	82

application of optimization methods in the domain of wind energy, the objective is to achieve enhanced efficiency in energy production, distribution, and storage. Optimization of the design and layout of wind turbines are also some of the areas of study. Table 10 summarizes the references in this chapter, categorized according to the algorithms used, the applications, the data considered, and the number of citations.

As seen in Table 10, Meta-heuristics are used in optimization at a very high rate in wind energy studies. Different meta-heuristic algorithms in the literature have been used for optimization. These algorithms have been used in different application areas, such as optimal power flow, turbine optimization, energy management, and sizing of energy systems. These studies used data such as wind speed, energy consumption, storage capacity, load demand, and ground angle. Meta-heuristics are also used in forecasting studies to optimize short and long-term wind forecasts. Apart from this, studies are conducted using meta-heuristic algorithms in fault detection, fault diagnosis, and fault prevention. Table 11 presents citation data for meta-heuristic applications in the field of wind energy.

TABLE 10 Meta-heuristic applications.

Application	Algorithm	Data/variables	References	Number of citations
Optimization	Mayfly algorithm-Aquila optimizer	Scale and shape parameters	(Khamees et al., 2021)	12
	PSO-Tabu search-Simulated annealing and harmony search	Load demand, solar radiation, wind speed, cost of components	(Maleki & Askarzadeh, 2014)	245
	HS	Pitch angle, static Var compensator, PI controller	(Keshta et al., 2016)	8
	PSO-Machine learning	Wind speed, air density, blade radius, flap's gap, overlap, deflection angle	(Acarer et al., 2020)	25
	GA-PSO	Energy consumption, types of wind turbines, types of solar panels, capacity of the storage system	(Torres-Madroñero et al., 2020)	27
	GA-Fuzzy logic	Error, change in error, duty cycle, blade angle	(Attia et al., 2012)	21
	Ant colony optimization	Load demand, wind turbine capacity, battery capacity, and so forth	(Fetanat & Khorasaninejad, 2015)	203
	Grey Wolf optimization-Machine learning	Fuel cell current, electrode area, techno-economic-environmental indicators, and so forth	(Behzadi & Sadrizadeh, 2023)	11
	SA	Key disciplinary parameters (KDPs)	(P. Chen et al., 2021)	10
	Chimpanzee optimization algorithm-Machine learning	Wind speed series	(Sun & Wang, 2023)	N/A
	PSO-SVM	Historical micro-grid data	(Lu & Liu, 2013)	2
	Fuzzy dragonfly algorithm-Machine learning	Power output of tidal and wind units, operation costs, and so forth	(Han et al., 2021)	10
	GA-Machine learning	Freshwater demand, wind speed, salinity, power consumption, and so forth	(Carta & Cabrera, 2021)	19
	Moth swarm algorithm	Wind power, power system parameters, constraints	(Shilaja & Arunprasath, 2019)	78
	Genetic algorithm (GA)	Reliability	(Rinaldi et al., 2020)	31
		Fatigue coefficient, wind characteristics	(Su et al., 2017)	8
		Power generation, costs	(Feng, Jia, et al., 2019)	14
		Component condition	(Su et al., 2020)	5
		Design process, finite element modelling	(Young et al., 2017)	23
		Economic and ecologic	(Hong et al., 2015)	35
			(Mohamed & Koivo, 2012)	140
		Power production, power fluctuation	(Ferdoues et al., 2017)	24
		Costs	(Meena et al., 2019)	13
			(N'guessan et al., 2020)	77
			(Ranjbar & Kouhi, 2015)	33
			(Shahirinia et al., 2008)	3
			(Soedibyo et al., 2012)	12
		Environmental aspects	(Suresh & Meenakumari, 2021)	45
		Reliability, costs, reliability benefits	(Xie & Billinton, 2010)	76
	PSO-ANN	Costs	(Roy, 2019)	18
	GA-Fuzzy logic	Costs, reliability	(Liu, Yang, et al., 2019)	16
			(Mao et al., 2019)	7
			(S. Zhong et al., 2019)	95

(Continues)

TABLE 10 (Continued)

Application	Algorithm	Data/variables	References	Number of citations
Forecasting	Derivative-free optimization-Machine learning	Wind speed, solar irradiance, temperature, humidity, pressure	(Pirhooshyaran et al., 2020)	21
	GA-ANN	SCADA data	(Zheng et al., 2017)	40
	PSO-Machine learning	Wind speed	(Zhang & Wang, 2022)	5
	PSO-Differential Evolution + ANN	Wind speed	(Jursa & Rohrig, 2008)	231
Fault detection	GA-Fuzzy logic	Wind speed, rotor speed, rotor flux, grid voltage, grid frequency	(Elnaghi et al., 2018)	10
	GA-PSO	Power output, wind farm data, simulation data	(Yan, Zhang, et al., 2015)	12
Fault diagnosis	PSO-ANN	Vibration	(Hu et al., 2019)	48
Fault prediction	GA-ANN	Vibration	(Jiang et al., 2012)	N/A

TABLE 11 Meta-heuristic applications and total number of citations.

Meta-heuristic applications	Total number of citations
Optimization	1346
Forecasting	297
Fault detection	22
Fault diagnosis	48

Table 11 shows that optimization studies receive the highest number of citations with 1346, indicating that meta-heuristic methods are widely used in wind energy optimization. Forecasting studies comes in second place with 297 citations, demonstrating the importance of meta-heuristic methods in predicting future performance in wind energy projects. However, the areas of fault detection and fault diagnosis received fewer citations than the other two application areas. This may indicate that meta-heuristic methods are not yet widely adopted in these areas in the wind energy industry, or that the effectiveness of these methods in these areas is less well known.

8 | STATISTICAL METHODS

Statistical methods can be used in many areas, such as analysing data, developing forecasting models, and optimizing energy production in the wind energy sector. Statistical methods help decision-making by transforming large amounts of data into meaningful information. Studies in this field in the literature are as follows: Using statistical methods to analyse the effect of imperfections in weather forecasts on wind power forecast performance (Spiliotis et al., 2020), using machine learning and statistical techniques to forecast daily wind power (Ekanayake et al., 2022; Valsaraj et al., 2022; Wickramasinghe et al., 2022), using Gaussian process models to detect anomalies in wind turbines (Bakrania et al., 2020), use of ARIMA, linear regression, and Random Forest Algorithms to predict solar and wind power generation (Chauhan et al., 2023).

In addition, the following examples can be given to the studies conducted in different fields using statistical methods. Using statistical analysis to assess the temporal and spatial synchronicity of wind-solar energy sources (Jani et al., 2022), using hidden Markov models and principal component analysis to diagnose faults in wind energy converter systems (Kouadri et al., 2020), using statistical learning to model and predict wind energy (Fischer et al., 2017), using statistical methods to reduce uncertainty in post-construction efficiency assessment of wind facilities (Bodini et al., 2022). Statistical methods have also been used to analyse the relationship between environmental air pollution and electricity consumption (Sarkodie et al., 2021), to study the effects of damaged rotors on vertical axis wind turbines (Asim & Islam, 2021), and to plan distributed renewable energy systems under uncertainty (Fu et al., 2022).

Statistical methods are used in many areas of wind energy, such as energy forecasting, anomaly detection, performance analysis, fault diagnosis, yield assessment, system planning, and so forth, and help develop wind energy systems more efficiently, environmentally friendly, and sustainably. Table 12 summarizes the studies in this section, categorizing them according to the algorithms they use, their application areas, the data they consider, and their total number of citations.

TABLE 12 Statistical applications.

Application	Algorithm	Data/variables	References	Number of citations
Condition monitoring	Gaussian process models	SCADA data	(Pandit & Infield, 2018)	103
Cost analysis	Markov processes	Economic, simulated data	(Memarzadeh et al., 2015)	63
Decision making	Bayesian analysis	Costs	(Davoudpour, 2019)	5
	Bayesian analysis	Blade deterioration process, blade inspection, cost	(Nielsen et al., 2021)	36
	Bayesian analysis	State of the wind turbine, weather conditions, revenue losses, cost	(Byon & Ding, 2010)	262
Fault diagnosis	Multiple linear regression (MLR)-Machine learning	Wind speed, temperature, time	(Bodini et al., 2022)	7
	ANFIS-PSO	Vibration data	(Gougam et al., 2021)	15
	Proper orthogonal decomposition	Wind speed, air density, blade radius, rotor blade design, and so forth	(Asim & Islam, 2021)	3
	Principal component analysis-Hidden Markov model	Simulated data	(Kouadri et al., 2020)	121
Fault detection	Bayesian analysis	Fault data	(Sørensen, 2009)	195
	Bayesian analysis	Turbine components	(Lazakis & Kougioumtzoglou, 2019)	14
	Principal component analysis	SCADA data	(Rezamand et al., 2019)	86
Forecasting	MLR-Support vector regression-ANN	Wind speed, temperature	(Wickramasinghe et al., 2022)	1
	MLR-Power regression-Support vector regression-ANN	Wind speed, temperature, energy data	(Ekanayake et al., 2022)	N/A
	Linear regression-Random forest-ARIMA	Wind speed, wind direction, global horizontal irradiance, temperature, humidity	(Chauhan et al., 2023)	2
	Locally weighted scatterplot smoother-Quantile regression	Wind speed, wind direction, wind turbulence, time	(Feng, Sun, et al., 2019)	24
	Bayesian analysis	Active power, generator speed, various temperatures	(Herp et al., 2017)	5
	Linear regression-Machine learning	Wind speed, air density, humidity, temperature, pressure, solar radiation	(Spiliotis et al., 2020)	6
Modelling	CART-Bagging algorithm	Wind speed, air density, blade radius, turbulence intensity, temperature, pressure, altitude	(Fischer et al., 2017)	43
Optimization	Statistical analysis-Machine learning	ERA5 data	(Jani et al., 2022)	11
	Recursive Gaussian process	Numerical data	(Deese & Vermillion, 2020)	7
	Gradient-Boosting decision trees	Relative density of soil, embedment ratio, helix spacing ratio, number of helices	(Wang et al., 2022)	1
	Weibull distribution	Wind speed, sea surface roughness length, turbine hub-height	(Band et al., 2021)	14
	Bayesian analysis-ANN	Fault data	(Sinha & Steel, 2015)	13
	Markov processes	Mechanical loads-economic data, weather data	(Byon, 2013)	55
			(Yang & Sørensen, 2019)	11
	Markov processes-ANN	SCADA data	(Du et al., 2018)	6
Planning and scheduling	Gaussian process models-Bayesian analysis-Probabilistic power flow	Renewable energy generation, load, transmission capacity, cost	(Fu et al., 2022)	22

Table 12 shows that Statistical Methods are frequently used as AI tools in wind energy. Statistical methods are mostly used in application areas such as fault detection, fault diagnosis, prediction, and optimization. Statistical methods have been used in studies on detecting anomalies in turbines, efficiency evaluation, the effect of damaged components on wind turbines, and system planning. Data such as simulation data, wind speed, wind direction, temperature data, and SCADA data are used in different structures according to the application areas. Statistical methods have been used relatively less in application areas such as decision making, condition monitoring, planning, and modelling. In most of these methods, a hybrid model was created using several techniques, and studies were carried out with this model. Table 13 presents citation data for statistical applications in the field of wind energy.

As shown in Table 13, decision-making and fault detection are among the most cited topics of statistical methods in wind energy. The extensive use of statistical modelling in decision-making is recognized as an essential tool to increase efficiency and optimize the operating costs of wind turbines. Similarly, the extensive use of statistical methods in fault detection is critical for monitoring system performance and predicting potential failures. On the other hand, topics such as planning and scheduling, forecasting, and modelling received fewer citations, indicating that these areas have yet to attract much attention for problems solved by statistical methods in the wind energy industry.

9 | DISCUSSION

In this article, we aimed to examine the studies conducted in wind energy with AI and identify the issues and potentials that need to be studied in this field. Our research results show that using AI techniques in the wind energy sector provides significant advantages and has great potential for sustainable energy production. This section will summarize our results and present a qualitative and quantitative analysis of the research conducted. Figure 7 illustrates the utilization of AI techniques within the wind energy sector.

Figure 7 shows the distribution of AI techniques in the wind energy sector: ANN methods are the most widely used technique, with 38%. Machine learning methods are the second most used technique after ANN. Machine learning plays a vital role in analysing and predicting wind energy data with 24%. Meta heuristics, used by 12% in the wind energy field, provide the best approaches for solving complex problems that need to be optimized in wind energy systems. Statistical methods and data mining methods are both used about 12%. Statistical methods are generally used in data analysis and trend forecasting, while data mining techniques are used to discover patterns and relationships within a dataset. In addition, the fuzzy logic method is used by 6%. Fuzzy logic is an approach used to analyse and control uncertain wind energy data.

Based on the distribution of AI techniques in the wind energy sector, research in the wind energy sector is mostly supported by AI techniques such as ANN and machine learning methods. Meta-heuristics, statistical methods, data mining, and fuzzy logic are other essential techniques used but less commonly. These techniques make meaningful contributions in areas such as improving the performance of wind energy systems,

TABLE 13 Statistical applications and total number of citations.

Statistical applications	Total number of citations
Condition monitoring	103
Cost analysis	63
Decision making	303
Fault diagnosis	146
Fault detection	295
Forecasting	38
Modelling	43
Optimization	118
Planning and scheduling	22

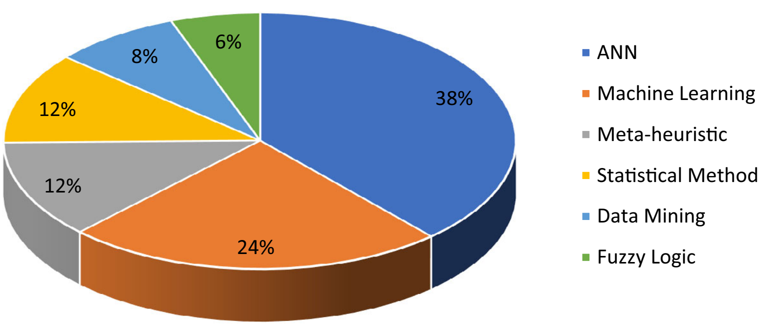

FIGURE 7 Distribution of artificial intelligence techniques in the wind energy sector.

analysing data, and optimizing decision-making. AI techniques have been used in various fields to solve various problems. These include fault detection, diagnosis, fault prediction, fault prevention, forecasting, modelling, decision-making, planning and scheduling, condition monitoring, control, and optimization. The citation rate of studies using AI techniques is shown in Figure 8. Analysing the number of citations received by techniques provides researchers with a valuable way to understand the popularity, frequency of use, and impact of wind energy AI techniques in the literature.

The graph displays the frequency of citation for six distinct AI techniques. When we evaluate the graph, we see that ANN has the highest citation rate, with a citation rate of 37%. This shows that ANN is a technique with a wide range of research and applications in the wind energy literature. The second most cited technique is machine learning, with 22%. Machine learning is popular among academics and industrial researchers as it has many applications and is frequently cited in the literature. Meta-heuristics, fuzzy logic, statistical methods, and data mining have lower citation rates than ANN and Machine Learning. This is because they are generally aimed at more specific or narrow application areas. For example, fuzzy logic is a technique for dealing with uncertainty (Zadeh, 1983). For this reason, it has gained more popularity in specific areas, such as analysing uncertain data or decision-making in specific circumstances. Similarly, meta-heuristic methods often focus on optimizing complex problems and are used in specific industrial or engineering applications (Pereira & Gomes, 2023). Statistical methods and data mining can be used in various fields, such as data analysis, trend prediction, and pattern discovery (Hamdi et al., 2022; Parmezan et al., 2019). However, while these techniques significantly impact a specific area, they are less prevalent in wind energy. These techniques have lower citation rates because, although they have a wide range of uses, they are methods suited to specific conditions. Therefore, researchers can use these techniques more effectively in specific contexts. Consequently, focusing on areas such as ANN and machine learning will give researchers a broader impact on the literature. However, other techniques may also be necessary in specific application areas, so researchers should choose the techniques that best suit their interests and topics of study. In addition, researchers can contribute to the literature by obtaining interesting results with new and emerging techniques and receiving high citations. Wind energy sector applications are given in Figure 9.

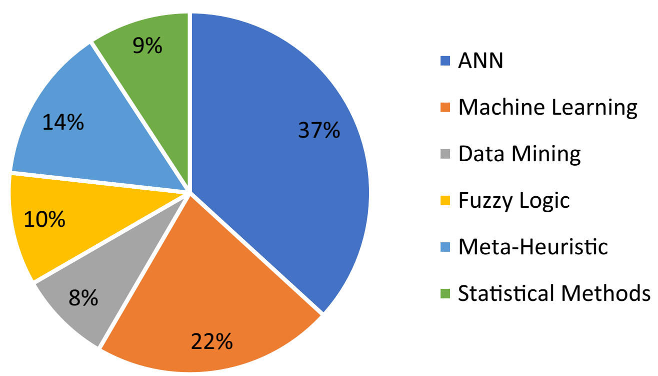

FIGURE 8 Citation distribution of artificial intelligence techniques in the wind energy sector.

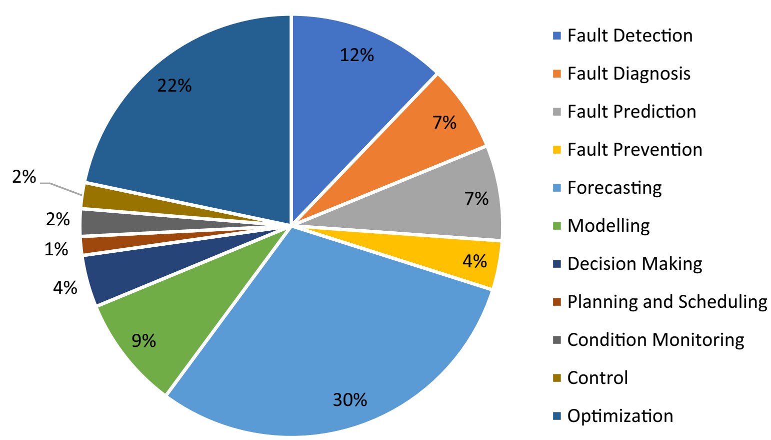

FIGURE 9 Distribution of artificial intelligence applications in the wind energy sector.

Figure 9 shows that forecasting is the most common application, with a total of 30%, and is generally used to predict the values of wind energy, wind speed, and other factors. Optimization is widely preferred, with a rate of 22%, and aims to increase the efficiency of wind energy systems and make the best use of resources. Fault detection follows forecasting and optimization with 12% and plays an important role in identifying and detecting faults in wind energy systems. Fault diagnosis is used at a rate of 7% to determine the causes and origins of faults in the system. Fault prediction is used at a rate of 7% to predict faults that may occur in wind energy systems. Fault prevention is used at a rate of 4% and aims to prevent and avoid potential faults in wind energy systems. Modelling is used at a rate of 9%. This technique is used to create and analyse mathematical models of wind energy systems. Decision making is used by 4%. This technique is used to help decisions and strategies be taken in the wind energy sector. Planning and scheduling is used by 1%. This technique is used to plan and schedule maintenance, repair, and operation activities of wind energy systems. Condition monitoring is used at a rate of 2% and aims to monitor and evaluate the operating conditions of wind energy systems. Control is used at a rate of 1% and aims to optimize the performance of wind energy systems and achieve desired outputs.

Based on this data, forecasting, and optimization techniques are among the most widely used techniques for various application areas in the wind energy sector. Other techniques, such as fault detection, modelling, and fault diagnosis, also play an important role but are less widely used. These techniques make essential contributions in areas such as improving the performance of wind energy systems, detecting faults in advance, and supporting system management decisions. Figure 10 shows the citation rates of artificial intelligence applications. Analysing these rates can help researchers identify which problems receive more attention, which is critical for planning and directing their work and linking it to existing literature.

Figure 10 shows that applications focused on predicting the future and improving business processes, such as forecasting (28%) and optimization (21%), are the most popular areas among researchers and academics. This situation shows that researchers are interested in increasing the efficiency of wind farms and optimizing decision-making processes and are doing more work in this area. More operationally oriented applications such as fault detection (15%), condition monitoring (11%), and decision-making (9%) are also important research topics, although less common than forecasting and optimization. These applications are related to the reliability and performance of industrial systems. Therefore, it is crucial to conduct more research and work in these areas, as they have the potential to have a significant impact and wider use in the industry. However, the lower citation rates of fault prediction (3%), modelling (2%), control (2%), and planning and scheduling (1%) applications are noteworthy. This situation could mean these applications receive less attention or are less studied. Increasing research in these areas could help AI technologies be more widely used and effectively applied. Therefore, by investing more effort in these areas, researchers can fully realize the potential of AI technologies and expand their practical applications.

The main findings of this review are summarized as follows.

ANN are among the most widely used AI techniques in the wind energy sector (38%). ANN is an effective tool for optimizing, predicting, and controlling energy production using important parameters such as wind speed, direction, and power, notable for its data analysis and prediction capabilities (Haupt et al., 2020; Lipu et al., 2021; Veerasamy et al., 2020). This technology predicts the potential for achieving a more efficient and sustainable future in the wind energy sector. With recent advances in deep learning, most studies are now performed with deep learning algorithms instead of ANN due to increased accuracy and speed.

Machine learning methods have been widely used by researchers in the wind energy sector and have achieved successful results. Studies show that various machine learning algorithms have been used in different fields, such as energy production prediction of wind turbines, wind energy management, wind speed prediction, anomaly detection, and power output prediction (Baquero et al., 2022; Malakouti, 2023). There are also studies with different hybrid algorithms and data sources, such as reanalysis data, meteorological characterization, and SCADA data (Li, 2022; Liu et al., 2021; Qian et al., 2018; Zhou et al., 2022). These studies show that machine learning methods are an essential second option in wind energy (24%).

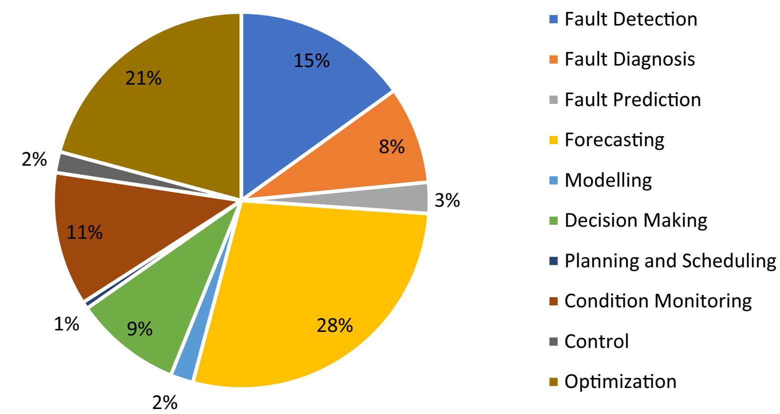

FIGURE 10 Citation distribution of artificial intelligence applications in the wind energy sector.

Data mining is an essential tool for fault detection and monitoring. With data mining methods, the maintenance of wind turbines can be made predictable, and failures can be predicted in advance. Thanks to these methods, the efficiency of wind energy systems can be increased, and better monitoring can be achieved. Data mining can also be used to plan offshore wind turbines to create data-driven models. These studies show that data mining and big data analytics methods are effective in fault prediction, fault detection, and condition monitoring in wind energy (Elasha et al., 2019; Jove et al., 2020; Phillips et al., 2022; Tran et al., 2020).

Fuzzy logic is a mathematical approach for modelling and controlling uncertain systems. This method expresses uncertainty using fuzzy sets and fuzzy values. Fuzzy logic is frequently used in wind energy and AI, especially in optimization and decision-making (Ayenew & Berhanu, 2022; Dhiman & Deb, 2020). The majority of research focuses on these two areas. Fuzzy logic is often combined with ANN to evaluate decision-making processes (Marugán et al., 2019; Simani & Castaldi, 2019). There are also some applications for fault detection, but this area has yet to be widely used (Salime et al., 2023; Ullah et al., 2020). These studies show that fuzzy logic plays an important role in solving optimization and decision-making problems.

Optimization is an important method used in wind energy to increase efficiency, ensure efficient use of resources, and maximize targeted results. Applying AI and optimization techniques in the wind energy sector offers various opportunities. Studies in this field focus on making wind energy systems more efficient, optimizing energy production, and improving design (Acarer et al., 2020; Behzadi & Sadrizadeh, 2023; Khamees et al., 2021; Pirhooshyaran et al., 2020; Sun & Wang, 2023). Solutions are being developed using optimization techniques in areas such as wind turbine siting, power flow management, and integration of energy storage systems. Optimization methods are practical tools that are expected to be used more in the wind energy sector in the future.

Statistical methods are essential analytical tools in wind energy and AI and have various application areas. These methods are effectively used in the wind energy sector in data analysis, forecasting models, and energy optimization (Jani et al., 2022; Wickramasinghe et al., 2022). Many studies in the literature use statistical methods in wind energy forecasting, error analysis, power generation modelling, and system planning (Fischer et al., 2017; Fu et al., 2022). In addition, statistical analyses have proven to be a valuable tool for wind-solar energy synchronization, diagnosing faults, analysing environmental impacts, and system planning under uncertainty (Bodini et al., 2022; Gougam et al., 2021). Statistical methods are essential in improving the efficiency of wind energy systems and achieving sustainability goals. Artificial intelligence techniques have achieved significant success in wind energy. However, limitations and challenges related to data quality, scalability, and complexity may arise.

Deep learning methods such as artificial neural networks require large amounts of data, which can negatively affect their performance if the data from wind turbines is insufficient or noisy. Other machine learning methods can similarly be limited by data density and computational power requirements, requiring time and computational power in the training and deployment processes.

Data mining, fuzzy logic, and statistical methods are generally effective in dealing with uncertainties in modelling processes, but their accuracy and predictive capabilities are limited due to the complex and dynamic nature of the wind energy field. Data mining methods require expertise in stages such as data cleaning and feature selection. While fuzzy logic and statistical methods can deal with uncertainty, their accuracy levels may need to be improved in imprecise problems such as wind energy forecasting.

Meta-heuristic algorithms are often used to optimize multiple variables but can be challenging to apply in real-time, dynamic, and complex systems such as wind energy systems. Awareness of these limitations is essential to increase the success of applying artificial intelligence techniques in wind energy.

When examining the development of artificial intelligence techniques in wind energy studies between 2021 and 2023, it is evident that ANN and other machine learning methods are utilized more frequently than other AI methods. This is due to the advancements in artificial neural networks, deep learning, and other machine learning methods. Since the history of machine learning methods other than artificial neural networks is older, these methods were frequently used in wind energy problems between 2017 and 2020. Fuzzy Logic and Data Mining methods started to be used to find solutions to wind energy problems in the years after 2013 when artificial neural networks and machine learning methods were not yet widespread, but recently, they lost their popularity. On the other hand, metaheuristic algorithms and statistical methods are much older and have been used to solve wind energy problems since 2008–2009. Although the use of statistical methods has decreased in recent years due to the success of artificial neural networks in producing generalized solutions to problems, metaheuristic algorithms, which are widely used in many engineering problems and can meet the high computational power requirement after the developments in computer hardware, are still one of the most widely used methods, especially in optimization problems in the field of wind energy.

This study addresses the global distribution, funding, interdisciplinarity, and publishers of wind energy and AI research. Our results highlight the importance and potential of the relationship between wind energy and AI. Future research is expected to fill the knowledge gaps in this field and continue to generate innovative solutions. Significantly, these studies bear substantial importance for the production of sustainable energy and the maintenance of environmental sustainability.

10 | PERFORMANCE COMPARISONS ON A STANDARD DATASET

This section presents performance comparisons of some studies on energy production on a standard dataset. As the standard dataset, a current dataset used in the Renewable Energy Generation Forecasting Competition held in China in 2021 and published openly in Nature in 2022 was

TABLE 14 Performance comparison of the different AI techniques for energy generation optimization and forecasting on a standard dataset.

Model No	AI technique	R^2	CC	MAE	RMSE
1	Inception-ResNet	0.98340	0.99175	1.630	2.860
2	Inception-Attention mechanism	0.97701	0.98845	1.885	3.665
3	CNN-RNN	0.96233	0.98096	2.495	4.315
4	CNN-Bidirectional weighted LSTM	0.96239	0.98101	3.125	5.389
5	GridSearchCV-CNN-Modified RNN	0.98507	0.99201	0.025115	0.03630
6	GridSearchCV-CNN-Bidirectional weighted gated recurrent unit	0.93339	0.96612	0.03660	0.04829
7	CNN-LSTM	0.89866	0.94797	0.04457	0.05830

preferred (Chen & Xu, 2022). This dataset consists of data collected with the help of SCADA systems at 15-min intervals for 2 years (2019–2020) on energy production and weather conditions. The performance comparisons of the techniques in wind energy generation optimization and forecasting using this dataset are given in Table 14. All compared methods used R^2 (coefficient of determination), CC (correlation-coefficient), MAE (mean absolute error) and RMSE (root mean square error) metrics as performance measures.

Models 1, 2, 3, and 4 are taken from the study titled 'Hybrid Inception-embedded deep neural network ResNet for short and medium-term PV-Wind forecasting' (Mirza et al., 2023b). When the performance metrics of these models are analysed, it is seen that the Inception-ResNet model has the highest R^2 score (0.98340). This model also has the highest CC value of 0.99175. It is noteworthy that it has the lowest MAE and RMSE values. Models 5, 6, and 7 are taken from 'A comprehensive approach for PV wind forecasting by using a hyperparameter tuned GCVCNN-MRNN deep learning model' (Mirza et al., 2023a). Among these models, the CNN-Modified RNN model optimized with GridSearchCV has the highest R^2 score (0.98507) and CC value (0.99201). It also has the lowest MAE and RMSE values. The GridSearchCV-CNN-Modified RNN model performs the best compared to the other models.

11 | CONCLUSION AND RECOMMENDATIONS

The interplay between wind energy and artificial intelligence has been thoroughly studied. The paper highlights the key AI techniques employed in monitoring wind turbines in the wind energy sector. This study aims to bridge current gaps in the literature and serve as a roadmap for future research. The results demonstrate that AI techniques are remarkably beneficial for sustainable energy production in the wind energy sector.

This paper comprehensively covers the key artificial intelligence techniques utilized in the wind energy industry, including ANN, other machine learning methods, data mining, fuzzy logic, meta-heuristics, and statistical methods. The analyses conducted with a focus on these techniques divulge several application areas, including the maintenance management of wind turbines, economic factors, farm location, data analysis, prediction models, optimization techniques, and decision-making processes. The conducted analyses and reviews demonstrate the significant potential of artificial intelligence techniques in the wind energy sector. The aforementioned techniques contribute significantly to areas such as enhancing the performance of wind turbines, performing data analysis, optimizing decision-making, and supporting sustainable energy production.

AI technology in the wind energy sector has significant advantages. First, there is the potential to increase the efficiency of wind energy facilities. AI algorithms can optimize the position and angle of wind turbines by analysing wind speed, direction, and other environmental parameters. This enables the turbines to generate wind energy more effectively while increasing energy efficiency. Second, AI has great potential in predicting wind power generation. AI systems can predict future energy production by analysing factors such as weather data, wind patterns, and turbine performance. This provides enormous advantages in terms of energy management and consumption planning. Accurately predicting energy demand and consumption enables more efficient and sustainable use of energy resources. Third, AI systems can optimize the operation and maintenance of wind energy facilities. They can detect potential failures in advance and plan maintenance processes using data analysis and monitoring techniques. This increases the reliability of wind power plants while reducing operating costs. Fourth, AI can be used to ensure the safety and control of wind energy systems. In hazardous weather conditions or failures, AI algorithms can automatically safeguard systems and ensure they continue to operate safely. Finally, AI technology can analyse large datasets from wind energy systems and draw significant insights. This highlights considerable data management and analysis potential in the wind energy industry. Big data analytics can detect energy production and consumption trends and enhance decision-making procedures.

Important topics for future research include:

1. Artificial intelligence applications such as forecasting, optimization, fault detection, condition monitoring, and decision-making are popular study topics among researchers. In particular, Forecasting and optimization problems are widespread and highly cited in the literature.

Researchers should focus on popular problems in their future work. However, researchers can unlock the potential of AI by focusing on low-cited research areas such as fault prediction, modelling, control, and planning and scheduling.

2. Besides the often-cited techniques such as neural networks and machine learning, less often-cited techniques such as metaheuristics, fuzzy logic, statistical methods, and data mining can also be considered. Efforts can be made to utilize these techniques more effectively to suit specific circumstances. There is a need to explore more extensive applications and improvements of AI algorithms in wind energy facilities. New approaches and techniques must be explored to improve these algorithms' efficiency, prediction, and optimization capabilities.
3. Integrating a variable resource such as wind energy into the power grid is essential to investigate the role of AI in decision-making processes. Studies focusing on AI's ability to stabilize the power grid, improve reliability, and cope with unexpected situations should be developed.
4. The effectiveness of AI in maintenance and repair processes in wind turbines should be examined in more detail. Studies should be conducted on increasing operational efficiency. For predictive maintenance to be more widely adopted in facilities in the energy sector, further research should be conducted to integrate different data sources effectively and determine how AI algorithms can deal with more complex data sets.
5. Greater use of AI in safety and control systems is needed. AI algorithms can safely and effectively manage wind power facilities during hazardous weather conditions or failures.
6. Analysing wind farms' social, economic, and environmental impacts is crucial. It is of paramount importance to understand and regulate the potential impacts resulting from the widespread use of these technologies. These analyses can be used to measure and understand public sentiment and reactions.

As a result, integrating AI technology into the wind energy sector has great potential. AI algorithms can increase the efficiency of wind energy facilities, predict energy production, optimize operation and maintenance processes, and improve safety and control systems. Future research should promote more expansive use of AI technologies and interdisciplinary studies to make further progress in these areas. This will provide more effective solutions for sustainable energy production and play an essential role in meeting the future needs of the energy sector.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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