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Review

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Abstract: Wind energy is an important renewable energy source, and artificial intelligence (AI) plays an important role in improving its efficiency, reliability and cost-effectiveness while minimizing its environmental impact. Based on an analysis of the latest scientific literature, this article examines AI applications for the entire life cycle of wind turbines, including planning, operation and decommissioning. A key focus is on AI-driven maintenance, which reduces downtime, improves reliability and extends the lifetime of the turbines. AI also optimizes the design of wind turbines, particularly in the development of aerodynamically efficient blade shapes through rapid design iterations. In addition, AI helps to reduce the impact on the environment, e.g., by reducing bird collisions, and improves wind energy forecasting, which is essential for balancing energy flows in power systems. Despite its benefits, AI applications face challenges, including algorithmic errors, data accuracy, ethical concerns and cybersecurity risks. Further testing and validation of AI algorithms is needed to ensure their effectiveness in advancing wind energy systems.

Keywords: artificial intelligence; wind turbine; AI-driven maintenance; turbine design; turbine efficiency

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1. Introduction

The issue of climate change and the security of electricity supply from conventional fueled power stations have led to renewable energy sources being prioritized. In this context, we observe that the installed capacity of wind turbines around the world is constantly increasing. According to the World Wind Energy Association (WWEA) Annual Report 2023 [1], the global installed capacity of wind turbines at the end of 2023 was around 1047 GW and the annual electricity production from wind turbines was around 2310 TWh (Figure 1).

However, it is important to realize that electricity generation from wind turbines is highly variable throughout the day and month in certain areas, as the wind is stochastic in nature. Equally important is the fact that the demand for electricity also varies throughout the day and month. The situation is similar for solar PV power plants, which, together with wind power plants, make up the largest share of renewable energy capacity (excluding hydropower plants). Although electricity generation from PV solar power plants and wind power plants will only account for 15% of total electricity generation worldwide in 2024, the planned share in 2028 is 25% [2]. Most of the remaining production comes from hydroelectric power plants, nuclear power plants and fossil fuel power plants. In 2023, renewable energy sources were the largest source of electricity in the EU. Their share was 44.7%, while the share of electricity from fossil thermal power plants was around 32% and that from nuclear power plants around 23%.

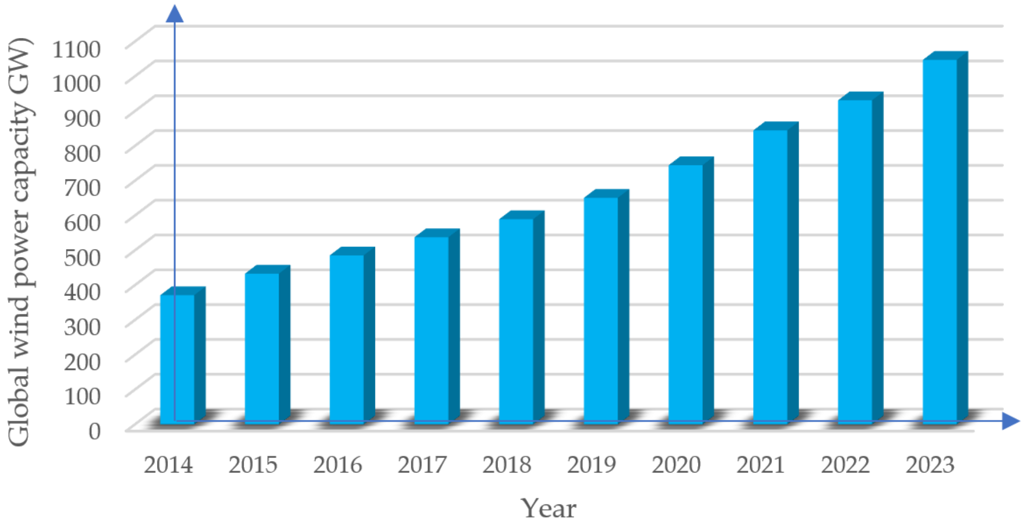

Figure 1. Global installed wind power capacity [1].

Renewable energy sources are a strategic choice, but in December and January, when solar energy and thus electricity generation from PV power plants is at its lowest and electricity consumption is high due to the cold, significant problems can arise. On the German mainland there is often winter fog without wind, and on the wind farms in the North Sea there is often a strong wind, so that the wind farms have to be put into standby mode. In such situations, the individual countries have to increase the import of energy from the European energy market. The European electricity market is physically highly interconnected and institutionally coordinated, but the laws of supply and demand lead to price instability. This is a minor problem for households, which generally have a long-term agreed price, but a serious problem for industry, which pays for electricity at the current market price.

The European electricity grid is also of the utmost importance to the European Commission: it is the only way to reduce Europe's dependence on energy imports and achieve the European Green Deal's goal of achieving a 55% reduction in greenhouse gas emissions by 2030 relative to 1990 levels. All of this will become even more important with the increasing number of electric cars that are supplied with electricity from the grid.

It should also be pointed out that the conventional electricity grid is not designed to cope with the integration of renewable energy sources. The variable nature of renewables results in variable and unstable loads on the grid, which makes maintaining grid performance within specified power, voltage and frequency tolerances a challenge. As mentioned earlier, in some relatively short periods there is a surplus of energy in the grid and in others there is a shortage. Therefore, the need for efficient management of energy flows in the electricity grid is becoming increasingly clear [3]. On the one hand, the lack of energy production from wind turbines and PV solar power plants should be compensated by increased production from other sources or by utilizing energy from energy storage systems, and excess energy in the grid should be efficiently stored in energy storage systems. However, the shutdown or reduction of electricity generation from conventional power plants cannot be achieved immediately or in a short time due to the nature of the energy conversion process in the power plant. It is therefore very important to predict the energy production of wind farms as well as possible on an hourly and daily basis. This production forecast now heavily depends on the advanced application of artificial intelligence (AI) to accurately predict wind speed and power [4,5].

AI refers to the ability of computer applications to mimic human intelligence when performing complex tasks and to act autonomously by analyzing data from the environment to achieve specific goals. Digital technological developments have the potential to significantly improve energy supply and energy trading (stabilize prices). In the foreseeable future, the integration of supply, demand and renewable energy sources into the electricity grid will be controlled by intelligent software that optimizes decision-making in connection with system operation. Artificial intelligence will play a key role in achieving this goal [6].

The problem at issue here is at the level of the energy system. However, if we move to the level of a wind farm or a single wind turbine, then we are faced with the problem of optimizing the operation of a single wind turbine and maximizing production for given wind characteristics (speed, power, direction, turbulence), but also ensuring the reliability and highest possible availability of the wind turbine. In other words, maintaining existing power plants [7] and minimizing the environmental impact of wind turbines (reducing collisions with birds and bats [8]) are of great importance, and the application of artificial intelligence in this area is becoming increasingly important.

If we analyze the topic of wind farms further, we come to the design phase, in which the individual components of the wind farm are determined. Each of the components should be optimized so that the wind farm produces the highest possible performance for a given site given the input data, but also has the lowest possible investment costs and the lowest possible impact on the environment. The optimal design of rotor blade profiles through rapid iterations of profile variants is enabled by the application of AI, together with the application of other tools related to computer simulations of rotor blade aerodynamics.

AI can also play an important role in the end-of-life phase of wind turbines by planning the optimal decommissioning process, recycling and material recovery. AI can assess the condition of ageing turbines and predict their remaining lifespan, helping to decide whether they should be refurbished, upgraded or decommissioned.

The extent of AI applications in wind energy has been analyzed by Barbosa et al. [9], Lee and He [10] and Wang et al. [11], who examined patents related to wind turbine technology, patents related to AI and patents covering both wind turbines and artificial intelligence. Wang et al. found that the number of patents in both areas increased significantly from 2010 to 2021, but that the overlap is quite small, meaning that there is still much room for progress in this area. Secondly, the patterns of interaction of AI and wind power technology knowledge show a shift from machine learning models (wind power technology on the production side) to deep learning models (wind power technology on the production, transmission and distribution side) to hybrid AI models (generation, transmission, distribution and energy consumption in the whole process of wind power technology).

Many studies have analyzed trends and opportunities for AI applications in wind energy forecasting, wind energy control, wind farm design, maintenance and optimization. For example, Lipu et al. [12] summarized recent advances in hybrid AI methods for wind energy forecasting based on the literature. Farrar et al. [13] gave a comprehensive overview of AI and machine learning (ML) methods for wind turbine control. Wang et al. [14] analyzed artificial intelligence algorithms in wind farm control and optimizations applications. Chatterjee and Dethlefs [15] investigated trends in the application of artificial intelligence in the operation and maintenance (O&M) of wind farms and analyzed future development directions. An overview of the latest research trends in the fields of wind energy and artificial energy and the identification of potential applications of artificial intelligence and machine learning in the wind energy sector has also been provided by Dörterler et al. [16].

A comprehensive analysis of the available literature shows that the application of AI in wind turbines is a very popular research topic [17]. The above studies show that AI technology is becoming a key factor and an important tool to increase the competitiveness of wind power technology [6]. This fact has led some universities to analyze the possibilities of applying AI to improve wind turbine technology through project-based learning (PBL) [18], with a focus on electricity generation at lower wind speeds.

AI technologies can help the energy industry capitalize on the growing opportunities presented by the introduction of the internet of things (IoT) and the integration of renewable energy sources [19].

With the significant increase in the use of AI and IoT in the energy industry and the monitoring of smart grid infrastructure, cyberattacks are also increasing, but the solutions to prevent these attacks are also growing rapidly [20].

The aim of this paper is to present a comprehensive analysis of the opportunities and challenges associated with the application of artificial intelligence in wind energy systems. The paper can serve as a valuable basis for young scientists to find a research niche and make a significant contribution to progress in this field. Likewise, the paper can serve as a source of information for investors and policy makers on the latest developments related to the application of AI in wind energy.

2. Materials and Methods

This study analyzes the application of artificial intelligence in wind turbines based on the available scientific literature. The research covers two main phases related to wind farms: the design phase of the wind farm and the operational phase of the wind farm. Subsequently, the end-of-life phase of wind farms was also briefly commented on. Finally, the AI algorithms that deliver the best results in the considered problem areas of wind turbines and the dangers of using AI are analyzed.

The research process involved the formulation of key questions for each content unit, which were addressed systematically. To achieve this, relevant keywords were identified and used for a comprehensive search of several document databases. The first phase of the search focused on well-known scientific databases, including Web of Science, PubMed, Scopus and Wiley Online Library, to name a few. In addition, relevant data and findings were extracted from peer-reviewed articles published by leading academic publishers such as Elsevier, IEEE and Taylor & Francis, as well as MDPI publications, proceedings of international conferences and specialized literature. In addition, supplementary information was extracted from reports from authoritative organizations such as the International Renewable Energy Agency (IRENA), the National Renewable Energy Laboratory (NREL) and various associations promoting the adoption of wind energy technologies. The Litmaps service was utilized to conduct two additional analyses. In the first analysis, the horizontal axis represented the publication year of the papers, while the vertical axis indicated the frequency of citations in other papers. Figure 2 highlighted which papers had a greater influence on the scientific community, prompting us to focus more on these papers during the analysis.

Figure 3 illustrates the relationship between the publication year of the paper (horizontal axis) and the number of references cited (vertical axis). The graph effectively highlights authors who conducted extensive literature reviews, with review articles generally exhibiting the highest number of references. In contrast, original scientific papers generally contained fewer references.

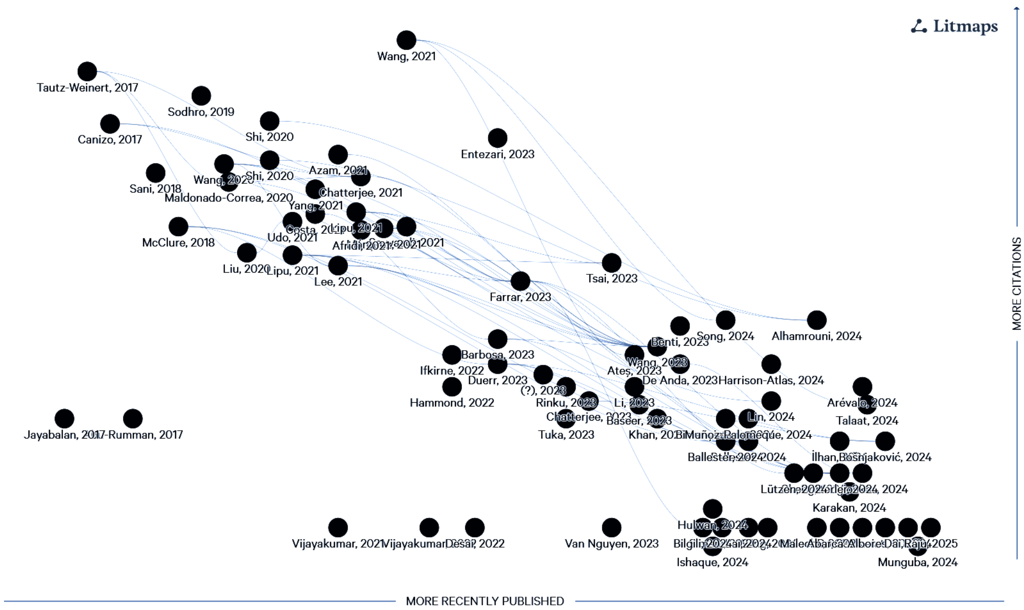

Figure 2. Temporal Citation Frequency: Identifying Highly Influenced Papers.

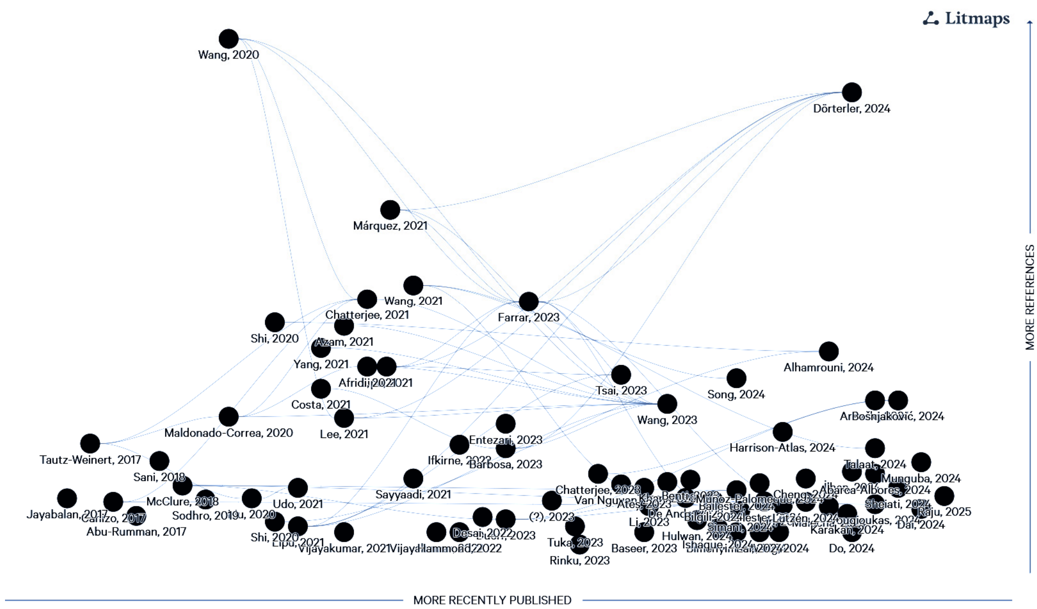

Figure 3. Reference density Over Time. Differentiating Review vs. Original Articles.

3. Results

Artificial intelligence is mainly used in the wind turbine design phase and in the wind turbine operation phase, while it is less used in the end-of-life phase. In the following, the overview is divided into four categories, with a third category relating to maintenance and a fourth relating to the end of life of wind turbines. The last category contains suggestions for topics that will become increasingly important.

3.1. Application of Artificial Intelligence in the Design of Wind Turbines

Artificial intelligence (AI) is increasingly being used in the design of wind turbines, bringing innovation and improvements to various aspects of the process, resulting in more efficient and adaptable energy systems. Some key applications and examples of the use of AI in this area are outlined below.

3.1.1. Design Process

The potential for using artificial intelligence (AI) to optimize the design of wind turbines is enormous. AI can improve various aspects of the design process, leading to more efficient and cost-effective wind turbines. The area of wind turbine design with the greatest potential for AI is the aerodynamic design of the rotor blades, as it directly influences the efficiency and energy output of a wind turbine. Using AI techniques and computational fluid dynamics (CFD), the shapes of the turbine blades can be optimized to minimize drag and turbulence while maximizing the energy yield of the turbine. AI can capture complex non-linear aerodynamic effects that may be overlooked in conventional design approaches, enabling more accurate modelling of the wind flow around the turbine blades. This is important for improving the efficiency of wind turbines under a wide range of environmental conditions, as it helps designers to select the best configurations for specific sites. Sahibzada et al. [21] report in their study that AI-optimized blades have a 15% better lift-to-drag ratio compared with conventional designs, based on CFD simulations. This leads to a 12% increase in performance in normal wind conditions.

To test these results, a wind farm in a windy area was selected. Over a period of 6 months, the turbines with optimized blades generated 18% more power than those with conventional blades. According to [22,23], the efficiency increase based on simulations is as high as 10–15%. AI can speed up the design process by enabling rapid simulations and evaluations of multiple design configurations. For example, advanced AI models can create new designs with improved aerodynamic properties in a fraction of the time compared with traditional methods. Zhang and Janeway [24] used CFD and ANN to optimize the aerodynamic design of a blade. To this end, they analyzed a large number of blade design variants (40,750 2D profiles). Among the optimal designs, a maximum performance increase of about 8% was found. The use of the ANN model required a relatively small number (163) of CFD analyses, resulting in a total calculation time of about 30 h. Without the use of the ANN model, 733 CFD evaluations would be required, resulting in an optimization time of approximately 135 h using the same computer resources.

The integration of artificial intelligence into existing engineering tools improves the overall design process and enables more comprehensive optimization, taking into account factors as diverse as structural integrity, cost and environmental impact. In the structural optimization of wind turbines, AI can help in the development of strong and lightweight structures. This can reduce material and labor costs and improve the durability of turbines, making wind energy more competitive with other forms of energy. Deep learning models can predict the dynamic responses of floating wind turbine platforms, ensuring stability in the deep sea. For example, LSTM networks predict the tension of mooring lines under different wave loads [25].

In the generative planning of wind turbines, the designers first determine the most important design parameters, e.g., turbine output, materials, installation location, wind speed, noise, production costs and environmental impact. Then algorithms, often based on machine learning and evolutionary algorithms, are used to generate a variety of variants of the potentially optimal design. All structural parts of a wind turbine can be optimized, e.g., the rotor blades, the wind turbine tower, the wind turbine foundation, the transmission elements, the electrical generator and others. The most common aim of optimization is to increase the efficiency of the wind turbine (rotor blades, generator) or to reduce the amount of material used (tower, foundation) in order to keep material costs as low as possible, but also to facilitate transport and installation.

When optimizing the blade profiles, AI algorithms take into account the given parameters and try to minimize drag and turbulence, increase the lift coefficient [26] and maximize the output energy for different environmental conditions. Each design created is then tested using computational fluid dynamics (CFD) simulations to evaluate its performance in real-world conditions. The simulations may include aerodynamics, structural analysis, noise calculations and other relevant factors. Based on the simulation results, the algorithms create new, improved designs. This process is repeated several times, iteratively improving the geometry of the wings and other structural elements until the optimal solution is achieved.

Research shows that AI-powered design can lead to next-generation turbines with improved wind energy utilization, which is key to advancing sustainable energy solutions [22].

For example, a wind turbine called the Birmingham Blade, which was developed by the British company EvoPhase+ in collaboration with KwikFab (Birmingham, UK), was designed with the help of artificial intelligence. The wind turbine is said to be able to generate seven times more energy in urban conditions than conventional models (not experimentally verified). This design was specifically developed to capture the lower wind speeds typical of urban environments (approx. 3.6 m/s) and to cope with the turbulence caused by the surrounding buildings [27].

The National Renewable Energy Laboratory (NREL), as part of the INTEGRATE project, is developing the next generation of aerodynamic tools for creating 2D airfoils and 3D designs of wind turbine blades using a specialized invertible neural network (INN) architecture that learns the complex relationships between blade airfoil shapes and their associated aerodynamic and structural properties [28].

Genetic algorithms (GAs) and particle swarm optimization (PSO) have been found to be particularly effective in dealing with large search spaces in the design of aerodynamic blades where multiple interdependent variables (e.g., blade chord length, twist distribution, blade shape) need to be optimized simultaneously [22,23]. Genetic algorithms are based on a population-based approach that performs random selection and recombination of design candidates, enabling a robust global search that prevents premature convergence to local optima [29]. These algorithms allow engineers to incorporate different objective functions—such as maximizing the lift-to-drag ratio while minimizing material consumption—and can thus propose a range of near-optimal designs for different wind conditions. However, the computational cost of GAs can quickly skyrocket when very large populations or extensive generations are required. In the context of rotor blade aerodynamics, the computational cost increases when high-resolution computational fluid dynamics (CFD) simulations need to be integrated into each iteration of the optimization loop [21].

Particle swarm optimization, on the other hand, uses a swarm of solution candidates that exchange velocity and position information with each other, which leads to accelerated convergence in many aerodynamic optimization scenarios [21,22]. PSO heuristics have been shown to be particularly valuable for wind turbine blade design when fewer design parameters (e.g., limited sets of cross-sectional profiles or simplified chord-twist parameterizations) need to be tuned. Comparative studies have shown that PSO can converge faster than GAs in certain aerodynamic contexts, although it may have a tendency to be trapped in local optima if swarm diversity is not well maintained [29]. In blade design, the fast convergence of PSO can be advantageous when a large number of iterative CFD evaluations are computationally intensive. However, the relative risk of partial convergence may require adjustments such as time-varying inertia coefficients or hybridized swarm intelligence.

Neural networks (NNs), including deep neural networks and convolutional neural networks (CNNs), offer another advantage in aerodynamic optimization: they can learn high-dimensional mapping functions that approximate fluid dynamic responses (e.g., lift, drag, and pressure distributions) for multiple blade geometries [30]. When trained with either numerical simulation data or empirical wind tunnel data, these models can perform rapid assessments of aerodynamic performance without the need to repeatedly invoke full-order CFD solvers. Therefore, NNs reduce the computational burden by acting as surrogates or meta-models. Once a neural network surrogate is created, gradient-based or gradient-free optimizers can be used on these learned representations to identify optimal blade shapes [27,30]. This approach accelerates the design cycle, especially when a large parameter space (e.g., multi-point aerodynamic conditions, different Reynolds numbers, or advanced composite materials) must be considered. However, NNs require carefully curated and sufficiently large training data sets. If the training data are sparse or not representative of the entire aerodynamic domain, extrapolation errors and model inaccuracies may occur.

In practice, a combined or hybrid approach is often chosen. Researchers have integrated neural networks as surrogate models in genetic algorithms or PSO systems to reduce the computational burden of aerodynamic blade calculations [22,30]. Such hybridizations exploit the global search capabilities of evolutionary algorithms together with the high-speed evaluations of machine-learned surrogate models. Studies have shown that, when the neural network models accurately capture the aerodynamic nonlinearity and the GA or PSO components preserve the robustness of the search, the overall design time can be significantly reduced—sometimes by more than 40%—with negligible trade-offs in the quality of the blade geometries found [22,27,30].

In summary, genetic algorithms are well suited for comprehensive global exploration but can be computationally expensive, particle swarm optimization offers faster convergence at the risk of being locally stagnant, and neural networks enable fast aerodynamic evaluations that depend on the amount and accuracy of available training data. The optimal choice of these methods depends on the complexity of the blade's parameter space, the underlying aerodynamic modelling fidelity, and the computational resources required to achieve a highly accurate blade design. Jayabalan et al. [31] argue that the optimal design of a wind turbine is influenced by various factors, such as blade profile, number of blades, power factor and tip speed ratio (TSR). They investigated different AI techniques, such as support vector machine (SVM), relevance vector machine (RVM) and genetic programming (GP), for the optimal design of wind turbines and came to the conclusion that the TSR is crucial for the design of wind turbines.

In addition to the rotor blades, the tower also plays an important role in wind turbines. The base diameter, the upper diameter and the tube wall thickness of tubular steel towers are design parameters that strongly influence two contradictory optimization objectives: mass and top deflection. In addition, the solutions must fulfil the requirements of natural frequency, stress and buckling. In their work, Cheng et al. [32] use convolutional neural network (CNN), back propagation neural network (BPNN) and support vector machine (SVM) algorithms to optimize the tower. They found that the CNN algorithm proved to be the best. De Anda et al. [33] presented a method to determine the optimal design of steel towers for wind turbines using artificial neural networks (ANNs) and the MOPSO algorithm. The optimization approach aimed to achieve three design goals: maximizing structural reliability, minimizing structural mass and maximizing wind energy utilization.

Artificial intelligence can help to design a cost-effective and structurally stable foundation for wind turbines. Although there is not yet much scientific research on this topic, two examples can be cited. Vougioukas et al. [34] applied an innovative approach using AI to analyze design loads and optimize foundation systems for overturning resistance while complying with Eurocode guidelines. This approach can significantly reduce the amount of concrete and steel required and thus reduce construction costs by up to 70%. Shen [35] developed a meta-model based on machine learning to optimize foundations for wind turbines in his master's thesis. Two multi-output machine learning algorithms, namely the multi-output random forest (RF) algorithm and the multi-output feedforward neural network (FFNN) algorithm, were selected and optimized using the proposed genetic algorithms (GA) method to determine the best model configuration and the best combination of input features. The author concluded that the multi-output RF model has better performance in terms of accuracy and computational time compared with other developed models. This approach replaces conventional finite element analysis (FEA) with machine learning models that predict optimal designs more effectively, reduce computational time and maintain the accuracy of structural performance estimates.

3.1.2. Performance Optimization for Local Wind Conditions

The ability of AI to analyze historical wind data and local weather conditions makes it possible to adapt the design of turbines. Traditional "one-size-fits-all" solutions often lead to sub-optimal results in different environments. AI models can identify optimal design parameters such as blade shape, rotor diameter and spacing that are tailored to the specific wind conditions to maximize energy production.

The Windstar project, for example, used AI to customize the shape of turbine blades based on local wind patterns. The results of the project suggest that this could capture up to 18% more wind energy compared with conventional designs, although this has not been scientifically proven.

EvoPhase utilized AI to develop a turbine that can operate efficiently in Birmingham's unique wind conditions. The AI-generated design included innovative features such as curved blades that rotate around a central point to optimize performance in the turbulent urban airflows. The ability to create and test over 2000 designs in just a few weeks significantly accelerated the development process compared with traditional methods [36].

3.1.3. Location Selection and Environmental Impact Assessment

Artificial intelligence (AI) is becoming increasingly significant in the selection of sites for wind turbines and the assessment of their environmental impact. Traditional methods are often time consuming and require a significant amount of manual work, while AI enables faster, more efficient and more precise analysis of large amounts of data. Geographic information systems (GIS) play a crucial role in mapping the suitability of wind turbines, as they facilitate the analysis and visualization of different spatial data layers that influence the potential for wind farm development. GIS is often combined with multi-criteria decision analysis (MCDA) techniques such as the analytic hierarchy process (AHP) to evaluate and prioritize sites based on different criteria. This approach allows stakeholders to weight factors according to their importance, resulting in a comprehensive suitability map that highlights optimal locations for wind energy projects.

In general, the application of AI in site selection includes the following:

- Analysis of meteorological data: UI algorithms can analyze huge amounts of meteorological data (wind speed and direction, temperature, humidity, etc.) collected from weather stations, satellites and other sources. This makes it possible to accurately predict the wind potential at different locations and identify optimal areas for the installation of wind turbines. AI can recognize patterns and trends in data that are not immediately visible to the human eye, leading to better estimates of a site's energy potential. For example, in their study, Bimenyimana et al. [37] used a geographic information system (GIS) and the multi-criteria AHP to conduct a spatial analysis of the suitability of sites for wind turbines in East African countries. The authors gathered and analyzed data from various freely available sources, including the Regional Centre for Mapping of Resources for Development (RCMRD), the African Geoportal, the

Global Wind Atlas, energydata.info and the East African Community website. In his research, Karakan [38] uses wind speed data from meteorological stations to predict the available wind energy at a given location. The analysis employed advanced deep learning techniques, including long short-term memory (LSTM), convolutional neural networks (CNNs), recurrent neural networks (RNNs), gated recurrent units (GRUs), as well as hybrid models such as LSTM-GRU, CNN-LSTM, CNN-GRU and CNN-RNN. Among these, the CNN-GRU model demonstrated superior performance, achieving a peak accuracy of 99.81% in wind energy prediction. The author used two different models and five different measurement systems to evaluate performance and reports that a high accuracy of 89% was achieved. As a result of this study, weekly, monthly, and annual predictions were made.

- Analyzing topographical data: AI is used to analyze topographic maps and digital terrain models to assess the suitability of the terrain for wind turbines. Algorithms can identify areas with favorable characteristics, such as open areas with minimal wind obstacles, and can avoid areas with excessive slopes or other topographical constraints. An example is the study by Ifkirne et al. [39]. The study used a method combining GIS with multi-criteria decision analysis (MCDA) to identify suitable sites for onshore wind farms in southern France. In addition to the environmental factors mentioned above, the study also considered technical and social factors in the site selection process.
- Integration of geographical information (GIS): UI can be integrated with GIS systems to combine different data layers, e.g., meteorological data, topographical data, infrastructure data (roads, power lines), protected areas, settlements and other relevant factors. This enables a comprehensive analysis of the area and the identification of optimal locations, taking all relevant aspects into account. It should be noted, however, that the existence of legal restrictions related to land use, environmental protection and community opposition can complicate site selection. An example of such an analysis was given by Benti et al. [40]. In their study, GIS and the analytic hierarchy process (AHP) are used to identify suitable sites for wind farms in Ethiopia. A similar analysis for Sudan was conducted by Zalhaf et al. [41], who used a fuzzy AHP approach in addition to GIS.
- Turbine layout optimization: Once a potential site is selected, UI can be used to optimize the layout and spacing of wind turbines within that area. The algorithms take into account the interaction between the turbines (the so-called "wake effect") to maximize energy production and reduce losses, as found in the research of Sa-maei and Ghahfarokhi [42] and Song et al. [22]. In this case, the ANN-based wake models speed up the design simulations by 40% compared with the traditional CFD methods. According to studies by Harrison-Atlas et al. [43], optimizing the plant layout can reduce the area required by an average of 18% per plant.

The application of AI in environmental impact assessment includes the analysis of the following:

- Impact on wildlife: AI is being used to analyze data on bird and bat migrations and the habitats of other animals to assess the potential impact of wind turbines on wildlife. Algorithms can predict risk areas and help plan mitigation measures to minimize negative impacts, such as switching off turbines at certain times or installing visual and acoustic deterrents. In their paper, Duerr et al. [44] present the development of an AI-powered bird detection system. This system integrates radar and camera technology to track the movements of birds with the aim of minimizing collisions with turbine blades. Using machine learning algorithms, the system can identify bird species and predict their flight paths, enabling proactive measures to avoid collisions.

- Noise from wind turbines: AI is used to model and predict the noise levels generated by wind turbines. This allows the impact of noise on neighboring settlements to be estimated and, if necessary, noise reduction measures to be planned. For example, Lai et al. [45] discuss in their study how AI can classify different types of wind turbine noise based on factors such as amplitude modulation and sound characteristics. The study emphasizes the potential of AI to improve noise assessment methods and provide insights into how different noise profiles affect wildlife and humans.
- Impact on soil and water: AI models can predict the long-term impact of wind turbines on soil and vegetation by simulating different scenarios. These models take into account factors such as turbine location, wind conditions and environmental conditions to predict potential changes in the environment and suggest mitigation strategies [23].

3.2. Application of Artificial Intelligence in the Operation of Wind Turbines

As electricity generation from wind energy is intermittent, the increasing integration of wind turbines into existing electricity grids poses a challenge for the flexibility, security and stability of electricity systems. Predicting power generation is becoming increasingly important in this context, and artificial intelligence is recognized as an essential component in the operational phase of wind farms. In addition, the integration of AI technologies into the management processes of wind farms leads to improved efficiency, and AI in this context includes the following:

- Improved accuracy of electricity generation and consumption forecasting
- Dynamic optimization of wind turbine performance
- Efficient remote monitoring and control of wind turbines
- Efficient bird collision avoidance system with wind turbine blades
- Integration of wind turbines with smart grids
- Improved predictive maintenance capabilities of wind turbines

3.2.1. Improved Accuracy of Forecasting Electricity Production and Consumption

It can be said that wind energy forecasting, although important, is not considered a key area for the greatest contribution of AI in wind farms for several reasons:

- Wind energy production is highly variable and is influenced by numerous unpredictable factors such as wind speed, wind direction, temperature and air pressure. This inherent instability makes accurate forecasting difficult and often leads to significant fluctuations between predicted and actual energy production.
- The complexity and randomness of these variables can limit the effectiveness of AI models in producing reliable forecasts [46].
- Significant progress has already been made in the field of wind energy forecasting using traditional meteorological methods and numerical weather prediction models. Many operators are effectively utilizing these proven techniques, which may reduce the current need for AI-driven solutions compared with other areas, such as predictive maintenance, where AI can provide more transformative benefits.
- As wind energy is increasingly integrated into power grids, generation and demand need to be balanced. While accurate forecasting is critical to this, it is primarily a tool rather than a transformative application of AI. The focus is often on optimizing grid management rather than improving the fundamental operational capabilities of the wind farms themselves.

However, analyzing and monitoring turbine performance in real time using AI has significant advantages. In response to changing wind conditions, AI algorithms can dynamically adjust turbine settings, such as blade pitch and nacelle rotation angles, to maximize energy production. As a result, energy production increases and overall efficiency is higher. According to some studies, AI can improve the efficiency of wind turbines by up to 20% [47].

Below are some of the most important research and applied AI methods related to wind power generation forecasting. AI algorithms are excellent at analyzing huge data sets, including historical weather patterns, turbine performance metrics and real-time environmental conditions. By processing this information, AI can produce highly accurate power generation forecasts based on expected wind conditions [46]. This allows operators to optimize energy use and manage grid stability more efficiently, reducing the risk of power outages or inefficiencies due to imbalances between supply and demand. Precise short-term wind energy forecasting plays a critical role in mitigating the challenges associated with voltage peaks and frequency regulation within the power grid, as well as the connection of wind farms to the electricity grid. Some research work has been carried out in this context. For example, Talwariya et al. [48] propose a conventional neural network algorithm based on machine learning to forecast production and calculate power production forecast errors. They used real data from a 40 kW wind farm at a site in Rajasthan. In their study, Baseer et al. [49] introduce a novel hybrid model that strategically integrates multiple complementary machine learning techniques to enhance the precision of wind turbine energy production forecasting. The ensemble learning (EL) approach demonstrates superior performance compared with long short-term memory (LSTM), light gradient boosting machine (LightGBM), and sequenced-gated recurrent unit (Sequenced-GRU) in predicting wind energy. The proposed model achieves an exceptional R^2 value of 0.9821, underscoring its high level of accuracy.

In their study, Ilhan et al. [50] propose several artificial intelligence techniques to simulate the rotation speed of the turbines and predict the wind energy production 10 min in advance. Four tools are used for the prediction: The fuzzy C-means (FCM) approach of the adaptive neuro-fuzzy inference system (ANFIS), the long-term memory (LSTM), the grid-partitioning (GP) method of the adaptive neuro-fuzzy inference system and the subtractive clustering (SC) algorithm of the adaptive neuro-fuzzy inference system. These methods use historical data as input for the physical parameters to be estimated and estimate the subsequent value as output. It has been shown that LSTM performs best when capturing real, observed wind turbine parameters, while the ANFIS-FCM model provides the most accurate results for wind energy. Ateş [51] has introduced an artificial neural network (ANN)-based methodology for short-term wind energy prediction, utilizing a swarm intelligence algorithm for optimization. The study includes a simulation of a real-world wind power system in Turkey under varying wind speeds, conducted using MATLAB/Simulink. The swarm intelligence algorithm is employed to fine-tune the parameters of the forecasting model. The proposed algorithm's effectiveness is assessed using actual data from a wind farm in Turkey. Three distinct approaches are applied for efficient data processing: ANN, ANN integrated with the firefly algorithm (ANN-FA), and ANN combined with particle swarm optimization (ANN-PSO). The findings demonstrate that the swarm intelligence algorithm surpasses conventional prediction methods, including statistical approaches and standard machine learning techniques, in terms of both accuracy and reliability.

Desai et al. [52] used artificial intelligence to attempt to predict electricity generation from wind energy one day in advance. The project was implemented on two SCADA data sets that provided different parameters. The first dataset provided information on wind speed, wind direction, theoretical power and active power. The output variable was energy production (KWh). The second data set provided data on power output over time. The article proposes and compares different machine learning methods and neural networks for predicting energy from wind energy. Five common machine learning regressor algorithms and long-term short-term models were compared, focusing on the target-output variable, and an approach for forecasting weather series in a scenario with insufficient weather parameters for wind data was proposed.

In their research, Talaat et al. [53] created data-driven models for wind speed and power prediction by employing machine learning (ML) and deep learning (DL) techniques, incorporating site-specific climatological data. Additionally, they designed an advanced recommendation system to optimize turbine placement and identify ideal locations for power plants based on wind strength and speed. The study highlights the real-time effectiveness of the proposed method, with XGBoost and random forest regressors achieving 94% accuracy and an average percentage error of 6 in forecasting 15-day power output.

A similar study to predict wind energy production was conducted by Bilgili and Gül [54]. They developed a model using the decision tree, random forest, K-nearest neighbor (KNN) and XGBoost algorithms. The dataset was sourced from real-time SCADA data obtained from wind turbines, allowing for a comprehensive analysis. The results of this study confirm the effectiveness of machine learning methods, especially XGBoost, in accurately predicting wind power generation and at the same time emphasize the importance of computational efficiency in practical implementation.

Li et al. [55] investigated the ways to estimate regional wind energy production and proposed a multi-aggregate model of wind energy characteristics based on three scaled Gumbel distribution functions for regional aggregated wind energy. The relative peak power and full load hours were compared for the proposed model and the actual measurements of the local distribution system operator using artificial intelligence models using neural networks such as long short-term memory (LSTM), compound LSTM and CNN-LSTM. The results show that the proposed compound LSTM is stable and reliable in predicting the regional performance.

3.2.2. Dynamic Optimization of Turbine Performance

AI facilitates real-time adjustment of turbine settings, such as blade pitch and yaw angle, in response to changing wind conditions. As mentioned earlier, this dynamic optimization can increase energy yield by up to 20% by ensuring that turbines operate at their highest efficiency under changing environmental conditions [47].

Maximum power point tracking (MPPT) is an essential step in the operation of wind turbines to ensure efficient power generation. Muñoz-Palomeque et al. [56] have given an overview of the existing techniques, explaining their benefits and providing a basis for future developments. Two intelligent control strategies are presented in more detail: neural networks and fuzzy logic controllers.

Artificial intelligence (AI) plays an important role in stabilizing the output voltage of a wind turbine in the grid, especially when a doubly fed induction generator (DFIG) is used. However, the dynamic characteristics of such generators depend on non-linear parameters such as stator flux, stator current and rotor current, which increases the overall complexity of the system. Therefore, to ensure system stability, robust controllers capable of supporting dynamic wind energy frequencies must be implemented. By applying AI, fuzzy logic (FL), fuzzy PI, artificial neuro-fuzzy inference system (ANFIS), fuzzy, fuzzy-PI, and hybrid controller (ANFIS-PI), controllers are developed which have an advantage over the classical proportional–integral controller as described in the work of Tuka et al. [57] and Ishaque [58].

3.2.3. Effective Remote Monitoring and Management

AI allows operators to monitor the operations remotely, which is particularly useful for offshore or remote sites. This capability reduces the need for a physical presence on site, enables a faster response to problems that arise and reduces operating costs. AI systems continuously analyze data from various sensors installed on the wind turbines. These sensors monitor parameters such as temperature, vibration and smoke levels and can detect anomalies that could indicate a fire hazard. Conventional fire detection methods, such as smoke and flame detectors, suffer from low detection accuracy and long response times. Fire detection methods based on the use of AI are therefore being investigated. These approaches often rely on neural networks for object recognition, which leads to high false alarm rates for pseudo-fire images. Do et al. [59] proposed a hierarchical deep neural network for fire detection that reduces the false alarm rate and accurately identifies smoke and fire locations. The proposed solution first uses a neural network to classify potential fire situations into three categories: fire, smoke or normal. By analyzing all image information, false alarms are effectively reduced. The proposed approach can be applied to wind turbine nacelles.

Research into the application of artificial intelligence in recognizing the conditions for ice formation on wind turbine rotor blades is only just beginning, so a significant increase in research can be expected. Ice formation on wind turbine blades is influenced by a number of factors, including outside temperature, wind speed, humidity and so on. However, lesser-known factors, such as the liquid water content and the mean volume diameter of the water droplets, can also have an influence. Using sensors and/or computer vision, AI can recognize the conditions for ice formation on turbine blades and activate de-icing systems such as heaters or mechanical scrapers [60]. Chatterjee et al. [61] have shown that training stand-alone deep learning (DL) models with augmented data capturing range-invariant icing features can improve prediction performance for multiple wind farms.

3.2.4. An Effective System for Avoiding Bird Collisions with Wind Turbine Blades

Artificial intelligence plays a crucial role in the development of systems to avoid collisions between birds and wind turbine blades, especially in a real-time context. These systems use a variety of AI technologies to minimize the number of collisions between birds and wind turbines and reduce the potential damage to the wind turbines.

AI systems use a variety of sensors, including cameras, radar and ultrasonic sensors, to collect data about the wind turbine environment [62]. Systems such as the MERLIN Detect radar and IdentiFlight camera system (DeTect Inc., Panama City, FL, USA) have been developed to monitor bird activity in real time, providing early warning and enabling automatic responses to prevent collisions [63,64]. By recognizing birds up to 1.3 km away and classifying them as protected species, IdentiFlight provides wind turbine operators with the critical visual and quantitative data they need to reduce or avoid collisions.

Using deep learning algorithms, such as convolutional neural networks (CNN) and computer vision, the AI can identify birds in the vicinity of wind turbines. These algorithms analyze images and videos to distinguish birds from other objects and can even identify protected bird species. AI can also use predictive models to assess the behavior of birds based on historical data about their migration patterns and weather conditions to predict potential collisions and take appropriate system responses. When a potential collision is detected, the system can activate collision avoidance mechanisms, such as changing the rotation speed of the rotor blades or stopping the rotation of the rotor blades.

3.2.5. Integration with Smart Grids

Artificial intelligence plays a very important role in the integration of wind farms into smart grids, where the stability and real-time control of the grid are key aspects [65]. The application of artificial intelligence can enable the processing of a huge amount of data from sensors and IoT devices in real time, allowing continuous monitoring of the grid status and immediate adjustment to maintain stability. For example, artificial intelligence can recognize fluctuations in electricity supply and demand and adjust the output of wind turbines accordingly [66].

AI can also predict potential instabilities in the grid before they occur. By analyzing historical data and current grid conditions, AI models can predict situations that could lead to instability, such as a sudden drop in wind speed or an unexpected increase in electricity demand. This capability gives grid operators the ability to take preventative measures in time to mitigate or avoid instability problems. Although traditional control systems can also deal with the variability and fluctuations of wind energy, control systems based on artificial intelligence can do so more efficiently, especially with a greater penetration of wind farms in the power grid [67].

Another important opportunity presented by the use of AI is the rapid detection and isolation of faults within the grid to prevent cascading failures that could lead to widespread outages. For example, if AI predicts that a transformer is likely to fail, operators can request maintenance before the failure occurs, preventing outages and reducing maintenance costs.

Another useful application of AI is optimizing the use of energy storage systems to balance the grid. When wind power production is high, surplus energy can be stored in energy storage systems (e.g., batteries, hydrogen or reversible hydropower plants) [68]. In times when no wind energy is generated (too little or too strong wind), AI can activate the use of stored energy from energy storage systems to maintain a stable power supply [66].

By providing insights and recommendations based on real-time data and predictive analyses, AI helps operators make decisions to maintain grid stability [67].

However, it should be noted that the complexity of artificial intelligence algorithms requires the creation of a clear legal framework to ensure that these technologies are used fairly and transparently and that they are not abused.

Economically, AI improves operational efficiency and helps to reduce costs for energy suppliers and consumers by optimizing energy generation, distribution and use [69], which should lead to less price volatility and potentially lower electricity prices.

In terms of environmental impact, artificial intelligence contributes to achieving climate goals by improving the integration and utilization of renewable energy sources, leading to a reduction in greenhouse gas emissions.

3.3. Wind Turbine Maintenance

One of the key areas in which artificial intelligence (AI) is expected to make the greatest contribution in wind farms is predictive maintenance. Predictive maintenance uses AI to analyze large amounts of sensor data and historical maintenance records to identify patterns and predict potential turbine failures before they occur. This capability is critical for several reasons, as follows:

- Minimizing downtime: By detecting problems early, predictive maintenance reduces unplanned outages and ensures turbines operate at maximum efficiency and reliability.
- Cost savings: Early detection of failures enables timely repairs and prevents costly damage to critical components. By accurately predicting maintenance needs, AI can help avoid unnecessary maintenance activities and focus resources on critical issues. This leads to significant cost savings and more efficient operations. The National Renewable Energy Laboratory (NREL) states that operation and maintenance (O&M) costs account for about one-third of the total lifecycle costs of wind farms. In other words, they amount to USD 15–27/kW/year for onshore wind farms and USD 40–60/kW/year for offshore wind farms [70]. The study by Abu-Rumman et al. states that O&M costs account for about 19% of the total LCC for wind farms [71], and Costa et al. [72] highlight that operation and maintenance costs generally constitute approximately 20% to 25% of the total life cycle cost, both of which are values that

are lower than those reported by NREL. Despite these differences, these sources emphasize the importance of effective maintenance strategies to increase profitability. Regular inspections and repairs help prevent major outages and costly repairs. Fewer breakdowns mean fewer power outages, which leads to higher revenues.

- Improved safety: Automated condition monitoring of wind turbines reduces the need for manual inspections at hazardous or remote sites, reducing the risk of industrial accidents while maintaining operational efficiency.
- Extended turbine lifetime: Ultimately, regular maintenance extends the lifetime of wind turbines, meaning the wind turbine produces more clean energy, which in turn contributes to lower greenhouse gas emissions and a positive impact on the environment. According to some analyses, AI can extend the service life of wind turbines by up to 10% [47].

Awareness of the importance of wind turbine maintenance has led to an 87% increase in the number of scientific papers on this topic between 2007 and 2019. As a result of increased research, the LCOE of onshore wind projects has fallen by 45%, while it has fallen by 28% for offshore projects [70]. The application of artificial intelligence (AI) in wind turbine maintenance has evolved over the past decades, with significant progress being made in recent years. Although the first mention of AI in wind turbine maintenance is not clearly documented, a literature review shows that AI applications in wind turbine technology have been used on a larger scale since around 1980 [10]. The emergence of the concept of predictive maintenance has significantly accelerated the application of AI to analyze wind turbine data to predict failures before they occur. In the last decade, most existing studies have utilized signal processing or physics-based numerical models for CBM in the context of turbine condition monitoring, using vibration data in particular for this purpose [15,73,74]. Chatterjee and Dethlefs [15] are of the opinion that, despite the increasing use of AI in the wind industry, more traditional techniques, such as those based on signal processing, will continue to complement AI models in this rapid transition. They also emphasize the need to ensure the quality of data and focus on more sophisticated and customized AI algorithms, especially using deep learning and natural language generation techniques for explainable AI.

Regarding the scope of application of AI in wind turbine maintenance management, according to García Márquez and Peinad Gonzalez [23], 25% of applications focus on optimization of any kind (cost, maintenance, route planning, etc.), 16% of applications are related to fault detection and the same number to decision making. Planning and scheduling waste is the focus of 9% of applications, condition monitoring 8%, maintenance 8%, etc.

The most widely utilized AI techniques for wind turbine maintenance include artificial neural networks (ANNs), genetic algorithms (GAs), particle swarm optimization (PSO), fuzzy logic, statistical methods, and decision-making techniques. Among these, ANN and its variants stand out as the most versatile, as they are applicable to monitoring, optimization, data prediction, and decision-making tasks. GA and PSO are primarily employed for optimization and decision-making, as these algorithms were specifically designed to optimize systems with multiple variables. Fuzzy logic is predominantly used for decision-making and risk mitigation, incorporating factors such as cost and component reliability. Statistical methods are mainly applied for maintenance and fault prediction, leveraging large datasets to generate accurate estimates.

The detection of faults in the pitch system of wind turbines plays a crucial role in the efficient and reliable operation of wind turbines. Therefore, Filipe de Lima Munguba et al. [75] tested sixteen artificial intelligence (AI) classification models for detecting faults in the pitch system of wind turbines. The random forest classifier (RF) and extra trees classifier (ET) models showed the best performance, while the models with the lowest performance were the K-nearest neighbor classifier (KNN) and linear discriminant analysis (LDA). The average hit effectiveness for the modes “healthy” and “faulty” was about 80% for most of the developed models.

The rotor blades of wind turbines are the most important component of wind turbines that enable the utilization of wind energy. Damage or breakage to the blades has a direct impact on the operation of wind farms. It is therefore extremely important to monitor changes in the blade surface over time. Advances in drone technology and artificial intelligence (AI) make it possible to capture and analyze numerous high-resolution images of rotor blades. However, images of wind turbine blades taken while the rotors were spinning resulted in a complex background in the blade images, with the surface features of the blades being relatively small. In their work, Sheiati et al. [76] applied a deep learning segmentation method to segment rotor blade images captured by drones and eliminate the influence of the image background. A Siamese convolutional neural network (S-CNN) was used to recognize individual blades captured by drones and compare them with a reference blade image.

Abarca-Albores et al. [77] assessed two models for detecting faults in wind turbine blades. The first employed logistic regression, which proved superior to Naive Bayes, decision trees, and neural networks, showcasing its efficacy in identifying fault-related patterns. The second utilized clustering techniques and achieved higher accuracy and improved data segmentation performance.

Lin et al. [78] used data on the predictive maintenance of wind turbines in Taiwan. On this basis, they developed a program for predicting wind turbine failures using a hybrid method that employs machine learning and deep learning. The random forest method is applied to identify features that are highly correlated with failures and to eliminate features with low correlation to maximize the performance of the model. The resulting failure prediction model provides an average prediction accuracy, precision and recall of 99%, 70% and 77%, respectively, for predictions from one to six hours ahead.

Udo et al. [79] developed a method for monitoring and detecting anomalies in critical components of a wind turbine, such as the gearbox and the generator. The approach is based on historical SCADA data. In the paper, models using extreme gradient boosting (XGBoost) and long short-term memory (LSTM) are proposed to predict the behavior of the characteristics of critical components of a wind turbine, and statistical process control (SPC) is used to evaluate their abnormal behavior. The proposed method is tested in practice. The approach is promising but requires an investigation of the sensitivity level of the deviation to perform a fault diagnosis by deducing which specific parts (subcomponents) of the main components will fail.

In [80], the generator temperature and gearbox oil temperature in SCADA data were used to model the normal temperature of wind turbine components. The residual between the predicted and actual values was calculated and the trend was monitored using an exponentially weighted moving average (EWMA) control chart.

Canizo et al. [81] presented the development of predictive maintenance solutions in a big data environment. The proposed approach aims to develop a predictive model generator for each monitored wind turbine that provides a dashboard with failure predictions every 10 min. The task of the maintenance manager is to understand the development of anomalies and make appropriate decisions.

Using machine learning techniques, artificial intelligence can analyze data from turbine sensors to identify patterns that indicate potential failures before they occur. However, unattended components or subsystems can occasionally lead to failures. Therefore, in their research, Lützen and Beji [82] analyzed and demonstrated the possibility of the practical application of artificial intelligence to predict failures in unattended components.

A proactive maintenance approach helps to reduce unplanned downtime and extend the lifetime of turbines by enabling timely interventions. Predictive maintenance not only increases operational safety, but also contributes to cost savings by minimizing repair costs and optimizing maintenance schedules [83].

3.4. The Impact of Extreme Weather Conditions on AI Performance

In extreme weather conditions, such as lower temperatures and higher wind speeds, AI technology in wind turbines faces several external challenges that affect its effectiveness. Extreme cold can affect the accuracy of sensors installed in wind turbines that monitor parameters such as vibration, temperature and blade rotation. Ice formation on sensors or mechanical components can lead to distorted data, reducing the reliability of AI-driven predictive maintenance and real-time adjustments [84]. For example, AI algorithms rely on precise vibration data to detect mechanical wear. However, ice formation can obscure or distort these signals, resulting in delayed maintenance alerts. AI-enabled drones used for automated inspections can struggle in harsh weather (e.g., ice) and delay fault detection.

Higher wind speeds increase the mechanical stress on turbine components (e.g., blades, gears). While AI dynamically optimizes the pitch and yaw angles of the rotor blades to maximize energy yield, extreme gusts or turbulence can stress turbines beyond their operating limits and cause structural damage. AI models must account for rapid wind changes and adapt control strategies to balance energy production and turbine safety. AI models trained with "normal" weather data may perform worse under extreme conditions. Deep learning architecture such as LSTM need to be trained with datasets containing extreme weather scenarios to improve resilience.

3.5. End of Life of a Wind Farm

Artificial intelligence can play a significant role in the end-of-life phase of wind turbines. Here are some important areas where AI can contribute [85]:

- Decommissioning planning: AI can analyze data to optimize the decommissioning process, ensuring that it is carried out efficiently and cost-effectively.
- Recycling and material recovery: AI can help identify and sort materials from turbines that are no longer in use, improving the efficiency of the recycling process and maximizing material recovery.
- Life extension analysis: AI can assess the condition of aging turbines and predict their remaining life, helping to make decisions about whether to refurbish, repower, or decommission them.
- Environmental impact assessment: AI can model and predict the environmental impact of decommissioning activities, helping to minimize negative impacts on the surrounding ecosystem.
- Resource allocation: AI can optimize the allocation of resources during the decommissioning process, ensuring that labor, equipment, and materials are used efficiently.
- Risk mitigation: Artificial intelligence tools can help identify potential risks associated with decommissioning, such as weather delays or logistical challenges. By quantifying these risks, operators can develop strategies to effectively mitigate them.

By using AI in these end-of-life areas, wind turbines can be managed in a more sustainable and efficient manner, reducing costs and environmental impact.

4. Artificial Intelligence Algorithms

As can be seen from the previous chapters, different algorithms of artificial intelligence are extensively applied to the problem of wind turbines. Below are more important observations related to applied AI methods and algorithms.

This chapter summarizes and expands on all of the key references to artificial intelligence (AI) and machine learning (ML) algorithms found in the paper, focusing on algorithms that have been shown to perform well in wind farm design optimization, operational decision making, maintenance management and end-of-life processes. The relevant results are categorized under supervised/unsupervised/semi-supervised learning, functionality (e.g., classification or regression), probabilistic vs. non-probabilistic, model type (e.g., neural networks, ensemble methods) and data representation.

Below is a detailed summary, starting with an overview of the AI/ML approaches mentioned in the paper and ending with a summarizing classification table. The citations refer either to the original references within the article or to additional sources where indicated.

4.1. Algorithms for Wind Turbine Design

Evolutionary algorithms (genetic algorithms and particle swarm optimization) are often used to iteratively improve wind turbine components such as blade aerodynamics, tower dimensions and foundations [22,23,31–34]. Representative examples are the use of genetic algorithms to refine the aerodynamic profile and particle swarm optimization for structural designs that balance mass and deflection.

Neural networks (fully connected networks and convolutional networks) are used to predict aerodynamic performance metrics (lift, drag, turbulence) and to optimize geometry by rapidly evaluating design candidates [25,28,32,33,35]. Convolutional neural networks can map the shape of airfoils to aerodynamic coefficients, while feedforward neural networks help to predict the results of foundation designs without expensive finite element analyses.

Support vector machines, relevance vector machines and genetic programming have also been explored for the control of blade design processes, especially for the determination of optimal tip speed ratios (TSR) [31].

4.2. Algorithms for Wind Turbine Operation

Time series forecasting models (LSTM, GRU, CNN-LSTM and CNN-RNN) are crucial for short-term forecasting of wind energy, typically minutes to hours in advance, as they capture temporal dependencies in wind speed and power data [38,49,50,52,55]. LSTM networks can reduce the mean absolute percentage error, and hybrid CNN-GRU or CNN-LSTM architectures often improve accuracy for high-frequency wind data.

Ensemble methods such as random forest, XGBoost and LightGBM combine predictions from multiple sub models to increase accuracy in power generation forecasting [49,50,54,79]. XGBoost is often used for predicting the electrical output of wind turbines and for temperature modelling, while random forest helps to identify features that are strongly correlated with system failures or power fluctuations.

Adaptive neuro-fuzzy inference systems (ANFIS) and fuzzy logic approaches enable the control of wind turbines (e.g., dynamic pitch or yaw adjustments), stabilize voltages in doubly fed induction generators and improve consumption prediction under uncertainty [50,56,58].

Computer vision and object recognition techniques based on deep learning enable real-time monitoring of birds and bats, collision avoidance and leaf icing detection [44,59–62].

4.3. Algorithms for Wind Turbine Maintenance

Machine learning classifiers (random forest, extra trees, logistic regression, K-nearest neighbor, naive Bayes) facilitate error detection and classification of sensor data such as vibration signals and the state of the pitch system [24,75,77]. Random forest and extra trees, for example, have shown a detection accuracy of around 80% for faults in the blade system, and logistic regression in combination with clustering can detect damage to the rotor blades.

Deep learning for image segmentation (using CNN and Siamese CNN architectures) is used for drone-based inspection of rotor blades, with segmented images highlighting cracks or surface defects [76].

Hybrid predictive models combining ML and DL focus on predictive maintenance using SCADA data to predict failures hours in advance [78–80]. For example, LSTM or XGBoost models can be integrated into statistical process control to detect anomalies in the temperatures of gearboxes or generators. Big data frameworks also support the continuous 10 min detection of anomalies in large turbine fleets [81].

4.4. Algorithms for End-of-Life Decision-Making

Predictive analytics and decision trees help to plan the decommissioning of turbines and decide whether they should be overhauled or recycled. These methods often classify turbines into categories for repowering or decommissioning by combining factors such as cost, structural integrity and location.

Clustering and optimal resource allocation techniques are then used to sort materials for recycling and optimize the logistics of dismantling multiple turbines at a site.

4.5. Summary Categorization Table

Table 1 contains a consolidated categorization of the algorithms discussed in the context of wind farm design, operation, maintenance and end of life. The categories are adapted to common distinctions in ML (e.g., learning approach, functionality, probabilistic vs. non-probabilistic), and the references refer to the relevant studies mentioned in the paper.

Table 1. Summary consolidated categorization of AI algorithms mentioned in paper.

Algorithm	Learning Approach	Functionality	Probabilistic vs. Non-Probabilistic	Model Type	Data Representation	Key Wind Power Application	References
Genetic algorithms (GAs)	Evolutionary/heuristic	Optimization (design)	Non-probabilistic	Evolutionary model	Structured and engineering data	Blade shape, tower foundation optimization	[22,23,31,34]
Particle swarm optimization (PSO)	Evolutionary/heuristic	Optimization (design)	Non-probabilistic	Evolutionary model	Structured and engineering data	Tower design and multi-objective cost-performance	[32–34]
Support vector machine (SVM)	Supervised	Regression/classification	Non-probabilistic	Instance-based/kernel methods	Structured (SCADA, simulations)	Blade design parameters prediction (TSR)	[31]
Convolutional neural network (CNN)	Supervised	Classification/segmentation	Non-probabilistic	Deep neural networks	Image (blade inspection), structured data	Blade defect detection, tower design optimization	[32,76]

Table 1. *Cont.*

Algorithm	Learning Approach	Functionality	Probabilistic vs. Non-Probabilistic	Model Type	Data Representation	Key Wind Power Application	References
Feedforward neural network (FFNN)	Supervised	Regression/ forecasting	Non-probabilistic	Neural network	Structured (wind speed, SCADA)	Performance predictions (foundations, loads)	[35]
Long short-term memory (LSTM)	Supervised	Sequence modeling/ forecasting	Non-probabilistic	Recurrent neural network	Time-series SCADA/weather	Short-term power prediction, anomaly detection	[38,49,50,52–55,79]
Gated recurrent unit (GRU)	Supervised	Sequence modeling/ forecasting	Non-probabilistic	Recurrent neural network	Time-series SCADA/weather	Wind speed/power forecasting	[38,49]
Extreme gradient boost (XGBoost)	Supervised	Regression/ classification	Non-probabilistic	Ensemble model	Structured (SCADA, weather)	Anomaly detection, power forecasting	[49,54,79]
Random forest (RF)	Supervised	Regression/ classification	Non-probabilistic	Ensemble model	Structured (SCADA, sensor data)	Fault diagnosis (pitch, gearbox), feature selection	[32,75,78,79]
Naive Bayes	Supervised	Classification	Probabilistic	Statistical model	Structured (sensor data)	Blade fault detection (logistic regression comparisons)	[77]
Adaptive neuro-fuzzy inference	Supervised	Control/ forecasting	Non-probabilistic	Hybrid (fuzzy + neural net)	Structured, time-series	MPPT control, voltage stabilization	[50,56–58]
Decision trees	Supervised	Classification/ decision rules	Non-probabilistic	Tree-based model	Structured (financial, sensor data)	End-of-life refurbishment vs. decommissioning	[85]
Clustering (K-means, etc.)	Unsupervised	Anomaly detection/ grouping	Non-probabilistic	Instance-based	Structured (sensor data)	Blade damage grouping, EoL resource allocation	[77,85]

5. Assessment of the Computational Demands and Costs of Applying Artificial Intelligence in Wind Farms

5.1. Computational Demands

The computational demands of AI in large wind farms can be large in some situations. AI-driven wind farms rely on continuous data streams from thousands of sensors monitoring turbine performance, weather conditions, and grid interactions. Predictive maintenance algorithms, for instance, analyze vibration, temperature, and power output data to prevent component failures. These are large data sets used to train such models, and the simplest sets with a resolution of 10 min are hundreds of megabytes in size on an annual basis [47,86]. The National Renewable Energy Laboratory (NREL) developed the Wind Plant Graph Neural Network (WPGNN), a surrogate model trained on 250,000 simulated wind plant layouts, to optimize design and turbine placement [87]. Such large-scale simulations demand high-performance computing (HPC) clusters capable of parallel processing [87,88]. Real-time analytics further strain computational resources. For example, GE's AI/ML logistics optimization tool employs digital twins to simulate turbine installation scenarios, necessitating edge computing infrastructure to minimize logistic costs in remote offshore environments [89]. The shift toward decentralized computing—where data preprocessing occurs at turbine-level edge devices—reduces cloud dependency but requires robust onboard processing units [90]. Machine learning models for wind forecasting and turbine control require large datasets for training. DNV's CFD.ML, a machine learning surrogate for computational fluid dynamics (CFD), uses graph neural networks to emulate high-fidelity wind flows. The speedup is significant: CFD.ML can produce results 2 million times faster than the CFD model it is trained on with only 2% of the computing resources [91]. The WPGNN's training on FLORIS-generated data highlights the dependency on physics-based simulations to ensure accuracy, further escalating computational costs but also increasing revenue [3]. Moreover, generative AI applications in site selection and turbine design, such as 4D digital twins, require iterative simulations of environmental impacts and energy yield. These processes are often run on supercomputers due to processor requirements [90]. To summarize, in some situations the energy footprint of AI infrastructure poses a critical challenge. Training a single large neural network can emit over 284 tons of CO_2, equivalent to five gasoline-powered cars driven for a year [92]. While wind farms inherently support renewable energy, powering onsite data centers and edge devices adds to operational costs. Nevertheless, the authors emphasize that edge computing brings a number of advantages, from lower consumption to faster reaction to problems with wind power plants [93].

5.2. Cost Implication

Adopting AI technologies in wind power systems entails both upfront investments and substantial long-term savings. On the input-cost side, expenses arise from deploying additional sensors (e.g., vibration, temperature, and acoustic sensors) on wind turbines, purchasing or developing AI software platforms, and training personnel in data science and turbine-specific analytics [70]. In particular, hardware costs vary by turbine size and condition, while software licensing or in-house development incurs ongoing fees for updates and support [22]. Moreover, incorporating advanced control systems or drone-based inspection tools adds to capital expenditures, which can be significant for large-scale wind farms [72].

Despite these initial outlays, AI can lower overall operating costs by predicting failures earlier, thus preventing expensive breakdowns and minimizing unplanned downtime [71]. Proactive, data-driven maintenance strategies have been shown to cut operation and maintenance (O&M) expenses, which, for onshore farms, can constitute up to one-third of total life-cycle costs [70]. Additionally, AI-driven design optimizations—such as rotor blade geometries adapted for local wind conditions—can yield higher turbine efficiency, translating into faster return on investment and improved long-term profitability [21,22]. AI can further extend turbine lifespans by better regulating stress on critical components (e.g., gearboxes, blades), which reduces component fatigue and spreads capital costs over a longer productive period [47]. Taken together, these reductions in maintenance outlays, enhanced energy production, and asset-life extensions typically outweigh the initial AI-related expenditures, making the technology a strategic investment for modern wind energy operators.

Layout optimization studies illustrate that wind farms can reduce overall costs by improving power generation capacity. In one project, applying particle swarm optimization (PSO) and the Mossetti cost function yielded a 10.75% boost in output and 9.42% lower costs [94]. Similarly, advanced wake control methods in offshore installations have shown a 33% power increase, which further drives down the levelized cost of energy [24]. These gains are achieved by harmonizing operational variables (e.g., thrust coefficients, yaw angles) and ensuring that cost-driving factors—like turbine spacing and control-actuation demands—are carefully managed.

In tandem, design optimizations for blades, rotors, and support structures bring marked economic benefits. Lighter blade architectures—realized through topology optimization (TO) and genetic algorithms (GA)—reduce material and transportation costs. Direct-drive machines can see mass reductions of 54–67% and power density improvements of 13–25%, curbing generator-related capital expenses [94]. Onshore foundations likewise benefit from metamodel-based design approaches, significantly cutting engineering time, while offshore monopiles and semi-submersible platforms save 10–25% in steel tonnage [94]. All these measures cumulatively lower both upfront investment and long-term operational expenditures, thereby enhancing wind projects' financial viability.

6. Dangers of Using Artificial Intelligence (AI) in Wind Turbines

The biggest risk in applying artificial intelligence (AI) to wind turbines can be seen as bias and discrimination in algorithms, which can lead to unpredictable and potentially harmful consequences. Other risks include cyberattacks, ethical issues, the complexity of the system and the question of liability in the event of accidents. Although the application of artificial intelligence is not considered a risk, it should be noted that it not only leads to higher electricity production, but also consumes a lot of electricity during its operation.

- Algorithmic bias and hallucinations: AI systems lack contextual understanding and can produce "hallucinations"—inaccurate or fabricated results. For example, in wind turbines, this can manifest itself through faulty maintenance schedules based on biased models. Fault detection models can focus on common minor problems (e.g., cracks on the blade surface) while missing rare but critical failures such as gearbox bearing wear. A study using matching contrastive learning (MCL) found that traditional methods struggle with unbalanced SCADA data, requiring specialized techniques to improve minority class fault detection [85]. A study on brake wear prediction in a slewing system using LSTM and SVM showed that models without contextual knowledge of the mechanical interactions between brake pads and rotors generated false alarms, underestimating actual gearbox problems [82].
- Data dependency: AI systems depend on large amounts of data for learning and decision making. Inconsistent or non-standardized data from turbines (e.g., different OEM status codes, sensor errors) can lead to inaccurate predictions. For example, mislabeled SCADA data can cause AI to misinterpret turbine health, delaying maintenance or causing unnecessary repairs [83]. Synthetic data generation, which is used to compensate for limited real-world data, risks increasing bias if the synthetic samples do not represent the actual operating conditions of the turbine [95]. Incorrect conclusions can also be drawn if tests are performed in laboratory conditions that differ from actual field conditions. For example, a convolutional LSTM model for diagnosing bearing failure achieved 99.5% accuracy in laboratory tests, but in field conditions due to environmental noise misclassified normal vibrations as failures [85].
- Data imbalance and data quality problems: Artificial intelligence (AI) methods for wind energy applications often struggle with data imbalances and quality issues, especially when analyzing large supervisory control and data acquisition (SCADA) datasets that contain significantly more "healthy" turbine measurements than true fault indicators. This discrepancy causes conventional machine learning approaches to under-detect the rare fault conditions while disproportionately focusing on the majority (normal) class [85]. To make matters worse, inconsistent labeling practices among different turbine manufacturers and irregularities in sensor reporting further complicate data quality [23]. Various solutions have been developed to mitigate these problems. Data augmentation strategies, including the synthetic minority oversampling technique (SMOTE) and other generative methods, artificially enrich the minority class (fault) and thus improve the classifier's ability to detect infrequently occurring but critical fault types [85]. Robust outlier detection and noise reduction techniques can further improve data integrity. Sensor readings that deviate from plausible physical ranges are discarded or reconciled using expert knowledge, and

labeling inconsistencies are resolved when data from different turbine models are integrated [23]. Incorporating physical or technical knowledge into feature engineering helps to isolate meaningful patterns in large amounts of predominantly normal data. For example, converting raw sensor measurements into torque signatures or vibration envelopes increases the signal-to-noise ratio and reduces the detrimental effects of class imbalance. Advanced learning architectures such as matching contrastive learning (MCL) and hybrid neural network/fuzzy logic designs are promising when adapted to wind turbine data with sparse fault events [85]. Ensemble methods (e.g. XGBoost, random forest) can also be configured with class weighting or cost-sensitive loss functions to correct biases in favor of majority classes. As the operating conditions in wind farms change over time, continuous retraining based on newly acquired, high-quality data is still essential. Complemented by active learning, where the model queries human expertise to flag uncertain cases, this retraining process helps to ensure the long-term robustness of predictions and close emerging gaps in data quality [23]. By integrating these approaches, AI-based systems can detect faults more accurately and optimize turbine performance, ultimately leading to more reliable fault prediction and timely maintenance actions.

- Cyberattacks: AI systems can be targeted by cyberattacks, which can lead to wind turbine outages or even physical damage. Attackers can exploit vulnerabilities in AI systems to take control of wind turbines. For example, manipulated sensor data could trick AI into ignoring blade cracks or bearing failures, risking catastrophic failures [13]. This is why cyber-protection systems are needed. An example of a cyber-secure wind turbine control system involves the integration of a support vector machine algorithm with an H∞ controller to identify communication attacks, combined with a machine learning algorithm to address errors resulting from communication or data injection attacks.
- Ethical issues: The application of AI can raise ethical issues, such as data privacy and accountability for decisions made by AI. It is important to ensure that AI systems are used in a way that is ethically acceptable and transparent. The use of AI in decision-making can lead to ethical dilemmas, especially when it comes to decisions that affect human lives or the environment. A lack of transparency in how AI makes decisions can lead to distrust among users and the public.
- System complexity: AI systems can be very complex, which can make them difficult to understand and manage. This can lead to problems in maintaining and optimizing the system.
- The issue of liability for accidents: In the event of accidents or malfunctions caused by decisions made by AI, it is difficult to determine who is responsible—whether it is the manufacturer, the developer or the user of the system. This ambiguity can lead to a lack of accountability and reduce motivation to develop safer and more efficient systems

7. Discussion

A critical observation from the literature and the data reviewed is that AI is increasingly being used to optimize the design of wind turbines, with particular attention being paid to rotor blades, tower structures and foundations. The aerodynamic shape of rotor blades has been consistently identified as critical to wind turbine performance, as optimized blade geometry can lead to significant improvements in energy harvesting and efficiency. It was found that, by applying computational fluid dynamics (CFD) simulations in conjunction with AI-driven design iterations, annual energy production can be increased by 6% to 15% compared with conventional approaches. Despite the differences in reported performance gains, several studies consistently indicate that neural networks and evolutionary algorithms, such as genetic algorithms (GA) and particle swarm optimization (PSO), have been shown to be effective in optimizing multivariable design objectives. These objectives include maximizing aerodynamic efficiency, minimizing structural mass and ensuring robust mechanical integrity.

The importance of local wind conditions has also taken center stage. AI-based models can integrate site-specific meteorological, topographical and environmental data to adapt the turbine design to local wind conditions. Such an approach departs from the traditional 'one size fits all' design philosophy and instead utilizes advanced machine learning techniques—namely convolutional neural networks (CNNs), support vector machines (SVMs) and hybrid algorithms—to identify the wind speed distributions, turbulence intensities and wind directions characteristic of each site. This capability has further underlined the usefulness of AI in site selection and land use optimization based on geographic information systems (GIS). Here, multi-criteria decision analysis can be coupled with machine learning to identify the most suitable areas for the installation of wind farms.

In the operational phase, one of the biggest challenges is the volatile nature of wind energy, which makes it difficult to stabilize the electricity grids. AI-based forecasting has already been widely used to predict energy generation several hours or days in advance. Models based on deep neural networks, including long short-term memory (LSTM) and gated recurrent units (GRUs), have been shown to reduce prediction error more effectively than classical statistical or purely meteorological methods. The ability of these AI models to process large, high-frequency data sets emphasizes their utility for short-term operations and real-time management.

However, it has been shown that predictive modelling is only one aspect of improving operations. Equally important is the dynamic control of turbine parameters. Sophisticated AI algorithms ensure that wind turbines can respond adaptively to rapidly changing environmental conditions through real-time adjustments to blade pitch, nacelle yaw angle and rotation speed. This approach not only improves the annual energy yield, but also reduces mechanical stress on key components, thereby extending the turbine's service life. In fact, fuzzy logic, neuro-fuzzy controllers and hybrid control strategies (e.g., ANFIS-PI) have been used to provide robust responses for doubly fed induction generators. This shows that AI is capable of increasing energy yield while maintaining grid stability.

Maintenance has proven to be one of the most fruitful areas for the use of AI, especially in the context of predictive and condition-based maintenance. As maintenance costs can account for a significant portion of a wind farm's total lifecycle costs, early detection of faults in the gearbox, generator and pitch system can prevent catastrophic component failures and reduce downtime. Several studies have reported that advanced classifiers—random forest (RF), extreme gradient boosting (XGBoost) or extra trees—can detect and classify faults with high accuracy, with detection rates sometimes exceeding 80% for certain fault modes. These results confirm that data-driven AI models trained on supervisory control and data acquisition (SCADA) streams can detect subtle anomalies in temperature, vibration and torque signals that may not be detectable using traditional threshold-based methods. In addition, drone-based inspections using image segmentation and deep learning have shown promise in assessing the integrity of the rotor blade surface, reducing the need for labor-intensive manual inspections in difficult or remote environments.

A final but increasingly relevant aspect is the end-of-life phase of wind turbines. AI-driven methods are known for their potential to optimize decommissioning plans and material recycling processes. These include analytical models that estimate the remaining lifetime of turbines based on operational data, as well as solutions that help dismantle and maximize material recovery from blades, towers and generators. Although such end-of-life applications are not yet widespread, they are likely to become increasingly important as more and more first-generation wind turbines are retired.

Despite impressive progress, algorithmic improvements are still essential. Challenges include ensuring data quality, especially for offshore wind turbines where the error rate of sensors is higher, as well as managing heterogeneous data collected by different turbine manufacturers. In addition, the interpretability of black box models is questioned, especially for critical decisions on grid stability or large-scale offshore developments. Cybersecurity risks are also high, as the use of AI and connectivity with the Internet of Things (IoT) can expose wind farms to targeted attacks if robust encryption and intrusion detection protocols are not used.

Future advances are expected in hybrid AI, where physics-based modelling is integrated with advanced machine learning to improved generalizability under rare or extreme weather conditions. The increasing use of explainable AI (XAI) methods is expected to improve transparency and compliance, thereby increasing acceptance by grid operators and environmental stakeholders. Multi-agent systems developed for large offshore clusters can further improve synergy between neighboring turbines, optimizing wake control and joint resource management. These ongoing developments will improve operational efficiency, extend system lifetime and improve the economic viability of wind power projects worldwide.

Algorithmic biases, data integrity issues, cybersecurity vulnerabilities and the complexity of AI models when integrated into the real world were each cited as potential obstacles. In addition, ethical considerations related to accountability and transparency in algorithmic decision-making remain unresolved. As wind turbine control systems become increasingly autonomous, safety and liability considerations will require additional clarity in the legal framework. Finally, it was emphasized that AI solutions themselves consume significant computing resources, resulting in an additional energy burden and necessitating careful lifecycle analysis of these digital technologies.

8. Conclusions

The work has confirmed that artificial intelligence offers new opportunities across the entire lifecycle of wind turbines, from initial planning through operation and maintenance to final decommissioning. By synthesizing data from meteorological records, advanced sensor streams and operational contexts, AI can generate actionable insights that lead to cost efficiencies, improved turbine performance and reduced environmental impact.

Firstly, in the field of design, AI has enabled significant advances in the optimization of rotor blades, tower statics and material-saving foundations. Iterative generative design processes utilize neural networks and evolutionary algorithms to rapidly converge on geometries that improve energy yield while meeting mechanical requirements. The ability to account for local wind conditions while meeting multiple targets such as aerodynamic performance, cost, noise and environmental factors demonstrates the multiple benefits of machine learning and deep learning modelling.

Secondly, in the operational phase, AI-based demand and supply forecasts have proven to be crucial for grid stability. Real-time optimization of rotor speed, blade pitch and yaw angle has also helped to reduce stress on structural components, extending turbine life. The integration of AI into smart grids, including the coordination of energy storage systems, enables a better balance between power generation and consumption, improving power quality and reducing the carbon footprint of electricity.

Thirdly, maintenance practices have benefited significantly from AI-based predictive analytics. The ability to pre-emptively detect anomalies in gearboxes, generators or rotor blades ensures a more stable power supply while reducing the risk of extended downtime and major repairs. As several studies have shown, the transition from reactive or scheduled maintenance to data-driven predictive maintenance has led to measurable cost savings and optimized maintenance planning. Drone-based inspections combined with computer vision techniques have further reduced the risks associated with manual inspections, especially in offshore or high-altitude scenarios.

Finally, end-of-life artificial intelligence applications, although not yet as mature, promise efficient decommissioning of turbines, strategic recycling of valuable materials and environmentally sound repowering or modernization. It can be assumed that these methods will become increasingly popular as a larger number of wind farms approach the end of their service life.

It can therefore be concluded that AI will play a central role in ensuring that wind energy systems remain competitive, reliable and environmentally friendly. Future research directions could include developing more transparent and explainable AI models that promote trust between engineers, regulators and the public. Exploring how AI-driven optimization solutions can be reconciled with emerging grid architectures—such as micro-grids and transactive energy markets—is also an interesting area. In addition, thorough assessments of the carbon footprint associated with the development and computation of AI should be undertaken to ensure that the net environmental benefits remain positive.

In summary, the results show that AI not only expands the technical capabilities of wind turbines, but also opens up new avenues for cost reduction, improved reliability and environmental protection. Nevertheless, rigorous testing, robust cybersecurity measures and clear regulatory guidelines are essential to minimize risks and maintain public trust. If these challenges are addressed strategically, AI-based solutions can help the global energy sector meet climate targets, improve grid resilience and promote a more sustainable future.

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Abbreviations

The following abbreviations are used in this manuscript:

HP	Analytic hierarchy process
AI	Three letter acronym
ANFIS	Artificial neuro-fuzzy inference system
BPNN	Back propagation neural network
CFD	Computational fluid dynamics
DL	Deep learning
EL	Ensemble learning
ET	Extra trees
EWMA	Exponentially weighted moving average
FCM	Fuzzy C-means

GA	Genetic algorithm
GIS	Geographic information system
GP	Grid-partitioning
GRU	Gated recurrent unit
INN	invertible neural network
IoT	Internet of things
IRENA	International Renewable Energy Agency
KNN	K-Nearest neighbors
LCC	Life cycle cost
LightGBM	Light gradient boosting machine
LSTM	Long short-term memory
MAPE	Mean absolute percentage error
MCDA	Multi-criteria decision analysis
ML	Machine learning
MLC	Matching contrastive learning
MPPT	Maximum power point tracking
NREL	National Renewable Energy Laboratory
O&M	Operation and maintenance
OEM	Original equipment manufacturer
PBL	Project-based learning
PSO	Particle swarm optimization
PV	Photovoltaic
RCMRD	Regional Centre for Mapping of Resources for Development
RF	Random forest
RNN	Recurrent neural network
RSME	Root mean square error
RVM	Relevance vector machine
SC	Subtractive clustering
SCADA	Supervisory control and data acquisition
SPC	Statistical process control
SVM	Support vector machine
TSR	Tip speed ratio
WWEA	World Wind Energy Association
XGBoost	Extreme gradient boosting

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