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Review

Artificial Intelligence and Machine Learning in Grid Connected Wind Turbine Control Systems: A Comprehensive Review

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Abstract: As grid-connected wind farms become more common in the modern power system, the question of how to maximize wind power generation while limiting downtime has been a common issue for researchers around the world. Due to the complexity of wind turbine systems and the difficulty to predict varying wind speeds, artificial intelligence (AI) and machine learning (ML) algorithms have become key components when developing controllers and control schemes. Although, in recent years, several review papers on these topics have been published, there are no comprehensive review papers that pertain to both AI and ML in wind turbine control systems available in the literature, especially with respect to the most recently published control techniques. To overcome the drawbacks of the existing literature, an in-depth overview of ML and AI in wind turbine systems is presented in this paper. This paper analyzes the following reviews: (i) why optimizing wind farm power generation is important; (ii) the challenges associated with designing an efficient control scheme for wind farms; (iii) a breakdown of the different types of AI and ML algorithms used in wind farm controllers and control schemes; (iv) AI and ML for wind speed prediction; (v) AI and ML for wind power prediction; (vi) AI and ML for mechanical component monitoring and fault detection; and (vii) AI and ML for electrical fault prevention and detection. This paper will offer researchers and engineers in the wind energy generation field a comprehensive review of the application of AI and ML in the control methodology of offshore and onshore wind farms so that more efficient and robust control schemes can be designed for future wind turbine controllers.

Keywords: wind turbine; pitch angle control; high voltage direct current; artificial neural network; machine learning

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1. Introduction

Wind turbine systems have become a common sight in the modern power grid, and their implementation only continues to increase globally. In 2008, the United States Department of Energy established a target of producing twenty percent of its electricity from wind resources by 2030 [1]. A report released by the International Energy Agency (IEA) announced that the total global renewable energy capacity will be 10,800 GW by the year 2040 [2]. Due to their incredible size, many wind farms are in remote locations or offshore, as they are subject to the right-of-way privileges of local and regional municipalities (Xu C et al., 2017) [3]. Wind farms also require a detailed analysis of wind currents through possible site locations to determine optimal tower placement for maximum wind power extraction, as reported in Kunakote T. et al. (2021) [4].

The complexity and vastness of the electrical topology of wind farms makes optimizing control of each wind turbine essential for maximum efficiency as well as maximizing returns for power providers (Al-Deen et al., 2021) [5]. Due to these factors, remote monitoring and control systems for grid-connected wind farms is essential to maximizing the amount of power generated by wind farms as well as limiting the amount of time a wind turbine or wind farm is down in the event of damage caused by electrical faults, mechanical failure, or extreme weather events. To aid in this process, researchers and engineers have turned to Artificial Intelligence (AI) and Machine Learning (ML) algorithms to aid in prediction, monitoring, and control for wind turbine systems.

In recent years, several review papers on these topics have been published [6–11], inter alia. However, so far, there are no comprehensive reviews of both AI and ML in wind turbine control systems available in the literature. To overcome the drawbacks of the existing literature, an in-depth overview of ML and AI in wind turbine systems is presented in this paper, especially with respect to the most recently published techniques. These differences highlights the originality and novelty of this paper. The research approach taken in this review paper was to use the key words "wind farm" + "machine learning" + "artificial intelligence" + "control" + "monitoring" in several scholarly search engines including Google Scholar and EBSCO.

The paper is organized as follows. Section 2 discusses various aspects such as the challenges in wind farms, AI and ML algorithms utilized in wind farm controllers and control schemes, AI and ML algorithms for wind speed prediction, AI and ML for wind power prediction, wind turbine mechanical monitoring and fault detection, and AI and ML algorithms for electrical component monitoring. Section 3 presents suggested future research areas for AI and ML in wind turbine control systems, and Section 4 concludes the paper with a quick wrap up of all the topics. Appendix A depicts the most recently published AI and ML wind farm control algorithms in tabular form, with the author, title, method, and results presented.

2. Materials and Methods

2.1. The Problem: Challenges in Wind Farms Monitoring and Control Systems

When it comes to wind power generation, there are many challenges that researchers are faced with when developing intelligent control schemes (Ali et al., 2021) [12]. The first issue, as stated in the introduction, is wind speed forecasting. Wind currents and densities are time varying and nonlinear, so an efficient wind turbine control system needs to be able to adapt to these types of conditions. The amount of power a wind farm can produce is directly related to the wind currents that pass through the wind farm. Historical wind current data is available for many locations globally, however, the actual wind speed and density measured by each tower's anemometer and barometer, respectively, can vary from forecasted wind speeds and densities by as much as fifteen percent [13]. According to Kosovic et al. (2020) [14], the National Center for Atmospheric Research (NCAR) has recently updated its weather prediction model to include AI to lower the error rate of weather forecasts [14].

Another important factor to consider with respect to wind currents through a wind farm is wake turbulence [15]. According to Krajinski et al. (2021) [16], wake turbulence is caused by oscillations in wind currents due to impact with the wind turbine blades (WTB) and can have a negative effect on the wind currents through a given wind farm [16]. To limit wake turbulence, a detailed analysis of wake currents through a potential wind farm location is necessary before placing the towers, as reported in Li et al. (2022) [17]. According to Le-Ren et al. (2013) [18], if towers are placed too close together, the tower clustering effect, caused by wind currents hitting the wind turbine towers, can have a negative impact on the wind currents through a wind farm, and thus requires a detailed analysis to determine proper tower placement [18]. Due to the nonlinear nature of wind power generation, traditional linear controllers such as PID with static reference set points are not ideal for wind turbine control systems (Wang et al., 2020) [9]. In Meyers et al. (2022) [19], flow control prospects and challenges with respect to wake turbulence and wind farms are presented [19]. The wake steering control is depicted in Figure 1 [19].

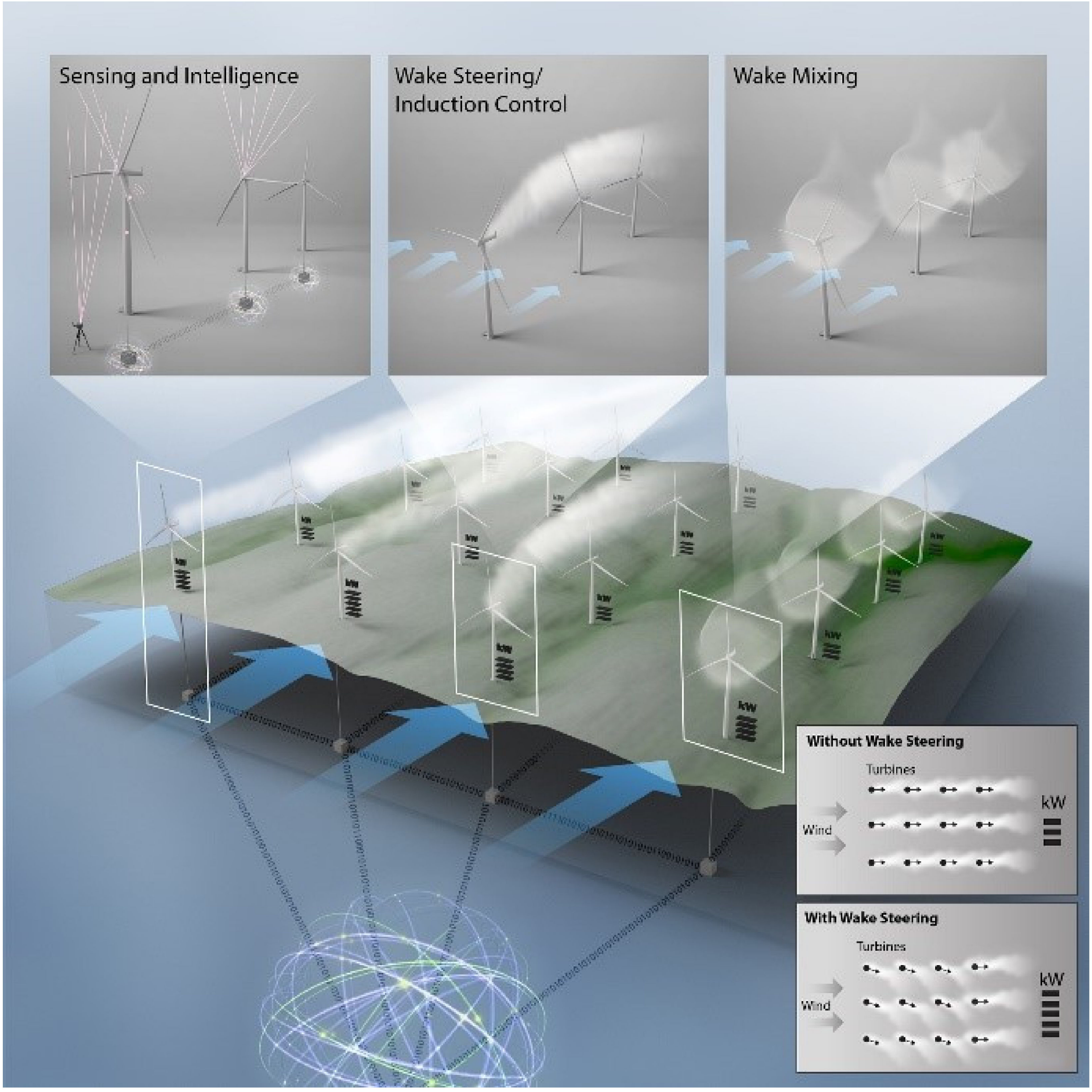

Figure 1. Wake steering control in wind farms [19].

Wind power is another factor that needs to be considered when designing controllers for wind farm systems. Wind power is directly related to the wind speed, wind density, blade pitch, blade size, and blade tip speed ratio. As the blade size is constant and blade tip speed ratio is dependent on the rotor shaft speed and the blade size, the variable parameters for wind power generation control are wind speed, wind density and blade pitch. As the issues with wind speed and density have already been considered, the main challenge with wind power forecasting is the blade pitch of each wind turbine in a wind farm. The blade pitch is controlled by actuators that are given commands by proportional-integral (PI) controllers, which have been relatively successful in implementation. The main issue with using proportional-integral-derivative (PID) controllers is that the rate at which the wind speed and density change can be much faster than PID controllers can compute and adapt to and, therefore, the optimal blade pitch may not be achieved, thus compromising efficiency. It is for this reason that AI algorithms and nonlinear controllers are preferable; more research should be devoted to this area.

Due to wind farms primarily being in remote locations or many miles offshore, the monitoring of mechanical components for maintenance is necessary to prevent the wind farm from suffering a mechanical failure and potentially disconnecting the wind farm from the power grid. As wind turbine generators have many mechanical components, such as the blades, actuators, rotor shaft, bearings, and the generator itself, it is necessary to monitor the system to develop a proper maintenance schedule. To optimize this schedule, AI monitoring algorithms can be extremely useful to help predict when a mechanical fault is occurring or if a mechanical component is about to fail. A typical wind turbine generator system is depicted in Figure 2 [20].

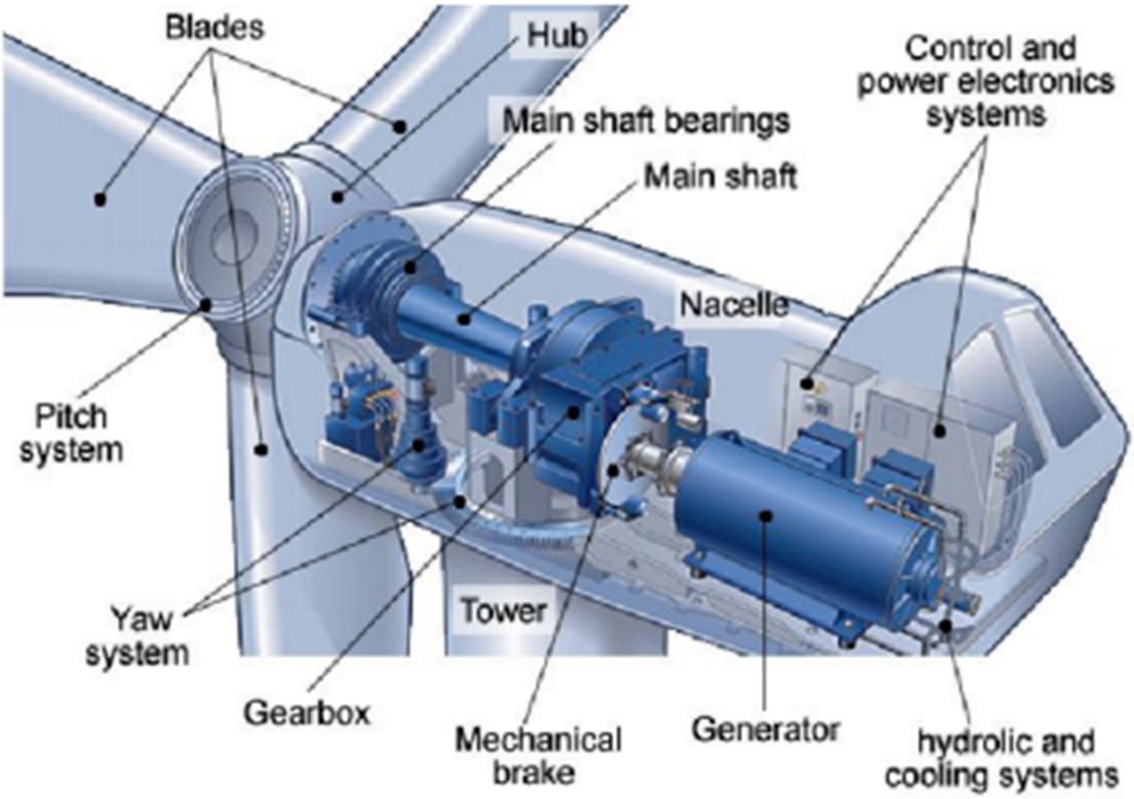

Figure 2. Wind turbine generator system [Reprinted/adapted with permission from Ref. [20]. 2013, IEEE].

Electrical faults in wind turbine systems can have a variety of effects, depending on the type of generator and the topology of the electrical network, so fault ride through (FRT) and low voltage ride through (LVRT) are extremely important when considering a control scheme for a wind farm. An example offshore wind farm with potential fault locations is displayed in Figure 3 [21]. The standard permanent magnet synchronous generators (PMSG) circuit topology for AC winds farms with electronic converters is depicted in Figure 4 [5] and the standard PMSG circuit topology for AC\DC wind farms with electronic converters is depicted in Figure 5 [5]. For type one, fixed-speed, squirrel cage induction generators, electrical faults in the system can be extremely detrimental to the generators in a wind farm. As fixed-speed generators are becoming less common due to the extreme stresses that occur on the generator and rotor shaft from varying wind currents and high unreliability during faults, doubly fed induction generators (DFIG) and PMSG have become more prominent in modern wind farms.

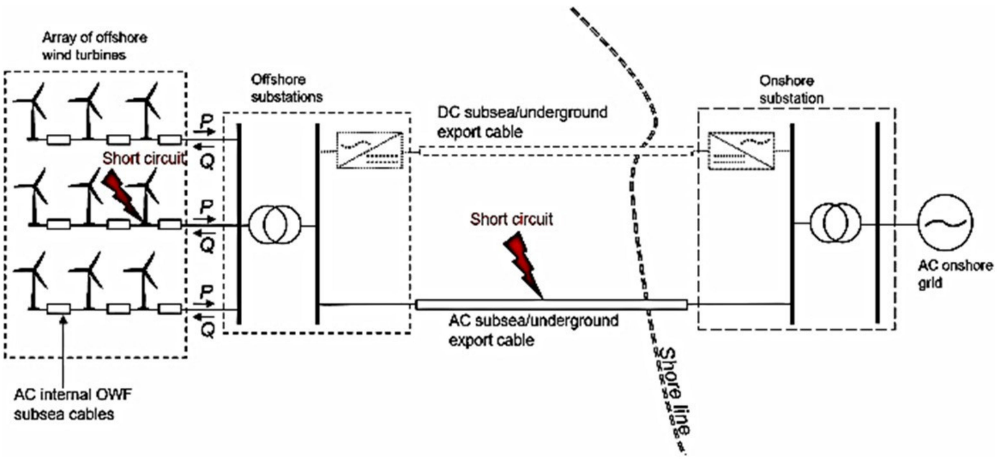

Figure 3. Potential fault locations on offshore wind farms [21].

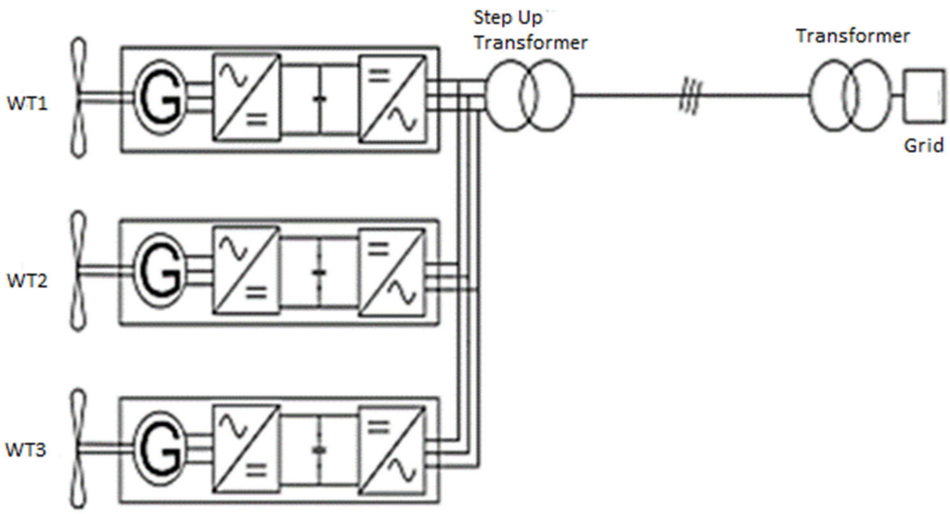

Figure 4. Standard PMSG AC wind farm circuit topology [Reprinted/adapted with permission from Ref. [5]. 2021, IEEE].

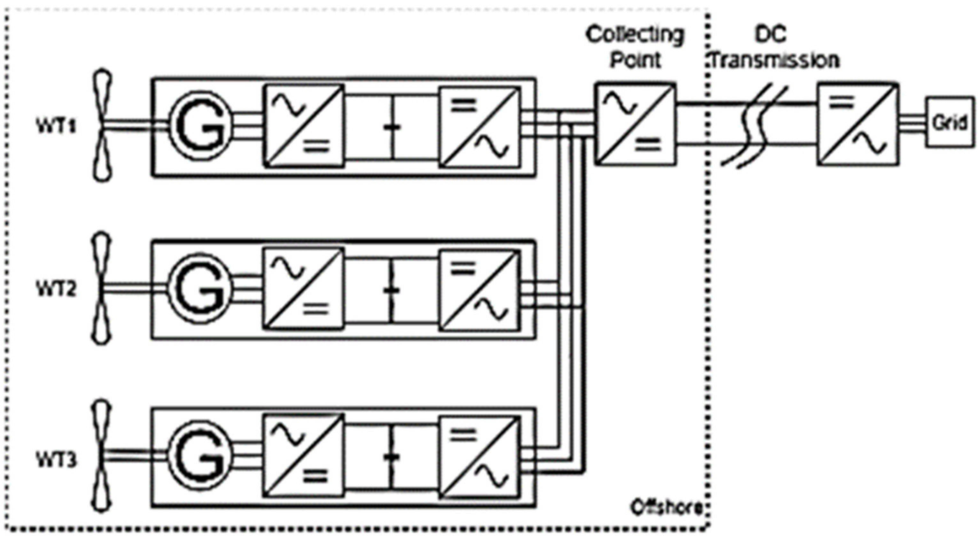

Figure 5. Standard PMSG AC/DC offshore wind farm circuit topology [Reprinted/adapted with permission from Ref. [5]. 2021, IEEE].

Although PMSGs are more robust than DFIGs when electrical faults occur, the efficiency and low cost of implementing DFIGs in wind farms has led many manufacturers and power providers to choose these generators over PMSGs for modern wind farms, especially with respect to offshore locations. The main advantages and disadvantages of PMSGs and DFIGs in wind farms can be found in Ali et al. (2021) [12]. The damage from an electrical fault is not limited to the generator, as intelligent electronic converters and inverters are utilized to remove frequency and voltage deviations caused by the varying speed and pressure of wind currents. To increase the efficiency and production of wind farms, controllers must be designed to detect and prevent any electrical faults in the system to limit damage and downtime of a wind farm.

2.2. AI and ML in Wind Farm Controllers and Control Schemes

According to Wang et al. (2020) [9], AI in wind turbine systems can be separated into three sub-categories: (1) artificial neural networks (ANN); (2) support vector machines (SVM); and (3) swarm optimization algorithms (SOA) [9]. ANNs are adaptive, self-organizing, fault tolerant, easy to implement, and have very high accuracy when used for prediction, so they have been implemented in many cases for predicting wind speed, density, and power. SVMs have primarily been used for fault detection and classification and have a very high accuracy in doing so. SVMs have been proposed for prediction purposes as well, although they tend to not perform as efficiently as ANNs. SOAs are population based, bionic algorithms that mimic swarm characteristics in nature. A commonly used SOA algorithm is the particle swarm optimization algorithm (PSO), which, according to Olsson and Andrea E. (2011) [22], is "an algorithm modeled on swarm intelligence that finds a solution to an optimization problem in a search space or model that predicts the social behavior in the presence of objectives [22]".

Machine learning is a subsection of AI but deals more with learning models and making predictions based on those models than making inferences about potential decisions based on the environment and the pervious action taken by the AI. ML algorithms, such as SVM, are great for classifying faults in electrical systems, as well as mechanical faults in gear boxes and bearings. Basically, any signal that has a table of normal operating conditions for a specific component can be controlled using a ML algorithm.

Based on the literature, conventional PID controllers are not the best choice for mapping nonlinear parameters, though several researchers have proposed hybrid controllers that utilize AI and ML algorithms in tandem with PID controllers. In Civelek et al. (2016) [23], a parameter optimization genetic algorithm is implemented with a PID controller to increase the efficiency of blade pitch control [23]. In Yang et al. (2018) [24], a democratic joint operation (DJO) algorithm is proposed to optimize PID controller parameters for PMSG based wind turbine control systems [24]. In Mahto and Mukherjee (2016) [25], gain tuning for PIDS utilizing a quasi-oppositional harmony search algorithm (has) is proposed [25].

In Soued et al. (2017) [26], Qais et al. (2018) [27], Qais et al. (2018) [28], Zhang et al. (2017) [29], Mahmoud et al. (2020) [30], and Chaine et al. (2017) [31], grey wolf optimization (GWO) algorithms are utilized to optimize input parameters for PI and PID controllers, with Qais et al. (2018) [28], Zhang et al. (2017) [29], Mahmoud et al. (2020) [30], and Chaine et al. (2017) [31] utilizing a hybrid cuckoo search algorithm (CSA) [26–31]. In Mazouz et al. (2016) [32], a PSO-based PI controller for voltage source converters (VSC) is proposed for HVDC offshore wind farms using a radial basis function neural network (RBFNN) [32]. In Chatterjee et al. (2016) [33], a teaching learning-based optimization (TLBO) and PSO ML algorithm are utilized to minimize damping phenomena, oscillation in rotor currents, and fluctuations in electromagnetic torque with respect to PID-controlled DFIGs [33].

In Douiri et al. (2018) [34], an ANN with direct power control is proposed for stability control of nonlinear DFIGs in wind farms [34]. In Ponce et al. (2018) [35] and Reddy and Ramasamy (2018) [36], an artificial organic network (AON) and RBFNN is proposed for DFIG control in wind turbine systems [35,36]. In Hafiz and Abdennour (2016) [37], Soliman et al. (2018) [38], and Darvish and Rafiee (2019) [39], an adaptive neuro-fuzzy inference system (ANFIS) is proposed to control the inertia of variable speed wind turbines [37], enhance the performance of wind turbine generators [38], and to increase FRT capability of DFIGs [39], respectively. In Yin et al. (2019) [40], a recurrent neural network (RNN) is proposed to maximize control for wind power systems [40]. In Dahhani et al. (2018) [41], an assessment of SVMs for the control of wind turbines systems is presented [41]. In Singh et al. (2020) [42], a symbiotic organism search algorithm (SOSA) is proposed for controller parameter turning for frequency regulation in grid connected wind turbine systems [42].

In Qais et al. (2019) [43], an enhanced salp swarm algorithm (SWA) is proposed to determine its effectiveness in wind turbine control schemes [43]. In Hashemi et al. (2017) [44] and Movahedi et al. (2019) [45], a gravitational search optimization (GSO) algorithm is proposed to detect the impact of oscillations in power generation by wind farms and to improve the transient stability of the system [44], with Movahedi et al. (2019) [45], utilizing an enhanced PSO algorithm [45]. In Pang et al. (2019) [46] and Yao et al. (2018) [47], PSO algorithms are utilized for optimal sizing and control of energy storage systems for wind farms and for sub-synchronous damping control for DFIGS, respectively [46,47]. In Elyaalaoui et al. (2021) [48], a fuzzy control scheme with voltage and reactive power control is proposed utilizing an optimal fractional-order based fuzzy control scheme [48].

In Yin et al. (2020) [49], a convolutional neural network (CNN) and a long-short term memory (LSTM) RNN are utilized for predictive control and max power generation of offshore wind farms using High-Fidelity LES data [49]. In Krajinski et al. (2021) [50], a deep reinforcement learning (DRL) algorithm is proposed for active wake turbulence control and set point calculations [50]. In Zhang et al. (2020) [51], a deep deterministic policy gradient (DDPG) algorithm for designing a damping controller for a static synchronous compensator (STATCOM) in wind farms is proposed [51]. In Zhao et al. (2019) [52], a firefly algorithm (FFA), GA, CSA, and ant colony optimization algorithm (ACO) is proposed for wind farm decision systems [52].

In Asghar and Lui et al. (2018) [53], an adaptive neuro-fuzzy algorithm is proposed to estimate wind speed and optimal rotor speed for variable speed wind turbines [53]. In Shilaja and Arunprasath (2019) [54], a control scheme for the optimal power flow through a wind turbine system is proposed using a moth swarm algorithm (MSA) in tandem with a gravitational search algorithm (GSA) [54]. In Stanfel et al. (2020) [55], a yaw-based wake steering control scheme is proposed using a reinforcement-based distributed approach to optimize wind farm power generation [55]. In Zhao et al. (2020) [56], a cooperative wind farm control scheme is considered in the presence of the wake effect, where a knowledge-assisted deep deterministic policy gradient (KA-DDPG) algorithm is proposed to maximize power output and ensure safety for the wind turbine during training [56].

Due to the adverse effects wake turbulence can have on wind turbine power generation, a cooperative yaw control ML algorithm is proposed in Yang et al. (2022) [57], in which a novel double-layer machine framework that combines an ANN yaw/wake model and a Bayesian ML algorithm is utilized [57].

2.3. AI and ML for Wind Speed Prediction in Wind Farms

Predicting wind speed for each individual turbine in a wind farm is a challenging task, so AI algorithms have been utilized to efficiently predict wind speeds based on specified historical data for a given wind farm location. In Alencar et al. (2018) [58], a hybrid, multi-step ahead wind speed forecasting algorithm is proposed by combining an autoregressive integrated moving average optimization function (ARMINA) with an ANN [58]. In Nascimento Camelo et al. (2018) [59], an ANN integrated moving average with exploratory variable (ARIMAX) and Holt-Winters algorithms are proposed to create a time series model of wind speeds for wind speed forecasting [59]. In Qu et al. (2019) [60], Liu et al. (2018) [61], Chen et al. (2019) [62], Wang et al. (2017) [63], Wang et al. (2018) [64], Peng et al. (2017) [65], Doucoure et al. (2016) [66], Liu et al. (2018) [67], Santhosh et al. (2018) [68], Sun and Liu (2016) [69], Sun et al. (2019) [70], Peng et al. (2017) [71], and Zhou et al. (2019) [72], a hybrid echo state network (ESN), wavelet neural network (WNN), and extreme learning machine (ELM) were utilized to predict wind speed [60–72].

In Ahmed and Khalid (2018) [73], a functional networked ANN is used to predict multi-step ahead wind speed [73]. In Luo et al. (2018) [74], a stacked ELM with generalized correntropy is used to predict short-term wind speed [74]. In Ulkat and Gunay (2018) [75], geographical and atmospheric variables are used to predict the mean monthly wind speed of a given location to optimize wind power generation by using an ANN [75]. In Madhiarasan and Deepa (2016) [76], an improved back propagation neural network (BPNN) is proposed for wind speed forecasting [76]. In Asghar and Liu (2018) [77] and Moreno and L. dos Santos Coelho (2018) [78], a hybrid ANFIS is proposed for wind speed probability distribution and wind speed forecasting, respectively [77,78]. In Jiang et al. (2017) [79], a short-term wind speed forecasting ML algorithm is proposed using a hybrid GA, SVM, and CSA model [79].

In Zhang et al. (2017) [80], Ranganayaki and Deepa (2018) [81], Gani et al. (2016) [82], and Adnan et al. (2019) [83], a SVM ML algorithm is utilized for wind speed prediction for short- and long-term forecasting [80–83]. In Li et al. (2019) [84], a novel backward bat algorithm (BBA) and SVM are utilized for state prediction for solar power and wind speed for wind power generation in hybrid solar and wind generation systems [84]. In Li et al. (2018) [85], an improved ant colony algorithm is proposed for a least square SVM (LSSVM) for short term wind speed forecasting [85]. In Wang and Li (2018) [86], a novel preprocessing technique and an evolutionary support vector regression machine (SVRM) is proposed for short term wind speed prediction [86]. In Dhiman et al. (2019) [87], a hybrid wavelet transform (WT) and SVM ML algorithm are used for wind forecasting and predicting ramping events [87].

In Jiang et al. (2018) [88], a novel discrete WT, LSSVM, and generalized autoregressive conditionally heteroscedastic (GARCH) prediction method is used for wind speed prediction [88]. In Xiang et al. (2019) [89], an improved empirical WT, LSSVM, and bird swarm algorithm (BDSA) are used for short-term wind speed prediction [89]. In Kang et al. (2017) [90], an ensemble empirical mode decomposition (EEMD) and LSSVM are used for short term wind speed predictions [90]. In Niu and Wang (2019) [91], an EEMD and a grasshopper optimization algorithm (GOA) are utilized for short-term wind speed forecasting [91]. In Lui et al. (2018) [92], a smart wind forecasting system is proposed using empirical wavelet transform (EWT) decomposition, LSTM, regularized ELM (RELM), and the inverse EWT (IEWT) to predict wind speed [92]. In Zhang et al. (2018) [93], an improved hybrid PSO and BPNN are used to predict wind speed based on the Lorenz disturbance [93].

In Xiao et al. (2017) [94] and Wang and Li (2019) [95], multi-step wind speed forecasting is proposed based on an improved bat algorithm (BA) [94,95]. In Sun et al. (2018) [96], multi-step wind speed and wind power is predicted using a proposed deep belief network (DBN) and an optimized random forest algorithm (RF) [96]. In Zhang et al. (2017) [97], a backtracking search algorithm (BSA) is proposed to create a compound structure ELM based on feature selection and parameter optimization for wind speed forecasting [97]. In Ma et al. (2017) [98], a generalized dynamic fuzzy neural network (GDFNN) based on singular spectrum analysis which is optimized by a brainstorm optimization algorithm (BSO) is proposed for short-term wind forecasting [98]. In Wang et al. (2018) [99], a hybrid wind speed forecasting system is proposed based on a novel sine cosine algorithm [99]. In Tian et al. (2019) [100], an artificial bee colony (ABC) algorithm with an optimized error minimized ELM is proposed for short-term wind forecasting [100].

In Jiang et al. (2018) [101], a ML algorithm utilizing two combined forecasting models based on singular spectrum analysis with an has is proposed for short-term wind speed modeling [101]. In Yu et al. (2018) [102], a data mining assisted wind speed forecasting algorithm utilizing wavelet packet decomposition (WPD) and an Elman neural network (ENN) is proposed [102]. In Wang et al. (2016) [103] and Yu et al. (2019) [104], a DBN is utilized for wind speed forecasting [103,104]. In Khodayar et al. (2018) [105], an "interval probability distribution learning (IDPL) model is proposed based on restricted Boltzmann machines and rough set theory to capture unsupervised temporal features from wind speed data." A real-valued interval DBN is also utilized with a fuzzy type II inference system (FT2IS) for the supervised regression of future wind speeds [105]. In Sun et al. (2018) [106], a hybrid ensemble empirical mode decomposition (EEMD) and a multi kernel function least square SVM (MKLSSVM) optimized by a hybrid (GSA) is proposed for short-term wind speed prediction [106].

A LSTM for wind speed prediction is proposed in Zhang et al. (2019) [107] and Wang and Li (2018) [108] using Gaussian process regression (GPR) and error correction, respectively [107,108]. In Liu et al. (2019) [109], a multi-step wind speed forecasting model is proposed using a convolutional gated recurrent network (CGRUN) and support vector regression [109]. In Liu et al. (2018) [110], a deep learning-based wind speed prediction model using WPD, convolutional neural network (CNN), and C-LSTM is proposed [110]. In Chen et al. (2019) [111], a multifactor spatio-temporal correlation model is proposed based on a CNN and LSTM for wind speed forecasting [111]. In Harbola and Coors (2019) [112], a one-dimensional CNN architecture is proposed for wind speed prediction [112]. In Mi et al. (2019) [113], a wind speed prediction model is created using singular spectrum analysis, empirical mode decomposition (EMD), and C-SVM [113]. In Li et al. (2019) [114], multi-step wind speed is predicted based on the intensity of wake turbulence and a hybrid deep neural network (HDNN) [114].

In Cheng et al. (2018) [115], a wavelet transform decomposition (WTD), RNN, and ANFIS hybrid system is considered for wind speed forecasting [115]. In Chen et al. (2018) [116], a novel method called "EnsemLSTM" is proposed based on LSTM, SVRM, and an extremal optimization (EO) algorithm for short-term wind speed forecasting [116]. In Yu et al. (2018) [117], a novel framework for wind speed prediction utilizing a RNN and SVM is proposed [117]. In Liu et al. (2018) [118], a wind speed forecasting method is proposed using EWT, LSTM, and ENN [118]. In Hu and Chen (2018) [119], a nonlinear hybrid wind prediction model is proposed using a LSTM, ELM, and a differential evolution (DE) algorithm [119]. In Liu et al. (2018) [120], a smart, multi-step wind speed forecasting deep learning model is proposed based on variational mode decomposition, singular spectrum analysis, LSTM, and ELM [120].

In Li et al. (2018) [121], a multi-step wind speed forecasting model is proposed using EWT decomposition, LSTM, ELM, and IEWT reconstruction [121]. To process the complex causality in wind speed prediction, a LSTM is proposed in Zhang et al. (2019) [122] based on neighborhood gates [122]. In Chen et al. (2019) [123], a two-layer, nonlinear combination method for short-term wind speed prediction is proposed based on ELM, ENN, and LSTM [123]. In Khodayar and Wang (2018) [124], a spatio-temporal graph deep neural network (DNN) for short-term wind speed forecasting is proposed [124]. A combinational forecasting method based on GPR and LSTM is proposed using EEMD in Huang et al. (2018) [125]. In Rodriguez H et al. (2017) [126], a hybrid neural genetic algorithm is proposed to reconstruct the wind speeds based on a given time series [126].

In Zhang et al. (2020) [127], random fluctuations in wind energy generation that can have adverse effects on the power system are addressed by proposing a new interval prediction model for multi-factor wind speed by utilizing a Fast Correlation Based Filter (FCBF) algorithm which is optimized with a Radial Basis Function (RBF) model [127]. The method is then improved by applying an improved PSO and a new evolutionary particle swarm optimization EPSO model to optimize the RBF model [127]. Lastly, the Fourier function is used to fit the error probability distribution which then allows the wind speed interval to be estimated [127].

Due to many studies ignoring the influence of virtual components and poor identification of wind speed characteristics, Zhang et al. (2022) [128] proposes an energy theory model to aid in modal over-decomposition [128]. In this study, different predictive methods are utilized to create a new optimization algorithm to improve nonlinear capabilities [128].

With the help of Monte Carlo theory, an adaptable set of interval prediction schemes is proposed [128]. The author claims that the results for the proposed system are significantly better than other comparative wind speed forecasting schemes [128].

2.4. AI and ML for Wind Power Prediction in Wind Farms

Due to wind generators being rated much lower than their conventional counterparts (i.e., 5 MVA vs. 100 MVA), maximizing the power produced by each turbine is essential to maximize the efficiency and reliability of a given wind farm. It is also important to be able to predict how much power a grid-connected wind farm will produce so that consumer load demands can be met without any power stability or quality issues.

In Wang et al. (2017) [129], an improved BPNN algorithm is proposed to forecast wind power [129]. In Abhinav et al. (2017) [130], a WNN is proposed to forecast short term wind power [130]. An ELM with variational mode decomposition (VMD) is proposed in Abdoos (2016) [131] and is utilized to forecast short-term wind power [131]. In Morshedizadeh et al. (2017) [132], Liu et al. (2017) [133], Zheng et al. (2017) [134], and Zheng et al. (2018) [135], an ANFIS is proposed to model wind turbine power production, short-term wind power, short term wind power for energy management in microgrids, and short-term wind power with PSO, respectively [132–135].

In Lu et al. (2018) [136], a novel hybrid method of ultra-short term wind power forecasting is proposed based on ensemble empirical mode decomposition-permutation entropy (EEMD-PE) and LSSVM with GSA optimization [136]. A hybrid kernel function SVM ML algorithm with RBF optimization is proposed in Tian et al. (2018) [137] to predict wind power [137]. An LSSVM with improved ACO is proposed in Yang (2018) [138] to forecast wind speed and power utilizing a novel multi-input multi-output prediction algorithm [138]. In Zhao et al. (2018) [139], a multi-stage wind power prediction algorithm is proposed by utilizing Beveridge-Nelson (B-N) decomposition, a LSSVM, and GOA [139]. In Zhang et al. (2019) [140], single spectrum analysis, LSSVM, DBN, and locality-sensitive hashing is used for short-term wind power forecasting [140].

In Yuan et al. (2017) [141], Zafirakis et al. (2019) [142], Diaz et al. (2017) [143], Liu et al. (2018) [144], Jiang et al. (2019) [145], Fu et al. (2019) [146], and Wu and Gao (2018) [147], a wind power forecasting model is proposed by leveraging a hybrid SVM ML algorithm with ARIMA [141], SVRM [142,143], integer wavelet transform (IWT) [144], multi-objective singular spectral analysis (SSA) [145], cuckoo optimization algorithm (COA) [146], and support vector machine- gray model (SVM-GM) [147], respectively. In Esfetang and Kazemzadeh (2018) [148], a novel hybrid wind power prediction technique is proposed using WT, RBF, multilayer perceptron (MLP), Bayesian regulation (BR), resilient back propagation (RP), Levenberg–Marquardt (LM), and optimized with weight improved PSO (WIPSO) [148]. To aid with wind power forecasting under uncertain data, Sharifian et al. (2018) [149] proposed a type 2 fuzzy neural network (T2FNN) to improve the accuracy of the prediction [149].

Data mining is another useful type of AI found in wind power prediction and is utilized in Sun et al. (2018) [150], and Li et al. (2018) [151] along with a WNN [150] and a SVM [151] to predict short-term wind power. In Wang et al. (2018) [152], a DBN model is developed to forecast wind power utilizing a k-means clustering algorithm [152]. In Azimi et al. (2016) [153], a k-means clustering method is proposed and implemented with discrete wavelet transform (DWT), harmonic analysis time series (HANTS) and a MLP to forecast wind power [153]. In Wu and Peng (2017) [154] a data mining approach combining k-clustering and bagging neural networks is proposed for short-term wind forecasting [154].

Wind power prediction based on data-oriented deep network (DDN), meta regression, and transfer learning is proposed in Qureshi et al. (2017) [155]. In Hong and Rioflorido (2019) [156], a novel CNN that is cascaded with a RBFNN and a double Gaussian activation function (DGF) is proposed for 24 h look ahead wind power forecasting [156]. In Qin et al. (2019) [157], a hybrid LSTM and CNN to predict wind power generation of a wind farm is proposed [157]. In Wang et al. (2017) [158], WT and CNN are utilized for probabilistic wind power forecasting [158]. In Yu et al. (2019) [159], the temporal and spatial changes of wind are considered a single feature called spatio-temporal, which is used with a deep CNN to improve wind power prediction and then compared with previous methods [159].

In Ju et al. (2019 [160]), a hybrid CNN and LightGBM algorithm is proposed to forecast ultra-short-term wind power [160]. In Shi et al. (2017) [161], prediction intervals are employed to track the uncertainty of wind power and used with a RNN and dragonfly optimization to predict wind power generation [161]. LSTM algorithms are also proposed in Zhang et al. (2019) [162], Yu et al. (2019) [163], and Han et al. (2019) [164] for wind power prediction while also utilizing a Gaussian mixture model [162], sequential correlation features [163], and a copula function [164]. A new way to develop non-parametric power curve models is proposed in J. C. de Albuquerque et al. (2021) [165] by comparing power curve models based on ANNs and fuzzy inference systems (FIS) as well as two new proposed FIS algorithms trained with the proposed preprocessing technique [165].

In Zhang et al. (2021) [166], the clustering effect is considered for wind power prediction and proposed utilizing a hybrid CNN and LSTM to predict power generation based on spatiotemporal correlations [166]. In Singh et al. (2021) [167], the performance of five different ML and AI algorithms for wind power prediction are compared. These algorithms include RF, K-nearest neighbor (KNN), gradient boosting machine (GBM), and extra tree regression (XTR), with the proposed GBM reporting to have the best results [167]. In Zhang et al. (2022) [168], a short-term wind power algorithm is proposed that includes a hybrid system composed of FCBF, VMD, and LSSVM [168].

2.5. AI and ML in Mechanical Component Monitoring and Fault Detection

One of the biggest issues associated with wind farms is that they are typically located in remote locations or offshore. Due to this challenge, accurate monitoring and detailed maintenance schedules are necessary to prevent the wind farm from shutting down due to damaged wind turbine components. AI can be an extremely useful tool for predicting how and when a generator may fail, or how likely the WTBs will be damaged from severe weather events or bird strikes. It is also necessary to monitor the bearings for the rotor shaft, the actuators for the pitch and yaw control, and the gearbox. In this section, proposed strategies for gearbox monitoring, fault detection, and fault diagnostics will be presented first, followed by WTB damage detection and diagnostics, and lastly, bearing monitoring and fault detection.

In Bangalore P. et al. (2017) [169], a gearbox anomaly detection algorithm is proposed in which the Mahalanobis distance considering the correlation between ANN model errors and normal operating conditions is used [169]. In Lin J. (2018) [170], a vibration-based gearbox monitoring system is proposed that utilizes Welch's method and principal component analysis (PCA) to extract features and then an outliner analysis is performed using a MLP with RBF to discriminate the data, respectively [170]. A hybrid regression model and multilayer ANN is used to predict the remaining useful life (RUL) of a wind turbine gearbox by measuring gearbox vibrations is proposed in Elasha F. et al. (2019) [171].

In Hu W et al. (2019) [172], an adaptive time domain sequenced approximate entropy algorithm is proposed based on wavelet packet transform WPT, cross-validated PSO, and kernel ELM (KELM) to identify potential gearbox faults [172]. A proposed time frequency estimation and CNN is utilized to detect drive train faults in Li J. et al. (2019) [173]. In Agasthian et al. (2019) [174], a gearbox fault detection and classification algorithm is proposed utilizing a COA and SVM [174]. In Peng Y. et al. (2017) [175], a RNN is proposed for fault prognosis in wind turbine gearboxes [175]. In Chen et al. (2019) [176], an intelligent fault diagnostics method is proposed for planetary gearboxes utilizing a CNN and DWT [176]. A fault detection algorithm for single stage helical planetary gearboxes is proposed in Hameed and Muralidharn (2021) [177], in which the vibrations of the gearbox are used with a decision tree (DT) algorithm and SVM to detect the fault [177].

In Peng et al. (2021) [178], a novel fault diagnosis system is proposed in which the gearbox vibration signals, and generator current signals are fused into a single signal [178].

An SVM is used to design two classifiers which output the probabilities of different gearbox faults and current faults individually [178]. A nontrainable combiner and a trainable combiner are designed based on the Dempster-Shafer theory with SoftMax regression, which fuses the information from the SVM classifiers at the decision level [178].

In Guo et al. (2021) [179], a multi-task paralleled CNN (MPCNN) with reinforced input (RI) is proposed to detect coupling faults in wind turbine gearboxes using WPT vibration signals, domain knowledge of the gearbox components, and operating conditions under RI-MPCNN input [179]. To improve classification speed of gearbox fault detection algorithms in wind turbine systems, a fast deep graph CN is proposed in Yu et al. (2021) [180] in which the vibration signals are decomposed using WPT, which presents time-frequency features [180].

At any given time, WTBs can be exposed to high wind speeds, extreme weather events, and even bird strikes. These events can have disastrous effects on WTBs that can render a wind turbine inoperable until the damage can be assessed, and repairs can be completed. AI and ML can not only predict when damage may occur to WTBs from high winds or bad weather, they can also be used to determine if a bird has struck a WTB.

In Reddy et al. (2019) [181], the author proposed using images of WTBs captured by drones in tandem with a CNN to detect and classify cracks in WTBs [181]. In Sun D. et al. (2019) [182], a lamb wave and GA-BPNN is proposed to classify damage that has occurred to WTBs [182]. In Rezamand M. et al. (2020) [183], a hybrid blade fault detection method is proposed utilizing recursive PCA ad wavelet-based PDF [183].

Ice collection on WTBs can be a big strain on power production; in Jiménez et al. (2019) [184], an ice detection algorithm is proposed that uses AR and PCA for linear features, nonlinear AR exogenous and hierarchical non-linear PCA for nonlinear features, and neighborhood component analysis for feature selection. Twenty classifiers were then used, including DT, discriminant analysis, SVM, KNN, and ensemble classifiers to classify the data [184].

The bearings of a wind turbine are consistently under high stress due to the weight of the wind turbine components. These bearings must operate smoothly at all times to maximize wind power extracted from the wind. Temperature is a main parameter that must be controlled to keep the bearings in good condition, and to do this, wind turbines utilize cooling and lubrication systems to extend the life of the bearings if possible.

In Rodríguez-López et al. (2018) [185], a methodology for detecting malfunctions in wind turbine bearings is proposed, utilizing generic and specific models from SCADA data [185]. In Guo P. et al. (2018) [186], a condition monitoring and fault diagnosis of wind turbine gearbox bearing temperature is proposed using the Kolmogorov–Smirnov test and a CNN [186]. In Cao et al. (2018) [187], a method for determining the RUL of wind turbine gearbox bearings is proposed in which the authors utilize an interval whitenization method with a GP algorithm [187].

In Yang et al. (2021) [188], a dual stage, attention based RNN trained on the normal behavior of wind turbine bearing operating temperatures is proposed [188]. An LSTM is used to predict bearing faults by utilizing time varying correlations among variables to enhance performance of variable estimation [188]. In Xu et al. (2022) [189], a multi-scale CNN and bidirectional LSTM is proposed to improve the generalization abilities of a wind turbine control system under complex working and testing environments for fault diagnostics in bearings [189]. A weighted majority voting rule is also proposed to fuse the information from the multi-sensors to improve the extrapolation of multisensory diagnosis [189]. In Vives (2022) [190], different methodologies for detecting faults in wind turbine gearbox bearings were used, including frequency analysis, KNN, and SVM [190].

2.6. AI and ML in Wind Farm Electrical Component Monitoring

Wind turbine systems are extremely dependent on electronic sensors, converters, and actuators to maximize the power extracted from the wind. If a sensor, actuator, or converter fails, voltage sags or swells could propagate the entire wind farm and cause a collapse of the system. The effects of these faults will also be felt on the grid side of the system and can have adverse effects on power quality and stability delivered to consumers. This has lead researchers and engineers to develop AI algorithms to monitor and detect faults in sensors, actuators, and converters in wind turbine control systems so that they can be repaired or replaced before a serious issue can develop or mitigated should the worst-case scenario occur.

In Bangalore and Patriksson (2018) [191], a preventative maintenance schedule for wind turbine systems is proposed to predict the age and to generate condition failure rate models of wind turbine components using an ANN based condition monitoring system [191]. In Vogt et al. (2018) [192], a multi-task distribution learning approach is proposed for anomaly detection in wind turbine operational states, allowing for early fault detection and prevention [192]. In De Souza Darma et al. (2019) [193], an evaluation of data behavior models based on normal operating conditions is presented with respect to fault detection in wind turbine systems [193]. In Simani and Castaldi (2019) [194], an intelligent fault detection technique is proposed for offshore windfarms that uses a fuzzy neural network to determine the nonlinear dynamics between input and output measurements and the considered fault signal [194].

In Tafazzoli and Mayo (2019) [195], an AI condition monitoring algorithm is proposed to detect mechanical and electrical faults in wind turbine systems [195]. Utilizing big data and data processing algorithms, the proposed method detects signs of faults in the stator and rotor to develop an early warning system to prevent critical failure of the wind turbine [195]. In Li M. et al. (2019) [196], a LSTM and RF network is proposed for early fault detection and isolation in wind turbine systems [196]. In Khan et al. (2020) [197], SCADA sensor data integrity is considered with respect to a failed sensor condition [197]. The authors find that the proposed Cartesian Genetic programming evolved ANN (CGPANN) as a "model having multi-layered feed-forward architecture arranged in Cartesian format" that "shows remarkable generalization and continues to perform better in diverse data conditions [197]."

In Samet et al. (2020) [198], the effect of flicker emissions caused by reactive power fluctuations in extremely short time variations in wind farms is discussed [198]. In the article, the authors proposed a novel CNN control algorithm for static volt-ampere reactive compensators (SVC) to directly learn the nonstationary and complex features from raw wind farm reactive power time series [198]. To compensate for potential mean square error losses in forecasting, a modified loss function is proposed to enhance and improve the proposed CNN [198] and thus, is able to successfully detect and prevent flicker emissions [198]. In Cho et al. (2021) [199], the authors propose using a Kalman filter to estimate blade pitch angle and spool valve position to detect faults in wind turbine control systems [199]. An ANN is used to produce the predictive model for fault detection [199].

In Xiao et al. (2021) [200], a voltage converter fault detection model is proposed utilizing a hybrid improved attention octave CN (IAOCN) and ResNet50 backbone network based on SCADA data [200]. In Venkateswaran et al. (2021) [201], robust stabilization for DFIG-based wind farms is investigated with respect to retarded sampled-data control (RSDC) to stabilize and mitigate frequency and speed deviations in DFIG-based wind farms [201]. In the article, an $H\infty$ performance-based RSDC is used to attenuate defined disturbances in the system [201]. A Lyapunov Krasovskii function is created by using the delay-dependent conditions in the form of linear matrix inequalities (LMI) by using the RSDC technique [201].

3. Recommendation for Future Research

When it comes to wind turbine control systems, the speed at which the data is processed must be considered when designing an effective control scheme. Future works should focus on the following aspects.

(a) Limiting the processing time required for prediction and control, as many control methods are computationally heavy, making prediction and control too slow for real-life applications. The proposed algorithms discussed in this paper are robust in functionality but require a great amount of processing time to perform adequately. Due to power systems requiring monitoring and control systems to compute and respond to faults in less than half a second, it is extremely important to consider the entire control system when proposing a new AI or ML algorithm in wind farms. Just because a singular algorithm can run in the specified time does not mean the entire system can respond and react in a similar timeframe. Further research is recommended to optimize current monitoring and control methods to minimize response time of the system.

(b) The effect of 5G communication for wireless prediction and control should be considered, as communication speed is an important area that can have an adverse effect on the control of a wind farm. The speed at which these algorithms can perform their tasks and then transfer the data to the main controller is extremely crucial to the stability of the power system, so a detailed analysis of real-world performance of the proposed algorithms in this paper utilizing 5G or better is recommended.

(c) When designing control schemes for wind turbine systems, cyber-attacks need to be considered. Cyber criminals could access the control or communication systems of a wind farm and cause damage to the wind turbine system or manipulate electronic components to cause damage to the connected power grid. Researchers and engineers should consider the cyber security of a control device when implementing new control schemes for wind farms. One example of a cyber secure wind turbine control system is an SVM algorithm with a H_∞ controller to detect communication attacks and a ML algorithm to mitigate faults caused by communication or data injection attacks.

(d) Another recommendation for future research could be autonomous maintenance for offshore or remote wind farms. Maintenance can be challenging for engineers to accomplish when wind turbines are in hard-to-reach locations, so autonomous systems that can handle small-scale repairs to wind turbine systems would be a huge improvement to the current maintenance schedule and would help improve the efficiency and the cost of maintaining a wind farm. This could be done by utilizing an autoencoder/decoder algorithm with optimization to predict electrical and mechanical faults before they happen, and then, dispatch an autonomous repair robot to perform the small-scale repair utilizing DRL such as a Markov Decision Process and a Q-table.

(e) Microgrids are becoming more popular as renewable energy becomes a tangible replacement for conventional energy sources. An AI or ML algorithm such as a BPNN and an optimization algorithm such as PSO or FOA could be leveraged in a wind farm multilevel converter control system to allow for bidirectional power flow. This could allow for better power sharing between a wind farm, a microgrid, and the main power system.

(f) DFIG-type wind farms utilize converter systems to remove power and frequency oscillations from generated wind energy as well as control the rotor speed of the generator. The converter system could be utilized to mitigate fault conditions in a wind farm by using the DC-link capacitor and the converter system as a STATCOM. Future works should consider the application of AI and ML algorithms, such as an ANN-BP algorithm, to validate and optimize this process. By utilizing components already existing in a wind farm control system, the cost to implement the proposed system could be greatly reduced compared to conventional methods.

(g) The last recommendation for future research is power and load sharing for a smart grid connected wind farm. Smart grids are quickly replacing the conventional power system, so research should be done to determine optimal operating conditions for electronic converters and controllers. This could be done by creating a hybrid PID/AI/ML controller with PSO or FOA to create optimal set points and control schemes for power and load sharing.

4. Conclusions

In this paper, an overview of different control schemes for wind turbine control systems utilizing AI and ML are presented and show how AI can be utilized in wind farm control schemes to maximize the power extracted from wind currents, as well as monitor the condition of the wind turbine system. The sheer volume of proposed monitoring and control methods published in just a six-year period reported in this paper, emphasize how vital a role researchers and engineers believe AI and ML will play in future monitoring and control algorithms for wind turbine systems. AI and ML also play a big role in maintaining the stability of a wind farm during mechanical and electrical fault conditions. Utilizing AI and ML, researchers and engineers can build predictive models to aid in maintenance schedules for remote wind farm locations to help prevent wind farms from being disconnected from the grid due to faults caused by old and aging equipment. In the future, more diverse control schemes for wind farms should be considered, such as what is reported in the future research section of this review paper, and continued research in autonomous energy generation with respect to wind farms should be prioritized. To aid in this effort, a comprehensive review of the most current AI and ML methods proposed for wind farm monitoring and control systems reported in this review paper can be found in Appendix A.

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Appendix A

Table A1. AI and ML Algorithms for WF Control Systems 2021.

Author/Title	Method	Results
Cho et al. 2021 [199]— Fault detection and diagnosis of a blade pitch system in a floating wind turbine based on Kalman filters and artificial neural networks.	Kalman filter + ANN Dataset sourced from NREL 5 MW wind turbine model as well as the OC3-Hywind floater parameters using Simo-Riflex simulations.	Overall accuracy of 97.5% with a 2.5% error rate.
Elyaalaoui et al. 2021 [48]—Optimal Fractional Order Based on Fuzzy Control Scheme for Wind Farm Voltage Control with Reactive Power Compensation.	PIFPI + PSO	(1) Improved voltage and reactive power compensation for LVRT control. (2) Settling time is reduced. (3) Oscillations are limited and damped faster than conventional PI, fractional-order PI, and constant reactive power control.
Guo et al. 2021 [179]— Coupling fault diagnosis of wind turbine gearbox based on multitask parallel convolutional neural networks with overall information.	RI-MPCNN Dataset sourced from PHM Data Challenge 2009	Increased diagnostic accuracies by 3–20%.

Table A1. *Cont.*

Author/Title	Method	Results
Hameed and Muralidharn (2021) [177]—Fault Detection in Single-Stage Helical Planetary Gearbox Using Support Vector Machine (SVM) and Artificial Neural Network (ANN) with Statistical Features.	DT + ANN + J48 feature selection algorithms Dataset generated by vibration sensor mounted to DC shunt generator with planetary gearbox.	For 100 data points: (1) If mean > -0.034317 = good class, if not go to step 2. (2) If mean ≤ -0.034317 & standard error ≤ 0.002141 = sun defects, if standard error > 0.002141, go to step 3. (3) If mean ≤ -0.034317 & standard error > 0.002141 & standard error > 0.002783 = planet defect class, if standard error $\leq$ 0.02783, go to step 4. (4) If mean ≤ -0.034317 & standard error ≥ 0.002141 & standard error < 0.002783 and kurtosis ≤ 3.126717 = ring defect, if kurtosis is > 3.126717, go to step 5. (5) If mean ≤ -0.034317 & standard error > 0.002141 and standard error ≤ 0.002783 & kurtosis > 3.126717 and mean $\leq$ -0.0066817 = ring issue, if mean is > -0.066817 = planet issue.
Krajinski et al. 2021 [16]—Advanced operation control in wind power plants using active wake control methods and artificial intelligence—state of research and concept for the project "SmartWind".	ANN+DRL+DNN Training dataset generated using SWiPLab.	(1) Implemented in a case study in Gökçeada WPP, Turkey. (2) Ten minute data acquisition window causes a deterioration of the optimization results compared to higher acquisition rates causing dynamic wind fluctuations cannot be considered, and only stationary wake interactions can be affected.
Singh et al. 2021 [167]—A Machine Learning-Based Gradient Boosting Regression Approach for Wind Power Production Forecasting: A Step towards Smart Grid Environments.	Comparison of RF, KNN, GBM, DT, and ETR Dataset sourced from Yalova wind farm in the northwest region of Turkey.	(1) GBM had the highest overall accuracy with a MAE of 0.0277, MAPE of 0.3310, RMSE value of 0.0672, and a MSE of 0.0045 and R^2 of 0.9651. (2) DT performed the lowest with a MAE of 0.0335, MAPE of 0.3309, MAPE of 0.3309, RMSE of 0.0884, MSSE of 0.0078, and R^2 of 0.9497.
Xiao et al. 2021 [200]—Deep Learning Method for Fault Detection of Wind Turbine Converter.	AOC applied to ResNet50 backbone network—dataset sourced from a wind farm in Hebei Province, China.	(1) Accuracy of 98%. (2) Was 5.48–7.52% higher than other ResNet50 models.
Yang et al. 2021 [188]—Fault Detection of Wind Turbine Generator Bearing using attention-based neural networks and voting-based strategy.	DA-RNN Datasets are sourced from four large windfarms in China.	(1) Accuracy: 86.7. (2) Recall: 100. (3) Precision: 100. (4) F_1: 89.9890. (5) F_5: 99.1515.
Yu et al. 2021 [180]—Fault Diagnosis of Wind Turbine Gearbox Using a Novel Method of Fast Deep Graph Convolutional Networks.	FDGCN Dataset sourced from vibration acquisition equipment mounted to the DDS test rig composed of a speed controller, drive motor, two-stage planetary gearbox, two-stage parallel shaft gearbox, and programmable electromagnetic brake.	(1) Had 99.60% recognition rate of various faults on the DDS test rig. (2) Shorter training time than comparable models. (3) Overcomes noise better than comparable models.

Table A1. *Cont.*

Author/Title	Method	Results
Zhang et al. 2021 [166]—Power prediction of a wind farm cluster based on spatiotemporal correlations.	CNN + LSTM Test dataset acquired from a wind farm cluster in Zhangjiakou, China from the years 2017 to 2019.	(1) Prediction Results: (a) Theoretical standard WF: [RMSE (MW): 20.67, MAE (MW): 18.29, MAPE (%): 9.56] (b) WF a: [RMSE (MW): 50.58, MAE (MW): 35.67, MAPE (%): 21.73]. (c) WF b: [RMSE (MW): 22.34, MAE (MW): 18.51, MAPE (%): 10.06].

Table A2. AI and ML Algorithms for WF Control Systems 2022.

Author/Title	AI/ML + Datasets	Results
Xu et al. 2022 [189]—Fault diagnosis of wind turbine bearing using a multi-scale convolutional neural network with bidirectional long short-term memory and weighted majority voting for multi-sensors.	MSCNN-BiLSTM Dataset sourced from Case Western Reserve University (CWRU), XTJU Xi'an Jiao Tong University (XJTU), and NREL wind turbine transmission database.	(1) F_1 score: 97.12%. (2) Proposed weighted majority voting rule is higher than similar methods by 1.23% and 5.7%.
Yang et al. 2022 [57]—Cooperative yaw control of wind farm using a double-layer machine learning framework.	ANN + Bayesian ML Trained using RANS/ALM coupling model.	(1) Mean Error: 1.13% and 0.96% for different inflow velocities and turbulence intensities, respectively. (2) Mean rise in power of 5.59% and 2.22% under four inflow velocities and turbulence intensities, respectively.
Zhang et al. 2022 [168]—Short term wind energy prediction model based on data decomposition and optimized LSSVM.	FCBF + VMD + FOA-LSSVM Datasets sourced from WFs in Changma China and Sotavento, Spain.	(1) Average MAE: 0.1856. (2) Average MSE: 0.0350. (3) Average MAPE: 4.4372%.
Zhang et al. 2022 [128]—A comprehensive wind speed prediction system based on Monte Carlo and artificial intelligence algorithms.	EVMD-SCCS-BPNN + MCMC Dataset sourced from WFs in Changma, China and Sotavento, Spain.	(1) MAPE: 4.22% and 5.82%. (2) RMSE: 0.3548 m/s and 0.5794 m/s.

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