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Review

Machine Learning Solutions for Offshore Wind Farms: A Review of Applications and Impacts

Masoud Masoumi

Department of Mechanical Engineering, Manhattan College, Bronx, NY 10471, USA;
mmasoumi01@manhattan.edu

Abstract: The continuous advancement within the offshore wind energy industry is propelled by the imperatives of renewable energy generation, climate change policies, and the zero-emission targets established by governments and communities. Increasing the dimensions of offshore wind turbines to augment energy production, enhancing the power generation efficiency of existing systems, mitigating the environmental impacts of these installations, venturing into deeper waters for turbine deployment in regions with optimal wind conditions, and the drive to develop floating offshore turbines stand out as significant challenges in the domains of development, installation, operation, and maintenance of these systems. This work specifically centers on providing a comprehensive review of the research undertaken to tackle several of these challenges using machine learning and artificial intelligence. These machine learning-based techniques have been effectively applied to structural health monitoring and maintenance, facilitating the more accurate identification of potential failures and enabling the implementation of precision maintenance strategies. Furthermore, machine learning has played a pivotal role in optimizing wind farm layouts, improving power production forecasting, and mitigating wake effects, thereby leading to heightened energy generation efficiency. Additionally, the integration of machine learning-driven control systems has showcased considerable potential for enhancing the operational strategies of offshore wind farms, thereby augmenting their overall performance and energy output. Climatic data prediction and environmental studies have also benefited from the predictive capabilities of machine learning, resulting in the optimization of power generation and the comprehensive assessment of environmental impacts. The scope of this review primarily includes published articles spanning from 2005 to March 2023.

Keywords: offshore wind; offshore energy; wind farm; wind turbine

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1. Introduction

The progression of machine learning (ML) techniques and artificial intelligence has left an impact on various fields of science and engineering. It has influenced everything from the initial stages of discovery and ideation to the implementation of previously established methods and the presentation of results. The field of offshore renewable energy stands as no exception to these advancements. As governments and communities around the world drive for an increase in renewable energy generation, the challenges related to augmenting the capacity of current systems and constructing more efficient and environmentally friendly infrastructures have become more urgent. This "race" to achieve these objectives has elevated the significance of ML in this field. Particularly, ML techniques function as a set of tools that can render the processes of design, optimization, development, implementation, and maintenance more cost-effective and expedited.

This work is centered around delivering a comprehensive review of the diverse ML methods employed in the offshore wind energy industry, along with the specific applications that have been targeted for these implementations. The objective is not merely to offer succinct descriptions of each study, but also to provide insights into the methodologies employed and the outcomes of these works. This will enable researchers to gauge the impact and utility of each application discussed.

The literature is categorized into three main sections. The initial category encompasses the literature that concentrates on the implementation of ML tools for predicting ocean data characteristics, as well as studies that delve into the potential environmental ramifications of offshore wind farms. Additionally, publications aimed at utilizing ML to identify potential locations for offshore wind farms are also included within this category.

The second category encompasses all studies that employed ML tools to model the performance and optimize the operations of wind farms. This category also includes research focusing on control systems utilizing ML tools, primarily aimed at performance modeling and enhancement. The third category within this literature pertains to investigations that specifically delve into structural health monitoring, damage identification and localization, as well as operation and maintenance procedures.

It is worth noting that certain studies could fit into either the first or second category. The classification of these studies was determined by their specific application of ML. If the method was employed to forecast environmental data like waves or wind, the study was categorized under the first category. If not, it was placed in the second category. It is also worth noting that the works have been reviewed chronologically for each topic. Furthermore, there is a "Prospective" section included to delve into the overarching views and perspectives of ML implementations, as well as explore potential future directions.

2. Methods

The research for this study employed both manual and systematic search approaches. For the systematic exploration of relevant existing literature, the USGS BiblioSearch was utilized [1]. This versatile cross-platform search tool is implemented in Python and leverages several APIs to query diverse databases, including Clarivate Web of Science and Elsevier Scopus. Additionally, the abstracts of the papers were obtained using pybliometrics [2], another Python library designed for querying data from the Scopus database.

The initial associated keywords in the query used for data collection were in the following format: "('machine learning' OR 'neural network' OR 'multilayer perceptron' OR 'deep learning' OR 'reinforcement learning' OR 'extreme learning machine' OR 'decision tree' OR 'random forest' OR 'nearest neighbour' OR 'nearest neighbor' OR 'support vector machine' OR 'artificial neural network' OR 'data driven modeling' OR 'data driven modelling') AND ('offshore energy' OR 'offshore wind energy' OR 'offshore wind' OR 'offshore renewable energy' OR 'offshore wind farm' OR 'floating wind' OR 'wind-wave farm' OR 'wave-wind farm' OR 'wind wave farm' OR 'wave wind farm')". Here, 'AND' and 'OR' are logical operators. The results were then filtered and analyzed to separate the relevant literature. Further, some of the reviewed works here were added to the list of publications through manual searches.

3. Climatic Data Prediction and Environmental Effects

In the context of climatic data prediction for offshore wind applications, ML enables accurate and robust forecasts of wind speed, direction, and wave patterns, crucial for optimizing power generation and ensuring efficient turbine operation. These techniques empower decision-makers with real-time, data-driven insights that enhance energy yield and economic viability. Moreover, the investigation of environmental effects necessitates a comprehensive understanding of intricate ecosystems surrounding offshore wind farms. ML facilitates the analysis of species distribution, habitat mapping, and collision risk assessment, aiding in the development of sustainable offshore installations that minimize ecological impact.

Beyond these applications, ML can also open avenues for innovation, such as autonomous navigation through wind farm areas, noise reduction in remote sensing data, and the creation of comprehensive datasets for infrastructure identification. In essence, the integration of ML techniques empowers the offshore wind industry to navigate the complexities of climate prediction, environmental sustainability, and operational efficiency.

Through multilayer pereceptrons (MLPs) clustering, deep learning, wave analysis, spatial modeling, and some other novel applications, researchers have addressed a spectrum of challenges, from predicting wind speed and ocean wave characteristics to modeling species distribution and analyzing habitats. This collective effort demonstrates ML's potential to reshape our comprehension of marine environments and to optimize the utilization of offshore wind energy systems.

The MLP neural network was used by Flores et al. to predict wind speed values in one-hour intervals [3]. They used the sigmoid activation function and trained the models using two sets of data: one-hour measurements of wind speed at a wind turbine located in Navarre (with one sample per minute), and another set collected over four months in a real wind farm located in a less windy area (Zizurkil) in the north of Spain, from June to September 2002. The model was used for two purposes: (1) optimization of power generation through the maximization of active power generation so that all the produced energy could be sold; and (2) to provide a constant reference point agreed upon by the buyer, one hour beforehand. In another study, Dankert and Horstmann investigated the possibility of using radar–image sequences of the ocean surface to provide reliable ocean wind vector measurements [4]. They trained an MLP to retrieve wind speed and wind direction from a series of radar–image sequences. The results were compared to the in situ wind speed measured at a platform with 30 m height. They concluded that the minimum wind speed that could be retrieved with the trained network is 0.5 m/s.

In a separate study, researchers developed algorithms to forecast wave elevation and exciting force, aiming to apply them in optimal control for load reduction [5]. The study involved two forecast algorithms: the approximate Prony method (a technique based on singular value decomposition) and support vector regression (SVR) method. To validate these algorithms, real-time measurements were employed. The data used in the study were collected during wave tank testing, encompassing two sets of records. The first set represented a sea state with a significant wave height of 1.7 m and a typical wave period of 8.7 s, whereas the second set represented a sea state with a significant wave height of 4.5 m and a wave period of 11.8 s. The measured wave records spanned 2.5 h. As the forecast horizon increased, the authors observed a notable decline in the performance of the forecasting models. Nevertheless, they determined that the forecast accuracy of wave elevations up to a 5-s horizon remained adequate for the purpose of controller design.

Kulkarni and Ghosh proposed a special framework to assess the impact of climate change on offshore wind potentials [6]. This framework involves selecting the most appropriate General Circulation Model based on reliability and uncertainty, analyzing wind simulation with two downscaling techniques over past and future periods, evaluating potential changes with various downscaling techniques and Representative Concentration Pathways combinations, comparing with regression-based past trends, and estimating future extractable wind power and seasonal changes. The study focused on three selected locations in India, finding a substantial increase in annual average wind potential over the next 27 years compared to the past 27 years, indicating potential benefits to the Indian offshore industry.

Niemi and Tanttu proposed an ML-based bird identification system specifically designed for offshore wind turbines [7,8]. The system operates by utilizing a series of images featuring a single target, effectively representing a sequence of temporally consecutive frames of the same bird. These images are then fed into a convolutional neural network (CNN) to extract relevant features. To achieve the best results, a two-step learning method is applied. Initially, the CNN was trained using the first N-1 layers, treating them as feature maps. Subsequently, these feature maps were used to train a support vector machine (SVM) classifier, enhancing the system's ability to recognize and classify different bird species accurately. To cope with limited data, the researchers integrated an image augmentation step into the process. This augmentation step helped to enhance the model's performance and accuracy even when working with a smaller dataset. Finally, to ensure effective classification, they defined eight distinct types of birds for the classifier to identify.

Yan et al. introduced an MLP-based model that accurately predicts the power of a wind farm based on wind speed and direction [9]. The model was trained on a vast dataset from the Lillgrund Wind Farm, spanning approximately 16 months (November 2006 to February 2008) and containing about 700,000 raw data samples collected at a frequency of 1 min or higher. To improve the model's performance, the authors replaced wind direction with two simple geometric properties calculated using a geometric model. The approach was validated on an onshore wind farm, Nørrekær in Denmark, collected between August 2009 and May 2016 at a frequency of 10 min. Results showed that the model achieved high accuracy, with a bias of approximately −0.7% and an absolute error of around 6%. The model also demonstrated promising transfer-learning ability, allowing predictions for any wind farm with the same turbine model faster and with similar or greater accuracy than existing wake loss models, including those in commercial software packages .

Keivanpour et al. presented a geo-clustering approach for assessing offshore wind energy potential worldwide [10]. By applying a neural network-based clustering approach, the study identifies five hotspots around the globe based on factors such as geographic location, wind capacity in shallow, transitional, and deep waters, coastline length, demand, investment leverage, and risk. The proposed segmentation approach offers strategic insights into the global deployment of offshore wind energy, encompassing technical, market, and spatial dimensions. The research aimed to develop an interactive decision-making tool to analyze the challenges associated with offshore wind energy deployment.

Zha et al. introduced a reinforcement learning-based path-planning algorithm designed to enable the safe and efficient navigation of ships in wind farm areas [11]. Through a series of simulations, they demonstrated the effectiveness of the proposed hybrid path-planning method, which combines A* and reinforcement learning. This approach successfully generated a feasible path-planning scheme for navigating through wind farm waters, even in the presence of obstacles. In a research study conducted by Lin et al., an unsupervised learning model was developed to discern various sound sources underwater [12]. This model was applied to analyze long-term underwater recordings collected near Phase I of the Formosa I wind farm, situated off the coast of Taiwan. The researchers aimed to assess the temporal, spatial, and spectral variabilities present in these recordings. To achieve this, the authors employed the periodicity-coded non-negative matrix factorization method, an unsupervised learning technique used for decomposing high-dimensional data into non-negative components. Figure 1 illustrates the general procedure adopted for their proposed approach. The significance of this research lies in its potential to evaluate the impact of noise-generating activities on soniferous marine animals and their acoustic behavior before, during, and after the construction of offshore wind farms. Additionally, the study provides an efficient tool for building an annotated database, facilitating further investigations in this domain.

In another study, researchers focused on constructing species distribution models for fish and macroinvertebrate taxa in the Northeast U.S. Continental Shelf marine ecosystem, using data from NOAA's long-term bottom trawl survey and ecosystem monitoring programs [13]. These models were used to assess the impact of lease areas designated for renewable wind energy installations in the Middle Atlantic Bight. The authors employed random forest to create models depicting the occurrence and biomass of 93 species, providing seasonal representations of their habitat distributions. A scoring index was developed to characterize each species' habitat use within the lease areas, leading to the identification of groups of species with varying levels of reliance on these habitats. The potential for impact was assessed based on the number of species dependent on the lease area habitats, which varied across continuous gradients. Habitats supporting high biomass were found more to the northeast, whereas high occupancy habitats were located further from the coast. The size of the lease area did not seem to significantly influence the importance of associated habitats.

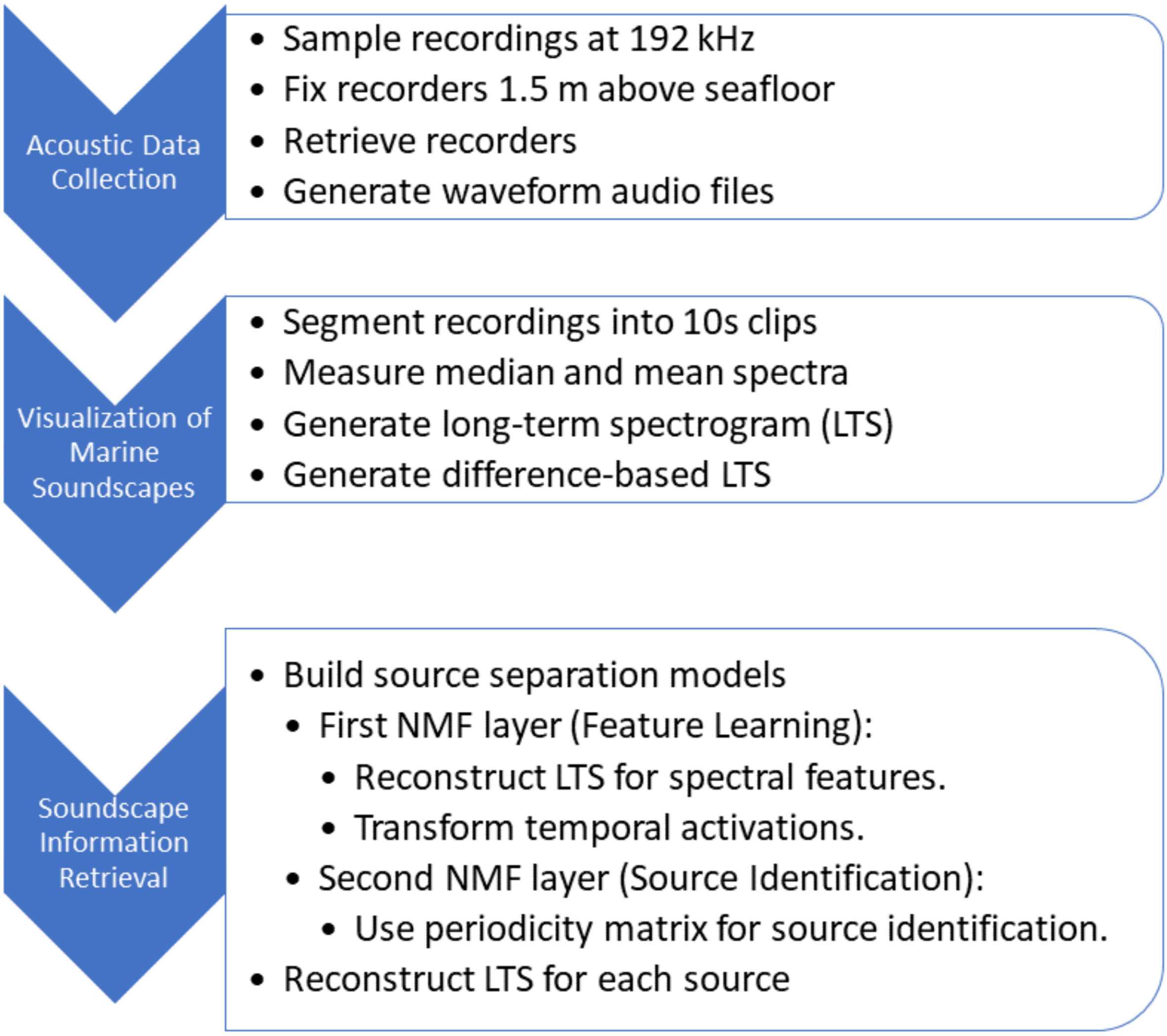


Figure 1. The approach proposed by [12] to visualize and retrieve information from soundscape of an offshore wind farm.

Stelzenmüller et al. utilized a random forest regression applied to vessel monitoring system data to identify and understand the drivers of passive gear fisheries, including the experimental brown crab pot fishery conducted near the offshore wind farm located near the island of Helgoland [14]. The authors examined cumulative spill-over potentials from all offshore wind farms and assessed their impact on fishing activities. The analysis results indicated that local spill-over mechanisms occurred at distances of 300 to 500 m from the nearest turbines, attracting pot fishing activities to specific wind farms. This suggests a growing attraction of fishing efforts towards offshore wind farms due to both an increasing international demand for brown crab and stable resource populations at suitable habitats. Additionally, Reijden et al. conducted a study presenting a new method for generating high-resolution habitat maps for diverse marine faunal groups [15]. They utilized hierarchical clustering to identify distinct biological assemblages for demersal fish, epifauna, and endobenthos in the offshore Central and Southern North Sea. By employing random forest models with abiotic predictors, they mapped these assemblages to high-resolution grids. The research revealed clear associations between demersal fishing, offshore wind farms, and specific habitats, leading to unequal anthropogenic pressure across different areas. The authors emphasized the significance of including habitat maps based on biological datasets in marine spatial planning, complementing traditional abiotic-based physiotope maps. This integrated approach facilitates identifying areas of conflicting interests and encourages balanced discussions between economic and ecological values.

Tapoglou et al. introduced a model that combines an MLP network and satellite remote monitoring to predict significant wave height and sea state in an operational wind farm [16]. They utilized synthetic aperture radar images from European Space Agency Sentinel-1 satellites and wave-buoy data from the UK. The model achieved an RMSE of 0.23 m for significant wave height below 3 m, making it suitable for offshore wind energy applications. The model's performance was comparable to physical modeling hindcasts and aligned with existing sea-state models in the North Sea and the Irish Sea. Furthermore, Masoumi used K-means clustering to group U.S. coastal regions based on wave height, wave period, and wind speed data from the National Data Buoy Center [17]. Three models were created using data from different time periods (2019, 2015–2019, and 2010–2019). Similar regions with consistent wave and wind patterns were identified in each model, providing a tool for identifying suitable areas for wave–wind hybrid energy platforms.

Hoeser et al. introduced the DeepOWT dataset (Deep-learning-derived Offshore Wind Turbines), which encompasses 9941 global offshore wind energy infrastructure locations, along with their corresponding deployment stages [18]. DeepOWT harnesses publicly accessible Earth observation data derived from the Sentinel-1 radar mission. The identification of offshore wind infrastructure locations was accomplished through a two-step process that employed deep learning-based object detection. Figure 2 shows the general procedure used for developing the dataset. The authors highlighted that with the availability of this free and accessible data, it becomes more likely that all stakeholders operating within marine and coastal environments will participate in the expansion of offshore wind farms. In another study, Hoeser et al. proposed "SyntEO", an approach to facilitate the automated creation of substantial deep learning-compatible datasets for Earth observation research [19]. The SyntEO methodology's application was exemplified in the context of identifying offshore wind farms within Sentinel-1 satellite images. The operational implementation involved the construction of an expansive dataset, encompassing approximately 90,000 training instances. A rudimentary CNN, exclusively trained on synthetic data, exhibits the capability to adeptly discern offshore wind farm installations within the images.

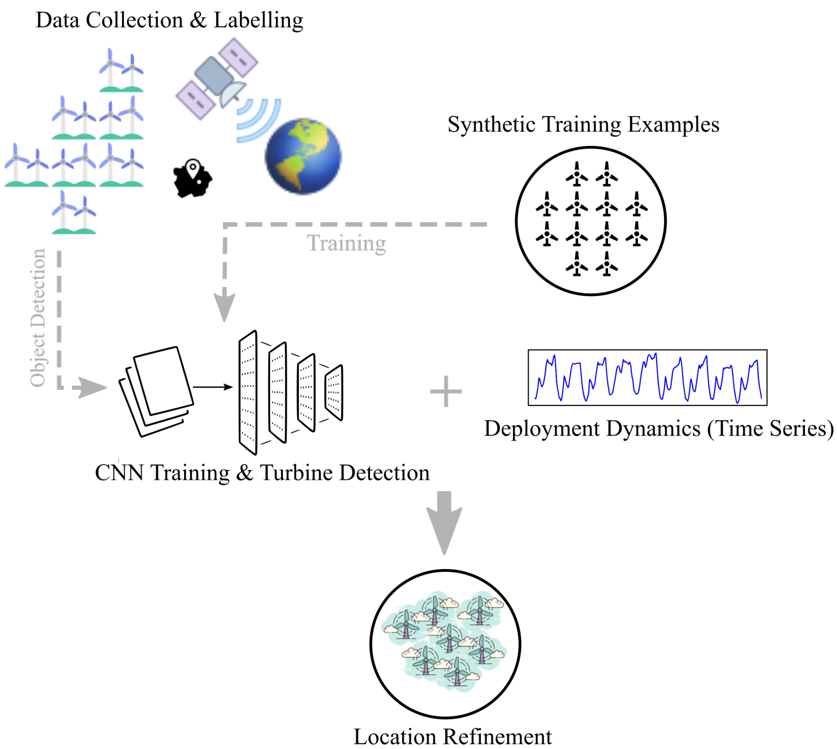


Figure 2. The procedural process employed to create the DeepOWT dataset using the Sentinel-1 archive by [18].

Nguyen et al. developed data-driven proxy models to capture the relationship between free-flow wind conditions and aggregated wind farm power [20]. For each wind farm, a database was created using computational fluid dynamics (CFD) simulations, then used to train ML models predicting offshore wind farm power based on free-flow wind data (speed and direction). The non-linear relationship between wind power and raw wind data was modeled using decision tree, random forest, gradient-boosting regression tree, and MLP. The study underscored the significant impact of enhanced wind energy modeling on reliability indices. Compared to traditional power curve methods, the proposed approach unveiled underestimations in Loss of Load Expectation [h/year] and Loss of Energy Expectation [MWh/year] values.

In addressing bird collisions with offshore wind turbines, Mikami et al. created a detailed collision risk map [21]. They employed a fine-scale spatial model, using data from bird flights over the sea, including 117 black-tailed gulls from three colonies and 21 slaty-backed gulls from four colonies in northern Hokkaido, Japan. Their model, utilizing a random forest algorithm, predicted flight patterns within the altitude range of 20–140 m. Geographic variables and species characteristics were used, showing a correlation coefficient of 0.57–0.94, despite variations among species, years, colonies, and areas. The study highlighted key factors in collision risk, emphasizing the significance of proximity to breeding colonies and harbors. Within 15 km of colonies and 5 km of harbors, collision risk increased by 6–7 times.

Xu and colleagues proposed an effective technique to diminish noise and interference caused by ocean waves in synthetic aperture radar images [22]. This involves the creation of a singular global random forest model within the Google Earth Engine platform. Additionally, the study introduced a mathematical morphology-based approach for analyzing time series spatial data, enabling the monitoring of changes in offshore wind turbine environments. The method's validation demonstrated exceptional accuracy metrics: an overall accuracy of 99.99%, a producer accuracy of 100%, and a user accuracy of 94.12%. Comparison with ground truth data substantiated the method's efficacy, yielding a precision rate of 93.67% for the dynamic surveillance of offshore wind turbines spanning the Yellow Sea of China and the North Sea of Europe from 2015 to 2021. Furthermore, Roy and colleagues conducted a study in northern France to detect sea breeze and nocturnal low-level jet meteorological events [23]. The researchers developed four distinct algorithms for identifying these events: the Sign Change of Sea-Breeze Component, a recurrent neural network tailored for sea breeze, the Haar wavelet threshold technique for nocturnal low-level jet, and the Symlets wavelet slope technique. The recurrent neural network algorithm proved effective in identifying sea breeze occurrences, exhibiting a 98% sensitivity, 91% specificity, and 95% classification accuracy. The results of their analysis showed that the peak power production during the highest hourly average could surge by up to fivefold compared to the baseline day. This surge was attributed to elevated wind speeds experienced during nocturnal low-level jet events. Additionally, during sea breeze events, the hourly average peak power production could experience an increase of up to 2.5 times.

Marin et al. presented an innovative wind speed prediction approach employing the MLP network [24]. This method utilized GPS coordinates of the target zone along with wind speed averages spanning from 1990 to 2050 across diverse Black Sea locations, facilitating offshore wind location determination. The outcomes derived from this approach were leveraged to optimize the siting of wind energy conversion systems, yielding enhancements in operational efficiency. Utilizing Bayesian neural networks, which treat the weights, biases, and outputs of the MLP as distributions rather than fixed values, Clare and Piggott aimed to tackle the challenge of predicting offshore wind resources for renewable energy applications [25]. They highlighted that their approach for determining these network parameters facilitated the potential for accurately calibrated uncertainty predictions for both wind speed and power. Their findings indicated that the accuracy and uncertainty of wind speed and direction predictions remained consistent despite the presence of the nearby Alpha Ventus wind farm.

Yu and colleagues have introduced a model to enhance the prediction accuracy of ultra-short-term offshore wind power by leveraging an SVM optimized through the dragonfly algorithm [26]. This algorithm emulates dragonfly group behaviors, encompassing global and local searches, navigation, predation, and evasion of adversaries. To validate their approach, they conducted simulations utilizing power data from a 115 MW offshore wind farm and numerical weather forecasts from 2018 and 2019. The training dataset employed 2018 data, whereas the test dataset utilized 2019 data. The results demonstrated the superiority of the proposed method in power prediction compared to SVM models combined with particle swarm optimization or firefly optimization algorithms.

Table 1 provides a summary of each work reviewed in this section, including a brief description of the research conducted and the machine learning techniques employed.

Table 1. Summary of the work reviewed in this section, focused on Climatic Data Prediction and Environmental Effects.

Auth. and Cit.	ML Technique	Summary
Flores et al. [3]	MLP	Neural networks used to predict wind speed values in one-hour intervals.
Dankert and Horstmann [4]	MLP	Models were used to retrieve wind speed and wind direction from radar–image sequences.
Ma et al. [5]	Prony and SVR	Algorithms developed to forecast wave elevation and exciting force.
Niemi and Tanttu [7,8]	CNN, SVM	Bird identification system designed for offshore wind turbines.
Kulkarni and Ghosh [6]	MLP-based Framework	Special framework proposed to assess the impact of climate change on offshore wind potentials.
Yan et al. [9]	MLP	Windfarm power prediction using wind speed and direction.
Keivanpour et al. [10]	K-means Clustering	K-means clustering used to assess offshore wind energy potential worldwide.
Zha et al. [11]	Reinforcement Learning	Hybrid path-planning method combining A* and reinforcement learning for ship navigation in wind farm areas.
Lin et al. [12]	Unsupervised Learning	Unsupervised learning model used to discern various sound sources underwater.
Friedland et al. [13]	Random Forest	Random forest models employed to construct species distribution models for marine species.
Stelzenmüller et al. [14]	Random Forest	Random forest regression used to identify drivers of passive gear fisheries near offshore wind farms.
Van der Reijden [15]	Hierarchical Clustering	Utilized hierarchical clustering to identify distinct biological assemblages for demersal fish, epifauna, and endobenthos in the offshore Central and Southern North Sea.
Tapoglou et al. [16]	MLP	Used satellite images and the data from buoys to predict significant wave height and sea state in a wind farm.
Masoumi [17]	K-means Clustering	K-means clustering applied to group coastal regions based on wave height, wave period, and wind speed.
Hoeser et al. [18]	CNN	Deep learning-based object detection used to identify offshore wind energy infrastructure locations.
Hoeser et al. [19]	CNN	SyntEO methodology used to create deep learning-compatible datasets for Earth observation research, exemplified in the context of identifying offshore wind farms.
Nguyen et al. [20]	Decision Tree, Random Forest, Gradient-Boosting Regression Tree, and MLP	Models used to capture the complex relationship between wind conditions and wind farm power.

Table 1. *Cont.*

Auth. and Cit.	ML Technique	Summary
Mikami et al. [21]	Random Forest	Fine-scale spatial model using random forest to create a collision risk map for bird collisions with offshore wind turbines.
Xu et al. [22]	Global Random Forest	Global random forest model used to diminish noise and interference caused by ocean waves in synthetic aperture radar images.
Roy et al. [23]	Recurrent Neural Network	Four algorithms developed for identifying sea breeze and nocturnal low-level jet meteorological events.
Marin et al. [24]	MLP	MLP network used for wind speed prediction to optimize the siting of wind energy conversion systems.
Clare and Piggott [25]	Bayesian NN	Bayesian neural networks employed for predicting offshore wind resources with calibrated uncertainty predictions.
Yu et al. [26]	SVM	SVM optimized through the dragonfly algorithm used to enhance ultra-short-term offshore wind power prediction.

A potential research gap that emerges from the literature is the limited mention of the integration of various machine learning techniques and data sources for a holistic environmental impact assessment. There is a need for research that integrates multiple machine learning techniques, such as wind speed prediction, bird and marine species monitoring, wave forecasting, and habitat analysis, into a cohesive framework for a holistic environmental impact assessment of offshore wind farms. This could involve the development of an integrated model that considers the combined effects of these factors on the marine ecosystem and the optimization of wind energy systems while minimizing their environmental footprint. Such research could provide valuable insights for sustainable offshore wind farm development and management.

4. Performance Modeling and Optimization

The significance of optimization in wind energy generation from wind farms is underscored by a multitude of research papers that have implemented neural networks as integral components within optimization processes, performance modeling, and controller design. A key observation is the precariousness of wind power output, posing substantial challenges to the stability of power grids. This has spurred the need for accurate ultra-short-term wind power prediction, a critical factor in ensuring the steadfastness of power system operations. Further challenges include layout optimization, maximal power generation, fatigue load mitigation, and power reference tracking. An exhaustive review that traverses the landscape of prevailing control methodologies applied across diverse objectives can be found in [27].

Shifting the focus to floating offshore wind turbines, an intriguing economic prospect emerges. These turbines are poised to offer more cost-effective solutions compared to fixed offshore wind turbines, especially in deep water depths. However, this innovative solution is not devoid of operational challenges. The complex interplay of wind and waves subjects these systems to six-degree-of-freedom (DOF) movements, imparting substantial effects on their performance dynamics. This intricate interaction leads to periodic oscillations in output power, mechanical loading, and the operational orientation of wind turbines, highlighting the challenging landscape these turbines navigate.

As an attempt to develop a bathymetric chart, Lee et al. developed an optimization algorithm that incorporated an MLP neural network to create a wind and bathymetric map [28]. The objective of this algorithm was to identify the optimal location for an offshore wind farm near Jeju Island in South Korea. The procedure utilized a genetic algorithm for the optimization process and could identify the most suitable location for the wind farm based on the criteria of maximum depth and distance from the coastline while maximizing energy density. In a separate study, Pappala et al. developed a neural network to forecast wind characteristics as part of their optimization model for wind farm predictive control [29]. The simulated wind farm in this study consisted of 80 turbines, each with a rating of 50 MW. However, to simplify calculations, they assumed a single equivalent turbine. The model utilized wind power generation data from past steps to predict the next three steps. The data used to develop the model consisted of a time series of wind power generation averages for five-minute intervals at 8000 time steps and the optimization algorithm employed for the model was the particle swarm optimization. The proposed model could reduce transformer tap changes, thus improving performance.

Japar et al. utilized data from Horns Rev offshore wind farm in Denmark to develop machine learning techniques for estimating power losses caused by wake effects in a wind farm [30]. The wake phenomenon in a wind farm can lead to energy losses of up to 20% annually [31]. Therefore, it is crucial to consider this effect when optimizing the farm's layout. The authors employed various ML models, including linear regression, linear regression with feature engineering, nonlinear regression, MLP, and SVR. Both SVR and MLP proved to be effective in accurately estimating power deficits. The study's results demonstrated that ML methods can play a valuable role in estimating power losses attributed to wake effects in large wind farms.

Antoniadou et al. utilized data from the Lillgrund Wind Farm and employed neural network Gaussian processes to construct reference power curves (wind speed versus power produced) for each of the 48 turbines in the farm [32]. These reference models were then used to predict power output for the remaining turbines, resulting in a confusion matrix of regression model errors for all combinations. The reference power curve used to build the models represented a healthy power curve, based exclusively on data from instances with a status code of '0' (indicating 'no error' in the turbines). The results demonstrated the robustness of the models, with consistently low MSE errors (see Figure 3). The study utilized one full year of operational data, collected in the form of SCADA extracts with 10 min averages. The data included maximum, mean, minimum, and standard deviation values for each 10 min interval.

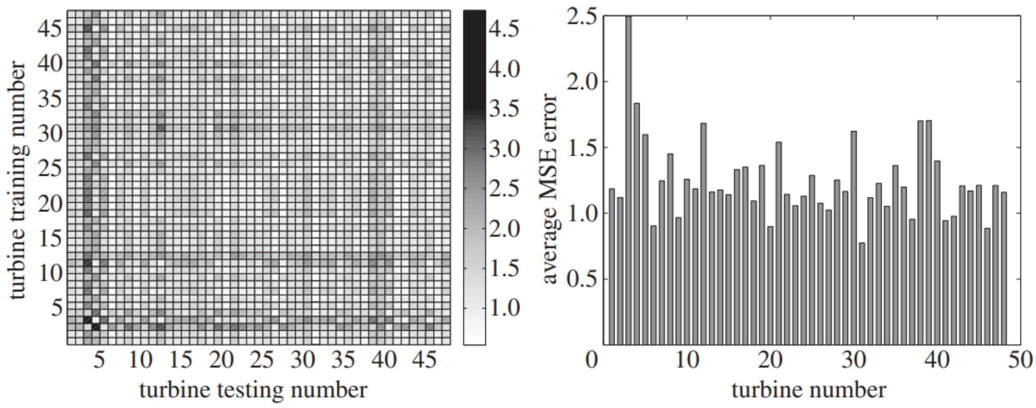


Figure 3. Confusion matrix depicting MSE errors on the testing set **[left]** and average MSE errors illustrating the predictive performance of each turbine (power produced) **[right]** [32].

Rodrigues et al. demonstrated the practicality of employing reinforcement learning techniques for the online control of a multi-terminal DC network, specifically for integrating offshore wind farms [33]. The developed procedure can be summarized as follows. The power production of offshore wind farms is measured and transmitted to the Distributed Voltage Control (DVC) located at the Transmission System Operator Center. Equipped with knowledge of the Multi-Terminal DC network topology, the DVC performs real-time optimization using Continuous Action Reinforcement Learning Automata (CARLA). In each control cycle, CARLA iteratively samples direct voltage values, evaluates them, and stores those with improved reward values in an archive. At the end of each cycle, the archived direct voltage references are sent to onshore stations, and the process is repeated.

The simulation involved a network with six nodes, interconnecting three offshore wind farms with the onshore AC networks of the UK, Germany, and Denmark.

Ou et al. proposed a novel approach for integrating an offshore wind farm and a seashore wave power farm through a high-voltage, alternating current electric power transmission line [34]. The hybrid multi-system consists of a battery energy storage system and a micro-turbine generation. The proposed approach, called intelligent damping controller, comprises a designed proportional-integral-derivative linear controller, an adaptive critic network, and a functional link-based novel recurrent fuzzy neural network. Test results demonstrated that the proposed controller achieves better damping characteristics and effectively stabilizes the network during unstable conditions. The approach mitigates oscillations and resolves power stability issues.

Furthermore, Fischetti and Fraccaro explored the potential implementation of linear regression and MLP for predicting the optimal production of offshore wind farms based on various factors, including the characteristics of the offshore wind site, turbine specifications, and wind measurements at that location [35]. The model they developed took into account proximity constraints, minimum and maximum turbine limits, and the wake effect. See Figure 4 for the simulation results of the wake effect of the wind farm. The central question they sought to address was, "Given a set of optimized wind farm layouts, can a machine predict the production value of the optimized solution for a new site?" To answer this question, they utilized a dataset comprising six different wind turbines with varying rotor diameters, along with characteristics from six existing wind parks. The study's key finding was that neural network models, trained on a large number of optimized solutions, could demonstrate an ability to accurately predict the optimal power output for new instances of wind farms. This suggested that their approach could be valuable for optimizing production in offshore wind farm development. In a follow-up investigation, Fischetti and Fraccaro provided another study looking further into whether a machine, trained on a vast number of optimized solutions, can accurately estimate optimized solutions for new instances in the context of offshore wind farm layout optimization [36]. The focus was on site-selection applications where a company aims to construct a specific number of turbines in an offshore area, taking into account factors such as production increase due to wake effect and infrastructure costs. Different rectangular instances with various wind scenarios and turbine types were considered in the study. Over 3000 instances were defined and optimized using a mathematical optimization tool powered by heuristic solutions obtained through machine learning. The machine learning model utilized several features related to turbine characteristics and site properties. The training set consisted of 2268 instances from real-world wind farm areas, and the remaining 1134 instances were used as a test set. The results showed that the machine learning estimate significantly outperforms human estimates in this optimization problem.

Lu et al. presented a novel hybrid technique involving the integration of recurrent Fuzzy neural network (FLRFNN) and genetic algorithm hybrid time-varying particle swarm optimization (GAHTVPSO) methods to design a damping controller for a Static Synchronous Compensator in an offshore wind farm [37]. In their simulations, the wind farm was connected to a power grid via a 50 km high voltage direct current transmission line. The proposed system included an adaptive critic network, FLRFNN, and the genetic algorithm hybrid time-varying particle swarm optimization. The simulation results demonstrated the effectiveness of this approach in mitigating oscillations and addressing power stability concerns in the offshore wind farm setup. In another study, Noppe et al. proposed a technique to reconstruct the thrust load history of a wind turbine using high-frequency SCADA data [38]. They utilized strain measurements for training a neural network and validated the method on two datasets: simulated data and real-world offshore wind turbine measurements. The technique showed promising results, with a relative error below 15%, and slightly better accuracy with simulated data compared to real-world measurements.

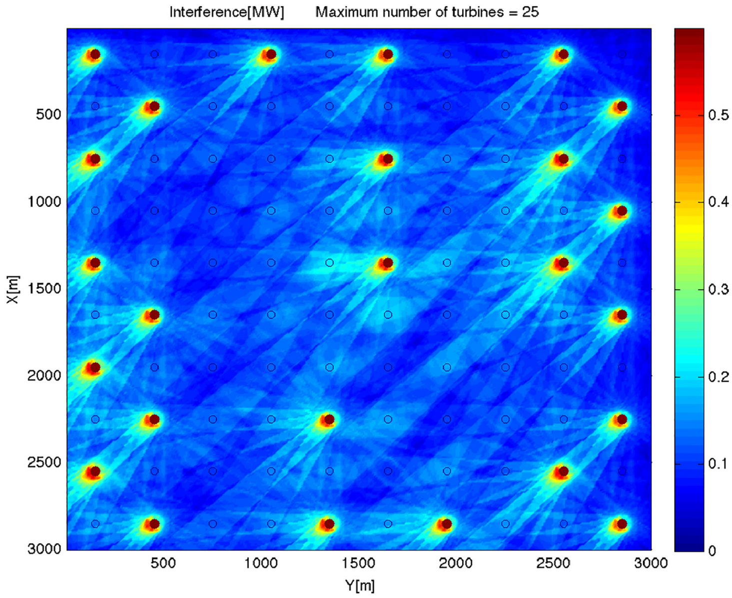


Figure 4. Visualizing the wave effect for the landscape of a wind farm. The nodes represent turbines, whereas the backdrop hues illustrate the degree of interference as per Jensen's model [36].

In a separate report, Lu et al. conducted a study investigating the utilization of a recurrent wavelet-based Elman neural network controller to integrate offshore wind and wave energy conversion systems, which were powered by a doubly fed induction generator [39]. The results were then compared to those obtained from classical proportional–integral and recurrent fuzzy neural network controllers. The proposed technique demonstrated higher effectiveness and robustness, outperforming other controllers in terms of the wind and wave energy conversion systems' performance. Further, Häfele et al. proposed a cost-effective framework for optimizing offshore wind turbine jacket substructures. They used an ML approach, specifically Gaussian process regression, to reduce numerical expenses and consider more design load cases [40]. The method was applied to the National Renewable Energy Laboratory (NREL) 5 MW turbine under FINO3 conditions, with 20 parameters (10 topology, 7 tube dimensions, and 3 material properties). The authors found that surrogate modeling is a promising solution for efficiently tackling the computationally expensive jacket optimization problem.

Yin and Zhao used ML with five algorithms, including general regression neural network, random forest, SVM, gradient-boosting regression, and recurrent neural network, to create predictive models for offshore wind farms [41]. The models aimed to support more cost-effective facilities by predicting wind farm power output and turbine thrust. They employed various predictor variables, including wind velocity, direction, torque, yaw offset, blade pitch, tilt angles, and turbine characteristic parameters. Data from the wind farm simulation platform FLORIS, developed by NREL and Delft University of Technology [42], was used for training and testing. The test results achieved approximately 99% accuracy or higher, making the methods suitable for practical applications. Moreover, recurrent neural network and SVM showed the highest accuracy, with recurrent neural network excelling in thrust predictions, whereas general regression neural network demonstrated higher computational efficiency.

Using a random forest-based surrogate model coupled with a genetic algorithm, Pillai et al. developed a multi-objective optimization for mooring systems of floating offshore wind turbines [43]. The optimization was to minimize cumulative lifetime fatigue damage and material costs. Variables like mooring line anchor position, length, material composition, and diameter were considered. Furthermore, random forest was used for both classification (constraint satisfaction) and regression (predicting fatigue damage and material costs), ensuring valid solutions through anomaly detection. Figure 5 shows the general procedure followed for the proposed optimization method. Data used for the study were from simulations of a semi-submersible designed for offshore wind turbines at the UK's Wave Hub test site; although the multi-objective approach did not pinpoint a single optimum, it could provide valuable trade-off information for decision-making along the proposed Pareto front to be assessed by decision-makers.

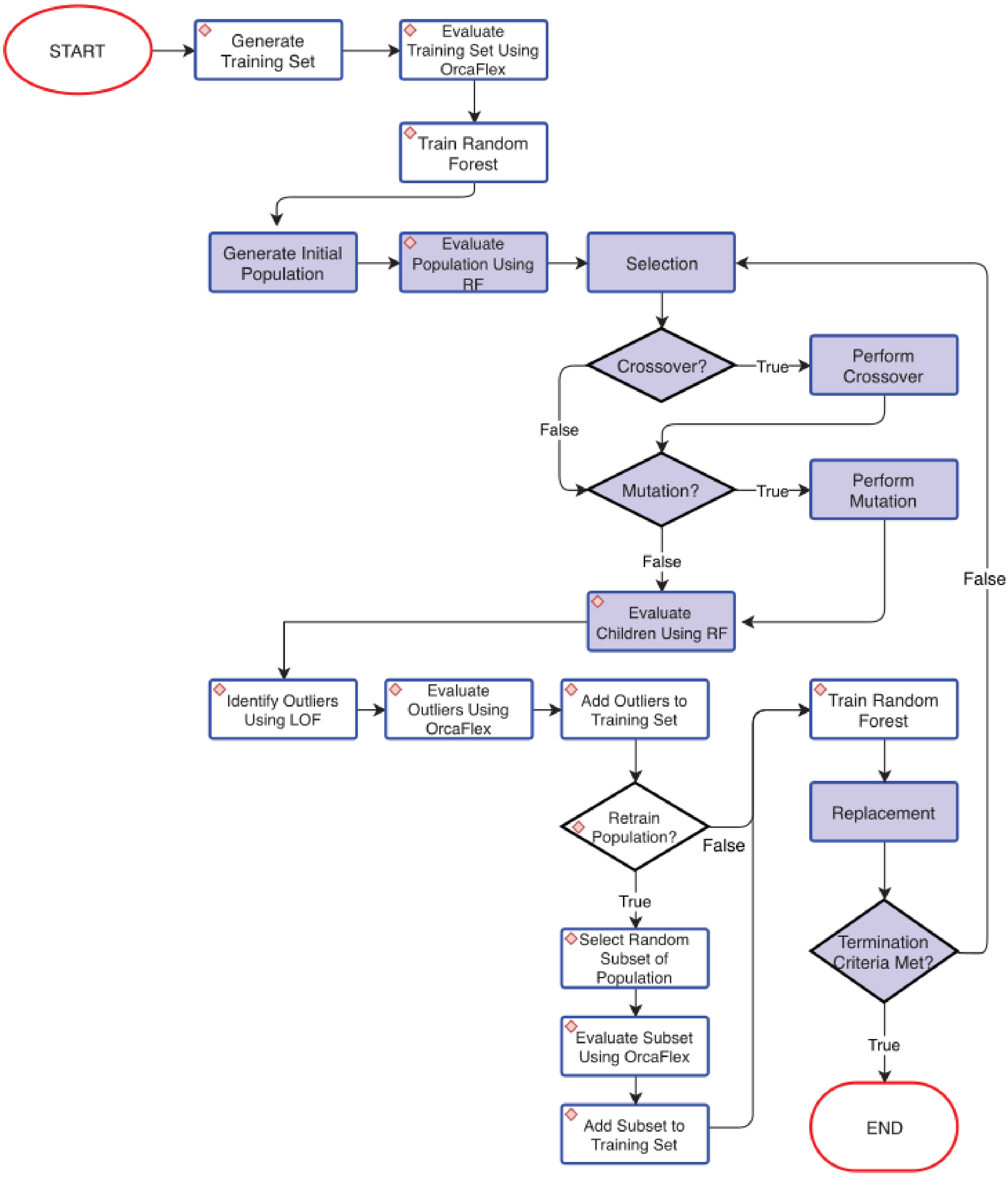


Figure 5. The optimization process, from [43], employing a random forest surrogate model. The steps associated with the surrogate model are denoted by a diamond in the top left corner, whereas the core steps of the genetic algorithm are represented by filled shapes.

Li et al. introduced an MLP-based sliding mode control for the blade pitch of offshore wind turbines [44]. The modeling was performed by coupling the aerodynamic model, hydrodynamic model, and mooring system model for the NREL 5 MW wind turbine and OC3-Hywind foundation [45]. A comparison between a proportional–integral controller and the proposed system revealed that the standard deviation of output power fluctuation was reduced by 25% when using the novel sliding mode control. In a different front, Penner et al. conducted measurements on a suction bucket jacket prototype at 'Borkum Riffgrund 1' in the North Sea [46]. Comprehensive data with strain, acceleration, inclination, and water pressure sensors were recorded every 10 min and correlations between vertical soil stiffness and bucket stiffness were observed. For modeling the system's behavior, the Frequency Domain Decomposition was utilized for identification and monitoring in the frequency range of the first and second eigenfrequency (0.2 Hz < f < 5 Hz), where the system behaved linearly. However, in the lower frequency band (0.05 Hz < f < 0.2 Hz), experiencing higher forces and displacements, an MLP was chosen to model the non-linear relationships between the measurements. This approach could enhance the understanding and prediction of system behavior in these critical frequency bands.

NREL researchers developed an advanced unsteady aerodynamics and dynamic stall model using an LSTM surrogate model for wind turbine load analysis codes, such as OpenFAST [47,48]. The model was trained on oscillating airfoil experimental data from Ohio State University wind tunnel tests and successfully validated against additional experimental data. Comparisons with existing aerodynamic models in OpenFAST revealed that the ML model results align well with diverse scenarios involving various airfoils, Reynolds numbers, and reduced frequencies. An added advantage of this ML approach is its automated model tuning, which could seamlessly integrate into the design workflow. To address the issue of uncertainty in ML models, Pandit and Kolios proposed two methods, pointwise confidence intervals (CIs) and simultaneous CIs, based on the work by [49], to quantify the uncertainty of an SVM-based power curve model using a radial basis function as the kernel [50]. The effectiveness of these techniques was verified with SCADA data from pitch-controlled wind turbines. Pointwise CIs were found to be more accurate, generating smaller CIs, making them a better choice for constructing fault detection algorithms based on SVM power curves. The reason for this is that pointwise CIs exhibit a relatively narrow width throughout the wind speed range, enabling them to detect anomalies at an early stage more effectively.

Yu et al. proposed a data integration method utilizing graph neural networks [51] to connect wind turbines within a certain range of wind farms based on their geographical locations and related information [52]. The authors employed a superposition graph neural network for feature extraction, maximizing the utilization of spatial and temporal features for prediction. In their experiments, they used data from four offshore wind farms (collected from the NREL open wind power dataset from 2010 to 2011, with a sampling interval of 10 min, and wind turbine output power ranging from 0 to 16 MW). Compared to common methods, the proposed approach resulted in a reduction in the mean square error by 9.80% to 22.53%, demonstrating significant improvement in prediction accuracy and stability.

Dong et al. developed a deep reinforcement learning-based wind farm control scheme to optimize power generation in wind farms [53]. They designed a reward regularization module to estimate wind turbines' normalized power outputs under various yaw settings and uncertain wind conditions, enhancing the control scheme's robustness and adaptability. The reward regularization module was integrated with the deep deterministic policy gradient algorithm to identify the optimal yaw settings for all wind turbines in the farm. Figure 6 shows the general framework for the proposed approach. The model was trained and validated using high-fidelity simulations with SOWFA [54] (a simulator for offshore wind farm applications) and Tensorflow [55]. They collected 90 sets of 1000 s large-eddy simulations with SOWFA to generate offline training data for their reinforcement learning. The proposed method significantly improved the wind farm's total power production by an average of 15% compared to the benchmark.

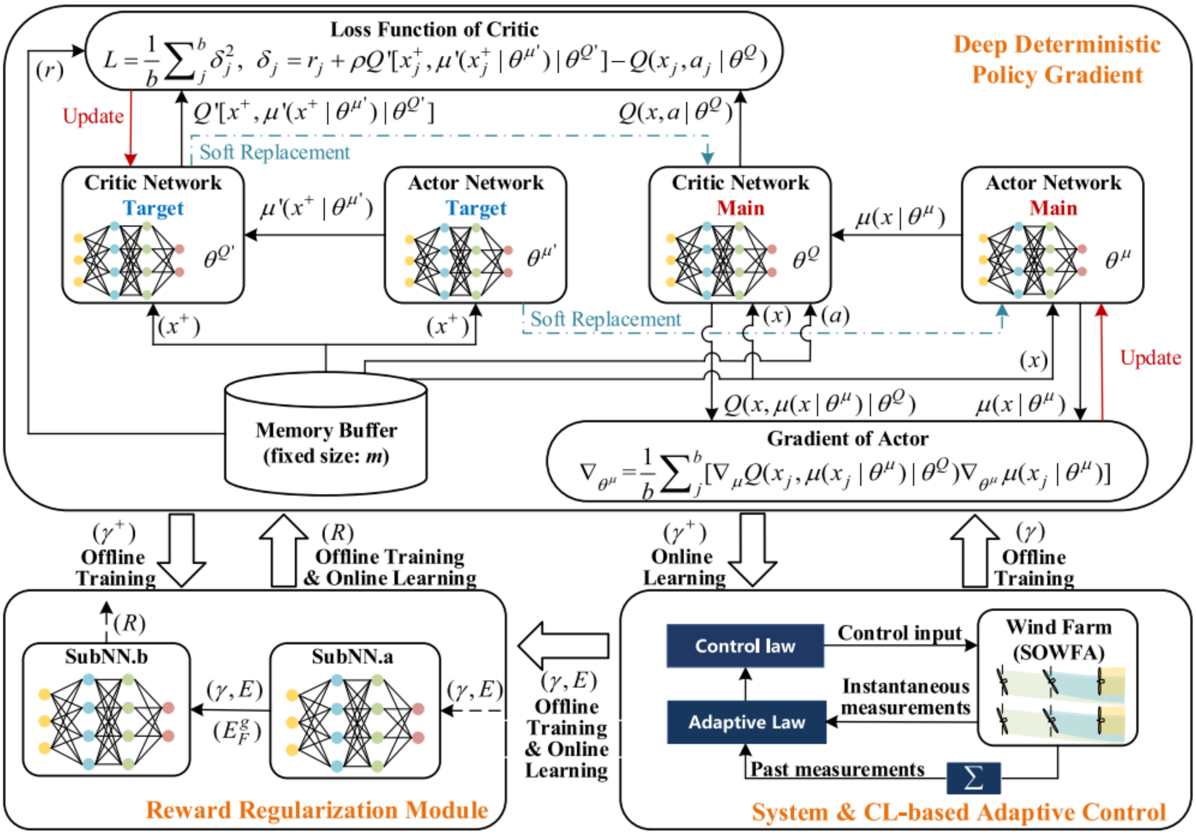


Figure 6. Illustration of the primary framework and data flow for the wind farm control system based on deep reinforcement learning proposed by [53].

Lian et al. developed an MLP-based regression model to relate loading conditions to the long-term performance of a wide-shallow bucket foundation model for offshore wind turbines in saturated sand [56]. They collected data through laboratory tests on a system with a bucket foundation model, soil box, and signal acquisition systems. Sensitivity analysis showed that loading frequency had the most significant impact on the foundation's long-term performance, followed by loading magnitude and cycle number. In a different study, Chen et al. proposed using the simulation annealing diagnosis algorithm to optimize the dynamic response prediction of floating offshore wind turbines [57]. They applied a reinforcement learning method to adjust key parameters based on six DOF motions' feedback.The proposed method was verified with 12 experimental cases. However, challenges remain, including agent dependence and hyperparameter tuning of the deep neural network. Further exploration and experience are needed to address these issues. Further, Miao et al. devised an approach for evaluating the reliability of offshore wind farms, incorporating various climatic factors such as wind speed and ocean wave characteristics along with failure rate and the allocation of maintenance resources [58]. To investigate the power generation capacity of these offshore wind farms, the study utilized both an MLP network and multiple linear regression techniques, effectively analyzing the influence of uncertain factors on the reliability of power generation.

Mattsson et al. used ML to generate synthetic hourly electricity demand series for large-scale energy system models worldwide [59]. They incorporated ECMWF ERA5 [60] global reanalysis data and other geospatial datasets to produce detailed supply curves and hourly capacity factors for various renewable energy sources like solar photovoltaic, concentrated solar power, onshore and offshore wind, as well as existing and future hydropower. The gradient-boosting regression model was the primary tool for generating synthetic data based on temperature and GDP input data. By considering ten independent variables, including annual per-capita electricity demand, purchase-power adjusted GDP, average hourly temperature profiles in densely populated areas, and other temperature-related metrics, the model could create hourly electricity demand for any region in the world.

Returning to the topic of ML-based control system design, Kheirabadi and Nagamune utilized Distributed Economic Model Predictive Control (DEMPC) [61] to optimize power generation in floating offshore wind farms [62]. As part of their approach, they incorporated MLP networks to estimate the dynamic behavior of the floating platforms during the optimization process. These networks consist of six input neurons, corresponding to the four turbine states (platform positions and velocities in downwind and crosswind directions) and two turbine inputs (axial induction factor and yaw misalignment relative to the dominant free stream wind direction). The network's output provided predictions for the turbine's states at the subsequent sampling time. In the case of a floating wind farm comprising three 5 MW turbines, aligned with the free stream wind, the use of DEMPC led to a 20.2% increase in energy production compared to conventional greedy operation. Furthermore, Yin and Zhao proposed a hybrid CNN-LSTM model, underpinned by a deep learning architecture, to forecast the outputs of offshore wind farms [63]. This innovative approach employs high-fidelity large eddy simulation data as its foundation. Through the established CNN-LSTM models, they devised distributed and decentralized model predictive control techniques, strategically geared towards optimizing the wind farm's power generation. To validate their methodology, they subjected it to computational simulations involving two distinct wind farm scenarios: a two-turbine wind farm and a more complex nine-turbine wind farm. The outcomes revealed a remarkable level of prediction accuracy, approximately 97%, attained by the trained CNN-LSTM models. Furthermore, the findings demonstrated the considerable potential of the distributed model predictive control approach, capable of yielding a notable increase of up to 38% in power generation within the wind farm context.

Anagnostopoulos and Piggott developed a wind farm flow field modeling framework using an MLP architecture [64]. Their model was trained on approximated turbine wake fields from FLORIS [65] wind farm software (v2.1.1). With a minimum of two hidden layers, each comprising 100 neurons, the MLP generated an m by n grid depicting the downstream velocity domain of the wake. Figure 7 shows a general overview of the model. This approach rapidly simulated a 5 MW wind turbine with yaw variations and diverse inlet hub speeds and turbulence intensities. The simulation outpaced analytical wake-based solutions by an order of magnitude while maintaining just a 1.5% mean absolute error. The model's yaw optimization feature exhibited remarkable efficiency as well. The MLP-derived optimal yaw settings produced power outputs comparable to FLORIS' optimization module, achieving this at a speed ten times faster.

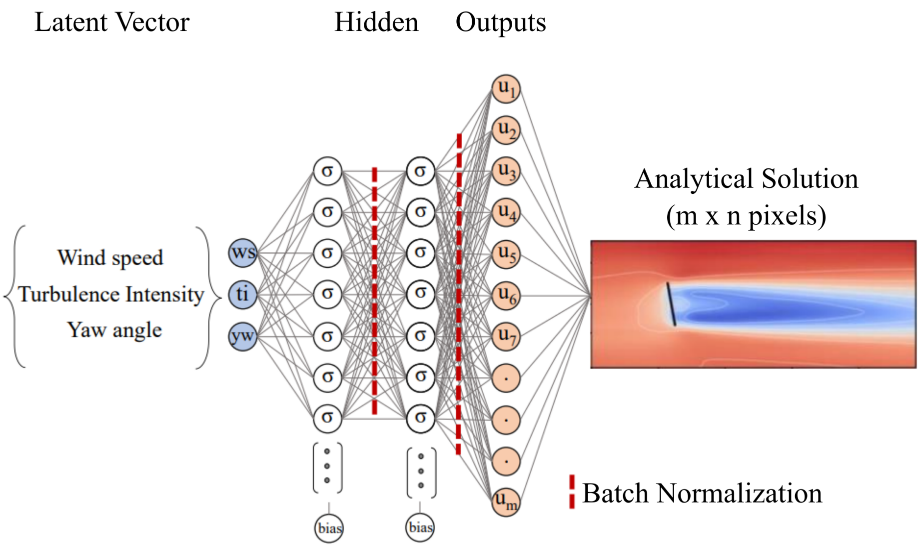


Figure 7. MLP-based model for simulating offshore wind farm flow field, proposed by [64].

Jothinathan et al. introduced an MLP-based controller for managing the nonlinear dynamics of offshore wind turbine jacket structures [66]. This controller's training leverages displacement time histories of the structure to predict the voltage needed for Magnetorheological (MR) dampers. They applied this approach to a fixed offshore wind turbine positioned in a water depth of 64.5 m. Both MLP-based and backstepping controllers were employed to manage the system. The neural network controller was specifically trained for tip displacement of the jacket structure, and its effectiveness was assessed across various load cases. Notably, the MR demonstrated efficient displacement control, achieving a rate of 61% at the tower top under the turbine's rated speed. For acceleration control, the MR damper achieved 31% at the tower top and 46% at the tip of the jacket structure. Furthermore, the MLP-based controller's performance closely resembled that of the passive-on approach, displaying nearly identical results for both displacement and acceleration control scenarios.

Keighobadi et al. designed an adaptive controller for a floating offshore wind turbine's key angles and torque [67]. They used a radial-based functional MLP controller to counter uncertainty effects, comparing it to a linear quadratic regulator. The model centered on a turbine with triangular floating cylinders and a central control tower. Forces like buoyancy, drag, and air thrust were analytically computed for modeling. The authors found their approach superior due to uncertainty compensation through radial basis approximation, but noted the need for more test data for optimal neural network tuning. In another investigation, a neural network-driven model predictive control was presented to enhance the operational effectiveness of the wind turbine control system in furnishing ancillary frequency control services to the grid [68]. Within this study, a closed-loop Hammerstein architecture was employed to approximate the behavior of a 5 MW floating offshore wind turbine equipped with a Permanent Magnet Synchronous Generator. The MLP network was deployed to gauge the aerodynamic characteristics of the nonlinear steady-state component, whereas the linear autoregression with exogenous input model was utilized to discern the linear time-invariant dynamic component. The authors performed a comparative evaluation of the performance of the proposed controller against the baseline controller. The suggested controller showed the ability to provide a stable response to fluctuations in frequency and could enhance the reference tracking.

Zhang and colleagues presented a structural control methodology for floating wind turbines, employing an active tuned mass damper implemented through a reinforcement learning-based strategy [69]. The proposed approach utilizes an adaptive dynamic programming algorithm to formulate the optimal control strategy, leveraging the nonlinear dynamics inherent in the structure. The architecture of the proposed system encompasses three fully connected MLPs: a plant network, a critic network, and an action network. The modeling was performed on the NREL 5 MW floating wind turbine model using FAST code, as shown in Figure 8. The simulation outcomes of the proposed technique showcased its commendable performance across both regular operational conditions and challenging scenarios. Notably, the standard deviation of the platform pitch displacement witnessed a reduction of approximately 40%. Moreover, the algorithm exhibited a balanced consideration between control effectiveness and power consumption trade-offs.

Dehghan Manshadi et al. assessed the feasibility of a hybrid energy system with vortex bladeless wind turbines and Searaser wave energy converters along the coast [70]. The study aimed to predict net power generation based on environmental conditions. The optimized setup included ten turbines and converters, with equations formulated for net force and wind turbine power. Using numerical simulation and experimental data [71], ML techniques like recurrent neural networks, LSTM, random forest, and SVM were applied to predict parameters. The algorithms were compared for prediction accuracy, and the individual and combined power output of the hybrid system was analyzed. The study proposed an optimal hybrid configuration and demonstrated the potential for integrating these technologies for coastal energy production. In a different study, Velino and their team introduced a ML-based control approach that employs a genetic program to iteratively evolve effective control strategies [72]. These strategies are developed using sensor data from simulated floating offshore wind turbines, simulated within the OpenFAST simulation environment. The method's viability was showcased by achieving a 41% reduction in fatigue and ultimate loading. This reduction was demonstrated under the conditions stipulated by the Aerodynamic Turbines with Load Attenuation Systems (ATLAS) competition, hosted by the Advanced Research Projects Agency–Energy (ARPA-E). Unlike approaches reliant on opaque models like some ML techniques, the proposed method generates interpretable outcomes. As a result, it aids in identifying crucial design aspects to inform future controller development.

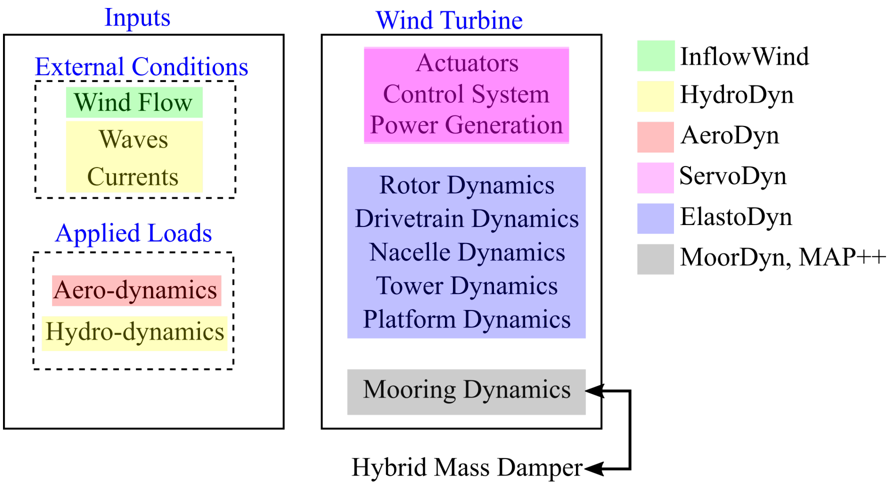
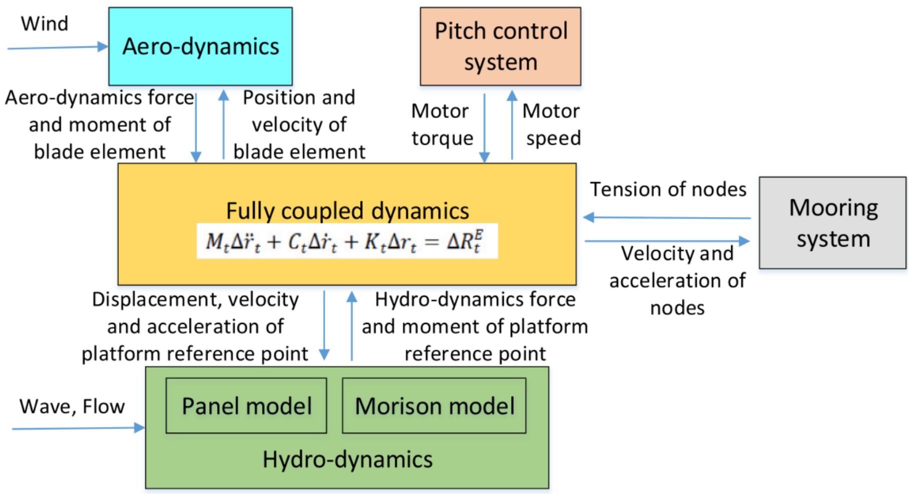


Figure 8. Diagrammatic representation of the floating wind turbine model incorporated into FAST, interconnected with the damping system formulated by [69].

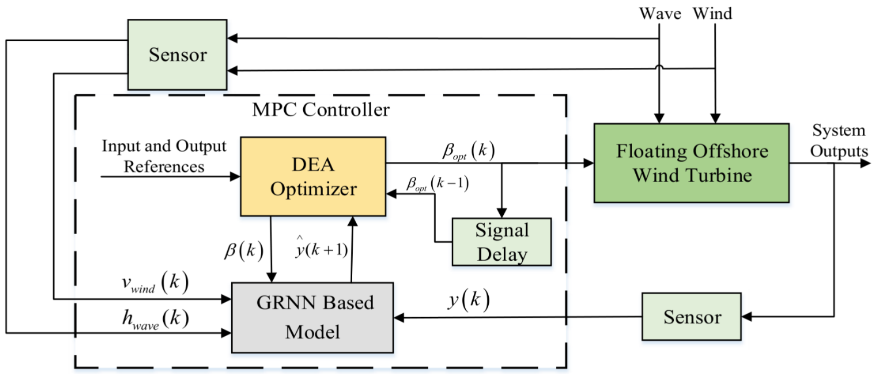
In their work, Yonggao and Yi presented a novel neural network-based approach for generating an auxiliary decision-making toolbox to optimize reactive power compensation in offshore wind farms [73]. They applied this approach to two 300 MW capacity projects: one with DFIG wind turbines connected by two submarine cables and another with PMSG wind turbines and a single submarine cable. By considering factors like turbine type, cable properties, voltage levels, and high-voltage shunt reactor location, their MLP network could predict capacities for onshore and offshore systems. The proposed compensation schemes were validated through assessments of reactive power balance, power frequency overvoltage, and voltage fluctuation, affirming the efficacy of the model.

Moreover, Meng et al. introduced an ML model that implements attention mechanism, CNN fusion, and bidirectional gated recurrent unit [74]. This model operates at an ultra-short-term horizon and focuses on predicting the output of individual wind turbines. By integrating real-time meteorological data within the wind farm, historical power data from turbines, and current operational data, the model undergoes parallel training. The proposed structure extracts salient features from the input data, enabling bidirectional modeling using CNN-derived dynamic feature variations. The model's efficacy was validated using actual observational data from wind farms with a rated power of 200 MW in Northwest China. The resultant predictions from individual turbines are used to compute the wind farm's overall power output. Comparative experimentation against advanced mainstream models could underscore the proposed model's better performance.

Furthermore, Zhang et al. introduced a multi-objective predictive control strategy for floating offshore wind turbines [75]. Their approach, based on a gated recurrent neural network, incorporated multi-objective optimization to enhance pitch angle control while adhering to constraints. Extensive FAST simulations covered diverse wind conditions. The study established a comprehensive coupled block diagram, showcasing the dynamic simulation environment and control scheme, as seen in Figure 9. The proposed approach used blade element momentum theory and the Morrison equation to estimate aerodynamic and hydrodynamic loads whereas the mooring system was modeled by MoorDyn [76]. Compared to collective pitch control and gain scheduling proportional–integral individual pitch control, the proposed method achieved power output closer to the rated level.



(a)



(b)

Figure 9. (**a**) The schematic of the modeling procedure for the floating offshore wind turbine and (**b**) the block diagram of the proposed control system by [75]. Here, DEA stands for distribution estimation algorithm and GRNN represents a gated recurrent neural network.

In response to the obstacles posed by offshore wind farms situated at a considerable distance from the primary grid and the necessity for precise power flow examination within the primary grid, Pham and Li devised an MLP model [77]. This model aimed to forecast power flow outcomes by leveraging historical power system data. An assessment of performance was carried out, comparing the newly suggested neural network-based power flow model with the conventional DC power flow model. The proposed model demonstrated a better capability to more precisely discover solutions in comparison to the DC power flow model. In another study, Chen and Hu introduced an AI-based approach to predict the dynamics of floating offshore wind turbines [78]. The work investigates key disciplinary parameters (KDPs) within the proposed approach, categorizing them into environmental, disciplinary, and specific groups. The study uses reinforcement learning to optimize the quantity and boundaries of KDPs, using experimental data. Results demonstrated that a well-chosen set of KDPs leads to more accurate predictions, with defined boundaries aiding algorithm convergence.

Unlike the construction of new offshore wind farms, the goal of the renovation is to incorporate new wind turbines while maintaining the existing configuration. This presents an optimization challenge constrained by the presence of initial wind turbines. Yang and

Deng introduced a wind farm layout optimization framework that employs an ML wake model to enhance power production while retaining the original wind turbines [79]. The approach optimized the arrangement of newly incorporated wind turbines within the constraints of the existing ones. Unlike conventional wind farm expansions, no additional land is necessary. Moreover, the integration of new turbines minimally affects the performance of the original ones, allowing for flexible application during the entire operational phase of offshore wind farms. The accuracy of their ML wake model was validated to be comparable to CFD simulations. Notably, their unconstrained optimization displayed similar performance to renovation plans, with an error margin under 0.3%. Increasing the number of wind turbines from 80 to 120 led to a slight decrease in normalized annual energy production, dropping from 96.6% to 93.4%, equating to a 3% to 4% rise in power loss. Simultaneously, capacity density surged by a significant 50%, all within the same area.

Ahmad et al. explored the application of an MLP network to model a hybrid floating wave energy–wind turbine platform and subsequently introduced a fuzzy logic control system to implement a structural controller aimed at mitigating undesirable vibrations within the platform [80,81]. The team employed OpenFAST and WAMIT for hydrodynamic modeling and the results showed that the MLP-based model could promise a simpler yet effective alternative to more complex nonlinear dynamical models for NREL 5 MW floating offshore wind turbines. Additionally, their control approach led to improved dynamic behavior of the platform, enhancing its stability across a wide range of wind and wave conditions.

All the works discussed in this section have been listed in Table 2, accompanied by concise research summaries and the corresponding ML techniques employed in each study.

Table 2. Summary of the work reviewed in this section, focused on Performance Modeling and Optimization.

Auth. and Cit.	ML Technique	Summary
Lee et al. [28]	MLP	Development of optimization algorithms using neural networks for wind and bathymetric maps.
Pappala et al. [29]	MLP	Forecast wind characteristics as part of their optimization model for wind farm predictive control.
Japar et al. [30]	Linear Regression, Nonlinear Regression, MLP, SVR	Employed machine learning models to predict power output and estimate losses due to wake effects in large wind farms.
Antoniadou et al. [32]	MLP with Gaussian process	Used neural network Gaussian processes to construct reference power curves for wind turbines and predicting power output.
Rodrigues et al. [33]	Reinforcement Learning	Utilized reinforcement learning for online control of multi-terminal DC networks connecting offshore wind farms.
Ou et al. [34]	Recurrent Fuzzy Neural Network	Proposed an intelligent damping controller for offshore wind and wave power integration.
Fischetti and Fraccaro [35]	Linear Regression, MLP	Predicted the optimal production of offshore wind farms based on various factors.
Fischetti and Fraccaro [36]	Mixed Integer Linear Programming	Used machine learning to optimize wind farm layouts, including considering factors like wake effects.
Lu et al. [37,39]	Recurrent Fuzzy Neural Network, Recurrent Wavelet-basedElman Neural Network	Design of a damping controller for a Static Synchronous Compensator in an offshore wind farm as well as integration of wind and wave energy conversion systems using machine learning controllers for improved performance.
Noppe et al. [38]	MLP	Used a technique to reconstruct the thrust load history of a wind turbine using high-frequency SCADA data.
Häfele et al. [40]	MLP with Gaussian Process	Implemented Gaussian process regression for cost-effective optimization of offshore wind turbine jacket substructures.

Table 2. *Cont.*

Auth. and Cit.	ML Technique	Summary
Yin and Zhao [41]	General Regression Neural Network, Random Forest, SVM, Gradient-Boosting Regression, and Recurrent Neural Network	Created predictive models for offshore wind farms using various machine learning algorithms.
Pillai et al. [43]	Random Forest	Developed a multi-objective optimization for mooring systems of floating offshore wind turbines.
Li et al. [44]	MLP	Developed models for optimization of wind turbine systems, including mooring and blade pitch control.
Penner et al. [46]	MLP	Utilized models, including MLP and Frequency Domain Decomposition, for modeling and monitoring offshore structures.
Jonkman and Vijayakumar [47,48]	LSTM	Developed an advanced unsteady aerodynamics and dynamic stall model using an LSTM surrogate model for wind turbine load analysis codes.
Pandit and Kolios [50]	SVM	Proposed methods to quantify the uncertainty of an SVM-based power curve model using radial basis functions and confidence intervals.
Yu et al. [52]	Graph Neural Network	Utilized graph neural networks to connect wind turbines within a wind farm based on geographical locations, improving prediction accuracy.
Dong et al. [53]	Reinforcement Learning	Developed a deep reinforcement learning-based wind farm control scheme to optimize power generation under various wind conditions.
Lian et al. [56]	MLP	Developed an MLP-based regression model to relate loading conditions to the long-term performance of a foundation model for offshore wind turbines.
Chen et al. [57]	Reinforcement Learning	Proposed a simulation annealing diagnosis algorithm to optimize dynamic response prediction of floating offshore wind turbines using reinforcement learning.
Miao et al. [58]	MLP, Multiple Linear Regression	Used MLP network and multiple linear regression to evaluate the reliability of offshore wind farms considering climatic factors.
Mattsson et al. [59]	Gradient-Boosting Regression Model	Used gradient-boosting regression to generate synthetic hourly electricity demand series for large-scale energy system models worldwide.
Kheirabadi and Nagamune [61,62]	MLP	Used MLP networks in Distributed Economic Model Predictive Control to optimize power generation in floating offshore wind farms.
Yin and Zhao [63]	CNN-LSTM	Proposed a hybrid CNN-LSTM model for forecasting the outputs of offshore wind farms, achieving high prediction accuracy.
Anagnostopoulos and Piggott [64]	MLP	Developed an MLP-based model for wind farm flow field modeling using FLORIS wake fields.
Jothinathan et al. [66]	MLP	Used MLP-based controllers to handle the nonlinear dynamics of offshore wind turbine jacket structures.
Keighobadi et al. [67]	MLP with Radial Basis Functions	Designed an adaptive controller for floating offshore wind turbines using a radial basis functional MLP controller.
Kayedpour et al. [68]	MLP	Used MLP networks in Model Predictive Control to enhance the operational effectiveness of wind turbine control systems.

Table 2. *Cont.*

Auth. and Cit.	ML Technique	Summary
Zhang et al. [69]	Reinforcement Learning	Developed a reinforcement learning-based strategy for structural control of floating wind turbines.
Dehghan Manshadi et al. [70]	Recurrent Neural Network, LSTM, Random Forest, SVM	Developed models to predict power generation in a hybrid energy system combining vortex bladeless wind turbines and wave energy converters.
Velino et al. [72]	Machine Learning Control	Introduced a machine learning-based control approach using genetic programming for floating offshore wind turbines.
Yonggao and Yi [73]	MLP	Used MLP networks to predict capacities for onshore and offshore systems for reactive power compensation.
Meng et al. [74]	CNN, Bidirectional Gated Recurrent Unit	Developed models for ultra-short-term wind farm power prediction using real-time meteorological data.
Zhang et al. [75]	Gated Recurrent Neural Network	Proposed a multi-objective predictive control strategy for floating offshore wind turbines using gated recurrent neural networks.
Pham and Li [77]	MLP	Developed an MLP model for power flow predictions in offshore wind farms.
Chen and Hu [78]	Reinforcement Learning	Used reinforcement learning to predict the dynamics of floating offshore wind turbines and optimize key parameters.
Yang and Deng [79]	MLP	Employed an ML wake model to optimize wind farm layout while retaining existing turbines.
Ahmad et al. [80,81]	MLP	Developed an MLP-based model for a hybrid floating wave energy-wind turbine platform and introduced a fuzzy logic control system.

A potential research gap that can be identified from the literature is the limited mention of the integration of real-time data and dynamic modeling for adaptive optimization. Although the literature discusses various machine learning methods for optimizing wind farm layouts, estimating power losses due to wake effects, and improving control strategies, there is less emphasis on the incorporation of real-time data and dynamic modeling into these optimization processes. Real-time data, such as weather conditions, power demand, and turbine health, can significantly impact the performance of wind farms. Research that focuses on developing adaptive optimization strategies that continuously adjust based on real-time data could lead to more efficient and reliable wind farm operations. Additionally, dynamic modeling techniques that account for changing environmental conditions and equipment degradation over time could further enhance the accuracy of performance predictions and optimization efforts.

5. Health Monitoring and Maintenance

The impending shift from onshore to offshore wind farms is inevitable, accompanied by a myriad of challenges. Foremost among these challenges is the conundrum of conducting offshore maintenance operations amidst unfavorable environmental conditions, leading to increased downtime. To address this, the concept of condition-based maintenance emerges, leveraging system condition information to facilitate decision-making while balancing financial constraints and energy productivity objectives.

The integration of upper and lower floating offshore wind turbine platforms necessitates the use of multiple tendons to ensure stability, safety, and reliability. To mitigate operation and maintenance costs associated with these intricate systems, effective damage diagnosis and prognostic management methods are indispensable. An intelligent fault diagnosis system can be developed for offshore floating wind turbine generators to enhance efficiency, accuracy, and reduced maintenance expenses [82].

A comprehensive review of ML-based offshore wind farm condition monitoring techniques can be found in [83]. Exploring the landscape of corrosion fatigue assessment in horizontal-axis offshore wind turbines, Okenyia et al. advocated the potential of digital twins, amalgamating finite element analysis, material modeling, artificial neural networks, data analytics, and Internet of Things (IoT) with sensor technologies to address challenges in shallow and deep water installations [84]. Additionally, Pezeshki and colleagues conducted an extensive literature review on structural health monitoring for offshore and marine structures, considering the prospect of ML implementations [85].

The criticality of power transmission systems in offshore wind farms cannot be overstated. Operating across demanding environmental conditions, subsea cables connect deep offshore installations to the mainland, enabling seamless integration with the power grid. The susceptibility of these cables to failure presents significant economic implications, with over 80% of insurance claims within the offshore wind energy sector attributed to subsea cable failures.

Researchers have been harnessing the power of ML to provide efficiency and reliability for wind farms. From predicting failures and maintenance requirements to making these systems more reliable in the harsh environment of the ocean, the ML techniques have been implemented in various capacities and forms.

Combining a self-organizing map (SOM) and an MLP neural network, Hameed et al. developed a model to predict the power output of turbines in the Lillgrund Wind Farm, which is situated approximately 10 km off the coast of southern Sweden [86]. SOM is an unsupervised machine learning technique that is often utilized for clustering and visualizing high-dimensional data by mapping them onto a low-dimensional grid. In this study, the SOM network was employed to cluster the turbines based on their power output data. Subsequently, an MLP neural network was utilized to predict power output in advance to efficiently plan and execute maintenance and repair tasks. The final model was able to predict the power output with an accuracy of 95%.

In order to develop an effective non-parametric model to detect gearbox failures in wind turbines, Wang and Infield utilized historical data obtained from a commercial wind farm [87]. The model took the form of a non-linear state estimation technique and was designed to perform anomaly detection. The data used for the study consisted of 10 min intervals of SCADA data. To construct the model, a total of ten turbines were employed, with seven turbines contributing to the training dataset, and an additional turbine being used for validation purposes. Further, they selected two turbines that had previously experienced gearbox failures, employing them in a series of case studies. The input parameters for the model were rotor (or generator) speed, power output, nacelle temperature, and generator cooling air temperature. They concluded that a model developed based on the operational conditions of one specific turbine could be successfully applied to other similar turbines situated in various locations within the same wind farm.

Focused on Lillgrund Wind Farm (see Figure 10), Dervilis et al. implemented an MLP network to predict the blade-loading response of wind turbines using power output data [88]. They proposed utilizing the regression model error as an indicator of anomalies in the structural response. The model was developed based on the results of numerical simulations of this wind farm previously presented by Creech et al. [89]. One potential application of these techniques was to examine the cascading effects of single turbine failure and optimize the layout of wind turbine arrays for reliability investigations.

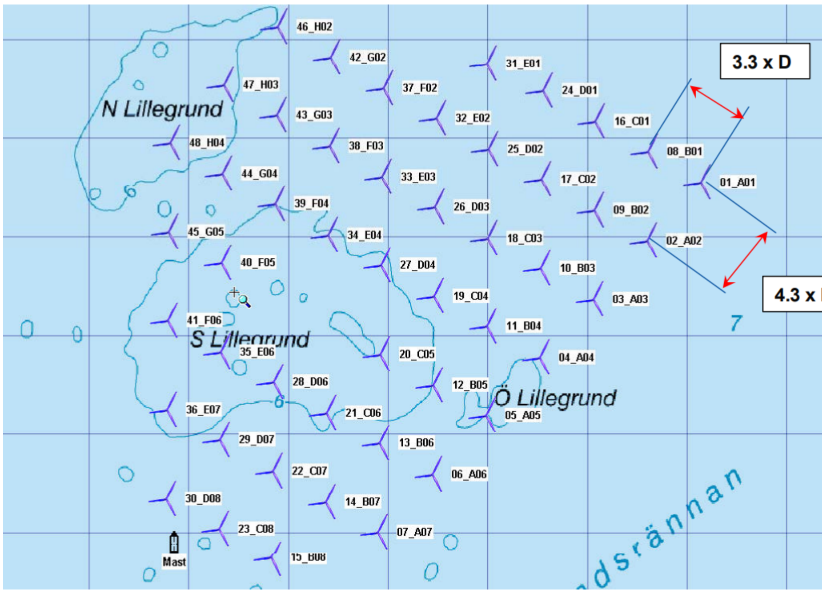


Figure 10. The layout of Lillgrund Wind Farm used for numerical simulations of the farm discussed in [88]. This information was obtained from the Lillgrund Wind Farm, owned and operated by Vattenfall [90].

Pattison et al. introduced an innovative maintenance architecture for offshore wind farms [91]. Their approach involved fault detection in a wind farm with over 100 turbines, updating survivability models, establishing a maintenance hierarchy, and optimizing schedules for maximum turbine availability and revenue. The solution included three main modules: Intelligent Condition Monitoring (ICM) analyzed SCADA and sensor data for mechanical features; the reliability and maintenance modeling (RMM) module modeled component survival using statistical analysis and ICM input; and the maintenance scheduling module created a context-enhanced maintenance schedule using RMM estimations. Twelve months of historical data and the random forest algorithm were used for model development. The overall goal was cost and downtime reduction through predictive maintenance.

In their study, Helsen et al. introduced a big-data approach aimed at gaining insights to predict component failure [92]. To achieve this, they required an integrated clean dataset encompassing all turbines in the fleet over an extended period. The researchers explored a multi-level monitoring approach that combined ML with advanced physics-based signal-processing techniques. To demonstrate the potential use of their approach, they conducted a multi-month measurement using accelerometers mounted on a wind turbine gearbox. However, it is important to note that although they showcased the potential of the proposed approach, they did not integrate actual ML techniques with the big data approach in their study. In a separate research, Li and Choung proposed using MLP networks to predict fatigue damages in the mooring lines of a floating offshore wind turbine platform [93]. To achieve this, they conducted dynamic analyses of the mooring lines using ANSYS in the time domain, considering various load cases involving a combination of the 5 MW baseline wind turbine [94] and a semi-submersible floating platform [95]. Tension histories were collected for all these load cases and subsequently transformed into tension range distributions. These outcomes served as the training data for the MLP. The network's input consisted of four variables: significant wave heights, zero-crossing periods, wave and wind directions, and current speeds. The researchers employed both time domain simulations and the MLP model to predict fatigue damage in the mooring lines for new load cases. Notably, the model demonstrated a strong capability in predicting fatigue damage in the mooring lines.

Kandukuri et al. conducted a study in which they extracted a total of 19 features based on the physics of failure, time, and frequency domain statistical parameters from the motor current Park's Vector components [96]. These features were then used as inputs for an SVM-based classifier. The primary aim of this research was to diagnose bearing faults in three-phase induction motors, specifically those suitable for applications in offshore wind farms. To verify the effectiveness of their proposed approach, the authors performed experiments using 600 test cases measured in a laboratory environment. Approximately 50% of the data was utilized for training the classifier, whereas the remaining data were used for validation purposes. The proposed SVM classifier achieved a classification accuracy of about 96% across all test cases.

In their study, Muller et al. utilized data collected from simulations of a hybrid offshore wind turbine model, which combined the DTU 10 MW reference turbine [97] with the SWE TripleSpar [98]. They employed the FAST software (v6.0) developed by NREL to implement an MLP for fatigue analysis of floating offshore wind turbines [99]. The model was trained using four environmental conditions, namely wind speed, turbulence intensity, wave height, and wave period, with a specific focus on the fatigue loads that occurred during power production. For training and validation purposes, 70% of the available data was utilized, whereas the remaining 30% was used for validation and testing. The study's findings indicated that a fully stochastic approach for fatigue assessment is feasible, highlighting the potential for reducing fatigue load estimates. Furthermore, Li et al. proposed an approach based on MLP to establish a mapping between the environmental conditions of catenary mooring lines of offshore wind turbines and fatigue damages [100]. For the case study, they utilized ANSYS AQWA to generate time domain hydrodynamic results for an 8 MW floating offshore wind turbine. To conduct their research, the authors collected oceanic data from the Jeju area offshore South Korea, which served as the input both for the ANSYS simulations and the MLP model training. The model's primary output was the tension distributions in each mooring line. To validate the effectiveness of their approach, the authors compared the fatigue damage predictions from the MLP models with those obtained through time-domain fatigue analyses. The results demonstrated that their MLP-based approach consistently predicted wide-banded fatigue damages with high accuracy.

In their study, Lu et al. conducted a comprehensive comparative analysis encompassing failure rates, maintenance costs, and repair times using data from 350 offshore wind farms aged between 3 and 10 years. The dataset included information from 5 to 10 wind farms located in Europe [101]. The statistics derived from this data are depicted in Figure 11. Next, the authors proposed the implementation of an MLP network to predict the life percentage of wind turbines by utilizing condition monitoring information. This involved leveraging a conditional failure probability value derived from the predicted failure-time distribution of the components. They sourced failure information and maintenance cost data for wind turbines from the relevant literature. The ultimate objective of their proposed technique was to optimize the maintenance cost for offshore wind turbines. Through a comparative study, the authors demonstrated the effectiveness of their method. Additionally, they performed an expense comparison between onshore and offshore wind turbines to emphasize the importance of adopting a condition-based maintenance strategy for offshore wind turbines.

Papatzimos et al. conducted a study at Teesside offshore wind farm, comprising 27 2.3 MW turbines, over a period of up to 2.5 years before a gearbox exchange [102,103]. They proposed a decision support framework integrating various supervised and unsupervised learning algorithms. Using SCADA and condition monitoring systems data from the faulty turbine, they employed statistical methods and ML techniques such as SVM, k-nearest neighbors (KNN), decision tree, logistic regression, and bagging ensemble to predict future failures. The results emphasized the significance of different data sources in gearbox failure diagnosis and early detection for Teesside offshore wind farm and similar turbines, with temperature readings serving as valuable early warning indicators for the gearbox's components. However, the analysis did not consider environmental temperature, which might have had a limited impact on the findings.

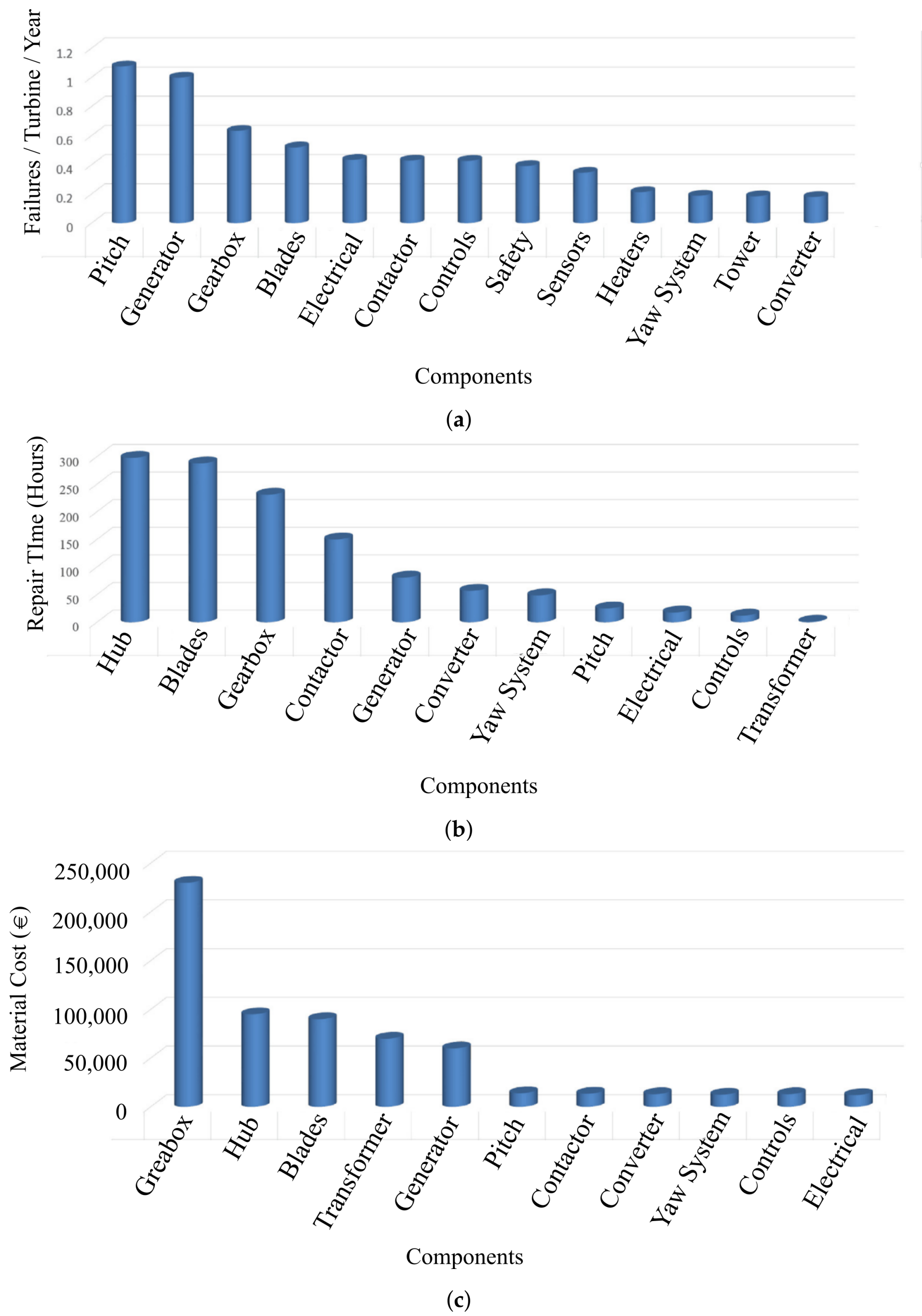


Figure 11. Statistics related to the maintenance of offshore wind turbine components: (**a**) failure rate, (**b**) repair time, and (**c**) maintenance cost [101].

A study published by Ziegler et al. presents a novel load monitoring concept for offshore wind turbines, requiring only strain gauges at one level of the support structure [104]. The method calculates damage equivalent loads from strain measurements and extrapolates them along a monopile using a regression algorithm. The authors verified the algorithm's performance using two consecutive months of measurement data from an offshore wind park, separately for two turbines with strain gauges installed at distances of approximately 15 m and 25 m. Both linear regression and nonlinear KNN approaches yielded similar results for total fatigue damage, but discrepancies were observed in individual 10 min damage equivalent loads, favoring the more robust KNN algorithm, especially for small loads. Unexpectedly, extrapolation results were better for the turbine with a larger distance between strain gauges, potentially indicating higher sensitivity to measurement noise than the distance between the gauges.

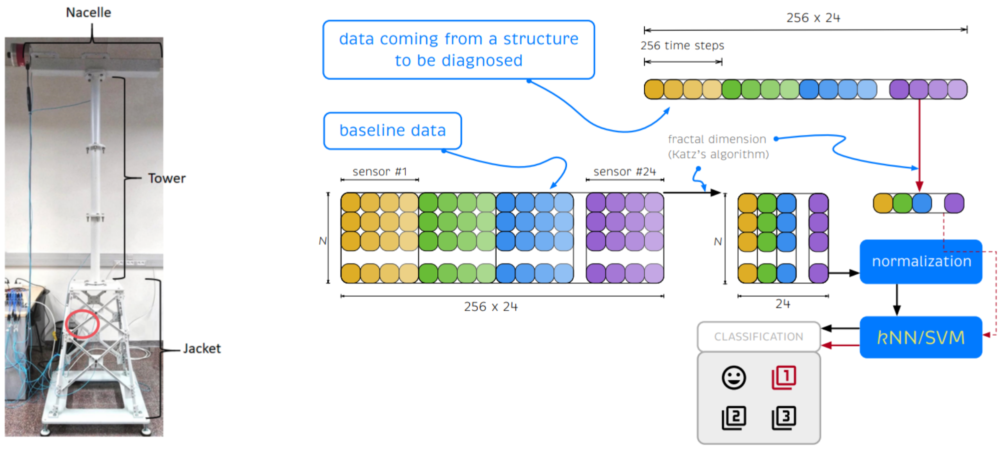
Cavazzini et al. introduced a modular wind turbine annual energy production loss prediction system, which addressed the lack of a reliable and rapid system for assessing energy losses and load variations in wind turbines due to blade surface damage [105]. The system combines data, CFD, and physics-informed models to predict the power curve of a turbine with damaged blade surfaces. It maps damaged blade geometries onto a database of airfoil geometries using a model developed with an MLP. The study demonstrated the system's capabilities on a damaged NREL 5 MW turbine, revealing an approximate 8% reduction in turbine annual energy production for the considered damage, consistent with other estimates in the literature.

Qiu et al. developed an improved neural network damage prediction method based on step-by-step identification for offshore wind turbine tower structures [106]. To map the relationship between modal parameters and damage degree of wind turbine towers, they utilized MLP with a genetic algorithm for global stochastic searching. They conducted experimental tests on simplified wind turbine models with steel cylinders with varying damage locations and degrees to verify the finite element models. The data, generated using the verified model in ABAQUS, were used to train and validate the proposed method. Results demonstrated that the step-by-step prediction method effectively reduced network complexity, improved prediction accuracy, and saved training time.

Langenkamper et al. introduced a visualization method called the "virtual twin" [107]. They employed three distinct image data collection techniques: first, a trained inspector/climber captured photos of specific parts using a hand-held digital camera; second, a remote-controlled UAV took images or videos of the wind turbine in a regular pattern, covering as much of the visually accessible surfaces as possible; and third, images were taken by a person from three or four different viewpoints around the wind turbine. For developing the ML model, they utilized Mask R-CNN object detection and instance segmentation [108]. The results demonstrated the model's efficacy in detecting and classifying patterns of interest, such as rust or coating damage. The authors concluded that by combining various imaging methods, deep learning computer vision algorithms, and visual data exploration by experienced users, the method holds the potential to overcome the bottleneck in data analysis, interpretation, and decision-making during future inspections of offshore wind platforms. In a different study, Wang et al. proposed a real-time hybrid method using wavelet noise reduction combined with decision tree algorithm for fault detection in deep-sea transmission lines of offshore wind farms [109]. The method was robust and immune to fault resistance, starting angle, and location, as shown in simulations with over 1600 fault data.

Hoxha et al. introduced a novel ML-based vibration-response-only strategy for real-time monitoring of the jacket-type foundation of an offshore wind turbine during its service [110]. To validate their approach, they conducted a series of laboratory tests on a down-scaled jacket wind turbine foundation, which measured 2.7 m in height (as depicted in Figure 12). These tests involved inducing different types of damage, encompassing four distinct structural states. The structure's vibration was measured using eight triaxial accelerometers, and a total of 100 experimental tests were performed at various turbine speed regions. For damage classification, they employed diverse classifiers, including KNN and SVM with different kernels. Figure 12 illustrates the overall data acquisition, processing, and damage classification procedure used in their study. The proposed model surpassed a 97% threshold for average accuracy.

Li and Zhang introduced a novel probabilistic long-term fatigue damage assessment approach, employing a copula model and surrogate model, for a spar-type floating wind turbine [111]. The study focused on the NREL 5 MW reference wind turbine installed on the OC3-Hywind spar-type floating platform, operating under realistic environmental conditions. To obtain the structural responses under different environmental conditions, coupled dynamic analyses were performed using the multiphysics code FAST. Six wind-and wave-related environmental parameters were utilized to accurately describe the on-site environmental conditions. An MLP network was established to predict the fatigue response for different combinations of these parameters. The proposed model exhibited great prediction accuracy for short-term fatigue damages in three structural components of the floating wind turbine; namely, the mooring lines, the tower base, and the tower top.



(a) (b)

Figure 12. (**a**) The laboratory test rig used by [110] showing also the location of the damaged bar by red circle, and (**b**) the flowchart summarizing the damage diagnose strategy proposed by [110].

Schröder et al. proposed a methodology to correlate loads with turbine reliability in wind farms by combining physical modeling and an MLP network [112]. The approach was demonstrated on an offshore wind farm, comparing performance, loads, and lifetime estimations against recorded main bearing failures from maintenance reports. Validating the estimated power against 10 min supervisory control and data acquisition power signals, the surrogate model showed an average error of 1.5% in predicting annual energy production. Unsurprisingly, turbines positioned at the wind farm's border, with higher expected annual energy production, were estimated to experience earlier main bearing failures. However, no definitive connection between load estimations and failure observations was established in this study. On the other hand, a work by Baboli et al. presents a model for optimal condition monitoring and anomaly detection in wind turbine key components [113]. The approach uses continuous temperature monitoring and a tailored MLP network to estimate normal conditions. By comparing real-time data, it detects abnormalities and predicts potential failures before they occur. The model's effectiveness was proven using real data from a German offshore wind farm.

Cho et al. presented a fault diagnosis approach centered around an MLP network structure, specifically designed to detect and diagnose predetermined faults in the hydraulic blade pitch system of a spar-type floating wind turbine [114]. The method employed a hybrid framework, combining the Kalman filter for fault detection and an artificial neural network for fault diagnosis. To assess its effectiveness, the proposed scheme underwent rigorous testing using case studies on the NREL 5 MW wind turbine model supported by a spar buoy floater (OC3-Hywind). In the experimental phase, researchers considered six specific types of faults, including biases and fixed outputs in pitch sensors, as well as excessive friction, slit-lock, wrong voltage, and circuit shortage in actuators. The results of the experiments demonstrated an overall accuracy rate of 97.5% for each type of fault.

Furthermore, Pandit et al. proposed a data-based Gaussian process for fault detection, which used additional operational parameters (rotor speed and blade pitch angle) to improve accuracy [115]. The model was validated against existing methods for early failure detection with a low false positive rate. Moreover, the proposed model was trained and validated using historical SCADA 10 min data of an operational variable pitch-regulated turbine manufactured by Siemens and rated at 2.5 MW. Comparative analysis showed that incorporating rotor speed into the fault detection algorithm significantly enhanced early fault detection capability. The new approach detected the first sign of yaw error in just 40 min, whereas the previous method without rotor speed took 1.5 h for the same detection. Additionally, Trizoglou et al. proposed a data-driven approach using the existing SCADA system and ML techniques to design a normal behavior model for fault detection in a 7 MW offshore wind turbine [116]. They compared an XGBoost ensemble model with an LSTM deep learning neural network, with the XGBoost model outperforming the LSTM in accuracy and training time. The model could detect faults and failures in generator subsystems.

Feijóo et al. introduced an innovative autoencoder neural network model in their study [117]. Their methodology encompassed the following steps: simulating wind excitation with Gaussian white noise, collecting wind turbine data using accelerometers, preprocessing raw data (including cleaning, normalization, feature engineering, and addressing imbalanced data), and employing an autoencoder neural network for damage classification. To validate their approach, experimental laboratory tests were conducted using a scaled model similar to a prior study [110]. Figure 13 visually outlines their procedure. Applying this methodology, they evaluated 5 mm crack damage across various jacket wind turbine structure bars and wind excitation levels. The model achieved an accuracy of 99.8%, a precision of 99.7%, and a recall of 100% in the controlled laboratory conditions.

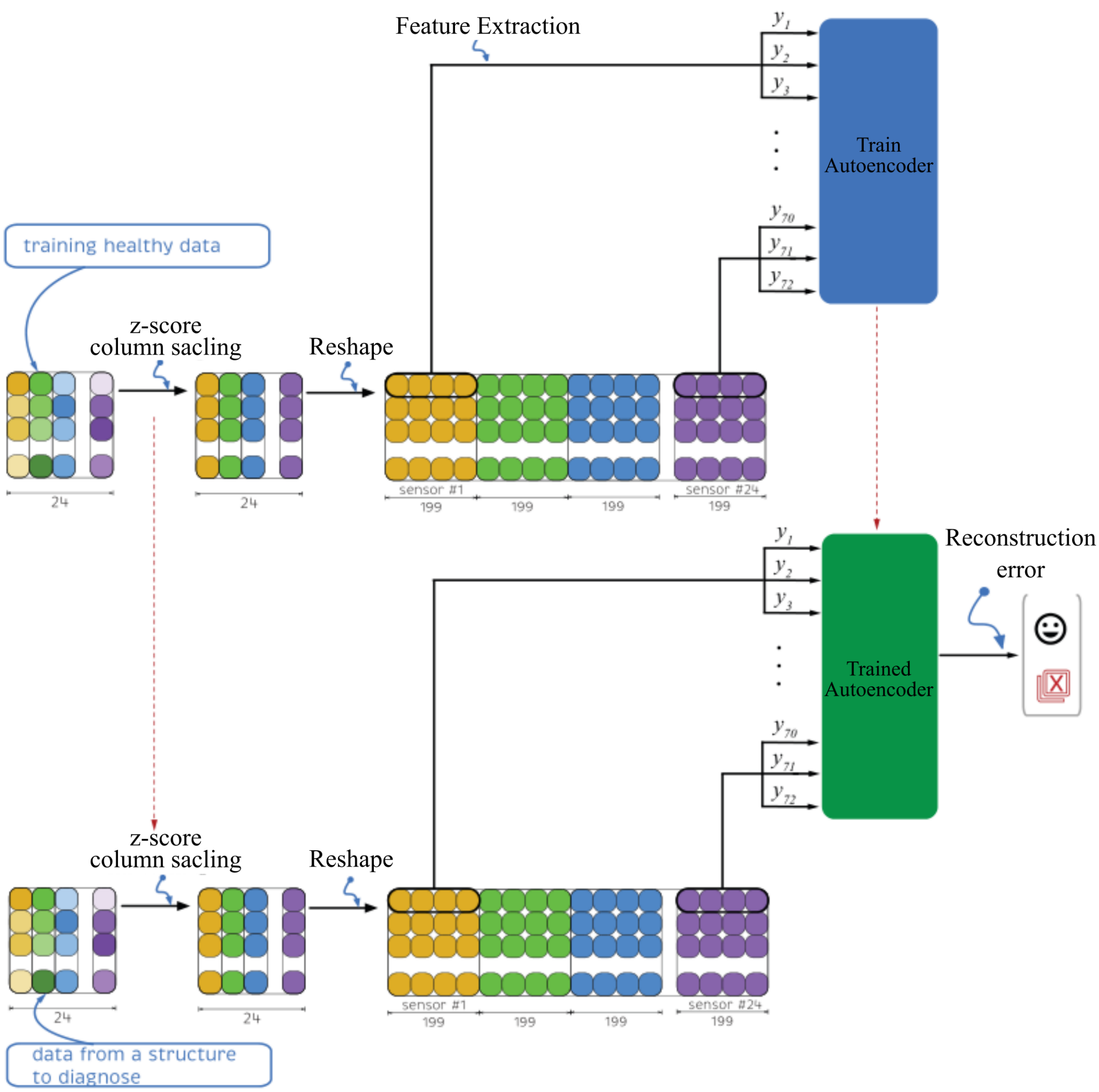


Figure 13. The health monitoring procedure proposed by Feijóo et al. [117].

Roelofs et al. introduced ARCANA, an innovative autoencoder-based method for pinpointing root causes behind anomalies detected by autoencoders [118]. The intention was to enhance the interpretability of ML model outputs, making them more human-friendly. The method employs an optimization algorithm to isolate input features responsible for triggering anomalies in the autoencoder model. The study employed the Open Wind Farm dataset from EDP [119], encompassing SCADA data and a failure logbook for five 2 MW wind turbines. These data involve 55 measurements, such as wind speed, generator temperatures, wind direction, and pitch angles, recorded as 10 min averages. The authors concluded that ARCANA simplifies anomaly cause identification by highlighting feature contributions. However, interpreting results and deducing underlying failures or environmental changes still requires domain knowledge.

Tang et al. introduced a feature extraction technique founded on mathematical morphology for categorizing internal transient overvoltages in offshore wind farms [120,121]. This approach involves a multi-scale mathematical morphology to discern the high-/low-frequency aspects of transient overvoltages. Subsequently, a high-frequency feature and a high-/low-frequency energy ratio feature are developed as identifying traits. The feature-rich framework is harnessed alongside an SVM to differentiate between diverse internal transient overvoltage types. The efficacy of the proposed feature extraction was validated using simulations and empirical results. Outcomes demonstrated that the proposed approach effectively distinguishes and classifies various internal transient overvoltage categories.

Yeter and colleagues introduced a nonlinear corrosion model to tackle offshore wind turbine life assessment [122]. The proposed model accounts for changing environmental and operational factors, as well as the impact of fractures on corrosion; although the study initially focused on a single offshore wind asset, its findings were extended to encompass various offshore wind farms. The researchers also conducted an economic analysis, combining revenue projections, operating costs, and factors like lifespan extension and discount rate. The life-extension evaluation's outcomes were graphed in a risk–return diagram, and an unsupervised ML k-means clustering algorithm was employed to categorize the life-extension projects. From the clustering results, the authors suggested leveraging operational intensity and hedging options to manage projects across different clusters based on risk preferences and time during the life-extension phase.

Furthermore, a study conducted by Santos et al. focused on determining the minimal instrumentation required for accurate assessment of fatigue damage in offshore wind turbines [123]. The SCADA data were transformed into 10 min interval features, resulting in 430 potential features. The authors compared feature selection algorithms to choose the most cost-effective sensor setup. The selected features were used as input for a second MLP that predicts tower fore-aft bending moment damage equivalent loads, a fatigue-related metric. The best-performing setups yielded accurate damage-equivalent load predictions with around 1% mean absolute error.The study concluded by applying the MLP-based method to a farm-wide scenario and investigated outlier behavior causes.

Xu et al. developed a multi-scale deep convolutional neural network model coupled with an attention mechanism to identify and quantify damages in complex tendons of multibody floating wind turbines [124]. This approach was evaluated using the TELWIND FOWT numerical framework, integrating FAST and ANSYS AQWA (F2A) for comprehensive aerohydro-servo-elastic analysis. The results showed an accuracy of 80%. The authors then further enhanced the approach by incorporating the Majority Weighted Voting rule, borrowed from the particle swarm optimization concept, to minimize false alarms and optimize collaborative diagnostics. Figure 14 illustrates the procedural workflow with the Majority Weighted Voting rule. This integration boosted diagnostic precision, with the F1 index improving from 90% for single-sensor analysis and 84% for multi-sensor results to a 94%.

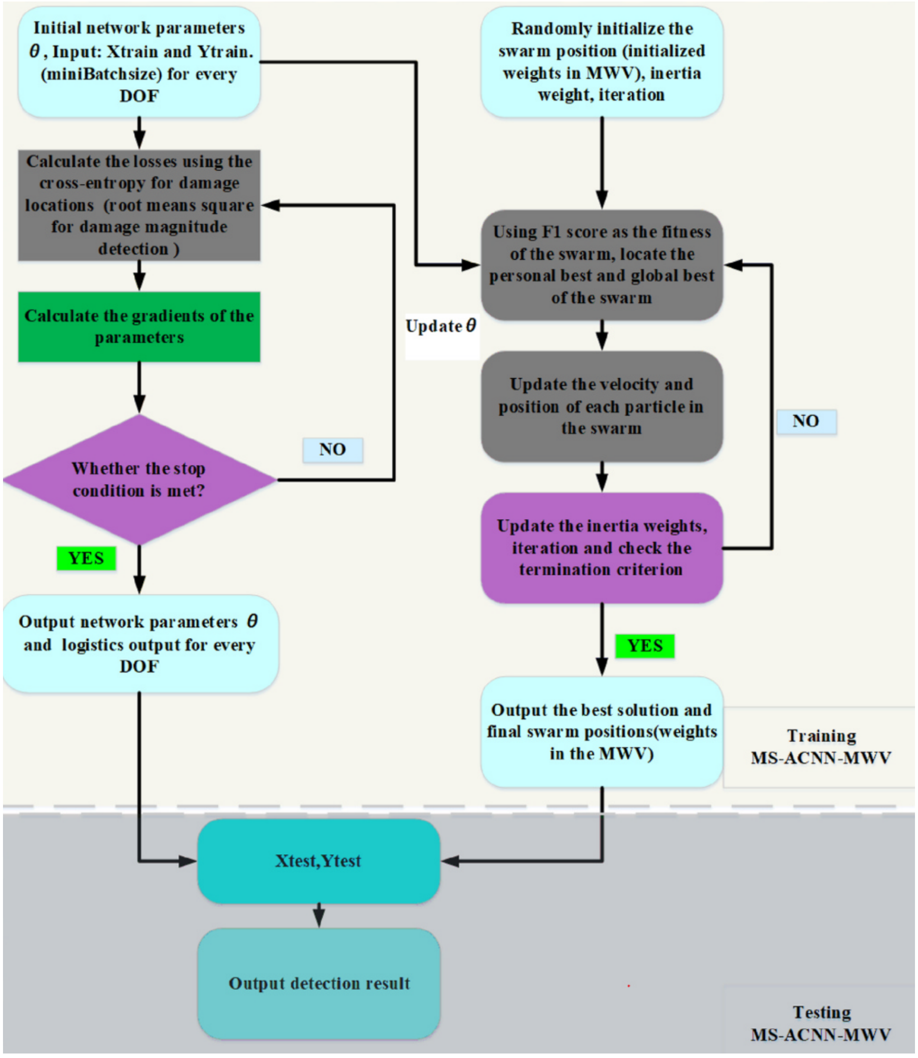


Figure 14. The health monitoring procedure proposed by Xu et al. [124]. Here, MWV stands for the Majority Weighted Voting and MS-ACNN-MWV represents the procedure introduced by the authors in their work.

Eze et al. introduced an ML-based methodology for the detection and prediction of faults in deep offshore subsea cables [125]. Their approach employed a combination of algorithms including extreme gradient-boosting ensemble, Gaussian naive Bayes, and decision tree models. The research data were obtained from Intelligent Electronic Devices installed at both ends of a power transmission system connecting a wind farm to an onshore station. The outcomes demonstrated that both XGBoost and decision tree algorithms exhibited optimal performance, achieving average accuracy, AUROC (a graphical representation commonly used for classification model assessment [126]), and MCC (a binary classification performance metric [127]) values of 99%, 98%, and 100%, respectively. In another study, Encalada-Davila et al. proposed a comprehensive approach involving a semi-supervised model based on a gated recurrent neural network for early detection of main bearing faults in faulty wind turbines [128]. They employed an exponentially weighted moving average technique to improve accuracy and reduce false alarms. The dataset used in the research covered 18 wind turbines with specific parameters such as the mean main bearing temperature, mean generator bearing temperature, mean gearbox oil temperature, and mean primary wind speed, gathered from 2015 to 2018. The model demonstrated robustness, accurately predicting faults two months in advance without generating false alarms.

Attallah and colleagues proposed an ML method to detect interturn short-circuit faults in induction rotating machines [129]. The dataset included thermographic images used in prior studies for fault diagnosis [130,131]. The procedure adjusts image sizes, augments them, constructs eight pre-trained CNNs for feature extraction, fuses features, selects impactful ones, and classifies faults for health, type, location, and severity. For the classification analysis, the authors used linear discriminate analysis, SVM, KNN, random forest, naive Bayes, and decision tree, where the first three could deliver the most accurate results. In another study, Saleh et al. combined advanced Petri net modeling with reinforcement learning, resulting in a versatile methodology applicable to optimizing various Petri net models [132]. The method, called intelligent Petri net, fuses reinforcement learning techniques with Petri net principles. The effectiveness of this approach was demonstrated through a practical case study focused on wind turbine operation and maintenance, leveraging real-world operation and degradation data. The method could achieve optimal condition-based maintenance with an availability rate of 99.4% while simultaneously minimizing operational costs.

Sun et al. tackled the fatigue issues in floating offshore wind turbine moorings due to prolonged exposure to wind, waves, and currents [133]. They introduced a CNN-t-distribution Stochastic Neighbor Embedding model to automatically detect damage severity in these systems. This involved analyzing platform bow rocking dynamics through deep learning and chaos theory, focusing on creep occurrence and its location within the mooring. Their study centered around a 5 MW floating wind turbine on the ITI Energy Barge platform developed by NREL. Specifically, the CNN structure shown in Figure 15 was used to assess mooring dynamics. The authors found that during mooring creep, the platform's response experienced minimal changes, but the response increased significantly after mooring failure. They concluded that the bow rocking response was highly sensitive, particularly observing that the yaw response showed the most sensitivity to structural damage.

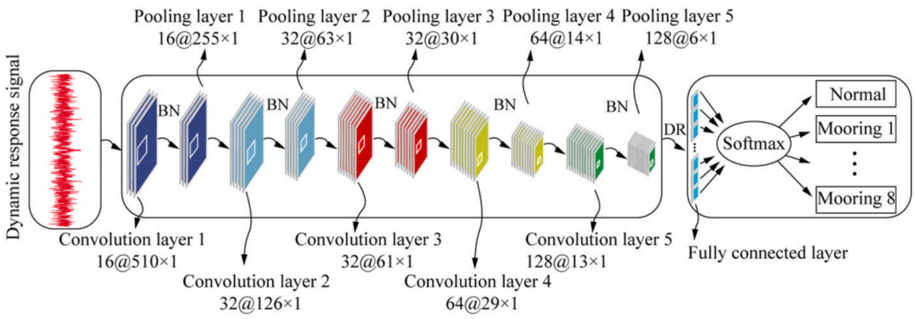


Figure 15. The architecture of the CNN used by [133] as part of their framework for damage detection in floating offshore wind turbine mooring systems.

Table 3 provides a list of the literature covered in this section, along with the corresponding ML techniques employed and concise summaries of the research conducted.

First and foremost, there is a pressing need for research that seamlessly integrates data from diverse sources, going beyond the confines of SCADA data to encompass environmental factors, sensor readings, and remote monitoring systems. Such integration must be complemented by the development of advanced data fusion techniques that can unravel complex interdependencies within the data.

Moreover, the industry stands to benefit significantly from models that can generalize their findings across various wind farms and turbine models, enhancing their adaptability to different offshore environments. The advent of Explainable AI is also paramount, particularly in providing transparent and interpretable insights to guide maintenance decision-making. Real-time monitoring and predictive maintenance systems should be explored further to enable continuous assessment of turbine health and on-the-fly maintenance scheduling. Environmental factors and load analysis require more in-depth investigation to comprehend their impact on turbine reliability. Additionally, ensuring data quality and noise reduction, conducting comprehensive cost-benefit analyses, addressing cybersecurity concerns, and developing adaptive models that learn and adapt over time are all critical aspects of future research in this field.

Table 3. Summary of the work reviewed in this section, focused on Health Monitoring and Maintenance.

Auth. and Cit.	ML Technique	Summary
Hameed et al. [86]	Self-Organizing Maps, MLP	Used self-organizing maps and MLP networks to efficiently plan and execute maintenance and repair tasks.
Wang and Infield [87]	Nonlinear State Estimation, MLP	The models used for gearbox failure detection in wind turbines using historical data.
Dervilis et al. [88]	MLP	Prediction of blade-loading response based on power output data.
Pattison et al. [91]	Random Forest	Modular maintenance architecture for offshore wind farms.
Helsen et al. [92]	-	Component failure prediction in wind turbines using a big-data approach. Did not integrate actual ML techniques.
Li and Choung [93]	MLP	Fatigue damage prediction in mooring lines of floating offshore wind turbines.
Kandukuri et al. [96]	SVM	Bearing fault diagnosis in three-phase induction motors for offshore wind farms using SVM.
Muller et al. [99]	MLP	Fatigue analysis of floating wind turbines using MLP networks.
Li et al. [100]	MLP	Established a mapping between the environmental conditions of catenary mooring lines of offshore wind turbines and fatigue damages.
Lu et al. [101]	MLP	Prediction of wind turbine life percentage using condition monitoring information.
Papatzimos et al. [102,103]	SVM, Decision Tree, KNN, Logistic Regression, Bagging Ensemble	Integration of supervised and unsupervised learning for gearbox failure prediction.
Ziegler et al. [104]	Linear Regression, Nonlinear KNN	Load monitoring concept for wind turbines using strain gauges and regression algorithms.
Cavazzini et al. [105]	MLP	Prediction of power curve of turbines with damaged blade surfaces using MLP and CFD models.
Qiu et al. [106]	MLP	Prediction of damage in wind turbine towers using MLP with genetic algorithm.
Langenkamper et al. [107]	Mask R-CNN	Visual inspection of wind turbines using deep learning computer vision algorithms.
Wang et al. [109]	Decision Tree	Detection of faults in deep-sea transmission lines of offshore wind farms using wavelet noise reduction and decision trees.
Hoxha et al. [110]	KNN, SVM	Vibration-based monitoring for offshore wind turbine foundation damage detection.
Li and Zhang [111]	MLP	Probabilistic fatigue damage assessment in floating wind turbines using MLP-based approach.
Schröder et al. [112]	MLP	Correlation of loads with turbine reliability using physical modeling and MLP network.
Baboli et al. [113]	MLP	Condition monitoring and anomaly detection in wind turbine components using temperature sensors and MLP network.
Cho et al. [114]	MLP	Fault detection and diagnosis in hydraulic blade pitch system using a hybrid framework with Kalman filter and artificial neural network.
Pandit et al. [115]	MLP with Gaussian Process	Improved fault detection in wind turbines incorporating rotor speed and blade pitch angle.

Table 3. *Cont.*

Auth. and Cit.	ML Technique	Summary
Trizoglou et al. [116]	XGBoost Ensemble, LSTM	Fault detection in wind turbine generator subsystems using SCADA data and ML models.
Feijóo et al. [117]	Autoencoders	Damage classification in wind turbine structures using autoencoders.
Roelofs et al. [118]	Autoencoders	Interpretable method for anomaly detection using autoencoders.
Tang et al. [120,121]	SVM	Classification of internal transient overvoltages using mathematical morphology features and SVM.
Yeter et al. [122]	K-means Clustering	Life assessment and risk management for wind turbines.
Santos et al. [123]	MLP	Cost-effective sensor setups selection for accurate fatigue damage prediction.
Xu et al. [124]	CNN, Majority Weighted Voting	Diagnosing complex tendon damages in multibody floating wind turbines using deep CNNs and Majority Weighted Voting.
Eze et al. [125]	Extreme Gradient-Boosting Ensemble, Gaussian Naive Bayes, Decision Tree	Fault detection in subsea cables with ensemble learning.
Encalada-Davila et al. [128]	Gated Recurrent Unit	Detection of main bearing faults in wind turbines using a semi-supervised model.
Attallah et al. [129]	CNN, Linear Discriminate Analysis, SVM, KNN, Random Forest, Naïve Bayes, Decision Tree	Detection of interturn short-circuit faults in rotating machines.
Saleh et al. [132]	Reinforcement Learning	Combining Petri net modeling with reinforcement learning for wind turbine operation and maintenance optimization.
Sun et al. [133]	CNN	Detection of creep and mooring damage in floating wind turbines using CNNs.

6. Prospective

The application of ML techniques in the implementation of offshore wind turbines has opened up a new era of possibilities. Researchers have made significant efforts in harnessing the power of ML to enhance various aspects of offshore wind energy systems. Structural health monitoring and maintenance have been greatly improved through the predictive capabilities of ML, allowing for accurate identification of potential failures and enabling precision maintenance strategies. Moreover, ML has played a pivotal role in optimizing wind farm layouts, power production forecasting, and wake effects mitigation, leading to increased energy generation efficiency. The integration of ML-driven control systems has shown a great potential for improving the operational strategies of offshore wind farms, further enhancing their overall performance and energy output. Finally, climatic data prediction and environmental studies have benefited from ML's predictive capabilities, aiding in the optimization of power generation and the assessment of environmental impacts.

As we look ahead, several promising research directions emerge in the domain of implementing ML techniques for offshore wind turbines:

- Advanced Predictive Maintenance: Further advancements can be made in the realm of predictive maintenance by integrating real-time data from various sensors and sources. Research could focus on developing comprehensive models that not only predict failures but also recommend optimal maintenance schedules and strategies.
- Intelligent Control Systems: ML's potential in control strategies is vast. Future research might delve into developing more intricate control algorithms that optimize the entire wind farm's operation, considering multiple variables such as weather conditions, power demand, and energy storage.

- Multi-Physics and Hybrid ML Modeling: Integrating ML with multi-physics modeling could enhance the accuracy of predictions related to structural behavior, fatigue, and performance. Combining ML's data-driven insights with physics-based models can provide a more holistic understanding of turbine dynamics. Further, combining the strengths of ML with physics-based models can lead to hybrid models that capture both empirical data and underlying physical principles. This can lead to more accurate and adaptable models that evolve with changing operational conditions.
- Enhanced Environmental Impact Assessment: ML can contribute significantly to environmental impact assessments, not just for marine ecosystems but also for interactions with other industries such as fishing. Future research might focus on developing more precise models that predict and mitigate the ecological consequences of offshore wind farms.
- Fusion of Data Types: The fusion of various data types, such as satellite imagery, weather forecasts, and oceanographic data, can lead to more accurate predictions. Future research could explore innovative techniques for combining these data sources effectively.
- Uncertainty Quantification: Addressing uncertainties in ML models, especially in power curve modeling and wake effects prediction, is crucial. Future studies could focus on developing methods to quantify and manage uncertainties, leading to more robust and reliable predictions.
- Explainability and Interpretability: As ML models become more complex, ensuring their interpretability and explainability becomes essential. Research could be directed towards developing techniques that provide insights into how these models arrive at their predictions, enhancing trust and adoption.
- Real-Time Decision Support: ML can play a pivotal role in providing real-time decision support for offshore operations. Future research might focus on developing systems that analyze vast amounts of data in real time and provide actionable insights for operators to optimize performance.
- Socio-Economic Impact Analysis: The expansion of offshore wind energy systems impacts not only the environment but also local economies and societies. Future research could delve into comprehensive socio-economic impact assessments, considering job creation, community development, and energy affordability. ML-based models can be implemented for the analysis and prediction of these potential impacts, especially resulting in the provision of insights for taking mitigating steps in the case of negative effects.

7. Conclusions

The integration of machine learning techniques in offshore wind turbine implementation has the potential to bring transformative changes to the field. The ongoing research in predictive maintenance, control strategies, multi-physics modeling, environmental impact assessment, and other areas holds immense potential to further optimize offshore wind energy systems. As we navigate these exciting developments, the collaboration between experts from various disciplines will be essential in shaping the future of offshore renewable energy.

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References

1. Kleist, N.; Enns, K. USGS BiblioSearch. 2022. Available online: https://code.usgs.gov/fort/bibliosearch/-/tree/v1.0.0 (accessed on 15 May 2023).
2. Rose, M.E.; Kitchin, J.R. Pybliometrics: Scriptable bibliometrics using a Python interface to Scopus. *SoftwareX* **2019**, *10*, 100263. [CrossRef]
3. Flores, P.; Tapia, A.; Tapia, G. Application of a control algorithm for wind speed prediction and active power generation. *Renew. Energy* **2005**, *30*, 523–536. [CrossRef]
4. Dankert, H.; Horstmann, J. Wind measurements at FINO-I using marine radar-image sequences. In Proceedings of the International Geoscience and Remote Sensing Symposium, Seoul, Republic of Korea, 25–29 July 2005; Volume 7, p. 4777.
5. Ma, Y.; Sclavounos, P.D.; Cross-Whiter, J.; Arora, D. Wave forecast and its application to the optimal control of offshore floating wind turbine for load mitigation. *Renew. Energy* **2018**, *128*, 163–176. [CrossRef]
6. Kulkarni, S.; Deo, M.; Ghosh, S. Framework for assessment of climate change impact on offshore wind energy. *Meteorol. Appl.* **2018**, *25*, 94–104. [CrossRef]
7. Niemi, J.; Tanttu, J.T. Deep learning case study for automatic bird identification. *Appl. Sci.* **2018**, *8*, 2089. [CrossRef]
8. Niemi, J.; Tanttu, J.T. Automatic bird identification for offshore wind farms. In *Wind Energy and Wildlife Impacts: Balancing Energy Sustainability with Wildlife Conservation*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 135–151.
9. Yan, C.; Pan, Y.; Archer, C.L. A general method to estimate wind farm power using artificial neural networks. *Wind Energy* **2019**, *22*, 1421–1432. [CrossRef]
10. Keivanpour, S.; Ramudhin, A.; Ait Kadi, D.; Kimiagari, S. Global offshore wind energy deployment: A geo-clustering approach. *Int. J. Green Energy* **2019**, *16*, 1054–1060. [CrossRef]
11. Zha, T.; Xie, L.; Chang, J. Wind farm water area path planning algorithm based on A and reinforcement learning. In Proceedings of the 2019 5th International Conference on Transportation Information and Safety (ICTIS), Liverpool, UK, 14–17 July 2019; pp. 1314–1318.
12. Lin, T.H.; Yang, H.T.; Huang, J.M.; Yao, C.J.; Lien, Y.S.; Wang, P.J.; Hu, F.Y. Evaluating changes in the marine soundscape of an offshore wind farm via the machine learning-based source separation. In Proceedings of the 2019 IEEE Underwater Technology (UT), Kaohsiung, Taiwan, 16–19 April 2019; pp. 1–6.
13. Friedland, K.D.; Methratta, E.T.; Gill, A.B.; Gaichas, S.K.; Curtis, T.H.; Adams, E.M.; Morano, J.L.; Crear, D.P.; McManus, M.C.; Brady, D.C. Resource occurrence and productivity in existing and proposed wind energy lease areas on the Northeast US Shelf. *Front. Mar. Sci.* **2021**, *8*, 629230. [CrossRef]
14. Stelzenmüller, V.; Gimpel, A.; Haslob, H.; Letschert, J.; Berkenhagen, J.; Brüning, S. Sustainable co-location solutions for offshore wind farms and fisheries need to account for socio-ecological trade-offs. *Sci. Total Environ.* **2021**, *776*, 145918. [CrossRef]
15. Van Der Reijden, K.J.; Govers, L.L.; Koop, L.; Damveld, J.H.; Herman, P.M.; Mestdagh, S.; Piet, G.; Rijnsdorp, A.D.; Dinesen, G.E.; Snellen, M.; et al. Beyond connecting the dots: A multi-scale, multi-resolution approach to marine habitat mapping. *Ecol. Indic.* **2021**, *128*, 107849. [CrossRef]
16. Tapoglou, E.; Forster, R.M.; Dorrell, R.M.; Parsons, D. Machine learning for satellite-based sea-state prediction in an offshore windfarm. *Ocean Eng.* **2021**, *235*, 109280. [CrossRef]
17. Masoumi, M. Ocean data classification using unsupervised machine learning: Planning for hybrid wave-wind offshore energy devices. *Ocean Eng.* **2021**, *219*, 108387. [CrossRef]
18. Hoeser, T.; Feuerstein, S.; Kuenzer, C. DeepOWT: A global offshore wind turbine data set derived with deep learning from Sentinel-1 data. *Earth Syst. Sci. Data* **2022**, *14*, 4251–4270. [CrossRef]
19. Hoeser, T.; Kuenzer, C. SyntEO: Synthetic dataset generation for earth observation and deep learning–Demonstrated for offshore wind farm detection. *ISPRS J. Photogramm. Remote Sens.* **2022**, *189*, 163–184. [CrossRef]
20. Nguyen, T.h.; Toubeau, J.F.; De Jaeger, E.; Vallée, F. Adequacy assessment using data-driven models to account for aerodynamic losses in offshore wind generation. *Electr. Power Syst. Res.* **2022**, *211*, 108599. [CrossRef]
21. Mikami, K.; Kazama, K.; Kazama, M.T.; Watanuki, Y. Mapping the collision risk between two gull species and offshore wind turbines: Modelling and validation. *J. Environ. Manag.* **2022**, *316*, 115220. [CrossRef]
22. Xu, Z.; Zhang, H.; Wang, Y.; Wang, X.; Xue, S.; Liu, W. Dynamic detection of offshore wind turbines by spatial machine learning from spaceborne synthetic aperture radar imagery. *J. King Saud Univ.-Comput. Inf. Sci.* **2022**, *34*, 1674–1686. [CrossRef]
23. Roy, S.; Sentchev, A.; Fourmentin, M.; Augustin, P. Machine Learning and Deterministic Methods for Detection Meteorological Phenomena from Ground Measurements: Application for Low-Level Jet and Sea-Breeze Identification in Northern France. *Atmosphere* **2022**, *13*, 1873. [CrossRef]
24. Marin, R.; Ciortan, S.; Rusu, E. A novel method based on artificial neural networks for selecting the most appropriate locations of the offshore wind farms. *Energy Rep.* **2022**, *8*, 408–413. [CrossRef]
25. Clare, M.C.; Piggott, M.D. Bayesian neural networks for the probabilistic forecasting of wind direction and speed using ocean data. In *Trends in Renewable Energies Offshore*; CRC Press: Boca Raton, FL, USA, 2022; pp. 533–540.
26. Yu, Y.; Wu, Y.; Zhao, L.; Li, X.; Li, Y. Ultra Short Term Power Prediction of Offshore Wind Power Based on Support Vector Machine Optimized by Improved Dragonfly Algorithm. *Distrib. Gener. Altern. Energy J.* **2022**, *37*, 465–484. [CrossRef]
27. Dong, H.; Xie, J.; Zhao, X. Wind farm control technologies: From classical control to reinforcement learning. *Prog. Energy* **2022**, *4*, 032006. [CrossRef]

28. Lee, K.H.; Jun, S.O.; Pak, K.H.; Lee, D.H.; Lee, K.W.; Park, J.P. Numerical optimization of site selection for offshore wind turbine installation using genetic algorithm. *Curr. Appl. Phys.* **2010**, *10*, S302–S306. [CrossRef]
29. Pappala, V.S.; Nakawiro, W.; Erlich, I. Predictive optimal control of wind farm reactive sources. In Proceedings of the IEEE PES T&D 2010, New Orleans, LA, USA, 19–22 April 2010; pp. 1–7.
30. Japar, F.; Mathew, S.; Narayanaswamy, B.; Lim, C.M.; Hazra, J. Estimating the wake losses in large wind farms: A machine learning approach. In Proceedings of the ISGT 2014, Washington, DC, USA, 19–22 February 2014; pp. 1–5.
31. Barthelmie, R.J.; Frandsen, S.T.; Rathmann, O.; Hansen, K.S.; Politis, E.S.; Prospathopoulos, J.; Cabezón Martínez, D.; Rados, K.; Van Der Pijl, S.; Schepers, J.; et al. Flow and wakes in large wind farms in complex terrain and offshore. In Proceedings of the European Wind Energy Conference & Exhibition (EWEC 2008), Brussels, Belgium, 31 March–3 April 2008.
32. Antoniadou, I.; Dervilis, N.; Papatheou, E.; Maguire, A.; Worden, K. Aspects of structural health and condition monitoring of offshore wind turbines. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2015**, *373*, 20140075. [CrossRef] [PubMed]
33. Rodrigues, S.; Pinto, R.T.; Bauer, P.; Brys, T.; Nowé, A. Online distributed voltage control of an offshore MTDC network using reinforcement learning. In Proceedings of the 2015 IEEE Congress on Evolutionary Computation (CEC), Sendai, Japan, 25–28 May 2015; pp. 1769–1775.
34. Ou, T.C.; Lu, K.H.; Huang, C.J. Improvement of transient stability in a hybrid power multi-system using a designed NIDC (Novel Intelligent Damping Controller). *Energies* **2017**, *10*, 488. [CrossRef]
35. Fischetti, M.; Fraccaro, M. Using OR+ AI to predict the optimal production of offshore wind parks: A preliminary study. In Proceedings of the Optimization and Decision Science: Methodologies and Applications: ODS, Sorrento, Italy, 4–7 September 2017; Springer: Berlin/Heidelberg, Germany, 2017; pp. 203–211.
36. Fischetti, M.; Fraccaro, M. Machine learning meets mathematical optimization to predict the optimal production of offshore wind parks. *Comput. Oper. Res.* **2019**, *106*, 289–297. [CrossRef]
37. Lu, K.H.; Chen, H.C.; Su, Y.; Xu, Q. Design of an Intelligent Damping Controller of STATCOM with HVDC for Large Offshore Wind Farm. *J. Mar. Sci. Technol.* **2018**, *26*, 10.
38. Noppe, N.; Weijtjens, W.; Devriendt, C. Modeling of quasi-static thrust load of wind turbines based on 1 s SCADA data. *Wind Energy Sci.* **2018**, *3*, 139–147. [CrossRef]
39. Lu, K.H.; Hong, C.M.; Xu, Q. Recurrent wavelet-based Elman neural network with modified gravitational search algorithm control for integrated offshore wind and wave power generation systems. *Energy* **2019**, *170*, 40–52. [CrossRef]
40. Häfele, J.; Gebhardt, C.G.; Rolfes, R. A comparison study on jacket substructures for offshore wind turbines based on optimization. *Wind Energy Sci.* **2019**, *4*, 23–40. [CrossRef]
41. Yin, X.; Zhao, X. Big data driven multi-objective predictions for offshore wind farm based on machine learning algorithms. *Energy* **2019**, *186*, 115704. [CrossRef]
42. Niayifar, A.; Porté-Agel, F. A new analytical model for wind farm power prediction. *J. Phys. Conf. Ser.* **2015**, *625*, 012039. [CrossRef]
43. Pillai, A.C.; Thies, P.R.; Johanning, L. Mooring system design optimization using a surrogate assisted multi-objective genetic algorithm. *Eng. Optim.* **2018**, *51*, 1370–1392. [CrossRef]
44. Li, F.; Zhou, L.; Li, L.; Wang, H.; Guo, H.; Liang, Y. Individual blade pitch control for floating wind turbine based on rbf-smc. In Proceedings of the 2019 IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2), Changsha, China, 8–10 November 2019; pp. 949–953.
45. Shin, H. Model test of the OC3-Hywind floating offshore wind turbine. In Proceedings of the ISOPE International Ocean and Polar Engineering Conference, Maui, HI, USA, 19–24 June 2011; ISOPE: Mountain View, CA, USA, 2011; p. ISOPE–I.
46. Penner, N.; Grießmann, T.; Rolfes, R. Monitoring of suction bucket jackets for offshore wind turbines: Dynamic load bearing behaviour and modelling. *Mar. Struct.* **2020**, *72*, 102745. [CrossRef]
47. Jonkman, J. OpenFAST: An Open Source Wind Turbine Simulation Tool. Available online: https://www.nrel.gov/wind/nwtc/openfast.html (accessed on 2 May 2023).
48. Vijayakumar, G.; Yellapantula, S.; Branlard, E.; Ananthan, S. Enhancement of unsteady and 3D aerodynamics models using machine learning. *J. Phys. Conf. Ser.* **2020**, *1452*, 012065. [CrossRef]
49. De Brabanter, K.; De Brabanter, J.; Suykens, J.A.; De Moor, B. Approximate confidence and prediction intervals for least squares support vector regression. *IEEE Trans. Neural Netw.* **2010**, *22*, 110–120. [CrossRef]
50. Pandit, R.; Kolios, A. SCADA data-based support vector machine wind turbine power curve uncertainty estimation and its comparative studies. *Appl. Sci.* **2020**, *10*, 8685. [CrossRef]
51. Zhou, J.; Cui, G.; Hu, S.; Zhang, Z.; Yang, C.; Liu, Z.; Wang, L.; Li, C.; Sun, M. Graph neural networks: A review of methods and applications. *AI Open* **2020**, *1*, 57–81. [CrossRef]
52. Yu, M.; Zhang, Z.; Li, X.; Yu, J.; Gao, J.; Liu, Z.; You, B.; Zheng, X.; Yu, R. Superposition graph neural network for offshore wind power prediction. *Future Gener. Comput. Syst.* **2020**, *113*, 145–157. [CrossRef]
53. Dong, H.; Zhang, J.; Zhao, X. Intelligent wind farm control via deep reinforcement learning and high-fidelity simulations. *Appl. Energy* **2021**, *292*, 116928. [CrossRef]
54. Fleming, P.; Gebraad, P.; Churchfield, M.; Lee, S.; Johnson, K.; Michalakes, J.; van Wingerden, J.W.; Moriarty, P. *SOWFA+ Super Controller User's Manual*; Technical Report; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2013.
55. Developers, T. *TensorFlow*; Zenodo: Honolulu, HI, USA, 2022.

56. Lian, J.; Zhao, Y.; Dong, X.; Lian, C.; Wang, H. An experimental investigation on long-term performance of the wide-shallow bucket foundation model for offshore wind turbine in saturated sand. *Ocean Eng.* **2021**, *228*, 108921. [CrossRef]
57. Chen, P.; Song, L.; Chen, J.h.; Hu, Z. Simulation-annealing diagnosis algorithm method for optimized forecast of the dynamic response of floating offshore wind turbines. *J. Hydrodyn.* **2021**, *33*, 216–225. [CrossRef]
58. Miao, Y.; Huang, L.l.; Liu, Y.; Ying, F.; Song, M. Energy Availability Analysis of Offshore Wind Farms Considering the Correlation between Wind Speed Cloud Model and Parameters. In Proceedings of the 2021 11th International Conference on Power and Energy Systems (ICPES), Virtual, 18–20 December 2021; pp. 707–712.
59. Mattsson, N.; Verendel, V.; Hedenus, F.; Reichenberg, L. An autopilot for energy models–Automatic generation of renewable supply curves, hourly capacity factors and hourly synthetic electricity demand for arbitrary world regions. *Energy Strategy Rev.* **2021**, *33*, 100606. [CrossRef]
60. ERA, C. *Fifth Generation of ECMWF Atmospheric Reanalyses of the Global Climate. Copernicus Climate Change Service Climate Data Store (CDS)*; ECMWF: Reading, UK, 2017.
61. Kheirabadi, A.C.; Nagamune, R. A Dynamic Parametric Wind Farm Model for Simulating Time-varying Wind Conditions and Floating Platform Motion. *arXiv* **2020**, arXiv:2009.02585.
62. Kheirabadi, A.C.; Nagamune, R. Real-time relocation of floating offshore wind turbines for power maximization using distributed economic model predictive control. In Proceedings of the 2021 American Control Conference (ACC), New Orleans, LA, USA, 25–28 May 2021; pp. 3077–3081.
63. Yin, X.; Zhao, X. Deep neural learning based distributed predictive control for offshore wind farm using high-fidelity LES data. *IEEE Trans. Ind. Electron.* **2020**, *68*, 3251–3261. [CrossRef]
64. Anagnostopoulos, S.; Piggott, M. Offshore wind farm wake modelling using deep feed forward neural networks for active yaw control and layout optimisation. *J. Phys. Conf. Ser.* **2022**, *2151*, 012011. [CrossRef]
65. Bay, C.; King, J.R.; Fleming, P.A.; Martinez, L.; Mudafort, R.M.; Simley, E.J.; Lawson, M.J. *Floris: A Brief Tutorial*; Technical Report; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2020.
66. Jothinathan, S.; Kashyap, S.; Kumar, D.; Saha, N. Response control of fixed offshore structure with wind turbine using MR damper. In Proceedings of the OCEANS 2022, Chennai, India, 21–24 February 2022; pp. 1–8.
67. Keighobadi, J.; KhalafAnsar, H.M.; Naseradinmousavi, P. Adaptive neural dynamic surface control for uniform energy exploitation of floating wind turbine. *Appl. Energy* **2022**, *316*, 119132. [CrossRef]
68. Kayedpour, N.; Samani, A.E.; De Kooning, J.D.; Vandevelde, L.; Crevecoeur, G. Model predictive control with a cascaded hammerstein neural network of a wind turbine providing frequency containment reserve. *IEEE Trans. Energy Convers.* **2021**, *37*, 198–209. [CrossRef]
69. Zhang, J.; Zhao, X.; Wei, X. Reinforcement learning-based structural control of floating wind turbines. *IEEE Trans. Syst. Man Cybern. Syst.* **2020**, *52*, 1603–1613. [CrossRef]
70. Dehghan Manshadi, M.; Mousavi, M.; Soltani, M.; Mosavi, A.; Kovacs, L. Deep learning for modeling an offshore hybrid wind–wave energy system. *Energies* **2022**, *15*, 9484. [CrossRef]
71. He, J. Coherence and cross-spectral density matrix analysis of random wind and wave in deep water. *Ocean Eng.* **2020**, *197*, 106930. [CrossRef]
72. Velino, J.; Kang, S.; Kane, M.B. Machine Learning Control for Floating Offshore Wind Turbine Individual Blade Pitch Control. *J. Comput. Civ. Eng.* **2022**, *36*, 04022034. [CrossRef]
73. Yonggao, G.; Yi, T. Auxiliary Decision-making Method for Reactive Power Compensation Configuration of AC Grid-connected Offshore Wind Farm. In Proceedings of the 2022 IEEE 5th International Electrical and Energy Conference (CIEEC), Nanjing, China, 27–29 May 2022; pp. 2887–2892.
74. Meng, Y.; Chang, C.; Huo, J.; Zhang, Y.; Mohammed Al-Neshmi, H.M.; Xu, J.; Xie, T. Research on ultra-short-term prediction model of wind power based on attention mechanism and CNN-BiGRU combined. *Front. Energy Res.* **2022**, *10*, 920835. [CrossRef]
75. Zhang, Y.; Yang, X.; Liu, S. Data-driven predictive control for floating offshore wind turbines based on deep learning and multi-objective optimization. *Ocean Eng.* **2022**, *266*, 112820. [CrossRef]
76. Hall, M. *MoorDyn User's Guide*; Department of Mechanical Engineering, University of Maine: Orono, ME, USA, 2015; Volume 15.
77. Pham, T.; Li, X. Neural Network-based Power Flow Model. In Proceedings of the 2022 IEEE Green Technologies Conference (GreenTech), Houston, TX, USA, 30 March–1 April 2022; pp. 105–109.
78. Chen, P.; Hu, Z.Q. A Study on Key Disciplinary Parameters of Artificial Intelligent-Based Analysis Method for Dynamic Response Prediction of Floating Offshore Wind Turbines. *J. Offshore Mech. Arct. Eng.* **2023**, *145*, 010906. [CrossRef]
79. Yang, K.; Deng, X. Layout optimization for renovation of operational offshore wind farm based on machine learning wake model. *J. Wind. Eng. Ind. Aerodyn.* **2023**, *232*, 105280. [CrossRef]
80. Ahmad, I.; M'zoughi, F.; Aboutalebi, P.; Garrido, I.; Garrido, A.J. Fuzzy logic control of an artificial neural network-based floating offshore wind turbine model integrated with four oscillating water columns. *Ocean Eng.* **2023**, *269*, 113578. [CrossRef]
81. Ahmad, I.; M'zoughi, F.; Aboutalebi, P.; Garrido, I.; Garrido, A.J. A regressive machine-learning approach to the non-linear complex FAST model for hybrid floating offshore wind turbines with integrated oscillating water columns. *Sci. Rep.* **2023**, *13*, 1499. [CrossRef]

82. Hui, H.; Xiu-wen, L.; Jing-yu, B. The application of artificial intelligence technology in the fault diagnosis of floating wind turbine generator. In Proceedings of the 2020 5th International Conference on Electromechanical Control Technology and Transportation (ICECTT), Nanchang, China, 15–17 May 2020; pp. 305–307.
83. Black, I.M.; Richmond, M.; Kolios, A. Condition monitoring systems: A systematic literature review on machine-learning methods improving offshore-wind turbine operational management. *Int. J. Sustain. Energy* **2021**, *40*, 923–946. [CrossRef]
84. Okenyi, V.; Bodaghi, M.; Mansfield, N.; Afazov, S.; Siegkas, P. A review of challenges and framework development for corrosion fatigue life assessment of monopile-supported horizontal-axis offshore wind turbines. *Ships Offshore Struct.* **2022**, 1–15. [CrossRef]
85. Pezeshki, H.; Adeli, H.; Pavlou, D.; Siriwardane, S.C. State of the art in structural health monitoring of offshore and marine structures. In *Institution of Civil Engineers-Maritime Engineering*; Thomas Telford Ltd.: London, UK, 2023; Volume 176, pp. 89–108.
86. Hameed, Z.; Wang, K. Development of optimal maintenance strategies for offshore wind turbine by using artificial neural network. *Wind. Eng.* **2012**, *36*, 353–364. [CrossRef]
87. Wang, Y.; Infield, D. Supervisory control and data acquisition data-based non-linear state estimation technique for wind turbine gearbox condition monitoring. *IET Renew. Power Gener.* **2013**, *7*, 350–358. [CrossRef]
88. Dervilis, N.; Creech, A.; Maguire, A.E.; Antoniadou, I.; Barthorpe, R.; Worden, K. An SHM view of a CFD model of Lillgrund wind farm. *Appl. Mech. Mater.* **2014**, *564*, 164–169. [CrossRef]
89. Creech, A.C.; Fruh, W.G.; Maguire, A.E. High-resolution CFD modelling of Lillgrund Wind farm. In Proceedings of the International Conference on Renewable Energies and Power Quality, Bilbao, Spain, 20–22 March 2013.
90. Dahlberg, J.A. *Assessment of the Lillgrund Windfarm, Power Performance and Wake Effects*; Lillgrund Pilot Project; Vattenfall Vindkraft AB: Solna, Sweden, 2009.
91. Pattison, D.; Segovia Garcia, M.; Xie, W.; Quail, F.; Revie, M.; Whitfield, R.; Irvine, I. Intelligent integrated maintenance for wind power generation. *Wind Energy* **2016**, *19*, 547–562. [CrossRef]
92. Helsen, J.; Gioia, N.; Peeters, C.; Jordaens, P.J. Integrated condition monitoring of a fleet of offshore wind turbines with focus on acceleration streaming processing. *J. Phys. Conf. Ser.* **2017**, *842*, 012052. [CrossRef]
93. Li, C.B.; Choung, J. Fatigue damage analysis for a floating offshore wind turbine mooring line using the artificial neural network approach. *Ships Offshore Struct.* **2017**, *12*, S288–S295. [CrossRef]
94. Jonkman, J.; Butterfield, S.; Musial, W.; Scott, G. *Definition of a 5-MW Reference wind Turbine for Offshore System Development*; Technical Report; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2009.
95. Robertson, A.; Jonkman, J.; Masciola, M.; Song, H.; Goupee, A.; Coulling, A.; Luan, C. *Definition of the Semisubmersible Floating System for Phase II of OC4*; Technical Report; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2014.
96. Kandukuri, S.T.; Senanayaka, J.S.L.; Huynh, V.K.; Robbersmyr, K.G. A two-stage fault detection and classification for electric pitch drives in offshore wind farms using support vector machine. In Proceedings of the 2017 20th International Conference on Electrical Machines and Systems (ICEMS), Sydney, Australia, 11–14 August 2017; pp. 1–6.
97. Bak, C.; Zahle, F.; Bitsche, R.; Kim, T.; Yde, A.; Henriksen, L.C.; Hansen, M.H.; Blasques, J.P.A.A.; Gaunaa, M.; Natarajan, A. The DTU 10-MW reference wind turbine. In *Danish Wind Power Research 2013*; DTU: Lyngby, Denmark, 2013.
98. Sandner, F.; Yu, W.; Matha, D.; Azcona, J.; Munduate, X.; Grela, E.; Voutsinas, S.; Natarajan, A. *INNWIND. EU D4. 33: Innovative Concepts for Floating Structures*; Technical Report; DTU: Lyngby, Denmark, 2014.
99. Müller, K.; Dazer, M.; Cheng, P.W. Damage assessment of floating offshore wind turbines using response surface modeling. *Energy Procedia* **2017**, *137*, 119–133. [CrossRef]
100. Li, C.B.; Choung, J.; Noh, M.H. Wide-banded fatigue damage evaluation of Catenary mooring lines using various Artificial Neural Networks models. *Mar. Struct.* **2018**, *60*, 186–200. [CrossRef]
101. Lu, Y.; Sun, L.; Zhang, X.; Feng, F.; Kang, J.; Fu, G. Condition based maintenance optimization for offshore wind turbine considering opportunities based on neural network approach. *Appl. Ocean. Res.* **2018**, *74*, 69–79. [CrossRef]
102. Papatzimos, A.K.; Dawood, T.; Thies, P.R. Data insights from an offshore wind turbine gearbox replacement. *J. Phys. Conf. Ser.* **2018**, *1104*, 012003. [CrossRef]
103. Papatzimos, A.K.; Dawood, T.; Thies, P.R. Operational data to maintenance optimization: Closing the loop in offshore wind O&M. In Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering, Madrid, Spain, 17–22 June 2018; American Society of Mechanical Engineers: New York, NY, USA, 2018; Volume 51975, p. V001T01A038.
104. Ziegler, L.; Cosack, N.; Kolios, A.; Muskulus, M. Structural monitoring for lifetime extension of offshore wind monopiles: Verification of strain-based load extrapolation algorithm. *Mar. Struct.* **2019**, *66*, 154–163. [CrossRef]
105. Cavazzini, A.; Minisci, E.; Campobasso, M.S. Machine learning-aided assessment of wind turbine energy losses due to blade leading edge damage. In Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering, St. Julian's, Malta, 3–6 November 2019; American Society of Mechanical Engineers: New York, NY, USA, 2019; Volume 59353, p. V001T01A005.
106. Qiu, B.; Lu, Y.; Sun, L.; Qu, X.; Xue, Y.; Tong, F. Research on the damage prediction method of offshore wind turbine tower structure based on improved neural network. *Measurement* **2020**, *151*, 107141. [CrossRef]
107. Langenkämper, D.; Möller, T.; Brün, D.; Nattkemper, T.W. Efficient visual monitoring of offshore windmill installations with online image annotation and deep learning computer vision. In Proceedings of the Global Oceans 2020: Singapore–US Gulf Coast, Virtual, 5–14 October 2020; pp. 1–6.
108. Girshick, R. Fast R-CNN. In Proceedings of the IEEE International Conference on Computer Vision, Santiago, Chile, 7–13 December 2015; IEEE: Piscataway, NJ, USA, 2015; Volume 2, pp. 1440–1448.

109. Wang, X.; Gao, X.; Liu, Y.; Wang, Y. WRC-SDT based on-line detection method for offshore wind farm transmission line. *IEEE Access* **2020**, *8*, 53547–53560. [CrossRef]
110. Hoxha, E.; Vidal, Y.; Pozo, F. Damage diagnosis for offshore wind turbine foundations based on the fractal dimension. *Appl. Sci.* **2020**, *10*, 6972. [CrossRef]
111. Li, X.; Zhang, W. Long-term fatigue damage assessment for a floating offshore wind turbine under realistic environmental conditions. *Renew. Energy* **2020**, *159*, 570–584. [CrossRef]
112. Schröder, L.; Dimitrov, N.K.; Verelst, D.R. A surrogate model approach for associating wind farm load variations with turbine failures. *Wind Energy Sci.* **2020**, *5*, 1007–1022. [CrossRef]
113. Teimourzadeh Baboli, P.; Babazadeh, D.; Raeiszadeh, A.; Horodyvskyy, S.; Koprek, I. Optimal temperature-based condition monitoring system for wind turbines. *Infrastructures* **2021**, *6*, 50. [CrossRef]
114. Cho, S.; Choi, M.; Gao, Z.; Moan, T. Fault detection and diagnosis of a blade pitch system in a floating wind turbine based on Kalman filters and artificial neural networks. *Renew. Energy* **2021**, *169*, 1–13. [CrossRef]
115. Pandit, R.; Infield, D.; Dodwell, T. Operational variables for improving industrial wind turbine yaw misalignment early fault detection capabilities using data-driven techniques. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 1–8. [CrossRef]
116. Trizoglou, P.; Liu, X.; Lin, Z. Fault detection by an ensemble framework of Extreme Gradient Boosting (XGBoost) in the operation of offshore wind turbines. *Renew. Energy* **2021**, *179*, 945–962. [CrossRef]
117. Feijóo, M.d.C.; Zambrano, Y.; Vidal, Y.; Tutivén, C. Unsupervised damage detection for offshore jacket wind turbine foundations based on an autoencoder neural network. *Sensors* **2021**, *21*, 3333. [CrossRef]
118. Roelofs, C.M.; Lutz, M.A.; Faulstich, S.; Vogt, S. Autoencoder-based anomaly root cause analysis for wind turbines. *Energy AI* **2021**, *4*, 100065. [CrossRef]
119. EDP Inovação. *EDPR Wind Farm Open Data: Wind Turbine SCADA Signals and Historical Failure Logbook from 2016 and 2017*; EDP Inovação: Lisbon, Portugal, 2018.
120. Tang, W.; Gu, Y.; Xin, Y.; Liang, Q.; Qian, T. Classification for transient overvoltages in offshore wind farms based on sparse decomposition. *IEEE Trans. Power Deliv.* **2021**, *37*, 1974–1985. [CrossRef]
121. Tang, W.; Gu, Y.; Xin, Y.; Liang, Q.; Qian, T. Classification for transient overvoltages in offshore wind farms based on multi-scale mathematical morphology. *Int. J. Electr. Power Energy Syst.* **2022**, *136*, 107157. [CrossRef]
122. Yeter, B.; Garbatov, Y.; Soares, C.G. Life-extension classification of offshore wind assets using unsupervised machine learning. *Reliab. Eng. Syst. Saf.* **2022**, *219*, 108229. [CrossRef]
123. Santos, F.d.N.; Noppe, N.; Weijtjens, W.; Devriendt, C. Data-driven farm-wide fatigue estimation on jacket-foundation OWTs for multiple SHM setups. *Wind Energy Sci.* **2022**, *7*, 299–321. [CrossRef]
124. Xu, Z.; Bashir, M.; Yang, Y.; Wang, X.; Wang, J.; Ekere, N.; Li, C. Multisensory collaborative damage diagnosis of a 10 MW floating offshore wind turbine tendons using multi-scale convolutional neural network with attention mechanism. *Renew. Energy* **2022**, *199*, 21–34. [CrossRef]
125. Eze, O.; Guile, G.R.; Wang, W. Detecting the Faults of Subsea Power Cables of Wind Farms with Boosting Ensemble Methods. In Proceedings of the 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Maldives, Maldives, 16–18 November 2022; pp. 1–6.
126. Narkhede, S. Understanding auc-roc curve. *Towards Data Sci.* **2018**, *26*, 220–227.
127. Chicco, D.; Jurman, G. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC Genom.* **2020**, *21*, 6. [CrossRef]
128. Encalada-Dávila, Á.; Tutivén Gálvez, C.; Moyón, L.; Puruncajas Maza, B.; Vidal Seguí, Y. Main bearing fault prognosis in wind turbines based on gated recurrent unit neural networks. *Renew. Energy Power Qual. J.* **2022**, *20*, 419–424. [CrossRef]
129. Attallah, O.; Ibrahim, R.A.; Zakzouk, N.E. CAD system for inter-turn fault diagnosis of offshore wind turbines via multi-CNNs & feature selection. *Renew. Energy* **2023**, *203*, 870–880.
130. Khanjani, M.; Ezoji, M. Electrical fault detection in three-phase induction motor using deep network-based features of thermograms. *Measurement* **2021**, *173*, 108622. [CrossRef]
131. Mahami, A.; Rahmoune, C.; Bettahar, T.; Benazzouz, D. Induction motor condition monitoring using infrared thermography imaging and ensemble learning techniques. *Adv. Mech. Eng.* **2021**, *13*, 16878140211060956. [CrossRef]
132. Saleh, A.; Chiachío, M.; Salas, J.F.; Kolios, A. Self-adaptive optimized maintenance of offshore wind turbines by intelligent Petri nets. *Reliab. Eng. Syst. Saf.* **2023**, *231*, 109013. [CrossRef]
133. Sun, K.; Xu, Z.; Li, S.; Jin, J.; Wang, P.; Yue, M.; Li, C. Dynamic response analysis of floating wind turbine platform in local fatigue of mooring. *Renew. Energy* **2023**, *204*, 733–749. [CrossRef]