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Review

Comprehensive Analysis and Evaluation of the Operation and Maintenance of Offshore Wind Power Systems: A Survey †

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Abstract: Offshore Wind Power Systems (OWPS) offer great energy and environmental advantages, but also pose significant Operation and Maintenance (O&M) challenges. In this survey, we analyze these challenges and propose some optimization strategies and technologies for OWPS comprehensively. The existing literature review mainly focuses on a certain field of offshore wind power O&M, but lacks a comprehensive introduction to offshore wind power. We consider the energy efficiency, reliability, safety, and economy of OWPS from various aspects, such as offshore wind and wave energy utilization, offshore wind turbine components, and wind power operation parameters, and compare them with onshore wind power systems. We suggest that OWPS can benefit from advanced design optimization, digital twin, monitoring and forecasting, fault diagnosis, and other technologies to enhance their O&M performance. This paper aims to provide theoretical guidance and practical reference for the technological innovation and sustainable development of OWPS.

Keywords: offshore wind power; O&M; systems and challenges; optimization methods and strategies; wind turbine components; digital twin technology

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1. Introduction

Offshore wind farms offer a promising avenue for generating clean and low-carbon energy rapidly. Several countries, such as the European Union and the United Kingdom, have adopted ambitious net-zero plans to decarbonize their economies by 2050 [1]. Ref. [2] examined the main features of offshore wind projects in Europe that are operational or under development (e.g., countries, installed capacity, number of turbines, water depth, project area, distance offshore, transmission technology, and investment costs). They reported that offshore wind in Europe has expanded at an average annual rate of 36.1% since 2001. There are currently 76 offshore wind projects in European waters with a cumulative installed capacity of 7748 MW and an additional 3198 MW under construction.

Despite having a larger carbon footprint than onshore wind projects, offshore wind projects have almost achieved similar Energy Payback Periods (EPP) due to increased renewable electricity production resulting from better wind resources [1]. The offshore wind power industry has to overcome various obstacles and seize potentials, such as marine geological survey, floating foundation design, flexible DC transmission technology, intelligent O&M, standardization, parity, and research and development [3]. First, marine geological surveys are conducted to better determine the site selection, design, and construction of wind farms. The second is the floating foundation design, a structure that can float on the surface of the water in the deep water area and is connected to the wind turbine, called the floating foundation. The third is the flexible DC transmission technology, which is an efficient, low-loss, and easy-to-control transmission technology. Intelligent operation and maintenance refer to the use of digital, intelligent, automation, and other technologies to achieve real-time monitoring, fault diagnosis, predictive maintenance, and other functions of wind turbines and other equipment.

Before implementing an offshore wind power project, it is necessary to evaluate its technical and economic feasibility, whether the project can operate stably technically and is economically cost-effective [4]. Ref. [5] proposed a design model for offshore wind power plants that can be derived from either a systematic theoretical analysis based on a comprehensive understanding of the system dynamics or a systematic experimental analysis using identification methods. The factors affecting the cost of offshore wind power were studied, scenarios with different wind turbine capacities and wind farm sizes were set up, and then the average electricity price under each scenario was calculated using a technical economic model [6].

Offshore Wind Turbines (OWT) are broadly divided into stationary and floating types, and Floating Wind Turbines (FWT) can overcome the environmental impact and cost constraints of Conventional Stationary Wind Turbines (CSWT) [7]. Strong winds and wave effects combine to shock OWT, creating vibration, fatigue, and heavy loads on the structure and other components of the wind turbine. From a control point of view, cost reduction can be achieved by operating the turbine close to its optimal operating point in the partial load, ensuring reliability by reducing the structural load, and regulating the power generated under strong wind conditions [8,9]. Economically, the support structure affects the cost of system balances and O&M. The purpose of cost reduction can be realized by operating the turbine close to its optimal operating point in partial load. The cost of the support structure and environmental factors significantly impact the energy parity level of offshore wind power [10]. Life-Cycle Engineering Services (LCES) is a method of evaluating and optimizing the O&M of wind turbines. A generic LCES method has been proposed, and a case study of an offshore wind farm gearbox has been presented [11]. A life-cycle cost analysis framework of offshore wind farms has been developed to help wind farm developers reduce costs of the medium to long term [12].

Historically, the approach to maintenance has been purely passive, and there is a shift towards a more active, condition-based approach to maintenance [13]. Offshore wind farms need better methods of O&M to improve economics and sustainability [14]. Some researchers have proposed a method of Condition-Based Maintenance (CBM) that can predict and prevent failures based on operational data [15]. Two different maintenance strategies have also been introduced, one predictive and the other prescriptive. They also explain how to optimize the maintenance measures to make them more suitable for the actual situation. Although existing models have been able to help formulate maintenance strategies, we still need to apply more advanced mathematical methods, include input uncertainties, and consider more influencing factors [16]. The uncertainty of failures has led to increasing scientific interest in how to deal with offshore wind farm failures in recent years [17]. The O&M of OWT covers strategic selection, plan optimization, site operation, repair, evaluation criteria, recycling, and environmental issues. Several approaches have been summarized and compared, and limitations in OWT operations and maintenance research and deficiencies in industrial development have been described [18]. The existing gaps, needs, and challenges in the industry have been analyzed to guide research and innovation to facilitate the development of the offshore wind industry [19].

The important role of condition monitoring instruments in improving the reliability and efficiency of offshore wind farms has been reviewed, as well as the trends and challenges of automation and digital transformation that the offshore maintenance industry is facing [20]. The application of data-driven technology in offshore asset management has been discussed, especially the latest progress and value calculation of digital twin technology in the optimization of offshore wind farm O&M [21]. The application of artificial intelligence technology in the field of wind energy includes the application of various intelligent algorithms and decision-making technologies in wind turbine design, control, fault diagnosis, prediction, and optimization [22]. The main challenges and future research directions of offshore wind farm maintenance management include maintenance strategy selection, path optimization solution, maintenance scheduling decision model establishment, etc.

Regarding the environmental and economic impacts of offshore wind farms, refs. [23,24] include case studies in Brazil, China, and Aland Islands, as well as comparisons between offshore and onshore wind farms. It mainly analyzes the following aspects: environmental impact, economic benefits [25], life-cycle generation and energy and environmental footprint, construction scale and solutions [10], and possibilities and options for sustainable energy systems. Related impact categories include fossil fuels and respiratory inorganic substances [26]. A preliminary analysis has been made on the impact of operators, treatment objects, and living and artificial environment objects of a 2 MW wind power plant on the possible increased profits and reduced costs of compensation for damage to the system, environment and people [5].

To reduce the cost of offshore wind and improve profits, offshore wind farms should be expanded in size and number. At the same time, wind farms should change their operational strategy from power maximization to profit maximization and reduce interference between wind turbines by utilizing wind farm flow control technology. To better evaluate the value of wind farm flow control technology, more advanced models need to be used, considering different price and system demand scenarios [14].

At present, most of the review articles are a review and summary of certain research content related to offshore wind farms. e.g., offshore wind turbine performance or failure monitoring forecast [15,22,27–31], the vibration of gear wear monitoring [27], and refs. [13,16,18,20,32] reviewed the types and characteristics of operation, scheduling and maintenance strategies required by offshore wind farms, as well as the related technologies of wind farm transmission and grid connection [33,34].

Instead, this paper provides a comprehensive review and analysis of the various research content involved in offshore wind power. Compared with our previous work [35], the number of literature citations in this paper is more than four times that of it, the content of the review is richer and clearer, and the current situation of research content and technology development is interpreted in more detail. The main contributions of this paper are as follows:

- This paper comprehensively analyzes the challenges and optimization strategies of offshore wind power system operation and maintenance and analyzes the energy efficiency, reliability, safety, and economy of offshore wind power systems from the aspects of offshore wind and wave energy utilization, offshore wind turbine components, digital twin technology, operation and maintenance, and transmission and grid connection.
- This paper summarizes several solutions to improve the operation and maintenance performance of offshore wind power systems, including advanced design optimization, digital twin technology, monitoring and forecasting, fault diagnosis, and other technologies, and puts forward some directions and suggestions for reference.
- This paper aims to provide theoretical guidance for the technological innovation and sustainable development of offshore wind power systems.
- This review can be used as a practical reference for researchers and practitioners in the field of offshore wind power system operation and maintenance.

The writing idea of this paper is based on the process of offshore wind farm power generation, operation, and maintenance to transmission and grid connection, as shown in Figure 1. Sections 2–6 comprehensively analyze and evaluate the offshore wind power system from different perspectives and levels, covering the problems and methods of offshore wind and wave energy utilization, offshore wind turbine components, digital twin technology, O&M, technological innovation, and sustainable development. These five sections are closely related and interactive, and they support, complement, and influence each other. For example:

- The use of optimized methods and strategies for offshore wind and wave energy can improve the performance and life of components of OWT, reduce their costs and risks, and thus improve the economy and reliability of OWPS;
- Technologies and methods for optimizing components of OWT can improve the application effect and value of digital twin technology in OWPS, thereby improving the intelligence level of OWPS;
- The application of digital twin technology in OWPS can improve the efficiency and reliability of O&M, thereby improving the stability and life of OWPS;
- The systems and challenges of O&M can promote technological innovation and sustainable development of offshore wind systems, thereby enhancing the important role and value of offshore wind systems in the future energy transition and low carbon development;
- Technological innovation and sustainable development can promote the development and innovation of methods and strategies for optimizing the use of wind and wave energy at sea, thereby improving the diversity and inclusiveness of the system.

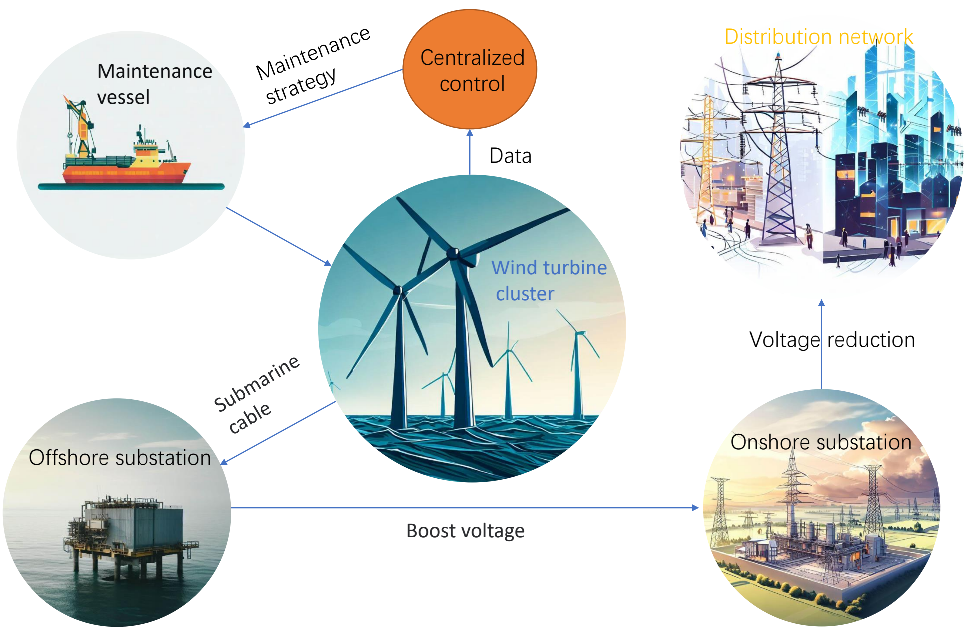

Figure 1. Offshore wind farm to power user process.

The remainder of the paper is organized as follows. We review the state-of-the-art works on OWPS in the above five aspects in Sections 2–6, respectively. The content framework of these five chapters is shown in Figure 2. We discuss this in Section 7. Finally, we conclude this paper in Section 8.

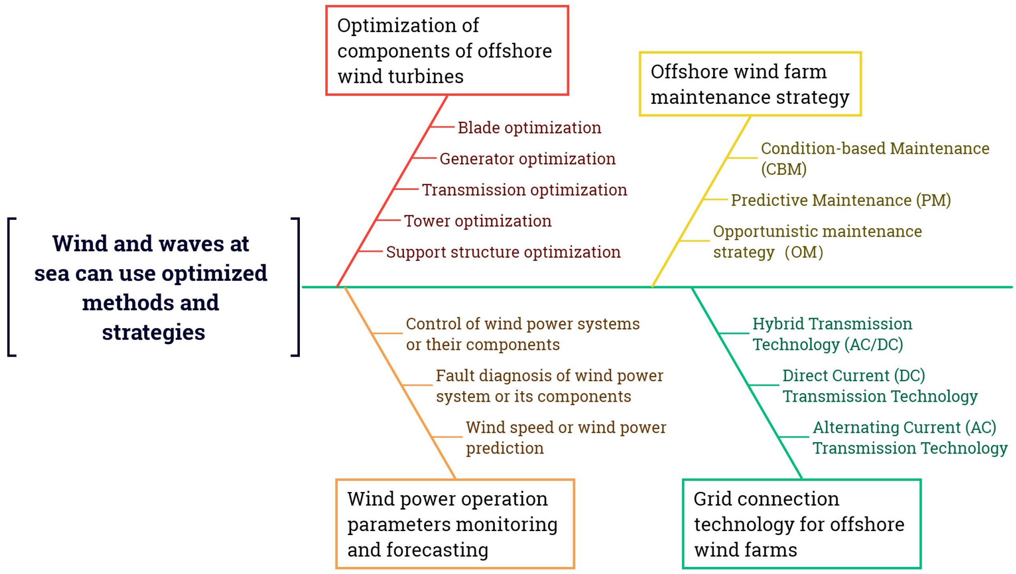

Figure 2. Framework of the full paper.

2. Optimization of Offshore Wind and Wave Energy Utilization

The ocean is the largest reservoir of renewable energy resources on the earth, which contains huge wind, wave, tidal and current energy, and other forms of energy. Offshore wind and wave energy utilization refers to the use of OWT and wave energy converters and other devices to convert wind and wave energy in the ocean into electricity, which has the advantages of being clean, efficient, and sustainable, and is one of the important directions of future energy transformation. However, offshore wind and wave energy utilization also face many challenges, such as the complexity and badness of the marine environment, the inefficiency and instability of power conversion and transmission, and the high cost and high risk of system construction and O&M. Wind energy resources and their utilization were evaluated by analyzing wind speed probability distribution, average wind speed, average wind energy density, effective utilization time of wind energy, and wind power output ratio [36]. Therefore, how to optimize the technology and strategy of marine wind and wave energy utilization and improve its economy and reliability is the hot and difficult point of current research.

This section aims to comprehensively analyze and summarize their main contents and contributions to the optimization of marine wind and wave energy utilization, analyze the correlation and differences between them, point out the current research gaps and deficiencies, and propose some feasible methods and strategies to optimize the utilization of marine wind and wave energy, including power converter, ocean-atmospheric boundary layer, Offshore Pumped Storage (OPS), rotary energy harvesting, fault-tolerant control, energy storage concept, wave energy converter, etc.

2.1. Sea Wind and Wave Utilization Optimization

The various aspects of optimizing the utilization of wind and wave energy at sea can be divided into the following categories:

- Power converters: [37] provided a comprehensive overview of power converters used in high-power wind turbines, analyzing key challenges and potential solutions for improving system efficiency, reducing costs, and enhancing flexibility. A fault-tolerant control strategy based on reconfiguration control was proposed to improve the reliability of parallel converters in permanent magnet synchronous generator wind power generation systems [38].
- Marine Atmospheric Boundary Layer (MABL): An experimental platform for characterizing the structure and dynamics of the MABL was presented to support offshore wind energy research [39]. The platform includes an unmanned aerial system, a

weather tower system, and a remote sensing system that can provide MABL data with high spatiotemporal resolution.

- OPS: A predictive operation strategy based on an event-triggered Model Predictive Control (MPC) approach was proposed to achieve the complementary power of OPS and real-time offshore waves [40]. This strategy can effectively smooth output power fluctuation and improve the operation efficiency of the OPS system. Similar to the concept of energy storage, Ref. [41] discussed the use of wind energy in low wind speed areas to provide microgrid solutions for offshore oil and gas platforms to improve the timeliness of wind energy utilization.
- The application of rotary energy harvesting technology in the field of self-powered sensing was reviewed in detail in [42]. Its performance characteristics at different scales, frequency ranges, and operating modes were analyzed, and its application in rotary machines and renewable energy systems was discussed.
- Energy storage concept: A novel offshore wind energy storage concept was proposed, whereby excess wind power is stored in underwater spherical tanks through compressed air and released through turbines to meet demand [43]. This concept can significantly reduce rated power costs and improve system stability. The studied Reversible Solid Oxide Cell (rSOC) system is compatible with the auxiliary system requirements of 2.3 MW wind turbines and can cover the auxiliary needs during wind speed shortages or maintenance [44].
- Wave energy converter: [45] evaluated the potential for offshore wind and wave energy utilization on a global scale and compared differences across regions and seasons. The Life Cycle Assessment (LCA) of a tidal stream power generation array composed of multiple underwater vehicles was carried out to analyze its performance in terms of environmental impact, resource consumption, and economic benefits [46]. Strategies to improve the sustainability of Wave Energy Converters (WEC) and offset their high initial capital expenditures are explored, including technological innovation, strategy support, and social engagement [47].

2.2. The Offshore Wind and Wave Energy Utilizes Optimized Methods and Strategies

Combined with the previous analysis on the optimization of wind and wave energy utilization at sea, this paper summarizes some corresponding feasible methods and strategies to optimize the utilization of wind and wave energy at sea through the investigation of the literature:

- Power converter: The power converter is the core component of the offshore wind and wave energy utilization system, and its performance directly affects the efficiency, cost, and flexibility of the system. To improve the performance of the power converter, the following methods can be used:
    (a) Selection of appropriate topologies and control strategies to accommodate different types of generators and loads and to improve the power density, efficiency, and reliability of the converter [37];
    (b) The use of modular, integrated, and intelligent technologies to reduce the volume, weight, and heat dissipation requirements of the converter, and improve the maintainability and fault tolerance of the converter [37];
    (c) Multi-stage, multi-port, and multi-function technologies are utilized to achieve collaborative control between converters and to improve the flexibility and compatibility of converters [37].
- MABL: The MABL is the operating environment of the offshore wind and wave energy utilization system, and its structure and dynamics have an important impact on the output power, stability, and lifetime of the system. To improve the characterization of MABL, the following methods can be used:

(a) A variety of platforms and means such as unmanned aerial vehicles, meteorological towers, and remote sensing are used to obtain MABL data with high spatiotemporal resolution, and perform data fusion and analysis [39];
(b) Use physical models, numerical simulation, machine learning, and other methods to establish accurate and real-time MABL prediction models, and conduct model validation and optimization [39];
(c) Use MABL data and models to guide the siting, design, control, and operation of offshore wind and wave energy utilization systems and to evaluate their performance under different MABL conditions [39].

- OPS: OPS is a technology that uses water pressure differences for energy storage and release, which can effectively smooth the output power fluctuations of offshore wind and wave energy utilization systems and improve the operational efficiency of the system. To improve the performance of OPS, the following methods can be used:

(a) Select suitable energy storage media (such as air, water, or liquid metal) to improve energy storage density, efficiency, and safety [40];
(b) Select suitable energy storage structures (such as spherical tanks, cylindrical tanks, or underwater caves) to reduce energy storage costs, risks, and environmental impacts [40,43,48].
(c) Advanced control methods such as predictive control and event-triggered control are utilized to realize the power complementary between OPS and real-time offshore waves, and to optimize the operation strategy of the OPS system [40].

- Rotational energy harvesting: Rotational energy harvesting is a technology that uses rotational motion to generate electrical energy, which provides a continuous and reliable power source for self-powered sensors in offshore wind and wave energy utilization systems. To improve the performance of rotational energy harvesting, the following methods can be used:

(a) Select an appropriate energy harvesting mechanism (such as electromagnetic induction, piezoelectric effect, electrostatic induction, etc.) to adapt to rotational motion at different scales, frequency ranges, and operating modes [42];
(b) Techniques such as multi-physical field coupling, non-linear vibration, and bistable state are used to improve the output power and frequency bandwidth of the rotating energy collector [42];
(c) Technologies such as energy management, power matching, and load regulation are utilized to improve the electrical matching and synergy between the rotating energy collector and the self-powered sensor [42].

- Energy storage concept: The concept of energy storage refers to the use of different physical or chemical principles for energy storage and release technology, which can effectively improve the economy and reliability of offshore wind and wave energy utilization systems. To improve the performance of the energy storage concept, the following approaches can be adopted:

(a) Select suitable energy storage media (such as compressed air, underwater vehicles, or liquid metals) to improve energy storage density, efficiency, and safety [43,48].
(b) Select suitable energy storage structures (such as underwater spherical tanks, underwater caves, or underwater reservoirs) to reduce energy storage costs, risks, and environmental impacts [43,48];
(c) Optimization algorithms, multi-objective planning, and other technologies are used to achieve optimal matching and coordinated control between the energy storage concept and the offshore wind and wave energy utilization system [43,48].

- Wave energy converter: A wave energy converter is a device that uses wave motion to generate electricity, which can effectively use the abundant wave resources in the ocean and complement OWT. To improve the performance of wave energy converters, the following methods can be used:

(a) Select suitable wave energy conversion mechanisms (such as oscillating water columns, point absorbers, or underwater vehicles, etc.) to adapt to different types and strengths of waves [45–47];
(b) The use of non-linear vibration, bi-stable, chaos, and other technologies to improve the output power and frequency bandwidth of the wave energy converter [45–47];
(c) The use of array layout, phase control, power regulation, and other technologies to improve the synergy between wave energy converters and the overall efficiency [45–47].

These methods and strategies design, analyze, evaluate, and optimize the marine wind and wave energy utilization system from different angles and levels, involving many factors such as system components, operating environment, storage mode, and conversion efficiency. They not only show the progress and achievements of offshore wind and wave energy utilization technology in recent years, but also reveal the problems and challenges in theoretical models, experimental verification, engineering implementation, and other aspects. In the future, there are still many directions and challenges worth further research in the optimization of marine wind and wave energy utilization, such as:

- How to comprehensively design, model, control, and evaluate multiple types of marine renewable energy collaborative utilization systems, such as mixed wind–wave–tidal current systems;
- How to systematically compare and analyze the optimization performance of offshore wind and wave energy utilization systems at different scales (such as individual devices, arrays, or regions), different scenarios (such as normal operation or fault conditions), and different objectives (such as maximum power or minimum cost);
- How to comprehensively assess and optimize the sustainability of offshore wind and wave energy utilization projects taking into account social and economic factors (such as job creation, community participation, etc.);
- How to improve the intelligence level of marine wind and wave energy utilization systems based on big data analysis and artificial intelligence technology.

The explicit methodologies employed in the process of the optimization of sea wind and wave energy utilization are selection of appropriate topology and control strategy, energy storage medium, and energy storage structure; and the use of various platforms and means such as drones, meteorological towers, and remote sensing, non-linear vibration, bi-stable state, chaos, and other technologies, and advanced control methods such as predictive control and event-triggered control. These key technologies can guide the siting, design, control, and operation of offshore wind and wave energy utilization systems and evaluate their performance under different ocean-atmosphere boundary layer conditions. They can also help offshore wind energy and wave energy utilization systems improve their economy and reliability, reduce their costs and risks, and enhance their flexibility and compatibility. They can promote the innovation and development of offshore wind energy and wave energy utilization technology and enhance its important role and value in future energy transformation and low-carbon development.

3. Optimization of Components of OWT

The main components of OWT include blades, generators, transmissions, towers, support structures, etc. In this paper, these components and related technical methods of offshore wind turbines are reviewed in detail, and the general composition of the wind turbine is shown in Figure 3. However, the design of OWT faces many challenges, such as complex design parameter space, different operating requirements and environmental conditions, and high construction and maintenance costs. To overcome these challenges, advanced optimization techniques are needed to improve the performance and lifetime of the components of OWT, balancing power generation efficiency and structural reliability.

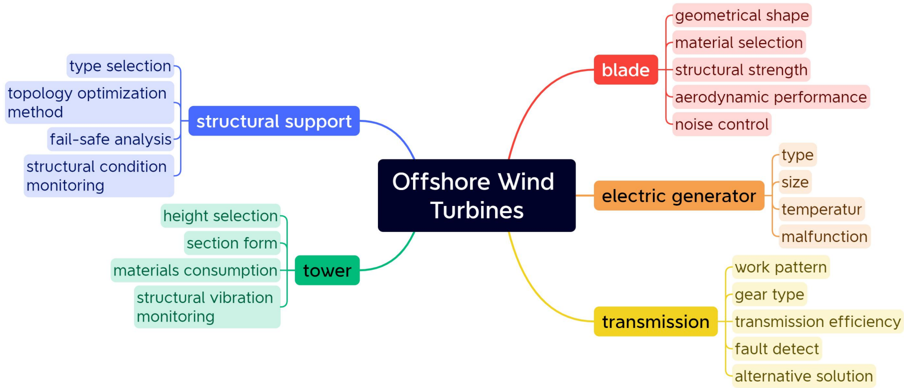

Figure 3. Framework of components of offshore wind turbine.

3.1. The Main Components of Offshore Wind Turbines

Blades are one of the core components of wind turbines, which directly bear wind loads and convert wind energy into mechanical energy. The design of the blade needs to consider its geometry, material selection, structural strength, aerodynamic performance, noise control, and other factors [49]. Based on numerical simulation, the variation law of blade angle of attack of floating OWT under different yaw conditions is studied, and corresponding suggestions are given [50]. The bending moment at the bottom of the tower and the root of the blade of an offshore wind turbine is also measured by the strain-electric method [51]. Ref. [52] indicated that the blade mode plays an important role in capturing the part of the torque dynamic higher than 1.5 Hz. Ref. [53] reviewed the atmospheric driving factors of wind turbine blade front erosion and proposed suggestions for future research.

Offshore wind power generation technology is one of the foundations and key points of offshore wind power technology, involving structure design, performance analysis, control strategy, fault diagnosis, etc. The effects of different types, sizes, temperatures, and faults on the performance and reliability of generators [54,55] have also been discussed. Additionally, the advantages and design suggestions of new generator technologies, such as silicon carbide MOSFETs [56], high-temperature superconductivity excited double-stator direct-drive wind turbine [57], permanent magnet synchronous generator [58–61] (Ref. [62] proposed E-type modularization), hydraulic transmission [63], etc. (for example, analysis of mechanical characteristics [59]), and their corresponding analysis and evaluation have been carried out.

The transmission is one of the important components of the wind turbine, which connects the blades to the generator and regulates the speed ratio and torque transfer. The design of the transmission needs to consider its working mode, gear type, transmission efficiency, fault detection, and other factors. A fault-tolerant single-paddle control method based on predictive repetitive control was proposed in Ref. [64] for floating OWT, which effectively suppressed transmission torque fluctuations and improved system stability. Gear wear monitoring and prediction techniques based on vibration signals were reviewed in Ref. [27], and their application prospects in OWT were analyzed. In Ref. [65], flexible dynamic modeling and analysis were carried out on the transmission chain of floating OWT, and the influencing factors under different working conditions were considered.

The tower is one of the main supporting components of the wind turbine, which carries the entire wind turbine system and is connected to the supporting structure. The design of the tower needs to consider its height selection, section form, material consumption, structural stiffness, and other factors. Ref. [66] analyzed the influence of three-legged suction bucket foundations on the dynamic characteristics of offshore wind turbine towers through full-scale tests, and gives corresponding suggestions. In Ref. [67], an acceleration sensor and data acquisition system were used to monitor the structural vibration of an offshore wind turbine tower, and its modal parameters were identified by the operational modal analysis method. Based on the finite-element method, ref. [51] analyzed the impact of ship collision on the load of offshore wind turbine tower structure, and provided corresponding evaluation methods.

The support structure is one of the main supporting components of OWT, which connects the tower with the seabed or floating body and bears complex and variable environmental loads [68]. The design of the support structure needs to consider its type selection, topology optimization, reliability analysis, and other factors to improve its performance and life and reduce its cost and risk. The optimal design of wind turbine support structure is an important research topic, which involves many techniques and methods. Some literature has reviewed and summarized the research in this aspect, such as Refs. [69,70]. In other literature, specific optimization schemes have been proposed, and numerical simulation or experimental verification has been carried out, such as in Refs. [71–73]. These optimizations take into account the reliability of the support structure, topological shape, load conditions, multi-objective performance, and other factors to improve the efficiency and lifetime of the offshore wind turbine and reduce its cost and risk.

The above describes the information on the components of offshore wind turbines and discusses the current research status and optimization methods of these components. A brief Figure 4 of an intuitive offshore floating wind turbine and its components is presented.

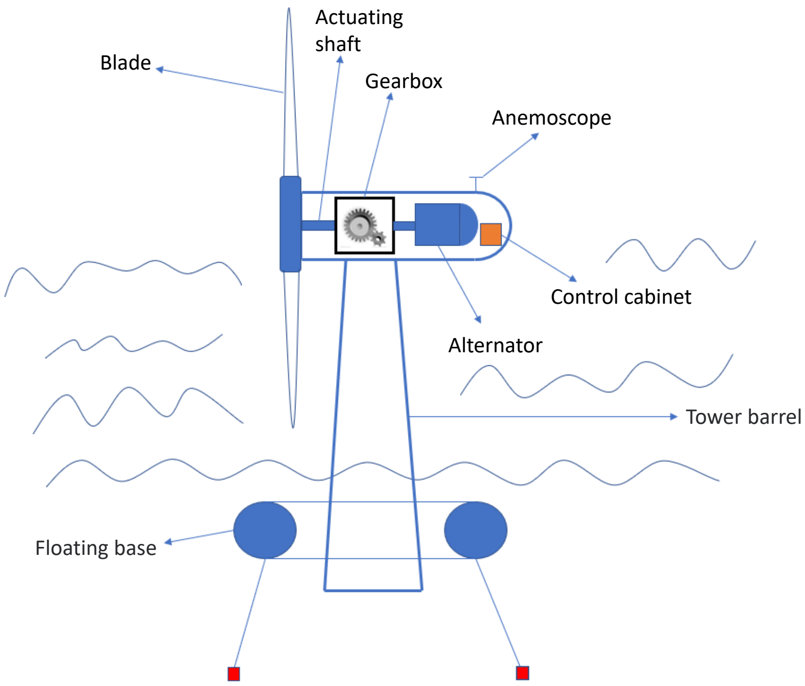

Figure 4. Structure diagram of offshore floating wind turbine.

At present, the most widely used Horizontal-Axis Wind Turbine (HAWT) is due to its efficient, reliable, and easy-to-control characteristics. However, when we need a wind turbine that can adapt to changing winds, is easy to maintain, and has a simple structure, then the Vertical-Axis Wind Turbine (VAWT) may be a suitable choice. The VAWT has some potential advantages over HAWT that could make it suitable for offshore wind power scenarios. For example, the VAWT's small size allows electrical components to be installed close to the water surface, reducing the difficulty and cost of construction, transportation, and maintenance. In addition, the VAWT is insensitive to wind direction and requires no complex yaw control system to adjust the direction of the turbine. Vawts also typically operate at a lower Tip-Speed Ratio (TSR) and therefore may produce less noise [74,75]. On the other hand, the VAWT also faces some challenges and limitations, such as low power conversion efficiency, large structural loads, and dynamic stall phenomena. Therefore, in order to improve the application potential of VAWT in offshore wind power generation, it is necessary to optimize the design of its blade geometry, rotation speed, array layout, etc., and consider its interaction with the marine environment and turbulent flow field. The spiral blade studied in [76] is one possible optimization that can reduce the time variability of torque and power, and reduce noise levels.

Digital twin technology is a technology that uses digital models and data analysis to simulate and predict the behavior and performance of real physical systems [77,78], which has wide application potential in the design, monitoring, maintenance, and other aspects of offshore wind turbine support structures. In recent years, some studies have reviewed and summarized the research in this field, pointing out existing problems and future directions, such as uncertainty modeling, data quality, computational efficiency, etc. [79]. Some other studies have proposed specific application cases and carried out numerical simulation or experimental verification, such as predictive management system [80], uncertain fatigue analysis [81], reliability update [82], virtual sensor [83], etc. Weibull distributions were used to describe the failure time of individual components to reflect their degradation properties, and Monte Carlo simulations were used to assess the reliability, availability, and O&M costs of FOWT systems [84]. These studies demonstrate the potential and value of digital twin technology in improving the efficiency and reliability of support structures for OWT.

The optimization techniques and characteristics found in the literature for components of OWT are listed in Table 1.

Table 1. Optimization technology and characteristics of components of OWT.

Technique	Characteristic
Topology optimization method	Flexible, efficient, and innovative, but needs to consider the manufacturability of the structure, reliability, multi-purposeness, and other factors
Digital twin technology	Intelligent, efficient, and visible, but requires the creation of accurate and real-time digital models, as well as the processing of large and complex data
Virtual sensor	Saves costs, improves accuracy, and enhances robustness, but you need to choose a suitable and efficient estimation algorithm, as well as ensure data quality and model accuracy
Multi-Agent approach	Distributed, parallel, self-organizing, but requires the design of a reasonable and efficient agent structure, coordination mechanism, and communication protocol
Finite-element method	Accurate, efficient, and versatile, but factors such as cell type, mesh division, and boundary conditions need to be considered

3.2. Progress and Future Directions

We can also think about the progress and prospects of some researchers in the diversified support structure, dynamic wake-up management, and multidisciplinary design and analysis optimization of offshore wind power. Refs. [10,85] studied the possibility of using a multi-element fixed-base structure to replace the single-pile support structure in future American offshore wind power plants, analyzed the impact of such changes on system balance and O&M cost, and pointed out the importance of reducing energy parity level. Ref. [86] reviewed the progress of dynamic wake-up management for offshore wind farms and analyzed its impact on energy harvesting and load reduction. Ref. [87] reviewed the application of multidisciplinary design analysis and optimization framework in floating offshore wind turbine design and pointed out existing problems and future directions.

The optimization of components of OWT is an important research topic that involves many problems and methods. Ref. [69] reviewed the research progress and future direction in this field and pointed out the challenges and problems in optimization models, algorithms, objectives, constraints, uncertainties, and reliability [88,89]. Some novel optimization methods have been proposed in the literature, including the integrated method (combining fluid mechanics method and mathematical model) [73], the buoyancy balance control technique [90], the multi-agent method [91], the integer programming model [92], etc. They have been used to solve the problems of array layout, wake-up interference [93], O&M, and transportation and installation [92,94] of OWT, and corresponding analyses and evaluations have been carried out.

4. Monitoring and Forecasting of Wind Power Operation Parameters

Wind power operation parameter monitoring and forecasting also face some challenges and problems, such as:

- The prediction of a wind speed or wind power is very difficult because the wind speed or wind power is affected by meteorological conditions, terrain characteristics, seasonal changes, and other factors, and has the characteristics of randomness, uncertainty, and non-linear, which brings difficulties to the operation and scheduling of wind power generation system. A comprehensive approach was proposed that combines climate model data, resource impact analysis, and energy system modeling to assess the impact of climate change on energy systems [95].
- The fault diagnosis of a wind power system or its components is difficult because the wind power system or its components are affected by harsh environments, complex loads, a variety of faults, and other factors, with diversity, complexity, and concealment characteristics, which brings difficulties to the maintenance and security of wind power systems.
- The control of the wind power generation system or its components is difficult because the wind power system or its components are affected by a variety of objectives, constraints, control technologies, and other factors, with the characteristics of multi-objectives, multi-constraints, and multi-technologies, which brings difficulties to the optimization and safety of wind power generation system.

A wind power system is made up of multiple subsystems, and any one of these subsystems can fail or become abnormal, resulting in reduced performance or loss of downtime. According to [96], common failure modes include blade cracking, gearbox bearing damage, transmission slip ring wear, generator winding short circuit, converter switch failure, etc. These failure modes can be caused by a variety of reasons, such as material aging, load fluctuations, temperature changes, humidity effects, corrosion erosion, etc. To detect and identify these fault modes in time, it is necessary to carry out condition monitoring and fault diagnosis for wind power generation systems.

To solve these challenges and problems, the wind power system needs to be effectively predicted, diagnosed, and controlled. This section classifies and summarizes the diagnostic, control, and forecasting literature related to wind power generation, and analyzes the advantages, disadvantages, and challenges of each study.

4.1. Wind Power Generation Fault Diagnosis Class

Condition monitoring refers to the observation of individual components of a wind power system to identify changes in operation that may be indicative of developing failures. Condition monitoring methods rely primarily on the analysis of specific measurement and operational aspects (e.g., vibration analysis, strain measurement, thermal imaging, and acoustic emission). A power curve Health Value (HV)-based approach was used to identify and prioritize low-performance Wind Turbines (WTS) [97]. Different data sets were also utilized to validate the applicability of HV methods for detecting short- and long-term power curve anomalies, predicting failures and outages, and monitoring performance degradation. The innovation of [98] is that it combines qualitative analysis and quantitative analysis to propose a reliable, economical, and robust condition monitoring and decision-making method. A low-cost and high-efficiency wind turbine condition monitoring method based on Supervisory Control and Data Acquisition (SCADA) data was proposed [99]. The methods presented in these three papers can effectively monitor the status of wind turbines and reduce maintenance costs and risks.

Wind power fault diagnosis is to locate and identify anomalies or faults of the wind power system or its components based on condition monitoring to determine the type, location, and extent of the fault. Fault diagnosis of wind power generation can improve the reliability and safety of wind power generation systems and reduce O&M costs. Wind power generation fault diagnosis methods are mainly divided into two categories: model-based methods and data-based methods, each of which has advantages and disadvantages.

The process of fault diagnosis of a wind power system or its components can be clearly understood from Figure 5. The model-based fault diagnosis method first establishes the physical model or mathematical model of the offshore wind power system or its components to describe its operating characteristics and dynamic behavior under normal or fault conditions. Then, the measured data after pre-treatment are input into the established physical model or mathematical model, the model output is calculated, and the residual or deviation is calculated by comparing it with the measured data. The residual error or deviation is analyzed to determine whether it exceeds the set threshold or tolerance range; if so, it is considered that there is an anomaly or fault, and the corresponding alarm signal is output. Finally, the diagnostic results were evaluated according to four indexes: accuracy, real-time, robustness, and interpretability. The data-based approach focuses on collecting historical or online data on offshore wind systems or their components, including temperature, pressure, rotational speed, power, vibration, and other parameters. Based on the existing rule base or historical data and expert opinions, determine the cause and impact of anomalies or failures, and output the corresponding maintenance or control recommendations.

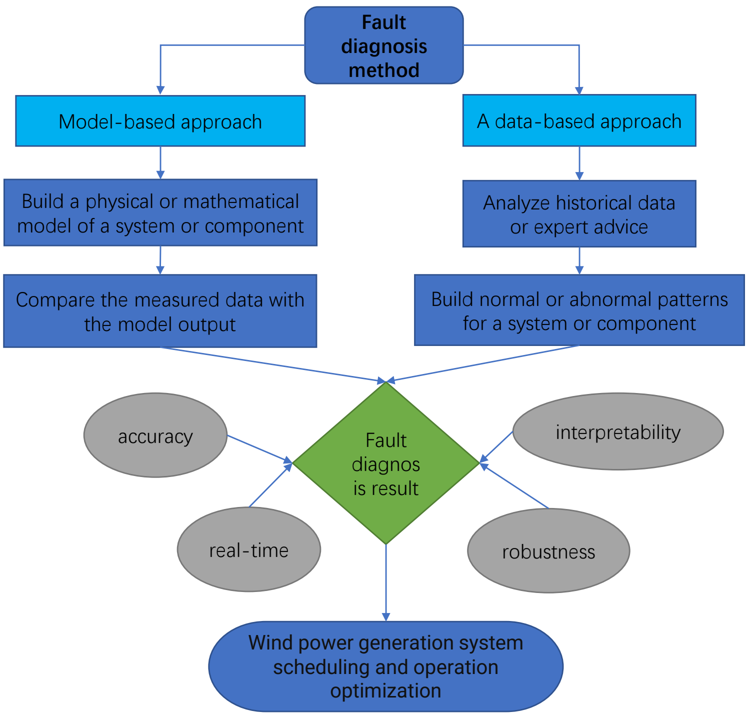

Figure 5. Fault diagnosis flow chart of offshore wind farm.

The power electronic system in the offshore wind power system mainly includes the power converter, back-to-back converter and wind energy converter of the wind turbine, etc. The failure of this equipment will affect the performance and safety of the wind power system. A large number of statistical studies have pointed out that the fault of the power converter is the main cause of the fault shutdown of the turbine system [33]. The main steps of fault diagnosis in power electronic systems are signal acquisition, feature extraction, feature fusion, and fault classification. Different fault diagnosis methods employ different techniques and algorithms in these steps to improve the accuracy, robustness, and efficiency of diagnosis, for example, Dempster–Shafer and Deng entropy fusion multi-scale approximate entropy (DSDEMAE) [100], intelligent fault diagnosis method based on knowledge and data driven [101], Long Short-Term Memory Network (LSTM) [102], Multivariate Empirical Mode Decomposition (MEMD), Fuzzy Entropy (FE), and Artificial Fish Swarm Algorithm (AFSA)–Support Vector Machine (SVM) [103].

DSDEMAE uses multi-scale approximate entropy to extract the features of the fault signal, and then uses Dempster–Shafer theory and Deng entropy to fuse the features of different scales, which effectively deal with the uncertainty and conflict between different features [100]. In [103], MEMD is used to decompress the three-phase output voltage signal synchronously and extract the common mode with the same time scale. Then, FE is used to calculate the complexity of each mode as the fault feature. Finally, AFSA is used to optimize the SVM parameters to realize the identification of fault types. The research of Refs. [101,102] focuses on the open-circuit fault. The method proposed in [101] is used to detect and locate the open-circuit fault of IGBT in the three-phase power electronic energy conversion system. Then, the data-driven method (random forest algorithm) is used to train the fault diagnosis classifier, which has the ability to adapt to different loads. The fault diagnosis method based on the Long Short-Term Memory Network (LSTM) in [102] is used to detect multiple open-circuit switch faults of back-to-back converters in a doubly-fed induction generator wind power system. All four papers show some advanced fault diagnosis methods for power electronic systems, each with its own advantages and limitations, which can be selected and combined according to different application scenarios and requirements.

According to [30,104–114], we can learn about some of the latest methods of wind power generation fault diagnosis. These cover the latest wind power generation fault diagnosis methods. Let us make a comprehensive analysis of their characteristics: First, Ref. [30] indicated that the use of machine learning in fault detection, diagnosis, and prediction is a promising approach to improving the reliability and efficiency of wind turbines. Secondly, Ref. [104] used the Gaussian Process Algorithm (GPA) to estimate operating curves and key variables to optimize power performance and detect critical failures of wind turbines. Ref. [114] focused on the condition monitoring of the gearbox, and uses envelope analysis technology to detect and locate faults, thereby improving the reliability of the fan. In addition, Ref. [112] used Failure Mode and Effect Analysis (FMEA) methods to improve the reliability and safety of OWT. Furthermore, Ref. [115] discussed the power change rates of co-located offshore wind farms and wave energy farms and their effects on system stability. Finally, based on the vibration characteristics of the wind turbine power chain, a condition monitoring and fault diagnosis method based on frequency domain analysis was proposed in [114] to effectively detect the faults of bearings, gearboxes, and blades.

Taken together, these methods include the use of reinforcement learning, GPA, SCADA data and non-parametric models, power spectral density analysis, FMEA methods, etc., to improve the performance, reliability, and safety of wind power generation systems, and to achieve this through condition monitoring and fault diagnosis. In summary, we can see that wind power generation fault diagnosis is a field involving a variety of sensors, a variety of signal processing, and a variety of diagnostic technologies, with high complexity and challenge. With the progress of sensor technology, signal processing technology, artificial intelligence technology, and other aspects, more and better fault diagnosis methods for wind power generation are expected to appear in the future. Different types of fault diagnosis methods have their advantages and disadvantages, and appropriate methods should be selected according to actual engineering requirements and system conditions [33].

4.2. Wind Power Generation Control Class

Wind power generation control refers to adjusting the speed of the fan, blade angle, or overall direction according to the change in wind speed or wind power, to achieve the optimal or safe operation of the wind power generation system. Wind power generation control can be divided into two goals: one is to optimize control, that is, to maximize the power coefficient of the fan under the rated power, to improve the utilization rate of wind energy. A detailed investigation was carried out on the turbulence effect existing in the operation of the offshore wind power fleet [116], and the downstream wind power generation loss was caused by the turbulence effect. The other is limiting control; that is, when the rated power is above, the output power of the fan is limited to protect the fan from overload or fatigue damage. The purpose of limiting the rate of change of wind power generation is to produce more stable electricity [117]. Control strategies used to enforce restrictions, including the use of energy storage systems or direct control of wind turbines, are designed to reduce costs and reduce energy waste. The power fluctuations of wind turbines significantly affect the lifetime of Insulated Gate Bipolar Transistor (IGBT) modules. Ref. [9] proposed a new IGBT thermal management strategy to obtain the best economic benefits.

Wind power generation control methods are mainly divided into two categories: model-based methods and data-based methods [28,116]. A model-based approach requires building a mathematical model of a wind power system or its components and using techniques such as feedback or prediction to design the controller and adjust the control inputs according to the control objectives. Model-based methods have a theoretical basis and physical significance, but require accurate and complete mathematical models, and may be affected by noise, interference, uncertainty, and other factors. For example, Ref. [118] proposed a robust control strategy based on MPC and Spatial Vector Modulation (SVM).

Data-based approaches do not require mathematical modeling but rather use historical or real-time data to learn control strategies and leverage techniques such as optimization or search to adjust control inputs. Data-based methods do not rely on mathematical models, but on the actual data, and can handle non-linear and high-dimensional data, but they require enough high-quality data and may have problems such as overfitting or insufficient generalization ability. Ref. [119] used the data-driven control method of Bayesian. The ascent algorithm proves that it has the potential to be used for real-time wind farm control. A passive fault-tolerant control method is summarized in [28]; that is, the response is made by the data collected by the monitoring device and the preset fault control mechanism. In the absence of unexpected failures, the failure of the turbine can be effectively reduced, although there will be some performance degradation.

In Refs. [120–125], some of the latest research results and development trends were mainly introduced. These involve wind turbine control strategy, optimization control, digital framework, reliability and fault cost modeling, digital twin application, load distribution, and mooring line management. Four different control strategies were introduced in [125], namely, sliding mode controller, PI neural network controller, reverse thrust controller, and H-FL controller, all of which take generator torque as the control input and rotor angular speed tracking as the control target to achieve the optimal power coefficient. The paper compares the performance of these control strategies in terms of energy capture and robustness and finds that the reverse thrust controller has the highest efficiency, but the control signal fluctuates more, while the H-FL controller has the lowest efficiency, but the torque is smoother. An optimal control strategy is also introduced for the co-positioning of wind farms and wave fields to meet the requirements of power system operators [120]. This control strategy can increase power production, reduce power fluctuations, and improve the power reserve of the system. A wind farm MPC is also proposed to optimize load distribution to extend wind turbine life, taking into account wake effects, as well as the effects of fluid dynamics on floating systems [124]. The controller can satisfy power generation and load distribution, and reduce system stress.

We can see that wind power generation control is a field involving a variety of objectives, a variety of constraints, and a variety of control technologies, with high complexity and challenge. With the progress of mathematical modeling technology, artificial intelligence technology, optimization search technology, and other aspects, more and better wind power generation control methods are expected to appear in the future.

4.3. Wind Power Forecasting Class

Wind power generation prediction refers to the estimation of a wind speed or wind power in the future period based on historical data or real-time data, using mathematical models or machine learning methods, and the prediction and evaluation of possible faults that may occur or worsen in the future based on fault diagnosis. Fault prediction methods mainly use historical data or real-time data to build prediction models, and use regression or classification techniques to predict the remaining life or failure probability. Fault prediction can help you make a reasonable and effective maintenance plan to avoid resource waste or loss caused by early or late maintenance. Wind power generation forecasts can be divided into different time scales, such as ultra-short-term (e.g., 15 min, 30 min ago), short-term (days before), medium-term (weeks, months before), and long-term (more than a month before). Different time scales correspond to different application scenarios, such as scheduling, trading, planning, etc. The accuracy of wind power forecasting is of great significance for improving the economy and reliability of wind power systems and reducing the uncertainty and stability of the power grid.

Wind power generation prediction methods are mainly divided into two categories: physical methods and machine learning methods. The physical approach is based on numerical weather prediction models that use meteorological data and geographic information to predict wind speed or wind power over some time in the future. Physical methods are suitable for medium- and long-term forecasting, but require significant computational resources and expertise. Ref. [126] mentioned that there is no single optimal model setup to accurately simulate all events. The combination of physical parameterizations is observed to play an important role in model sensitivity. The use of scale-aware physical parameterization shows the potential for better performance but is largely driven by a combination of model physics and event types. The statistical method is based on historical data or real-time data [127], and uses techniques such as time-series analysis [31] or regression analysis to establish the relationship between wind speed or wind power and other variables [7], and makes predictions based on this relationship.

The machine learning method is based on artificial intelligence technology, using neural networks, support vector machines, fuzzy logic, and other algorithms to learn the complex mapping between wind speed or wind power and other variables and make predictions based on this mapping. Machine learning methods are flexible and adaptable, and can handle non-linear and high-dimensional data, but they require suitable parameter selection and training processes and may have problems such as overfitting or insufficient generalization ability. Figure 6 defines several learning methods associated with machine learning and shows some algorithms applied to the field of wind power prediction and their characteristics.

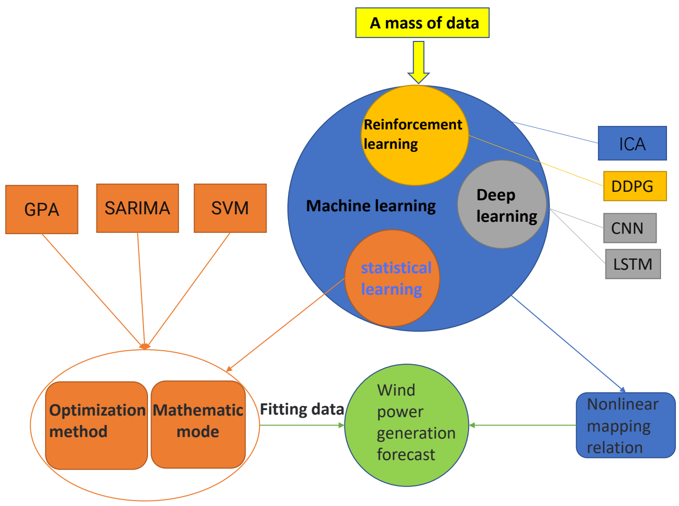

Figure 6. Application of artificial intelligence technology in wind power forecasting.

Statistical learning methods are suitable for ultra-short or short-term predictions but require sufficient and high-quality data and can be affected by factors such as mutations or non-linearities. Refs. [29,31,128–134] mainly used machine learning, deep learning, wavelet transform, time-series analysis, and other methods to predict wind speed, wind power, wave height, and wave period, and to design optimal maintenance strategies. These studies have been empirically validated in different sea areas and time frames, and the results show that they outperform other traditional models. They mainly use the following methods:

- The performance of different neural network training methods for wind prediction was then compared using a reproduction plot and correlation analysis to select the appropriate set of inputs [31]. It is proved that the neural network optimized by Imperialist Competitive Algorithm (ICA) has the lowest prediction error and the fastest convergence speed, showing superior prediction ability.
- Refs. [29,128] used a mix of DWT, Seasonal Autoregressive Integrated Moving Average (SARIMA), and Long Short-term Memory (LSTM) Network models for wind power forecasts for Scotland and the south coast of the UK.
- Refs. [129,130] used a hybrid model of high-frequency SCADA data, depth auto coding, Convolutional Neural Networks (CNN), and LSTM for wind power prediction in the East China Sea and other seas.
- Ref. [131] used high-frequency vibration data and a supported vector machine algorithm for wind turbine fault prediction.
- A deep convolutional recurrent neural network and inverse weighted loss function were used for the spatiotemporal prediction of extreme wind speed events [134].
- A Markov decision process was used for the design of optimal maintenance strategies for wave energy converters [132].
- Support vector regression was used for wave height and wave period prediction [133].

In particular, offshore weather uncertainty has a significant ongoing impact on offshore wind farm siting, turbine reliability, power output, operations, and maintenance. This depends on breakthroughs in existing technology to enable more effective weather forecasting. As a traditional weather forecasting method, the bottleneck of numerical weather forecasting is becoming more and more prominent with the slow growth of computing power and the gradual complexity of physical models. However, the accuracy of existing AI forecasting methods is still significantly lower than that of numerical forecasting methods, and is restricted by the lack of interpretability and inaccurate prediction of extreme weather. Recently, the Huawei Cloud Pangea Meteorological Model broke through the worldwide problem that the accuracy of AI weather forecasts is less than that of traditional numerical forecasts. This model is the first AI prediction model whose accuracy exceeds that of traditional numerical forecast methods, the prediction speed is 10,000 times faster than that of traditional methods, and the global weather prediction can be completed in seconds [135]. Different from existing weather prediction models based on 2D neural networks, the Huawei Cloud Pangea Meteorological Large Model adopts 3D Earth-specific transformer (3DEST) deep network architecture, which can well handle uneven 3D meteorological data.

The content of the Huawei Cloud Pangea Meteorological Grand Model is a major breakthrough in the field of weather prediction, and readers who are interested in this field can get an in-depth understanding of this article. It is necessary for us to actively apply more valuable AI weather forecasting technology (such as the Huawei Cloud Pangea Meteorological Model) to the operation process of offshore wind farms, which will certainly generate a lot of benefits for offshore wind power projects, such as better strategy development in the operation and maintenance process of wind farms.

The above aspects of fault diagnosis, control, and prediction are based on the relevant parameters of offshore wind power generation operations. In the future, in-depth research can be carried out from the following aspects:

- Improve the accuracy and robustness of wind speed or power forecasts with more diversified, refined, and real-time meteorological data sources combined with more advanced, accurate, and faster numerical weather prediction models.
- Improve the efficiency and accuracy of fault diagnosis of wind power systems or their components by leveraging more types, locations, frequencies, and channels of sensor devices combined with more efficient, intelligent, and adaptive signal processing technologies.
- Improve the flexibility and adaptability of the control of wind power systems or their components by optimizing search technologies with more levels, dimensions, constraints, and targets, combined with more flexible, adaptive, and collaborative AI technologies.

To sum up, wind power operation parameter monitoring and prediction is a complex and diverse field, involving multi-data sources, multi-time scales, and multi-prediction techniques. With advances in computing power, artificial intelligence technology, and big data management, there will be more and better monitoring and forecasting methods in the future. The algorithms involved in the monitoring and prediction of wind power operation parameters in this chapter are shown in Table 2.

Table 2. Wind power operation parameters monitoring and forecasting.

Arithmetic	Year	Literature Resources
ICA	2013	[31]
GPA	2018	[104]
FMEA	2022	[112]
CNN	2021	[129]
LSTM	2022, 2021, 2020, 2020	[29,128–130]
DWT	2022	[128]
SARIMA	2022	[128]
SVM	2019	[131]

5. Offshore Wind Farm Maintenance Strategy

The O&M of offshore wind farms also faces many challenges, such as fan failure, marine environment, transportation difficulties, and high costs. Therefore, formulating a reasonable and effective maintenance strategy for offshore wind farms to improve the reliability, efficiency, and benefit of wind farms is an important and complicated problem. In this section, we review the research on maintenance strategies of offshore wind farms in recent years, classify and analyze the types of maintenance strategies and optimization objectives, and point out the existing problems and future development directions.

5.1. Maintenance Strategy Type

According to the decision basis and execution mode of maintenance strategies, three types of maintenance strategies are mainly proposed in the literature: Condition-Based Maintenance (CBM), Preventive Maintenance (PM), and Opportunistic Maintenance (OM).

5.1.1. Condition-Based Maintenance Strategy

The CBM strategy determines the maintenance time and mode based on the fan running status and environment information. This strategy can effectively avoid early or late maintenance, thereby improving maintenance efficiency and reducing costs. CBM strategies require the use of a variety of sensors, monitoring systems, and data analysis methods to collect and process real-time data on fans and wind farms to identify failure patterns, assess remaining life, predict when failure will occur, and more. [42] suggested that the use of rotational energy in offshore wind systems to power distributed or embedded sensing electronics will enable a paradigm shift from timetable-driven to CBM. This paper mainly studies the application of the CBM strategy in wind turbines, including the following aspects: (1) Wind turbine condition monitoring method based on power curve HV and genetic algorithm optimization uncertain hierarchical analysis process (GA-UHAP) [136,137];

(2) Path planning method for offshore wind farm O&M based on a Multi-Agent System (MAS) [138]; (3) Technical and economic analysis method of offshore wind farms based on the stochastic O&M model and Monte Carlo simulation [139]; (4) Wind turbine fault diagnosis, remaining life estimation, fault prediction, and other methods based on failure rate, maintenance time, and cost [140].

5.1.2. Preventive Maintenance Strategy

The PM strategy for offshore wind farms refers to the strategy of developing regular or regularly spaced maintenance plans based on historical fault data and reliability models of wind turbines to improve the reliability and availability of wind farms. To achieve this goal, Refs. [98,141–143], respectively, proposed different optimization techniques and methods, including multi-objective optimization, meta-heuristic optimization, Monte Carlo simulation, etc., taking into account the uncertainties of the marine environment, fan failure, ship transportation, etc. Through mathematical models, simulation models, and test methods, optimal or sub-optimal maintenance strategies, logistics schemes, and access fleet schemes were generated and evaluated, and their robustness was tested. This study provides a valuable reference for PM strategies of offshore wind farms. Ref. [144] applied the concept of Maintenance 4.0 to wind turbines and proposed an implementation procedure that combines reliability modeling, algorithm design, real-time performance monitoring, failure prediction, and preventive task prescription. For reliability modeling, a robust two-layer programming method was proposed, which fully considers the influence of prediction errors on multi-source system planning schemes [145].

In a CBM strategy, different generator types may have different reliability, efficiency, and maintenance requirements that affect their O&M costs. For example, Double-fed Induction Generators (DFIG) and Permanent Magnet Synchronous Generators (PMSG) are two common types of wind turbine generators.

DFIG is suitable for variable-speed wind turbines with gearboxes, which allow variable-speed operation over a smaller power range, but require more complex controllers and converters, as well as additional slip rings and brushes [146]. For DFIG, too-high or too-low machine parameters will affect its performance in the transient state, while moderately equivalent machine parameters can improve its performance [147]. PMSG is suitable for gearless variable-speed wind turbines, which can achieve variable-speed operation over a large power range, but require larger permanent magnets and higher manufacturing costs [146]. For PMSG, too-low machine parameters will affect its performance in the transient state, and the stator winding resistance parameters have a great influence on its variables [147].

Therefore, the impact of different generators on wind asset maintenance and inspection plans may be as follows:

- First of all, both DFIG and PMSG need to pay attention to the change of their stator resistance parameters, because it has a great impact on their variables. This parameter may need to be measured and adjusted more frequently to guarantee its stability and reliability.
- Maintenance and inspection plans for DFIG need to consider the wear and failure of these components, as well as the protection and stability of the grid.
- PMSG maintenance and inspection plans need to consider demagnetization and damage to permanent magnets, as well as regulation and control of the power grid.
- Environmental impact assessments were carried out for different types of wind turbines and factors such as their failure rate, replacement rate, and recovery rate were analyzed [148]. These factors need to be considered in wind energy asset maintenance and inspection programs to improve efficiency and save costs.

5.1.3. Opportunistic Maintenance Strategy

The OM strategy refers to the strategy that dynamically adjusts the maintenance plan and priority according to the operation status and production demand of the wind farm, as well as the mutual influence and cooperation between the fans. This strategy can improve the maintenance effect and the overall performance of the wind farm, but it needs to use various scheduling algorithms and decision models to analyze and model the dependency relationship between the fans, the operational constraints of the wind farm, the market demand, and other factors to determine the optimal maintenance time and way. The research on OM strategy mainly includes the following aspects:

- The impact of weather forecasts on the O&M of offshore wind farms. Ref. [127] proposed a performance comparison method for long-term weather forecasting models based on sequential data. This method compares the performance of different sequential data-driven models (such as recurrent neural networks, long short-term memory networks, gated cyclic unit networks, etc.) in terms of prediction accuracy, robustness, and computational efficiency. To provide more reliable and efficient weather forecasting information for offshore wind farms.
- OM scheduling approach. Refs. [149,150] proposed an OM scheduling method, which adopts mixed-integer linear programming. Opportunity is defined as based on crew scheduling (initiated by maintenance crews already dispatched to adjacent turbines), based on production (initiated by projected low production levels), or based on access (initiated by a temporary opening of turbine access Windows) [150]. The branch and bound method and cut plane method are used to solve MILP problems, which improves the efficiency and accuracy of solving [149].
- The joint use of service vessels and safe transfer vessels in offshore wind farms. In Ref. [151], it was modeled as a multi-period position and maintenance problem, the influence of uncertainty factors on problem-solving was considered, and a method based on mixed-integer programming and random programming was proposed to find the optimal layout and path planning scheme. Ref. [151] provided an effective model and method for the layout and path planning of OWT.
- Offshore wind turbine rotor blades have a variety of internal and external damage conditions. In response to this problem, Ref. [152] proposed an opportunistic PM strategy. The model employs secondary, primary, and OM strategies. The model refers to the blades of wind turbines, and the ultimate goal is to determine the optimal secondary and primary maintenance rates to maximize asymptotic availability. A numerical example based on empirical data was used to illustrate the effectiveness of the proposed model and maintenance strategy.
- The impact of wind turbine production losses on maintenance scheduling and routing issues. Ref. [153] proposed a new mathematical model to optimize maintenance scheduling and routing problems, highlighting the significance of PL items before and during maintenance activities. In the proposed method, the PL term takes the latest wind turbine power curve and predicted wind resources as model inputs. Subsequently, a new GA solver was designed to minimize wind turbine PL along with technician wages and transportation costs.
- The application of Internet of Things (IoT) technology and multi-agent systems in OWPS. Ref. [154] proposed a research method for offshore wind power systems based on IoT technology. This method uses IoT technology to realize real-time collection and transmission of status information of each subsystem of the offshore wind power system (such as fans, substations, transmission lines, etc.) and carries out data analysis and processing through a cloud computing platform. To improve the operational efficiency and safety of OWPS. Ref. [155] proposed a modeling and simulation method for the maintenance strategy of offshore wind farms based on multi-agent systems. This method utilizes the autonomous and cooperative mechanism among various agents in the multi-agent system to realize real-time sharing and updating of status information of various subsystems (such as fans, ships, warehouses, etc.) in offshore wind farms. The simulation platform is used to evaluate the impact of different maintenance strategies on the operating costs and benefits of offshore wind farms.

CBM refers to a strategy that predicts the time of failure according to the operating state of the equipment and carries out maintenance at an appropriate time [156]. CBM generally improves equipment availability and reduces maintenance costs compared to Age-Based Maintenance Strategies (ABMS) because it avoids unnecessary PM and unplanned downtime [157]. PM refers to the strategy of carrying out regular or quantitative maintenance according to the preset life or cycle of the equipment [156]. Compared with corrective maintenance strategies, PM can generally reduce the failure rate of equipment and extend the life of equipment because it can detect and eliminate potential sources of failure promptly [157]. OM refers to the strategy of taking advantage of planned or unplanned maintenance of one device to maintain other devices [156]. OM generally saves maintenance resources and time compared to performing maintenance alone because it reduces repetitive preparation and downtime [157].

Figure 7 briefly shows the characteristics of three maintenance strategies through some elements of offshore wind farm maintenance. Readers can better understand these three strategies through this figure combined with the information in the paper. The three colors of the wind turbine are used to represent different states, with green indicating good operation, red indicating failure, and yellow indicating uncertainty of state. At the bottom is a timeline, the periodic maintenance of PM has periodic time points on the top, and the maintenance time points of the other two maintenance strategies must be determined based on other circumstances.

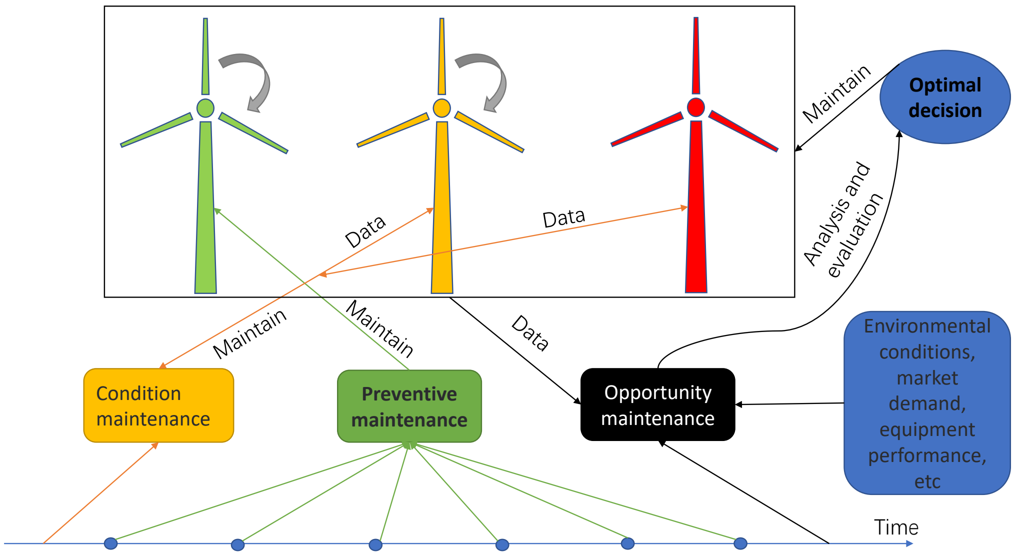

Figure 7. Classification of maintenance strategies.

The above three maintenance strategies have their advantages and disadvantages and apply to different situations and conditions. However, both require the accessibility of offshore wind farms, which may not be able to arrive or complete maintenance in time due to the limitations of marine weather and maintenance resources [158]. Generally speaking, CBM is suitable for equipment with certain regularity or monitoring characteristics of fault occurrence, PM is suitable for equipment with certain periodicity or distribution of fault occurrence, and OM is suitable for the situation where multiple devices have economic correlation or common shutdown impact [159,160]. Periodic maintenance is necessary to ensure the reliability and safety of OWT, but it should be carried out at an optimal frequency to minimize the maintenance cost [161]. Comprehensive inspection after major repairs can make efficient use of maintenance resources and detect potential faults in advance. Condition monitoring systems can reduce the burden of periodic maintenance, and reduce downtime and maintenance costs by providing real-time data and early warning signals [162]. However, the cost of installing and operating a condition monitoring system needs to be considered to avoid making the operation of OWT uneconomical. In practical applications, these three maintenance strategies can be flexibly combined according to specific conditions to achieve optimal or sub-optimal maintenance effects.

This paper proposes a framework for the formation of maintenance strategies for offshore wind farms. The determination of the maintenance strategy should consider the current situation of wind turbines, the marine environment, market demand, and other factors that affect the operation and maintenance of offshore wind farms. The framework consists of five steps: (1) Data collection and analysis; (2) Determining maintenance requirements; (3) Making maintenance plan; (4) Maintenance execution and control; (5) Maintenance evaluation and improvement. The flow diagram of this framework is shown in Figure 8:

- Step 1: Data collection and analysis. This step is mainly through various sensors, monitoring equipment, IoT technology, real-time or regular collection, and transmission of offshore wind farm operating data, and the use of data analysis and processing technology, such as fault diagnosis, fault prediction, and remaining life assessment, to evaluate and predict the status and performance of the fan, to provide information support for subsequent maintenance decisions.
- Step 2: Determine maintenance requirements. This step is mainly based on the results of data analysis, as well as the marine environment, market demand, and other factors, to determine the maintenance needs of offshore wind farms, that is, which fans need to be maintained, and the type, timing, and priority of maintenance. Maintenance requirements are classified into planned maintenance and unplanned maintenance. Planned maintenance refers to periodic or quantitative maintenance based on the preset service life or period of the fan. Unplanned maintenance refers to emergency maintenance or conditional-triggered maintenance based on actual faults or performance degradation of the fan.
- Step 3: Make a maintenance plan. This step is mainly based on the maintenance needs of offshore wind farms, as well as the available maintenance resources, such as personnel, materials, ships, etc., to develop a reasonable and effective maintenance plan, that is, to determine the maintenance tasks, time and sequence of each fan. Maintenance planning needs to consider a variety of factors and objectives, such as cost, efficiency, reliability, benefit, etc., and use a variety of optimization models and algorithms to solve the optimal or sub-optimal solution.
- Step 4: Maintenance execution and control. This step is mainly to organize and dispatch the corresponding maintenance resources according to the maintenance plan of the offshore wind farm, carry out specific maintenance operations, and monitor and control the maintenance process in real-time or regularly to ensure the smooth completion of the maintenance plan. Maintenance implementation and control need to consider the impact of uncertain factors, such as weather changes, failures, market fluctuations, etc., and use a variety of information systems and intelligent systems to provide information sharing and decision support.
- Step 5: Maintenance assessment and improvement. This step mainly evaluates and analyzes the maintenance process and effect according to the results of maintenance implementation and control of the offshore wind farm, and proposes improvement measures and suggestions for the maintenance strategy according to the results of evaluation and analysis, to improve the effect and level of the offshore wind farm maintenance strategy. Maintenance evaluation and improvement need to consider a variety of evaluation indicators and standards, such as cost, efficiency, reliability, benefit, etc., and use a variety of evaluation models and methods to carry out qualitative or quantitative evaluation.

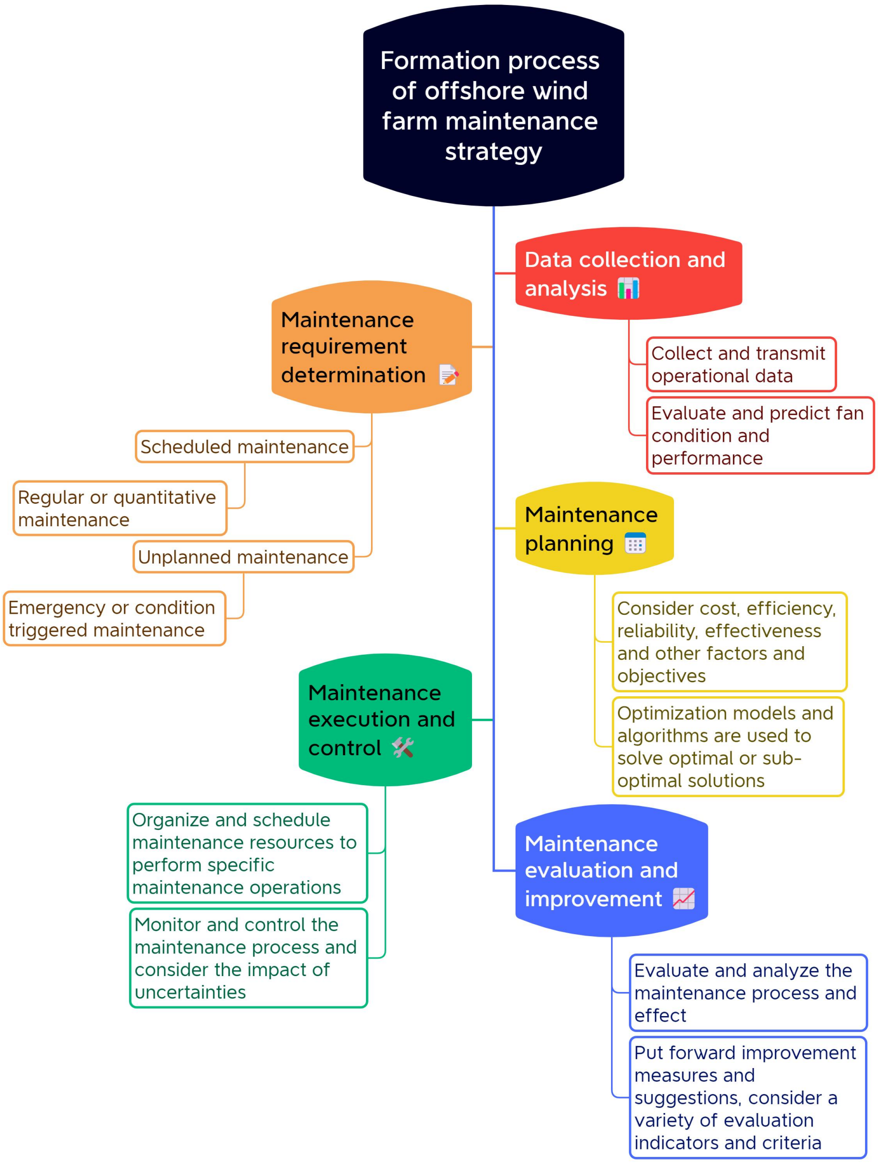

Figure 8. The formation process of offshore wind farm maintenance strategy.

5.2. Optimization Goals of Maintenance Strategies

According to the evaluation indexes and expected effects of maintenance strategies, five types of optimization objectives are mainly proposed in the literature: cost minimization, efficiency maximization, reliability maximization, benefits maximization, and multi-objective optimization.

5.2.1. Cost Minimization

Cost minimization refers to the maintenance optimization method of offshore wind farms to ensure the normal operation of offshore wind farms. This method uses Bayesian networks to model the failure probability and maintenance cost of fans and determines the optimal maintenance time and the way by solving a stochastic programming model to maximize the reliability and benefits of offshore wind farms. Refs. [163,164] are about uncertainty analysis and control in the operation of offshore wind farms. Parametric risk control strategies and time-series methods are used respectively to model and predict uncertain factors, and to evaluate the impact of different strategies on the reliability and revenue of offshore wind farms. Refs. [165,166] used a two-stage stochastic programming model and a multi-step probabilistic wave prediction model, respectively, to determine the optimal fleet configuration and the transport path, taking into account the uncertainty of weather conditions and the occurrence of failures. The concept of self-reconfiguration of wind turbine position in Floating Offshore Wind Farms (FOWF) is discussed. Self-restructuring mechanisms move degraded turbines to different farm locations to delay failure and reduce power loss [167].

5.2.2. Benefit Maximization

Benefit maximization means to improve various benefits, including economic benefits and environmental benefits, in the maintenance process of offshore wind farms under the premise of ensuring the normal operation of offshore wind farms. This is a comprehensive and meaningful optimization goal because the benefits of an offshore wind farm reflect not only its operation but also its contribution to society and the environment. To maximize the benefits, various income models and evaluation methods are mainly used in the literature to analyze and model the income and loss generated during the O&M of offshore wind farms and formulate corresponding maintenance measures and programs.

The O&M of offshore wind farms is an important factor affecting their economics and sustainability, which needs to consider multiple aspects such as uncertainty, safety, cost, and environment. A risk control strategy based on simulation was proposed to improve the profitability of offshore wind farms by adjusting the number and speed of ships and personnel [163]. To optimize maintenance operations, a repair kit determination method based on mixed-integer programming was proposed [168], which can select appropriate tools and vessel routes according to different weather conditions and maintenance needs. A new motion stabilization technique was proposed to reduce the vertical, roll, and pitch motions of ships under different wave conditions, especially in the resonant frequency region [169]. A sustainable O&M method was proposed to reduce the number of transmission changes and transportation distance by using on-site inspection, online monitoring, remote diagnosis, and other technologies [170].

5.2.3. Multi-Objective Optimization

Multi-objective optimization refers to balancing multiple objectives that may conflict or compete during the maintenance of offshore wind farms, such as cost and efficiency, or cost and reliability, on the premise of ensuring the normal operation of offshore wind farms. This is a complex and challenging optimization goal because the maintenance process of offshore wind farms involves several related or mutually restrictive factors, such as human resources, material resources, transportation resources, time resources, etc. To achieve multi-objective optimization, various multi-objective programming models and solving algorithms are mainly used in the literature to solve the optimal or sub-optimal maintenance plan and maintenance resource allocation [171].

The O&M scheduling strategy of offshore wind farms refers to arranging appropriate maintenance tasks and power generation tasks according to the operating status, maintenance requirements, resource conditions, and other factors of wind farms, to improve the economy and reliability of wind farms. Based on the relevant literature, this paper introduces the following four operation and maintenance scheduling strategy models: The maintenance strategy combination model based on multi-objective mixed-integer nonlinear programming can balance the objectives of operating cost, reliability, and availability, and consider different types of maintenance tasks [141]. The O&M scheduling model based on O&M task priority and O&M scheduling constraints can arrange the optimal maintenance sequence and path according to task urgency and actual constraints to reduce maintenance costs [136]. The strategic decision support model based on the two-layer stochastic model can simultaneously consider the uncertainty of long-term strategy and short-term operation, and support strategic decisions such as ship leasing [172]. The asynchronous O&M scheduling strategy model based on the two-stage model can arrange maintenance tasks and power generation tasks respectively, and balance maintenance costs, power generation income, wind farm stability, and other objectives [173]. These models are all based on optimization methods and take into account multiple objectives and constraints, but they also have their characteristics and differences. They provide different methods and ideas for the O&M scheduling of offshore wind farms.

The relevant models or algorithms of offshore wind farm maintenance strategies in recent years are shown in Table 3.

Table 3. Related models or algorithms for offshore wind farm maintenance strategies.

Model or Algorithm	Year	Literature Resources
Monte Carlo simulation	2015, 2017	[142,174]
Multi-Agent systems	2022, 2015	[138,155]
Genetic Algorithm	2022, 2019	[116,153]
Internet of Things	2022	[154]
Mixed-integer linear programming	2022	[150]

5.3. The Existing Problems and the Future Development Direction

Through the review of recent studies on offshore wind farm maintenance strategies, it can be found that many valuable and meaningful methods and models have been proposed in the literature, and the offshore wind farm maintenance strategies have been analyzed and optimized from different perspectives and levels. However, offshore wind farm maintenance strategies remain a complex and dynamic issue, with several issues that have not been resolved or need to be improved, such as:

- The modeling and solving process of offshore wind farm maintenance strategy involves many uncertain factors, such as fan failure, marine environment, market demand, etc. Changes in these factors may lead to the failure or inefficiency of the maintenance strategy. Therefore, how to deal with and utilize this uncertain information effectively to improve the robustness and adaptability of the maintenance strategy is a problem worth studying.
- The evaluation and optimization of an offshore wind farm maintenance strategy involve multiple potentially conflicting or competing objectives, such as cost, efficiency, reliability, effectiveness, etc., and the weights and preferences between these objectives may change over time and circumstances. Therefore, how to balance and coordinate these objectives effectively to achieve multi-objective optimization of offshore wind farm maintenance strategy is a problem worth studying.
- The development and implementation of maintenance strategies for offshore wind farms involve several related or mutually restricted subsystems, such as fans, ships, warehouses, etc. The information exchange and collaboration among these subsystems have an important impact on the effect of maintenance strategies. Therefore, how to effectively use data-driven and intelligent system technologies to improve information sharing and decision support among subsystems in offshore wind farm maintenance strategy is a problem worth studying.

Based on the above analysis, this paper believes that future research on offshore wind farm maintenance strategies can be developed from the following aspects:

- Introduce more uncertain information processing and utilization methods, such as probability theory, fuzzy theory, evidence theory, etc., to improve the robustness and adaptability of offshore wind farm maintenance strategies.
- Introduce more multi-objective optimization methods, such as genetic algorithm, particle swarm optimization, simulated annealing algorithm, etc., to achieve multi-objective optimization of offshore wind farm maintenance strategies.
- Introduce more data-driven and intelligent system technologies, such as IoT, cloud computing, artificial intelligence, etc., to improve information sharing and decision support among the various subsystems in the offshore wind farm maintenance strategy.

6. Grid Connection Technology for Offshore Wind Farms

This section introduces the basic concepts, main features, key problems, solutions, and future directions of offshore wind power technology from eight aspects, such as grid connection, transmission, power generation, array cable, digital twin, transformer, microgrid planning, and fault control.

6.1. Offshore Wind Farm Power Transmission

Offshore wind power transmission technology refers to the technology of transferring electric energy from offshore wind farms to the onshore power grid, mainly in the form of AC or direct flow. Offshore wind power transmission technology involves the output fluctuation of offshore wind farms, the loss and protection of transmission lines, the control and stability of the converter, and other factors, which is one of the key problems and difficulties faced by offshore wind power technology. Refs. [34,175–177], respectively, introduced Multi-Terminal Direct Current Transmission (MTDCT) systems based on Modular Multi-Level Converter High-Voltage Direct Current (MMC-HVDC) wind farms based on Voltage Source Converter (VSC) high-voltage direct current (HVDC) connections and dual-rotor bidirectional flux modulation; four kinds of offshore wind power transmission methods, including a Permanent Magnet Generator (PMG) and VSC-HVDC parallel operation system; and a hybrid HVDC converter composed of M2C and a diode rectifier. Their basic principle and topology, control strategy and protection scheme, performance characteristics, advantages and disadvantages, development prospects, and challenges are analyzed.

Transmission fault control technology of offshore wind power refers to the technology to ensure the safe and stable operation of offshore wind power systems when a failure occurs, mainly including fault detection, fault isolation, fault recovery, and so on. Offshore wind power fault control technology is one of the important guarantees of offshore wind power technology, which involves the complexity, uncertainty, and dynamic characteristics of offshore wind power systems. Ref. [178] summarized the application of artificial intelligence technology to realize big data service in distribution networks, introduced the basic concept and classification of artificial intelligence technology, analyzed the main application scenarios and challenges of artificial intelligence technology in distribution networks, and looked forward to the future development trend of artificial intelligence technology in the distribution network. A fault-crossing control method for offshore wind farms connected by MMC-HVDC based on harmonic injection was proposed. The harmonic injection was used to realize fault detection and location [179]. An adaptive control strategy was designed, and the effectiveness and reliability of the control method are verified by simulation. A method to reduce the frequency fluctuation of hybrid power systems by variable speed and variable pitch control was proposed [180]. Considering the output characteristics of offshore wind farms and diesel generators, a dynamic variable discharge control strategy was designed. The effectiveness and reliability of the control strategy were verified through simulation and testing.

Offshore wind power transformer technology refers to the technology of increasing or decreasing the voltage of offshore wind farms, mainly including transformer types, parameters, faults, protection, and so on. Offshore wind power transformer technology involves the electrical characteristics, environmental conditions, safety performance, and other factors of offshore wind farms, and is one of the important components of offshore wind power technology. Ref. [181] analyzed the causes of over-temperature combustion failure of the transformer of a 4 MW offshore wind turbine; detected and analyzed the structure, materials, and working state of the transformer; found out the main factors leading to the failure; and put forward measures and suggestions to prevent the failure. A method was proposed to optimize the dynamic design of transformers for offshore wind farms, taking into account the reliability and emergency of transformers, and using mixed-integer linear programming to solve the optimization problem [182]. The cost and performance of different design schemes were compared through case analysis.

Submarine cables are an important part of connecting OWT to the onshore power grid, but they are also vulnerable to erosion and stress from seabed sediments, affecting their performance and longevity. Therefore, analyzing the deposition and stress conditions of submarine cables to improve their reliability and safety is a key issue for offshore wind power generation. Some literature has studied this. For example, the erosion parameters of submarine cables under different conditions were obtained by numerical simulation and experiment citer196, and their effects on the stress state of cables were analyzed. A multi-beam sounding system and side-scan sonar technology were used to detect and evaluate the safety of underwater structures in offshore wind farms [183]. These studies provide effective methods and data support for sediment and stress analysis of submarine cables, but there are still some shortcomings, such as the influence of sediment type, water velocity, water depth and other conditions on the erosion parameters and stress state is not clear enough, and the erosion detection technology needs to further improve the accuracy and efficiency.

Offshore wind power array cable technology refers to the technology that connects the fans inside the offshore wind farm, mainly including the type, length, weight, cost, reliability, and protection of the cable. Offshore wind power array cable technology involves the scale, layout, environment, and other factors of offshore wind farms, and is one of the important components of offshore wind power technology. A method for optimizing cable configuration between floating OWT was proposed [184]. Considering cable length, weight, cost, reliability, and emergency conditions, a genetic algorithm is used to solve the optimization problem, and the advantages and disadvantages of different configuration schemes are compared through case analysis. A method was proposed to compare the internal grid topologies of different offshore wind farms, taking reliability and economy into consideration [185]. The performance indexes of different topologies were calculated through Monte Carlo simulation, and the influence of different parameters on the performance indexes was evaluated through sensitivity analysis.

Therefore, future research can be improved from the following aspects: (1) Establish more precise numerical models and experimental devices, consider more influencing factors, and reveal the erosion and stress mechanism of submarine cables; (2) Develop more advanced scour detection technology to improve the measurement accuracy and real-time performance of scour parameters; (3) Design a more optimized submarine cable layout and protection measures to reduce the risk of erosion and stress of submarine cables.

6.2. Digital Twin Technology for Offshore Wind Power

Digital twin technology of offshore wind power refers to the technology that combines the physical entity and digital model of offshore wind power system, mainly including the construction of a digital twin model, data interaction, synchronous update, system monitoring, fault diagnosis, optimization control, and so on. The digital twin technology of offshore wind power involves the complexity, uncertainty, and dynamic characteristics of offshore wind power systems, and is one of the frontiers and hotspots of offshore wind power technology. Ref. [186] discussed the digital twin technology of large-scale offshore wind power flexible direct transmission system, constructed the digital twin model and platform, realized the data interaction and synchronous update between the digital twin and the physical system, and used the digital twin for system monitoring, fault diagnosis, and optimization control. The validity of the Electromagnetic Transient (ET) digital twin model for evaluating the dynamic voltage performance of a 66 kV offshore transmission network was verified [187]. The experimental data were used to identify and calibrate the parameters of the digital twin model, and the accuracy and reliability of the digital twin model were proved through comparison and analysis with physical experiments.

6.3. Offshore Wind Power Grid-Connected Technology

The grid-connected technology of offshore wind power refers to connecting offshore wind farms with onshore power grids to realize the transmission and consumption of offshore wind power. The grid-connected technology of offshore wind power involves the output characteristics of offshore wind farms, the loss of transmission lines, and the stability of power grids, which is one of the core and difficult points of offshore wind power technology. A grid connection scheme for offshore wind power based on multi-objective optimization was proposed, taking into account the output characteristics of offshore wind farms, the loss of transmission lines, and the stability of the grid [188]. The optimal grid connection scheme was obtained by solving the optimization problem through a genetic algorithm. Ref. [189] summarized the current situation and trend of the integration of offshore wind power into the future power system, analyzed the advantages and challenges of offshore wind power, discussed the coordinated operation and complementarity of offshore wind power and other renewable energy sources, and put forward some future research directions. Ref. [190] introduced the operational practice and regulatory framework of the grid-connected offshore wind power system, analyzed the technical requirements and standards of the grid-connected offshore wind power system, summarized the operational experience and lessons of the grid-connected offshore wind power system, and put forward improvement measures and suggestions for the grid-connected offshore wind power system. Based on the finite-element method, Ref. [191] analyzed the influence of grid connection of large-scale offshore wind farms on the stability of sub-synchronous oscillation, and provided corresponding evaluation methods. The integration technology of offshore wind farms and the power grid was reviewed, and the integration of offshore wind farms and the power grid was analyzed [192]. The article also compared previous and recent developments, including power quality and stability challenges and their solutions; discussed Low-Voltage Ride Through (LVRT) schemes and related grid specifications, as well as various power quality issues and mitigation measures; and summarized recommendations and future trends for improving power quality. Three aspects of future research should be focused on: OWP special equipment technology, OWP-integrated optimization technology, and complementary power generation technology [193]. The relevant technical methods and their advantages and disadvantages are shown in Table 4.

Table 4. Offshore wind power grid-connected technology.

Method	Advantage	Shortcoming
Grid connection scheme of offshore wind power based on multi-objective optimization	It can comprehensively consider the output characteristics of offshore wind farms, the loss of transmission lines, and the stability of the grid	It takes a lot of computing resources and time
Coordinated operation and complementarity of offshore wind power with other renewable energy sources	It can reduce the impact and fluctuation of the power grid and increase the flexibility and robustness of the power system	The characteristics and constraints of multiple energy sources need to be considered,increasing the complexity and operating costs of the system
Operational practices and regulatory framework for offshore wind power grid-connected systems	It can sum up the operation experience and lessons of offshore wind power grid-connected system, and put forward improvement measures and suggestions	Develop appropriate technical requirements and standards to ensure the safety and compatibility of offshore wind power grid-connected systems
Integration technology of offshore wind farm and power grid	Improve the output quality and stability of offshore wind farms and reduce the impact and loss on the grid	It is necessary to solve various technical problems encountered in the integration process, such as LVRT solutions

The offshore wind power microgrid planning technology refers to the technology that combines offshore wind farms with other energy sources and loads to form an independent or semi-independent power system, mainly including the structure, capacity, location, control, and other aspects of the microgrid. Offshore wind power microgrid planning technology involves the economy, reliability, environmental benefits, and other factors of offshore wind farms, and is one of the innovation and development directions of offshore wind power technology. A two-layer multi-objective planning method was proposed for microgrid planning containing offshore wind power, taking into account the economy, reliability, environmental benefits, and other objectives of microgrid, using an improved genetic algorithm to solve the planning problem, and comparing the performance indicators of different planning schemes through case analysis [194]. A method was proposed to comprehensively optimize the position and capacity of the reactive power compensation device at the offshore wind farm and its connection point with VSC-HVDC [195]. Considering the output characteristics of offshore wind farms, loss of transmission line, cost and benefit of reactive power compensation device, and other factors, mixed-integer non-linear programming is adopted to solve the optimization problem. The results of different optimization schemes are compared by case analysis.

The types of technologies covered in this section are shown in Table 5.

Table 5. Grid connection technology for offshore wind farms.

Type of Technology	Year	Literature Resources
MMC-HVDC	2022, 2021, 2023	[176,177,179]
MTDCT	2016, 2021	[34,175]
VSC	2021, 2022, 2021	[175,176,195]
HVDC	2016, 2021	[34,177]
ET	2020	[187]
LVRT	2021	[192]

7. Discussion

There are also some differences and contradictions between these five sections, which need to be coordinated and balanced. For example:

- Methods and strategies for optimizing the use of offshore wind and wave energy may increase the complexity and uncertainty of components of OWT, thereby increasing their failure rates and maintenance difficulties;
- Technologies and methods for the optimization of components of OWT may increase the cost and data volume of the application of digital twin technology in offshore wind systems, thereby increasing their computational efficiency and data quality requirements;
- The application of digital twin technology in OWPS may increase the dependency and security of O&M, thus increasing the requirements for network communication and data protection. The latest research progress of digital twin technology for OWF O&M is reviewed, and an O&M optimization framework based on data mining is proposed [32]. Figure 9 illustrates the application and value of digital twin technology in offshore wind power systems;
- Systems and challenges of O&M may constrain technological innovation and sustainable development of offshore wind systems, thereby increasing their requirements for support and community engagement;
- Technological innovation and sustainable development may affect the adaptability and compatibility of methods and strategies for optimizing the use of wind and wave energy at sea, thereby increasing the need for standardization and integration.

The application and value of digital twin technology in offshore wind power system		
The core concepts and characteristics of digital twin technology		Match real physical objects with virtual models and update them synchronously in real time
		Physical models, sensor data, operational analysis and visualization techniques are used to map and simulate real physical objects in real time
		Provides intelligent services such as data analysis, fault diagnosis, performance evaluation, and optimization suggestions
Different digital models	Physical model	Based on physical laws and mathematical equations
		Accurate parameters and boundary conditions are required
		Applicable to deterministic and linear systems
	Data-driven model	Built on historical data and machine learning methods
		Large amounts of high-quality data are required
	Hybrid model	Combine the benefits of physical and data-driven models
		Make up for the shortcomings and limitations of a single model
		The need to balance physical knowledge and data information
Different data sources	Sensor data	The state or behavior of a physical object
		Sensor layout, calibration, communication, etc
		High frequency, high precision, high dimensional data
	SCADA data	Indirectly reflects the running or control status of physical objects
		SCADA system configuration, sampling rate, compatibility and other issues
		Low frequency, low precision, low dimension data
	Metadata	A property or characteristic of a physical object
		Metadata acquisition, management, update and other issues
		Static, sparse, diverse data

Figure 9. The application and value of digital twin technology in offshore wind power system.

Artificial intelligence technology and digital twin technology are two important technologies in offshore wind power O&M, and they have a wide range of applications and opportunities in OWPS. Artificial intelligence technology can make use of big data analysis, machine learning, deep learning, and other methods to intelligently process and analyze the operating data of the offshore wind power system, to realize functions such as fault diagnosis, predictive maintenance, and optimization control, and improve the intelligence level of the offshore wind power system [22]. Digital twin technology can use digital models and data analysis to simulate and predict the real physical state of the offshore wind power system, to realize functions such as operation monitoring, performance evaluation, and reliability update, and improve the efficiency and reliability of the offshore wind power system [77,78].

To better leverage the applications and opportunities of artificial intelligence technology and digital twin technology in offshore wind power O&M, the following recommendations and directions are proposed:

- Strengthen the integration and collaboration of artificial intelligence technology and digital twin technology in the operation and maintenance of offshore wind power and use artificial intelligence technology to provide data support and intelligent decision-making for digital twin technology. For example, Ref. [32] used machine learning, deep learning, neural network, and other methods to analyze, predict and optimize the data of offshore wind power, and use physical models, simulation models, data-driven models, and other methods to update, visualize and evaluate the status of offshore wind power in real-time. The artificial intelligence model of offshore wind power is verified, improved, and optimized by information value calculation and value-driven development. Digital twin technology can also be used to provide model verification and feedback adjustment for artificial intelligence technology, such as [32] using physical models, simulation models, data-driven models, and other methods to update, visualize and evaluate the status of offshore wind power in real-time. The artificial intelligence model of offshore wind power is verified, improved, and optimized by information value calculation and value-driven development.

- Strengthen the innovation and development of artificial intelligence technology and digital twin technology in offshore wind power operation and maintenance and explore more advanced algorithms, models, methods, and application scenarios to adapt to the complexity, uncertainty, and multi-objective nature of offshore wind power systems [186]. It is pointed out that the implementation of digital twin technology in large-scale offshore wind power flexible direct transmission systems provides great help for unmanned operation and maintenance, remote management, and real-time scheduling of offshore wind power flexible direct transmission systems, and is an innovative application of digital twin technology in power system. Even the author [77] used game engines to develop digital twin technology for offshore wind power. Game engines can provide high-quality physical environment simulation and a rich 3D content library, which provides strong support for offshore wind power digital twin technology.
- Strengthen the standardization and standardization of artificial intelligence technology and digital twin technology in the O&M of offshore wind power, and establish uniform data formats, interface protocols, evaluation indicators, etc., to ensure the compatibility and credibility of artificial intelligence technology and digital twin technology in OWPS.

8. Conclusions

This paper provides a comprehensive review of the state-of-the-art technologies and challenges for OWPS, with a focus on their O&M. It covers the optimization of offshore wind power components, the integration and utilization of offshore wind and wave energy, and the monitoring and forecasting of offshore wind power operating parameters. It also discusses the future research directions and suggestions for enhancing the performance, sustainability, and intelligence of OWPS, such as designing, simulating, controlling, and evaluating collaborative marine renewable energy systems, comparing and analyzing the optimal wind and wave energy utilization systems under different scales, scenarios, and objectives, considering the social and economic factors in offshore wind power project evaluation and optimization, and applying big data analysis and artificial intelligence techniques to OWPS. This paper aims to provide a useful reference for researchers in related fields.

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Abbreviations

The following abbreviations are used in this manuscript:

OWPS	Offshore Wind Power Systems
O&M	Operation And Maintenance
EPP	Energy Payback Periods
FWT	Floating Wind Turbines
FOWF	Floating Offshore Wind Farms
CSWT	Conventional Stationary Wind Turbines
LCES	Life Cycle Engineering Services
OWT	Offshore Wind Turbines
MABL	Marine Atmospheric Boundary Layer
MPC	Model Predictive Control
OPS	Offshore Pumped Storage
rSOC	Reversible Solid Oxide Cell
LCA	Life Cycle Assessment
WEC	Wave Energy Converters
HV	Health Value
GA	Genetic Algorithm
UHAP	Uncertain Hierarchical Analysis Process
ICA	Imperialist Competitive Algorithm
GPA	Gaussian Process Algorithm
SCADA	Supervisory Control And Data Acquisition
FMEA	Failure Mode And Effect Analysis
MAS	Multi-Agent System
DWT	Discrete Wavelet Transform
SARIMA	Seasonal Autoregressive Integrated Moving Average
LSTM	Long Short-term Memory
CNN	Convolutional Neural Networks
SVM	Support Vector Machine
ABMS	Age-Based Maintenance Strategies
CBM	Condition-Based Maintenance
PM	Preventive Maintenance
OM	Opportunistic Maintenance
MTDCT	Multi-Terminal Direct Current Transmission
ET	Electromagnetic Transient
MMC	Modular Multi-Level Converter
VSC	Voltage Source Converter
HVDC	High-voltage Direct Current
PMG	Permanent Magnet Generator
IoT	Internet of Things
LVRT	Low-Voltage Ride Through

References

1. Kaldellis, J.; Apostolou, D. Life cycle energy and carbon footprint of offshore wind energy. Comparison with onshore counterpart. *Renew. Energy* **2017**, *108*, 72–84. [CrossRef]
2. Rodrigues, S.; Restrepo, C.; Kontos, E.; Pinto, R.T.; Bauer, P. Trends of offshore wind projects. *Renew. Sustain. Energy Rev.* **2015**, *49*, 1114–1135. [CrossRef]
3. Fan, Q.; Wang, X.; Yuan, J.; Liu, X.; Hu, H.; Lin, P. A Review of the Development of Key Technologies for Offshore Wind Power in China. *J. Mar. Sci. Eng.* **2022**, *10*, 929. [CrossRef]
4. Maandal, G.L.D.; Tamayao-Kieke, M.A.M.; Danao, L.A.M. Techno-Economic Assessment of Offshore Wind Energy in the Philippines. *J. Mar. Sci. Eng.* **2021**, *9*, 758. [CrossRef]
5. Tomporowski, A.; Flizikowski, J.; Kruszelnicka, W.; Piasecka, I.; Kasner, R.; Mroziński, A.; Kovalyshyn, S. Destructiveness of Profits and Outlays Associated with Operation of Offshore Wind Electric Power Plant. Part 1: Identification of a Model and its Components. *Pol. Marit. Res.* **2018**, *25*, 132–139. [CrossRef]
6. Shields, M.; Beiter, P.; Nunemaker, J.; Cooperman, A.; Duffy, P. Impacts of turbine and plant upsizing on the levelized cost of energy for offshore wind. *Appl. Energy* **2021**, *298*, 117189. [CrossRef]

7. Saeed, K.; McMorland, J.; Collu, M.; Coraddu, A.; Carroll, J.; McMillan, D. Adaptations of Offshore Wind Operation and Maintenance Models for Floating Wind. *J. Phys. Conf. Ser.* **2022**, *2362*, 012036. [CrossRef]
8. Salic, T.; Charpentier, J.F.; Benbouzid, M.; Boulluec, M.L. Control Strategies for Floating Offshore Wind Turbine: Challenges and Trends. *Electronics* **2019**, *8*, 1185. [CrossRef]
9. Cui, H.; Guo, T.; Yang, C.; Dai, Y.; Wang, C.; Du, H.; Qin, L.; Yu, H. A New Thermal Management Strategy of IGBT in DFIG for Economic Benefit Maximization. *IEEE Trans. Ind. Inform.* 2023, *in press*. [CrossRef]
10. Damiani, R.; Ning, A.; Maples, B.; Smith, A.; Dykes, K. Scenario analysis for techno-economic model development of U.S. offshore wind support structures. *Wind Energy* **2016**, *20*, 731–747. [CrossRef]
11. Igba, J.; Alemzadeh, K.; Durugbo, C.; Eiriksson, E.T. Through-life engineering services of wind turbines. *CIRP J. Manuf. Sci. Technol.* **2017**, *17*, 60–70. [CrossRef]
12. Shafiee, M.; Brennan, F.; Espinosa, I.A. A parametric whole life cost model for offshore wind farms. *Int. J. Life Cycle Assess.* **2016**, *21*, 961–975. [CrossRef]
13. Fox, H.; Pillai, A.C.; Friedrich, D.; Collu, M.; Dawood, T.; Johanning, L. A Review of Predictive and Prescriptive Offshore Wind Farm Operation and Maintenance. *Energies* **2022**, *15*, 504. [CrossRef]
14. Kölle, K.; Göçmen, T.; Eguinoa, I.; Román, L.A.A.; Aparicio-Sanchez, M.; Feng, J.; Meyers, J.; Pettas, V.; Sood, I. FarmConners market showcase results: Wind farm flow control considering electricity prices. *Wind. Energy Sci.* **2022**, *7*, 2181–2200. [CrossRef]
15. de Novaes Pires Leite, G.; Araújo, A.M.; Rosas, P.A.C. Prognostic techniques applied to maintenance of wind turbines: A concise and specific review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1917–1925. [CrossRef]
16. Seyr, H.; Muskulus, M. Decision Support Models for Operations and Maintenance for Offshore Wind Farms: A Review. *Appl. Sci.* **2019**, *9*, 278. [CrossRef]
17. Ángel M. Costa.; Orosa, J.A.; Vergara, D.; Fernández-Arias, P. New Tendencies in Wind Energy Operation and Maintenance. *Appl. Sci.* **2021**, *11*, 1386. [CrossRef]
18. Ren, Z.; Verma, A.S.; Li, Y.; Teuwen, J.J.; Jiang, Z. Offshore wind turbine operations and maintenance: A state-of-the-art review. *Renew. Sustain. Energy Rev.* **2021**, *144*, 110886. [CrossRef]
19. Ciuriuc, A.; Rapha, J.I.; Guanche, R.; Domínguez-García, J.L. Digital tools for floating offshore wind turbines (FOWT): A state of the art. *Energy Rep.* **2022**, *8*, 1207–1228. [CrossRef]
20. Rinaldi, G.; Thies, P.R.; Johanning, L. Current Status and Future Trends in the Operation and Maintenance of Offshore Wind Turbines: A Review. *Energies* **2021**, *14*, 2484. [CrossRef]
21. Hadjoudj, Y.; Pandit, R. A review on data-centric decision tools for offshore wind operation and maintenance activities: Challenges and opportunities. *Energy Sci. Eng.* **2022**, *11*, 1501–1515. [CrossRef]
22. Márquez, F.P.G.; Gonzalo, A.P. A Comprehensive Review of Artificial Intelligence and Wind Energy. *Arch. Comput. Methods Eng.* **2021**, *29*, 2935–2958. [CrossRef]
23. Shadman, M.; Amiri, M.M.; Silva, C.; Estefen, S.F. La Rovere, E. Environmental impacts of offshore wind installation, operation and maintenance, and decommissioning activities: A case study of Brazil. *Renew. Sustain. Energy Rev.* **2021**, *144*, 110994.
24. Yang, J.; Chang, Y.; Zhang, L.; Hao, Y.; Yan, Q.; Wang, C. The life-cycle energy and environmental emissions of a typical offshore wind farm in China. *J. Clean. Prod.* **2018**, *180*, 316–324. [CrossRef]
25. Johnston, B.; Foley, A.; Doran, J.; Littler, T. Levelised cost of energy, A challenge for offshore wind. *Renew. Energy* **2020**, *160*, 876–885. [CrossRef]
26. Huang, Y.F.; Gan, X.J.; Chiueh, P.T. Life cycle assessment and net energy analysis of offshore wind power systems. *Renew. Energy* **2017**, *102*, 98–106. [CrossRef]
27. Feng, K.; Ji, J.; Ni, Q.; Beer, M. A review of vibration-based gear wear monitoring and prediction techniques. *Mech. Syst. Signal Process.* **2023**, *182*, 109605. [CrossRef]
28. Habibi, H.; Howard, I.; Simani, S. Reliability improvement of wind turbine power generation using model-based fault detection and fault tolerant control: A review. *Renew. Energy* **2019**, *135*, 877–896. [CrossRef]
29. Hanifi, S.; Liu, X.; Lin, Z.; Lotfian, S. A Critical Review of Wind Power Forecasting Methods—Past, Present and Future. *Energies* **2020**, *13*, 3764. [CrossRef]
30. Khan, P.W.; Byun, Y.C. A Review of machine learning techniques for wind turbine's fault detection, diagnosis, and prognosis. *Int. J. Green Energy* 2023, *in press*. [CrossRef]
31. Bigdeli, N.; Afshar, K.; Gazafroudi, A.S.; Ramandi, M.Y. A comparative study of optimal hybrid methods for wind power prediction in wind farm of Alberta, Canada. *Renew. Sustain. Energy Rev.* **2013**, *27*, 20–29. [CrossRef]
32. Xia, J.; Zou, G. Operation and maintenance optimization of offshore wind farms based on digital twin: A review. *Ocean. Eng.* **2023**, *268*, 113322. [CrossRef]
33. Liang, J.; Zhang, K.; Al-Durra, A.; Muyeen, S.; Zhou, D. A state-of-the-art review on wind power converter fault diagnosis. *Energy Rep.* **2022**, *8*, 5341–5369. [CrossRef]
34. Zhang, Y.; Ravishankar, J.; Fletcher, J.; Li, R.; Han, M. Review of modular multilevel converter based multi-terminal HVDC systems for offshore wind power transmission. *Renew. Sustain. Energy Rev.* **2016**, *61*, 572–586. [CrossRef]
35. Jia, J.; Yang, C.; Cui, H.; Wu, M.; Shao, J.; Zhao, B.; He, K. Systems and Challenges in Operation and Maintenance of Offshore Wind Power: A Review. In Proceedings of the 2023 8th Asia Conference on Power and Electrical Engineering (ACPEE), Tianjin, China, 14–16 April 2023; pp. 1407–1412. [CrossRef]

36. Liu, Q. Optimization of Wind Fan Selection and Operation Maintenance in the Wind Power Stations. *Earth Environ. Sci.* **2018**, *170*, 042017. [CrossRef]
37. Catalán, P.; Wang, Y.; Arza, J.; Chen, Z. A Comprehensive Overview of Power Converter Applied in High-Power Wind Turbine: Key Challenges and Potential Solutions. *IEEE Trans. Power Electron.* **2023**, *38*, 6169–6195. [CrossRef]
38. Chen, G.; Cai, X. Reconfigurable Control for Fault-Tolerant of Parallel Converters in PMSG Wind Energy Conversion System. *IEEE Trans. Sustain. Energy* **2019**, *10*, 604–614. [CrossRef]
39. Jiang, H.; Edson, J.B. Characterizing marine atmospheric boundary layer to support offshore wind energy research. *J. Phys. Conf. Ser.* **2020**, *1452*, 012027. [CrossRef]
40. Yin, X.; Zhao, Z.; Yang, W. Predictive operations of marine pumped hydro-storage towards real time offshore wind-wave power complementarity: An event-triggered MPC approach. *J. Energy Storage* **2023**, *62*, 106583. [CrossRef]
41. Iqbar, I.M.; Muhammad, M.; Gilani, S.I.U.H.; Adam, F. Feasibility Study of Harnessing Low Wind Speed Turbine as Hybrid Power Source for Offshore Platforms. *J. Mar. Sci. Eng.* **2022**, *10*, 963. [CrossRef]
42. Fu, H.; Mei, X.; Yurchenko, D.; Zhou, S.; Theodossiades, S.; Nakano, K.; Yeatman, E.M. Rotational energy harvesting for self-powered sensing. *Joule* **2021**, *5*, 1074–1118. [CrossRef]
43. Qin, C.; Saunders, G.; Loth, E. Offshore wind energy storage concept for cost-of-rated-power savings. *Appl. Energy* **2017**, *201*, 148–157. [CrossRef]
44. Lamagna, M.; Ferrario, A.M.; Garcia, D.A.; Mcphail, S.; Comodi, G. Reversible solid oxide cell coupled to an offshore wind turbine as a poly-generation energy system for auxiliary backup generation and hydrogen production. *Energy Rep.* **2022**, *8*, 14259–14273. [CrossRef]
45. Weiss, C.V.; Guanche, R.; Ondiviela, B.; Castellanos, O.F.; Juanes, J. Marine renewable energy potential: A global perspective for offshore wind and wave exploitation. *Energy Convers. Manag.* **2018**, *177*, 43–54. [CrossRef]
46. Kaddoura, M.; Tivander, J.; Molander, S. Life Cycle Assessment of Electricity Generation from an Array of Subsea Tidal Kite Prototypes. *Energies* **2020**, *13*, 456. [CrossRef]
47. Foteinis, S.; Tsoutsos, T. Strategies to improve sustainability and offset the initial high capital expenditure of wave energy converters (WECs). *Renew. Sustain. Energy Rev.* **2017**, *70*, 775–785. [CrossRef]
48. Crespi, E.; Mammoliti, L.; Colbertaldo, P.; Silva, P.; Guandalini, G. Sizing and operation of energy storage by Power-to-Gas and Underwater Compressed Air systems applied to offshore wind power generation. *E3S Web Conf.* **2021**, *312*, 01007.
49. Cormier, M.; Lutz, T. Numerical Investigation of the Unsteady Flow Field Past an Offshore Wind Turbine in Maintenance Operations. In *Notes on Numerical Fluid Mechanics and Multidisciplinary Design*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 592–603.
50. Wen, B.; Tian, X.; Dong, X.; Peng, Z.; Zhang, W.; Wei, K. A numerical study on the angle of attack to the blade of a horizontal-axis offshore floating wind turbine under static and dynamic yawed conditions. *Energy* **2019**, *168*, 1138–1156. [CrossRef]
51. Wang, H.J.Q.W.X.F. Ship collision impact on the structural load of an offshore wind turbine. *Glob. Energy Interconnect.* **2020**, *3*, 43–50.
52. Lin, Z.; Cevasco, D.; Collu, M. A methodology to develop reduced-order models to support the operation and maintenance of offshore wind turbines. *Appl. Energy* **2020**, *259*, 114228. [CrossRef]
53. Pryor, S.C.; Barthelmie, R.J.; Cadence, J.; Dellwik, E.; Hasager, C.B.; Kral, S.T.; Reuder, J.; Rodgers, M.; Veraart, M. Atmospheric Drivers of Wind Turbine Blade Leading Edge Erosion: Review and Recommendations for Future Research. *Energies* **2022**, *15*, 8553. [CrossRef]
54. 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]
55. Artigao, E.; Honrubia-Escribano, A.; Gomez-Lazaro, E. Current signature analysis to monitor DFIG wind turbine generators: A case study. *Renew. Energy* **2018**, *116*, 5–14. [CrossRef]
56. Tiwari, S.; Undeland, T.; Midtgård, O.M.; Nilsen, R. SiC MOSFETs for Offshore Wind Applications. *J. Phys. Conf. Ser.* **2018**, *1104*, 012032. [CrossRef]
57. Zhu, X.; Cheng, M. Design and Analysis of 10 MW Class HTS Exciting Double Stator Direct-Drive Wind Generator With Stationary Seal. *IEEE Access* **2019**, *7*, 51129–51139. [CrossRef]
58. Carroll, J.; McDonald, A.; Dinwoodie, I.; McMillan, D.; Revie, M.; Lazakis, I. Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations. *Wind Energy* **2016**, *20*, 361–378. [CrossRef]
59. Shin, K.H.; Bang, T.K.; Kim, K.H.; Hong, K.; Choi, J.Y. Electromagnetic Analysis and Experimental Study to Optimize Force Characteristics of Permanent Magnet Synchronous Generator for Wave Energy Converter Using Subdomain Method. *Processes* **2021**, *9*, 1825. [CrossRef]
60. Moghadam, F.K.; Desch, N. Life Cycle Assessment of Various PMSG-Based Drivetrain Concepts for 15 MW Offshore Wind Turbines Applications. *Energies* **2023**, *16*, 1499. [CrossRef]
61. Tian, X.; Sun, X.; Liu, G.; Deng, W.; Wang, H.; Li, Z.; Li, D. Optimization design of the jacket support structure for offshore wind turbine using topology optimization method. *Ocean. Eng.* **2022**, *243*, 110084. [CrossRef]
62. Wang, A.; Li, S. Investigation of E-Core Modular Permanent Magnet Wind Turbine. *Energies* **2020**, *13*, 1751. [CrossRef]

63. Roggenburg, M.; Esquivel-Puentes, H.A.; Vacca, A.; Evans, H.B.; Garcia-Bravo, J.M.; Warsinger, D.M.; Ivantysynova, M.; Castillo, L. Techno-economic analysis of a hydraulic transmission for floating offshore wind turbines. *Renew. Energy* **2020**, *153*, 1194–1204. [CrossRef]
64. Liu, Y.; Frederik, J.; Ferrari, R.M.; Wu, P.; Li, S.; Wingerden, J. Fault-tolerant individual pitch control of floating offshore wind turbines via subspace predictive repetitive control. *Wind Energy* **2021**, *24*, 1045–1065. [CrossRef]
65. Li, Z.; Wen, B.; Wei, K.; Yang, W.; Peng, Z.; Zhang, W. Flexible dynamic modeling and analysis of drive train for Offshore Floating Wind Turbine. *Renew. Energy* **2020**, *145*, 1292–1305. [CrossRef]
66. Seo, Y.H.; Ryu, M.S.; Oh, K.Y. Dynamic Characteristics of an Offshore Wind Turbine with Tripod Suction Buckets via Full-Scale Testing. *Complexity* **2020**, *2020*, 3079308. [CrossRef]
67. Dong, X.; Lian, J.; Wang, H.; Yu, T.; Zhao, Y. Structural vibration monitoring and operational modal analysis of offshore wind turbine structure. *Ocean. Eng.* **2018**, *150*, 280–297. [CrossRef]
68. Zhu, C.; Zhang, L.; Liao, C.; Wei, X.; Ye, G. Estimation of horizontal bearing capacity of mat foundation on structured and over-consolidated clays under cyclic wave loads. *Soil Dyn. Earthq. Eng.* **2022**, *161*, 107426. [CrossRef]
69. Kim, J.C.H. Review of Recent Offshore Wind Turbine Research and Optimization Methodologies in Their Design. *J. Mar. Sci. Eng.* **2022**, *10*, 28.
70. Zhang, C.; Long, K.; Zhang, J.; Lu, F.; Bai, X.; Jia, J. A topology optimization methodology for the offshore wind turbine jacket structure in the concept phase. *Ocean. Eng.* **2022**, *266*, 112974. [CrossRef]
71. Muskulus, L.E.S.S. Reliability-based design optimization of offshore wind turbine support structures using analytical sensitivities and factorized uncertainty modeling. *Wind Energy Sci.* **2020**, *5*, 171–198.
72. Gentils, T.; Wang, L.; Kolios, A. Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. *Appl. Energy* **2017**, *199*, 187–204. [CrossRef]
73. He, F.; Wagner, M.; Zhang, L.; Shao, C.; Xu, W.; Chen, W.; Yan, Y.; Li, Y. A novel integrated approach for offshore wind power optimization. *Ocean. Eng.* **2022**, *266*, 112827. [CrossRef]
74. Casini, M. Small Vertical Axis Wind Turbines for Energy Efficiency of Buildings. *J. Clean. Energy Technol.* **2015**, *4*, 56–65. [CrossRef]
75. Hezaveh, S.H.; Bou-Zeid, E.; Lohry, M.W.; Martinelli, L. Simulation and wake analysis of a single vertical axis wind turbine. *Wind Energy* **2017**, *20*, 713–730. [CrossRef]
76. Gharaati, M.; Xiao, S.; Wei, N.J.; Martínez-Tossas, L.A.; Dabiri, J.O.; Yang, D. Large-eddy simulation of helical- and straight-bladed vertical-axis wind turbines in boundary layer turbulence. *J. Renew. Sustain. Energy* **2022**, *14*, 053301. [CrossRef]
77. Sørensen, J.V.; Ma, Z.; Jørgensen, B.N. Potentials of game engines for wind power digital twin development: an investigation of the Unreal Engine. *Energy Inform.* **2022**, *5*, 39. [CrossRef]
78. Walker, J.; Coraddu, A.; Collu, M.; Oneto, L. Digital twins of the mooring line tension for floating offshore wind turbines to improve monitoring, lifespan, and safety. *J. Ocean. Eng. Mar. Energy* **2021**, *8*, 1–16. [CrossRef]
79. Wang, M.; Wang, C.; Hnydiuk-Stefan, A.; Feng, S.; Atilla, I.; Li, Z. Recent progress on reliability analysis of offshore wind turbine support structures considering digital twin solutions. *Ocean. Eng.* **2021**, *232*, 109168. [CrossRef]
80. Haghshenas, A.; Hasan, A.; Osen, O.; Mikalsen, E.T. Predictive digital twin for offshore wind farms. *Energy Inform.* **2023**, *6*, 1–26. [CrossRef]
81. Jorgensen, J.; Hodkiewicz, M.; Cripps, E.; Hassan, G.M. Requirements for the application of the Digital Twin Paradigm to offshore wind turbine structures for uncertain fatigue analysis. *Comput. Ind.* **2023**, *145*, 103806. [CrossRef]
82. Augustyn, D.; Ulriksen, M.D.; Sørensen, J.D. Reliability Updating of Offshore Wind Substructures by Use of Digital Twin Information. *Energies* **2021**, *14*, 5859. [CrossRef]
83. Mehlan, F.C.; Nejad, A.R.; Gao, Z. Digital Twin Based Virtual Sensor for Online Fatigue Damage Monitoring in Offshore Wind Turbine Drivetrains. *J. Offshore Mech. Arct. Eng.* **2022**, *144*, 060901. [CrossRef]
84. Elusakin, T.; Shafiee, M.; Adedipe, T.; Dinmohammadi, F. A Stochastic Petri Net Model for O&M Planning of Floating Offshore Wind Turbines. *Energies* **2021**, *14*, 1134. [CrossRef]
85. Yang, B.; Wei, K.; Yang, W.; Li, T.; Qin, B. A feasibility study of reducing scour around monopile foundation using a tidal current turbine. *Ocean. Eng.* **2021**, *220*, 108396. [CrossRef]
86. Zhao, L.; Xue, L.; Li, Z.; Wang, J.; Yang, Z.; Xue, Y. Progress on Offshore Wind Farm Dynamic Wake Management for Energy. *J. Mar. Sci. Eng.* **2022**, *10*, 1395. [CrossRef]
87. Patryniak, K.; Collu, M.; Coraddu, A. Multidisciplinary design analysis and optimisation frameworks for floating offshore wind turbines: State of the art. *Ocean. Eng.* **2022**, *251*, 111002. [CrossRef]
88. Hamzah, S.K.; Lacey, G.; Pillai, G. Optimization Modeling for Offshore Wind Farms. In Proceedings of the 2020 55th International Universities Power Engineering Conference (UPEC), Turin, Italy, 1–4 September 2020.
89. Jimmy, G.; McDonald, A.; Carroll, J. Energy Yield and Operations and Maintenance Costs of Parallel Wind Turbine Powertrains. *IEEE Trans. Sustain. Energy* **2020**, *11*, 674–681. [CrossRef]
90. Grant, E.; Johnson, K.; Damiani, R.; Phadnis, M.; Pao, L. Buoyancy can ballast control for increased power generation of a floating offshore wind turbine with a light-weight semi-submersible platform. *Chem. Eng. J.* **2023**, *330*, 120287. [CrossRef]
91. Dahane, M.; Sahnoun, M.; Bettayeb, B.; Baudry, D.; Boudhar, H. Impact of spare parts remanufacturing on the operation and maintenance performance of offshore wind turbines: A multi-agent approach. *J. Intell. Manuf.* **2015**, *28*, 1531–1549. [CrossRef]

92. Sarker, B.R.; Faiz, T.I. Minimizing transportation and installation costs for turbines in offshore wind farms. *Renew. Energy* **2017**, *101*, 667–679. [CrossRef]
93. Kuang, L.; Lu, Q.; Huang, X.; Song, L.; Chen, Y.; Su, J.; Han, Z.; Zhou, D.; Zhao, Y.; Xu, Y. Characterization of wake interference between two tandem offshore floating vertical-axis wind turbines: Effect of platform pitch motion. *Energy Convers. Manag.* **2022**, *265*, 115769. [CrossRef]
94. Ahsan, D.; Pedersen, S. The influence of stakeholder groups in operation and maintenance services of offshore wind farms: Lesson from Denmark. *Renew. Energy* **2018**, *125*, 819–828. [CrossRef]
95. Seljom, P.; Rosenberg, E.; Fidje, A.; Haugen, J.E.; Meir, M.; Rekstad, J.; Jarlset, T. Modelling the effects of climate change on the energy system—A case study of Norway. *Energy Policy* **2011**, *39*, 7310–7321. [CrossRef]
96. Scheu, M.N.; Kolios, A.; Fischer, T.; Brennan, F. Influence of statistical uncertainty of component reliability estimations on offshore wind farm availability. *Reliab. Eng. Syst. Saf.* **2017**, *168*, 28–39. [CrossRef]
97. Martin, M.; Pfaffel, S.; te Heesen, H.; Rohrig, K. Identification and prioritization of low performing wind turbines using a power curve health value approach. *J. Phys. Conf. Ser.* **2020**, *1669*, 012030. [CrossRef]
98. Zhou, L.; Huang, P.; Chi, S.; Li, M.; Zhou, H.; Yu, H.; Cao, H.; Chen, K. Structural health monitoring of offshore wind power structures based on genetic algorithm optimization and uncertain analytic hierarchy process. *Ocean. Eng.* **2020**, *218*, 108201. [CrossRef]
99. Pandit, R.K.; Infield, D. SCADA based nonparametric models for condition monitoring of a wind turbine. *J. Eng.* **2019**, *2019*, 4723–4727. [CrossRef]
100. Liang, J.; Zhang, K.; Al-Durra, A.; Zhou, D. A Multi-Information Fusion Algorithm to Fault Diagnosis of Power Converter in Wind Power Generation Systems. *IEEE Trans. Ind. Inform.* 2023, *in press*.
101. Wang, W.C.; Kou, L.; Yuan, Q.D.; Zhou, J.N.; Liu, C.; Cai, G.W. An Intelligent Fault Diagnosis Method for Open-Circuit Faults in Power-Electronics Energy Conversion System. *IEEE Access* **2020**, *8*, 221039–221050. [CrossRef]
102. Xue, Z.Y.; Xiahou, K.S.; Li, M.S.; Ji, T.Y.; Wu, Q.H. Diagnosis of Multiple Open-Circuit Switch Faults Based on Long Short-Term Memory Network for DFIG-Based Wind Turbine Systems. *IEEE J. Emerg. Sel. Top. Power Electron.* **2020**, *8*, 2600–2610. [CrossRef]
103. Liang, J.; Zhang, K. A New Hybrid Fault Diagnosis Method for Wind Energy Converters. *Electronics* **2023**, *12*, 1263. [CrossRef]
104. Pandit, R.; Infield, D. Gaussian Process Operational Curves for Wind Turbine Condition Monitoring. *Energies* **2018**, *11*, 1631. [CrossRef]
105. Artigao, E.; Sapena-Bano, A.; Honrubia-Escribano, A.; Martinez-Roman, J.; Puche-Panadero, R.; Gomez-Lazaro, E. Long-Term Operational Data Analysis of an In-Service Wind Turbine DFIG. *IEEE Access* **2019**, *7*, 17896–17906. [CrossRef]
106. Vieira, M.; Henriques, E.; Snyder, B.; Reis, L. Insights on the impact of structural health monitoring systems on the operation and maintenance of offshore wind support structures. *Struct. Saf.* **2022**, *94*, 102154. [CrossRef]
107. 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]
108. 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]
109. Wu, Y.; Ma, X. Alarms-related wind turbine fault detection based on kernel support vector machines. *J. Eng.* **2019**, *2019*, 4980–4985. [CrossRef]
110. Su, X.; Shan, Y.; Li, C.; Mi, Y.; Fu, Y.; Dong, Z. Spatial-temporal attention and GRU based interpretable condition monitoring of offshore wind turbine gearboxes. *IET Renew. Power Gener.* **2021**, *16*, 402–415. [CrossRef]
111. Wu, P.; Liu, Y.; Ferrari, R.M.; van Wingerden, J. Floating offshore wind turbine fault diagnosis via regularized dynamic canonical correlation and fisher discriminant analysis. *IET Renew. Power Gener.* **2021**, *15*, 4006–4018. [CrossRef]
112. Li, H.; Yazdi, M. Developing Failure Modes and Effect Analysis on Offshore Wind Turbines Using Two-Stage Optimization Probabilistic Linguistic Preference Relations. In *Advanced Decision-Making Methods and Applications in System Safety and Reliability Problems*; Springer: Cham, Switzerland, 2022; pp. 47–68.
113. Wang, X.; Wu, P.; Huo, Y.; Zhang, X.; Liu, Y.; Wang, L. Data-driven fault detection of a 10 MW floating offshore wind turbine benchmark using kernel canonical variate analysis. *Meas. Sci. Technol.* **2022**, *34*, 034001. [CrossRef]
114. Romero, A.; Soua, S.; Gan, T.H.; Wang, B. Condition monitoring of a wind turbine drive train based on its power dependant vibrations. *Renew. Energy* **2018**, *123*, 817–827. [CrossRef]
115. Rasool, S.; Muttaqi, K.M.; Sutanto, D.; Hemer, M. Quantifying the reduction in power variability of co-located offshore wind-wave farms. *Renew. Energy* **2022**, *185*, 1018–1033. [CrossRef]
116. Dong, H.; Xie, J.; Zhao, X. Wind farm control technologies: From classical control to reinforcement learning. *Prog. Energy* **2022**, *4*, 032006. [CrossRef]
117. D'Amico, G.; Petroni, F.; Vergine, S. Ramp Rate Limitation of Wind Power: An Overview. *Energies* **2022**, *15*, 5850. [CrossRef]
118. Ramirez, D.; Blanco, M.; Zarei, M.E.; Gupta, M. Robust control of a floating OWC WEC under open-switch fault condition in one or in both VSCs. *IET Renew. Power Gener.* **2020**, *14*, 2538–2549. [CrossRef]
119. Park, J.; Law, K.H. A data-driven, cooperative wind farm control to maximize the total power production. *Appl. Energy* **2016**, *165*, 151–165. [CrossRef]

120. Gonzalez, H.D.P.; Bianchi, F.D.; Dominguez-Garcia, J.L.; Gomis-Bellmunt, O. Co-located wind-wave farms: Optimal control and grid integration. *Energy* **2023**, *272*, 127176. [CrossRef]
121. Vives, J.; Palaci, J.; Heart, J. Framework for Bidirectional Knowledge-Based Maintenance of Wind Turbines. *Comput. Intell. Neurosci.* **2022**, *2022*, 1020400. [CrossRef]
122. Peiffer, A.; Roddier, D. Floating Wind Turbines: The New Wave in Offshore Wind Power. In *Alternative Energy and Shale Gas Encyclopedia*; Wiley: Hoboken, NJ, USA, 2016; pp. 69–79.
123. Dao, C.D.; Kazemtabrizi, B.; Crabtree, C.J. Offshore wind turbine reliability and operational simulation under uncertainties. *Wind Energy* **2020**, *23*, 1919–1938. [CrossRef]
124. González, H.D.P.; Domínguez-García, J.L. Non-centralized hierarchical model predictive control strategy of floating offshore wind farms for fatigue load reduction. *Renew. Energy* **2022**, *187*, 248–256. [CrossRef]
125. Nouriani, A.; Moradi, H. Variable speed wind turbine power control: A comparison between multiple MPPT based methods. *Int. J. Dyn. Control.* **2021**, *10*, 654–667. [CrossRef]
126. Vemuri, A.; Munters, W.; Buckingham, S.; Helsen, J.; van Beeck, J. Modeling extreme weather events for offshore wind in the North Sea: A sensitivity analysis to physics parameterizations in WRF. *J. Phys. Conf. Ser.* **2022**, *2265*, 022014. [CrossRef]
127. Pandit, R.; Astolfi, D.; Tang, A.M.; Infield, D. Sequential Data-Driven Long-Term Weather Forecasting Models' Performance Comparison for Improving Offshore Operation and Maintenance Operations. *Energies* **2022**, *15*, 7233. [CrossRef]
128. Zhang, W.; Lin, Z.; Liu, X. Short-term offshore wind power forecasting—A hybrid model based on Discrete Wavelet Transform (DWT), Seasonal Autoregressive Integrated Moving Average (SARIMA), and deep-learning-based Long Short-Term Memory (LSTM). *Renew. Energy* **2022**, *185*, 611–628. [CrossRef]
129. Khan, M.; Al-Ammar, E.A.; Naeem, M.R.; Ko, W.; Choi, H.J.; Kang, H.K. Forecasting renewable energy for environmental resilience through computational intelligence. *PLoS ONE* **2021**, *16*, e0256381. [CrossRef]
130. Lin, Z.; Liu, X. Wind power forecasting of an offshore wind turbine based on high-frequency SCADA data and deep learning neural network. *Energy* **2020**, *201*, 117693. [CrossRef]
131. Turnbull, A.; Carroll, J.; Koukoura, S.; McDonald, A. Prediction of wind turbine generator bearing failure through analysis of high-frequency vibration data and the application of support vector machine algorithms. *J. Eng.* **2019**, *2019*, 4965–4969. [CrossRef]
132. Pradhan, P.; Kishore, S.; Defourny, B. Optimal Predictive Maintenance Policy for an Ocean Wave Farm. *IEEE Trans. Sustain. Energy* **2019**, *10*, 1993–2004. [CrossRef]
133. Zhang, G.; Yin, J.; Cheng, C.; Han, Q.; Li, L. Study on Fine Wave Forecasting for Offshore Wind Farms. *J. Phys. Conf. Ser.* **2023**, *2452*, 012008. [CrossRef]
134. Scheepens, D.R.; Schicker, I.; Hlaváčková-Schindler, K.; Plant, C. Adapting a deep convolutional RNN model with imbalanced regression loss for improved spatio-temporal forecasting of extreme wind speed events in the short to medium range. *Geosci. Model Dev.* **2023**, *16*, 251–270. [CrossRef]
135. Bi, K.; Xie, L.; Zhang, H.; Chen, X.; Gu, X.; Tian, Q. Accurate medium-range global weather forecasting with 3D neural networks. *Nature* **2023**, *619*, 533–538. [CrossRef]
136. Yang, L.; Li, G.; Zhang, Z.; Ma, X.; Zhao, Y. Operations & Maintenance Optimization of Wind Turbines Integrating Wind and Aging Information. *IEEE Trans. Sustain. Energy* **2021**, *12*, 211–221.
137. Toftaker, H.; Bødal, E.F.; Sperstad, I.B. Joint optimization of preventive and condition-based maintenance for offshore wind farms. *J. Phys. Conf. Ser.* **2022**, *2362*, 012041. [CrossRef]
138. Yu, M.; Sheng, Y.; Sun, H.; Zheng, Y.; Li, H.; Yang, W. Research on Operation and Maintenance Route Planning of Offshore Wind Farm Based on Multiagent. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 3278239. [CrossRef]
139. Rinaldi, G.; Garcia-Teruel, A.; Jeffrey, H.; Thies, P.R.; Johanning, L. Incorporating stochastic operation and maintenance models into the techno-economic analysis of floating offshore wind farms. *Appl. Energy* **2021**, *301*, 117420. [CrossRef]
140. Nguyen, T.A.T.; Chou, S.Y. Maintenance strategy selection for improving cost-effectiveness of offshore wind systems. *Energy Convers. Manag.* **2018**, *157*, 86–95. [CrossRef]
141. Wang, Q.; Luo, K.; Wu, C.; Tan, J.; He, R.; Ye, S.; Fan, J. Inter-farm cluster interaction of the operational and planned offshore wind power base. *J. Clean. Prod.* **2023**, *396*, 136529. [CrossRef]
142. Sperstad, I.B.; Stålhane, M.; Dinwoodie, I.; Endrerud, O.E.V.; Martin, R.; Warner, E. Testing the robustness of optimal access vessel fleet selection for operation and maintenance of offshore wind farms. *Ocean. Eng.* **2017**, *145*, 334–343. [CrossRef]
143. Stock-Williams, C.; Swamy, S.K. Automated daily maintenance planning for offshore wind farms. *Renew. Energy* **2019**, *133*, 1393–1403. [CrossRef]
144. Hammami, A.; Djemal, F.; Hmida, A.; Chaari, F.; Haddar, M. Maintenance 4.0 of Wind Turbine. In *Mechatronics 4.0: Proceedings of the First International Workshop on Mechatronics 4.0, Mahdia, Tunisia, 8–9 June 2019*; Lecture Notes in Mechanical Engineering; Springer: Berlin/Heidelberg, Germany, 2020; pp. 1–10.
145. Jian, Q.; Liu, X.; Du, X.; Zhang, Y.; Wang, N.; Sun, Y. Robust Bi-Level Planning Method for Multi-Source Systems Integrated With Offshore Wind Farms Considering Prediction Errors. *Front. Energy Res.* **2022**, *10*, 884886. [CrossRef]
146. Ahuja, H.; Bhuvaneswari, G.; Balasubramanian, R. Performance comparison of DFIG and PMSG based WECS. In Proceedings of the IET Conference on Renewable Power Generation (RPG 2011), Edinburgh, UK, 6–8 September 2011.
147. Okedu, K.E.; Tobi, M.A.; Araimi, S.A. Comparative Study of the Effects of Machine Parameters on DFIG and PMSG Variable Speed Wind Turbines During Grid Fault. *Front. Energy Res.* **2021**, *9*, 681443. [CrossRef]

148. Schreiber, A.; Marx, J.; Zapp, P. Comparative life cycle assessment of electricity generation by different wind turbine types. *J. Clean. Prod.* **2019**, *233*, 561–572. [CrossRef]
149. Liu, L.; Fu, Y.; Ma, S.; Huang, L.; Wei, S.; Pang, L. Optimal scheduling strategy of O&M task for OWF. *IET Renew. Power Gener.* **2019**, *13*, 2580–2586.
150. Papadopoulos, P.; Coit, D.W.; Ezzat, A.A. Seizing Opportunity: Maintenance Optimization in Offshore Wind Farms Considering Accessibility, Production, and Crew Dispatch. *IEEE Trans. Sustain. Energy* **2022**, *13*, 111–121. [CrossRef]
151. Irawan, C.A.; Starita, S.; Chan, H.K.; Eskandarpour, M.; Reihaneh, M. Routing in offshore wind farms: A multi-period location and maintenance problem with joint use of a service operation vessel and a safe transfer boat. *Eur. J. Oper. Res.* **2023**, *307*, 328–350. [CrossRef]
152. Psomas, P.M.; Platis, A.N.; Koutras, V.P. Optimizing the Maintenance Strategy for Offshore Wind Turbines Blades Using Opportunistic Preventive Maintenance. In *New Advances in Dependability of Networks and Systems*; Springer: Cham, Switzerland, 2022; pp. 227–236.
153. Feng, J.; Jia, X.; Zhu, F.; Yang, Q.; Pan, Y.; Lee, J. An intelligent system for offshore wind farm maintenance scheduling optimization considering turbine production loss. *J. Intell. Fuzzy Syst.* **2019**, *37*, 6911–6923. [CrossRef]
154. Zhou, F.; Tu, X.; Wang, Q. Research on offshore wind power system based on Internet of Things technology. *Int. J. Low-Carbon Technol.* **2022**, *17*, 645–650. [CrossRef]
155. Sahnoun, M.; Baudry, D.; Mustafee, N.; Louis, A.; Smart, P.A.; Godsiff, P.; Mazari, B. Modelling and simulation of operation and maintenance strategy for offshore wind farms based on multi-agent system. *J. Intell. Manuf.* **2015**, *30*, 2981–2997. [CrossRef]
156. Xiaohong, G.J.W.S. Joint decision of condition-based opportunistic maintenance and scheduling for multi-component production systems. *Int. J. Prod. Res.* **2022**, *60*, 5155–5175.
157. Koochaki, J.; Bokhorst, J.A.; Wortmann, H.; Klingenberg, W. Condition based maintenance in the context of opportunistic maintenance. *Int. J. Prod. Res.* **2012**, *50*, 6918–6929. [CrossRef]
158. Huang, L.L.; Fu, Y.; Mi, Y.; Cao, J.L.; Wang, P. A Markov-Chain-Based Availability Model of Offshore Wind Turbine Considering Accessibility Problems. *IEEE Trans. Sustain. Energy* **2017**, *8*, 1592–1600. [CrossRef]
159. Yang, S.; Wang, Y.; Xu, Y.; Wang, M.; Sun, D.; Li, W. A Condition-based Maintenance Strategy Considering Opportunistic Maintenance In Multiple Failure Modes. In Proceedings of the 2021 International Conference on Artificial Intelligence and Mechatronics Systems (AIMS), Gothenburg, Sweden, 8–12 October 2018; Volume 186, p. 012039.
160. Wang, J.; Makis, V.; Zhao, X. Optimal condition-based and age-based opportunistic maintenance policy for a two-unit series system. *Comput. Ind. Eng.* **2019**, *134*, 1–10. [CrossRef]
161. Yan, R.; Dunnett, S. Improving the Strategy of Maintaining Offshore Wind Turbines through Petri Net Modelling. *Appl. Sci.* **2021**, *11*, 574. [CrossRef]
162. Lubing, X.; Xiaoming, R.; Shuai, L.; Xin, H.; Maintenance Optimization of Offshore Wind Turbines Based on an Opportunistic Maintenance Strategy. *Energies.* **2019**, *12*, 2650.
163. Ioannou, A.; Angus, A.; Brennan, F. Informing parametric risk control policies for operational uncertainties of offshore wind energy assets. *Ocean. Eng.* **2019**, *177*, 1–11. [CrossRef]
164. Taylor, J.W.; Jeon, J. Probabilistic forecasting of wave height for offshore wind turbine maintenance. *Eur. J. Oper. Res.* **2018**, *267*, 877–890. [CrossRef]
165. Stålhane, M.; Halvorsen-Weare, E.E.; Nonås, L.M.; Pantuso, G. Optimizing vessel fleet size and mix to support maintenance operations at offshore wind farms. *Eur. J. Oper. Res.* **2019**, *276*, 495–509. [CrossRef]
166. Zhang, H.; Yan, J.; Han, S.; Li, L.; Liu, Y.; Infield, D. Uncertain accessibility estimation method for offshore wind farm based on multi-step probabilistic wave forecasting. *IET Renew. Power Gener.* **2021**, *15*, 2944–2955. [CrossRef]
167. Brooks, S.; Mahmood, M.; Roy, R.; Manolesos, M.; Salonitis, K. Self-reconfiguration simulations of turbines to reduce uneven farm degradation. *Renew. Energy* **2023**, *206*, 1301–1314. [CrossRef]
168. Neves-Moreira, F.; Veldman, J.; Teunter, R.H. Service operation vessels for offshore wind farm maintenance: Optimal stock levels. *Renew. Sustain. Energy Rev.* **2021**, *146*, 111158. [CrossRef]
169. Yang, W.; Tian, W.; Wei, K.; Peng, Z.; Huang, Z. Research on a cost-effective measure dedicated to stabilizing offshore wind farm crew transfer vessels. *Renew. Energy* **2019**, *133*, 275–283. [CrossRef]
170. Wang, F.; Sun, S. Low cost of sustainable work and maintenance for offshore wind power speed-increasing device. *E3S Web Conf.* **2019**, *118*, 02016. [CrossRef]
171. Rinaldi, G.; Pillai, A.C.; Thies, P.R.; Johanning, L. Multi-objective optimization of the operation and maintenance assets of an offshore wind farm using genetic algorithms. *Wind Eng.* **2019**, *44*, 390–409. [CrossRef]
172. Stålhane, M.; Bolstad, K.H.; Joshi, M.; Hvattum, L.M. A dual-level stochastic fleet size and mix problem for offshore wind farm maintenance operations. *INFOR Inf. Syst. Oper. Res.* **2020**, *59*, 257–289. [CrossRef]
173. Zhang, B.; Zhang, Z. A two-stage model for asynchronously scheduling offshore wind farm maintenance tasks and power productions. *Int. J. Electr. Power Energy Syst.* **2021**, *130*, 107013. [CrossRef]
174. Shafiee, M. Maintenance logistics organization for offshore wind energy: Current progress and future perspectives. *Renew. Energy* **2015**, *77*, 182–193. [CrossRef]
175. Lin, C.H.; Wu, Y.K. Overview of Frequency-Control Technologies for a VSC-HVDC-Integrated Wind Farm. *IEEE Access* **2021**, *9*, 112893–112921. [CrossRef]

176. Nami, A.; Rodriguez-Amenedo, J.L.; Arnaltes, S.; Cardiel-Alvarez, M.A.; Baraciarte, R.A. Control of the Parallel Operation of DR-HVDC and VSC-HVDC for Offshore Wind Power Transmission. *IEEE Trans. Power Deliv.* **2022**, *37*, 1682–1691. [CrossRef]
177. Nguyen, T.H.; Quach, N.T. A hybrid HVDC converter based on M2C and diode rectifiers without DC capacitors for offshore wind farm integration. *Int. J. Electr. Power Energy Syst.* **2021**, *133*, 107260. [CrossRef]
178. Barja-Martinez, S.; Aragüńs-Peñalba, M.; Íngrid Munnń-Collado.; Lloret-Gallego, P.; Bullich-Massaguń, E.; Villafafila-Robles, R. Artificial intelligence techniques for enabling Big Data services in distribution networks: A review. *Renew. Sustain. Energy Rev.* **2021**, *150*, 111459. [CrossRef]
179. Jia, K.; Dong, X.; Wen, Z.; Wu, W.; Bi, T. Harmonic Injection Based Fault Ride-through Control of MMC-HVDC Connected Offshore Wind Farms. *IEEE Trans. Sustain. Energy* **2023**, *14*, 1796–1806. [CrossRef]
180. Jahan, E.; Hazari, M.R.; Mannan, M.A.; Umemura, A.; Takahashi, R.; Tamura, J. Damping of Frequency Fluctuations of Hybrid Power System by Variable Deloaded Operation of PMSG Based Offshore Wind Farm. *IEEJ Trans. Power Energy* **2019**, *139*, 259–268. [CrossRef]
181. Zhu, Y.M.; Gong, Y.; Yang, Z.G. Failure analysis on over-temperature combustion of transformers in 4 MW offshore wind turbines. *Eng. Fail. Anal.* **2019**, *96*, 211–222. [CrossRef]
182. Kazmi, S.H.H.; Laneryd, T.; Giannikas, K.; Ahrenfeldt, S.F.; Sørensen, T.S.; Olesen, T.H.; Holbøll, J. Cost optimized dynamic design of offshore windfarm transformers with reliability and contingency considerations. *Int. J. Electr. Power Energy Syst.* **2021**, *128*, 106684. [CrossRef]
183. Chen, C.; Tian, Y. Comprehensive Application of Multi-beam Sounding System and Side-scan Sonar in Scouring Detection of Underwater Structures in Offshore Wind Farms. *Earth Environ. Sci.* **2021**, *668*, 012007. [CrossRef]
184. Ahmad, I.B.; Schnepf, A.; Ong, M.C. An optimisation methodology for suspended inter-array power cable configurations between two floating offshore wind turbines. *Eng. Appl. Artif. Intell.* **2023**, *278*, 114406. [CrossRef]
185. Pereira, T.; Castro, R. Comparison of internal grid topologies of offshore wind farms regarding reliability and economic performance metrics analysis. *IET Renew. Power Gener.* **2019**, *13*, 750–761. [CrossRef]
186. Wang, Y.; Xu, K.; Du, Y.; Ren, X.; Wang, C. Research on digital twin technology of large-scale offshore wind power flexible direct transmission system. *J. Phys. Conf. Ser.* **2023**, *2450*, 012046. [CrossRef]
187. Ganesh, S.; Perilla, A.; Torres, J.R.; Palensky, P.; van der Meijden, M. Validation of EMT Digital Twin Models for Dynamic Voltage Performance Assessment of 66 kV Offshore Transmission Network. *Appl. Sci.* **2020**, *11*, 244. [CrossRef]
188. Niu, Y.; Wen, J.; Ma, L.; Wang, S. Analysis of Offshore Wind Power Integration. *J. Phys. Conf. Ser.* **2021**, *1920*, 012009. [CrossRef]
189. Fernández-Guillamón, A.; Das, K.; Cutululis, N.A.; Molina-García, Á. Offshore Wind Power Integration into Future Power Systems: Overview and Trends. *J. Mar. Sci. Eng.* **2019**, *7*, 399. [CrossRef]
190. Zhao, F.; Han, X.; Ma, J.; Sun, Y.; Ye, X. Operation practice and regulatory framework of offshore wind grid connection system. *J. Phys. Conf. Ser.* **2021**, *1914*, 012013. [CrossRef]
191. Jiang, H.; Ma, S.; Song, R.; Xiang, Z. Analysis on subsynchronous oscillation stability for large scale offshore wind integration. *Energy Rep.* **2020**, *6*, 189–195. [CrossRef]
192. Ali, S.W.; Sadiq, M.; Terriche, Y.; Naqvi, S.A.R.; Hoang, L.Q.N.; Mutarraf, M.U.; Hassan, M.A.; Yang, G.; Su, C.L.; Guerrero, J.M. Offshore Wind Farm-Grid Integration: A Review on Infrastructure, Challenges, and Grid Solutions. *IEEE Access* **2021**, *9*, 102811–102827. [CrossRef]
193. Gao, J.T.; Ding, J.; Zhu, X.R.; Tang, T.; Lin, Z.S.; Lin, Y.; Yang, X.D.; Song, Y.T.; Li, X.J. Overview on Integration Characteristics of Offshore Wind Power. *Appl. Mech. Mater.* **2014**, *521*, 128–134. [CrossRef]
194. Du, X.; Sun, Y.; Wang, J.; He, Y.; Wu, P.; Cui, G. A bi-level multi-objective planning method for microgrid with offshore wind power. In Proceedings of the 2022 IEEE 5th International Electrical and Energy Conference (CIEEC), Nanjing, China, 27–29 May 2022.
195. Li, Y.; Qiao, X.; Chen, C.; Tan, Y.; Tian, W.; Xia, Q.; Cao, Y.; Lee, K.Y. Integrated Optimal Siting and Sizing for VSC-HVDC-link-based Offshore Wind Farms and Shunt Capacitors. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 274–284. [CrossRef]