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Overview of Offshore Wind Power Technologies

Xiaomei Ma [1], Mengxue Li [1], Wenquan Li [1,*] and Yongqian Liu [2]

[1] School of Physics and Electronic Information Engineering, Qinghai Normal University, Xining 810016, China; ncepumxm@163.com (X.M.); 18797176208@163.com (M.L.)
[2] School of New Energy, North China Electric Power University, Beijing 102206, China; yqliu@ncepu.edu.cn
* Correspondence: liwq09@sina.com

Abstract: Optimizing offshore wind power technology and reducing the levelized cost of electricity throughout the lifecycle are key measures for the large-scale development of offshore wind power, contributing significantly to the transition toward sustainable energy systems. However, compared to onshore wind power, the internal flow dynamics of offshore wind farms are more complex, which poses challenges for operation and maintenance. Therefore, there is an urgent need for updated, smarter, more efficient, and economic offshore intelligent operation control technologies to facilitate the large-scale development and utilization of offshore wind power. This paper approaches the topic from two perspectives, offshore wind turbines and offshore wind farms, introducing popular research directions and technical bottlenecks in these two related fields. This includes offshore wind turbine capacity development and fundamental technologies, offshore wind power forecasting technology, and offshore wind power operation and control technology, offshore intelligent operation and maintenance technology, as well as offshore wind power and integrated marine area utilization technology. Firstly, the challenges faced by the intensive development of offshore wind resources and operational environments are analyzed. Secondly, the challenges encountered in the aforementioned technological areas and their potential solutions are summarized. Finally, a systematic reflection and outlook on the large-scale development of offshore wind power are provided, reinforcing its critical role in achieving global sustainability goals.

Keywords: offshore wind power; operation and maintenance technology; wind power forecasting; operation control; sustainable energy system

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1. Introduction

In response to issues such as energy shortages, environmental pollution, and global warming, countries around the world are actively promoting the sustainable and clean transition of energy [1–3]. Offshore wind power is a renewable energy source that can significantly reduce air pollution caused by coal usage at its source. In 2009, the global installed capacity of wind power was 2 GW, which increased to 23 GW in 2018, representing an increase of over 11 times within a decade. Europe is the fastest-growing region for offshore wind power development globally, while China started relatively late, beginning localized offshore wind measurement in 2006. In 2008, the construction of China's first large-scale offshore wind power project (the Shanghai Donghai Bridge Offshore Wind Power Project) marked the beginning of offshore wind power development in China [4].

With the development of industries in the west and the exploitation of clean energy in the east, the unsustainability of "west-to-east electricity transmission" and the bottlenecks of centralized development and long-distance transmission have gradually become

evident. Developing offshore wind power will become an important strategic support for the transformation of China's energy structure. Currently, China has established a relatively complete policy system for the application of offshore wind power, including it in the development direction of national strategic emerging industries. The market environment and technological conditions for developing offshore wind power are gradually maturing [5,6].

By the end of 2023, the cumulative installed capacity of offshore wind power is 75 GW [7]. According to the China Wind Energy Association (CWEA), during the 14th Five-Year Plan period, the planned capacity for offshore wind power in coastal provinces of China is approximately 50 GW. This will play a crucial role in promoting China's energy structure transformation and developing a safe and efficient modern energy system [8]. Figure 1 shows the China's 14th Five-Year Period Renewable Development Plan.

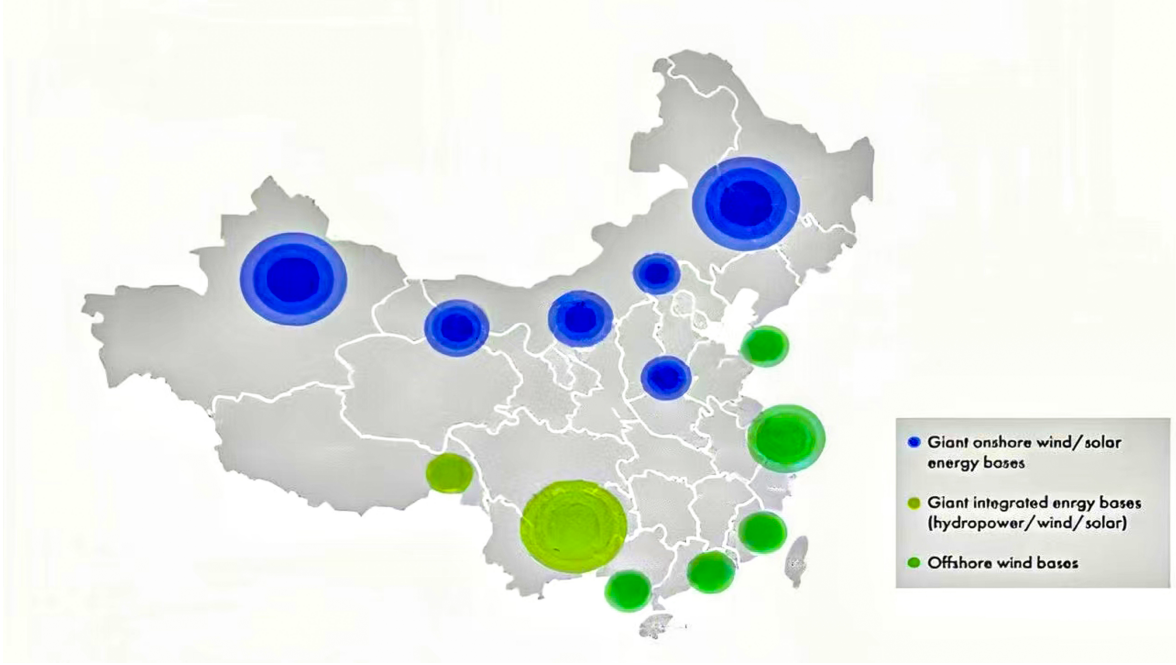


Figure 1. China's 14th Five-Year Period Renewable Development Plan.

Currently, due to the influence of policies from national forestry and environmental protection departments, the development of onshore wind energy resources in China has essentially reached saturation and stagnation. Most power development companies and wind turbine manufacturing industries are shifting their focus from land to offshore projects. Compared to onshore wind energy resources, the development of offshore wind energy resources is more competitive.

Firstly, the wind energy density offshore is generally higher than that onshore. With a coastline of approximately 18,000 km, the average wind speed at a height of 100 m in the main offshore areas of China is about 8.3 m/s, with an annual average wind power density of approximately 632.2 W/m² [9]. Secondly, the friction at the sea surface is low, and the roughness of the ocean surface is not high, meaning that wind speed is less affected by height. Thus, towers do not need to be excessively tall, which can reduce the cost of investment in wind turbines. Thirdly, offshore wind farms are located far away from populated areas to avoid being a visual or sound annoyance to people [10] .

In recent years, offshore wind power technology has become a hot spot for scientific research and engineering practice both domestically and internationally. It can be divided into two categories: offshore wind turbine technology and offshore wind farm technology. At the turbine level, major technological development trends and frontiers include

large-scale turbines [11], and floating wind turbines. At the wind farm level, existing research mainly covers aspects such as offshore wind farm design [12], offshore wind power grid connection and transmission technology [13], fault diagnosis and operation and maintenance technology for offshore wind turbines [14], and the comprehensive utilization of marine resources [15].

Addressing the shortcomings of existing studies, this paper analyzes and summarizes the status and development trends of different technical fields from two perspectives: offshore wind turbines and offshore wind farms. The first part introduces the current technological status of offshore wind turbines, while the second part analyzes and summarizes four technical fields related to intelligent offshore wind farms: power forecasting, operational control, maintenance management, and the comprehensive utilization of marine areas.

2. Offshore Wind Turbine Technology

2.1. Offshore Wind Turbine Capacity

With the continuous advancement of offshore wind power technology, the increase in individual capacity has become a key approach to improving the power generation efficiency of wind farms and reducing the levelized cost of electricity [16]. Large-scale, high-efficiency offshore wind turbines have become the mainstream direction of industry development.

In 2022, the average capacity of new offshore wind installations in China reached 11.5 MW, an increase of 2.87 MW compared to 2021. Goldwind launched a 16 MW model, while China Haizhuang completed the assembly of an 18 MW main unit by the end of 2022, with the maximum single-unit capacity increasing by as much as 7 MW compared to 2021 [17]. The overall trend continues to develop towards larger-capacity, lightweight designs with higher reliability. Figure 2 shows the cumulative installation share of offshore wind power with different single unit capacities by the end of 2022.

When it comes to the type of offshore wind turbine generators, there are mainly two technical routes: permanent magnet direct drive and permanent magnet semi-direct drive synchronous generator sets. From an economic perspective, the permanent magnet direct drive synchronous wind turbine system has the highest annual power generation, whereas the permanent magnet semi-direct drive synchronous wind turbine system has the lowest cost per kilowatt hour [18].

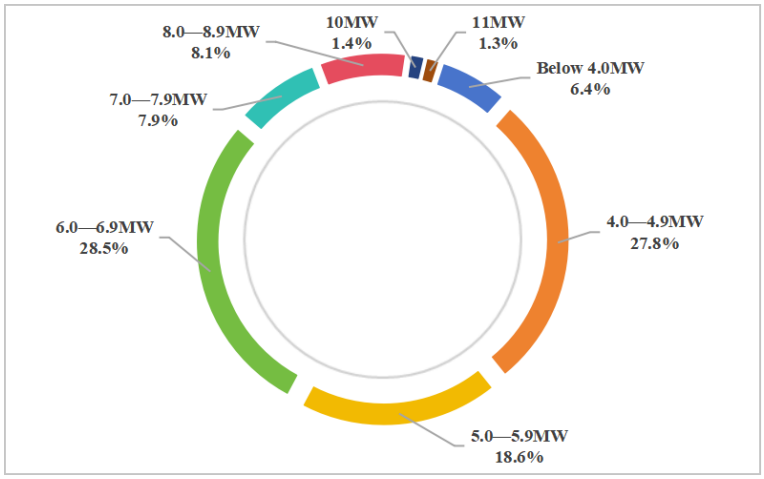


Figure 2. The cumulative installation share of offshore wind power with different single unit capacities by the end of 2022 [17].

2.2. Offshore Wind Turbine Foundation

Compared to onshore wind turbines, the foundational structures of offshore wind turbines are more complex. This is mainly due to the harsh offshore environment, where wind turbines must withstand greater wind loads, wave loads, and current loads [19].

Offshore wind turbines come in various foundation types, with the choice primarily depending on water depth, terrain, and turbine capacity. Currently, floating wind turbines commonly use semi-submersible platform foundations, as these foundations are suitable for a wider range of water depths and are more appropriate for turbines above 10 MW compared to monopile foundations. Additionally, semi-submersible foundations offer significant cost advantages when accommodating larger-capacity units.

Specifically, when the turbine capacity increases from 8 MW to 12 MW, the cost of monopile foundations rises by 60%, while the cost of semi-submersible foundations decreases by 20%. If the turbine capacity further increases to 16 MW, the cost of semi-submersible foundations will drop by an additional 10%. This trend indicates that semi-submersible foundations have better economic viability when addressing larger turbine capacities [20]. Figure 3 shows the different types of foundations of offshore wind turbines.

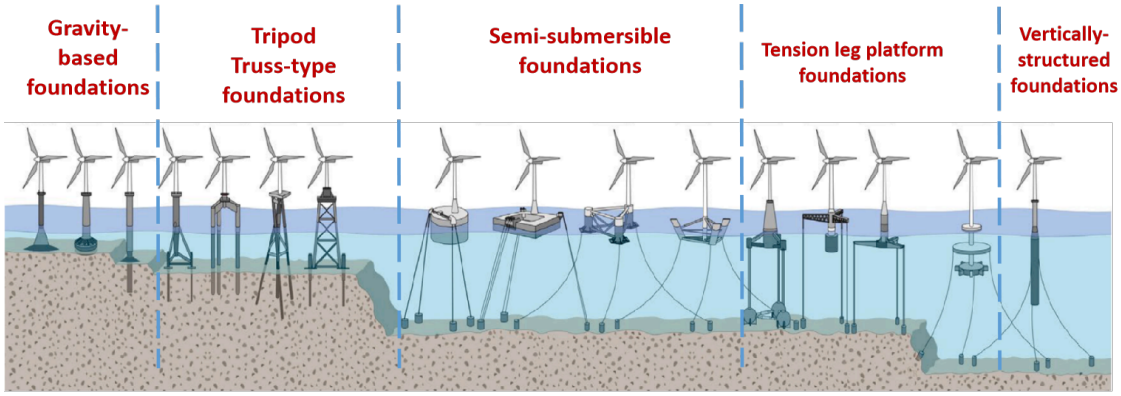


Figure 3. The foundations of offshore wind turbines [20].

2.3. The Technological Development Directions of Offshore Wind Turbines

Although the cost of large wind turbines is higher, the increase in power, rotor diameter, tower height, and capacity factor means an increase in annual electricity generation. Additionally, in wind farms of the same scale, using large turbines reduces the number of units required, which in turn lowers the investment in foundations, cables, installation, and operation, thus reducing the overall cost of electricity from wind power. Therefore, offshore wind power will continue to develop towards larger and lighter designs [21].

Eighty percent of the world's offshore wind resources are located in waters deeper than 60 m. To fully exploit these offshore wind energy resources and accelerate the energy transition, offshore wind power projects will move towards deep-sea development. Floating offshore wind power is considered the main technology for deep-sea wind energy development [22,23]. However, different floating technologies are mostly at the demonstration stage. Due to the specific challenges related to equipment and construction, the average cost of electricity from floating offshore wind power is about three times higher than that of traditional fixed offshore wind power. It is still in the early stages of commercialization and has not yet entered the industrialization phase.

3. Offshore Wind Power Forecasting Technology

Compared to onshore power forecasting technologies, offshore wind power forecasting faces greater challenges [24], mainly reflected in the following aspects: (1) Offshore weather systems are complex and diverse, with rapid evolution. Meteorological elements such

as temperature, pressure, and wind speed can change abruptly, leading to significant fluctuations in wind farm output over short periods and an increased frequency of ramp events. (2) Although offshore micro siting is not affected by terrain, obstacles, and other factors, allowing for a wider range and more flexible layout options, offshore wind farms are often arranged in a regular pattern due to the constraints of collector line costs and operational management costs. This results in a higher density of turbine layouts compared to onshore wind farms. The concentrated layout of offshore wind farms makes the power aggregation effect and volatility more pronounced, increasing output uncertainty and complexity. (3) Due to the complex coupling interactions among the atmosphere, ocean, and waves, offshore numerical weather prediction models need to consider more complex coupled model variable interactions.

In response to the above challenges, this section will categorize the issues from both the temporal and spatial dimensions, detailing the definitions of forecasting technologies, major technical routes, and technical difficulties across different time spans and multiple spatial scales. This involves four time spans: real-time, ultra-short-term, short-term, and medium-to-long-term.

3.1. Multi-Time-Scale Forecasting

Currently, the wind power prediction models are roughly divided into physical, statistical and hybrid models [25]. Physical models typically require two types of data for predictions: numerical weather prediction and geographic information of wind farms. However, the real-time performance and accuracy of numerical weather predictions are often not ideal, making physical models more suitable for medium- to-long-term power forecasting. Statistical models, on the other hand, need to identify the relationships between other variables and power from historical data, making them primarily suitable for short-term predictions. Hybrid models combine the advantages of different models and often achieve a higher prediction accuracy.

3.1.1. Real-Time Forecasting

There is no unified consensus on the definition of real-time forecasting for offshore wind power. However, compared to short-term and ultra-short-term forecasting, real-time forecasting focuses on higher-resolution results, with prediction resolutions generally at the second and minute levels. The IEA Wind Tasks 32 and 36 working groups define the scope of real-time forecasting for offshore wind farms as predictions at the second and minute levels, ranging from 1 s to 60 min [26].

The realization of real-time forecasting mainly relies on upstream observational data from wind turbines to infer the flow field results of the wind farm. The main sources of observational data include offshore meteorological tower data [27–29], mesoscale numerical weather prediction models [30], lidar, and satellite remote sensing [31]. When lidar is used as input data, the wind speed distribution across the entire wind farm can be inferred based on the propagation laws of the flow field, and the power distribution for the entire farm can be obtained after converting through the power curve. When using meteorological tower data as the input, the wake model can be applied to estimate the wind speed of wind turbines, allowing for the derivation of the overall power distribution.

Researchers [32] incorporated dual Doppler radar data into minute-level forecasting for wind farms, using the Lagrangian persistence method to estimate the probability distribution of future wind speeds for each turbine and to perform induced correction. Figure 4 shows the research details of the forecasting at the minute level for wind farms.

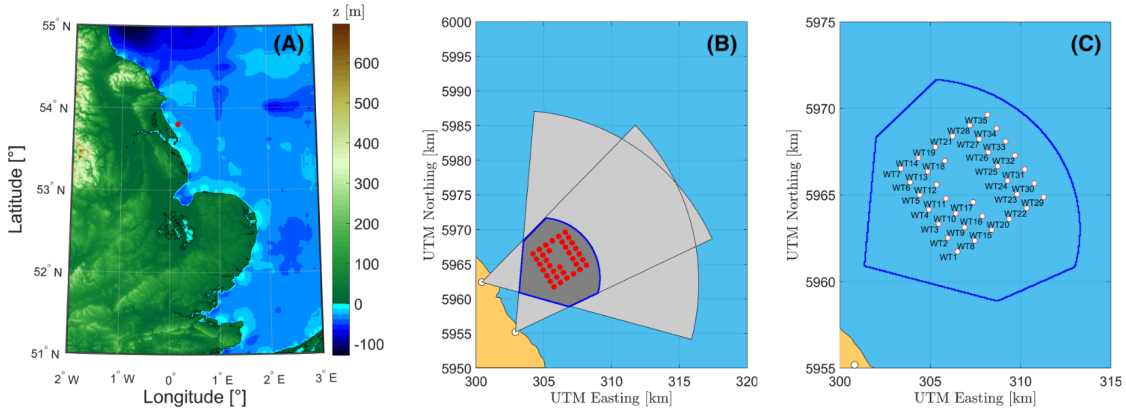


Figure 4. Minute−level forecasting for wind farms [32]; (**A**) Location of the wind farm; (**B**) Layout of the wind farm showing the position of the radars; (**C**) Layout of the wind farm indicating the wind turbine numbering.

3.1.2. Ultra-Short-Term Forecasting

According to the Interim Measures for the Management of Wind Farm Power Forecasting and the Implementation Rules for Wind Power Forecasting and Coordinated Operation with Power Grids, the requirements for forecasting standards indicate that ultra-short-term forecasting refers to predictions for the next 15 min to 4 h, with a time resolution of 15 min. Like real-time power forecasting for wind farms, ultra-short-term forecasting is primarily achieved through time series methods, usually using historical observation sequences to infer future observation sequences.

Due to the significant occurrence of ramp events in offshore wind farms, the output fluctuations can reach approximately 60% of the rated power within a 15–20-min time scale. On an hourly scale, output fluctuations can be as high as around 90%. Therefore, ultra-short-term forecasting is critical for the safety and stability of the power system. It plays a crucial role in automatic generation control, reserve management, real-time economic dispatch, real-time safety analysis, and real-time aspects of the power market.

Currently, scholars both domestically and internationally improve the accuracy of ultra-short-term forecasting through two approaches: firstly, by enhancing the ability of deep learning networks to extract temporal features from data [33]; and secondly, by identifying and classifying the characteristics of offshore weather processes and output scenarios, and then establishing separate forecasting models or conducting error correction for each category [34].

Zheng Wang [35] proposed a combined model of principal component analysis (PCA), sparrow algorithm (SSA), variational modal decomposition (VMD), and bidirectional long- and short-term memory neural network (BiLSTM).This approach ensures flexibility and effectiveness in feature extraction, enabling a deeper exploration of the impacts of multiple meteorological factors on wind power output.

3.1.3. Short-Term Forecasting

Short-term wind power forecasting refers to predictions for the next 0–24 h starting from the following day. Given that the forecast range for short-term predictions covers the next day, numerical weather prediction (NWP) becomes the core input data for short-term power forecasting, while other observational data can serve as auxiliary inputs. By establishing a mapping relationship between NWP resource parameters and output power, future short-term forecast power can be obtained. The results of short-term forecasting are the main reference information for dispatching plans set by power scheduling organizations and play an important role in unit combination optimization, economic dispatch, and

reserve optimization. Therefore, offshore wind power forecasting is one of the important means to enhance the grid integration ratio of offshore wind power. Moreover, short-term forecasting for offshore wind farms can also support day-ahead power market trading, power demand response, and operational strategy optimization.

A single atmospheric model has shown good operational application capabilities for land wind farm forecasting; however, offshore meteorological conditions evolve rapidly, and the operational states of turbines are complex. How to extract effective information from numerous state and temporal features is key to improving the accuracy of offshore wind power output forecasting [36]. When applied to offshore meteorological forecasting, a single atmospheric model cannot fully describe the interaction processes between the atmosphere and the ocean. A single atmospheric model always assumes that the sea surface temperature (SST) remains constant; however, the SST often changes with variations in the atmospheric humidity and is also influenced by physical quantities such as shortwave radiation and latent heat flux. At the same time, the SST displays a negative feedback mechanism with the atmosphere, where changing sea temperatures can affect precipitation, atmospheric stability, oceanic fields, and even tropical cyclones to varying degrees. Wave fields can further alter the state of the sea surface, influencing the momentum, heat, and material exchange processes at the air–sea interface. Therefore, to achieve accurate offshore wind speed forecasting, especially for low-altitude wind speeds over the sea surface, regional air–sea–wave coupling models are the necessary choice [37].

Regional air–sea–wave coupling models incorporate regional meteorological models, ocean circulation models, and wave forecasting models as component models and utilize mesoscale couplers to facilitate extensive data transmission and exchange among the sub-models. The atmospheric, oceanic, and wave component models within the system employ an open computational framework that allows for bidirectional parameter transfer and data exchange. Coupling control functions are added and invoked within the integral control functions of each respective component model. Currently, scholars both domestically and internationally have proposed a series of coupled models for offshore wind farms and typhoon forecasting, such as COAMPS [38], COAWST [39], IFS-NEMO [40], and so on.

3.1.4. Medium- to Long-Term Forecasting

Medium- to long-term forecasting for offshore wind farms typically focuses on electricity generation predictions over future weeks, months, or years, with a forecast resolution of hours or days. Medium- to long-term forecasts can be achieved using time series methods or by transforming medium- to long-term meteorological forecast observational data. Time series methods require a certain volume of historical observation data, while medium- to long-term meteorological forecasts involve significant computational demands. The accessibility of offshore wind farms is relatively poor, and quarterly or annual maintenance requires meticulous planning and arrangement. Medium- to long-term electricity generation forecasting can guide maintenance and repair schedules, aiming to avoid maintenance during periods of high winds, thereby ensuring the production efficiency of the wind farm. As the electricity market becomes increasingly regulated, medium- to long-term electricity generation forecasting is also an important measure for offshore wind farms to further address integration issues.

3.2. Multi-Scenario Forecasting

Based on the forecast results, offshore wind power forecasting can be divided into deterministic forecasting and uncertainty forecasting. Deterministic forecasting aims to provide a specific point forecast value for wind power at a future moment, typically representing the expected value or median of the wind power. In traditional power systems

dominated by thermal power, the low proportion of wind power allows the system to cope with the uncertainties brought by wind energy using the limited information from point forecasts.

Uncertainty forecasting, on the other hand, is a conditional probability estimate of power at a future moment, providing more comprehensive decision-making information. Common forms of uncertainty outputs include probability density, quantiles, intervals, and scenarios.

However, with the large-scale integration of wind power into the grid, addressing the uncertainties brought by renewable energies such as wind and solar power has become a core issue for power systems and electricity market transactions. Hence, there is a greater need for high-precision quantification of the uncertainty in wind power.

An improved deep mixed density network has been proposed for the joint uncertainty forecasting of regional wind farm clusters [41]. This method introduces a mixed beta distribution to replace the traditional mixed Gaussian distribution and controls the shape of the beta distribution to avoid the issue of density leakage.

3.3. The Technological Development Directions of Offshore Wind Power Forecasting

Compared to onshore wind power, offshore wind power forecasting mainly faces challenges such as variable weather conditions, difficulties in extracting spatiotemporal characteristics, and a lack of historical data. To further address these issues, research can be conducted in the following two areas:

3.3.1. High-Precision, High-Spatiotemporal-Resolution Offshore Weather Forecasting

Weather forecasting serves as a predictive input parameter across various time scales and directly affects the forecasting accuracy. In addition to researching mesoscale forecasting models suitable for offshore conditions, exploring how to leverage the big data mining capabilities of deep learning algorithms to partially replace or optimize the computational processes of physical models is one of the feasible research directions for the future.

3.3.2. Fine-Grained Prediction Modeling Methods

The variability of offshore weather conditions makes fine-grained prediction modeling effective in improving the forecasting accuracy. However, the insufficient accumulation of historical data offshore limits the precision of fine-grained modeling. Therefore, employing transfer learning to make full use of data from different marine areas can help address the data dependency issues faced in offshore wind power forecasting.

4. Offshore Wind Power and Control Technology

This section reviews the existing research on wake control, fatigue load control, and operational control of offshore wind farms (clusters) aimed at providing auxiliary services to the power system.

4.1. Lifecycle-Oriented Wake Control

When wind farms are arranged in proximity, they experience wake interference, which significantly reduces the power generation of downstream turbines, increases structural loads and maintenance, shortens their lifespan, and ultimately raises energy costs. Limited by the buildable areas, the spacing between wind turbines in a wind farm is about 6–10 turbine diameters in the prevailing wind direction, which is not sufficient for the full recovery of the turbine wake, leading to a strong wake effect [42]. Niayifar A. proposed a new analytical wind farm wake model to predict wake flows and associated power losses inside wind farms [43]. Wake coordination control is an important research direction at present. The wake effect refers to the situation where wind turbines extract energy from

the wind, creating an area downstream with reduced wind speed and increased turbulence. When downstream turbines are within the wake region, their input wind speed is lower than the inflow wind speed of upstream wind turbines. The wake effect leads to an uneven wind speed distribution within the wind farm, affecting the inflow conditions, operational status, and power generation of each turbine [44]. Compared to onshore wind farms, the wake effect in offshore wind farms is more complex, primarily due to two reasons: (1) the lower roughness of the sea surface results in smaller vertical wind shear, leading to lower environmental turbulence and a longer wake recovery distance; (2) the relatively stable offshore atmospheric environment and smooth underlying surface cause the turbulent flux to interact slowly in the vertical direction, weakening the wake recovery speed. The compact layout of offshore wind farms enhances the wake effect, leading to greater power loss due to wake effects. After averaging the wake effects from different wind directions, the power loss in onshore wind farms is about 8%, while for offshore wind farms, the power loss approaches 12% [13]. Meanwhile, studies have shown that due to wake effects, the fatigue load increase can achieve 5–15% in large offshore wind farms [45].

By studying wake control technologies for offshore wind farms and constructing steady-state wake models aimed at control, it is possible to quantify the power coupling relationships between turbines due to wake effects, thereby reducing the power generation losses caused by wake interference and significantly enhancing overall power generation.

Sun J. used multi-objective particle swarm optimization to locate the optimal wind farm yaw settings for both power optimization and load mitigation based on the wake model and the load indicator [46]. Dong designed a preview-based robust deep reinforcement learning (PR-DRL) method that combines data-driven approaches to achieve model-free power tracking for wind farms [47]. These methods highlight the potential for optimizing the overall performance of wind farms by real-time adjustment of wind turbine operating parameters in response to variations in wind speed and wake effects. The integration of surrogate models with intelligent optimization algorithms proves to be particularly effective for wake control in large and floating wind farms [48]. Wake control technology is a core frontier technology in the field of offshore wind farms and is a key support area in research programs in countries such as China, Norway, Denmark, and the United States, as well as in European research framework programs.

4.2. Fatigue Load Control for Offshore Wind Farms Aimed at Extending Turbine Lifespan

During operation, wind turbines are subjected to alternating fatigue loads for extended periods. Fatigue is a major cause of wind turbine failures, reduces their lifespan, and impacts the reliability of wind farms [49]. Compared to onshore wind turbines, offshore wind turbines exhibit the following characteristics regarding fatigue loads: they are affected by natural environmental factors such as tides, waves, ocean currents, vortices, ice floes, and typhoons, leading to long-term exposure to a combination of various loads, including wind loads, wave loads, current loads, and ice loads. Additionally, the high tower structures, long blades, and high wind speeds characteristic of offshore wind farms result in loads on offshore turbines that are significantly greater than those on onshore turbines. Therefore, implementing fatigue load control focused on extending the lifespan of offshore wind farms can mitigate the adverse effects of operations such as starting, stopping, and switching on turbine longevity. This approach helps prolong the lifespan of the turbines and reduces the levelized cost of electricity (LCOE) over the entire lifecycle of the wind farm [50].

4.3. Optimized Operational Control of Offshore Wind Farms (Clusters) for Ancillary Services in Power Systems

Offshore wind farms exhibit strong randomness and distinct intermittency in their power output. The operational characteristics of the turbines and the uncertainty of

wind resources mean that wind turbines lack the power regulation capabilities found in conventional thermal power plants. The grid connection of offshore wind farms can have several adverse effects on the operation of the power system [51]. To address these issues, it is necessary to study the characteristics of offshore wind power output and the negative impacts of offshore wind integration on the grid, focusing on smoothing power fluctuations, system voltage, frequency, and system stability. Corresponding optimization and operational control strategies aimed at providing auxiliary services to the power system for offshore wind farms (clusters) should be developed. The main applications of the real-time control of offshore wind power include three aspects: (1) operational control of wind turbines and the entire wind farm [52]; (2) balance control of the power system, including automatic generation control, real-time economic dispatch, real-time safety analysis, reserve capacity estimation, and the coordinated control of energy storage [53]; (3) real-time spot trading in power markets and ancillary service transactions.

5. Offshore Intelligent Operation and Maintenance Technology

Data indicate that, under the same installed capacity, the operation and maintenance (O&M) costs of offshore wind power exceed those of onshore wind power by more than two times [54]. The O&M costs of offshore wind power account for over 25% of the LCOE [55]. The intelligent operation control of offshore wind farms is a core technology for enhancing overall power generation, reducing fatigue loads on wind turbines, improving grid integration and support capabilities, and maximizing profitability throughout the entire lifecycle of wind power.

Offshore wind farms exhibit significant flow effects, frequent load variations, and considerable distances from shore. Therefore, it is essential to implement intelligent wind power technologies, such as pervasive perception, intelligent decision-making, and autonomous execution, to achieve intelligent operation control characterized by rapid optimization, load reduction, extended lifespan, and stable operation [56]. In China, there is a lack of extensive experience in the O&M field for offshore wind power. Currently, O&M methods mainly draw on practices from onshore wind power, primarily employing scheduled maintenance supplemented by fault repair strategies. This maintenance model does not adequately address the operational characteristics of offshore wind power. Regarding fault repair in offshore wind power, the transportation of maintenance personnel is heavily influenced by sea conditions, and significant uncertainties can lead to the prolonged downtime of turbines, severely affecting the production efficiency of the wind farm. The key issues that urgently need to be addressed in the field of offshore wind power operation and maintenance (O&M) include the following: (1) The improvement of offshore turbine operating status monitoring systems: utilize turbine health diagnostic technologies to achieve the identification of abnormal turbines and predict their lifespan [57]. (2) The further optimization of offshore wind farm maintenance strategies: standardize O&M practices, optimize resource management plans, and allocate various O&M resources reasonably [58]. The formulation of maintenance strategies should integrate reliability data of the turbines to enhance the efficiency of offshore operations, thereby avoiding frequent trips to sea and reducing O&M costs [59]. (3) The fault-tolerant operation capability of turbines: turbines should be able to operate smoothly for a certain period after experiencing partial failures. In situations where faults in offshore wind turbines are unavoidable, the fault-tolerant operation functionality of turbines has significant research value [60]; (4) Research on the correlation of multiple component failures in offshore wind turbines: analyze the functionality and structural correlations between multiple components across various turbines [61].

5.1. Time and Weather Windows

The operation and maintenance of offshore wind farms are significantly influenced by environmental factors, with vessel accessibility being one of the key considerations. Research has revealed that the construction efficiency has significant spatial and temporal variation characteristics. The annual and monthly averaged workloads of pile foundation construction and wind turbine installation are distinctly different due to their specific weather and time windows [62]. According to statistics, with the current level of technology, the time available for accessing offshore wind turbines each year is approximately only 200 days, and this can decrease sharply due to deteriorating sea conditions. Two elements that determine vessel accessibility are the transportation time and weather windows. (1) Transportation time: This refers to the round-trip time taken by a vessel to travel from the dispatch center or the last task execution point to the location of the offshore wind turbine that requires maintenance. Generally, the larger the wind farm and the farther it is from shore, the longer the transportation time. (2) Weather windows: These refer to the time periods during which, based on ocean wave conditions and weather, the transport vessels can safely reach the maintenance site. Weather windows also affect the transportation time; given a fixed maintenance duration, shorter weather windows result in a reduced transportation time for vessels.

5.2. Operation and Maintenance Strategy

It is necessary to adopt a more comprehensive and complex approach, considering multiple factors simultaneously rather than relying on single-factor solutions and to develop relevant maintenance plans accordingly. Reference [63] discusses the optimization and scheduling of maintenance paths for multiple maintenance bases and multiple wind farms, proposing an algorithm based on the Dantzig–Wolfe decomposition method. This method applies mixed-integer linear programming to determine the optimal maintenance paths and scheduling plans for wind turbines.

Reference [64] introduces Divide-Merge, a high-performance hybrid algorithm that synergizes heuristic and exact algorithms to address large-scale multi-vessel cooperative maintenance scheduling challenges in offshore wind farms.

The principle of offshore wind farm operation and maintenance strategy is to minimize the cost of energy and maximize the profitability of wind projects. Decision-making in all areas of the wind industry is currently based on artificial intelligence and machine learning models [65]. Over time, the current tendency of using large databases with the largest amount of possible variables for developing hybrid models that possess the advantages of all the available models and that are capable of obtaining results very close to perfection. Figure 5 shows the maintenance scheduling of large scale offshore wind farms.

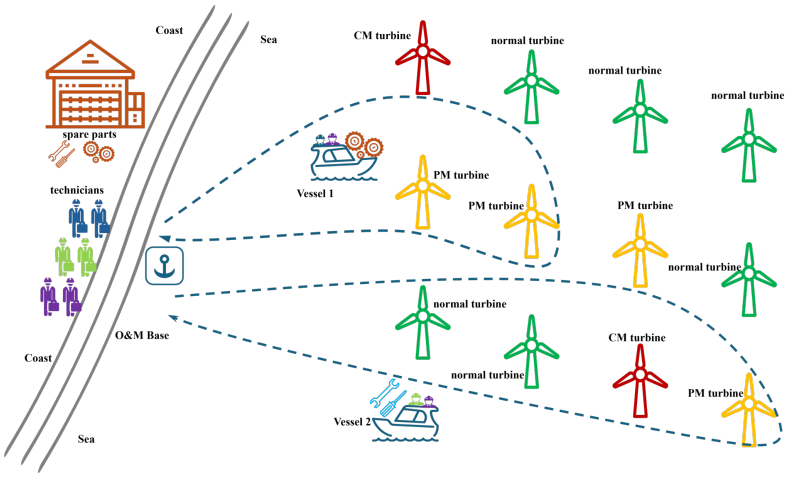


Figure 5. Large-scale multi-vessel cooperative maintenance scheduling.

6. Offshore Wind Power and Integrated Marine Area Utilization Technology

The comprehensive development of offshore wind farms holds significant importance, and it is essential to consider the overall layout and planning of wind farms, particularly from the perspective of utilizing maritime spatial resources. The potential negative impacts of offshore wind power typically include disturbances to the sedimentary environment during the development process, the emission of physical energy, and visual disturbances to birds. Strengthening the construction of offshore ecological civilization and reducing the impact of wind power projects on marine environmental resources is crucial [66]. Utilizing a multi-energy complementary power supply system to comprehensively harness the diverse and variable marine energy resources is beneficial for transforming the multiple unstable power outputs generated by marine energy devices into a stable single power output. This system can independently supply power to oil and gas platforms and islands or be directly integrated into the grid. Moreover, a multi-energy complementary power supply system can share transmission lines and generation facilities, while also drawing on the successful construction experiences of offshore wind farms, thereby increasing the power generation capacity, reducing construction costs, and promoting the industrialization process of marine energy in China. Among these developments, the coupling of offshore wind power with seawater desalination and hydrogen production is currently a hot topic. However, this area faces significant economic challenges. On one hand, the cost per kilowatt-hour of offshore wind power is high, making the direct use of offshore wind power for seawater desalination or hydrogen production economically unfavorable. On the other hand, as offshore wind power gradually extends into deeper waters, the construction of facilities such as cables and pipelines further increase the cost of hydrogen and freshwater production. Existing research indicates that hydrogen production from desalinated seawater offers better durability and economic viability [67], which can further reduce hydrogen production costs and address the issue of freshwater resource scarcity [68]. Due to the influence of the wake effect, the operational states of different turbines in distributed wind-to-hydrogen clusters are coupled, leading to differences in the hydrogen production capacity [32].

7. Conclusions

In the context of the dual carbon goals, offshore wind power, as a key area for the large-scale development of renewable energy, is maintaining a trend of stable growth. Particularly in recent years, offshore wind power has entered a period of rapid growth and is in the stage of large-scale development. As offshore wind power rapidly advances towards large capacity, scalability, and deep-sea applications, the innovative application of a new generation of digital, informational, and intelligent technologies will play an

increasingly important role. (1) The offshore weather environment differs significantly from that on land, posing various technical challenges for the power forecasting of offshore wind farms across different spatial and temporal scales. (2) The intelligent operation and control of offshore wind power is a cutting-edge technology internationally, encompassing various aspects such as wake control, fatigue load control, and operational control for ancillary services in power systems. (3) Offshore wind power is heavily influenced by the marine environment and involves numerous upstream and downstream links and factors, leading to operational and maintenance methods that differ significantly from those on land. (4) The development of offshore wind power technology is shifting from a single utilization model to a more integrated approach, giving rise to various fusion development models such as offshore wind power + marine ranching, offshore wind power + seawater hydrogen production and offshore wind power + offshore photovoltaics.

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