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Review

Progress on Offshore Wind Farm Dynamic Wake Management for Energy

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Abstract: The wake management of offshore wind farms (OWFs) mainly considers the wake effect. Wake effects commonly occur in offshore wind farms, which cause a 5–10% reduction in power production. Although there have been many studies on wake management, many methods are not accurate enough; for instance, look-up table and static wake model control methods do not consider the time-varying wake state. Dynamic wake management is based on the real-time dynamic wake, so it can increase the energy of the OWFs effectively. For OWFs, dynamic wake control is the main method of dynamic wake management. In this paper, the existing wake model and control progress are discussed, mainly emphasizing the dynamic wake model and the dynamic wake control method, solving the gap of the review for dynamic wake management. This paper presents a digital twins (DT) framework for power and fatigue damage for the first time.. The structure of this paper is as follows: (1) the mechanism of wind farm wake interference is described and then the dynamic wake model is reviewed and summarized; (2) different control methods are analyzed and the dynamic wake management strategies for different control methods are reviewed; (3) in order to solve the problems of dynamic wake detection and real-time effective control, the technology of DT is applied to the dynamic wake control of OWFs. This new DT frame has a promising application prospect in improving power and reducing fatigue damage.

Keywords: offshore wind farm; dynamic wake management; wake model; energy maximization; digital twins

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1. Introduction

In 2020, countries such as the United States and China as well as some of the European Union, which account for two-thirds of the global economy, are responsible for 63% of global greenhouse gas emissions per year; they have made a commitment to net-zero carbon neutrality [1]. In order to achieve the goal of net-zero carbon emissions and in response to soaring oil and gas prices, it is imperative to complete the transformation from fossil fuels to renewable and sustainable energy. Many scholars have carried out in-depth research on comprehensive energy [2–5], among which wind energy is the most promising energy type. Although the wind power incentive policies of some countries are weakening, the installed capacity of wind power is still on the rise [6]. Wind energy currently accounts for 9% of the world's electricity and only 20% of the world's total energy consumption. It is a promising energy-consumption method. According to the statistics of Global Wind Energy Development Report 2022 [7] released by the Global Wind Energy Council (GWEC), the newly installed capacity of global wind turbines was about 93.6 GW in 2021, and the cumulative global wind power capacity has reached 837 GW, as shown in Figure 1. According to the International Energy Agency, wind energy will account for 35% (8174 GW) of total energy by 2050 [8]. The newly added installed capacity of offshore wind turbines (OWTs) had a record year with more than 21 GW of grid-connected offshore energy generation, and the total installed capacity of OWTs exceeded 57 GW, accounting for 6.8% of the total installed capacity of wind power in the world. Compared with onshore wind power, offshore wind power (OWP) has longer available hours [9,10], proximity to coastal areas with strong demand for electricity, distance from residential areas, and no occupation of land resources. Due to these advantages, OWP has better prospects in comparison to onshore wind power.

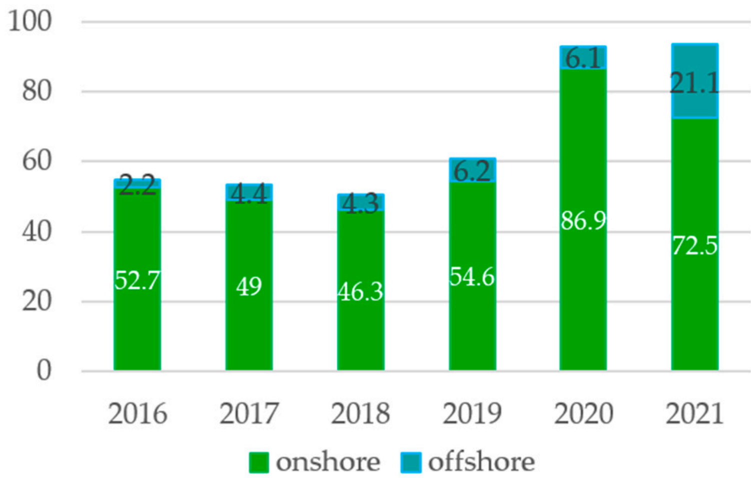

Figure 1. Analysis of installed capacity of wind power.

However, there are still many constraints on the development of OWP, which make offshore wind uncompetitive. The reasons are as follows: firstly, the construction cost of offshore wind farms (OWFs) is more than onshore wind farms, owing to more complex construction [11,12], a more severe environment (marine) [13], high requirements for equipment material load and corrosion protection, and expensive materials and structures [14]; Secondly, OWF has high operation and maintenance (O&M) costs [15,16], a high failure rate due to high salt spray and humidity, a limited window for offshore operations, high rental costs of O&M vessels, and high maritime safety risks [17–19]. Despite the continuous optimization of OWT designs [20], the OWP Levelized Cost of Energy (LCOE, which represents the average lifecycle price per MWh of electricity generation for a given energy source) [21] has decreased to approximately 47% over ten years (2009 to 2019) [18,22]. One of the ways to improve the competitiveness of OWP is to increase the power generation [23]. The wake of the wind farm threatens the reliability of the wind turbine, causing a loss of up to 54% [24]. Mitigating wake effects has great potential to improve the power efficiency of OWT [25,26].

There are three main approaches to mitigate wake effects, including wind farm siting [27–30], layout optimization [12,31,32], and wind farm operation control [33–35]. A sensible wind farm site and layout can reduce the interference of the wake effect [36,37]. However, the siting and layout of wind farms are complex and need to be integrated with various factors, so it is very difficult to make a completely reasonable solution for wind farms; the distance between the wind turbines cannot be idealized, so the wake interference between OWTs is inevitable [38]. For non-floating wind farms that have been built, the siting and layout cannot be optimized [39–41]. Different from the above two methods, controlling the degrees of freedom of wind turbines [35,42] reduces the influence of the wake effect [43,44], and the power generation can be improved with fewer constraints and high feasibility [45].

There have been many analyses and reviews of wake management methods and wake models. For example, Kheirabadi et al. [46] conducted a summary and quantitative analysis of reducing wake interferences for wind farm power maximization and evaluated the effectiveness of the strategies; Gokman et al. [47] evaluated the wake modelling method developed by the Technical University of Denmark; Kaldellis et al. [48] conducted a comprehensive comparison of nine well-established wake models and demonstrated their accuracy. To meet the needs of online dynamic wake control, it is necessary to evaluate and compare dynamic wake models and control methods. However, no one has analyzed the control methods of dynamic wake for power maximization systematically. The paper's purpose is to judge the practicability of dynamic wake models and control methods in the existing literature by analyzing and comparing, and to provide engineers and researchers with a practical introduction to wind farm dynamic wake models and control methods by presenting a review of the progress. Digital twin (DT) technology is considered as a promising tool [49]; a virtual model can be used to make up for a lack of some sensors, and in this paper, a new DT framework for dynamic wake management is proposed for the first time to control wind farm power and fatigue damage, but the possibility of DT-based dynamic wake control needs to be studied further in future.

Section 2 reviews the influence mechanism of the wake effect and wake models. Section 3 introduces the research status of wind farm power improvement methods. Section 4 introduces a new DT framework of OWF dynamic wake management. Section 5 presents the conclusion of this paper.

2. Wake Effect

In this section, the wake effect is described, the required wake models for wind farm control are analyzed and compared, and the demands of the dynamic wake model for online control are suggested.

2.1. Wake Effect and Wind Energy

As shown in Figure 2, the wind passes through two wind turbines, which are named T1 and T2. T1 extracts wind power, the wind speed behind the wind turbine decreases, and the wind direction changes due to the viscous action between the airflow and blades [29,50–52]; this phenomenon is called the wake effect [53]. In the wake zone, because of the decrease in wind speed and increase in turbulence intensity, the power of T2 decreases and the fatigue damage increases [54]. The wake effect adds additional fatigue damage to downwind wind turbines [55], which poses a serious threat to their power, reliability, and life [56,57].

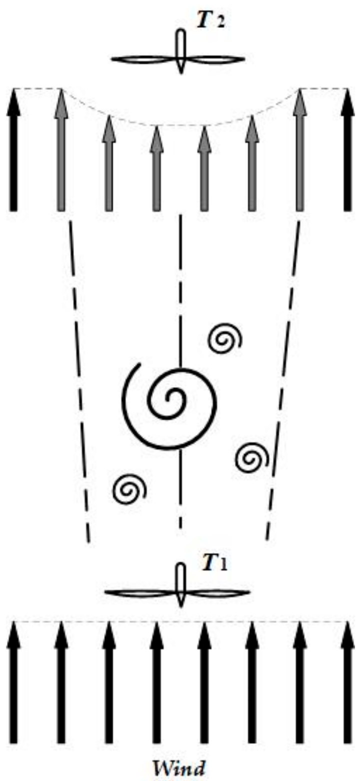

Figure 2. Schematic diagram of wake-deficit evolution.

The data simulated by the Simulator for Wind Farm Applications (SOWFA) [51] shows the evolution process of wake generation, revealing that the wake is related to spatial displacement, which can be seen in Figure 2. From the visualization of wake generation by the yaw turbine [58], the center of the wake deviates after the yaw turbine, which indicates that the wake is related to the operation state of the upstream turbine. The wake generation and evolution are complex [59], which depend on a variety of parameters [60]. An accurate description of wake evolution is helpful for accurate control and power improvement. It is necessary to study the wake model for accurate wake description.

2.2. Wake Model

A wake model is necessary for the wind farm controller, and the fidelity varies from low to high depending on the accuracy of the wake models [61]. In order to reduce wake interferences in the design and operation stages of OWFs, different wake models are listed in this part. Some old wake models, including Jensen's model [62] and Katic's model [63], are compared, showing the evolution of wake models.

The low-fidelity wake model is based on the integral relationship of hydrodynamics, relying on the parametric assumptions of wake diffusivity [61]. Compared with the high-fidelity wake model, the low-fidelity wake model does not take fluid details into account [64]. Jensen's model is a widely used simplified model for flat terrain, which can effectively predict the distribution characteristics of the wake flow field and evaluate the power generation of wind farms [63,65]. In order to improve the accuracy of the model and obtain more features of the wake phenomenon, Jensen's model has been continuously modified and extended. Katic et al. [63] extended and modified Jensen's model, proposing a wake superposition model suitable for different incoming winds, which is used to predict wind farm annual power generation. The Flow Redirection and Induction in Steady-state (FLORIS) model [66] was released by the National Renewable Energy Laboratory (NREL) and was used to model the impact of yaw on the wake evolution. The wind speed distribution in Jensen's wake model is uniform; however, three wake regions in FLORIS are divided according to the wake recovery characteristic, and high-fidelity simulations were used to determine the model parameters of FLORIS, which can predict the wake wind speed distribution more accurately. Gebraad et al. [67] tested the accuracy of FLORIS at Horns Rev and Nysted, showing that the relative errors ranged from 0.1 to 5.3% in different wind conditions. The dynamic wake model Flow Redirection and Induction Dynamics (FLORIDyn) [68] and the static wake model Floating Offshore Wind Farm Simulator (FLOWFSim) [69] are extended on the basis of FLORIS model. In comparison with FLORIS, FLORDyn considers the time delay caused by the changing state of the wake and makes an effective judgment on the position and speed of the wake. The FLOWFSim is developed for simulating the platform movement of offshore floating wind farms.

High-fidelity models capture relatively accurate details of velocity and pressure gradients in the fluid domain through differential relationships of fluid dynamics [62]. SOWFA [70] adopts 3D large eddy simulation (LES) and uses the actuator linear potential flow theory modeling, which can obtain additional flow phenomena compared with a model such as SP-wind [71]. SP-wind is modeled by the actuator disk theory; SP-wind has a lower computational cost than SOWFA, and the power prediction accuracy is slightly lower than SOWFA. There are other wake models based on Computational Fluid Dynamics (CFD) designs, such as star-CCM+ [72], developed by Siemens. The common feature of high-fidelity wake models is a high calculation accuracy, but the calculation cost is very high. Obviously, although the high-fidelity wake models can obtain the details of the wake and the calculation accuracy is high, it is consequently hard for them to meet the work requirements of computing time.

The medium-fidelity model is a simplified solution of the Turbulent Navel–Stokes equation, and the computational complexity is lower than that of the high-fidelity model. The WFSim (Wind Farm Simulator) model is used to study wake redirection control by solving the two-dimensional unsteady turbulent Navel–Stokes equations [73], ignoring ground effects and the wake redirection. The dynamic wake model (DWM) [74] is based on the boundary layer equation and vorticity formula, which can meet the needs of fast calculation and relatively accurately calculate the advection and meandering of wind speed. In spite of DMW ignoring the phenomenon of wake swirling and the effect of the ground on the wake, this model has been used in some wind farm simulation models [75,76].

With the development of big data, machine learning algorithms based on data mining are gradually applied to the study of wake models. A high-fidelity wake model is established by the training of valid data and the data of wind turbine SCADA, and then the free stream is used as the training input, and the entire flow field is used as the training output. Well-established models can capture fluid dynamics [68]. The deep learning dynamic wake model (DLDWM) was proposed by Zhang et al. [77]. Multiple sets of large eddy simulations were performed to generate flow-field data for wind turbines operating under various operating conditions. Appropriate orthogonal decomposition techniques were then employed to reduce the flow-field dimensionality and a long short-term memory network to predict the flow field at future time steps. However, from the simulation results, the wake calculation method based on machine learning can support the needs of wind farm control.

In addition, the inclusion of time-series prediction of the wake is of importance, especially for the individual turbine feedforward control; wake time-series prediction based on artificial intelligence (AI) has made some progress. Manohar et al. [78] proposed to apply machine learning to a sensor-placement optimization method for achieving high-precision signal reconstruction and called it sparse sensor placement optimization for reconstruction (SSPOR). Ali et al. [79] proposed the use of bidirectional long short-term memory (Bi-LSTM) for wake prediction, which can capture more wake features in the far-wake region and achieve high prediction correlation compared with the actual, but this method does not perform well in the near-wake region. Classification-based machine learning (CBML) algorithms were used by Geibel and Bangga [80] for wake data reduction and reconstruction; SSOPR [78] and Bi-LSTM [79] are also applied. The data for machine learning training and testing came from high-fidelity simulations to ensure the accuracy of the machine learning model. The test results showed that the method could predict the wake cycle signal and obtain high-precision flow-field reconstruction of the near-wake of the turbine by orthogonal decomposition, which can replace the traditional prediction method.

Considering the real-time fluctuation of power and fatigue damage, a dynamic wake model with low computational cost and accurate capture of flow-field information is required for online dynamic control. The dynamic wake models are summarized and compared in Table 1. A fast and accurate dynamic wake model suitable for online control can be selected from the above models. Based on the above analysis, FLORIDyn, DWM, WFSim, and the machine learning method are useful for online dynamic wind farm wake control, and the machine learning method shows great potential for the future.

Table 1. Dynamic wake model literature.

Model	Time	Computing Speed	Fluid Details	Fidelity
DWM	2007	medium	yes	medium
SOWFA	2012	slow	yes	high
FLORIDyn	2014	fast	no	low
SP-Wind	2015	slow	yes	high
WFSim	2016	medium	yes	medium
STAR-CCM+	2018	slow	yes	high
DLDWM	2020	fast	yes	high
Bi-LSTM	2020	fast	yes	high
CBML	2022	fast	yes	high

2.3. *Application of Wind Estimation in Wake Model*

The wake model is an important basis for model-based control, and the accuracy of wake model affects the wind farm control [81]. However, the wake characteristics are affected by many factors, including ambient wind direction, wind speed, atmospheric turbulence, shear, and the spacing of nearby OWTs. Due to the complexity of the physical process, the wake cannot be accurately predicted using a single numerical model, which requires correction from field data.

Due to the aerodynamic coupling effect of airflow and blades, towers, nacelles, etc., wind-speed and wind-direction measurement at the nacelle are not accurate except for the use of lidar wind measurement equipment [82]. Lidar wind measurement equipment is expensive and greatly affected by weather, so it is still not widely used in wind farms at present. It is important to obtain the corrected wind speed to predict the wind turbine action [83]. Bottasso [84] calculated the wind estimation around the rotor by measuring the blade bending moment. Using this method, both the effective wind speed on the rotor disk and the local area could be obtained. However, no identification of the wind direction was involved. Annoni et al. [83] proposed a wind direction estimation method by comparing the wind direction of adjacent wind turbines. The estimated wind direction is used to adjust the wake model parameters [84] or build a state estimator [85] for the correction of the flow-field information in wind farm

Doekemeijer et al. [86] and Gebraad et al. [87] designed a Kalman filter to correct the wake model parameters, making the control more accurate, realizing power optimization, and reducing the large error of the wake model prediction data during initial operation. The difference is that the correction of wake models are different, Doekemeijer et al. [86] used Kalman filters to correct WFSim wake model, and Gebraad et al. [87] used Kalman filters for the design of the parameters wake model FLORIDyn and the state estimation of wake, but both of them have achieved better results.

Wind estimation plays a very important role in wake detection and wake center determination. Although many of these methods have been verified in field measurement, they have not been combined with wind farm control. It is believed that the use of wind estimation methods can guide the wake control of wind farms in future research effectively.

3. Dynamic OWF Control

High-power generators are usually used in OWF [88]; the wake effect of high-power generators is more obvious than that of low-power generators [62], and the attenuation coefficient of the wake effect in OWF is smaller than that of onshore wind farm [89]. Therefore, the wake effect in OWF is more obvious, and the optimization of OWF is also more urgent. At present, the dynamic OWF control focuses on yaw-based wake redirection, axial induction factor control and wind turbine repositioning (wind turbine repositioning is only applicable in floating wind farms). The corresponding control studies are listed in Table 2.

3.1. Axial Induction-Based Control

Changing aerodynamic coupling could optimize wind-farm power generation through load control, also known as axial induction-based control.

Axial induction factor (a) is the percentage reduction in wind speed between the free stream and the turbine rotor. The blade pitch angle, generator torque, tip ratio, and thrust coefficient affect the axial induction coefficient. As shown in Figure 3, when the upstream wind turbine T1 deviates from its optimal operating point, its power decreases, but the wind speed in the wake region of T1 increases significantly, resulting in an increase in the power of T2. Annoni [52] also found that the power of T1 decreased slightly, its power value did not drop too much, while the power increase in T2 was very significant. Many studies have shown that controlling upstream wind turbines can increase the wind speed in the wake region, thereby increasing downstream wind turbines' power [52,90,91].

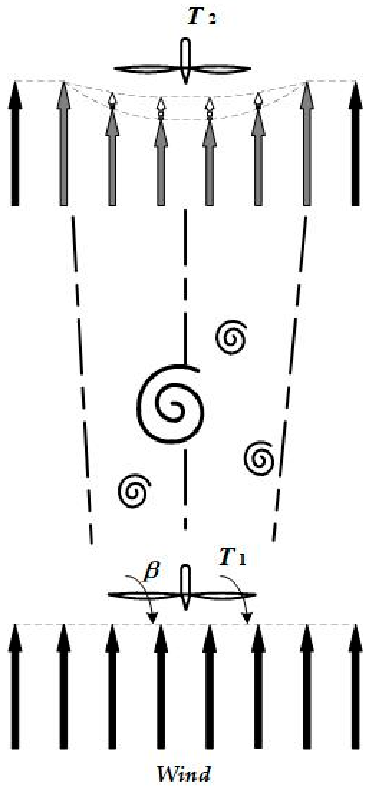

Figure 3. Control diagram of axial induction-based control.

Goit and Meyers [92] proposed an optimal control method for boosting power, taking the turbine thrust coefficient as the control input and adopting the backward horizontal control method. The control problem in their research was decomposed into several optimal control sub-problems. The applied wake model was an LES-based high-fidelity dynamic model, and the actuator disk model (ADM) was applied as the wind turbine model. They simulated in a 10 × 5 aligned wind farm with a spacing of seven rotor diameters (D) to demonstrate the feasibility of axial induction factor control. High-fidelity simulations showed a 25% increase in power compared to dynamic control using a low-fidelity wake model. Although this method makes the wind-farm power increase in simulation, the expensive computational cost of dynamic LES-based is not feasible for online dynamic optimization.

Vali et al. [93,94] used the WFsim wake model [73] to improve the computational cost and proposed an adjoint-based model predictive control method (AMPC). The method was verified by simulation of a 2 × 3 wind farm. The result showed that a 4% power growth was achieved in time-varying turbulent wind conditions with full wake coverage. AMPC was properly parameterized to achieve an efficient execution time of 7 s, but this may affect control performance, and the method has not been tested in wind field. In the experiment of Van et al. [95], pitch angle was controlled, and the optimal pitch angle for each wind direction was calculated to maximize wind farm power. It was tested at the Goole fields wind farm, which consists of three rows of sixteen wind turbines of 2050 kW. After a year of measurement, it was found that the single-row wind turbines achieved a power growth of 3.3% under a specific wind direction and wind speed. The improved power of simulation analysis was higher than the measured power in field, which may be caused by the following: firstly, the distance between the turbines is short in the tested wind farm (the distance of the tested wind farm between the wind turbines is 2.3–3.1D, while the distance between the wind turbines of the general wind farm is 6D); secondly, yaw misalignment of the wind turbine leads to low power despite the wind direction filter; finally, the induction control is not timely, for example, due to the control delay in actual operation, the time in the wake region is greater than the time of the axial induction control of wind turbines.

The accuracy of the wake model may reduce the real-time performance and accuracy of model-based control, so it is very important to choose a suitable wake model. However, model-free control strategies are based on data-driven rather than complex interaction between wake aerodynamics and turbines, which reduces a lot of work for wind farm power optimization. Marden et al. [96] realized model-free real-time dynamic optimization to obtain the optimal power operation point of wind farm and proposed a control optimization method based on distributed game theory. The method achieved the maximum power by pursuing the satisfaction of each turbine. The distributed controller needs to iterate 10^5 times to complete a control calculation. Obviously, the expensive computational cost of farm control algorithm for time-varying wind conditions and dynamic wake is not enough.

In order to improve the control efficiency, Gebraad et al. [97] carried out the following research: a maximum-power point-tracking (MPPT) control scheme was proposed, and gradient optimization was carried out to achieve efficient distributed control according to the power response and adjacent wind turbine power. In contrast to the distributed game theory simulation of Marden et al. [96], this method only considers adjacent wind turbines, not the entire wind farm. The power increase in the MPPT control is 4%, which is lower than that of the game theory control method, but the MPPT control can converge in 1 h, while the game theory requires 80 h. Obviously, MPPT control is more suitable for online control.

Yang et al. [98] proposed a nested loop extremum search control method. The control input was the generator torque. The array of three turbines was simulated under different conditions of (a) 8 m/s mean wind speed, 5% turbulence intensity; and (b) 6 m/s steady-state wind and (c) 10 m/s steady-state wind. The results showed that the power increased by 1.3%, 9.09%, 0.55% in wind conditions of a, b, c, respectively. Because the power reference at low wind speed was much lower than that of high wind speed, the magnitude of the power increase was more at low wind speed. Compared with wind conditions of b, the power boost under wind conditions of a was much smaller. Optimizing the power efficiency greatly under turbulent wind remains a difficult problem.

Wu et al. [99] improved the nested loop extremum search control method. Delay compensation was used to enhance the nonlinear disturbance control of the nested loop extremum search control method and improve the convergence speed. Three turbine arrays were simulated and compared with a nested loop extremum search control method. The results showed that the total average power of the wind turbine was good under a wind speed of 8 m/s and turbulence intensity of 10%. The wind turbine power of the nested loop extremum search control method was increased by 0.34%, while the total power of the delay compensated nested loop extremum search control method was increased by 0.61%.

Similar to the distributed game theory algorithm proposed by Marden et al. [96], Zhong et al. [100] proposed a distributed discrete adaptive filtering algorithm. In their algorithm, the axial induction factor of each control unit was perturbed by the probability distribution function. Additionally, the reference axial induction factor and power were updated when the power of the wind farm increased. The difference is that the interference is suppressed by the adaptive filtering method, so they can converge faster. The method was tested with a dynamic park model, and the results showed that the power efficiency was improved by 3.87% after 200 iterations. The method of Zhong et al. [100] is more suitable for time-varying wind conditions and dynamic wake wind farms.

3.2. Yaw-Based Wake Redirection

Yaw-based wake redirection means that upstream wind turbine T1 changes the wake direction in the downwind direction by yaw misalignment [101]. Wind turbine T2, originally located in the wake area, is no longer covered, as shown in Figure 4. Due to the misalignment between the rotor and the incoming wind, the deflection of the wake makes the force on both sides of the rotor unbalanced, which leads to a gain in momentum in the crosswind direction. In this way, downstream wind turbines arranged downwind can reduce the interference of the upstream wake. Various control methods of yaw-based wake redirection are developed based on the above principle.

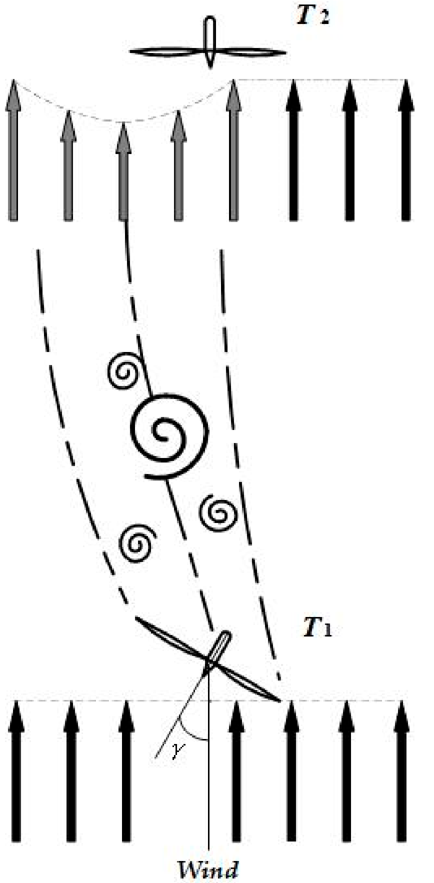

Figure 4. Control diagram of yaw-based wake redirection.

Fleming et al. [102] investigated the feasibility of increasing power through yaw-based control, in which the wake centerline is redirected by rotor tilt. It was found that the fatigue damage of yaw bearing increased. Churchfield et al. [103] found that wind farm power could be improved of 10% by turbine yaw control in a specific wind direction, but with a lower power increase in other directions, even for negative power gains. The scholars also tested their method in the Fishermen Atlantic City wind farm, finding that the efficiency of the wind farm was improved by 1% with the effective yaw misalignment.

Archer et al. [104] studied a wind farm with 28 wind turbines by LES and came to the same conclusion: the net power increases with a positive yaw error angle due to the Coriolis effect, while the net power decreases with a negative yaw error angle decrease. The wake generated by yaw misalignment was narrower than that generated by non-yaw. Furthermore, for a wind farm with eight rows of wind turbines, a higher power increase was generated when the first row and sixth row of the wind farm yaw effectively. The above studies showed that yaw control was useful for power boosting.

Gebraad et al. [67] used the game theory optimization method to optimize the wind farm power, and SOWFA was adopted to correct the wake model parameter of FLORIS for the optimal yaw misalignment angle. In addition, SOWFA was used to simulate a 3×2 scale wind farm, while the turbulence density of simulation inflow wind was 6% and the average wind speed was 8 m/s. The simulation result showed that the power increased by 13%. Fleming et al. [105] modeled the Princess Amalia wind farm by FLORIS and adopted yaw control optimization to increase the power generation per square meter by 7.7%.

Different from the FLORIS wake model, flow delays the wake effect and can describe the linear state space of wake propagation, and the nonlinear feedback term of wake characteristics was considered in the FLORIDyn wake model [68]. Gebraad et al. [87] proposed a wide range of grid search methods, of which the control parameters were evaluated by wake dynamic FLORIDyn. In the simulation experiment of three wind turbines with streamwise spacing of 5D, the adaptive control could increase the power generation by 0.19%, and the calculation time was short, which is suitable for online control.

Because the control is greatly affected by the simulation environment or the actual wind field environment, the simulation results vary greatly in different simulations or experiments. For example, Munters et al. [35] developed a yaw-based and axial induction factor control method that combined backward horizontal and continuous adjoint gradient evaluations. By simulating a 4×4 aligned wind farm, there were power gains of over 92% in steady-state wind conditions and over 21% in turbulence conditions (turbulence intensity of 8%) by yaw control. In Munters' study [106], the effect of wind turbine spacing and layout on this control method was investigated. Yaw-based control was considered to be effective for aligned wind farms and closely spaced wind farms.

In addition, Ciri et al. [107] developed a model-free nested extreme value optimization algorithm, which implemented the real-time gradient algorithm. The yaw error angle was updated with the estimated gradient in each loop until the power iteratively converged to the optimum. The power increase was up to 7% in turbulence wind with an 8% turbulence intensity.

Table 2. Summary of reference wind farm dynamic control algorithms.

Reference	Method	Input	Streamwise Spacing	Wake Model	Power Gain
Goit and Meyers [92]	Centralized receding horizon optimal control	CT	7D	Dynamic LES	15.8%
Munters and Meyers [35]	Centralized receding horizon optimal control	CT	6D	Dynamic LES	15%
Vali et al. [93,94]	Centralized adjoint-based model predictive control	a	5D	Dynamic WFSim	23.59%
Van et al. [95]	Lookup table for optimal blade pitch angle settings	β	2.3~3.1D	FarmFlow	3.3%
Marden et al. [96]	game-theoretic control	a	5D	Model-free	34.05%
Gebraad et al. [97]	Maximum tracking control	a	5D	Model-free	4%
Yang et al. [98]	Nested ring extremum search control	Torque gain	5D	Model-free	1.3%; 9.09%; 0.55%
Wu et al. [99]	Delay compensation nested loop extremum search control	Torque gain	5D	Model-free	0.72%; 0.34%.
Gebraad et al. [66]	Optimization of game theory	γ	5D	FLORIS	13%
Fleming et al. [96]	Lookup table for optimal yaw settings	γ	7D	FLORIS	7.7%
Gebraad et al. [67]	Nonlinear model predictive control using extensive grid search	γ	5D	FLORIDyn	0.19%
Munters and Meyers [35]	Combination of backward level and continuous adjoint gradient evaluation	γ	6D	Dynamic LES	21%
Ciri et al. [107]	Nested extremum optimization algorithm	γ	5D	Dynamic LES	7% (rotor diameter of 126 m); 3% (rotor diameter of 27 m)

According to the current literature [52,103], although yaw misalignment control is better than the axial induction factor control for optimizing the wind farm power, when the yaw error is too large, it will cause an increase in the wind turbine load. Therefore, there are more and more methods of combining yaw control and axial induction factor [106,108], which can consider wind turbine fatigue damage and power comprehensively. The method of combining yaw and axial induction factors is one of the most effective methods for wake control in wind farms with fixed wind turbines.

3.3. Repositioning

Boersma et al. [61] optimized the layout of the floating offshore turbine in OWF according to the wind direction in real time for reducing the wake overlapping. As shown in Figure 5, when T2 is in the wake interference area of T1, the wake overlapping at wind turbine T2 is reduced by increasing the spacing between the two wind turbines in the vertical wind direction.

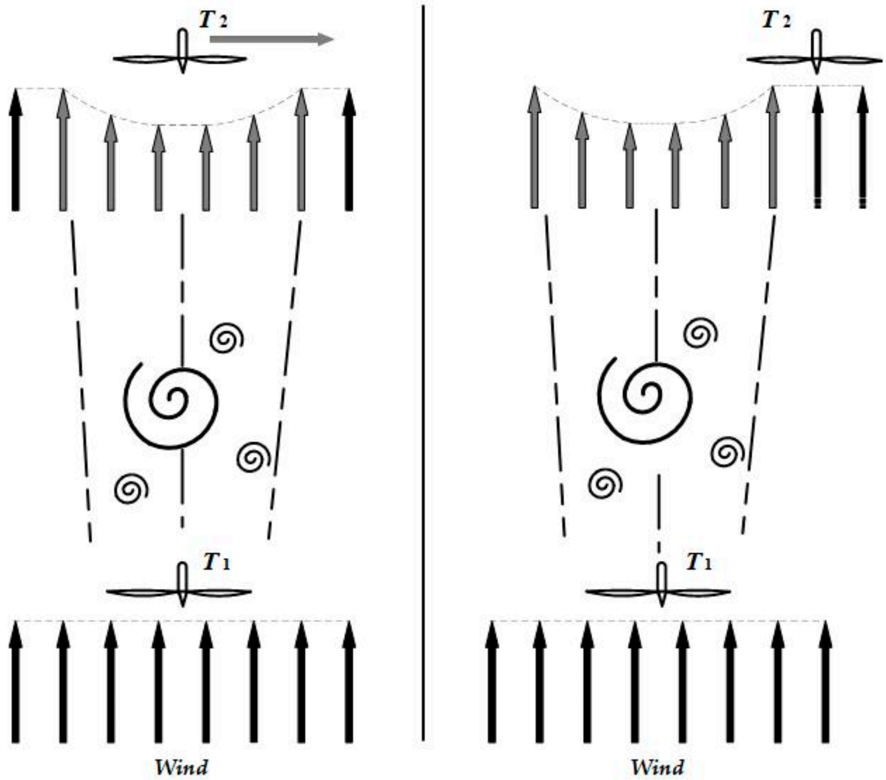

Figure 5. Control diagram of repositioning.

The development of repositioning is still in its infancy [109]; it is suitable for offshore floating wind turbines with mooring lines, two types of floating wind turbines shown in Figure 6 [110]. Repositioning simulation research was proved to be of great potential for power increase. Fleming et al. [111] studied the relocation open-loop control of two wind turbines by moving 1 diameter in the wind vertical direction, during which the power of the wind farm was improved by 41%.

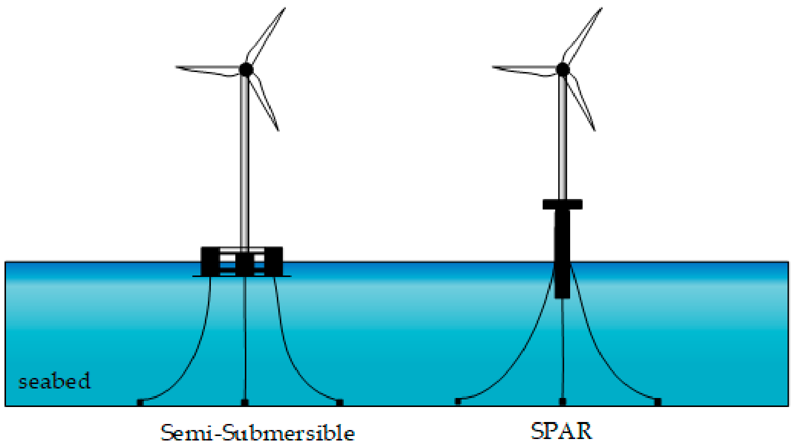

Figure 6. Floating wind turbine structures.

Rodrigues et al. [112] proposed a real-time reposition control strategy for a floating wind turbine, using the evolutionary strategy of covariance matrix adaptations. The strategy was used to verify a wind farm with 36 wind turbines, and the distance between the turbines was 1 km. This strategy was used to reposition the wind turbines, resulting in a maximum efficiency improvement of 18.11%.

Han et al. [113] used a greedy control algorithm to reposition offshore floating wind turbines to maximize power. The basic principle was to change the thrust acting on the rotor by changing the axial induction factor and yaw misalignment. In order to balance the thrust and restoring force generated by the mooring line, the position of the wind turbine was moved and repositioned by the force.

Kheirabadi et al. [69] developed FOWFSIM to study the repositioning of floating wind turbines. By optimizing the design parameters and configuration of floating wind farms, they determined the best operating parameters of wind turbines and realized the relocation [40]. This model was then used to evaluate the potential of the method proposed by Han et al. [113]. The simulation results showed that the power of a 7×7 wind farm increased by 42.7% under the condition that the specific mooring system direction and anchor point position was sufficient for mooring lines.

Although studies have shown that wind turbine repositioning plays a huge role in reducing wake interferences [69,109], there are still few studies in the literature on wind turbine repositioning, and this control method is still in its infancy. In practical applications, the length of the mooring line, the material properties, the fixed structure, and the installation and control of the winches also need to be considered [112]. Because the floating wind turbine is subject to wind thrust and wave motion, which causes the wind turbine itself to vibrate, there are still many factors that need to be considered in the study of repositioning.

3.4. Remaining Issues

(1) The wind estimation algorithm of the corrected wake model cannot be calculated online, and the calculation of the wake model cannot be combined with the actual wind farm control.

(2) Operation data is obtained from the SCADA data feedback, which is not enough to support the control requirements of wind turbines operation, such as no blade cracking signal, icing status signal, etc.

(3) Although there are many studies on power enhancement, few studies focus on both power and fatigue damage. Many wind turbines are not installed with some moment sensors that directly sense the wind, such as blade root moment sensors and yaw moment sensors, which are required for wind farm load control, so it is difficult to comprehensively control wind farm power and fatigue damage at the same time.

(4) Machine learning, artificial intelligence (AI), and multi-criteria decision making (MCDM) can discover more information from data, so the technologies have developed very rapidly and been applied to the wind power industry gradually, such as the application of machine learning algorithms and AI in wind farm fault diagnosis/wind farm control, and MCDM research on micro-siting of wind farms. If it can be applied to the control of dynamic wakes in wind farms, it may make great progress in fatigue damage and power control of wind farms [114–116].

To cope with the above challenges, this paper proposes the combination of the currently popular digital twin (DT) technology with wind farm wake models to guide OWF wake control. The academic perspective on applying DT to OWF control will be explained in the following sections.

4. Suggestion of Digital Twins on OWTs

4.1. Introduction of Digital Twins

The concept of DT was first proposed by Grieves [117] and subsequently received more attention. A common definition of DT is the replication of complex physical processes from a physical model to a virtual model, enabling the virtual model to react to the physical model, which is used to simulate one or more physical systems in real time to reflect the real physical phenomena [118].

DT technology is used for food [119], healthcare [120], engineering technology and manufacturing [121], industrial internet of things [122], smart agriculture [123], construction [124], etc. It is also used for equipment monitoring, operation, and maintenance. For example, NASA used DT technology in spacecraft monitoring to make remote status detection and action decisions easier [119]. It brings convenience for early warning of wind farm failure status and decision-making of operation and maintenance and is very useful for reducing downtime and increasing annual power generation [125]. The equipment state can be predicted and the operation of equipment can be improved [126]. In recent years, DT techniques have been gradually combined with big data and machine learning algorithms [127]. In order to better fit the physical model, the temporal evolution of DT model parameters can be predicted by using machine learning algorithms [128], AI and MCDM [114–116].

4.2. Recommendations for DT Application to OWF Dynamic Wake Management

The wake effect produced by one wind turbine can be described and predicted by wake models. However, the dynamic wake of wind farms is complex, and the parameters of the wake model are difficult to determine accurately. Especially in the initial stage of wake influence, the wake is unpredictable, and there are wake superpositions and deep array effects in the wake evolution process. In addition, the fatigue damage of the wind turbine without blade root, yaw, and tower base moment sensors cannot be measured. Therefore, the control process is not easy to determine; it is more difficult to considering both power and fatigue damage. DT technology has great application potential in the study of dynamic wake. DT technology can copy the physical model into a virtual model, and the virtual model can be used for all moment calculation of wind turbines. This section gives specific suggestions.

The DT frame for OWF wake control is shown in Figure 7, which consists of physical models, virtual models, twin databases and service systems. The data obtained from the physical model (including OWT aerodynamic load, OWF turbulence calculation, SCADA data, OWTs and OWF control data) is stored in the twin database and mapped to the virtual model. The turbulence prediction model and high-fidelity simulation model of dynamic wake analysis are established for the virtual model. Combined with wind estimation, the wake model is constantly corrected by aerodynamic load and noise. The optimal control is implemented by the flow field details, which is from the constantly updated wake model by adding control disturbance and enabling what-if analysis risk assessments. At the same time, the optimal control decision is transmitted to the physical model, and the virtual model and service system are modified according to the real-time operational data of the physical model, so as to increase the power and the fatigue damage of wind turbines.

The physical model is composed of OWTs, OWF operation and control data, anemometer tower used to measure turbulence wind, wake interferences detection and state detection of wind farm. The OWF anemometer tower detects inflow wind speed and direction. Sensors installed on each OWTs monitor the operation status of the OWTs, of particular importance to which the load sensors that detect the aerodynamic load and noise. The real-time operation data of OWF and OWTs is stored in the twin database, which provides more physical information and parameters updating for the virtual model and service system.

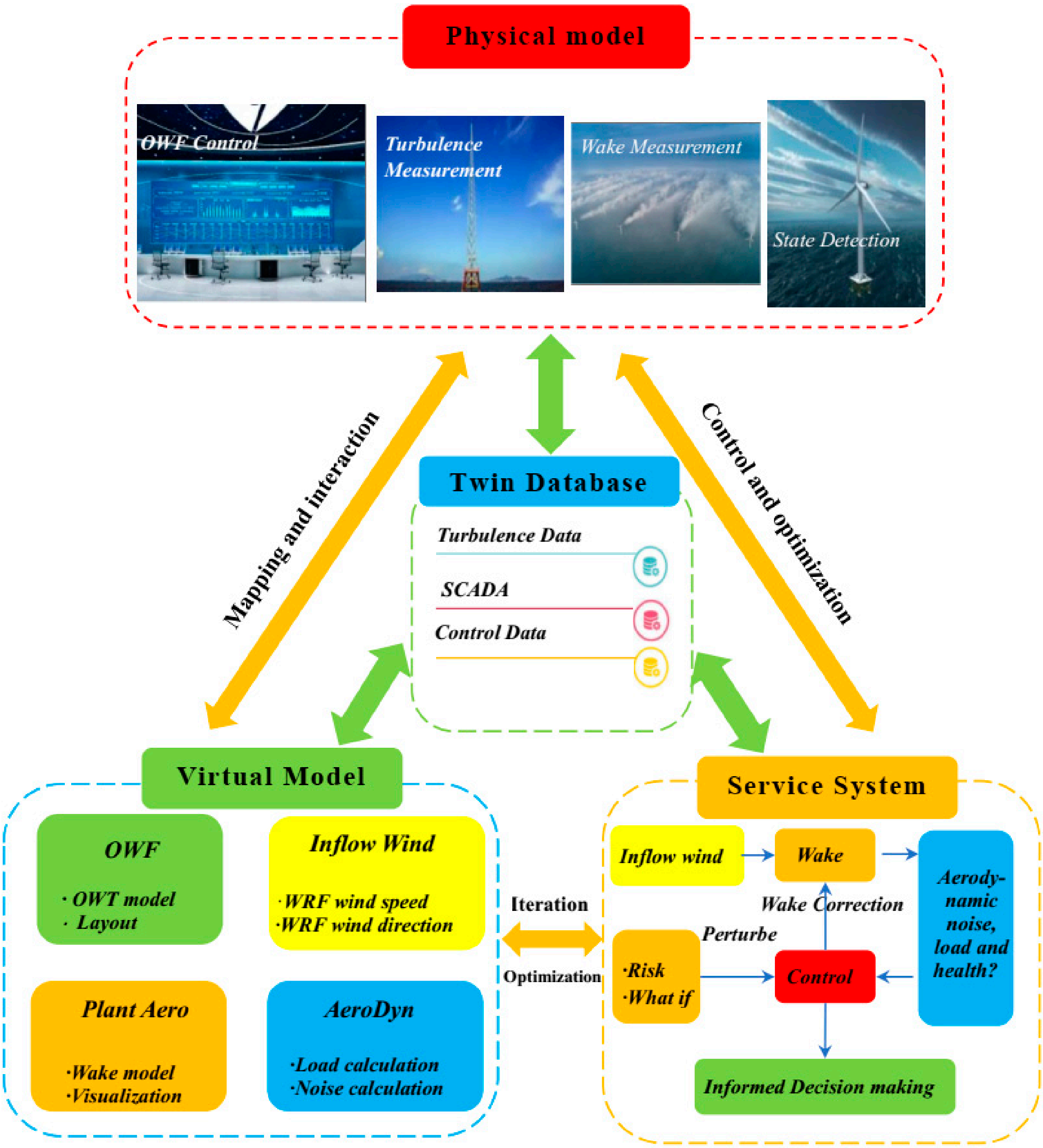

Figure 7. Schematic diagram of the digital twin of the OWF dynamic wake management.

The virtual model is a mapping of the physical model, which is realized by several sub-models: wind farm model, mesoscale Weather Research and Prediction Model (WRF), wind farm wake aerodynamic prediction [78–80] and virtual blade coupling model [129]. FAST. Farm software of NREL company is used to build wind farm model. It is a mid-fidelity wind farm simulation tool capable of satisfying dynamic wake field analysis and accuracy [130,131]. A mesoscale weather research and forecast model considering wind farm conditions is established to obtain downscaled wind speed and direction data. Taking numerical weather data as the initial condition and power prediction data as the boundary condition, the high-fidelity aerodynamic simulation and virtual blade coupling model of the wake of the wind farm are established and the wind field simulation parameter is calculated. Aerodynamic load is used to check whether OWTs are affected by wake and to estimate wind conditions, so the fatigue damage is obtained. The virtual model is updated in real time according to the data generated by the physical model, which is taken as the input of the virtual model.

The service system consists of the input part, disturbance part, and decision. When there is wake interference in a wind farm, the flow field details provided by the wake model are used for wake control of OWF. The control effect is evaluated according to the results of simulated power and fatigue damage. Hypothetical outcomes are predicted by perturbation of real-time data, which is convenient for the optimal control of the imaginary situation. Finally, the optimal decision is made and transmitted to the physical model.

DT data are derived from SCADA data, control data, and wind data in the physical model. The virtual model and service system were driven by DT data, while DT data are continuously updated according to the control data in the virtual model, physical system, and service system.

5. Conclusions and Recommended Future Research Directions

Wind power is a clean, safe, and cheap power source. The installed capacity of wind power is increasing rapidly under the international situation that many countries around the world make commitments to net-zero carbon neutrality. Marine wind energy resources are abundant, so OWP has a broader space for development. Compared with onshore wind power, one of the shortcomings of OWP is that it is affected by the wake severely. OWTs under the wake interference not only reduce the power but also increase the fatigue damage.

This paper reviews the main features of wake models and control methods in the existing literature, puts forward the requirements of dynamic wake management, and solves the gap in the research of dynamic wake control. Considering both power and fatigue damage is proposed for the first time, and a DT framework of dynamic OWF wake management is proposed in this paper. This new DT framework is expected to address dynamic wake detection, dynamic wake optimization control, risk prediction, and control decisions to increase the wind farm power and reduce the fatigue loads.

The following suggestions may be helpful to people for the future of wind farm dynamic wake management:

(1) Correction of dynamic wake model: Accurate wake information is of great importance for wind farm wake control, especially the wake center position and wind direction. The dynamic wake model can be corrected by using wind estimation, and there are already many effective wind-estimation methods. However, studies combining wind estimation and wind farm control remain the focus of future research.

(2) Repositioning of floating wind farms: In the control of floating wind farms, repositioning of wind turbines has great potential to alleviate wake interference, but it poses great challenges to the stability of the floating wind turbine and the reliability of winches and mooring lines. In addition, there is little research in this area. This may be one of the key considerations for floating wind farm repositioning control in the future.

(3) Consideration of time-varying wind direction: Although many wind farm control methods have achieved good results, they are obtained without considering time-varying wind direction. The effect will be greatly reduced when considering the simulation or measurement of time-varying wind direction. Therefore, the way to deal with this challenge needs to be considered in future wind farm control.

(4) Application of machine learning, AI and MCDM in wind farm dynamic wake control: In the future, machine learning, AI and MDCM will have great potential in the application of wind farms, but their applicability in actual dynamic wake management needs more research.

(5) DT technology application: Although there have been studies on the application of DT technology in the operation and maintenance and fault diagnosis of wind farms [132], there may be a high requirement for the calculation speed of DT virtual model aimed at real-time dynamic control of wind farms.

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