Wind Farm Control Technologies: From Classical Control to Reinforcement Learning

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Abstract. Wind power plays a vital role in the global effort towards net zero. The recent figure shows that 93GW new wind capacity was installed worldwide in 2020, leading to a 53% year-on-year increase. Control system is the core in wind farm operations and has essential influences on the farm's power capture efficiency, economic profitability, and operation & maintenance cost. However, wind farms' inherent system complexities and the aerodynamic interactions among wind turbines bring significant barriers to control systems design. The wind industry has recognized that new technologies are needed to handle wind farm control tasks, especially for large-scale offshore wind farms. This paper provides a comprehensive review of the development and most recent advances of wind farm control technologies. This covers the introduction of fundamental aspects in wind farm control in terms of system modelling, main challenges, and control objectives. Existing wind farm control methods for different purposes, including layout optimization, power generation maximization, fatigue loads minimization, and power reference tracking, are investigated. Moreover, a detailed discussion regarding the differences and connections among model-based, model-free and data-driven wind farm approaches is presented. In addition, highlights are made on the state-of-the-art wind farm control technologies based on reinforcement learning - a booming machine learning technique that has drawn worldwide attention. Future challenges and research avenues in wind farm control are also analysed.

1. Introduction

Wind power is one of the most efficient renewable energy and is critical for the global effort in achieving net-zero emissions and clean growth. It is regarded as the cornerstone of green recovery and is of great significance to accelerate the global energy transition. Statistics in 2018 showed that wind power's share in the total power generated by green energy was over one third, showing it is currently the most essential renewable sources [1]. Tremendous efforts have been made to the development of wind power and wind farms. Global Wind Energy Council [2] expects around 94GW of new wind capacity to be installed annually for the next five years. Europe had installed over

220GM wind power capacity by the end of 2020 [3], which is currently contributing over 15% of the total electricity usage in Europe. In addition, wind power has become an important economic sector in many countries. For example, it brings almost £7bn GVA and contribute over 30,000 full-time jobs in the UK. Though onshore wind is still in a dominant position in the worldwide wind power capacity, the development of offshore wind has accelerated enormously in recent years, due to its various advantages compared with its onshore counterpart, such as being capable of capturing better wind energy resources with reduced noise influence. Many large offshore wind farms are planned to be put into operation in the next five years [3].

Control system is the core in wind farm operations and has critical influences on the power capture efficiency, economic profitability, and maintenance cost of wind farms. The enormous growth of both onshore and offshore wind farms imposes various requirements to wind farm control techniques. However, wind farms' inherent system complexities bring significant barriers to control system design. The main challenges in wind farm control come from the strong aerodynamic interactions among wind turbines, the complexities related to wind farm modelling, the stochastic features of environments, and the enormous data involved in control system design. All these aspects can lead to big influences on the effectiveness, adaptability, robustness and applicability of wind farm optimization & control approaches. The most challenging issue among them is the complex aerodynamic interactions in wind farms, which are induced by wake effects. Specifically, after an upstream wind turbine in the farm extracts power from the inflow wind, its downstream wind flow will be changed, leading to a wake with reduced wind speed and increased turbulence. Such a wake can lead to the deterioration in downstream turbines' power extraction process, resulting in degraded control performance. Fig. 1 provides a qualitative illustration of the wake effect. It can have a significant influence on wind farm operations. For example, the wake effect is reported to account for a roughly 20% annual power generation loss of Denmark's Horns Rev Offshore Wind Farm [4].

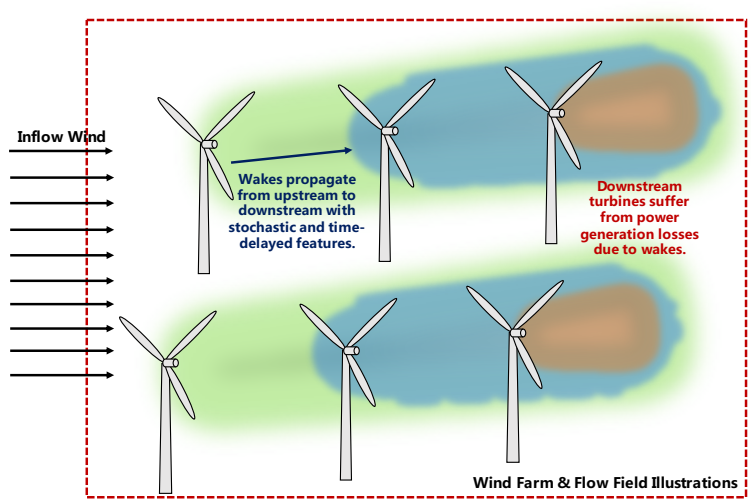

Figure 1. Illustration of wind farm and wake effects.

Substantial research efforts have been made in wind farm control (without loss of generality, in this paper, we regard optimization methods as a special class of open-loop control methods) to address these challenges, and many achievements have been reported with meaningful simulation and experiment results. With the rapid development of wind farms, a review that comprehensively summarizes and analyses the development and the most recent advances of wind farm control technologies is needed. That can help researchers and engineers in the wind energy community understand the key needs, the pros and cons of existing methods, the mainstream & new research trends, and the unresolved issues regarding wind farm control, promoting this essential research & application area and inspiring next-generation wind farm & other renewable energy technologies. This paper aims to fulfil such a timely need. Particularly, a detailed introduction to the requirements & challenges in wind farm operations are provided. That covers the fundamental aspects of wind farm control technologies in terms of system modelling, main challenges, and control objectives. After that, we carry out a systematic analysis, evaluation & comparison of existing wind farm control methods. Methods for different purposes, including layout optimization, power generation maximization, fatigue loads minimization, and power reference tracking, are organised and classified. Moreover, the comparison regarding the differences and connections between the model-based, model-free, and data-driven wind farm control methods is elaborated in detail. In addition, highlights are made on the state-of-the-art wind farm control technologies based on reinforcement learning (RL) - a booming machine learning technique that has drawn worldwide attention. Future challenges and future research avenues in wind farm control are also investigated.

The remainder of this paper is organized as follows. The fundamental aspects of wind farm control are introduced in Section 2, including system models, main challenges, and essential objectives. Based on different objectives, existing wind farm control approaches are reviewed in Section 3, and typical model-based, model-free & data-driven wind farm control methods are considered. After that, most recent RL-based wind farm control approaches are introduced and analysed in Section 4. Finally, conclusions and future prospects are given in Section 5.

2. Fundamentals in Wind Farm Control: Models, Challenges, and Objectives

This section introduces the key aspects that lay the foundation of the control system design of wind farms, including wind farm models, main challenges, and main objectives in wind farm control. Additionally, historical milestones of wind farm control algorithms are also discussed.

2.1. Wind farm models

Wind farm models are the prerequisite for many wind farm control methods. Actually, the majority of mainstream wind farm control approaches are model-based. Accurate wind farm models serve as a significant tool to provide key information for wind farm controllers, such as the relationship between the captured power and the wind speed. Wind farm modelling is a challenging yet hot and important research topic [5]. To describe the aerodynamic interactions among turbines, a proper wind farm model should not only consider the dynamics of turbines, but also take into account the dynamics of flow fields. However, due to the complexity of flow field dynamics, wind farm modeling must consider the trade-off between fidelity and computational complexity, which is also an essential issue for model-based control system design. On the one hand, some wind farm models may have high accuracy, but their high computational loads make them difficult for real-time implementation. On the other hand, some models neglect partial dynamics to reduce computational complexity, but that may lead to degraded control performance. Therefore, choosing proper wind farm models is an important issue in the control system design of wind farms. This subsection is dedicated to introducing existing wind farm models, providing potential choices for designing and validating wind farm control methods.

According to the fidelity, mainstream wind farm models can be roughly classified into low-fidelity models, medium-fidelity models, and high-fidelity models.

Low-fidelity models are usually steady-state. They reflect the time-averaged characteristics of wind farms and flow fields. Although this type of models has less computational complexity, the primary drawback of them is that they provide few details regarding temporal dynamics like wake meandering, leading to limited accuracy. One of the typical and easy-to-implement low-fidelity models is the Jensen model [6]. The Park model was proposed [7] with further modifications. National Renewable Energy Laboratory (NREL) of US recently developed the so-called FLOw Redirection In Steady-state (FLORIS) model [8], aiming to improve the accuracy of steady-state wind farm models with measurement data. Other examples include FLORIDyn model [9] and FOWFSim model [8].

Different from low-fidelity models, medium-fidelity models are dynamic and can reflect more flow-field details. But to reduce computational complexities, medium-fidelity models usually simplify the full Navier-Stokes (NS) equations and ignore some physics. One of the typical medium-fidelity models is the control-oriented Wind Farm Simulator (WFSim) model proposed in [10], [11]. This model was built upon two-dimensional NS equations, neglecting the vertical dimension to reduce the computational time. The idea of system matrices sparsity was employed to further improve the computation efficiency. The turbulence model in WFSim was formulated by the Prandtl's mixing length model, and turbines were described by the actuator disk model (ADM). The Ainslie model proposed in [12] was also built upon a simplified NS equation with the assumption of axisymmetric, zero circumferential velocities, and fully turbulent

wakes [13]. Other medium-fidelity models include the FarmFlow model [14], and the Fast.Farm model [15].

High-fidelity models usually apply large-eddy simulations (LES) to solve the three-dimensional Navier-Stokes equations with high temporal and spatial densities. They provide high modelling accuracy at the cost of significant computational complexities. One of the commonly used high-fidelity models is SOWFA (Simulator for Offshore Wind Farm Applications) [16]. SOWFA was formulated with computational fluid dynamic (CFD) tools based on OpenFOAM and wind turbine models based on the FAST (Fatigue, Aerodynamics, Structures and Turbulence) simulators [17]. It has the ability to accurately reflect flow field changes under varying atmospheric conditions [18]. Another famous high-fidelity wind farm model is PALM (Parallelized Large-Eddy Model), developed by Leibniz Universitat Hannover [19]. Distinct from SOWFA that was developed with CFD tools, PALM was formulated with finite element methods and structured staggered meshes [20]. PALM is a Fortran-based code that is parallelized through the decomposition method on a Cartesian grid [19]. Some other high-fidelity models include the SP-Wind model [21] and the EllipSys3D model [22].

Some recently developed wind farm modeling methods apply deep learning techniques to balance fidelity and computational complexity. For example, a novel dynamic wind farm wake model was designed in Ref. [23] via a deep learning-based reduced-order method. The proposed model has the ability to describe unsteady flow features as high-fidelity wake models while rendering significantly reduced computational complexity like low-fidelity wake models. Ref. [24] developed a physics-informed deep-learning-based model for spatiotemporal wind field predictions. It combined LIDAR measurements and flow physics by incorporating a deep neural network into Navier-Stokes equations.

2.2. Main challenges

One of the critical challenges for wind farm control is the aerodynamic interaction among wind turbines. As demonstrated in Fig. 1, the power generation of upstream wind turbines results in downstream regions with reduced wind velocity and increased turbulence intensity. This process is commonly referred as the wake effect, which can influence the power generation process of downstream turbines and the operating efficiency of the whole farm. In addition, the increased turbulence intensity induced by wake effects can lead to fatigue loads in downstream wind turbines [25]. Therefore, it is of paramount importance to consider wake effects in the design of wind farm controllers.

Moreover, the selection of wind farm models is essential in the design of model-based wind farm controllers. As introduced in Section 2.1, a trade-off between model fidelity and computational complexity must be made in model selection. The higher the model accuracy, the greater the computational complexity. Some commonly-used steady-state models [26] have significantly reduced computational complexity, making them easy-to-implement in control system design. But the downside is that these models

largely neglect temporal dynamics, which may lead to degraded control performance. High-fidelity models, on the other hand, have adequate accuracy but suffer from heavy computational costs and poor real-time performance.

The existence of various uncertainties in practice, such as time-varying wind conditions and turbine parameter uncertainties, brings another challenge for wind farm control. On the one hand, those uncertainties make it challenging to build an accurate analytical wind farm model [27], which is a must for model-based wind farm controllers. On the other hand, they also lead to difficulties in developing wind farm controllers with strong robustness and adaptability.

Furthermore, with the continuous increase in wind farm scales and numbers of wind turbines, the measurement datasets in wind farms become larger and larger, which may require excessive computational resources to process and could cause high computational loads. Some data, such as flow field states, are difficult to handle given their time-delayed and distorted features, bringing difficulties for the practical deployment of wind farm controllers. Therefore, it is necessary to improve data-processing efficiency in wind farm control system design, particularly for data-driven wind farm controllers.

In addition, wind farm control methods sometimes need to pursue multiple and conflict objectives subject to various constraints [28], which also brings difficulties to controller design.

All of these aspects render the design of wind farm controllers a highly complicated and challenging task.

2.3. Essential objectives in wind farm control

The fundamental aim of wind farm control is to improve operating efficiency, increase economic profitability, and reduce maintenance & operation costs. Considering the above-mentioned challenges, some specific wind farm control objectives are introduced as follows. A comprehensive review for wind farm control methods towards these objectives are given in Section 3.

(i) **Wind farm layout optimization:**
Wind farm layout optimization aims to find the optimal positions for all turbines in a wind farm to maximize the total power production or minimize costs. An objective function usually needs to be constructed in such problems, which should be a function of wind turbines' positions and the corresponding objective, such as the farm-level power production. These objective functions are commonly based on wind farm models with wake descriptions, such as the Park model [29], which assumes that the wake expands linearly with wind moves to the downstream region [30]. Many optimization techniques have been explored for wind farm layout optimization and will be introduced in Section 3.1.

(ii) **Power generation maximization:**
In practice, most of the wind farms employ the greedy strategy in power generation. This means each individual wind turbine is operated separately to maximize

its own power generation [31], [32], [33] while ignoring the potential influence to other turbines. However, the greedy strategy is not optimal due to the existence of wake effects. As we mentioned, wake effects induced by upstream turbines can significantly influence the power generation of downstream turbines, therefore influence farm-level power production. Wind turbines in a farm should be cooperatively controlled in order to improve the total power production of the whole farm [34]. This class of wind farm control strategies can be achieved by controlling axial induction factors and yaw angles of all turbines in the farm [35]. Specifically, adjusting the axial induction factors of upstream wind turbines would lead to decreased momentum & wind-speed deficits of wake [36] in downstream wind turbines, which can potentially increase the power generation of downstream turbines. As a result, the total power production of the whole farm can be potentially improved. The adjustment of axial induction factors can be achieved by regulating blade pitch angles, and/or rotor torques of turbines [37]. Another way to mitigate wake effects is adjusting the yaw misalignment of upstream turbines to redirect the wakes around downstream turbines [38]. That can decrease the overlapping areas between wakes and downstream turbines, providing downstream wind turbines with higher wind speed and allowing them to generate more power than the cases without wake re-directions [39].

(iii) **Fatigue loads minimization:**
The aerodynamic interactions of wind turbines will cause an increase in turbulence intensity, which can potentially lead to heavy fatigue loads that shorten the lifetime of turbines. Therefore, minimizing the fatigue loads is another crucial aspect of wind farm control. It is usually implemented by combining with power output regulation. For example, Ref. [40] solved the fatigue load minimization problem while keeping the power production at the desired level.

(iv) **Power reference tracking:**
Modern wind farms are required to perform compatibly to traditional power plants, in order to eventually replace conventional power plants [41], [42]. Therefore, wind farms should meet more rigorous technical requirements and provide auxiliary services to guarantee the safety and operation stability of the power grid. For example, secondary frequency control, as one of the typical auxiliary services, can regulate grid frequency, balance power capture & loads, and maintain power exchanges between areas [43]. To fulfill these requirements, a wind farm's power generation should be capable of tracking a specific power reference generated by transmission system operators in a few to tens of minutes [44]. Some works like [45], [46], [42] had shown success in such tasks.

As we mentioned before, these wind farm control tasks aim to improve operating efficiency, increase economic profitability, and reduce maintenance & operation costs, and they are the main focus of the discussions in this paper. In addition, many other wind farm control studies consider the important tasks in the grid integration and

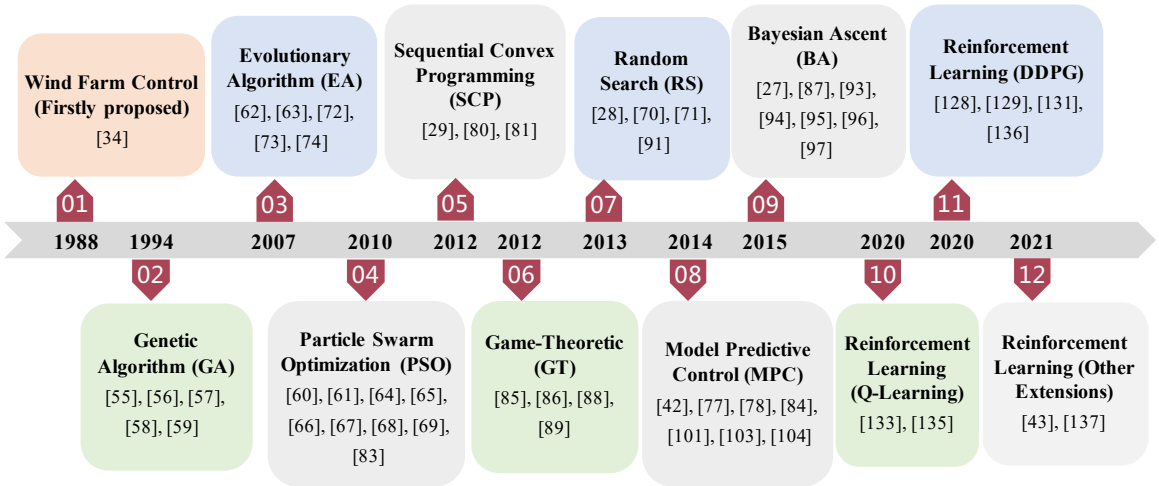

Figure 2. The development of wind farm control methods.

transmission network of wind energy. For example, Ref. [47] designed a reinforcement learning-based adaptive wind farm control method to enhance the stability of power systems with wind energy penetration. Ref. [48] proposed a cooperative control method to maximize the reactive power capacity of network-connected wind farms.

2.4. Historical milestones

To the authors' best knowledge, the first wind farm control strategy was proposed in [34], focusing on improving the wind farm dynamic performance. Then, various optimization techniques (in this paper, we regard optimization methods as a special class of open-loop control methods) and closed-loop wind farm control algorithms have been developed to achieve different objectives. We briefly depict an illustration in Fig. 2 to show the development of wind farm control methods. Typical methods include genetic algorithm (GA), evolutionary algorithm (EA), particle swarm optimization (PSO), sequential convex programming (SCP), game-theoretic (GT) method, random search (RS), model predictive control (MPC), Bayesian ascent (BA), and reinforcement learning (RL). A detailed introduction for them will be provided in the following sections.

3. Wind Farm Control Approaches

Given the essential objectives introduced in Section 2.3, this section provides a detailed review of existing wind farm control methods.

3.1. Wind farm layout optimization

Wind farm layout optimization aims to determine optimal locations for wind turbines, maximizing the whole farm's power production or minimize costs while considering various aspects such as wake effects, wind farm boundaries, and wind turbines types [49], [28]. Such tasks usually can be formalized as multi-objective

nonlinear constrained optimization problems. Various problem formulations and many optimization approaches have been developed to deal with such problems. Typical methods include mixed-integer linear programming [50], ant colony algorithm [51], particle filtering approach [52], lazy greedy algorithm [53], extended pattern search algorithm [54], genetic algorithm (GA) [55], [56], [57], [58], [59], particle swarm optimization (PSO) [60], [61], random search (RS) algorithm [28], sequential convex programming (SCP) [29], evolutionary algorithm (EA) [62], [63], and so on. Typical results are discussed in detail as follows.

To the authors' best knowledge, the first work for tackling the wind farm layout optimization problem was proposed in [55], which utilized GA to obtain candidate solutions. Ref. [56] also employed GA to optimize wind turbine positions while considering the limitations of wind turbine numbers and land acreage. Moreover, as variants of conventional GA, multi-objective genetic algorithm (MOGA), binary real coded genetic algorithm (BRCGA), and adaptive genetic algorithm (AGA) were developed and applied to wind farms. Specifically, in [57], MOGA was employed to solve a wind farm layout optimization problem. Simulation cases were conducted with commercial turbine parameters and various real wind conditions. Different from conventional GA, the MOGA method proposed in [57] denoted the turbines placement, types, and hub heights by mixed discrete strings, which could optimize not only regular wind farm layouts but also irregular wind farm layouts. Ref. [58] investigated BRCGA for wind farm layout optimization. The position of wind turbines was denoted by the binary part of GA, while the power capture was characterized by the real part of GA. It employed the Jensen wake model. In Ref. [59], AGA and SIGA were designed to optimize the wind farm layout. Specifically, AGA was used to relocate the worst turbine locations and SIGA designed to find the optimal locations. In addition, a surrogate model using multivariate adaptive regression was introduced to balance exploitation and exploration, mitigating the disadvantages of conventional GA.

In [64], the PSO method was for the first time utilized to optimize the positions of wind turbines, whose efficiency was verified by simulation results. PSO was also investigated in Ref. [65] for same purposes, in which the minimal allowed distance of wind turbines was considered. An improved Gaussian PSO algorithm combined with a local search strategy was proposed in [66] to optimize the positions of turbines, which could significantly reduce the execution time. Furthermore, a binary particle swarm optimization (BPSO) with time-varying acceleration coefficients (TVAC) was developed in [67]. In [68], the PSO was applied to solve a wind farm layout optimization problem formulated by the Levelized production cost (LPC). Ref. [69] also employed PSO to handle wind farm layout optimization, and it considered three different levels of wind farm constraints. In [60], a constrained PSO technique was used to solve the unrestricted wind farm layout optimization problem, which was formulated to maximize the power production by optimizing positions and rotor diameters of wind turbines. Simulation results showed that, compared with an experimental farm, the farm with the optimal layout could achieve an up-to-30% increase in the total power generation, and the farm

equipped with turbines with different rotor diameters could achieve an up-to-43% rise in the total power generation. In [61], the PSO method combined with multiple adaptive methods (PSO-MAM) was designed to solve offshore wind farm layout optimization problems. A restriction zone concept with a penalty function was constructed to solve the limitations of the seabed or marine traffic. Simulation results indicated an increase of 3.84% in power generation was achieved using PSO-MAM compared with the baseline method.

In [70], a refinement method using RS was proposed to find the optimal locations of wind turbines. In [28], a RS algorithm was also designed for wind farms, but it was formulated to minimize the cost of power production considering various constraints. An adaptive mechanism was added to this RS method, aiming to improve control performance and reduce computation costs. The authors in [71] also utilized a RS algorithm to maximize total power generation and minimize full electrical cable length while considering geographic limitations.

In [29], the SCP technique was used to solve the wind farm layout optimization problem. A continuous wake model was constructed to relate the power function to turbine locations. Then, by determining the gradient and Hessian matrix of the wind farm power function, the SCP method proposed in [29] could iteratively find the optimal solution. Simulation results indicated that it was efficient when applied to a large wind farm with 80 turbines.

An EA method was proposed in [72] for wind farm layout optimization to maximize profits. Another EA method was proposed in [73] for similar purposes, in which a more realistic cost model was designed, allowing the algorithm to consider restricted areas or terrains. Moreover, a multi-objective evolutionary algorithm (MOEA) was proposed in [74] for wind farm applications. This method selected a combination of two turbines from 26 wind turbines with respect to different wind speeds distributed over different time spans. A decomposition-based multi-objective evolutionary algorithm (MOEA/D) was developed in Ref. [62], in which a set of Pareto optimal vectors was derived for maximizing power generation and improving operating efficiency. To reduce computational costs, a data-driven EA was designed in Ref. [63] to maximize farm-level power generation. Particularly, it employed a data-driven surrogate model constructed by general regression neural networks (GRNNs), and a fast filtering strategy for potentially bad candidate solutions was employed to improve the optimization efficiency.

As a short summary, optimization methods for wind farm layout optimization have aroused extensive interest and are widely investigated. Existing techniques can increase farm-level power production and/or reduce costs. Relevant results are validated by extensive simulations.

3.2. Wind farm power generation maximization

In this subsection, we introduce wind farm control methods for farm-level power generation maximization. In terms of model dependency, wind farm control strategies can be roughly divided into model-based and model-free methods. Relative works of these two types of methods are discussed in detail as follows.

3.2.1. Model-based methods

Model-based control methods rely on analytical wind farm models to guide control actions, and wake effects should be considered in the control process. Many model-based algorithms have been developed to maximize wind farm power generation. A typical example is the MPC (model predictive control) technique, which aims to solve closed-loop optimal control problems with multi objectives subject to various constraints [75], [76]. A deep neural learning-based predictive control method was developed in Ref. [77] to maximize the farm-level power generation and minimize control costs. This method was constructed by long short-term memory (LSTM) units combined with convolutional neural networks (CNNs) and MPC methods. It employed CNN-LSTM to predict wind farm outputs based on high-fidelity LES data. Both distributed and decentralized MPC methods were employed to find optimal solutions. Numerical simulations showed that the distributed MPC could achieve power production increase by up to 38% compared with the decentralized MPC method. In Ref. [78], a novel closed-loop model-based wind farm controller was proposed to maximize the power production by adjusting yaw angles. This controller was constructed by estimating surrogate model parameters and carrying on real-time setpoint optimization. A high-fidelity simulation of a 6-turbine wind farm was tested to validate the effectiveness of this controller in time-varying inflow conditions. Simulation results showed that this approach could achieve 11% power gains compared with the benchmark. In Ref. [79], a learning model predictive control (LMPC) algorithm was proposed to increase wind farm power production. This LMPC method could learn the state trajectory and input cost based on previous iterations. Its recursive feasibility, stability, and convergence analysis were provided. Simulation results showed that the power production could be increased by up to 15% by the LMPC proposed in [79]. In addition to MPC-based methods, many other model-based wind farm control algorithms for farm-level power maximization are introduced as follows.

A SCP method was developed in Ref. [80] for wind farm power optimization. A coupling matrix was utilized to provide a simple relationship for wind turbine interactions. Simulations were carried out to prove the efficiency of this SCP method. In Ref. [81], SCP was also employed for wind farm cooperative control to maximize power generation. A Gaussian-shape basis function was used to capture the wind speed information, and a differentiable function was constructed using the control variables as input and the measured power as output. Simulation results with Horns Rev wind farm showed that an increase of around 7% in power generation was achieved by using this SCP technique compared with the greedy strategy.

In [82], a cooperative static GA was designed to improve the power production efficiency of wind farms by controlling the nacelle yaw and blade pitch angles. The steepest descent algorithm was employed to find optimal control actions. Ref. [83] introduced a distributed PSO algorithm based on a cooperative co-evolution technique for wind farm power maximization considering aerodynamic wake effects. This model-based distributed architecture had the potential to rapidly converge to the optimal solution, showing a potential advantage in real-time operations of wind farms. In Ref. [84], a receding horizon control was applied to optimize the thrust coefficient of each turbine towards farm-level power maximization, in which gradients were determined by a conjugate gradient method. Cases studies indicated that this method increased the total power generation by 7% compared with the greedy strategy.

Note that the above-mentioned model-based wind farm control methods directly utilize analytical models to compute optimal solutions. However, those model-based controllers often suffer from modeling errors and are sensitive to uncertainties, leading to degraded control performance and lack of robustness to real-time changes. Distinct from model-based wind farm control schemes, data-driven model-based wind farm control methods employ learning mechanisms or system identification tools to approximate wind farm models or utilize measured data to update model parameters. In addition, these methods can potentially carry on model validation & calibration based on the dynamic responses of wind farms instead of employing time-averaged data as in most of the model-based approaches [85]. We introduce some related works as follows.

Ref. [37] introduced a data-driven model-based method for wind farm power optimization by controlling the yaw angles of wind turbines. A novel parametric model was designed to predict flow velocities and power generation, and its parameters were estimated by data. A game-theoretic (GT) technique was applied based on this parametric model to find the optimal yaw angles. As a significant extension of [37], another yaw control strategy for farm-level power maximization was proposed in [86]. This controller was designed based on the so-called FLORIS (FLOw Redirection and Induction in Steady-state) model, in which the parameters of this model were estimated by the data generated by SOWFA [18] (a high-fidelity CFD model). Then, a GT approach was applied to FLORIS to optimize yaw angles. Ref. [87] proposed a closed-loop model-based wind farm control technique based on a steady-state surrogate model and the Bayesian optimization method. This control strategy was evaluated via simulations with a wind farm consisting of nine 10MW DTU turbines. Results showed a 4.4% increase in time-averaged power generation compared with the conventional greedy strategy.

In summary, this section introduces model-based methods for wind farm power generation maximization. Due to the existence of underlying models, model-based methods are relatively easy to implement and can potentially be employed to handle multi-objective tasks under various state and input constraints (e.g. MPC methods). Extensive numerical results have shown that model-based wind farm control methods can lead to better performance than the conventional greedy strategy. A challenge

for model-based strategies is that they highly rely on the accuracy of analytical wind farm models. Nevertheless, the mismatch between wind farm models and real physics are inevitable. Such a mismatch can be caused by many reasons, including uncertainties & modelling errors, time-varying & stochastic wind conditions, or some other unexpected changes (e.g. actuator faults). These aspects can potentially degrade the control performance and/or reliability. Many studies have been devoted to solving the limitations of model-based methods by investigating model-free alternatives, aiming to provide better robustness, adaptability and performance. Typical model-free wind farm control methods are introduced in the following subsection.

3.2.2. Model-free methods

Model-free wind farm controllers bring new avenues to deal with the limitations of their model-based counterparts. They are usually driven by measurement data while without using analytical models. Typically, they aim to iteratively acquire optimal control actions subject to user-defined objective functions or rewards. Literature exploring model-free wind farm control strategies for farm-level power maximization is discussed in this subsection.

Ref. [88] explored a game-theoretic (GT)-based distributed learning algorithm to achieve model-free wind farm control, aiming to maximize power production by adjusting axial induction factors. Ref. [89] also developed a model-free GT method for wind farms, in which a payoff-based distributed learning approach for Pareto optimality was applied. Simulation results showed that the power production under this method could be increased by up to 25% compared with the greedy control.

Ref. [90] proposed a decentralized model-free optimization approach for power maximization. Two decentralized discrete adaptive filtering techniques were developed based on partial wind farm information. Such a strategy could lead to a faster convergence rate and low computational efficiency. Ref. [91] investigated a model-free RS approach. This method was constructed by finding the optimal control parameters for each turbine in the wind farm. The Horns Rev wind farm model was employed to conduct simulations. Ref. [92] investigated a cooperative time-varying extremum seeking control (TVESC) method for maximizing farm-level power under time-varying wind conditions. A dynamic estimator was used to estimate the cost function and a parameter estimator was employed to evaluate the gradient.

The Bayesian Ascent (BA) algorithm was developed in [93], [94], [27], [95], [96] to achieve wind farm power generation optimization. It is a data-driven model-free method that only utilizes control variables as inputs and the farm-level power generation as output. BA is a probabilistic optimization approach and employs Gaussian regression to approximate the relationship between the system inputs and outputs. Different from conventional Bayesian optimization, constraints on the trust region was imposed on the optimization framework in BA, aiming to monotonically increase the target value. Simulation results and wind tunnel experiments [95], [94], [96] showed the effectiveness of BA. As an extension, Ref. [97] proposed a contextual Bayesian optimization method

with Trust-Region (CBOTR) modifications and applied it to wind farms. CBOTR determines a trust region of the next input based on the environment condition, aiming to rapidly find the next optimal input.

As a short summary, these works, along with extensive numerical results, show the effectiveness of model-free methods in farm-level power maximization tasks. They aim to release the reliance on analytical wind farm models. A shortcoming is that they are usually open-loop optimization methods that require steady-state data to carry out learning, lacking adaptability and robustness to time-varying wind conditions and wake effects. How to address these issues is a promising research topic for model-free wind farm control methods.

The architectures of model-based, data-driven model-based, and model-free wind farm controllers are illustrated in Fig. 3, which shows the differences and connections of these three types of wind farm controllers. Note that data-driven techniques can be applied to both model-based methods and model-free methods. For data-driven model-based methods, optimal control actions are acquired based on a model approximated/modified by data. For data-driven model-free methods, the optimal control actions are solved by measurement data directly. Data-driven approaches have the ability to improve the adaptability of wind farm control methods. But they may suffer from high computational loads by carrying on a large-scale search to find optimal control inputs in a large action space. Data-driven model-based methods can lead to less computational time than fully data-driven model-free methods. This is because they are usually based on parametric models, which could provide smaller or parametric action spaces for finding the optimal control inputs [98]. But model-free methods potentially have better performance because they are not restricted by underlying analytical models during the learning process.

3.3. Fatigue loads minimization and power reference tracking

As we discussed before, one of the main challenges in wind farm control is mitigating the wake effects among wind turbines. Wake effects can increase the downstream turbulence intensity, leading to substantially increased fatigue loads on downstream turbines [25]. These fatigue loads could significantly shorten the service life of wind turbines [99]. Thus, minimizing fatigue loads is essential in wind farm operations. In practice, wind farm controllers are expected to have the ability to dynamically regulate power outputs while minimizing the influence of fatigue loads.

In order to meet more rigorous technical requirements and provide auxiliary services to guarantee the safety and operation stability of the power grid, power reference tracking is another key objective for wind farm control [41]. The power tracking task is a complicated problem because it can have a set of different solutions. For example, a same farm-level power generation can be achieved by derating upstream wind turbines and uprating downstream wind turbines or conversely. Usually, power tracking problems are formulated together with other performance indexes such as reducing control efforts,

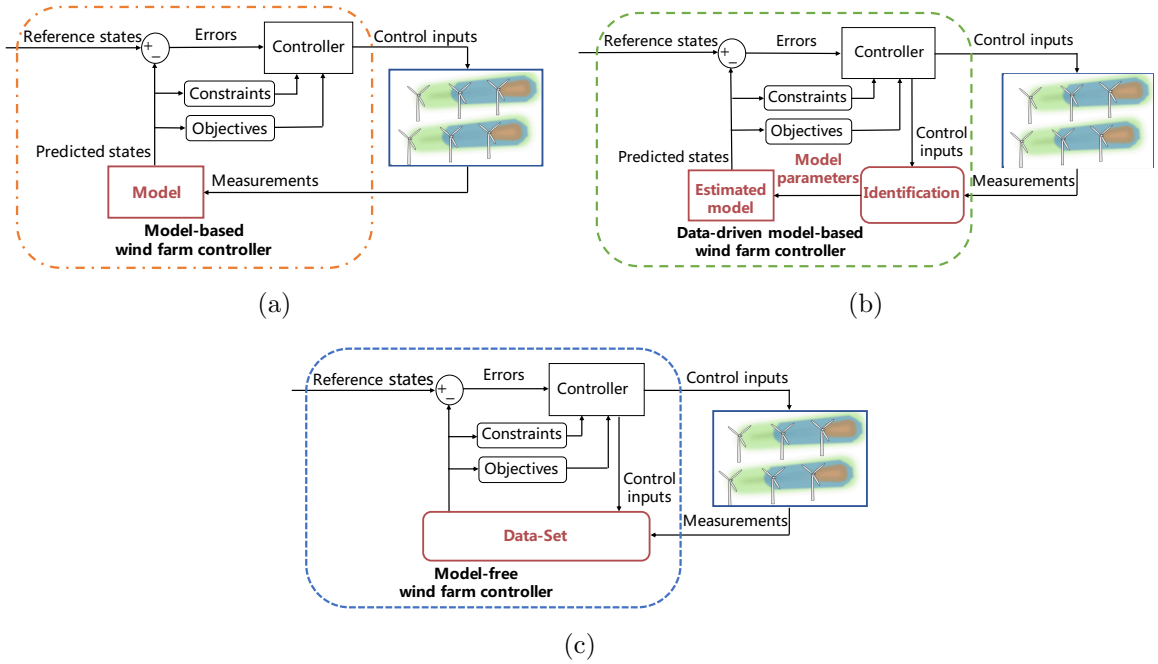

Figure 3. The main architectures of three different types of wind farm controllers. (a) Model-based wind farm control. (b) Data-driven model-based wind farm control. (c) Model-free wind farm control.

and minimizing fatigue loads. Such multi-objective optimal control tasks can be solved by adjusting yaw angles and axial induction factors (determined by thrust coefficients and/or generator torques and/or pitch angles) [100].

Ref. [46] explored an optimization-based method for a wind farm to minimize the mechanical loads and generate the desired power. A parametric programming strategy was designed to this end. Simulation under different wind speeds showed that this method had the ability to achieve power tracking and load reduction. A distributed MPC (DMPC) approach was explored in Ref. [101] for wind farm active power control. DMPC aims to make a trade-off between wind farm power tracking and load reduction objectives. It could alleviate the shaft torque deviation and the thrust force change. An extension work of DMPC was presented in [42]. Simulation cases under different wind conditions and uncertainties showed that DMPC greatly reduced the mechanical loads while the power tracking performance remained satisfactory compared with centralized MPC algorithms. Ref. [102] developed a data-driven multi-objective predictive controller (MOPC) using evolutionary optimization for wind farm fatigue load reduction and power maximization. The data-driven predictor was designed with inputs (yaw angles) and outputs (power and fatigue loads) under different wind conditions. The FLORIS model was used to characterize the aerodynamic interactions and generate data. Simulation results showed that compared with the traditional MPC method, a thrust load reduction of up to 12.96% was achieved by MOPC while the power output remained almost the same.

A distributed optimal control method was developed in Ref. [40] for minimizing wind farm fatigue loads considering constraints as well as regulating the power to a given reference. This technique could improve computational efficiency and guarantee the asymptotic convergence under certain conditions. Ref. [45] proposed a closed-loop active power control method for wind farms to track the reference power trajectory and reduce structural loads by controlling axial induction factors. It employed a coordinated load distribution law that regulated the wind turbine power set-points according to feedback measurements. A LES model with a 3×4 wind farm was employed to demonstrate this method's effectiveness. Another work for wind farm load reduction was presented in [103], in which wind farms with wake interactions were presented by relevance vector machine (RVM) models. A reliability-aware multi-objective predictive controller was designed based on RVM models, which was solved by meta-heuristic evolutionary algorithms. In Ref. [104], a distributed economic MPC approach was developed for large-scale wind farm power tracking and economic optimization. An iterative calculation was employed to realize the Nash optimality. Simulation results with varying wind speed conditions showed that this method could achieve accurate power tracking and reduce fluctuations on pitch/torque.

To conclude, substantial research efforts have been made to achieve different wind farm control objectives, including wind farm layout optimization, power generation maximization, fatigue loads reduction, and power reference tracking. Extensive simulations and experiments have been conducted to validate the effectiveness of existing methods.

Although the important methods mentioned in this section have shown superior performance and advantages over conventional approaches, some essential aspects can be improved further.

(1) Model-based wind farm control methods commonly suffer from inevitable modelling inaccuracy and stochastic environment uncertainty. Most of the existing model-based methods for wind farm power generation maximization are open-loop optimization methods. They usually rely on steady-state wind farm models to search optimal wind farm settings (such as fixed yaw angles and induction factors), therefore, their adaptability and robustness need to be enhanced.

(2) Though some model-free approaches are developed to mitigate the limitations of model-based methods, most of them are still built upon steady-state data (such as the time-averaged data or the data generated by steady-state models) to carry out learning. These methods still largely neglect the dynamical changes of environmental conditions and wake effects, and it is difficult for them to provide closed-loop control actions based on online measurements subject to time-varying environmental conditions and dynamical wake effects.

(3) The high system complexity of wind farm dynamics is still a significant barrier in control system design. It is challenging to extract key information from a large measurement dateset and maximize long-term rewards for different control objectives.

Aiming to handle these challenges and improve the performance of wind farm

operations, some recent works applied reinforcement learning (RL) – a state-of-the-art machine learning technique that has drawn worldwide attention, to wind farm control tasks. A detailed introduction for them are provided in the next section.

4. Reinforcement Learning-Based Wind Farm Control

Reinforcement learning (RL) is a cutting-edge machine learning technique and one of the most popular hotspots in artificial intelligence. RL is built upon the trial-and-error principle, aiming to improve control performance to optimize long-term rewards iteratively. With the help of artificial neural networks (NNs, which are employed as information processors in RL), RL can handle high-complexity control problems of 'black-box' systems – problems that are almost impossible to be addressed by conventional control methods. For example, The AlphaGO program [105], [106] developed by Google DeepMind beat the best human players in the board game Go. A key advantage of RL algorithms is that they usually learn the information of systems and the optimal control actions by data or through directly interacting with environments without employing system models.

These features render RL a promising new technique for developing next-generation wind farm control methods. It has the ability to handle the high system complexities and stochastic natures associated with wind farms and flow fields. RL-based wind farm control methods have the potential to mitigate the limitations of model-based wind farm control methods, such as reliance on analytical models and lack of adaptability & robustness to modelling errors & uncertainties. Compared with the mainstream model-free wind farm methods that commonly require steady-style data to carry out open-loop optimization, RL-based methods have the ability to handle dynamic measurements and achieve closed-loop control under time-varying environmental conditions. Moreover, it can address some complicated tasks in wind farm operations, such as farm-level power tracking with a reference signal beyond the greedy-mode output, enhancing the task capacity, improving the control performance, and promoting the economic profitability of wind farms.

Motivated by these benefits of RL, some studies have been devoted to investigating wind farm control methods by employing/developing various RL algorithms.

4.1. Reinforcement learning overview and problem formulation

The fundamentals of RL are briefly introduced in this subsection. After that, we show an example of moulding wind farm control problems into the RL framework.

4.1.1. Fundamentals of reinforcement learning

The RL technique has attracted dramatically increasing attention in recent years. It can deal with black-box optimization and control problems without knowing the complete structures of systems. It can extract the core information of systems through

data/measurements to achieve multiple tasks [107], [108], [109]. RL techniques have made great contributions to a wide range of fields, such as the control problems of robots [110], spacecraft [111], and autonomous vehicles [112]. In addition, some studies have applied RL methods to wind turbine control [113], [114], [115], [116], [117]. RL also has been successfully applied to many aspects related to renewable energy systems operations, such as in energy storage management [118], [119], power system stabilization [120], frequency control [121], wind energy scheduling [122], [123], and system maintenance [124], [125].

An RL agent is usually modelled as a Markov decision process (MDP) [126]. MDP is commonly described by a tuple $[s_t, a_t, r_t, M, \gamma, \pi]$, where $s_t \in S$ is the current state at time t, $a_t \in A$ is the action, $r_t \in R$ is the reward, and S, A, and R denote the state, action and reward spaces, respectively. M denotes the transition process with the form of $M(s_{t+1}|s_t, a_t)$, which determines the probability of transitioning to the next state s_{t+1} when the current state s_t and action a_t are given. Note that s_{t+1} only depends on its immediate past s_t and the action a_t. Moreover, $\gamma \in [0, 1]$ is a discount factor to balance immediate and future rewards, and π denotes the policy mapping from the state s to the action a.

A single loop for an RL agent to interact with the environment is as following. At any time step t, the agent has the state s_t and takes a candidate action a_t. Then it receives a reward r_t from the environment and is transferred to a successor state s_{t+1}. The goal of RL is to learn an effective policy $\pi(s) : S \to A$ to maximize the long-time reward $R_T = \sum_t^\infty \gamma_t r_t(s_t, a_t)$, where $r_t(s_t, a_t)$ indicates the instantaneous reward at s_t after taking the action a_t.

It is noteworthy that many wind farm control tasks are originally partial-Markov processes due to the stochastic nature of environmental conditions and the time-delayed feature of wakes. This issue can be mitigated by properly setting/designing states, rewards and actions, therefore transforming partial-Markov decision problems into Markov decision problems. Based on the requirements of different control objectives, many studies have addressed this issue via different designs/settings. For example, Ref. [127] formulized the problem of STATCOM-ADC (static synchronous compensator with additional damper controller) parameter settings under stochastic environments as a Markov decision process, and tested the performance of their reinforcement learning-based controller with simulations based on an actual wind farm in China. Refs. [128, 129] employed regulated power generation outputs under different wind conditions to mitigate the partial-Markovian feature in farm-level power maximization tasks, and Ref. [43] addressed this issue by utilizing time-series data to form the MDP for wind farm power tracking tasks.

4.1.2. Problem formulation

In this subsection, we demonstrate an example about how to mould the wind farm control problem into the RL framework. For simplicity, we employ a commonly-used RL structure and consider a typical wind farm description. What we are showing here

is an easy-to-follow example among various possible application forms of RL in wind farm control.

Based on the actuator disk theory [130], the force and power generated by every single turbine in a wind farm can be represented in the following two equations, respectively.

$$F_i = \frac{1}{2}\rho A_d (U_i \cos(\phi_i))^2 C'_{T_i}(\alpha_i, \phi_i) \tag{1}$$

$$P_i = \frac{1}{2}\rho A_d (U_i \cos(\phi_i))^3 C_{P_i}(\alpha_i, \phi_i) \tag{2}$$

Here $i = 1, 2, ..., N$, and N is the total number of wind turbines. A_d is the area of rotor plane, U_i is the wind speed, ϕ_i is the yaw angle, α_i is the axial induction factor, C'_{T_i} is the thrust coefficient, C_{P_i} is the power coefficient. C'_{T_i} and C_{P_i} satisfy

$$C'_{T_i} = 4\alpha_i/(\cos(\mu\phi_i) - \alpha_i) \tag{3}$$

$$C_{P_i} = 4\alpha_i/(\cos(\mu\phi_i) - \alpha_i)^2 \tag{4}$$

where μ is a constant parameter. The total power production of the wind farm can be defined as

$$P_{all} = \sum_{i=1}^{N} P_i \tag{5}$$

It should be emphasized that Eqs. (1) - (4) from the actuator disk theory are actually not indispensable for the applications of reinforcement learning in wind farm control. Here they just aim to provide insights into the physical relationships of key wind farm states. The relationship of α_i, ϕ_i and U_i with P_i can be a "black box" in RL-based wind farm controllers, i.e., the h function in the following equation can be unknown for the RL agent.

$$P_i = h(U_i, \alpha_i, \phi_i) \tag{6}$$

The tasks of wind farm power generation maximization, fatigues loads reduction, and power reference tracking can be achieved by controlling the yaw angle ϕ_i and axial induction factor α_i of each wind turbine in the farm. Without loss of generality, the power/thrust coefficient, torque or pitch can be adjusted alternatively to control the induction factor. Moreover, the control inputs can be selected to be yaw angles and induction factors or other related variables, such as their increments, changes, and error values. Considering wind turbine physics, the control inputs also can be rotor torques and pitch angles. For simplicity, here we set yaw angles and axial induction factors as control inputs, denoted as $a_t = [\alpha_{1_t}, ..., \alpha_{N_t}, \phi_{1_t}, ..., \phi_{N_t}]^{\mathrm{T}}$.

Based on these preliminaries and assumptions, we set the goal of RL to be finding an optimal control policy $a_t^* = [\alpha_{1_t}^*, ..., \alpha_{N_t}^*, \phi_{1_t}^*, ..., \phi_{N_t}^*]^{\mathrm{T}}$ to maximize a long-time reward formalized in (7).

$$R_t = k_p \sum_{t}^{\infty} \gamma^{-t} g(P_{all}) + k_f \sum_{t}^{\infty} \gamma^{-t} f(s_t, a_t) + k_h \sum_{t}^{\infty} \gamma^{-t} h(P_{all} - P_{ref}) \tag{7}$$

where k_p, k_f, k_h are user-defined weighting constants to balance different tasks. In (7), the first term $g(P_{all})$ denotes a function related to the farm's total power generation. The second term $f(s_t, a_t)$ is related to fatigue load reduction tasks, which is a function of wind farm states and actions. The third term $h(P_{all} - P_{ref})$ is a function of the error between the total power production and a reference power P_{ref}, which is for achieving power reference tracking. Therefore, by choosing different values for k_p, k_f and k_h, Eq. (7) can represent different control tasks. For example, the case that $k_p = 1$, $k_f = 0$ and $k_h = 0$ indicates a pure power maximization task.

A typical RL structure to solve the optimal control problem indicated by (7) is the critic-actor framework, which is demonstrated in Fig. 4. Here the critic neural network evaluates the complicated reward functional R_t. The actor neural network is to derive the optimal control action based on the estimated reward functional. All the studies that are introduced in the following subsection are based on such a RL framework or its variants.

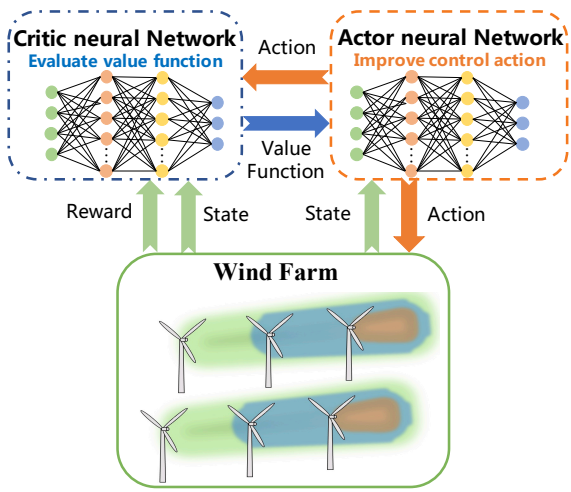

Figure 4. A typical RL structure for wind farm control.

4.2. Applications of RL in wind farm control

This subsection highlights the existing works that developed RL-based methods for wind farm control problems.

4.2.1. Power generation maximization via reinforcement learning

During the past several years, different RL-based approaches had been developed to handle wind farm power maximization tasks, aiming to achieve superior performance than mainstream methods.

Many RL-based wind farm control methods are based on the Q-learning algorithm [131]. A decentralized Q-leaning algorithm was developed in Ref. [132] for optimizing farm-level power production. This scheme had the ability to avoid sharp changes of control variables. In Ref. [133], a distributed RL algorithm was proposed to increase

power generation by controlling yaw angles. Particularly, the delay of wake propagation and the stepwise-varying inflow conditions were considered in this study. Another wind farm control method based on the Q-learning algorithm was proposed in Ref. [134], in which the idea of gradient approximation of RL and incremental comparison (GARLIC) was constructed for solving the optimal control actions. The simulation tests of these studies showed that RL-based wind farm control methods could achieve improved performance than other commonly-employed methods. However, a drawback of the Q-learning framework is that the action space must be discrete. Other RL algorithms are developed for wind farm applications to address this issue and handle more general wind farm control problems with the continuous action space.

Ref. [128] developed a RL-based wind farm control architecture by combing the deep deterministic policy gradient (DDPG) algorithm with a reward regularization module (RRM) and a composite learning-based control strategy. Particularly, RRM was used to normalize the changes of power generation under different wind conditions. The high-fidelity simulator SOWFA [18] was employed to conduct numerical tests, showing that an up to 15% increase in total power generation could be achieved with this method. In Ref. [129], another RL method with improved learning efficiency was proposed and applied to wind farm control. Particularly, a composite experience replay (CER) strategy was designed to balance rewards and temporal difference (TD) errors during the learning process. CER-RL had a better sampling & learning efficiency than mainstream RL methods, enhancing its applicability to practical wind farms.

The RL-based wind farm control methods in [128] and [129] employed yaw angles as control inputs. As an extension study, Ref. [135] explored a double-network-based DDPG (DN-DPPG) approach that considered both yaw angles and induction factors as control signals to enhance flexibility and improve control performance further. A key design was that two sets of critic-actor networks were constructed to generate control policies for induction factors and yaw angles simultaneously and separately. This allowed DN-DDPG to deal with the incompatibility between different control signals, ensuring a reliable training process. Another RL-based wind farm control method called knowledge-assisted deep deterministic policy gradient (KA-DDPG) method was proposed in [136]. KA-DDPG also employed both yaw angles and induction factors as control inputs. The key idea of KA-DDOG is to accelerate the learning process by employing analytical models to initialize the RL agent and guide it in the early stage.

4.2.2. Power reference tracking via reinforcement learning

In addition to power generation maximization, RL can also be applied to handle many other complex tasks in wind farm operations, such as farm-level power tracking, aiming to provide ancillary services like the frequency regulation.

Wind farm power tracking is a relatively more challenging task than power maximization because the former requires tracking a time-varying reference input. In addition, in such a tracking task, real-time control signals can have a long-term &

Table 1. Key features of existing RL-based wind farm control methods

Ref.	Method	Objective	Control Input	Simulator	Efficiency Gain
[136]	KA-DDPG	Power maximization	Induction factor	WFSim	10%
[129]	DDPG	Power maximization	Yaw angle	WFSim	25%
[128]	DDPG	Power maximization	Yaw angle	SOWFA	15%
[135]	DN-DDPG	Power maximization	Thrust coefficient & Yaw angle	WFSim	33%
[43]	PR-DRL	Power tracking	Thrust coefficient & Yaw angle	WFSim	–
[133]	Distributed RL	Power maximization	Yaw angle	FLORIS	8.2%
[137]	Deep RL	Power tracking	Yaw angle	FLORIS	–

time-delayed impact on the aerodynamic interactions of wind turbines and the power generation of the whole wind farm [43], which should be considered in control system design to optimize the performance. Conventional wind farm power tracking methods usually ignore these aspects. Moreover, conventional methods carry out power tracking by de-rating turbines. This means they can only track references below the power curve under the greedy strategy. RL's strong information exaction and learning abilities can address these limitations and achieve better task capacity & control performance. Some most recent works have investigated this interesting topic.

Ref. [137] explored a deep RL framework for wind farm power tracking, which is a model-free method and can solve the optimal actions in real time considering varying environmental conditions. The FLORIS (FLOw Redirection and Induction in Steady State) model was employed to conduct the numerical simulations. Ref. [43] designed a preview-based robust deep RL (PR-DRL) for the same purpose. PR-DRL is also data-driven and model-free. It is based on the H_∞ control technique, leading to solid robustness against stochastic environment conditions. In addition, by employing time-series data in neural network training, PR-DRL addresses the short-sighted issue in conventional wind farm power tracking methods and can track non-trivial references that are higher than the greedy-mode power curve.

These existing RL-based wind farm control methods show the feasibility of employing RL to handle challenging tasks in wind farm operations and achieve improved performance in multiple tasks, including farm-level power maximization & tracking. Table 1 summarizes the features and control performance of these existing RL-based wind farm control methods, where the efficiency gains are obtained through comparing with the conventional greedy strategy.

5. Conclusions and Future Prospects

5.1. Conclusions

This paper reviewed the development and most recent advances of wind farm control technologies. We introduced fundamental aspects of wind farm control regarding system modeling, main challenges, and control objectives. After that, existing wind farm control methods for different purposes, including layout optimization, power generation maximization, fatigue loads minimization, and power reference tracking, were reviewed and analyzed. Discussions regarding the differences and connections among model-based, model-free, and data-driven wind farm control methods were provided. In addition, the application of RL techniques in wind farm operations were highlighted. Some key observations include:

(1) Various optimization techniques have been developed for wind farm layout optimization. They mainly focus on adjusting the positions of wind turbines to maximize power production and minimize costs. Typical methods include particle swarm optimization (PSO), random search (RS) algorithm, genetic algorithm (GA), sequential convex programming (SCP), and so on.

(2) The majority of wind farm control tasks require direct adjustments in wind turbine states. Relevant tasks considered in this paper include power generation maximization, fatigue loads minimization, and power reference tracking. The existing wind farm control approaches for these tasks can be roughly divided into model-based and model-free methods. The former is developed directly based on analytical wind farm models. They are relatively easy to implement and can deal with multi-objective tasks under various constraints. A downside of model-based approaches is that they are sensitive to uncertainties and modelling errors and lack adaptability and robustness to stochastic environmental conditions. Model-free methods aim to release the reliance on analytical wind farm models. They employ measurement data to carry out learning and find out optimal solutions. Many results have demonstrated that model-free approaches have the ability to achieve superior performance compared with their model-based counterparts. But these important methods still have limitations. One example is that most model-free strategies for farm-level power maximization are still built upon steady-style data (such as the time-averaged data or the data generated by steady-state models) to carry out learning.

(3) Due to the various merits of the reinforcement learning (RL) technique, including the ability to handle high system complexities, the data-driven and model-free features, and the strong adaptability, attempts to apply RL to wind farm control tasks have been made in recent years. Results show that RL-based wind farm control methods have the potential to achieve enhanced performance in many tasks, such as power maximization & tracking. On the one hand, they can mitigate the limitations of model-based wind farm control methods, such as reliance on analytical models and lack of adaptability & robustness to modelling errors & uncertainties. On the other hand, compared with the mainstream model-free wind farm methods

that commonly require steady-style data to carry out open-loop optimization, RL can handle dynamic measurements and achieve closed-loop control under time-varying environmental conditions.

5.2. Future prospects

Though existing wind farm control methods have shown effectiveness in multiple tasks, many aspects still need further improvements in future research to promote the development of wind farm control technologies. We name a few here.

(1) Handling the stochastic nature of environmental conditions (such as time-varying wind speeds and wind directions) is still challenging for wind farm control. Though some methods, especially RL-based wind farm control methods, have a certain level of robustness to this aspect, such robustness is still limited. Most existing wind farm control methods cannot deal with rapid wind direction changes. In addition, ensuring robustness and safety under extreme environmental conditions remains a research gap.

(2) The computational complexity of many existing wind farm control methods increases exponentially with the increase of the numbers of wind turbines. Therefore, how to reduce computational costs is another important research topic. A potential solution is to apply grouping strategies for large-scale wind farms, dividing the whole wind farm into small sub-groups based on the aerodynamic interactions among turbines. This can potentially reduce algorithm complexities from exponential to linear. Although some attempts have been made to this end, a systematic result is still lacking.

(3) Due to the diversity of task requirements, it is common for wind farm controllers to pursue multiple (or even conflicting) objectives. Existing methods usually achieve that by designing simply weighted objective functions. More practical objective functions that can fully reflect the trade-off among different objectives from an economic perspective are needed, which will be beneficial to improve the generality of wind farm control methods.

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