

## Review

# Review on the Application of Artificial Intelligence Methods in the Control and Design of Offshore Wind Power Systems

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**Abstract:** As global energy crises and climate change intensify, offshore wind energy, as a renewable energy source, is given more attention globally. The wind power generation system is fundamental in harnessing offshore wind energy, where the control and design significantly influence the power production performance and the production cost. As the scale of the wind power generation system expands, traditional methods are time-consuming and struggle to keep pace with the rapid development in wind power generation systems. In recent years, artificial intelligence technology has significantly increased in the research field of control and design of offshore wind power systems. In this paper, 135 highly relevant publications from mainstream databases are reviewed and systematically analyzed. On this basis, control problems for offshore wind power systems focus on wind turbine control and wind farm wake control, and design problems focus on wind turbine selection, layout optimization, and collection system design. For each field, the application of artificial intelligence technologies such as fuzzy logic, heuristic algorithms, deep learning, and reinforcement learning is comprehensively analyzed from the perspective of performing optimization. Finally, this report summarizes the status of current development in artificial intelligence technology concerning the control and design research of offshore wind power systems, and proposes potential future research trends and opportunities.

**Keywords:** offshore wind farm; artificial intelligence technology; control of wind turbines; wake control; layout optimization; power collection system optimization



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## 1. Introduction

With the rapid increase in global energy consumption, climate change and ecological issues are gaining increasing attention. In this context, the use of clean and renewable energy is becoming more important. Under the goals of “carbon peak” and “carbon neutrality”, the new energy industry is expected to undergo high-quality, leapfrog development, with a significant increase in the proportion of clean power installations like wind power [1,2]. Compared to onshore wind, offshore wind features more stable and stronger wind speeds, along with lower turbulence intensity and more stable dominant directions, which are beneficial in reducing wind-induced fatigue loads on turbines. Consequently, offshore wind energy is receiving special attention globally, with active development in many countries [3]. The “2023 Global Offshore Wind Report” [4] shows that in 2022, the global offshore wind power added an installation capacity of 8.8 GW, ranking second in annual growth throughout the years, with China contributing 5 GW of the new installations, bringing the total global offshore wind power installation capacity to 64.3 GW.

Offshore wind power systems, comprising offshore wind turbines and wind farms, are crucial in harnessing and collecting marine wind energy. The economic utilization of wind energy is difficult, which is greatly influenced by environmental wind conditions and the wind energy system [5]. Therefore, favorable design and stable operation of offshore wind energy systems cannot be achieved without the development and application of various technologies such as wind speed and wind power prediction [6], turbine control, wind energy system design [7], condition and structural health monitoring [8], and fault diagnosis [9]. Combined with the application of AI technology in these fields, this report focuses on the control and design technology of offshore wind energy systems. Control technology of offshore wind power systems encompasses the regulation of individual wind turbines and the wake control of offshore wind farms, and design technology includes turbine selection, layout optimization, and power collection system design for offshore wind farms. The control of offshore wind turbines focuses on efficient and reliable management of individual wind turbines, while wake control aims to regulate wake between turbines, reducing wake loss and maximizing energy output. Turbine selection and layout optimization are closely linked, with selection focusing on choosing turbine types best suited for specific marine environments and conditions, and layout optimization determining their optimal placement in the wind farm to maximize energy capture while minimizing costs and environmental impact. Lastly, optimizing the power collection system is crucial to ensure efficient and safe energy transfer from the turbines to the grid.

As offshore wind energy expands, offshore wind turbines and farms are trending towards larger and more integrated development, increasing the complexity of control and design issues in offshore wind power systems. Artificial intelligence (AI) is playing an increasingly important role in addressing these challenges. To promote the application of AI in the control and design of offshore wind power systems, and to further the development of offshore wind energy, an exhaustive systematic review of relevant literature is provided in this paper. The fields covered include control of wind turbines, wake control of offshore wind farms, turbine selection, layout optimization, and optimization of power collection systems for offshore wind farms. This review aims to provide reference for researchers and engineers engaged in the control and optimization design of offshore wind energy systems. Keywords used to identify relevant literature, as shown in Table 1, were used to search for related documents in comprehensive databases including ScienceDirect, IEEE, and Web of Science.

**Table 1.** Searched keywords.

| Field                                             | Language | Searched Keywords                                                                       |
|---------------------------------------------------|----------|-----------------------------------------------------------------------------------------|
| Wind turbine control                              | English  | "Offshore wind turbine" AND "MPPT", "Fatigue control"                                   |
| Offshore wind farm wake control                   | English  | "Offshore wind farm" AND "Wake control"                                                 |
| Offshore wind farm turbine selection              | English  | "Offshore wind farm" AND "Wind turbine selection"                                       |
| Offshore wind farm layout optimization            | English  | "Offshore wind farm" AND "Layout optimization"                                          |
| Offshore wind farm collection system optimization | English  | "Offshore wind farm" AND "Collection system optimization", "Cable network optimization" |

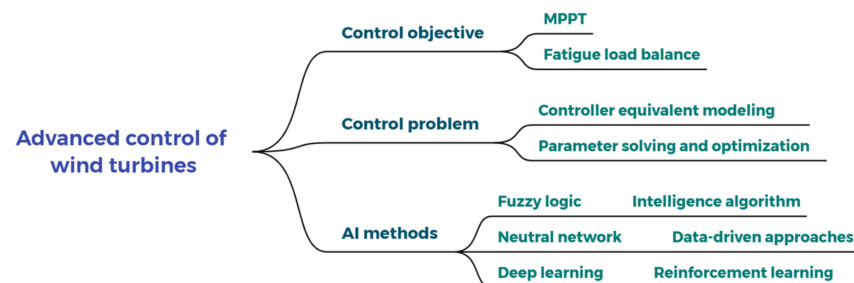
A comprehensive review of literature related to offshore wind power systems is provided in this paper, with a focus on two main themes: control technology and design technology of offshore wind power systems. The control technology encompasses the control of wind turbines and wake control in offshore wind farms. The design technology covers three fields: turbine selection, layout optimization, and power collection system optimization for offshore wind farms. The review elaborates on the relevant issues in each field, analyzing the current application status and development trends in artificial intelligence technology for these fields. Finally, this report briefly summarizes the main findings and future research directions in these fields.

## 2. Control Technology of Offshore Wind Power Systems

The control technology of offshore wind power systems is designed to improve system performance, enhance collaborative operation efficiency, and address reliability and robustness challenges in complex marine environments. Considering the complexity of offshore wind power systems, there are several levels of control issues involved. Therefore, the control technology of offshore wind power systems can be categorized into WT (wind turbine) level and WF (wind farm) level based on system hierarchy. With the application of artificial intelligence methods, it can be further divided into advanced control of wind turbines and wake control of wind farms. Method selection and refinement in these fields are crucial for the overall efficiency and economic viability of offshore wind farms. Wind turbine control, which determines the energy capture from the wind, mainly involves controller modeling and solving; the AI method is mainly used to solve the coupling problem between the WT and the external environment. Wake control in wind farms, on the other hand, focuses on improving the overall performance through coordinated control of multiple turbines; the AI method is mainly used to solve the coupling problem among internal individuals in a wind farm. The application of artificial intelligence technologies in these fields are elucidated in this section.

### 2.1. Advanced Control of Wind Turbines

As depicted in Figure 1, the control problems of wind turbines mainly revolve around maximum power point tracking (MPPT) and the fatigue load balance. MPPT is a primary and widespread concern, while fatigue load considerations are typically specific to certain operational scenarios. With the increasing scale of modern wind turbines, there is an augmentation in system inertia and complexity in application scenarios. This necessitates enhanced performance requirements for the MPPT of wind turbines and further consideration of the impacts of complex offshore environments on turbine fatigue load.



**Figure 1.** Advanced control of wind turbines.

Based on the characteristics of problems, the wind turbine control problems can be divided into two categories: controller equivalent modeling; parameter solving and optimization. The artificial intelligence methods applied for these problems include, but are not limited to, fuzzy logic, genetic algorithm, neural network, data-driven approaches, reinforcement learning, and deep learning.

For the MPPT (maximum power point tracking) problem in wind turbine control, the primary goal is to optimize turbine performance and enhance the system's power generation efficiency. Significant research has been conducted using artificial intelligence methods, often combining one or more techniques. Regarding the fatigue load control issue of wind turbines, it involves comprehensive optimization of the turbine in conjunction with other indicators. The intelligent methods for load assessment and optimization are mainly reviewed in this paper. Representative literature in this field is illustrated in Table 2.

**Table 2.** Representative literature on advanced control of wind turbines.

| Ref. | Year | Objective                                                           | Decision Variable      | Framework | Method | Contribution                                                                                                                                                 |
|------|------|---------------------------------------------------------------------|------------------------|-----------|--------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [10] | 2023 | MPPT                                                                | Rotor speed            | FLC       | GA     | The proposed method is straightforward to implement, effectively minimizes steady-state oscillations, and swiftly adapts to changes in wind speed.           |
| [11] | 2018 | MPPT                                                                | Yaw angle              | MPC       | MOPSO  | The proposed method adjusts control parameters based on wind direction changes and desired performance, resulting in improved power extraction efficiency.   |
| [12] | 2021 | Maximum wind energy extraction and minimum motor torque fluctuation | Rotor speed            | MPC       | YYGWO  | The proposed algorithm demonstrates robustness in solving dynamic optimization problems, with a high optimization rate and rapid convergence performance.    |
| [13] | 2023 | MPPT                                                                | Generator speed        | DSC       | ANN    | The control system, based on neural network online learning, can adapt to disturbances in MPPT control.                                                      |
| [14] | 2023 | MPPT                                                                | Generator torque       | MPC       | DNN RL | In scenarios with uncertainty and unexpected actuator failures, the proposed method exhibits superior robustness and control performance.                    |
| [15] | 2022 | MPPT                                                                | Pitch angle            | PID       | RL     | The method enhances the efficiency of intelligent control strategies, reducing the power output error of the optimal hybrid controller by approximately 41%. |
| [16] | 2023 | Minimum the asymmetric load of wind turbines                        | Individual pitch angle | PI        | BO     | The strategy introduces an actuator derating control approach, enhancing the fault tolerance of derating controls.                                           |

Summaries on the application of AI methods in MPPT control of wind turbines are provided, as follows:

**Fuzzy Logic** is primarily used to address the uncertainties and ambiguities in MPPT (maximum power point tracking). For instance, some studies have focused on developing fuzzy fractional-order proportional–integral controllers to enhance the performance of direct-drive permanent-magnet synchronous generator wind turbines. This highlights the flexibility of fuzzy logic in adapting to rapidly changing wind speed conditions [17]. Further research includes comparative analyses of different fuzzy logic controllers in semisubmersible platform wind turbines [18]. In addition, some research also involves comparing the performance differences between fuzzy logic control and the traditional proportional integral controller [19], and combining the fuzzy logic method of sliding mode control to improve the robustness and performance of doubly-fed induction generator systems [20]. Fuzzy logic offers effective solutions to wind turbine control in complex environments.

**Intelligent Algorithms** are recognized as powerful optimization tools, they are widely applied in MPPT (maximum power point tracking) control of wind turbines. Research has shown that control strategies optimized through intelligent algorithms significantly enhance the performance and efficiency of wind turbine systems [21,22]. For instance, the genetic algorithm (GA) has been used to adjust FLC (fuzzy logic control) system parameters for optimizing wind turbine MPPT strategy [10], as well as the intelligent control strategies for the offshore wind turbine MPPT zone [23]. Methods like MOPSO (multiobjective particle swarm optimization) have been utilized to optimize the control parameters of yaw control systems in horizontal-axis wind turbines, aiming to improve energy capture efficiency [11]. The YYGWO (yin–yang grey wolf optimizer) algorithm, through nonlinear model predictive control, has been employed for maximizing wind energy extraction in large wind turbines [12]. These examples highlight the advantages of intelligent optimization algorithms in parameter optimization and their potential to enhance system stability and adaptability.

**Neural Networks** are primarily used for model prediction and system behavior simulation in MPPT (maximum power point tracking) applications. For instance, an unsupervised neural network-based MPPT control strategy for wind turbines has been proposed, which can adapt to different environmental conditions and optimize turbine actions to achieve maximum power [13]. Other research includes power prediction models for wind turbines

using artificial neural networks, optimizing yaw angles across wind farms to reduce wake effects and enhance overall efficiency [24]. The flexibility of neural networks enables them to handle complex nonlinear systems, such as optimizing wind energy capture under variable speed conditions [25], and enhancing the performance of wind power systems with neural network controllers based on transfer function models [26]. These applications demonstrate the capabilities of neural networks in prediction and optimization, as well as their potential in real-time control and adaptive adjustments.

**Data-driven methods** exhibit advantages in handling large volumes of complex data in MPPT control for wind turbines. These methods rely on historical and real-time data to enhance the accuracy and efficiency of control strategies [27]. In addition, the extended Kalman filter is used to improve MPPT control of wind turbines with the permanent magnet synchronous generator [28], and MPPT control based on wind speed estimation technology is applied to a double-fed induction generator [14]. These research efforts demonstrate the potential of data-driven approaches in enhancing the performance and adaptability of wind turbine control systems.

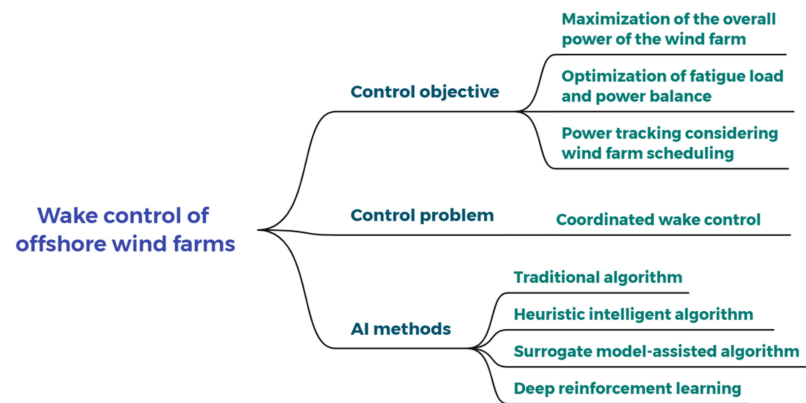
**Deep Learning** has shown significant capabilities in data processing and feature extraction within the field of MPPT control for wind turbines. Research leveraging deep learning techniques has been successful in creating power curve models for wind turbines to predict power output under various conditions [29]. Additionally, deep learning solutions have been developed for power prediction in multiple wind turbine units within a wind farm [30]. These studies demonstrate the remarkable role of deep learning in enhancing the accuracy of performance prediction and optimization of wind turbine systems.

**Reinforcement Learning** has increasingly demonstrated unique advantages in MPPT control for wind turbines, especially in managing complex dynamic systems. Research indicates that using reinforcement learning to improve the pitch control of wind turbine units effectively addresses the nonlinear characteristics and dynamic complexities of wind power equipment [15]. Additionally, a method combining data-driven and reinforcement learning approaches has been proposed for the torque and blade pitch control of wind turbines [14], showcasing the potential of reinforcement learning in optimizing complex control systems. There are also studies on blade pitch control [31] and MPPT methods for wind turbines [32] using reinforcement learning, highlighting its promising future in adapting to environmental uncertainties and optimizing complex control strategies.

Moreover, for modern large-scale and floating wind turbines, the integration of artificial intelligence methods with key structural fatigue load modeling and optimization is particularly important. For instance, a CNN-t-SNE-based neural network model for structural fatigue analysis of floating wind turbine platforms is developed [33], enabling automatic detection of damage in mooring equipment. Further, a control network model based on multiagent theory has been proposed to assess fatigue loads in offshore wind turbines [34]. Addressing the uneven distribution of fatigue loads, which increases operational and maintenance costs, the multiobjective adaptive yin–yang pair optimization (M-AYYPO) algorithm is utilized to propose a comprehensive optimization method for fatigue loads in wind turbines [35]. To optimize power and load performance, a fault-tolerant control strategy based on Bayesian optimization (BO) is proposed, aimed at reducing asymmetric loads in offshore wind turbine units and extending their lifespan [16].

## 2.2. Wake Control of Offshore Wind Farms

As illustrated in Figure 2, the wake control issues in offshore wind farms are mainly categorized into three types [36,37]: maximization of the overall power of the wind farm, optimization of fatigue load and power balance, and power tracking that considers wind farm scheduling. Unlike the control of individual wind turbines, wind farm-level control is primarily achieved through coordinated wake control. Additionally, wind farms need to select suitable wake models based on different application scenarios. With the advent of floating turbines, the wake effects in wind farms have become more pronounced, raising higher demands for the efficiency and effectiveness of wake control solutions.



**Figure 2.** Wake control problem of offshore wind farms.

In addressing the accuracy and efficiency of models in different scenarios, the methods used for solution and optimization are often related to the complexity of model calculations. Initially, wake control relied mainly on simple mathematical models, like linear programming based on wake models. With increased computing power, researchers began using more complex models, like fluid dynamics models, to simulate wake effects. These models often require solving complex partial differential equations, leading to the development of numerical optimization algorithms like game theoretic (GT) [38,39], sequence quadratic program (SQP) [40,41], and alternating direction method of multipliers (ADMM) [42]. Additionally, a hybrid method combining ADMM and SQP are proposed according to the wake coupling degree [43]. However, numerical optimization algorithms often struggle with nonconvex optimization problems, leading to growing interest in artificial intelligence algorithms. Representative literature on heuristic intelligent algorithms, deep reinforcement learning, and surrogate model-assisted algorithms are shown in Table 3. These AI-based methods offer promising alternatives for optimizing complex wake control scenarios in wind farms.

**Table 3.** Representative literature on wake control of offshore wind farms.

| Ref. | Year | Objective                           | Decision Variable                 | Method         | Contribution                                                                                                                                                |
|------|------|-------------------------------------|-----------------------------------|----------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [44] | 2017 | Power and fatigue load balance      | Active power setting              | GA             | The proposed method addresses real-time optimization issues under constraints related to the active power limitations of wind turbines and wind farms.      |
| [45] | 2020 | Maximum power                       | Axial induction factor            | PSO            | The proposed approach is highly efficient in solving problems for medium- and small-scale wind farms.                                                       |
| [46] | 2021 | Maximum power                       | Axial induction factor, yaw angle | MC-BAS         | The proposed approach enhances the capability of the BAS algorithm to handle high-dimensional nonlinear problems effectively.                               |
| [47] | 2022 | Maximum power, minimum fatigue load | Axial induction factor, yaw angle | CMC-BSO        | This proposed method solves multiobjective nonconvex optimization problems based on decentralized communication network topologies.                         |
| [48] | 2023 | Maximum power                       | Axial induction factor, yaw angle | IEO            | The proposed method combines centralized and distributed optimization strategies through iterative updates and cluster processing to improve the algorithm. |
| [49] | 2020 | Maximum power                       | Yaw angle                         | Distributed RL | Considering the delay in wake propagation and the time-stepping variation of inflow conditions, this method achieves an efficiency gain of 8.2%.            |
| [50] | 2020 | Maximum power                       | Axial induction factor            | KA-DDPG        | Combining expert knowledge with a reinforcement learning framework while ensuring learning safety, this approach results in a gain of 10%.                  |
| [51] | 2021 | Maximum power                       | Yaw angle                         | DDPG           | The proposed control scheme demonstrates strong robustness and utilizes a sparse dataset, resulting in an efficiency gain of 15%.                           |

Table 3. Cont.

| Ref. | Year | Objective      | Decision Variable                 | Method   | Contribution                                                                                                                                                  |
|------|------|----------------|-----------------------------------|----------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [52] | 2022 | Maximum power  | Yaw angle                         | CER-DDPG | It has improved sampling and learning efficiency, enhancing its applicability in real wind farms, with a gain of 25%.                                         |
| [53] | 2022 | Maximum power  | Thrust coefficient, yaw angle     | DN-DDPG  | The proposed method is able to handle incompatibilities between different control signals, ensuring a reliable training process, and achieving a gain of 33%. |
| [54] | 2021 | Power tracking | Yaw angle                         | Deep RL  | Using a model-free approach, it can solve the optimal behavior in real-time considering different environmental conditions.                                   |
| [55] | 2022 | Power tracking | Thrust coefficient, yaw angle     | PR-DRL   | It addresses the short-sightedness issue of traditional power-tracking methods.                                                                               |
| [56] | 2023 | Maximum power  | Axial induction factor, yaw angle | SA-ISPSO | An intelligent optimization method based on a surrogate model is proposed, used for the first time in the power maximization problem of floating wind farms.  |
| [57] | 2023 | Maximum power  | Axial induction factor, yaw angle | SAFDR    | It proposes a dimensionality reduction-based surrogate modeling-assisted global optimization framework, further reducing the time cost of optimization.       |

Traditional algorithms provided a fundamental theoretical framework and preliminary solutions for wake control in wind farms, laying the groundwork for further development. Early BO methods [58–60] were widely applied and combined with wind farm trust regions [61] and steady-state models [62] for improvement. However, as wind farms expanded in size, the complexity of wake control problems increased, necessitating the consideration of more factors. Consequently, intelligent optimization algorithms like the genetic algorithm (GA) [44] and particle swarm optimization (PSO) [45,63], known for their adaptability and efficiency, were employed in the field of power optimization research. These algorithms, capable of handling complex constraints and nonlinear problems, emulate natural group behaviors to find optimal solutions. Advanced intelligent algorithms have also been developed for specific scenarios, such as Monte Carlo-based beetle annealing search (MC-BAS) for distributed wind farms [46] and combined Monte Carlo and beetle swarm optimization (CMC-BSO), combining Monte Carlo and beetle swarm optimization, to consider load and power optimization [47]. Moreover, an improved equilibrium optimizer (EO) based on the turbine subset size is proposed to regulate the wake effect in wind farms [48]. Heuristic intelligent optimization algorithms have significantly improved the efficiency of wake control optimization in large-scale offshore wind farms.

With advancements in parallel computing and intelligent learning capabilities, deep reinforcement learning (DRL) is increasingly being applied to wake control in wind farms, exploring hybrid methods. This algorithm learns optimal strategies through interaction with the environment, making it suitable for dynamic and uncertain conditions. Many wind farm control methods based on reinforcement learning (RL) use the Q-learning algorithm [64]. Additionally, distributed Q-learning is developed for optimizing farm-level power production [65], with strategies to avoid abrupt changes in control variables. Further research has proposed distributed RL algorithms for increasing power generation through yaw angle control [49], and concepts like gradient approximation and incremental comparison in RL for optimal control actions [66]. Moreover, a knowledge-assisted deep deterministic policy gradient (KA-DDPG) method is introduced [50], utilizing an analytical model to initialize the RL agent and early-guide it to accelerate the learning process. Additionally, new wind farm control frameworks have been developed by combining deep deterministic policy gradient (DDPG) algorithms with reward regularization modules and composite learning-based control strategies [51]. A compound experiential replay strategy CER-RL is designed to balance the reward and time difference errors in the learning process [52]. To ensure reliable training processes, a dual-network-based DDPG method is explored [53], which is capable of handling incompatible control signals. In addition to power maximization, RL can also be employed to address field-level power tracking issues. Vijayshankar et al. [54] explored a deep RL framework for wind farm power tracking,

which is a model-free approach capable of real-time optimization considering various environmental conditions. Dong and Zhao [55] designed the preview-based robust deep RL (PR-DRL) method, combining data-driven approaches to achieve model-free power tracking for wind farms. These methods emphasize DRL's potential in real-time adjustment of wind turbine operational parameters to adapt to wind speed variations and wake effects, thereby optimizing the performance of the entire wind farm.

Finding global optimal solutions using nonlinear optimization algorithms like SQP can be challenging, and intelligent optimization algorithms and deep reinforcement learning methods often face the challenge of high time costs and low efficiency due to evaluating numerous objective functions. To address these issues, surrogate model methods have gained widespread attention [67]. These methods, combining surrogate models with intelligent optimization algorithms, are particularly effective for wake control in large and floating wind farms. Focused on developing reliable surrogate models for yaw-based wind farm control, the relationship between total power gain and surrogate model error or uncertainty is discussed [68]. Given the complexity of power optimization in floating wind farms, intelligent optimization algorithms face challenges in their application. A surrogate-model-assisted intelligent optimization method is introduced [56], which is first applied to the problem of power maximization in floating wind farms. Additionally, a dimensionality reduction-based surrogate-model-assisted global optimization framework is proposed [57], further reducing the computation cost while improving its effectiveness.

In summary, traditional solving methods initially used for wake control in wind farms, based on mathematical models, are suitable for deterministic problems but struggle with high computational complexity and large-scale, nonlinear problems. This leads to the development of intelligent optimization algorithms like the genetic algorithm and particle swarm optimization, suitable for global searches. Furthermore, deep reinforcement learning, utilizing multilayer neural networks for data feature learning, is appropriate for complex pattern recognition and has been evolving recently. However, these methods still face challenges such as becoming trapped in local optima and requiring extensive data and computation time. Currently, surrogate models, combined with intelligent optimization algorithms, are used to simplify problems and reduce computational load, achieving better control outcomes.

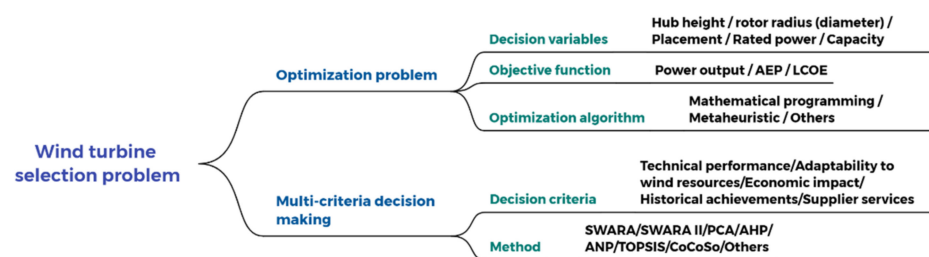
### 3. Layout and Integrated Design of Offshore Wind Farms

The design process of wind farm projects mainly includes wind farm site selection, wind farm optimization design (configuration or layout of wind turbines and their electrical connections), relevant regulatory consultation, and project financing [7,69]. With the expansion of wind farm project scale, wind farm optimization design problems (including turbine selection, layout optimization, and power collection system design) are difficult to solve by classical optimization technology, and the application of artificial intelligence technology in these problems is gradually increasing. Therefore, this paper focuses on the design technology of offshore wind farms in three areas: turbine selection, layout optimization, and power collection system design. The selection and optimization in these fields are crucial for the overall efficiency and economic viability of offshore wind farms. Turbine selection, fundamental in determining the performance of the wind farm, involves choosing wind turbines suitable for specific marine environments. The AI method is mainly used to solve the problem of component (turbine) selection under environmental and system constraints. Layout optimization considers the positioning of all turbines to minimize wake effects and enhance power generation efficiency. The optimization of the power collection system is essential for the reliable and efficient collection of offshore wind energy. The optimization problem of offshore wind farm layout is essentially an arrangement problem, and the optimization of power collection system is a topological structure problem. The AI method is mainly used to solve the optimal adjustment problem of component (turbine) interaction under the constraints of environment and system. This

section explores the application of artificial intelligence technologies in these fields and discusses their significant role in the design process of offshore wind farms.

### 3.1. Turbine Selection for Offshore Wind Farms

As shown in Figure 3, the turbine selection problem for offshore wind farms can be categorized into two types: optimization based on turbine parameters and decision-making based on multiple criteria. The first type involves selecting parameters like hub height, rotor diameter, and rated power, considering energy output or levelized cost of electricity as the objective function, and determining suitable turbine parameters through algorithms. The second type encompasses a comprehensive evaluation of various turbine types offered by suppliers, considering multiple factors such as technical performance, adaptability to wind resources, economic impact, historical achievements, and supplier services, to select the most suitable turbine model for the specific region.



**Figure 3.** Turbine selection for offshore wind farms.

As indicated in Table 4, optimization problems related to turbine selection based on parameters can be solved using metaheuristic algorithms, the mixed integer nonlinear method, and other methods. A novel approach using self-organizing maps (SOM) is proposed for solving problems based on turbine diameter and placement [70]. Some studies [71–75] have also established levelized cost of energy (LCOE) models for wind farms using variables like rotor diameter, employing metaheuristic algorithms to find optimal solutions. Regarding wind turbine power and capacity parameters as design variables, a turbine index is innovatively proposed to rank and find the most suitable turbine [76]. The Weibull density distribution is utilized to analyze the productivity of different turbine types, aiming to select the most efficient one [77]. Additionally, mixed integer nonlinear programming models for wind farm LCOE have been developed, taking into account turbine hub height, rotor radius, and layout, with the genetic algorithm applied to determine the best parameters and turbine types [78].

**Table 4.** Representative literature on turbine selection for offshore wind farms (optimization based on turbine parameters).

| Ref. | Year | Objective    | Decision Variable                          | Method                          | Contribution                                                                                                                                                                      |
|------|------|--------------|--------------------------------------------|---------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [70] | 2019 | LCOE         | Rotor diameter, placement                  | SOM                             | As an unsupervised learning technique, the self-organizing map (SOM) algorithm, is used for solving the turbine selection problem.                                                |
| [71] | 2019 | LCOE         | Rotor diameter<br>WTs number placement     | GA                              | Compared to similar studies, fine modeling of the cost for wind farms is studied.                                                                                                 |
| [75] | 2021 | LCOE         | Hub height, rotor diameter,<br>rated power | GA                              | The algorithm and mathematical model are versatile, improving the economic output of wind farms.                                                                                  |
| [76] | 2021 | Power output | Power, capacity                            | Turbine<br>performance index    | The reference introduces a turbine performance index and uses the ranking based on this index to identify the most suitable turbine type for a wind farm.                         |
| [77] | 2021 | AEP          | WT type                                    | Weibull density<br>distribution | The productivity of multiple types of wind turbines is analyzed to select the most efficient turbine type.                                                                        |
| [78] | 2023 | AEP          | Hub height, rotor radius,<br>placement     | MINLP                           | A mixed integer nonlinear programming (MINLP) model is established, then a recursive algorithm is utilized to enhance the annual electricity generation from offshore wind farms. |

As outlined in Table 5, the selection of the wind turbine based on multiple criteria essentially involves a multicriteria decision-making (MCDM) problem. This kind of problem begins with various indicators, assigning different weight coefficients to each, and integrating the scores to rank all types of turbines. Reference [79] proposes a new method based on TOPSIS, which is universal and verified by using real Saudi Arabian datasets. Innovative approaches in this field have incorporated fuzzy logic to allow for flexible decision-making rules in turbine selection [80], the application of SWARA methods to enhance decision quality in turbine selection [81], and the use of hybrid MCDM techniques combining the analytic network process (ANP) and entropy weight method (EWM) for turbine choice in specific offshore wind projects [82]. The integration of fuzzy preference programming has been explored to build sophisticated decision models for turbine selection [83,84]. In addition, D-number [85] and D-S evidence theory [86] are also introduced into the MCDM model for fan selection problems to improve decision-making performance. Reference [87] for the first time combined the PWA operator, SWARA II, MEREC, CPT, and CoCoSo methods into a scientific decision-making process, expanding the methodology and applications in this field.

**Table 5.** Representative literature on turbine selection for offshore wind farms (decision-making based on multiple criteria).

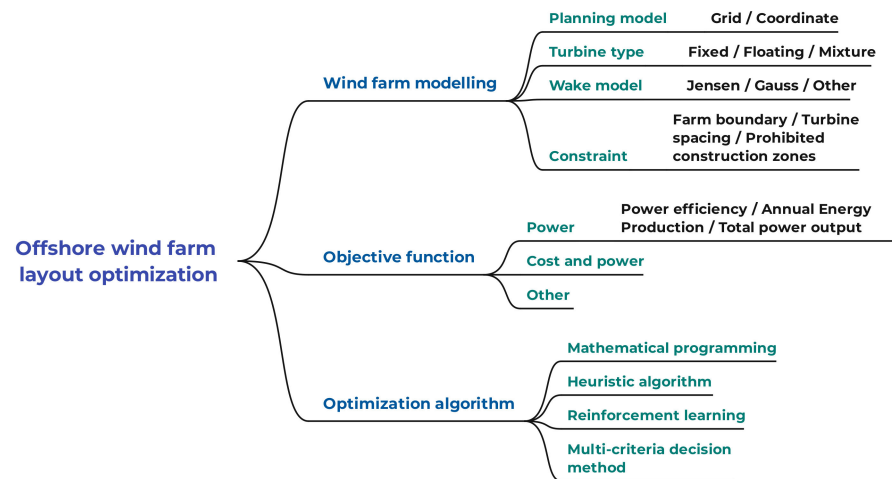
| Ref. | Year | Criteria                                                                                                           | Method            | Contribution                                                                                                                                                                                                                           |
|------|------|--------------------------------------------------------------------------------------------------------------------|-------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [79] | 2020 | Hub height, wind speed, percentages of zero and rated output, annual energy production (AEP)                       | TOPSIS            | The proposed TOPSIS-based method is versatile and has been validated using a real dataset from Saudi Arabia.                                                                                                                           |
| [80] | 2020 | Hub height, wind speed, percentage of zero power, percentage of rated power, net capacity factor                   | Fuzzy logic       | A fuzzy logic-based approach has been introduced, allowing decision-makers to develop flexible decision rules for turbine selection problems.                                                                                          |
| [81] | 2020 | Machine characteristics, economic impact, environmental impact, technical specification                            | SWARA-SVNS-TOPSIS | The SWARA method is utilized for weighting process, and it has not been used in previous relevant research.                                                                                                                            |
| [82] | 2021 | Technology, adaptability to wind resources, economy impact, historical achievements, supplier services             | ANP-EWM           | Subjective ANP is combined with objective EWM to fully leverage their respective strengths in selecting wind turbines.                                                                                                                 |
| [83] | 2021 | Reliability, economic impact, supplier services                                                                    | FPP-ANP           | Triangular fuzzy numbers and fuzzy comparison matrices are introduced, and fuzzy preference programming (FPP) is combined with the analytic network process to construct a fuzzy analytic network process (FANP) unit selection model. |
| [85] | 2022 | Technical performance, adaptability to wind farm, economic impact, historical achievements, supplier services      | PCA-TOPSIS        | The reference develops the D-number to address the uncertainty arising from the fuzziness of linguistic evaluations and the subjectivity of expert assessments in language evaluation.                                                 |
| [86] | 2022 | Technical performance, adaptability to wind resources, economic impact, historical achievements, supplier services | SWARA-TOPSIS      | The reference establishes a MCDM model based on the Dempster–Shafer evidence theory for offshore wind turbine selection.                                                                                                               |
| [87] | 2022 | Technical performance, economic impact, supplier services                                                          | SWARA II-CoCoSo   | The reference combines the PWA operator, SWARA II, MEREC, CPT, and CoCoSo methods for the first time.                                                                                                                                  |

In summary, most studies treat the turbine selection problem in offshore wind farms as a multicriteria decision-making issue, with a few considering it as an optimization problem based on turbine parameters, often combined with wind farm layout optimization. The primary application of artificial intelligence in this context lies in algorithmic problem-solving, utilized to determine design variables like turbine positioning and rotor radius in wind farms.

### 3.2. Layout Optimization of Offshore Wind Farms

As illustrated in Figure 4, the optimization of offshore wind farm layouts can be categorized based on three aspects: wind farm modeling, objective function, and optimization algorithm. Concerning the aspect of wind farm modeling, the planning model, turbine type, wake model, and constraint are considered. The planning model refers to the format of the turbine coordinates, typically grid or coordinate-based; turbine types can be uniform or mixed, with most literature assuming uniform types in a wind farm. There

is only one paper on layout optimization of different types of wind turbines [88]. Wake models commonly include the Jensen and Gaussian models, along with artificial neural network models. Constraints usually encompass wind farm boundaries, turbine spacing, and no-build zones. Recent research in wind farm layout optimization primarily focuses on maximizing energy output and the cost–energy output ratio. A unique study considered minimizing the interference of turbine layouts on radar tracking performance [89], establishing a turbine–radar interference model for layout optimization to reduce impacts on nearby radar tracking capabilities of wind farms.



**Figure 4.** Layout optimization problem of offshore wind farms.

Algorithmic problem-solving is a key application of artificial intelligence in optimizing offshore wind farm layouts. As shown in Table 6, the primary methods include metaheuristic algorithms and reinforcement learning algorithms. Additionally, global optimization algorithms [89–93] and multicriteria decision methods [94] are also employed. Due to their broad applicability and ease of use, metaheuristic algorithms are widely reported in most literature for solving offshore wind farm layout optimization problems. These include the genetic algorithm [95–104], particle swarm optimization [88,96,105], and other intelligent algorithms like the grey wolf optimizer (GWO) [106,107], random search (RS) [108], differential evolution (DE) [109], solid isotropic material interpolation techniques with penalization (SIMP) [110], EO [111], variable neighborhood search (VNS) [112], and simulated annealing (SA) [113,114]. Reference [115] modeled offshore wind farm layout optimization as a Markov decision process, using hybrid algorithms combining genetic algorithms and the Monte Carlo tree search (MCTS), demonstrating the potential of reinforcement learning in this field.

**Table 6.** Representative literature on layout optimization of offshore wind farms.

| Ref. | Year | Objective        | Decision Variable               | Method                   | Contribution                                                                                                                                                                                                                     |
|------|------|------------------|---------------------------------|--------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [88] | 2023 | Mixture          | Continuous layout, turbine type | IPSO                     | For the retrofitting of old wind farms, a layout optimization framework is proposed to achieve a balance between power generation, equipment investment, and aesthetic objectives.                                               |
| [89] | 2022 | Effect on radar  | Discrete layout                 | Mathematical programming | The reference establishes a wind turbine–radar interference analysis model and uses it to optimize the wind turbine layout appropriately, significantly improving radar tracking performance above the wind farm.                |
| [90] | 2023 | Power efficiency | Continuous layout               | SQP                      | An efficient and accurate machine learning wake model is used in this reference.                                                                                                                                                 |
| [91] | 2022 | AEP              | Continuous layout               | SLSQP                    | Simultaneously considering wave loads and wind energy output in wind farm layout optimization, the reference aims to minimize the total wave loads within the wind farm while maintaining a high annual energy production (AEP). |

Table 6. Cont.

| Ref.  | Year | Objective             | Decision Variable                    | Method      | Contribution                                                                                                                                                                                                |
|-------|------|-----------------------|--------------------------------------|-------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [94]  | 2023 | Mixture               | Discrete layout                      | WPM         | A MCDM optimization approach is innovatively proposed for wind farm layout.                                                                                                                                 |
| [95]  | 2023 | AEP                   | Continuous layout                    | GA          | The reference addresses the issue of retrofitting old wind farms by simultaneously maintaining the initial wind turbines and renovating the wind farm without the need for additional wind farm area.       |
| [96]  | 2023 | Cost/<br>Power        | Discrete layout                      | HPSOGA      | A hybrid algorithm that combines particle swarm optimization (PSO) and the genetic algorithm (GA) is proposed, which effectively combines PSO's global search capability with GA's local search capability. |
| [105] | 2022 | COE                   | Discrete layout,<br>turbine number   | PSO         | The reference introduces a hybrid optimization approach that uses a greedy algorithm to optimize the number of turbines and employs particle swarm optimization (PSO) to optimize the turbine layout.       |
| [106] | 2023 | Total power<br>output | Continuous layout                    | GWO         | A low-complexity grey wolf optimization (GWO) algorithm with a two-dimensional encoding mechanism is proposed for solving the problem.                                                                      |
| [108] | 2023 | Total power<br>output | Continuous layout                    | RS          | The paper conducts the optimization of floating multiturbine platform layout with consideration of adaptive characteristics.                                                                                |
| [109] | 2023 | Cost/<br>Power        | Discrete layout                      | LSHADE      | A new variant of DE is developed to enhance the algorithm's local search capability.                                                                                                                        |
| [110] | 2022 | AEP                   | Discrete layout                      | SIMP        | First-time attempt to apply interpolation techniques in the context of wind farm layout optimization.                                                                                                       |
| [111] | 2022 | Cost/<br>Power        | Discrete layout                      | EO-PS       | A hybrid algorithm EO-PS is developed for wind farm layout optimization, introducing PS (pattern search) techniques to enhance the local search capability of the EO (evolutionary optimization) algorithm. |
| [112] | 2022 | Mixture               | Discrete layout                      | VNS         | A variable neighborhood search metaheuristic method is employed to optimize wind farm layout, and a novel initial solution algorithm is developed.                                                          |
| [115] | 2022 | Cost/<br>Power        | Discrete layout                      | GA-MCTS     | The wind turbine layout is modeled as a reinforcement learning problem, and the Monte Carlo tree search algorithm is embedded in a genetic algorithm to enhance problem-solving capabilities.               |
| [116] | 2022 | AEP                   | Continuous layout,<br>Mooring system | pyOptSparse | The mooring system design is incorporated as part of the floating offshore wind turbine (FOWT) layout design. An open-source tool is provided for this method.                                              |

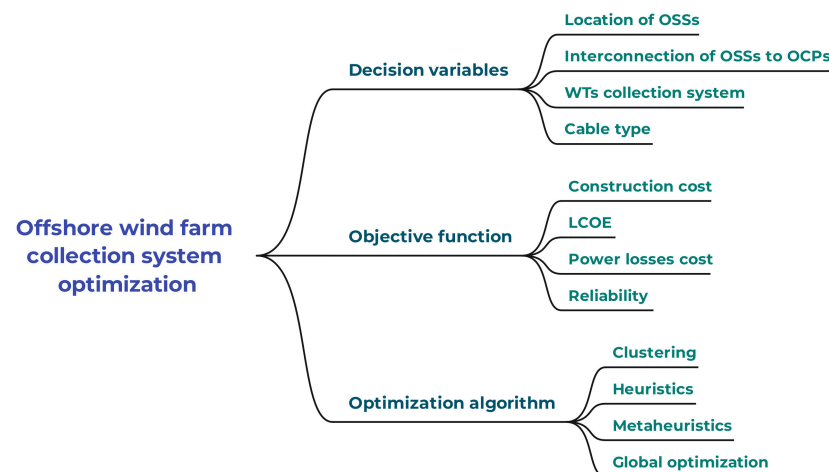
In summary, artificial intelligence is primarily utilized for algorithmic problem-solving in the optimization of offshore wind farm layouts. A few studies use ANN-based wake models for wind farm modeling, but the majority employ metaheuristic algorithms, likely due to their simplicity and ease of use. However, the iterative and random nature of metaheuristic algorithms can lead to longer solution times and unstable results. With the advancement in AI technology, data-driven wind farm models and more efficient intelligent solution algorithms are emerging as trends in the research of wind farm layout optimization.

### 3.3. Power Collection System Optimization of Offshore Wind Farms

As shown in Figure 5, the optimization study of offshore wind farm power collection systems can be classified into three main aspects: design variables, optimization objective, and optimization algorithm. Design variables mainly involve the location of offshore substations (OSSs), their interconnection of OSSs to onshore collection points (OCPs), wind turbine collection system, and cable type. The optimization objectives primarily focus on construction cost, levelized energy cost, wind energy loss costs, and cable reliability, with cable construction cost often being a key objective function. Cable reliability is only considered in a few studies [117–119]. Most research uses a combination of multiple objective functions, typically integrated through linear weighting. Notably, reference [120] describes multilayered optimization problems with distinct objectives for each layer.

The optimization methods for offshore wind farm power collection systems, as summarized in Table 7, can be divided into clustering algorithm, heuristic algorithm, metaheuristic algorithm, and global optimization algorithm. Artificial intelligence is mainly applied in heuristic and metaheuristic methods for optimization. Clustering algorithms segment wind turbines into smaller groups for system optimization. Heuristic algorithms, like Prim [121], Dijkstra, sequential Monte Carlo (SMC) [118], travelling salesman problem (TSP) [118,122,123], and minimum spanning tree (MST) [124,125], follow deterministic procedures to sequentially solve problems. Heuristic methods can be combined with

clustering algorithms to address their limitations. In reference [118], the agglomerative hierarchical clustering (AHC) algorithm is employed to obtain clustered combinations of wind turbines, and then the TSP method is used to evaluate the clustering effectiveness, thereby selecting suitable combinations of clustered wind turbines. Heuristic algorithms are typically only applicable to specific conditions and specific problems, while metaheuristics are designed to enhance traditional heuristic algorithms, making them simpler and more versatile. Commonly used metaheuristic algorithms include particle swarm optimization (PSO) [117,121,124,126–128], ant colony optimization (ACO) [122,123,129,130], and the genetic algorithm (GA) [130–132]. Metaheuristic algorithms offer flexibility in their application to various steps of the OWF collection system optimization process, such as optimizing OSS (offshore substation) locations and WT (wind turbine) topology connections, among others. Metaheuristic algorithms are simple and easy to use, but their results are stochastic. In contrast, global optimization methods typically yield deterministic results. Researchers propose different formulations based on practical requirements, categorized by equation types, including binary integer programming (BIP), mixed integer linear programming (MILP) [133–135], mixed integer quadratic programming (MIQP) [119,120], and others. Global optimization requires external solvers (e.g., CLPEX) to solve the problems, and their internals utilize algorithms such as Benders decomposition.



**Figure 5.** Power collection system optimization of offshore wind farms.

**Table 7.** Representative literature on power collection system optimization of offshore wind farms.

| Ref.  | Year | Objective                                                                                                                                                                           | Design Variables                                                                                                                                      | Method   | Contribution                                                                                                                                                            |
|-------|------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [117] | 2021 | Construction cost, reliability                                                                                                                                                      | WTs collection system, cable type                                                                                                                     | APSO     | The cost model considers the dynamic power cables of floating wind turbines.                                                                                            |
| [118] | 2022 | Construction cost, reliability                                                                                                                                                      | Location of OSSs, WTs collection system, interconnection OSSs to OCPs                                                                                 | AHC-SMC  | A SMC method is developed to estimate the reliability of the measurement system.                                                                                        |
| [119] | 2023 | Construction cost, power loss cost, reliability                                                                                                                                     | WTs collection system, cable type                                                                                                                     | GSA-MIQP | The proposed method is applicable to large-scale topology optimization problems. The time complexity of the method is analyzed in this paper.                           |
| [120] | 2022 | Layer 1:<br>Impact on onshore substations and construction cost of onshore substations<br>Layer 2:<br>Construction cost of OSSs and cable<br>Layer 3:<br>Construction cost of cable | Layer 1:<br>Location and capacity of onshore substations<br>Layer 2<br>Location and capacity of OSSs<br>Layer 3:<br>WTs collection system, cable type | MLQP     | For the first time, a detailed analysis from the perspective of grid planning is conducted on the concept of offshore grids that integrate offshore wind farm clusters. |

Table 7. Cont.

| Ref.  | Year | Objective                          | Design Variables                                    | Method                                                                            | Contribution                                                                                                                                                                            |
|-------|------|------------------------------------|-----------------------------------------------------|-----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [121] | 2023 | Construction cost, power loss cost | Location of OSSs, WTs collection system, cable type | Prim-PSO-AO                                                                       | The hybrid optimization method combines the search characteristics of both PSO and AO to enhance the search effectiveness.                                                              |
| [126] | 2023 | LCOE                               | Location of OSSs, WTs collection system, cable type | BPSO-IMCTS                                                                        | The reference establishes a lifecycle cost optimization model for floating wind farm collection systems considering environmental factors.                                              |
| [129] | 2023 | Construction cost                  | WTs collection system, cable type                   | ACO                                                                               | The reference proposes a novel optimization algorithm based on ant colony heuristics, enhancing computational performance through the introduction of problem decomposition techniques. |
| [131] | 2022 | LCCOE                              | Location of OSSs, WTs collection system, cable type | IPGA                                                                              | For the first time, the reference proposes an optimization model for series-parallel collection systems that considers curtailment.                                                     |
| [132] | 2021 | Construction cost, power loss cost | Location of OSSs, WTs collection system, cable type | Outer layer: FCM-GA<br>Inner layer: Two-phase Clark and Wright's saving algorithm | The reference combines GA with deterministic algorithms to enhance algorithm performance.                                                                                               |

Combining different algorithms can lead to the creation of new hybrid methods that blend the strengths of each to overcome their individual weaknesses. For instance, reference [119] proposes a hybrid approach combining the greedy search algorithm (GSA) with mixed integer quadratic programming (MIQP) for global optimization. This method uses GSA to find the optimal cable topology and then applies MIQP to solve subproblems like selection of the cable type. Other research [121] uses Prim's algorithm to generate quality initial solutions and then a hybrid PSO-AO algorithm for final optimization, addressing the limitations of heuristic algorithms.

In current research on optimizing offshore wind farm (OWF) power collection systems, artificial intelligence primarily plays a role in algorithmic problem-solving. Metaheuristic algorithms are predominant in this area. Hybrid methods, combining clustering, heuristic, metaheuristic, and global optimization approaches, are now the main focus. These methods blend the strengths of different algorithms to enhance the optimization of OWF power collection systems. Among them, the clustering algorithm is usually used to cluster wind turbine groups, the heuristic algorithm is usually used to quickly obtain the initial solution of the problem, and the further solution is usually completed by the metaheuristic algorithm and the global optimization algorithm. The trend is towards these hybrid methods, emphasizing the analysis of various algorithms' pros and cons and combining them effectively to meet specific requirements. This approach is crucial in advancing OWF power collection system optimization research.

#### 4. Conclusions

This article provides a comprehensive analysis of the current applications and advancements in artificial intelligence for controlling and designing offshore wind power systems. It delves into the control technologies for wind turbines, strategies for wake control in offshore wind farms, turbine selection, and optimization of wind farm layout and power collection systems. The evolving trends and developments in AI technology across these fields are highlighted, as follows:

- (1) Wind Turbine Control: Rapid development in wind turbine advanced control techniques is evident, especially in maximum power point tracking (MPPT) and fatigue load optimization. AI methods like neural networks, fuzzy logic control, and reinforcement learning have shown substantial benefits in optimizing turbine performance and adapting to complex marine conditions.

- (2) Wake Control in Offshore Wind Farms: Significant progress is made in effectively managing power maximization, load–power balance optimization, and scheduling issues in wind farms, especially through heuristic intelligent algorithms and deep reinforcement learning, enhancing wake control efficiency.
- (3) Turbine Selection: AI's role in this domain primarily revolves around solving algorithms, aiding in optimizing key design variables like turbine placement and rotor radius.
- (4) Layout Optimization: AI is applied mainly in constructing wake models and algorithmic problem-solving. ANN-based wake models speed up calculations while maintaining accuracy, enhancing solution efficiency. Metaheuristic algorithms and reinforcement learning are powerful tools for handling complex, large-scale layout optimization.
- (5) Power Collection System Optimization: Given the complexity, researchers often use hybrid methods. Combining clustering, heuristic, metaheuristic, and global optimization algorithms offers effective solutions for cost-optimization and system reliability.

As offshore wind power systems expand, AI's role in addressing control and design issues becomes increasingly crucial. Future trends and research opportunities may include:

- (1) Developing high-performance offshore wind power system simulation tools to enhance modeling methods and capabilities for various scenarios. For example, in the scenario of large-scale wind farm design, the data-driven model of wind farm internal wake is studied to speed up wind energy system simulation while ensuring certain accuracy.
- (2) Focusing on efficient data processing methods to manage and analyze vast wind farm data and enhancing existing algorithms to better handle complex, dynamic marine environments. For instance, deep learning is used to learn and process massive sensor data to predict possible environmental changes to improve the control performance of offshore wind power systems.
- (3) Creating standard models for case studies tailored to different regions and environments, providing benchmarks for comparing the effectiveness of various research solutions. For example, the types of offshore wind turbines suitable for marine environments with different depths may vary. Deep-sea areas typically require floating wind turbines, yet there is currently a lack of standardized case studies related to floating wind farms.
- (4) Ensuring technological innovations are economically viable and market-adaptable, including cost–benefit analysis, market policy research, and decision support for policymakers and investors. Deep learning technology may be helpful to fit and predict market data such as electricity price, providing reference for decision-makers in the wind energy industry.

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