Control Technology of Offshore Wind Power Systems

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Contributor: Dongran Song, Guoyang Shen, Chaoneng Huang, Qian Huang, Jian Yang, Mi Dong, Young Hoon Joo, Neven Duić

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.

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

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.

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.

2. 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.

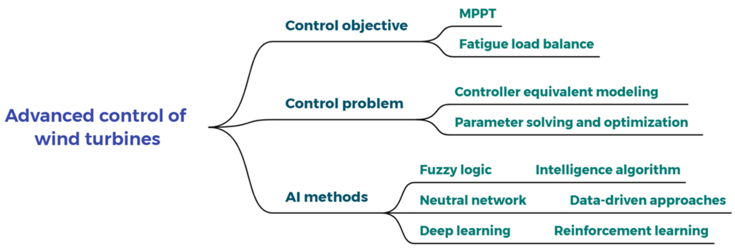

Figure 1. Advanced control of wind turbines.

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 research. Representative literature in this field is illustrated in **Table 1**.

Table 1. 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.

Ref.	Year	Objective	Decision Variable	Framework	Method	Contribution
[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].

3. 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.

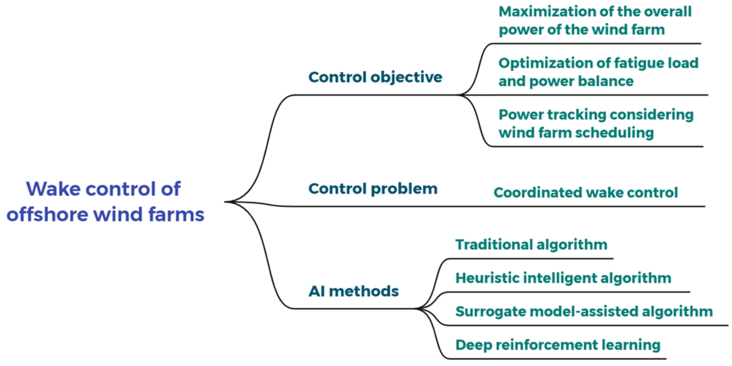

Figure 2. Wake control problem of offshore wind farms.

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 2**. These AI-based methods offer promising alternatives for optimizing complex wake control scenarios in wind farms.

Table 2. 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%.
[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%.

Ref.	Year	Objective	Decision Variable	Method	Contribution
[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][59][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.

References

1. Amin, A.Z.; Birol, D.F.; Zervos, D.A. Renewable Energy Policies in a Time of Transition; IRENA: Abu Dhabi, United Arab Emirates, 2018.
2. Yang, B.; Liu, B.; Zhou, H.; Wang, J.; Yao, W.; Wu, S.; Shu, H.; Ren, Y. A critical survey of technologies of large offshore wind farm integration: Summary, advances, and perspectives. Prot. Control Mod. Power Syst. 2022, 7, 233–264.
3. Chen, J.; Kim, M.-H. Review of Recent Offshore Wind Turbine Research and Optimization Methodologies in Their Design. JMSE 2021, 10, 28.
4. Global Wind Energy Council. Global Offshore Wind Report 2023; Global Wind Energy Council: Lisbon, Portugal, 2023.
5. Lakatos, L.; Hevessy, G.; Kovács, J. Advantages and Disadvantages of Solar Energy and Wind-Power Utilization. World Futures 2011, 67, 395–408.
6. Wang, Y.; Zou, R.; Liu, F.; Zhang, L.; Liu, Q. A Review of Wind Speed and Wind Power Forecasting with Deep Neural Networks. Appl. Energy 2021, 304, 117766.
7. Herbert-Acero, J.; Probst, O.; Réthoré, P.-E.; Larsen, G.; Castillo-Villar, K. A Review of Methodological Approaches for the Design and Optimization of Wind Farms. Energies 2014, 7, 6930–7016.
8. Civera, M.; Surace, C. Non-Destructive Techniques for the Condition and Structural Health Monitoring of Wind Turbines: A Literature Review of the Last 20 Years. Sensors 2022, 22, 1627.
9. Lei, J. Fault Diagnosis of Wind Turbine Based on Long Short-Term Memory Networks. Renew. Energy 2019, 133, 422–432.
10. Guediri, A.; Hettiri, M.; Guediri, A. Modeling of a Wind Power System Using the Genetic Algorithm Based on a Doubly Fed Induction Generator for the Supply of Power to the Electrical Grid. Processes 2023, 11, 952.
11. Song, D.; Fan, X.; Yang, J.; Liu, A.; Chen, S.; Joo, Y.H. Power Extraction Efficiency Optimization of Horizontal-Axis Wind Turbines through Optimizing Control Parameters of Yaw Control Systems Using an Intelligent Method. Appl. Energy 2018, 224, 267–279.
12. Song, D.; Liu, J.; Yang, Y.; Yang, J.; Su, M.; Wang, Y.; Gui, N.; Yang, X.; Huang, L.; Hoon Joo, Y. Maximum Wind Energy Extraction of Large-Scale Wind Turbines Using Nonlinear Model Predictive Control via Yin-Yang Grey Wolf

Optimization Algorithm. Energy 2021, 221, 119866.

13. Muñoz-Palomeque, E.; Sierra-García, J.E.; Santos, M. Wind Turbine Maximum Power Point Tracking Control Based on Unsupervised Neural Networks. J. Comput. Des. Eng. 2023, 10, 108–121.
14. Xie, J.; Dong, H.; Zhao, X. Data-Driven Torque and Pitch Control of Wind Turbines via Reinforcement Learning. Renew. Energy 2023, 215, 118893.
15. Sierra-Garcia, J.E.; Santos, M.; Pandit, R. Wind Turbine Pitch Reinforcement Learning Control Improved by PID Regulator and Learning Observer. Eng. Appl. Artif. Intell. 2022, 111, 104769.
16. Liu, Y.; Patton, R.J.; Shi, S. Actuator Fault Tolerant Offshore Wind Turbine Load Mitigation Control. Renew. Energy 2023, 205, 432–446.
17. Otmane Rachedi, M.; Larbi Saidi, M.; Arbaoui, F. MPPT Control Design for Variable Speed Wind Turbine. Int. J. Electr. Comput. Eng. 2020, 10, 4604.
18. Zambrana, P.; Fernández-Quijano, J.; Mayorga Rubio, P.M.; Fernandez-Lozano, J.J.; García-Cerezo, A. Development and Evaluation of Fuzzy Logic Controllers for Improving Performance of Wind Turbines on Semi-Submersible Platforms under Different Wind Scenarios. Appl. Sci. 2023, 13, 2422.
19. Dahbi, A.; Benmedjahed, M.; Khelfaoui, A.; Aoun, N.; Harrag, A.; Bouraiou, A.; Benlahbib, B.; Sara, K.; Abdeldjalil, S.; Necaibia, A.; et al. A Comparative Study between MPPT Using PI and Fuzzy Logic Control for Wind Turbine System. In Proceedings of the 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD), Sétif, Algeria, 6–10 May 2022; IEEE: Sétif, Algeria, 2022; pp. 1228–1233.
20. Saihi, L.; Ferroudji, F.; Berbaoui, B.; Koussa, K.; Roummani, K.; Bakou, Y. Sliding Mode Fuzzy MPPT Controller of a Wind Turbine System Based on DFIG. In Artificial Intelligence and Heuristics for Smart Energy Efficiency in Smart Cities; Hatti, M., Ed.; Lecture Notes in Networks and Systems; Springer International Publishing: Cham, Switzerland, 2022; Volume 361, pp. 604–612.
21. Debbabi, F.; Mehazzem, F.; Soubdhan, T. Genetic Algorithm-Based MPPT For Wind Power Conversion System: Study And Comparison with Conventional Method In Tropical Climate. In Proceedings of the 2023 5th Global Power, Energy and Communication Conference (GPECOM), Nevsehir, Turkey, 14–16 June 2023; IEEE: Nevsehir, Turkey, 2023; pp. 218–224.
22. Amine, H.M.; Abdelaziz, H.; Najib, E. Wind Turbine Maximum Power Point Tracking Using FLC Tuned with GA. Energy Procedia 2014, 62, 364–373.
23. Muñoz-Palomeque, E.; Sierra-García, J.E.; Santos, M. MPPT Control in an Offshore Wind Turbine Optimized with Genetic Algorithms and Unsupervised Neural Networks. In Artificial Intelligence Applications and Innovations; Maglogiannis, I., Iliadis, L., MacIntyre, J., Dominguez, M., Eds.; IFIP Advances in Information and Communication Technology; Springer Nature Switzerland: Cham, Switzerland, 2023; Volume 676, pp. 465–477.
24. Sun, H.; Qiu, C.; Lu, L.; Gao, X.; Chen, J.; Yang, H. Wind Turbine Power Modelling and Optimization Using Artificial Neural Network with Wind Field Experimental Data. Appl. Energy 2020, 280, 115880.
25. Samir, L.; Said, G.; Mustapha, D.; Youcef, S. A Neural MPPT Approach for a Wind Turbine. In Proceedings of the 2017 6th International Conference on Systems and Control (ICSC), Batna, Algeria, 7–9 May 2017; IEEE: Batna, Algeria, 2017; pp. 210–214.
26. Karthik, R.; Harsh, H.; Pavan Kumar, Y.V.; John Pradeep, D.; Pradeep Reddy, C.; Kannan, R. Modelling of Neural Network-Based MPPT Controller for Wind Turbine Energy System. In Control and Measurement Applications for Smart Grid; Suhag, S., Mahanta, C., Mishra, S., Eds.; Lecture Notes in Electrical Engineering; Springer Nature Singapore: Singapore, 2022; Volume 822, pp. 429–439.
27. Zhang, X.; Jia, J.; Zheng, L.; Yi, W.; Zhang, Z. Maximum Power Point Tracking Algorithms for Wind Power Generation System: Review, Comparison and Analysis; Wiley: Hoboken, NJ, USA, 2022.
28. Honarbari, A.; Najafi-Shad, S.; Pour, M.S.; Ajarostaghi, S.S.M.; Hassannia, A. MPPT Improvement for PMSG-Based Wind Turbines Using Extended Kalman Filter and Fuzzy Control System. Energies 2021, 14, 7503.
29. Wang, Y.; Duan, X.; Zou, R.; Zhang, F.; Li, Y.; Hu, Q. A Novel Data-Driven Deep Learning Approach for Wind Turbine Power Curve Modeling. Energy 2023, 270, 126908.
30. Chen, X.; Zhang, X.; Dong, M.; Huang, L.; Guo, Y.; He, S. Deep Learning-Based Prediction of Wind Power for Multi-Turbines in a Wind Farm. Front. Energy Res. 2021, 9, 723775.
31. Sierra-García, J.E.; Santos, M. Wind Turbine Pitch Control First Approach Based on Reinforcement Learning. In Intelligent Data Engineering and Automated Learning—IDEAL 2020; Analide, C., Novais, P., Camacho, D., Yin, H., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2020; Volume 12490, pp. 260–268.

32. Arianborna, M.; Faiz, J.; Erfani-Nik, A. MPPT Control of a PMSG Connected to the Wind Turbine Based on Deep Q-Network. In 2023 10th Iranian Conference on Renewable Energy & Distributed Generation (ICREDG); IEEE: Shahrood, Iran, 2023; pp. 1–5.

33. Sun, K.; Xu, Z.; Li, S.; Jin, J.; Wang, P.; Yue, M.; Li, C. Dynamic Response Analysis of Floating Wind Turbine Platform in Local Fatigue of Mooring. Renew. Energy 2023, 204, 733–749.

34. Zhao, R.; Su, Y.; Knudsen, T.; Bak, T.; Shen, W. Multi-Agent Model for Fatigue Control in Large Offshore Wind Farm. In 2008 International Conference on Computational Intelligence and Security; IEEE: Suzhou, China, 2008; pp. 71–75.

35. Yang, J.; Zheng, S.; Song, D.; Su, M.; Yang, X.; Joo, Y.H. Comprehensive Optimization for Fatigue Loads of Wind Turbines in Complex-Terrain Wind Farms. IEEE Trans. Sustain. Energy 2021, 12, 909–919.

36. Kheirabadi, A.C.; Nagamune, R. A Quantitative Review of Wind Farm Control with the Objective of Wind Farm Power Maximization. J. Wind Eng. Ind. Aerodyn. 2019, 192, 45–73.

37. Dong, H.; Xie, J.; Zhao, X. Wind Farm Control Technologies: From Classical Control to Reinforcement Learning. Prog. Energy 2022, 4, 032006.

38. Marden, J.R.; Ruben, S.D.; Pao, L.Y. A Model-Free Approach to Wind Farm Control Using Game Theoretic Methods. IEEE Trans. Control Syst. Technol. 2013, 21, 1207–1214.

39. Gebraad, P.M.O.; Teeuwisse, F.W.; van Wingerden, J.W.; Fleming, P.A.; Ruben, S.D.; Marden, J.R.; Pao, L.Y. Wind Plant Power Optimization through Yaw Control Using a Parametric Model for Wake Effects—A CFD Simulation Study. Wind Energy 2016, 19, 95–114.

40. Annoni, J.; Bay, C.; Taylor, T.; Pao, L.; Fleming, P.; Johnson, K. Efficient Optimization of Large Wind Farms for Real-Time Control. In Proceedings of the 2018 Annual American Control Conference (ACC), Milwaukee, WI, USA, 27–29 June 2018; IEEE: Milwaukee, WI, USA, 2018; pp. 6200–6205.

41. Park, J.; Law, K.H. Cooperative Wind Turbine Control for Maximizing Wind Farm Power Using Sequential Convex Programming. Energy Convers. Manag. 2015, 101, 295–316.

42. Xu, Z.; Chu, B.; Geng, H.; Nian, X. Distributed Power Optimization of Large Wind Farms Using ADMM for Real-Time Control. IEEE Trans. Power Syst. 2022, 37, 4832–4845.

43. Shu, T.; Song, D.; Joo, Y.H. Non-Centralised Coordinated Optimisation for Maximising Offshore Wind Farm Power via a Sparse Communication Architecture. Appl. Energy 2022, 324, 119705.

44. Su, Y.; Li, Q.; Duan, B.; Wu, Y.; Tan, M.; Qiao, H. A Coordinative Optimization Method of Active Power and Fatigue Distribution in Onshore Wind Farms. Int. Trans. Electr. Energy Syst. 2017, 27, e2392.

45. Gu, B.; Zhang, Y.; Ren, Y.; Liu, Y. Wake Distribution Calculation and Optimization Control Method for Wind Farms. Autom. Electr. Power Syst. 2017, 41, 124–129.

46. Chen, Y.; Joo, Y.-H.; Song, D. Modified Beetle Annealing Search (BAS) Optimization Strategy for Maxing Wind Farm Power through an Adaptive Wake Digraph Clustering Approach. Energies 2021, 14, 7326.

47. Chen, Y.; Joo, Y.H.; Song, D. Multi-Objective Optimisation for Large-Scale Offshore Wind Farm Based on Decoupled Groups Operation. Energies 2022, 15, 2336.

48. Yang, J.; Huang, C.; Song, D.; Dong, M.; Chen, S.; Hu, Y.; Fang, F. Distributed Optimization Method for Operation Power of Large-scale Offshore Wind Farm Based on Two-step Processing. Autom. Electr. Power Syst. 2023, 47, 94–104.

49. Stanfel, P.; Johnson, K.; Bay, C.J.; King, J. A Distributed Reinforcement Learning Yaw Control Approach for Wind Farm Energy Capture Maximization. In Proceedings of the 2020 American Control Conference (ACC), Denver, CO, USA, 1–3 July 2020; IEEE: Denver, CO, USA, 2020; pp. 4065–4070.

50. Zhao, H.; Zhao, J.; Qiu, J.; Liang, G.; Dong, Z.Y. Cooperative Wind Farm Control With Deep Reinforcement Learning and Knowledge-Assisted Learning. IEEE Trans. Ind. Inform. 2020, 16, 6912–6921.

51. Dong, H.; Zhang, J.; Zhao, X. Intelligent Wind Farm Control via Deep Reinforcement Learning and High-Fidelity Simulations. Appl. Energy 2021, 292, 116928.

52. Dong, H.; Zhao, X. Composite Experience Replay-Based Deep Reinforcement Learning With Application in Wind Farm Control. IEEE Trans. Control Syst. Technol. 2022, 30, 1281–1295.

53. Xie, J.; Dong, H.; Zhao, X.; Karcanias, A. Wind Farm Power Generation Control Via Double-Network-Based Deep Reinforcement Learning. IEEE Trans. Ind. Inform. 2022, 18, 2321–2330.

54. Vijayshankar, S.; Stanfel, P.; King, J.; Spyrou, E.; Johnson, K. Deep Reinforcement Learning for Automatic Generation Control of Wind Farms. In Proceedings of the 2021 American Control Conference (ACC), New Orleans, LA, USA, 25–28 May 2021; IEEE: New Orleans, LA, USA, 2021; pp. 1796–1802.

55. Dong, H.; Zhao, X. Wind-Farm Power Tracking Via Preview-Based Robust Reinforcement Learning. IEEE Trans. Ind. Inform. 2022, 18, 1706–1715.
56. Song, D.; Shen, X.; Huang, C.; Yang, J.; Dong, M.; Liu, J.; Li, Q. Power Optimization of Floating Offshore Wind Farm Based on Surrogate-assisted Standard Particle Swarm Algorithm. Proc. CSEE 2023, 43, 217–228.
57. Song, D.; Shen, X.; Gao, Y.; Wang, L.; Du, X.; Xu, Z.; Zhang, Z.; Huang, C.; Yang, J.; Dong, M.; et al. Application of Surrogate-Assisted Global Optimization Algorithm with Dimension-Reduction in Power Optimization of Floating Offshore Wind Farm. Appl. Energy 2023, 351, 121891.
58. Park, J.; Kwon, S.-D.; Law, K. A Data-Driven, Cooperative Approach for Wind Farm Control: A Wind Tunnel Experimentation. Energies 2017, 10, 852.
59. Park, J.; Law, K.H. A Bayesian Optimization Approach for Wind Farm Power Maximization. In Smart Sensor Phenomena, Technology, Networks, and Systems Integration 2015; International Society for Optics and Photonics: Bellingham, WA, USA, 2015; Volume 9436, p. 943608.
60. Park, J.; Law, K.H. Bayesian Ascent: A Data-Driven Optimization Scheme for Real-Time Control With Application to Wind Farm Power Maximization. IEEE Trans. Control Syst. Technol. 2016, 24, 1655–1668.
61. Park, J. Contextual Bayesian Optimization with Trust Region (CBOTR) and Its Application to Cooperative Wind Farm Control in Region 2. Sustain. Energy Technol. Assess. 2020, 38, 100679.
62. Doekemeijer, B.M.; Hoek, D.C.V.D.; Wingerden, J.-W.V. Model-Based Closed-Loop Wind Farm Control for Power Maximization Using Bayesian Optimization: A Large Eddy Simulation Study. In In Proceedings of the 2019 IEEE Conference on Control Technology and Applications (CCTA), Hong Kong, China, 19–21 August 2019; IEEE: Hong Kong, China, 2019; pp. 284–289.
63. Liu, J.; Cao, M. Optimal Control of Wind Farm Power Maximization Considering Wake Effect. Electr. Drive 2020, 50, 54–58.
64. Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A.A.; Veness, J.; Bellemare, M.G.; Graves, A.; Riedmiller, M.; Fidjeland, A.K.; Ostrovski, G.; et al. Human-Level Control through Deep Reinforcement Learning. Nature 2015, 518, 529–533.
65. Xu, Z.; Geng, H.; Chu, B.; Qian, M.; Tan, N. Model-Free Optimization Scheme for Efficiency Improvement of Wind Farm Using Decentralized Reinforcement Learning. IFAC-Pap. 2020, 53, 12103–12108.
66. Stanfel, P.; Johnson, K.; Bay, C.J.; King, J. Proof-of-Concept of a Reinforcement Learning Framework for Wind Farm Energy Capture Maximization in Time-Varying Wind. J. Renew. Sustain. Energy 2021, 13, 043305.
67. Chen, G.; Zhang, K.; Xue, X.; Zhang, L.; Yao, C.; Wang, J.; Yao, J. A Radial Basis Function Surrogate Model Assisted Evolutionary Algorithm for High-Dimensional Expensive Optimization Problems. Appl. Soft Comput. 2022, 116, 108353.
68. Hulsman, P.; Andersen, S.J.; Göçmen, T. Optimizing Wind Farm Control through Wake Steering Using Surrogate Models Based on High-Fidelity Simulations. Wind Energy Sci. 2020, 5, 309–329.