Sustainable Energy Technologies and Assessments 87 (2026) 104888

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Review article

# A comprehensive framework for data challenges and intelligent resource optimization for offshore wind energy

Yucheng Lyu, Hao Chen *, Devrim Murat Yazan

*IEBIS, Department of High-tech Business and Entrepreneurship, Faculty of Behavioural, Management and Social Sciences, University of Twente, the Netherlands*

ARTICLE INFO

*Keywords:*
Offshore wind energy
Renewable energy
Data-driven
Sustainable development
Circular economy

ABSTRACT

Offshore wind parks are central to the global energy transition, yet efficiently utilizing resources remains challenging. This review synthesizes data-driven approaches for improving offshore wind system performance, covering natural resources (e.g., wind and meteorological conditions) and artificial resources (e.g., turbines and supporting infrastructure). Three recurring data challenges—data imbalance, distribution shift, and data sparsity—are identified as key constraints in wind power forecasting, turbine layout optimization, and maintenance planning. For natural resource management, machine learning and deep learning models enhance wind and power forecasting under highly variable offshore conditions, while surrogate modeling and spatial optimization reduce wake losses and layout costs. Across representative studies, hourly and daily capacity-factor prediction errors are typically reduced by around 10% and 15–20%, respectively. For artificial resources, data-driven lifecycle management and preventive maintenance increasingly rely on SCADA data, sensor networks, and digital twins to assess equipment health and mitigate operational risks, although limited failure data remains a major bottleneck. Existing evidence suggests maintenance cost reductions of approximately 20–30%. Beyond operational efficiency, this review examines the integration of sustainability and circular-economy principles into offshore wind development, including material recycling, component lifetime extension, and wind-to-hydrogen integration. Overall, effective data-driven optimization depends on advanced algorithms, high-quality data, and system integration. By linking data challenges with circular-economy objectives, this study proposes a unifying framework to support intelligent and sustainable offshore wind systems.

## Introduction

Reducing reliance on fossil fuels and transitioning to renewable energy sources has become a global priority [1]. Offshore wind parks, characterized by abundant wind resources, stable wind speeds, and minimal land occupation, have become a key part of renewable energy development. By 2024, global offshore wind capacity reached a considerable level and will play a vital part in the future energy system [2]. According to the Renewable Energy Pulse report, by February 2025, the global operational offshore wind installed capacity had reached 80.9 GW, with an additional 22.7 GW under construction. China dominates the sector, contributing over 50% of the global installed capacity (41 GW), followed by the United Kingdom with 14.7 GW. Driven by continuous advancements in wind energy technology, favorable policies, and financial investments, offshore wind parks, with their advantages of abundant resources and stable wind speeds, will significantly increase their installed capacity and become an essential direction for optimizing the future energy structure [3].

Despite these advancements, the efficient utilization of wind resources, as well as the operational efficiency and sustainability of offshore wind parks, remain formidable challenges. The performance of offshore wind parks heavily depends on favorable environmental

*Abbreviations:* ANN, Artificial Neural Network; ARIMA, Autoregressive Integrated Moving Average; CFD, Computational Fluid Dynamics; CNN, Convolutional Neural Networks; ConvLSTM, Multi-layered convolutional long short-term memory; GAN, Generative Adversarial Networks; GBM, Gradient Boosting Machines; GWEC, Global Wind Energy Council; ISO-NE, Independent System Operators New England; K-NN, K-Nearest Neighbors; LCA, Life Cycle Assessment; LCCA, Life Cycle Cost Assessment; LHS, Latin Hypercube Sampling; LiDAR, Laser Imaging Detection and Ranging; LSTM, Long Short-Term Memory Networks; MMD, Maximum Mean Discrepancy; O&M, Operation and Maintenance; ONS, The National Operator of the Electric System; OPEX, Overall Operational Expenditure; RF, Random Forest; SARIMA, Seasonal ARIMA; SCADA, Supervisory Control and Data Acquisition; SVM, Support Vector Machines.

* Corresponding author.
*E-mail address:* h.chen-3@utwente.nl (H. Chen).

https://doi.org/10.1016/j.seta.2026.104888
Received 2 October 2025; Received in revised form 6 February 2026; Accepted 14 February 2026
Available online 17 February 2026

conditions and state-of-the-art technological infrastructure [4]. Furthermore, these available resources generate vast datasets, including equipment status, meteorological conditions, and power generation performance, making data management and analysis a key component of offshore wind parks [5]. Nonetheless, the presentation format of the available data presents specific challenges. Effectively utilizing this data are imperative for optimizing resource allocation, refining operational strategies, and ensuring the long-term sustainability of offshore wind energy. Addressing these challenges requires integrating advanced data-driven approaches to enhance decision-making and predictive capabilities.

Offshore wind power is pivotal in optimizing the global energy structure. With the increasing digitalization of energy, advanced data processing and analytical techniques have become essential. This study investigates the key data challenges associated with offshore wind park resource utilization and explores potential solutions. This research systematically analyses data-related issues and provides insights into practical strategies for leveraging data-driven methodologies to enhance resource allocation and power generation efficiency.

*Contribution.* This paper makes several contributions to the field of offshore wind energy management. First, it proposes a structured classification framework that distinguishes natural and artificial resources within offshore wind parks. This framework enables a clearer understanding of resource characteristics and supports more targeted optimization strategies. Second, it systematically identifies and analyzes three core data challenges—imbalance, distribution change, and sparsity—which are often overlooked yet critical in applying data-driven methods across the wind park lifecycle. By mapping these challenges to specific application scenarios such as forecasting, layout design, and maintenance, the paper offers a practical lens for improving data reliability and model robustness. Third, it extends the discussion to sustainability and circular economy perspectives, positioning offshore wind parks not only as energy producers but also as active participants in resource recovery and long-term environmental stewardship. By linking data-driven technologies with resource reuse, component lifespan extension, and wind-hydrogen integration, the study outlines feasible paths toward a more resilient and low-impact offshore wind ecosystem. These advancements can improve the economic benefits of wind parks and promote the intelligent transformation of the wind power industry.

Fig. 1 presents the global offshore wind park installed capacity distribution based on the Global Wind Energy Council (GWEC) data. Fig. 2 illustrates the global offshore wind installed capacity trends from 2009 to 2023, as reported by Statista, along with the cumulative offshore wind capacity distribution by country/region in 2023. The overall trend indicates a continuous expansion of offshore wind capacity worldwide. China remains at the forefront of offshore wind park development, driven by environmental policies. European countries are also accelerating their offshore wind power infrastructure expansion, with the United Kingdom positioning wind energy as a cornerstone of its future energy system. Other nations are integrating offshore wind into their national energy strategies to enhance energy sustainability.

To collect relevant literature on data-driven issues in offshore wind parks, we searched for relevant records in the Scopus database. The search terms are as follows: *("offshore wind park" OR "offshore wind power" OR "offshore wind turbines layout" OR "offshore wind park preventive maintenance" OR "offshore wind park lifecycle management" OR "offshore wind park sustainable") AND (data-driven OR data)*. A total of 969 papers were collected, including 808 papers in English. To further limit the scope of analysis, only papers published in international academic journals are considered, and the time frame is set from 2015 to present. There are a total of 385 articles. In addition, some papers were excluded from analysis due to the inability to obtain the full text. The final database contains 214 papers. The overall review process is presented in the form of Fig. 3.

This paper is structured into six sections. Section 1 introduces fundamental concepts, including offshore wind park resource classification (1.1) and key data challenges (1.2). Section 2 explores data-driven optimization approaches for managing natural resources, focusing on wind energy forecasting and wind turbine layout optimization. Section 3 examines data-driven optimization in artificial resource management, explicitly discussing equipment lifecycle management and preventive maintenance. Section 4 analyzes the application of sustainability and circular economy principles in offshore wind parks. Section 5 discusses the challenges and opportunities associated with offshore wind power generation under data-driven problems. Finally, Section 6 concludes the study.

### *Natural and artificial resources for offshore wind parks*

The efficient operation and economic viability of offshore wind parks depend on a comprehensive understanding and optimal utilization of available resources. In constructing offshore wind parks, natural environmental factors, such as wind, meteorological, and oceanographic conditions, and artificial resources, including wind turbines and support

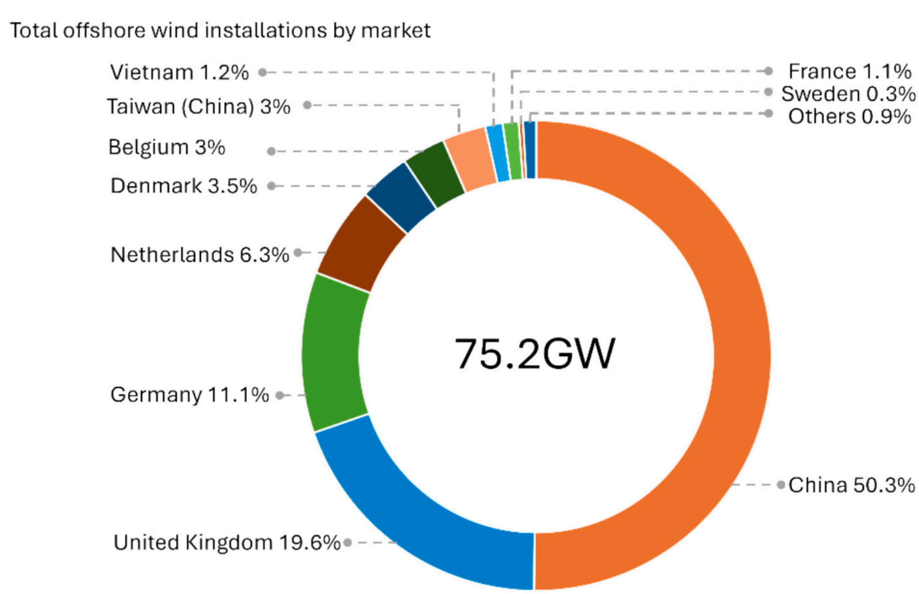


**Fig. 1.** Proportion of global wind park installed capacity by market.

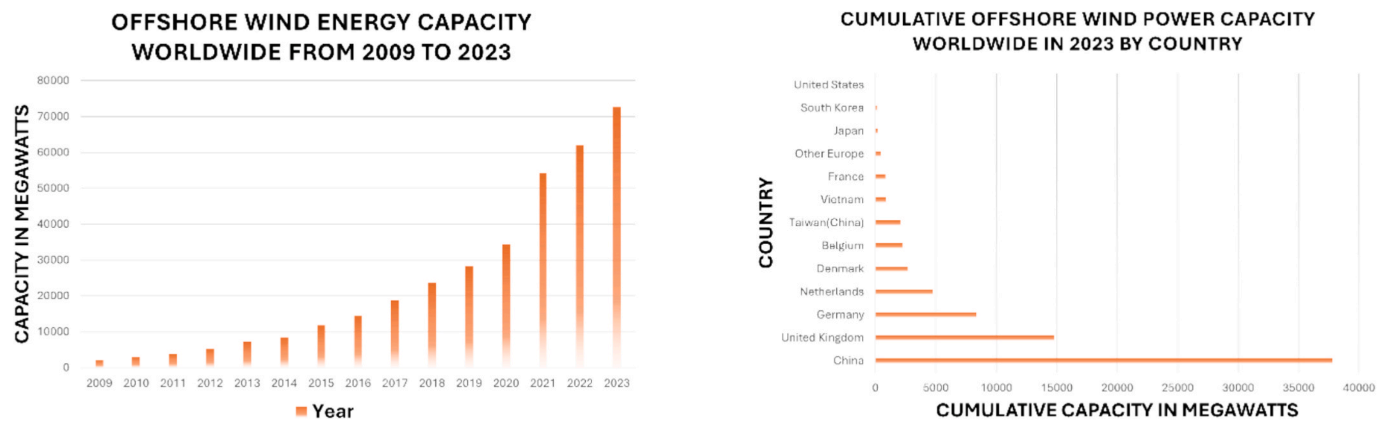


**Fig. 2.** Global trend chart of offshore wind energy installed capacity and 2023 global cumulative offshore wind power installed capacity chart.

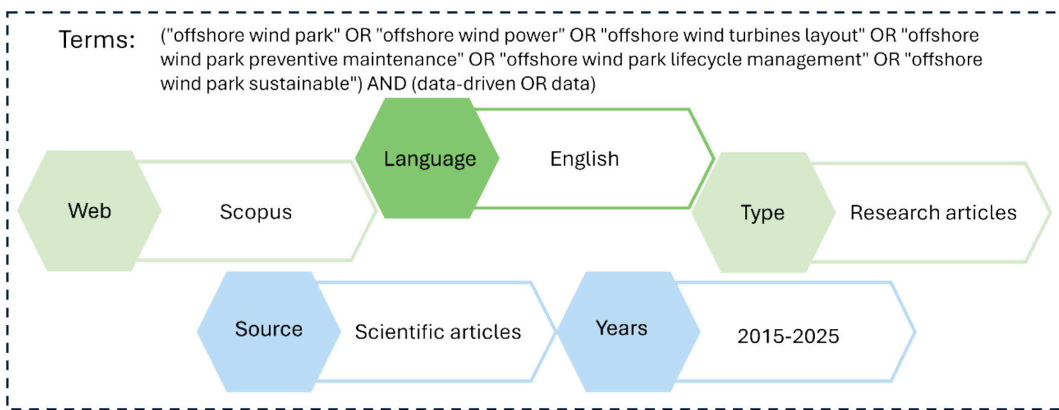


**Fig. 3.** Overview of the review process.

structures, must be considered. To systematically categorize offshore wind park resources, we adopt the classification framework proposed by the United Nations Environment Programme, which divides resources into natural and artificial. Natural resources refer to environmental factors and conditions that generate economic value under specific temporal and technological constraints, thereby contributing to human welfare [6]. Although no universally accepted definition for artificial resources, they are generally understood as human-created or modified resources, including infrastructure, mechanical equipment, and technological systems. In offshore wind park research, we propose classifying resources into natural and artificial resources, which provides a clearer understanding of the characteristics and management strategies for different types of resources.

Natural resources form the fundamental basis for offshore wind power generation, primarily wind, meteorological, and oceanographic resources [7]. Among these, wind resources are the most critical, including wind speed, direction, and power density, which directly determine turbine efficiency and stability [8]. Additionally, seasonal and diurnal variations in wind energy significantly influence power generation. In the Mediterranean and Black Sea regions, wind speeds are most vigorous during the winter months of December to February, while the Sea of Marmara and Alboran Sea exhibit the most pronounced diurnal variations in wind power density [9]. Meteorological resources such as temperature, atmospheric pressure, humidity, and precipitation indirectly affect turbine performance and wind energy conversion efficiency [10]. Oceanographic resources, including waves, tides, seawater corrosion, and ice formation, place stringent demands on offshore wind infrastructure's structural stability, durability, and operational safety [11]. Among natural resources, wind speed and direction are the most critical factors in wind power generation. Wind speed determines the rotational velocity of wind turbine blades and their power output, with higher wind speeds significantly increasing energy generation efficiency [12]. Wind direction influences the adjustment angle of wind turbines to capture maximum wind energy. For example, a study by the University of Minnesota found that counterclockwise wind turbines are more efficient in regions dominated by veering-veering and veering-backing conditions, whereas clockwise wind turbines are preferable under opposite conditions [13]. Assessing and optimizing natural resources are fundamental in wind energy forecasting, wind park site selection, and operational management, aiming to maximize power generation efficiency and minimize energy losses.

On the other hand, artificial resources include wind turbines and associated infrastructure [14]. These primarily consist of wind turbines, converters, cable systems, foundation support structures, and monitoring and control systems within the wind park. These resources involve data on turbine performance, equipment status, and maintenance activities [15], which are crucial for optimizing turbine layout, improving operational efficiency, and implementing predictive maintenance strategies. Among artificial resources, wind turbines are the core equipment for converting wind energy into electrical power, and their design and operational status directly impact power generation performance [16]. Furthermore, support structures must be carefully selected based on water depth and environmental conditions to ensure stability in harsh marine environments. Fixed structures are suitable for deployment near coastlines with uncomplicated seabeds, while floating wind turbines are better suited for deep-sea or complex seabed locations. Fixed structures are ideal for deployment near coastlines with uncomplicated seabeds, while floating wind turbines are better suited for deep-sea or complex seabed locations [17]. Additionally, advanced technologies such as SCADA and equipment condition monitoring systems provide real-time monitoring and data acquisition capabilities, facilitating intelligent and data-driven management of the wind park. For example, researchers at Jeju National University developed a wind power prediction model by integrating Laser Imaging Detection and Ranging (LiDAR) and SCADA data with deep learning algorithms, achieving an average forecast accuracy of 6.8% within a 3-hour prediction interval, with an output error ranging from 3.11% to 10.95% [18]. In the latest research, researchers used SCADA data for Gaussian process regression analysis bending moment response prediction of offshore wind turbine, and its reliability was verified [19]. Wang et al. integrated on-site experiments with SCADA drive to quantify power and yaw angle distributions. The results show that mean absolute changes of 6.9% in power and 10.5% in flapwise DEL [20].

*What are the data issues in utilizing offshore wind park resources?*

Data collected from any source may suffer from incompleteness, noise, and inconsistencies, leading to challenges in data analysis and processing. Data-related issues primarily manifest as overload, scarcity, and incomplete data [21]. Once the resources in offshore wind parks are identified, relevant data are collected through various monitoring instruments. Introducing data-driven technologies can significantly enhance wind energy forecasting, equipment management, and system optimization accuracy and efficiency. However, extracting accurate and usable information from complex, diverse natural and artificial resource datasets remains challenging. So, what specific data issues exist in the utilization of resources in offshore wind parks?

*Data skewness and imbalance:* When datasets exhibit an uneven distribution across different classes, models tend to be biased toward the dominant class, reducing predictive performance for minority-class data [22]. In offshore wind parks, wind speed and direction data are often concentrated in the low-to-medium range, making it difficult to obtain reliable data on extreme wind speeds. This results in increased prediction errors under extreme weather conditions, where the output characteristics of wind power cannot be ignored. Similarly, in equipment monitoring data, normal operating conditions are typically over-represented compared to fault conditions, making it challenging for models to detect early failure patterns. Such imbalances in dataset composition pose significant obstacles to accurate predictive modeling.

*Data distribution change:* Also known as "*concept drift*," data distribution change occurs when the statistical properties of data change over time [23]. For example, during summer, weaker wind speeds may result in wind turbines operating at low loads and reduced power output. In contrast, winter months may bring higher power generation levels due to stronger winds. Additionally, as wind turbines age, their efficiency declines, causing a gradual reduction in overall power generation. These evolving distributions complicate model training, as algorithms trained on historical data may become less effective when applied to new conditions.

Data sparsity refers to missing or low-density data, where information is either unavailable or insufficiently sampled [24]. Offshore wind parks operate in highly dynamic environments influenced by sudden weather changes, tides, and waves, leading to drastic fluctuations in turbine operational states. Since these fluctuations are often unpredictable, specific periods may have extremely sparse data records. Furthermore, low-frequency sampling further exacerbates sparsity along the time dimension. Sparse datasets hinder accurate resource allocation and operational optimization, making it necessary to develop strategies to compensate for missing information.

The mentioned data issues—data skewness and imbalance, data distribution change, and data sparsity—persist throughout the entire lifecycle of offshore wind parks, posing critical challenges for data-driven approaches. Fig. 4 illustrates the application of data-driven technologies in the resource utilization of offshore wind parks from a technical perspective. We rely on high-quality datasets to investigate the resource characteristics of offshore wind parks and their influencing factors. Current research typically relies on several main categories of data: *i.* Wind park operational data. The most representative source is the SCADA system, which records real-time turbine operating status, power output, wind speed and direction, blade pitch angle, temperature, vibration, and other multidimensional parameters. These data are automatically collected at second-level or minute-level intervals and transmitted to the wind park control center via fiber-optic or satellite links. *ii.* O&M data. Maintenance personnel use mobile terminals or handheld diagnostic devices to log inspection results. Critical components are equipped with RFID or QR code tags to automatically record replacement and repair information. *iii.*Structural health monitoring data. Fiber Bragg grating sensors, strain gauges, laser displacement sensors, accelerometers, and internal blade stress sensor networks are installed on the tower and blade surfaces. These sensors continuously transmit stress, fatigue, and vibration measurements through wired fiber-optic or wireless networks, with initial processing performed by edge-computing units. Table 1 summarizes the currently available and representative offshore wind energy-related data resources, categorizing them into natural and artificial resource datasets. It also outlines the data indicators and characteristics of each dataset. Due to the regional nature of wind energy resource distribution, the availability of datasets varies across different countries on a global scale. Although the datasets

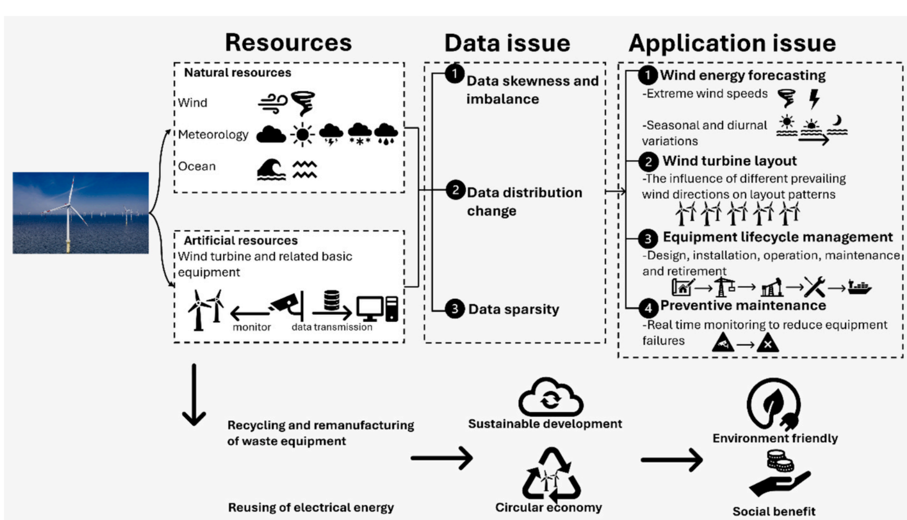


**Fig. 4.** Application technology perspective on resource utilization of offshore wind parks based on data-driven issues.

**Table 1**
Classification and Data Indicators of Public Dataset.

| Type | Data set | Main indicators | Data problem |
|---|---|---|---|
| Natural Resource Dataset | Global Wind Atlas | Wind Energy Class, Wind Speed, Power Density | Mainly based on numerical simulations, lacking actual measurement data；Unable to reflect detailed changes in local wind resources. |
| | OpenEI Dataset | Wind Map, Meteorological Data, Wind Power Maps | Data sources are unbalanced and primarily focused on the United States；Some datasets have low update frequencies and may be outdated. |
| | ZONDA | Wind Speed, Wind Direction, Air Temperature | Mainly targets Brazilian wind resources, with limited global applicability; Data from some measurement stations is sparse, affecting modeling accuracy. |
| | Ethiopia Wind Measurement Data | Daily Wind Speed, Wind Direction, Air Pressure, Relative Humidity, Air Temperature | Limited coverage, including only wind energy data from Ethiopia; The dataset update frequency is low and may be outdated. |
| | Dutch Offshore Wind Atlas | Wind Speed, Wind Direction, Air Pressure, Relative Humidity, Air Temperature | The dataset spans from 2008 to 2017 and is outdated, providing a low reference value; Reliance on meteorological models and satellite data may introduce estimation errors; Wind resource estimates under extreme weather conditions are not precise. |
| | National Renewable Energy Laboratory | Wind Speed, Wind Direction, Air Pressure, Wind Generation, Turbine Capacity, Turbine State | Some datasets are limited to the United States, restricting their global applicability; Some datasets are subject to confidentiality restrictions and cannot be fully accessed. |
| Artificial Resource Dataset | United States Wind Turbine Database | Location, Turbine State, Project Online Year, Turbine Capacity, Turbulence Velocity | Only includes U.S. wind turbine data, making it unsuitable for global analysis; Data updates may lag, making reflecting the latest wind power installation trends difficult. |
| | The Wind Power | Region, Location, Turbine Model, Turbine State, Generator Speed, and Temp | Integrated from multiple sources, resulting in uneven data quality; Some regional wind park information is incomplete and lacks key data such as operational status. |
| | UK Wind Energy Database | Energy Produced, CO2 Reductions(per year) in Tonnes | Not available for download; Mainly focused on the UK market, with limited international applicability; Historical data for some wind parks is incomplete, affecting long-term trend analysis. |
| | Sotavento Wind Park | Wind Speed, Wind Direction, Turbines' Production, Capacity Factor, Air Temperature, Air Density | The dataset is limited to a single wind park, reducing its representativeness; Measurement data may be affected by equipment maintenance and environmental changes. |
| | EDP Wind Park | Wind Speed, Wind Direction, Generator Speed and Temp, Failure Logs, Air Temperature, Air Pressure, Humidity, Precipitation | Focused on specific wind asset management with low data openness; Wind speed and power generation data may not be suitable for general research. |
| | Global Energy Monitor | Region, Turbine State, Turbine Capacity | Mainly relies on public sources and estimates, potentially leading to low data accuracy; Some wind project data lacks detailed technical parameter information. |

used in this study do not cover all countries, they represent the current accessibility of offshore wind energy data worldwide. The paper contributes to a review of offshore wind park resources, identifies key data-related challenges, and explores how data-driven methodologies can enhance model robustness and adaptability to optimize resource utilization.

## Applications in natural resources based on data-driven problems

Natural resources are the key factor for improving the efficiency of offshore wind parks, and this process heavily relies on high-quality wind resource data. Such data are typically derived from on-site measurements, satellite remote sensing, and numerical weather prediction models. The diverse sources of wind data present significant challenges when applying data-driven methods to analyze their impact on offshore wind energy generation. The characteristics of natural resources in offshore wind parks lead to different forms of data representation:

1) Variability: Wind speed and direction are influenced by geographic location, meteorological conditions, and seasonal changes, exhibiting significant temporal fluctuations. For example, wind speeds are generally higher in winter than summer, and daily wind speeds fluctuate over time. (In the UK, wind power generation is higher in winter and lower in summer, correlating with seasonal electricity demand fluctuations) [25]. Additionally, interannual variations, such as the El Niño phenomenon, impact wind resource stability. For example, during warm phases, wind speeds and power generation in some wind parks in north-central Chile decrease by 4% to 12% [26].

2) Regional differences: Wind speed and direction vary significantly. For example, the North Sea region, characterized by low altitude, flat terrain, and consistently strong winds, has become Europe's central offshore wind hub. According to European Wind Energy Association statistics, Northern European countries invest heavily in offshore wind due to higher and more stable wind speeds. The Irish and North Seas hold Northern Europe's most significant offshore wind potential. In contrast, the Aegean Sea, southern France, and southern Spain are the most suitable regions for offshore wind deployment in Southern Europe. [27]. In contrast, coastal areas in East Asia are more affected by typhoons and exhibit more significant seasonal variability in wind energy

resources [28]. These regional differences necessitate site-specific considerations for wind park location and equipment design.

3) Complexity and uncertainty: Wind resources' complexity is further reflected in their interactions with other natural factors. For instance, marine environments' temperature gradients and humidity fluctuations influence wind field formation and stability [29]. Researchers applied the Typical Meteorological Year approach in the Caribbean region of Colombia, incorporating multiple meteorological parameters to evaluate wind resource potential and produce highly representative and accurate data [30].

This section explores how data-driven methods can address these challenges in wind energy forecasting and turbine layout optimization while reviewing the latest research advancements in these areas.

### *Data-driven issues in wind energy forecasting*

Wind energy forecasting involves estimating future wind speed, wind direction, and wind power generation at a specific moment or over a defined period, based on historical data and real-time monitoring [31]. Based on the prediction time scale, we categorize predictions into ultra-short-term, short-term, medium-term, and long-term forecasts. In terms of prediction methods, with the development of artificial intelligence technology, researchers have gradually transitioned from traditional numerical and statistical methods to machine learning approaches and, more recently, deep learning methods for solving wind energy prediction problems. This can better leverage the ability of artificial intelligence technology to improve predictive performance in wind energy forecasting.

In wind energy forecasting, commonly used datasets include meteorological data centered on wind speed and wind direction, historical power generation data, and equipment operational data (such as blade pitch angle and generator status). In recent years, numerous researchers have conducted extensive studies on wind energy forecasting, continuously optimizing prediction models and data processing methods to enhance prediction accuracy and adaptability. Table 2 summarizes the methods employed in various studies on wind energy forecasting, along with the data issues they address. It also evaluates the applicability and limitations of each method, providing a reference for future research.

Wind energy forecasting heavily relies on high-quality wind speed data. However, several challenges arise due to the characteristics of wind data. Firstly, wind speed data are predominantly concentrated in the low-to-medium range, while high and extreme wind speed data are relatively scarce. This imbalance makes it difficult for models to accurately predict wind energy output under extreme conditions, limiting their generalizability. Second, seasonal and diurnal variations cause short-term and long-term data distribution change, potentially rendering models trained on historical data ineffective in new environments. Additionally, limitations in equipment data collection may lead to missing wind speed and power data for certain time periods or sparse data in specific wind speed ranges, affecting prediction stability. Finally, significant differences in wind energy data distribution across geographical locations make it challenging to integrate cross-regional

**Table 2**
Analysis of Different Studies on Wind Energy Forecasting.

| Researcher | Methods&Data | Solved data issues | Main achievements | Summary |
|---|---|---|---|---|
| Zi Lin, et al. [99] | Deep learning neural network + SCADA data | Data skewness and imbalance | 1. Predict the power of wind turbines;<br>2. Resolve variability issues and detect errors in SCADA databases.<br>3. Use the Isolation Forest algorithm to identify anomalies in wind power measurement data. Remove 5% of outliers to improve prediction accuracy. | Solved the issue of outliers in SCADA data but relies on high-quality datasets, making it difficult to apply in scenarios where data are extremely scarce. |
| Liam Hayes et al. [100] | Global Wind Atlas performs deviation correction + ERA5 weather data | Data distribution change | 1. Modeling the long-term hourly wind power generation of a single offshore wind park;<br>2. Analyze the impact of wind speed, seasonal variations, and diurnal data drift on prediction accuracy.<br>3. Adjust the wind turbine power curve to convert interpolated wind speeds into capacity factors. The root mean square error is reduced by 10% (hourly scale) and 18% (daily scale), while the annual power generation forecast error decreases to 7.0%. | A strategy has been proposed to correct deviations in wind speed data, which is suitable for long-term forecasting. However, its adaptability to short-term wind energy fluctuations still needs optimization. |
| Daan R. Scheepens, et al [101] | ConvLSTM network + inverse weighted loss + European weather forecast data | Data skewness and imbalance | 1. Perform regression analysis on imbalanced wind speed data.<br>2. The results indicate that inverse weighted loss is the most effective method for adapting ConvLSTM to short-term extreme wind speed forecasting with imbalanced spatiotemporal data. | Deep learning is used to address data imbalance problems, but it has high computational complexity and requires large datasets and significant computing power. |
| Junior, et al. [102] | Optimal reconciliation methods + ONS data + ISO-NE data | Data distribution change | 1. Integrate the hierarchical structure of wind energy data from multiple geographical locations and prediction ranges to enhance temporal correlation and improve forecasting accuracy.<br>2. This method can be effectively applied to energy management and grid integration. | The method is suitable for cross-regional wind energy prediction and can effectively handle changes in data distribution, but it heavily depends on multi-level data, limiting its applicability. |
| Mutaz AlShafeey et al. [103] | ANN + SVR + K-NN hybrid model + empirical data on wind power generation in Hungary provided by E.ON Hungary | Data skewness and imbalance | 1. An analysis of 2 MW wind park data in Hungary reveals significant differences in power generation, indicating an imbalance in wind power data.<br>2. Propose a method for adaptively selecting the optimal algorithm to improve prediction accuracy. | Combining multiple algorithms improves prediction accuracy and is suitable for different wind parks. However, due to high computational costs, real-time applications are challenging. |
| Daeyoung Kim et al. [18] | Neural network + SCADA + LiDAR data | Data sparsity | Integrate multiple data sources for short-term wind energy prediction in a 400 MW offshore wind park to verify model adaptability under sparse data conditions. | Multi-source data fusion enhances prediction accuracy, but the high cost of acquiring LiDAR data may limit its large-scale application. |

data and capture multi-temporal wind energy variations [32].

*Emerging developments and open research*

Recent studies indicate that offshore wind power forecasting is increasingly moving toward data-driven methods that consider complex operating and environmental conditions. Several works improve prediction accuracy by introducing weather-process classification [33] and information from neighbouring offshore wind parks [34], which helps capture regional and temporal variations in wind power. In addition, multi-source data fusion, especially the combination of SCADA and LiDAR data, has been shown to enhance model robustness by jointly describing turbine operating states and offshore wind conditions [35]. Recent models mainly adopt hybrid deep learning structures [36], including attention-based recurrent networks [37], and decomposition-assisted models [38], to address the strong fluctuation and non-stationarity of offshore wind power and wind speed time series. Moreover, emerging studies explicitly model spatiotemporal correlations among offshore wind park clusters [39] and apply adaptive strategies such as dynamic time-delay analysis [40]. Although these methods demonstrate clear accuracy improvements, most of them are still validated in limited case studies, and challenges related to scalability, real-time deployment, and performance under extreme weather conditions remain. Therefore, the main research directions for the future could include:

1) **Regional or cluster-based forecasting**: Most research still focuses on single-park predictions, with limited studies on the spatio-temporal correlations among neighbouring wind parks. The primary barriers are data sharing constraints (different parks are managed by different owners and platforms), as well as high model complexity and communication costs.

2) **Multi-source data fusion**: SCADA systems are standard in practice, but LiDAR and ocean observation data are not yet fully deployed. In addition, differences in sampling frequency and timing across databases, combined with high collection costs and missing data, limit the ability of real-time systems to update promptly.

3) **High-impact, low-frequency events**: Most models are still dominated by regular wind speed samples. While extreme wind speed prediction has been studied extensively, it is rarely applied in practice. The main challenges include imbalanced datasets and the lack of standardized evaluation metrics.

*Data-driven issues in wind turbine layout optimization*

Optimizing wind turbine layout is critical for improving offshore wind park efficiency. Wind turbine layout optimization involves designing the spatial arrangement of turbines within a wind park to maximize energy capture while minimizing wake effects and construction costs [41]. Key optimization objectives typically include [42]: ① maximizing wind energy capture efficiency; ② minimizing wake effects; ③ minimizing infrastructure costs; ④ maximizing site utilization. Additionally, wind park design should align with local environmental conditions to select the most suitable layout strategy [43]. Fig. 5 provides an overview of optimization objectives and layout strategies, both of which are fundamental considerations in offshore wind turbine layout planning.

The spatial arrangement of wind turbines directly affects power generation and overall economic viability. In layout optimization, data quality significantly influences optimization outcomes. Table 3 summarizes the main achievements in solving data problems in wind park layout optimization.

*Emerging developments and open research*

Recent studies have advanced wind park layout optimization by moving beyond traditional sequential and single-objective approaches. Integrated optimization frameworks now consider both wind turbine micro-siting [44] and cable network design [45] simultaneously, improving economic efficiency and operational performance. Some researchers developed multi-objective models to balance power generation, turbulence intensity, and fatigue damage of turbines, using advanced wake models[46] and analytical turbulence representations [47]. Additionally, emerging methods incorporate machine learning and control optimization, such as neural-network-based power prediction combined with layout and yaw control optimization [48], or two-stage frameworks integrating layout generation and operational control of floating offshore turbines [49]. These advances demonstrate that considering co-effects among layout, cable routing, fatigue, and turbine control can substantially increase power production and reduce operational risks.

Despite significant advances in wind park layout optimization in academic research, these methods have not yet been widely applied in large-scale offshore wind parks. The main barriers include high computational complexity, data and system compatibility issues, difficulties in implementing real-time control, and high deployment costs. Therefore, future research should focus on real-time adaptive optimization, scalable multi-objective layout optimization for large offshore wind parks, and the practical implementation of layout and control strategies.

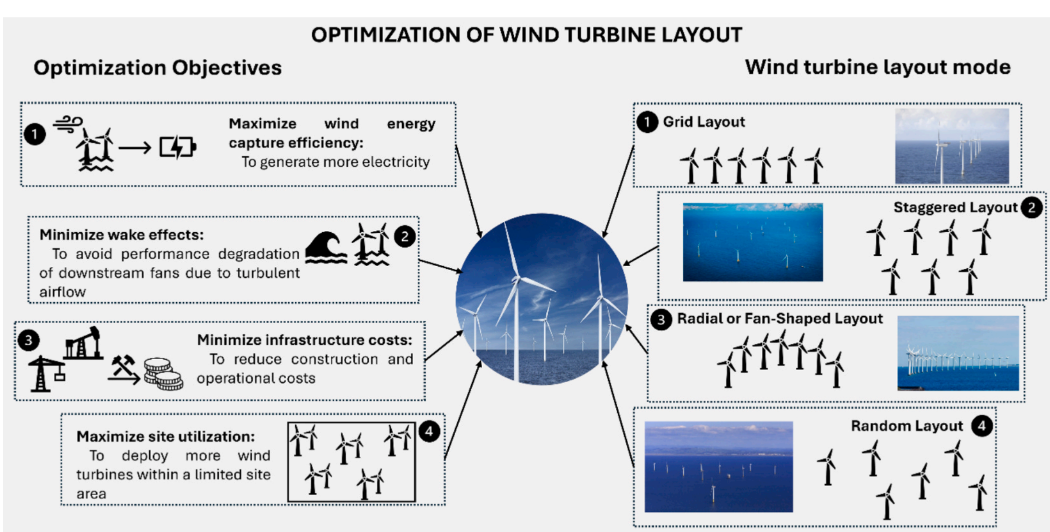


**Fig. 5.** Optimization objectives and layout modes for wind turbine layout.

**Table 3**
Different research and analysis on optimization of wind park layout.

| Researcher | Methods&Data | Solved data issues | Main achievements | Sumary |
|---|---|---|---|---|
| Ajit C., et al. [104] | Wind park layout evaluation function and layout optimization framework, using cost function + Middelgrunden wind park data | Data skewness and imbalance | 1. Proposed a cost function-based method for wind park layout optimization;<br>2. Analyzed the limitations of existing methods, particularly the omission of layout-related factors when applying cost functions. | Provided an evaluation framework for optimizing wind park layout. However, the cost function overlooks critical layout-related factors and is not applicable to new projects, making it ineffective in handling complex layout requirements. |
| Davide Cazzaro, et al [105] | Variable neighborhood search meta heuristic algorithm + mixed use of public data + hypothesis-based dataset | Data sparsity | 1. Designed a new metaheuristic algorithm and proposed a mixed dataset approach to address data sparsity;<br>2. By considering the minimum distance constraint and basic cost, the optimization of the offshore wind park layout was improved. | Addressed the problem of data sparsity by integrating multiple datasets, improving optimization accuracy. However, relying on assumption-based data may introduce inaccuracies in practical applications. |
| Fenglan He et al. [106] | CFD model combined with optimization theory + Kriging accelerated calculation + NREL 5 MW wind turbine | Data distribution change | 1. Proposed a method combining CFD and optimization theory, introducing the Kriging model as a surrogate to accelerate wind park layout optimization;<br>2. Developed layout optimization schemes for different wind directions. It is recommended to use a Staggered Layout for wind parks with one or two prevailing wind directions and a Grid or Circular distribution for wind parks with multiple prevailing wind directions throughout the year. | The combination of CFD and Kriging models effectively reduces computational complexity and enhances optimization efficiency. However, CFD models remain computationally expensive, and the effectiveness of Kriging models depends on data accuracy. |
| Zhenfan Wang, et al [107] | Kriging surrogate model optimization framework + LHS method + CFD optimization layout + representative case data | Data distribution change | An optimization framework based on the Kriging surrogate model was proposed, combined with the LHS method to generate initial samples. This framework can adaptively update the wind park layout dataset and optimize it effectively. | A flexible optimization framework was developed using proxy models and adaptive update methods, addressing the limitations of traditional wake analysis models. However, it relies on CFD calculations and surrogate models, which may affect the accuracy of the final optimization results. |
| Xiaofeng Zhang, et al. [108] | A proxy model combining artificial neural network and genetic algorithm + Hangzhou Bay and Horns Rev1 wind park data | Data sparsity | 1. Proposed a proxy model combining artificial neural networks and genetic algorithms;<br>2. Analyzed a single-core full wind condition case, showing that the average absolute percentage error of the load channel meets the accuracy requirements for wind park layout optimization. | Combined multiple algorithms to improve prediction accuracy, making the method applicable to different wind parks. However, due to high computational costs, real-time application remains challenging. |
| Kun Yang, et al [109] | Machine learning wake-up model + Horns Rev wind park data | Data distribution change | 1. Used a machine learning wake model to compare heuristic and gradient-based optimization algorithms;<br>2. Compare power loss in wind turbine data for units ranging from 80 to 120. | Optimized the number of wind turbines under initial layout conditions, reducing power loss and increasing electricity generation. However, when wind turbine data changes, power loss increases by 3% to 4%. Although power generation improves, some losses remain. |

*Challenges and prospects under data-driven technology*

The rapid advancement of data-driven technologies has significantly enhanced wind energy forecasting and wind park optimization. By leveraging advanced computational techniques, researchers have improved prediction accuracy and operational efficiency. However, despite these advancements, several challenges remain unresolved. The dynamic nature of wind resources, data imbalance issues, and evolving environmental conditions pose significant obstacles to the robustness and adaptability of predictive models. Moreover, wind park layout optimization under data-driven approaches faces uncertainties in wind patterns, turbine placement constraints, and wake effect modeling limitations. This section discusses the existing difficulties and explores potential strategies, such as Generative Adversarial Networks (GAN) for data augmentation and transfer learning for model generalization, to enhance wind energy forecasting and wind park optimization under complex and evolving conditions.

To address these data-driven challenges in wind energy forecasting, it is suggestable to use GAN for data augmentation combined with transfer learning to improve the model's generalization and adaptability. One of the key issues in wind energy forecasting is the imbalance in wind speed data, particularly under extreme conditions (high or low wind speeds), where data scarcity prevents models from effectively learning wind energy variations. GAN can be used to generate synthetic wind speed data, enhancing data balance and improving the model's ability to learn from underrepresented conditions. Weibin Weng et al. introduced a data augmentation framework that combines a Generative Adversarial Imputation Network (GAIN) with eXtreme Gradient Boosting (XGBoost), and applied it to SCADA datasets from offshore wind parks to enhance data quality and improve anomaly detection performance [50]. Karadeniz employed GAN to generate synthetic meteorological data, augmenting the wind speed dataset from Bozcaada, Turkey, thereby improving prediction accuracy [51]. Shuang Feng et al. proposed a transfer-learning-based Wasserstein GAN for synthetic data generation in wind park sub-synchronous oscillation analysis, addressing training instability caused by small-sample learning scenarios [52]. These imply that GAN models are gradually being adopted and implemented by researchers in offshore wind park applications. Thus, it can effectively expand datasets.

Furthermore, differences in the spatial and temporal distribution of wind park data make it difficult to apply a model trained on one wind park directly to another. Additionally, seasonal variations, climate change, and equipment aging cause shifts in the statistical properties of historical data, making traditional static models less effective in adapting to new environments. Transfer learning can help address these issues by enabling models trained on one wind park to be fine-tuned for use in another, reducing the need for extensive new data collection and enhancing generalization.

Despite the growing interest in applying GAN for offshore wind scenario generation, several critical technical challenges remain. One major issue is physical consistency, as most GAN-based models are designed to reproduce statistical distributions rather than enforce underlying physical laws. Consequently, generated wind speed or power scenarios may violate fundamental constraints such as power curve relationships, wake-induced spatial dependencies, or temporal continuity, which limits their reliability for engineering applications. Another challenge is mode collapse, where GAN tend to generate repetitive scenarios, failing to capture the full variability of offshore wind conditions. This issue is particularly pronounced for rare but high-impact events, since imbalanced datasets cause the learning process to be dominated by frequent, moderate wind conditions. These limitations highlight the gap between current GAN-based scenario generation methods and the requirements of practical offshore wind energy applications, and they motivate further research toward physically consistent, diverse, and reliably validated generative models.

What are the challenges of wind energy forecasting and wind turbine layout optimization under data-driven technology? While data-driven methods improve the accuracy of wind energy forecasting, several challenges remain. Firstly, frequent data shifts and dynamic changes: Wind park data undergo continuous variation due to environmental factors. How to design a real-time and efficient dynamic adjustment mechanism to enable the model to adapt quickly to environmental changes is the key to further improving its predictive ability. Secondly, the lack of data during high-wind-speed scenarios limits model performance, affecting the safety and reliability of wind park operations. Finally, as global climate conditions change, historical data may no longer accurately reflect current wind energy characteristics. Updating datasets to ensure models remain adaptable to new climate trends is essential for improving forecasting precision [53].

Regarding the optimization of wind turbine layout, the following limitations need to be addressed in the long term: (i) Wind conditions fluctuate due to seasonal changes, meteorological factors, and diurnal cycles. Wind speed and direction exhibit high uncertainty, and their distribution varies significantly across both time and space. Obtaining accurate wind condition data and systematically evaluating optimization methods under different wind conditions remain critical challenges (Antonini et al. explored this issue [54]); (ii) Layout constraints for wind park should be less restrictive, especially those related to shape and overall size (the optimal wind park size may require further optimization); (iii) The selection of the optimal wind turbine type and its reasonable placement remain critical issues in layout optimization. How to comprehensively consider turbine performance, cost, wake effects, and environmental conditions to determine the optimal turbine type and layout combination still requires further research; (iv) Current wake effect models struggle with multi-directional and multi-speed wind conditions, making it difficult to simulate wake interactions under complex meteorological scenarios accurately. Improving existing models or developing more adaptive wake modeling techniques will enhance the reliability and precision of wind park layout optimization.

## Application in artificial resources based on data-driven problems

Artificial resources from the technological and physical infrastructure are essential for converting natural resources into electrical energy in the offshore wind park. Unlike natural resources, artificial resources are designed, manufactured, and managed by humans, and their status and performance directly impact the operational efficiency, reliability, and economic viability of the wind park [55]. These resources are characterized by their complexity, high maintenance requirements, and long-term operational costs. During wind park operations, data on artificial resources mainly come from SCADA systems [56], Condition Monitoring System data [57], Environmental Monitoring Systems [5], and Maintenance and Repair Logs [58]. The status information derived from these sources directly influences power generation efficiency and operational costs. Therefore, optimizing data management is crucial for ensuring the sustainable operation of wind parks. Through effective equipment lifecycle management and preventive maintenance, wind parks can reduce equipment failures, optimize operational conditions, and extend equipment lifespan. This section examines the challenges and recent research advancements in artificial resource data management from two perspectives: equipment lifecycle management and the implementation of preventive maintenance.

### *Data-driven challenges in equipment lifecycle management*

Equipment Lifecycle Management (ELM) encompasses the entire process of design, installation, operation, maintenance, and decommissioning of wind park equipment. The objective is to enhance performance, reliability, and cost-effectiveness through systematic planning and management [59]. However, optimizing lifecycle management requires extensive operational data.

Over the years, several overall operational expenditure (OPEX) estimation and operation and maintenance (O&M) tools have been developed for offshore wind parks and are widely applied in commercial and scientific research. Although these studies compared the effectiveness of various tools, none have been fully validated across the entire lifecycle of offshore wind parks [60,61]. Most studies rely on simulated turbine lifespans, typically around 20 years, though some analyses extend beyond the standard service period to evaluate the feasibility of lifetime extension. Additional operational data becomes available in these cases, allowing for more accurate estimations. Regarding offshore wind reliability data, only one study analyzed approximately 350 offshore wind turbines, providing nine years of failure rate statistics [62]. Additionally, Dinwoodie et al. provided fault rate statistics for offshore wind parks based on expert knowledge [60]. The SPARTA database, managed by Offshore Renewable Energy (ORE) Catapult, contains data on all UK offshore wind parks, though its dataset lacks detailed information [63]. Table 4 summarizes key studies in equipment lifecycle management.

Significant progress in equipment lifecycle management has been achieved, largely due to the adoption of digital twin technology, multi-source data fusion, and Life Cycle Cost Analysis (LCCA). These methods have enhanced equipment performance and cost efficiency. However, the complex operating environment of offshore wind parks poses persistent challenges for fault detection. Wind turbine operations involve complex conditions and diverse failure types, making early fault detection and accurate diagnostics difficult. Additionally, equipment lifespan is influenced by multiple environmental factors (e.g., wind speed, wind direction, temperature, humidity, and ocean waves), limiting the accuracy of lifetime prediction models. For example, the lifespan prediction accuracy of critical components—such as blades, gearboxes, and bearings—remains low, affecting maintenance planning, increasing costs, and reducing operational efficiency.

### *Data-driven issues in preventive maintenance implementation*

Preventive Maintenance aims to reduce the frequency of equipment failures by leveraging real-time monitoring and predictive technologies, optimizing turbine operation and maintenance planning, and ultimately improving the overall efficiency of offshore wind parks. The maintenance strategies for offshore wind parks primarily include preventive maintenance and corrective maintenance, with this section focusing on the former. Before implementing preventive maintenance, it is important to identify the components most prone to failure. However, failure data for wind turbines is often difficult to obtain, especially in offshore environments where data collection presents even greater challenges. Existing studies have attempted to analyze and utilize limited failure data to optimize maintenance strategies. For example, over the past five years, a research group from Strathclyde University has completed a study using data collected over five years from 350 turbines manufactured by the same company. This research has resulted in multiple publications [62,64,65], which provide more precise offshore fault rates

**Table 4**
Analysis of different research on equipment lifecycle management.

| Researcher | Methods&Data | Solved data issues | Main achievements | Summary |
|---|---|---|---|---|
| Maria Martinez-Luengo, et al [110] | Noise cleaning and missing value data interpolation + HMS data | Data sparsity | atigue assessment was conducted using four combinations derived from noise cleaning and data interpolation. | The predictive ability for lifespan is improved by extending the dataset length. However, the adaptability of data interpolation to different fatigue models is not considered. |
| Chuan Sun, et al [111] | Integrated online learning algorithm + SCADA data | Data sparsity | An ensemble online learning method is proposed, which includes:<br>Designing spatiotemporal correlation methods for scenarios where all features are missing (referred to as the "Lazy ST Algorithm").<br>Interpolating missing data using inter-feature correlation methods for cases where only partial features are missing (referred to as the "Online Variation Algorithm"). | This method can adapt to varying degrees of feature loss and improve the stability of wind park data analysis. However, it may be sensitive to the selection of the data time window, which affects the interpolation performance. |
| Cuong D.Dao, et al [112] | Probability method for Monte Carlo simulation of time series + reliability data from the literature | Data skewness and imbalance | 1. Quantitative parameter estimation of available reliability data resources is conducted to simulate the issue of data imbalance caused by insufficient reliability data sources.<br>2. The availability, energy production, operating expenses, and levelized cost of energy (LCOE) of offshore wind turbines are evaluated. | This method is suitable for offshore wind parks with scarce data and enhances the reliability of decision-making. However, the computational complexity of the model is relatively high, which may impact real-time analysis. |
| Cevasco, et al. [113] | Digital Twin Framework + Transfer Learning + Representative Data | Data sparsity | Digital twin and transfer learning solutions are provided to enhance the fault diagnosis capability of wind turbines. | By integrating continuous monitoring data, historical databases, and advanced numerical models with deep learning, significant production losses in offshore wind parks can be mitigated. |

segmented in various ways based on subcomponents, drivetrain configurations, and more. The findings indicate that pitch and hydraulic systems are the most significant contributors to overall failure rates, accounting for 13%. "Other components" (mainly auxiliary parts such as trap doors, ladders, and door seals) are the second-largest factor, making up 12.2% of total failures. Generators, gearboxes, and blades rank as the third, fourth, and fifth most critical failure factors, respectively. Apart from Strathclyde's offshore failure data, another key source is the SPARTA database. However, SPARTA primarily publishes data in graphical formats, making it difficult to extract numerical values. Additionally, it lacks explicit definitions of failure, which limits its usability. Despite these data constraints, researchers continue to explore failure analysis and maintenance optimization. Lubing Xie et al. applied a three-parameter Weibull distribution method for fault rate estimation based on limited data samples, aiming to reduce maintenance costs for offshore wind turbines [66]. Mingxin Li et al. proposed a numerical example to demonstrate the effectiveness of their strategy in managing data distribution changes due to generator degradation, accidents, and opportunity aging, helping to avoid frequent and unnecessary maintenance [67].

In offshore wind parks, predictive and prescriptive strategies can reduce wind turbine downtime by minimizing the need for sea trips, extending component life, and preventing catastrophic failures. However, these strategies also face limitations, such as restricted access to fault data and the inherent issue that wind park datasets typically contain very few faults, making it difficult to train accurate models. Additionally, predictive algorithms may produce false positives (predicting a fault when the turbine is healthy) or false negatives (predicting the turbine is healthy when a fault is imminent). While false positives can result in unnecessary repair costs, false negatives may lead to more severe consequences by overlooking impending failures. Another challenge in deploying predictive or prescriptive strategies is the cost of installing monitoring systems and developing predictive models. However, Onyx Insight found that adopting data-driven strategies could reduce maintenance budgets by 30% [68]. Given that maintenance can account for up to 70% of O&M costs, this represents a significant potential savings [69].

*What are the issues worth considering in preventive maintenance?*

1) Preventive maintenance models must be capable of integrating real-time data, continuously updating themselves, and learning from new information. However, most existing studies rely on historical data for training and testing, with little focus on real-time adaptation.

2) Current models primarily focus on individual component failure prediction. A more practical approach would be to develop an integrated wind turbine model capable of predicting failures of critical components. The HOME Offshore project has identified this as a key research area and has dedicated efforts to studying this topic [70]. Expanding such models to be scalable across different turbines and adaptable across sites would significantly enhance their applicability.

3) There is an inherent trade-off between early predictions with uncertainty and shorter, more accurate warning periods. The optimal warning strategy depends on factors such as component size, availability of replacements, and seasonal constraints due to limited data access. Minimum remaining useful life prediction remains an underexplored area with potential for further research.

## Application of sustainable circular economy methods in offshore wind parks

With the growing global demand for green energy and sustainable development, offshore wind parks increasingly incorporate sustainability and circular economy principles as a key renewable energy sector. These approaches aim to optimize wind resource utilization, extend equipment lifespan, minimize waste generation, and ensure offshore wind parks' economic viability, environmental friendliness, and long-term stability. However, their implementation largely depends on large-scale data. This section explores the application of sustainability and circular economy strategies in offshore wind parks under data-related challenges.

### *Sustainable development in offshore wind parks*

Sustainability in offshore wind parks is reflected in optimizing wind energy utilization, extending equipment lifecycle, and reducing environmental impact. By adopting advanced wind energy forecasting technologies, real-time monitoring, and dynamic optimization, wind parks can balance resource utilization efficiency and equipment reliability. Researchers have increasingly focused on data-driven sustainability strategies in offshore wind parks in recent years. Table 5 summarizes the efforts made in this field.

**Table 5**
Sustainable development of offshore wind power.

| Researcher | Research perspective | Main achievements | Summary |
|---|---|---|---|
| Eva Topham et al. [114] | Sustainable decommissioning of an offshore wind park | 1. Identified key factors influencing wind turbine decommissioning and cost reduction. 2. Developed a model to optimize transportation and minimize environmental impact. 3. Found discrepancies between predicted and actual decommissioning costs and timelines. | Decommissioning plans often underestimate costs due to financial discounting over time. Future research should focus on extending asset lifespan or improving decommissioning models. |
| Eva Topham et al. [97] | Sustainable recycling of offshore wind parks during the decommissioning stage | 1. Evaluated the feasibility and economic impact of recycling offshore wind turbine components. 2. Compiled a dataset on turbine material composition for economic analysis. 3. Recycling could offset up to 20% of decommissioning costs, depending on scrap metal prices. | Recycling offshore wind turbine components can significantly offset decommissioning costs, particularly for monopile-based projects. However, material separation remains challenging, and scrap metal price fluctuations influence optimal decommissioning timing. |
| Jingjing Chen, et al [115] | Sustainability of offshore wind power and its environmental impact throughout its entire lifecycle | 1. Conducted an LCA to quantify the environmental impact of offshore wind parks. 2. We identified construction and turbine manufacturing as the most impactful phases. 3. Found that steel, copper, and electricity consumption significantly contribute to environmental impact. | Collaboration with the steel industry and green manufacturing can further reduce environmental impact. As offshore wind expands into deeper waters, lowering costs for exploitation, installation, and transportation is crucial, as is guiding the industry's green transition. |
| Armando Díaz-Motta, et al. [116] | Energy sustainability assessment of offshore wind-powered ammonia | 1. Examined advanced technologies, costs, environmental impact, and social acceptance of ammonia as an energy carrier. 2. Compare offshore wind-based ammonia with fossil-based (SMR) and low-emission (SMR-CCS) ammonia in terms of cost, energy use, efficiency, and $CO_2$ emissions. | Offshore wind-powered ammonia supports decarbonization, but high production costs challenge its competitiveness. Future research should optimize hybrid renewable energy use, improve efficiency, and identify cost-effective production regions. |

Wind energy plays a crucial role in achieving offshore wind sustainability goals. The United Nations Sustainable Development Goals (SDGs) aim to increase the share of renewable energy in the global electricity mix to at least 70% by 2030. Wind energy is environmentally friendly, inexhaustible, and reduces reliance on fossil fuels, which are a major contributor to the greenhouse effect [71].

*Circular economy in offshore wind parks*

Achieving modernization that fosters harmony between humanity and nature requires a fundamental shift from the traditional linear economy model of resource use and production. The circular economy offers a transformative alternative to the conventional "produce–consume–discard" system, challenging unsustainable patterns of mass production, consumption, and waste. By improving product design and extending product lifespans, the circular economy aims to reduce resource inputs and environmental impacts through three key strategies: narrowing, slowing, and closing resource loops [72]. To evaluate circular solutions across different stages of a product's lifecycle, this study draws on the framework proposed by Bocken et al. [73], which classifies circular economy practices into three core strategies:

1) Narrowing loops focus on using fewer materials, components, and energy throughout the value chain—essentially improving resource and energy efficiency to reduce consumption.
2) Slowing loops aim to extend the useful life of products and components by improving durability, reparability, and maintenance practices, thereby postponing the need for new materials.
3) Closing loops seek to recover and reintegrate materials at the end of their service life through recycling, reducing dependency on virgin resources.

The core of the circular economy in offshore wind parks lies in recycling and reusing wind turbine materials. Turbine towers, blades, and infrastructure contain significant amounts of high-value materials, such as steel and composites, whose recovery can significantly reduce the overall environmental footprint of wind parks. However, existing recycling systems are constrained by incomplete and sparse data on equipment decommissioning and recycling. Additionally, prolonged operation can lead to material degradation, further complicating resource reutilization. Despite these challenges, efficient data management and process optimization can enable effective recycling and reuse of resources. Fig. 6 illustrates a conceptual framework for integrating circular economy principles into offshore wind parks based on [73].

Within the narrowing resource loops concept, the focus lies in maximizing the use of both natural and artificial resources to improve the overall efficiency of wind energy utilization. This entails reducing the resource input required per unit of electricity generated by enhancing the effectiveness of wind resource capture through advanced technological interventions. Strategies in this domain include wind energy forecasting, optimized turbine layout, and intelligent maintenance scheduling. Data-driven prediction models, for instance, can significantly minimize curtailment and energy waste by improving the accuracy of wind forecasting. Yang and Liu proposed a probabilistic forecasting model aimed at improving the predictive accuracy of circular economy resource markets [74]. Additionally, optimizing turbine spatial distribution can mitigate wake losses, thereby enhancing the collective power output. Anne P.M.Veleturf introduced a sustainability-oriented circular economy framework embedded in the full life cycle of offshore wind infrastructure, outlining its potential application across other energy sectors [75]. Indeed, leveraging big data and AI technologies allows for more efficient allocation of operation and maintenance resources, minimizing redundant procedures and reducing labor and material consumption.

The slowing resource loops concept targets the extension of wind turbines' service life to reduce the frequency of equipment replacement,

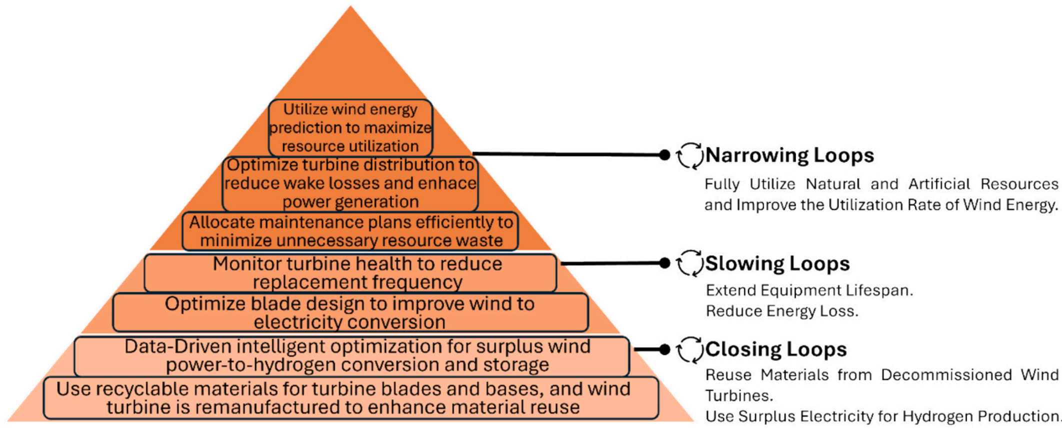


**Fig. 6.** Analysis of offshore wind parks based on the Bocken circular economy framework.

thereby decreasing long-term energy and resource demands. In offshore wind parks, this is primarily achieved through continuous monitoring of equipment health and predictive maintenance strategies. Such approaches help identify potential failures early and allow for timely interventions, avoiding resource-intensive breakdowns and unplanned downtimes [76]. Moreover, structural optimization of critical components like turbine blades enhances energy conversion efficiency while simultaneously reducing mechanical wear.

The closing loop emphasizes the reuse and recycling of materials and energy, especially during the decommissioning phase or in periods of surplus resources. As the number of retired wind turbines grows, the recovery and remanufacturing of components—such as blades, towers, and foundations—emerges as a crucial strategy to reduce raw material extraction and associated carbon emissions. Ashal Tyurkay et al. incorporated circular economy principles into an offshore wind turbine blade decommissioning management framework, assessing the wind industry's readiness for sustainable decommissioning and recycling. Based on the concept of circular hierarchy, they classified waste prevention strategies, processing technologies, and waste reuse options, exploring the synergistic development of the circular economy and wind energy [77]. Athanasios Rentizelas et al. investigated the feasibility of using decommissioned blades in composite material manufacturing through mechanical recycling pathways in the context of the circular economy. By developing and solving a mixed-integer linear programming (MILP) model to determine optimal solutions, their experiments demonstrated that the proposed circular economy approach is economically viable even without additional policy support [78].

Finally, the intermittency of wind energy often leads to periods of electricity surplus. Instead of curtailing this excess, it can be used to produce green hydrogen via electrolysis. This not only facilitates energy storage and reuse but also positions wind power as a versatile contributor in future energy systems. Antoine Rogeau and colleagues developed a detailed cost model for hydrogen production by incorporating key operational parameters from offshore wind parks, conducting a large-scale resource assessment across Europe [79]. By integrating material and energy loops, offshore wind parks can evolve beyond clean energy generators to become pivotal nodes in the circular economy network. In the future, optimizing data collection and management processes will be essential for supporting the achievement of sustainable development goals through efficient resource recovery and reuse in wind parks. Fig. 7 shows the entire process of offshore wind parks from power generation to energy transmission, energy storage, and achieving sustainable development and circular economy.

We further summarized the main recycling pathways for offshore wind turbine blades, highlighting their technology readiness level, cost implications, and key economic constraints.

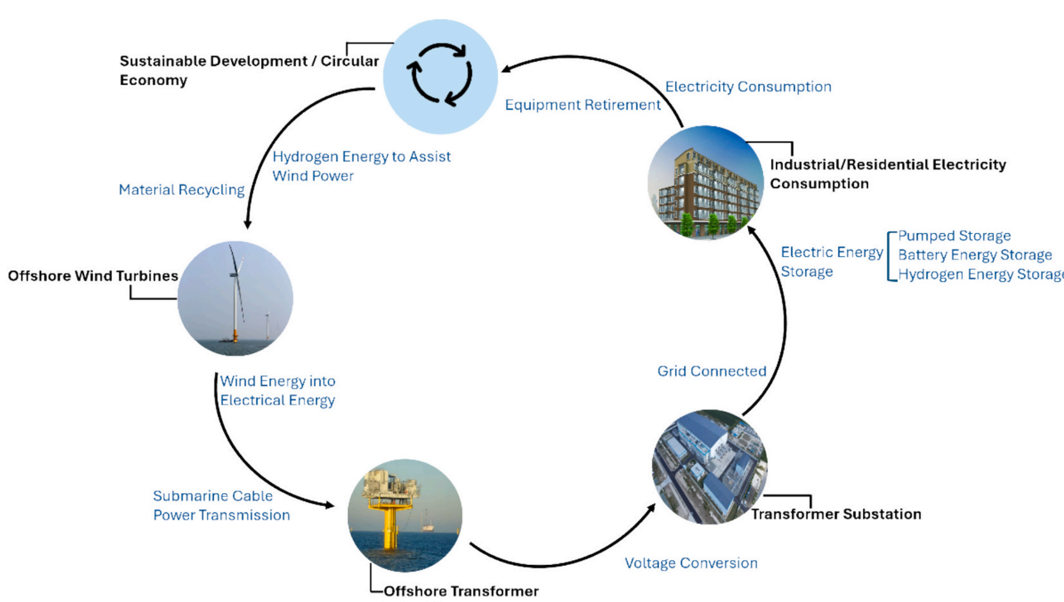


**Fig. 7.** Sustainable circular economy in the operation process of offshore wind park.

1) **Mechanical Recycling:** Mechanical recycling is currently applied at a limited scale, mainly to reduce blade waste volume. The recycled material is primarily used as filler in low-value products [80]. This pathway has a high technology readiness level (TRL 8–9) and relatively low cost. However, its main limitation lies in the low economic value of the recycled material, as it does not enable the recovery of fibers with structural performance.

2) **Thermal Recycling:** Thermal recycling enables the recovery of recyclable fibers, although their performance is partially degraded [81]. This approach has reached a medium technology readiness level (TRL 6–8) and is associated with medium to high costs. Its key constraints include high energy consumption and the reduced mechanical properties of the recovered fibers, which limit their applicability in high-performance uses.

3) **Chemical Recycling:** Chemical recycling is mostly still at the laboratory stage, but it demonstrates the potential to achieve high-quality fiber recovery [81]. Its technology readiness level remains low to medium (TRL 4–6), and the expected cost level is high. The main economic and technical barriers include high process complexity, high operational costs, as well as challenges related to solvent handling and large-scale implementation.

4) **Thermal Pyrolysis Variant:** A thermal pyrolysis variant represents an emerging recycling strategy that is being explored by manufacturers, although its deployment in real-world applications remains limited [81]. This approach shows a low to medium technology readiness level (TRL 5–7) and a medium cost level. Its primary constraint is the trade-off between recyclability, structural performance, and cost, which complicates large-scale adoption.

5) **Reuse and Repurposing:** Reuse and repurposing strategies are currently confined to niche applications, such as civil engineering structures and noise barriers [82]. These approaches have achieved a medium technology readiness level (TRL 6–7) and are associated with low costs. Nevertheless, their broader application is restricted by limited scalability, regulatory and certification barriers, as well as site-specific logistical challenges.

The above content shows that current recycling pathways for offshore wind turbine blades differ markedly in technological maturity and economic feasibility. Mature options, such as mechanical recycling, are readily deployable but largely result in material downcycling. In contrast, thermal and chemical recycling methods offer higher material recovery potential but remain limited by high costs and low technology readiness [83]. Emerging design-for-recyclability strategies are promising but not yet validated under offshore conditions. Overall, the table highlights a persistent gap between blade material characteristics and recycling economics, which remains a key barrier to the large-scale implementation of circular solutions in offshore wind energy systems.

Although circular economy concepts are often discussed at a conceptual level in the reviewed literature, they can be explicitly linked to data-driven optimization through measurable circularity-related indicators. In this context, lifecycle assessment (LCA) and lifecycle cost analysis (LCCA) act as evaluation methods that provide quantifiable indicators such as lifecycle greenhouse gas emissions, cumulative energy demand, and material recovery rates [84]. These indicators can be embedded as objective functions or constraints in data-driven decision-making, for example by minimizing lifecycle carbon emissions or energy use in layout optimization and maintenance scheduling, rather than focusing solely on power output [85]. Similarly, indicators including the share of secondary materials in turbine components, expected lifetime extension enabled by predictive maintenance, and avoided $CO_2$ emissions due to reduced unplanned downtime can be incorporated into multi-objective optimization frameworks [86]. By integrating such circularity-related indicators into algorithmic optimization processes, data-driven models can jointly address energy performance, economic efficiency, and environmental sustainability, thereby supporting more practical and implementable circular economy strategies for offshore wind systems.

## Challenges of wind power generation in offshore wind parks under data-driven problems

### *Challenges faced by offshore wind power development*

As an important component of renewable energy, offshore wind power is currently in a rapid development stage but still faces multiple challenges and bottlenecks.

From a resource perspective: **(1)Unstable Power Output:** Offshore wind speed and direction fluctuate due to seasonal and weather changes, and extreme events like typhoons further affect power generation and grid stability; **(2)Spatial Constraints and Marine Resource Conflicts:** Nearshore areas are becoming saturated, requiring future development to balance marine spatial use with fisheries, shipping, and tourism; **(3) High Construction Costs:** Major costs include anti-corrosion turbine designs, submarine cables, and offshore substations. Digital twin technologies can simulate marine operational conditions, optimize turbine design, and reduce failure risks; **(4)Complex and Costly Operation & Maintenance (O&M):** Harsh sea conditions limit accessibility and increase reliance on vessels and manpower, leading to high O&M costs.

From a data-driven perspective: Surrogate models are widely employed in offshore wind applications such as wind energy forecasting [87], turbine layout optimization [88], and operation and maintenance planning [89] because they can approximate complex physical processes with relatively modest computational resources. Nevertheless, their use in large-scale offshore wind parks faces two notable limitations. First, many surrogate models still require high-fidelity numerical simulations or extensive measurement data for training, so their computational cost is not truly negligible; in multi-turbine, large-area wind parks, model construction and parameter tuning can still demand substantial time and computing power. Second, their generalization capability remains limited when confronted with complex marine conditions and multi-scale meteorological variability, and prediction accuracy can degrade sharply when operating conditions deviate significantly from the training set. Future research should therefore recognize the value of surrogate models while addressing their scalability and computational efficiency, for example by integrating dimensionality-reduction techniques, sparse learning, or parallel computing to reduce training overhead, and by developing adaptive training and dynamic updating mechanisms to improve robustness and long-term applicability under changing offshore environments.

In the future, we can further combine multi-source real-time monitoring data and open databases to establish a multi-scale training framework suitable for different sea areas and explore few sample prediction methods based on GAN and transfer learning to break through the limitations of data scarcity and distribution changes on model training.

### *Trends in offshore wind power development*

Driven by technological innovation and industry maturity, offshore wind power is moving toward larger capacity, smarter systems, and deep-sea deployment:

**(1)Larger-Capacity Turbines:** Advances in turbine design are increasing unit capacity and improving energy efficiency, helping lower the levelized cost of electricity (LCOE) [16]; **(2)Deep-Sea Deployment:** As coastal areas fill up, future wind parks will be located in deeper waters, often exceeding 50 m in depth [90]; **(3)Smarter O&M:** With digital twin technology, predictive maintenance and remote diagnostics are becoming more automated and less reliant on manual inspections [91]; **(4)Cost Reduction:** Improved technology, economies of scale, and data-driven optimization of supply chains and inventory are reducing capital and O&M costs. Future research can further combine deep-sea floating wind power technology with intelligent predictive operation and maintenance platforms to explore collaborative optimization with multi energy systems such as ocean energy, hydrogen energy, and energy storage, to achieve higher energy utilization efficiency and economy.

Meanwhile, data-driven frameworks similar to those discussed in this review have already demonstrated practical value in several adjacent energy sectors, offering useful insights for offshore wind applications. For example, in smart grids, data-driven optimization and predictive analytics have been widely used to jointly improve operational efficiency, reliability, and lifecycle costs by integrating forecasting, asset health monitoring, and system-level decision-making [92]. Recent studies in offshore and floating solar energy systems have also adopted data-driven performance modeling and degradation-aware optimization to address environmental variability and lifecycle efficiency [93]. These experiences suggest that cross-sector data-driven methodologies—particularly those combining operational data with lifecycle and reliability indicators—can provide transferable inspiration for enhancing the practical implementation of offshore wind park optimization frameworks.

*Offshore wind power and sustainable development*

As a novel renewable energy source, offshore wind power plays a crucial role in ecological protection and sustainable development.

**(1) Reducing Emissions:** It helps displace fossil fuel use, with data-driven models enabling accurate assessment of its carbon reduction potential; **(2) Easing Land Pressure:** Offshore deployment avoids land-use conflicts and allows for better land conservation. GIS-based data supports efficient site planning; **(3) Enabling Energy Transition:** Offshore wind is accelerating the shift to clean energy, aided by long-term wind forecasting and data analytics for better project planning; **(4) Stimulating Regional Economies:** Offshore wind supports industries like turbine manufacturing, shipbuilding, and grid integration. For instance, a 300 MW demonstration project combined with marine ranching reduced 790,000 tons of $CO_2$ emissions and saved 290,000 tons of standard coal annually [94].

In the future, we can further promote the life cycle assessment and social environmental economic triple benefit evaluation system based on multidimensional environmental data, establish a cross regional and cross industry comprehensive decision-making platform to support larger scale sustainable energy layout.

*Offshore wind energy and the circular economy*

As a clean and renewable energy source, offshore wind power not only facilitates energy structure transformation but also promotes a circular economy through full lifecycle management of equipment and multi-energy integration, maximizing resource utilization efficiency. The key aspects include: **(1)Full Lifecycle Management:** Turbine blades, gearboxes, and generators pose challenges for end-of-life recovery. Lifecycle management is crucial for improving recycling rates; **(2)Blade Material Recycling:** Composite blades are hard to degrade, but technologies like pyrolysis and chemical recycling offer promising solutions; **(3)Wind-Hydrogen Integration:** Surplus offshore wind power can be converted into hydrogen via electrolysis, enabling long-term energy storage and reuse through wind–hydrogen–power systems [95]; **(4)Data-Driven Circularity:** Monitoring platforms can track equipment performance, resource use, and emissions. This supports transition from a linear to circular economy and improves lifecycle sustainability.

This facilitates supply chain and lifecycle resource management optimization. Such a data-driven approach will accelerate the transition of the wind power industry from a "linear economy" to a "circular economy," enhancing the sector's sustainability and environmental performance [96]. As offshore wind technology matures and global adoption increases, it will further optimize the energy structure and accelerate the green energy transition, supporting global sustainability goals.

*Potential Negative impacts of offshore wind energy*

While offshore wind parks play a crucial role in advancing low-carbon energy systems, they may also generate a range of potential environmental and socio-economic impacts throughout their lifecycle [97]. During construction, activities such as pile driving and seabed preparation can produce significant underwater noise and physical disturbances, which may affect marine mammals, fish behavior, and benthic habitats. In the operational phase, turbine foundations and subsea cables can modify local hydrodynamics and sediment transport, while rotating blades pose collision risks to birds and may disrupt migratory patterns [98]. Additionally, offshore wind parks can lead to spatial conflicts with fisheries, shipping routes, and other marine activities. Decommissioning may also cause environmental disturbances, including waste generation and seabed disruption, if not carefully managed.

Data-driven approaches and circular economy strategies offer promising means to mitigate these impacts. Advanced monitoring systems combined with data analytics can enable real-time assessment of underwater noise, wildlife interactions, and ecosystem responses, supporting adaptive scheduling and operational adjustments that reduce ecological stress. From a circular economy perspective, lifecycle-focused design, modular turbine components, extended service life, and enhanced recycling strategies, particularly for blades and foundations can decrease material consumption, waste generation, and environmental pressures during decommissioning. By integrating environmental monitoring with lifecycle management and recycling-oriented planning, offshore wind development can move beyond efficiency optimization to a more holistic approach that balances energy production, ecological protection, and long-term sustainability.

## Conclusion

This paper reviews the critical role of data-driven strategies in optimizing natural and artificial resources in offshore wind parks. It explores three core data challenges—data imbalance, data distribution change, and data sparsity—and their profound impact on wind energy forecasting, turbine layout optimization, equipment lifecycle management, and predictive maintenance. Operational data from offshore wind parks often exhibit imbalance, with rare events such as extreme wind speeds and equipment failures making up a small portion of the dataset. This imbalance hinders traditional models from accurately capturing critical states, affecting power prediction and asset health management. Data distribution change is another major challenge, as seasonal variations and extreme weather cause fluctuations in wind speed and direction, making it difficult for models to adapt over time, reducing forecasting and scheduling accuracy. Additionally, data sparsity and missing values, often due to equipment malfunctions or communication failures, weaken condition assessment and lifespan prediction, impacting the effectiveness of preventive maintenance.

To address these challenges, data-driven technologies offer significant potential. Deep learning and multimodal data fusion can enhance predictions for rare event data, mitigating imbalance issues. Dynamic adaptation techniques such as online learning and transfer learning help counter distribution change, improving model robustness across different conditions. The integration of digital twin technology with data completion algorithms enables the simulation of full lifecycle operations, compensating for data gaps and enhancing precision in equipment management and maintenance.

Furthermore, promoting the sustainable development of offshore wind power and circular economy practices are essential. Strategies such as full lifecycle management, material recycling, and wind-hydrogen-power integration optimize resource utilization, reducing environmental impact and improving energy efficiency. A comprehensive data collection, monitoring, and management system is crucial to achieving these goals. The reviewed findings also indicate practical implications for key stakeholders: operators may improve reliability and reduce downtime through data-driven forecasting and maintenance scheduling; developers can support sustainable investment by integrating lifecycle-aware layout and cost optimization; and policy-makers could enhance regulatory frameworks and data standards to promote circular economy practices in offshore wind development. Future research should focus on developing adaptive data models to enhance offshore wind park stability and flexibility in dynamic environments. Additionally, establishing cross-industry data-sharing platforms will facilitate collaborative resource development, driving the global sustainable development and energy transition of offshore wind power.

## CRediT authorship contribution statement

**Yucheng Lyu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Hao Chen:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Formal analysis, Conceptualization, Funding acquisition. **Devrim Murat Yazan:** Writing – review & editing, Validation, Supervision, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

Y.L. appreciate the China Scholarship Council (CSC) for its financial supporting. The authors thank Section Industrial Engineering & Management Science (IEMS), the University of Twente for supporting the research.

## Data availability

No data was used for the research described in the article.

## References

[1] Hassan Q, Viktor P, Al-Musawi TJ, et al. The renewable energy role in the global energy Transformations. Renewable Energy Focus 2024;48:100545.
[2] Global Wind Energy Council, Global offshore Wind Report 2024. GWEC, 2024, Online.
[3] Díaz H, Guedes Soares C. Review of the current status, technology and future trends of offshore wind farms. Ocean Eng 2020;209:107381.
[4] Bilgili M, Alphan H. Global growth in offshore wind turbine technology. Clean Techn Environ Policy 2022;24:pp2215–2227.
[5] Cevasco D, Koukoura S, Kolios AJ. Reliability, availability, maintainability data review for the identification of trends in offshore wind energy applications. Renew Sustain Energy Rev 2021;136:110414.
[6] Shen Lei. “Discussion on the classification of natural resources and a new classification framework and scheme.” Resources Science, vol.43, no.11, pp: 2160-2172, 2021.
[7] Huang J, Huang X, Song N, et al. Evaluation of the Spatial Suitability of Offshore Wind Farm—A Case Study of the Sea Area of Liaoning Province. Sustainability 2022;14(1):449.
[8] Li Z, Tian Guohua, El-Shafay AS. Statistical-analytical study on world development trend in offshore wind energy production capacity focusing on Great Britain with the aim of MCDA based offshore wind farm siting. J Clean Prod 2022;363:132326.
[9] Görmüş T, Aydoğan B, Ayat B. Offshore wind power potential analysis for different wind turbines in the Mediterranean Region, 1959–2020. Energ Conver Manage 2022;274:116470.
[10] Akhtar N, Geyer B, Schrum C. Impacts of accelerating deployment of offshore windfarms on near-surface climate. Sci Rep 2022;12:18307.
[11] Mou J, Jia X, Chen P, et al. Research on operation Safety of Offshore Wind Farms. Journal of Marine Science and Engineering 2021;9(8):991.
[12] Shi J, Guo J, Zheng S. Evaluation of hybrid forecasting approaches for wind speed and power generation time series. Renew Sustain Energy Rev 2012;16(5): 3471–80.
[13] Linyue Gao, Bochen Li, and Jiarong Hong. “Effect of wind veer on wind turbine power generation.” Physics of Fluids, vol.33, no.1, 2021.
[14] Baldi F, Coraddu A, Kalikatzarakis M, et al. Optimisation-based system designs for deep offshore wind farms including power to gas technologies. Appl Energy 2022; 310:118540.
[15] Ren Z, Verma AS, Li Ye, et al. Offshore wind turbine operations and maintenance: a state-of-the-art review. Renew Sustain Energy Rev 2021;144:110886.
[16] Pryor SC, Barthelmie RJ, Shepherd TJ. Wind power production from very large offshore wind farms. Joule 2021;vol. 5, no. 10:pp2663–2686.
[17] Mohammad Barooni, Truaj Ashuri, Deniz Velioglu, et al. “Floating Offshore Wind Turbines: Current Status and Future Prospects.” *Energies*, vol.16, no.1, 2023.
[18] Kim D, Ryu G, Moon C, et al. Accuracy of a short-term wind power forecasting model based on deep learning using LiDAR-SCADA integration: a case study of the 400-MW Anholt offshore wind farm. Appl Energy 2024;373:123882.
[19] Moynihan B, Tronci EM, Hughes MC, et al. Virtual sensing via Gaussian Process for bending moment response prediction of an offshore wind turbine using SCADA data. Renew Energy 2024;227:120466.
[20] Wang H, Wang K, He S, et al. Wake steering in offshore wind farms: Field experiment and SCADA-driven simulations for quantifying power and blade root loads. Ocean Eng 2026;347:124001.
[21] Maharana K, Mondal S, Nemade B. A review: Data pre-processing and data augmentation techniques. Global Transitions Proc 2022;3(1):pp91–99.
[22] López V, Fernández A, García S. An insight into classification with imbalanced data: Empirical results and current trends on using data intrinsic characteristics. Information Sci 2013;250(20):pp113–141.
[23] Geoff Hulten, Laurie Spencer, and Pedro Domingos. “Mining time-changing data streams.” KDD '01: Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining, pp:97-106, 2001.
[24] Idrissi N, Zellou A. A systematic literature review of sparsity issues in recommender systems. Soc Netw Anal Min 2020;10.
[25] Potisomporn P, Vogel CR. Spatial and temporal variability characteristics of offshore wind energy in the United Kingdom. Wind Energy 2022;vol. 25, no. 3: pp537–552.
[26] Watts D, Durán P, Flores Y. How does El Niño Southern Oscillation impact the wind resource in Chile? a techno-economical assessment of the influence of El Niño and La Niña on the wind power. Renew Energy 2017;103:pp128–142.
[27] Rodrigues S, Restrepo C, Kontos E, et al. Trends of offshore wind projects. Renew Sustain Energy Rev 2015;49:1114–35.
[28] Tuy S, Lee HS, Chreng K. Integrated assessment of offshore wind power potential using Weather Research and Forecast (WRF) downscaling with Sentinel-1 satellite imagery, optimal sites, annual energy production and equivalent CO2 reduction. Renew Sustain Energy Rev 2022;163:112501.
[29] Ryu GH, Kim Y-G, Kwak SJ, et al. Atmospheric Stability Effects on Offshore and Coastal Wind Resource Characteristics in South Korea for developing Offshore Wind Farms. Energies 2022;15(4):1305.
[30] Ospino-Castro, A., Navas, S. R., and Robles-Algarín, C. “Methodology for Generating a Reference Wind Year for Offshore Wind Energy: A Case Study in La Guajira, Colombia.” International Journal of Energy Economics and Policy, vol.14, no.5, 2024.
[31] Wang Y, Zou R, Liu F, et al. A review of wind speed and wind power forecasting with deep neural networks. Appl Energy 2021;304:117766.
[32] Cheng-Dar Yue, Che-Chih Liu, Chien-Cheng Tu, et al. “Prediction of Power Generation by Offshore Wind Farms Using Multiple Data Sources.” Energies, vol.12, no.4,2019.
[33] Yang Z, Peng X, Zhang X, et al. Short-Term Offshore Wind Power Prediction based on significant Weather Process Classification and Multitask Learning considering Neighboring Powers. Wind Energy 2024;27(10):pp1011–1023.
[34] Chen J, Xueying Fu, Zhang L, et al. A novel offshore wind power prediction model based on TCN-DANet-sparse transformer and considering spatio-temporal coupling in multiple wind farms. Energy 2024;308:132899.
[35] Sun Yu, Zhou Q, Sun Li, et al. CNN–LSTM–AM: a power prediction model for offshore wind turbines. Ocean Eng 2024;301:117598.
[36] Anping Wan, Shuai Peng, Khalil AL-Bukhaiti, et al. A novel hybrid BWO-BiLSTM-ATT framework for accurate offshore wind power prediction. Ocean Engineering, vol.312, Part 2, 119227, 2024.
[37] Qiang Wang, Feiyan Xu, Jiahua He, et al. A new fusion model for enhanced ultra-short-term offshore wind power forecasting. Renewable Energy, vol.256, Part A, 123876, 2026.
[38] Gong Z, Wan A, Ji Y, et al. Improving short-term offshore wind speed forecast accuracy using a VMD-PE-FCGRU hybrid model. Energy 2024;295:131016.
[39] Ruoyun Du, Hongfei Chen, Min Yu, et al. 3DTCN-CBAM-LSTM short-term power multi-step prediction model for offshore wind power based on data space and multi-field cluster spatio-temporal correlation. Applied Energy, vol.376, Part A, 124169, 2024.
[40] Huang J, Qin R. Elman neural network considering dynamic time delay estimation for short-term forecasting of offshore wind power. Appl Energy 2024; 358:122671.
[41] Javier Serrano González, Ángel Luis Trigo García, Manuel Burgos Payán. “Optimal wind-turbine micro-siting of offshore wind farms: A grid-like layout approach.” Applied Energy, vol.200, pp:28-38, 2017.
[42] Charhouni N, Sallaou M, Mansouri K. Realistic wind farm design layout optimization with different wind turbines types. Int J Energy Environ Eng 2019; 10:pp307–318.
[43] Chutian Wu, Yang X, Zhu Y. On the design of potential turbine positions for physics-informed optimization of wind farm layout. Renew Energy 2021;164: pp1108–1120.

[44] Zuo T, Zhang Y, Xiong L, et al. Complete joint-optimization for offshore wind farm planning. Int J Electr Power Energy Syst 2024;157:109832.
[45] He J, Ge M, Žarković SD, et al. A novel integrated optimization method of micrositing and cable routing for offshore wind farms. Energy 2024;306:132443.
[46] Ling Z, Zhao Z, Liu Y, et al. Multi-objective layout optimization for wind farms based on non-uniformly distributed turbulence and a new three-dimensional multiple wake model. Renew Energy 2024;227:120558.
[47] Peng W, Li B, Ge M, et al. Layout optimization for offshore wind farms considering both fatigue damage and power generation. Renew Energy 2025;246:122878.
[48] Yang S, Deng X, Yang K. Machine-learning-based wind farm optimization through layout design and yaw control. Renew Energy 2024;224:120161.
[49] Tao S, Yang J, Zheng G, et al. A two-stage optimization model for floating offshore wind farm layout and control. Renew Energy 2025;253:123614.
[50] Weng W, Gong W, Wan A, et al. Early warning system for offshore wind turbine runaway using combined multi-method missing value filling. Ocean Eng 2025;334:121620.
[51] Alp Karadeniz. Advancing harmonic prediction for offshore wind farms using synthetic data and machine learning. Computers and Electrical Engineering, vol.127, Part B, 110613, 2025.
[52] Feng S, Zhang Z, Zheng Y, et al. Transfer-Learning-based BiLSTM-WGAN Approach for Synthetic Data Generation of Sub-Synchronous Oscillations in Wind Farms. J Mod Power Syst Clean Energy 2025;13(4):pp1199–1210.
[53] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:pp1224–1239.
[54] Antonini EGA, Romero DA, Amon CH. Continuous adjoint formulation for wind farm layout optimization: a 2D implementation. Appl Energy 2018;228:pp2333–2345.
[55] Mingfeng Hu, Shi J, Yang S, et al. Current Status and Future Trends in installation, operation and Maintenance of Offshore floating Wind Turbines. Journal of Marine Science and Engineering 2024;12(12):2155.
[56] Gonzalez E, Stephen B, Infield D, et al. Using high-frequency SCADA data for wind turbine performance monitoring: a sensitivity study. Renew Energy 2019;131:841–53.
[57] Koukoura S, Scheu MN, Kolios A. Influence of extended potential-to-functional failure intervals through condition monitoring systems on offshore wind turbine availability. Reliab Eng Syst Saf 2021;208:107404.
[58] Xia J, Zou G. Operation and maintenance optimization of offshore wind farms based on digital twin: a review. Ocean Eng 2023;268:113322.
[59] Bonou A, Laurent A, Olsen SI. Life cycle assessment of onshore and offshore wind energy-from theory to application. Appl Energy 2016;180:327–37.
[60] Dinwoodie I, Iain O, Endrerud EV, et al. Reference cases for Verification of operation and Maintenance simulation Models for Offshore Wind Farms. Wind Eng 2015;39(1):1–14.
[61] Sperstad IB, Stålhane M, Dinwoodie I, et al. Testing the robustness of optimal access vessel fleet selection for operation and maintenance of offshore wind farms. Ocean Eng 2017;145:334–43.
[62] Carroll J, McDonald A, McMillan D. Failure rate repair time and unscheduled O cost analysis of 310 offshore wind turbines. Wind Energy 2016;19:1107–19.
[63] N. Simpson. "SPARTA project - System Performance Availability and Reliability Trend Analysis", Proc. All-Energy Exhibition Conference, May 2014.
[64] Carroll J, McDonald A, McMillan D. Reliability Comparison of Wind Turbines with DFIG and PMG Drive trains. IEEE Trans Energy Convers 2015;30(2):663–70.
[65] Carroll J, McDonald A, Dinwoodie I, et al. Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations. Wind Energy 2016;20(2):361–78.
[66] Lubing Xie, Xiaoming Rui, Shuai Li, et al. "Maintenance Optimization of Offshore Wind Turbines Based on an Opportunistic Maintenance Strategy." Energies, vol.12, no.14, 2019.
[67] Li M, Jiang X, Negenborn RR. Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch. Ocean Eng 2021;231:1090062.
[68] How Full Data Access Helps Predict Future Failures and Reduce Operational Expenditure; Technical Report; Onyx Insight: Nottingham, UK, 2019.
[69] Christine Röckmann, Sander Lagerveld, and John Stavenuiter. "Operation and Maintenance Costs of Offshore Wind Farms and Potential Multi-use Platforms in the Dutch North Sea." Aquaculture Perspective of Multi-Use Sites in the Open Ocean, pp:97-113, 2017.
[70] J. Carmona-Sanchez, Z. Lin, M. Collu, et al. "An analysis of the impact of an advanced aero-hydro-servo-elastic model of dynamics on the generator-converter dynamics, for an offshore fixed 5MW PMSG wind turbine." 15th IET International Conference on AC and DC Power Transmission (ACDC 2019), 2019.
[71] A. G. Olabi, Khaled Obaideen, Mohammad Ali Abdelkareem, et al. "Wind Energy Contribution to the Sustainable Development Goals: Case Study on London Array." Sustainability, vol.15, no.5, 2023.
[72] Eric C.D. Tan, and Patrick Lamers. "Circular Bioeconomy Concepts—A Perspective." Frontiers in Sustainability, vol.2, 2021.
[73] Bocken NMP, de Pauw I, Bakker C, et al. Product design and business model strategies for a circular economy. J Ind Prod Eng 2016;33:208–320.
[74] Yang Y, Liu Z. A novel probabilistic approach for driving the sustainable energy circular economy: Innovating efficiency in renewable resource markets. Sustain Cities Soc 2024;108:105461.
[75] Velenturf APM. A Framework and Baseline for the Integration of a Sustainable Circular Economy in Offshore Wind. Energies 2021;14(17):5540.
[76] So Young Oh, Joung C, Lee S, et al. Condition-based maintenance of wind turbine structures: a state-of-the-art review. Renew Sustain Energy Rev 2024;204:114799.
[77] Tyurkay A, Kirkelund GM, Lima ATM. State-of-the-art circular economy practices for end-of-life wind turbine blades for use in the construction industry. Sustainable Prod Consumption 2024;47:17–36.
[78] Rentizelas A, Trivyza N, Oswald S, et al. Reverse supply network design for circular economy pathways of wind turbine blades in Europe. Int J Prod Res 2022;60:1795–814.
[79] Rogeau A, Vieubled J, de Coatpont M, et al. Techno-economic evaluation and resource assessment of hydrogen production through offshore wind farms: a European perspective. Renew Sustain Energy Rev 2023;187:113699.
[80] Qureshi J. A Review of Recycling Methods for Fibre Reinforced Polymer Composites. Sustainability 2022;14(24):16855.
[81] Cieślewicz N, Pilarski K, Pilarska AA. End-of-Life strategies for Wind Turbines: Blade Recycling, Second-Life applications, and Circular Economy Integration. Energies 2025;18(19):5182.
[82] Xuemei Yu, Zhang C, Li J, et al. Reuse of Retired Wind Turbine Blades in Civil Engineering. Buildings 2025;15(14):2414.
[83] Sorte S, Martins N, Oliveira MSA, et al. Unlocking the potential of Wind Turbine Blade Recycling: Assessing Techniques and Metrics for Sustainability. Energies 2023;16(22):7624.
[84] Arvesen A, Hertwich EG. Assessing the life cycle environmental impacts of wind power: a review of present knowledge and research needs. Renew Sustain Energy Rev 2012;16(8):5994–6006.
[85] Carroll J, McDonald A, McMillan D. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. Wind Energy 2016;19(6):1107–19.
[86] Tchakoua P, Wamkeue R, Ouhrouche M, et al. Wind Turbine Condition monitoring: State-of-the-Art Review, New Trends, and Future challenges. Energies 2014;7(4):2595–630.
[87] Golparvar B, Papadopoulos P, Ezzat AA, et al. A surrogate-model-based approach for estimating the first and second-order moments of offshore wind power. Appl Energy 2021;299:117286.
[88] Mahulja S, Chr G, Larsen, Elham Ali. Engineering an optimal wind farm using surrogate models. Wind Energy 2018;21(12):1296–308.
[89] Slot RMM, Sørensen JD, Sudret B, et al. Surrogate model uncertainty in wind turbine reliability assessment. Renew Energy 2020;151:1150–62.
[90] Kumar P, Paul S, Saha AK, et al. Recent Advancements in Planning and Reliability Aspects of Large-Scale Deep Sea Offshore Wind Power Plants: a Review. IEEE Access 2024;13:3738–67.
[91] Evi Elisa Ambarita, Anniken Karlsen, Francesco Scibilia, et al. "Industrial digital twins in offshore wind farms." Energy Informatics, vol.7, 2024.
[92] Fang Xi, Misra S, Xue G, et al. Smart Grid — the New and improved Power Grid: a Survey. IEEE Communications Surveys & Tutorials 2012;14(4):944–80.
[93] Sahu A, Yadav N, Sudhakar K. Floating photovoltaic power plant: a review. Renew Sustain Energy Rev 2016;66:815–24.
[94] John K. Kaldellis, and Despoina Boulogiorgou. "Chapter 24 - Renewable energy: Wind energy." Living with Climate Change, pp:513-557, 2024.
[95] Jensen PD, Purnell P, Velenturf APM. Highlighting the need to embed circular economy in low carbon infrastructure decommissioning: the case of offshore wind. Sustainable Prod Consumption 2020;24:266–80.
[96] Woo SM, Whale J. A mini-review of end-of-life management of wind turbines: current practices and closing the circular economy gap. Waste Manag Res 2022;col.40(12).
[97] Topham E, McMillan D, Bradley S, et al. Recycling offshore wind farms at decommissioning stage. Energy Policy 2019;129:698–709.
[98] Dannheim J, Bergström L, Birchenough SNR, et al. Benthic effects of offshore renewables: identification of knowledge gaps and urgently needed research. ICES J Mar Sci 2020;77(3):1092–108.
[99] Lin Zi, Liu X. Wind power forecasting of an offshore wind turbine based on high-frequency SCADA data and deep learning neural network. Energy 2020;201:117693.
[100] Hayes L, Stocks M, Blakers A. Accurate long-term power generation model for offshore wind farms in Europe using ERA5 reanalysis. Energy 2021;229(12):0603.
[101] Scheepens DR, Schicker I, Hlaváčková-Schindler K, et al. Adapting a deep convolutional RNN model with imbalanced regression loss for improved spatio-temporal forecasting of extreme wind speed events in the short to medium range. Geosci Model Dev 2023;16(1):pp251–270.
[102] M.Y. Junior, R.Z. Freire, L.O. Seman, et al. "Optimized hybrid ensemble learning approaches applied to very short-term load forecasting." International Journal of Electrical Power & Energy Systems, vol.155, Part B, 109579, 2024.
[103] Mutaz AlShafeey, and Csaba Csaki. "Adaptive machine learning for forecasting in wind energy: A dynamic, multi-algorithmic approach for short and long-term predictions." Heliyon, vol.10, no.15, 2024.
[104] Pillai AC, Chick J, Khorasanchi M, et al. Application of an offshore wind farm layout optimization methodology at Middelgrunden wind farm. Ocean Eng 2017;139:pp287–297.
[105] Cazzaro D, Pisinger D. Variable neighborhood search for large offshore wind farm layout optimization. Comput Oper Res 2022;138:105588.
[106] Fenglan He, Markus Wagner, Lijun Zhang. "A novel integrated approach for offshore wind power optimization." Ocean Engineering, vol.266, Part 2, 112827, 2022.
[107] Zhenfan Wang YT, Zhang K, et al. An optimization framework for wind farm layout design using CFD-based Kriging model. Ocean Eng 2024;293:116644.
[108] Zhang X, Wang Q, Ye S, et al. Efficient layout optimization of offshore wind farm based on load surrogate model and genetic algorithm. Energy 2024;309:133106.

[109] Yang K, Deng X. Layout optimization for renovation of operational offshore wind farm based on machine learning wake model. J Wind Eng Ind Aerodyn 2023;232: 105280.
[110] Martinez-Luengo M, Shafiee M, Kolios A. Data management for structural integrity assessment of offshore wind turbine support structures: data cleansing and missing data imputation. Ocean Eng 2019;173:867–83.
[111] Sun C, Chen Y, Cheng C. Imputation of missing data from offshore wind farms using spatio-temporal correlation and feature correlation. Energy 2021;229: 120777.
[112] Dao CD, Kazemtabrizi B, Crabtree CJ. Offshore wind turbine reliability and operational simulation under uncertainties. Wind Energy 2020;23(10):1919–38.
[113] Debora C. Failure diagnosis for offshore wind turbines with low availability of run-to-failure data. University of Strathclyde; 2023. PhD thesis.
[114] Topham E, McMillan D. Sustainable decommissioning of an offshore wind farm. Renew Energy 2017;102:470–80.
[115] Chen J, Mao B, Yufeng Wu, et al. Green development strategy of offshore wind farm in China guided by life cycle assessment. Resour Conserv Recycl 2023;188: 106652.
[116] Díaz-Motta A, Díaz-González F, Villa-Arrieta M. Energy sustainability assessment of offshore wind-powered ammonia. J Clean Prod 2023;420:138419.