Empowering digital twins for wind energy operation and maintenance: A prospective framework and future directions

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Empowering digital twins for wind energy operation and maintenance: A prospective framework and future directions

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HIGHLIGHTS

- Identify key components to clarify DT deployment targets for wind turbine O&M.
- Review general and wind-specific DT models to map current developments.
- Propose a DT-enabled O&M framework with a closed digital process.
- Summarize key techniques and advancements across each DT implementation stage.
- Identify research gaps and suggest future directions for practical DT adoption.

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ABSTRACT

Wind energy is a cornerstone in the global transition toward carbon neutrality, with its long Operation and Maintenance (O&M) phase playing a significant role in affecting overall profitability, efficiency, safety, and sustainability. Digital twin (DT) technology has emerged as a key frontier in the wind energy sector due to its potential to construct comprehensive virtual representations of physical wind turbines and enable a digitalized loop to enhance performance across the entire life cycle. While research on DT technology in wind energy O&M is rapidly gaining visibility, there remains a substantial gap between current academic developments and practical implementation across methodological, technical, and operational aspects. In order to address this issue, this paper begins by briefly summarizing recent trends in wind turbine technology and identifying the most critical components that deserve DT technology. The existing DT capability levels and modeling approaches are then reviewed, and a prospective DT framework specifically tailored for the O&M of wind energy systems is proposed. The proposed framework encompasses a closed-loop process from the physical to the virtual domain and back again. The physical-to-virtual loop includes data acquisition, data management, virtual model construction, and adaptive operations. Conversely, the virtual-to-physical loop involves diagnostics and prognostics, maintenance decision-making, resource planning, and maintenance execution. Each stage is analyzed in terms of its enabling technologies and representative methodologies. By comparing the state of the art with the envisioned DT-enabled O&M paradigm, this paper identifies key research gaps and outlines promising directions for future investigation.

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List of Abbreviations

Abbreviation and Definition

AI	Artificial Intelligence
AR	Augmented Reality
CBM	Condition-Based Maintenance
CTV	Crew Transfer Vessel
DL	Deep Learning
DP	Dynamic Programming
DT	Digital Twin
EKF	Extended Kalman Filter
FEA	Finite Element Analysis
FL	Federated Learning
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode, Effects, and Criticality Analysis
FSV	Field Support Vessel
GA	Genetic Algorithms
GAN	Generative Adversarial Network
HLV	Heavy Lift Vessel
IoT	Internet of Things
KF	Kalman Filter
KG	Knowledge Graph
LCoE	Levelized Cost of Energy
LTE	Long-Term Evolution
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
ML	Machine Learning
MR	Mixed Reality
MTBF	Mean Time between Failures
MTTR	Mean Time to Repair
NEDO	New Energy and Industrial Technology Development Organization
O&M	Operation and Maintenance
PdM	Predictive Maintenance
PF	Particle Filter
PHM	Prognostics and Health Management
PINN	Physics-Informed Neural Network
PSO	Particle Swarm Optimization
RAM	Reliability, Availability, Maintainability
RL	Reinforcement Learning
RUL	Remaining Useful Life
RxM	Prescriptive Maintenance
SCADA	Supervisory Control and Data Acquisition
SP	Stochastic Programming
TL	Transfer Learning
TSP	Traveling Salesman Problem
UQ	Uncertainty Quantification
VR	Virtual Reality
VRP	Vehicle Routing Problem

1. Introduction

1.1. Background

In order to align with the objective of the Paris Agreement which limit the temperature increase to 1.5 °C, it is necessary to promote the development of clean energy sources as a primary strategy to reduce carbon dioxide emissions [1]. Wind energy has the potential to act as a major player in meeting the growing demand for clean energy across the world due to the advantages of widespread availability, cost-free fuel, and low life-cycle pollutant emissions [2]. As the most mature among the existing renewable energy resources, wind power has the potential to provide 30%–50% of the electricity demand in many countries in the future [3]. Fig. 1 illustrates the annual new installations and cumulative installed capacities of onshore and offshore wind energy from 2020 to 2030, with data from 2025 onward representing outlook values [4]. It can be observed that the total new installations have been steadily increasing, and the share of offshore wind in both new and cumulative capacity is becoming progressively more significant. By 2030, the wind industry is anticipated to reach a significant milestone with a capacity of 2 TW [5]. China and Europe have emerged as global frontrunners in this sector [6].

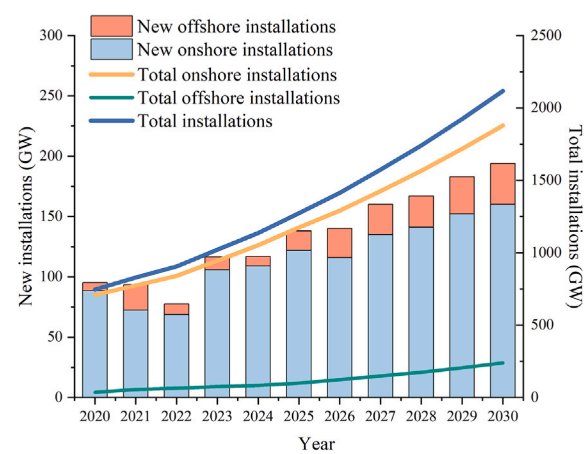


Fig. 1. Annual new installations and cumulative installed capacity of onshore and offshore wind energy from 2020 to 2030 [4].

Some studies indicate that wind energy may not demonstrate a clear economic advantage over other power generation or renewable technologies, depending on the specific context and evaluation criteria [7]. Particularly, offshore wind energy is adversely affected when considering the significant impact of the marine environment on economic feasibility [8]. The wind industry has set an ambitious goal to reduce the Levelized Cost of Energy (LCoE) over the coming decades, thereby enhancing the economic competitiveness of wind energy. In 2020, the LCoE for onshore wind, fixed-bottom offshore wind, and floating wind was approximately 45 €/MWh, 86 €/MWh, and 184 €/MWh, respectively [9]. These costs are expected to decrease to 25 €/MWh, 37 €/MWh, and 40 €/MWh, respectively, by 2050 [9].

Operation and Maintenance (O&M) activities have been identified as one of the main contributors to the overall expenditure of wind farm projects [10]. O&M costs represent about 25% of the life-cycle costs for onshore wind farms, and more than 30% for offshore wind farms [11,12]. From the perspective of availability, onshore wind turbines are able to reach the values in the range of 95–97% [13]. However, due to their remote locations, system complexity and harsh marine environments, offshore wind turbines are prone to more frequent failures, leading to considerably lower availability of approximately 88% [14,15]. Enhancing availability, reliability, and O&M cost-effectiveness is essential to improve performance and reduce life-cycle costs for wind turbines, particularly those situated offshore [16].

Industry 4.0 is perceived as a novel era in the industrial sector, characterized by the adoption of cutting-edge and transformative digital technologies to enhance industrial efficiency [17,18]. Within the Industry 4.0 paradigm, the Digital Twin (DT) technology is recognized as a highly promising tool that can be applied to the entire life cycle and various aspects of wind turbines, including design, construction, and control. Among these applications, maintenance is one of the most critical and value-generating areas where DT can demonstrate its full potential. By leveraging real-time data collected through remote monitoring, DTs facilitate the simulation and prediction of wind turbine conditions. Hence, the physical turbine is translated into a virtual model that provides actionable insights to decision-makers, guiding subsequent maintenance logistics and implementation to improve turbine health. This loop of digitalization is effectively closed in this manner.

1.2. Overview of the existing reviews

The digital transition of the industry over the past decade has significantly promoted the emergence of research and development in Prognostics and Health Management (PHM) [19,20]. Meanwhile, the rapid expansion of wind power deployment as a strategy to mitigate carbon dioxide emissions has garnered burgeoning interest within the academic community. Under these trends, utilizing DT techniques to enhance wind turbine O&M has emerged as an active area of research in recent years.

Fig. 2 displays the published articles on DT and O&M for wind turbines in the past decade (2016 – 2025), as indexed by the Web of Science. The background on wind energy is searched using "TS = ("wind turbine" OR "wind energy" OR "wind farm")". DT and O&M are respectively searched using "TS = ("digital twin" OR "digital twins")" and "TS = ("operation and maintenance" OR "operations and maintenance")".

It is noteworthy that although only a portion of the relevant articles are covered in this search engine, the information can clearly reflect an overall trend for published articles in these research fields in the past decade. It is observed that the number of publications in the two fields both show an upward trend over time. Publications related to DT technology were not found prior to 2018, but have experienced marked growth in subsequent years, indicating a surge in research interest in this area. Research on O&M has generally experienced a gradual increase since 2016, potentially reflecting advancements in technology or theory in this field. Overall, although the number of studies in the two fields has differed significantly over the past decade, the gap is narrowing rapidly. Notably, by May 2025, publications related to DT already account for approximately 60% of the total research on wind turbine O&M. This indicates that digitalization has become a key focus in wind energy development, with the potential to drive the transformation of O&M practices.

The significant expansion in research outcomes has led to the publication of several review papers in recent years. Table 1 summarizes these papers on wind turbine DT and O&M published in the past decade.

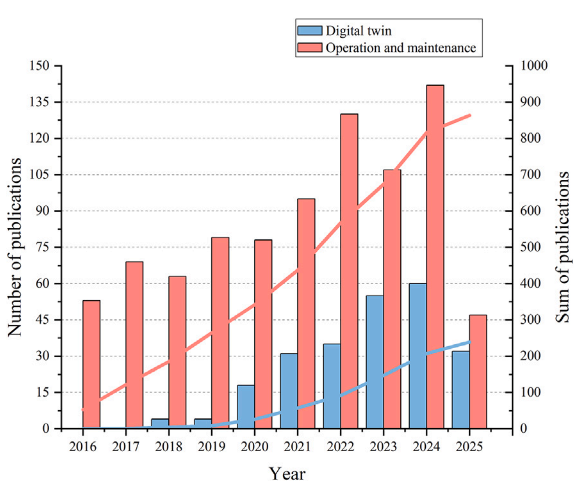


Fig. 2. Annual number and the sum of publications on wind turbine DT, prognosis, and maintenance indexed in the Web of Science.

Considering that many review papers encompass multiple fields for wind turbines, the papers with substantial content related to at least one of the fields among DT and O&M are summarized in the table. The papers are listed in a chronological order and it is observed that the number of publications in these domains has been steadily increasing since 2019, with a particularly notable surge in DT-related papers since 2021. This trend is consistent with the observations based on Fig. 2. Nearly half of the papers focus on general wind turbines which are not specified as onshore, offshore, or novel wind turbines. However, most of the papers specifically related to O&M concentrate on offshore wind turbines, floating and novel designs. The reason is that offshore wind power is developing rapidly, and the unique design of these wind turbines and the harsh marine environment make O&M particularly challenging and costly, thereby deserving increased research attention. Furthermore, most DT-related review papers summarize developments mainly from the perspectives of reliability, condition monitoring, and maintenance. This proves the strong correlation between DT applications and O&M, highlighting the need for further in-depth exploration in this area.

These review papers listed in the table are constructive and add value to the field, summarizing the current progress of research while fostering the development of the fields. However, there are still a few gaps existing in the reviews to be addressed as follows:

(1) While there have been review studies exploring DT applications in the wind energy sector, most adopt a broad industrial or technological perspective, emphasizing the strategic importance of DT adoption but offering limited insight into the specific needs of O&M. Conversely, the relatively few review papers that do focus on DT for wind turbine O&M tend to rely on generic frameworks adopted from general equipment or industrial systems, without sufficient adaptation to the characteristics of wind turbine systems, particularly in offshore environments, including high internal heterogeneity, limited accessibility, and complex O&M procedures. This disconnect highlights a critical gap, namely a well-defined, domain-specific DT framework tailored to wind turbine O&M remains absent from current literature.
(2) Current review papers on DT applications for wind turbine O&M often provide only a high-level overview of digitalized O&M processes, lacking in-depth analysis of the key implementation steps required to realize a functional DT-enabled O&M loop. Moreover, there is a notable lack of systematic organization, comprehensive summary, and thorough discussion of the enabling technologies and methodologies essential for the practical deployment of DT in wind turbine O&M. This fragmented perspective poses a substantial barrier to translating DT concepts into effective, real-world solutions.
(3) To realize the full potential of DT-enabled O&M, existing methods and technologies require significant upgrades and breakthroughs. Although previous reviews have summarized advancements across individual fields, they fall short in identifying the core implementation bottlenecks and do not adequately outline the future directions for advancing DT applications in wind energy O&M.

1.3. Scope of this review

Motivated by the rapid development of digitalization in wind energy and increasing attention on relevant fields, along with the gaps identified in the existing literature review papers, the objectives of this paper are summarized below.

(1) By summarizing the wind turbine system and identifying its critical components, the deployment targets of DT technology are clarified for the purpose of O&M. Subsequently, a review and comparison of existing general DT models are presented, followed by a focused examination of DT frameworks developed

Table 1
Summary of review papers on wind turbine DT and O&M in recent years.

Reference	Year	Target wind turbines			Focus		Brief description
		General	Offshore	Floating and novel concepts	DT	O&M	
[21]	2015		✓			✓	This paper reviews the state-of-the-art of maintenance logistics in offshore wind energy following a classification scheme with strategic, tactical and operational decision-making levels.
[22]	2019		✓			✓	This paper reviews the state of the art in decision support models for maintenance scheduling.
[23]	2019	✓				✓	This paper reviews maintenance policy optimization and inspection planning of wind energy systems and structures.
[24]	2019		✓			✓	This paper reviews condition-based maintenance for offshore wind energy, including condition monitoring, fault diagnosis and prognosis, and maintenance optimization.
[25]	2019	✓				✓	This review aims to identify and classify the different types of models used at the strategic, tactical, and operational decision levels of wind turbine maintenance.
[26]	2020	✓				✓	This paper makes a review of the state of the art in maintenance strategy optimization for wind energy.
[27]	2021	✓			✓		This paper provides an overview of the application of DT technology in the fault diagnosis and condition monitoring of wind turbine mechanical components.
[28]	2021		✓		✓		This paper introduces the state-of-the-art on the reliability analysis of offshore wind turbine support structures and proposes a DT framework.
[29]	2021		✓			✓	This paper reviews the studies on maintenance optimization models for offshore wind farms.
[30]	2021	✓				✓	This paper reviews the state of the art on wind farm O&M, including failure rate, reliability, condition monitoring, maintenance strategies.
[31]	2021		✓			✓	This paper reviews the state-of-the-art research on offshore wind turbine O&M, covering strategy selection, schedule optimization, onsite operations, assessment criteria, recycling, and environmental concerns.
[32]	2021		✓			✓	This paper reviews the existing literature and novel approaches in the O&M of offshore wind turbines.
[33]	2022			✓		✓	This paper reviews the decision support systems for offshore wind farm maintenance with a focus on the applicability of these models to novel turbine concepts, including X-Rotor and Multi-Rotor System turbines.
[34]	2022			✓		✓	This paper reviews the existing literature surrounding floating offshore wind O&M models.
[35]	2022		✓			✓	This paper reviews the current methods and technologies in predictive and prescriptive maintenance strategies.
[36]	2022		✓			✓	This paper summarizes the condition monitoring and O&M of offshore wind farms
[37]	2023	✓			✓		This paper provides a comprehensive overview of the DT technology in the wind energy sector, highlighting the capability levels, recent developments, and research needs from an industrial viewpoint.
[38]	2023		✓		✓	✓	This paper reviews recent advancements in DT technology, specifically focusing on offshore wind farm maintenance.
[39]	2023		✓		✓		This paper explores the potential of applying knowledge from industrial DTs to offshore wind sector.
[40]	2023		✓			✓	This paper provides an overview of the opportunistic maintenance strategy used within other industries and an in-depth review of the work specific to offshore wind.
[41]	2023	✓			✓	✓	This paper reviews the damage detection, maintenance, and monitoring techniques, diagnosis, and DT for wind turbine blades.
[42]	2024	✓			✓		This paper investigates the commonly employed methodologies, the integration of data, key features and technologies behind real-time systems, and challenges in predictive DT platforms for wind energy systems.
[43]	2024			✓	✓		This paper explores the application and impact of DT technology in bolstering the reliability of floating offshore wind turbines and their supporting platforms.
[44]	2024	✓				✓	This paper reviews health monitoring, damage diagnosis, prognosis, and condition-based maintenance strategies to ensure reliable and secure operations of wind turbine structures.
[45]	2024	✓				✓	This paper reviews the research on the predictive and prescriptive maintenance of wind turbines.
[46]	2024			✓		✓	This paper presents the latest advancements in the technologies for the installation and maintenance of floating wind turbines.
[47]	2025	✓				✓	This paper provides a review for degradation modeling, prognosis, and prognostics-driven maintenance techniques for wind energy systems.

specifically for wind turbines. This provides a clear understanding of the current development of DT in the wind energy sector, particularly in the context of O&M.

(2) A prospective framework is proposed to enable DT-enabled O&M for wind turbines. The essential steps involved in the digitalized O&M process, from the physical domain to the virtual representation and back, are systematically reviewed. A comprehensive and in-depth summary of key challenges and recent advancements at each stage is provided, highlighting the potential and practical pathways for implementing this framework.

(3) By comparing existing research with the proposed framework, critical gaps that hinder the realization of DT-enabled O&M for wind energy are identified. Important future research directions are outlined to guide further development and practical application of DT in wind turbine O&M.

The remainder of this paper is structured as follows. Section 2 summarizes the critical components within wind turbines that require particular attention and merit the deployment of DT. The digital solutions for the critical components are also reviewed. Section 3 outlines the current capability levels of DT technologies, introduces generic DT models, and reviews DT-based models specifically developed for wind turbines. Section 4 introduces a DT-enabled O&M framework for wind turbines. The framework consists of a bi-directional loop between the physical and digital domains, comprising eight critical steps. Key methodologies and technologies employed throughout this loop are comprehensively reviewed. In Section 5, the challenging issues in DT-enabled O&M are discussed, highlighting the imperative directions for future research. Finally, concluding remarks are presented in Section 6.

2. Digitalization of wind turbine systems: system evolution, critical components and current solutions

As noted in the study [48], the systematic implementation of digitalization of maintenance services begins with identifying critical components that have a significant impact on the system in terms of performance, availability, reliability, or productivity. Due to the complexity of wind turbine systems and the heterogeneity among their internal components, it remains very difficult for DT technology to fully simulate an entire wind turbine. A more feasible approach at present is to implement DT for individual critical components and then integrate them. Therefore, it is essential to have a brief understanding of the evolution and composition of wind turbine systems. By analyzing failure statistics and related operational data, the critical components influencing turbine performance can be identified. This information helps to clarify the key targets of DT technologies in O&M, thereby enabling an assessment of the progress of existing solutions.

This section begins with a general overview of the latest advancements in wind turbine technology, with a focus on how component design and configuration vary across different turbine types. It also summarizes the advantages and disadvantages of these designs from an O&M perspective. Subsequently, the components of the most typical wind turbine types are introduced and the past studies on identifying critical components are reviewed to highlight the critical components in wind turbines. Lastly, a brief overview of the existing studies focusing on digital solutions for these critical components is provided.

2.1. Trend in wind turbine technology

This section provides an overview of recent developments in wind turbine technology, reviewing different turbine types based on design and installation location, and outlining their O&M advantages and disadvantages. Such developments will provide insights for adapting DT and O&M to the specific characteristics of wind turbines in future applications.

2.1.1. Design: from horizontal-axis dominance to diverse alternatives

The first wind powered machine operated in 1887 [49]. Nowadays, the most common configuration of wind turbines, characterized by a horizontal axis, three blades, variable speed, and pitch control, represents the result of numerous explorations and improvements over time [50], as shown in Fig. 3(a). In addition, another configuration is the vertical axis wind turbine, as illustrated in Fig. 3(b), which feature a vertically oriented main rotor shaft [51]. This design offers several advantages, including easier O&M, lower noise emissions, enhanced static stability with reduced mass, and reduced aerodynamic wake effects, representing a feasible and popular option in peri-urban or offshore floating environments [51,52]. However, they also face drawbacks such as more complex power scaling, higher mooring line loads, and increased difficulty in compensating for fatigue damage [51–53].

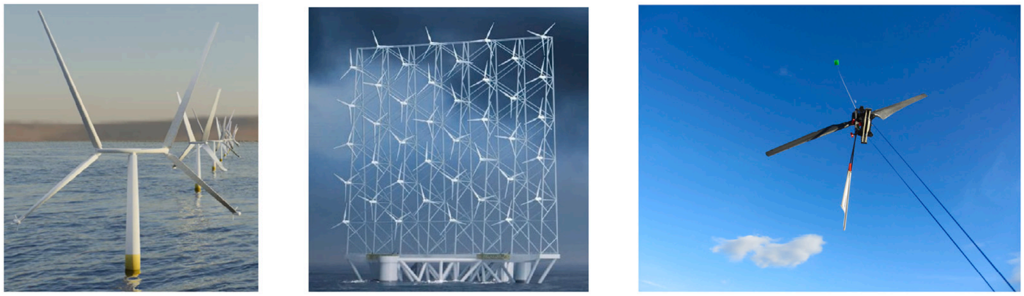
Drivetrains of wind turbines can be categorized into geared and direct-drive types, as shown in Fig. 3(c). The gearbox is a key component that converts the low-speed, high-torque output of the turbine shaft into high-speed, low-torque input for the generator. However, it is one of the leading causes of overall failure downtime, resulting in long downtime, low reliability, and high maintenance costs [54,55]. In order to address these challenges, the direct-drivetrain technology was developed to remove the gearbox with the expected benefits of reducing failures and lowering maintenance problems [56]. In recent years, the capacity of wind turbines has increased significantly, causing larger, heavier, and more costly direct-drivetrain generators, which pose greater challenges for on-site maintenance, particularly in marine environments.

In addition to the wind turbine types mentioned above, novel designs have been proposed or developed in recent years, such as X-rotor wind turbines [60] (illustrated in Fig. 4(a)), multi-rotor systems [61] (Fig. 4(b)), and Airborne wind turbines [62] (Fig. 4(c)). The X-rotor wind turbine features conventional blades that slope in an "X" shape upwards and downwards from the ends of its short cross-arm. The X-rotor design removes the power take-off from the vertical rotor, reducing capital costs [33]. Furthermore, the rotation around the vertical axis increases energy capture and offers rotational symmetry, which eliminates the need for yawing. From an O&M perspective, some studies have indicated that this novel design can reduce O&M costs due to the lower failure rates and downtime by avoiding high-downtime components (e.g., gearboxes or direct-drive generators), operational redundancy, and a reduced reliance on jack-up vessels [60,63]. It should be clarified, however, that progress in full-scale prototyping and field testing for X-rotor wind turbines remains limited to date. The O&M advantages reported thus far are based on simulations and expert judgment. Further development is required to advance the concept to at least TRL-3 before these advantages can be substantiated. Moreover, realizing these potential benefits in practice would require the changes in O&M management, including adjustments to maintenance practices (e.g., onshore maintenance of secondary rotors) and greater use of mid-sized service vessels in place of jack-ups [63]. It is also foreseeable that new O&M challenges may be introduced, such as coordinating maintenance across multiple rotors and accommodating the increased spare parts requirements and associated supply chain pressures.

A multi-rotor system is defined as a horizontal axis wind turbine where two or more rotors are installed. The use of smaller rotors enables high energy output across the same surface area while reducing weight due to the smaller blade size. These savings in weight and materials have a positive impact on the overall LCoE. Moreover, the design also offers

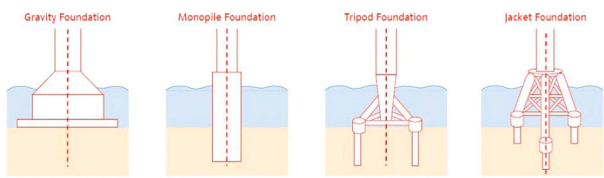
(a) (b) (c)

Fig. 3. Visualization of various types of wind turbines: (a) horizontal axis wind turbines [57] (b) vertical axis wind turbines [58] (c) geared and direct-drive wind turbines [59].



(a) (b) (c)

Fig. 4. Novel wind turbine design: (a) a 5 MW X-rotor concept [67] (b) a multi-rotor system [68] (c) airborne wind turbines [69].



a. Gravity b. Monopile c. Tripod d. Jacket

Fig. 5. Design of fixed-bottom wind turbine concepts [75].

advantages including reduced installation and O&M costs, as well as less system load [64,65]. Airborne wind harnesses energy without the cost of large, material-heavy towers and foundations. Considering the lightweight and inexpensive nature of this type of wind turbine, along with the generator being located on the ground, maintenance implementation may be easy and cheap [62,66]. Similarly, for multi-rotor and airborne wind turbines, the claimed O&M benefits remain largely model-based and inferential, as these concepts have not yet been validated at scale.

2.1.2. *Location: from onshore to offshore*

Another fundamental distinction in wind turbine design exists between onshore and offshore applications. Onshore wind turbines dominated installations in the early days of wind energy. Recent data indicate a significant shift toward offshore wind energy, driven by factors such as technological advancements leading to greater efficiency, policy incentives aimed at achieving carbon neutrality, and the need to exploit the stronger, more consistent winds offshore [3,31,70]. In this context, the future trend is increasing the size of offshore wind turbines, with taller towers and longer blades, to harness more wind energy [71,72].

Another trend is to install offshore wind turbines at locations farther from shore in deeper waters, where wind speeds are higher and more consistent [73,74]. In shallow waters, fixed-bottom foundations are commonly used (Fig. 5), including gravity base foundations, monopile foundations, tripod foundations, and jacket foundations [75,76]. Once the water depth exceeds 50–60 meters, floating foundations become necessary. Common types include semi-submersible platforms, spar-buoy structures, and tension leg platforms [77], as illustrated in Fig. 6. Offshore wind energy, especially floating wind, has the potential to provide a stronger and more reliable energy supply, which is shaping the future of wind energy utilization.

These ongoing trends make DT technology more important than ever. These large-scale turbines, operating in harsh environments with limited accessibility, significantly increase the complexity, cost, uncertainty, and risk associated with O&M. By leveraging DT technology, operators can gain remote and real-time insights into turbine conditions and plan timely and adaptive maintenance, enhancing both the effectiveness and efficiency of O&M activities.

2.2. *Critical component for DT deployment*

Even with the adoption of DT technology, it is not feasible for a virtual model to replicate every aspect of an entire wind turbine. Instead, DT models are typically developed for specific components to address O&M challenges. Fig. 7 demonstrates a typical horizontal-axis wind turbine [78]. It consists of key components, including blade systems, pitch systems, main shafts, gearboxes, generators, support structures, etc. Each one has its own failure rates, failure modes, and contribution to the wind turbine downtime and O&M costs. Current digitalization efforts are still primarily tailored to this mainstream wind turbine type. However, with the ongoing evolution of turbine designs, future approaches should also incorporate digital solutions customized for specific turbine configurations.

With respect to the significant Reliability, Availability, Maintainability (RAM) data on failure rates and downtime, there have been a number of studies performing statistical analysis on various wind turbine types in different regions and countries. For instance, in the study [79], the authors investigated the failure rate and downtime for onshore wind turbines in Japan, provided by the New Energy and Industrial Technology Development Organization (NEDO). The paper [80] presented the failure rate and downtime for 75 wind turbines located in Spain over a period of 11 years. It is worth noting that, in different studies, variations exist in the statistical data regarding wind turbine age, type, capacity, location, system classification methods, and the ways different countries and companies report failure data. These variations may affect the interpretation of result trends. Overall, electrical systems, control systems, and pitch systems exhibit higher failure rates. Failures in the gearbox, generator, rotor, and blades result in longer downtimes [14,81,82].

Based on failure data and failure modes, various qualitative and quantitative methods can be used to analyze the reliability of wind turbine systems and identify critical components [83]. Typical methods include Failure Mode and Effects Analysis (FMEA), Failure Mode, Effects, and Criticality Analysis (FMECA), and their derived methods. In the paper [84], the authors presented an overview of the wind turbine system and failure modes, and compared the criticality of components identified in previous studies. These comparison results are reproduced in this paper to provide a clearer display, as shown in Fig. 8. The studies 1–7 are [84–90], respectively. To identify the most critical components, we aggregated the relative criticality proportions of each component across the selected studies. Although the conclusions of different studies are not completely consistent, it is generally agreed that components such as the generator, tower and structure, pitch system, gearbox, and blade are of high criticality. Other studies, such as [91,92], also present similar insights. Moreover, with the rapid development of floating wind turbines in recent years, the mooring system has increasingly been recognized as a critical component [93]. These critical components are the primary focus of the studies in Section 2.3, which are anticipated to be the key targets in DT-enabled O&M for wind turbines in Section 4. It

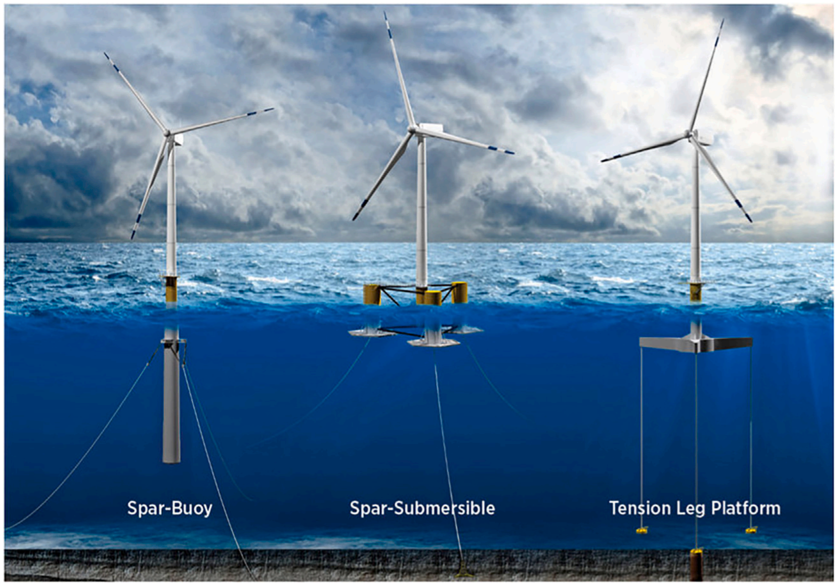


Fig. 6. Design of floating wind turbine foundations [77].

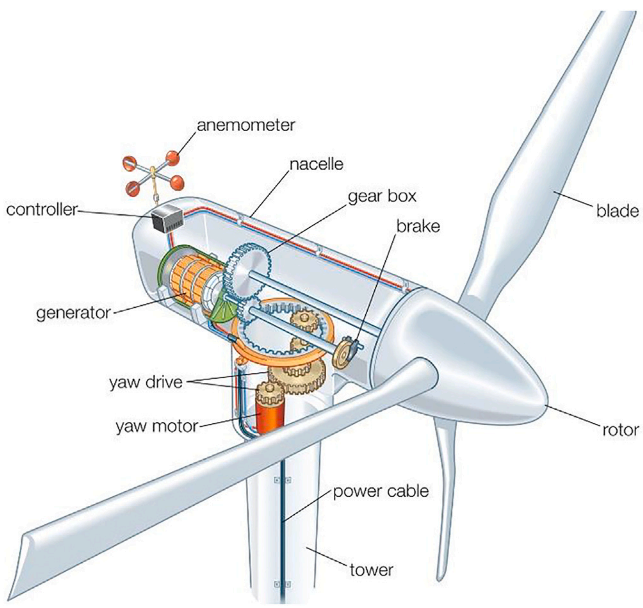


Fig. 7. Main components of a typical wind turbine [78].

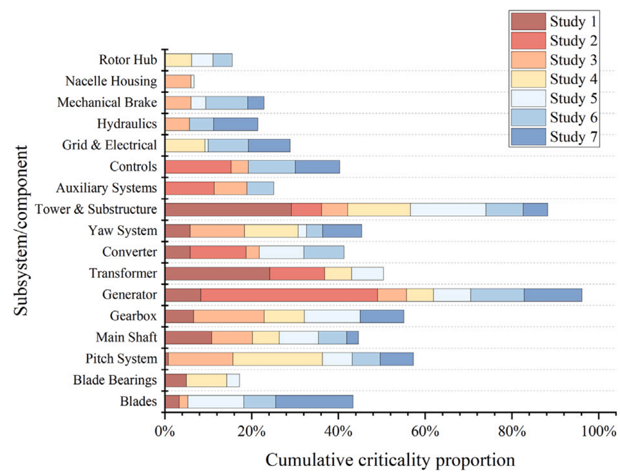


Fig. 8. Criticality comparison of components among past studies [84].

should be clarified that this review focuses exclusively on the wind turbine itself. While other associated components, such as cables, are also critical, they are not within the scope of this study.

2.3. Existing digital solutions for wind energy

In recent years, a growing number of studies have explored DT solutions for wind energy. Table 2 summarizes recent or representative contributions at the component, turbine and farm levels. It can be observed that the components most frequently considered mainly include the tower and substructures, mooring system, blade, gearbox, generator, main bearing, main shaft, and pitch system. This focus is generally consistent with the findings discussed in Section 2.2. Moreover, current research efforts remain mainly focused on onshore wind turbines, particularly components such as blades. However, for components like the tower and substructures, offshore wind turbines are receiving more attention.

Table 2
Summary of the considered work on digital solutions for wind energy.

	Onshore	Offshore	Reference
Blade	✓		[98,103–106]
Tower and substructure	✓		[107,108]
		✓	[94–96,109–111]
Gearbox	✓		[99,112]
		✓	[113,114]
Generator	✓		[101]
Main bearing	✓		[115,116]
Main shaft		✓	[117]
Mooring system		✓	[118]
Pitch system	✓		[102,119]
Wind turbine	✓		[121]
		✓	[97,120–122]
Wind farm	✓		[123]
		✓	[124]

The focal point of these existing solutions is scale-dependent, spanning component, turbine, and farm levels. At the component level, the objectives include damage and fatigue detection [94], structural response reconstruction [95], lifetime prediction [96], and inspection and maintenance planning [97]. These objectives are directly aligned with O&M. Beyond O&M, other objectives comprise fast simulation and computation [98], design improvement [99], virtual testing [100], wind speed estimation [101], and control performance enhancement [102].

Specifically for blades, Zhao and Chen [103] developed an improved acoustic emission–based damage source localization method to support DT. Hu et al. [104] proposed an unmanned aerial vehicle inspection-based DT model for detecting blade surface damage. Bingkai et al. [98] developed a fast strain computation method to enable synchronous health state mapping required by DT for blades. Li et al. [105] established a finite element-based structural DT to simulate the dynamic response of wind turbine blades under impact loading. In addition, Chetan et al. [106] integrated design specifications, manufacturing information, and structural test data to construct a multi-fidelity virtual blade model comprising a high-fidelity finite element model and a beam type aeroelastic model.

For towers and substructures, Zhu et al. [107] developed an algorithm to estimate unknown excitations and unmeasured dynamic responses of turbine towers to support DT, with experimental validation on a 1:50-scale operating turbine model. Momber et al. [108] proposed a DT framework for condition monitoring and maintenance planning of the tower surface. Pacheco-Blazquez et al. [96] introduced an open-source DT platform for real-time structural health monitoring and Remaining Useful Life (RUL) prediction of floating wind turbines by tracking structural fatigue. Mousavi et al. [94] proposed a DT for floating wind turbines that uses physics-based modeling to analyze damage scenarios and trains Machine Learning (ML) models on simulated data for damage identification. Jorgensen et al. [109] presented a DT paradigm for evaluating the fatigue limit state of bolted ring-flange connections in offshore turbine structures, including surrogate modeling uncertainty quantification and propagation. Bull et al. [110] proposed a probabilistic DT framework for offshore wind turbines that proceeds from initial measurements through probabilistic stress estimation to inspection planning. Jiang et al. [95] proposed a graph neural network-based DT method for real-time reconstruction of offshore turbine structural stresses from sparse monitoring data. Lim et al. [111] developed a DT model to perform structural assessment for the entire substructure and the turbine tower to substructure connection of a floating wind turbine platform.

For nacelle components (e.g., gearbox, generator, main bearing, main shaft), Zhou et al. [112] proposed a vibration-based DT model for damage monitoring with online intelligent assessment for the gearbox. Llopis-Albert et al. [99] presented a DT-enabled multi-objective design optimization method for the gearbox, which integrates computer-aided design and computer-aided engineering tools, enabling high-fidelity virtual simulation and ingestion of historical datasets. Moghadam et al. [113] developed a multi-degree-of-freedom torsional drivetrain model and employed it as a DT to monitor the RUL of gearboxes in floating wind turbines. Mehlan et al. [114] developed a virtual sensing approach for offshore wind turbine gearboxes within a DT framework to perform load monitoring and RUL estimation. Ibrahim et al. [101] built a generator test bench and developed a MATLAB/Simulink-based virtual model with real-time data exchange between the virtual and physical systems to estimate wind speed from power output. Yucesan and Viana [115] proposed a physics-based and data-driven hybrid DT specifically for main bearing fatigue monitoring. Zhao et al. [116] mapped the main bearing into the digital domain to generate a bearing fault dataset and used Transfer Learning (TL) for life prediction. Moghadam and Nejad [117] proposed a DT-based condition monitoring method for the main shaft of floating wind turbines, combining a torsional dynamics model, online measurements, and fatigue damage estimation for failure prediction.

For the mooring system and the pitch system, the existing studies are comparably limited. Walker et al. [118] used data from Hywind Pilot Park (the world's first commercial floating offshore wind farm) to build the DT and assessed the effectiveness of predicting mooring-line axial tension. Jahanshahi Zeitouni et al. [102] proposed a DT-based adaptive controller that reduces discrepancies between the software-in-the-loop controller and the physical controller for turbine pitch control. Parvaresh et al. [119] presented a real-time probabilistic model as a DT of the pitch angle controller for a variable speed wind turbine, implemented on a digital signal-processor computing platform.

At the turbine level, the existing studies focus on visualization, integration of component-level models, etc., for entire wind turbines. For instance, Liu et al. [120] established a DT-based unified framework for floating wind turbines enabling online condition monitoring and analytics, visualization of installation and operation procedures, early warning of structural anomalies, and estimation of platform attitude and metocean states. In [121], a DT of an onshore wind turbine is first developed to continuously track accumulated fatigue damage and evaluate alternative operational strategies. A preliminary numerical model for a floating wind turbine is then constructed to prototype and test the monitoring tool. A DT platform for floating wind is proposed in [97], which integrates a Unity3D-based visualization with an OPC unified architecture realizing real-time data communication. Zhao et al. [122] employed reduced-order modeling for major components (blade, hub, nacelle, tower, etc.) and integrated these within a parametric DT of offshore wind turbines.

At the wind-farm level, the emphasis shifts to power estimation, flow system, and layout optimization for entire wind farms. For example, Zhang and Zhao [123] developed a physics-informed neural network–based DT of wind farm flow fields. In addition, Kandemir et al. [124] proposed a layout optimization approach for offshore wind farms that leverages DT and dynamic repositioning to mitigate wake effects and increase total energy production.

Existing studies provide a solid technical foundation for the implementation of DT. However, from a strict classification perspective, the activities such as visualization, simulation modeling, estimation and prediction, digital platform development, and fast computation are better categorized as digital solutions that correspond to a specific stage within a DT model, rather than as comprehensive DT models in their own right. This is because they fail to establish a closed-loop process that spans from data acquisition to virtual modeling and ultimately to executable decisions. A DT model should operate at a higher level of integration, incorporating the full range of enabling technologies and methodologies across all stages of the loop. Therefore, the question of how to evolve from existing digital solutions to a complete DT model or framework for O&M will be addressed in Section 3.

3. Overview of digital twin models

The concept of "digital twin" dates back to the 1960s with the launch of Apollo 13 by NASA [125]. An almost identical physical model of Apollo 13 was constructed on the ground, used for monitoring spacecraft operations, managing risks, and responding to emergencies [126]. In [127], the definition of the DT concept is first documented, which has gathered increasing attention over the past decades across various application fields, such as manufacturing, healthcare, energy, and construction. In [128], the DT is generalized as a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems. In this section, we provide an overview of the capability levels and model comparisons of DT. The DT frameworks in existing studies for wind turbines are then summarized and discussed.

3.1. Capability levels

From the perspective of capability, DT technology can be categorized into six levels: 0-standalone, 1-descriptive, 2-diagnostic, 3-predictive, 4-prescriptive, and 5-autonomous [37], as shown in Fig. 9. In the context of wind turbine maintenance, the differences among levels are explained below, which also indicate the developmental trajectory of DT

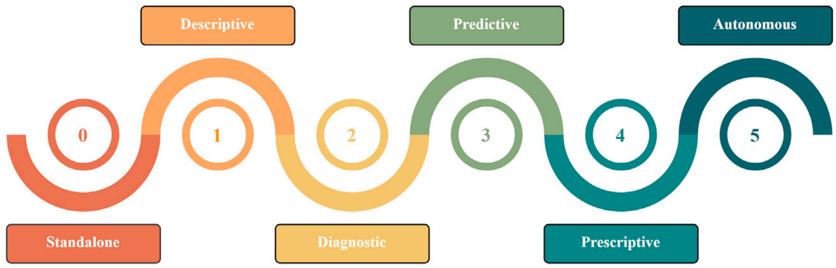


Fig. 9. Capability levels of DT from 0 to 5.

applications in wind turbine O&M. As reviewed in Section 2.3, current DT implementations in the wind energy sector predominantly operate at Levels 1 to 3, demonstrating descriptive, diagnostic, and predictive capabilities.

- **Level 0 – Standalone**. A standalone DT is a model of the physical wind turbine created prior to its construction and operation. This type of DT aids in enhancing the RAM and performance of wind turbines.
- **Level 1 – Descriptive**. A descriptive DT can provide detailed insights into the internal working conditions of the wind turbine system, along with visualization of data collected from sensors, facilitating remote monitoring.
- **Level 2 – Diagnostic**. At the diagnostic level, DT can be utilized for fault detection and diagnosis, enabling remote inspection of wind turbines affected by malfunctions or downtime.
- **Level 3 – Predictive**. Predictive DT leverages current and historical states to predict the future state of wind turbines and continuously updates based on real-time data flow from the physical system. For instance, the prediction of the RUL of components enables the planning of maintenance in advance, thereby reducing downtime caused by failures.
- **Level 4 – Prescriptive**. At the prescriptive level, DT can overcome multiple limitations of predictive DT, being capable of providing a set of selectable options and outcomes. DT at this level not only predicts the timing of failures but also enables the delay of these failures by adjusting the operation of the wind turbines. This capability opens up opportunities to improve efficiency by significantly reducing downtime.
- **Level 5 – Autonomous**. The DT model is able to establish bidirectional communication with the physical system, facilitating closed-loop management in wind farm operations. It consistently adjusts the turbine operations to enhance efficiency, considering the prevailing external conditions and the component RUL. Moreover, it autonomously organizes maintenance schedules when maintenance conditions are appropriate.

3.2. Comparison of general digital twin models

Researchers have varying interpretations of what constitutes DT model development, as demonstrated in Fig. 10. These DT models are proposed as general concepts rather than being tailored to specific physical assets. For clarity of explanation, the wind turbine is used as an example here. In [127], a three-dimensional DT model is proposed containing physical products in the real space, virtual products in the virtual space, and bidirectional connections between them, as illustrated in Fig. 10(a). The connection facilitates the mapping of virtual space to physical space by exchanging data and information. The physical space refers to the actual wind turbine located in the onshore/offshore environment, while the virtual space denotes the digital model of the wind turbine that simulates its behavior, performance, and interactions with environmental factors using data collected from the physical wind turbine. The connection indicates the data collected from sensors and inspections as well as the actionable information, e.g., maintenance. The proposed model can be defined as follows:

$$DT = f\,(PS, VS, CN) \tag{1}$$

where PS denotes physical system; VS represents virtual system; CN signifies connection; $f\,(\cdot)$ represents the integration of multiple dimensions.

In addition to the three-dimensional DT model, in [129], a five-dimensional model is proposed, consisting of a physical entity, virtual equipment, services, DT data, and connections, as demonstrated in Fig. 10(b). The new service dimension is developed based on DTs to improve the reliability and performance of wind turbines. DT data occupy a central position among the physical part, the virtual part, and the service part. The connections serve as a bridge linking different parts. The proposed model can be defined as follows:

$$DT = f\,(PS, VS, DD, SE, CN) \tag{2}$$

where DD denotes DT data; SE represents services.

Moreover, a new five-dimensional DT model is proposed in [130], which is extended based on the three-dimensional model in [127]. The connection between virtual and physical systems is further refined into an updating engine (physical to virtual) and a prediction engine (virtual to physical). The collected data is fed into the updating engine, serving to update the state of the virtual system. Utilizing the updated virtual system, the prediction engine then predicts the future state of the physical system. Maintenance decisions are formulated based on these predictions to influence the physical system. Optimization supports the functionalities of the other four dimensions within the DT framework. The model is illustrated in Fig. 10(c) and can be defined as

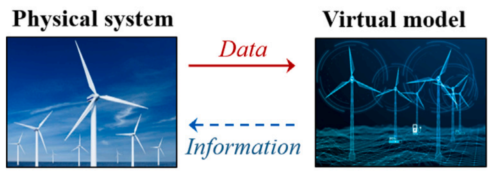
$$DT = f\,(PS, VS, UE, PE, OP) \tag{3}$$

where UE denotes updating engine; PE represents prediction engine; OP represents optimization.

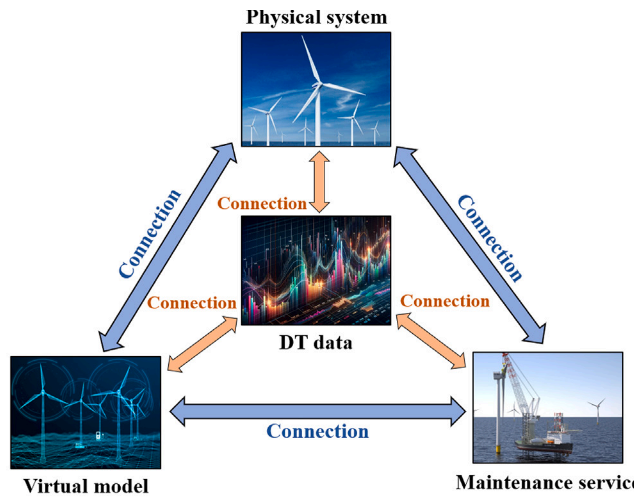
3.3. Existing digital twin-enabled operation and maintenance for wind turbines

In the wind energy domain, several DT models have been proposed based on the classical models introduced in Section 3.2. Representative examples include the studies [28,38], as illustrated in Fig. 11. It can be observed that both models follow the five-dimensional DT architecture presented in Fig. 10(b) and both are directly related to O&M applications.

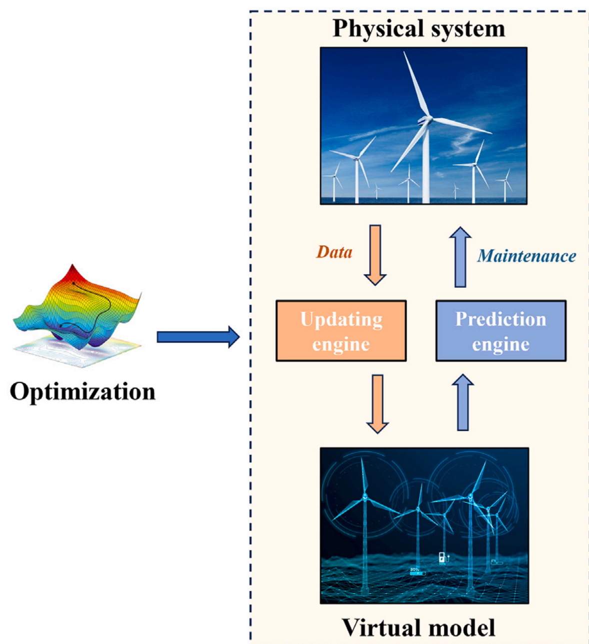
The model presented in Fig. 11(a) targets the support structures of offshore wind turbines, featuring a twin database as the core element that connects the physical model, virtual model, and service system. The main objective of this model is to support reliability analysis of wind turbine structures. First, based on load and damage parameters



(a) The three-dimensional DT model (reproduced from [127])



(b) The five-dimensional DT model (reproduced from [129])



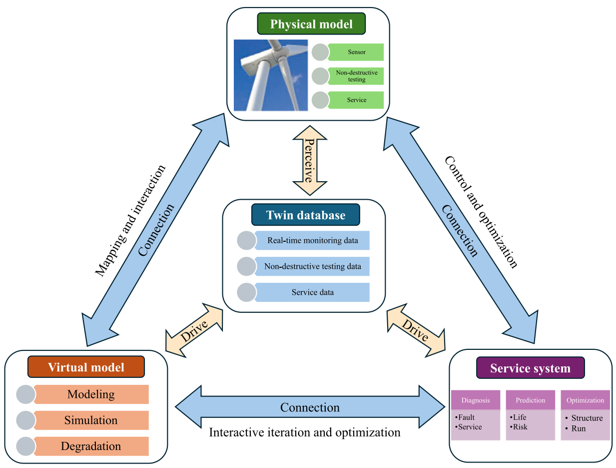
(c) The five-dimensional DT model extended from the three-dimensional model (reproduced from [130])

Fig. 10. DT models for wind turbine maintenance.

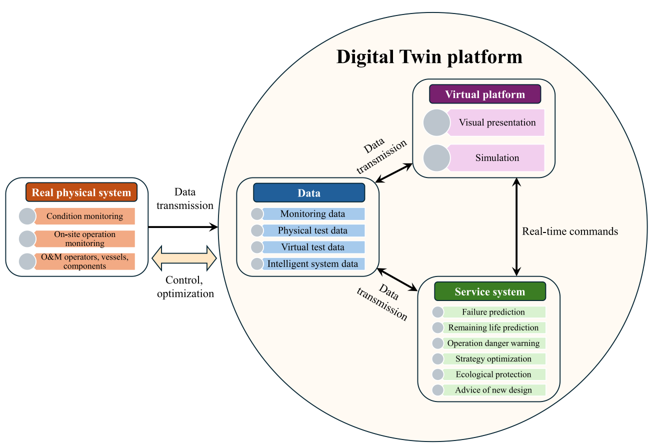
collected by sensors, the structural condition information is mapped into the virtual environment to construct a digital model. Subsequently, a multi-scale modeling approach is adopted to develop a full-scale simulation tool for the reliability analysis of support structures. High-fidelity models are built to enable crack propagation prediction. To improve prediction efficiency and meet the real-time and computational performance requirements of DTs, model order reduction techniques are further applied to these high-fidelity models. Finally, considering structural uncertainties, multi-source heterogeneous data are integrated, and a dynamic Bayesian approach is employed to perform probabilistic reliability assessment of offshore wind turbine support structures.

The model shown in Fig. 11(b) aims to establish a DT-based O&M framework for offshore wind turbines. Building upon the conceptual model in Fig. 11(a), this model expands its scope beyond structural aspects, incorporating more modules including O&M optimization, ecological protection, and risk alerting.

These models offer valuable insights into the development of DT technologies for wind energy. However, there still exist limitations. First, both models tend to be overly general, with their main contribution being the adaptation of the five-dimensional DT model to the wind energy by incorporating wind turbine-specific data and techniques. However, such a generic structure may lead to an incomplete representation and organization of the complex technical processes involved in wind turbine O&M. Key aspects such as the management of multi-source heterogeneous data, continuous updating of the virtual model, and on-site offshore maintenance operations are not adequately addressed. As a result, these models fall short of establishing the closed loop that is essential for a fully functional DT. Second, the studies provide only a



(a) A DT model for offshore wind turbine support structures (reproduced from [28])



(b) A DT-based O&M model for offshore wind turbines (reproduced from [38])

Fig. 11. DT models for wind turbines in past studies.

high-level overview of the proposed model, without offering detailed discussions of the key enabling methods and technologies. As a result, the models lack sufficient methodological depth and may offer limited insights for future research and practical implementation.

4. A prospective framework for digital twin-enabled operation and maintenance

Although the DT models proposed in different studies may vary in structure and focus, there is a clear need to establish a unified framework that systematically summarizes the overall process of DT-enabled wind turbine O&M. The DT-enabled O&M framework can be described as a process that monitors the state of the wind turbines and predicts the future states by analyzing and fusing real-time data from multiple sources, thereby enhancing the decision-making process for maintenance activities and feeding maintenance actions back to the wind turbines [28,131,132].

This section proposes a prospective framework for realizing the DT-enabled wind turbine maintenance, as demonstrated in Fig. 12. We will offer a comprehensive understanding of the framework, provide an overview of the critical steps, explain the connections between the steps, summarize the enabling methods and technologies involved, and elucidate the benefits and potential of DT technology. Considering the high complexity of the entire process, it is difficult to provide a detailed review and discussion of all the technologies and methods used at each step.

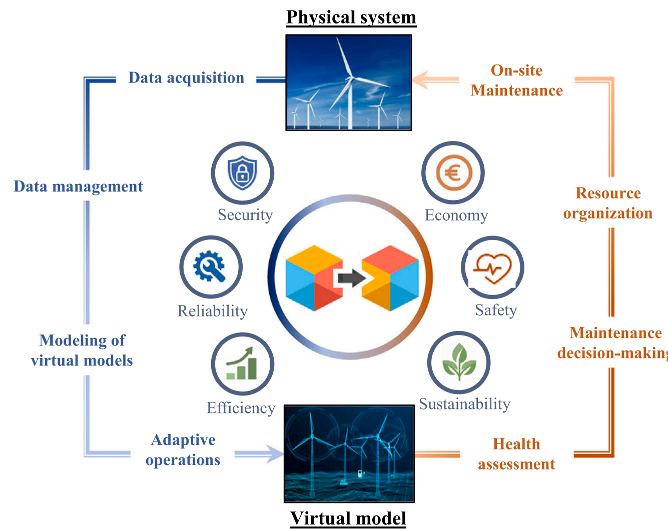


Fig. 12. Schematic representation of the loop for realizing DT-enabled wind turbine O&M.

The overall concept of this framework is similar to the structure shown in Fig. 10(c), which emphasizes a closed-loop interaction between the physical and virtual models. In this study, we categorize the process into eight key stages. The forward loop from physical to virtual comprises data acquisition, data management, modeling of virtual models, and adaptive operations, representing the transformation from multi-source data collection to the establishment of a stable, reliable, and dynamically responsive virtual model. Conversely, the backward loop includes health assessment, maintenance decision-making, resource organization, and on-site maintenance operations, reflecting the process of making and executing maintenance decisions based on the health status provided by the virtual model.

It is worth noting that the framework is presented in a sequential manner to establish a clearer logical structure. However, this does not imply that non-adjacent stages are entirely isolated. For instance, while data acquisition is only linked to data management in Fig. 12, the acquired data are indeed essential for all subsequent stages throughout the loop. It is placed as the first stage because it serves as the foundation of the entire process.

4.1. From physical to virtual

4.1.1. Data acquisition

Data is the cornerstone for linking physical wind turbines with their virtual counterparts, enabling the latter to function as computational representations of the physical systems. A broad range of data is encompassed in this process, including the data collected from physical wind turbines, operational environments, and maintenance services. Accurate and real-time data is the basis for achieving comprehensive and precise virtual model construction [133]. In fact, a complete DT involves a wide range of data types, including simulation data from virtual models, preliminary experimental data, and knowledge provided by domain experts or extracted from existing data. In this section, we mainly focus on the data collected directly from the physical system.

4.1.1.1. Condition monitoring data. Condition monitoring data represents the operating status of wind turbines. Based on the changes in the operating parameters, diagnosis can be performed to detect, locate, and identify occurring faults and prognosis can be conducted to predict when the failure will occur. Condition monitoring technologies can be roughly divided into two categories based on data collection methods, i.e., online and offline [134]. Offline condition monitoring requires wind turbines to cease operation for on-site inspections, whereas online condition monitoring can be conducted while the turbines are in service, which is able to reduce the production losses and the costs associated with physical inspections.

From the perspective of data types, condition monitoring data is collected based on the structural characteristics and operating modes of wind turbine components. Commonly used techniques include Supervisory Control and Data Acquisition (SCADA) systems, vibration analysis, acoustic emission, lubrication oil analysis, strain measurement, temperature monitoring, electrical signal analysis, torque sensing, infrared thermography, ultrasonic testing, and X-ray inspection [135,136]. These monitoring systems rely on a wide range of sensors installed across critical components of the wind turbine to reflect its dynamic operational state and health condition, thereby enabling a digital representation of the physical wind turbine [137,138].

For example, accelerometers and vibration sensors installed on the gearbox, generator, and bearing are used to detect bearing defects, gear meshing faults, and rotational imbalance [139,140]. Strain gauges and Fiber Bragg Grating sensors, typically deployed on blades and tower structures, can capture structural deformation, fatigue-induced cracks, and load variations [41,44,141]. Various sensors including gyroscopes, accelerometers, mooring line load-pins and mooring line declinometers are combined to monitor the degradation of mooring lines under different loads and environmental conditions [142]. Acoustic emission sensors are suitable for identifying early-stage crack initiation and material fractures, especially in composite components such as blades [143,144]. Ultrasonic testing and X-ray imaging are effective in detecting internal cracks, corrosion, and material defects, particularly in the blades and tower sections [145,146].

In addition to these sensors and monitoring systems deployed at wind turbines, an emerging development is to employ autonomous systems to fulfill inspection activities on blades, towers, both fixed and floating foundations, and mooring systems [147], such as climbing robots [148], unmanned underwater vehicles [149], unmanned aerial vehicles [150], and unmanned surface vehicles [151]. The employment of autonomous systems can improve access to locations that are difficult for technicians to reach, which can significantly increase the efficiency of inspection and maintenance, reduce associated costs, and enhance the safety of technicians during operations.

4.1.1.2. Environmental data. Besides continuous monitoring of the wind turbine system, it is essential to measure the parameters of the environment where wind turbines operate. Environmental conditions impact the performance and condition of wind turbines and play a significant role in updating the virtual model. The environmental data mainly contain meteorological information about the environmental conditions like wind speed and direction, wave period and height, temperature, humidity, lightning activity, and noise levels [28,152,153].

To acquire such environmental data, various types of sensors are deployed on or around the wind turbine system. For instance, anemometers, typically mounted on the nacelle or meteorological masts, are used to measure wind speed and direction [154]. Wave buoys deployed near offshore turbines capture wave height, period, and direction [155]. Temperature sensors are often installed in both the nacelle and tower to monitor ambient and internal thermal conditions [156]. Acoustic sensors and microphones may also be used to monitor noise levels [157].

4.1.1.3. Maintenance service data. Maintenance services can generate a significant amount of data which can indicate the maintainability of wind turbines, such as maintenance logs, operation and alarm logs, and performance metrics. Maintenance logs contain detailed information on failures, downtimes, and past maintenance activities, including dates, replaced components, service duration, and cost information for repair and replacement [158]. Operation and alarm logs record the frequency and duration of wind turbine alarms and stoppages [13]. Performance metrics provide insights into the overall efficiency and performance of wind turbines by focusing on key aspects that affect their O&M. The core performance metrics include Mean Time Between Failures (MTBF), failure rates, operational availability, and Mean Time to Repair (MTTR).

4.1.2. Data management

4.1.2.1. Data transmission. The data derived from wind turbines is required to be transmitted both timely and reliably to ensure an efficient twinning process synchronizing the virtual models with the physical systems. This process places strict requirements on information transmission technologies. To reduce latency in data transmission, technologies such as Long-Term Evolution (LTE), 5G, and even 6G have been vigorously developed [159], which can be applied in onshore wind infrastructure. For offshore wind farms, data transmission through cable or satellite connections is more feasible and reliable when facing the challenge of long distances between the turbines and shore [160].

The Internet of Things (IoT) technology integrating sensors and communication technologies is recognized as a commonly used foundational platform for implementing DT technologies for wind turbine O&M [161]. It allows for up-to-date monitoring of wind turbine conditions and the swift identification of potential issues, thus enabling rapid response and optimal decision-making [162]. Furthermore, wind farm operators can leverage edge computing to bring data storage and computational capabilities closer to wind farms. This method replaces the conventional approach of transmitting data to data centers or cloud-based systems, followed by feedback processing. The demands of remote operation can be met by shifting computational resources directly to the turbines. This is particularly advantageous in onshore and especially offshore wind farms [163], which are often located in areas with weak signal coverage, enhancing reaction speed and improving both security and reliability [164].

4.1.2.2. Data storage. Hundreds of GB of condition monitoring data are received from numerous sensors on wind turbines each day [165]. In addition to data acquired on-site, DT technology also requires the data from physical experiments, the knowledge provided by domain experts, and the data generated by virtual models. In this context, data storage becomes a challenge with the rapidly increasing installation of wind turbines. Cloud storage which enables storing data on the internet through a cloud computing provider offers advantages in cost-effectiveness and computing speed, making it more suitable for the era of big data compared to local storage methods at data centers [166]. Moreover, the data in DT-based databases are collected from multiple sources (e.g., various applications and scenarios). The data need to be transformed into a unified format, and standardized for consistency. It is essential to account for the different interfaces and communication protocols used by various data sources to ensure unified access to the database [133].

4.1.2.3. Data security. Implementing robust encryption and secure channels is crucial for protecting sensitive O&M data from network threats in the process of data transmission and storage. It is necessary to establish cybersecurity measures for wind farms to ensure a secure network, defend against physical cyber intrusions, and protect the O&M data stream [167]. Some emerging technologies, such as blockchain and Federated Learning (FL), have the potential to address these challenges in wind power O&M, including insufficient security and weak sharing [168,169].

4.1.2.4. Data fusion. As discussed earlier, the data supporting the DT technology is collected from physical wind turbines, maintenance services, domain knowledge, virtual models, and so on. Hence, the characteristics of DT data include multi-temporal scales, multiple dimensions, multiple sources, and heterogeneity [170]. Data fusion is required to systematically integrate the data from diverse sources.

The data fusion can be generally categorized into three levels, i.e., raw-data-level fusion, feature-level fusion, and decision-level fusion [171]. At the raw-data-level fusion, when multiple sensors measure the same physical attribute, the raw data can be fused at this level. If the sensors measure different attributes, the data needs to be fused at higher levels. Feature-level fusion involves combining features from different independent sensors and converting the extracted features into individual feature vector representations [172]. Decision-level fusion classifies various features and uses the resulting data to make informed decisions responding to the environment, identifying any necessary actions that need to be performed. The benefits of data fusion include reducing data uncertainty, improving data accuracy, enhancing the relevance between data and specific target indicators, and ultimately creating more consistent and accurate information than any single data source alone [173].

4.1.2.5. Data analysis. Ideally, DT technology is driven by big data, characterized by volume (the extremely large scale of data), variety (the diversity in size, content, format, and application of data), velocity (the rapid generation of data and the high timeliness required for data processing), and value (the immense value it provides) [174]. It is necessary to use big data analysis methods to efficiently extract valuable information and knowledge from massive datasets.

However, in the wind energy domain, the unavailability of high-quality data is still an obstacle [21]. This is influenced by various factors, including disturbances from the marine environment, the highly variable operational characteristics of wind turbines, and confidentiality regarding available data in the industry. Extracting useful information from incomplete, unreliable, imprecise, and redundant sources while meeting online analysis requirements is crucial, but remains highly challenging. Furthermore, as noted by the study [175], high-quality small datasets can potentially be more meaningful than large volumes of unverified observational data in specific scenarios, which highlights the value of small data. In the wind power sector, particularly in offshore wind, integrating complementary strengths of both small and big data methods may offer a more effective pathway to yield better results.

4.1.3. Modeling of virtual models

With the data input, modeling the virtual model is to create a digital replica of the physical system. According to [176], the construction of virtual models encompasses four dimensions: geometric, physical, behavioral, and rule. The geometric dimension depicts the physical attributes including shape, size, and spatial relationships. The physical dimension involves modeling the material properties and physical interactions within the model, encompassing aspects such as mass, strength, thermal performance, and other material characteristics. The behavioral dimension focuses on the dynamic aspects of the model, including how it operates and responds to different inputs over time, allowing for the prediction of system behavior under various scenarios. The rule dimension utilizes historical data and tacit knowledge to depict the evolutionary trends and patterns of physical systems, making the virtual model more closely aligned with the physical wind turbine.

It is noteworthy that the components often possess various characteristics which can be modeled and it is difficult to fully reflect these characteristics in the virtual space simultaneously. Hence, it is more feasible to specify which characteristics need to be defined before constructing virtual models, in accordance with the requirements of the specific O&M problem. Building upon these dimensions, the modeling enabling technologies can begin with geometric modeling which involves creating the virtual geometric shapes of wind turbines and their components to observe how wind turbines operate in reality [130].

Subsequently, models are developed to reflect the real-time state of the system, while ensuring that they operate within acceptable computational time. Achieving this requires the accurate reproduction of multi-physics and multi-scale coupling processes in wind turbine systems, especially under scenarios with complex structures and highly dynamic operating environments. For example, modeling of bearings needs to incorporate dynamics, friction, and thermodynamics, in order to capture the degradation process over time leading to wear and fatigue cracks. Likewise, modeling of substructures and blades must consider aero-hydro-servo-elastic coupling analysis for structural integrity assessment. The available enabling technologies can be broadly categorized into physics-based modeling, data-driven modeling, and hybrid modeling [177]. Physical modeling involves observing physical phenomena, developing a partial understanding of them, formulating this understanding into mathematical equations that govern the motion of matter and other physical phenomena through space and time, and ultimately solving these equations [178]. For example, a multi-fidelity model for wind turbine blades including a high-fidelity model using Finite Element Analysis (FEA) and consistent beam-type models for aeroelastic simulations is developed in [106]. Data-driven modeling aims to address the challenges posed by complex physical models that are difficult to establish accurately or have high computational costs that make them impractical for use in DTs. In such cases, data-driven models are developed to represent the underlying physical input/output behavior, enabling efficient and economical predictions of the digital state. For instance, a multi-fidelity surrogate model is proposed to calibrate the mechanism calculation of wind turbine blades by using sensor data, leading to a tremendous increase in computational efficiency [98]. However, both physical modeling and data-driven modeling have their limitations. For instance, data-driven models often lack interpretability, while physical models demand a high level of understanding of physical mechanisms. By developing hybrid methods combining these two modeling approaches, integrating physical principles with real-time data, the accuracy and reliability of real-time simulations and predictions can be improved.

Finally, system modeling is required to characterize the coupling relationships and overall interconnection structure among component-level models within a wind turbine. This process involves not only accurately capturing the interaction mechanisms between components, such as blades, hub, gearbox, generator, tower, and foundation, but also defining the interface variables (e.g., force, torque, temperature, vibration) and their spatial-temporal transfer pathways and boundary conditions. By clearly specifying these interfaces and enabling data flow coupling, high-fidelity models can be integrated into a coordinated and unified system-level model.

4.1.4. Adaptive operations

Once the initial virtual model is established, it enters an adaptive operational phase, with continuous improvements relying on model updating, Uncertainty Quantification (UQ), visualization and interaction. Model updating keeps the virtual model in sync with real-world conditions, while UQ assesses the trustworthiness of the model and its predictive outputs. Visualization translates complex outputs into comprehensible insights, and user interaction facilitates expert-driven adjustments to enhance results.

4.1.4.1. Model updating. Accurate and precise models are the foundation for achieving real-time monitoring, accurate life prediction, and effective health management services. However, discrepancies often arise between model results and actual performance due to deviations in parameters and assumptions [179]. It is necessary to address this issue and ensure consistency with the real-world performance of wind turbines. Therefore, as new data become available or the system is observed over a longer period, the model state and parameters need continuous and iterative updating [180].

In the process of model updating, data-related issues need to be addressed first. The collected data always contain noise and may encounter data drift or sensor errors caused by faults and occasional improper instrument operation [181,182]. Hence, it is essential to perform a priori analysis of the real-time data output from the system to detect incorrect data and evaluate the decision to initiate updates [183].

Model updating is a process that involves improving model accuracy based on new data or discoveries, fundamentally applying parameter estimation. Once new data is acquired, it can be used to update unknown or uncertain model parameters more accurately, thereby better reflecting observed system dynamics. This process also requires consideration of the potentially large number of physical parameters included in the model, making it difficult to update all parameters using new data. Therefore, criteria must be established to select a subset of parameters to update [184].

A common method of model updating is a deterministic optimization strategy. This is usually accomplished by formulating the problem as a constrained optimization problem. Optimization methods such as global optimization algorithms, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), and local optimization algorithms are used to find the optimal model parameters that minimize the discrepancy between measured values and model predictions [185–187]. However, this optimization-based method cannot assess the uncertainty of estimates and may become ill-conditioned when the cost function does not have a global minimum [188].

Another method is the probabilistic method, with Bayesian model updating being the most typical example. This method combines prior knowledge and the likelihood of observed data to estimate the posterior distribution of uncertain model parameters [189]. Bayesian methods can be divided into batch methods, where data is processed in individual batches and then integrated, and recursive methods. Recursive methods are particularly useful in real-time applications where data arrives sequentially [188]. The method offers higher computational efficiency and can enable near-real-time or near-online updates. Typical recursive Bayesian filters include the Kalman Filter (KF), Extended Kalman Filter (EKF), and Particle Filter (PF) [188,190,191]. As new data becomes available or the system is observed over a longer period, the model state and parameters may need continuous and iterative updating to remain closely aligned with real-world observations.

4.1.4.2. Uncertainty quantification. The model updating process and the predictions made using virtual models are significantly influenced by uncertainty. The sources of uncertainty can be broadly classified into three categories: parameter uncertainty, model form uncertainty, and experimental uncertainty [192]. These uncertainties can be further summarized into two types, namely aleatory uncertainty and epistemic uncertainty. Aleatory uncertainty arises from inherent variability or randomness. Although it cannot be reduced, it can be accurately described given a sufficient number of samples. Epistemic uncertainty, on the other hand, arises from a lack of knowledge and can be reduced through model updating as more information becomes available [193]. In fact, it is challenging to distinguish between these two types of uncertainty in practical problems in certain cases, because the categorization of uncertainty for the same issue may differ depending on the context [194]. The quantification of uncertainty is crucial for DT technology, as it assesses the impact of uncertainty on updated model parameters, thereby ensuring the predictive capability of the virtual model and the robustness of maintenance decisions provided.

There are different classification methods for UQ techniques, such as probabilistic and non-probabilistic methods [189]. Probabilistic methods include frequentist and Bayesian methods [195]. Typical Bayesian methods include Monte Carlo Dropout [196], Gaussian Process Regression [197], and Bayesian Neural Networks [198]. The difficulty in obtaining sufficient data from complex engineering systems has led to the development of non-probabilistic methods. Unlike probabilistic techniques, non-probabilistic methods can handle uncertainty using small sample sizes [199]. Typical non-probabilistic methods include interval probabilities [200], evidence theory [201], and fuzzy theory [202].

UQ methods can also be classified into forward UQ methods and inverse UQ methods [203]. Forward UQ methods quantify the uncertainty in the system output that results from the propagation of uncertainty in the inputs, indicating that it focuses on the impact of parameter variability on the output. Forward UQ methods mainly aim to assess the lower-order moments, reliability, and complete probability distribution of the outputs [204]. Inverse UQ, in contrast, aims to estimate both the discrepancies between experiments and mathematical models and the unknown parameter values present in the model. It typically involves interrelated components including parameter calibration, model discrepancy modeling, measurement noise quantification, and posterior inference.

4.1.4.3. Visualization and interaction. Wind turbines are often located in remote areas or harsh marine environments, leading to access challenges. Visualization and remote interaction in DT technology can significantly address this issue. By utilizing technologies such as Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR), visualization of wind turbines includes digitizing existing structures according to selected levels of detail, online sharing, discussion, and classification of visual representations, comprehensive visualization of various data domains through data frames, and management of image or video data [108]. Each technology has its unique advantages and application scenarios. VR provides basic immersive experiences, AR emphasizes interaction and augmented reality, while MR offers a more comprehensive and interactive bridge between the two. A comparison of the characteristics of VR, AR, and MR in DT is discussed in [205].

Implementing visualization aids in further promoting human-machine interaction in DT. The study [206] indicates that, in industrial applications, human tasks during the process of transferring control to the DT are divided into operation, decision-making, supervision, and implementation. These tasks are arranged in a sequence that reflects a gradual reduction in human operator authority. From independently performing all tasks, to overseeing and validating DT decisions, and ultimately to merely executing actions determined by the DT. In maintenance scenarios, the DT is expected to enable human operators to focus solely on implementing maintenance tasks. However, we argue that this conclusion is not fully applicable in the context of wind turbines considering the complexity of wind turbine maintenance scheduling and execution. It is essential for human operators to remain involved in decision-making and higher-level tasks to ensure the reliability and effectiveness of O&M.

4.2. From virtual to physical

4.2.1. Health assessment

In the virtual space, continuously updated high-fidelity models enable ongoing health assessment of critical components based on new monitoring data. Health assessment, including fault/failure diagnostics and prognostics, which represent the current damage state and the estimation of the remaining time before the wind turbine breaks down are the key outputs of the virtual model. Wind turbines are complex systems in which failures may occur in any component, including blades, towers, generators, gearboxes, mooring lines, and electrical systems. These structural, mechanical, and electrical components exhibit diverse and complex failure modes including corrosion, fatigue, and wear.

DT-based O&M aims to prevent physical system failures through early prediction and intervention. The health information could be used as the input for maintenance optimization problems to determine the optimal maintenance timing. Faults and failures are two different conditions, although some papers do not clearly distinguish between them or use the terms interchangeably. A fault occurs when there is an unacceptable deviation in the system structure or parameters from the normal condition [207]. A failure is characterized by the inability of a component to perform its intended function, ultimately leading to system breakdown [208].

Given the information derived from condition monitoring processes, the diagnosis is performed to detect, isolate and identify faults/failures which have occurred in the wind turbine system [209]. Detection involves recognizing the presence of abnormal situations [187]. Isolation pinpoints the exact location and identification determines the nature and cause [210,211]. Prognostics aim to predict the time and likelihood of future system failures, which is also known as RUL prediction, estimating the remaining life before failures occur [212]. Indeed, prognostics and diagnostics are inherently interconnected, and should not be treated as isolated tasks. The process of failure prognosis inherently involves diagnostic capability. The prognosis model needs to identify the transition point between healthy and degraded states, meaning that the predicted degradation trajectory implicitly reflects the diagnosed failure patterns. Therefore, the methods used in both domains are often interrelated.

There are differing viewpoints in various papers regarding the classification methods for diagnostics. In [213], the fault diagnosis methods are broadly categorized into data-driven methods and model-based methods. Some papers further divide data-driven methods. For instance, in [214], data-driven methods are categorized into signal-based methods relying on sensor data, and knowledge-based methods relying on historical data and knowledge. Moreover, the aforementioned methods can be combined into hybrid methods. In comparison, in [215], the data-driven methods are divided into statistical-based methods and ML-based methods which are also recognized as Artificial Intelligence (AI)-based methods [216]. In the wind turbine domain, a number of comprehensive and specialized review articles on diagnostics have been published in recent years. For instance, the paper [217] examines the topic from the perspective of Deep Learning (DL) methods. The paper [218] focuses on bearings. The study [219] concentrates on gearboxes, and the paper [220] addresses blade damage.

For RUL prediction, a commonly used solution is sequence-to-one regression, where monitored data sequences are mapped to a single scalar RUL value. This method typically requires full life-cycle degradation data. An alternative is sequence-to-sequence regression, which aims to forecast the future trajectory of health indicators or degradation trends. This approach enables partial life-cycle modeling and tends to be more robust in scenarios with limited data availability. Similar to diagnostics, a variety of classification schemes have been proposed for prognostics methods. For example, Badihi et al. [221] categorized them into hardware signal-based techniques, mathematical model-based techniques, and hybrid approaches. Fox et al. [35] classified the methods into data-driven, physics-based, stochastic, and hybrid approaches. The current research progress can be further understood through insightful review papers [20,221–223].

To meet the requirements of DTs, recent research has focused not only on improving diagnostic and prognostic performance, but also increasingly on other desirable properties such as interpretability, data efficiency, and physical consistency. Emerging AI methods offer promising solutions to address these needs. A representative example is physics-informed neural networks (PINNs). By embedding governing equations (e.g., aeroelastic dynamics, structural vibration, or fatigue damage evolution) into the loss function, PINNs can enforce physical consistency while learning from limited and noisy monitoring data. This enables the DT to reconstruct unmeasured states and to enhance health assessment performance under data-scarce conditions, while providing better interpretability than purely black-box AI models. For instance, Sun et al. [224] proposed a PINN-based approach for detecting damage in wind turbine blades, demonstrating that PINNs can significantly reduce the amount of training data required and improve the interpretability and reliability of the results. De Florio et al. [225] developed a physics-informed ML model to estimate the RUL of wind turbine gearbox bearings during fatigue crack growth. The results show that, even when trained on only a small subset of the damage evolution data, the predicted degradation trajectories remain smooth and monotonic, exhibiting strong predictive and trend-tracking capabilities.

Despite these advantages, several technical challenges remain before PINNs can be fully deployed in DTs for wind turbines. First, scaling PINNs to high-dimensional, multi-physics DT models that couple aerodynamics, hydrodynamics, and structural dynamics can lead to severe optimization difficulties and prohibitive computational costs, especially when enforcing complex boundary conditions over long time horizons. Second, real operating environments involve model-form uncertainty and evolving damage mechanisms, whereas most existing PINN formulations assume fixed governing equations and parameters. To address these issues, future research should first focus on developing modular and multi-fidelity PINN architectures tailored to high-dimensional multi-physics models, so that high-fidelity solvers can be approximated at a lower computational cost. Exploiting parallelization and other acceleration solutions will also be essential to enable fast training and inference within DT applications. In addition, there is a need for adaptive PINN formulations that can cope with model-form uncertainty and time-varying degradation mechanisms. For example, one could learn correction terms for the governing equations and update them as new monitoring data become available, allowing the DT to progressively adapt to turbine-specific behavior and degradation patterns, thereby providing updated health indicators and RUL estimates with quantified uncertainty.

Besides PINNs, several other AI paradigms can further strengthen the health assessment capabilities required by DTs. Lifelong (continual) learning has been applied to enable continuous health monitoring over extended periods by incrementally updating models as new data arrive, while mitigating catastrophic forgetting of previously learned degradation patterns [226]. This allows the DT to track evolving failure signatures and adapt health indicators to gradual changes in operating conditions. TL enables the adaptation of models to different turbines, sites, and evolving operational environments by reusing knowledge learned from source domains and fine-tuning it with limited target data [227]. In a DT context, TL can substantially reduce the data and labeling requirements for new turbines or wind farms. Knowledge graphs (KGs) have been employed to enhance model interpretability by explicitly encoding the relationships among components, operating conditions, failure modes, and maintenance actions [228]. When coupled with DT data streams, KGs can support explainable failure diagnosis and prognosis and provide more understandable reasoning paths for recommended maintenance decisions. Federated learning (FL) has been utilized to strengthen data privacy protection by collaboratively training models across multiple turbines or wind farms without sharing raw data [229]. This paradigm is particularly attractive for DT implementation in the real industry, where operators are often reluctant to exchange proprietary monitoring data but are willing to share model updates.

4.2.2. Maintenance decision-making

Based on the diagnosis and prognosis results, more advanced and effective maintenance decision-making can be developed. In the virtual space, the effectiveness of different maintenance decisions is simulated and evaluated for optimization. Compared to previous technologies and methods that mainly focus on the component level, maintenance decision-making and subsequent activities can be elevated to higher levels, such as the turbine level, farm level, or even multi-farm level, where integrated component-level DT models across the scope are comprehensively considered.

Decision-making related to wind turbine O&M is a multi-level process rather than a one-time event. The review paper [21] established a three-level maintenance decision-making framework including strategic, tactical, and operational levels. The strategic decision refers to decisions that have long-lasting effects (from 5 years to the entire lifetime) on the O&M. The tactical decisions are typically updated periodically, ranging from once a year to once every five years. The operational decisions refer to short-term decisions, with time spans ranging from several weeks to daily. In this paper, maintenance decisions specifically refer to the maintenance strategy at the strategic level and the maintenance scheduling at the operational level.

4.2.2.1. Maintenance strategy. Corrective maintenance and time-based maintenance are the conventional maintenance strategies applied in the wind industry [26]. Corrective maintenance is performed after a failure has occurred, with the goal of restoring or recovering operational conditions [230]. In contrast, time-based maintenance is scheduled at regular intervals or according to specific criteria, such as the age of the wind turbine [231]. Some studies have explored other maintenance strategies, such as risk-based maintenance and reliability-based maintenance, aiming to reduce overall risks by making decisions in a decision tree or ensuring that the reliability level remains above an acceptable threshold [232,233].

The current trend is to use condition monitoring data obtained from sensors to make more informed maintenance decisions. Condition-based Maintenance (CBM) is a widely adopted method in which maintenance actions are triggered when monitored parameters exceed an unacceptable threshold, thereby preventing potential failures [234]. However, CBM primarily focuses on assessing the current state of wind turbines and relies on predefined maintenance conditions set by human operators. In contrast, Predictive Maintenance (PdM) advances this method by using predictive analytics to predict potential component failures, allowing for more intelligent maintenance planning [235].

Economic dependence refers to the cost variations associated with performing grouped maintenance on multiple components as opposed to maintaining them individually [236], which exists among wind turbines, especially offshore wind turbines. Opportunistic maintenance utilizes this economic dependence between components and turbines to plan additional maintenance when maintenance is already required for some components in order to reduce costs [237]. This type of maintenance strategy is also referred to as "group maintenance" in some studies [238].

DT enables real-time responses to changes in system conditions or external disturbances by leveraging dynamic sensor data to continuously monitor system behavior and determine optimal decisions. However, the traditional methods, which still rely on human decision-makers to interpret predictions and formulate maintenance [239], are constrained by short decision time windows and high computational costs in the context of DT. Against this backdrop, Prescriptive Maintenance (RxM) holds the potential to start with real-time monitoring data collected from wind turbine assets, simulate all possible O&M scenarios, evaluate their impact on turbine performance, and determine the optimal decisions to execute [240]. In addition to guiding maintenance actions, RxM also facilitates operational decisions, such as adjusting operations to mitigate degradation effects and enhance reliability [241]. Given these characteristics, the successful implementation of DT-enabled O&M is heavily dependent on RxM [242].

4.2.2.2. Maintenance scheduling. Under the predetermined maintenance strategy, the challenge lies in scheduling on-site maintenance effectively in the short term, which is known as maintenance scheduling problems. Maintenance scheduling involves precisely planning maintenance activities within suitable weather windows and dispatching maintenance teams to perform various tasks across different turbines, with the objectives of reducing maintenance costs, downtimes, and fuel consumption [243–245].

The maintenance scheduling problem is usually considered alongside routing issues, forming typical Vehicle Routing Problem (VRP) and Traveling Salesman Problem (TSP) scenarios [246,247]. The most critical constraint in the problem is the accessibility of the wind turbines, which is required when identifying the optimal maintenance window. For onshore wind turbines, the maintenance window is influenced by factors such as mean wind speed and wind gusts [248]. Offshore conditions are more complex, requiring consideration of additional factors like wave height and vessel carrying capacity [249].

Scheduling maintenance within time windows under various constraints is a typical operations research problem. Modeling approaches for such problems can be broadly categorized into mathematical programming methods and simulation-based methods [250]. In mathematical programming, a mathematical model is constructed by minimizing or maximizing objective functions subject to a set of constraints. These approaches can be further classified into deterministic and stochastic models. Deterministic models assume that all parameters are known with certainty, and commonly employ methods such as Mixed-Integer Programming (MIP) and Mixed-Integer Linear Programming (MILP) [251,252]. However, this assumption oversimplifies the inherent uncertainties in real-world maintenance scenarios [253]. To address this, Stochastic Programming (SP) and Dynamic Programming (DP) models have been introduced to capture randomness and time-dependent dynamics [254,255]. Simulation-based methods are typically used to model vessel operations and predict outcomes. Common techniques include discrete-event simulation and agent-based simulation [10,256]. The models built with these approaches are usually solved using optimization algorithms or solvers to support scheduling decision-making.

4.2.3. Resource organization

Once maintenance decisions are made, the implementation requires the support of various maintenance resources, including spare parts, maintenance technicians, and transportation tools (e.g., maintenance support vessels for offshore operations and trucks for onshore operations). While maintenance decisions and resource organization are interdependent, maintenance decisions are generally given priority, and resource organization is subsequently adjusted to accommodate the prescribed maintenance actions.

4.2.3.1. Spare parts. The complex wind turbine systems involve hundreds of components [135]. The randomness of failures makes it difficult to predict the demand for spare parts, which vary in type and supply characteristics, turning spare parts management into a complex supply chain problem. A sophisticated inventory network is required for the manufacturing, transportation, and storage of spare parts. In the study [21], the authors proposed a multi-echelon inventory network that includes off-site warehouses (manufacturers), wind farm depots, and on-site warehouses. Spare parts are manufactured at the manufacturing factory, transported to warehouses at different echelons for storage, and finally delivered to the maintenance site. Typical inventory policies include the (s, S) policy (i.e., min/max policy) [257], the (R, Q) policy (i.e., reorder point/order quantity policy) [258], and the (T, S) policy (i.e., periodic order-up-to policy) [259]. Storing spare parts in warehouses incurs holding costs, so it is essential to control inventory levels to avoid excessive expenses [260]. However, if inventory levels are too low, maintenance demands cannot be met timely [261]. Therefore, it is important to formulate effective inventory policies that balance the reliability of the supply chain with cost-effectiveness. A brief review of existing spare parts inventory models for wind turbines can be found in [262].

4.2.3.2. Technicians. Maintenance tasks for wind turbines require technicians with different skill sets, such as electrical and mechanical skills [246]. Maintenance technicians are typically assigned to stay at O&M bases [263]. When a maintenance task is triggered, technicians with the appropriate skills are selected and transported to the site to perform the maintenance activities from these O&M bases [264,265]. As the wind project scales, capacity, and offshore distance increase, not only does transit time increase, but the number of suitable weather windows significantly decreases, making technician transportation more challenging. To address this, offshore accommodation solutions have been proposed, such as offshore floating bases (e.g., advanced service operation vessels) and fixed bases (e.g., offshore maintenance bases), aiming to reduce the need for long technician transfers between an O&M base port and the wind farm site [266].

4.2.3.3. Maintenance support vessels. Different types of maintenance support vessels form a vessel fleet employed for loading and transporting necessary spare parts, accessing offshore sites, supporting maintenance implementation, and providing accommodation for maintenance technicians [267]. Typical maintenance service vessels include Heavy Lift

Vessels (HLVs), Field Support Vessels (FSVs), and Crew Transfer Vessels (CTVs). HLVs are vessels equipped with specialized cranes capable of lifting thousands of tons, handling huge wind turbine components. FSVs carry large spare parts and maintenance tools and provide on-site accommodation and platform support for maintenance. CTVs are small-sized vessels used to transport technicians and other personnel to the site daily. Maintenance implementers maintain a mixed vessel fleet to execute maintenance tasks. When faced with excessive maintenance demands that exceed the current capacity of the fleet, vessels need to be temporarily chartered from the spot market. However, when the available vessels are scarce in the spot market, the lead times may be highly uncertain, leading to prolonged wind turbine downtime and excessive costs. Conversely, maintaining an oversizes fleet can handle maintenance tasks efficiently but can lead to significant initial investment [10]. Therefore, a balanced configuration of the mixed fleet is essential to avoid overcapacity and undercapacity. Besides owning and leasing vessels, the concept of sharing vessels has also been proposed [268] to share large maintenance service vessels (e.g., jack-up vessels) in order to reduce maintenance costs and increase vessel utilization.

4.2.4. On-site maintenance

Compared with the onshore wind turbine maintenance by using trucks equipped with maintenance equipment and spare parts, the on-site maintenance operations for offshore wind turbines are more complex, which mainly include two steps. First, technicians are transferred via the docking operation between service vessels and offshore wind turbines [269]. Second, lifting operations are performed for heavy components and a reverse procedure of installation is conducted [270]. It is noted that conventional major component replacement vessels will not be feasible given the significant depths of some floating wind sites, where the maximum water depth exceeds the capabilities of jack-up vessels. Novel solutions, such as “tow to shore” and “tow to shallow”, can be adopted to tow the floating wind turbines to the suitable port or shallow water for maintenance activities [34,271].

There are several different types of docking systems used between service vessels and offshore wind turbines. The simplest form is a fender made of rubber or other materials, primarily used for small CTVs. This method allows the bollard push force from the propulsion system to maintain the connection between the vessel and the wind turbine tower, facilitating the movement of personnel from the vessel to the ladder on the tower. Fenders are cost-effective and easy to install on service vessels. However, numerical analysis of fenders is challenging because they rely on friction to keep relative motion within acceptable limits [269].

Another common type of docking system is based on the active motion compensation principle and can be installed on service vessels of any size. These systems can counteract the relative motion of the vessels within the limits of the hydraulic system, leading to a higher operational threshold compared to fenders. The drawback is that they are more costly than fenders. The workability of maintenance operations is significantly influenced by wave height and wind speed [272]. To improve the operational limits of service vessels in challenging environmental conditions, innovative designs like walk-to-work vessels have also been developed in recent years [273].

For maintenance operations involving heavy components, especially the replacement of components undergoing an overhaul, heavy lift cranes are required at onshore sites. Offshore operations require the use of heavy lift vessels, and the complex wind and wave conditions at sea further complicate these tasks. The response to sea and wind conditions, combined with the six degrees of freedom of the vessel and on-site operational activities, results in the lifting block tracing a complex three-dimensional path in space. The task for floating wind turbines is more challenging than the fixed-bottom. The dynamic nature of floating wind turbines results in higher accelerations, especially at the nacelle level. Therefore, wave and wind conditions that are acceptable for maintenance on fixed-bottom offshore wind turbines may not be suitable for floating wind turbines [274].

Additional important factors to consider during maintenance operations include sling failures and vessel positions. The tension on the sling fluctuates with environmental conditions, so it is essential to determine and ensure the tension stays below the breaking load [275]. The vessel position should be maintained during lifting and unloading operations to avoid any operational hazards, such as the vessel locating too close to or colliding with the platform [276]. Early methods for maintaining position, such as mooring and jack-ups, but both are time-consuming [277,278]. Nowadays, most heavy lift vessels employ dynamic positioning systems. While the vessels can be partially automated with dynamic positioning systems and low-level load controllers, most high-level control tasks, including adaptive adjustments of the DP controller and load control, are still performed manually [279].

4.3. Benefits

DT-enabled O&M is not an entirely novel technology detached from existing O&M practices, nor is it a mere combination of current O&M techniques. Instead, it should be viewed as a comprehensive framework that involves upgrading existing O&M technologies and methods, followed by their integration. This promising technology has the ability to provide significant advantages from various perspectives, including economy, safety, sustainability, efficiency, reliability, and security.

- **Economy**. Utilizing DT technology to predict potential issues in a timely manner before they escalate into serious failures can help avoid costly repairs and downtime. The DT technology can also facilitate the continuous optimization of wind turbine operations to maximize energy production. Consequently, this optimization leads to an enhanced return on investment by improving the overall capacity factor and extending the lifespan of the wind turbines [280].
- **Safety**. DT technology provides a comprehensive view of the real-time operational states of wind turbines and enables the simulation of various operational and environmental scenarios, including extreme weather conditions. This capability assists in the timely detection of potential safety hazards or abnormal states. Thus, it is able to effectively respond to various emergencies, safeguarding equipment safety and eliminating the need for emergency maintenance under hazardous conditions. DT technology can also be employed for safety training and simulations. The integration of additional unmanned technologies, such as unmanned aerial vehicles, unmanned boats, and robots, can further improve the safety of maintenance personnel during on-site maintenance operations [38].
- **Sustainability**. DT technology contributes to reducing the carbon footprint over the entire life-cycle and protecting natural resources [281]. It enables extending the lifespan of wind turbines and reducing the raw materials and energy consumed in producing new wind turbines, while also minimizing resource waste caused by malfunctions or over-maintenance [38]. It can also support sustainable resource management by improving the disassembly, recycling, and reuse processes of turbines to facilitate the practice of a circular economy. Furthermore, the interference with the surrounding environment and wildlife can be mitigated by optimizing the operation of wind turbines and real-time monitoring of environmental parameters (e.g., noise).
- **Efficiency**. DT technology can reduce downtime and enhance the efficiency of wind power generation. Furthermore, it offers an integrated platform that consolidates all relevant data and analysis results about wind turbines, providing decision-makers with in-depth insights into wind turbine performance and a comprehensive O&M view. This assists decision-makers in making more effective decisions and increasing O&M efficiency [282].

- **Reliability**. DT technology offers real-time monitoring capabilities, enabling continuous tracking of the performance and health states of wind turbines [109]. When an abnormal condition is diagnosed or a potential issue is predicted, response time can be shortened and timely actions can be taken to strengthen the long-term reliability of wind turbines.
- **Security**. The DT platform monitors the security state of the system in real time and utilizes advanced encryption technologies to protect data transmitted and stored within the system [283]. It can promptly identify and respond to security threats, such as potential cyber-attacks or attempts at system intrusion, to prevent data breaches or unauthorized access, thereby ensuring the integrity and confidentiality of sensitive data.

5. Challenges and future directions

Section 4 introduced the DT-enabled O&M and outlined the characteristics and requirements of its key aspects. Based on the above analysis, it becomes clear that significant gaps remain between current research and the realization of efficient and effective interaction between physical systems and virtual models within DT. Therefore, in this section, we identify and discuss key research challenges in DT-enabled O&M for wind energy that need to be addressed, in order to highlight future research directions and provide insights for further exploration by researchers in the field.

5.1. Holistic and highly-integrated DT systems

The current situation of wind turbine O&M in practice is that, although monitoring information can be acquired and preliminarily analyzed, and maintenance activities are organized and executed following the predefined procedure, a fully integrated linkage mechanism between these two aspects has yet to be established. The available sensing and analytical information is not fully utilized to support systematic and optimized O&M decision-making.

In Section 4, we proposed a framework that systematically characterizes the complexity and multi-dimensionality of O&M when empowered by DT technologies. The core concept of DT emphasizes synchronized updating and interaction between physical entities and virtual models. However, its practical realization requires the coordination of a wide range of heterogeneous processes and functional modules. Therefore, a critical challenge to be addressed is the development of a feasible and holistic DT system that enables integration and coordination among its key technologies and modules. In addition, most current DT models for wind turbines focus on the component level. However, practical decision-making for O&M requires models that operate at the turbine or even farm level. This further highlights the significant challenge of integrating multiple component-level DTs into a coherent and scalable turbine/farm-level framework.

In the future, DT-enabled O&M systems should evolve toward end-to-end optimization capabilities and progress from current DT models toward more advanced levels (i.e., prescriptive and autonomous). Specifically, these systems should be able to dynamically ingest multi-source information, including the health status of the entire wind turbine or even the farm, maintenance task demands, and resource availability, and directly generate system-level integrated decision outputs, such as maintenance scheduling, inventory management, and procurement instructions, thereby realizing real-time iterative updates and autonomous optimization through this closed-loop process.

5.2. Data acquisition and management

Significant challenges remain in the acquisition and management of wind turbine condition monitoring data. First, due to structural constraints and cost considerations, comprehensive and accurate condition monitoring of wind turbines is still unfeasible. Limited accessibility restricts the acquisition of high-resolution condition data, resulting in blind spots in system health monitoring. Second, monitoring data are highly heterogeneous, encompassing a wide range of signal types. These data sources differ considerably in sampling frequency and signal correlation. When leveraging the diverse monitoring data, direct integration is hindered by the distinct properties of each data modality. In addition, the data are often independently operated by different stakeholders, making direct data aggregation impractical. Third, failure data, especially data related to early-stage or rare failure modes, and long-term degradation records, are scarce in reality. This imbalance in the dataset largely limits the performance of health assessment models.

To address these challenges, future research should focus on the development of more advanced sensing technologies and monitoring systems, aiming to enable the estimation of critical parameters in components where direct sensor installation is difficult or even impractical. Furthermore, monitoring systems at the farm level can be developed to capture information that is often inaccessible through single-turbine monitoring. This enables a more comprehensive and systemic DT model. Special attention should be paid to the effective fusion of multisource and multimodal monitoring data and maintenance records across the data, feature, and decision levels, thereby strengthening the reliability of subsequent health assessment and maintenance decision-making. To overcome issues related to data silos and privacy protection, FL techniques can be employed to enable joint modeling across different wind farms without requiring the sharing of raw data. In addition, data augmentation methods should be developed to increase the diversity and volume of available training data. For example, model-based simulations can be developed to generate synthetic data under various conditions, using degradation mechanisms such as drivetrain dynamics or bearing wear. Generative models, such as Generative Adversarial Networks (GANs), can be used to learn the underlying distributions of sensor signals and create realistic failure data samples.

5.3. High-fidelity modeling and computational efficiency

An inherent conflict exists between the fidelity of virtual modeling and computational efficiency in DT. High-fidelity models are crucial for accurately capturing the multi-physics coupling, nonlinear dynamics, and dynamic responses of wind turbine systems, such as those involved in fully coupled aero-hydro-servo-elastic analysis. However, achieving such fidelity typically requires computational times on the order of days. It becomes more challenging when online assimilation of sensor data is required to dynamically calibrate high-dimensional nonlinear systems. The computational burden severely limits the applicability of high-fidelity models in real-time monitoring and decision-making contexts, where operational requirements often demand model responses on the order of minutes or even seconds.

Future research directions may focus on the development of advanced model order reduction techniques and surrogate modeling approaches to simplify complex high-fidelity models without significantly compromising their accuracy. Moreover, selectively integrating high-fidelity models for critical components with lightweight models for non-critical components, combined with the implementation of dynamic fidelity adjustment mechanisms, could allow computational resources to be allocated more efficiently and enable model resolution to adapt based on the operational environment. Beyond algorithmic and software improvements, leveraging advanced computing hardware is also important for improving the efficiency of DT systems.

5.4. Health assessment performance

Current wind turbine diagnosis and prognosis methods still require advancements in trustworthiness interpretability, transferability, and continuity to fully support DT applications. First, although many high-performance models, particularly those based on AI, demonstrate excellent accuracy on specific datasets, their black-box nature often hinders interpretability. It is difficult to understand the underlying reasoning behind the predictions, and such models may produce overconfident yet unreliable outputs when applied to unseen conditions. As a result, decision-makers may find it challenging to trust and effectively utilize these assessments in operational contexts. To address this, enhancing the trustworthiness and interpretability of models is essential. This includes the development of explainable AI approaches and physics-informed ML techniques that establish clear links between feature importance and physical degradation mechanisms. In parallel, more emphasis should be placed on UQ, enabling models to provide confidence intervals that reflect the reliability of their outputs and support risk-aware maintenance decisions.

Second, most existing models are trained on fixed datasets collected from specific geographic locations, turbine types, and operating conditions. When applied to different turbines or under varying environmental conditions, these models often fail to generalize and may experience significant performance degradation. Future research should explore TL techniques to address this challenge. Domain generalization can be used to develop models capable of learning invariant features across multiple operational domains, and domain adaptation aims to reduce the distributional shift between the source and target domains. These approaches are expected to enhance the generalizability of DT technologies across different turbine configurations and real-world deployment scenarios.

Third, a critical requirement for DT systems is the ability to perform continuous health assessment. Most existing models require full retraining when new data becomes available, which contradicts the need for real-time, continuously updated responses. To address this limitation, continual learning approaches should be developed. Such methods allow the model to incorporate new data streams while retaining previously acquired knowledge, enabling model updates without complete retraining. This supports efficient and stable learning over time and is essential for realizing reliable and responsive DT systems under dynamic operating conditions.

5.5. Transformation of maintenance approaches

Compared to conventional uniform maintenance approaches, future maintenance should possess the flexibility to adapt to variations in component characteristics and operational conditions. Different components are subjected to diverse operating environments and degradation mechanisms, making it infeasible for a single pre-defined maintenance strategy to simultaneously achieve global optimization and localized performance enhancement. Furthermore, significant uncertainties exist across the entire chain—from data collection to the final execution of on-site maintenance—and these uncertainties propagate through the process. As a result, adaptive decision-making mechanisms are required to effectively respond to such evolving conditions.

Future maintenance paradigms will evolve toward RxM or even autonomous maintenance, which not only predicts failures but also uses AI to enable autonomous decision-making. It becomes necessary to develop intelligent mechanisms capable of dynamically listing a range of possible operational and maintenance actions and flexibly selecting the most appropriate one based on real-time system states, rather than rigidly applying fixed maintenance rules. This requires achieving a deep integration between this transformative maintenance approach and DT technologies and ultimately establishing a new paradigm for intelligent decision-making. Reinforcement Learning (RL) offers a promising AI solution to address this challenge. Within a high-fidelity DT environment, agents can explore and evaluate the long-term impacts of various O&M actions, such as component replacement, lubrication, or parameter adjustments, thus enabling the realization of fully autonomous and adaptive maintenance.

In addition, current DT technologies and O&M remain largely focused on conventional, fixed-bottom wind turbines, which have dominated the market thus far. These methods and technologies are typically developed based on the structural characteristics, operational conditions, and failure patterns of mainstream turbine models. However, as the wind energy industry continues to evolve, particularly with the emergence of novel designs and floating offshore wind turbines equipped with mooring systems, new challenges and requirements are arising. Floating turbines, for example, operate in more dynamic and harsh marine environments, which introduce additional complexities in terms of structural dynamics, sensor data interpretation, and maintenance accessibility. As these new turbine types move toward commercialization and large-scale deployment, it will be essential to adjust the existing DT-enabled O&M framework accordingly. This includes developing turbine-specific models, integrating new sensing technologies, and accounting for unique failure modes.

5.6. Sustainable and health-aware maintenance implementation

Regardless of the maturity of digital technologies, the final stage of O&M ultimately relies on physical maintenance execution. Although robotics and automation systems have the potential to reduce workload and operational risks, it remains largely unavoidable for technicians to physically access wind turbines via vessels and perform tasks onsite. However, the environmental sustainability and occupational health and safety aspects of these O&M activities have not received sufficient attention.

As the installed capacity of wind farms continues to grow, the cumulative environmental sustainability impacts of maintenance operations, such as emissions from transportation equipment, operational waste from component replacements and lubricant handling, and disturbances to marine ecosystems due to repeated vessel trips and subsea inspections, are becoming increasingly significant. Simultaneously, O&M tasks inherently present considerable health and safety challenges. These include high-risk activities such as working at heights, confined space operations within nacelles or towers, and personnel transfers in unstable sea conditions. Such operations expose workers to significant risks, while the inaccessibility of the site hampers timely medical support and prolongs rescue procedures.

Future research includes integrating life cycle assessment tools into DT platforms to facilitate real-time evaluation of the environmental performance of O&M activities and support the design of sustainable maintenance plans. For example, embedding emissions estimates within maintenance optimization problems and prioritizing the deployment of low-emission or hybrid-propulsion vessels can enable carbon-aware maintenance planning. Moreover, it is recommended to emphasize the development of health and safety-aware O&M by incorporating key performance indicators to evaluate health and safety outcomes and assess operational risks. Integrating DT systems with advanced remote inspection technologies and autonomous platforms also holds significant potential for effectively addressing this challenge.

6. Conclusions

Within the evolving landscape of Industry 4.0 and moving toward Industry 5.0, DT technology has emerged as a pivotal catalyst driving the digital transformation of the wind energy sector. By enabling real-time monitoring, advanced simulation, and predictive analytics, etc., DT-enhanced O&M is expected to substantially elevate the performance of wind turbines. This paper firstly highlights the critical components that deserve special attention for DT deployment in wind turbines. Afterwards, a comparative review of various DT models developed for general scenarios is conducted, and the classical DT models in the wind energy sector are also summarized. Building upon these classical DT frameworks, a DT-enabled O&M framework specifically tailored to wind turbines is proposed, and the enabling technologies involved in each stage are systematically reviewed. Finally, we summarize the research gaps identified between current literature and the envisioned role of DT in future wind turbine O&M, and outline promising research directions. As the digitalization of energy systems continues to evolve, this study aims to provide a knowledge base and inspiration for future research in this emerging field.

CRediT authorship contribution statement

Mingxin Li: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Yuka Kikuchi:** Writing – review and editing. **Jonas W. Ringsberg:** Writing – review and editing. **Konstantinos C. Gryllias:** Writing – review and editing. **Piero Baraldi:** Writing – review and editing. **Enrico Zio:** Writing – review and editing. **James Carroll:** Writing – review and editing.

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.

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Data availability

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

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