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Digital twins and AI integration in offshore renewable energy: A Review

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Abstract. The integration of digital twins and AI in offshore renewable energy systems represents a transformative approach to improve operational efficiency, scalability, and sustainability. This paper provides a review of innovative applications of digital twins and AI in the context of offshore wind energy and floating energy islands. It examines the existing literature and published case studies to highlight the challenges in this field. Digital twins are revolutionizing the design, monitoring, and maintenance of offshore platforms. By incorporating AI-driven analytics and predictive maintenance capabilities, these systems enable precise decision-making, reduce downtime, and extend the lifespan of infrastructure subjected to harsh marine environments. Case studies discussed include the application of digital twins for structural health monitoring in offshore wind farms, where significant reductions in maintenance costs were achieved through predictive analytics.

1. Introduction

Offshore renewable energy has been experiencing growth, driven by the global push for decarbonization and the increasing demand for sustainable energy sources. In 2024, the global wind energy sector reached an installation of 117 GW of new wind power capacity, slightly exceeding the 116.6 GW added in 2023. This marked the second consecutive year of growth following earlier declines. According to the GWEC Global Wind Report, China led this expansion by contributing 79.8 GW, which represented 68.2% of the global additions. By the end of December 2024, China hosted 521 GW of wind capacity, accounting for 45.8% of the world's total installed wind power capacity of 1.14 TW. In comparison, the United States ranked second with 4.1 GW of new capacity and a cumulative total of 154.3 GW, followed by Germany with 4 GW, India with 3.4 GW, and Brazil with 3.3 GW. While overall wind capacity grew significantly, the offshore segment saw a decline in new installations, with 8 GW added in 2024 compared to 10.8 GW in 2023. Nonetheless, global projections indicate sustained momentum, with new wind installations expected to climb to 138.2 GW in 2025 and reach 194.1 GW annually by 2030. These show both the strong role of wind energy in the global renewable energy transition and the dominant position of China in current capacity growth [1-3]. Offshore wind energy is needed due to its higher capacity factors and reduced land-use conflicts compared to onshore wind. As of 2023, the global offshore wind capacity reached 75.2 GW, with 10.8 GW added that year alone, representing a 24% increase from the previous year. This expansion is expected to continue, with forecasts predicting an additional 410 GW of offshore wind capacity to be installed by 2030 [4].

However, operating in offshore environments presents challenges. Harsh marine conditions, such as strong winds, saltwater corrosion, and limited accessibility, can lead to increased maintenance costs and operational risks. Traditional maintenance strategies often result in unplanned downtimes, which can be costly. The unplanned equipment failures cost top global companies up to $1.4 trillion annually across different industries [5]. To address these challenges, the integration of digital twins and artificial intelligence has become a transformative approach. Digital twins represent virtual replicas of physical assets that enable real-time monitoring, simulation, and optimization of operations. In offshore wind farms, digital twins can replicate various components, such as foundations, towers, wind turbine generators, and cables, allowing for improved design, monitoring, and maintenance. AI further improves the capabilities of digital twins by enabling predictive maintenance and anomaly detection. AI structural health monitoring systems have been developed to predict and optimize the performance and reliability of wind turbines. These models use existing sensor data to predict potential component failures, allowing for proactive maintenance and reduced downtime [5].

The integration of digital twins and AI not only improves operational efficiency but also extends the lifespan of offshore infrastructure. By enabling precise decision-making and reducing unplanned downtimes, these technologies contribute to the overall sustainability of offshore renewable energy systems [6]. As shown in [6], digital twins offer a multi-level capability framework, from standalone visualization models to advanced predictive systems, supporting remote planning, monitoring, and optimization of offshore assets. The study showed a digital twin developed for a floating offshore wind turbine that evolved through standalone and predictive capability levels. At the standalone level, a 3D model of the wind turbine and its environment enabled visualization and interaction in a virtual reality environment. At the descriptive level, real-time data streams from 58 parameters, ranging from wave spectra to turbine rotation and structural motion, were integrated into the digital twin for monitoring. The predictive level introduced neural network models and transfer learning techniques to forecast turbine behaviour several seconds to hours ahead, supporting maintenance planning. This work highlights the potential of digital twins in offshore wind operations by enabling data-driven decision-making, reducing operational risk, while also underlining the need for development across all capability levels of the digital twin framework. According to [7], predictive digital twins combine physics-based models, machine learning algorithms, and hybrid modelling to simulate and analyse wind turbine behaviour under different conditions. These digital twins incorporate data from IoT sensors, SCADA systems, weather APIs, and historical performance logs to build real-time monitoring and decision-making platforms. By capturing interactions between components, environmental forces, and operational strategies, predictive digital twins improve energy forecasting, optimize performance, but also reduce unplanned downtimes. They also enable anomaly detection and support predictive maintenance scheduling, needed for offshore applications where service logistics are complex and costly. Despite their promise, challenges remain in model validation, data fusion, and computational resource demands. According to [8], AI improvements are in rotor blade aerodynamics, real-time performance optimization, predictive maintenance strategies, and smart grid integration. The paper showed that performance gains of up to 20% in energy yield and a potential 10% increase in turbine lifespan using AI. The authors also identify AI algorithms such as genetic algorithms, particle swarm optimization, convolutional neural networks, and LSTM models, explaining their practical use and benefits. Therefore, the growth of offshore renewable energy shows that an intelligent system is needed to overcome operational challenges. The integration of digital twins and AI is a solution that improves efficiency, resilience, but also sustainability in offshore energy operations.

This review aims to systematically synthesize existing literature and to identify technical challenges, classify use cases. The main objective of this research is to review and analyze published studies and real-world cases where digital twins and AI are used in offshore renewable energy systems. It aims to understand how current research and practice apply these technologies. The study also identifies technical challenges such as data integration, accuracy of models, real-time processing, and how different systems work together. Another goal is to group existing applications into clear categories. These include monitoring structural health, predicting when maintenance is needed, improving turbine performance, and forecasting energy production.

2. Digital twins in wind energy systems

A digital twin represents a dynamic virtual representation of a physical system that continuously evolves with real-time data. In energy systems, digital twins function as a central tool to simulate, monitor, and optimize performance across the asset's lifecycle. They replicate the behaviour and conditions of physical infrastructure, such as wind turbines or entire offshore energy platforms, by integrating sensor data, environmental inputs, and system dynamics [9]. The digital twin is composed of several elements. It begins with the physical entity itself, such as a turbine or a floating substation. Real-time data is collected from this asset using sensors and IoT devices, capturing measurements such as wind speed, vibration, torque, temperature, and humidity. This data is transmitted through communication networks to a digital environment, where it is processed and visualized using modelling software. Machine learning and AI methods are applied to interpret the incoming data, to enable real-time diagnostics, forecasting, and recommendations. A feedback loop is established so that the insights from the digital model can be applied to the physical system, in order to allow continuous adaptation and optimization.

The concept of digital twin maturity has been presented through a five-level framework. At the first level, descriptive twins provide static visualizations of the asset, reflecting its basic configuration and current status. The second level, diagnostic twins, analyze historical and real-time data to identify faults and performance issues. Predictive twins, at the third level, forecast failures and degradation using data-driven or physics-based models. The fourth level, prescriptive twins, suggests optimal responses to predicted issues, such as adjusting turbine blade pitch or scheduling maintenance. At the highest level of maturity, autonomous digital twins are capable of independently making operational decisions and implementing control actions without human input. This maturity model has been discussed in recent studies, such as [10, 11], which define digital twins in industrial systems along these five levels. Digital twins have shown potential in the energy sector. A study [12] shows that using a digital twin for offshore wind turbine maintenance scheduling can reduce unplanned downtime by up to 35% and extend component lifespan by over 20%. Another study [13] showed that predictive digital twins in wind forecasting could provide a 61-hour forecast horizon with a mean absolute percentage error below 8%, which improves operational planning. In offshore renewable energy, these benefits are important.

Table 1. Digital twin applications in wind energy

Application Area	Models / Algorithms Used	Case Studies / Locations	Critical Findings	Reference
maintenance scheduling	Predictive DT, ML-based degradation models	Haghshenas et al. [12], offshore wind farms, Norway	Unplanned downtime reduced by 35%, component life extended by 20%	[12]
wind forecasting	Physics-informed DT, time-series ML models	Stadtmann et al. [13], complex terrain wind farm, Norway	Forecasting accuracy with MAPE < 8%, 61-hour horizon	[13]
maturity framework implementation	Five-level DT maturity model (Descriptive - Autonomous)	Stadtmann et al. [10], industry-wide survey and test beds	Operational autonomy maturity increasing across projects	[10]
real-time monitoring and control	Sensor-IoT + ML + simulation feedback loop	Stadtmann et al. [6], floating offshore turbine prototype	Enabled real-time feedback control in harsh marine conditions	[6]
predictive diagnostics	Hybrid ML-DL diagnostics with SCADA	Lutzen & Beji [5], online clustering of subsystems	Improved clustering accuracy and anomaly detection	[5]
lifecycle optimization	RUL estimation, economic/environmental multi-objective DT	Bosnjakovic et al. [8]on turbine bearings	20-day RUL lead time, MAE of 0.047, supports sustainable EOL management	[8]

Harsh marine conditions, limited access to infrastructure, and high costs of manual intervention make the use of predictive and autonomous digital twins needed. Their ability to simulate real-world conditions with accuracy, recommend optimized control strategies, and minimize downtime supports not only the resilience of offshore energy systems but also their scalability and long-term economic viability. Table 1 shows digital twin applications in wind energy systems.

3. AI in wind turbines

AI algorithms such as genetic algorithms, particle swarm optimization - PSO, and artificial neural networks - ANNs help optimize complex aerodynamic shapes of rotor blades. These algorithms minimize drag and turbulence while maximizing lift and energy output [14]. It was shown that AI optimized blade profiles can lead to a 12–18% increase in performance compared to conventional

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designs [15]. Using ANNs with CFD simulations reduces simulation time from 135 hours to 30 hours, achieving similar accuracy. AI also supports structural design by optimizing turbine towers and foundations [16-18]. Convolutional neural networks - CNN and support vector machines - SVM have been applied to reduce tower mass and maximize structural stability [19]. This reduces material use and transport costs. AI improves design flexibility by customizing configurations to local wind conditions. Deep learning models predict mooring line tension for floating turbines, ensuring structural integrity under dynamic sea conditions [20]. Additionally, AI design tools can explore thousands of design variants based on constraints like cost, noise, site topography, and energy yield.

AI has been used in operational optimization and grid integration. The significant contribution is short-term forecasting of power generation [21]. Models such as LSTM, GRU, and CNN-LSTM analyze historical and real-time data to predict wind speed and output with high accuracy. Hybrid AI models have achieved over 98% accuracy (R^2 = 0.9821) in predicting energy output. This supports better planning of energy use and stabilizes power grids [22]. AI also dynamically adjusts turbine performance. It controls parameters like blade pitch and yaw angle to respond to changing wind conditions. This optimization can improve turbine efficiency by up to 20% [14,23]. AI maximum power point tracking systems increase power generation and reduce mechanical stress. AI supports integration with smart grids. It balances power supply and demand by controlling storage and distribution in real time. AI also predicts instabilities and supports fault isolation to prevent blackouts. Predictive models can trigger energy storage when wind output drops suddenly [24]. In offshore applications, AI enables coordination between turbines to optimize wake effects, reduce losses, and increase grid responsiveness [25].

Predictive maintenance is one of the most valuable AI applications in wind energy. AI models analyze data from SCADA systems, sensors, and inspection drones to detect faults before they cause failures. Random forest -RF, XGBoost, and deep learning models can detect anomalies in turbine components like gearboxes, generators, and blades with over 80% accuracy [26-28]. AI reduces operational costs by predicting when maintenance is needed and avoiding unnecessary inspections. According to NREL, operational and maintenance costs account for about 15–27 USD/kW/year for onshore and 40–60 USD/kW/year for offshore wind farms. Reducing unplanned outages increases revenue and turbine availability. Studies [29-30] show AI can extend turbine lifespan by up to 10%. Advanced models like Siamese CNNs and drone-based inspections enable fast detection of blade damage [31]. Hybrid models combining machine learning and statistical process control have proven effective in detecting subtle anomalies [32]. AI also enables thermal and vibration analysis to track component degradation in real time [33].

Explainable Artificial Intelligence - XAI has been used in wind turbine operations. As AI systems take on more control tasks, understanding their decision-making processes is needed [34,35]. XAI techniques, such as SHAP (SHapley Additive exPlanations) values, help interpret complex models by highlighting which input features most influence predictions [36,37]. In wind turbine power curve modeling, applying SHAP values has revealed how variables like wind speed and blade pitch affect power output predictions, making the models more transparent and trustworthy [38]. In predictive maintenance, XAI aids in diagnosing faults by providing insights into model reasoning [39]. A study introduced a hybrid deep neural network combined with XAI methods for wind turbine fault detection. This approach not only improved detection accuracy but also offered explanations for each prediction, assisting maintenance teams in understanding and trusting the AI system [40]. Regarding the end-of-life stage of wind turbines, AI models are employed to predict the remaining useful life - RUL of components [41,42]. Accurate RUL predictions enable operators to plan maintenance or decommissioning activities effectively.

Table 2. AI applications in wind energy.

Application area	Models / Algorithms used	Case studies / Locations	Findings	Reference
aerodynamic design optimization	Genetic Algorithms (GA), Particle Swarm Optimization (PSO), ANN, CNN	UK: ANN+CFD blade design [14, 15]	Performance gain of 12-18%, CFD time reduced from 135h to 30h	[14], [15]
structural optimization (towers & foundations)	CNN, SVM, BPNN, PSO, ANN	China, Serbia: Tower & foundation optimization [16-19]	CNNs reduce tower material; PSO improves structural stability	[16], [17], [18], [19]
performance forecasting	LSTM, GRU, CNN-LSTM, CNN-GRU, XGBoost, LightGBM	Turkey, India: Wind output forecasting [21, 22]	$R^2 > 0.98$; CNN-GRU accuracy 99.81% in forecasting	[21], [22]
dynamic control & MPPT	Fuzzy Logic, ANFIS-PI, Neural Controllers	India, Pakistan: MPPT & voltage control [23, 24]	Efficiency improved by 20%; fuzzy logic ensured voltage stability	[23], [24]
smart grid integration	XGBoost, RF, CNN	Egypt: Grid interaction & stabilization [25]	Improved fault detection, better load balancing	[25]
predictive maintenance	Random Forest, XGBoost, Siamese CNN, Hybrid ML-SPC	Europe, Global: SCADA-based diagnostics [26-30]	Over 80% fault detection accuracy; 10% turbine life extension	[26], [27], [28], [29], [30]
drone-based fault detection	Siamese CNN, Deep Learning Segmentation	Global: Drone inspection of blades [31]	Accelerated fault identification; reduced inspection effort	[31]
remaining useful life estimation	Regression Models (RF, MLP), Statistical Process Control (SPC)	Taiwan, Global: SCADA RUL estimation [41-43]	MAE = 0.047, lead time = 20 days for failure prediction	[41], [42], [43]
explainable AI	SHAP, LIME, Hybrid Deep Neural Networks	Europe, Global: Power prediction explainability [34-40]	SHAP explained blade pitch/wind speed impact; boosted trust	[34], [35], [36], [37], [38], [39], [40]

A framework [43] using regression models fed with operational data from SCADA systems estimated the RUL of main bearings with a mean absolute error of 0.047 and mean squared error of 0.012, providing an average lead time of 20 days for maintenance planning. This approach improves safety, minimizes downtime, and maximizes turbine productivity, specifically for sustainable wind farm operation. The applications of AI in wind turbines are presented in table 2.

4. Offshore renewable energy systems

Offshore wind farms harness wind energy over open seas, where wind speeds are higher and consistent than on land. The Seagreen Offshore Wind Farm in Scotland exemplifies this, with a capacity of 1,075 MW, making it the largest in Scotland. It uses 114 Vestas V164-10.0 MW turbines installed on steel jacket foundations at depths up to 58.7 meters [44-46]. Floating wind turbines enable energy generation in deeper waters beyond the reach of fixed-bottom structures. The Kincardine Offshore Wind Farm, located 15 km off the coast of Aberdeen, Scotland, operates six turbines on semi-submersible platforms, total 49.5 MW. Floating platforms like spar-buoy, semi-submersible, and tension-leg designs are being refined to improve stability and reduce costs [47,48]. Energy islands represent artificial platforms designed to serve as hubs for offshore energy generation and distribution. Denmark plans to construct two such islands: one in the North Sea with an initial capacity of 3 GW, expandable to 10 GW, and another on the island of Bornholm in the Baltic Sea with a capacity of 3 GW. These projects have the aim to centralize energy collection and transmission, improving integration into the mainland grid [49].

Offshore renewable energy systems have operational and design challenges. Installation and maintenance are demanding due to harsh marine environments. Environmental impacts are another concern. The construction and operation of offshore wind farms can affect marine ecosystems. Studies indicate that turbine noise and physical presence may disrupt marine life patterns [50,51]. Underwater noise from pile driving during construction can cause behavioral changes in marine mammals and fish. The presence of turbines can alter habitat structures, potentially affecting local biodiversity [51]. Grid integration poses further challenges. Transmitting electricity from offshore sites to onshore grids requires infrastructure. Energy islands have been proposed as centralized nodes to support this process. However, their development involves logistical and financial planning. The North Sea Wind Power Hub project, for example, aims to increase offshore wind capacity by 36 GW using artificial islands and high-voltage direct current links, but it faces technical and economic challenges [52].

Offshore wind projects: Dogger Bank Wind Farm, Hywind Scotland, and WindFloat Atlantic show new findings in offshore wind technology, operational efficiency, and maintenance strategies. Dogger Bank Wind Farm, located over 130 km off the northeast coast of England, is becoming the world's largest offshore wind farm upon completion. The project is divided into three phases: Dogger Bank A, B, and C, each with a capacity of 1.2 GW, totaling 3.6 GW. The wind farm uses GE's Haliade-X 14 MW turbines, marking the first commercial deployment of this model. Once operational, Dogger Bank is expected to generate approximately 18 TWh of electricity annually, sufficient to power around 6 million UK homes [53]. Operational and maintenance strategies for Dogger Bank have been planned to improve efficiency and reduce costs. A maintenance program was developed, focusing on the 95 turbines, offshore substations, onshore converter stations, and associated cabling. This program integrates original equipment manufacturer maintenance requirements and aims to ensure operational efficiency, safety, and longevity of the assets. Hywind Scotland, situated 25 km off the coast of Peterhead, Aberdeenshire, is the world's first commercial floating offshore wind farm. Commissioned in October 2017, the project comprises five Siemens SWT-6.0-154 turbines, each with a capacity of 6 MW, totaling 30 MW. The turbines are mounted on Hywind floating monopile structures, allowing operation in water depths of up to 120 meters [54]. In its first five years, Hywind Scotland achieved an average capacity factor of 54%, outperforming expectations and demonstrating the viability of floating wind technology. The project has withstood challenging conditions, including 10-meter waves and hurricane-force winds, without significant downtime. A study investigating the inflow and wake conditions of a 6 MW floating turbine from Hywind Scotland found that even small variations in ambient turbulence intensity (~1%–2%) can result in up to a 10% faster wake recovery, highlighting the importance of atmospheric conditions on turbine performance. WindFloat Atlantic, located 20 km off the coast of Viana do Castelo, Portugal, is a pioneering floating offshore wind farm using semi-submersible platforms. The project consists of three MHI Vestas V164-8.4 MW turbines, totaling 25 MW. Commissioned in July 2020, WindFloat Atlantic has demonstrated the feasibility of floating wind technology in deep waters [55]. In 2022, WindFloat Atlantic produced 78 GWh of electricity, achieving a technical availability of 93%. The project's success shows the potential of floating wind farms to contribute to renewable energy targets, especially in regions with deep coastal waters where traditional fixed-bottom turbines are not feasible. These case studies present the best practices but also challenges in offshore wind energy. Dogger Bank shows large-scale deployment, and Hywind Scotland demonstrates the resilience and performance of floating wind technology. WindFloat Atlantic highlights the potential for floating wind farms in deep waters.

5. Conclusion

This review has examined the integration of digital twins and AI in offshore renewable energy systems, with a focus on offshore wind farms, floating platforms, and energy islands. The findings confirm that digital twins provide a scalable framework for real-time monitoring, simulation, and predictive control, with significant gains in operational efficiency and lifecycle management. The reviewed literature highlights the progression of digital twins across five maturity levels, showing increasing autonomy and value creation, specifically in offshore contexts where logistical constraints and environmental exposure heighten operational risk. Predictive digital twins have shown the ability to reduce unplanned downtime by up to 35% and extend component lifespan by over 20%, validating their economic and technical viability for offshore wind applications.

Despite proven advantages, challenges remain in data standardization, model validation, sensor integration, and system interoperability. Continued research is required to improve models, reduce computational demands. Future research should focus on integrated, multi-scale digital ecosystems that support adaptive decision-making and drive performance optimization across the entire offshore renewable energy lifecycle.

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