EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Application of Offshore Wind Power Digital Twin Technology in Remote Operation and Maintenance

Huatao Si [1*], Xiaotao Chen [2], Qingyu Men[2]

[1]Shandong Guohua Era Investment Development Co., Ltd., Shandong Guohua 250000, China
[2]Guohua (Rushan) New Energy Co., Ltd., Rushan, Shandong 264500, China

Abstract

INTRODUCTION: Offshore wind (OsW) energy has emerged as a key factor in the global transition towards high-energy-return renewable energy, with stable winds and minimal land take. However, the Maintenance and Operation (O&M) of OsW wind farms are very challenging due to their hostile marine conditions, huge running costs, and poor accessibility.
OBJECTIVES: To address these issues, the proposed method offers a Digital Twin (DT) strategy designed to enhance the remote operation and maintenance (O&M) of OsW wind power equipment. From the use of high-resolution global OSW wind turbine observations from Sentinel-1, combined with domain-specific feature engineering and data preprocessing, including outlier removal and normalization, the approach provides robust input for modelling and analysis.
METHODS: One of the most important aspects of the system is the integration of real-time sensor feeds through Arduino devices, secure data exchange through OPC UA, and middleware processing through Node-RED. The sensor-based data architecture feeds into a Unity 3D-based digital twin environment, which continuously synchronizes virtual models with the physical conditions of the turbines.
RESULTS: Besides, fault classification is handled with a Categorical Network (CatNet), where attention mechanisms and convolutional layers are used to detect abnormalities such as gearbox faults, generator faults and yaw misalignment. Interactive dashboards, 3D visualization, and predictive analytics are supported within the framework, enabling operators to monitor, diagnose, and control offshore turbines remotely.
CONCLUSION: Ultimately, this approach significantly reduces unplanned downtime, enhances safety, and maximizes power output through intelligent, data-driven decision-making.

Keywords: Maintenance and Operation, Categorical Network, Digital Twin, Wind Turbine, Normalization, Visualization.

Received on 30 May 2025, accepted on 13 August 2025, published on 22 September 2025

doi: 10.4108/ew.9435

*Corresponding author. Email: chuz_cz2012@163.com, huatao_si25@outlook.com

1. Introduction

Due to its high capacity and minimal environmental impact, OsW wind energy has helped propel the world toward utilizing renewable resources [1]. Operating OSW wind farms in remote or deep locations presents new challenges for their traditional maintenance approaches [2]. Digital twin technology, which replicates assets in digital form, is gaining popularity as a means to address these issues by providing fine-tuned observation [3]. Integrating real data and simulations allows digital twins to report on the state and performance of OsW wind turbines [4]. By utilizing technology, this industry can adhere to budgets and manage the OSW wind assets more efficiently [5].

The daily activities of maintaining and operating OsW wind farms are shaped by challenging conditions at sea, supply chain issues, and the high risk to those on the job [6]. Wind turbines are sometimes blocked by powerful winds, high waves, and storms, resulting in downtime and increased maintenance delays [7]. Because OsW installations are so large and complex, it is essential to utilize advanced systems for early detection of faults and for planning maintenance schedules [8]. It is also challenging to inspect and maintain wind turbines due to their remote locations [9]. Therefore, it is necessary to explore solutions that can make remote monitoring and predictive maintenance better [10]. As the offshore wind energy sector continues to grow rapidly, remote maintenance presents a critical challenge that must be overcome. Our system addresses this requirement by integrating real-time monitoring with offshore turbine predictive fault detection. This technology minimizes operational hazards associated with rough marine conditions, providing a timely and efficient solution to keep pace with the increasing demands of the offshore wind industry.

Some drawbacks mean that OsW wind power systems are not as efficient and value for money as they could be [11]. The harsh marine setting necessitates more frequent and specialized care for turbine components [12]. Predictive maintenance is often unsuccessful with current remote monitoring tools, which frequently result in equipment breakdowns and prolonged downtime [13]. Additionally, because installing OsW turbines is both expensive and technically challenging, growing and sustaining the sector proves to be a significant challenge [14]. Therefore, it is vital to enhance digital tools to successfully carry out remote operations and maintenance (O&M) [15].

To overcome the digital twin-based approach suggested here, it meets major challenges in OsW wind energy management by facilitating real-time, remote, and smart monitoring of turbine operations. The integration of sensor networks, robust communication protocols, and sophisticated data processing layers enables continuous performance evaluation, early fault detection, and predictive maintenance. The utilization of virtual simulations and interactive dashboards reduces dependence on on-site inspections, lowers maintenance expenses, and enhances safety in adverse marine conditions. Although technologies like Unity3D and OPC UA have been used in the past in offshore wind turbine systems, our work's real novelty is an integrated system that unites these technologies with a novel AI model (CatNet). The CatNet model, which is based on convolutional layers and attention mechanisms, enables more accurate and real-time fault detection compared to traditional techniques. This amalgamation provides an overall solution to offshore wind turbine maintenance, catering to both the requirements of real-time monitoring and early fault warning. This holistic approach not only enhances reliability and energy performance but also opens doors to more scalable, sustainable OSW wind operations. The contribution of this research is as follows:

- Create a Digital Twin Framework to simulate OsW wind turbine operations with real-time information for advanced monitoring, simulation, and control.
- Enhance Remote O&M through the fusion of sensor networks, OPC UA communication, and middleware processing to facilitate condition-based and predictive O&M.
- Maximise turbine performance through smart diagnostics of yaw misalignment, energy efficiency analysis, and real-time wake flow control informed by simulation-driven insights.
- Enable Fault Detection and Classification through the integration of a Categorical Network (CatNet) model that scrutinizes multi-sensor information to detect gearbox and generator faults.
- Empower Data-Driven Decision Making with interactive dashboards and 3D visualization software for real-time turbine status, performance trends, and remote training.
- Improve Sustainability and Reduce Costs by reducing downtime, optimizing turbine life, and minimizing dependence on human inspections through the use of predictive analytics.

Section 1 displays the introduction and literature survey in Section 2. Section 3 presents the proposed research methodology. Section 4 presents the outcomes and discussions, while Section 5 outlines the conclusion and future work.

2. Literature Survey

Y. Cao et al. (2024) have proposed using digital twins and CFD simulations, in conjunction with monitoring data, to measure the efficiency of the turbine. Researchers designed and tested a VWFT to ensure the connection between the turbine's motion and the rotation of the blades. Missing data in torque, thrust, and lateral force were handled by a recurrent neural network that predicted the energy harvesting parameters with errors less than 10% [16].

E. Kandemir et al. (2023) have proposed Unity 3D to handle a digital twin; this work devised a method to find the best turbine placements by continuously repositioning the equipment. It utilized wind speed and direction, along with Jensen's model, to simulate the behaviour of wind. To determine the optimal positioning of the turbines, both reactive and optimal methods were employed. The simulations revealed that making small changes to turbine positions could help create more energy in actual situations [17].

M. Mahmoud et al. (2024) have proposed a work that outlines a clear set of steps for incorporating the four important systems that need to be included. Physical, digital, connection, and service. It examined key components of the turbine and identified the essential design, measured, and calculated values necessary to enhance the helicopter design. The digital system utilized machines and computers to store data and facilitate calculations, while the connection system employed technologies such as SCADA, wireless sensors, smart devices, smart grids, and cloud systems to enable seamless integration. The service system helped resolve issues that arose with the turbines and ensured they were operating at their best. This approach's dependency on a predefined group of turbine components and design factors could prove unsuitable for offshore wind farms that feature more dynamic or variable turbine configurations, thereby restricting generalizability [18].

M. Wang et al. (2023) introduced a system that combines OSP to determine the optimal number of sensors to use and their optimal locations, ensuring a balance between cost and analysis accuracy. Within this model, MCMC-Bayesian methods helped estimate the damage to the structure while computing the associated uncertainties. Testing on the OsW site demonstrated that damage locations and their severity could be identified correctly [19].

A. K. Sleiti et al. (2022) have introduced an architecture suitable for use in power plants and other major engineering structures as part of the work. Key DT tools were built, which included models based on physics, analysis of sensor data, real-time observation, simulations at the local location, and a digital link between all these aspects. The research employed anomaly detection, deep learning, and dynamic models, along with vector autoregressive (VAR) models. The use of operational gas turbine data confirmed improvement in finding anomalies [20]. Modern research in offshore wind turbine fault detection is primarily based on conventional approaches, such as threshold-based detection and basic machine learning methods. Our methodology, however, proposes a new classification system employing CatNet, which combines both convolutional neural networks and an attention mechanism to detect faults with higher accuracy, namely gearbox failure, generator failure, and yaw misalignment. This approach is stronger and larger-scale than legacy models because it takes into account multi-source sensor readings and operational conditions in real-time

Y. Cao et al. (2023) proposed a work that utilized computer simulations to assemble a digital model and simulation data from wind tunnel tests, enabling the rapid visualization of how air and water interact with and exert pressure on fixed OsW turbines. It effectively separated the important factors to simplify the model and stored the data in a combination of different types of databases. Uncalculated data were roughly estimated using a method that looks at nearby points with various weights and balance them out, and a special algorithm called Bayesian regularization-back propagation was used to fix bigger errors and keep prediction errors down to less than 10% Yet, this research delivers a thorough method through the application of digital twin and CFD simulations, it fails to mitigate the problem of missing or incomplete sensor readings, potentially influencing the predictive accuracy of the efficiency[21].

C. Kim et al. (2022) have suggested that a FOWT was developed for a digital twin; the simulation model was created in ANSYS Twin Builder and linked with sensors using TCP/IP, allowing for live output generation. Test data from multiple marine situations suggest that it performs well and could increase the flexibility of power systems by predicting real-time OsW wind farm output [22].

X. Zhao et al. (2023) suggested that reduced-order Modelling (ROM) based on components was applied to form a DT anchored on a monopile whose characteristics were often changing. To build the ROM version, a set of component archetypes was created and loaded into the ROM model dedicated to the blade, hub, nacelle, and Tower. With a speed that is nearly 650 times faster than Finite Element Analysis and a low error rate of 0.2%, the DT can predict the responses and health of the structure in situations of wind and wave loading almost instantly [23].

M. T. Qaiser et al. (2023) suggested that the Hywind Tampen wind farm was developed using Unity 3D, which comprises digital models. It utilized known rules of physics and historical records to determine the energy results in every season. The findings showed that the wind farm was able to supply approximately one-third of the local oil and gas platforms' electricity each year, significantly reducing their annual CO_2 and NOx emissions [24].

Durga Praveen Devi et al. (2023) demonstrate the use of digital twins and IoT-enabled AI to enhance operations through predictive analytics and real-time monitoring. In the proposed work, these concepts are integrated into offshore wind power systems for the optimization of remote operation and maintenance, utilizing digital twins created from sensor data. This strategy offers benefits such as predictive maintenance, remote monitoring, and performance optimization. The result is reduced operational downtime, lower maintenance costs, and enhanced energy efficiency in offshore wind energy systems [25].

Dinesh Kumar Reddy Basani et al. (2025) integrate AI and digital twin technology to optimize healthcare systems through real-time monitoring and task management. This technique is leveraged in the proposed offshore wind power system to optimize remote maintenance and operation of wind turbines. The benefits include enhanced efficiency, proactive maintenance scheduling, and reduced costs and downtime in offshore energy operations [26].

Kannan Srinivasan (2020) demonstrates how digital twins are used for predictive analytics in system performance. For the current research, this strategy is adopted to enhance offshore wind power operations by utilizing digital twin technology for real-time simulation and predictive maintenance. The key benefits of this adoption include improved reliability, cost savings through remote maintenance, and more informed operational decisions [27].

E. Katsidoniotaki et al. (2022) have introduced a computer model to forecast the forces when the waves are extremely strong. The digital twin was 90.36% accurate on average and significantly reduced the time required to complete calculations, reducing them from multiple days to seconds. This new method replaced old approaches and calculations, quickly and dependably assessing loads on important parts and making it safer to operate in unfavourable OsW conditions [28]. Modern research in offshore wind turbine fault detection is primarily based on conventional approaches, such as threshold-based detection and basic machine learning methods. Our methodology, however, proposes a new classification system that employs CatNet, which combines both convolutional neural networks and an attention mechanism to detect faults with higher accuracy, specifically gearbox failure, generator failure, and yaw misalignment. This approach is stronger and larger-scale than legacy models because it takes into account multi-source sensor readings and operational conditions in real-time. OPC UA integration for safe communication with Unity 3D enables real-time simulation and visualization of offshore wind turbines, facilitating seamless interaction and collaboration. OPC UA protocols are used to transmit sensor data (e.g., temperature, vibration, pressure) securely and reliably. Node-RED middleware is used to synchronize data over the network and process it smoothly for transfer to Unity3D, where it is visualized in real-time to display turbine performance and identify any faults.

2.1 Problem Statement

OSW wind systems that use digital twins have some key limitations. Due to the large amount of computer processing required, waking up movements are complicated and cannot be easily performed in real-time [29]. Hybrid-model-based digital twins rely on accurate hybrid models and access to good-quality data, so sometimes the failure predictions can be inaccurate [30]. Accuracy and calibration problems with sensor data can hamper the accuracy of monitoring using virtual sensors [31]. Successfully implementing predictive maintenance for gearboxes requires large amounts of sensor data and is complex to build and unite the models [32]. Moreover, relying on digital twin data to improve the reliability of OsW substructures meets difficulties due to the challenges involved in quantifying structural uncertainty and in applying the methods [33]. This suggests that further research is needed to enhance model accuracy, improve data quality, and expedite calculations in digital twin methods for OSWOOSW wind.

3. Proposed Methodology of Offshore Wind Power Digital Twin Technology to Enhance Remote Operation and Maintenance

Data from OsW wind turbines, as well as temperature, vibration, pressure, speed, and electrical current/voltage sensors, is gathered and fed into a digital twin platform through physical twin and sensor integration, OPC UA server resource streams, and Node-RED middleware processing. Fault classification is achieved through CatNet, allowing proper identification of equipment faults. The digital twin enables smart optimization and performance monitoring, including fault diagnostics, energy output optimization, and wake flow control in wind farms. Smart diagnosis and early warning systems also support OsW wind power operation to facilitate proactive maintenance, improving overall system efficiency and reliability. Figure 1 illustrates the overall architecture diagram for improving remote operations and maintenance (O&M) using digital twin technology.

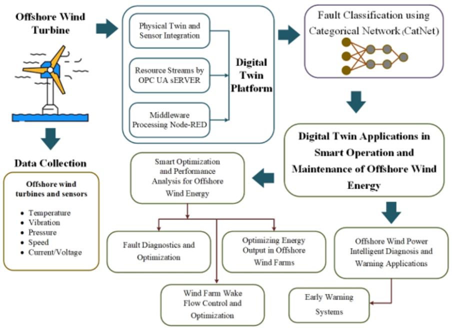

Figure 1. Overall Architecture Diagram for Improving Remote Operation and Maintenance Using Digital Twin Technology

3.1 Dataset Description

The purpose of “Global dynamics of the OsW energy sector monitored with Sentinel-1” is to provide data in a way that is useful for others. Count of turbines, how much power they generate, and the details of the location." Data on OsW farms from all over the world is collected using Sentinel-1 SAR images and validated using public and commercial sources. The dataset contains information on turbine hub heights, installed capacity, the number of turbines, and geographic details useful for mapping, estimating wind power, and constructing digital twins. The two main files contain the data. Turbine specifications for each project are provided in a CSV file, along with a corresponding GeoJSON file, which enables the visualization of turbines on maps and in remote viewing programs. Table 1 shows the parameters and descriptions of the global OsW turbine supplementary dataset derived from Sentinel-1 [34]. In remote sensing data, such as Sentinel-1 SAR images, missing data arises due to cloud cover, satellite pass, or other environmental reasons. To overcome the effect of missing data, imputation methods such as interpolation (nearest neighbour or linear) are used to estimate missing values and maintain the integrity of the dataset during analysis. Sentinel-1 images may contain various types of noise (e.g., speckle noise) that can affect the quality of the data. To reduce noise, we undertake preprocessing steps such as spatial filtering and smoothing to limit their effects on the dataset. Biases can arise due to various reasons, including satellite angle, weather conditions, and measurement errors. Normalization of data and the use of correction algorithms to compensate for dataset biases are strategies employed to correct these errors.

Table 1. Parameters and descriptions of the global OsW turbine supplementary dataset

Parameter	Description
Hub Height (m)	Average height of turbine hubs in meters
Installed Capacity (MW)	Total electrical capacity installed for the project in megawatts
Number of Turbines	Total number of turbines in the wind farm
Source	Origin of the data (e.g., official reports, manufacturers, public databases)
Latitude & Longitude	Geographic coordinates of each turbine
Hub Height (m)	Estimated hub height derived from Sentinel-1 and auxiliary sources
Rotor Diameter (m)	Diameter of the turbine rotor
Installed Capacity (MW)	Estimated or reported capacity per turbine
Additional Attributes	Other derived or observed turbine features (e.g., commissioning year, region)

3.1.1 Data preprocessing

During preprocessing, outliers are removed from the data, and all features are scaled to ensure equal importance for all variables. By taking these steps, one can ensure that machine learning models are reliable and accurate in OSW turbine analysis [35]. To fill the missing values, linear interpolation is done between the present observations found before and after absent data records, in order to maintain time continuity and keep the dataset intact. In order to remove noise, the sensor readings first undergo low-pass and then Kalman filtering. The low-pass filter eliminates most of the high-frequency noise, while the Kalman filter determines adaptively the true nature of the signal by modelling measurement uncertainties and process uncertainties. With dual-stage denoising, the input data becomes reliable and consistent, which, in turn, paves the path for better training of any downstream machine learning algorithm.

3.1.2 Cybersecurity and Data Integrity Considerations

The OPC UA communication protocol offers robust security features, including encryption, authentication, and data integrity, achieved through message signing. This ensures that data being passed between sensors, middleware, and the digital twin platform is secure against unauthorized access. To ensure the safe operation of middleware (Node-RED), secure MQTT protocols are implemented, and firewalls are configured to restrict unauthorized access to data. Furthermore, data integrity is maintained through the use of hash functions and digital signatures, which verify the authenticity of the transmitted data.

To maintain data integrity, offshore wind turbine real-time sensor data is verified for validity using error-checking methods, such as checksums and cyclic redundancy checks (CRCs). These methods prevent corrupting data and ensure that only valid and reliable data is used for fault detection and performance analysis

3.1.1.1 Outlier Detection

Detecting outliers before analysis is crucial, as they can significantly distort the performance or accuracy of models that utilize the data. It removes inconsistencies in the data by eliminating OSW turbines whose height or capacity is much greater than usual. The main formula is in Equation (1).

$$Z = \frac{X-\mu}{\sigma} \tag{1}$$

where Z is the Z-score, X denotes the actual data value (hub height of 250 m), μ denotes the mean of the feature (average hub height) and $\sigma$is the standard deviation of the feature. Z-score in outlier detection because it proves to be very effective in detecting extreme values in datasets that tend to follow a normal distribution. Offshore wind turbine datasets often exhibit significant deviations due to sudden changes in environmental conditions (e.g., wind speed, vibrations). The Z-score effectively detects such extreme values as outliers and is a more accurate method than other robust statistical methods, such as the Interquartile Range (IQR), which does not perform as well in this situation.

3.1.1.2 Normalization

Normalization is the process of rescaling features to ensure they have a fixed range. It is most essential when varying features have different orders of magnitude, which would hurt some ML algorithms, notably those distance-based ones. The formula for Min-Max scaling is performed in Equation (2).

$$X_{\text{scaled}} = \frac{X-X_{\min}}{X_{\max}-X_{\min}} \tag{2}$$

were$X$ represented by the original value, $X_{\min}$ and$X_{\max}$ denotes the minimum and maximum values of the feature, respectively and X_{scaled} is the normalized value. Min-Max normalization normalizes all features to a range of [0, 1]. This is important to prevent features with varying units or magnitudes from having disproportionate effects on the machine learning models. This is especially crucial for CatNet with its use of convolutional layers that are sensitive to input feature scales. Normalizing the data ensures that all features contribute equally to the model's performance, which is essential for achieving precise fault detection.

3.2 Feature Extraction using Domain-Specific Feature Engineering

Experts in the OSW energy use domain-specific feature engineering to extract useful details from raw data, such as the size of the hub, the rotor blades, and the capacity of the turbines. They are used to check the productivity, efficiency, and required maintenance of the turbines. This technique enhances model accuracy and is specifically designed for digital twins and predictive maintenance. Measuring the amount of energy produced by wind power is crucial for evaluating its performance, as shown in Equation (3).

$$P = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \cdot C_p \tag{3}$$

wPhere denotes the power output in watts (W), ρ is the air density, A denotes the swept area of the rotor(m^2), v denotes the wind speed$(\mathrm{m/s})C_p$, and is the power coefficient, typically ranging from 0.35 to 0.45 for modern turbines. Swept Area in Equation (4);

$$A = \pi \cdot \left(\frac{D}{2}\right)^2 \tag{4}$$

where$A$: Swept area of the rotor$(\mathrm{m}^2)D$, Rotor diameter (m). This process uses useful features such as wind power output and the area of the rotor swept by the wind. The approach facilitates more accurate performance predictions, facilitates future maintenance planning, and enables remote monitoring with reduced reliance on external data.

3.3 Structural Foundations and Smart Modelling in Offshore Wind Energy

OSW power systems rely on robust structural supports, such as monopiles, jackets, or floating foundations, to withstand the challenges of hostile marine environments. Smart modelling combines these structures with turbine elements to optimize performance, durability, and resilience, enabling effective energy conversion and stable operation in extreme OSW conditions.

3.3.1 Basic Structure of offshore wind

An OsW power system has important parts that work together to transform wind into useful electricity in the ocean. They involve the turbine, made up of the blades, hub, and nacelle, the Tower, Foundation, such as a monopile, jacket, or a floating base, and subsea cables to carry the electricity. The turbine transforms kinetic energy in the wind into electricity by rotating a generator inside its nacelle [36]. Lifted on high by the Tower, the turbine captures steady winds and rides out stormy seas on the sturdy base foundation. These OsW turbines are positioned to generate enormous amounts of renewable energy while minimizing their impact on both people and the environment. Figure 2 shows the basic structure of OsW.

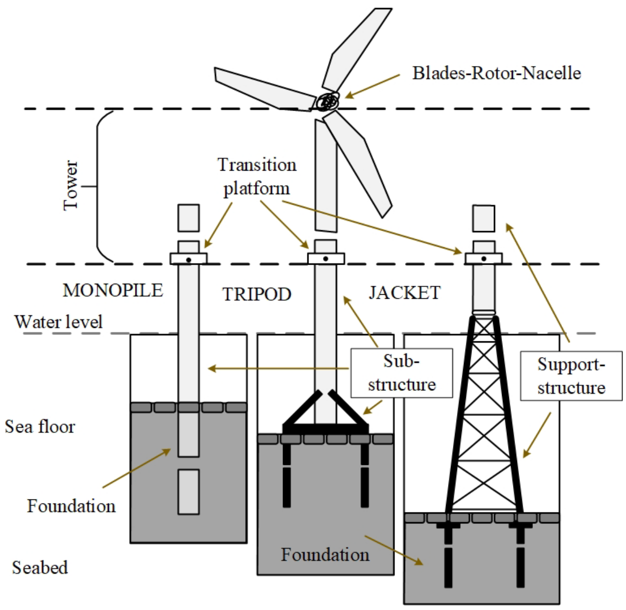

Figure 2. Structure of offshore wind

3.3.2 Digital Twin Framework for Offshore Wind Operations

Digital twin modelling produces digital replicas of OsW turbines or farms that are constantly updated in real time with operational data. The models combine information from design specifications and live performance, and weather data to reproduce real-world behaviour. It helps operators analyze and forecast behaviour by replicating operating scenarios on virtual platforms. Up-to-the-minute information updated in the digital twin proves instrumental in gaining insight and improving the performance of wind turbines.

Models are created using FEM to predict and evaluate how various turbine parts react to conditions such as high winds and rough seas while they're in operation. Setting the parameters for hub height and installed capacity ensures that the model accurately represents the turbine's real-world capabilities. It enables improved forecasts, streamlined development of maintenance strategies, and better-informed decisions in farm management. Figure 3 shows the schematic diagram for the digital twin platform. OPC UA integration for safe communication with Unity 3D enables real-time simulation and visualization of offshore wind turbines, facilitating seamless interaction and collaboration. OPC UA protocols are used to transmit sensor data (e.g., temperature, vibration, pressure) securely and reliably. Node-RED middleware is used to synchronize data over the network and process it smoothly for transfer to Unity3D, where it is visualized in real-time to display turbine performance and identify faults.

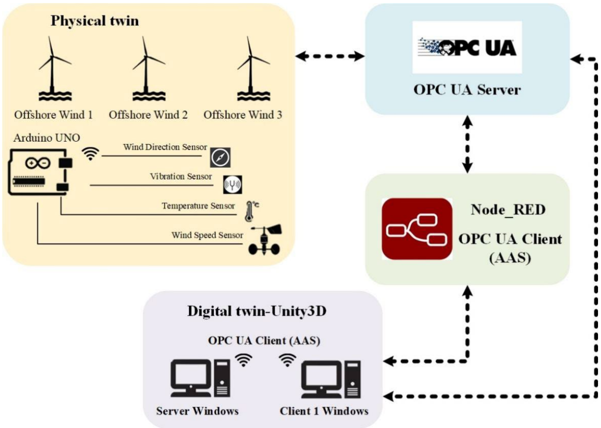

Figure 3. Schematic Diagram of the Digital Twin Platform

3.3.2.1 Physical Twin and Sensor Integration

The initial stage of the system uses several OsW turbines outfitted with critical sensors. All vital turbine parameters are captured by varying sensors that constantly measure the surrounding environment and operating state. The Arduino Uno is used to gather and transmit the raw environmental data from the physical systems. This initial configuration enables the system to monitor turbine functioning reliably, identify deviations and predict optimum maintenance activities.

3.3.2.2 An OPC UA Server manages resource streams.

The information gathered by the Arduino is sent to an OPC UA Server. The OPC UA server establishes an industry-standard, secure connection between physical systems and digital systems. It organizes and makes the data available for later analysis and interpretation. OPC UA enables the reliable and coherent transfer of data, facilitating the remote monitoring of distributed wind farms.

3.3.2.3 Middleware Processing through Node-RED

The data collected from the sensors is processed by a middleware module, Node-RED, which is configured as an OPC UA client. Node-RED takes the raw data and transforms it into organized and formatted outputs that other components can easily access. The processed data is in a format that various simulation tools and remote interfaces can use. With this middleware, maintenance staff can create logic rules and automated warnings using the transformed data.

3.3.2.4 Digital Twin Modelling in Unity3D

The processed data is then routed to a digital twin layer created using Unity3D. The platform creates a digital model of the wind turbines and keeps it continuously in sync with real-time sensor readings. The digital twin features both graphical and numerical representations of each turbine's current functioning condition. Users can connect to the platform from both server and client systems that use the Windows operating system. Using this virtual environment, staff can monitor key indicators, run virtual tests and diagnose issues even when they aren't on the offshore platform. Joining these components together enables OsW operators to operate more efficiently and reliably in a remote setting. Technicians can monitor turbine efficiency, identify potential issues, and plan maintenance activities before they escalate into major problems. The use of a digital twin supports maintenance approaches based on the equipment's condition, which reduces idle time and lowers costs. The integration of these layers into an efficient process enables enhanced predictions and sustains the reliable functioning of renewable energy systems in the face of adverse conditions at sea. Sensor data updates the Unity3D digital twin every 10 seconds to simulate the turbine in near real time. To that end, asynchronous data handling and buffered interpolation methods are employed to smooth over delay due to sensors, network transmission, and rendering. OPC UA with binary encoding, in conjunction with Node-RED middleware optimized for the purpose, ensures minimum data transfers latency. The system guarantees an end-to-end delay of fewer than 3 seconds to allow for real-time visualization with acceptable accuracy.

3.4 Fault Classification using Categorical Network (CatNet)

CatNet, a convolutional attention model, enables fault classification in OsW power systems by processing various sensor data flows. It analyses signals from multiple sensors, including vibration, temperature, pressure, and rotational speed, coming from vital machinery such as the gearbox and generator. CatNet extracts spatial relationships between different points in time using convolutional layers, and it gives more significance to the aspects of the input that are most related to the presence of faults using attention. It allows the model to correctly identify whether faults originate from the gearbox or the generator, as well as yaw misalignment. The CatNet model consists of four convolutional layers, each utilizing 3x3 kernels and 64, 128, 256, and 512 filters, respectively. ReLU activation functions then precede the convolutional layers to inject non-linearity. The network employs an attention mechanism, allowing the model to focus on the most relevant sensor features by assigning larger weights to important data points, thereby improving accuracy in fault detection. The network is terminated with a fully connected layer and a softmax activation for fault classification into categories such as gearbox failure, generator failure, and yaw misalignment.

CatNet can provide rapid and dependable detection of equipment faults from multi-source data, aiding initiatives for predictive maintenance and reducing unplanned outages in offshore turbines. CatNet is a fault detection model based on deep learning that incorporates convolutional layers to learn spatial features from sensor data, and then utilizes an attention mechanism to focus on the most important features for fault detection. There are four convolutional layers with 3x3 kernels and ReLU activation functions. The attention mechanism enhances the model's capacity to focus on the most important features of sensor data, such as aberrant spikes in vibration or temperature, thereby improving fault classification accuracy. Figure 4 shows the architecture diagram for CatNet.

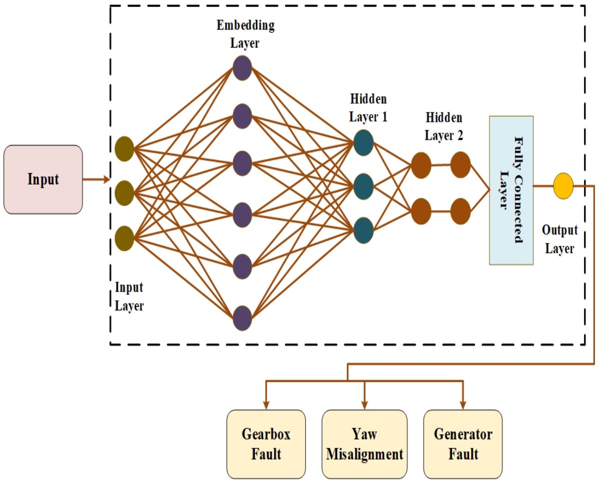

Figure 4. Architecture Diagram for Categorical Network (CatNet)

3.4.1 Input Layer

Data from OsW turbine sensors, combined in datasets, is fed into the Input Layer of the model. Typically, the inputs encompass vibration from the gearbox and generator, bearing and nacelle temperatures, levels of liquid pressure in the lubrication system, and aerodynamic stress on the rotor, as indicated by speed readings and measurements of generator current and voltage. The input vector is represented in Equation (5)

$$\mathbf{x} = [x_1, x_2, \ldots, x_n]^\top$$

$\mathrm{x_i}$. (5)

where denotes the distinct sensor feature.

3.4.2 Embedding Layer

An embedding layer transforms high-dimensional sensor input data into a dense, lower-dimensional vector space that encompasses relationships among the underlying features. This enables the model to learn more complex patterns and interactions between different sensor parameters, thereby improving its fault classification accuracy. The Equation (6) shows the embedding layer,

$$\mathrm{e}_i = E \cdot x_i$$
$$\mathrm{e} = [\mathrm{e}_1, \mathrm{e}_2, \ldots, \mathrm{e}_n] \quad (6)$$

Where$E$ is the embedding matrix, $\mathrm{e}_i$and is the embedded feature vector of the inputx_i?

3.4.2.1 Attention Mechanism for Fault Detection

The attention mechanism enables the model to attend to the most pertinent segments of the sensor information while fault-classifying. In offshore wind turbines, certain periods or characteristics (e.g., anomalous vibrations or temperature surges) may be emphasized that are highly correlated with faults, such as gearbox failure or generator faults. It significantly enhances fault class accuracy by allowing the model to focus on essential signals among the vast amounts of sensor measurements.

3.4.3 Hidden Layers (Hidden Layer 1 & 2)

These fully connected layers extract a deeper nonlinear pattern from the embedded feature vectors through the activation functions, such as ReLU or tanh, with each layer applying a transformation given in Equation (7):

$$\mathrm{h}^{(l)} = f\left(W^{(l)} \cdot \mathrm{h}^{(l-1)} + \mathrm{b}^{(l)}\right) \quad (7)$$

Where$\mathrm{h}^{(0)} = \mathrm{e}$ is the output from the embedding layer$W^{(l)}, \mathrm{b}^{(l)}$? The weights and biases of the layer l $f(\cdot)$are an activation function.

3.4.4 Fully Connected Layer

The final fully connected layer acts to pool and combine the learned features within the hidden layers into a single vector. The learned representation encodes the most significant patterns necessary for the proper classification of fault types in the output layer. The mathematical formula for a fully connected layer is in Equation (8)

$$\mathrm{z} = W^{(fc)} \cdot \mathrm{h}^{(L)} + \mathrm{b}^{(fc)}$$

z. (8)

where denotes the output vector, $W^{(fc)}$ is the weight matrix, $\mathrm{h}^{(L)}$ is the output vector from the hidden layer and$\mathrm{b}^{(fc)}$ is the bias vector.

3.4.5 Output Layer (Classification)

The output layer returns the final classification result, indicating whether a fault exists in either the gearbox or generator. It employs the softmax activation function to transform the output scores into probabilities so that the model chooses the most likely class in Equation (9);

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{2} e^{z_j}}, i = 1,2 \quad (9)$$

were, $\hat{y}_1$ = Probability of gearbox fault and $\hat{y}_2$ =the Probability of generator fault. CatNet efficiently categorizes OsW turbine faults by recognizing multivariate sensor signals through convolutional and attention mechanisms. It identifies gearbox faults (gear wear, loss of oil pressure), generator faults (overheating, rotor imbalance), and yaw misalignment with high accuracy. The model highlights key features, enhancing classification accuracy. This aids in the diagnosis of faults and predictive maintenance. During each epoch, the 50 iterations ran the training on the CatNet model. Batch size was 32; Adam was the optimizer behind a 0.001 learning rate. The setup was done with 70% of the dataset for training, 15% each for validation and testing. Multi-class fault categorization was done by a system; hence, categorical cross-entropy was chosen as the loss function. Meanwhile, the robustness of the system was assured with a five-fold cross-validation on never-before-seen sensor data in the presence of different operational conditions. The evaluation parameters include accuracy, precision, recall, and F1-score.

3.5 Digital Twin Applications in Smart Operation and Maintenance of Offshore Wind Energy

The OsW farm digital twin modelling platform provides next-generation intelligent O&M for commercial-scale OsW farms. Through the fusion of real-time sensor information, OPC UA communication protocols, and interactive visualization environments such as Unity 3D, the platform enables remote simulation, performance monitoring, and predictive maintenance. Applied to a standard 300MW OsW farm with 4MW-class turbines, this framework can help improve operational efficiency and minimize unplanned downtime, yielding an estimated annual value of RMB 31.703 million through better maintenance and power generation. The digital twin platform facilitates OsW O&M in two main aspects: (1) smart analysis and optimization by constant modelling and performance assessment, and (2) intelligent diagnosis & warning. The subsequent sections provide an in-depth discussion of the applications.

3.5.1 Smart Optimization and Performance Analysis for Offshore Wind Energy

Three fundamental applications of the OsW power digital twin system for intelligent analysis and operation optimization are energy efficiency assessment over the wind farm, yaw alignment diagnostics and optimization, and the application of wake flow control measures to enhance turbine performance.

3.5.1.1 Optimizing Energy Output in Offshore Wind Farms

To maximize the operating effectiveness of OsW turbines, an energy efficiency assessment framework is established through a digital twin-based simulation system. This system utilizes real-time sensor readings and simulation technologies to evaluate power generation capability and monitor continuous deterioration in turbine output. Through a combination of structural properties, weather conditions, and operational conditions, it provides real-time diagnoses of turbine health, enabling the early detection of inefficiency. This approach minimizes unexpected breakdowns, increases turbine uptime, and optimizes energy production efficiency. Figure 5 indicates the architecture of this digital twin-driven energy efficiency monitoring system.

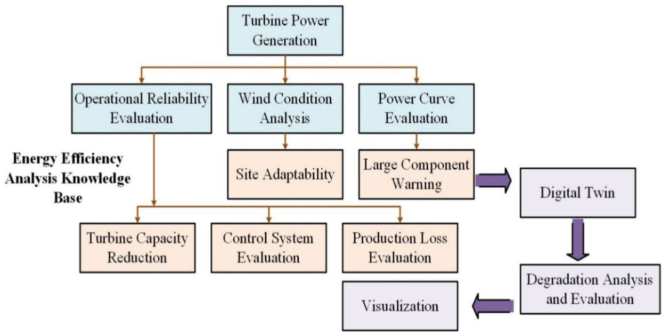

Figure 5. Digital Twin Wind Turbine Energy Efficiency Analysis System Structure

3.5.1.2 Fault diagnostics and optimization

Conventional SCADA-based manual diagnosis of wind turbine yaw alignment provides instantaneous access to data and prevents losses during downtime. Nevertheless, it is still reliant on experienced technicians for daily interpretation, and therefore, it is time-consuming and labour-intensive. In our process, a digital twin-aided yaw diagnostics and optimization model is constructed by combining SCADA information with knowledge of fault mechanisms. This model enables the use of machine learning-based yaw misalignment prediction and detection, thereby improving diagnostic accuracy and reducing the need for human intervention. Figure 6 shows the digital twin-based yaw prediction decision-making architecture.

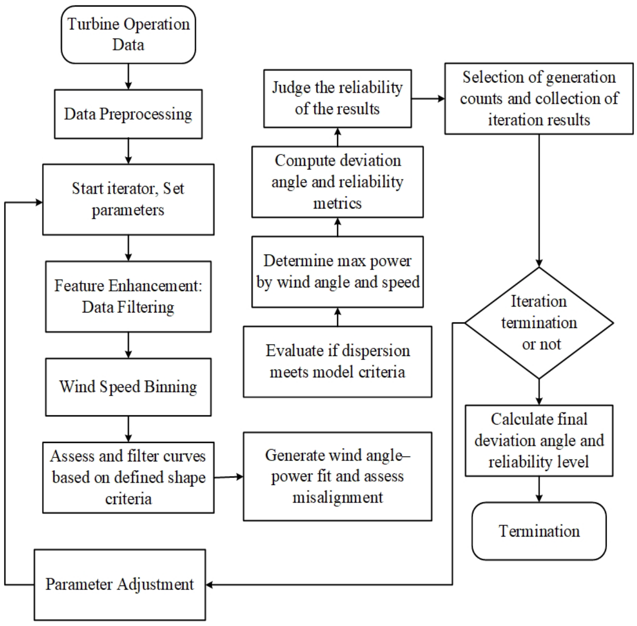

Figure 6. Digital Twin-Based Yaw Prediction Decision-Making Architecture

3.5.1.3 Wind farm wake flow control and optimization

Wake effects of coastal wind farms significantly impact overall power generation efficiency, operational costs, and turbine lifespan, resulting in increased fatigue loads and reduced energy capture. In offshore cases, where sea surface roughness is low and wake attenuation is minimal, wake action is more aggressive and complex due to fluctuating atmospheric wind fields. This makes accurate wake evaluation and control very challenging.

Traditional approaches borrow computational fluid dynamics (CFD) simulations and LiDAR wind measurements to investigate wake behaviour. Such approaches are, however, not endowed with smart control or real-time adaptability. It is possible to simulate the interaction between wakes by deploying a digital twin framework within OsW farms. This enables the real-time evaluation of wake loss, wind speed variability, and turbine power output across varying operational conditions. Based on this information, optimal yaw strategies can be executed via field-level controllers to enable smart wake reduction and increase the overall efficiency of power generation.

3.5.2 Offshore wind power intelligent diagnosis & warning application

For early warning of and diagnosis in the operation of a single wind turbine's main equipment, the transmission system and generator are used as objects to build gearbox temperature and generator fault early warning systems, respectively. At the same time, for the overall operation of the wind farm, the digital twin system of a single wind turbine is combined to build the field group early warning system.

3.5.2.1 Early Warning Systems for Gearbox Temperature and Generator Faults in Offshore Wind Turbines

The wind turbine transmission system, being one of the most vital components, is likely to fail under adverse environmental conditions and high-load operation. It is challenging to identify initial damage to the transmission system, and prolonged negligence can lead to a serious breakdown of key elements, such as the gearbox and main shaft, resulting in substantial economic losses. General fault diagnosis techniques for the transmission system are oil and fluid data analysis and acoustic emission data analysis. The oil-based technique employs iron spectrum and spectral analyzers to measure wear particles in the lubrication system, but tends to be lacking in timeliness when detecting faults. The acoustic emission technique identifies failure types and severity by detecting changes in elastic wave frequencies, but at the expense of requiring expensive sensors and being sensitive to noise.

The generator, an essential unit that ensures the conversion of mechanical to electrical energy, is prone to faults such as overheating, rotor imbalance, and insulation deterioration, which can significantly affect turbine operation and safety. Generator fault diagnosis typically involves measurements of temperature, vibration, current, and voltage through available sensors. Predictive models apply artificial intelligence algorithms to these sensor data sets to detect early warning signs of faults by identifying abnormal patterns and deviations from standard operating behaviour.

Based on wind turbine digital twin technology, real-time monitoring, diagnosis, and early warning systems for faults have been established for the gearbox and generator. For the gearbox, an early warning system based on temperature monitoring using SCADA and vibration analysis, combined with digital twins, was developed to extract fault features hidden in vibration signals and SCADA data. This methodology accurately identifies fault locations and severity, visualizing them within the digital twin gearbox model. Likewise, for the generator, predictive models based on AI scan sensor measurements—temperature, vibration, and electrical values—inside the digital twin platform to find anomalies characteristic of faults such as overheating or rotor imbalance. This integration enables timely fault prediction and early warning, enhancing maintenance scheduling and minimizing unplanned downtime through precise diagnostics and visualization within the digital twin environment.

3.6 Remote Operation & Visualization

Digital twin technology enables remote operators to monitor, operate, and simulate offshore turbines from various locations worldwide. Virtual models of turbines would allow operators to remotely monitor their status, analyze performance data, and predict upcoming maintenance needs. This method helps optimize decision-making processes, lowers costs, and ensures higher performance by providing continuous updates, forecasts, and 3D representations designed for challenging offshore conditions. Figure 7 illustrates the process of an Offshore wind farm to power a user.

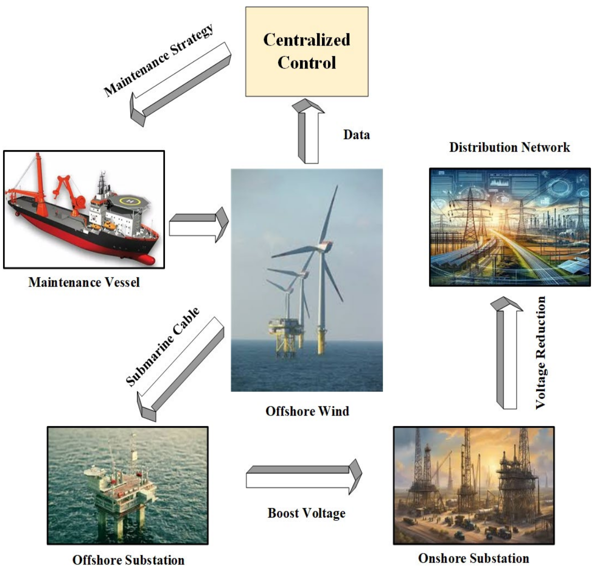

Figure 7. An offshore wind farm to power the user process

3.6.1 Virtual Turbine Operation using Digital Twins

Digital twins enable the remote control of OsW turbines by replicating real-time behaviour using actual sensor data. Virtual models replicate turbine conditions like wind speed, rotation speed, power, and structural stress. The twin allows engineers to control schemes, modify performance parameters, and simulate operational scenarios without physically accessing the turbines. Downtime is minimized and decision-making improved for offshore operations.

3.6.2 Interactive Dashboards for Monitoring and Control

O&M crews utilize interactive dashboards that synthesize key turbine metrics, including hub height data, rotor performance, vibration levels, and energy output. The dashboards are provided to display both real-time and historical performance information in an easily consumable format. They also have integrated maintenance alerts, failure logs, and status indicators to assist with task prioritization and the swift resolution of issues. Using such tools, crews can track dozens of turbines from one onshore command centre.

3.6.3 3D Visualization for Simulation and Training

Advanced digital twin technologies, such as Unity3D, enable the creation of fully interactive 3D models of OSW farms. The digital replicas accurately simulate the motion and operation of every turbine under the influence of environmental factors. Operators and technicians utilize these visualization tools to navigate turbine configurations, monitor structural behaviour under load, and practice maintenance routines in a simulated environment. The visualized representation is especially beneficial for training and maintenance planning in hostile marine conditions.

3.6.4 Improving Remote Operation and Maintenance

Through the integration of virtual operations, monitoring dashboards, and 3D simulations, digital twin technology significantly enhances the remote operation of offshore turbines. It minimizes the frequency of physical site visits, decreases maintenance costs, and facilitates the early identification of system inefficiencies or failures. The methodology ensures safer, smarter, and more sustainable operating and maintenance of all OsW installations.

4. Results And Discussions

The findings demonstrate significant improvements in OsW turbine performance through repeated simulation calibration, which are highly correlated with actual power output. The CatNet model accurately identifies temperature anomalies, issuing early fault alerts based on specified thresholds. Structural analysis indicates an increasing focus on the mass and strength of major turbine components as a response to rising capacity requirements. A breakdown of O&M expenses highlights vessel-related costs as the primary factor, promoting effective logistics and minimizing downtime. Overall, the results confirm the effectiveness of the integrated methodology in modelling, monitoring, and economic assessment for achieving maximum turbine reliability and sustainable operation. Performance comparison of our CatNet model with state-of-the-art fault detection methods, including thresholding methods and decision trees. The results demonstrate that CatNet outperforms these methods in terms of precision, accuracy, and recall.

4.1 Active Power vs. Wind Speed Performance

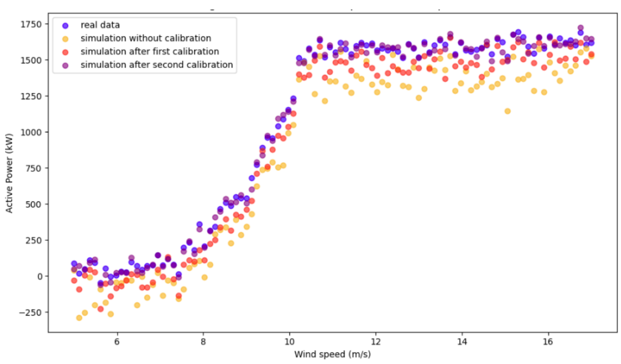

Figure 8. Generated Active Power vs. Wind Speed

The correlation of wind speed (m/s) and produced active power (kW) under various simulation and calibration conditions is shown in Figure 8. The actual data (blue dots) indicate that power generation rapidly increases from nearly 0 kW at approximately 6 m/s, reaching a peak of around 1700 kW at 12–16 m/s, and then levels off. The uncalibrated simulation (orange points) underestimates power at both lower and higher wind speeds, with values starting from below -250 kW and never reaching full power. The initial calibration (red points) represents a step towards agreement with real data, but differences remain. Upon second calibration (purple dots), the simulated result is almost identical to the real data, particularly within the range of 8–16 m/s, representing a significant improvement in accuracy. This indicates that iterative calibration plays a critical role in simulating the power performance of wind turbines.

4.2 Detected Temperature Anomalies in Wind Turbine System

The temperature anomalies identified by the CatNet model in a wind turbine system across time, with the x-axis as sample index and the y-axis as temperature anomaly in °C. Figure 9 has warning thresholds at ±1°C (dotted lines) and alarm thresholds at ±2°C (solid lines). Early on, temperature excursions are within safeguarding limits, but as the sample index increases (especially above ~300), increasingly frequent and significant excursions are identified, often overcrossing warning and alarm limits. This illustrates the evolution of potential fault or abnormal thermal response behaviour, indicating CatNet's capability to identify accurately early failure signs for effective maintenance intervention.

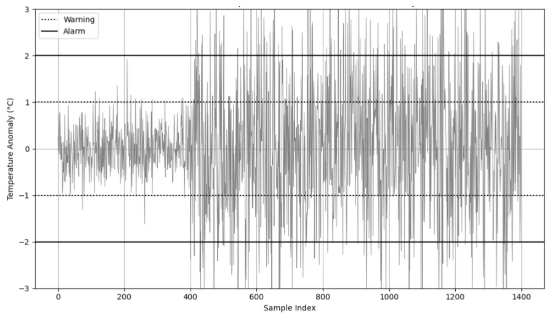

Figure 9. CatNet Detected Temperature Anomalies in Wind Turbine System

4.3 Fault Detection Performance

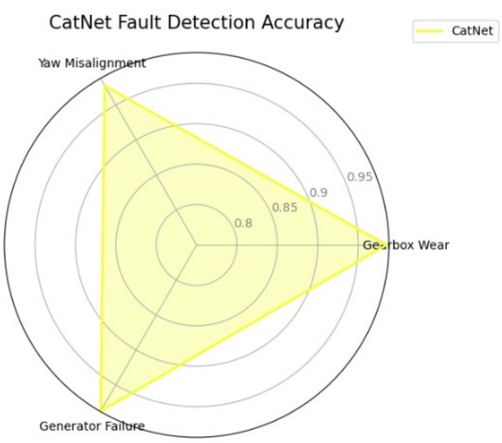

Figure 10. Fault Detection Accuracy using CatNET

Temperature anomalies from the CatNet model in a wind turbine system over time, plotted against sample index, are shown in Figure 10. Most differences in temperature are within a normal range, but from around sample number 400, more fluctuations become apparent, which suggests possible system anomalies. Two threshold values are marked: warning level of ±1°C (dotted lines) and alarm level of ±2°C (solid lines). Beyond sample 400, the majority of the temperature differences exceed the warning level, and some even exceed the alarm level, indicating possible faults or thermal instability in the turbine system that require further inspection or repair.

4.4 Economic and Structural Analysis of Offshore Wind Turbine Systems

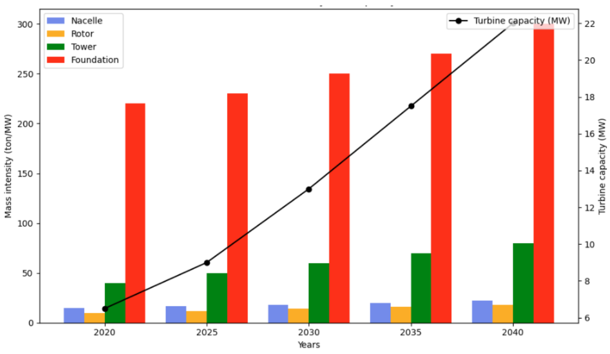

Figure 11. Turbine Mass Intensity and Capacity Over Years

The changing mass-intensity of major offshore-turbine components, reflecting the increase in nameplate capacity between 2020 and 2040, is illustrated in Figure 11. Every five-year snapshot indicates that the base continues to be the largest contributor, increasing from approximately 220 ton/MW in 2020 to 300 ton/MW in 2040, while the Tower increases from around 40 ton/MW to 80 ton/MW. The nacelle and rotor make smaller but progressively larger proportions. Superimposed on these bars, the black line indicates a steep ramp-up in capacity from approximately 6.5 MW turbines in 2020 to approximately 22 MW units by 2040, highlighting how larger turbines necessitate more substantial structural requirements, particularly for foundations and towers.

4.4.1 Definition of Mass Intensity

Mass intensity refers to the weight (tons) of major turbine components (nacelle, rotor, Tower, foundation) per megawatt (MW) of turbine capacity. Mass intensity is calculated with the following Equation:

$$\text{Mass Intensity} = \frac{\text{Mass of Turbine Component (tons)}}{\text{Turbine Capacity (MW)}} \qquad (10)$$

This unit can also help designers recognize the structural requirements of larger turbines as their capacity increases, thereby further emphasizing the importance of materials and structural strength in turbine design.

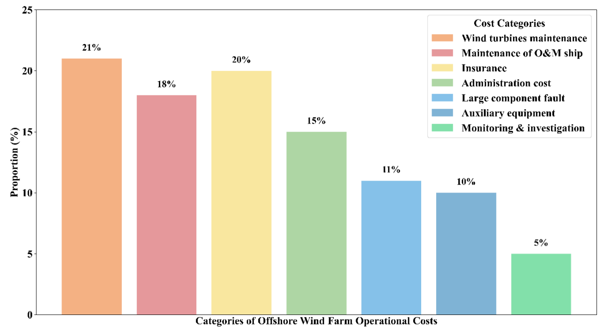

Figure 12. O&M Cost Distribution of Offshore Wind Power

The evolution of mass intensity (ton/MW) for various wind turbine components, Nacelle, Rotor, Tower, and Foundation from 2020 to 2040, along with the relative growth in turbine capacity (in MW) display in Figure 12. The Foundation's mass intensity is consistently the highest and increases from approximately 220 tons/MW in 2020 to nearly 300 tons/MW by 2040. The Tower also steadily rises, whereas the Rotor and Nacelle grow more slowly. At the same time, turbine capacity increases from 6 MW in 2020 to well over 22 MW by 2040, meaning that as turbines get much larger and more powerful, their structural elements must similarly expand in terms of weight, particularly in the Foundation and Tower, to accommodate this increase.

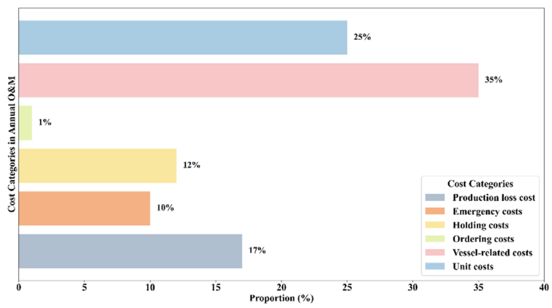

Figure 13. Breakdown of Annual O&M Costs

The customized annual breakdown of O&M costs for OsW energy systems, illustrating the relative magnitude of cost components, is shown in Figure 13. Vessel-related costs are the highest at 35%, indicating the cost of transportation and logistics to transport equipment and personnel for offshore maintenance activities. 25% of unit costs reflect a significant amount of cost in equipment and components. The 17% production loss costs reflect the maintenance downtime costs, illustrating the financial impact of such downtime. 12% holding costs and 10% emergency costs show inventory and unscheduled repair costs, respectively, while order costs are minimal at 1%. This segmentation highlights OsW O&M's most critical areas financially, particularly good vessel utilization, effective inventory management, and production loss prevention, to achieve the lowest total maintenance expenditures.

5. Conclusion And Future Works

In conclusion, the digital twin-based approach significantly enhances the remote operations and maintenance (O&M) capabilities of OsW farms by providing a virtualized, real-time operating interface and smart diagnostic capabilities. The methodology improves turbine reliability, decreases maintenance costs, and enables condition-based maintenance strategies through integrated 3D simulations and fault classification using machine learning-based methods. One of the key innovations of the proposed work is the use of an early warning system based on real-time sensor information and predictive modelling to detect potential faults or generator anomalies in their pre-critical phases of fault development. By continuously monitoring operational parameters and employing threshold-based notifications in conjunction with CatNet-based anomaly detection, the system enables timely intervention and minimizes unplanned downtime. Our system largely eliminates the need for on-site maintenance visits, a crucial factor in offshore environments where accessibility is challenging. The early fault detection and real-time monitoring features not only increase safety but also enhance economic efficiency by reducing unplanned downtime and lowering operational costs. Through ongoing monitoring and predictive maintenance functionality, our system offers a more cost-effective and safer alternative for the offshore wind sector. Future work activities will focus on enhancing the fidelity of digital twin models by incorporating more diverse datasets, refining fault classification models with recent attention-based deep learning models, and scaling up the platform for application across farms. The addition of Augmented Reality (AR) tools for technician training and blockchain to ensure safe exchange of data could further improve the resilience, security, and transparency of OsW systems. With this multi-layered digital twin ecosystem, the strategy lays the Foundation for intelligent, scalable, and anticipatory OsW turbine management. Future endeavours will see the implementation of reinforcement learning (RL) into the digital twin infrastructure to further bolster adaptive defence capabilities. RL allows the system to learn and adapt from real-time performance data of the turbine, refining fault detection methods by learning to improve decision-making through trial and error on an ongoing basis. This can enhance system robustness by enabling it to predict and respond more accurately to varying operating conditions, like turbine wear or unforeseen environmental conditions.

Declarations

Funding: The Authors did not receive any funding.
Conflicts of interest: The authors declare that they have no conflicts of interest.
Data Availability Statement: The data generated and analyzed during the current study are available from the author, Huatao Si, upon reasonable request; however, they are not yet publicly available due to ongoing research.
Code availability: Not Applicable.
Authors' Contributions: Huatao Si and Xiaotao Chen are responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Qingyu Men is responsible for collecting the required information for the framework, providing software, conducting critical reviews, and administering the process.

References

[1] Lloret J, et al. Unravelling the ecological impacts of large-scale offshore wind farms in the Mediterranean Sea. Sci Total Environ. 2022; 824:153803.
[2] Hoeser T, Kuenzer C. SyntEO: Synthetic dataset generation for earth observation and deep learning – Demonstrated for offshore wind farm detection. ISPRS J Photogramm Remote Sens. 2022; 189:163–184.
[3] Megía M, Melero FJ, Chiachío M, Chiachío J. Generative Adversarial Networks for Improved Model Training in the Context of the Digital Twin. Struct Control Health Monit. 2024;2024(1):9997872.
[4] Liu Y, Zhang J-M, Min Y-T, Yu Y, Lin C, Hu Z-Z. A digital twin-based framework for simulation and monitoring analysis of floating wind turbine structures. Ocean Eng. 2023; 283:115009.
[5] Schneider J, Klüner A, Zielinski O. Towards Digital Twins of the Oceans: The Potential of Machine Learning for Monitoring the Impacts of Offshore Wind Farms on Marine Environments. Sensors. 2023;23(10):4581.
[6] Li M, Jiang X, Carroll J, Negenborn RR. Operation and maintenance management for offshore wind farms integrating inventory control and health information. Renew Energy. 2024; 231:120970.
[7] Sovacool BK, Carley S, Kiesling L. Energy justice beyond the wire: Exploring the multidimensional inequities of the electrical power grid in the United States. Energy Res Soc Sci. 2024; 111:103474.

[8] Li H, Huang C-G, Guedes Soares C. A real-time inspection and opportunistic maintenance strategies for floating offshore wind turbines. Ocean Eng. 2022; 256:111433.
[9] Zhang W, Lin Z, Liu X. Short-term offshore wind power forecasting - A hybrid model based on Discrete Wavelet Transform (DWT), Seasonal Autoregressive Integrated Moving Average (SARIMA), and deep-learning-based Long Short-Term Memory (LSTM). Renew Energy. 2022; 185:611–628.
[10] Hosamo HH, Svennevig PR, Svidt K, Han D, Nielsen HK. A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics. Energy Build. 2022; 261:111988.
[11] Wang B, Wang X, Qian T, Ning L, Lin J. A fast dimension reduction framework for large-scale topology optimization of grid-layout offshore wind farm collector systems. Int J Electr Power Energy Syst. 2023; 149:109066.
[12] Zhang Y, Shi W, Li D, Li X, Duan Y, Verma AS. A novel framework for modelling floating offshore wind turbines based on the vector form intrinsic finite element (VFIFE) method. Ocean Eng. 2022; 262:112221.
[13] Peinado Gonzalo A, Benmessaoud T, Entezami M, García Márquez FP. Optimal maintenance management of offshore wind turbines by minimizing the costs. Sustain Energy Technol Assess. 2022; 52:102230.
[14] Koondhar MA, et al. Critical Technical Issues with a Voltage-Source-Converter-Based High Voltage Direct Current Transmission System for the Onshore Integration of Offshore Wind Farms. Sustainability. 2023;15(18):13526.
[15] Zhao J, Feng H, Chen Q, Garcia de Soto B. Developing a conceptual framework for the application of digital twin technologies to revamp building operation and maintenance processes. J Build Eng. 2022; 49:104028.
[16] Cao Y, Tang X, Zhang T, Chu W, Bai Y. Fast prediction of turbine energy acquisition capacity under combined action of wave and current based on digital twin method. Ships Offshore Struct. 2024;19(4):446–460.
[17] Kandemir E, Liu J, Hasan A. Digital twin-driven dynamic repositioning of floating offshore wind farms. Energy Rep. 2023; 9:208–214.
[18] Mahmoud M, Semeraro C, Abdelkareem MA, Olabi AG. Designing and prototyping the architecture of a digital twin for wind turbine. Int J Thermofluids. 2024; 22:100622.
[19] Wang M, Incecik A, Feng S, Gupta MK, Królczyk G, Li Z. Damage identification of offshore jacket platforms in a digital twin framework considering optimal sensor placement. Reliab Eng Syst Saf. 2023; 237:109336.
[20] Sleiti AK, Kapat JS, Vesely L. Digital twin in energy industry: Proposed robust digital twin for power plant and other complex capital-intensive large engineering systems. Energy Rep. 2022; 8:3704–3726.
[21] Cao Y, Tang X, Li J, Chu W, Wang F. Flow field distribution and structural strength performance evaluation of fixed offshore wind turbine based on digital twin technology. Ocean Eng. 2023; 288:116156.
[22] Kim C, et al. Design, Implementation, and Evaluation of an Output Prediction Model of the 10 MW Floating Offshore Wind Turbine for a Digital Twin. Energies. 2022;15(17):6329.
[23] Zhao X, Dao MH, Le QT. Digital twining of an offshore wind turbine on a monopile using reduced-order modelling approach. Renew Energy. 2023; 206:531–551.
[24] Qaiser MT, Ejaz J, Osen O, Hasan A. Digital twin-driven energy modelling of Hywind Tampen floating wind farm. Energy Rep. 2023; 9:284–289.
[25] Devi, D. P., Allur, N. S., Dondapati, K., Chetlapalli, H., Kodadi, S., & Perumal, T. Digital Twin Technology and IoT-Enabled AI Using Real-Time Analytics for Smart Warehouse Management and Predictive Inventory Optimization. International Journal of Marketing Management. 2023; 11(4): 78-98.
[26] Basani, D. K. R., Gudivaka, R. L., Grandhi, S. H., Gudivaka, B. R., Gudivaka, R. K., & Kamruzzaman, M. M. AI-Enabled Digital Twin Framework for Healthcare Task Offloading Strategies with MADDPG, AHP, Multimodal Digital Twins, DRM, and mHealth Applications. In Accelerating Product Development Cycles with Digital Twins and IoT Integration. IGI Global Scientific Publishing, 2025; 409-436.
[27] Srinivasan, K. Digital twin-based predictive analytics for software reliability: Simulating real-world scenarios for performance optimization. International Journal of Mechanical Engineering and Computer Applications, 2020; 8(4): 123-130.
[28] Katsidoniotaki E, Psarommatis F, Göteman M. Digital Twin for the Prediction of Extreme Loads on a Wave Energy Conversion System. Energies. 2022;15(15):5464.
[29] Zhao L, Xue L, Li Z, Wang J, Yang Z, Xue Y. Progress on Offshore Wind Farm Dynamic Wake Management for Energy. J Mar Sci Eng. 2022;10(10):1395.
[30] Pujana A, Esteras M, Perea E, Maqueda E, Calvez P. Hybrid-Model-Based Digital Twin of the Drivetrain of a Wind Turbine and Its Application for Failure Synthetic Data Generation. Energies. 2023;16(2):861.
[31] Ibrahim M, et al. Digital Twin as a Virtual Sensor for Wind Turbine Applications. Energies. 2023;16(17):6246.
[32] Moghadam FK, Rebouças GFS, Nejad AR. Digital twin modelling for predictive maintenance of gearboxes in floating offshore wind turbine drivetrains. Forsch Im Ingenieurwesen. 2021;85(2):273–286.
[33] Augustyn D, Ulriksen MD, Sørensen JD. Reliability Updating of Offshore Wind Substructures by Use of Digital Twin Information. Energies. 2021;14(18):5859.
[34] Global offshore wind turbine analysis. Kaggle; 2025 [cited 2025 May 20]. Available from: https://www.kaggle.com/datasets/pythonafroz/global-offshore-wind-turbine-analysis.
[35] S. Jayanthi, R. Lakshmana Kumar, P. Punitha, BalaAnand Muthu, C.B. Sivaparthipan, Sustainable energy harvesting techniques for underwater aquatic systems with multi-source and low-energy solutions, Sustainable Computing: Informatics and Systems, Volume 46, 2025, 101126.
[36] Muthu, B., Sivaparthipan, C.B., Kumar, R.L, Jayanthi. S, Cheng-Chi Lee, Trust-Based Energy Efficient Protocol Over MANET Using PTORA and RRFO, Wireless Personal Communication, Vol. 139, pp. 653–678, 2024.