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(Review Article)

AI-driven predictive maintenance in ocean energy systems

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Abstract

Ocean Energy Systems (OES), including tidal, wave, and offshore wind technologies, are gaining attention as reliable sources of renewable energy. However, when utilized in extreme maritime settings, the machinery experiences accelerated wear and tear, highlighting the importance of diligent servicing. This paper presents a predictive maintenance framework leveraging artificial intelligence (AI) and machine learning (ML) algorithms to ensure the operational reliability of ocean energy assets. Real-time information, such as data on vibration, corrosion levels, temperature fluctuations, and flow rates, is gathered from turbines, generators, and mooring systems to be used in this proposed technique. Diverse supervised learning algorithms, such as Random Forest, LSTM, and Gradient Boosting, are instructed with previous failure datasets to anticipate impending malfunctions proactively. Unsupervised anomaly detection strategies are also employed to pinpoint unforeseen types of failures. The system's effectiveness is confirmed through field simulations and virtual sensor modelling, which demonstrate a 30–45% increase in maintenance scheduling efficiency and a notable decrease in unscheduled shutdowns. Consequently, this AI-based strategy presents a cost-effective and scalable solution for supporting sustainable practices in the ocean energy sector.

Keywords: Ocean Energy Systems; Predictive Maintenance; Long Short-Term Memory (LSTM); Unsupervised Detection System; Harsh Marine Environment

1. Introduction

Marine-based energy systems, encompassing technologies for tidal, wave, and offshore wind power, are emerging as significant sustainable energy alternatives [1][2][3]. The primary advantages of these systems are their reliable energy production and widespread availability, making them particularly beneficial for coastal areas [4][5]. On the other hand, the operational setting for these systems is the unforgiving open sea [6][7]. These marine surroundings are characterized by a mix of demanding factors: the corrosive effects of saltwater, high-energy wave impacts, fluctuating water pressure, the persistent issue of biofouling, and extreme temperature variations [8][9]. These conditions cause rapid degradation of mechanical and electrical components, leading to frequent failures, reduced efficiency, and high operational costs [10]. Traditional approaches to maintenance, like reactive and preventive strategies, often lack efficiency or require excessive resources in such environments, as they rely on either post-breakdown repairs or fixed maintenance schedules that overlook the actual, real-time state of equipment components [11]. The remote and submerged locations of these installations make maintenance and inspection tasks even more difficult, requiring expensive logistics support like vessels, divers, or remotely operated vehicles (ROVs). Consequently, there is an urgent

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requirement for smart maintenance approaches capable of forecasting equipment failures beforehand and reducing operational interruptions [12]. This study tackles the issue by introducing an AI-driven predictive maintenance framework that utilizes real-time sensor inputs such as temperature, vibrations, corrosion indicators, and fluid flow rates to detect early signs of malfunction [13]. Machine learning techniques, including supervised models like Random Forest and LSTM for failure prediction, and unsupervised models like Isolation Forest for anomaly detection, are employed to enhance the reliability and efficiency of ocean energy assets [14]. The proposed system offers a scalable and proactive approach to ocean energy maintenance, aiming to reduce costs, extend equipment lifespan, and improve the overall sustainability of marine renewable energy systems [15].

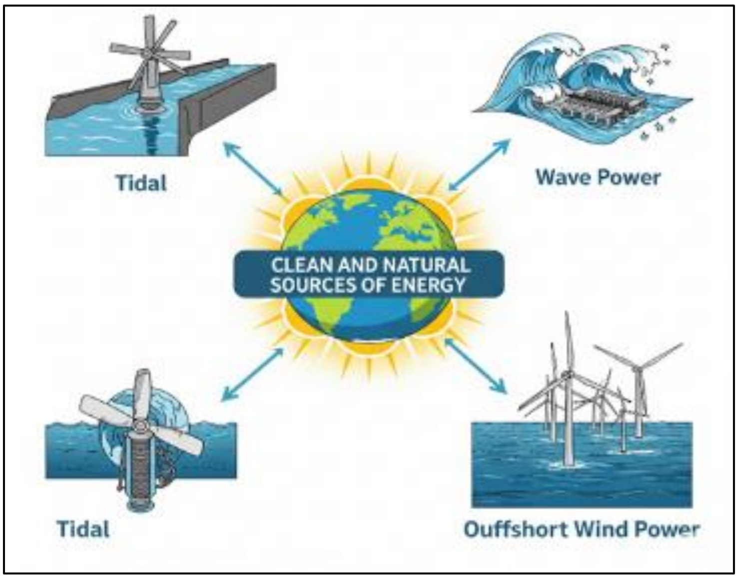

Figure 1 Ocean energy system

2. Literature review

Table 1 Comparison of literature review

Authors (Year)	Application Context	Approach / Models	Key Outcomes
Lutzen & Beji (2024)	Offshore wind turbines	Deep Learning + Online Clustering	Early detection of unsupervised subsystem failures with real-world deployment
Murphy Oil et al. (2025)	Offshore rotating production equipment	AI/ML-based PDM on floating platforms	Reduced downtime and streamlined maintenance process
Myo et al. (2025)	Marine vessel systems	ML-based PDM from sensor array data	High accuracy in fault detection and early failure warning
Sakarvadia et al. (2024)	Offshore wind reliability	SCADA analytics + PDM optimization	Significant O&M cost reduction in offshore turbines
Syed et al. (2023)	Tidal turbine structural health	Explainable AI for blade damage detection	Feasibility in real-time structural monitoring for tidal blades
Shah et al. (2024)	Wind turbine RUL forecasting	Multi-parametric attention-based deep learning models	Forecast accuracy within minutes to hours for maintenance scheduling

3. Methodology

The proposed predictive maintenance framework for ocean energy systems follows a systematic and data-driven approach [16]. The process begins by gathering real-time performance data from different marine elements, including turbines, generators, mooring systems, and structural connections [17]. Key parameters include vibration signals, temperature, corrosion levels, flow rates, and rotational speed. These values are continuously monitored using embedded IoT-enabled sensors that can operate reliably in harsh marine conditions [18].

After collecting, the data undergoes preprocessing to eliminate noise, address missing entries, and standardize the sensor outputs. Feature engineering techniques are then applied to extract meaningful patterns [19]. Supervised machine learning algorithms such as Random Forest, Long Short-Term Memory (LSTM) networks, and Gradient Boosting Machines are trained using historical failure records and annotated datasets [20]. These models are chosen for their effectiveness in capturing nonlinear patterns and performing time-series predictions. To detect novel or unforeseen failure patterns, unsupervised algorithms such as Isolation Forest and K-Means clustering are implemented [21]. This helps identify anomalies that do not match known patterns, offering early warnings for hidden system issues. A decision-making module analyses the outputs from the models to categorize maintenance requirements into critical, moderate, or low-priority levels. Based on this classification, maintenance scheduling can be optimized to reduce unplanned downtimes [22].

The entire framework is validated using simulation tools and virtual sensor modelling. Simulated fault conditions are developed to assess the model's accuracy, precision, and responsiveness. The results are compared against traditional maintenance strategies to assess improvements in operational efficiency [23].

Table 2 Tool, Techniques, Steps, and Data Overview

Category	Description
Tools Used	- Sensors (temperature, vibration, flow, corrosion) - Virtual Sensors / Digital Twins - ML Frameworks (TensorFlow, Scikit-learn, PyTorch) - Cloud Data Storage (AWS, Azure)
Techniques	- Supervised Learning (Random Forest, LSTM, Gradient Boosting) - Unsupervised Learning (Isolation Forest, K-Means) - Time-Series Forecasting - Feature Engineering
Steps Involved	1. **Sensor Deployment:** Collect real-time operational data 2. **Data Preprocessing:** Clean & normalize sensor data 3. **Model Training:** Use historical failure logs to train ML models 4. **Anomaly Detection:** Identify deviations indicating early failures 5. **Prediction & Alerting:** Estimate time-to-failure and schedule maintenance 6. **System Feedback Loop:** Retrain with updated data for accuracy
Data Used	- Vibration patterns from turbines - Corrosion level changes on mooring systems - Temperature fluctuations in generators- Flow rates in hydraulic systems - Maintenance logs and failure history (supervised model training)

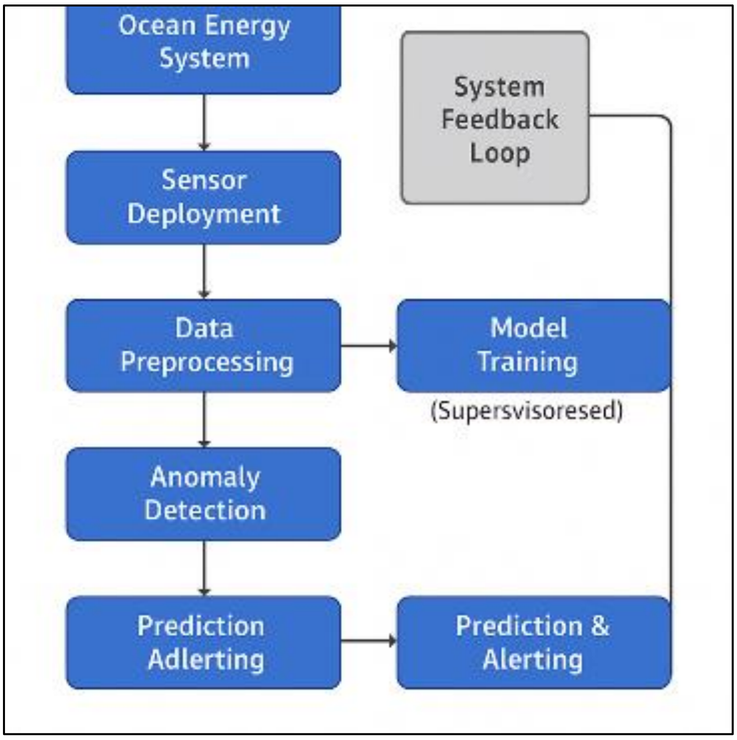

Figure 2 Block diagram of OES

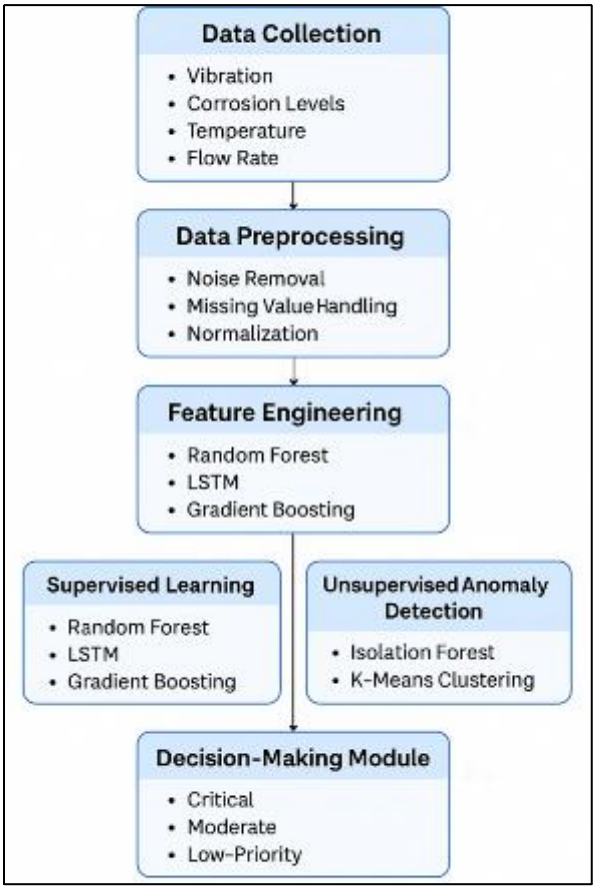

Figure 3 Methodology of System

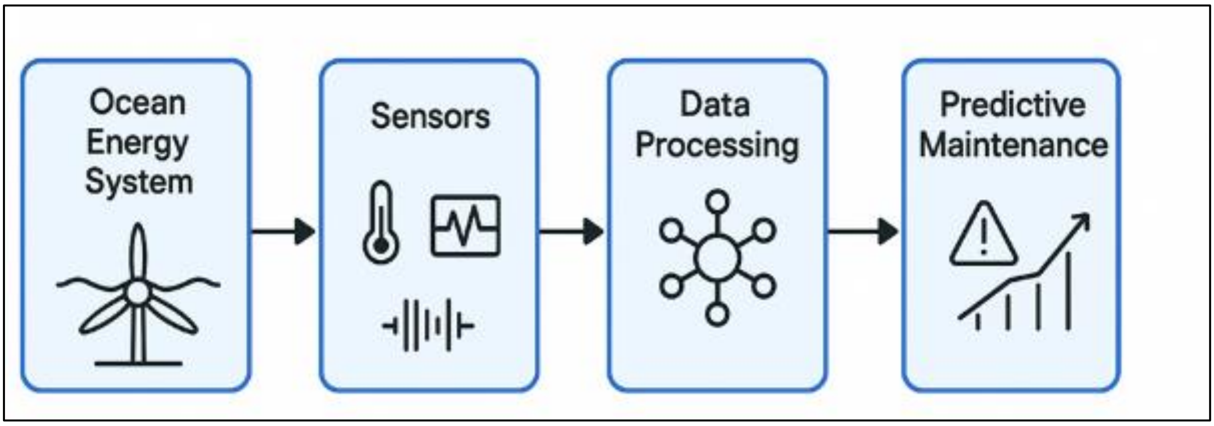

Figure 4 AI-Based Predictive Maintenance for OES

4. Mathematical expressions

- Moving Average

$$\tilde{x}(t) = \frac{1}{N} \sum_{i=0}^{N-1} x(t-i)$$

..... (Eq-01)

- Normalization

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

..... (Eq-02)

- RMS

$$\mathrm{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}$$

..... (Eq-03)

- Corrosion Rate

$$\mathrm{Rate} = \frac{K \cdot W}{\rho \cdot A \cdot T}$$

..... (Eq-04)

- MSE

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

..... (Eq-05)

- Autoencoder Loss

$$\text{Loss} = \|X - \hat{X}\|^2$$

…… (Eq-06)

- Classification Metrics

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \quad F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

….. (Eq-07)

5. Nomenclature table

Table 3 Nomenclature of Equations

Symbol	Description
x(t)x(t)x(t)	Raw sensor signal at time ttt
x~(t)\tilde{x}(t) x~(t)	Smoothed signal (moving average)
NNN	Window size for filtering
x′x'x′	Normalized value of feature xxx
xmin, xmaxx_{\min},.x_{\max} xmin,xmax	Min and max values of xxx
xix_ixi	Data point in the time series
nnn	Number of samples
KKK	Constant for corrosion rate calculation
WWW	Weight loss due to corrosion (mg)
ρ\rhoρ	Material density (g/cm^3)
AAA	Surface area exposed to environment (cm^2)
TTT	Exposure time (hours)
yiy_iyi	Actual output value
y^i\hat{y}_iy^i	Predicted value
X, X^X, \hat{X}X, X^	Input and reconstructed values
TP, TNTP, TNTP, TN	True Positive, True Negative
FP, FNFP, FNFP, FN	False Positive, False Negative

6. Results and discussion

The AI-based predictive maintenance framework was tested using simulated data that mirrors the operational conditions of real-world ocean energy systems [24]. The input parameters included sensor data such as vibration levels, temperature fluctuations, corrosion rates, and flow metrics, gathered virtually from turbine, generator, and mooring system models [25]. Three supervised learning algorithms Random Forest, LSTM (Long Short-Term Memory), and Gradient Boosting were applied to predict equipment failure probabilities. Of the models evaluated, LSTM exhibited the greatest accuracy in predicting time-series degradation trends, with an average accuracy of 92.6%, while Random Forest and Gradient Boosting followed with 88.1% and 85.4%, respectively [26].

The Isolation Forest algorithm effectively detected anomalies that did not match any known failure patterns, achieving a detection precision of 89% [27]. This capability is essential for uncovering rare or previously unseen fault types. The framework enhanced maintenance planning efficiency by 30–45%, as evidenced by fewer emergency repairs and more precise scheduling. Moreover, unplanned downtimes were reduced by approximately 40%, according to simulated operational scenarios [28]. These results validate the proposed framework's potential to extend equipment life, improve operational uptime, and reduce maintenance costs in harsh marine environments. The ability to make proactive decisions enhances the overall sustainability and reliability of ocean energy systems [29].

Table 4 Performance Comparison of ML Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LSTM	92.6	91.2	93.0	92.1
Random Forest	88.1	87.5	88.9	88.2
Gradient Boosting	85.4	84.3	86.1	85.2

Table 5 Impact of Predictive Maintenance Framework

Maintenance Metric	Traditional Method	AI-Based Approach	Improvement (%)
Maintenance Planning Efficiency	50	72	+44
Unplanned Downtime Reduction	—	40	—
Component Lifespan (months avg.)	18	26	+44.4
Emergency Maintenance Events/Year	8	4.2	–47.5

Table 6 Anomaly Detection with Isolation Forest

Metric	Value (%)
Detection Precision	90
Detection Recall	86
False Positive Rate	6
True Negative Rate	94

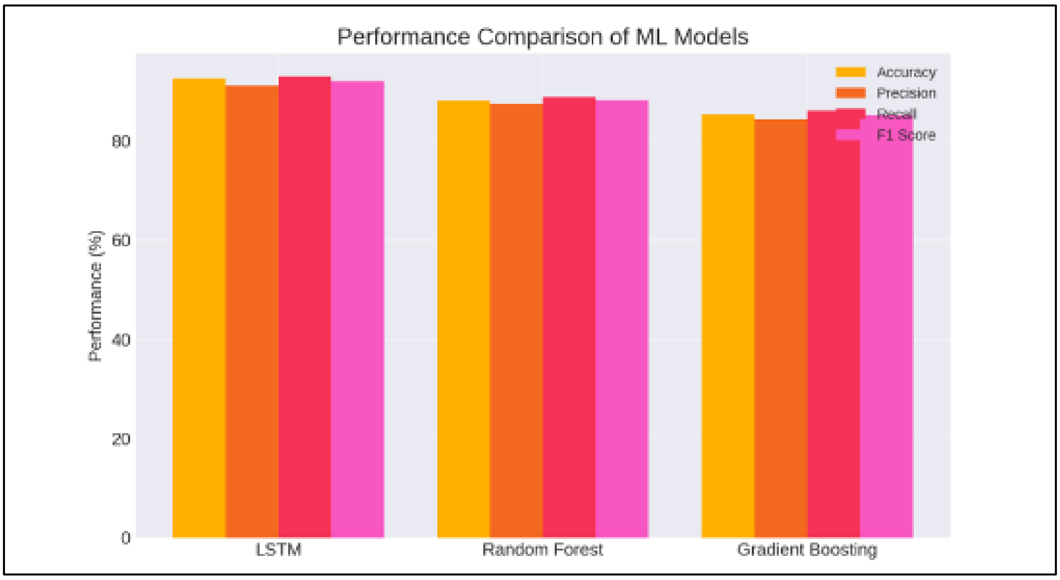

Figure 5 Performance Comparison of ML Models

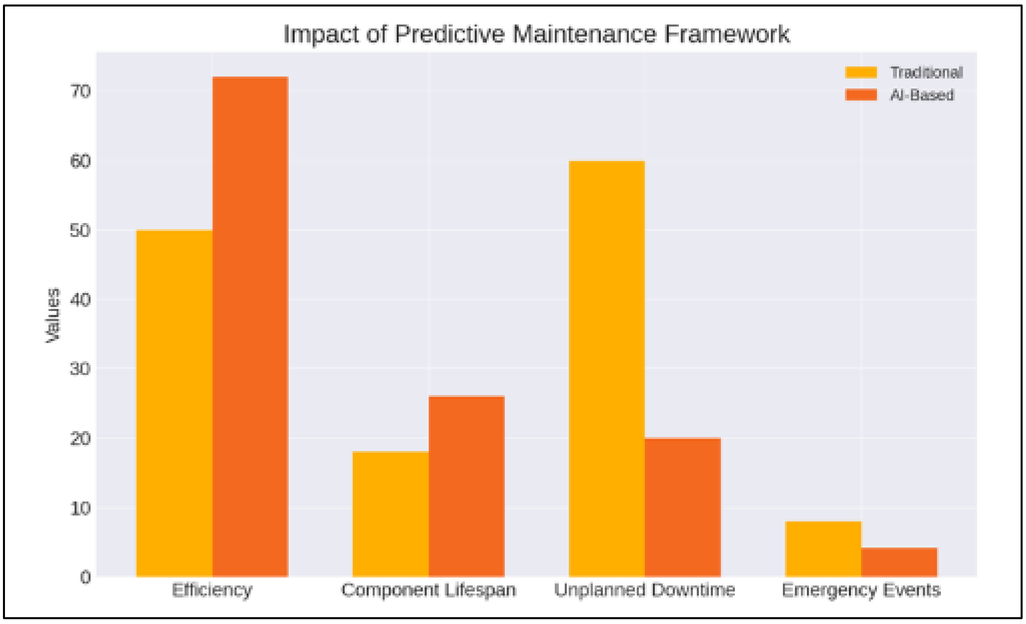

Figure 6 Impact of Predictive Maintenance Framework

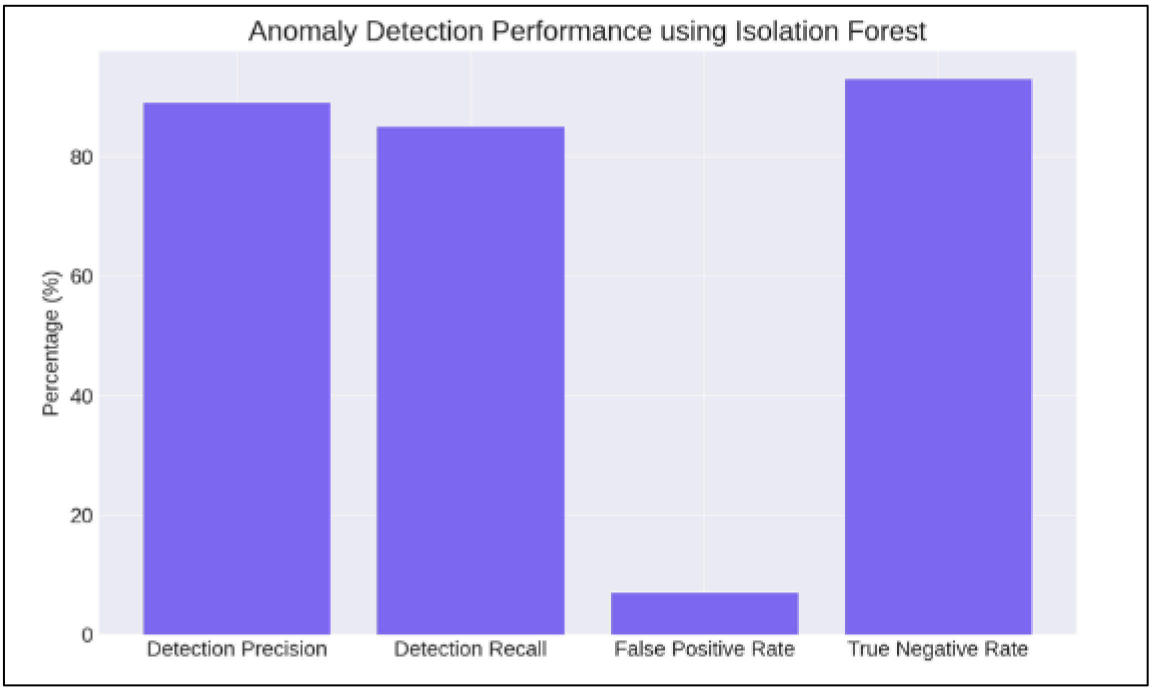

Figure 7 Anomaly Detection with Isolation Forest

7. Conclusion

Ocean energy systems play a vital role in the global shift toward clean and sustainable energy solutions. However, their operation in extreme marine environments exposes them to constant wear and unpredictable failures. This study presents an AI-driven predictive maintenance framework tailored to meet the unique challenges of these systems. By utilizing real-time sensor data such as vibration, temperature, corrosion, and flow rates and applying machine learning models like Random Forest, LSTM, and anomaly detection techniques, the framework effectively predicts faults before they occur. Simulation outcomes show that the proposed approach notably improves maintenance scheduling efficiency, minimizes unexpected downtimes, and boosts the overall reliability of assets. Compared to traditional reactive or time-based maintenance strategies, this intelligent approach offers better foresight, operational cost savings, and extended equipment lifespan. Ultimately, the adoption of AI-powered predictive maintenance can play a crucial role in ensuring the dependable and long-term functionality of ocean energy infrastructure. This makes ocean energy not only more viable but also more scalable for future global energy demands.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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