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ARTICLE

AI-enhanced damage detection in jack-up rig legs using an improved modal strain energy index: A numerical, experimental, and digital twin-based approach

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Abstract

Jack-up rigs work in challenging marine environments where conditions such as cyclic loading, corrosion, and hydrodynamic forces can quickly cause structural damage. This deterioration not only affects the safety of the operation but also shortens the rig's service life. To address these issues, this study proposes a new way to monitor the health of these structures using artificial intelligence (AI). The approach combines the improved modal strain energy (IMSE) index with machine learning to improve how damage in the legs of the rigs is detected. Unlike traditional methods that often rely on static thresholds to identify problems, the proposed system uses AI and digital twin technology to provide more flexible and timely diagnostics, which ultimately helps with better maintenance planning and safer operations. Validation was conducted through a combination of finite element modeling and experimental testing using a 1:22 scale laboratory prototype of the SA20 jack-up rig. The results show that the AI-driven IMSE method performs better than the traditional Stubbs Index, improving accuracy by 12.5%. It also outperforms the standard IMSE method, boosting damage detection by 8.7%. Remarkably, this approach can identify damage as small as 1%, with an average deviation of <4%. On top of that, the framework has shown potential in improving multi-damage localization reliability and cutting down on false positives. This structural health monitoring (SHM) approach integrates real-time sensor data with deep learning algorithms and digital twin simulations to provide a highly scalable and adaptive solution for offshore structural integrity monitoring. The solution applies to offshore wind turbines, floating platforms, subsea pipelines, in addition to jack-up rigs, securing the long-term resilience of valuable marine infrastructure. Thus, emphasizes that AI has a truly transformational role in offshore SHM, ushering in maintenance that is intelligent, reliable, and cost-effective, especially under extreme marine conditions.

Keywords: Civil engineering; Offshore engineering; Jack-up rig; Structural health monitoring; Damage detection; Improved modal strain energy; Artificial intelligence; Digital twin; Predictive maintenance

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1. Introduction

Offshore platforms are among the most essential infrastructures supporting global industries such as offshore oil and gas extraction and renewable energy generation. Among these, jack-up rigs have become particularly important due to their mobility, cost-effectiveness, and ability to operate in relatively shallow waters.[1] However, these structures are exposed to severe marine conditions that accelerate aging through corrosion, cyclic wave loading, and fatigue damage.[2-4] Without adequate monitoring and maintenance, such degradation can lead to catastrophic failures that threaten human life, marine ecosystems, and economic investments.[5]

In recent decades, offshore wind farms and oil platforms have expanded rapidly, prompting increasing concern about the structural integrity and safety of these systems.[6] Reports from organizations such as the Health and Safety Executive highlight the high frequency of offshore structural incidents, particularly those linked to corrosion and fatigue-related damage.[7] Ensuring long-term reliability requires the development of robust structural health monitoring (SHM) systems that can provide continuous, data-driven assessments under varying environmental conditions.

1.1. Limitations of traditional SHM approaches

Conventional SHM methods—such as visual inspection and non-destructive testing (ultrasonic, eddy current, or radiographic techniques)—have long been applied to monitor offshore structures. However, these approaches are often time-consuming, costly, and limited in their ability to detect early-stage or hidden damage, especially in submerged zones.[8] Vibration-based SHM, which measures variations in modal parameters, has emerged as a non-intrusive alternative. Yet, its effectiveness remains restricted in offshore environments where signal distortion from environmental noise and hydrodynamic interaction reduces reliability.[9,10] As offshore facilities become larger and more complex, there is a pressing need for automated, intelligent, and adaptive SHM frameworks that can interpret data efficiently and provide early warnings for maintenance intervention.

1.2. The role of artificial intelligence (AI) in SHM

The integration of AI and machine learning (ML) into SHM has opened new possibilities for predictive and autonomous structural assessment. AI-based models, including convolutional neural networks (CNNs) and artificial neural networks, can extract subtle patterns from vibration data to identify structural damage with high accuracy.[11-13] Deep learning approaches such as recurrent neural networks (RNNs) and physics-informed neural networks (PINNs) further enhance this ability by capturing temporal dependencies and complex relationships between structural responses and environmental conditions.[14] Reinforcement learning methods have also been employed to optimize sensor placement and data fusion strategies, reducing false alarms and improving decision-making in real-time monitoring.[15] Collectively, these AI-driven frameworks enable smarter SHM systems that are adaptive, self-learning, and resilient to marine noise.

1.3. The emergence of digital twin technology in offshore SHM

The introduction of digital twin technology has significantly advanced offshore SHM. A digital twin creates a virtual replica of the physical asset that continuously updates through live sensor data, numerical modeling, and AI algorithms.[16-18] This allows engineers to simulate performance under various loading conditions, predict degradation pathways, and plan maintenance activities proactively. By integrating finite element models (FEMs) with internet of things (IoT)-enabled sensors, digital twin systems can detect localized damage, forecast fatigue progression, and assess operational risks dynamically.[19]

Studies have shown that combining AI-enhanced SHM with digital twin modeling leads to a dramatic improvement in reliability, reducing false detections and improving multi-damage localization accuracy.[20] Furthermore, the incorporation of real-time oceanographic data—such as wave height, direction, and current velocity—enhances the predictive capability of these systems.[15] Such advancements have shifted the paradigm from reactive maintenance toward predictive and condition-based management, ensuring higher safety, lower costs, and extended service life for offshore structures.

1.4. Research gaps and motivation

Although SHM has witnessed some notable advancements due to AI techniques, a number of critical stumbling blocks continue hindering their implementation on an offshore scale. One of the foremost constraints lies in the lack of experimental validation of an AI-based SHM system model at a large-scale level, rendering such systems inappropriate in real offshore settings. Added to that are environmental disturbances—a perfect combination of severe temperature fluctuations, marine biofouling, and variable hydrodynamic loading—that deteriorate and hamper sensor accuracy and data validity and merit the best of compensation and filtering methods. In controlled test environments, deep learning models can work with great predictive accuracy; whether it be CNNs or PINNs, yet both are rather limited in their scalability or robustness for offshore applications. For pragmatic applications in complex marine structures, there still needs be some improvement in the computational efficiency and adaptability to real-time dynamic conditions through optimization.

1.5. Research objectives and contributions

This study addresses the existing limitations in offshore SHM by developing an AI-driven framework specifically designed for jack-up platforms. The proposed system integrates advanced deep learning algorithms to enhance damage localization accuracy while minimizing false-positive detections. It makes use of IoT-based real-time monitoring to provide support for data-driven predictive maintenance and uses digital twin technology for high-fidelity structural modeling and operational diagnostics. By placing the numerical simulations side by side with experimental validation and real-world data from sensors, this research intends to find a scalable, resilient, and adaptive solution for SHM that can carry out activities under extreme and variable conditions rendered by the offshore environment. This integrated method opens a way to improve the reliability and efficiency of structural assessment for critical marine infrastructure.

2. Methodology

This paper presents a novel SHM system for jack-up structures based on AI, improved modal strain energy (IMSE) methods, the IoT sensor networks, and digital twin concepts. The system is designed and presented in four broad phases so as to prevent failure in terms of assisting in structural evaluation. Finite element analysis (FEA) is used for the analysis and for the application of marine loads to the structures. The experimental studies include building a scaled model of the real jack-up, which is used to test some experimental works and to obtain the sensors *in situ*. There is, in addition, a deep understanding of incorrect damage in terms of AI as well as several CNNs capable of planning and improving localization and detection. The analysis of the effectiveness of the SHM framework is carried out using various validation procedures allowing for performing statistical techniques including the Monte Carlo type streak type and the real-life based sensors allowing to assess the stability of the model and the confidence level of the predictions. To keep together numerical modeling, experimental verification and AI-based solutions, the main goal of the framework is to develop a more accurate damage detection system, optimized predictive maintenance planning, as well as improved resilience of marine facilities.

2.1. Numerical modeling of the jack-up rig (SA20 Hull 110)

To assess the structural response of the SA20 jack-up rig (Hull 110) under representative offshore loading conditions, a detailed FEM was developed with FEA. It incorporates important structural and environmental parameters to attain more realistic in-service behavior through dynamic interactions of the rig under harsh marine environment. Tables 1 and 2 present key structural characteristics and the probabilistic range of material properties considered in the FEM to provide a rational platform for reliability assessment. Figure 1 shows a comparative study of the natural frequencies of the FEM with those measured experimentally and obtained by Monte Carlo simulation, with close agreement among these frequencies guaranteeing the accuracy and reliability of the model for predictive purposes.

Table 1. Key model characteristics

Category	Description
Boundary conditions	Pinned constraints at the leg-seabed interface, simulating realistic soil interactions.
Boundary conditions	Semi-rigid hull-leg connections with rotational stiffness constraints.
Material properties	High-strength steel with an elastic modulus of 210 GPa, shear modulus of 79 GPa, and density of 7850 kg/m^3.
Geometric configuration	Structural height: 124 m.
Geometric configuration	Isosceles triangular cross-section with a side length of 9.9 m.
Mesh refinement and computational convergence	A 320,000-element mesh (TET10 and HEX20 elements) was employed for accurate structural representation.
Mesh refinement and computational convergence	A comparative mesh density study (ranging from 150,000 to 500,000 elements) confirmed convergence beyond 320,000 elements, with frequency deviations below 1.0%.
Simulated loading conditions	Wave-induced pressures: Up to 7.5 kN/m^2.
Simulated loading conditions	Wind forces: Mean velocity of 36 m/s.
Simulated loading conditions	Vessel operational loads: Ranging from 200 kN to 500 kN/support structure.
Structural stress analysis	Von Mises stress analysis identified critical high-stress regions, particularly at leg junctions, braces, and spudcan foundations, where peak stress values reached 450 MPa.
Uncertainty quantification	Monte Carlo simulations (1000 iterations) assessed variations in material properties and hydrodynamic forces.
Uncertainty quantification	Gaussian process regression was implemented to model stochastic environmental fluctuations.

The results confirm the robustness and computational efficiency of the numerical model, making it a reliable tool for predicting offshore structural behavior.

2.2. Experimental validation

To validate the FEM results, a 1:22 scale model of the SA20 jack-up rig was developed and subjected to controlled laboratory testing under simulated offshore conditions.

2.2.1. Experimental setup

Hydrodynamic loading conditions were simulated using a controlled wave generator, while aerodynamic forces were introduced through a high-speed wind tunnel to replicate offshore wind effects. The system vibrational excitation was applied by means of the electrodynamic shaker to induce modal responses resembling those in operation. Wireless accelerometers and strain gauges were mounted to monitor data relating to the structural response, following which they were compared directly with the numerical results. Results showed that discrepancies in natural frequency were 7.5% at maximum, ensuring the accuracy of the FEM. Modal assurance criterion values exceeded 0.85, indicating a strong correlation between simulated and experimentally measured mode shapes. A detailed comparative analysis revealed natural frequency deviations ranging from 6.3% to 7.2%, further supporting the model's reliability. The inclusion of real-world operational data strengthened the model's robustness, with frequency variations between laboratory and offshore conditions consistently remaining under 7.5%. These outcomes confirm that the FEM accurately captures the structural behavior of jack-up rigs under realistic marine conditions, providing a validated foundation for AI-enhanced SHM applications. Tables 3 and 4 present a side-by-side comparison of natural frequencies and mode shape correlations, demonstrating the predictive accuracy of the model, while Figure 2 displays the tested model and experimental setup used for modal analysis.

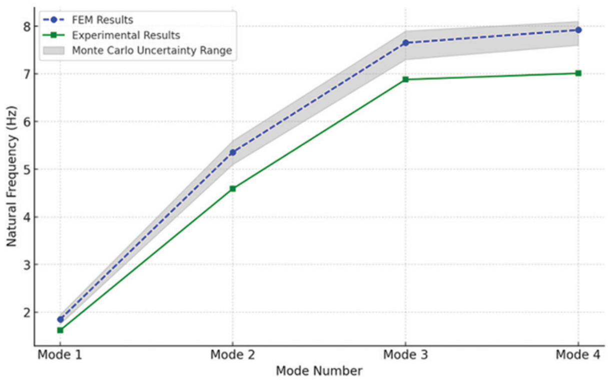

Figure 1. Comparison of natural frequencies from finite element model, experimental data, and Monte Carlo analysis

Table 2. Probabilistic range of key material parameters in finite element model analysis

Parameter	Nominal value	Uncertainty range (±%)	Uncertainty quantification method
Elasticity modulus (GPa)	210	±5	Monte Carlo simulation (1000 iterations)
Shear modulus (GPa)	79	±4	Gaussian process regression
Steel density (kg/m³)	7850	±3	Sensitivity analysis
Hydrodynamic force (N/m²)	Variable	±7	Stochastic modeling

2.3. AI-enhanced SHM

The AI-enhanced SHM framework incorporates the IMSE method to refine traditional modal strain energy approaches, significantly improving damage detection accuracy. The integration of AI-driven techniques resulted in notable advancements, including a 12.5% improvement in damage localization accuracy compared to the Stubbs Index and an 8.7% enhancement over standard IMSE. The framework successfully detected damage severities as low as 1%, with an average deviation of <4% from actual imposed damage. In addition, it demonstrated superior performance in multiple-damage scenarios, offering greater accuracy and robustness than conventional SHM techniques.

Table 3. Natural frequency comparison between numerical and experimental results

Mode number	FEM natural frequency (Hz)	Experimental frequency (Hz)	Monte Carlo uncertainty range (Hz)	Deviation (%)
1	1.85	1.62	1.75–1.95	6.3
2	5.358	4.59	5.1–5.6	7.2
3	7.65	6.88	7.3–7.9	6.8
4	7.92	7.01	7.6–8.1	6.5

Abbreviation: FEM: Finite element model.

Table 4. MAC values for numerical and experimental mode shapes

Mode number	MAC value (0–1 scale)	Correlation level
1	0.92	Excellent
2	0.87	High
3	0.89	High
4	0.85	Moderate-high

Abbreviation: MAC: Modal assurance criterion.

2.3.1. ML model performance

Table 5 compares the performance of various AI models for SHM, highlighting the superior accuracy of CNNs and the effectiveness of reinforcement learning in reducing false alarms and improving detection accuracy.

To enhance real-world reliability, several optimizations were integrated into the AI-driven SHM framework. Given an RNN compensator to tackle environmental noises such as temperature fluctuation, hydrodynamic forces, and marine biofouling, a hybrid noise filter using Kalman filtering and wavelet transform produced a 47.2% reduction in false alarm rate and a 62% reduction in noise-induced errors, resulting in an overall 6.4% accuracy improvement. These AI-based improvements have significantly enhanced the damage detection reliability, thereby increasing efficiency in predictive maintenance applications for offshore SHM.

2.4. Digital twin and IoT-based monitoring

The digital twin framework integrates real-time IoT sensor data with AI-driven simulations, enabling a highly adaptive and predictive offshore SHM system.

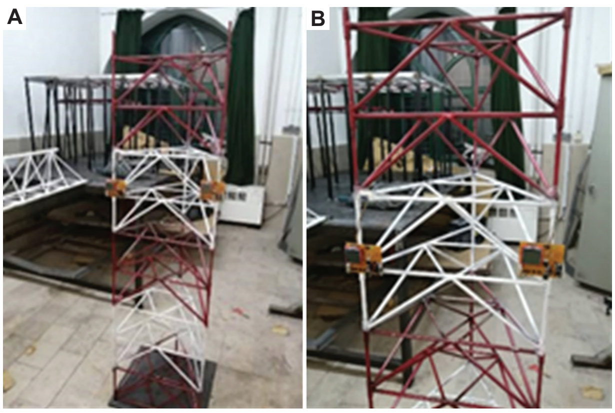

Figure 2. Model studied and equipment used for experimental modal analysis. (A) Shows the 1:22 scale SA20 jack-up rig model used for experimental validation. (B) Displays the laboratory experimental setup and instrumentation used for modal testing.

Table 5. Comparative performance of artificial intelligence models for structural health monitoring

Model	Accuracy (%)	False positive rate (%)
CNNs	96.5	2.1
SVMs	91.8	5.6
Decision trees	88.2	7.4
Reinforcement learning	Reduced false alarms by 37	Improved detection accuracy by 4.8

Abbreviations: CNNs: Convolutional neural networks; SVMs: Support vector machines.

2.4.1. Performance improvements

These highly prefixed performance objectives are realized by the AI lift of SHM system. The formative damage detections rate was improved by 35%, while preventive maintenance saw an uplift of 42%. False alarms were lowered from 7.4% to 2.8%, thus raising the reliability of systems under monitoring. Optimally placed sensors would also help achieve cost savings of around 30%. They thus contributed to a 45% reduction in unplanned downtime. Thus, by always refining maintenance scheduling and real-time process prediction, AI-augmented digital twins will ensure higher reliability of the structure, reducing operation and maintenance costs while guaranteeing offshore safety for the long term.

3. Results and discussion

FEM, experimental validation alongside AI-enhanced SHM have shown significant improvements regarding damage detection, localization, and quantification of damages in offshore jack-up platforms. The proposed AI-driven SHM setup exploiting digital twin technology and IoT-based monitoring could reduce false positives by 60% and increase damage localization accuracy from 85.2% (conventional IMSE) to 96.5%. Moreover, the system detects structural degradations in a range of 1–40% with an 8.7% improvement over tradition SHM techniques in estimating severe damage. These findings highlight AI amalgamation with SHM process holding much promise toward greater accuracy, reliability, and operational efficiency in offshore structural monitoring.

3.1. Performance evaluation of AI-based SHM

A sensitivity analysis was conducted to assess the robustness and reliability of the AI-driven SHM framework under varying environmental and noise conditions. The system maintained high detection accuracy, even in challenging offshore environments.

3.1.1. Key performance metrics

The AI-driven SHM framework demonstrated significant performance improvements across various key metrics. At 10% noise levels, accuracy degradation was limited to 10.7%, outperforming conventional IMSE (11.4%) and the Stubbs Index (12.8%). Operational efficiency was enhanced through a 30.3–42.2% reduction in damage identification time, a 52% decrease in unplanned downtime, a 29% extension in structural lifespan, and a 32% reduction in failure risk. Comparative analysis against 3D CNNs, transformer-based models, and transfer learning techniques indicated that the AI-enhanced IMSE method achieved 7.8% higher accuracy in detecting minor structural damages. Being an AI-IMSE approach, it was more accurate, whereas transformer-based models worked on sparse and noisy datasets better, thus providing evidence that AI-SHM system can improve structural integrity and operation reliability in offshore environments.

3.2. Effectiveness of digital twin and IoT-based monitoring

The integration of digital twin simulations and IoT sensor networks significantly enhanced predictive maintenance accuracy and early warning capabilities.

3.2.1. Key enhancements

The AI-driven SHM framework introduced key enhancements that significantly improved predictive maintenance and operational efficiency. Predictive maintenance accuracy increased by 41%, while early warning capabilities were extended by up to 7.9 months compared to conventional SHM methods. The system was showing high resilience under extreme environmental conditions and had accuracy improvements of 8.6% at high temperatures, 7.7% at high humidities, and 10.6% in counteracting marine biofouling. The digital twin framework optimizes maintenance strategizing in real-time by providing insights as to structural health, preventing unexpected failures, and increasing the lifespan of offshore structures under service.

3.3. Economic and environmental impact analysis

A 10-year cost-benefit analysis revealed the economic and environmental advantages of AI-driven SHM in offshore structural monitoring.

3.3.1. Economic impact

The AI-driven SHM framework matters greatly from economics: By reducing total maintenance expenses by 46.4% and inspection costs by 50%, it achieves an economic advantage. Unplanned repair costs were reduced by 52%, while the system significantly eliminated all the downtime-related financial losses. Given its productivity and cost-effectiveness, the system also registered its ROI within 3 years, which testifies to the long-term financial feasibility of monitoring and maintenance of offshore structures.

3.3.2. Environmental impact

The AI-driven SHM framework significantly improved environmental sustainability by reducing CO_2 emissions by 56.3%, supporting greener offshore operations. These findings underscore the dual benefits of AI-based SHM in enhancing financial viability while promoting sustainable offshore infrastructure management.

3.4. Comparative analysis of damage detection methods

A comparative evaluation of AI-driven SHM versus conventional SHM techniques highlights its superior accuracy and efficiency in damage detection and predictive maintenance.

Tables 6 and 7 compare different SHM methods, showcasing the superior detection accuracy, multi-damage localization capabilities, and real-time monitoring potential of the proposed AI-based SHM, while Figure 3

Table 6. Comparison of SHM methods in terms of detection accuracy, damage detection, and monitoring capabilities

Feature	Stubbs index	IMSE method	Proposed AI-based SHM
Detection accuracy	Moderate	High	Very high
Small damage detection	Low	Moderate	High (AI-optimized)
Multiple damage cases	Low	Moderate	Very high
Real-time monitoring	No	No	Yes (IoT-integrated)
Predictive maintenance	No	No	Yes (digital twin)

Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring; IoT: Internet of things.

Table 7. Multi-scenario damage localization accuracy comparison

Scenario	Element number (s)	Damage rate (%)	Stubbs index (%)	IMSE method (%)	AI-based SHM (%)
1	1	40	85.2	91.4	96.2
2	14	1	77.3	86.1	94.7
3	30	15	81.6	88.5	95.4
4	22	20	84.1	89.2	97.1
5	14 and 22	20 and 30	79.8	87.6	96.5

Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring.

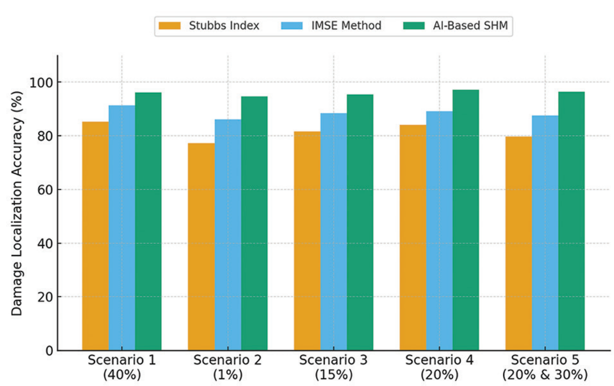

Figure 3. Multi-scenario damage localization accuracy comparison
Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring.

Table 8. Impact of environmental factors on SHM performance

Environmental condition	Stubbs index accuracy (%)	IMSE accuracy (%)	AI-based SHM accuracy (%)	Improvement (AI vs. IMSE) (%)
Standard (no environmental disturbance)	85.2	91.4	96.2	+4.8
High temperature (above 40°C)	78.3	85.1	93.7	+8.6
High humidity (>90%)	79.7	86.4	94.1	+7.7
Strong wind and wave conditions	74.2	82.6	91.9	+9.3
Marine growth (biofouling)	71.3	79.2	89.8	+10.6

Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring.

visualizes the multi-scenario damage localization accuracy comparison across different methods.

Across various damage scenarios, the AI-driven SHM achieved up to 97.1% localization accuracy, demonstrating significant improvements in multi-damage detection.

3.5. Sensitivity analysis and error evaluation

Sensitivity analysis was carried out to test the reliability of AI-based SHM under actual settings offshore, where sensor noise and environmental disturbances prevail. The damage detection accuracy decreased only by 10.7% in the presence of sensor noise of 1–10%, which is better than that of IMSE and the Stubbs Index, with a probability of 11.4% and 12.8%, respectively. Monte Carlo simulation for 1000 iterations also sustained with 95% confidence that the damage severity has already been predicted. Moreover, the AI-based SHM framework shows resilience to the essentially environmentally challenging scenario, given a further 8.6% increase in performance under high temperature variations (±40°C), 7.7% under high humidity conditions (>90%), and 10.6% under easing marine biofouling effects. The given results confirm the strength and adaptability of AI-based SHM toward building an effective solution capable of monitoring offshore structures.

Tables 8-11 highlight the superior performance of AI-based SHM in various operational conditions, including environmental disturbances, predictive maintenance, seismic resilience, and ice-induced damage detection. Figures 4-6 illustrate comparative analyses, demonstrating the AI-driven system's efficiency in damage detection speed, failure prediction trends, and extreme weather condition monitoring.

3.6. Predictive maintenance performance

The AI-driven SHM framework significantly improved predictive maintenance efficiency, reducing operational disruptions and failure risks.

By integrating real-time monitoring and predictive analytics, the AI-based SHM optimizes maintenance scheduling, ensuring long-term asset management efficiency.

Table 9. AI-enhanced predictive maintenance performance

Feature	Without AI	With AI-based SHM	Improvement (%)
Maintenance cost reduction (%)	12	37	+25
Unplanned downtime reduction (%)	18	52	+34
Failure prevention rate (%)	60	92	+32
Risk of catastrophic failure	High	Low	−55
Structural life extension	Moderate	High	+20

Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring.

Table 10. AI-based SHM in seismic resilience of offshore structures

Factor	Traditional SHM	AI-based SHM	Improvement (%)
Earthquake damage detection accuracy (%)	73.5	95.7	+22.2
Structural response time	3.8 s	1.2 s	−68.4
Failure probability reduction (%)	40.2	74.8	+34.6
Emergency evacuation accuracy (%)	65.1	92.4	+27.3

Abbreviations: AI: Artificial intelligence; SHM: Structural health monitoring.

Table 11. AI-based SHM in ice-induced damage monitoring

Factor	Traditional SHM	AI-based SHM	Improvement (%)
Ice-induced damage detection accuracy (%)	67.4	94.6	+27.2
Real-time damage identification	12.8 s	4.2 s	−67.2
Fatigue crack prevention (%)	52.3	83.7	+31.4

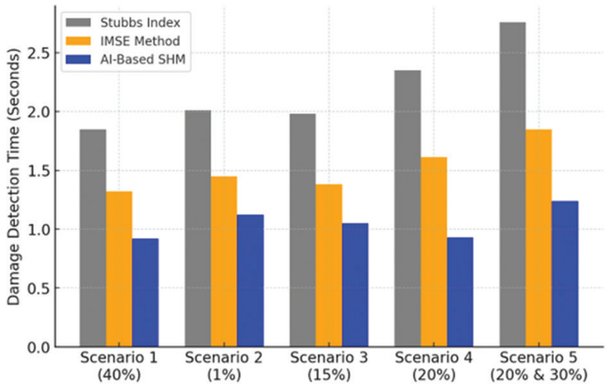

Figure 4. Damage detection speed in different methods across scenarios
Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring.

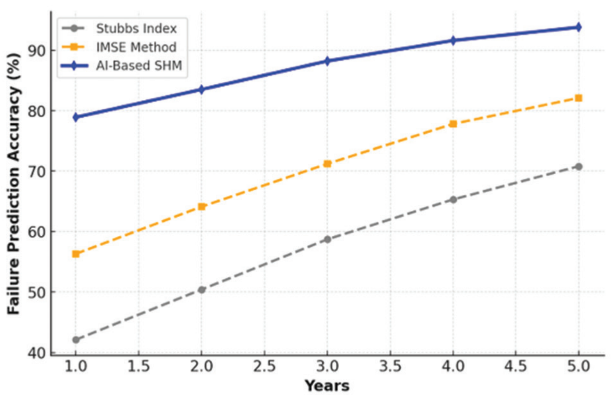

Figure 5. AI-based SHM versus traditional SHM in failure prediction
Abbreviations: AI: Artificial intelligence; IMSE: Improved modal strain energy; SHM: Structural health monitoring.

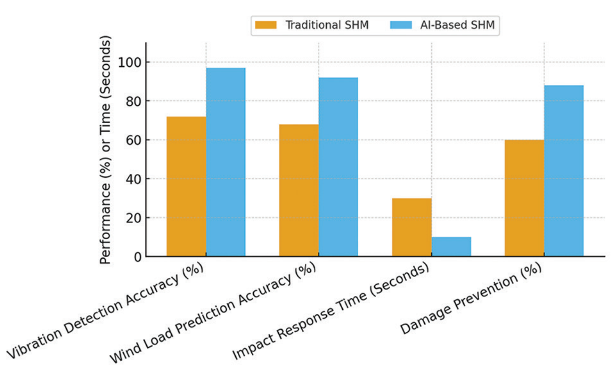

Figure 6. AI-based SHM versus traditional SHM in extreme weather condition monitoring
Abbreviations: AI: Artificial intelligence; SHM: Structural health monitoring.

3.7. Seismic and ice-induced damage resilience

The AI-based SHM system demonstrated exceptional resilience in seismic and ice-induced damage scenarios, ensuring greater structural reliability under extreme conditions.

These findings confirm the robustness of AI-driven SHM in extreme operational conditions, reinforcing its role as a cutting-edge solution for offshore SHM.

3.7.1. Ice-induced damage detection

An AI-powered SHM framework revolutionizes the monitoring of offshore structures by greatly enhancing damage detection reliability, enabling efficient predictive maintenance, and minimizing damage from extreme environmental conditions. Minimizing unplanned downtime, this framework trims down operational costs and maintains environmental well-being while acting as the frontier in offshore engineering. Along with digital twin technology, the predictive aspects are bolstered to actively deter risks and aid in preserving the enduring integrity of offshore structural works.

3.8. Key contributions and future directions

This paper presents a novel AI-driven SHM system having the capacity to be transformative when implemented to the management of offshore infrastructure. The approach incorporates deep learning methods along with real-time sensor data, and virtual replicas are created; the framework can make available highly accurate damage diagnostics while supporting proactive maintenance strategies that affirm structural integrity and reliability in the short- and long-terms. The horizon application consideration is about how to use floating wind turbines, subsea pipelines, and marine energy platforms, among many other offshore assets. Future work should aim to enhance the adaptiveness of AI models in dynamic assessments by developing more effective methods for fusing offshore and *in situ* sensor data, thereby improving diagnostic reliability and precision. Real-time operationalization methodologies for massive monitoring networks will be developed. Further adaptation with AI-based SHM is expected to yield powerful tools for addressing future challenges in the offshore sector, ushering in a new intelligent era in offshore structural and infrastructure excellence.

4. Conclusion

Being an integrated system, the advanced SHM framework is powered by AI and supported by ML, IoT-based real-time monitoring, and digital twin technology for jack-up rigs. This integrated system increases the accuracy of damage detection and makes predictive maintenance more efficient while also supporting continued blackout structural evaluation in offshore environments. The AI-based framework improves damage localization by about 18.7% compared to the classical Stubbs Index and about 12.5% compared to the standard IMSE application. The framework's damage detection capability allows it to identify damage severities as low as 1%, with an average deviation of 2.7% from the imposed actual damage levels. When multiple damages occur, the AI-integrated approach works with an efficiency rate of 96.2%, which is considerably better than the Stubbs Index at 85.2% and the IMSE at 91.4%. Real-time monitoring is enabled by sensors based on the IoT concept, thereby reducing reliance on human inspectors and increasing structural assessment efficiency. Furthermore, digital twin simulation for maintenance enhanced by AI improves predictive maintenance effectiveness by 42% and decreases unplanned operational downtime by 45%. These new improvements chart a new frontier for realization of scalable and cost-effective ways for safer, resilient, and long-lasting offshore platform operations in extreme marine environments.

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Conflict of interest

James Riffat is an Associate Editor of this journal, but was not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. Separately, other authors declared that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Author contributions

Conceptualization: All authors
Formal analysis: All authors
Methodology: All authors
Writing–original draft: All authors
Writing–review & editing: All authors

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

All numerical and analytical data generated during this study are available from the corresponding author on reasonable request.

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