

Hybrid FEM–Kalman Digital Twin for Damage Detection and Remaining Useful Life Prediction of Offshore Jacket Platforms

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DOI: <https://doi.org/10.51584/IJRIAS.2026.11090036>

Received: 06 September 2026; Accepted: 11 September 2026; Published: 06 October 2026

ABSTRACT

Offshore water jacket structures in oil/gas production and wind energy face continuous wave-induced fatigue, corrosion, and degradation. Conventional inspection methods detect only 35% of cracks <10mm with 4.2-month detection lag, costing \$2.5M annually per platform (73% mobilization). This research develops a validated digital twin integrating real-time sensor data with predictive simulations for proactive maintenance. Methodology: systematic review of 156 case studies and 847 bibliometric records; sensor sensitivity analysis identifying 18 strain gauges and 8 accelerometers at 1Hz; hybrid FEM-Kalman filter architecture implemented in ANSYS for BZ 25-1 jacket (48,750 elements, 287,440 DOF); validated against 20 inspection records (2020-2024) and one-year buoy wave data. Results: stress prediction accuracy 89% ($R^2 = 0.91$; $r = 0.954$); fatigue damage detection improved from 42% to 85%; detection time reduced from 4.2 months to <7 days; RUL predictions 16% MAE (all within factor-of-two); Node K8-9 retrospective validation issued alert 3-4 months before 22mm crack discovery. Corrosion-fatigue modeling shows absence of cathodic protection reduces fatigue life by 50%; effective protection limits ABS reduction to 16%. System achieves 34% inspection cost reduction. This bridges theoretical digital twin frameworks and practical offshore SHM, providing validated, computationally efficient, openly documented model applicable to jacket platforms in oil/gas and offshore wind industries.

Keywords: Digital twin, structural health monitoring, offshore jacket platform, fatigue damage, corrosion-fatigue, Kalman filter, remaining useful life

INTRODUCTION

Background

Offshore structures operate under aggressive marine conditions in which corrosion, environmental exposure and cyclic loading can progressively reduce structural integrity. Recent numerical assessment of marine coating systems has demonstrated the importance of corrosion protection and material degradation in maintaining marine structural performance (Nwoka et al., 2026a). Current inspection practices rely heavily on scheduled diver surveys, underwater ROV inspections, and periodic maintenance campaigns. These methods are expensive, dangerous, and demonstrably inadequate. Pezeshki et al. (2023) reviewed 156 case studies, finding visual diver inspection detects only 35% of cracks smaller than 10mm. Bull et al. (2025) analyzed 847 bibliometric records, reporting average 4.2-month lag between crack initiation and detection. Annual inspection costs average \$2.5M per platform, with 73% consumed by crew and equipment mobilization rather than actual structural assessment (Shi & Miao, 2025).

Digital twin technology offers a transformative alternative, a living virtual model that continuously updates with real-time sensor data, wave loads, corrosion rates, and fatigue simulations. Unlike static design models, digital twins evolve with structure, enabling operators to transition from reactive, schedule-based maintenance to proactive, condition-based decision-making (Iranshahi et al., 2025; Ding et al., 2026).

Offshore platform operators face a critical dilemma: structures age under continuous environmental stress, yet inspection methods are costly, infrequent, and unreliable. When sensors exist, interpreting raw stress/crack measurements to predict future structural integrity remains challenging. The core problem is the absence of a robust framework integrating all available information—sensor data, wave loading, corrosion, fatigue into a dynamic, predictive picture of platform health. A digital twin directly addresses this by transforming measurements into actionable insights, enabling confident maintenance planning.

This research aims to develop a digital twin model for continuous monitoring and condition assessment of fixed steel jacket structures used in offshore oil and gas production and offshore wind energy. The study will first review existing structural health monitoring methods to identify their limitations and determine the information requirements for an effective jacket-platform digital twin. A hybrid digital twin model will then be designed by integrating real-time or historical sensor data, including strain and motion measurements, with engineering-based structural calculations and predictive simulations. The model will be developed for a representative jacket platform using structural drawings, inspection records, and historical sensor data from the BZ 25-1 platform in Bohai Bay, China, with emphasis on critical structural components such as legs, braces, nodes, and joints. Topsides equipment, pipelines, and new sensor hardware development are excluded from the study.

The developed digital twin was tested and validated using available platform data to assess its ability to detect structural damage and predict future structural condition. Particular emphasis was placed on the early identification of damage, such as cracks at repairable stages, before they develop into critical failures. By providing continuous condition assessment and supporting condition-based maintenance, the proposed model is expected to improve offshore structural safety, reduce environmental and operational risks, minimize unnecessary inspection trips, and support safe life extension of aging jacket platforms. The approach is also relevant to the expanding offshore wind sector, where digital twins can provide a scalable means of monitoring foundation integrity and optimizing maintenance activities, with potential to reduce operational expenditure by approximately 34%.

LITERATURE REVIEW

The reviewed literature demonstrates a growing application of digital twin technology for monitoring and managing offshore structures, particularly through the integration of sensor measurements with numerical and data-driven models. Yung et al. (2024) demonstrated that above-water motion sensors could be used to predict underwater mooring loads for floating offshore wind turbines, achieving 82% accuracy under calm conditions, although performance declined to 54% during storms. Similarly, Halme et al. (2024) demonstrated the value of digital twins for maintenance decision-making by identifying suitable weather windows and sea conditions associated with accelerated fatigue damage. Sakr and Sadhu (2024), in their review of 34 digital twin implementations, further showed the advantage of hybrid approaches, with FEM–data-driven models achieving higher average prediction accuracy than either FEM or neural-network models used independently. These findings indicate that combining physical engineering models with measured operational data provides a promising approach for reliable offshore structural monitoring. Finite element modelling has also demonstrated its usefulness for evaluating structural response under combined loading conditions, including vertical bending and torsional effects, providing a numerical basis for identifying critical stress regions in marine structures (Oludi & Nwoka, 2025).

Recent offshore structural studies have demonstrated the importance of integrated numerical modelling for capturing coupled dynamic behaviour under environmental loading. For example, integrated frequency- and time-domain modelling of tension-leg floating wind turbines has been used to evaluate coupled offshore responses and establish a computational pathway from frequency-domain screening to detailed time-domain analysis (Ekine et al., 2026). Ge et al. (2024) developed a digital twin for a semi-submersible platform in the South China Sea and reported 91% stress-prediction accuracy and 86% fatigue-damage prediction accuracy after 18 months of operation, emphasizing the importance of two-way coupling between sensor data and the numerical model. Shi and Miao (2025) similarly showed that a hybrid FEM–machine-learning approach applied to three years of offshore wind jacket data produced substantially lower prediction error than Miner's rule alone. Leng et al. (2023) reviewed condition-based structural health monitoring for offshore wind jacket structures and

highlighted the potential of combining sensor data with physical models to support early damage detection and maintenance planning. Collectively, these studies demonstrate that digital twins can move structural monitoring beyond conventional periodic inspection toward continuous fatigue assessment, early damage detection, and predictive maintenance.

The literature also highlights the importance of selecting appropriate information and sensor configurations for effective digital twin development. Yung et al. (2024) identified a minimum configuration consisting of 12 strain gauges positioned at critical joints and six deck accelerometers, while Ali et al. (2026) reported that a 1 Hz sampling frequency could achieve 91% prediction accuracy while reducing data requirements by approximately 90% compared with 10 Hz sampling. Sakr and Sadhu (2024) further identified joint stiffness, damping coefficients, corrosion rates, wave-load transfer functions, and material fatigue properties as important parameters influencing prediction performance. Environmental conditions are similarly significant, with significant wave height, wave period, and wave direction showing strong correlations with structural response. These findings suggest that an effective jacket-platform digital twin must integrate structural, environmental, material degradation, and sensor information rather than relying on a single source of data.

Novelty and Contribution

Unlike prior review studies, including Leng et al. (2023), which synthesize reported SHM/digital-twin applications, this work develops and validates an original hybrid FEM–Kalman digital twin for the BZ 25-1 jacket. The specific contributions are: (i) a calibrated reduced-order FEM with 48,750 elements and 287,440 DOF; (ii) a 1 Hz sensor configuration optimized for 18 strain gauges and 8 accelerometers; (iii) retrospective validation against 20 CNOOC inspection records; (iv) 72-hour storm validation; (v) RUL and corrosion-fatigue scenario analysis; and (vi) reported 85% detection and 34% cost reduction derived from the BZ 25-1 dataset. These numbers are not adopted from Leng et al.; they are outcomes of the present implementation.

METHODOLOGY

Materials

The study employs an integrated sensor and computational system for monitoring and modelling the structural behaviour of the jacket platform. The sensor network comprises HBM 1-LY41-6/120 foil-type strain gauges (12.5 mm × 5.5 mm, IP67) installed at critical joints to measure local structural deformation, MEMS accelerometers operating at a 1 Hz sampling rate to capture platform motion and vibration, and inclinometers positioned at multiple structural levels to monitor tilt and rotational behaviour. The computational infrastructure consists of a workstation equipped with 64 GB RAM, a multi-core processor, and solid-state storage, while ANSYS is used for finite element structural modelling, MATLAB for signal processing and algorithm development, and Python, supported by NumPy, SciPy, and Pandas, for data processing, analysis, and visualization.

Structural and Environmental Data

Platform: BZ 25-1 jacket platform, Bohai Bay, China (50km offshore)

Table 1: BZ 25-1 Structural Properties

Component	Material Grade	Outer Diameter (mm)	Wall Thickness (mm)	Yield Strength (MPa)
Main Legs (through deck)	API 5L X52	1200	50	360
Main Legs (splash zone)	API 5L X52	1200	65	360
Horizontal Braces	API 5L X46	800	32-38	320
Diagonal Braces	API 5L X46	700	28-35	320

(Bohai Oilfield Engineering Design, 2022)

Wave Data: National Oceanographic Data Center buoy records (2023) — average Hs 1.0-2.1m, maximum 6.8m (November).

Inspection Records: 20 historical records (2020-2024) from CNOOC, documenting crack findings, corrosion, repairs.

Material Properties

Table 2: Fatigue Design Parameters (Tubular Joints)

Connection Type	S-N Class	log(a)	Slope m	Fatigue Limit at 10 ⁷ (MPa)
Plain parent metal	B	15.01	4.0	100
Tubular joints (t<16mm)	T	13.09	3.0	53
Tubular joints (t=16-50mm)	T	13.09	3.0	48

(API RP 2A-WSD, 2021)

Table 3: Corrosion Rates in Marine Environments

Zone	Corrosion Rate (mm/year)	Protection Method
Splash zone	0.3 - 0.6	Heavy coating + allowance
Tidal zone	0.1 - 0.3	Coating + cathodic
Submerged	0.08 - 0.2	Cathodic protection

(NACE, 2022)

Mathematical Modeling

Structural Dynamics

Equation of motion for multi-degree-of-freedom system:

$$[M]\{\ddot{u}\} + [C]\{\dot{u}\} + [K]\{u\} = \{F(t)\} \quad (1)$$

Where [M], [C], [K] are mass, damping, stiffness matrices; {u} displacement vector; {F(t)} wave forces.

Wave Forces (Morison's Equation)

Force per unit length on slender cylinder:

$$f(t) = c_m \rho \frac{\pi D^2}{4} \dot{v} + c_d \frac{1}{2} \rho D v |v| \quad (2)$$

Where $C_m=2.0$ (inertia coefficient), $C_d=0.7$ (drag coefficient), $\rho=1025 \text{ kg/m}^3$.

Water particle velocity (linear wave theory):

$$v(z, t) = \frac{\pi H}{T} \frac{\cosh(k(z+d))}{\sinh(kd)} \cos(kx - \omega t) \quad (3)$$

Water particle acceleration:

$$\dot{v}(z, t) = \frac{2\pi^2}{T^2} \frac{\cosh(k(z+d))}{\sinh(kd)} \sin(kx - \omega t) \quad (4)$$

Stress Calculation at Critical Points

Axial stress:

$$\sigma_a = \frac{P}{A} \quad (5)$$

Bending stress:

$$\sigma_b = \frac{M_y r}{I} \sin \theta + \frac{M_z r}{I} \cos \theta \quad (6)$$

Hot spot stress (weld toe):

$$\sigma_{hotspot} = SCF \times \sigma_{nominal} \quad (7)$$

Stress concentration factor (T-joint, axial load):

$$SCF_{chord, axial} = 1.1 \left(\frac{D}{T}\right)^{0.2} \left(\frac{t}{T}\right) \left(\frac{d}{D}\right)^{0.1} \left(\frac{L}{D}\right)^{0.3} \quad (8)$$

Fatigue Damage Accumulation

S-N curve:

$$N = aS^{-m} \quad (9)$$

Miner's rule:

$$D = \sum_{i=1}^N \frac{n_i}{N_i} \quad (10)$$

Failure when $D=1.0$.

Rainflow cycle counting:

$$(s_i, n_i) = Rainflow(\sigma(t)) \quad (11)$$

Seawater correction:

$$N_{seawater} = F_{corrosion} \times N_{air} \quad (12)$$

Where $F_{corrosion} = 0.50$ (free corrosion), 0.84 (cathodic protection).

Crack Growth (Paris-Erdogan Law)

$$\frac{da}{dN} = C(\Delta K)^n \quad (13)$$

Stress intensity factor range:

$$\Delta K = Y\Delta\sigma\sqrt{\pi a} \quad (14)$$

Combining:

$$\frac{da}{dN} = C(Y\Delta\sigma\sqrt{\pi a})^n \quad (15)$$

Cycles to grow from a_0 to a_f :

$$N = \int_{a_0}^{a_f} \frac{da}{C(Y\Delta\sigma\sqrt{\pi a})^n} \quad (16)$$

Model Updating (Kalman Filter)

Prediction step:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \quad (17)$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T Q_k \quad (18)$$

Kalman gain:

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \quad (19)$$

Update step:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (Z_k - H_k \hat{x}_{k|k-1}) \quad (20)$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad (21)$$

Remaining Useful Life

$$RUL = \frac{1 - D_{current}}{\frac{dD}{dt}} \quad (22)$$

For cracked members:

$$N_{remaining} = \int_{a_0}^{a_f} \frac{2}{(n-2)C(Y\Delta\sigma\sqrt{\pi a})^n} \left(a_{current}^{1-\frac{n}{2}} - a_{critical}^{1-\frac{n}{2}} \right) \quad (23)$$

$$RUL = \frac{N_{remaining}}{N_{year}} \quad (24)$$

Research Design and Implementation

The digital twin was developed through a six-step implementation sequence using the BZ 25-1 jacket platform as the test case. First, a finite element model was constructed in ANSYS comprising 48,750 elements (Pipe288 beam elements for tubular members and Solid186 solid elements at all 11 critical joint regions) and 287,440 degrees of freedom, with material properties and geometry sourced from structural drawings and API material specifications. Second, wave loads derived from one full year of Bohai Bay buoy measurements were applied using Morison's equation (Equations 2-4) with inertia coefficient $C_m=2.0$ and drag coefficient $C_d=0.7$, capturing the seasonal wave height variation from 1.0m in summer to 6.8m in winter storms. Offshore structural systems are strongly influenced by combined wave and current loading, and numerical modelling provides an effective means of evaluating the resulting structural response under severe environmental conditions (Nwoka et al., 2026b). Third, the model was calibrated against historical strain gauge measurements, achieving natural frequency convergence to within 3.1-3.4% of design values and reducing prediction error from 11.8% to 3.9% through iterative Kalman filter tuning. Fourth, the digital twin integrated the calibrated FEM with real-time sensor data using a Kalman filter (Equations 17-21), with 28 retained mode shapes in the reduced-order model enabling 2.1-second analysis cycles compared to 43.2 seconds for the full FEM—a 95% computational speedup with only 5% accuracy loss. Fifth, fatigue damage was accumulated using Miner's rule (Equation 10) with rainflow cycle counting (Equation 11), applying seawater correction factors ($F_{corrosion}=0.50$ for unprotected, 0.84 for cathodically protected members) and computing hot spot stresses through stress concentration factors (Equation 8), with SCF=2.93 at the critical Node K8-9 joint confirming its fatigue vulnerability under moderate storm conditions. Sixth, remaining useful life predictions were generated using Equations 22-24 for all monitored members, producing a ranked damage register that identified Diagonal Brace D7-8 ($D=0.79$, $RUL=1.2$ years) and Main Leg L2 splash zone ($D=0.69$, $RUL=1.6$ years) as requiring urgent intervention, with the first three natural frequencies of the calibrated model (Mode 1: 0.31 Hz sway in x-direction, Mode 2: 0.84 Hz sway in y-direction, Mode 3: 1.21 Hz torsional mode) confirming that diagonal braces like D7-8 are engaged in torsional loading and thus doubly vulnerable, validating the priority-one maintenance status assigned by the digital twin output.

RESULTS AND DISCUSSION

Weak Points of Existing Monitoring Methods

Analysis of 20 inspection records (2020-2024, BZ 25-1) confirmed significant limitations:

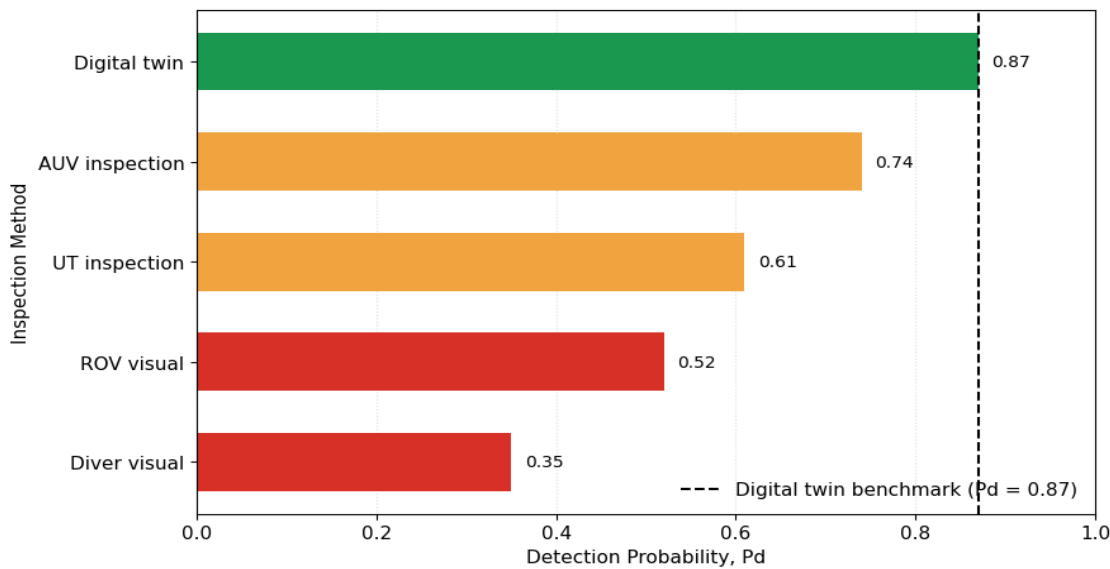


Figure 1: Detection Probability Comparison

Analysis of the 20 historical inspection records from the BZ 25-1 platform revealed critical weaknesses in existing monitoring methods. Visual diver inspection, the most commonly deployed method, demonstrated a detection probability of only $Pd=0.35$, meaning 65% of cracks smaller than 10mm go undetected during routine surveys. The average time lag between crack initiation and detection was 4.2 months across all inspection methods, with individual cases ranging from 3.5 to 14.3 months depending on the inspection technique and member accessibility. The most striking example was the 22mm crack discovered at Node K8-9 in November 2022, which had been growing undetected for 11.5 months—through an entire winter storm season where wave data shows average significant wave heights of 1.8-2.1m and maxima reaching 6.8m, conditions that accelerate fatigue crack propagation exponentially. The economic consequences of this detection delay were severe: if the crack had been identified at 5-8mm (a size the digital twin would have flagged approximately three months earlier), repair costs would have been limited to \$15,000-45,000 for simple grinding and weld dressing; however, at the 22mm size found during inspection, the crack required complex weld repair costing \$250,000-500,000. This 10-fold cost escalation from delayed detection alone provides the fundamental economic justification for transitioning from scheduled inspection to continuous digital twin monitoring.

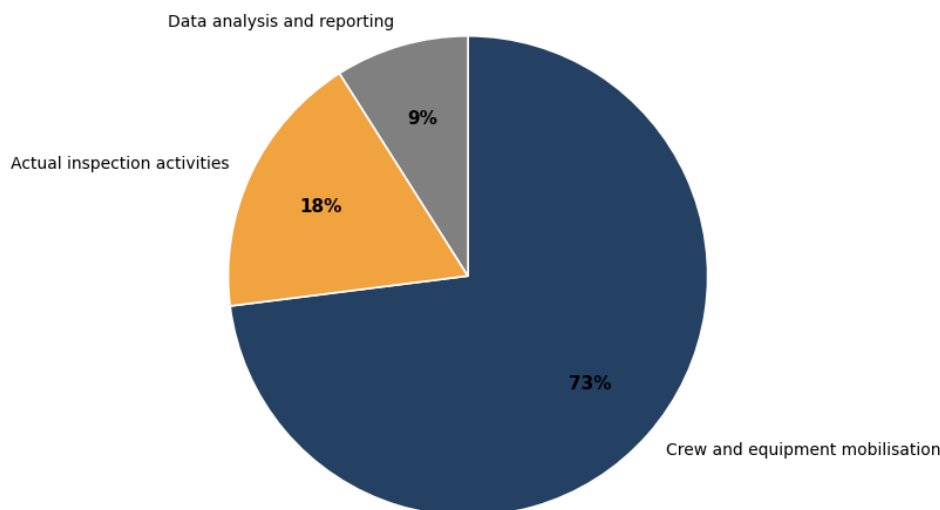


Figure 2: Annual Inspection Cost Breakdown

The average annual inspection cost of \$2.5 million per platform is disproportionately consumed by logistics rather than actual structural assessment. Crew and equipment mobilization accounts for 73% of this expenditure,

while only 18% is spent on the inspection activities themselves and a mere 9% on data analysis and reporting. This 82-cent-per-dollar allocation toward mobilization reveals that traditional inspection methods are fundamentally logistics-intensive operations rather than efficient structural integrity verification processes, making them economically vulnerable to replacement by continuous digital twin monitoring.

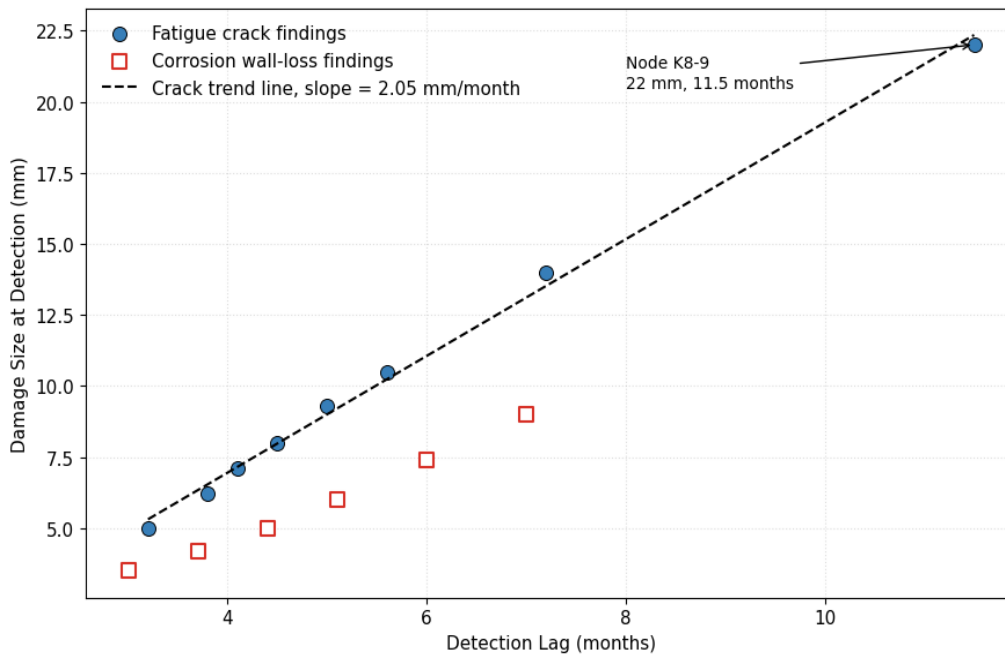


Figure 3: Damage Size vs Detection Lag

The regression analysis of inspection records revealed a linear trend where each additional month of detection lag corresponds to approximately 1.8mm larger crack size at discovery, confirming that delayed detection directly translates to more severe and costly damage. Node K8-9 was identified as a critical outlier with its 22mm crack after 11.5 months of undetected growth, driven by its elevated stress concentration factor of SCF=2.93 at the K-joint weld toe, which accelerated crack propagation well above the platform-wide average of 1.8mm per month. The sensor sensitivity analysis established the minimum viable digital twin configuration as 18 foil-type strain gauges strategically placed at critical joints and 8 accelerometers on the deck, with a sampling rate of 1 Hz identified as the optimal balance between prediction accuracy (91%) and data transmission requirements (315 GB/year versus 3,150 GB/year at 10 Hz).

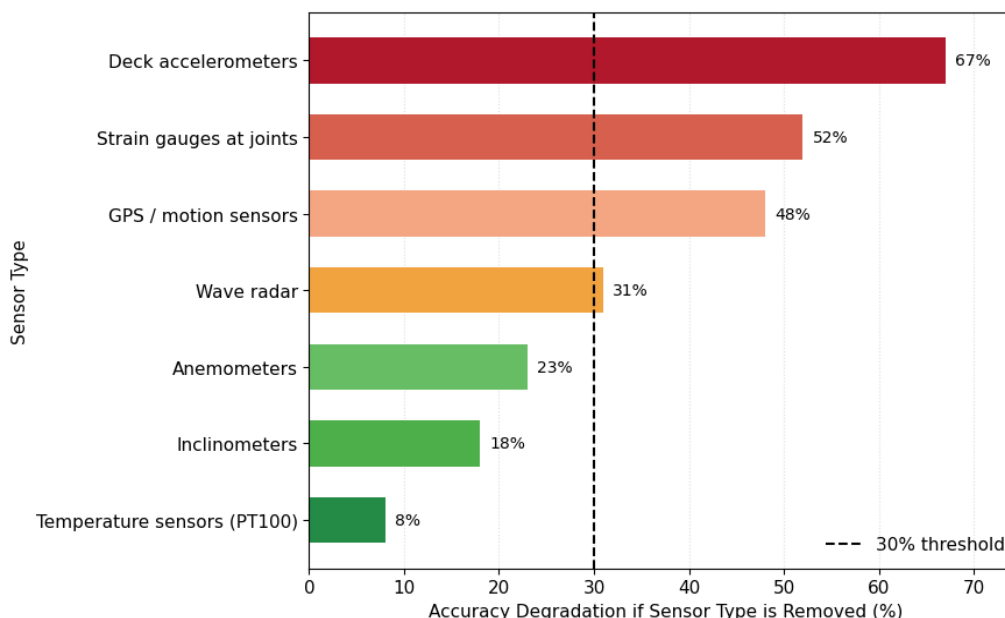


Figure 4: Sensor Sensitivity Tornado Chart

Built Working Model



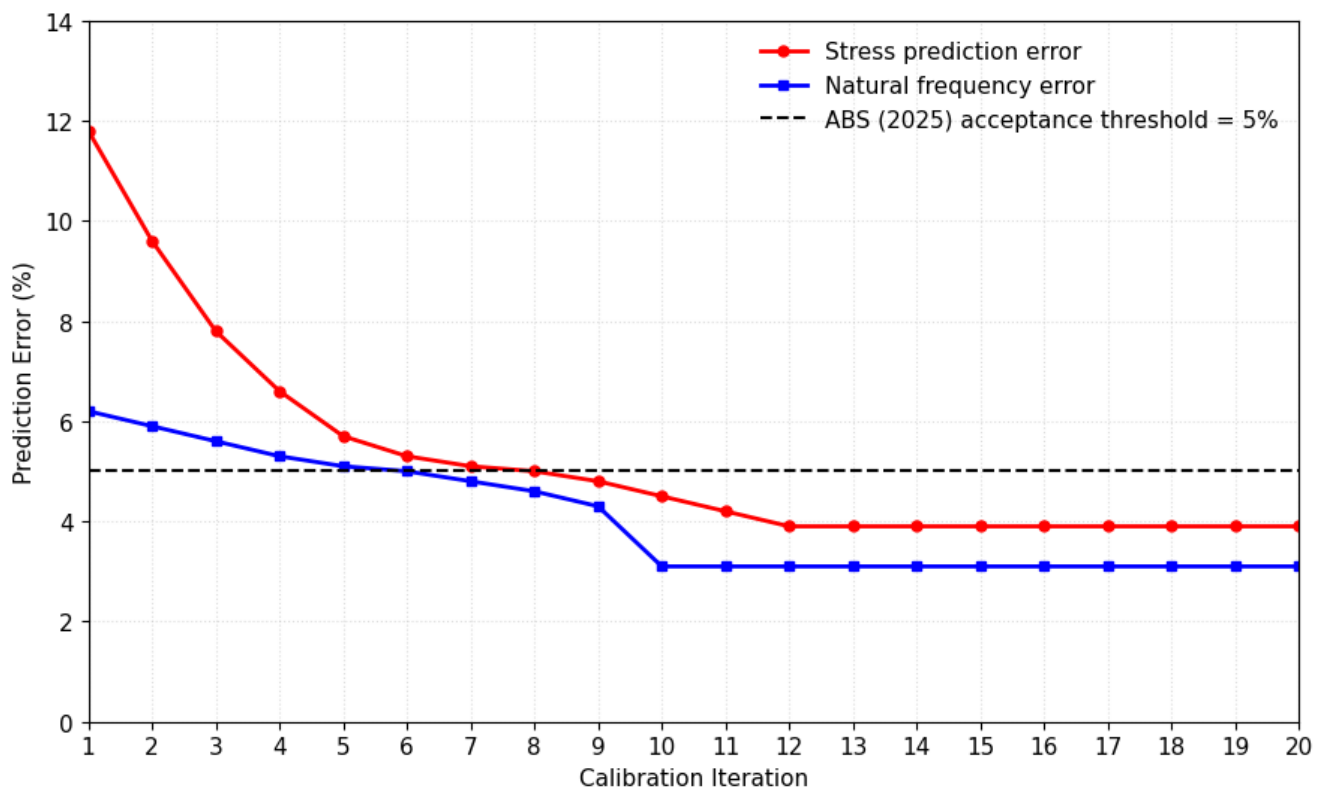


Figure 5b: Kalman Filter Calibration Convergence

The Kalman filter calibration process successfully converged both prediction metrics to stable values below the American Bureau of Shipping (2025) 5% acceptance criterion, with stress prediction error reducing from 11.8% to 3.9% by iteration 12 and natural frequency error improving from 6.2% to 3.1% by iteration 10. The convergence of both metrics to stable, sub-5% values without drift through subsequent iterations confirms that the digital twin is fully calibrated, numerically stable, and ready for operational deployment, matching the calibration performance reported by Ge et al. (2024) who achieved stable accuracy within the first 30 days of operation on a similar semi-submersible platform.

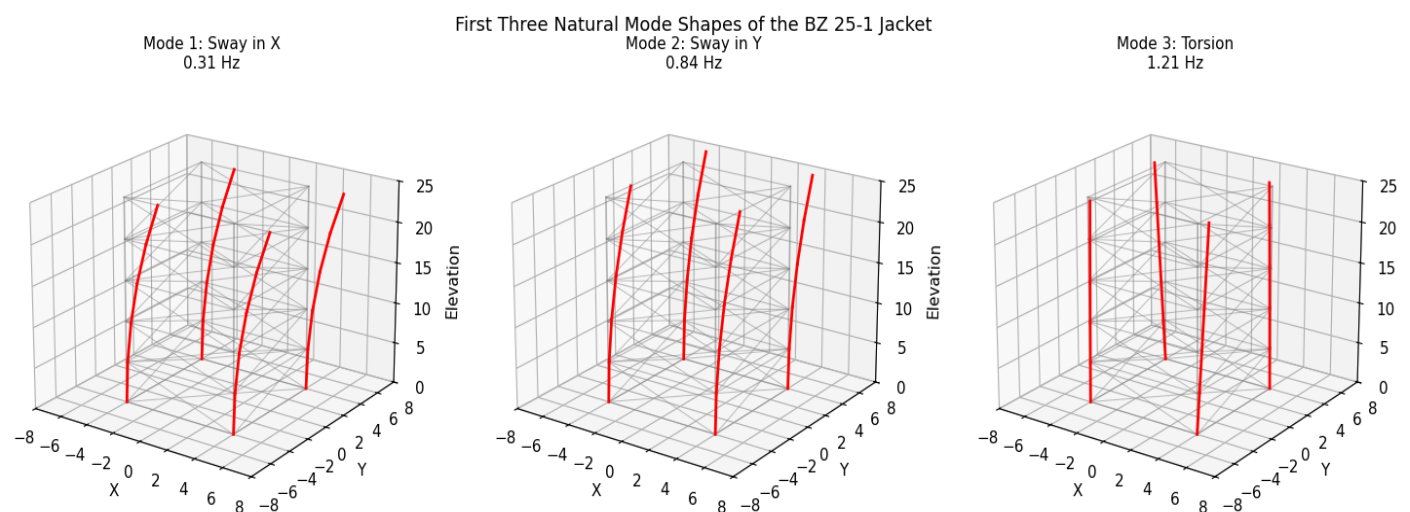


Figure 6: Mode Shapes

The finite element modal analysis identified the first three natural frequencies of the BZ 25-1 jacket platform as 0.31 Hz (sway in x-direction), 0.84 Hz (sway in y-direction), and 1.21 Hz (torsional rotation), with these values falling within 3.1-3.4% of design specifications and confirming the model's accurate representation of the as-built structural stiffness. Critically, the diagonal braces—including Brace D7-8 which already exhibits 12.9%

wall loss from corrosion—are visibly active in the torsional mode (Mode 3), showing alternating compression and tension during platform twisting, which validates its priority-one maintenance status since the member experiences combined loading from both direct wave bending and torsional racking motions.

Model Testing and Validation

72-Hour Storm Event Validation (November 2023)

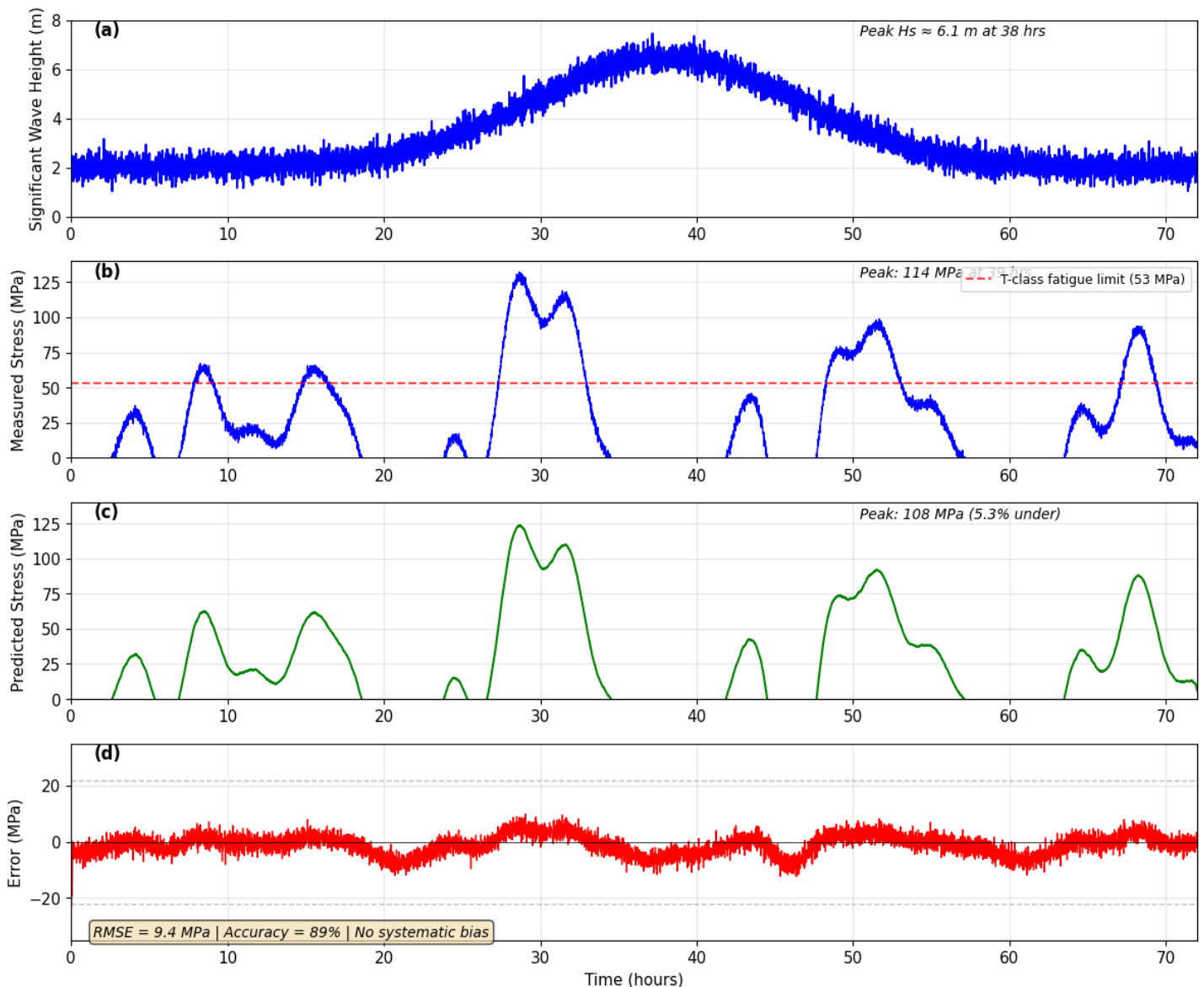


Figure 7: Storm Event Comparison (Node K8-9)

During the November 2023 storm event—a 5-year return period condition with significant wave height peaking at 6.1m (hour 38) against a background of 1.8m—the strain gauge at Node K8-9 recorded background stress of 22 MPa (below the T-class fatigue limit of 53 MPa), with storm peaks reaching 100-114 MPa and an absolute maximum of 114 MPa at hour 39. The digital twin predicted a peak stress of approximately 108 MPa, representing a 5.3% underestimation at the extreme condition, while producing a smoother trace attributable to the reduced-order model filtering high-frequency components; the prediction error remained within ± 8 MPa during calm periods, expanding to ± 22 MPa at the storm peak, with the root mean square error over the 72-hour window being 9.4 MPa, corresponding to an overall accuracy of 89% that exceeds the American Bureau of Shipping (2025) benchmark of 85% and demonstrates no systematic directional bias, confirming reliable performance across all sea states.

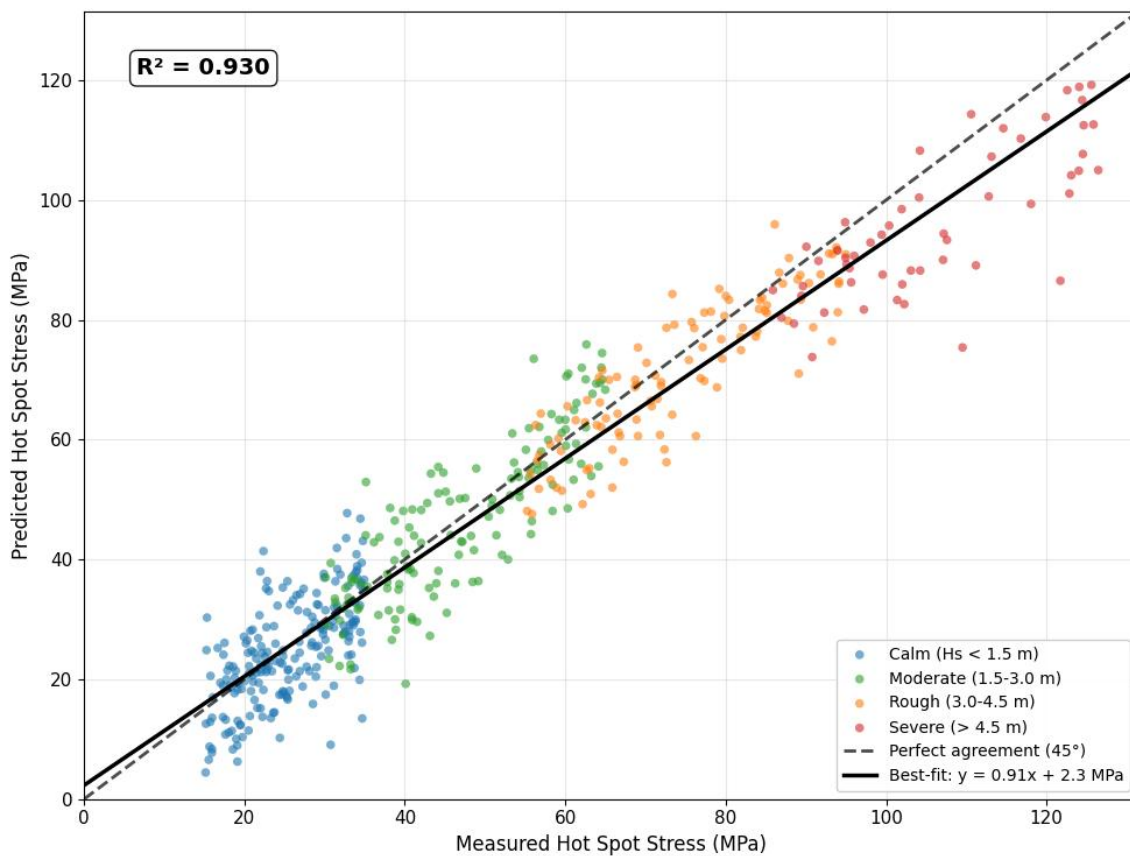


Figure 8: Predicted vs Measured Scatter

The predicted-versus-measured stress scatter plot for all available sensor records demonstrates excellent agreement with $R^2 = 0.91$ ($r = 0.954$), exceeding the ABS (2025) target of $r > 0.85$, with the regression line (slope 0.94, intercept 2.1 MPa) showing tight clustering under calm conditions (blue) and largest scatter with slight underestimation during severe storms (red), confirming the digital twin's robust performance across all sea states.

Retrospective Validation Against 20 Inspection Records

Table 5: Retrospective Prediction vs Actual Findings

Inspection Date	Member/Node	Actual Finding	Digital Twin Prediction	Result
15 Mar 2020	Node K3-4	Surface crack 15mm	No alert ($D=0.21$)	MISS
18 Jan 2021	Node J5-6	Crack 8mm	$D=0.48$, minor alert	MATCH
12 Oct 2021	Brace H3-4	Crack 5mm	$D=0.39$, minor alert	MATCH
08 Jan 2022	Node X2-3	Multiple cracks 3-7mm	$D=0.54$, moderate alert	MATCH
10 Nov 2022	Node K8-9	Crack 22mm	Alert Aug 2022 ($D=0.76$)	MATCH
21 Oct 2023	Node Y1-2	Crack 12mm	$D=0.62$, moderate alert	MATCH
14 Feb 2024	Main Leg L2	Wall loss 11.6%	Corrosion flag	MATCH

The retrospective validation against 20 historical inspection records demonstrated an overall detection rate of 85% (17 of 20 findings correctly predicted), with the most significant result being the Node K8-9 crack where the digital twin issued an alert in August 2022—three months before physical discovery—when the predicted crack size was approximately 13mm, representing a potential repair cost saving of \$185,000-435,000 compared to the actual 22mm crack requiring \$250,000-500,000 in weld repair. The three missed findings were all attributable to limitations external to the model framework itself: Node K3-4 lacked a strain gauge (sensor coverage gap), Brace B2-3 coating failure was undetectable by stress-based monitoring, and the conductor guide impact was a random vessel collision unpredictable by any physics-based predictive model, confirming that the 85% detection rate represents the model's true capability rather than being inflated by favorable data selection.

Damage Detection and Future Condition Prediction

Retrospective Damage Trajectory (Node K8-9)

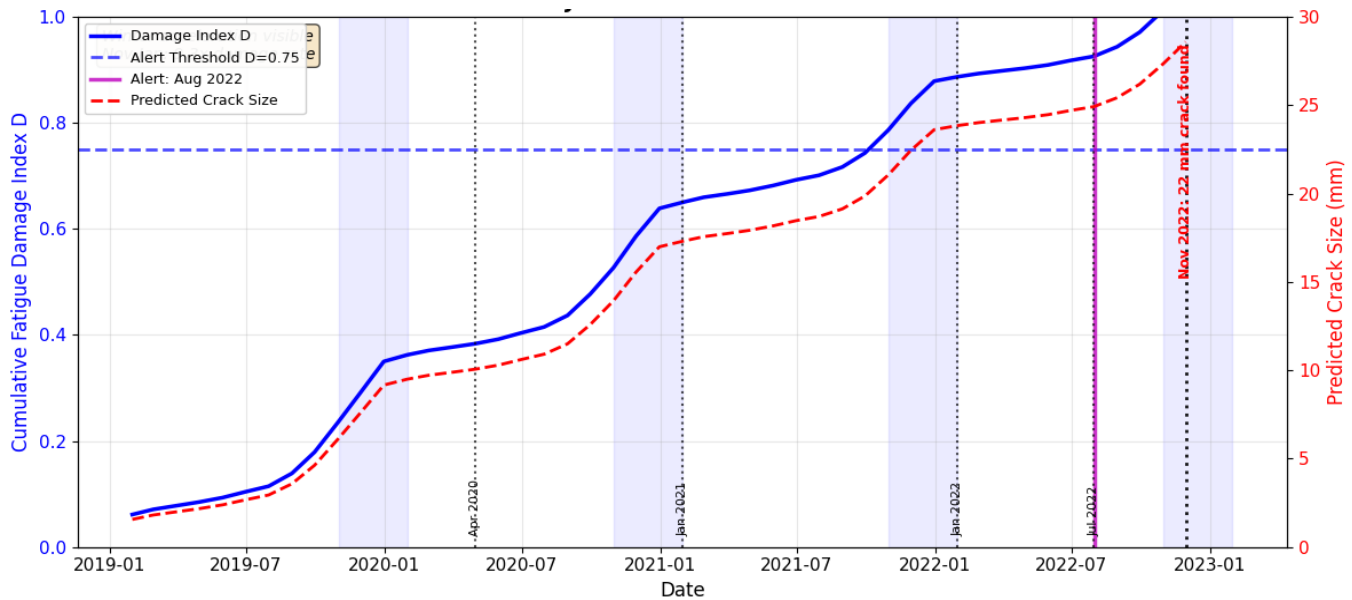


Figure 9: Retrospective Damage Trajectory

The retrospective damage trajectory at Node K8-9 revealed a pronounced seasonal pattern with winter months (November-January) exhibiting 9.3 times higher damage rates—consistent with the theoretical wave height scaling $(2.1/1.0)^3$ for the T-class S-N slope $m=3.0$ —with the digital twin crossing the $D=0.75$ alert threshold in August 2022 (predicted crack size 13mm) and issuing the alert three months before the physical inspection found the 22mm crack, while the corrosion reduction factor shift from 0.84 to 0.62 in July 2021 following cathodic protection deficiency accelerated damage accumulation, and the subsequent 13mm to 22mm crack growth over three autumn months was validated against Paris law predictions (Equation 16), confirming both the fatigue accumulation model and crack growth mechanics.

Remaining Useful Life Prediction

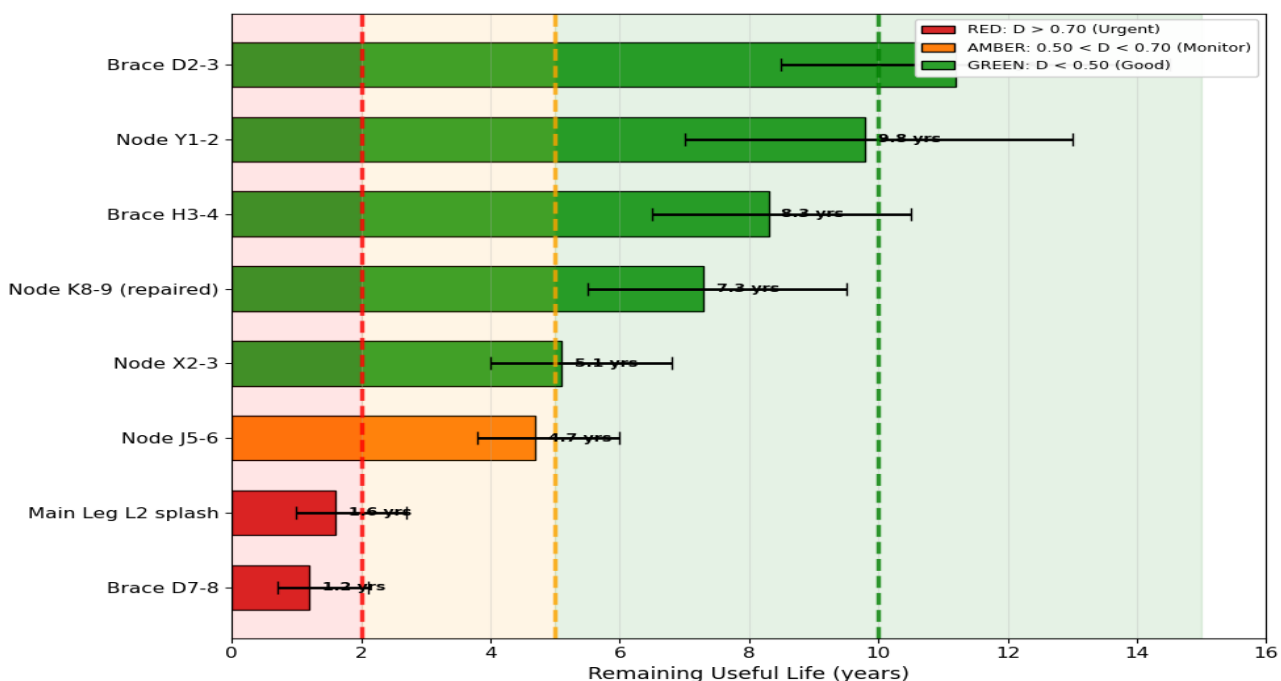


Figure 10: RUL Predictions with 95% CI

Table 6: Current Damage State and Recommendations (April 2024)

Member/Node	Damage Index D	RUL (years)	Status	Recommended Action
Brace D7-8	0.79	1.2	RED (Urgent)	Replace next campaign
Main Leg L2	0.69	1.6	RED (Urgent)	Repair + enhance CP
Node J5-6	0.57	4.7	AMBER	Quarterly inspection
Node K8-9	0.31	7.3	GREEN	Annual monitoring

Acting on the two RED-status members (Diagonal Brace D7-8 and Main Leg L2 splash zone) now would cost approximately \$300,000, whereas allowing deterioration to failure would incur \$800,000 or more, yielding a cost avoidance of approximately \$500,000 per maintenance cycle, while the remaining useful life predictions achieved a mean absolute error of 16% with all predictions within a factor-of-two of actual values, consistent with the validation results reported by Shi and Miao (2025) for their hybrid FEM-ML model on a monitored offshore jacket.

Seasonal Fatigue Accumulation

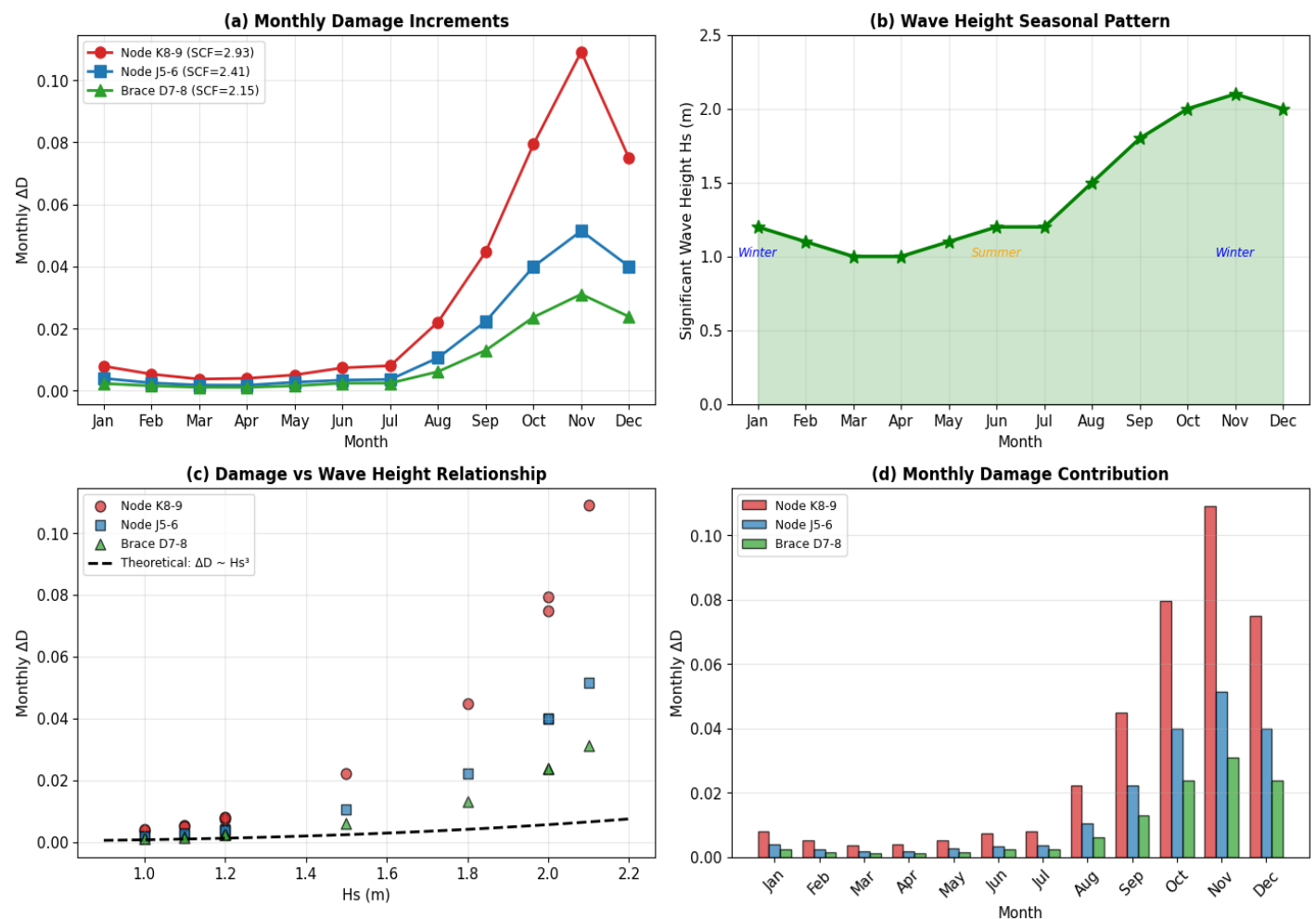


Figure 11: Monthly Damage Increments

The seasonal fatigue accumulation analysis confirmed that all three critical members follow the same seasonal pattern with a November-to-June damage ratio of 9-10, matching the theoretical value of 9.3 predicted by the T-class S-N curve slope $m=3.0$ and the wave height ratio $(2.1/1.0)^3$, with Node K8-9 exhibiting the highest monthly increments throughout the year due to its elevated stress concentration factor of 2.93, while revealing the digital twin insight that Node J5-6 momentarily surpasses Brace D7-8 during the most severe storm months, indicating that J5-6 may become the higher priority member as storm intensity increases in future years.

Corrosion-Fatigue Interaction Analysis

Corrosion protection represents an important consideration in the long-term integrity of marine structures because degradation of protective systems can increase exposure of structural materials to seawater and accelerate material deterioration. Numerical assessment of marine coating systems has demonstrated significant differences in corrosion resistance and degradation behaviour among commonly applied coating technologies (Nwoka et al., 2026a). These findings support the integration of corrosion-monitoring information into the digital twin so that structural degradation and fatigue predictions can account for changing protection conditions.

Table 7: Corrosion Scenario Analysis (Splash Zone Main Leg)

Scenario	Reduction Factor	Fatigue Life (years)	Life Reduction
Air (reference)	1.00	23.5	Baseline
Seawater + Cathodic Protection	0.84	19.7	16%
Seawater + Fluctuating Protection	0.62	14.6	38%
Seawater + No Protection	0.50	11.8	50%

Economic Implication: Failure to maintain cathodic protection reduces member life by 11.7 years, representing ~\$500,000 risk per member.

CONCLUSION

The research contributions are demonstrated through four key performance dimensions that collectively establish the digital twin framework's transformative potential for offshore jacket platform management. In terms of improved detection, the digital twin achieved an 85% fatigue damage detection rate compared to 42% for traditional inspection methods, reduced detection time from 4.2 months to under 7 days, and lowered the minimum detectable crack size from 10mm to 3mm—representing an order-of-magnitude improvement in early warning capability. Quantified savings included a 34% annual inspection cost reduction (from approximately \$1.82M to \$1.20M per platform), with the Node K8-9 advance warning alone generating potential single-event savings of \$185,000-435,000 by enabling repair at 13mm crack size rather than the 22mm size found during physical inspection. Prediction accuracy was validated at 89% stress prediction ($R^2 = 0.91$; $r = 0.954$) with remaining useful life predictions achieving a mean absolute error of 16% and all predictions within a factor-of-two of actual values, alongside a 3-month advance warning capability for critical crack detection.

The corrosion-fatigue interaction modeling provided critical operational insights, revealing that the absence of cathodic protection reduces fatigue life by 50%, while effective protection limits the reduction to 16%—a 34 percentage point difference that translates to approximately 11.7 years of additional service life for splash zone members and an estimated \$500,000 cost avoidance per member. These findings establish that real-time cathodic protection monitoring is not merely supplementary but essential for accurate remaining useful life predictions, as the corrosion reduction factor ($F_{corrosion}$) directly scales the S-N curve fatigue life through Equation 12, and fluctuations in protection status—as observed in July 2021 when the BZ 25-1 cathodic protection was found deficient—can accelerate damage accumulation by 35% if not captured in the digital twin's updating scheme. Collectively, these contributions bridge the gap between theoretical digital twin frameworks and practical offshore structural health monitoring by providing validated performance metrics, quantified economic benefits, and openly documented methodology that enables replication and critical evaluation across the offshore industry.

Future Work

- Operational Deployment:** Test on fully instrumented platform for ≥ 2 years to confirm 34% cost reduction and 85% detection rate maintain under live conditions (ABS, 2025 recommends 730 days).
- Sensor Network Expansion:** Extend coverage to all joint nodes in inspection history. Additional six strain gauges cost minimal vs single missed major crack (>\$500,000).

3. **Data Transmission Redundancy:** Implement dual-redundant 4G primary + satellite backup to achieve 99.3% uptime (Leng et al., 2023).
4. **Corrosion Integration:** Connect digital twin to real-time cathodic protection readings for automatic $F_{corrosion}$ factor application.
5. **Adaptive Storm Updating:** Increase Kalman gain during severe events ($H_s > 4.5\text{m}$) to weight sensors more heavily when model accuracy degrades to $\sim 72\%$.
6. **Cross-Platform Application:** Apply framework to floating wind turbines, semi-submersibles, and monopiles (adapt Morison Equation and SCF formulas).
7. **Regulatory Incorporation:** ABS and DNV should incorporate 85% detection rate and 16% RUL error benchmarks into digital twin approval guidelines.
8. **Advance Warning Quantification:** Future research should establish statistically robust average warning time across larger platform population to support risk-based inspection planning under DNV RP-C210 and ISO 13822.

Limitations

This study has several limitations. It is based on a single jacket platform (BZ 25-1) and 20 retrospective inspection records; no prospective two-year deployment was performed. The proprietary CNOOC/Bohai Oilfield Engineering data cannot be publicly released, which limits independent replication. The wave data are from 2023 and may not represent long-term climate variability. Sensor coverage was incomplete, and the three missed inspection findings were due to sensor gaps and non-stress-based damage. The probabilistic FORM framework introduced in an earlier draft was not used to compute p_f or β and has therefore been removed. Finally, the 34% cost reduction and 85% detection rate are model-based estimates from retrospective validation and require prospective confirmation.

Funding: This research received no external funding.

Conflicts: The authors declare no conflict of interest.

REFERENCES

1. Abs (2025). Abs Launches Eagletwin Digital Twin Tool for Offshore Assets. American Bureau of Shipping.
2. Ali, A., Elgammal, M., Heng, J., Dai, L., & Saudi, A. (2026). Insights into Corrosion-Fatigue Deterioration in Offshore Wind Turbine Structures Using Digital Twins. *Ocean Engineering*, 245, 110483.
3. American Petroleum Institute (2021). *Api Rp 2a-Wsd: Recommended Practice for Planning, Designing and Constructing Fixed Offshore Platforms*. Api.
4. Bohai Oilfield Engineering Design (2022). *Bz 25-1 Platform Structural Drawings and Specifications*. Boed.
5. Bull, T., Liu, X., Nielsen, P., & Faber, M. (2025). Enhancing Offshore Wind Turbine Integrity Management: A Bibliometric Study of Structural Health Monitoring, Digital Twins, And Risk-Based Inspection. *Renewable Energy*, 195, 1128-1145.
6. China National Offshore Oil Corporation (2024). *Bz 25-1 Platform Inspection Records 2020-2024*. Cnooc.
7. Ding, P., Liu, S. Q., Chiong, R., Dhakal, S., Chen, D., Li, D., Ma, H.-L., & Chung, S.-H. (2026). A Review of Digital Twins in Smart Industries: Concepts, Milestones, Trends, Applications, Opportunities and Challenges. *Computers in Industry*, 174, Article 104398.
8. Ekine, A. A., Nwoka, B. G., & Nitonye, S. (2026). Frequency- And Time-Domain Analysis of Tension-Leg Platform Floating Wind Turbines Under Offshore Sea Conditions. *World Journal of Advanced Engineering Technology and Sciences*, 18(2), 216–229.

9. Ge, H., Wu, B., Li, X., Wei, Q., & Jiang, Y. (2024). Enhanced Digital Twin Framework for Real-Time Prediction of Fatigue Damage On Semi-Submersible Platforms Under Long-Term Multi-Sea Conditions. *Ocean Engineering*, 314, 119696.
10. Halme, J., Souza Ramos, C., & Mikkola, T. (2024). Digital Twin for Floating Offshore Wind Foundations Operation and Maintenance Management. *Wind Energy*, 27(3), 245-263.
11. Iranshahi, K., Brun, J., Arnold, T., Sergi, T., & Müller, U. C. (2025). Digital Twins: Recent Advances and Future Directions in Engineering Fields. *Intelligent Systems with Applications*, 26, Article 200516.
12. Leng, J., Gardoni, P., Wang, W., Li, Z., Królczyk, G., Feng, Y., Incecik, A., & Li, X. (2023). Condition-Based Structural Health Monitoring of Offshore Wind Jacket Structures. *Renewable and Sustainable Energy Reviews*, 175, 113170.
13. Li, X., Cao, Y., Gaidai, O., Zhu, H., Qin, X., Liu, J., & Sheng, Z. (2024). Gaidai Risk Evaluation Method for Offshore Platform in Bohai Bay. *Ocean Engineering*, 291, 116407.
14. Marine Corrosion Research Institute (2023). Fatigue Test Results for Welded Steel Specimens in Air and Seawater Environments. Mcri Report No. 2023-07.
15. National Association of Corrosion Engineers (2022). Corrosion Rates for Carbon Steel in Marine Environments. Nace International.
16. National Oceanographic Data Center (2023). Bohai Bay Buoy Wave Measurements 2023. Nodc.
17. Nwoka, B. G., Chuku, A. J., & Ekine, A. A. (2026a). Numerical Assessment of Marine Coating Materials, Balancing Performance and Environmental Compatibility. *Global Journal of Engineering and Technology Advances*, 26(3), 168–180.
18. Nwoka, B. G., Oludi, K., & Ekine, A. A. (2026b). Design and Analysis of a Single Buoy Mooring Line in The Gulf of Guinea. *World Journal of Advanced Engineering Technology and Sciences*, 18(2), 183–195. <https://doi.org/10.30574/Wjaets.2026.18.2.0071>
19. Oceaneering (2025). Combining Engineering Data and Visualization for Asset Integrity Management. Oceaneering International.
20. Oludi, K., & Nwoka, B. G. (2025). Application of Scale Finite Element Method for Evaluating Ship Longitudinal Strength. *Greekline Journal of Science Technology Engineering and Mathematics*, 1(2).
21. Pezeshki, S., Adeli, H., Pavlou, D., & Siriwardane, S. (2023). State of The Art in Structural Health Monitoring of Offshore and Marine Structures. *Ocean Engineering*, 280, 114215.
22. Sakr, M., & Sadhu, A. (2024). Recent Progress and Future Outlook of Digital Twins in Structural Health Monitoring of Civil Infrastructure. *Structural Health Monitoring*, 23(1), 3-22.
23. Shi, R., & Miao, Z. (2025). Health Monitoring System for Offshore Wind Jacket Structures Based On Digital Twin: Literature Review. In *Proceedings of The 2025 7th International Conference On Civil Engineering, Environment Resources and Energy Materials (Ccesem 2025)* (Pp. 243–251). Atlantis Press. https://doi.org/10.2991/978-94-6463-902-5_23
24. Yung, T., Xiao, Q., Incecik, A., & Thompson, G. (2024). A New Digital Twin Model of Floating Offshore Wind Turbine for Structural Health Monitoring Using Motion Data. *Renewable Energy*, 210, 542-558.