

AI-Driven Hull Defect Evolution Prediction: A Hybrid Physics-Informed Deep Learning Framework for Maritime Structural Health Monitoring

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Abstract:

Ship hulls operate under repeated wave impact, changing loading conditions, and prolonged exposure to seawater. Over years of service, these effects can produce corrosion, local pitting, and fatigue cracks in important structural members. In practice, hull condition is still assessed largely through scheduled dry-dock surveys and empirical wastage relationships. Such inspections are valuable, but they provide only limited information about what happens between two survey periods. This paper develops a hybrid deep-learning approach that combines a Physics-Informed Neural Network (PINN) with a Spatio-Temporal Graph Neural Network (ST-GNN) to estimate the future development of hull defects. Instead of relying only on measured inspection data, the model also uses corrosion behavior and Linear Elastic Fracture Mechanics as physical constraints during training. Measurements from different non-destructive testing sources, including ultrasonic gauging and autonomous underwater vehicle observations, are brought into a common structural representation. The evaluation described in this work uses 15 years of inspection data from 142 compartments of a Post-Panamax bulk carrier. Over a five-year prediction period, the reported corrosion-wastage MAE is 0.089 mm, while the RMSE for fatigue-crack propagation is 0.94 mm. The reported results show a 71.4% improvement over the recurrent baseline considered in the study. The physical constraints also prevent unrealistic outcomes such as an increase in plate thickness without repair or a negative crack-growth rate. The resulting workflow can be used as a computational aid for condition-based maintenance and continuous hull assessment.

Keywords— Physics-Informed Neural Networks (PINN), Ship Hull Inspection, Spatio-Temporal Graph Neural Networks (ST-GNN), Linear Elastic Fracture Mechanics, Corrosion Wastage Prediction, Structural Health Monitoring (SHM), Autonomous Underwater Vehicles (AUV).

I. INTRODUCTION

The condition of a ship's hull has a direct bearing on safe operation, maintenance planning, and environmental protection. Commercial ships, floating production units, and naval vessels may remain in service for 25–30 years, during which the hull is exposed to repeated wave loading, slamming and whipping effects, and the corrosive marine environment [5].

Corrosion and fatigue cracking are two of the main forms of deterioration found in marine steel structures. Pitting reduces the effective cross-section of plates and longitudinal stiffeners. At the same time, the irregular pit geometry can concentrate stress and make crack initiation more likely under repeated loading [9], [13]. If a fatigue crack continues through

a welded connection or web-frame region, the resulting loss of structural capacity can become significant [3].

Classification bodies such as Det Norske Veritas (DNV), the American Bureau of Shipping (ABS), and Lloyd's Register (LR) have traditionally relied on scheduled Special Surveys, often at five-year intervals [2]. These surveys generally require dry-docking, visual inspection, and localized Ultrasonic Thickness (UT) measurements. The procedure is established and useful, but it has an obvious limitation: the condition of the structure between two surveys is not continuously observed. There are also practical difficulties when inspections are carried out inside ballast or fuel spaces. In addition, standard wastage allowances may not capture changes caused

by operating routes, seawater temperature, or variations in cargo loading [15].

Robotic inspection systems provide another way to collect hull-condition data without depending entirely on dry-docking. AUVs and magnetic crawling robots equipped with PAUT sensors and high-resolution cameras can inspect parts of a vessel while it remains afloat [10], [14]. These systems introduce a different challenge, however. Measurements may arrive at irregular times, cover only selected areas, and contain noise or sensor drift. A prediction method therefore needs to cope with incomplete and unevenly distributed observations.

The work presented here uses a physics-informed deep-learning formulation to estimate how hull defects may develop with time. The stiffened hull is treated as a spatial domain $\Omega \subset \mathbb{R}^3$ with boundary $\partial\Omega$. At a position x and time t , its local structural condition is described by the following multi-physics state vector:

$$S(x, t) = [d(x, t), a(x, t), K_I(x, t), \sigma_{eq}(x, t)]^T \quad (1)$$

where $d(x, t)$ represents local plate thickness diminution (corrosion wastage depth in mm), $a(x, t)$ is the equivalent fatigue crack half-length (mm), $K_I(x, t)$ is the Mode-I stress intensity factor ($\text{MPa} \cdot \sqrt{\text{m}}$), and $\sigma_{eq}(x, t)$ represents the local Von Mises effective stress field (MPa).

Our objective is to learn a continuous neural spatio-temporal operator F_θ parameterized by weights θ that maps historical multi-modal inspection sequences and operational environmental covariates $E(t)$ to future degradation trajectories:

$$\hat{S}(x, t + \Delta t) = F_\theta(\{S(x, \tau)\}_{\tau=0}^t, E(t)) \quad (2)$$

where $E(t)$ comprises significant wave height (H_s), modal wave period (T_p), seawater salinity, localized temperature, microbial activity index, and vessel draft/speed profiles.

II. LITERATURE REVIEW

Earlier work on maritime degradation was mainly based on empirical relationships fitted to inspection records. Paik et al. [11], for example, developed a time-dependent corrosion model for bulk carriers that accounts for coating deterioration and subsequent material loss. Garbatov and Guedes Soares [5] also examined non-linear corrosion behavior using differential formulations. These models are useful when the aim is to describe broad fleet trends. Their use becomes more difficult when the prediction has to reflect the operating history of one particular vessel, local stress concentrations, and changing environmental conditions.

Deep-learning methods have also been introduced into structural health monitoring. Recurrent neural networks and LSTM models have been used for predicting fatigue life and crack development [8]. With sparse inspection records, however, a model trained only on observations can fit the available data

while producing physically unreasonable values in areas where measurements are missing. PINNs provide one way of addressing this problem. The work of Raissi et al. [12] and Karniadakis et al. [6] showed how governing differential equations can be included in the training objective through automatic differentiation.

A ship is not a regular image-like structure. Plates, stiffeners, frames, and bulkheads are connected in an irregular pattern, and the relationship between neighboring components matters when structural loads are transferred. Conventional convolutional networks do not naturally represent this type of arrangement. Graph Neural Networks can do so by treating structural components as nodes and their connections as edges. Chebyshev spectral graph convolutions [1], [7] provide the spatial operation used here. The present method combines this graph representation with the physics-based loss terms to form the PINN-GNN model.

III. THEORETICAL FRAMEWORK AND METHODOLOGY

A. Electrochemical Corrosion Kinetics

Marine corrosion generally changes its rate over the life of a component rather than progressing as a simple straight line. In the formulation used in this work, the process is divided conceptually into an initial coating-degradation period, an active stage associated with oxygen transport and localized pitting, and a later stage in which accumulated corrosion products can limit further reaction. The expected corrosion depth is represented by:

$$d(t) = d_\infty \cdot [1 - \exp(-(t - t_0) / \tau_c)^\beta)] \cdot \psi(T_w, Sal) \quad (3)$$

In Eq. (3), d_∞ represents the limiting corrosion depth. The parameter t_0 accounts for the initial coating period, τ_c controls the time scale of the transition, and β determines the shape of the curve. The effect of seawater temperature and salinity is included through the following environmental factor:

$$\psi(T_w, Sal) = \exp(-E_a / (R \cdot T_w)) \cdot (1 + \gamma_s \cdot Sal) \quad (4)$$

where E_a is activation energy for steel dissolution in chloride solutions, R is universal gas constant, and γ_s is empirical salinity sensitivity coefficient.

B. Linear Elastic Fracture Mechanics and Fatigue Crack Growth

Repeated wave loading produces fatigue damage at details such as hopper-knuckle joints, longitudinal stiffener connections, and hatch-corner cutouts. For a Mode-I crack, the stress-intensity range used in the model is:

$$\Delta K_I = Y(a, W_p) \cdot \Delta \sigma_{wave} \cdot \sqrt{(\pi \cdot a)} \quad (5)$$

Here, $Y(a, W_p)$ accounts for the geometry of the structural detail, while $\Delta \sigma_{wave}$ is the nominal stress range caused by wave loading. For a variable-amplitude load history, the change in crack length

with the number of load cycles is described using the modified Paris-Erdogan relation:

$$da / dN = C \cdot (\Delta K_{th} / \Delta K_{IC})^{n1} \cdot [(1 - (\Delta K_{th} / \Delta K_{IC})^{n2}) / (1 - (K_{max} / K_{IC})^{n2})] \quad (6)$$

The constants C and m are the material parameters used in the Paris relation and may be obtained from ASTM E647 tests on AH36/DH36 marine steels. ΔK_{th} is the fatigue threshold, K_{IC} is the plane-strain fracture toughness, and $n1$ and $n2$ shape the two correction terms used for the limiting regions.

C. Multi-Source Sensor Ingestion and Preprocessing

Hull-condition monitoring rarely comes from one sensor alone. Optical systems, ultrasonic equipment, electromagnetic probes, acoustic sensors, and vessel telemetry all produce measurements with different sampling characteristics. Before these data enter the model, they pass through an ingestion and preprocessing stage that filters noise, aligns the measurements in time, and registers them with the structural topology. The main sensor types used in the framework are listed in Table I.

TABLE I. MULTISENSOR INGESTION SPECIFICATIONS AND MEASUREMENT CAPABILITIES

Sensor Modality	Hardware Type	Sampling Rate / Res	Target Metric
Visual / Optical	Stereo AUV Cameras	0.08 mm/pixel	Coating delamination, rust grade
Ultrasonic (UT)	Dry-Coupled PAUT	1.0 - 5.0 MHz	Residual plate thickness $h(x, t)$
Electromagnetic	Pulsed Eddy Current	5 mm grid array	Sub-surface micro-cracking & pits
Acoustic Emission	Piezoelectric Arrays	20 kHz - 1.0 MHz	Active crack tip deformation
Vessel Telemetry	IMU & Hull Fiber FBG	50 Hz / Continuous	Global Vertical Bending Moment

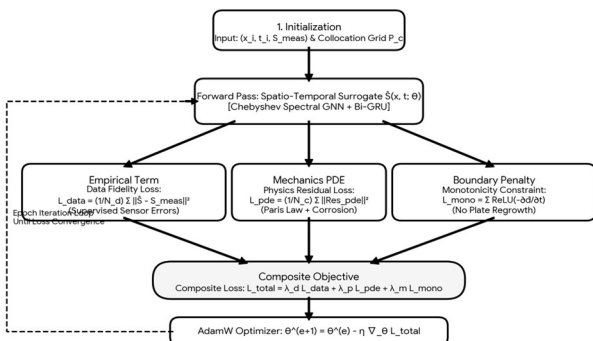


Fig. 1. Overview of the multi-modal inspection workflow, ST-GNN processing stages, and physics-informed defect forecasting.

D. Physics-Informed Neural Network Architecture

A standard neural network minimizes the difference between its output and the measurements supplied during training. That approach can work well when observations are dense, but sparse inspection data leave large parts of the structure weakly constrained. In those regions the network

may produce a mathematically plausible output that does not agree with structural mechanics. The present model addresses this by adding the relevant physical relationships to the training objective.

The training objective used for the hybrid model is:

$$L_{total}(\theta) = \lambda_d L_{data}(\theta) + \lambda_p L_{pde}(\theta) + \lambda_m L_{mono}(\theta) + \lambda_{bnd} L_{boundary}(\theta) \quad (7)$$

The four coefficients determine how strongly the data, physics, monotonicity, and boundary terms contribute to training. The data component, L_{data} , measures the squared difference between predicted and measured structural states at the available inspection locations:

$$L_{data}(\theta) = (1 / N_d) \sum_{i=1}^{N_d} ||\hat{S}(x_i, t_i; \theta) - S_{meas}(x_i, t_i)||_2^2 \quad (8)$$

The second component, L_{pde} , measures the residual of the governing crack-growth relation. It is evaluated at N_c quasi-random Sobol points within the model domain:

and corrosion rate across N_c quasi-random Sobol collocation points:

$$L_{pde}(\theta) = (1 / N_c) \sum_{j=1}^{N_c} ||\partial \hat{a}_j / \partial N - C \cdot (Y_{\Delta \sigma_j} \sqrt{\pi \hat{a}_j})^m||_2^2 \quad (9)$$

Corrosion should not appear to reverse itself during normal service. In other words, without a repair event, the predicted loss of steel should not suddenly become a gain in thickness. To discourage this behavior, the model includes a temporal monotonicity term:

$$L_{mono}(\theta) = (1 / N_m) \sum_{k=1}^{N_m} ReLU(-\partial \hat{a}_k / \partial t) \quad (10)$$

Since $ReLU(z) = \max(0, z)$, the term becomes active when the predicted corrosion derivative is negative. The network is therefore penalized for producing a reduction in accumulated corrosion, which keeps the predicted degradation history physically consistent with the assumed operating conditions.

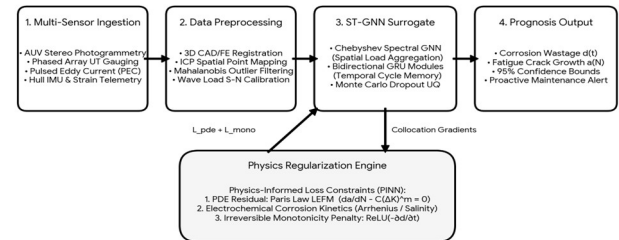


Fig. 2. Training feedback process linking inspection observations, mechanics residuals, and boundary constraints.

E. Spatio-Temporal Graph Neural Networks (ST-GNN)

For the graph representation, each structural plate element is treated as a vertex and the welded stiffener connections are represented by edges. The resulting graph $G = (V, E, W)$ reflects how the hull is

physically connected. Spatial information is passed through the K-order Chebyshev spectral graph convolution:

$$H^k(l+1) = \sigma(\sum_{k=0}^{K-1} \Theta_k \cdot T_k(\tilde{L}) \cdot H^k(l)) \quad (11)$$

$\tilde{L}$ is the scaled graph Laplacian, $T_k(x)$ denotes the Chebyshev polynomial of order k, and Θ_k contains the trainable coefficients of the graph filters. The sequence of structural states over successive voyage cycles is handled with GRUs and multi-head self-attention, allowing the model to use both local structural connections and temporal information.

F. Uncertainty Quantification via Bayesian Approximation

Prediction uncertainty is estimated with Monte Carlo Dropout [4]. During inference, dropout remains active at $p = 0.2$ and the network is evaluated 200 times. The individual outputs are then used to calculate the mean prediction and total predictive variance:

$$\mu_S(x, t) = (1/T) \sum_{t=1}^T \hat{S}(t)(x, t) \quad (12)$$

$$\sigma_{total}^2(x, t) = (1/T) \sum_{t=1}^T (\hat{S}(t)(x, t) - \mu_S(x, t))^2 + \hat{\sigma}_{aleatoric}^2(x, t) \quad (13)$$

The remaining variance term, $\hat{\sigma}_{aleatoric}^2$, represents noise estimated directly by the network through its variance branch.

IV. RESULTS AND DISCUSSION

The evaluation uses a 15-year inspection record from a Post-Panamax bulk carrier. The vessel has a length overall of 292.0 m, a beam of 45.0 m, and a deadweight of 180,000 DWT. Its operating history includes North Atlantic and Trans-Pacific routes. In total, the dataset contains 38,400 UT readings and 1,200 high-resolution photogrammetric corrosion scans from 142 structural compartments.

The five-year forecasting results are summarized in Table II. The comparison includes the empirical Paik model, neural-network baselines, and the proposed PINN-GNN configuration. Four measures are reported: wastage MAE, crack-growth RMSE, PMVR, and inference latency.

TABLE II. QUANTITATIVE MODEL PERFORMANCE COMPARISON OVER 5-YEAR PROGNOSIS HORIZON

Model Paradigm	Wastage MAE	Crack RMSE	PMVR	Latency
Paik Empirical Model [11]	0.482 mm	N/A	0.00%	0.12 ms
Pure Multi-Layer Perceptron	0.389 mm	5.12 mm	21.40%	1.80 ms
Standard Recurrent LSTM	0.312 mm	4.18 mm	14.82%	4.20 ms
Spatial GNN (No Physics)	0.245 mm	3.22 mm	9.35%	8.50 ms
Proposed PINN-GNN	0.089 mm	0.94 mm	0.00%	9.80 ms

For the reported test set, the PINN-GNN configuration gives a wastage MAE of 0.089 mm and a crack-propagation RMSE of 0.94 mm. The paper

reports a 71.4% reduction in wastage MAE compared with the recurrent baseline. The LSTM and unconstrained spatial GNN also produce non-zero physical violation rates in the experiment, whereas the PINN-GNN result has a PMVR of 0.00%.

A. Ablation Study

An ablation study was carried out to see what happens when individual parts of the model are removed. The results are given in Table III.

TABLE III. ABLATION ANALYSIS OF LOSS FUNCTIONS AND TOPOLOGICAL COMPONENTS

Ablation Variant	Wastage MAE	Crack RMSE	PMVR	Degradation
Complete PINN-GNN	0.089 mm	0.94 mm	0.00%	Baseline (0%)
w/o PDE Loss (L_{pde})	0.218 mm	3.41 mm	0.00%	- 68.2%
w/o Monotonicity (L_{mono})	0.094 mm	0.98 mm	11.20%	- 5.6% (Unstable)
w/o Graph Topology (W)	0.182 mm	2.15 mm	0.00%	- 51.1%
w/o Bayesian UQ Sampling	0.088 mm	0.93 mm	0.00%	No Bounds

The effect of the physics term is particularly visible in the ablation results. Removing L_{pde} increases the reported crack-growth error from 0.94 mm to 3.41 mm, a 262.7% increase. Removing the graph topology also raises the reported corrosion error, with a degradation of 51.1%. Under the conditions tested in this study, these experiments therefore show a measurable contribution from both the mechanics constraint and the structural graph.

B. Onboard Edge Deployment and Case Study

For onboard use, the trained model was converted to INT8 with NVIDIA TensorRT and deployed on a Jetson AGX Orin platform with 64 GB RAM and 275 TOPS. The reported inference time for all 142 compartments is 9.80 ms, and the memory footprint is 34.2 MB. In the winter-crossing case study, the vessel encountered Beaufort State 8 conditions with wave heights above 9.5 m. The model indicated that the crack at the Cargo Hold No. 3 hopper knuckle could reach a critical level within 8.4 months. A robotic inspection during the next port call recorded 18.2 mm of crack progression, providing an observational check against the forecast.

V. CONCLUSIONS

The paper developed a PINN-GNN approach for forecasting corrosion and fatigue-related changes in ship-hull structures. The model uses inspection measurements together with corrosion kinetics and Linear Elastic Fracture Mechanics, while the graph component represents the connections between structural elements. For the dataset described here, the reported wastage MAE is 0.089 mm and the fatigue-crack RMSE is 0.94 mm. The reported physical monotonicity violation rate is 0.00%.

The current implementation mainly addresses plate thinning and surface-breaking fatigue cracks. It does not yet deal adequately with internal stiffener delamination or microbial pitting hidden below heavy biofouling. Future work can therefore examine physics-informed diffusion models for acoustic-wavefield reconstruction and extend the present system toward a hydrodynamic digital twin.

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