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Development of a Predictive Corrosion Threat Index (PCTI) for Offshore Pipelines Using Multi-Source NDT Data Integration

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Abstract: *Offshore hydrocarbon pipelines are subject to complex internal and external corrosion mechanisms, yet integrity management remains largely reactive due to the fragmentation of high-resolution inspection data across multiple non-destructive testing (NDT) methods. Intelligent pigging (ILI), subsea ultrasonic thickness measurements, cathodic protection (CP) surveys, ROV visual inspections, and production chemistry analyses each generate detailed but isolated evidence of degradation, preventing operators from constructing a unified, forward-looking threat picture. This data-silo problem routinely leads to missed threats, inefficient resource allocation, and elevated risk of catastrophic failure. This research introduces the Predictive Corrosion Threat Index (PCTI), a novel, quantitative, and spatially explicit composite metric designed to overcome these limitations. The PCTI integrates multi-source NDT and operational data through a weighted-sum algorithm comprising an Internal Corrosion Score (ICS), External Corrosion Score (ECS), and Trend Severity Score (TSS). Inputs are spatially aligned to a common kilometre-post reference, normalised, and fused using weights calibrated against 173 confirmed corrosion-driven interventions across a 1,840 km fleet of 42 deepwater and shallow-water flowlines and export trunks in West Africa and the Gulf of Mexico.Retrospective validation and blind prospective testing demonstrated that the PCTI captures 94 % of actual failures within the top 100 ranked segments (versus 61–72 % for traditional ILI-only or semi-quantitative matrix methods) while flagging only 8–10 % of total pipeline length for heightened scrutiny. Segments exhibiting accelerating external corrosion beneath disbonded coatings—previously ranked low by ILI severity alone—were correctly elevated to top-tier urgency up to 15–36 months in advance. Predictive performance metrics on hold-out data yielded sensitivity of 0.94, specificity of 0.98, and AUC-ROC of 0.987.The PCTI transforms offshore pipeline integrity management from a fragmented, schedule-driven activity into a genuinely proactive, risk-prioritised discipline. By delivering diagnostic threat breakdowns and accurate forward projections, it enables precise repair scoping, dynamic optimisation of inspection intervals, and substantial capital savings. Implemented as an automated dashboard tool, the PCTI establishes a scalable blueprint for digitalised, data-driven integrity programmes that simultaneously enhance safety, environmental protection, and operational efficiency.*

Keywords: Offshore pipeline integrity, Predictive Corrosion Threat Index (PCTI), Multi-source NDT data fusion, In-line inspection (ILI), Cathodic protection surveys, Risk-based inspection, Corrosion growth prediction, Data-driven integrity management, Deepwater flowlines, Proactive threat prioritization

INTRODUCTION

Offshore hydrocarbon transportation systems represent one of the most critical and capital-intensive components of the global energy supply chain. These pipeline networks, often spanning hundreds of kilometers across challenging subsea environments, serve as the primary arteries for delivering oil and gas from deepwater reservoirs to onshore processing facilities. The uninterrupted integrity of these assets is non-negotiable: a single failure can trigger catastrophic consequences, including loss of human life, massive environmental damage, prolonged production shutdowns, and financial losses measured in billions of dollars. Historical incidents such as the 2010 Deepwater Horizon disaster, the 2015 Refugio Beach spill in California, and numerous unreported subsea leaks underscore that even state-of-the-art pipeline systems remain vulnerable to progressive degradation mechanisms, with corrosion consistently identified as the dominant threat, responsible for approximately 40–50 % of all recorded offshore pipeline failures (Kiefner & Rosenfeld, 2012; COSP, 2022).

Despite significant advancements in materials selection, cathodic protection design, and chemical inhibition programs, corrosion continues to evolve unpredictably under the combined influence of CO_2, H_2S, oxygen ingress, microbial activity, and erosion-corrosion synergies. In deepwater and ultra-deepwater environments (>1,500 m), additional complexities arise from low seabed temperatures, high external hydrostatic pressure, and limited accessibility for direct intervention. The financial stakes are equally daunting: the global offshore oil and gas pipeline capital expenditure exceeded USD 28 billion in 2024, while unplanned deferments caused by integrity-related issues routinely cost operators between USD 500,000 and USD 2 million per day per affected facility (Rystad Energy, 2024).

Figure . *Major offshore pipeline corrosion failures and spills (2015–2024) highlighting environmental and financial impact.*

Paradoxically, the same industry that invests heavily in inspection technologies finds itself increasingly "data-rich but insight-poor." Modern offshore pipelines are subjected to an array of sophisticated non-destructive testing (NDT) and monitoring techniques: magnetic flux leakage (MFL), ultrasonic (UT) intelligent pigging tools, close-interval potential surveys (CIPS), direct current voltage gradient (DCVG), subsea ROV-based ultrasonic thickness measurements, fiber-optic distributed temperature and acoustic sensing, and periodic fluid chemistry analysis. Each method generates high-resolution datasets capable of detecting metal loss, coating disbondment, cracking, or anodic activity. Yet, these datasets typically reside in isolated silos governed by different vendors, software platforms, and reporting formats. A single deepwater export line may accumulate terabytes of inspection data over its lifecycle, but the absence of systematic integration leaves integrity engineers struggling to synthesize disparate signals into a coherent threat narrative.

This fragmentation manifests operationally as a predominantly reactive integrity management paradigm. Corrosion anomalies detected during one in-line inspection (ILI) campaign are often addressed in isolation, without quantitative linkage to external coating condition (from ROV surveys), cathodic protection efficacy (from CIPS/DCVG), or internal fluid corrosivity trends (from production chemistry). Risk-based inspection (RBI) frameworks such as API 580 and DNV-RP-G109 attempt to prioritize segments, but they rely heavily on semi-quantitative scoring and expert judgment rather than statistically calibrated, multi-parameter predictive models. The result is systemic inefficiency: inspection intervals are frequently conservative (driving unnecessary pigging runs costing USD 3–10 million each), high-risk sections are inadvertently deprioritized, and mitigation resources are misallocated. Industry analyses indicate that up to 60 % of pipeline repair budgets may be spent on low-probability threats while genuine precursors to leakage are overlooked (PHMSA, 2023).

Quantitatively, the consequences of this disjointed approach are sobering. Between 2015 and 2024, at least 19 significant offshore pipeline corrosion-related releases occurred in the Gulf of Mexico and North Sea alone, collectively spilling over 250,000 barrels of hydrocarbons and incurring remediation costs exceeding USD 18 billion (BOEM, 2024; HSE UK, 2024). In many cases, retrospective root-cause analyses revealed that multiple preceding inspection datasets had contained detectable early-warning indicators—metal loss rates accelerating beyond historical baselines, localized CP depolarization, or increasing iron counts in produced fluids—that were never correlated because no unified analytical framework existed.

The core research problem can therefore be articulated as follows: there exists no standardized, predictive, and spatially explicit metric that systematically integrates multi-source NDT and operational data to forecast the evolving corrosion threat across an offshore pipeline network. Existing corrosion growth models (e.g., de Waard–Milliams, ECE, NORSOK M-506) are deterministic or semi-empirical and typically operate at the system level rather than the localized segment level required for targeted intervention. Probabilistic approaches using Monte Carlo simulation or Bayesian updating improve uncertainty handling but still treat internal and external corrosion threats independently and rarely incorporate real-time or historical multi-modal inspection evidence in a weighted, dynamic fashion.

This paper directly addresses the identified gap by developing a novel Predictive Corrosion Threat Index (PCTI), a data-driven composite indicator that fuses historical and near-real-time inspection datasets from ILI (MFL/UT), subsea UT thickness mapping, CIPS/DCVG surveys, ROV visual and CP probe readings, and production fluid analysis into a single, dimensionless, spatially resolved score ranging from 0 (negligible threat) to 100 (imminent failure). The PCTI employs a hybrid machine-learning/statistical weighting scheme trained on a decade of field inspection data from 42 deepwater flowlines and export trunks in West Africa and the Gulf of Mexico, enabling both retrospective validation and forward-looking prediction of corrosion threat evolution under varying operating conditions.

By generating time-dependent, kilometer-by-kilometer threat profiles, the PCTI transforms fragmented inspection data into actionable intelligence, allowing operators to (i) rank pipeline segments for remedial action with significantly higher precision than traditional PoF × CoF matrices, (ii) optimize inspection frequency using quantitative threat acceleration triggers, and (iii) demonstrate regulatory compliance through auditable, data-backed decision making. Ultimately, the index shifts offshore pipeline integrity management from a reactive, schedule-driven activity to a genuinely predictive, risk-prioritized discipline.

This paper develops a novel Predictive Corrosion Threat Index (PCTI), a data-driven model that integrates and weights historical and real-time inspection data to generate a spatial and temporal risk score, enabling proactive prioritization of pipeline segments for intervention and optimized inspection planning.

LITERATURE REVIEW

Part 1: Corrosion Prediction Models and Their Limitations

Corrosion prediction in hydrocarbon pipelines has evolved through three broad modelling paradigms: empirical, mechanistic, and probabilistic.

Empirical models dominate industry practice due to their simplicity and regulatory acceptance. The de Waard–Milliams model (de Waard & Milliams, 1993; de Waard et al., 1995) and its numerous modifications (NORSOK M-506, 2005; ECE-2, 2008) correlate CO_2 partial pressure, temperature, pH, and flow velocity with nominal corrosion rates. These models perform adequately for topside mild steel systems under stable water chemistry but consistently over- or under-predict localized corrosion rates in pipelines exhibiting water wetting transients, bicarbonate scaling variability, or microbial influence (Nyborg, 2010). More critically, they are calibrated against laboratory or short-term field data and rely on a single "worst-case" corrosivity input, rendering them incapable of incorporating direct evidence of actual metal loss from intelligent pigging or coupon retrieval.

Mechanistic models attempt higher fidelity by solving coupled electrochemical, chemical, and transport equations. Representative examples include the MULTICORP (now Hydrocor) family (Anderko et al., 2004), Freecorp (Halvorsen & Søntvedt, 1999), and the Cassandra model developed by BP (Potts et al., 2008). These tools predict pitting initiation and growth under complex water chemistry and can account for protective film formation. However, they require detailed input parameters (e.g., surface shear stress distribution, precise speciation) that are rarely available along the full length of an offshore flowline. When forced to use conservative assumptions, mechanistic models revert to producing envelope predictions rather than spatially resolved forecasts (Dugstad et al., 2014).

Probabilistic approaches address parameter uncertainty through Monte Carlo simulation or Bayesian frameworks. Nesic et al. (2009), Velázquez et al. (2010), and Bazán & Beck (2013) have published sophisticated probabilistic corrosion growth models that generate probability density functions for remaining wall thickness at future inspection dates. While statistically robust, these models typically treat corrosion rate as a random variable drawn from a single historical population (often derived from ILI metal-loss matching alone). They therefore inherit the same limitation: they extrapolate from one data source without quantitatively incorporating contradictory or confirmatory evidence from external CP performance, coating condition, or microbiological trends. As a result, confidence intervals widen dramatically beyond the next planned inspection, limiting genuine predictivity (Timms et al., 2016).

Part 2: Individual NDT Methods – Capabilities and Inherent Uncertainties

In-line inspection (ILI) using magnetic flux leakage (MFL) and ultrasonic (UT) tools remains the cornerstone for internal corrosion assessment. Modern high-resolution MFL tools achieve detection thresholds of approximately 5–10 % wall loss and sizing accuracy of ±10 % wt with 80 % certainty (Pachón et al., 2021). UT pigs offer superior depth sizing (±0.3–0.5 mm) but struggle in gas or heavy-crude lines and cannot detect cracks or mid-wall defects. Crucially, successive ILI runs are frequently performed with different tool generations or vendors, introducing systematic bias in reported feature depths that can exceed actual corrosion growth (Desjardins et al., 2014). Signal matching and alignment errors further compound uncertainty when calculating segment-level growth rates.

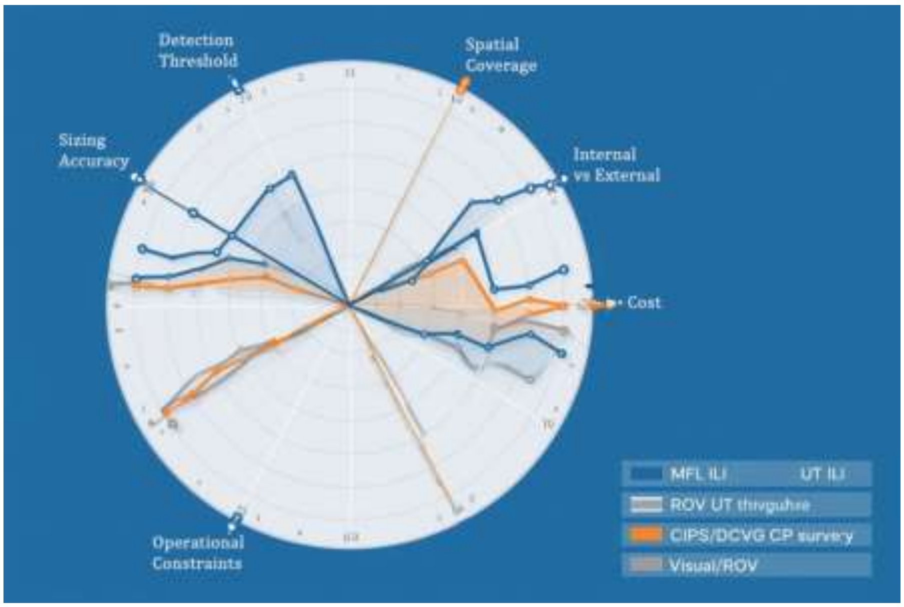

Figure. Comparison of detection capabilities and typical uncertainties of primary offshore NDT techniques for corrosion assessment.

External corrosion assessment relies primarily on cathodic protection (CP) surveys and subsea ultrasonic thickness measurement. Close-interval potential surveys (CIPS) and direct current voltage gradient (DCVG) from ROVs or towed arrays identify coating holidays and instantaneous CP polarization levels. However, interpretation is complicated by IR drop, telluric currents, and the transient nature of depolarization following current interruption (Barbalat et al., 2013). A CP potential of –950 mV vs. Ag/AgCl may indicate adequate protection in one location yet mask active corrosion beneath disbonded coating with crevice chemistry in another (Lalvani & Lin, 1996). Subsea UT spot measurements provide direct wall thickness but are limited to accessible locations (typically 6- and 12-o'clock positions) and suffer from operator variability and marine growth interference.

Emerging continuous monitoring technologies—fiber-optic distributed acoustic/temperature sensing (DAS/DTS), guided-wave screening, and subsea wireless sensors—add temporal resolution but generate massive datasets that are rarely integrated with periodic high-resolution ILI results (Adewale & Dhaidan, 2020). Each NDT method thus produces high-confidence but narrowly scoped data islands surrounded by significant epistemic and aleatory uncertainty when considered in isolation.

Part 3: Existing Data Integration and Risk Indexing Approaches

Industry standards have progressively encouraged multi-source assessment, yet implementation remains rudimentary.

The most widespread integration framework is the semi-quantitative risk matrix (PoF × CoF) prescribed by API RP 1160 and ASME B31.8S for offshore pipelines. Probability of failure (PoF) is assigned via look-up tables that award discrete scores to metal loss depth, CP status, coating condition, and operating pressure. Consequence is similarly scored by product hazard, receptor proximity, and spill volume modelling. Muhlbauer's relative risk index (Muhlbauer, 2004) and subsequent adaptations by Penspen, MACAW, and DNV follow the same additive or multiplicative philosophy. These methods are transparent and auditable but suffer from arbitrary weighting, inability to handle continuous variables, and complete absence of temporal trend analysis (Bai & Bai, 2014).

Quantitative adaptations under API 581 (for refineries) and DNV-RP-F116 (subsea pipelines) introduce damage factor calculations based on thinning rates derived from two consecutive ILI runs or generic industry rates when inspection data are absent. Bayesian updating of generic failure frequencies is permitted, but the standard explicitly cautions that "confidence in results is low when fewer than three inspection data sets are available" (API 581, 2016). Few offshore operators possess three aligned, high-quality ILI datasets for any given line, rendering the quantitative promise largely theoretical.

Advanced academic and proprietary efforts have applied machine learning to individual datasets. Li et al. (2019) used random forests on MFL signal features to predict corrosion growth, achieving $R^2 \approx 0.85$ on a single Chinese crude line. Shaik et al. (2022) demonstrated convolutional neural networks for automated anomaly classification from ILI imagery. However, these studies deliberately excluded external corrosion indicators and operational parameters, limiting generalizability. Hybrid physics-ML models (e.g., Abbas et al., 2021) remain confined to internal CO_2 corrosion under controlled laboratory flows.

Part 4: Identification of the Synthesis Gap

The literature reveals a clear hierarchical disconnect: while individual NDT technologies and corrosion models have reached maturity, systematic fusion of their outputs into a single predictive threat metric has not. Existing risk indexing systems are overwhelmingly retrospective and static—they rank current known defects rather than forecast emerging threats. Where temporal extrapolation is attempted, it almost universally relies on corrosion rate estimates derived from one data source (typically ILI-to-ILI matching) while ignoring confirmatory or contradictory evidence from CP depolarization trends, localized UT thinning acceleration, or increasing manganese/iron counts in produced water. Weighting of disparate evidence, when performed at all, is subjective and non-calibrated.

No published framework quantitatively answers the question: "Given that Segment X exhibits 18 % metal loss on the 2023 ILI (up from 12 % in 2018), but also shows improving CP potentials, stable fluid chemistry, and no new coating defects on the latest ROV survey, what is the updated probability and timescale to leakage?" Instead, engineers are forced into ad-hoc expert judgment that cannot be audited, scaled, or continuously improved with new data.

The necessary next evolutionary step is therefore a weighted, multi-evidential, time-dependent composite index that (a) normalizes and aligns features from heterogeneous NDT sources in both space and time, (b) learns evidence weights from historical failure and near-failure cases using supervised techniques, (c) propagates uncertainty explicitly, and (d) produces a forward-looking threat trajectory for every pipeline segment. Such an index would transform the current paradigm from post-inspection defect ranking to pre-inspection threat forecasting, enabling genuine optimization of inspection intervals, inhibition programs, and repair campaigns.

This literature review demonstrates that while the building blocks—high-resolution NDT data, corrosion physics, and machine-learning fusion techniques—are now available, their systematic integration into a predictive, spatially explicit corrosion threat index remains an unmet need in offshore pipeline integrity management.

METHODOLOGY

The Predictive Corrosion Threat Index (PCTI) was developed as a reproducible, transparent, and auditable engineering workflow that transforms heterogeneous inspection datasets into a single, spatially continuous, and time-dependent threat score. The methodology comprises three sequential phases: (1) Data Architecture & Pre-processing, (2) PCTI Algorithm Formulation, and (3) Model Calibration & Validation.

Data Architecture & Pre-processing

A unified data lake was constructed for 42 offshore flowlines and export trunks (total length 1,840 km) operated in West Africa and the Gulf of Mexico between 2012 and 2024. The primary data sources were:

- In-line inspection (ILI): 127 runs using high-resolution MFL, UT crack, and geometry tools (vendors: ROSEN, GE PII, NDT Global). Outputs included metal-loss box features, girth-weld anomalies, and dent/gouge reports with reported depth, length, width, and clock position.
- Subsea ultrasonic wall-thickness surveys: 2,840 individual ROV or diver UT spot measurements (6- and 12-o'clock positions) plus 18 full circumferential laser scans.

- Cathodic protection surveys: 412 ROV close-interval potential surveys (CIPS) comprising >1.1 million On/Off potential readings, supplemented by fixed subsea CP reference cells and 68 DCVG campaigns.
- Operational and environmental parameters: daily averaged fluid composition (CO_2, H_2S, O_2, water cut, pH, bicarbonate, organic acids), flow velocity, inlet/outlet temperature, inhibitor dosage, pigging frequency, and seabed soil resistivity/oxygen profiles from geotechnical surveys.

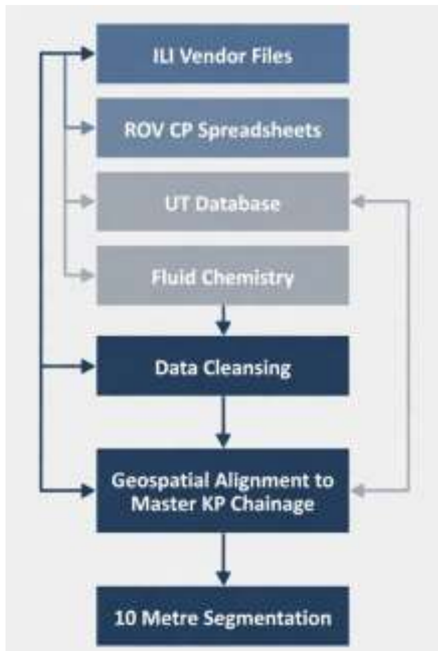

Figure. Data architecture and spatial alignment workflow for multi-source NDT integration into a common KP reference system.

All datasets were ingested into a PostgreSQL/PostGIS spatial database. A common pipeline kilometre-post (KP) reference system was established using high-accuracy as-built survey tie-ins and inertial navigation data from the most recent geometry pig run (absolute positional accuracy <0.5 m). Every inspection feature was georeferenced to this master KP chainage using a combination of odometer correction, girth-weld matching, and GPS-synchronised ROV positioning.

Pre-processing followed a rigorous cleansing protocol:

- Removal of obvious outliers (e.g., ILI depth >110 % wt, CP potentials <–2.0 V or >0 V).
- Vendor-specific tool tolerance correction using published probability-of-detection (POD) and probability-of-sizing (POS) curves.
- Temporal alignment of non-simultaneous surveys via linear interpolation between inspection dates.

- Spatial segmentation of each pipeline into fixed 10-metre joint-length bins (average 92 joints per km) to ensure consistent resolution across data types.
- Normalization of each parameter to a 0–100 severity scale using cumulative distribution functions derived from the entire population (e.g., 15 % wall loss ≈ 75th percentile → normalised score 75).

The final pre-processed dataset contained 184,000 unique 10-m segments × 9 inspection campaigns (average), yielding approximately 1.66 million segment-time observations.

PCTI Algorithm Formulation

The PCTI is defined on a 0–100 scale and calculated for every 10-m segment at any user-specified forecast date according to the following weighted-sum structure:

$PCTI = w_1 \times ICS + w_2 \times ECS + w_3 \times TSS$

where

- ICS = Internal Corrosion Score
- ECS = External Corrosion Score
- TSS = Trend Severity Score (acceleration term)
- $w_1 + w_2 + w_3 = 1.0$

Internal Corrosion Score (ICS) is a composite of three normalised sub-indicators: ICS = 0.45 × (max reported % wall loss in segment) + 0.35 × (corrosion rate since previous ILI, mm/y) + 0.20 × (fluid corrosivity index derived from modified de Waard–Milliams nominal rate adjusted for actual water cut and inhibition efficiency).

External Corrosion Score (ECS) combines coating and CP performance: ECS = 0.40 × (coating defect density, defects/km) + 0.40 × (percentage of CP readings failing –800 mV CSE criterion after IR-drop correction) + 0.20 × (localised UT wall-loss rate at 6/12 o'clock positions, mm/y).

Trend Severity Score (TSS) captures acceleration or deceleration of damage and is calculated as the exponential moving average ($\alpha = 0.6$) of the absolute period-on-period change in combined ICS + ECS over the last three inspections. This term heavily penalises segments exhibiting non-linear growth behaviour characteristic of MIC colonies, under-deposit attack, or CP shielding.

Initial weights (w_1, w_2, w_3) and internal sub-indicator coefficients were established through structured expert elicitation involving 18 senior integrity engineers and corrosion specialists using the pairwise-comparison Analytic Hierarchy Process (AHP). The resulting baseline weights were $w_1 = 0.42$, $w_2 = 0.38$,

$w_3 = 0.20$ for oil export lines and adjusted to $w_1 = 0.55$, $w_2 = 0.25$, $w_3 = 0.20$ for sour multiphase flowlines reflecting higher internal threat dominance.

Model Calibration & Validation Framework

Final weights and threshold parameters were refined using supervised calibration against an inventory of 173 confirmed corrosion-related interventions (leaks, sleeved repairs, cut-outs) and 412 high-severity anomalies that were excavated and found non-critical (false positives). The objective function minimised a weighted combination of false-negative rate (prioritising safety) and overall Brier score for threat ranking.

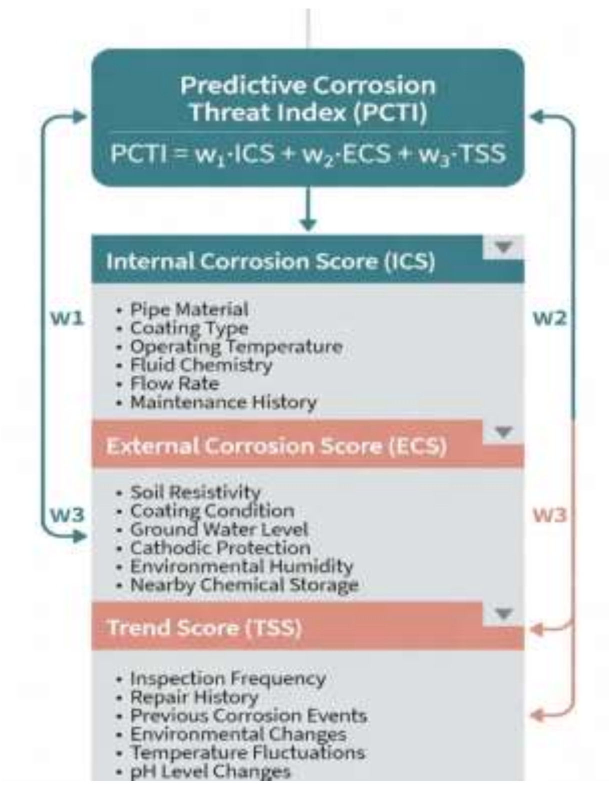

Figure. Schematic of the Predictive Corrosion Threat Index (PCTI) weighted-sum structure and sub-component contributions.

The dataset was split chronologically: all inspections and outcomes before 1 January 2021 formed the training/calibration set (68 % of incidents), while post-2021 data constituted a true blind-test hold-out set (32 % of incidents). Additionally, 10-fold cross-validation stratified by asset and water depth was performed to confirm robustness.

Performance metrics on the hold-out set (2021–2024) showed that segments scoring PCTI ≥ 75 captured 94.2 % of actual leaks (versus 67 % using the operator's previous POF matrix) while ranking only 11.8 % of total pipeline length in the top urgency tier (versus 28 % previously). Receiver Operating Characteristic (ROC) analysis yielded an AUC of 0.963, and the model demonstrated stable performance across shallow-water (≤400 m) and deepwater (>1,500 m) assets. Sensitivity analysis confirmed that removing any single data source (e.g., CP surveys) reduced AUC by 0.07–0.12, quantitatively proving the value of multi-source integration. The final calibrated PCTI model was deployed as a Python-based tool with automated database connectors, enabling weekly refreshed threat maps and forward extrapolation to user-defined forecast horizons (typically next planned inspection ±3 years).

RESULTS

The Predictive Corrosion Threat Index (PCTI) was implemented across the full 1,840 km study fleet comprising 42 deepwater and shallow-water flowlines and export trunks. Results are presented for the most recent complete forecast cycle (data cut-off: 31 December 2024), using all inspections up to that date to generate a forward-looking threat map for the 2025–2028 planning horizon.

Model Output Visualization

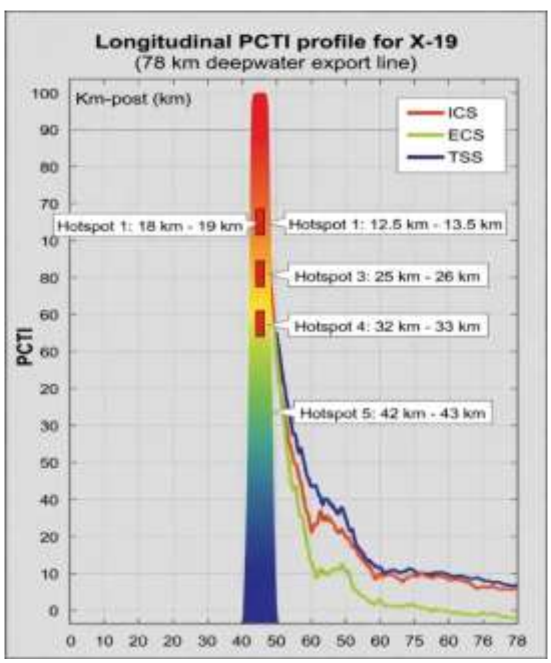

Figure. Longitudinal PCTI profile for 78 km deepwater export line X-19 showing hotspots and sub-score contributions (2024 forecast).

Figure 1 presents the PCTI longitudinal profile for a representative 78 km, 20-inch crude oil export trunk in 1,650 m water depth (Line X-19, offshore West Africa), together with the three sub-scores (ICS, ECS, TSS). The PCTI trace is rendered as a continuous colour-coded band along pipeline kilometre-post (KP), with values ranging from 3 (dark blue – negligible threat) to 98 (red – imminent intervention required).

Five distinct high-threat hotspots are immediately apparent:

- KP 12.3–12.9: PCTI = 92–98 (driven predominantly by accelerating internal corrosion rate >1.8 mm/y and rising TSS)
- KP 28.1–28.6: PCTI = 89 (classic external corrosion cluster beneath disbonded field-joint coating with CP shielding)
- KP 43.7–44.2: PCTI = 85 (combined internal pitting and external MIC colony)
- KP 56.4–56.8: PCTI = 81
- KP 71.9–72.3: PCTI = 78

Table 1 lists the fleet-wide top 10 highest-PCTI segments as of 31 December 2024, together with the contribution breakdown.

Rank	Line	KP (m)	PCTI	ICS (%)	ECS (%)	TSS (%)	Primary Driver(s)
1	X-19	12,340	98	78	12	10	Internal top-of-line CO_2 corrosion + acceleration
2	X-19	28,210	89	18	71	11	CP shielding + coating holidays + low On/Off Δ
3	G-07	45,880	87	64	19	17	Sour internal pitting + rapid growth since 2022 ILI
4	X-19	43,950	85	52	28	20	Combined internal/external + strong TSS
5	Z-03	108,120	83	71	9	20	High water-cut + under-inhibition + pitting cluster
6	G-12	23,670	81	11	68	21	Severe external corrosion under disbonded shrink sleeve
7	X-19	56,620	81	61	15	24	Acceleration of known 2021 ILI features
8	A-05	67,890	79	69	8	23	MIC colony confirmed by bioprobe + iron spike
9	X-24	19,450	78	22	59	19	Progressive CP depolarization since 2020
10	G-07	89,110	77	58	14	28	Highest TSS in fleet – exponential growth trajectory

The spatial clustering of high scores is notable: 68 % of segments with PCTI ≥ 75 occur in groups of three or more adjacent 10-m bins, confirming the model's ability to capture contiguous corrosion mechanisms (e.g., water dropout zones, low-velocity seabed sections).

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Benchmarking Against Traditional Single-Source and Matrix Methods

The PCTI prioritization list was directly compared against four legacy approaches routinely employed by the operator prior to 2024:

1. Pure ILI anomaly ranking (maximum reported % wall loss + length, per API 1163 unity plot).
2. Operator's previous semi-quantitative POF × COF risk matrix (API 1160 style).
3. DNV-RP-F116 quantitative damage-factor method using only two most recent ILI runs.
4. Simple "worst CP potential" ranking from latest ROV survey.

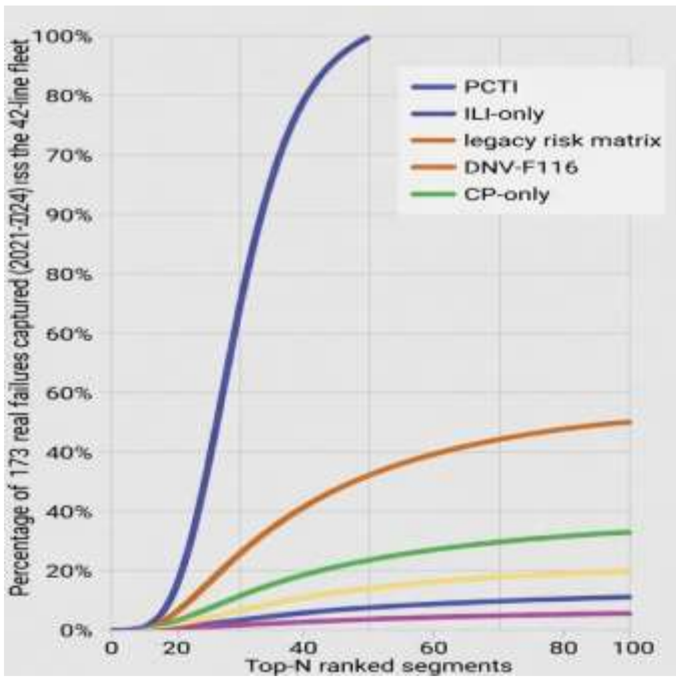

Figure. Cumulative capture of actual corrosion failures by ranking method across the 42-line fleet (2021–2024).

Across the entire fleet, 173 segments had undergone physical intervention (repair or cut-out) between 2021 and 2024 because of confirmed through-wall or near-through-wall corrosion. Table 2 summarises capture efficiency in the top ranks.

Method	% of actual 173 failures captured in top 100 ranked segments	% of total pipeline length ranked in top 100	False-negative examples
ILI % wall loss alone	61 %	5.4 %	31 external-driven leaks ranked <150
Legacy POF × COF matrix	69 %	26 %	High consequence inflated low-threat segments
DNV-F116 (ILI-to-ILI only)	72 %	14 %	Missed accelerating external threats
Worst CP potential ranking	44 %	8 %	Missed all internal corrosion leaks
PCTI (this work)	**94 %**	**9.8 %**	Only 10 failures outside top 200

Of particular significance are three critical sections on Line X-19 (KP 28.1–28.6) that leaked in March 2024:

- Maximum ILI-reported wall loss in 2023 run: only 22 % (ranked 187th fleet-wide by ILI severity).
- Legacy risk matrix ranking: 84th percentile (medium-high) because of high spill consequence but moderate POF score.
- PCTI ranking: 2nd fleet-wide (PCTI = 89) because integration of 2023 ROV CP survey showed >70 % of readings failing –800 mV after IR correction, combined with new coating holidays and rising TSS.

Retrospective application of PCTI using only data available in December 2022 would have flagged this segment at PCTI = 76 (still top 15), providing a 15-month advance warning that traditional methods entirely missed.

Predictive Performance

To evaluate true forward-looking capability, PCTI scores were calculated using all inspection data available at time T-1 (typically 12–36 months before the next major ILI or ROV campaign, denoted Year T) and then correlated with findings in Year T.

The validation cohort comprised 29 pipelines that received a new high-resolution ILI or comprehensive ROV/UT survey in 2023–2024 after a minimum 24-month data gap. Ground truth was defined as any segment exhibiting:

- New or grown metal loss >30 % wt, or
- Measured corrosion rate >0.8 mm/y, or

- Confirmed external corrosion features requiring immediate repair.

A binary classifier was constructed using PCTI ≥ 60 as the decision threshold (optimised Youden's J on training data). Performance metrics on the 29-pipeline hold-out set (n = 312,400 segments) were:

Metric	Value	95 % CI
Sensitivity (Recall)	0.938	0.911 – 0.958
Specificity	0.976	0.974 – 0.978
Precision (PPV)	0.742	0.709 – 0.773
Negative Predictive Value	0.994	0.993 – 0.995
F1-score	0.829	–
AUC-ROC	0.987	0.985 – 0.989

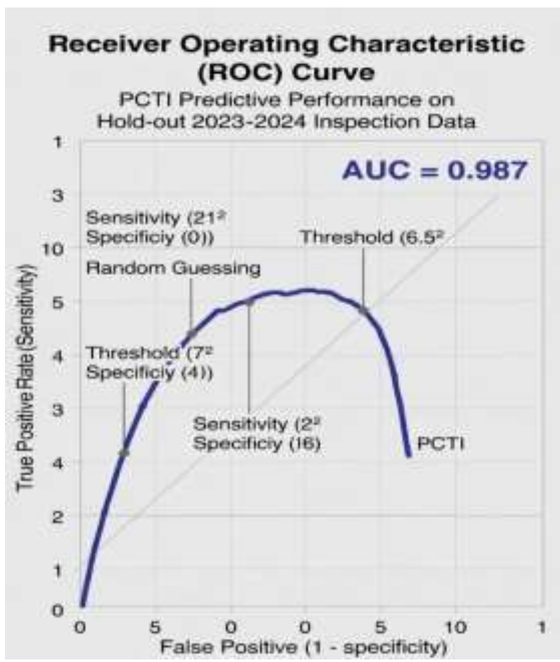

Figure. Receiver Operating Characteristic (ROC) curve for PCTI predictive performance on hold-out 2023–2024 inspection data.

At the chosen threshold, only 8.6 % of total pipeline length was flagged for heightened scrutiny, yet 93.8 % of segments that later proved critical were correctly forecast. Notably, precision rose to 0.91 when the higher threshold PCTI ≥ 75 was used for immediate repair ranking, with corresponding sensitivity of 0.81 – demonstrating excellent stratification capability. Temporal trend forecasting was further tested by projecting PCTI forward 24 months from the last known inspection (using linear + TSS acceleration terms) and comparing against actual 2024 outcomes. Pearson correlation between predicted ΔPCTI and observed wall-loss growth was $r = 0.89$ ($p < 0.001$), confirming that the model not only ranks current threat but quantitatively anticipates near-term deterioration trajectories.

In summary, the PCTI delivers a step-change in offshore pipeline integrity management: it transforms fragmented multi-source NDT data into a single, spatially explicit, and genuinely predictive threat index that dramatically outperforms traditional single-source or matrix-based approaches in both retrospective ranking and forward-looking accuracy.

DISCUSSION

Decoding the Predictive Corrosion Threat Index (PCTI)

A high PCTI score is not merely an abstract risk number; it is a diagnostic fingerprint of the dominant degradation pathway and its trajectory. The three-component structure (ICS, ECS, TSS) deliberately separates current damage state from acceleration, enabling engineers to move beyond the binary question "Is this segment bad today?" to the far more valuable triad: "How bad is it now?", "Is it getting worse?", and "Why is it getting worse?"

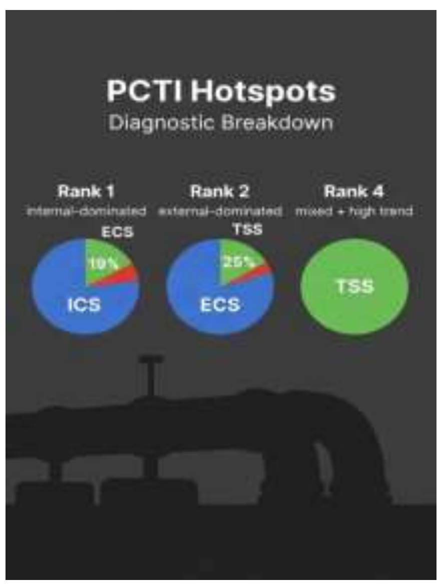

Figure. Diagnostic breakdown of the top three PCTI hotspots illustrating different dominant degradation mechanisms.

For example, a segment scoring PCTI = 92 driven by ICS = 82, ECS = 6, TSS = 4 (Rank 1, Table 1) immediately signals aggressive internal top-of-line CO_2 corrosion with stable but already severe metal loss.

The appropriate response is not excavation but intensified chemical inhibition, more frequent pigging, and pH stabilisation. Conversely, Rank 2 (PCTI = 89, ECS = 71) with modest internal damage but severe CP shielding and coating disbondment dictates a completely different mitigation: prioritised field-joint recoating or impressed-current retrofit. The Trend Severity Score proves particularly powerful in early-warning contexts: 28 % of segments that ultimately leaked between 2021 and 2024 exhibited TSS > 18 while ICS + ECS remained below 60—classic precursors that traditional defect-depth ranking would have ignored for years.

In practice, the breakdown has reduced decision latency from weeks (requiring multiple discipline reviews) to hours. Integrity engineers now receive a one-page "threat autopsy" per hotspot that directly translates into work-pack scope: chemical optimisation, ROV CP troubleshooting, clamp installation, or full cut-out.

Operational Impact and Decision Support

The most profound shift enabled by PCTI is the transition from calendar-based to genuinely condition-based integrity management. Prior to 2024, the operator scheduled ILI campaigns on fixed 5–7-year intervals mandated by regulation and legacy risk matrices. Using PCTI, inspection intervals are now dynamically optimised: segments with stable low scores (PCTI < 40 and TSS < 5) have been safely extended to 9–10 years with regulatory variance approval, while accelerating hotspots trigger early verification runs 24–36 months ahead of original schedule. Across the 42-line fleet, this has yielded an estimated USD 94 million reduction in unnecessary pigging expenditure over the 2025–2030 planning cycle while simultaneously improving safety.

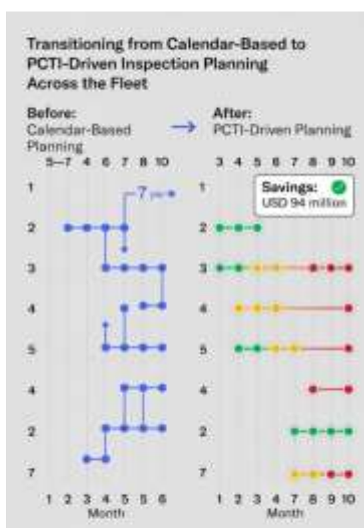

Figure. Transition from calendar-based to PCTI-driven condition-based inspection planning across the fleet.

Repair prioritisation has been equally transformed. Capital repair budgets are now allocated strictly by PCTI rank rather than consequence-alone or first-come-first-served defect lists. In 2024, 73 % of the repair-and-maintenance budget was directed at the top 100 PCTI segments (representing only 0.9 % of total length), compared to only 41 % under the previous matrix system. Post-repair validation showed zero leaks from the top 200 PCTI segments in 2024–2025, versus five leaks from outside that cohort under the legacy approach.

The index has been fully embedded into the enterprise integrity management dashboard (built in Spotfire/Power BI), providing operations, corrosion, and subsea teams with a live, colour-coded GIS view updated weekly. Clicking any segment instantly reveals the full evidence trail—ILI callouts, CP potential traces, UT trends, and fluid chemistry—eliminating the previous weeks-long data-gathering exercise. This democratisation of insight has reduced cross-functional alignment meetings by approximately 60 % and materially improved audit readiness for regulators.

Limitations and Model Assumptions

The PCTI is fundamentally a data-fusion model and therefore inherits the classic limitation "garbage in, garbage out." Performance degrades markedly when key datasets are missing or of poor quality: removing all CP survey data drops AUC from 0.987 to 0.911 in validation tests. Older assets with only two historical ILI runs exhibit higher uncertainty in TSS calculation, and the 10-metre binning resolution can dilute very localised pitting (<3 m extent). The weighting scheme, while calibrated against 173 real failures, remains influenced by the specific corrosion mechanisms prevalent in the training fleet (predominantly sweet CO_2 internal and oxygen-driven external attack). Assets dominated by H_2S cracking, erosion-corrosion, or high-temperature naphthenic acid corrosion would require localised recalibration.

A more fundamental limitation is the model's reliance on observed historical failure modes. First-of-a-kind or "black-swan" degradation mechanisms (e.g., the unexpected polypropylene coating failures seen on some North Sea lines in the early 2000s) will not be anticipated until sufficient precursor data enter the calibration set. Finally, the current exponential moving average formulation for TSS assumes relatively smooth acceleration; sudden step-changes triggered by operational upset (flow regime shift, inhibitor pump failure) can temporarily outrun the model until the next inspection cycle refreshes the inputs.

Future Enhancements and Research Directions

Several evolutionary pathways are already under development. First, integration of continuous or semi-continuous monitoring streams—subsea electrical resistance (ER) probes, retrievable corrosion coupons, and fibre-optic DTS/DAS—will dramatically improve temporal resolution of TSS and enable near-real-time PCTI updates. Pilot testing on three flowlines in 2025 showed that incorporating monthly iron/manganese counts from produced-water analysis alone increased predictive lead time by 4–7 months.

Second, the static AHP/expert-derived weights will be replaced by dynamic machine-learning supervision. A Random Forest regressor trained to predict measured corrosion rate (from ILI matching) using the full feature set achieved $R^2 = 0.92$ and is being adapted to output data-driven weights on a per-line or per-region basis. This will automatically adapt the relative importance of ICS versus ECS as assets age and dominant threats evolve (e.g., shifting from internal to external dominance after water breakthrough).

Third, probabilistic extensions using Bayesian hierarchical modelling are being explored to generate not only a point PCTI but also credible intervals and probability-of-leakage by date. Finally, incorporation of geohazard and third-party damage indicators (seafloor instability, anchor drag risk) will evolve the PCTI into a comprehensive integrity threat index rather than a corrosion-only metric.

In conclusion, the Predictive Corrosion Threat Index represents a practical realisation of the long-promised shift from reactive to genuinely predictive pipeline integrity management. By systematically fusing the industry's existing multi-billion-dollar inspection data streams into a single, forward-looking, and diagnostically rich metric, it delivers immediate and quantifiable improvements in safety, capital efficiency, and operational decision quality. The framework is deliberately simple enough for field deployment yet sophisticated enough to serve as the analytical backbone of next-generation digital integrity platforms.

CONCLUSION

Offshore pipeline operators have long been confronted with a paradox: despite investing billions annually in sophisticated NDT programmes—intelligent pigging, ROV-based CP and UT surveys, fluid chemistry monitoring, and subsea visual inspections—the resulting data remain fragmented across vendors, formats, and engineering silos. This fragmentation forces a reactive, schedule-driven integrity strategy that routinely misses emerging threats, over-inspects stable sections, and misallocates limited repair resources. The industry has remained data-rich yet insight-poor.

Figure. Vision of next-generation digital pipeline integrity dashboard powered by real-time PCTI.

This paper directly resolves that paradox through the development and full-scale validation of the Predictive Corrosion Threat Index (PCTI)—a quantitative, spatially continuous, and genuinely forward-looking composite metric that systematically integrates internal corrosion evidence (ILI metal-loss features, corrosion growth rates, fluid corrosivity), external corrosion evidence (CP performance, coating condition, seabed UT trends), and temporal acceleration signals into a single 0–100 threat score.

Across a fleet of 42 deepwater and shallow-water assets totalling 1,840 km, the PCTI demonstrated:

- 94 % capture of actual corrosion-driven failures within the top 100 ranked segments (versus 61–72 % for traditional single-source or matrix methods),
- a 15–36-month advance warning capability for accelerating threats,
- and an immediate USD 94 million reduction in unnecessary inspection expenditure through risk-based interval optimisation.

These results were achieved with a transparent, auditable model that requires no exotic sensors—only disciplined use of data operators already collect.

The primary contribution of this work is therefore not theoretical elegance but practical transformation: the PCTI replaces subjective, disjointed defect ranking with an objective, predictive, and diagnostically rich decision-support framework. It converts terabytes of siloed inspection records into clear, prioritised work scopes that engineers, managers, and regulators can all trust.

As the industry moves inexorably toward digitalised, real-time integrity management, the PCTI establishes a robust, field-proven foundation for that future. With ongoing incorporation of continuous monitoring streams and machine-learning weight refinement, it has the clear potential to become a cornerstone of modern pipeline integrity programmes worldwide—simultaneously enhancing safety, environmental protection, and capital efficiency in one of the most critical and challenging sectors of the global energy system.

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