

A corrosion-aware digital-twin framework for condition monitoring of saline-water centrifugal pumps

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Abstract

Coexisting corrosion surface degradation and Metallo mechanical condition evolution in marine centrifugal pumps are rarely captured in a condition-monitoring paradigm. A corrosion-aware digital-twin paradigm for saline-water centrifugal pumps is demonstrated by secondary analysis of a 200-h saline-water experimental data. Empirical data are separates from derived quantities, model-form assumptions, and virtual-model outputs; an ambiguity in surface-roughness uncertainty is included in the formation of an equivalent sand grain-roughness parameter for computational fluid dynamics model of as-created pumps.

A 316L stainless-steel centrifugal pump operating in 30 parts per thousand synthetic seawaters at 2900 rpm is studied at 0, 50, 100, 150, and 200 h.

Over 200 h, head decreased from 12.0 to 10.7 m, flow from 1.50 to 1.38 L/s, electrical-input efficiency from 70.6% to 58.0%, vibration from 0.20 to 0.75 mm/s, and Ra from 0.8 to 3.4 μm . The dataset is reorganized into a multidomain state representation. Using $k_{\text{eq}} = \alpha \text{Ra}$ with $\alpha = 0.5, 1.0$ and 2.0 gives a 200 h screening envelope of 1.7–6.8 μm . The framework combines sensing, state estimation, virtual modeling, residual analysis, and maintenance support without claiming validated CFD, machine-learning, failure probability or RUL models.

The contribution is thus probably a reproducible, explainable digital-twin framework, with the right evidence, state representation, and model interfaces, for enabling and validating fleet management.

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1 Introduction

Most marine and offshore assets rely on centrifugal pumps in seawater cooling, firewater systems, ballasting, produced-water applications, process circulation, and other fluids-service applications. Given the combination of their hydraulic, mechanical, material, and environmental sensitivities, their highly missioncritical nature, and the advantages of predictive maintenance, the advent of smart marine systems that incorporate sensors, big-data analytics, and numerical modelling makes the equipment level digital twin a promising paradigm for linking operating data to maintenance decisions. The scope of Intelligence Marine Technology and Systems (IMTS) includes marine artificial intelligence, marine environment sensing, and marine instrumentation and engineering, and so equipment-level intelligent condition monitoring is within scope.

5.1 Digital twins for rotating machinery: Dimensions and challenges in the literature Technical papers on digital twins for rotating machinery highlight the relationship between physical assets, the virtual domain, data interaction, and model-based decision support systems (Inturi et al. 2024; Ma et al. 2025).

Additionally, the literature points to numerous issues still faced when implementing digital twins, including the virtual model's fidelity, quality of data, model validation, and physics-based and data-driven

models.

In the marine equipment domain, these challenges will be compounded by varying operating environments and degradation modes causing similar symptomology.

The methodical problem discussed herein does not relate to the definition of a second digital twin; rather, it concerns the evidence and interface architecture required to derive an actualized and validated equipment-level virtual model out of a corrosion degradation measurement.

Corrosion is especially challenging to represent because its functional effect manifests via a variety of mechanisms. Roughening can cause additional pressure head or power loss, localized loss can cause geometric mismatch, and uneven corrosion can cause imbalance or vibration. But loss of head or efficiency is not a definitive clue, since fouling, clearance change, cavitation, movement of the operating point, and mechanical faults can produce the same results. Thus an effective intelligent monitoring architecture would retain physically meaningful channels rather than collapsing the pattern into one overall health indication.

In a current IMTS study series (Liang et al., 2023), they showed that wall roughness influences the pressure distribution and performance of a centrifugal dredge pump through experimental and computational investigation. They incorporated equivalent sandgrain roughness in their CFD simulations while differentiating explicitly between k and experimentally obtained R_a . This paper deals with a related problem: how to organize the measured corrosion-induced surface degradation and multi-domain condition indicators to serve as traceable measurements for an equipment-level digital-twin framework.

The author's previous experimental study consisted of a 200-hour controlled saline-water test of a 316L stainless-steel centrifugal pump, together with corrosion coupons (Udo 2026). It informed the experimental degradation observations but not the equipment-level digital-twin architecture nor uncertainty-aware interface between the measured R_a and a future CFD roughness state. This paper is intentionally a secondary analysis and makes no claim to novelty of the earlier measured data.

The proposed research questions are: 1. How can corrosion-related surface condition, hydraulic response, and vibration be characterized as a machine-readable multidomain state to support an intelligent marine-pump twin? 2. How sensitive is the CFD-facing roughness state to explicit R_a -to- k transfer assumptions? 3. How can residuals and uncertainty be related to maintenance support without unsupported assertions of failure probability or remaining useful life?

The main contributions are: (i) corrosion-aware state-vector structure for monitoring a marine centrifugal-pump condition; (ii) explicit accounting of measured evidence, derived quantities, transfer assumptions, virtual-model outputs and maintenance interpretation; (iii) a fully numeric, five-point demonstration of the observed degradation condition; (iv) a deterministic model-form sensitivity envelope for the R_a -to- k transfer; and (v) a staged outlook on CFD, field validation and future data-driven

intelligence. This study does not claim to produce a validated digital twin, roughness-to-Ra transfer, failure threshold, machine-learning classifier or remaining useful life model.

2 Background and research gap

2.1 Digital twins for marine and rotating equipment

Marine digital-twin research has been divided into those using data, virtual-data, intelligent modeling, and prediction. A digital-twin-of-the-ocean architecture that links data pools, modeling, and prediction is proposed by Chen et al. (2023), and reviews on the latest digital twin of rotating machinery shows that sensing, physics-based models, and data-driven models may work in collaboration to have a better digital twin (Inturi et al. 2024; Ma et al. 2025).

The important aspect for this work is that a digital twin is not just a diagram, but that the virtual model, data, connectivity, state update, and validation status are simply stated.

In the realm of rotating machinery, digital-twin practice has been more inclined toward fault diagnosis and predictive maintenance. Nevertheless, there have been some isolated recent reviews that cited ongoing problems in this area regarding model fidelity, data quality, generalization, and validation. These comments support a cautious equipment-level perspective, and the current paper probably will introduce the state and data interfaces of the twin before declaring a fully functional predictive twin.

2.2 Intelligent condition monitoring of centrifugal pumps

The condition monitoring of a centrifugal pump usually combines the measurement of hydraulic parameters with power or efficiency parameters, vibration, and inspection data. Within the marine domain, these data streams fulfill two different purposes: first, the condition of the hydraulic system may deviate from expected (if no mechanical deficiency has been confirmed) and, vice-versa, the condition of the mechanical system may indicate abnormal vibration without any perceptible hydraulic deviation. Thus, the present concept assumes the intelligence to be based on mostly explainable state fusion and context specific residual analysis, not necessarily on deep-learning.

This difference is important for the body of existing evidence. The source experiment has five exposure-time conditions, but no claimed failure end points. Newer digital-twin fault diagnosis literature has demonstrated promise for machine learning when enough virtual-model and condition data is collected, but also points to the importance of good data and careful validation (Xia et al., 2024; Ma et al., 2025). Thus, a deep classifier or RUL model trained on the five-point data set would likely make it look more intelligent, but too was probably be overly weak scientifically.

2.3 Corrosion, roughness and hydraulic degradation

The source experiment demonstrates real-time the surface roughness, vibration, and condition change with calibration saline consumption (Udo, 2026). We treat this as a shared evidence pathway for the

simultaneously evolving R_a , but not as a priori evidence that it is a full corrosion state descriptor, nor that the quantified change in hydraulic profile was due solely to the roughness. R_a is a surface defect descriptor which may be transferred as an explicit transfer model, prior to being used as a future CFD input.

Equivalent sand-grain roughness k_s is not identical to arithmetic roughness R_a . Adams et al. (2012) developed an algorithm for converting measured roughness parameters into equivalent sand-grain roughness and obtained $k_s = 5.863R_a$ for the R_a -based relation under their idealized roughness model. Liang et al. (2023) adopted this relationship in their centrifugal dredge-pump CFD study. The existence of such a benchmark is useful, but its direct application to a corroded 316L impeller remains an assumption requiring validation.

2.4 Research gap and contribution boundary

The current literature points to three relevant lines of research: Marine digital twins and intelligent systems, Rotating machinery condition monitoring and diagnostics, Roughness-aware modeling of centrifugal pumps. But the middle link of evidence at equipment level (the key intermediate step that enables the transformation of experimentally observed corrosion-related surface degradation into an uncertainty-bearing pump state) is not well-explored; it must ensure the separation of measured conditions, assumed roughness equivalence, and predictive modeling.

This work is more of a methodical than an experimental contribution. Published observations are reformatted into a corrosion-conscious state vector, with the transfer from observed values to CFD roughness being a model-form sensitivity step. Moreover, the state is connected to a residual-based virtual-model interface and maintenance workflow. As a result, the contribution is presented in form of a digital-twin architecture, not a validated operational digital twin.

2.5 Digital-twin implementation boundary

The digital twin stated in the present manuscript comprises only the proposed equipment-level architecture and associated interfaces, which defines the limits of the currently feasible experiment, not a working twin. In this paper, evidence has been presented and model interfaces have been designed for the implementation and validation of a corrosion-aware virtual pump. Physical asset observations are translated into an explicit multidomain state, with surface roughness represented by a CFD-facing equivalent sand-grain roughness value, while model-form uncertainty is retained.

This state is then mapped to a virtual-model prediction and residual interface, although the virtual-model layer has not been computationally realized.

Thus, there are no claims that a CFD solver, live data feed, calibrated virtual pump, or validated model-measurement residual has been demonstrated. This is a conscious decision, given the evidence takes the form of a secondary analysis of just five data points from a systematic laboratory experiment.

The essential achievement here is the creation of a demonstrable evidence-to-model architecture and validation loop that can be reproduced and exploited in future work.

3 Materials and methods

3.1 Study design and data provenance

This paper is secondary research of the controlled saline-water experiment reported by Udo (2026). The initial research utilized a 316L stainless-steel centrifugal pump in 30 ppt synthetic seawater for 200 hours, with assessments taken at 50-hour intervals. This paper does not state the doing laboratory measurements.

The source system used a compact closed loop circulating system. Pump characteristics included a nominal flow of 0.00150 m s^{-1} at 12 m nominal design head and 0.25 kW motor. The system was maintained at a temperature of $25 \pm 2^\circ\text{C}$ and flow of 0.00150 m s^{-1} and pump head of 12 m at around 2900 rev/min.

Data was averaged across three measurements for flow, head, input power, efficiency and vibration at 0, 50, 100, 150, and 200 hours. Data was reported as averages, with flow and head uncertainty being reported at 2.5%.

In addition, the source study used static corrosion coupons for 316L SS, bronze, and carbon steel. Interestingly, only the 316L assembly was hydraulically tested, so the equipment level analysis presented here is restricted to the 316L pump. Results for bronze and carbon steel coupons are included here for context on use as materials; no pump extrapolation was performed.

Table 1
Source experiment, data provenance and modelling boundary

Item	Source evidence	Role in present analysis
Pump material	316L stainless steel	Equipment state and hydraulic evidence
Exposure medium	30 ppt synthetic seawater	Controlled marine-saline context
Exposure duration	200 h; observations every 50 h	Five-point time series
Temperature	$25 \pm 2^{\circ}\text{C}$	Operating context
Speed	≈ 2900 rpm	Operating context
Nominal pump point	$Q = 0.00150 \text{ m}^3/\text{s}$; $H = 12 \text{ m}$	Baseline state
Motor/input power	0.25 kW nominal; 250 W reported in time series	Efficiency calculation context
Replicates	Triplicate measurements; means reported	Repeatability evidence
Flow/head uncertainty	$\pm 2.5\%$	Measurement-uncertainty tag
CFD status	No CFD performed in present paper	Future model only
Data status	Secondary analysis of Udo (2026)	No new experiment claimed

Table 1 summarizes the principal previous experiment and indicates the source of the data, thereby defining the modeling boundary for this secondary analysis. Table 1 also makes clear distinctions between the measured evidence and future modeling and establishes that no CFD simulation was performed in this study.

3.2 Observed condition variables and calculations

.State of the condition includes flow rate (Q), pump head (H), electrical-input efficiency, vibration velocity (v), and arithmetic surface roughness (R_a). The word "electrical-input efficiency" is used with deliberate purpose here, as the experiment cited indeed determined this value based on dividing the hydraulic output by the electrical input power measured. However, it is not considered a shaft-power efficiency.

For a variable x , the normalized state is $x^*(t) = x(t)/x(0)$. Normalization is used for visualization only. Performance variables such as Q , H and η retain their direction of change, while degradation-oriented variables such as v and R_a are retained as independent channels. Endpoint degradation magnitudes are calculated as $D_H = [H(0) - H(t)]/H(0)$, $D_Q = [Q(0) - Q(t)]/Q(0)$, $D_\eta = [\eta(0) - \eta(t)]/\eta(0)$, $D_v = [v(t) - v(0)]/v(0)$, and $D_{R_a} = [R_a(t) - R_a(0)]/R_a(0)$. These are descriptive state changes, not failure probabilities.

Table 2
Five-point operating and performance dataset used in the secondary analysis

Time (h)	Q (L/s)	H (m)	Input power (W)	η (%)	v (mm/s)
0	1.50	12.0	250	70.6	0.20
50	1.47	11.6	250	66.7	0.32
100	1.44	11.3	250	63.7	0.45
150	1.41	11.0	250	61.0	0.61
200	1.38	10.7	250	58.0	0.75

Table 2: The five point data set of operational and performance data used in the secondary analysis. This data set show how the flow, head, input power, efficiency and vibration change gradually as the exposure time progresses over the 200hr duration.

Figure 1 shows the Normalized trajectories of the five main condition variables during the 200h exposure duration. Based on the observation there is a trend of changing the hydraulic condition, efficiency, vibration, surface condition relative to the starting measured state. This may give us some idea about the lag in these condition variables.

3.3 Surface-degradation observations

The results from the source study imply deterioration of the surface over time: the number of pits increased from 0 at the start of the study to 68p/m at 200 hours, mean pit diameter increased from 45 μm at 50h to 132 μm at 200h, and the surface roughness average (Ra) increased from 0.8 to 3.4 μm . The maximum pit depth detected at the final inspection was 210 μm . These data are maintained as representations of surface condition rather than converted into a full corrosion-state estimator.

Table 3
Surface-degradation observations from the source experiment

Time (h)	Pit density (pits/mm ²)	Mean pit diameter (μm)	Ra (μm)
0	0	—	0.8
50	12	45	1.4
100	28	78	2.1
150	46	105	2.8
200	68	132	3.4

Table 3 summarizes the surface-degradation observations from the source experiment, showing the progressive increase in pit density, mean pit diameter and arithmetic surface roughness over the 200-h exposure period.

Figure 2. Surface degradation variables in original measurement units. Pit density increased from 0 pits/mm at 0 h, initial condition, to 68 pits/mm² at 200 h. Mean pit diameter was first reported at 50 h at 45 μm, increased to 71 μm at 100 h, then to 84 μm at 150 h, and finally to 132 μm at 200 h.

Arithmetic surface roughness increased from 0.8 to 3.4 μm from 50 to 200 h. The three surface-degradation variables are presented here without baseline normalization because the pit density had an initial value of zero at 0 h and the mean pit diameter was not reported at 0 h, so the absolute value preserves the provenance of the measurements and does not introduce a normalization reference that is not present.

3.4 Corrosion-to-roughness transfer

A future CFD-enabled twin needs a numerical representation of wall roughness, but measured arithmetic roughness R_a and equivalent sand-grain roughness k_s are not identical quantities. The present study therefore uses the explicit screening relation $k_s = \alpha R_a$, where α is a transfer multiplier. The primary sensitivity cases are $\alpha = 0.5, 1.0$ and 2.0 . These values are not experimentally calibrated coefficients; they define a deterministic model-form sensitivity envelope.

At 200 h, $R_a = 3.4 \mu\text{m}$, so the primary cases give $k_s = 1.7, 3.4$ and $6.8 \mu\text{m}$. With impeller diameter $D = 145 \text{ mm}$, k_s/D ranges from 1.17×10^{-5} to 4.69×10^{-5} . These are prospective CFD inputs, not CFD results.

For comparison, Adams et al. (2012) derived the R_a -based relationship $k_s = 5.863 R_a$ under a specific idealized roughness representation, and Liang et al. (2023) adopted that relationship in their dredge-pump CFD study. At $R_a = 3.4 \mu\text{m}$, the benchmark gives $k_s \approx 19.9 \mu\text{m}$. It is included here only as a literature benchmark. The difference between $19.9 \mu\text{m}$ and the present $1.7\text{--}6.8 \mu\text{m}$ screening envelope demonstrates why a roughness-transfer relation should not be treated as universally calibrated for a corroded pump surface.

Table 4
Roughness-transfer sensitivity at selected exposure times

Time (h)	R_a (μm)	$k_s, \alpha = 0.5$ (μm)	$k_s, \alpha = 1.0$ (μm)	$k_s, \alpha = 2.0$ (μm)	k_s/D range
0	0.8	0.4	0.8	1.6	2.76×10^{-6} – 1.10×10^{-5}
50	1.4	0.7	1.4	2.8	4.83×10^{-6} – 1.93×10^{-5}
100	2.1	1.05	2.1	4.2	7.24×10^{-6} – 2.90×10^{-5}
150	2.8	1.4	2.8	5.6	9.66×10^{-6} – 3.86×10^{-5}
200	3.4	1.7	3.4	6.8	1.17×10^{-5} – 4.69×10^{-5}

Table 4 shows how the equivalent sand-grain roughness, k_s , changes with the assumed transfer multiplier. It illustrates how uncertainty in the roughness transfer affects the k_s/D range used in the proposed future virtual-model analysis.

Figure 3 CFD-facing roughness parameter, k_s , vs. transfer multiplier. The Adams et al. (2012) relation is provided as a literature standard, and is not utilized as a calibration standard in the current work.

3.5 Residual-based virtual-model interface

Virtual layer has $\hat{y} = V(z,u,\theta)$ in which z is the degradation state, u is operating context and θ is the vector of model parameters. The predicted vector y will have head, flow, power, or other quantities that the future virtual pump is able to predict. The monitoring residual: $r = y_{obs} - \hat{y}$. The residual has no physical meaning unless the operating context for the virtual model is the same as the observation.

The structure maintains a residual vector, not a single score. A head residual can be isolated from a vibration residual. A valuable residual record should include observed value, predicted value, residual, operating condition, model version, state version and uncertainty information. This renders the residual auditable and enables maintenance staff to discern between consistent anomalies and those driven by operating environment.

No numerical virtual-model prediction is made up in this paper: specifically, we do not plug in previously computed residuals, unless we can separately record the type of model used, the fitting data, the holdout status, and where it is from. The paper presents only the residual interface, and the dependency requirements; numerical-twin validation is future work.

Table 5
Residual-interface specification and evidence status

Element	Definition	Status in present paper
Observed output, y_{obs}	Measured Q , H , η , v or other monitored quantity	Available from source experiment
Virtual output, $\hat{y}$	$\hat{y} = V(z,u,\theta)$	Not numerically evaluated
Residual, r	$r = y_{obs} - \hat{y}$	Interface defined; no validated distribution
Operating context, u	Speed, flow, pressure, temperature, salinity and duty information	Controlled context only in source study
Model parameters, θ	Pump geometry, physical parameters and numerical-model settings	Future CFD/model calibration
Uncertainty tag	Measurement and model-form uncertainty kept separate	Implemented conceptually
Maintenance interpretation	Inspection/diagnostic information from persistent residual patterns	Decision logic proposed, not validated

As shown in Table 5, the residual interface is defined as the difference between the combined measured evidence and the future virtual-model output. It identifies which data are available, conceptually defined, or which must be made available through future CFD/model development and validation.

3.6 Uncertainty treatment and provenance

Roughness-transfer uncertainty is parametrically specified as a model-form sensitivity range, and produces an envelope of $[0.5Ra, 2Ra]$. This is not a confidence interval or probability distribution, but a sensitivity range for a model-form uncertainty parameter. Flow and head measurement uncertainty of $\pm 2.5\%$ is preserved from the original work. Since this paper does not recompose the entire covariance structure of all repeated measures, it does not produce a formal multivariate confidence region.

Each state element is labeled as measured, derived, assumed or simulated. For instance, $Ra = 3.4 \mu\text{m}$ at 200 h is a source-study observation measured from the source; $k_{\alpha} = 3.4 \mu\text{m}$ for $\alpha = 1.0$ is a derived value for a sensitivity; and a CFD head prediction at a future time is a simulation. This source-study/future-series distinction is at the heart of the framework, because a well-behaved number can have little evidential status if based on an uncalibrated model assumption.

Figure 4 As threats are monitored, how data is securely transferred through the proposed monitoring system without losing its integrity The diagram shows: Data Ingestion collects the flow of live events and captures each item using a cryptographic hash digest, a unique fingerprint. Active Monitoring applies this digest and all associated threat metadata back to the source data in order to track its origins Provenance Verification Securely transfers the data through a blockchain to validate an unbroken chain of custody before storing the validated data into Secure Storage as an encrypted, time-stamped archive for perfect auditability.

3.7 State-vector formulation for intelligent condition monitoring

The proposed twin uses a vector rather than a scalar health score. At an observation time t , the physical condition state is represented as $z(t) = [Q(t), H(t), \eta(t), v(t), Ra(t), k_{\alpha}(t;\alpha), u_m(t), u_o(t)]$, where u_m denotes measurement-uncertainty information and u_o denotes operating-context information. The last two terms are included conceptually because an intelligent monitoring system should carry not only numerical state but also information on how the state was obtained.

For this secondary analysis, the operating context is approximately 30 ppt synthetic seawater, $25 \pm 2^{\circ}\text{C}$, and approximately 2900 rpm. For a field deployment, operating context would include, at least, speed, flow, pressure, temperature, and salinity, in addition to any available data on cavitation state, valve configuration, and duty cycle.

The state vector is deliberately heterogeneous. Q , H and η describe performance; v describes mechanical response; and Ra describes a surface condition that is usually less than frequently observed online measurements of the process.

This facilitates asynchronous updating: a vibration observation may be used to update the mechanical channel, without necessarily implying that the surface-roughness channel was observed at that instant.

A practical application would save each state element with timestamp, source, unit, calibration state, uncertainty, operating context and provenance class. The metadata layer enables auditability and future explainable intelligence.

Table 6 State-variable provenance and intended role in the digital-twin framework			
State element	Evidence class	Current role	Future role
Q	Measured	Hydraulic response	Virtual-model output/residual
H	Measured	Hydraulic response	Virtual-model output/residual
η	Derived from Q, H and input power	Energy-performance response	Model calibration/residual
v	Measured	Mechanical response	Mechanical residual/diagnosis
Ra	Measured	Surface-degradation descriptor	Surface-state update
$k_{\square}$	Assumed/derived from αRa	CFD-facing sensitivity variable	Validated roughness boundary condition
u_m	Derived metadata	Measurement uncertainty	Uncertainty propagation
u_o	Measured/context metadata	Operating context	Condition matching

Table 6 – Serves to identify the source and purpose of each state variable in the proposed digital-twin architecture. Tables show measured, derived and assumed variables, and how they can be used to enable the development of virtual models and uncertainty-aware condition monitoring.

4 Results

4.1 Five-point degradation trajectory

The 5-point series have a better reproducibility than an endpoint-only summary. Head falls monotonically from 12.0 to 10.7 m; flow from 1.50 to 1.38 L/sec; electrical-input efficiency from 70.6% to 58.0%; vibration from 0.20 to 0.75 mm/sec; and Ra from 0.8 to μm . The normalized trajectories in Fig. 1 display the multidomain signature over the series with the relative different physical meanings of each variable still apparent.

The endpoint relative change is -10.83% for head, -8.00% for flow, -17.85% for electrical-input efficiency, 275% for vibration and 325% for Ra. These are simply descriptive markers of the change in state; they are not severity levels or failure probabilities.

Table 7
Endpoint condition state and relative change after 200 h

Variable	0 h	200 h	Relative change	State-channel role
Head H (m)	12.0	10.7	-10.83%	Hydraulic
Flow Q (L/s)	1.50	1.38	-8.00%	Hydraulic
Electrical-input efficiency η (%)	70.6	58.0	-17.85%	Energy performance
Vibration velocity v (mm/s)	0.20	0.75	+ 275%	Mechanical
Surface roughness Ra (μm)	0.8	3.4	+ 325%	Surface degradation

Table 7 gives the variations of the five main condition variables over the interval 0 to 200 h. It depicts the relative devaluation of the four condition states identified in the hydro-mechanical surface condition channels of the monitoring.

4.2 Surface degradation and material context

The originating test revealed corrosion rates of 0.048mm/yr 316L SS, 0.083mm/yr bronze and 0.212mm/yr carbon steels, for the specified coupon conditions. This information helps give the materials perspective, but we don't use these rates to try to predict performance on the pumps for the bronze or carbon steels as these materials weren't tested as pumped assemblies. The equipment twin ultimately relies on the 316L pump evidence alone.

The surface metrics contain more information on the degradation than the relatively straightforward Ra alone. Pit density was 68 pits/mm² of surface and mean pit diameter 132 μm at 200 h, while the deepest maximum pit depth was 210 μm . These results show that the surface is evolving during the degradation process, but also highlight why one can never expect a single arithmetic roughness number to account for all relevant aspects of the geometries. The links between corrosion morphology and hydraulic response therefore is a hypothesis, which must be independently verified using matched-surface studies.

4.3 Roughness-transfer sensitivity

The main values yield 200 h k ranges from 1.7–6.8 μm . The upper-to-lower ratio is 4; it is based on the range of sensitivity chosen, not on an experimentally observed uncertainty ratio. For D = 145 mm, k/D is less than about 5×10^{-5} . The benchmark of Adams et al. (2012) taken mechanically at the same Ra is about 19.9 μm , far outside the main screening envelope.

The benchmark comparison does not reveal a necessarily correct coefficient, but it does demonstrate that the CFD-facing input can be largely contingent on the roughness-transfer convention. Correct interpretation is thus model-form sensitivity. Future calibration should rely on direct roughness topology and matched hydraulic measurements rather than blindly adopting a coefficient because it is in the literature.

.4.4 Digital-twin architecture and implementation boundary

Figure 3. Conceptual presentation of the equipment-level digital-twin architecture being proposed. The physical layer includes the water centrifugal pump in the environment in which it operates. The sensing layer captures flow, pressure, vibration, power and inspection data. The degradation-state layer maintains separate deconstructed surface degradation, hydraulic and mechanical responses rather than immediately combining into a single health or remaining-life score. The virtual-model interface receives the degradation state in addition to operating conditions and is where the physics-based pump model would reside to produce predicted performance. The residual layer then produces residuals to compare measured and predicted performance, and the maintenance layer interprets the residuals and their associated uncertainties.

In the current study, the first three layers and the interfaces between them are supported by published experimental evidence and the resulting analysis. The R_a to k_s relationship offers a direct and explicit surface-condition input to the virtual-model interface, $k_s = \alpha R_a$ evaluated for $\alpha = 0.5, 1.0$, and 2.0 . However, the virtual pump itself has not been implemented here. In particular, no pump CAD/CFD model, turbulence-model solution, calibrated hydraulic solver, live data-assimilation coupling or experimentally validated model measurement residual has been provided. As such, the virtual layer depicted in Fig. 3 should be regarded as an implementation interface defined here rather than as a computational twin in its own right.

This is significant for reproducibility of the proposed method. A subsequently developed implementation can feed the measured state and operating condition into a pump-specific physics model, constrain k_s to the chosen scenario surface, and calculate predicted head, flow, power, or other response variables that can be directly compared with synchronized measurement through the residual formulation outlined in Section 3.5. Model verification, calibration and validation would be used to assess if the virtual pump is sufficiently accurate for condition monitoring in operation. Therefore, this paper has presented the framework and proof-of-concept demonstration, and we are not claiming that implementation or operational validation has already been completed.

Figure 5 Digital-twin architecture for a marine pump When sensors provide data in real time, the twin can incorporate physics, corrosion models, and machine-learning algorithms to keep tabs on the asset's health, estimate its RUL, and enable maintenance alerts.

4.5 Maintenance information and explainable monitoring

The framework is not designed to tell you if a failure has occurred but to give you maintenance information. For instance, a hypothetical future implementation could show three parallel states: one dedicated to the hydraulic state, one dedicated to mechanical state and one to degradation of the surfaces. In the case of residuals of the hydraulic signal increasing with stable vibration and inspection indicating higher roughness, the evidence would lead you to investigate the effects of the hydraulic surface.

It is also feasible to enable inspection planning. Surface metrology is less easy to watch continuously in comparison with pressure, flow, power, or vibration. Online variables can alert you when a surface inspection update might be helpful, but the last Ra value can be maintained until the subsequent measurement arrives. This asynchronous structure is more reasonable than assuming each state variable is observable at all times.

4.6 Verification and validation pathway

Figure 6 shows the staged pathway that must be followed before the framework can achieve its ultimate purpose as a run-to-failure predictive-maintenance twin: Direct surface characterization and virtual-model verification -> Matched-hydraulic validation -> Independent validation data -> Residual calibration -> Data-driven anomaly detection or prognostic modelling.

Figure 6 outlines a three-stage engineering pathway that progresses from initial software simulation (Verification) and real-world physical testing (Validation) to an AI-driven, real-time control system (Intelligent-Decision Pathway) for adaptive asset maintenance.

5 Discussion

5.1 Principal findings and evidence boundary

The secondary analysis provides a tangible form for the published experiment as a multidomain degradation state. The pump was not altered in only one way: it had hydraulic output loss, electrical-input efficiency loss, vibration loss, and measurement of surface roughness increased. The key methodical product is the discontinuity between observation and inference: $3.4 \mu\text{m}$ at 200 h is a source-study observation; $k_{\text{a}} = 1.7\text{--}6.8 \mu\text{m}$ a deterministic sensitivity envelope formed by an explicit assumption; a CFD prediction in the future would be a third kind.

It is worth noting here because the title and architecture now describe a framework, they do not suggest that a verified digital twin has previously been realized. The use of the term intelligent is retained in the condition-monitoring idea, where it means an explainable, multi-domain, state integration, and context-dependent residual interpretation. No unvalidated AI algorithm is used solely to fill the journal context.

The published evidence boundary naturally constrains the interpretation of digital twin used in this paper. A complete digital twin would have an implemented virtual pump solution with which data exchange can be made, validated, and verified against independent measurements. However, we have defined the data

representation, state-space variables, surface-condition interface, residual formulation and method of maintenance of the pre-implementation virtual solution – yet not implemented the virtual solver or obtained the evidence which validates it. So, the realization of a digital twin is best understood as being at the level of this pre-implementation framework, avoiding the implication that an operational twin has been presented while clearly providing a path from this secondary analysis to a validated equipment-level digital twin.

5.2 Relationship to IMTS research

This framework is applicable to IMTS as it accounts for all marine equipment, sensing, intelligent monitoring, and digital representations, in an engineering asset core. IMTS research has spanned marine digital-twin ideas, roughness aware centrifugal-pump modelling, and further progressed intelligent marine systems. This contribution ties all those lines together in the equipment-condition domain, with measured corrosion surface states into an explicit and uncertainty-carrying state variable for a virtual pump.

There is nothing new with a generic digital-twin definition and there is nothing new with the CFD model. What there is benefit with is the corrosion-to-state-to-virtual-model pathway and the associated explicit evidence provenance that stops an assumed CFD input being confused for a measured property or validated prediction.

5.3 Implications for offshore maintenance

For offshore maintenance, this architecture means a staged process. Idle sensor data can reveal various changes in head, flow, power and vibration; regular inspection can populate surface-degradation descriptors; and after virtual-model validation, lingering anomalies can prompt for inspection instead of automatic component failure. This is valuable in applications in which corrosion, fouling, erosion, cavitation, and mechanical defects can all induce similar symptoms.

This approach also enables maintenance prioritisation without the need to define an unsupported universal threshold. Any site-specific threshold should be determined after obtaining larger field datasets and incorporating pump duty, operating point, material, salinity, temperature, speed, and measurement uncertainty.

5.4 Why a scalar health index is not used

However, a scalar health index may be convenient but can conceal mechanism details. For instance, a large increase in vibration can occur with a small head reduction, or a significant change in roughness can be important for future hydraulic modelling but not measurable online over the course of the experiment. To combine these quantities requires weights and direction conventions not uniquely specified by the five-point experiment.

This design allows for explainability; even if a future virtual model can successfully predict the hydraulic behaviour, an increase of the residuals of vibration inspections can be attributed to mechanical issues

without jumping to the conclusion that the roughness of the virtual model is at fault. Likewise, if the residuals of the hydraulic model increase with the residuals of the roughness inspection, virtual model can be looked into.

5.5 Practical pathway from the present framework to a validated twin

This is only the establishment of the pre-implementation evidence chain and interfaces for a validated equipment-level digital twin. This is not a validated twin itself. Implementation and verification of the virtual pump follows, with experimental validation under increasing operating and degradation conditions.

A second "appropriate" follow-on test is a matched-surface test of poorly degraded vs. artificially generated matched-surface surfaces, selected to match R_a but with their topology characterized independently. Significant differences in the hydraulic responses at matched R_a would, in fact, prove the inadequacy of R_a alone. Close agreement with the artificially-generated surface would establish a feasible method of developing a (roughness-based) reduction in roughness for a given flow situation on the poorly degraded surface. This Surface-Equivalence and Performance-Degradation Hydrodynamic Test (SEP-DHT) would be the experimentalist's way to validate whether the twin's roughness descriptor is physically valid.

5.6 Digital-twin verification and validation

Verification ensures the computational implementation solves the correct equations and boundary conditions; validation ensures the model accurately represents the physical pump under the given conditions. This paper mainly defines the architecture and data interface before those activities are carried out. Further CFD validation should start with geometry verification, then baseline validation at the reference condition, sensitivity testing using the cases, and comparison with measured head, flow and power at the same operating points. Independent validation data should then be added before using the results for predictive maintenance.

The limited five-point dataset makes it impossible to trained a general machine-learning-based failure model or RUL estimator. Following development of an accurate virtual model and a more extensive dataset, data-driven approaches can be introduced as an interpretable layer of residual or anomaly classifiers followed by prognostics. The framework described thus far lay the groundwork for prognostics analytics, not to argue that they have already been demonstrated.

6 Limitations

The analysis is based on one previously published 316L pump configuration and a 200 h controlled saline-water exposure. Generalization to other pump geometries, marine duty cycles and field environments is not established.

The source experiment used static corrosion coupons for material comparisons. Their corrosion rates can't be expected to be equal to the degradation of a rotating impeller surface. Therefore, the bronze and carbon-steel coupon results aren't translated into pump predictions.

Due to the experimental constraints within this work the Ra-to- k_{eq} relation has not been calibrated. The range from $\alpha = 0.5$ – 2.0 is a specific sensitivity envelope, but may not be used as a probabilistic distribution or physical universal conversion.

No CFD simulation is conducted in this paper. Hence, no pressure field, change of turbulence, change of hydraulic efficiency (specifically due to k_{eq}), or CFD validation metric is claimed.

There are 5 exposure-time conditions in this dataset. This is enough for descriptive trajectory analysis and framework construction but not enough to build a general machine-learning model, failure threshold or RUL estimator.

Source test was conducted at around $25 \pm 2^\circ\text{C}$ and 30 ppt salinity. Actual marine environments will have variable temperature, salinity, suspended solids, biological fouling, operating point, cavitation condition, transient loading. All of these variables will need validation during field testing.

The current manuscript defines a residual interface but did not include any numerical virtual-model prediction. This was intentional: a prediction would have needed a documented model, fitting/validation procedure and an independent validation data set.

7 Conclusions

This article constructed a corrosion-released digital-twin paradigm for the condition monitoring² of saline-water centrifugal pumps via an explainable secondary analysis of the published controlled experiment. The introduced can pass the chain of evidence from the data of measured degradation to the future digital-twin while transparent transfer assumptions, uncertainty, and data provenance are shown explicitly.

The complete five-point source series show a 10.83% reduction in head, an 8.00% reduction in flow, a 17.85% relative reduction in electrical-input efficiency, a 275% increase in vibration velocity and a 325% increase in arithmetic surface roughness over 200 h. These changes support a multidomain monitoring representation rather than an immediate scalar health index.

At $R_a = 3.4 \mu\text{m}$, $k_{\text{eq}} = \alpha R_a$ gives 1.7, 3.4 and $6.8 \mu\text{m}$ for $\alpha = 0.5$, 1.0 and 2.0, corresponding to $k_{\text{eq}}/D = 1.17 \times 10^{-5}$ – 4.69×10^{-5} for $D = 145 \text{ mm}$. The Adams et al. (2012) benchmark of $5.863 R_a$ gives approximately $19.9 \mu\text{m}$ at the same R_a and is retained only as a literature comparison, demonstrating the need for model-form transparency.

Consequently, this work establishes the evidence, methodology, and interface specifications necessary to both deploy and validate a corrosion-aware equipment-level digital twin. This manuscript should be

viewed as a digital-twin methodology and demonstration in principle, not as a validated operational twin. It offers the provenance-maintaining links between measured corrosion-related surface degradation and multidomain condition state variables; uncertainty-attentive roughness transfer; virtual-model interface specifications; residual modelling and maintenance interpretation. Deployment of the virtual pump, communication synchronization with physical-asset data streams, and validation and verification against independent experimental and field data are required to demonstrate a validated digital twin.

The subsequent research phase should thus include direct roughness characterization, matched-surface CFD/experimental testing, extended operating conditions, independent pump data and field maintenance evidence.

Declarations

8.1 Funding

No external funding was received specifically for the preparation of this secondary analysis.

8.2 Competing interests

The author declares no relevant financial or non-financial competing interests related to this manuscript.

8.3 Ethics approval and consent to participate

Not applicable. The study involves engineering equipment and previously published experimental measurements and does not involve human participants, animals or clinical procedures.

8.4 Consent for publication

Not applicable.

8.5 Data availability

The underlying experimental evidence was previously published by Udo (2026). The present manuscript is a secondary analysis of that dataset. The five-point numerical dataset reproduced in Tables 2 and 3 is reported in the source publication. Supporting derived calculations for the present analysis should be deposited in a suitable repository before submission where practicable; a persistent identifier can then be added to this statement.

8.6 Code availability

No custom production software is required to reproduce the present calculations. The analysis can be reproduced with standard spreadsheet or scientific-computing software using the equations and numerical values reported in this manuscript. A machine-readable calculation file is recommended for repository deposit.

8.7 Author contributions

Nsini I. Udo: conceptualization; methodology; formal analysis; data curation; interpretation; writing—original draft; writing—review and editing.

8.8 Previous publication and originality of the present analysis

The experimental dataset underlying the present analysis was previously published by Udo (2026). The present manuscript does not claim those measurements as new. Its distinct contribution is the corrosion-aware state representation, uncertainty-bearing Ra-to-k_t transfer framework, provenance-preserving residual interface and digital-twin architecture. The figures in this manuscript are newly generated from the reported numerical evidence and the proposed framework; previously published figures are not reproduced.

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Figures

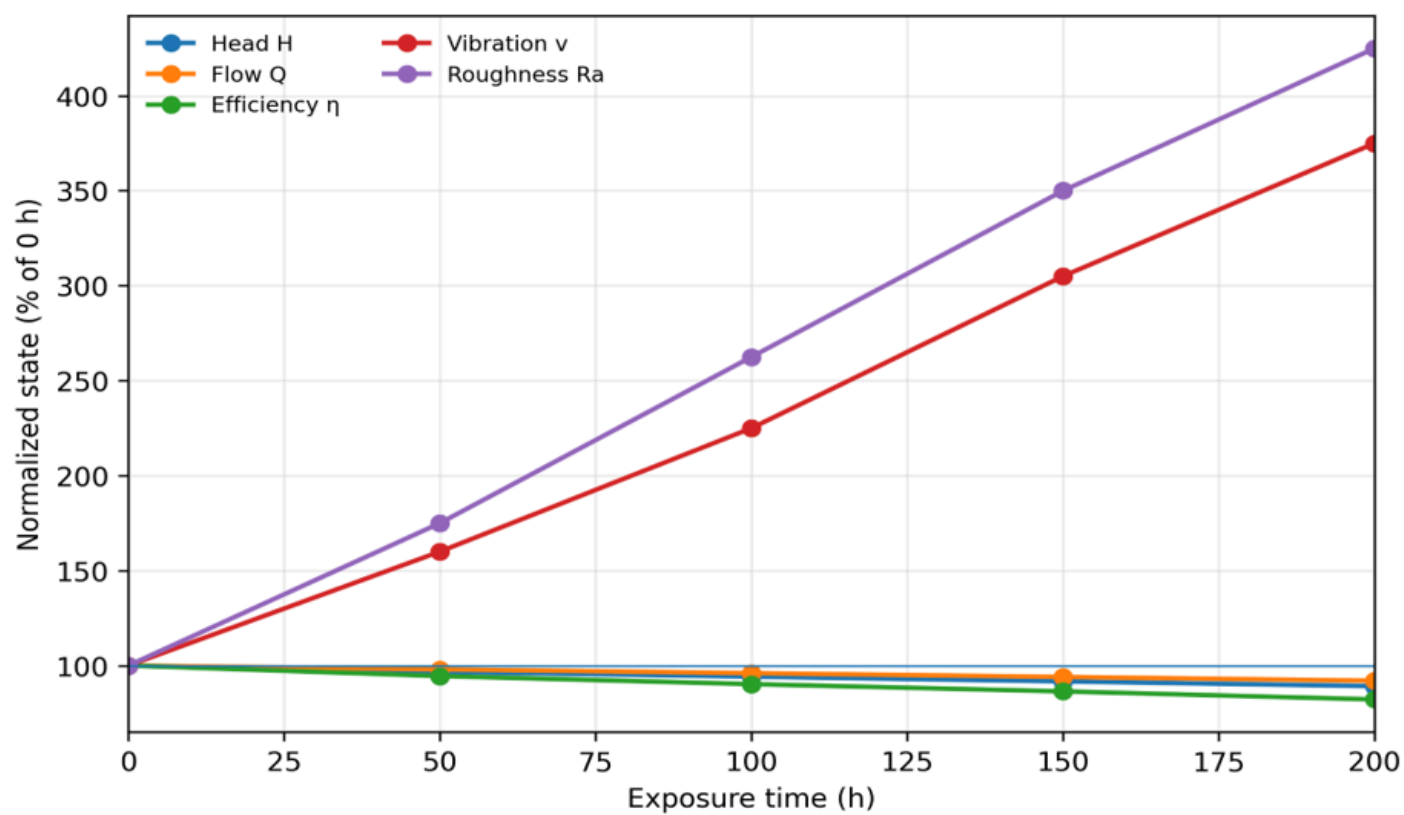


Figure 1

Normalized trajectories of the five principal condition variables over the 200 h controlled exposure

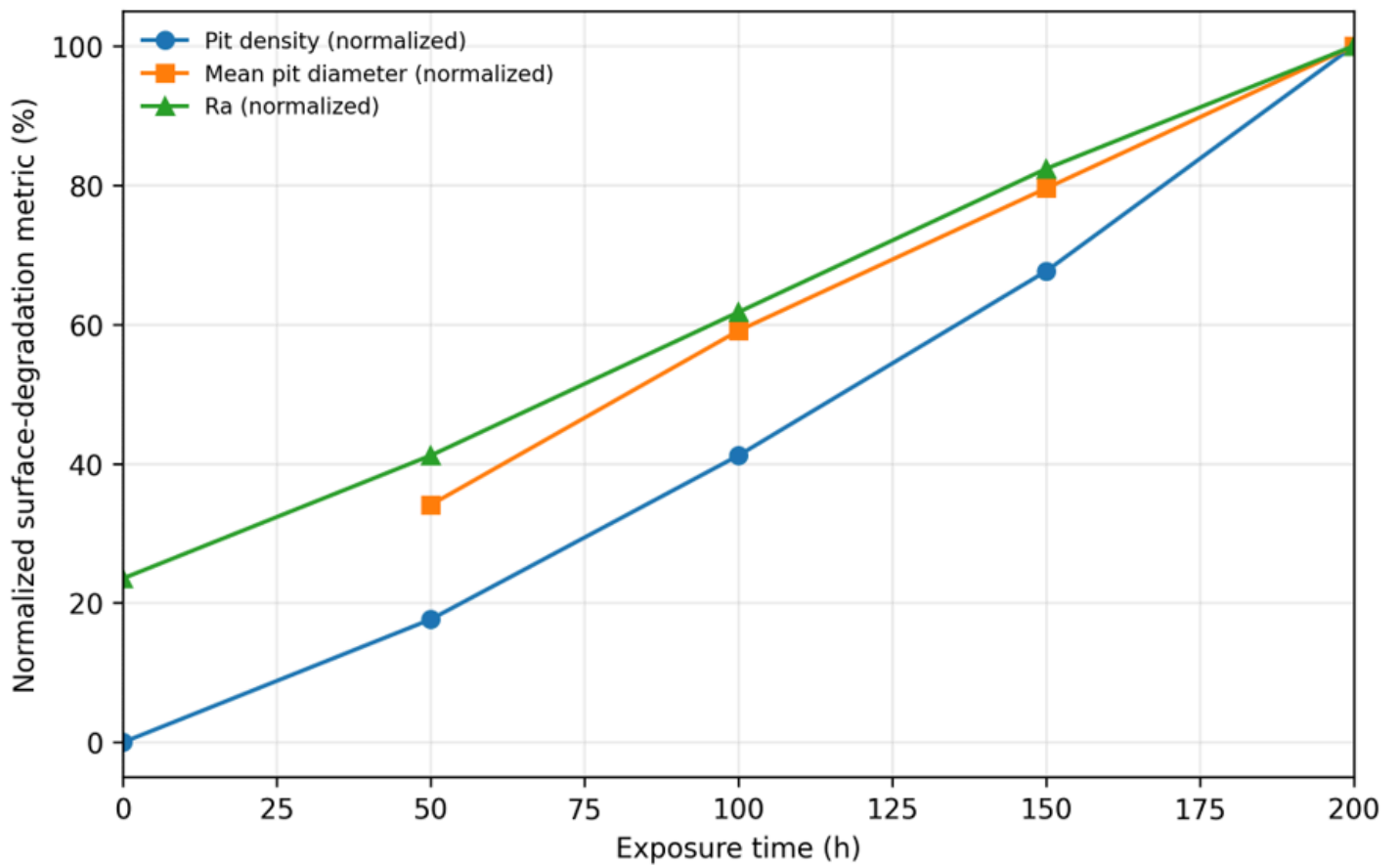


Figure 2

Evolution of surface-degradation indicators during the controlled saline exposure

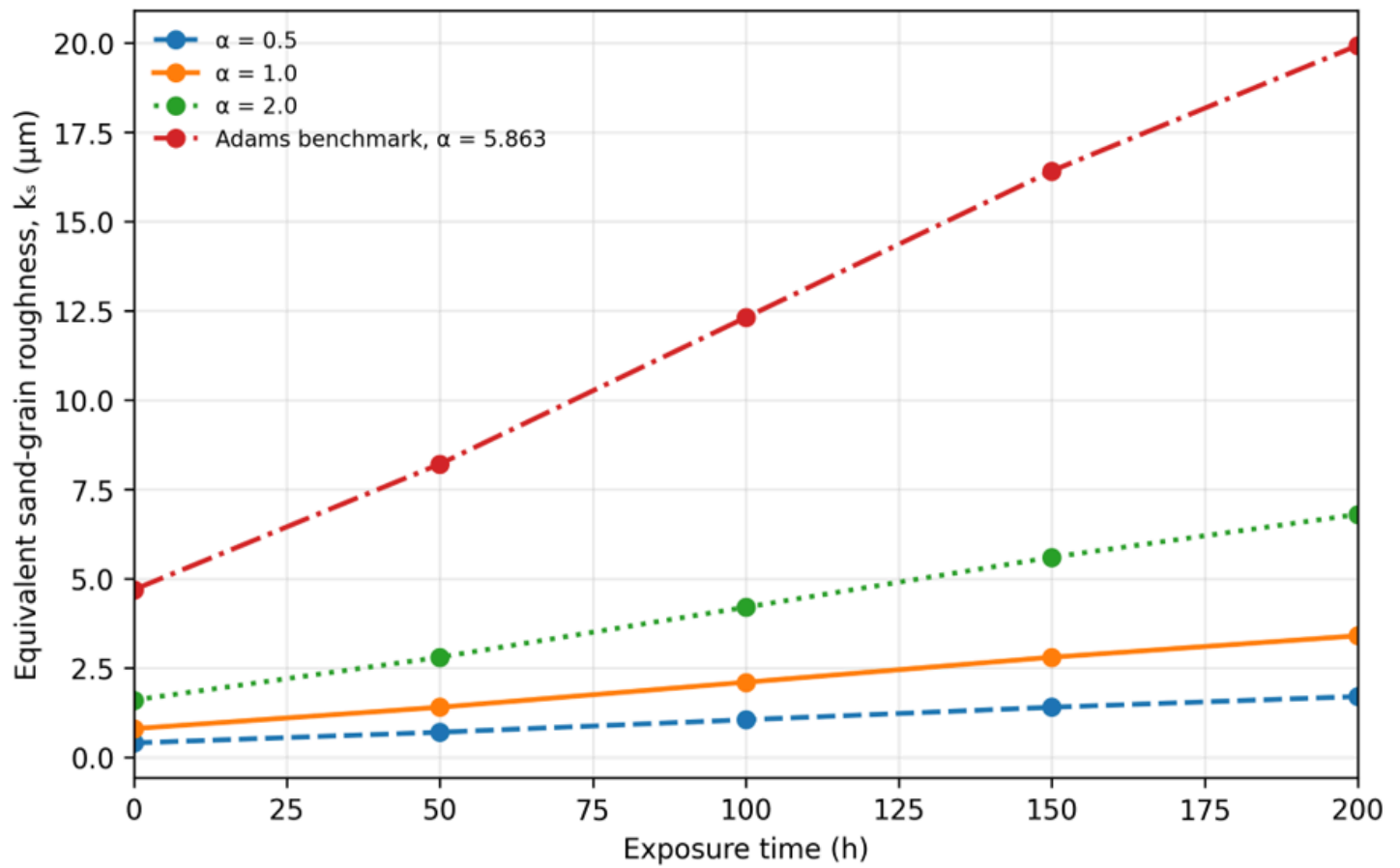


Figure 3

Sensitivity of the CFD-facing roughness parameter to the selected transfer multiplier; the Adams et al. (2012) benchmark is shown for context only

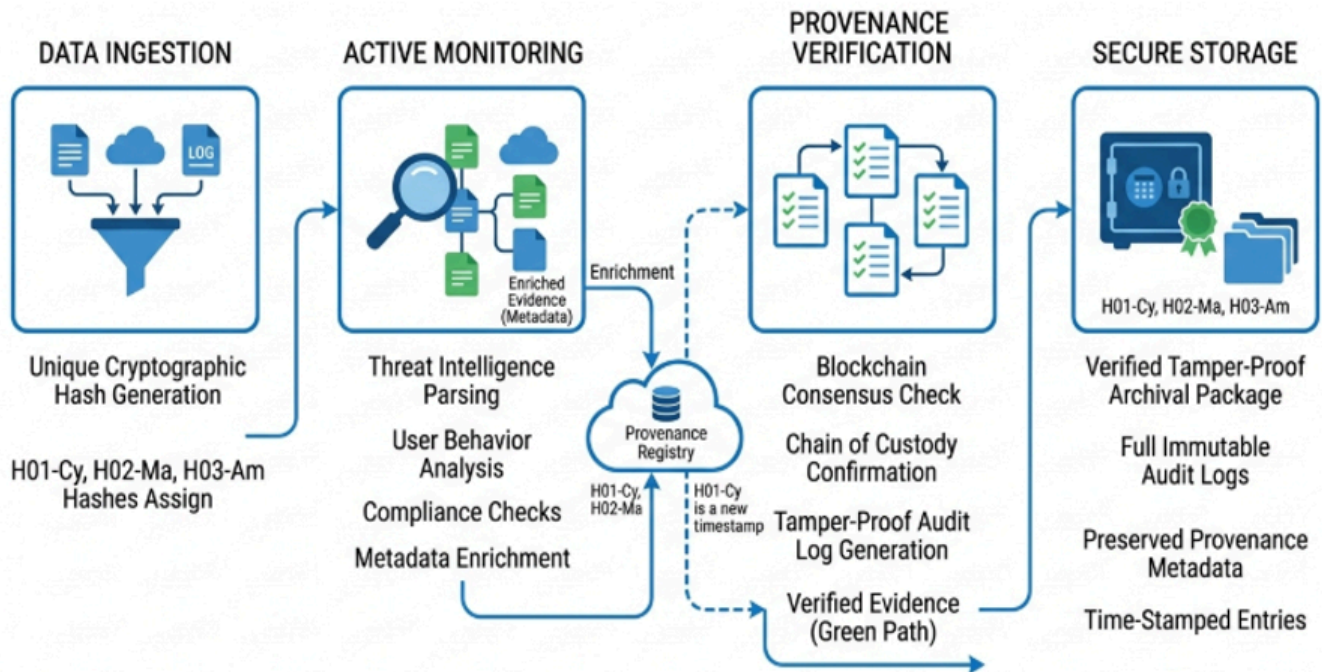


Figure 4

Evidence provenance preserved across the proposed monitoring state

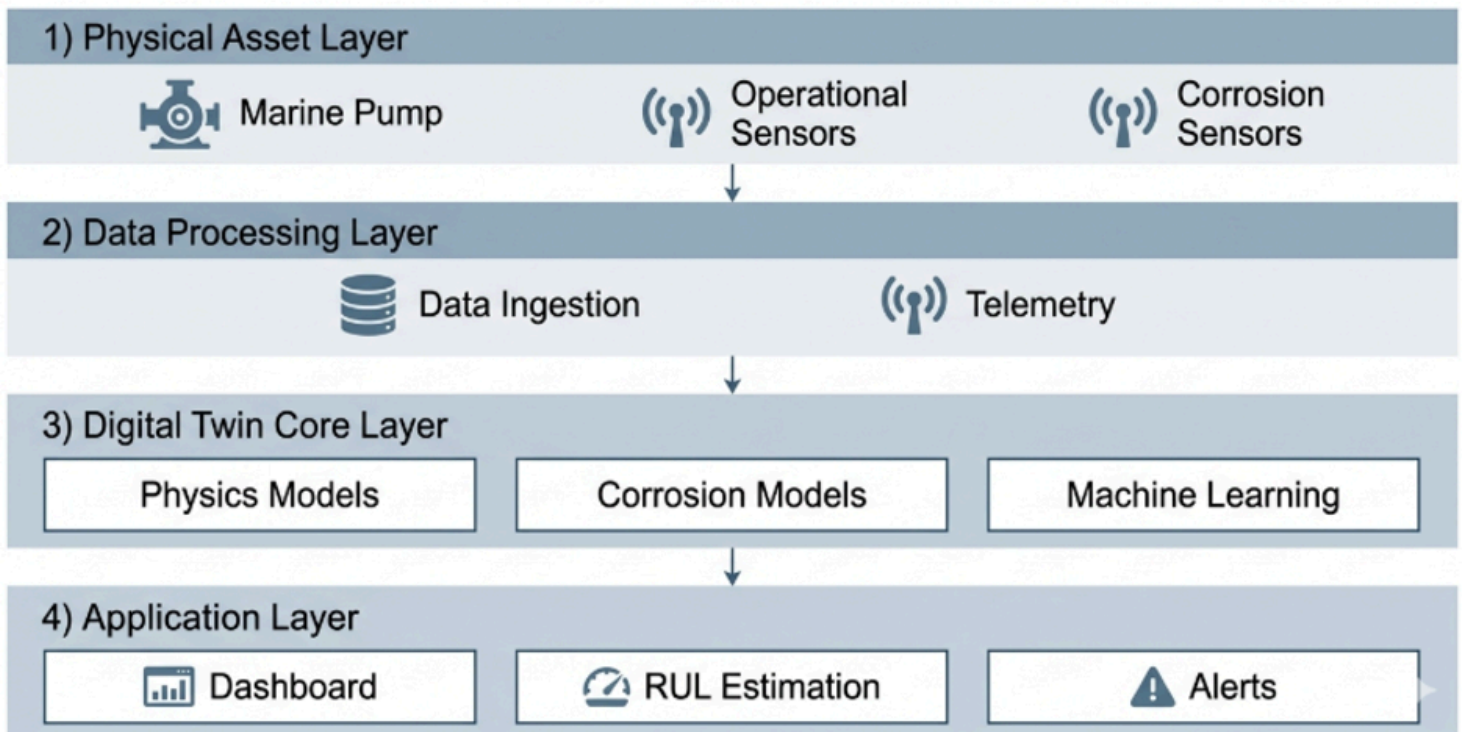


Figure 5

Proposed corrosion-aware digital-twin architecture for marine centrifugal-pump condition monitoring

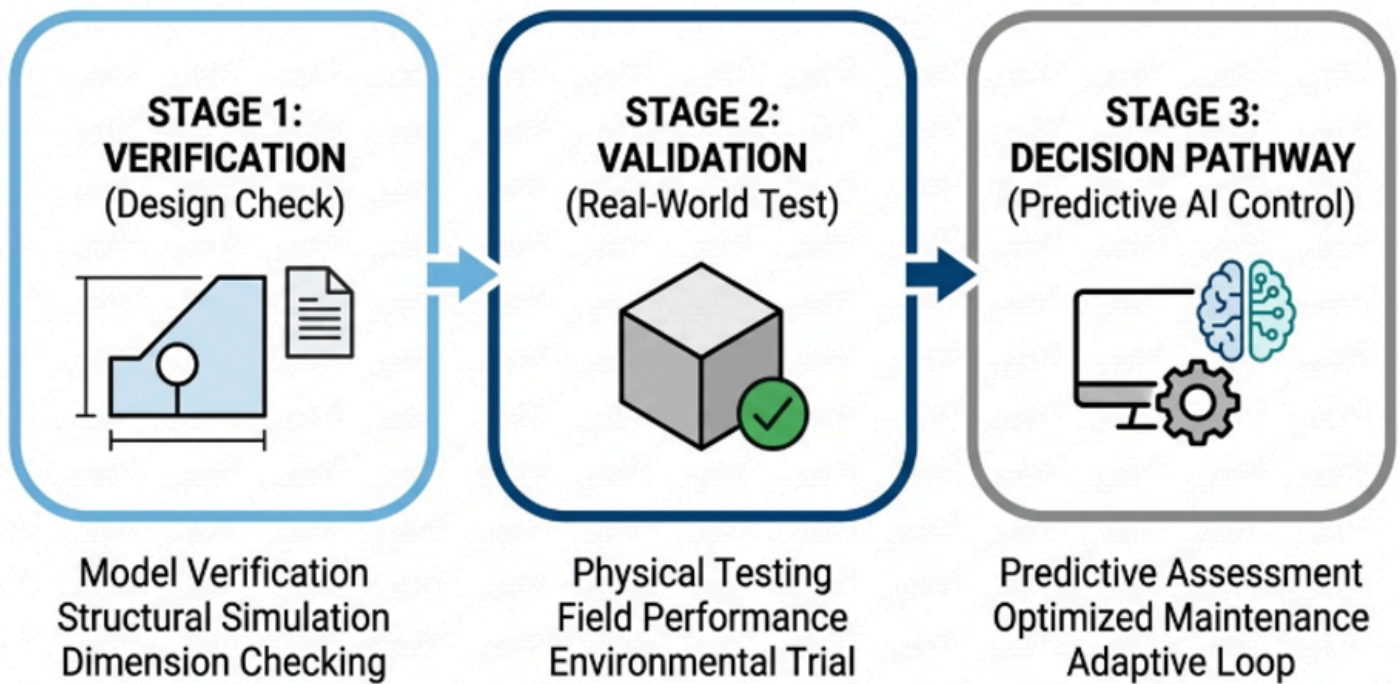


Figure 6

Staged verification, validation and future intelligent-decision pathway