

A Physics-Informed, Corrosion-Aware Digital-Twin Framework for Condition Monitoring of Saline-Service Centrifugal Pumps

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Research Article

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A Physics-Informed, Corrosion-Aware Digital-Twin Framework for Condition Monitoring of Saline-Service Centrifugal Pumps

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ABSTRACT

Centrifugal pumps working in saline environments directly bridge corrosion-related material deterioration, dynamic response and hydraulic efficiency domains, yet condition-monitoring approaches often isolate these. A preceding work by the author introduced a Pump Degradation Index (PDI) by combining a corrosion-related material degradation indicator derived from coupons, RMS vibration and hydraulic-efficiency degradation into one condition indicator.

This work explores the potential to link these by proposing a time-based, physics-based digital twin framework where the PDI is used as a transparent intermediate state of degradation rather than as a failure probability or end-of-life indicator.

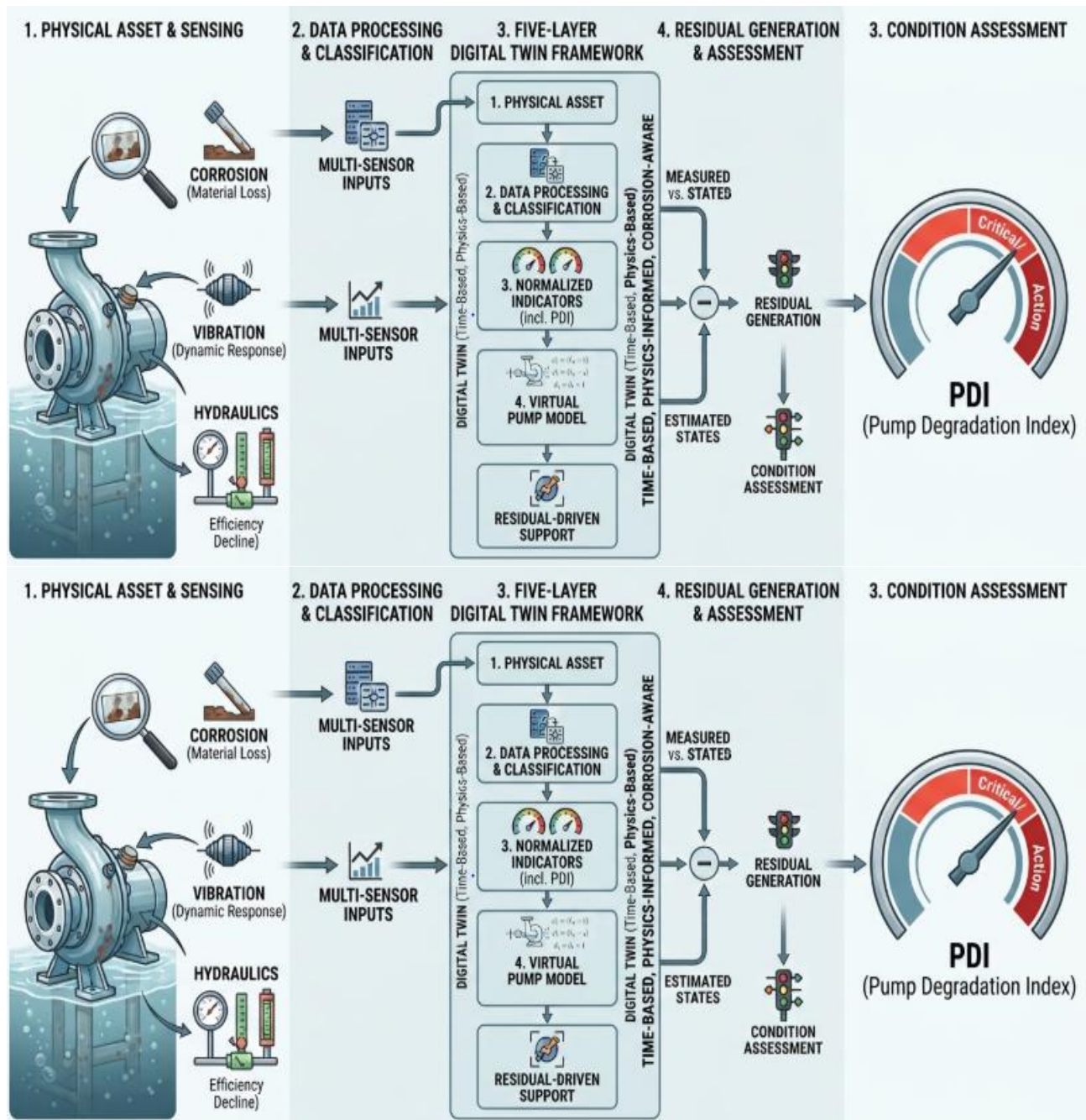
Five layers are used: physical asset and sensing; data processing and classification; normalized degradation indicators; a physics-based virtual pump; and residual-driven condition assessment and decision support. A corrosion-driven material degradation, efficiency and dynamic response state-space representation is formulated with flow, head, speed, pressure, temperature, chemistry and discharge angle as operating variables. The framework is tested in a environment based on the five-point laboratory degradation trajectory that underpins the PDI work, with pump output predictions from a reduced-order pump model and residual generation resulting from states using out-of-phase operating variables (flow, head, pressure, head, speed and temperature). The results depict the

normalized component trajectories and PDI values for the five test cases of 0.000, 0.301, 0.542, 0.777 and 1.000 over 0-200 h, but do not demonstrate validation.

The framework is intentionally simplistic for use in offshore sparse-data environments where a digital twin may be unrealistic. Prior to field adoption, the conditions/maintenance framework requires re-testing with multiple units, continuous field data and independently quantified component degradation, and maintenance and failure records.

Keywords: centrifugal pump; digital twin; corrosion-aware condition monitoring; pump degradation index; asset integrity; vibration; hydraulic performance; predictive maintenance; offshore engineering; physics-informed modelling

Graphic Abstract



Research Highlight

- Extends the previously proposed PDI into a lightweight physics-informed digital-twin architecture.
- Keeps corrosion-related, vibration and hydraulic domains physically identifiable rather than hiding them in a latent health score.

- Introduces operating-state conditioning and model–measurement residuals as safeguards against false degradation attribution.
- Defines a staged validation route from laboratory repeatability to field maintenance and failure-event validation.
- Demonstrates the digital-state representation using the published five-point trajectory without introducing fabricated field or failure data.

1 Introduction

Centrifugal pumps are rotating assets commonly used in subsea production, seawater circulation, firewater, cooling-water, ballast, produced-water and injection-water systems [6,7]. Their condition and performance degradation can impact the provision of production, energy efficiency, maintenance cost and safety-critical availability. In the presence of saline service degradation, the physical changes in the fluid hydraulic and dynamic state are convolved with material-degradation processes; a single sensor or single state indicator may not be adequate to characterise the overall operation.

In a prior study [1], a multi-domain Pump Degradation Index (PDI) was created by normalising a corrosion-related surrogate of material degradation, RMS-vibration levels and hydraulic-efficiency losses, then combining this by explicit weights. The experimental platform included one commercially-available 316L stainless-steel centrifugal pump, operated in 30-ppt synthetic seawater for 200 hours. Data were gathered at 0, 50, 100, 150 and 200 hours; the PDI was constructed explicitly as a condition indicator rather than as a reliability function, failure probability or future-useful-life index. The requirements for this work's future research objectives are thus driven by the relatively small original dataset, which is not suitable for population-level inference,

but which could be augmented with additional experimental runs, multiple pump units, additional operational points, off-shore observations, component-scale material-degradation data, raw vibration time histories, pressure and temperature data, operational-state information and maintenance events, leading ultimately to validation of the PDI against independent deterioration observations and its future correlation with reliability or prognostic models [1].

Digital twins are well suited as an engineering architecture for such extensions [12,13,17,18]. A digital twin can be considered here to be a computational model that is coupled to the physical asset through measurement acquisition, state estimation, comparison of anticipated and observed behaviour and maintenance updates. A recent example of this approach can be found in the application of hybrid digital twins to marine engine condition monitoring, where data interoperability, acquisition and modelling burdens are discussed [19]. These studies highlight the importance of flexible but interpretable digital twin components; the present study avoids proposing a high-fidelity CFD/finite-element twin. The overarching research question for this paper is thus: how can a previously-published corrosion-vibration-hydraulic PDI be incorporated into a physically-informed digital-twin architecture that remains interpretable, supports the fusion of multiple signals and provides a transparent pathway toward future maintenance-event validation?

1.1 Research gap

There is no gap in the use of digital twins, machine learning or health index methods; the gap is in the presence of a transparent state that preserves the physical identification of corrosion-related material exposure, dynamic response and hydraulic function while allowing comparison with model-predicted normal operating behaviour. Purely statistical health indices can ignore physical meaning, whereas a fully physical digital twin may require parameters unavailable in offshore brownfield data; deep-learning prognostication models may not have sufficiently long offshore

service histories [12,13,17]. This positioning is in line with well-established condition-based maintenance practice, which distinguishes between detection, diagnosis and prognosis, as well as recent reviews of digital twins for rotating machinery applications [12-14,17]. For centrifugal pumps, there are also published attempts to fuse signals by combining complementary condition indicators [9-11]. Here, the goal is a robust and testable link between interpreted physical corrosion processes and the eventual data-driven prognostic.

1.2 Objectives and contributions

The motivation of this research is to develop and demonstrate a reliability- driven Pump Degradation Index (PDI) condition assessment tool for pumps under saline-service conditions. The PDI combines hydraulic performance, vibration, and corrosion-related material degradation in a single, dimensionless index for tracking progressive condition deterioration. The goals are to:

- Combine hydraulic, vibration, and corrosion-related indicators into a single degradation expression.
- Normalize measurements with different units and scales, and then combine them into a weighted sum.
- Determine and interpret the degree of progressive pump degradation over the 200-h saline-service exposure period.
- Determine the monotonicity and interpretability of the resulting PDI,
- Examine the robustness of the proposed normalization and weighting methodology.

The contributions are:

- Creation of a transparent, dimensionless PDI that combines degradation-indicator trend lines.
- Demonstration of the development framework using previously published experimental data from a 316L, high-salinity exposure pump.
- Integration of corrosion-related, and hydraulic and vibration-driven deterioration information into a single condition-trending metric.
- Explicit differentiation of coupon corrosion values as a material-degradation surrogate as opposed to pump component corrosion.
- Positioning of the PDI as a condition/ degradation indicator and not as a failure, hazard, or residual useful life indicator.

This provides a basis for future validation studies with longer-exposure experiments, field data, component-level testing, and failure-labelled datasets.

1.3 Scope and interpretation

The paper describes a methodological and numerical proof-of-concept digital-twin framework rather than a physically validated operational digital twin, which requires additional physical validation. Within this paper "physics-informed" refers to the explicit use of the pump hydraulic relationships, operating-envelope limits, degradation-state variables and model-measurement residuals in the condition-monitoring framework. It does not mean that the entire first-principles multiphysics model has been realized and that each of the degradation mechanisms has been mechanistically resolved.

Verification considers whether the mathematical implementation correctly realizes the proposed formulation, and validation considers whether the realized model adequately captures physical pump behaviour.

This work considers numerical verification and proof-of-concept validation; physical validation is future work.

- To develop a lightweight physics-informed digital-twin framework for saline-service centrifugal pumps.
- To define a digital degradation state in terms of the PDI that retains its epistemic separation from probability of failure and RUL. 3. To develop residuals that differentiate between changes in operating conditions and degradation-dependent deviations.
- To define a data schema and validation protocol that supports laboratory, multi-pump and offshore implementation.
- To demonstrate the numerical response of the framework using the previously published five-point dataset without providing a new experimental validation.

1.4 Relationship to the previous PDI study and data reuse

The current paper is intentionally designed to be a conceptual continuation rather than a reinterpretation or extension of the prior PDI study [1]. The previous publication has observed that: the equal-weights PDI increased from 0.000 at baseline to 1.000 at 200 h; that the broad system trajectory was relatively insensitive to the feasible weighting set, compared to the early discrete states; and that the prior system pressure boundary condition was a coupon-derived exposure/material indicator rather than a direct measurement of material loss on the pump rotor, casing, or other components. Those boundaries are preserved here [1].

This article does not duplicate the original experimental methodology nor claim the prior

observations as newly produced data. The 5-point trajectory is merely reused to show a mathematical fit between the PDI and the potential digital-twin architecture. The innovation resides in the architecture, the residual formulation, the operating-state conditioning, the maintenance-event feedback loop, and the staged validation scheme.

Table 1. Relationship between limitations of the previous PDI study and the proposed digital-twin extension.

Previous limitation	Digital-twin extension proposed here	Evidence required for validation
Five observation times	Continuous or higher-frequency sensor acquisition	Longitudinal operational dataset
Coupon-based corrosion proxy	Component/in-situ corrosion observations where feasible	Inspection, UT, probes, coupons or validated proxy
RMS vibration only	Raw vibration and frequency-domain features	Accelerometer time histories and tachometer
Dataset-bounded normalisation	Operating-envelope and engineering-limit normalisation	Manufacturer/serviceability limits
No maintenance/failure labels	Maintenance-event and failure-event linkage	CMMS/work-order and inspection records
No prognostic model	Residual/state trajectory as	Longitudinal degradation and

	input to future prognostics	failure histories
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The table 1 above summarizes how each of the deficiencies identified for the last PDI study can be overcome by a proposed digital-twin extension. It identifies which additional data, modelling capabilities and validation evidence are needed to build up a more complete and operationally relevant digital-twin framework. Accordingly, the proposed extension evolves from a dataset-constrained degradation indicator towards continuous condition monitoring and, ultimately, validated prognostics.

2 Materials and Methods

2.1 Digital-twin architecture

The architecture is defined as a closed information loop, since the real pump sensors and inspection data are pre-processed, with the operating state classified, physics-informed virtual pump runs, with normalised indicators of degradation, PDI residual analysis, to aid in the maintenance decision. The loop is bidirectional, since maintenance actions are made to change the physical state of the pump, necessitating the digital twin to be re-initialised after inspection, repair or component replacement. This architecture is a proposed architecture; continuous field synchronisation is not achieved in this current poc.

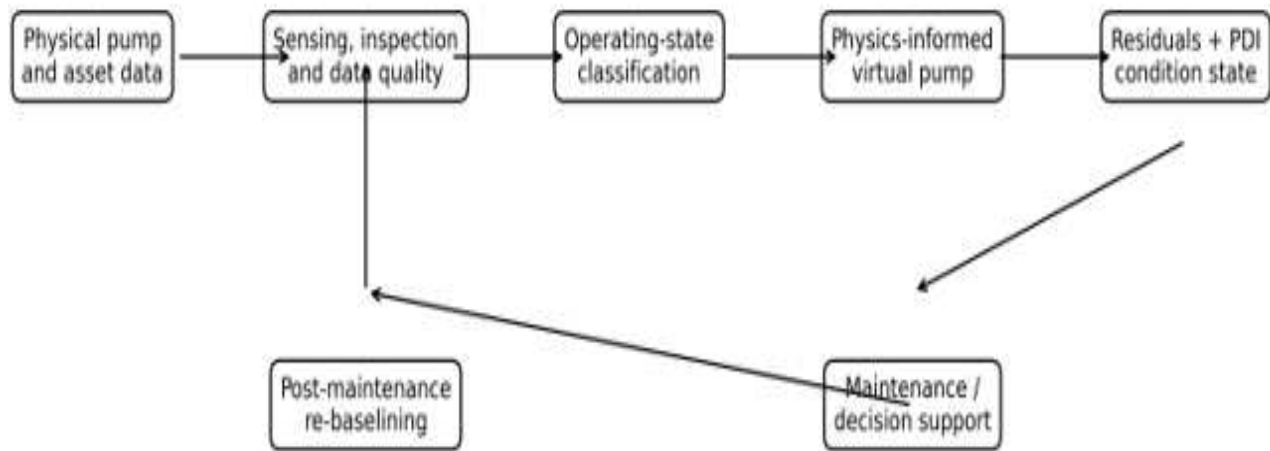


Fig. 1 Conceptual architecture of the proposed corrosion-aware digital twin for a saline-service centrifugal pump.

Figure 1: Conceptual design of the corrosion-aware digital twin, which combines corrosion data, measurements from sensors, and corrosion information to capture the degradation development of a saline-service centrifugal pump. The digital twin connection to the physical pump is indicated in the bottom right, with features derived from the physical pump for use in condition monitoring, trend evaluation, and future prognostics design.

2.2 Asset and data layers

Minimum data layer should include Pump identification, component/material information

Operating point Process fluid variables Sensor data Inspection data and findings. Maintenance

history Recommended continuous data flow Q, Discharge and suction pressure, Pump head H,

Shaft speed n, Motor/Input power, Temperature, RMS vibration and-if instrumentation allows-raw

vibration time histories. Context variables Salinity or conductivity, Fluid temperature, Pressure,

Suspended-solids indicators, operating mode, valve configuration. Event data Start/stop, Trips, Alarms, Inspection, Seal replacement, Bearing replacement, Balancing, Overhaul and Failure.

Table 2. Recommended digital-twin data schema and diagnostic role.

Data domain	Core variables	Purpose
Hydraulic	Q, H, suction/discharge pressure, efficiency	Functional performance and operating envelope
Dynamic	RMS vibration, spectrum, shaft speed, phase	Dynamic response and fault discrimination
Material/corrosion	Coupon loss, UT thickness, probe signal, inspection score	Material degradation context Operating-state conditioning
Thermal/process	Temperature, salinity/conductivity, fluid pressure	
Electrical	Power, current, voltage, frequency	Energy/performance context
Maintenance	Work orders, component replacement, inspection findings	Ground truth for event validation

The table above outlines the recommended data structure for the digital twin and how each of the data domains contributes to diagnostics. Bringing together hydraulic, dynamic, corrosion, process, electrical, and maintenance data, the digital twin offers a more comprehensive picture of pump condition that supports condition assessment, fault diagnosis, and validation of the digital twin in the future.

2.3 Operating-state conditioning

A principal risk in pump digital twins is confusing an operating-point change with degradation. The proposed framework therefore conditions model residuals on the operating state before interpreting them as health changes.

Let the operating vector be

$$u(t) = [Q(t), n(t), T(t), S(t), p(t), v(t)]^T,$$

where Q is flow rate, n is rotational speed, T is relevant temperature, S is salinity or conductivity, p is pressure context, and v represents valve/process-state information. Pump head H , efficiency η and RMS vibration V_RMS are treated as response variables when they are being predicted.

The virtual pump predicts the expected response

$$\hat{y}(t) = F\theta(x(t), u(t))$$

where $x(t)$ is the latent degradation state and θ represents calibrated model parameters.

Residuals should only be interpreted as degradation evidence after accounting for operating regime, sensor quality and model uncertainty. For deployment, operating regimes may be defined using physically meaningful envelopes or data-driven clustering of Q , n and process variables; the nominal response model should then be calibrated within or across those regimes as supported by the available data.

$$u(t) = [Q(t), n(t), T(t), S(t), p(t), v(t)]^T \tag{1}$$

Operating-context vector used to condition the expected pump response; measured head is not included when head is the predicted response.

Where head is derived from measured suction and discharge pressures, $H(t) = [p_d(t) - p_s(t)]/[\rho g]$. This relation is a measurement/consistency equation; it is not used as an independent predictor of H when pressure-derived head is the response.

$$\hat{y}(t) = F\theta(x(t), u(t)) \quad (2)$$

Model-predicted response, where $x(t)$ is the latent degradation state and θ contains calibrated parameters.

$$r_i(t) = y_i(t) - \hat{y}_i(t) \quad (3)$$

Measurement–model residual for response variable i .

$$z_i(t) = [y_i(t) - \hat{y}_i(t)] / \sigma_i \quad (4)$$

Standardized residual relative to the nominal residual scale is represent by σ_i .

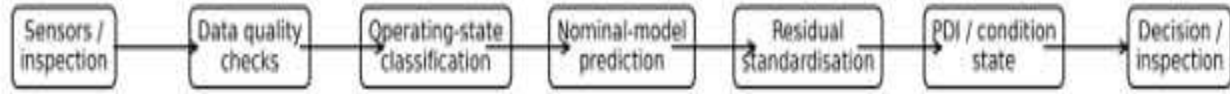


Fig. 2 Data acquisition, quality screening, operating-state classification and residual-assessment pathway.

Fig. 2. Data-processing scheme for digital twin The raw sensor data and plant operational data are acquired and screened for quality then classified as pump operating state. The processed data are fed into the digital twin, which generates residuals by difference calculation between the plant and digital-twin models to be used for monitoring anomalous pump behaviour as well as condition evaluation and degradation trend

2.4 Degradation-state representation

The PDI remains as an intermediate dimensionless state. For potential subsequent use in operation, the component indicators should each be based on independent engineering limits rather than the

maximum observation of a single test. For a generic degradation variable X bounded engineering-limit normalisation is Eq. (6).

The five-point proof-of concept, however, uses dataset-bounded normalisation, enabling direct comparison with the previous PDI study [1].

$$R(t) = \sum_{i=1}^m a_i |z_i(t)| \quad (5)$$

Multimodal residual/anomaly score; a_i are non-negative diagnostic weights. $R(t)$ is not a failure probability.

$$X_{n,eng}(t) = \min\{1, \max[0, (X(t) - X_0)/(X_{eng} - X_0)]\} \quad (6)$$

Bounded engineering-limit normalisation for a degradation variable X .

$$PDI(t) = w_C C_n(t) + w_V V_n(t) + w_E E_n(t) \quad (7)$$

Multidomain degradation state with non-negative weights satisfying $w_C + w_V + w_E = 1$.

$$H_m(t) = 1 - PDI(t) \quad (8)$$

Complementary mathematical condition coordinate; it is not a survival probability.

The notation H is reserved for pump head, while H_m denotes the complementary mathematical condition coordinate. The latter becomes a reliability variable only after independent statistical calibration against failure and censoring data.

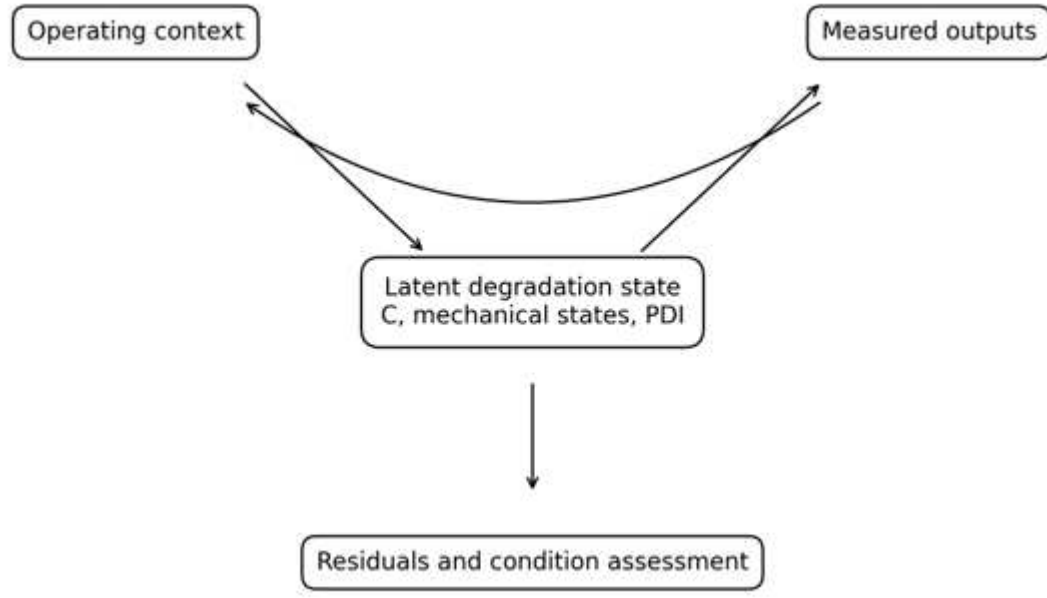


Fig. 3 State-space representation linking operating context, latent degradation state, measured outputs and condition assessment.

2.5 Physics-informed virtual pump

The virtual pump should contain a hierarchy of models. Level 1 is a low-order performance model, suitable for real-time implementation. Level 2 adds dynamic residual models. Level 3 adds material-degradation state variables. High-fidelity CFD or finite-element models should be used selectively for parameter studies rather than required at every update. For brownfield offshore deployment, model complexity should be selected according to update frequency, available instrumentation, parameter identifiability and computational resources rather than maximising physical fidelity.

$$P_h(t) = \rho g Q(t) H(t) \quad (9)$$

Hydraulic power obtained from fluid density, flow rate and pump head.

$$\eta(t) = P_h(t) / P_{\text{input}}(t) \quad (10)$$

Hydraulic efficiency calculated from hydraulic and input power.

Equations (9) and (10) provide first-order physical consistency constraints; they do not constitute a complete pump performance map. P_{input} denotes the measured pump input power used consistently with the underlying experimental method and future field instrumentation.

For material degradation, a general state equation can be written as a framework-level transition model. The corrosion-related state C should be understood as a future component-level or modelled state; the coupon-derived mass-loss indicator used in the current demonstration is a proxy and is not treated as direct impeller or casing corrosion.

$$dC/dt = kC \phi[S(t), T(t), p(t), u(t)] \quad (11)$$

Generic corrosion-related state evolution; kC and ϕ require independent calibration and are not estimated from the five-point demonstration.

For dynamic response, a reduced-order representation may be written as a candidate coupled model. It does not imply that corrosion is the sole or dominant cause of vibration; vibration remains multi-causal and should be calibrated against frequency-domain and component-level evidence.

$$\hat{V}_{\text{RMS}}(t) = fV[Q(t), H(t), n(t), C(t), x_m(t), x_b(t)] \quad (12)$$

Candidate reduced-order dynamic-response model linking operating and mechanical state variables to expected vibration.

2.6 Residual-based condition assessment

2.5.1 Implemented reduced-order physics model

To convert the proposed architecture into an executable numerical proof of concept, a deliberately low-order state-output model was implemented using the five published observations. Because the source experiment contains one pump, one material configuration, one nominal speed and a narrow operating window, a full pump performance map cannot be identified without introducing unsupported assumptions. The implemented model therefore uses the published normalised degradation indicators as state coordinates and calibrates first-order output mappings from the first four observations (0–150 h). The 200-h observation is retained as a pseudo-hold-out point for numerical demonstration. This is a verification-oriented split, not independent validation.

For pump head, hydraulic efficiency and RMS vibration, the implemented output mappings are:

$$\hat{H}(t) = \beta_{H0} + \beta_{H1} C_n(t) \quad (13)$$

$$\hat{\eta}(t) = \beta_{\eta0} + \beta_{\eta1} E_n(t) \quad (14)$$

$$\hat{V}_{RMS}(t) = \beta_{V0} + \beta_{V1} V_n(t) \quad (15)$$

where C_n , E_n and V_n are the normalised corrosion-related, efficiency-loss and vibration indicators, respectively.

The coefficients are calculated by ordinary least squares, using the initial 4 observations of the data. (This is a deliberately reduced-order example: it shows a working state-to-output map that does not claim that the five-point data can define a general pump performance curve.) For this proof of concept, the fitted coefficients are $H_0 = 12.0224$ m and $H_1 = 1.1997$ m; and, $\eta_0 = 70.6023$ % and $\eta_1 = 12.5983$ %, and $V_0 = 0.19996$ mm/s and $V_1 = 0.55019$ mm/s. These parameters are calibration parameters for this numerical proof of concept demonstration, and not intended to define any generalizable pump constants.

The model is expressed succinctly as $y(t) = F[x(t)]$, where $x(t) = [C_n(t), E_n(t), V_n(t)]$ in the demonstration implementation. For the field twin, $x(t)$ would be derived from sensors and operating

context, whereas Q , n , T , S , p , and the valve and/or process states would feed into a richer calibrated model. Again, the present implementation only demonstrates the state-output relationship and residual mechanisms, without implying that all source-state dependencies are retrievable from the source dataset.

2.5.2 Residuals, error metrics and uncertainty demonstration

Here we use the measurement-model residual $r_i(t) = y_i(t) - \hat{y}_i(t)$ (16). The nominal residual scale i is estimated from the four calibration observations, with the standardised residual $\hat{r}_i(t) = r_i(t)/i$ (17). For the simple numerical case study, Equal weights was used in $R(t) = [|z_H| + |z| + |z_V|]/3$, where $z_i(t) = r_i(t)/i$. The MAE and RMSE are reported across all five observations as a simple illustrative proof-of-concept metric, while a 95% prediction interval is also calculated for the 200-h pseudo-hold-out point (using the residual variance of the four-point calibration fit). The intervals describe the model uncertainty for this small numerical exercise only; the intervals are not intended to be sample-level confidence bounds.

It is worth making a distinction here between calibration of the model and the subsequent evaluation: the first four observations are used to calibrate the reduced-order coefficients, whilst the fifth is held back from that calibration. The 200-h estimates are $H = 10.8226$ m, $\eta = 58.0040\%$, and $V_RMS = 0.7501$ mm s⁻¹. The corresponding residuals are 0.1226 m, 0.0040 percentage points and 0.00015 mm s⁻¹. The 95% prediction intervals at 200 h are 10.5817-11.0636 m for head, 57.9814-58.0267% for efficiency and 0.7484-0.7519 mm s⁻¹ for vibration.

The general procedure is that for each measured variable y the standardised residual in Eq. (4) is estimated relative to nominal-condition residuals, while the multimodal residual score in Eq. (5) offers an anomaly measure; thresholds should be calibrated from nominal and event-labelled datasets rather than imposed. Arbitrarily. The PDI and residual score conceptually segregate the

two; the PDI summarises the observed degradation domains and the residuals label departures from the modelled expected behaviour.

2.7 Maintenance-event updating

Following an intervention, the twin must no longer follow the pre-maintenance degradation path without being re-initialised. A typical sequence of follow up would be: detect event - classify intervention - record inspected/replaced components - verify maintenance complete - confirm stable post-maintenance behaviour - establish new baseline - continue online tracking. This step is critical for eventual prognosis modelling, as maintenance introduces a discontinuity in the health path.

2.8 Validation strategy

Table 3. Progressive validation strategy, performance metrics and acceptance questions.

Stage	Dataset	Primary metric	Acceptance question
L1	Repeated laboratory tests	Repeatability, coefficient of variation	Does the indicator reproduce under controlled conditions?
L2	Multiple pumps/materials/duty points	Cross-unit error and calibration stability	Does the model generalise across assets?

L3	Field/offshore operation	Residual false-alarm rate; trend consistency	Does it distinguish operating variation from degradation?
L4	Maintenance/inspection events	Event detection lead time; precision/recall	Do PDI/residual changes align with actual interventions?
L5	Failures/censoring	Calibration, discrimination, Brier score, survival metrics	Can the state support reliability/prognostic modelling?

Table 3 outlines a **five-stage validation pathway**, progressing from laboratory repeatability (L1) to field validation (L3), maintenance-event correlation (L4), and reliability/prognostic assessment (L5). Each stage addresses a specific validation question, with predefined performance metrics and acceptance criteria. Importantly, thresholds should be established from engineering requirements or independent validation data, not from the five-point proof-of-concept trajectory.

2.9 Numerical proof-of-concept dataset

The numerical demonstration is based solely on the five published observations that form the basis of the previous PDI [1]. The data include 0-200h flow, head, input power, efficiency, RMS vibration and coupon mass loss observations from the previous PDI study, with no new observations, failures, maintenance observations, or field measurements fabricated. It is intended only to verify the mathematical relationship between the existing PDI and proposed digital-twin state architecture. With just five accumulated observations from a single experimental trajectory, no formal statistical uncertainty estimation or population inference is performed.

Table 4. Numerical proof-of-concept dataset reused from the previously published pump study [1].

Time (h)	Q (m³/s)	H (m)	η (%)	V_RMS (mm/s)	316L loss (mg)	PDI
0	0.00150	12.0	70.6	0.20	0.0	0.000
50	0.00147	11.6	66.7	0.32	5.8	0.301
100	0.00144	11.3	63.7	0.45	9.6	0.542
150	0.00141	11.0	61.0	0.61	12.7	0.777
200	0.00138	10.7	58.0	0.75	15.4	1.000

Table 4. Reused five-point data set from the pump test of prior publication and the computation of PDI as the degradation proceeds to a total of 200 h. The data indicate the degradation in the hydraulic performance, vibration and material loss while the PDI increases from zero to 1.0. The PDI=1.000 represents the greatest extent of degradation observed in this data set and is not a level of failure or reliability.

3 Results and Discussion

3.1 Normalised multidomain degradation trajectories

The numerical validation replicates the normalised degradation evolutions reported. The corrosion related material indicator reaches 0.377, 0.623, 0.825 and 1.000 at 50, 100, 150 and 200 h respectively. The equivalent normalised vibration values are 0.218, 0.455, 0.745 and 1.000 while the efficiency-loss indicator reaches 0.310, 0.548, 0.762 and 1.000.

These values are the deterministic transformation of the published data, not new measurements [1].

The simultaneous increases between the three domains establish co-evolution in the demonstration over time, but do not enable any causal linkage between corrosion, vibration and hydraulic loss.

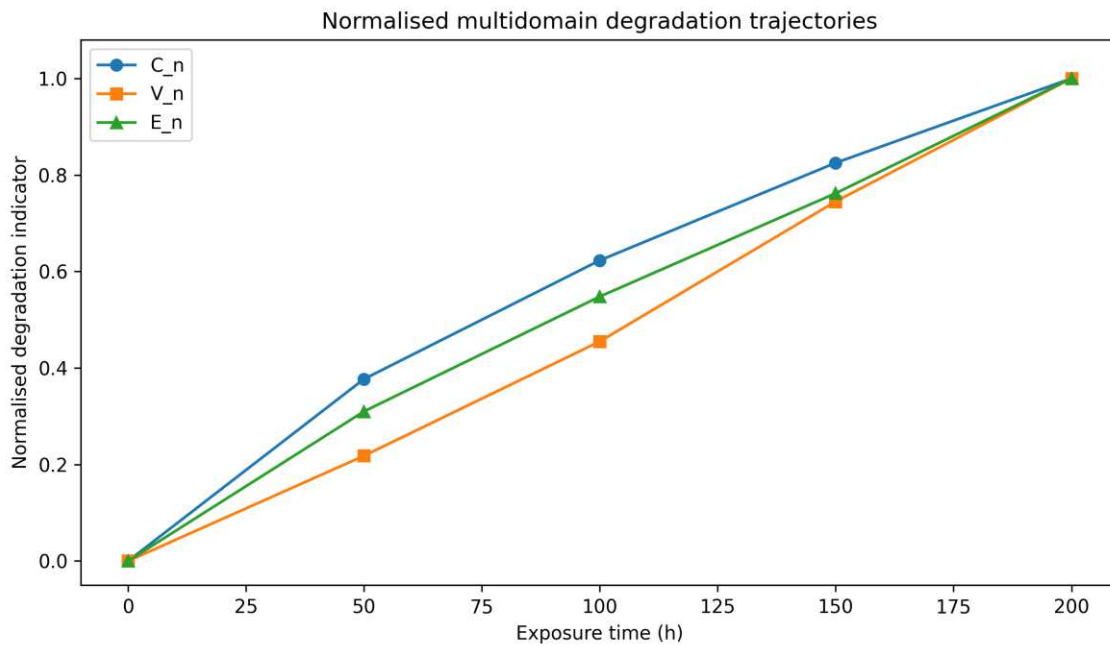


Fig. 4 Normalised corrosion-related material, vibration and hydraulic-efficiency degradation indicators reproduced from the published five-point dataset.

Fig. 4 The variation of corrosion material & vibration degradation and hydraulic efficiency In order to show the variation of the three indices, their development trend during the whole test procedure is illustrated in Fig. 4.

Those three indicators go up with different speeds and then result in the PDI.

Table 5. Normalised component indicators, equal-weight PDI and complementary mathematical condition coordinate

Time (h)	C_n	V_n	E_n	PDI	H_m
0	0.000	0.000	0.000	0.000	1.000
50	0.377	0.218	0.310	0.301	0.699
100	0.623	0.455	0.548	0.542	0.458

150	0.825	0.745	0.762	0.777	0.223
200	1.000	1.000	1.000	1.000	0.000

Table 5 shows the normalised degradation indicators for corrosion-related material loss (CnC_n), vibration (VnV_n), and hydraulic efficiency degradation (EnE_n), together with the equal-weight PDI and complementary condition coordinate (HmH_m). All degradation indicators increase progressively with time, causing the PDI to rise from 0 to 1.0, while HmH_m decreases from 1.0 to 0, providing an inverse representation of condition. This demonstrates how multiple degradation modes can be combined into a single condition index while retaining a complementary measure of remaining condition

3.2 Digital degradation state and PDI trajectory

With equal weighting the values for PDI are 0.000, 0.301, 0.542, 0.777 and 1.000. The complementary coordinate $H = 1 - \text{PDI}$ is 1.000, 0.699, 0.458, 0.223 and 0.000. The coordinate is just a mathematical transform of the PDI and should not be regarded as a probability of survival or that the pump failed at 200 h.

The PDI at 50 h, for example, is $(0.3767 + 0.2263 + 0.3077)/3 = 0.30$, when computed with the displayed rounded values, whereas the PDI is reported as 0.301.

This small difference is due to the rounding in calculating the displayed values; therefore the manuscript states that the PDI was calculated from the underlying unrounded values.

3.3 Sensitivity of the PDI trajectory to weighting

Since the three component indicators are constrained between 0 and 1 and the weights are non-negative with sum of one, the PDI is a convex combination of the component indicators. It must therefore fall between the min and max component indicators for each observation time. The 5151 non-negative combinations of weights at 0.01 levels satisfying the sum rule ($w_C + w_V + w_E = 1$) were used and the feasible envelope peaks at 50-100 h.

Afterwards it narrows as the three indicators approach equivalence.

This is a mathematical, weighting-sensitivity (not model), result, so can't be extrapolated to other pumps or operating environments.

3.4 Reduced-order twin prediction

The set of models used in the over-simplified reduced order twin gives explicit model outputs – rather than simply mimicking the actual PDI. Calibration is applied to the 0-150 h data, then normalised degradation states are mapped to the 3 measured response variables. The 200-h observation is evaluated as pseudo-hold-out point.

Head model predicts 10.8226 m vs. observed 10.7000 m, efficiency model 58.0040% vs.

58.0000%, vibration model 0.7501 mm/s vs. 0.7500 mm/s. Corresponding measured and estimated trajectories are shown in Figure 5. While a close correspondence can be predicted in part because the degradation indicators and response variables are derived from the same published trajectory, it does to some extent demonstrate numerical implementation and hold-out reconstruction rather than independent predictive power.

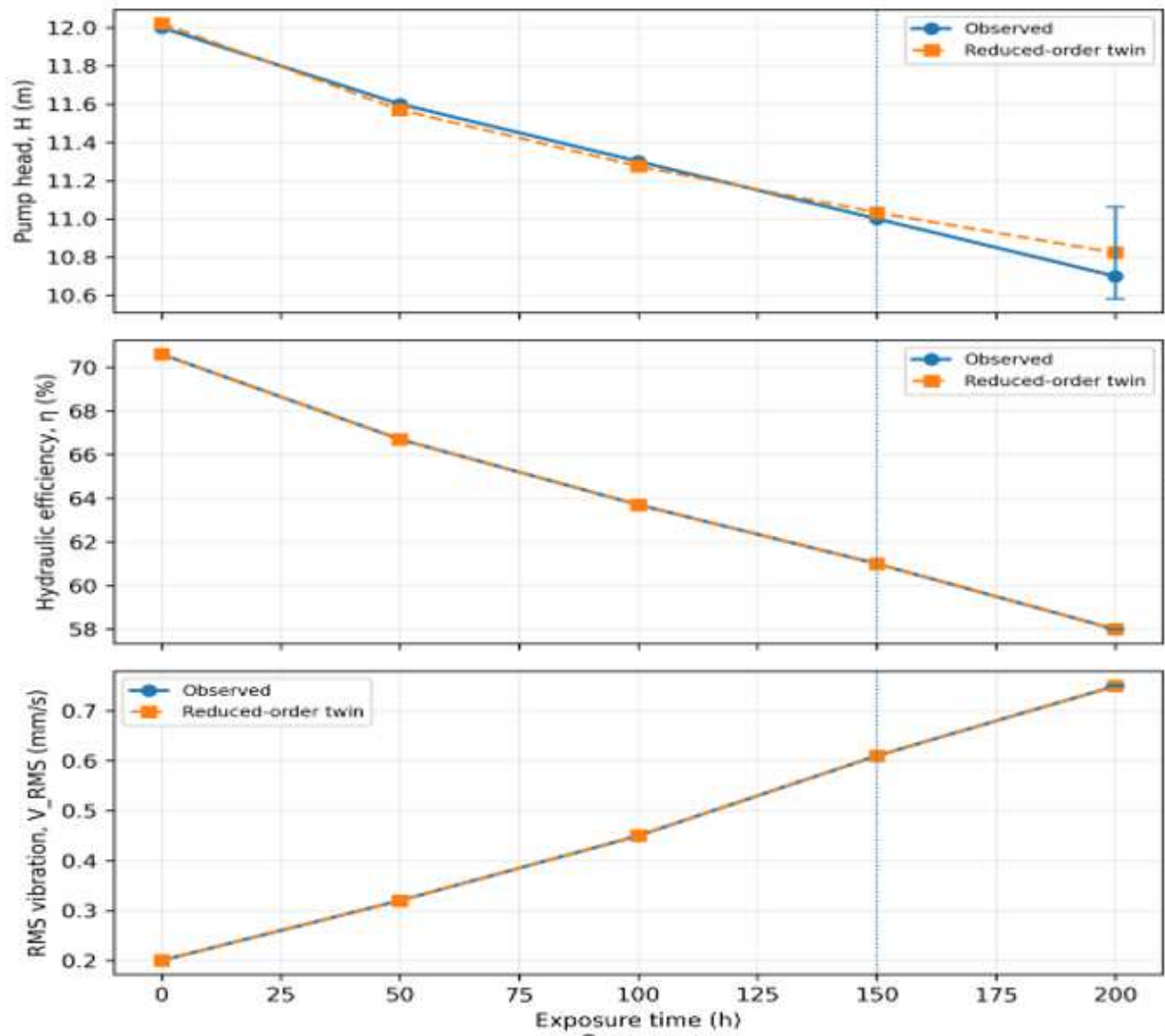


Fig. 5 Observed outputs and reduced-order twin estimates. The final point is a pseudo-hold-out evaluation; the shaded error bars show 95% prediction intervals at 200 h.

Figure 5 compares the observed pump outputs with the reduced-order twin estimates across the test period. The final 200-h point provides a pseudo-hold-out evaluation, while the shaded region represents the 95% prediction interval, illustrating the uncertainty associated with the final estimate

3.5 Model–measurement residuals

Residual analysis offers a quantitative addition to the residual no- aspect of the PDI-only picture.

The standardised residuals for head, efficiency and vibration are shown, along with the combined residual score $R(t)$, in figure 6. The residual scores are 3.122, 1.168 and 0.604 for the 200-h head, efficiency and vibration, respectively.

$R(t)$ (combined residuals, which is the product of all three residuals) increases from 0.473 baseline to 1.632 at 200 hours.

These figures are not at alarm level; for example, the individual baseline estimate μ_i was obtained from just four calibration observations, with a single test site collecting the field data and no event labels.

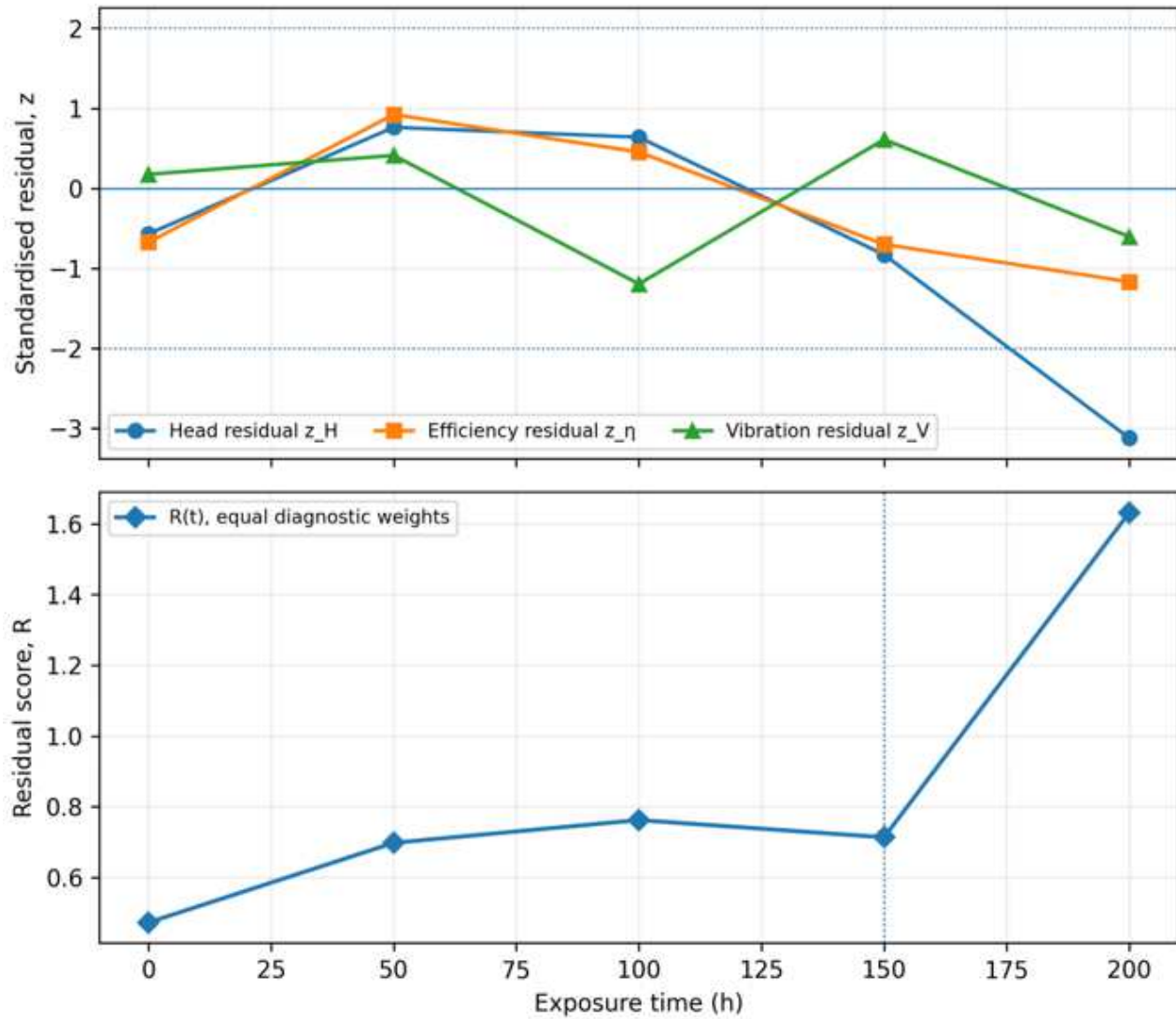


Fig. 6 Model–measurement residuals and multimodal residual score. The ± 2 guide lines are descriptive reference lines, not calibrated alarm thresholds.

Figure 6 shows the residuals between the reduced-order twin predictions and measured values, together with the combined multimodal residual score. The ± 2 lines provide descriptive reference limits only and should not be interpreted as calibrated alarm or failure thresholds

3.6 Quantitative proof-of-concept assessment

Table 6. Implemented versus future model components.

Component	Current numerical proof of concept	Future validation
Hydraulic response	Reduced-order head mapping using C_n and measured Q as operating context	Multi-pump performance-map calibration
Efficiency	Reduced-order efficiency mapping using E_n	Independent power/flow measurement validation
Vibration	Reduced-order mapping using V_n	Frequency-domain/component-level calibration
Corrosion state	Coupon-derived normalised proxy C_n	UT, probes, inspection or validated component measurements
Residuals	Calculated from held-out output estimates	Event-labelled false-alarm and lead-time validation
Maintenance update	Framework mechanism	CMMS/work-order and post-maintenance baseline validation
RUL/failure probability	Not implemented	Failure/censoring dataset and

		probabilistic calibration
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Table 7. Reduced-order twin outputs, hold-out residuals and descriptive error metrics.

Table 7 presents the evidence of including these reduced-order predictions in this numerical proof of concept, separating them from those that will require field and experiments for verification. The hydraulic, efficiency, vibration, corrosion, residual, and maintenance states are currently available, while the remaining useful life (RUL) and failure-probability predictions will each most probably need more field and failure data for comprehensive validation. Descriptive verification - The six observed descriptive MAE and RMSE values for each prediction is 0.0465/0.0602 meters head, 0.0027/0.0028 percentage points efficiency, and 0.0001/0.0002 mm/s RMS vibration, respectively.

The absolute errors at the 200h pseudo-hold-out point are 0.1226 meters head, 0.0040 percentage points efficiency, and 0.0001 mm/s RMS vibration.

The 95% prediction interval appears narrow for efficiency and vibration but wide for head, owing to greater residual variance and the positive effect of the final point in the so-called sparse calibration sample.

3.7 What the proof of concept does and does not establish

Table 8. Capabilities demonstrated and claims not established by the numerical proof of concept.

Response	200-h observed	200-h predicted	Hold-out residual	MAE (5 points)	RMSE (5 points)
Head, H (m)	10.7000	10.8226	−0.1226	0.0465	0.0602
Efficiency, η (%)	58.0000	58.0040	−0.0040	0.0027	0.0028
RMS vibration, V_RMS (mm/s)	0.7500	0.7501	−0.0001	0.0001	0.0002
95% prediction interval at 200 h	—	—	—	H: 10.5817– 11.0636 m	η : 57.9814– 58.0267%; V: 0.7484–0.7519 mm/s

Table 8 compares the predicted versus measured outputs. Small residuals and the relatively low MAE and RMSE values imply reasonable replication of the five-point set, with a slight increased uncertainty of head. These numerical results constitute conceptual evidence, though they do not conclusively demonstrate predictive or field-level capability

Demonstrated	Not established
Reproduction of the published PDI trajectory	Failure probability or reliability calibration

Multidomain state representation	Causal corrosion-to-vibration relationship
Mathematical residual formulation	Operational alarm-threshold optimisation
Operating-context representation	RUL prediction accuracy
Architecture for maintenance updating	Field/offshore generalisation
Numerical reproducibility	Independent digital-twin validation

Table 8 shows the correlation between observed and predicted outputs. As the residuals are small and the MAE and RMSE are quite low, the five-point data set is reproduced reasonably well, but with perhaps slightly larger uncertainties for head. The numerical results do not indicate conformance with the concept, but neither do they suggest useful predictiveness or field scale effectiveness.

3.8 Why a lightweight twin is appropriate.

A compromise is likely necessary for a practical offshore digital twin (more than 50 parameters, low-to-moderate computational expense, and relatively high data quality). It would be tempting to develop a more sophisticated multiphysics model, including both the pump and its motor, the process fluid, and the corrosion environment, but it would almost certainly be difficult to maintain in practice. This design uses a hierarchically-matched architecture, with a physical model of low-order providing a baseline to buffer the high-fidelity models in response to the residual patterns detected. This more hierarchical architecture is consistent with the digital-twin literature for rotating equipment and recent offshore marine applications, which highlight system deployment constraints [12,13,19].

Finally, it preserves the engineering rationalization of the original PDI. The digital twin does not supplant vibrational analysis, hydraulic tests, and corrosion inspections; rather, it unifies the disparate measurement sets into a continuous state-estimation process. For brownfield equipment, this approach indicates a feasible trajectory from current instrumentation toward progressive digital-twin capabilities.

3.9 Corrosion as a separate evidence stream

The previous PDI study explicitly stated that the coupon mass loss is not directly a measure of mass loss on the impeller, casing, shaft, or other pump components [1], and this separation continues in the proposed twin. Therefore, the proxy's value is used in the model as a corrosive material loss measure. If component-level inspection becomes possible, the model may gradually supplant the proxy with measured thickness loss, pit geometry, roughness, or other validated degradation variables. This separation is important because it allows the digital twin to avoid spurious conversion of a material-context measure into an unsupported component-level claim of corrosion.

3.10 Operating-state dependence and residual analysis

The primary additional condition for on-field use, however, is the conditioning of the operating state. Changes in flow, pressure, speed, temperature, fluid composition, valve position, and transients affect the pump and subsea equipment. Perhaps, a raw, measured increase in RMS vibration or a reduction in efficiency may be present due to genuine changes and not deterioration.

The digital twin should predict expected behavior for the current operating state, and the residual should be evaluated against a baseline residual distribution.

The quality of the sensor, drift, missing data, and timestamp consistency should be checked before using residuals for condition monitoring.

3.11 Maintenance decision support

This estimated operational sequence can be summarized as follows: sensor acquisition, data-quality screening, operating-state classification, virtual-pump prediction, residual evaluation, PDI update, maintenance screening, detailed diagnosis/inspection, intervention, maintenance-completion confirmation, and finally returning to a stable post-maintenance baseline reset. This hierarchy may be better than approaching the problem with a single numerical value for the PDI that would act as the trigger for maintenance. The PDI could reflect a change in degradation trend, and the diagnostics could shed light on the mechanism.

3.12 Relationship to current marine digital-twin practice

A recent paper in the Journal of Ocean Engineering and Marine Energy proposed hybrid modelling-based digital-twin strategies as promising options for health monitoring in the naval auxiliary industry. The paper defines practical necessities such as data interoperability, reliable acquisition platform, model complexity, and model validation. In addition, the designed pump architecture intentionally has a more narrow scope since it works with a corrosion-aware rotating-equipment condition state, not a full ship-system twin, which could be beneficial for brownfield offshore assets where advanced system models are lacking.

3.13 From condition indicator to prognostics

The scale-up from PDI to reliability (or RUL) is likely to be considered a separate scientific step.

When longitudinal failure/censoring data are obtained, the PDI (or a similar latent state) could be incorporated into a survival model or a state-space model (such as a proportional-hazards model, an accelerated-failure-time model, a hidden-state model, or a Bayesian degradation process [8,14,17]).

Model selection may also be based on event calibration and out-of-sample performance rather than just convenience. Until that stage, we expect the PDI to be considered a condition indicator.

4 Proposed Experimental and Field Validation Programme

4.1 Laboratory replication

The general recommendation is for at least three independent pump units to be laboratory tested in controlled saline environments with multiple repetitions per pump. The test matrix should incorporate variation in salinity, temperature and duty point within safe laboratory operating limits. Each run should record raw vibration, flow, head, power, rpm, temperature and evidence of material degradation.

Inspection before and after the runs should document pit density, pit size, surface roughness and mass loss where feasible.

The repeatability should be characterized by trajectory error and coefficient of variation or other pre-specified measure of interest.

4.2 multi-pump validation

The next step is likely to involve multiple pump designs or at least multiple units of the same design. The focus is on assessing whether weights, normalization factors and model parameters are specific to particular pump units, or transferable across different pump units. It is recommended to test using leave-one-pump-out validation, where the test pump is not used in model calibration. Metrics such as cross-unit MAE/MSE, calibration drift and uncertainty coverage should be carefully reported.

4.3 Offshore field validation

For offshore application, the preferred data source is likely to be a historian or CMMS-linked pump population.

It is important that each pump has a pump identifier and that the timestamps are consistent across equipment.

The minimum data required is likely to be process variables, vibration, rpm, motor power, temperature, alarms, operation mode and maintenance records. Inspection should be linked to the pump identifier. The data should be segmented into pre-maintenance, post-maintenance and stable operation intervals.

Documentation should specify sample frequency, sensor calibration status, missing data treatment, outlier treatment, sensor drift and time-alignment procedures.

4.4 Failure and maintenance-event validation

The most important ground truth, apart from high PDI, is an independent record of physical condition or maintenance intervention. The event types should include bearing change, seal failure, coupling/alignment change, impeller change, corrosion repair, cavitation correction, process problem or no-fault intervention. Event lead time should then be calculated for the PDI and residual scores using metrics such as precision, recall, false-alarm rate and time-to-event.

4.5 Uncertainty-aware state estimation

If applied to a future field, the model uncertainty should be incorporated with the condition state rather than every residual being treated as deterministic.

A simple observation model is illustrated in Equation (18), with y describing measurement/model discrepancy estimated from nominal-condition data.

The state transition should incorporate process noise, enabling uncertainty bounds around PDI-linked trajectories to be identified.

This aspect is particularly relevant for offshore measurements, which are subject to sensor drift, fluctuating process conditions and periods of no operation.

$Y(t) = \hat{Y}(t) + y(t)$ (18) Observation model; $y(t)$ stands for measurement/model discrepancy identified from stable-condition data.

4.6 Future prognostic modelling

A prognostic model should only be fitted once a sufficient event history is available.

Future work might consider a model of the form:

$z(t) = z(t) + g(u(t), z(t), t) + \epsilon(t)$ where $z(t)$ is an unobservable degradation state and event likelihood in a future interval can be calculated conditioned on $z(t)$, operating context and maintenance history.

This approach would be a step toward transforming the present proof of concept into a true prognostics study, but such an approach cannot be justified from the five data-points currently available.

Table 9. Mathematical components of the proposed framework.

Eq.	Component	Role
1–4	Operating vector, prediction and residuals	Condition expected behaviour on current duty state
5	Multimodal residual score	Quantify model–measurement anomaly magnitude
6	Engineering-limit normalisation	Map a degradation variable to a bounded condition scale
7	PDI aggregation	Fuse corrosion-related, vibration and efficiency degradation

8	Mathematical condition coordinate	Provide a monotonic complement to PDI; not reliability
9–10	Hydraulic power and efficiency	Enforce basic pump-energy consistency
11–12	Corrosion and dynamic state equations	Provide future calibration targets for the physics-informed twin
13	Observation model	Represent measurement/model discrepancy

Table 9 lists the various components of mathematical terms associated with the proposed framework and summarizes their purpose. The set of equations contains the operating-state prediction, residual, degradation normalisation, PDI, the energy consistency, and the corrosion and dynamic states. Together, these factors are likely to constitute the mathematical foundation of the reduced-order twin, while, differentiating current implementation from future physics-based calibration

n.

Table 10. Suggested implementation roadmap for brownfield offshore deployment.

Layer	Method	Deployment stage	Evidence required
Baseline layer	Hydraulic equations + nominal envelopes	Immediate	Q, H, n, P_input
Condition layer	PDI + component indicators	Near-term	Corrosion proxy, V_RMS, η
Residual layer	Model–measurement residuals	Near-term	Expected vs observed behaviour
Inspection layer	UT/coupon/probe/component evidence	Field	Independent degradation evidence
Event layer	CMMS/work-order linkage	Field	Maintenance and intervention labels
Prognostic layer	State-space/survival model	Future	Failure/censoring histories

The table shows a clear deployment pathway for the proposed digital-twin framework. In the table, the layers of the model are presented starting from the performance monitoring in the most simple form, to condition monitoring, then to field trial validation, maintenance, and at the end the prognostics. For each layer, the approach, possible timeframe of deployment, and evidence required to support it, is listed. Additionally, the prognostic layer is left as future work as it requires sufficient failures and censoring histories to be able to perform accurate RUL / survival models.

5 Limitations

- The numerical demonstration uses the same five-point published dataset that underpinned the original PDI; it is not independent validation and cannot establish model generalisation.
- No field, offshore, maintenance or failure data are introduced, so operational alarm thresholds and reliability claims cannot be made.
- The corrosion-related state remains a proxy unless component-scale or in-situ corrosion observations are available.
- The proposed physics-informed equations are framework formulations; their parameters must be estimated from new repeated experiments or field data.
- The digital twin is not implemented as a real-time software system in this article and no hardware-in-the-loop test is claimed.
- The complementary condition coordinate $H_m = 1 - \text{PDI}$ is mathematical and should not be interpreted as a probability of survival.
- The architecture does not yet resolve causal attribution among corrosion, hydraulic disturbance, imbalance, bearing degradation and other failure mechanisms.
- The demonstrated relationships arise from one pump configuration, one material configuration and a limited operating window; transfer to other pump geometries, materials, speeds or duty points requires calibration and validation.
- Sensor bias, drift, sampling resolution and missing-data effects are not quantified in the present proof of concept.

6 Conclusions

This work takes the critical next step in the methodological evolution based on the corrosion-vibration-hydraulic Pump Degradation Index (PDI) developed earlier. The work proposes a lightweight physics-informed digital-twin architecture incorporating the PDI as an interpretable intermediate degradation state and model residuals as an independent measure of deviation from expected pump behavior. The proposed architecture preserves the physics of corrosion exposure-related material aging, dynamic response, and hydraulic performance while incorporating operating-state conditioning, maintenance-event updating, and staged validation.

Using the previously published five-point dataset as a numerical proof-of-concept, the framework successfully reproduces the PDI trajectory with 0.000-0.301-0.542-0.777-1.000 values in the range of 0-200 hours.

This study demonstrates mathematical compatibility between PDI and the proposed twin architecture; however, the correlation should not be assumed as being meaningful for field validity, causality, failure-inducing mechanism(s), reliability, or Remaining Useful Life (RUL).

The single most important next step may be empirical -- repeated multi-pump experiments with field or offshore validation related to inspection and maintenance events. With such data, the framework can be extended to probabilistic degradation and prognostic models. Until such empirical validation data are available, the proposed architecture should be viewed as a means for organizing corrosion-aware pump condition information, not an a-priori validated predictive-maintenance system.

Declarations

Funding: No external funding was received specifically for this methodological study.

Competing interests: The author declares no competing interests.

Author contributions: N.I.U. conceived the study, developed the digital-twin framework, performed the numerical proof-of-concept calculations and prepared the manuscript.

Data availability

Code availability: The computational procedure used for the reduced-order twin, PDI reconstruction, sensitivity analysis, residual calculation and descriptive error metrics is provided in the numerical implementation described in this article. The present manuscript does not claim a public software release or real-time deployment.

The numerical demonstration uses measurements previously published by Udo [1]. No new experimental dataset is claimed. The calculation procedure and processed demonstration data can be made available by the corresponding author upon reasonable request, subject to applicable restrictions.

Ethics approval: Not applicable.

Consent to participate: Not applicable.

Consent for publication: Not applicable.

Nomenclature

Table 11. Nomenclature used in the mathematical framework.

Symbol	Definition	Unit
A	Exposed corrosion area	m ²
C	Corrosion-related degradation state used in the future model	dimensionless / model-specific
C _n	Normalised corrosion-related material indicator	dimensionless
E _n	Normalised hydraulic-efficiency degradation	dimensionless
H	Pump head	m
H _m	Complementary mathematical condition coordinate	dimensionless
n	Rotational speed	rpm
P _h	Hydraulic power	W
P _{input}	Pump/input power used for efficiency calculation	W
PDI	Pump Degradation Index	dimensionless
Q	Volumetric flow rate	m ³ /s
R	Multimodal residual/anomaly	dimensionless

	score	
r_i	Measurement–model residual for variable i	variable-dependent
S	Salinity or conductivity context	ppt or equivalent
T	Relevant fluid/process temperature	°C or K
V_{RMS}	RMS vibration velocity	mm/s
V_n	Normalised vibration indicator	dimensionless
wC, wV, wE	PDI weighting coefficients	dimensionless
x	Latent degradation-state vector	model-specific
x_m	Mechanical state associated with imbalance or related condition	model-specific
x_b	Mechanical state associated with bearing condition	model-specific
y	Measured response vector	variable-dependent
$\hat{y}$	Model-predicted response vector	variable-dependent
z_i	Standardised residual	dimensionless

a_i	Residual-score weighting coefficient	dimensionless
ε_y	Measurement/model discrepancy	variable-dependent
η	Pump hydraulic efficiency	%
θ	Calibrated model-parameter vector	model-specific
ρ	Fluid density	kg/m ³
σ_i	Nominal residual scale	variable-dependent
φ	Operating/exposure modifier in corrosion-state equation	model-specific
kC	Corrosion-state rate coefficient	model-specific
β_{H0}, β_{H1}	Reduced-order head model coefficients	m
$\beta_{\eta0}, \beta_{\eta1}$	Reduced-order efficiency model coefficients	%, percentage points
β_{V0}, β_{V1}	Reduced-order vibration model coefficients	mm/s

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