

A Multidomain Pump Degradation Index Integrating Corrosion, Vibration and Hydraulic Performance in Saline-Service Centrifugal Pumps

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Abstract

Concurrent material, dynamic, and hydraulic degradation of centrifugal pumps has been observed in the marine and offshore industries. This work develops a multidomain Pump Degradation Index (PDI) for combining a coupon-derived corrosion-related material degradation indicator, vibration, and hydraulic performance degradation into a single dimensionless pump condition trajectory for saline-service centrifugal pumps. An existing experimental dataset on a 316L stainless-steel centrifugal pump, operated in 30-ppt synthetic seawater for 200 h, previously published measures of pump efficiency degradation (70.6% to 58.0%), root-mean-square (RMS) vibration (0.20 to 0.75 mm/sec), flow rate (0.00150 to 0.00138 m/sec), and pump head (12.0 to 10.7 m), were converted to equivalent corrosion rates (0.048, 0.083, and 0.212 mm/yr) for 316L stainless steel, bronze, and carbon steel coupons, respectively.

In this secondary analysis, time-series cumulative coupon mass loss, RMS vibration, and hydraulic efficiency degradation were normalized and combined in equal weights with min-max dataset-bounded range normalization.

The original PDI increased from 0.000 at baseline to 0.301, 0.542, 0.777, and 1.000 at 50, 100, 150, and 200 h, respectively. An exhaustive sweep of 5,151 feasible equal-weights combinations at 0.01 increments demonstrated that the continuous PDI trajectory is relatively insensitive to weighting after the early exposure period, although the sampling state boundary at 50 h is weighting-sensitive. This simple, transparent low-data pump condition assessment and decision support framework has numerous applications, including normalized, interpretable early warning within the experimental data time window. Since the normalization endpoints are the maximum observations in the experimental window, PDI = 1.000 does not imply failure, end-of-life, or probability of failure.

The single-pump, five-point dataset does not generalize to other pumps, failed equipment, maintenance history, failure modes, or failure probability, requiring independent multi-pump, field, maintenance, and failure data for further validation.

1 Introduction

Centrifugal pumps are major rotating assets in offshore crude and product oil production, seawater recirculation, cooling-water, firewater, ballast, and fluid transfer systems. Degradation of a pump can have implications for production integrity, operations and maintenance costs, and safety-critical service availability. Operating in saline environment, it is possible that material, dynamic and hydraulic degradation will occur simultaneously in a pump, thus a single parameter condition measure may be insufficient.

Salinity environments can be corrosive and lead to material degradation [1, 2]. This may impact the condition of pump components and then manifest as dynamic and/or hydraulic degradation of the pump. Vibration monitoring can be a good indicator of dynamic condition and be sensitive to imbalance,

misalignment, bearing degradation, hydraulic instability, cavitation, and other mechanical or process conditions [3, 4]. Hydraulic variables such as flowrate, head, and efficiency are a good indicator of functional condition [5, 6]. Therefore, integrating these indicators in a common dimensionless measure can give a broader indicator of degradation.

There has been an increasing application of multimodal sensing, machine-learning, prognostic, and digital-twin based condition monitoring of centrifugal pumps [7–12]. Although these approaches can give powerful fault diagnosing and prognostic functions, they are often reliant on large volumes of sensor data, feature extraction, computational models or labeled degradation/failure data. For applications with sparse data, such transparent intermediate condition indicators that can synthesize heterogeneous degradation measurements are preferable.

The research gap addressed here is to produce an interpretable, dimensionless, common pump-level measure combining material, dynamic, and functional degradation. Since corrosion, vibration, and hydraulic efficiency are measured in different units and scales and have different physical significance, normalization of these degradation measures prior to integration is required.

This paper presents a multidomain Pump Degradation Index (PDI) synthesizing corrosion-based material degradation, vibration response, and hydraulic-efficiency degradation into a single trajectory. It is intended as a pump condition-degradation indicator and not a reliability function, failure probability distribution, or remaining-useful-life predictor.

The experimental basis for the analysis has been published previously by the author [13], with the earlier publication investigating response of austenitic 316L pump to high salinity whilst this paper performs a secondary methodological analysis of those data. No new experimental data are provided.

The contribution of the paper is analytical and methodological. It normalizes three axes of degradation, combines them into a common dimensionless PDI, explores alternative weighting assumptions and demonstrates the PDI trajectory. The value of the method is as a transparent, low-data, stage of condition monitoring scale that can supplement, but not negate, advanced diagnostics, reliability, and digital-twin, systems.

2 Research Gap and Methodological Contribution

2.1 Single-indicator condition assessment

However, relying solely on any individual domain for assessment can lead to inaccurate conclusions. For example, vibration measurement is highly sensitive to dynamic issues but is multi-causal so failing to identify the specific cause of the damage. Hydraulic efficiency, head and flow rate are indicative of how well the pump performs but do not reveal whether any performance degradation is due to material degradation, hydraulic disturbances, mechanical failures or operating conditions.

Corrosion measurement reveals the material response but reveals nothing of its hydraulic or dynamic implications.

The current work considers the three domains as being different and complementary.

2.2 Existing multidomain health-index approaches

Existing health-index approaches are weighted aggregation, PCA, PCA with entropy-based weights, fuzzy inference, and machine-learning approaches. These approaches can produce a suitable aggregation of condition-monitoring variables, subject to availability of data, physical meaning, and the intended application. The PCA and other data-reduction methods can extract dominant statistical trends, but these do not necessarily relate in a straightforward way to individual degradation mechanisms, and the entropy-based approaches extract weights based on statistical information content rather than engineering significance, whereas the fuzzy approaches require membership functions and inference rules, and machine-learning approaches can model complex nonlinear behaviour but require large amounts of representative data, in particular when degradation or failure labels need to be predicted.

For the example of centrifugal pumps in saline service, corrosion, vibration, and hydraulic efficiency are three different but potentially-interacting dimensions of degradation. These have different units, magnitude scales, and physical meaning, so direct aggregation would require prior normalization. The value added of this research gap is not the lack of mathematical aggregation strategies, but a transparent, adaptable framework for physically disparate dimensions of degradation accounting for normalization, weighting, sensitivity, uncertainty, and degradation progression for cases of failure-labelled data.

Table 1
Comparison of multidomain health-index approaches

Approach	Typical inputs	Normalization / fusion	Main advantage	Main limitation	Role relative to PDI
Vibration health index	Vibration features	Feature scaling / statistical aggregation	Sensitive to dynamic faults	Limited material information; multi-causal	Complementary specialist diagnostic
PCA-based health index	Multivariate condition measurements	Statistical standardization; PCA	Dimension reduction	Reduced direct physical interpretability	Alternative multidimensional representation
Entropy-weighted index	Multiple indicators	Normalization; entropy weighting	Objective data-derived weighting	Weights depend on statistical dispersion	Alternative weighting strategy
Fuzzy health index	Multiple condition indicators	Membership functions and rules	Can represent graded states	Rule and membership subjectivity	Alternative decision framework
ML-based health index	Multisensor / feature data	Learned representation	Strong nonlinear modelling capability	Data- and training-intensive	Higher-complexity future benchmark
Proposed PDI	Coupon-derived material indicator + vibration + efficiency	Engineering normalization; explicit weights	Transparent, low-data, physically interpretable	Requires independent validation and calibrated limits	Condition-assessment layer under limited-data conditions

Table 1. Cross-comparison of the PDI and other health-index approaches showing inputs, fusion methods, interpretability, and data requirements. The PDI uses transparent engineering normalization and weighting to fuse material degradation, vibration, and efficiency into a single indicator that is a low-data, readily understandable approach that is still independently validated.

2.3 Positioning of the proposed PDI relative to existing approaches

- The PDI described in the paper addresses this gap with a methodology framework that involves: Engineering-based normalization of corrosion-specific, vibration and hydraulic-performance indicators to a common dimensionless scale.
- User-defined explicit weighting of the three degradation dimensions to incorporate different engineering priorities.
- PDI aggregation to a single dimensionless condition-degradation measure.

- Weight sensitivity analysis to test the stability of the integrated index under different weighting assumptions.
- Qualitative evaluation of the degradation trajectory, including normalized indicator monotonicity and integrated PDI behaviour. The contribution of this methodology approach is thus not the introduction of a new mathematical aggregation operator, but the use of an engineering methodology approach to define, normalize, and interpret multiple heterogeneous indicators of degradation in a limited-data condition monitoring context.

This explicitly maintains the separation of the corrosion-related material-degradation surrogate as a distinct feature from the in-situ dynamic and hydraulic responses, while providing an integrated, interpretable measure for condition monitoring and maintenance decision-making.

2.4 Design principles

The PDI is distinguished from PCA-based health indices in maintaining the physical identity of corrosion, vibration and hydraulic degradation components rather than statistically combining these into latent components. It differs from entropy-weighted methods in explicitly defined physical weightings whose effects are then investigated via sensitivity analysis. Compared with fuzzy formulations, the PDI is not reliant on membership functions, rule-based inference, or inputs, and compared with machine-learning based health indicators, it has much lower training data requirements and is directly interpretable by reference to physical quantities. The PDI is therefore not intended to be superior to these methods but as providing a transparent, conditionspecific, assessment layer for use where physically meaningful degradation-related data are needed and failure-labeled training data are not available.

2.5 Contribution of the present study

The key innovation of the present paper is in the systematic development of a data-mediated and multi-domain pump degradation index that combines a coupon-driven corrosion-related indicator of material degradation, vibration and hydraulic performance decline in a common condition-assessment framework. Unlike data intensive health-index based approaches that may involve large labelled datasets, model training or sensing, this framework comprises physically transparent indicators that are then combined by explicit weighting to create a low-data representation of observed progressive degradation. In contrast to much previous work, we explicitly define the continuous PDI in terms of experimentally validated failure probability, reliability and residual life predictions. The framework is positioned as a condition-assessment and decision-support technique for further validation using independent multi-pump datasets and maintenance records.

3 Materials and Methods

3.1 Experimental system

The base experiment consisted of a single-stage centrifugal pump fabricated of 316L stainless steel, mounted in a laboratory closed-loop system. Pump nominal head was 12 m and flow rate approximately 0.0015 m³/s. Pump was driven by a 0.25 kW motor, with approximately 250 W of input power. Impeller diameter was 145mm, and the rotation speed was approximately 2900 rpm.

Table 2
Principal characteristics of the experimental pump

Parameter	Specification
Pump configuration	Single-stage centrifugal pump
Pump material	316L stainless steel
Impeller diameter	145 mm
Rotational speed	Approximately 2900 rpm
Motor rating	0.25 kW
Input power	Approximately 250 W
Nominal flow rate	0.0015 m ³ /s
Nominal head	12 m
Test configuration	Closed-loop circulation
Exposure duration	200 h
Measurement interval	50 h
Vibration parameter	RMS vibration velocity

Table 2 provides an overview of the main features and testing conditions of the experimental pump. The hydraulic tests were performed only on the 316L stainless-steel centrifugal pump, whereas the bronze and carbon steel were tested only with the static corrosion coupons.

3.2 Saline environment

The pump was operated in synthetic seawater with a salinity of 30 ppt at approximately 25 ± 2°C for 200 h.

Table 3
Experimental environmental conditions

Parameter	Condition
Test fluid	Synthetic seawater
Salinity	30 ppt
Temperature	25 ± 2°C
Exposure duration	200 h
Circulation	Closed-loop operation
Measurement interval	50 h

Table 3: Summary of the exposure parameters employed in the pump test:

Synthetic seawater Salinity: Temperature: Time: Conditions: Controlled saline exposure was achievable in the laboratory setting. However, not all offshore parameters could be mirrored, including temperature cycles, suspended solids, biological activity, transient loading, variations in pressure, cavitation, process modifications, and shutdowns and start-ups for maintenance.

As a result, it is important to view the results as laboratory observations of saline service degradation rather than as a direct indication of offshore performance.

3.3 Materials and corrosion measurements

Three metallic materials were considered:

- 316L stainless steel;
- bronze (CuSn alloy); and
- carbon steel.

The 316L material represented the pump construction material. Bronze and carbon steel were static corrosion-comparison coupons.

Table 4
Materials and experimental roles

Material	Experimental role
316L stainless steel	Pump material and corrosion coupon
Bronze (CuSn alloy)	Static corrosion coupon
Carbon steel	Static corrosion coupon

Table 4 summarizes the materials and their experimental roles. 316L stainless steel is the pump material and corrosion coupon; bronze and carbon steel are tested only as static coupons.

Corrosion mass loss was obtained from coupon measurements in the original study [13]. Laboratory specimen preparation, cleaning, and evaluation followed standard corrosion testing procedures [14, 15]. Corrosion-associated material degradation was derived from 316L stainless steel coupon mass-loss measurements in the saline environment from the original study [13]. Corrosion rate was derived from coupon mass-loss measurements.

The coupon measurements are to be viewed as an indicator of the corrosive exposure environment and thus are only indirectly related to corrosion degradation of the pump components, particularly on the impeller, casing, shaft, and wetted components. Variations in component geometry and surface finish, local flow velocity and turbulence, galvanic coupling, and component-specific exposure could lead to corrosion behavior that departs from that measured by the coupon.

Hence, the present work defines the corrosion variable as a corrosion-related material degradation indicator that is associated with the saline exposure environment rather than as a direct measurement of the corrosion degradation of any specific component. The normalized form of the corrosion variable is denoted by C_n :

C_n = normalized corrosion-related material degradation indicator

where C_n is the corrosion-related material degradation indicator normalized to that measured with coupons in the investigated environment. This distinction is important since the PDI combines a coupon-based corrosion variable with the pump-level vibration and performance measurements.

The corrosion variable thus supplies exposure environment and component-specific degradation context rather than a direct measure of corrosion on the various components.

From $W / (\rho A t)$, equivalent corrosion rate is given by:

$$CR = K W / (\rho A t) \quad (1)$$

where CR is the equivalent corrosion rate, K is the unit-conversion constant, W is the mass loss, ρ is the material density, A is the exposed surface area, and t is the exposure time.

In the present study, the resulting corrosion rates are to be regarded as derived equivalent corrosion rates based upon 200-hour coupon tests and are not directly related to long-term corrosion rates in the field.

3.4 Hydraulic-performance measurements

The original experiment recorded flow rate, pump head and input power at 0, 50, 100, 150 and 200 h.

Hydraulic power was calculated as:

$$P_h = \rho \times g \times Q \times H \quad (2)$$

where P_h is hydraulic power, ρ is fluid density, g is gravitational acceleration, Q is flow rate and H is pump head.

Pump efficiency was calculated as:

$$\eta = (\rho \times g \times Q \times H / P_{\text{input}}) \times 100 \quad (3)$$

where P_{input} is pump input power.

Flow rate and head were retained as supporting hydraulic-performance variables, whereas efficiency loss was selected as the functional degradation variable incorporated into the PDI.

This distinction is significant as the PDI being put forward does not explicitly weight flow, head and efficiency. These should not be weighted as to do so may skew the influence of the hydraulic domain.

3.5 Vibration measurements

The vibration variable used in the PDI is RMS vibration velocity, reported in mm/s.

RMS vibration was selected because it provides a compact measure suitable for condition trending and is commonly used in machinery condition monitoring [3, 4].

The pump rotational speed was approximately 2900 rpm. The corresponding running frequency was:

$$f_r = 2900 / 60 = 48.33 \text{ Hz} \quad (4)$$

The corresponding angular velocity was approximately:

$$\omega = 2 \times \pi \times f_r \approx 304 \text{ rad/s} \quad (5)$$

The current analysis does not provide frequency-specific fault diagnosis, since the secondary data set available to us does not include the raw vibration time histories for FFT, order-tracking, or time-frequency analysis. So, the vibration part of the PDI should be regarded as a transient condition indicator only, rather than a diagnosis of a particular vibration fault.

3.6 Normalization framework

Since the degradation indicators have incompatible units, scales and physical interpretations of magnitude before aggregating as PDI, they need to be normalized. There are three normalization frameworks, separating dataset-relative assessment from independently reference or statistically derived condition measures.

3.6.1 Dataset-bounded normalization

The primary analysis uses dataset-bounded min–max normalization, expressed in plain text as:

$$X_n = (X - X_0) / (X_{lim} - X_0) \quad (6)$$

where X is the measured degradation indicator, X_0 is the baseline value, and X_{lim} is the limiting value observed within the experimental dataset. For indicators in which increasing values represent increasing degradation, this normalization assigns $X_n = 0$ to the baseline condition and $X_n = 1$ to the maximum degradation observed within the experimental period.

This method is deemed appropriate for this secondary analysis, as the experimental data do not have independently determined failure or serviceability limits for all three degradation parameters. But this method also implies that the maximum observation in the analysis window is thereon bound by a normalized value of 1.0; the corresponding $PDI = 1.000$ at 200 h is thus not related to pump failure, a failure limit, or a failure probability, but just to the maximum observed degradation in the analyzed dataset.

3.6.2 Engineering-limit normalization

For operational deployment, a more physically meaningful alternative is normalization against an independently established engineering limit:

$$X_n(eng) = \min[1, \max(0, (X - X_0) / (X_{eng} - X_0))] \quad (7)$$

where X_{eng} represents an independently established engineering, serviceability, alarm, or component-condition limit. The bounding operation constrains the normalized indicator to the range 0 to 1.

Compared with dataset-bounded normalization, the present formulation does not require the last experimental data point to be 1.0, unless the engineering limit is approached. It thus offers a possible method for comparing the pump condition to criteria established for operation or maintenance. Engineering limits are not set in this work, since independently verified values for the combined corrosion, vibration, and hydraulic indicators were not available from the source experiment.

3.6.3 Statistical normalization

For larger datasets containing multiple pumps, operating conditions, and degradation states, a statistical formulation can also be considered using the empirical cumulative distribution function (ECDF):

$$X_n(stat) = FX(X) \quad (8)$$

where $FX(X)$ is the empirical cumulative distribution function of the degradation indicator.

The population-guided approach normalizes based on the observation relative to the statistical population of a reference set instead of relative to the maximum observation from a single experiment. It can therefore be potentially useful when rich and representative data sets are available. Its value again

hinges upon the completeness and accuracy of the reference population and should not be interpreted as a failure probability per se.

In this study, the data set bounded definition is chosen as the normalization as it is more directly supported by the available experimental observations. The engineering-limit and population-guided definitions are presented here as a basis for future validation and operational use, rather than as a statement that that population or engineering limits have been established experimentally.

3.7 Normalized degradation indicators

The primary corrosion indicator is based on cumulative 316L coupon mass loss, not on the equivalent corrosion-rate value. The corrosion rate is retained as a supporting material-response metric. The normalized corrosion-related material degradation indicator is $C_n = (ML_t - ML_0) / (ML_{lim} - ML_0)$, where ML_t is cumulative 316L coupon mass loss at time t and ML_{lim} is the maximum observed cumulative mass loss.

The normalized vibration indicator is $V_n = (V_t - V_0) / (V_{lim} - V_0)$, where V_t is RMS vibration velocity, V_0 is the baseline value and V_{lim} is the maximum observed value. The normalized hydraulic-efficiency indicator is $E_n = (\eta_0 - \eta_t) / (\eta_0 - \eta_{lim})$, where η_0 is baseline efficiency, η_t is efficiency at time t and η_{lim} is the minimum observed efficiency.

For the present dataset, $\eta_0 = 70.6\%$, $\eta_t = 63.7\%$ at 100 h, and $\eta_{lim} = 58.0\%$, giving $E_n = 0.548$ at 100 h. The normalized indicators are bounded to the interval $[0,1]$ after calculation.

3.8 Pump Degradation Index formulation

$$PDI = w_C C_n + w_V V_n + w_E E_n \quad (9)$$

$$w_C + w_V + w_E = 1, w_i \geq 0 \quad (10)$$

Where

w_C is the relative weight of corrosion-related material degradation.

w_V is the relative weight of vibration.

w_E is the relative weight of hydraulic-efficiency degradation.

C_n , V_n and E_n are the corresponding normalized indicators.

For the primary analysis, $w_C = w_V = w_E = 1/3$, giving $PDI = (C_n + V_n + E_n)/3$ (11).

The weighted arithmetic form is intentional since it allows a clear auditable link between each degradation domain and the outcome of a condition index. The PDI is a dimensionless condition-degradation indicator, not a probability of failure, not a $R(t)$ reliability function, not a hazard rate, not an MTBF, not an MTTF or a remaining-useful-life prediction.

3.9 Weighting strategy and sensitivity

Table 5
Weighting scenarios used for sensitivity analysis
of the Pump Degradation Index (PDI)

Scenario	w_C	w_V	w_E
Equal weighting	0.333	0.333	0.333
Corrosion dominant	0.500	0.250	0.250
Vibration dominant	0.250	0.500	0.250
Hydraulic dominant	0.250	0.250	0.500

Five weighting scenarios (Table 5) to test the sensitivity of PDI to the relative weightings of corrosion, vibration and hydraulic-efficiency loss were considered.

In each scenario the sum of the weights is 1.00, enabling the validity of the PDI trend to be tested if certain assumptions about weights are to be made.

Equal weighting was chosen as the primary case in the absence of an independent field dataset from which statistically optimal weightings could be obtained. Three scenarios were also maintained for use: corrosion dominant, 0.50, 0.25, 0.25; vibration dominant, 0.25, 0.50, 0.25; and hydraulic dominant, 0.25, 0.25, 0.50.

A global feasible-weight sweep was defined for $w = (w_C, w_V, w_E)$, subject to $w_C + w_V + w_E = 1$ and $w_i \geq 0$, using 0.01 increments. This produces 5,151 feasible combinations. The resulting PDI range, mean and standard deviation are reported in Section 4.5. This tests mathematical sensitivity rather than statistically optimizing operational weights.

3.10 Illustrative condition-state mapping

To demonstrate how a continuous PDI could be mapped into discrete maintenance-oriented states, the following provisional boundaries were used:

State I: $PDI < 0.33$

State II: $0.33 \leq PDI < 0.67$

State III: $PDI \geq 0.67$

The boundaries 0.33 and 0.67 are illustrative only. They are not experimentally validated alarm, maintenance, regulatory or failure thresholds and are used solely to demonstrate how the continuous PDI could be translated into qualitative condition states.

They are not manufacturer limits, regulatory limits, statistical failure thresholds or validated maintenance boundaries.

3.11 Analytical treatment

Underlying dataset Five summarized observation points are available at 0, 50, 100, 150, 200h. The present work thus puts focus on descriptive trajectory analysis and deterministic index calculation, rather than extensive inferential statistics. The infrequent observations and single-pump experimental foundation do not allow population-level statistical inference, formal predictive modelling, or statistical evaluation of the proposed degradation threshold.

The published experimental data on which the analysis relies exhibits a statistical correlation between cumulative 316L mass loss and hydraulic efficiency, with $R = 0.87$ and $p < 0.05$ [13].

The present work maintains the relationship for contextual discussion only from the source work. It is not used as validation of the PDI proposed herein, because the correlation was derived from the published experimental data and does not evaluate the multidomain index proposed here. Presently calculated index The normalized corrosion-related, vibration, and hydraulic-performance indexes are calculated for each of the five observation times, and then combined with the chosen weighting formulation to generate the PDI trajectory. These values are presented and discussed purely in the descriptive tradition in order to analyze the pattern of change observed.

Because the three normalized indexes increase monotonically across the five observational times, their pairwise correlations are also presented in a descriptive fashion to quantify the degree of pairwise dependence among the indexes in this observational scenario.

These correlations are not interpreted as causal links in corrosion, vibration, and hydraulic deterioration, because the common observation-time trajectory accounts for some of the observed dependence. In particular, the limited number of observational points is unlikely to constitute a population-level dependency. Sensitivity analysis of the index with respect to alternative feasible weightings Sensitivity to alternative feasible combinations of the three weights within the observed data are assessed with the weighting analysis.

This output provides a deterministic assessment of the index dependence on the input assumptions of the weights within the given data set, but does not perform any statistical validation, uncertainty quantification, or derivation of an optimal weighting method.

4 Results and Discussion

4.1 Experimental observations

The analysis data set in the current study was prepared from the already published experimental study [13]. This current manuscript does not include an experimental procedure, but it analyzes experimentally

observed degradation data via a secondary method in order to illustrate the application of the corrosion-vibration-hydraulic PDI (CVHPDI).

Table 6
Experimental observations used for the present secondary analysis

Time (h)	Flow (m ³ /s)	Head (m)	Input power (W)	Efficiency (%)	Vibration (mm/s)	316L mass loss (mg)	Bronze mass loss (mg)	Carbon-steel mass loss (mg)
0	0.00150	12.0	250	70.6	0.20	0.0	0.0	0.0
50	0.00147	11.6	250	66.7	0.32	5.8	8.2	20.4
100	0.00144	11.3	250	63.7	0.45	9.6	13.8	34.7
150	0.00141	11.0	250	61.0	0.61	12.7	18.5	45.6
200	0.00138	10.7	250	58.0	0.75	15.4	22.8	54.2

The observations show a progressive deterioration in hydraulic and dynamic performance during the 200-h saline exposure. Pump efficiency decreased from 70.6% at the initial measurement to 58.0% at 200 h, representing an absolute reduction of 12.6 percentage points and a relative reduction of 17.85%. Over the same period, RMS vibration increased from 0.20 to 0.75 mm/s, corresponding to a 275% increase. Flow rate decreased by approximately 8.0%, while head decreased by approximately 10.8%.

Figure 1 illustrates the progressive reduction in pump efficiency during the 200-h saline exposure. Efficiency decreased from 70.6% at baseline to 58.0% at 200 h, corresponding to a 12.6-percentage-point reduction. The approximately monotonic decline provides the functional-performance basis for the hydraulic-efficiency component of the proposed PDI

Figure 2. The continuous increase in RMS vibration velocity from 0.20 mm s⁻¹ at baseline to 0.75 mm s⁻¹ after 200 h, as a result of the degradation process. The increase in vibration velocity signifies a change in pump dynamic condition while exposed to saline. Given the multi-factor nature of this dynamic property, the increase in RMS vibration is viewed as an indicator of dynamic degradation rather than a specific vibration fault mechanism.

These potential simultaneous changes are used as the basis for demonstrating the integrated degradation framework proposed in this paper as they reflect three different qualities of pump condition: material degradation, dynamic response and hydraulic capability. However, they are still an extension of the existing published experiment and should not be considered as new experimental results. The degradation changes in efficiency and vibration data, therefore, serve to motivate the general application of the PDI, rather than serve as direct empirical evidence of its value.

4.2 Corrosion and surface degradation

The previously published experiment also documented progressive surface degradation during saline exposure. The corresponding observations are reproduced in Table 6.

Table 7
Surface-degradation observations during saline exposure

Time (h)	Pit density (pits/mm ²)	Average pit diameter (μm)	Surface roughness, 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

In Table 7 above, the density of the pits increased from zero at baseline to 68 pits/mm at 200 h, and the mean diameter of the pits increased from 45 to 132 m between 50 and 200 h, which shows ongoing localised surface degradation. The surface roughness increased from 0.8 to 3.4 m during the same exposure period.

SEM at 1000 had previously shown localized pitting on 316L stainless steel, selective phase corrosion on bronze, and severe pitting and corrosion-product formation on carbon steel [13].

Figure 3 shows clearly that the corrosion responses of the three materials in the test regime are very different. Carbon steel lost the most mass, followed by bronze and then 316L stainless steel. The 316L specimen has the appropriate (hydraulically tested) pump corrosion response trajectory, while bronze and carbon steel represent static corrosion-coupon comparisons, rather than alternative pump configurations.

Using the 200-h coupon mass-loss data, the equivalent corrosion rates were 0.048, 0.083 and 0.212 mm/year for 316L stainless steel, bronze and carbon steel, respectively. These demonstrate the different corrosion responses of the materials tested within the laboratory saline environment. They should only be interpreted as laboratory-measured equivalent corrosion rates over the course of the test exposure period, rather than as representative off-shore field corrosion rates.

It is important to note that only the 316L stainless steel coupon was associated with the hydraulically tested pump, while bronze and carbon steel were static corrosion coupons, and not alternative pump configurations. The use of the 316L mass-loss trajectory therefore feeds into the corrosion component of the PDI. The test results support the use of material degradation as one dimension of this proposed framework, while also showing why material-specific calibration would be necessary before the approach could be applied to other alloys or material combinations.

4.3 Normalized degradation indicators

The three types of degradation were then transformed into dimensionless indicators by applying the normalization scheme outlined in Section 3.6. Since failure bounds were not independently known, normalization employed a "dataset-bounded range normalization" scheme. As a result, the upper bounds of the normalized indicators were set to the maximum degradation values observed over the 200-h experimental period and not to physically defined failure limits.

Table 8
Normalized degradation indicators

Time (h)	Cn	Vn	En
0	0.000	0.000	0.000
50	0.377	0.218	0.310
100	0.623	0.455	0.548
150	0.825	0.745	0.762
200	1.000	1.000	1.000

The three indicators exhibit broadly progressive degradation, although their rates differ. At 50 h, the normalized corrosion indicator (Cn) was 0.377, compared with 0.218 for vibration (Vn) and 0.310 for efficiency loss (En). At 100 h, these values increased to 0.623, 0.455 and 0.548, respectively. By 150 h, the values had reached 0.825, 0.745 and 0.762.

Figure 4 displays the three heterogeneous condition measurements all normalized to (dimensionless) degradation indicators. As shown, the corrosion indicator increased from 0.000 to 1.000, the vibration indicator from 0.000 to 1.000, and the efficiency-loss indicator from 0.000 to 1.000 within the experimental window. Despite the different intermediate rates of increase of the three trajectories, all three indicators reached a value of unity at 200 h because the final observed values were used as the normalization endpoints.

The relatively higher Cn-values within the earlier and intermediate portions of the exposure windows suggest that the observed 316L material-loss trajectory was advancing faster in relation to its observed final value than that of the vibration trajectory. It should be noted that a higher rate of advance of the observed material-loss within the time window does not necessarily imply that corrosion was responsible for the increase in vibration; it simply reveals that the three indicators were revealing different perspectives on the one observed degradation process.

At 200 h, the three normalized indicators were all equal to 1.000, again by design of the normalization process, since the last observed point was used to serve as the endpoints for the three normalization processes. These normalized values were therefore suitable for illustrating the mathematical behavior of the PDI but were not indicative of independent failure thresholds or predictive capability.

4.4 Integrated PDI trajectory and interpretation

The equal-weight PDI was calculated according to Eq. (11), with $w_C = w_V = w_E = 1/3$. The resulting trajectory is presented in Table 8.

Table 9
Equal-weight PDI trajectory

Time (h)	Cn	Vn	En	PDI
0	0.000	0.000	0.000	0.000
50	0.377	0.218	0.310	0.301
100	0.623	0.455	0.548	0.542
150	0.825	0.745	0.762	0.777
200	1.000	1.000	1.000	1.000

Table 9 shows the PDI trajectory under equal weighting of the three degradation indicators. The PDI increases progressively from 0.000 to 1.000 over 200 h, consistent with the concurrent increases in normalized corrosion-related and vibration indicators and the decline in hydraulic efficiency.

The PDI increased monotonically from 0.000 at baseline to 1.000 at 200 h:

$$PDI_0 = 0.000$$

$$PDI_{50} = 0.301$$

$$PDI_{100} = 0.542$$

$$PDI_{150} = 0.777$$

$$PDI_{200} = 1.000$$

That is, because the three degradation indicators show a common trend the three measurements can be combined to generate a common dimensionless pattern (from a condition-monitoring viewpoint). Although this novel usage of a common 'dimensionless pattern' is highly useful, the real methodological contribution is the inclusion of corrosion-related material degradation, vibration response and hydraulic function degradation within the same condition-degradation scheme; ultimately providing a transparent corrosion-aware condition-monitoring scheme for these pumps.

The other major point of difference from the state of the art is the focus on corrosion-related material degradation, vibration response and hydraulic response, with the contextual information afforded by considering the trend in the PDI. While recent centrifugal-pump condition-monitoring research has moved increasingly towards vibration analysis, advanced signal processing, machine learning methods and multimodal sensing for fault detection [8–10, 12], the PDI tackles a different problem: a simple

dimensionless picture of overall observed degradation may form a useful intermediate condition-state variable.

This may be particularly useful, when the normalization endpoints are based on the final states of the testing experiment, in which case the PDI can only be interpreted as a representation of the observed degradation process and not an independent fault predictor.

4.4.1 Descriptive degradation rates

Average degradation rates over the 200-h period were calculated for descriptive purposes. The average efficiency change was:

$$(58.0 - 70.6) / 200 = -0.063 \text{ percentage points/h.}$$

The corresponding average vibration increase was:

$$(0.75 - 0.20) / 200 = 0.00275 \text{ mm/s/h.}$$

The average 316L cumulative mass-loss rate was:

$$15.4 / 200 = 0.077 \text{ mg/h.}$$

The numerical change in the PDI was:

$$(1.000 - 0.000) / 200 = 0.005/\text{h.}$$

The second value cannot be taken as the physical degradation rate of the pump. The PDI is normalized to the maximum measured degradation for the experiment, such that the value of 1.000 at 200 h is a consequence of the normalization. The PDI slope is therefore an index velocity rather than an actual physical degradation rate.

This nuance is relevant for future prognostic use. A physically significant degradation-rate model would involve much longer duration tests, repeated measurements and ideally multiple degradation trajectories (something greater than 200 h of laboratory exposure).

4.5 Robustness and comparative evaluation of the PDI

Four example weightings were then initially contrasted: an equal weighting, corrosion-dominant, vibration-dominant and hydraulic-dominant weighting. Their trajectories are clearly clustered, but this is not surprising as they all are monotonically increasing in each of the three normalized indicators. Subsequently a global sweep of 5,151 feasible weightings was undertaken.

Table 10
PDI values under alternative weighting scenarios at different exposure times.

Time (h)	Equal weighting	Corrosion dominant	Vibration dominant	Hydraulic dominant
0	0.000	0.000	0.000	0.000
50	0.301	0.320	0.281	0.303
100	0.542	0.562	0.520	0.543
150	0.777	0.789	0.769	0.773
200	1.000	1.000	1.000	1.000

Table 10 lists PDI values resulting from the four weighting scenarios defined by the sensitivity analysis. The absolute PDI numbers, although higher for the corrosion, vibration or hydraulic-efficiency degradation weighting scenarios, follow a similar degradation trend for all four scenarios.

As in the qualitative case, the PDI increases with time of exposure and becomes 1.000 by 200 h for all cases, which suggests that the main qualitative conclusion about progressive degradation is not sensitive to the choice of weighting scenario.

For 50 h, the feasible PDI range is 0.218–0.377 and includes the illustration value of 0.33; for 100 h, it is 0.455–0.623; for 150 h, it is 0.745–0.825; and for 200 h, it is 1.000 for all feasible weights.

The continuous degradation index therefore appears more robust than early state assignment.

Figure 5 summarizes the set of 5,151 feasible weight combinations at 0.01 increments that are consistent with $w_C + w_V + w_E = 1$.

These define a set of minimum and maximum PDI values at each observation time, which corresponds to the minimum and maximum of the three normalized indicators respectively.

At 50 h the feasible PDI range cuts through the illustrative 0.33 boundary, but at 100, 150 and 200-h all feasible weights are in State II or III indicating a less qualitative but more continuous PDI response.

Thus, the broad path of the degradation trajectory appears resilient to the weights tested. This is fortunate as the relative importance of corrosion, vibration and hydraulic degradation are likely to vary according to pump duty, equipment system and criticality.

Table 11
Global feasible-weight sensitivity of the PDI

Time (h)	Minimum PDI	Maximum PDI	Mean PDI	SD	5th percentile	95th percentile
0	0.000	0.000	0.000	0.000	0.000	0.000
50	0.218	0.377	0.302	0.033	0.244	0.355
100	0.455	0.623	0.542	0.035	0.482	0.599
150	0.745	0.825	0.777	0.017	0.753	0.810
200	1.000	1.000	1.000	0.000	1.000	1.000

Table 11 illustrates the global sensitivity of the PDI to all possible combinations of weighting coefficients. The response data indicate that the PDI is confined to narrow ranges at each exposure time, with the average values fairly close to those obtained using equal weights. In addition, the general trend towards a 200 h PDI of 1.0 as the mean PDI increases from 0.302 at 50 h to 0.777 at 150 h reveals a steady degradation trend, which when combined with the small standard deviations (0.033–0.035 at 50–100 h and 0.017 at 150 h) illustrates the poor sensitivity of the degradation pattern to the actual weighting scheme.

The convergence to 1.000 at 200 h, achieved in equal weights as well, is explained by the normalization.

Thus, the results provide further evidence of the stability of the degradation trend across all feasible weightings.

4.5.1 Normalization sensitivity and uncertainty considerations

The primary analysis adopts dataset-bounded normalization due to the lack of independently validated engineering limits. As a result, engineering-limit normalization and ECDF normalization are shown as deployment options, rather than results that have been quantitatively redetermined. Engineering limits were not arbitrarily created for this secondary analysis. Without knowledge of instrument accuracy and repeatability from the original dataset, a full measurement-uncertainty budget was not reconstructed, and no mock confidence intervals or Monte Carlo uncertainty bounds are shown.

4.6 Illustrative degradation-state mapping

To demonstrate how the continuous PDI could be translated into discrete maintenance-oriented states, three illustrative ranges were applied:

- State I: $\text{PDI} < 0.33$
- State II: $0.33 \leq \text{PDI} < 0.67$

- State III: $PDI \geq 0.67$

Table 12
Illustrative condition-state interpretation

Time (h)	PDI	Illustrative state	Demonstration
0	0.000	State I	Baseline
50	0.301	State I	Early observed degradation
100	0.542	State II	Developing observed degradation
150	0.777	State III	Advanced observed degradation
200	1.000	State III	Maximum observed degradation

As an example, some interpretation of PDI to condition states based on the degradation trend can be seen in Table 12. These states are only used for demonstration and do not represent fail levels, reliability levels or maintenance intervention levels. This table can be seen as a demonstration of the ability to convert a continuous degradation index into a number of discrete condition states.

The selected boundaries of 0.33 and 0.67 should be interpreted as examples only and are used here solely to demonstrate the potential maintenance-screening capability of the PDI.

They are not manufacturer-defined, inspection or alarm set-points, or failure set points, since these are dependent on the details of the particular application as would be the case if the PDI were used as a maintenance tool within an industrial operation. (State III, for example, would not in any way indicate that the pump had failed or that failure was imminent. It would only indicate that the PDI fell within the upper range of the performance index.)

4.7 Comparison with individual indicators

The integrated approach can be further understood by comparing it with individual monitoring indicators.

Table 13
Conceptual comparison of monitoring approaches

Monitoring approach	Principal information	Principal limitation
Corrosion indicator alone	Material degradation	Does not directly represent dynamic or hydraulic condition
Vibration indicator alone	Dynamic condition	Multi-causal and may not identify the degradation mechanism
Efficiency indicator alone	Functional degradation	Does not identify the physical cause
PDI	Integrated material, dynamic and functional degradation	Requires validated normalization and weighting

On the other hand, the comparison in Table 13 suggests that the PDI can never be a substitute for the existing specialist diagnostics: corrosion inspection will still be needed to locate corrosion cells, vibration analysis will still be needed to detect dynamic faults and hydraulic testing will still be needed to evaluate pump performance. The PDI's role is to offer a shared condition-degradation description from those complementary indicators.

Thus, the conceptual hierarchy is:

Individual measurements → normalized indicators → PDI → detailed diagnosis

rather than:

Individual measurements → PDI instead of diagnosis.

This distinction clarifies the inferences made from the framework and minimizes the chance of misinterpreting the PDI as a new condition-monitoring indicator.

Normalized observations and descriptive Pearson correlations between the indicators C, V, and E were $r(C_n, V_n) = 0.979$, $r(C_n, E_n) = 0.995$, and $r(V_n, E_n) = 0.993$ using the 5 normalized observations.

These high correlation coefficients show that the three indicators had a very similar covariation in this experiment. Since $n = 5$, and the variables were all observed on the same exposure trajectory, these correlations cannot be interpreted as causal independence or population-level statistical significance; they can only be considered as partial evidence of the common trend in all three variables.

4.8 Inter-indicator dependence and causal interpretation

The simultaneous increase of corrosion, vibration and efficiency loss could suggest that the different degradation processes had emerged in saltwater. Nevertheless, the data do not support a causal link between these variables. In the initial experimental publication, a correlation was observed between the accumulated 316L mass loss and efficiency ($R = 0.87$, $p < 0.05$) [13].

Similarly, it would be inappropriate to conclude from the present dataset that:

corrosion → impeller mass loss → measured imbalance → vibration increase

was demonstrated experimentally.

The 15.4 mg 316L mass-loss is a cumulative coupon mass loss, and not a direct measurement of a 15.4 mg mass imbalance on the pump impeller. Additionally, RMS vibration, like any multi-causal symptom indicator, will be affected by hydraulic disturbance, imbalance, surface degradation, flow instability, mechanical variation, or other operating factors. Proper attribution must therefore be to ongoing concurrent degradation, with physical interaction, but no demonstrated Cii at this point.

4.9 Physical and mechanistic interpretation

The trend of increased vibration, if physical, could be consistent with progressive degradation, but the evidence does not currently support a direct causal link between corrosion and imbalance of the rotating component. A loss of material to one side of a rotating component could conceivably change the rotor mass distribution and thus affect dynamic forces, in a relationship such as.

$$F_u = m \times r \times \omega^2 \quad (11)$$

where m is the effective rotating mass imbalance, r is its radial position and ω is the angular velocity.

Equation (12) is included solely as an illustration of this physical mechanism. The coupon mass-loss data cannot be used to infer the value of (m), because the experiment did not assess the location or geometry or spatial distribution of the mass loss on the rotating elements. Thus, the present data do not indicate that corrosion caused rotor imbalance. Such a verification would require component-level measurements, such as spatial mapping of the mass loss, the associated mass lost and its location, direct balance measurements, and frequency domain vibrational measurements.

4.9.1 Surface roughness and hydraulic-performance context

Surface roughness increased from 0.8 to 3.4 μm during saline exposure [13]. This deterioration provides a plausible hydraulic mechanism that may contribute to the observed reduction in pump efficiency by increasing frictional effects and disturbing local flow conditions.

A simplified representation of frictional head loss is:

$$\Delta h_f = f \times (L/D) \times (v^2/2g) \quad (12)$$

where f is the friction factor, L is the characteristic flow length, D is the hydraulic diameter and v is the mean flow velocity.

The increase in surface roughness and decrease in efficiency are therefore physically consistent with an increasing flow impairment. However, the current data set does not allow the proportion of the reduction in efficiency that can be accounted for by the increase in surface roughness to be estimated. Effects such as variation in hydraulic efficiencies, alteration of local flow conditions, surface pitting and operational variation can also be contributing effects and as such surface roughness is assumed to be a possible contributing factor only.

4.10 Maintenance and condition-assessment implications

The PDI is designed to facilitate a reliability-informed approach to condition assessment. It should not be used to perform formal reliability calculations. More specifically, PDI is not a probability-of-failure model, reliability function $R(t)$, hazard model, mean time to failure, mean-time-between-failures, or remaining-useful-life estimator.

Subject to future validation, an equipment-specific PDI could potentially assist maintenance organizations in identifying:

- progressive degradation;
- relative maintenance priority;
- inspection candidates;
- changes in degradation trajectory; and
- equipment requiring more detailed diagnostic analysis.

A potential maintenance workflow is therefore:

PDI trend → Condition-state screening → Detailed diagnostic assessment → Inspection → Maintenance decision

This categorisation effectively relegates the PDI to a screening and decision-support role, while using the proven inspection, vibration-analysis and hydraulic-performance methods as the backbone of detailed engineering decisions.

4.11 Potential integration with digital-twin systems

The concept of digital-twin is more and more studied for condition monitoring, fault diagnosis, prognostics and predictive maintenance of rotating machinery [17–19]. In this type of architecture, the PDI could be a meaningful intermediate degradation-state variable that merges corrosion, vibration, and hydraulic-performance information.

A conceptual future architecture is:

Physical pump → Sensors and inspection → Data preprocessing → Normalized degradation indicators → PDI → Digital degradation state → Prognostics → Maintenance decision

The main potential benefit is interpretability. Instead of having multiple independent sensor features, the PDI could provide a unified degradation indicator while remaining the original measurements for diagnostic purposes. Of course, this study does not build, train or validate a digital twin; integration of the diagnostics should only be seen as one possible avenue for future work.

Future work could explore whether PDI trajectories can be integrated into physics-informed digital-twin models, multimodal sensor-fusion approaches, and probabilistic prognostics models, which would require additional operational data and validation of the PDI in the presence of independently observed degradation, maintenance interventions and failures.

4.12 Offshore engineering applicability

The source experiment was conducted under controlled laboratory saline conditions rather than under actual offshore operating conditions. Nevertheless, the three selected degradation dimensions have

practical relevance to offshore rotating equipment.

Potential applications include:

- seawater pumps;
- firewater pumps;
- cooling-water pumps;
- ballast pumps;
- produced-water pumps;
- injection-water pumps; and
- other centrifugal pumps operating in saline or corrosive service.

The PDI suggested must therefore be considered an importable analytic methodology that requires calibration for each equipment set rather than a universal offshore alarm value.

Real-world offshore application would include factors such as the pump operating envelope, design and material system; fluid chemistry; temperature and pressure; suspended solids; cavitation; variable-speed operation; transient conditions; maintenance history; equipment criticality; and the manufacturer limits for operations.

The laboratory-based PDI suggested here should therefore be re-calibrated for each targeted equipment class and service environment prior to use in operational decisions.

5 Validation and Future Deployment Framework

5.1 Staged validation framework

Table 14
Proposed validation framework for the PDI

Validation level	Required evidence	Primary objective
Level 1: Laboratory repeatability	Replicated experiments under controlled saline conditions	Establish repeatability and measurement robustness
Level 2: Multiple-pump validation	Different pump units, materials and operating points	Test generalizability across equipment
Level 3: Field/offshore validation	Operational seawater, firewater or other saline-service pumps	Assess transferability to real operating conditions
Level 4: Maintenance-event validation	Inspection, repair, overhaul and failure records	Relate PDI states to actual maintenance outcomes
Level 5: Reliability/prognostic validation	Longitudinal degradation and failure datasets	Determine whether PDI can support reliability or RUL modelling

Table 14 Summary PDI validation and guidance to field validation. The staged validation shown in Table 14 would give the PDI a robustness, generalizability and field-relevance, not achievable with the single second-of-laboratory experimental set-up in the current study.

Such a staged validation is particularly important because the five-point data set in this paper is adequate to illustrate the analytical principle but inadequate to verify the generality, the universal thresholds, or the predictive reliability of the PDI.

Overall, the criteria for future dataset should be repetitions, multiple pump units, multiple duty points, longer periods of observation. Measurements should, where feasible, include raw time history vibration measurements, frequency domain features, pressure measurements, temperature measurements, shaft speed, power quality, inspection measurements and maintenance-event records. Such data would support exploration of the capability of the PDI to provide a quantitative statistically validated degradation- or prognostics- related assessment in addition to the presentation of condition.

5.2 Independent multi-pump and field validation

Further validation of future data needs to be underpinned by multiple pump units, materials and operating points and saline-service condition's using repeated experiments. Transferability must be tested by independent field or offshore data sets. Data on maintenance, inspection, overhaul, component-replacement and failures must then be associated with PDI profiles to determine equipment-specific thresholds and assess early-warning capability.

5.3 Maintenance-event validation

Maintenance-event validation should compare the PDI states and trajectory changes with documented interventions and actual equipment state changes before the approximate state boundaries of PDI can be used operationally.

5.4 Future reliability linkage

A future normalized health would be defined as $H(t) = 1 - PDI(t)$. Using independent future longitudinal failure data, future investigations could examine relationships like $P(F \mid H(t))$ or $(t \mid PDI) = \int_0^t \exp(PDI)$. These are suggested only as a validation for future data; no failure-probability, hazard or RUL model is fit to this five observation data set.

6 Limitations

The corrosion term comes from coupon mass loss in the same saline environment, not from directly measuring material loss on the pump pressure containing or rotating components. The coupon is therefore a proxy for corrosion-based material loss caused by the same exposure condition. Variability in the local flow velocity, turbulence, geometry, surface condition and electrochemical conditions may cause the coupon response to differ from that of the pump components. Subsequent validation should include component scale corrosion data, in situ monitoring or independently validated corrosion proxies.

The present study has several key limitations. First, the study is limited to a single published experimental data set [13]. Second, only five summarized time points are reported.

Third, the normalization endpoints correspond to the maximum observation value within the 200-h experimental window.

Fourth, the normalization endpoints are not failure thresholds. Fifth, the PDI weighting factors have not been statistically optimized. Sixth, the condition-state boundaries of 0.33 and 0.67 are only provided as working definitions. Seventh, the experiment was conducted in a laboratory setting and does not capture the full oilfield operational environment.

Eighth, vibration was sampled by RMS velocity and not raw time-series or frequency-domain vibration information.

Ninth, corrosion and vibration were simultaneously observed but their causal relationship remains undetermined. Tenth, bronze and carbon steel corrosion coupons were used only, and were not representative of alternative pump designs. Eleventh, the PDI has not been verified against actual pump failure or maintenance histories.

Finally, the PDI does not directly provide estimates of probability of failure, or corresponding reliability function, hazard rate, MTBF, MTTF or remaining useful life. These limitations are the scientific boundary within which the present work is valid.

7 Conclusions

Multidomain Pump Degradation Index (PDI) – a transparent way of integrating corrosion, vibration and hydraulic-performance degradation in saline-service centrifugal pumps The main conclusions are:

- This is not a new experimental study but a methodological secondary analysis of previously published experimental results. Its main new development is integrating multidomain material, dynamic and hydraulic degradation dimensions into a common dimensionless index.
- The experimental results over the 200-h exposure period observed time-dependent degradation in efficiency, vibration, flow rate, and head, contrasted with time-dependent material-dependent corrosion behaviour observed in previously reported coupon measurements [13].
- For equal weighting, the PDI progressively increased from 0 at time zero to 1.000 at 200h, although alternative corrosion-, vibration- and hydraulic-dominant weighting cases gave broadly similar degradation trends, with the progression relatively insensitive to the weighting scenarios tested.
- Because the 200-h observation was used as the PDI normalization point, the observed PDI = 1.000 is not a pump failure or failure-probability but the maximum observed condition within the study window, and the illustrative condition boundaries defined require independent validation for operational use.

- The PDI should therefore be seen as a condition indicator, not as a failure-probability, reliability or remaining-useful-life model; and the simultaneous corrosion and performance observation provides context for degradation, but does not confirm a causal link or validate a specific corrosion-induced vibration mechanism.
- Validation, including using repeated experimental runs, multiple pumps, field or offshore measurements, and documented pump maintenance and failure cases, is necessary to establish potentially transferable thresholds and provide evidence of whether the PDI can be used for prognostic, reliability or predictive-maintenance purposes.

Overall, this presents a transparent engineering approach to integrating multidomain pump degradation, whilst clearly differentiating between a condition indicator and a validated failure-prediction model.

Abbreviations

A	m ²
C ₀	Dimensionless
CR	mm/year
E ₀	Dimensionless
F ₀	N
f ₀	Hz
g	m/s ²
H	m
K	—
M ₀	mg
P ₀	W
PDI	Dimensionless
P _{input}	W
Q	m ³ /s
r	m
V ₀	Dimensionless
V _{RMS}	mm/s
w _C	—
w _V	—
w _E	—
η	%
ρ	kg/m ³
ω	rad/s

Declarations

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Competing interests: The author declares no competing interests.

Author contributions: N.I.U. conceived the present analytical study, developed the Pump Degradation Index framework, performed the secondary analysis and prepared the manuscript.

Data availability: The experimental measurements analyzed in this study were previously published by Udo [13]. The present manuscript derives additional normalized indicators and the proposed PDI framework from those published measurements. Processed calculations and analysis scripts may 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.

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Figures

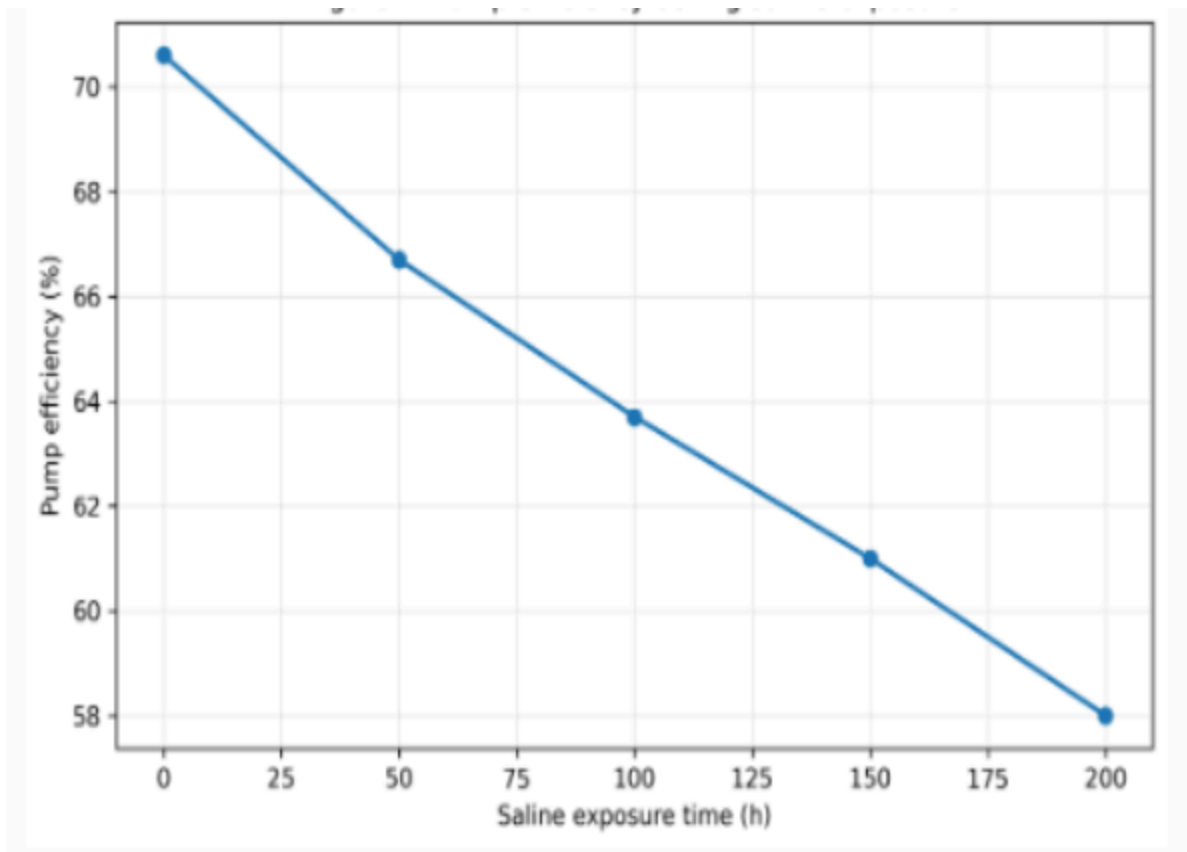


Figure 1

Pump efficiency during saline exposure.

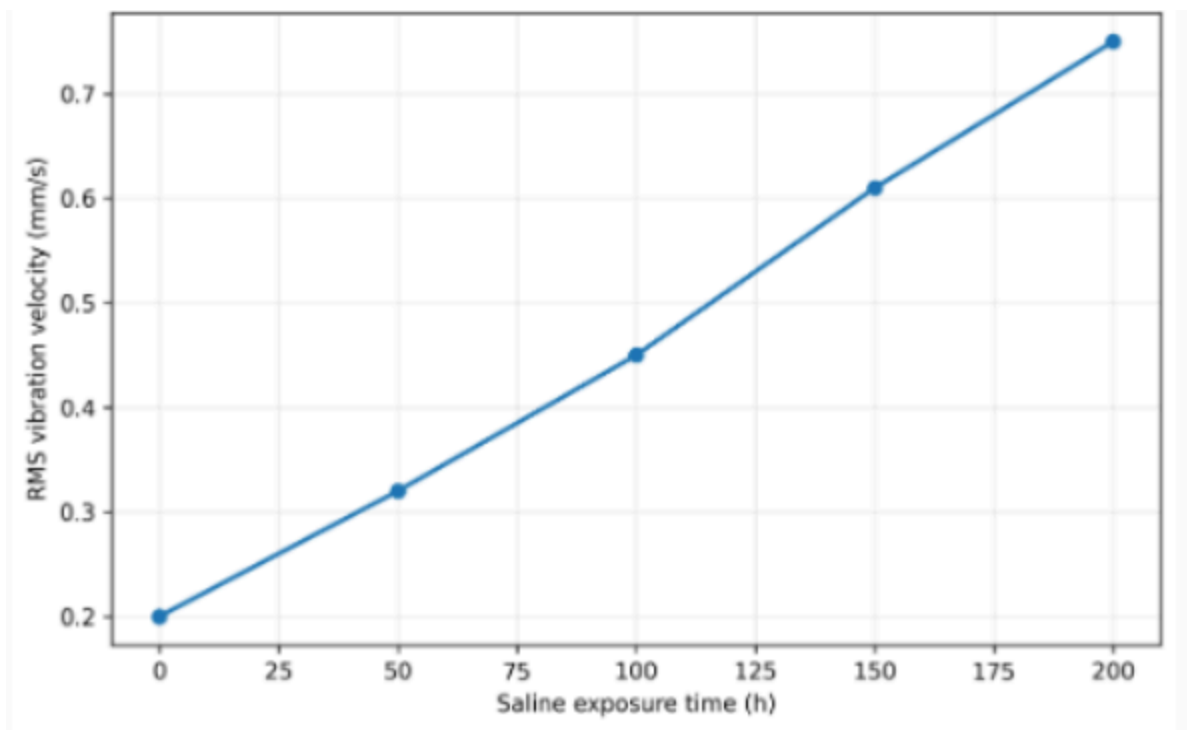


Figure 2

RMS vibration response during saline exposure.

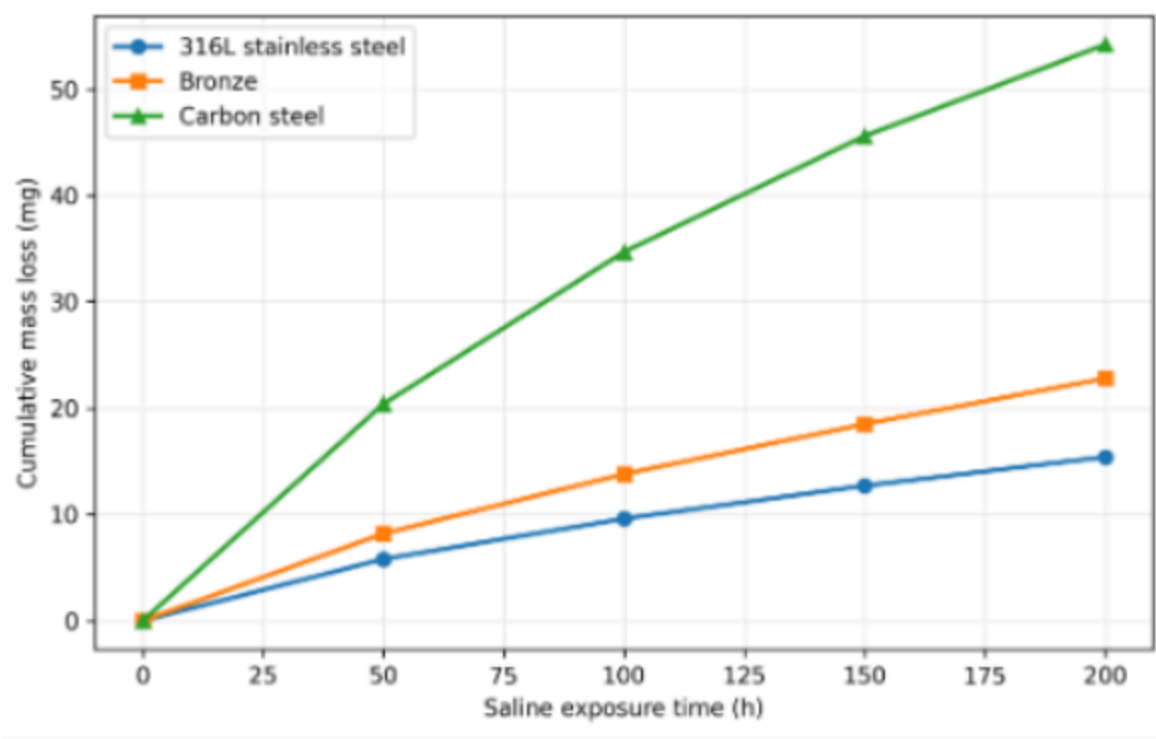


Figure 3

Cumulative mass loss of 316L stainless steel, bronze and carbon-steel corrosion coupons during saline exposure.

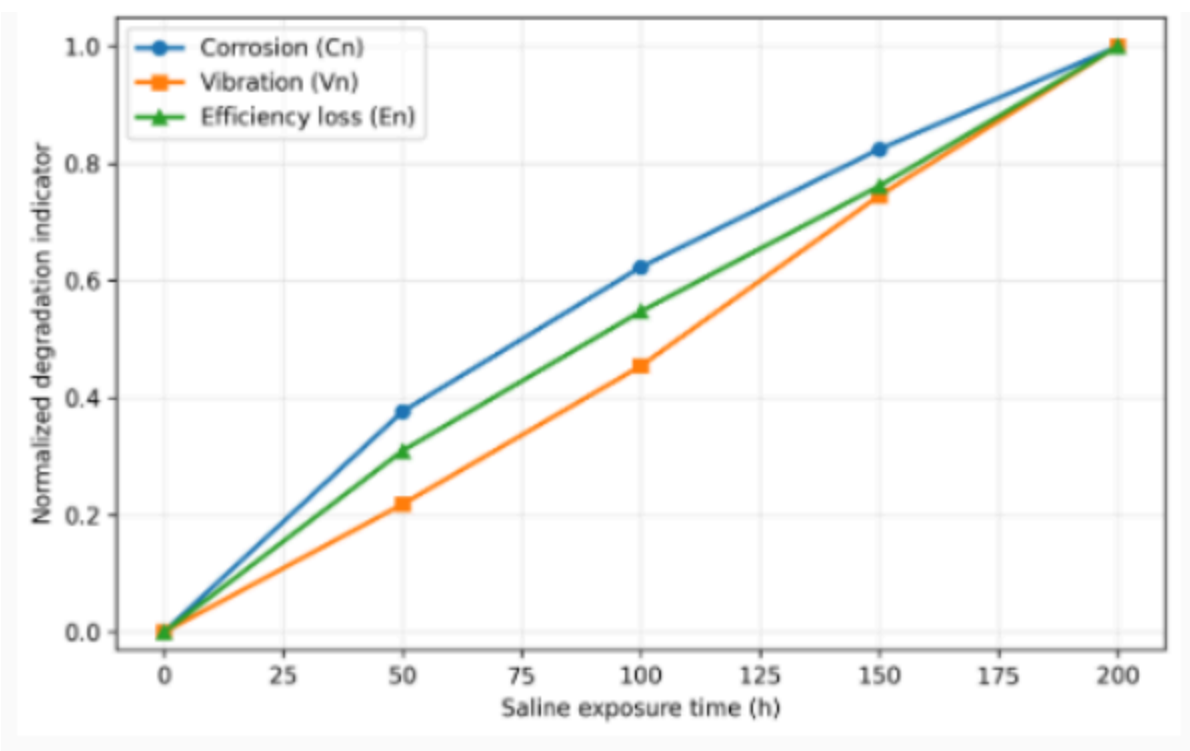


Figure 4

Normalized corrosion, vibration and hydraulic-efficiency degradation indicators.

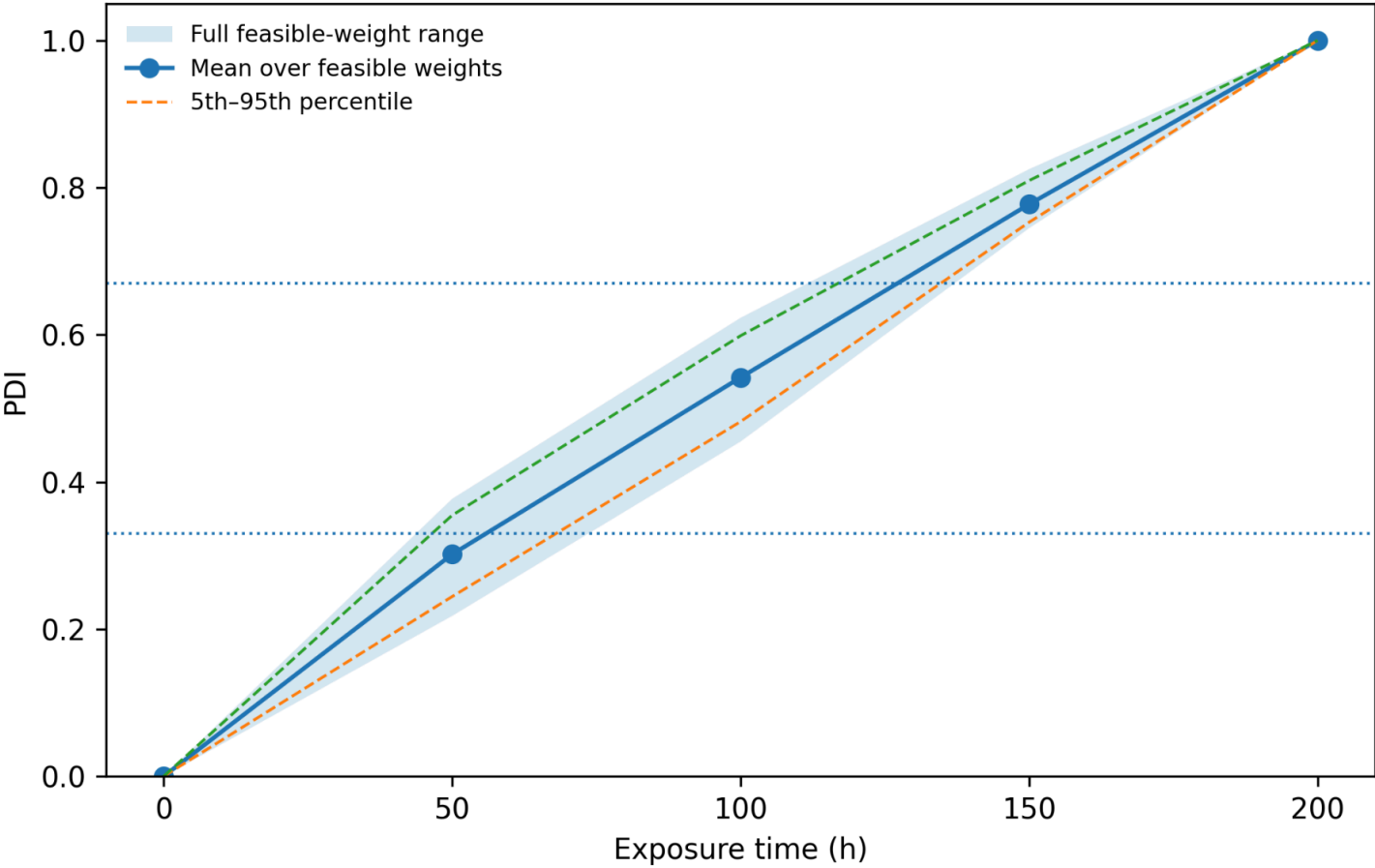


Figure 5

Global sensitivity of the PDI to corrosion, vibration and hydraulic-performance weighting coefficients.