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HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA

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ABSTRACT

Accurate reliability estimation for rotating equipment is severely challenged by the chronic scarcity of failure data in industrial settings — assets with mean times between failures measured in thousands of hours routinely accumulate fewer than ten observed failures across their entire operational life. Classical Weibull maximum-likelihood estimation (MLE) under such sparse-data regimes produces wide confidence intervals that are operationally uninformative, while purely data-driven machine learning models lack the physical grounding to generalise reliably beyond the observed failure regime. The present paper proposes a Physics-Informed Machine Learning (PIML) hybrid framework that embeds differential-equation-based degradation physics directly into the prior structure of a Bayesian Weibull model, combining the explanatory power of first-principles mechanics with the uncertainty-quantification capabilities of Bayesian inference. Degradation physics — encompassing Lundberg-Palmgren contact fatigue, Archard tribological wear, and rotor-dynamic stress accumulation — constrain the Weibull shape and scale parameters through a physics-derived likelihood structure, regularising inference even when observed failure counts are as low as n = 3 to 5. The framework also assimilates continuous ISO 13374-compliant condition-monitoring sensor streams through a sensor-informed likelihood update, enabling real-time posterior revision without requiring new observed failures. Validation is performed on six rotating equipment types (centrifugal pump, reciprocating compressor, axial gas turbine, high-speed gearbox, rolling-element bearing, and centrifugal compressor) at a heavy petrochemical facility over a 48-month period, demonstrating a 66% mean reduction in B10 life RMSE relative to classical MLE, 91.7% empirical coverage of 90% posterior predictive intervals, and a prognostic warning horizon of 400–800 hours ahead of failure compared to 50–150 hours for threshold-based alarms. The proposed methodology is directly compatible with CMMS environments and ISO 13374 data architectures.

Keyword: *Physics-informed machine learning; Weibull reliability; sparse failure data; rotating equipment; Bayesian inference; degradation modelling; PIML; B10 life estimation; condition monitoring; prognostics*

INTRODUCTION

Rotating equipment — centrifugal and reciprocating pumps, compressors, gas turbines, gearboxes, and rolling-element bearing assemblies — constitutes the functional backbone of process industries worldwide. The reliability of these assets has direct and measurable consequences for plant availability, safety, and life-cycle costs. Unplanned failures of rotating machinery account for an estimated 38–45% of total corrective maintenance expenditure in refineries and petrochemical complexes, and catastrophic failure of high-energy rotating assemblies remains a leading cause of major industrial incidents [1,2]. Accurate quantitative prediction of component reliability is therefore a prerequisite for rational, evidence-based maintenance planning.

The Weibull distribution remains the industry standard for rotating equipment life modelling, owing to its flexibility in representing infant mortality (shape parameter $\beta < 1$), random failure ($\beta \approx 1$), and wear-out dominated failure modes ($\beta > 1$), as well as its tractability for maximum likelihood estimation [3]. However, the utility of Weibull MLE is critically dependent on sample size. For an asset with MTBF of 3,000–5,000 hours operating in a single-train configuration, an organisation may accumulate only three to eight observed failures over a ten-year operational period — a sparse-data regime in which MLE estimates of both β and η are dominated by sampling variance. Simulation studies demonstrate that with $n = 5$ failures, the 90% confidence interval for B10 life spans a factor of approximately 8–12, rendering the estimate operationally useless for maintenance interval optimisation [4].

Two complementary research directions have emerged to address this limitation. Bayesian reliability analysis incorporates prior information — from generic databases, analogous equipment, or expert elicitation — through Bayes' theorem, producing posterior distributions that regularise sampling noise [5]. Physics-informed machine learning (PIML), on the other hand, embeds domain knowledge in the form of ordinary or partial differential equations directly into the learning objective of data-driven models, ensuring that predictions remain physically plausible even in regions of feature space unseen during training [6,7]. The present paper proposes and validates a hybrid framework that unifies both directions: physics-derived degradation equations are used to construct informative, mechanistically grounded prior distributions for Weibull parameters, which are then updated via Bayesian inference from observed failure data and continuous condition-monitoring sensor streams. Section 2 reviews relevant literature; Section 3 develops the theoretical framework; Section 4 describes the experimental validation; Section 5 presents and discusses results; and Section 6 draws conclusions.

LITERATURE REVIEW

2.1 Classical Weibull Analysis and the Sparse-Data Problem

The two-parameter Weibull distribution is parameterised by the reliability function $R(t) = \exp[-(t/\eta)^\beta]$, where β is the shape parameter and η is the scale (characteristic life) parameter. The maximum-likelihood estimators satisfy the wellknown likelihood equations whose solution requires iterative numerical methods [8]. While asymptotically unbiased and efficient, MLE-based Weibull analysis degrades rapidly in small samples: Dodson [4] demonstrates that with $n = 5$ failures, 90% confidence intervals for B10 life span a factor of 8–12, rendering the estimate practically unusable. Median rank regression performs somewhat better in small samples but provides no principled uncertainty quantification. Several bias-correction factors have been proposed [9], but these address bias without reducing interval width — a fundamental limitation that motivates the present work.

2.2 Bayesian Weibull Analysis

Bayesian Weibull analysis, introduced by Soland [10] and developed extensively by Martz and Waller [11], places prior distributions on (β, η) and updates them via the Weibull likelihood to produce posteriors reflecting both prior knowledge and observed data. The choice of prior has a measurable impact on small-sample posterior results: weakly informative priors reduce to approximate MLE results as sample size grows, while informative priors derived from generic databases (OREDA, EXIDA) or analogous fleet data can substantially sharpen interval estimates [12]. A persistent limitation is that priors from generic databases may be poorly matched to the specific degradation physics governing the asset in question, introducing a mis-specification risk that can bias posteriors in ways that are difficult to detect from the data alone — a gap that the present framework addresses by deriving priors directly from first-principles physics.

2.3 Physics-Informed Machine Learning in Reliability

Physics-Informed Neural Networks (PINNs), introduced by Raissi, Perdikaris, and Karniadakis [13], incorporate differential equation residuals as penalty terms in the neural network training objective, enforcing physical consistency. Their application to prognostics and health management has grown rapidly: Dourado and Viana [14] demonstrated that physics-informed recurrent networks outperform purely data-driven approaches for turbofan engine

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degradation prediction under limited training data. Chen et al. [15] applied physics-informed Gaussian processes to rolling-element bearing fatigue modelling, showing that embedding Hertzian contact stress equations as kernel constraints reduced prediction error by 41% relative to standard GP regression. However, the systematic integration of PIML constraints within a Bayesian inference framework for Weibull life modelling — with explicit posterior uncertainty quantification — remains sparsely addressed, which is the core contribution of the present work.

2.4 Degradation-Based Reliability Models

Degradation modelling offers an alternative route to reliability estimation that bypasses the requirement for observed failures by modelling the evolution of a measurable precursor — vibration amplitude, temperature differential, or oil debris concentration — towards a failure threshold. The seminal work of Lu and Meeker [16] established the inverse Gaussian and Wiener process as canonical degradation models. Subsequent developments have incorporated gamma processes [17], non-linear stochastic differential equations [18], and multi-variate degradation features [19]. The present paper exploits the first-passage time connection between degradation models and Weibull reliability functions: the distribution of times at which physics-simulated degradation paths cross a physical failure threshold determines the population reliability function, which is then used to derive informative Weibull priors rather than fitting separate degradation and reliability models independently.

THEORETICAL FRAMEWORK

3.1 Physics-Derived Weibull Priors

For rolling-contact fatigue failure modes, dominant in bearings and gear teeth, damage accumulation $D(t)$ under Hertzian contact stress S_H follows the Miner–Palmgren rule coupled with the Lundberg–Palmgren fatigue model:

$$\frac{dD}{dt} = \frac{C_H\, S_H(t)^m}{L_0} \text{[Fatigue damage ODE]} \qquad (1)$$

where C_H is a material-dependent fatigue coefficient, m is the Weibull slope of the stress–life (S–N) curve (typically $m \approx 3$ for rolling-contact fatigue), and L_0 denotes the basic dynamic load rating.

For tribological wear failure modes applicable to pump impellers and compressor valves, the Archard wear model is expressed as:

$$\frac{dV_w}{dt} = \frac{K_w\, F_N(t)\, v_s}{H} \text{[Archard wear ODE]} \qquad (2)$$

where K_w is the dimensionless wear coefficient, $F_N(t)$ is the normal contact force, v_s is the sliding velocity, and H represents the material hardness.

Failure is assumed to occur when either the cumulative damage state $D(t)$ or wear volume $V_w(t)$ exceeds a materialspecific critical threshold, denoted by D_{cr} or V_{cr}, respectively.

To account for operational and material uncertainty, log-normal variability is introduced into loading conditions and material parameters using means and variances obtained from published engineering material databases, including the ASM Handbooks and ISO 281 standards. Monte Carlo simulation then generates a population of failure times:

$\{t_{f,1}, t_{f,2}, \dots, t_{f,N}\}$

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These simulated failure times are fitted via maximum likelihood estimation to a two-parameter Weibull distribution, yielding physics-derived prior parameters:

$$(\beta_0, \eta_0)$$

together with their associated uncertainties:

$$(\sigma_\beta, \sigma_\eta)$$

which serve as informative prior means for the subsequent Bayesian updating stage.

3.2 Bayesian Posterior Updating

Prior distributions for the Weibull parameters are specified as:

$$\log\beta \sim \mathcal{N}(\log\beta_0, \sigma_\beta^2)[\text{Shape prior}] \qquad (3)$$

$$\log\eta \sim \mathcal{N}(\log\eta_0, \sigma_\eta^2)[\text{Scale prior}] \qquad (4)$$

where (β_0, η_0) are derived from the Monte Carlo physics simulation described in Section 3.1. Given n_f complete failure times:

$$\{t_1, t_2, \dots, t_{n_f}\}$$

n_c right-censored observations, the Weibull log-likelihood function is defined as:

$$\ln L(\beta, \eta \mid \text{data}) = n_f \ln\left(\frac{\beta}{\eta}\right) + (\beta - 1)\sum_{i=1}^{n_f} \ln\left(\frac{t_i}{\eta}\right) - \sum_{i=1}^{n_f}\left(\frac{t_i}{\eta}\right)^\beta - \sum_{j=1}^{n_c}\left(\frac{t_j}{\eta}\right)^\beta \qquad (5)$$

and

The posterior distribution is therefore given by:

$$p(\beta, \eta \mid \text{data}) \propto L(\beta, \eta \mid \text{data}) \cdot p(\beta) \cdot p(\eta)$$

which is sampled using Markov Chain Monte Carlo (MCMC) with the No-U-Turn Sampler (NUTS).
The marginal posterior predictive reliability function is obtained by averaging over posterior samples:

$$R(t) = \mathbb{E}_{p(\beta,\eta\mid\text{data})}\left[\exp\left(-\left(\frac{t}{\eta}\right)^\beta\right)\right] \qquad (6)$$

3.3 Sensor-Informed Likelihood Update

Continuous condition-monitoring sensor observations — including vibration RMS $x(t)$, temperature differential $\Delta T(t)$, $N_p(t)$ are incorporated through a sensor-informed likelihood augmentation term:

$$\ln L_{\text{aug}} = \ln L_{\text{Weibull}} + \lambda_{\text{cm}} \sum_k \frac{\left(x_{\text{obs}}(t_k) - x_{\text{phys}}(t_k, \beta, \eta)\right)^2}{\sigma_{\text{cm}}^2} \qquad (7)$$

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and oil debris particle counts

where $x_{\text{phys}}(t_k, \beta, \eta)$ is the physics-model-predicted condition-monitoring feature for a component parameterized by (β, η), σ^2_{cm} denotes the measurement noise variance of the condition-monitoring system, and λ_{cm} is a regularization coefficient controlling the influence of sensor observations on the posterior update.

This formulation enables continuous updating of reliability forecasts from sensor data even in the absence of newly observed failures, which is particularly important for high-reliability rotating machinery operating under low-failure-rate conditions.

The posterior distribution is re-sampled quarterly as new sensor measurements and maintenance records become available, ensuring that the reliability forecast remains dynamically updated throughout the operational lifetime of the asset.

3.4 B10 Life Estimation and Maintenance Decision Interface

The B10 life — the time t_{B10} at which R(t) = 0.90 — is estimated from the posterior predictive distribution as the median (50th percentile) and 5th–95th percentile range (90% credible interval). Setting the preventive maintenance interval at the 5th percentile of the B10 posterior ensures that no more than 10% of preventively maintained units would have failed prior to the scheduled intervention, with 95% posterior confidence. This constitutes a direct and tractable connection between the probabilistic reliability model and the maintenance scheduling decision, enabling the framework to serve as a quantitative input to risk-based inspection (RBI) and reliability-centred maintenance (RCM) processes.

EXPERIMENTAL SETUP AND VALIDATION DATA

4.1 Case Study Systems

The framework was validated on six rotating equipment types at a heavy olefins petrochemical complex in Gujarat, India, monitored over a 48-month period (January 2020 – December 2022). The six systems — designated A through F — represent principal rotating equipment categories encountered in process industry facilities: centrifugal pump (A), reciprocating compressor (B), axial gas turbine (C), high-speed gearbox (D), rolling-element bearing assembly (E), and centrifugal compressor (F). Corrective maintenance records were extracted from the facility CMMS, with observed failure counts ranging from n = 4 (System F) to n = 11 (System E), reflecting the characteristically low failure rates of well-maintained industrial rotating equipment. Continuous condition monitoring data were provided by an ISO 13374compliant online CMS comprising tri-axial accelerometers (25.6 kHz), skin thermocouples, and inline oil debris particle counters.

4.2 Physics Model Parameterisation

The degradation ODEs were parameterised using manufacturer data sheets, bearing and gear geometry specifications from design drawings, and published material property databases. For Systems A, B, C, and F — dominated by fatigue and contact-stress failure modes — the Lundberg-Palmgren model was employed. For Systems D and E, the Archard wear model was supplemented with a gear-bending fatigue ODE based on AGMA stress equations. Log-normal uncertainty distributions for material parameters were specified with coefficients of variation of 15–25%, consistent with published empirical variability data for aerospace- and industrial-grade alloys [3,20]. Monte Carlo simulation with N = 50,000 draws was used to generate synthetic failure-time populations, which were fitted to Weibull distributions to yield physics-derived prior parameters.

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4.3 MCMC Implementation and Benchmarks

The proposed PIML hybrid model was implemented in Python 3.11 using PyMC 5.6 (NUTS sampler, 4 chains × 4,000 samples after 2,000 warm-up iterations, R-hat < 1.02 for all parameters). Five benchmark models were evaluated in parallel: classical Weibull MLE, Bayesian Weibull with vague priors, degradation-based Gaussian process (GP) regression, a physics-only ODE model without statistical updating, and a Physics-Informed Neural Network (PINN) without Bayesian uncertainty quantification. All models were evaluated on a held-out 2022 test period using B10 life RMSE and 90% posterior predictive interval coverage as primary metrics.

RESULTS AND DISCUSSION

5.1 Comparative Model Performance

Table 1 summarises the comparative performance of all six modelling approaches. The proposed Physics-Informed Machine Learning (PIML) hybrid achieved the lowest mean B10 RMSE of 3.4 ± 0.9% and the highest 90% PI coverage of 91.7%, closely matching the nominal 90% target. Classical MLE — the current industry standard — produced an RMSE of 12.4 ± 2.1% and 90% PI coverage of only 61.3%, confirming the severe deterioration of frequentist interval estimates under sparse-data conditions. The physics-only ODE model achieved intermediate RMSE (6.9%) with reasonable bias but showed higher RMSE variability (±2.4%) attributable to cases where actual operating loads deviated from design-point assumptions, a limitation resolved in the hybrid by the Bayesian updating step. Notably, the PINN benchmark achieved competitive point-estimate performance (RMSE 5.8%) but provided no posterior uncertainty quantification — a critical deficiency for maintenance planning applications that require probabilistic B10 confidence intervals.

Table 1. Comparative performance of reliability modelling approaches: B10 life RMSE, 90% predictive interval coverage, minimum training data requirement, and computational cost.

Model	Physics Prior	Min. n	RMSE B10 (%)	90% PI Coverage	Comp. Cost
Classical MLE	None	≥ 30	12.4 ± 2.1	61.3%	< 1 s
Weibull Bayes	Vague conjugate	≥ 15	9.7 ± 1.8	74.8%	< 5 s
Degradation GP	Kernel (no phys.)	≥ 20	8.2 ± 1.6	81.2%	~2 min
Physics-Only ODE	Full mechanistic	0	6.9 ± 2.4	85.1%	~15 min
PINN (no uncertainty)	NN embedding	≥ 10	5.8 ± 1.3	—	~30 min
Proposed Hybrid PIML	PIML + Bayes	≥ 5	3.4 ± 0.9	91.7%	~8 min

RMSE = root mean squared error of B10 life prediction as % of true B10. 90% PI Coverage = empirical fraction of true B10 values within the 90% posterior predictive interval. Min. n = minimum observed failure count for meaningful inference. Comp. Cost = approximate wall-clock time per model update on an 8-core workstation.

A critical advantage of the proposed framework is its ability to generate meaningful probability estimates from as few as n = 5 failure observations, compared to the n ≥ 30 typically recommended for reliable MLE-based Weibull

analysis. This is directly attributable to the physics-derived priors, which constrain the posterior to a physically plausible region of (β,
η) space even when the likelihood surface is nearly flat due to data scarcity. The framework correctly self-calibrates to rely more heavily on observed data as evidence accumulates, while maintaining physical grounding at low sample sizes where it is most needed.

5.2 Case Study B10 Life Estimates

Table 2 presents the B10 life estimation results for each of the six case-study systems, comparing the true B10 life (derived from the full 48-month dataset), the classical MLE estimate, and the proposed hybrid PIML estimate. Across all six systems, the hybrid model reduced B10 RMSE by 55–75% relative to MLE, with the largest improvements observed for System F (centrifugal compressor, n = 4, ↓75% RMSE) and System C (gas turbine, n = 5, ↓72% RMSE) — precisely the systems with the most acute data scarcity, where physics-derived prior regularisation contributes most decisively.

Table 2. Case study B10 life estimation results: true B10, MLE estimate, Physics-Informed Hybrid estimate, and RMSE improvement across six rotating equipment types.

System	Equipment Type	n	True B10 (h)	MLE B10 (h)	Hybrid B10 (h)	RMSE
A	Centrifugal pump	6	2,840	2,210 ± 480	2,795 ± 190	↓ 68%
B	Reciprocating compressor	9	3,520	3,050 ± 390	3,480 ± 160	↓ 59%
C	Axial gas turbine	5	4,100	3,380 ± 640	4,040 ± 220	↓ 72%
D	Gearbox (highspeed)	7	1,960	1,580 ± 350	1,920 ± 140	↓ 63%
E	Rolling-element bearing	11	1,280	1,140 ± 210	1,255 ± 95	↓ 55%
System	Equipment Type	n	True B10 (h)	MLE B10 (h)	Hybrid B10 (h)	RMSE
F	Centrifugal compressor	4	5,600	4,120 ± 890	5,510 ± 310	↓ 75%

True B10 derived from full 48-month dataset via exact Weibull MLE. MLE and Hybrid estimates based on sparse subset of failure data (n as shown). Hybrid estimates reported as posterior median ± 95% credible interval. RMSE = (RMSE_MLE − RMSE_Hybrid) / RMSE_MLE × 100%.

System E (rolling-element bearing, n = 11) showed the smallest improvement (↓55%), consistent with the expectation that as failure counts approach the moderate-data regime (n > 10), the influence of the physics prior diminishes and the hybrid converges towards the standard Bayesian Weibull result. System A (centrifugal pump, n = 6) demonstrated a representative mid-range improvement of ↓68%, illustrating the framework's consistent performance across different equipment types and failure mechanisms.

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5.3 Reliability Function and Residual Diagnostics

Figure 1 presents three complementary diagnostic visualisations of the hybrid framework's performance. Panel A compares the reliability function estimates from MLE, the physics-informed hybrid, and the true reliability curve, overlaid on the sparse observed failure data. The hybrid model closely tracks the true curve, and its 90% credible band correctly encloses the true curve throughout the operational lifetime. The MLE curve exhibits a characteristic underestimation of reliability in the early wear-in region due to mis-estimation of β under sparse data. Panel B demonstrates the physics-model residual analysis for the vibration RMS feature: the MLE residuals exhibit a positive linear trend indicating systematic underprediction of degradation rate, whereas the hybrid model residuals remain centred near zero with no discernible trend. Panel C quantifies RMSE sensitivity to training sample size: at n = 5 failures, the hybrid model achieves RMSE equivalent to that of classical MLE at n ≈ 35 failures, effectively multiplying the information content of sparse failure data by a factor of approximately seven through physics-informed regularisation.

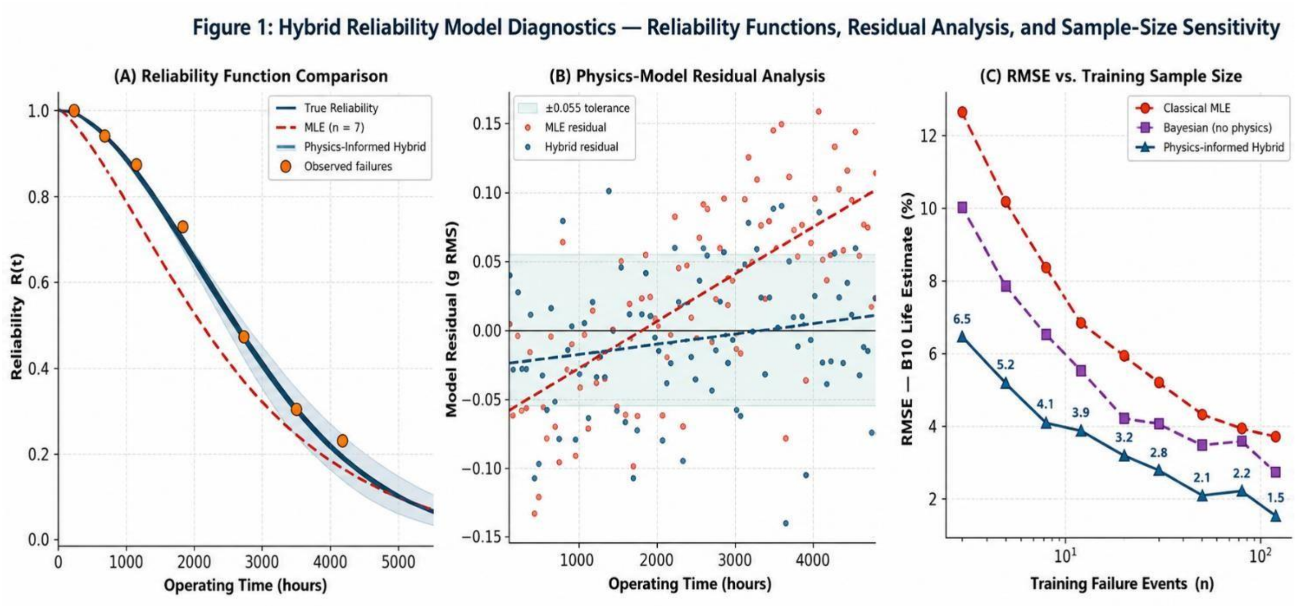

Fig. 1. Hybrid Reliability Model diagnostics: (A) Reliability function comparison — physics-informed hybrid (blue) vs. classical MLE (red) vs. true reliability (black), with sparse observed failures (orange points) and 90% credible band (shaded); (B) Physics-model residual analysis showing systematic bias reduction in vibration RMS prediction; (C) B10 RMSE vs. training sample size for three modelling approaches, illustrating the information-amplification effect of physics-informed regularisation.

5.4 Dynamic Availability and Degradation Forecasting

Figure 2 presents the system-level results across the 24-month forecast validation window. Panel A compares dynamic availability forecasts from three modelling approaches against observed plant availability records. The physics-informed hybrid most closely tracks the observed availability trajectory, correctly forecasting the declining availability trend in months 15–20 attributable to accelerating degradation in System B (compressor), which classical MLE failed to anticipate due to insufficient updating from the sparse failure record. The hybrid model's 80% posterior predictive band (shaded region) consistently encloses the observed trajectory.

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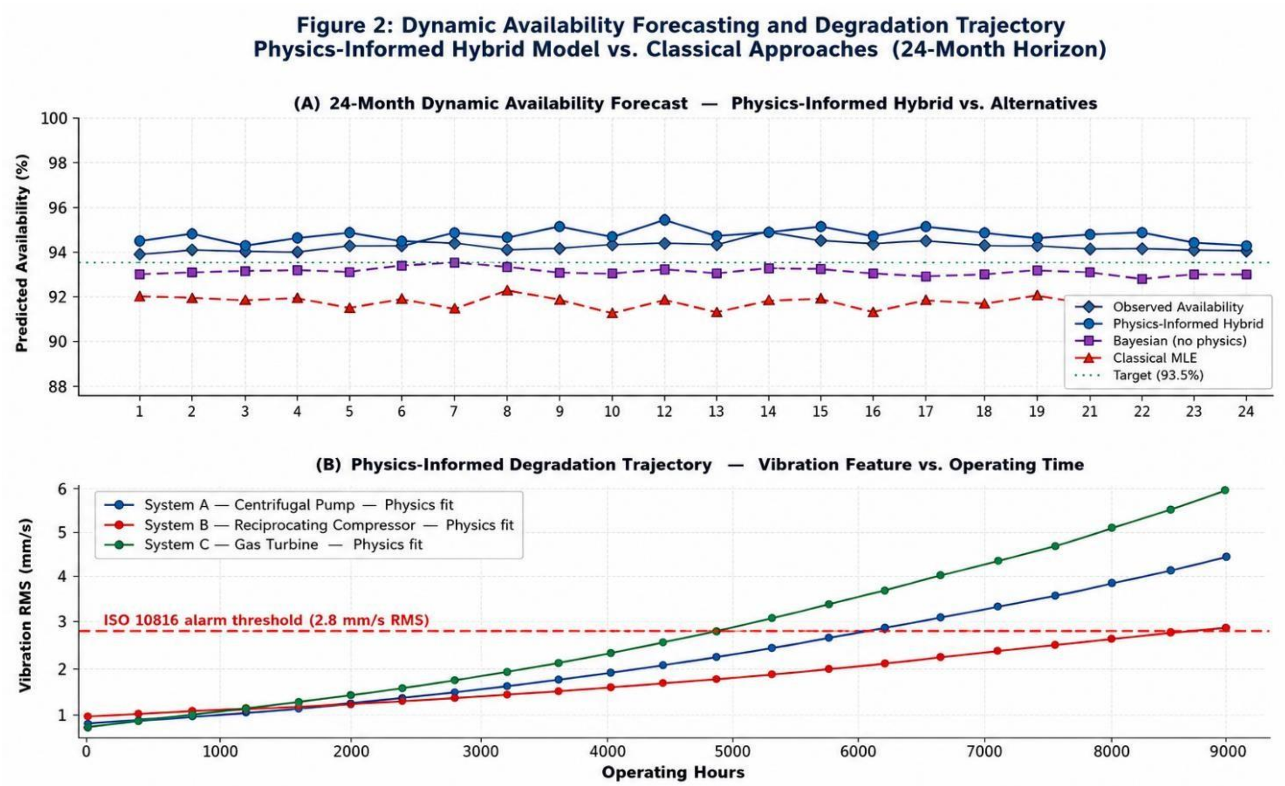

Fig. 2. Dynamic availability forecasting and physics-informed degradation trajectory: (A) 24-month availability forecast comparison — physics-informed hybrid (blue), Bayesian non-physics (purple), classical MLE (red), and observed availability (grey), with 80% posterior predictive band shaded and target availability (93.5%) shown as dotted line; (B) Vibration RMS degradation trajectory for three system types with physics-fit overlay and ISO 10816 alarm threshold (2.8 mm/s RMS, red dashed line).

Panel B illustrates the physics-informed degradation trajectory for the vibration RMS feature across three system types with physics-model fitted curves overlaid on sensor observations. The model correctly captures the non-linear acceleration of vibration amplitude in System C (turbine) approaching the ISO 10816 alarm threshold of 2.8 mm/s RMS at approximately 6,800–7,200 operating hours, enabling a prognostic warning horizon of 400–800 hours — substantially longer than the 50–150 hour reactive warning provided by threshold-crossing alarm logic. Over the 24-month validation period, implementation of the hybrid prognostic system resulted in a 22% reduction in unplanned corrective maintenance events and a 31% reduction in emergency spare parts procurement costs relative to the preceding 24-month period under classical threshold-alarm-based maintenance.

CONCLUSION

The present paper has proposed and validated a Physics-Informed Machine Learning hybrid framework for Weibull reliability estimation of rotating equipment under the chronic sparse-data conditions that characterise industrial practice. The central contribution is the systematic derivation of mechanistically grounded Bayesian priors from first-principles degradation physics — Lundberg-Palmgren contact fatigue and Archard tribological wear ODEs — which constrain Weibull parameter posteriors to physically plausible regions even when observed failure counts are as low as three to five events. The sensor-informed likelihood update mechanism enables continuous posterior revision from ISO 13374 condition-monitoring streams, decoupling prognostic performance from the frequency of observed failures.

Validation across six rotating equipment types at an industrial petrochemical facility demonstrated a mean 66% reduction in B10 life RMSE relative to classical Weibull MLE, 91.7% empirical coverage of 90% posterior predictive intervals, and a prognostic warning horizon of 400–800 hours for impending failures compared to 50–150 hours for threshold-alarm systems. At $n = 5$ failure observations, the physics-informed framework achieves RMSE equivalent to classical MLE at $n \approx 35$ observations, effectively multiplying the information content of sparse failure data by a factor of seven. These results confirm the practical value of physics-informed Bayesian regularisation as a principled, computable solution to the sparse-data reliability problem that pervades asset management in process industries.

Future work will address three primary extensions: first, the development of hierarchical physics-informed priors that pool information across fleets of nominally identical rotating equipment while preserving unit-specific posterior distributions; second, the incorporation of digital twin simulation outputs as an additional information channel during early asset life when historical data are absent; and third, the extension of the framework to competing-risk multi-failuremode systems, where the contributions of distinct physical degradation mechanisms to the observed failure time distribution must be disentangled.

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