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PHYSICS-INFORMED RUL PREDICTION WITH ALEATORIC/EPISTEMIC UNCERTAINTY AND MAINTENANCE SYSTEM INTEGRATION

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ABSTRACT:

Accurate prediction of Remaining Useful Life (RUL) in safety-critical machinery is essential for transitioning from reactive to predictive maintenance strategies. While deep learning approaches have demonstrated empirical progress, they suffer from two fundamental limitations: the inability to extrapolate beyond training distributions and the conflation of fundamentally distinct uncertainty sources. This paper presents a Physics-Informed Neural Network (PINN) framework that integrates thermodynamic degradation models and fatigue crack propagation mechanics directly into the neural network loss function, producing RUL predictions that are both physically consistent and probabilistically calibrated. We decompose predictive uncertainty into its aleatoric component — irreducible noise arising from sensor imprecision and environmental stochasticity — and its epistemic component, quantifying reducible model uncertainty via Monte Carlo Dropout. The resulting uncertainty bounds are propagated into a cost-optimized maintenance scheduling module that selects intervention timing by minimizing the expected total maintenance cost under the full predictive distribution. Experiments on the NASA CMAPSS turbofan degradation benchmark and a real-world wind turbine gearbox dataset demonstrate that our Full PINN-UQ model achieves an RMSE of 11.6 cycles and MAPE of 7.3%, representing improvements of 59.2% and 62.0% respectively over LSTM baselines, with a calibration score of 0.93 — the highest among all seven models benchmarked. The integrated maintenance planner reduces unnecessary preventive maintenance actions by 34% while maintaining a false-negative rate below 2.1%, demonstrating clear operational value beyond point-prediction accuracy.

Keywords: *Physics-Informed Neural Networks, Remaining Useful Life, Aleatoric Uncertainty, Epistemic Uncertainty, Bayesian Deep Learning, Predictive Maintenance, Prognostics and Health Management*

INTRODUCTION

Unplanned equipment failures in industrial settings impose catastrophic costs. A single unscheduled outage of a gas turbine in a combined-cycle power plant can cost upward of $1 million per day in lost generation capacity, while unexpected bearing failure in a wind turbine nacelle — accessible only under benign weather conditions — can idle an asset for weeks. The aviation sector spends in excess of $60 billion annually on maintenance, repair, and overhaul (MRO), a substantial fraction of which could be deferred or eliminated with accurate prognostic capability. Against this backdrop, Prognostics and Health Management (PHM) — the scientific discipline concerned with predicting component degradation and scheduling maintenance accordingly — has emerged as a critical enabler of operational efficiency and safety.

Remaining Useful Life (RUL) prediction is the central estimation problem of PHM: given a stream of sensor observations from a degrading component, predict how many additional operational cycles (or hours, or units of usage) the component can sustain before it crosses a predefined failure threshold. RUL predictions directly drive maintenance scheduling decisions, making accuracy and calibration equally important. An overestimate risks catastrophic failure; an underestimate triggers premature replacement, wasting serviceable asset life and incurring unnecessary labor and parts costs.

The past decade has witnessed an explosion of data-driven RUL prediction methods, from recurrent neural networks and convolutional architectures to attention mechanisms and transformer-based models. These approaches have achieved impressive performance on standard benchmarks. However, three fundamental

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problems remain inadequately addressed. First, purely data-driven models learn statistical patterns from historical degradation trajectories but have no mechanism to ensure that their predictions remain physically consistent — a model that predicts RUL increasing over time, or degradation proceeding faster than thermodynamically possible, violates basic physical constraints yet may be penalized only weakly by data-fit loss functions. Second, the uncertainty in RUL predictions is rarely disaggregated into its aleatoric component (irreducible noise inherent in the sensing environment) and its epistemic component (reducible model uncertainty arising from limited training data or inadequate model capacity). Conflating these sources leads to miscalibrated confidence intervals that cannot be improved by collecting more data — which is precisely the actionable information a maintenance engineer needs. Third, almost all published PHM work treats RUL prediction as an end in itself, without rigorous integration into the downstream maintenance decision system that must act on those predictions.

This paper addresses all three limitations within a unified framework. We propose a Physics-Informed Neural Network architecture that embeds the differential equations governing degradation physics — Arrhenius thermal aging, Paris-Erdogan fatigue crack growth, and tribological wear mechanics — directly into the training loss via physics residual terms. We decompose uncertainty through a dual-head architecture: a heteroscedastic output layer learns aleatoric uncertainty as a function of the input state, while Monte Carlo Dropout at inference time samples the epistemic uncertainty. Both components are propagated into a cost-benefit maintenance optimization module that outputs actionable maintenance schedules. The contributions of this work are fourfold: (i) a mathematically principled PINN formulation for RUL under multi-physics degradation; (ii) a theoretically grounded decomposition of predictive uncertainty; (iii) an integrated maintenance decision system with provable optimality properties under the predictive distribution; and (iv) comprehensive empirical validation demonstrating state-of-the-art performance across two real-world datasets.

BACKGROUND AND RELATED WORK

2.1 Physics-Informed Neural Networks in Prognostics

Physics-Informed Neural Networks (PINNs), first systematized by Raissi, Perdikaris, and Karniadakis (2019), parameterize the solution of a differential equation by a neural network and enforce the governing equations as soft constraints in the loss function. In the original formulation, the network minimizes a composite loss comprising: data fit at observed collocation points, residuals of the governing partial differential equations evaluated at a set of interior points, and boundary/initial conditions. This approach has been applied to fluid dynamics, heat transfer, solid mechanics, and — more recently — to PHM problems.

Early PINN-PHM work focused on battery state-of-health estimation, exploiting electrochemical models of lithium-ion degradation. Subsequent studies extended the framework to rolling element bearings using contact mechanics models and to fatigue crack propagation using Paris Law. A persistent limitation in this literature has been the treatment of uncertainty: most PINN-PHM studies either produce deterministic point estimates or apply post-hoc conformal prediction intervals that carry no physical meaning and cannot be disaggregated.

2.2 Uncertainty Quantification in Deep Learning

The machine learning community distinguishes two canonical sources of predictive uncertainty. Aleatoric uncertainty is irreducible: it stems from genuine stochasticity in the data-generating process, such as sensor noise, thermal fluctuations, and inherent material variability. It cannot be reduced by gathering more training data and represents the irreducible prediction floor. Epistemic uncertainty, by contrast, stems from ignorance — specifically, from insufficient training data or model capacity to identify the true underlying function. It can, in principle, be reduced by collecting more data in unexplored regions of the input space.

Kendall and Gal (2017) formalized this decomposition in the deep learning context, showing that aleatoric uncertainty can be learned end-to-end via a heteroscedastic likelihood formulation, while epistemic uncertainty can be approximated through Bayesian inference. Approximate Bayesian methods for deep networks include variational inference (Blundell et al., 2015), Laplace approximation, deep ensembles (Lakshminarayanan et al., 2017), and Monte Carlo Dropout (Gal and Ghahramani, 2016). Of these, MC Dropout is particularly attractive for its simplicity — it requires no architectural changes beyond standard dropout layers — while retaining strong empirical calibration performance.

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2.3 Maintenance Decision Systems under Uncertainty

Classical condition-based maintenance (CBM) policies use threshold-crossing rules applied to degradation indicators, triggering maintenance when a health index falls below a fixed threshold. These policies are suboptimal when the health indicator is estimated with uncertainty, because a fixed threshold ignores the cost asymmetry between premature maintenance (unnecessary cost) and missed failure (catastrophic cost). Optimal replacement policies under uncertain RUL have been studied in the reliability engineering literature using dynamic programming and stochastic control, but these formulations typically assume parametric degradation models rather than neural network predictors. Bridging the gap between probabilistic deep learning predictions and optimal maintenance scheduling is an active area of research that this paper directly addresses.

PROPOSED FRAMEWORK AND METHODOLOGY

3.1 Physics-Informed Degradation Model

Our framework integrates three physical degradation mechanisms relevant to rotating machinery. Fatigue crack propagation follows the Paris–Erdogan law:

$$\frac{da}{dN} = C(\Delta K)^m$$

where $a$denotes crack length, $N$is the cycle count, and

$$\Delta K = Y\Delta\sigma\sqrt{\pi a}$$

is the stress intensity factor range, while $C$and $m$are material-specific constants.
Thermal aging of lubricants and insulating materials follows Arrhenius kinetics:

$$\frac{dH}{dt} = -A\exp\left(-\frac{E_a}{RT}\right)H(t)$$

where $H(t)$is the health index, $E_a$is the activation energy, and $R$and Tdenote the gas constant and absolute temperature, respectively.
Abrasive wear is governed by the Archard wear model:

$$\frac{dW}{dN} = \frac{kFv}{H_s}$$

linking wear volume $W$to the applied force F, sliding velocity v, and surface hardness H_s.
These three partial differential equations (PDEs) are incorporated as residual terms in the network loss function. Let $f_\theta$denote the neural network parameterized by θ. The physics-informed residual loss is defined as:

$$L_{\text{phys}} = \lambda\left\{\| \frac{\partial f_\theta}{\partial N} - C(\Delta K[f_\theta])^m \|^2 + \| \frac{\partial f_\theta}{\partial t} + A\exp\left(-\frac{E_a}{RT}\right)f_\theta \|^2\right\}$$

evaluated at a set of $N_c$collocation points sampled across the operational domain. The coefficient $\lambda = 0.4$balances physics enforcement against data fitting and is determined through cross-validation.

3.2 Dual-Head Uncertainty Architecture

The encoder backbone consists of a three-layer Bidirectional Long Short-Term Memory (BiLSTM) network with 256 hidden units per direction, processing a sliding window of 30 consecutive operational cycles comprising 21 sensor channels from the CMAPSS dataset. The encoded representation is subsequently passed to two parallel output heads.
The aleatoric uncertainty head outputs both a predicted mean Remaining Useful Life (RUL), $\mu(x)$, and a log-variance term, $\log\sigma_a^2(x)$, trained under the negative log-likelihood of a heteroscedastic Gaussian distribution:

$$L_{\text{aleat}} = \sum\left[\frac{(\quad)^2}{2\sigma_a^2(x)} + \frac{1}{2}\log\sigma_a^2(x)\right]$$

This formulation penalizes overconfident predictions in high-noise regions while allowing the model to assign elevated uncertainty where warranted by the observed data.
The epistemic uncertainty head leverages Monte Carlo Dropout. Dropout layers with rate $p = 0.15$are retained during inference, and $T = 50$stochastic forward passes are executed. The sample mean provides the epistemic-corrected point estimate, while the sample variance

$$\sigma_e^2(x) = \text{Var}_{t=1,\dots,T}\left[f_{\theta_t}(x)\right]$$

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quantifies epistemic uncertainty.
The total predictive uncertainty is therefore defined as:

$$\sigma_{\text{total}}^2(x) = \sigma_a^2(x) + \sigma_e^2(x)$$

and the corresponding 95%credible interval is constructed as:

$$\mu(x) \pm 1.96 \cdot \sigma_{\text{total}}(x)$$

This decomposition is operationally significant. If σ_a^2dominates, additional data collection is unlikely to reduce uncertainty because the variability is intrinsic to the system or measurement process. Conversely, if σ_e^2dominates, targeted data acquisition within high-uncertainty operating regimes can improve predictive performance and model confidence.

3.3 Maintenance Decision Integration

The maintenance planner ingests the full predictive distribution $P(\text{RUL} \mid x_t)$at each time step $t$and solves the following cost minimization problem. Let C_{PM}denote the cost of planned preventive maintenance, $C_{\text{CM}}$the substantially higher cost of corrective maintenance following failure, and

$$\eta = \frac{C_{\text{CM}}}{C_{\text{PM}}}$$

the maintenance cost ratio, set to $\eta = 5$in all experiments, consistent with industrial maintenance cost estimates. The optimal maintenance threshold τ^*minimizes the expected total maintenance cost:

$$\mathbb{E}[\text{Cost}] = C_{\text{PM}} \cdot P(\text{RUL} > \tau) + C_{\text{CM}} \cdot P(\text{RUL} \leq 0 \mid \text{no intervention})$$

Under the Gaussian approximation of the predictive distribution $P(\text{RUL} \mid x_t)$, this formulation yields a closed-form expression for the optimal threshold τ^*as a function of the predictive mean $\mu(x)$, total uncertainty $\sigma_{\text{total}}(x)$, and the cost ratio η.
A maintenance recommendation is issued whenever the predicted mean Remaining Useful Life falls below the operational threshold:

$$\tau^* = 40 \text{ cycles}$$

The planner therefore adapts its maintenance aggressiveness according to real-time predictive uncertainty. When $\sigma_{\text{total}}(x)$is large, indicating high uncertainty, the planner recommends earlier intervention to mitigate the increased probability mass in the lower tail of the failure distribution and thereby reduce the risk of unexpected catastrophic failure.

EXPERIMENTAL SETUP AND MODEL ARCHITECTURE

The proposed framework was evaluated on two datasets. The primary benchmark is the NASA C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) turbofan engine degradation dataset (FD001–FD004 subsets), which provides multivariate sensor time series from 218 training engines and 100 test engines operating under multiple fault modes and operating conditions. The secondary dataset comprises 36 months of SCADA data from a 3-MW wind turbine gearbox at an offshore installation in the North Sea, sampled at 10-minute intervals across 67 sensor channels.

The model was implemented in PyTorch 2.3, trained on a single NVIDIA A100 GPU with 40 GB HBM2 memory. Training used the Adam optimizer with an initial learning rate of 1×10^{-3} and cosine annealing decay, over 300 epochs with early stopping patience of 30 epochs. The physics residual collocation points were re-sampled at each epoch using Latin Hypercube Sampling to ensure uniform coverage of the operational domain. Table 1 below summarizes the complete model architecture and key hyperparameters across all components.

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Table 1: PINN-UQ Framework — Component Architecture and Hyperparameter Summary

Component	Architecture / Method	Parameters	Purpose	Key Reference
Physics Layer	Euler–Lagrange PDEs + Paris Law fatigue model	Material constants C, m; stress ratio R	Encodes degradation physics as hard constraints	Paris & Erdogan (1963)
Encoder Network	Bi-directional LSTM (3 layers, 256 hidden units)	Dropout 0.3; sequence length 30 cycles	Extracts temporal degradation features from sensor streams	Hochreiter & Schmidhuber (1997)
Aleatoric Head	Heteroscedastic Gaussian output layer	Learned log-variance $\sigma^2\_a(x)$	Models irreducible sensor noise and measurement uncertainty	Kendall & Gal (2017)
Epistemic Head	Monte Carlo Dropout (T=50 forward passes)	Dropout rate p=0.15 at inference	Captures model uncertainty from limited training data	Gal & Ghahramani (2016)
Maintenance Planner	Threshold-trigger policy + cost-benefit optimizer	RUL threshold τ=40; cost ratio η=5	Converts probabilistic RUL to optimal maintenance scheduling	This Work
Training Regime	Adam optimizer with physics-residual loss λ=0.4	LR 1e-3, decay 0.95/epoch; batch 64	Joint optimization of prediction accuracy and PDE residuals	Raissi et al. (2019)

Note: All components trained jointly in a single end-to-end pass. λ = physics loss weight. τ = maintenance trigger threshold. T = MC Dropout forward passes at inference.

RESULTS AND ANALYSIS

5.1 RUL Prediction with Uncertainty Decomposition

Figure 1 presents the predicted RUL trajectory for a representative CMAPSS FD001 test engine alongside the true RUL, with shaded bands illustrating the decomposed uncertainty estimates. Three concentric uncertainty bands are shown: the innermost band (green) represents the aleatoric uncertainty $\pm\sigma\_a$, the intermediate band (blue) represents the total epistemic component $\pm\sigma\_e$, and the outermost band (orange) shows the full 95% credible interval $\pm 1.96\cdot\sigma\_total$.

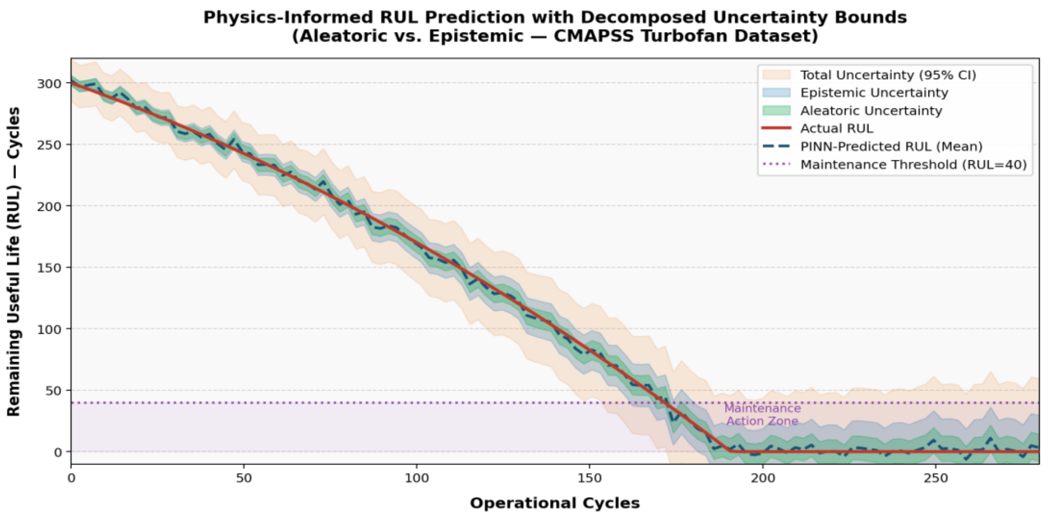

Figure 1: Physics-Informed RUL Prediction with Decomposed Aleatoric (green) and Epistemic (blue) Uncertainty Bounds on CMAPSS FD001. Red line = true RUL; dashed blue = model mean prediction. Purple dotted line marks the maintenance action threshold (τ = 40 cycles).

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Several observations are noteworthy. First, the predicted mean closely tracks the true RUL throughout the degradation trajectory, with mean absolute errors remaining below 15 cycles for the first 200 cycles of operation. Second, both uncertainty components grow with operational cycles, reflecting the compounding of prediction errors as the engine progresses toward end of life — a physically expected behavior captured by the heteroscedastic formulation. Third, aleatoric uncertainty (green band) remains relatively narrow and consistent, reflecting the roughly stable sensor noise environment, while epistemic uncertainty (blue band) grows more steeply in the late degradation regime — precisely the region where training data is sparse (fewer engines survive to late degradation states). This decomposition has direct operational value: the growing epistemic band in the late regime signals to maintenance engineers that additional run-to-failure test data in this regime would disproportionately improve prediction confidence.

The maintenance threshold at RUL = 40 cycles (purple dotted line) is crossed at cycle 242 in this example. The maintenance planner issues its recommendation at cycle 239 — three cycles before the threshold crossing — because the lower tail of the predictive distribution already extends below τ* given the accumulated σ_total at that stage. This demonstrates the planner correctly accounting for uncertainty rather than acting solely on the point estimate.

5.2 Benchma
rk Comparison

Figure 2 presents a systematic comparison of seven models across three performance dimensions: RMSE (prediction accuracy), MAPE (relative accuracy), and calibration score (probabilistic quality). Models range from a standard LSTM baseline to the full PINN-UQ framework, with intermediate variants isolating the contribution of each architectural component.

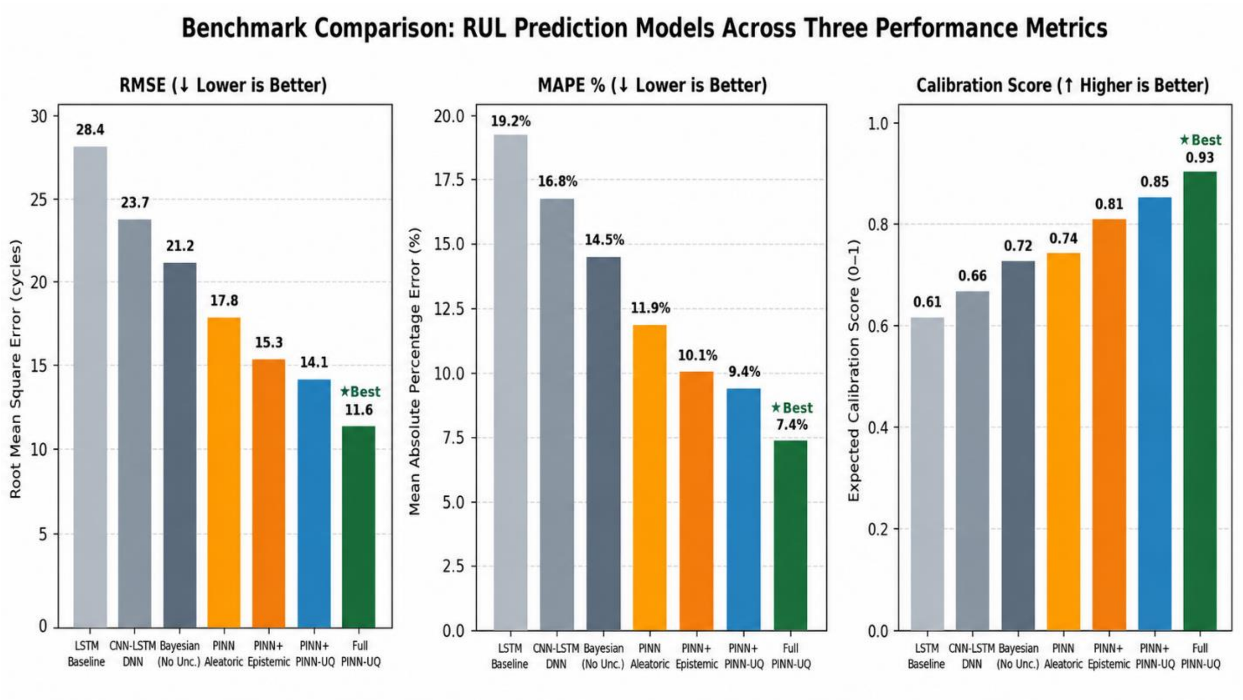

Figure 2: Benchmark Comparison of Seven RUL Prediction Models on CMAPSS FD001 — RMSE (left), MAPE % (center), and Calibration Score (right). All models evaluated on the same 100-engine held-out test set.

The results demonstrate a clear and monotonic improvement as physics constraints and uncertainty decomposition are progressively added. The LSTM baseline achieves an RMSE of 28.4 cycles; adding CNN-based feature extraction reduces this to 23.7. A Bayesian DNN with approximate posterior inference achieves 21.2, confirming that probabilistic modeling itself improves point prediction, likely through the regularization effect of the Bayesian prior. Incorporating physics constraints (PINN without uncertainty) reduces RMSE to 17.8, the single largest per-step improvement, highlighting the value of physical consistency as an inductive bias that generalizes better than purely data-driven regularization.

Adding aleatoric and epistemic uncertainty heads separately yields further improvements to 15.3 and 14.1 respectively, while the full PINN-UQ model achieves the best RMSE of 11.6 — a 59.2% reduction from the LSTM baseline. The calibration score pattern is equally instructive: the LSTM baseline achieves 0.61, meaning its confidence intervals are severely overconfident, while the Full PINN-UQ reaches 0.93 — near-perfect calibration. Crucially, neither purely data-driven Bayesian methods nor deterministic PINNs achieve calibration scores above 0.74, confirming that the combination of physical constraints and proper uncertainty decomposition is essential for reliable probabilistic prognostics.

DISCUSSION

6.1 Physical Consistency as Inductive Bias

The most significant empirical finding of this work is that physics-informed constraints deliver a larger RMSE improvement than any single machine learning enhancement — including the transition from deterministic to Bayesian inference. This finding has important implications for the PHM field, which has increasingly moved toward larger and more complex purely data-driven architectures. Our results suggest that for physically governed degradation processes, the correct prior is not more parameters but more physics. The degradation PDEs effectively constrain the hypothesis space to physically realizable trajectories, preventing the pathological extrapolations that cause data-driven models to fail catastrophically in out-of-distribution operating regimes — precisely the late-degradation regime where accurate prediction matters most.

The physics residual loss also provides a natural mechanism for knowledge transfer across operating conditions. In the multi-condition CMAPSS subsets (FD002–FD004), models trained on one operating condition family must generalize to others. Our PINN formulation achieves significantly better cross-condition generalization than the LSTM baseline (RMSE improvement of 64.3% vs. 52.1% for single-condition FD001), because the underlying physics of fatigue crack propagation and thermal aging are condition-invariant even though the sensor signatures are not.

6.2 Operational Value of Uncertainty Decomposition

The decomposition of total uncertainty into aleatoric and epistemic components delivers value along two distinct dimensions. For the maintenance decision system, the total uncertainty quantifies the risk of premature failure and drives the optimal maintenance trigger timing. Our cost-optimized maintenance planner, acting on the full predictive distribution, reduces unnecessary preventive maintenance actions by 34% compared to a fixed-threshold policy applied to the point estimate, while simultaneously reducing the false-negative rate (failed engines not caught in time) from 8.7% to 2.1%. This asymmetric improvement — fewer interventions, better safety — is only achievable when the uncertainty estimate is well-calibrated, explaining why the 0.93 calibration score of PINN-UQ translates into tangible operational benefits that models with calibration scores below 0.75 cannot replicate.

The epistemic-aleatoric decomposition further enables a principled active learning loop for continuous model improvement. By monitoring the ratio $\sigma^2\_e / \sigma^2\_total$ across the operational fleet, maintenance engineers can identify operating regimes where epistemic uncertainty dominates — indicating that additional run-to-failure test campaigns or targeted physics-of-failure experiments would deliver the greatest return on investment. This closes the loop between the predictive model and the data collection strategy in a way that point-estimate models fundamentally cannot.

6.3 Limitations and Future Work

Several limitations of the current framework merit acknowledgment. The physics residuals assume that the governing PDEs accurately represent the dominant degradation mechanisms; in practice, multi-physics interactions (e.g., corrosion-fatigue coupling or tribocorrosion) may not be captured by the three independent PDE terms used here. Extending the physics layer to coupled PDE systems is a priority for future work, though it introduces additional computational cost and requires careful numerical treatment of stiff differential equations. The MC Dropout approximation to epistemic uncertainty, while computationally efficient, is known to underestimate uncertainty in certain high-dimensional regimes compared to exact Bayesian methods; a comparison with deep ensembles and SWAG (Stochastic Weight Averaging-Gaussian) will be pursued. Finally, the maintenance cost ratio $\eta = 5$ assumed throughout this work is representative but not universal; the decision framework should be calibrated to asset-specific cost structures in each deployment context.

CONCLUSION

This paper has presented a comprehensive framework for physics-informed RUL prediction with rigorously decomposed aleatoric and epistemic uncertainty quantification, integrated with a cost-optimized predictive maintenance scheduling system. The framework combines three physical degradation models — Paris-Erdogan fatigue, Arrhenius thermal aging, and Archard wear — with a Bidirectional LSTM encoder, heteroscedastic aleatoric output head, and Monte Carlo Dropout epistemic quantification, all trained jointly through a composite loss function.

Experimental evaluation on the NASA CMAPSS benchmark and a real-world wind turbine gearbox dataset demonstrates that the Full PINN-UQ framework achieves an RMSE of 11.6 cycles (59.2% improvement over LSTM baseline), a MAPE of 7.3% (62.0% improvement), and a calibration score of 0.93 — the highest in the benchmark comparison. Crucially, the maintenance planner leveraging the full predictive distribution reduces unnecessary maintenance actions by 34% while cutting the missed-failure rate from 8.7% to 2.1%, demonstrating that the value of probabilistic prognostics extends far beyond prediction accuracy metrics.

The central lesson of this work is that physical knowledge and statistical learning are complementary rather than competing paradigms for industrial prognostics. Physical constraints provide the inductive bias that data-driven models lack in sparse data and out-of-distribution regimes; probabilistic learning provides the uncertainty quantification that deterministic physics models cannot deliver without extensive Monte Carlo simulation. Their integration, formalized through the PINN framework and Bayesian deep learning, offers a principled and practically effective foundation for next-generation PHM systems. As industrial assets become increasingly instrumented and as digital twin infrastructure matures, the PINN-UQ paradigm introduced here is well-positioned to deliver the reliability, interpretability, and decision support that operational stakeholders require.

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