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IoT-Enabled Predictive Maintenance in Industrial Manufacturing Systems

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Abstract

Purpose: The study critically interrogates the techno-economic and mathematical foundations of IoT-enabled predictive maintenance (PdM) in industrial manufacturing, questioning whether current data-driven reliability models genuinely optimize maintenance decisions or merely shift uncertainty into algorithmic opacity.

Methodology: A purely quantitative framework is developed by integrating stochastic degradation modelling, Remaining Useful Life (RUL) estimation, and multi-objective cost-reliability optimization. A simulated but methodologically valid industrial dataset is analysed using Weibull hazard functions, proportional hazards modelling, and deep learning-based prognostics. Model performance is evaluated through RMSE, precision-recall, availability, and lifecycle cost functions.

Findings: Results show that IoT-driven PdM improves system availability by 18.7% and reduces expected lifecycle maintenance cost by 23.4% compared with preventive maintenance. However, accuracy gains are non-linearly constrained by sensor data entropy, class imbalance, and degradation non-stationarity. The study demonstrates that hybrid physics-informed/data-driven models outperform purely data-driven architectures in RUL prediction stability.

Value: Rather than celebrating PdM as an Industry 4.0 inevitability, the paper exposes unresolved mathematical, architectural, and decision-theoretic contradictionsparticularly the tension between predictive accuracy, interpretability, and economic optimality. It provides a unified reliability-optimization model linking IoT data streams to maintenance policy selection.

Keywords: Predictive maintenance; Industrial IoT; Remaining useful life; Reliability engineering; Smart manufacturing; Cost optimization

1. Introduction

Industrial maintenance has historically been governed by deterministic scheduling logic that assumes failure as a temporally predictable phenomenon. This assumption collapses under high-variability manufacturing environments where degradation trajectories are stochastic, multi-scale, and path-dependent. Predictive maintenance (PdM) emerges as a response to this epistemic limitation by reframing maintenance as a probabilistic inference problem driven by continuous condition monitoring through IoT infrastructures [1][2]. Yet, the dominant discourse treats IoT-enabled PdM as a technological inevitability rather than a mathematically and economically contested decision system. If failure is predicted through data, what is the ontological status of degradation: a physical process, a statistical construct, or an artefact of sensor resolution? The industrial promise of reduced downtime and cost optimization conceals unresolved questions about model generalizability, data sufficiency, and decision optimality [3]. Industry 4.0 architectures embed cyber-physical systems in which asset health becomes a streaming data problem. However, streaming data does not guarantee predictive knowledge. The shift from preventive to predictive maintenance replaces time-based uncertainty with model-based uncertainty. Thus, the central research problem is not whether PdM improves performance, but under what mathematical conditions IoT-generated data leads to optimal maintenance policies.
This study develops a quantitative reliability-cost optimization framework to evaluate IoT-enabled PdM in manufacturing systems.

2. Literature Review

Contemporary research on IoT-enabled predictive maintenance (PdM) reveals a sustained and intensifying focus on comparative evaluation of machine learning and deep learning models, motivated by the critical need to determine not merely whether models perform, but which models perform best under real-world industrial conditions and why. Rather than cataloguing individual algorithms, the literature increasingly situates comparison studies within broader questions about model robustness, interpretability, computational feasibility, and integration with Industrial Internet of Things (IIoT) sensor data flows. Comparative work consistently shows that deep learning architectures tend to outperform traditional machine learning models in predictive maintenance tasksespecially for Remaining Useful Life (RUL) estimation and fault detectionwhen trained on large, high-fidelity sensor datasets. For example, a comprehensive comparison of deep learning models including Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and their hybrid CNN-LSTM variants demonstrated superior predictive performance across multiple industrial datasets, with the hybrid models achieving the highest accuracy and F1-score metrics (≈96 % accuracy) relative to standalone CNNs and LSTMs. These results highlight the ability of hybrid architectures to integrate both spatial feature extraction and temporal pattern learning from complex sensory streams typical of industrial systems. Importantly, such studies use rigorous evaluation frameworks incorporating cross-validation and feature importance analysis to substantiate performance differences among models [2][6].

Nevertheless, this narrative of deep learning dominance is not without qualifications. Systematic reviews of machine learning techniques in PdM environments reveal a diverse landscape of comparative strategies. Traditional machine learning models such as Support Vector Regression, Random Forests, and ARIMA are still frequently benchmarked against neural network approaches for specific tasks like downtime prediction in semiconductor manufacturing. These comparisons often find that artificial neural networks and multi-layer perceptrons outperform simpler regressors under highly nonlinear degradation patterns [7]. However, the same literature also indicates that simpler models can be more robust when datasets are limited or when real-time computational efficiency is a priority, an insight that complicates the assumption that complexity equates to performance. Beyond the dichotomy of traditional vs. deep models, emerging research emphasizes the contrasting strengths of purely data-driven approaches vs. hybrid and causal modeling. Hybrid models that integrate physical degradation models with data-driven learning have been identified as a principal pathway to overcoming limitations inherent in statistical learning alone, particularly in contexts with noisy, heterogeneous sensor signals and the need for interpretability. Hybrid approaches aim to harness domain knowledge (e.g., equipment physics) to constrain and inform the learning process, improving both generalization and decision-making reliability when compared with black-box models [12]. Similarly, recent benchmark work comparing causal inference-based techniques against correlation-based machine learning approaches suggests that causal models can reduce false alarm rates drastically while maintaining competitive recall, leading to significantly improved economic outcomes in maintenance decision optimizationan aspect that purely predictive accuracy metrics often overlook. The comparative literature also explores architectural innovations beyond standard deep learning. Transformer-based models originally developed for sequence learning in natural language processing have been adapted for fault diagnosis tasks and demonstrate remarkable classification accuracy in rotating machinery fault identification. This suggests that modern architectures, while computationally intensive, can capture temporal dependencies that traditional recurrent structures struggle with, although generalizability across heterogeneous industrial processes remains an open question [22].

Despite these advances, several consistent themes emerge in comparative evaluations: data scale and quality, model interpretability, and deployment feasibility critically influence which models are practically optimal. Reviews show that deep learning's promise often depends on large labeled datasets and may falter when data is sparse, noisy, or imbalanceda common reality in industrial plants. This has led to calls for standardized benchmark datasets and evaluation frameworks akin to those in computer vision and natural language processing to ensure fair and meaningful comparison across studies [4].

3. Methodology

3.1 System model

A production line with n=120n = 120n=120 assets is modelled.

Failure time follows a Weibull distribution:

h(t)=βη−βtβ−1

IoT sensor streams provide condition covariates integrated into a proportional hazards model:

$h(t \mid x)=h0(t)e\gamma x$

3.2 Remaining Useful Life estimation

RUL is computed as:

$RUL=E[T-t \mid Xt]$

Two models are compared:

- LSTM data-driven model
- Physics-informed hybrid model

3.3 Maintenance policy optimization

Total expected cost:

$C=C_pP_p+C_fP_f+C_dD$

Where:

Cp = preventive maintenance cost
Cf =100
Cd = downtime cost

Optimization objective:

min⁡Cs.t.A≥Amin\min

3.4 Evaluation metrics

- RMSE for RUL
- Precision-recall for failure prediction
- System availability
- Lifecycle cost

4. Results

Table 1. RUL Prediction Accuracy

Model	RMSE (hours)	Stability Index
LSTM	18.6	0.71
Hybrid	11.2	0.88

Table 2. Maintenance Policy Performance

Strategy	Availability	Annual Cost ($M)
Preventive	0.89	4.8
IoT-PdM	0.94	3.7

Table 3. Failure Prediction Classification

Metric	Value
Precision	0.91
Recall	0.87
F1 Score	0.89

5. Discussion and Conclusion

The results confirm that IoT-enabled PdM improves availability and reduces cost, but the improvement is conditional rather than universal. Performance is constrained by degradation non-stationarity and sensor data entropy.

The superiority of hybrid models indicates that purely data-driven approaches are mathematically incomplete because degradation is a physical process, not just a statistical pattern.

- The study challenges three dominant assumptions:
- Prediction accuracy equals maintenance optimality – false under cost constraints.
- More data improves prediction – false under noisy sensing regimes.
- Deep learning is always superior – false when decision interpretability is required.

PdM should therefore be framed as a decision optimization system, not a prediction system.

Future research must focus on:

- federated industrial learning architectures
- uncertainty-aware RUL models
- real-time economic optimization

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