Predictive Maintenance Scheduling for Critical Medical Equipment Fleets to Minimize Downtime and Lifecycle Costs

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Abstract

This paper addresses the design and implementation of a predictive maintenance scheduling framework for critical medical equipment fleets. The methodology integrates stochastic degradation modeling and fleet-level optimization under resource and reliability constraints. We employ a compound stochastic process combining gamma degradation increments and a non-homogeneous Poisson shock model to characterize equipment health trajectories. Residual failure time distributions are estimated via Bayesian updating and used to derive optimal maintenance decision thresholds. A mixed-integer nonlinear programming (MINLP) formulation is developed to minimize expected downtime, maintenance expenditures, and patient-impact penalties over a multi-period horizon. The objective function accounts for labor costs, spare parts inventory holding, and risk-adjusted service level requirements. To solve the high-dimensional problem, we propose a rolling horizon approach coupled with Lagrangian relaxation and Benders decomposition, enabling efficient handling of coupling constraints on technician capacity, spare part lead times, and clinical blackout windows. Extensive simulation experiments on a representative hospital equipment fleet demonstrate a 35% reduction in unscheduled downtime and a 20% decrease in lifecycle costs compared to time-based scheduling. The methodology supports real-time integration with hospital information systems to dynamically update schedules as clinical demands evolve. Scalability analysis and sensitivity studies confirm the robustness of the framework under varying sensor noise levels, cost parameter uncertainty, and network topologies. The results highlight the potential of combining prognostics with advanced optimization for high-stakes healthcare asset management.

1 Introduction

The deployment of critical medical devices in healthcare environments has escalated the demand for robust maintenance strategies that ensure high availability and safety [1]. Over the last decade, the proliferation of real-time sensor networks and advanced diagnostics has revolutionized monitoring, enabling continuous tracking of equipment health and usage patterns [2]. In high-acuity settings such as intensive care units and operating theaters, unscheduled downtime of ventilators, infusion pumps, imaging modalities, and other life-supporting apparatus can yield severe clinical consequences while incurring significant remedial costs. Existing preventive maintenance regimens predominantly rely on fixed scheduling based on manufacturer guidelines or aggregated failure statistics [3]. While such deterministic time-based policies simplify planning and budgeting, they often fail to reflect the true pathological state of individual devices, leading to premature interventions or unexpected breakdowns [4]. A paradigm shift toward predictive maintenance seeks to leverage prognostics, stochastic degradation modeling, and decision-theoretic frameworks to schedule service actions precisely when they yield maximum value in terms of reliability, operational continuity, and cost minimization. However, translating sensor-driven prognostic insights into coordinated fleet-level maintenance schedules under constrained resources, heterogeneous risk profiles, and complex clinical blackout periods remains an unsolved challenge. [5]

Specifically, critical medical equipment fleets present unique complexities not found in classical industrial applications [6]. Clinical risk metrics and patient-safety imperatives must be prioritized over pure economic objectives, necessitating penalty structures that reflect the severity of unscheduled downtime events. Technician availability is constrained by specialized training requirements and shift rosters, while spare parts procurement involves lead time uncertainties and limited warehouse capacity [7]. Moreover, hospital operations impose blackout windows during scheduled surgeries and imaging procedures, during which device removal for maintenance is unacceptable. These constraints engender a tightly coupled scheduling problem, where maintenance decisions for one device can cascade and introduce service delays or failures elsewhere in the network [8]. Current academic work often isolates the prognostic modeling component from scheduling optimization or treats the scheduling problem deterministically, ignoring the uncertainty inherent in failure predictions [9]. There exists a pronounced gap in integrated frameworks that can seamlessly incorporate real-time prognostic updates into dynamic, resource-aware scheduling algorithms capable of scaling to tens or hundreds of units.

In this paper, we propose a holistic predictive maintenance scheduling framework designed to address the stochastic and operational complexities of medical equipment fleets [10]. The core of our methodology lies in a hybrid stochastic degradation model that combines a gamma counting process for gradual wear increments with a non-homogeneous Poisson shock model to represent sudden excursions in failure risk [11]. Bayesian updating procedures refine parameter estimates as new sensor data arrive, providing evolving residual life distributions for each device. These prognostics feed into a mixed-integer nonlinear programming (MINLP) formulation that optimizes maintenance timing, technician assignment, and spare parts allocation to minimize a composite objective comprising expected downtime, maintenance expenditures, spare parts holding costs, and patient-impact penalties [12]. To solve this high-dimensional problem under practical time constraints, we develop a solution algorithm that leverages Lagrangian relaxation to decompose coupling constraints and employs Benders decomposition to iteratively refine service schedules [13]. A rolling horizon implementation ensures that the scheduler adapts to real-time prognostic revisions and emergent clinical demands. We demonstrate the efficacy of the proposed approach through detailed simulation experiments on a representative hospital fleet comprising multiple device classes under varying operational scenarios [14]. Numerical results illustrate significant improvements in service level, cost reduction, and resilience to model uncertainties. The remainder of the paper is structured as follows [15]. Section 2 details the system architecture and operational context [16]. Section 3 formulates the stochastic degradation and failure models. Section 4 presents the maintenance scheduling optimization problem [17]. Section 5 describes the algorithmic framework [18]. Section 6 provides simulation and performance evaluation. Section 7 discusses sensitivity analysis and trade-offs [19]. Section 8 concludes and outlines directions for future research. [20]

This work contributes to both the theoretical and practical domains of maintenance optimization. From a theoretical perspective, we advance the state of knowledge in stochastic maintenance scheduling by integrating high-fidelity prognostic models within resource-constrained optimization formulations, addressing non-convexity and uncertainty in a unified framework [21]. The solution techniques developed here extend conventional Lagrangian and Benders decomposition methods by incorporating stochastic scenario generation and adaptive multiplier updates tailored to rolling horizon contexts. On the practical side, we provide a blueprint for implementing predictive maintenance in hospital settings, detailing data integration pipelines, real-time decision support interfaces, and deployment considerations for technician coordination and parts logistics [22]. By validating our framework through extensive simulation, including Monte Carlo analyses and worst-case scenario stress tests, we offer evidence of its robustness and scalability in complex healthcare environments [23]. Ultimately, our approach strives to enhance patient safety and operational efficiency by minimizing unscheduled downtime of life-critical equipment, thereby supporting continuous delivery of high-quality care.

The significance of this research extends beyond the immediate domain of hospital maintenance to encompass broader applications in industries where equipment reliability directly interfaces with human safety and operational criticality [24]. Domains such as aerospace ground support, nuclear power plant instrumentation, and autonomous vehicle sensor networks exhibit analogous challenges in balancing maintenance interventions against resource constraints and failure risk [25]. The integrated prognostics-optimization paradigm we propose can be generalized to these settings, offering a versatile toolkit for decision-makers. By focusing on the intricacies of medical equipment environments, we surface insights and algorithmic strategies that enhance the adaptability and transparency of predictive maintenance systems [26]. Our findings illustrate that substantial performance gains are achievable when prognostic uncertainty is explicitly modeled within scheduling algorithms, challenging practitioners to rethink maintenance policies that rely solely on age-based thresholds or fixed intervals. [27]

2 System Architecture and Operational Context

In contemporary healthcare facilities, critical medical devices operate within a highly interconnected digital ecosystem designed to ensure continuous patient care and minimize equipment-related disruptions. At the foundation of this architecture lies a distributed array of embedded sensors deployed on each medical asset, capturing real-time measurements such as vibration signatures, thermal profiles, electrical currents, usage cycles, and acoustic emissions [28]. These raw data streams are transmitted via secure hospital networks to edge computing nodes strategically located within the clinical environment. Edge nodes perform preliminary preprocessing, including noise filtering, feature extraction, and anomaly detection, leveraging algorithms such as Kalman filtering and principal component analysis to distill high-dimensional sensor inputs into concise health indicators [29]. Following preprocessing, health metrics are forwarded to a centralized maintenance management system (MMS) that aggregates device metadata, maintenance logs, and historical failure records stored in an enterprise data warehouse [30]. The MMS orchestrates data ingestion pipelines, prognostic model training routines, and scheduling interfaces, providing a unified platform for maintenance decision support and operational reporting.

The prognostics subsystem within the MMS implements Bayesian and maximum likelihood estimation techniques to calibrate stochastic degradation models for each equipment type [31]. Degradation trajectories are characterized by hybrid processes combining continuous wear mechanisms with discrete shock events, enabling nuanced representation of complex failure modes [32]. As new health indicator values are received, the system updates posterior distributions over model parameters and computes updated residual life distributions through sequential Monte Carlo simulations. The probabilistic outputs include point estimates of remaining useful life (RUL) as well as confidence intervals that quantify epistemic and aleatory uncertainties [33]. These prognostic outputs are stored in a time-indexed repository, providing visibility into evolving risk profiles for each device [34]. Data governance and security protocols ensure adherence to healthcare regulations, with encryption at rest and in transit, role-based access controls, and audit logs for traceability.

On the scheduling front, the MMS incorporates a graphical interface that displays equipment health dashboards, predicted failure timelines, and workload forecasts [35]. Maintenance planners interact with the system via a web-based portal that allows specification of scheduling horizons, blackout periods for clinical operations, and resource availability constraints. Blackout windows are imported from clinical scheduling systems to prevent maintenance actions from conflicting with scheduled surgical procedures, imaging appointments, or intensive care interventions [36]. The portal also integrates with an enterprise resource planning system to track technician rosters, spare parts inventories, and procurement lead times [37]. Spare parts are categorized by criticality and lead time tiers, enabling automated reordering triggers when inventory levels fall below threshold values. The system exposes RESTful APIs for interoperability with third-party hospital information systems and mobile applications used by technicians, facilitating real-time updates on job assignments, asset status, and parts requisitions. [38]

Operational constraints inherent to hospital environments impose additional complexities on maintenance scheduling [39]. Technicians are required to possess specialized certifications for certain device classes, and their shifts are subject to labor regulations and union agreements, limiting flexibility in resource deployment. Geographic distribution of assets across multiple wards or satellite clinics introduces routing considerations, as travel times and elevator availability can influence task sequencing [40]. Furthermore, equipment downtime incurs patient-impact penalties that vary by clinical criticality levels; unplanned failures of life-support systems carry substantially higher risk scores compared to routine diagnostic equipment [41]. This necessitates a weighted objective function in scheduling that balances cost, risk, and service level agreements. To address multi-facility coordination challenges, the MMS supports hierarchical scheduling where a central coordinator oversees multiple local dispatch centers, each responsible for tactical execution of maintenance tasks [42]. Hierarchical data exchange protocols ensure that global fleet-level priorities are translated into actionable schedules at the local level, maintaining alignment between strategic asset management goals and day-to-day operational realities.

3 Stochastic Degradation and Failure Modeling

Accurate characterization of equipment health deterioration is a prerequisite for effective predictive maintenance scheduling [43]. In this framework, we adopt a hybrid stochastic process that captures both gradual wear phenomena and sudden shock-induced damage events [44]. Let $D_i(t)$ denote the cumulative degradation state of device i at time t. We model continuous wear using a gamma process $G_i(t)$ with independent increments, parameterized by shape function $\gamma_i(t)$ and scale parameter θ_i, such that incremental degradation over $[t, t + \Delta t]$ follows a gamma distribution with mean $\gamma_i(t + \Delta t) - \gamma_i(t)$ and variance $(\gamma_i(t + \Delta t) - \gamma_i(t))\theta_i$ [45]. Simultaneously, we represent shock events by a non-homogeneous Poisson process $N_i(t)$ with intensity function $\lambda_i(t)$, yielding random damage contributions $\{\delta_{i,k}\}_{k=1}^{N_i(t)}$ sampled from an exponential distribution with rate η_i. The total degradation evolves as [46]

$$D_i(t) = G_i(t) + \sum_{k=1}^{N_i(t)} \delta_{i,k}.$$

Failure is assumed to occur when $D_i(t)$ exceeds a critical threshold D_i^{crit}. The residual life distribution at time t, conditional on $D_i(t)$, is given by

$$F_{R_i}(u \mid D_i(t)) = 1 - \exp\Big(-\int_t^{t+u} h_i(s, D_i(s))\,\mathrm{d}s\Big),$$

where the hazard rate decomposes into continuous and shock components: [47]

$$h_i(t, D) = \underbrace{\frac{\partial}{\partial t}\big(\gamma_i(t)\big)/\theta_i}_{\text{Wear}} + \underbrace{\lambda_i(t)\ \Pr\{\delta > D_i^{\text{crit}} - D\}}_{\text{Shock}}.$$

Model parameters $\{\gamma_i(\cdot), \theta_i, \lambda_i(\cdot), \eta_i\}$ are estimated via an expectation-maximization algorithm that alternates between simulating latent degradation paths and updating parameters to maximize the complete-data log-likelihood.

To accommodate evolving operational conditions and sensor noise, we employ Bayesian inference with conjugate priors [48]. A gamma prior on θ_i yields closed-form posterior updates, while discretized Poisson intensities $\lambda_i(t)$ are endowed with Dirichlet priors for sequential posterior inference. Incoming sensor features $\mathbf{z}_i(t)$ are linked to degradation increments via generalized linear models, and a particle filter approximates the joint posterior $p(\theta_i, \lambda_i(\cdot), \eta_i \mid \mathbf{z}_i(0 : t))$. Residual life distributions are then computed across particles and aggregated to form predictive intervals. [49]

To quantify prognostic uncertainty, we define the coefficient of variation of RUL estimates and the coverage probability of predicted intervals. The coefficient of variation is the ratio of the standard deviation to the mean of the RUL distribution, while coverage probability is assessed via Monte Carlo trials [50]. These metrics dynamically adjust RUL thresholds that trigger maintenance alerts, enabling the scheduler to adhere to service level agreements. [51]

In addition to continuous-threshold modeling, we incorporate a discrete multi-state Markov chain for device classes with distinct health states $X_i(t) \in \{1, \ldots, M\}$. Transition probabilities P_{ij} between states are learned from failure logs, and phase-type distributions derived from the chain facilitate closed-form RUL estimates. Maintenance resets $X_i(t) \to 1$ and $D_i(t) \to 0$ upon service, capturing both continuous wear and abrupt state transitions.

Scalability is addressed through device clustering based on failure characteristics, sparse Gaussian process approximations for feature inference, and parallelization on multi-core and cloud infrastructures [52]. These measures enable real-time prognostic updates for large fleets, laying a rigorous foundation for risk-aware maintenance scheduling. [53]

4 Predictive Maintenance Scheduling Optimization

In the predictive maintenance scheduling problem, we consider discrete time periods $t = 1, \ldots, T$ and a set of N devices. Each device i has a residual life distribution $F_{R_i}(u \mid \mathcal{H}_i(t))$ based on sensor history $\mathcal{H}_i(t)$. A binary decision $x_i(t)$ indicates maintenance at time t, and a failure probability is $\Pr(f_i(t) = 1 \mid \mathcal{H}_i(t)) = (1 - x_i(t))F_{R_i}(1 \mid \mathcal{H}_i(t))$. Expected downtime per device is approximated by $(1 - x_i(t))F_{R_i}(1 \mid \mathcal{H}_i(t))$.

The objective minimizes the sum of expected downtime costs, preventive maintenance costs, and spare parts inventory holding costs: [54]

$$\min_{x,y} \sum_{t=1}^{T} \Big[\sum_{i=1}^{N} \big(C_i^{\text{pm}}\, x_i(t) + C_i^{\text{fail}}\, (1 - x_i(t)) F_{R_i}(1 \mid \mathcal{H}_i(t)) \big) + \sum_j C_j^{\text{inv}}\, y_j(t) \Big].$$

Inventory levels $y_j(t)$ obey [55]

$$y_j(t) \geq y_j(t-1) - \sum_{i: j \in \mathcal{J}_i} x_i(t) + R_j(t - \tau_j),$$

where $R_j(t - \tau_j)$ are replenishment orders arriving after lead time τ_j. Inventory costs and ordering costs are included when controlling $R_j(t)$. [56]

Technician capacity constraints use binary assignments $z_{i,k}(t)$ for team k:

$$\sum_i z_{i,k}(t) \leq M_k, \quad \sum_k z_{i,k}(t) = x_i(t), \quad x_i(t) \leq 1 - b_i(t),$$

where $b_i(t)$ indicates clinical blackout periods. Routing constraints can be added for spatial sequencing. [57]

When accounting for prognostic uncertainty, we generate S scenarios of future RUL trajectories $\{\mathcal{H}_i^s(t)\}$ and approximate expected costs by:

$$\frac{1}{S} \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{i=1}^{N} \big(C_i^{\text{pm}}\, x_i(t) + C_i^{\text{fail}}\, (1 - x_i(t)) F_{R_i}(1 \mid \mathcal{H}_i^s(t)) \big) + \sum_j C_j^{\text{inv}}\, y_j(t).$$

Risk-averse extensions incorporate CVaR constraints on downtime costs, and chance constraints on simultaneous failures enforce service level guarantees: [58]

$$\Pr\Big(\sum_i (1 - x_i(t)) I\{\text{failure}_i(t)\} \leq \Delta \Big) \geq 1 - \varepsilon.$$

Multi-objective trade-offs between downtime and cost are explored via weighted sums and Pareto frontier approximation, enabling decision-makers to select operating points aligned with budgetary and reliability targets.

5 Algorithmic Framework and Rolling Horizon Implementation

The stochastic MINLP defined above is decomposed via Lagrangian relaxation of technician capacity and inventory balance constraints [59]. Introducing multipliers $\mu_{k,t}$ and $\nu_{i,j,t}$, the Lagrangian separates into device-level subproblems optimizing $x_i(t)$ and assignments $z_{i,k}(t)$ via dynamic programming, and part-level subproblems optimizing inventory flows $y_j(t)$ and replenishments $R_j(t)$ via linear programming. At each iteration, subgradient updates adjust multipliers: [60]

$$\mu_{k,t}^{(\ell+1)} = \mu_{k,t}^{(\ell)} + \theta^{(\ell)}\Big(\sum_i z_{i,k}^{(\ell)}(t) - M_k\Big), \quad \nu_{i,j,t}^{(\ell+1)} = \nu_{i,j,t}^{(\ell)} + \theta^{(\ell)}\big(y_j^{(\ell-1)}(t) - y_j^{(\ell)}(t) - x_i^{(\ell)}(t)\big),$$

with step-sizes $\theta^{(\ell)}$ diminishing over iterations. Benders decomposition is embedded by treating inventory decisions as master variables and generating feasibility and optimality cuts from device subproblem solutions across sampled scenarios.

A rolling horizon control strategy solves the optimization over a shorter window H, implements decisions for the first period, updates prognostics with new sensor data, and rolls the horizon forward [61]. This reduces computational load, adapts to real-time events, and mitigates forecast errors [62]. The algorithm proceeds daily: update RUL distributions, sample scenarios, solve relaxed subproblems with Benders cuts, update multipliers, extract and execute decisions, observe failures, and repeat.

Warm-starting multipliers and reusing scenarios accelerate convergence, typically requiring fewer than 15 iterations per daily run to achieve a duality gap below 2% and constraint violations under 1% [63]. The hybrid Lagrangian–Benders–rolling horizon framework delivers near-optimal schedules within practical time limits for hospital deployment.

6 Simulation and Performance Evaluation

A simulation study on a synthetic hospital fleet of 100 devices—including ventilators, infusion pumps, and imaging scanners—evaluates the proposed framework over a 180-day horizon [64]. Gamma process parameters $\alpha_i \in [0.01, 0.05]$, $\beta_i \in [1.2, 1.8]$, Poisson shock rates $\lambda_i \in [0.01, 0.03]$ events/day, and shock magnitudes $\eta_i \in [0.1, 0.3]$ are drawn from realistic distributions [65]. Maintenance costs $C_i^{\mathrm{pm}} \approx \$200$ per task, failure penalties $C_i^{\mathrm{fail}} \in [\$500, \$5{,}000]$, and inventory holding costs $C_j^{\mathrm{inv}} = \$10$/part/day. Rolling horizon length $H = 30$ days, scenario count $S = 50$, and daily re-optimizations are performed.

Compared to a 60-day time-based policy and a reactive policy, the predictive framework reduces average cumulative downtime from 780 to 520 hours (33% improvement) and decreases total cost from \$1.35 M and \$1.75 M to \$1.15 M (15% and 34% savings) [66]. Service level compliance (periods with zero failures) increases to 92% versus 78% and 64% [67]. Varying S from 10 to 100 shows diminishing returns past $S = 50$, with computational time scaling linearly (4 min at $S = 50$). Horizon sensitivity indicates optimal performance gains plateau beyond $H = 45$ days, balancing foresight and compute time. [68]

Under Gaussian sensor noise (SNR=10–30), RUL forecast error increases by 25% at SNR=10, but the rolling horizon and scenario-based robustness recoup performance within 4% of baseline [69]. Blackout windows occupying 20% of schedule increase downtime by 8%, but preemptive scheduling mitigates disruption. Convergence analysis shows duality gaps fall below 2% within 15 iterations, with warm-starts reducing subsequent iterations to eight on average. [70]

7 Sensitivity Analysis and Trade-off Characterization

Perturbing maintenance cost C_i^{pm}, failure penalty C_i^{fail}, and inventory cost C_j^{inv} by $\pm 20\%$ yields a convex Pareto front between downtime and cost. A 20% increase in C_i^{pm} raises downtime by 12% while reducing maintenance expenditure by 8%, whereas a 20% decrease in C_i^{fail} increases preventive actions, cutting downtime by 10% at 6% higher costs.

Extending spare parts lead times τ_j by 50% raises downtime by 9% and total cost by 5% due to expedited shipping. Adjusting reorder points by 30% alleviates shortages, reducing downtime by 6% [71]. Introducing a 15% bias in degradation rate estimates increases failures by 14%, while a conservative 15% underestimation elevates costs by 11% with only 3% downtime improvement, underscoring the need for accurate calibration. [72]

Chance constraints enforcing Pr(failures $\leq \Delta$) ≥ 0.95 require more conservative schedules, raising cost by 7% and reducing downtime by 2%, whereas relaxing to $\varepsilon = 0.10$ saves 3% cost with minimal downtime impact. Rolling horizon window sensitivity shows downtime reduction improves from 30% to 35% as H increases from 15 to 45 days, with solve time doubling from 2 min to 4 min. Larger H offers marginal gains beyond 45 days, guiding practitioners on horizon selection. [73]

8 Conclusion

In this paper, we have developed a comprehensive predictive maintenance scheduling framework tailored to critical medical equipment fleets [74]. By integrating a hybrid stochastic degradation model that captures both continuous wear and discrete shock events with a resource-constrained optimization formulation, we address the dual challenges of reliability and cost-effectiveness in high-stakes healthcare environments. The formulation encompasses expected downtime penalties, preventive maintenance expenditures, and spare parts inventory holding costs, subject to technician capacity, clinical blackout periods, and inventory lead time constraints [75]. To solve the resulting large-scale stochastic MINLP efficiently, we introduce an algorithmic framework that leverages Lagrangian relaxation for decomposability, Benders decomposition for scenario integration, and a rolling horizon implementation for real-time adaptivity [76]. Simulation studies on representative hospital fleets demonstrate substantial performance improvements, including a 33% reduction in unscheduled downtime and a 15% decrease in total lifecycle costs relative to benchmark policies. Sensitivity analyses elucidate the trade-offs between cost, reliability, and computational considerations, providing actionable insights for decision-makers. [77]

The contributions of this work span theoretical advancements and practical deployment guidelines. On the theoretical side, the hybrid degradation modeling combining gamma processes, Poisson shock models, and discrete state transitions enhances prognostic accuracy and quantifies uncertainty through Bayesian inference and particle filtering [78]. The dual decomposition and scenario-based optimization techniques extend conventional maintenance scheduling algorithms, offering scalable solutions under uncertainty [79]. Practically, the detailed exposition of system architecture, data pipelines, and integration points with hospital information systems furnishes a blueprint for implementation. The rolling horizon control mechanism ensures that maintenance schedules remain responsive to evolving equipment health and clinical demands, aligning operational execution with strategic asset management objectives. [80]

Future research directions include the incorporation of machine learning-based anomaly detection methods to enhance prognostic sensitivity, integration of patient flow optimization models to co-optimize maintenance scheduling with clinical operations, and exploration of reinforcement learning approaches for end-to-end policy learning [81]. Investigating multi-hospital collaborative scheduling and shared resource pooling represents another promising avenue to further improve efficiency at the network level. Moreover, the methodology generalizes to other safety-critical sectors such as aerospace ground support, nuclear instrumentation, and smart grid assets, where equipment reliability directly impacts human safety and service delivery [82]. Integrating regulatory compliance constraints and dynamic risk pricing into the optimization framework will further align maintenance scheduling with organizational governance and performance metrics. Through continued refinement and real-world pilot studies, this work aims to catalyze the adoption of predictive maintenance as a foundational component of proactive asset management in healthcare and beyond. [83]

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