Part Analytics using Digital Threads

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ABSTRACT

Determining whether a component is Beyond Economical Repair (BER) depends on multiple technical and business factors, including repair cost thresholds, replacement/market value, component availability and lead time, persistency of faults (recurrence after repair), and the time required to restore operational readiness. This work evaluates a predictive, data-driven approach that uses a digital thread tying serialized parts to their host aircraft and leverages aircraft utilization forecasts (e.g., from FlightRadar24) to generate flight-hour-based usage forecasts. By combining usage forecasts with part-level reliability models and historical failure data, we produce one-year risk forecasts for part failure (remaining useful life / failure probability).

Enriching the digital thread with part attributes (repair cost, new-purchase cost, repair cycle time, vendor lead time) and part-family trend analytics enables a cost–benefit analysis of repair versus replacement that explicitly considers total cost of ownership and operational downtime. Applying configurable business rules and inventory state (on-hand, pipeline, critical spares) allows the system to recommend actions (repair, replace, or retire excess inventory) that minimize expected lifecycle costs and mission-impacting downtime. This paper presents the approach that supports proactive supply-chain and maintenance decisions, improves fleet availability, and identifies systemic part-family issues that may warrant engineering or supplier corrective action.

1. INTRODUCTION

Maintenance organizations continuously face the challenge of determining whether a failed component should be repaired, rebuilt, or replaced. The decision directly affects component availability, lifecycle cost, downtime, and operational risk. Traditional maintenance programs relied heavily on corrective maintenance (repair after failure), but modern Prognostics and Health Management (PHM) and predictive maintenance techniques enable earlier, more informed interventions by estimating degradation trends and risk of failure (Apeiranthitis et al., 2026; Robinson, 2026). These advances improve planning and reduce unplanned downtime, yet they do not by themselves yield a standardized, economically grounded rule for when repeated repair is no longer justified.

This paper presents a probabilistic, risk-and-cost repair-versus-replace framework that offers a different point of view from Beyond Economic Repair by integrating historical removal count, probability of removal, aircraft utilization, and component digital-thread/ PHM indicators data. The framework computes expected total cost for repairing versus replacing by combining immediate repair and replacement costs, downtime impact, and a modeled probability of future failure that depends on removal history and aircraft utilization. When continuous sensor data are not available, the number of past removals can serve as a practical proxy for wear.

A key enabler is the component digital thread, a continuous, auditable record that traces a part's serial number through manufacture, installation on the aircraft, exposure in service, removals, repairs, inventory movements, and reinstallation. The digital thread supplies standardized lifecycle records (manufacturing timestamps, maintenance and repair history, and operational exposure metrics) from which removal counts, exposure hours or cycles, and inventory lead-time estimates can be derived, and it enables rigorous back-testing and validation of probabilistic models and decision thresholds (Singh et al., 2019; Zhang et al., 2024). By combining economic considerations, PHM-derived risk measures, and digital-thread-enabled empirical reliability indicators, the framework aims to (a) reduce lifecycle maintenance cost, (b) limit repeated downtime for parts with declining reliability, and (c) produce auditable, data-driven repair-versus-replace recommendations tunable to fleet context and operational criticality.

2. LITERATURE REVIEW

2.1. Prognostics and Health Management

Maintenance strategies have evolved from corrective and preventive maintenance toward approaches that leverage asset health information to support maintenance decision making. Prognostics and Health Management integrates diagnostics, prognostics, condition monitoring, and decision support into a unified framework designed to improve system reliability, reduce downtime, and optimize lifecycle costs (Apeiranthitis et al., 2026). Unlike traditional maintenance approaches that rely on fixed schedules or failure events, Prognostics and Health Management enables maintenance decisions to be based on the actual condition and predicted future state of a component.

A key capability of Prognostics and Health Management is estimating remaining service capability or time-to-degraded-state, which informs planners when a component is likely to require intervention (Apeiranthitis et al., 2026). Robinson (2026) emphasized that accurate estimates of future degradation timing are particularly important in safety-critical industries because maintenance decisions must account for uncertainty and operational risk. Zaman et al. (2025) showed that degradation indicators derived from physical and material properties can improve maintenance decisions by linking measurable wear mechanisms to future component health.

Recent research has also highlighted event-based Prognostics and Health Management approaches that use maintenance records, inspections, removals, alarms, and failure events as indicators of degradation. Le et al. (2025) found that event-based data can support diagnostic and prognostic modeling while reducing data storage and processing requirements. These findings suggest that historical maintenance actions and repeated component removals contain valuable information that can be incorporated into maintenance decision making.

2.2. Predictive Maintenance and Failure Detection

Predictive maintenance builds on Prognostics and Health Management by using degradation indicators and prognostic models to forecast failures before they occur, with the objective of scheduling maintenance based on actual component condition rather than predetermined intervals. This reduces unnecessary maintenance while minimizing the risk of unexpected failures.

Saha et al. (2025) demonstrated that degradation detection methods can identify the onset of abnormal operating conditions before catastrophic failure occurs, allowing interventions before repair costs escalate and disruptions occur. Predictive maintenance models use health indicators and degradation trends to estimate future failure risk and support maintenance planning.

Digital Twin technologies have further strengthened predictive maintenance capabilities. Norcaro et al. (2025) proposed a Digital Twin–based Integrated Vehicle Health Management framework that combines operational data, engineering models, and predictive analytics to improve maintenance decision making. Zhong et al. (2023) found that Digital Twin enabled predictive maintenance improves fault prediction, maintenance planning, and operational efficiency by providing a more accurate representation of asset condition throughout the lifecycle. These technologies enable a shift from reactive maintenance toward proactive, data-driven strategies.

2.3. Maintenance Decision Making and Optimization

Even when predictive maintenance identifies when intervention is needed, organizations must still determine the most appropriate corrective action. Deciding whether a failed component should be repaired, rebuilt, or replaced remains a core challenge.

Maintenance optimization research has examined this problem from economic, reliability, and operational perspectives. Dekker (1996) reviewed maintenance optimization models and concluded that decisions should balance repair costs, replacement costs, system reliability, and operational risk to minimize long-term average operational expenses. Additionally, Alaswad and Xiang (2017) reviewed condition-based maintenance optimization models, highlighting that modern policies use real-time sensor data and stochastic deterioration modeling to drive interventions, rather than relying strictly on traditional time-based maintenance schedules.

Condition-based maintenance research has emphasized integrating reliability information into decision making. Jardine et al. (2006) argued that maintenance decisions should balance reliability, risk, and economic factors to achieve optimal lifecycle performance. Collectively, these studies demonstrate that effective maintenance decisions require consideration of economic factors, reliability trends, degradation behavior, and operational risk rather than relying solely on immediate repair cost.

2.4. Repair-versus-Replace Economic Analysis

Economic frameworks for repair-versus-replace decisions compare the expected total cost of continued repair against the cost of replacement and associated downtime. LeMay (2011) summarizes practical methods used in industry that compare repair costs with replacement costs to determine whether continued repair remains economically justified. Typical cost components include unit replacement cost, repair labor cost, support labor, repair materials, and inventory/lead-time impacts.

Traditional economic analyses focus primarily on immediate and recurring repair costs. Components that repeatedly fail or require many repair attempts tend to produce higher cumulative costs and longer downtime, which shifts the economics toward replacement. However, conventional economic analyses often do not explicitly incorporate predictive health indicators or the empirical history of repeated removals and repairs when estimating future failure risk.

2.5. Digital Thread and Lifecycle Data Management

The Digital Thread concept provides a continuous flow of data through a component's lifecycle, connecting information generated during design, manufacture, operation, maintenance, and retirement. Singh and Willcox (2019) described the Digital Thread as a data-driven architecture that links lifecycle data to enable traceability for serialized components. Zhang et al. (2024) further explained that the Digital Thread serves as an authoritative source of lifecycle information by eliminating data silos and improving traceability across engineering, manufacturing, and maintenance processes.

In maintenance environments, Digital Thread records can include operating hours, maintenance actions, removals, repairs, inspections, inventory transactions, and component replacements. For serialized aerospace components, these records provide an auditable history of usage, repairs, removals, and reinstalls that can be used to detect trends such as increasing maintenance frequency or recurrent failures.

2.6. Use of Removal History and Repair Effectiveness as Reliability Indicators

A growing body of work treats removal history and repair outcomes as empirical indicators of declining reliability or diminishing repair effectiveness. Le et al. (2025) and related event-based studies show that maintenance event sequences can be used to infer degradation regimes even when continuous sensor data are sparse. Repeated removals and recurring failures can indicate that a component is experiencing an escalating failure process or that repairs are becoming less effective over time. When continuous sensor streams are unavailable, removal count and repair outcomes can serve as practical proxies for cumulative wear and changing failure probability.

2.7. Synthesis and Research Gap

Existing research provides strong foundations in Prognostics and Health Management, predictive maintenance, maintenance optimization, economic repair-versus-replace analysis, and Digital Thread technologies. However, these areas are often treated independently: Prognostics and Health Management focuses on degradation detection and prediction, economic analyses focus on immediate and recurring costs, and Digital Thread research emphasizes data integration without prescribing how empirical maintenance histories should be converted into decision metrics.

There is limited work that explicitly integrates economic repair-versus-replace analysis with prognostic indicators and Digital Thread–derived maintenance history.

This study addresses that gap by combining economic decision principles, predictive health indicators, and Digital Thread lifecycle data, using removal history and repair outcomes as observable inputs, to support consistent, auditable, and data driven repair versus replace decisions for aerospace components. At a high level, the model balances the expected costs of immediate repair versus replacement while accounting for operational impacts (downtime, inventory lead time, and aircraft utilization), empirical indicators of reliability from the Digital Thread (prior removals and repair outcomes), and prognostic uncertainty. Detailed parameter definitions, cost terms, probability formulations, and complete analysis are provided in the proposed model section 4 below.

3. PROBLEM STATEMENT

Many maintenance organizations repeatedly repair the same component without fully evaluating the long term economic and reliability consequences. Repeated repairs can increase downtime, labor use, consumption of reparable inventory, and operational risk. Organizations may continue repairs because replacement cost appears high in the short term; however, multiple failures of the same part often signal accelerated wear, declining effectiveness of repairs, and a rising probability of future failure, factors that raise lifecycle cost and increase operational risk.

This paper presents a probabilistic risk and cost repair versus replace framework that takes a different point of view from traditional beyond economic repair practice by explicitly incorporating historical removal and repair history as practical degradation indicators when sensor-based prognostics are unavailable. The objective is a tunable, validated decision framework that combines single event economics with empirical failure behavior at the part number and serialized part level to support risk aware repair versus replace decisions.

Key objectives:

- Combine economic assessment with reliability indicators derived from maintenance history, including prior removals and repairs, empirically estimated failure probability, and observed failure recurrence.
- Produce a single, configurable decision score that integrates economics, reliability, downtime impact, and operational criticality.
- Ensure decision thresholds are configurable and validated against historical fleet data to avoid arbitrary or nonportable cutoffs.

Required data inputs (minimum):

- Part number and serial number if available.
- Count of prior removals and repairs for the part or serial, as an empirical indicator of degradation.
- Empirical failure probability for a repaired part, estimated from historical removal counts and repair records (used in the model as the probability that the repair part will fail again).
- Repair cost components, including labor, materials, and shop overhead (cost for immediate repair) .
- Downtime hours and monetized downtime cost (cost of downtime).
- Replacement cost, including purchasing and installation (cost for purchasing and installing a new part).
- Expected total cost of future failure events, including cascading and consequential costs (total cost of future failure).
- Inventory availability and expected replacement lead time (inventory availability).
- Aircraft or asset utilization forecasts in flight hours, cycles, or mission exposure (aircraft utilization).

4. PROPOSED REPAIR-VERSUS-REPLACE MODEL

4.1. Framework Overview

The proposed framework employs a probabilistic risk-and-cost model to determine whether a component should be repaired or replaced. The model quantifies and assesses the following variables:

1. Cost for purchasing and installing new part
2. Cost for immediate repair
3. Cost of downtown
4. Probability that the repair part will fail again
5. Total cost of future failure
6. Count of removals
7. Inventory availability
8. Aircraft Utilization

The framework makes repair-versus-replace decisions by comparing the expected total cost of replacing a component with the expected total cost of repairing it, choosing replacement when expected cost of replace is less than expected cost of repair. This expectation-based approach incorporates not only immediate repair expense but also the component's observed post-repair reliability, the projected frequency and cost of future failures, and any performance degradation after each repair. Unlike a simple rule of thumb that replaces a part when repair costs exceed a fixed percentage of new-unit price, the framework quantifies the trade-off over the component's remaining life, explicitly accounting for failure probabilities, repair lead times, downtime costs, and performance-related penalties to produce a context-specific, economically optimal decision.

4.2. Expected Repair & Expected Replace Equation

The expected repair equation is defined as:

E(Repair) = Cost of immediate repair + (Probability that repair part will fail again x Total cost of future fail)

The expected replace equation is defined as:
E(Replace) = Cost of purchasing + Cost of downtime

The repair decision threshold is:

If E(Replace) < E(Repair) → Replace; otherwise, repair

The expected-repair and expected-replace equations can be extended into an operational decision model by explicitly incorporating time discounting, multiple future failures, condition-dependent failure probabilities, inventory and lead-time effects, and decision-maker risk preferences: for a planning horizon.

4.3. Digital Threads

A digital thread for an aircraft component is a continuous, auditable digital record that traces a component's serial number across its lifecycle, from initial installation on-wing, through removal for maintenance, repair, and overhaul

(MRO), to entry into rotable inventories and eventual re-installation.

By linking serial numbers, part-pairings, work orders, shop reports, condition-monitoring sensor streams, and logistics events, the digital thread enables granular visibility into cumulative usage (flight hours, cycles), environmental and operational context, failure modes, and the details and outcomes of every maintenance action. Using the digital thread, analysts can compare multiple serials of the same part type to detect systematic defects, assess variability in post-repair reliability, and quantify how prior removals, repair history, or specific shops influence future failure probability. Visualizing a part's digital thread lets maintainers and reliability engineers capture the cumulative flight hours and condition indices recorded before removal, correlate those with repair effectiveness and time-to-next-failure, and feed those empirical observations back into probability of repair and cost of future fail estimates in the repair versus replace model. Beyond reliability modeling, digital threads support anomaly detection via pattern recognition, and closed-loop learning where field outcomes continuously improve predictive models and recommended maintenance policies.

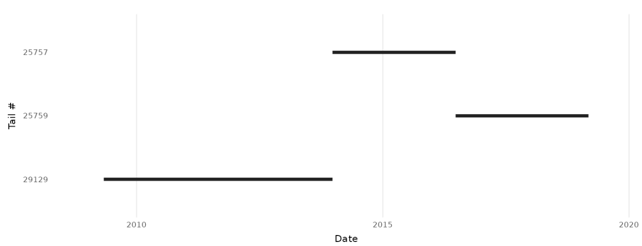

Figure 1. Component Thread

Looking at the digital thread, we can track each serial number's profile to capture the cumulative flight hours recorded before removal. By following an individual part's history, it shifts aviation maintenance from reactive troubleshooting to predictive, data-driven reliability.

4.4. Probability of Fail

The probability of a part failing again is the likelihood that a component will experience another breakdown within a specific timeframe given that it has already failed and been repaired or replaced. We utilize digital threads to record historical failure events for both installed and removed parts, together with the flight hours each component accrued prior to removal.

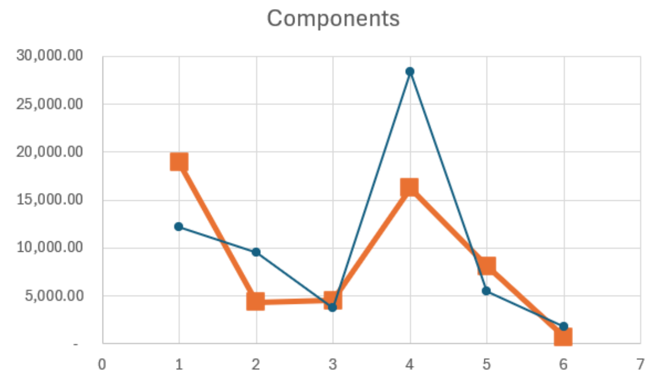

Figure 2. Component Removal

Empirical patterns, often part-type specific, can show non-linear degradation with repair count (for some hardware the effective reliability materially declines after roughly four to five repairs, as seen in above image), so the number of prior removals/repairs should be treated as an explicit covariate (and potentially as a threshold or step change) rather than ignored.

4.5. Aircraft Utilization

Aircraft utilization measures an aircraft's productivity, typically expressed in flight hours or cycles. Forecasting fleet usage from the flight-hour base helps predict component wear and maintenance demand. High-utilization aircraft accelerate component degradation and increase the probability of failure, so it is critical to extend inspection and replacement planning into those higher-use regimes to reduce unscheduled events and reduce downtime.

High utilization matters to the proposed repair-versus-replace framework because it increases both the likelihood and the cost impact of future failures: higher flight hours/cycles raise the hazard rate for many failure modes and shorten the expected time-to-next-failure after a repair, which increases probability of fail giver repair in the decision model; at the same time, frequent flying amplifies downtime costs (lost revenue, repositioning, reserve aircraft usage, and contractual penalties), so cost of downtime and consequential-damage terms in expected repair and expected replace grow with utilization. As a result, utilization shifts the economic tradeoff components that are repair-optimal on lightly used aircraft may be replacement-optimal on high-use assets.

4.6. APPLICATION

Consider a component with multiple serial numbers, each serial number has its own digital thread associated with it and its own probability of fail. Now if those serial numbers are summarized at the component level and account for the number of removals and total flight hours flown with them, we can capture that components probability of fail over time. The below shows a practical example:

- Sum of total hours flown by component = 18,609
- Total count of component removed = 4
- Time= 15,000
- Best Cost = 18,968
- Repair price: 7,693

We used the Weibull distribution for the probability of failure because its shape parameter allows modeling of increasing, constant, or decreasing hazard rates—thereby capturing burn-in, useful-life, and wear-out phases that the memoryless exponential cannot. This flexibility produces more accurate estimates of the conditional failure probability supports covariate-adjusted life models, and yields more robust repair-versus-replace decisions.

Probability of fail:

P = 1-exp(-(15,000/259,340)^0.79)

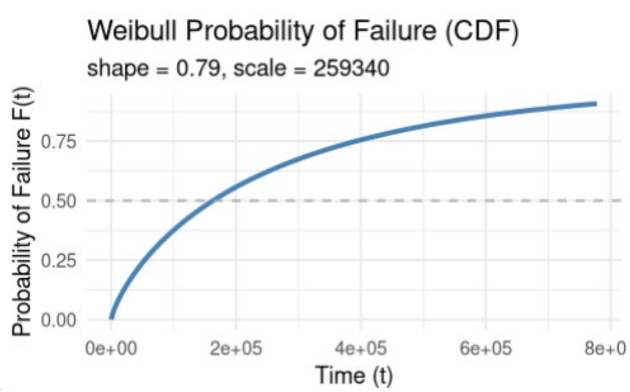

Figure 3. Weibull Probability of Failure (CDF)

Expected values:
E(replace) = 18,968 + 10,000
E(repair) = 7,693 + (P * 110,000)

Applying this probabilistic risk-and-cost framework reduces total life-cycle cost by replacing ad hoc heuristics with data-driven optimization. By quantifying uncertainty in future failures, repair outcomes, and downtime, the model improves maintenance prioritization, budget allocation, and operational efficiency. Continuous updating of failure probabilities and cost inputs (from condition monitoring and maintenance history) enables the identification of the "sweet spot" at which an aging asset transitions from a manageable repair candidate into an unacceptable liability mitigating safety risks and reducing the likelihood of regulatory noncompliance.

5. BENEFITS OF THE PROPOSED FRAMEWORK

The probabilistic repair-versus-replace framework delivers measurable benefits across economic, operational, and safety dimensions by replacing ad hoc heuristics with an auditable, data-driven decision process. First and foremost it reduces total life-cycle cost by explicitly comparing the expected costs of repair and replacement, accounting for immediate work, future failure likelihood, downtime impacts, and discounting over a planning horizon; this reduces unnecessary replacements and avoids repeated, costly failures that propagate downstream expenses. By embedding serial-level digital threads and condition data into the model, the framework improves asset-specific accuracy of probability of fail given repair and cost of future fail enabling more precise, part-level decisions rather than blanket policy rules.

Operational availability and schedule reliability improve because the model internalizes utilization-dependent hazard rates and downtime economics: high-use aircraft that face higher hazard rates and greater opportunity cost of downtime will have replacement thresholds that differ from low-use assets, so the framework yields aircraft-specific actions that reduce unscheduled removals and lost revenue.

6. LIMITATIONS

Several limitations exist within the proposed model. First, replacement-count thresholds may vary across industries and component types. Some components naturally require more frequent repair than others. Second, the model depends on accurate maintenance records and repair cost estimates. Incomplete historical data may reduce decision accuracy.

Third, operational constraints such as spare-part shortages or obsolescence may require continued repair even when replacement is economically preferable. Finally, the model relies on assumptions about failure distributions, cost projections, and future utilization that may not hold under changing operational regimes or rare, dependent failure modes; consequently, results should be interpreted with uncertainty bounds, and governance processes should be in place to validate model inputs, regularly recalibrate parameters, and review decisions against real-world outcomes.

7. FUTURE RESEARCH

The current implementation adopts a Weibull distribution form for the post-repair failure process, which can be unstable with small sample sizes or heavy censoring, leading to unreliable hazard forecasts. Future work should relax the Weibull assumption and adopt more flexible, component-specific models that capture aging, burn-in, and wear-out behavior. In addition, components of the same type often exhibit heterogeneous failure behavior driven by manufacturing lot, supplier, repair shop, installation environment, or usage profile. Future research should cluster components into failure-profile groups and estimate separate hazard models for each cluster. Practical approaches include feature engineering on digital-thread attributes and applying unsupervised or model-based clustering or clustering of estimated hazard functions. Mixture-model survival approaches and hierarchical/Bayesian multi-level models can concurrently capture between-serial variability and within-cluster commonalities while sharing strength where data are sparse.

Large-scale validation on diverse industrial maintenance datasets would further increase confidence in the framework's accuracy and generalizability.

8. CONCLUSION

Repair-versus-replace decisions significantly affect maintenance cost, operational reliability, and equipment availability. Traditional BER methods provide useful economic guidance but often fail to account for repeated failures and long-term degradation trends.

Repair-versus-replace decisions materially influence maintenance cost, operational reliability, and asset availability, and traditional break-even replacement (BER) rules, while useful, often overlook repeated failures and cumulative degradation. This paper proposes a probabilistic, data-driven framework that augments BER analysis with historical removal counts and prognostics-and-health-management (PHM) inputs: it jointly evaluates immediate repair cost and yield, the conditional probability of repeat failure, downstream downtime and operational criticality, and the long-term cost trajectory of continued repairs. By explicitly modeling repeated-failure behavior and incorporating utilization, inventory and shop-level effects, the framework identifies when a component's repair yield and reliability have eroded to the point that replacement is economically and operationally preferable, rather than allowing repairs to continue simply because a single repair appears affordable.

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