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Article

A RAM-Based Analytical Framework for analysis of Critical Components in Turbofan Engines

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Abstract: Turbofan jet engines are critical to commercial aviation, where unplanned failures pose severe risks to safety, operational continuity, and airline finances, with each unplanned engine removal costing approximately USD 1.5–2.2 million due to flight cancellations, crew repositioning, and maintenance expenses. Therefore, the present study develops and validates a comprehensive Reliability–Availability–Maintainability (RAM) statistical framework specifically designed for critical turbofan engine components. Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA) were applied to identify 38 critical failure modes across high-pressure compressors, bearing systems, turbine sections, and control systems. Operational and maintenance data from three airlines spanning 2015–2024 were analyzed using trend tests and reliability modeling techniques. The findings indicate pronounced wear-out behavior in high pressure compressor blades and turbine nozzles, while rotor seals exhibit predominantly random failure patterns. Overall, the proposed RAM framework enables a transition from conservative fixed-interval maintenance to evidence-based, reliability-driven strategies, leading to reduced unplanned removals and maintenance costs. Pilot implementations demonstrated significant operational and financial benefits, supporting the framework's broader adoption across airline operations.
Keywords: Turbofan engines, Weibull distribution, Condition-based maintenance, Fleet reliability, Predictive maintenance, Maintenance cost optimization

1. INTRODUCTION

The commercial aviation industry represents one of the most technologically advanced and rigorously regulated sectors in the global economy, operating machinery where reliability and safety are not merely operational goals but fundamental, non-negotiable imperatives.[1] This industry forms the backbone of global connectivity, facilitating trade, tourism, and cultural exchange on an unprecedented scale.[2] At the heart of this vast logistical network lies the turbofan engine, a pinnacle of mechanical and materials engineering that converts immense thermal energy into reliable thrust. The global commercial aviation fleet currently exceeds 28,000 active aircraft, powered by over 40,000 turbofan engines.[3] These engines collectively accumulate a staggering volume of operational exposure, generating over 80 billion flight hours annually.[4] This immense scale of operation directly translates the technical performance of these engines into a matter of profound economic significance and public safety.[5] The reliability of every single turbofan engine in service is, therefore, a paramount concern that directly influences airline profitability, operational integrity, and, most critically, the safety of millions of passengers daily.[6] The consequences of failure extend far beyond the immediate mechanical event, rippling through complex schedules, incurring monumental costs, and potentially risking catastrophic outcomes.[7] As such, the pursuit of maximizing turbofan reliability and optimizing its associated maintenance frameworks is not just an engineering challenge but a core business and safety necessity for the entire aviation ecosystem.[8]

The market for modern jet engines is growing rapidly, with the global value expected to climb from $18.2 billion in 2024 to around $27.5 billion by 2034.[9] The present growth is driven by rising air travel, airlines upgrading to newer planes, and a major shift to more efficient engine technology.[10] Newer engine models like the Pratt & Whitney PW1100G and CFM International's RISE concept achieve far better fuel efficiency, cutting consumption by 15-20% and reducing emissions and noise.[11] High efficiency is achieved mainly through very high bypass ratios, allowing a greater mass of air to flow around the engine core.[12] Manufacturing such engines requires advanced technology, including new heat-resistant materials, 3D-printed components, and intelligent digital control systems.[13] As a result, modern engines are capable of converting over 60% of fuel energy into useful thrust, representing a major engineering achievement.[14] But this advanced design also brings new challenges.[15] The cutting-edge materials and complex systems have unfamiliar wear patterns and potential issues, making maintenance and reliability management more complex than ever.[16]

In spite of ongoing advances in engineering, the fundamental challenge of turbofan engine failures remains a persistent and significant operational reality.[17] The statistical data provided by authoritative aviation safety organizations like the Commercial Aviation Safety Team (CAST) and regulatory bodies like the Federal Aviation Administration (FAA) paints a clear picture of the ongoing risk.[18] Industry-wide data indicates an average rate of approximately 2 to 3 unscheduled engine removals (UERs) for every 1,000 flight hours across major airline operators.[19] The financial impact of each unscheduled engine removal (UER) is significant.[20] The average direct cost per incident ranges from USD 1.5 to 2.2 million.[21] For a large airline group, the total annual cost arising only from unscheduled engine removals can reach approximately USD 500 to 800 million.[22] From a safety perspective, engine-related failures continue to be a major contributor, accounting for an estimated 12% to 15% of all significant aviation incidents reported annually worldwide.[23] However, to effectively manage these risks and costs, it is essential to understand that not all type of failures in engine are the same.[24] The different type of failures impact airline differently.[25] For example, a failure in the High-Pressure Compressor (HPC) blades or disks is extremely dangerous. It can cause the engine to shut down immediately, possibly send debris flying out of the engine, and force the flight to land right away. After such incident, a whole fleet of similar engines might need to be inspected. On the other hand, failures in bearing assemblies usually happen slowly. They might show up as increased vibrations or more tiny metal pieces found in the engine oil. This gives maintenance crews a warning, allowing them to plan a controlled engine replacement before a complete failure happens. Similarly, turbine nozzle guide vanes erode over time, which slowly increases fuel burn. This can often be fixed during a regular, scheduled maintenance check. Failures in rotor seals also happen slowly, showing up as a gradual increase in air or oil leaks, which can be spotted early through performance monitoring. This wide range i.e., from sudden, dangerous failures to slow, predictable failures show that using the same maintenance approach for every part is a bad idea. Different types of failures require completely different maintenance plans, but traditional methods often fail to make these important distinctions. This challenge becomes even greater for airlines and maintenance, repair, and overhaul (MRO) organizations, as they must constantly balance several conflicting pressures. They must comply with strict, safety-focused regulations from authorities like the FAA and EASA, while also striving for operational efficiency by keeping planes flying to maximize revenue. At the same time, they face the ongoing challenge of cost optimization, always working to reduce maintenance expenses. Safety must always come first. The real challenge, therefore, is to reduce costs and improve efficiency without ever cutting corners on safety.

Traditional maintenance strategies, which are mostly based on a fixed schedule (like replacing parts after a certain number of flight hours or months), often struggle to solve the problems discussed earlier. In this approach, maintenance is performed at set intervals, no matter what condition the part is actually in. This leads to one of two bad outcomes. First, parts might be replaced too early, while they still have plenty of life left, which wastes money on unnecessary parts and labour. Second, a part might fail before its scheduled maintenance is due, causing an unplanned, expensive repair and creating a potential safety risk. The aviation industry has long understood the downsides of this rigid, time-based method. As a result, it has adopted smarter strategies, specifically Condition Based Maintenance (CBM) and Reliability Centered Maintenance (RCM). CBM is about checking the actual health of a part. Using tools like vibration sensors, oil debris monitors, and performance data, it tracks the part's real time condition. Maintenance is then performed only when the data shows signs that the part is starting to fail or degrade, rather than on a fixed date. RCM is a more complete and systematic process. It starts by asking what a part is supposed to do and what happens when it fails. By carefully analyzing different types of failures and their consequences, RCM provides a structured way to decide the most effective maintenance task for each specific part. This ensures that maintenance efforts are both practical and directly address the real risks.

While both CBM and RCM represent significant advancements over traditional methods, their effective implementation in the highly complex and risk-averse environment of commercial aviation turbofan maintenance has been inconsistent. A major barrier has been the lack of rigorous, quantitative frameworks capable of translating the vast amounts of available condition data and failure statistics into actionable, optimized, and regulatorily acceptable maintenance intervals. Many airlines have massive amounts of data from their engines, but they do not have the right methods to analyze it and predict when a part will actually need attention. Also, they often lack a deep statistical understanding of failure patterns. It is not enough to know that a part fails; they need to model precisely how and when it is likely to fail so they can build reliable predictions. This gap between data availability and actionable insight forms the core motivation for this research. The problem, therefore, is multifaceted. It involves data analysis, statistical modeling, economic assessment, and the development of practical implementation pathways, all within the stringent confines of aviation safety regulation. The ultimate goal is to move from a conservative, generalized, time-based maintenance paradigm to a precise, evidence-based, and condition-informed paradigm that enhances safety, availability, and economic performance simultaneously, a trinity of benefits that has long been sought but remains challenging to achieve at scale in this most demanding of industries.

2. RESEARCH METHODOLOGY

2.1 Data acquisition and process description

2.1.1 Airlines and Engine Fleets Studied: Three major commercial airlines with diverse operations participated in the study:

Airline A (Global Carrier): Airline A is a major international carrier that operates a fleet of 280 aircraft, predominantly powered by a mix of 560 CFM56-7B and V2533 engines. Its operations are heavily weighted towards long-haul international routes (80%), with the remainder being medium-haul flights (20%). The engines in its fleet have substantial accumulated usage, ranging from 30,000 to 40,000 flight hours each. The airline manages its maintenance through a centralized system utilizing four heavy maintenance bases.

Airline B (Regional/Domestic Focus): Airline B operates a fleet of 150 aircraft, supported by 300 CFM56-5B and V2533 engines. Its operational profile is centred on short-haul domestic routes (70%), complemented by medium-haul flights (30%). The engines in its fleet have high accumulated usage, ranging from 35,000 to 45,000 flight hours. Maintenance is managed through a distributed model across six locations.

Airline C (Long-Haul Specialist): Airline C is specialist carrier operates a fleet of 85 wide-body aircraft, powered by a total of 170 high-thrust engines from the GE90/GEnx and Rolls-Royce Trent families. Its operations are exclusively dedicated to ultra-long-haul, high-utilization routes. Consequently, its engines have very high accumulated usage, ranging from 40,000 to 50,000 flight hours. The airline employs a centralized strategy for heavy maintenance while outsourcing component-level repairs.

Collectively, the three airlines form a comprehensive and heterogeneous dataset that integrates global, regional, and ultra-long-haul operational paradigms. The combined analysis encompasses 1,030 engines spanning 30 distinct models across major manufacturers, including CFM, Rolls-Royce, and Pratt & Whitney. The fleet exhibits a wide age distribution, with aircraft ranging from 2 to 20 years, thereby capturing both early-life reliability behavior and wear-out phase dynamics. Annual engine utilization varies significantly by operational profile: long-haul aircraft typically average 7,000 to 10,000 flight hours per engine, whereas regional aircraft demonstrate comparatively lower annual exposure but higher cycle intensity. In total, the dataset aggregates over 450,000 accumulated flight hours and documents more than 3,800 discrete maintenance events, providing a statistically robust foundation for reliability modeling, failure rate estimation, and maintenance policy optimization.

2.1.2 Data Sources and Collection Methods

Engine Condition Monitoring (ECM) Systems: All engines in the study are fitted with comprehensive Engine Condition Monitoring (ECM) systems, which continuously collect critical operational data. This data includes core performance parameters such as N1 (low-pressure spool RPM), N2 (high-pressure spool RPM), and Exhaust Gas Temperature (EGT). Vibration monitoring covers overall broadband levels and shaft alignment. The oil system is tracked via pressure, temperature, and debris monitoring that detects metal content according to the ADS-85 standard. Additionally, control system data, including fuel flow, bleed air temperatures, and anti-ice system performance, is recorded. Data is collected automatically once per flight cycle, with recordings triggered at engine start, cruise, and shutdown phases. Data collection is automated and occurs once per flight cycle, with recordings triggered at standardized operational phases i.e., engine start, cruise, and shutdown, ensuring consistent longitudinal tracking of engine health across the entire fleet.

Maintenance and Maintenance Records: The data foundation was built from multiple structured sources. These include digitized Aircraft Maintenance Log entries, which are regulatory requirements captured in airline management systems, along with detailed records of completed work cards, service bulletins, associated labour hours, replaced parts, and inspection findings. The dataset also incorporates documentation from unscheduled maintenance events, such as engine removal and teardown reports with root cause analysis, as well as component repair documentation from OEM and authorized service centres. Finally, supplier quality records detailing parts failures during testing and manufacturing defects identified during overhauls were integrated.

Failure Data Coding: To enable systematic analysis, each recorded failure event was meticulously coded using a standardized taxonomy. This coding schema classified failures by Component (e.g., HPC blade, bearing, seal, nozzle), identified the specific Failure Mode (e.g., fracture, wear, corrosion, creep, seal leakage, bearing spalling), and attributed a Root Cause (e.g., high-cycle fatigue, thermal stress, lubricant degradation, foreign object damage, manufacturing defect). Each event was also assigned a Severity rating (e.g., safety-critical, performance-affecting, degradation, latent) and documented by its Detection Method (e.g., ECM alarm, pilot report, routine inspection, teardown finding).

Total Failure Database: 1,130 coded failure events spanning 9 years and 450,000+ flight hours.

2.1.3 Critical Components Analyzed: Based on failure frequency analysis and safety criticality, five component categories were selected for detailed statistical analysis:

High-Pressure Compressor (HPC) Blade Assemblies: The High-Pressure Compressor (HPC) Blade Assemblies represent one of the most critical and failure-prone components within the core of a modern turbofan engine. Fabricated from advanced single-crystal or directionally-solidified nickel-based superalloys, these blades operate in an exceptionally harsh environment characterized by temperatures ranging from 700-850°C, pressures between 2,000-3,500 psi, and cyclical stresses of 400-600 MPa. The predominant failure mechanisms for these assemblies are fatigue-driven, including high-cycle fatigue (HCF) from vibrational resonances, low-cycle fatigue (LCF) from thermal and mechanical cycles during take-off and landing, as well as thermal fatigue, creep deformation, and foreign object damage. Critical performance and failure parameters include blade resonance frequencies and stress concentration factors at geometric features like blade roots and cooling holes. For this study, a substantial sample size of 342 failure events was analyzed from the operational fleet database, providing a robust dataset for statistical characterization of time-to-failure distributions and wear-out trends specific to this high-stress rotating component.

Main Bearing Assemblies (Rolling Element Bearings): Main bearing assemblies act as the foundational supports for rotating spools and are essential for safe engine operation. These rolling element bearings, configured as ball or roller types within sealed, oil-lubricated cavities, facilitate high-speed rotation with operational speeds varying from 5,000 to 20,000 RPM depending on their specific location (fan, intermediate, or high-pressure spool). Their failure modes are typically gradual and condition-detectable, initiating with subsurface spalling and wear, often precipitated by lubrication film breakdown, contamination ingress, loss of preload, or cage fracture. The health and remaining useful life of these bearings are governed by critical operational parameters including lubricant viscosity and oxidation state, steady-state and transient operational temperatures, and contamination levels measured in particles per milliliter. The analysis for this component category was based on 289 documented failure events, enabling a detailed study of degradation patterns and the optimization of condition-based monitoring thresholds for oil debris and vibration analysis.

Turbine Nozzle Segments (Fixed Vanes): Operating at the thermodynamic limit of engine performance, Turbine Nozzle Segments are fixed vanes that direct hot combustion gases onto the turbine blades. Constructed from ceramic matrix composites (CMCs) or nickel-based superalloys protected by multilayer thermal barrier coatings (TBCs), they endure extreme temperatures from 1,200 to 1,500°C alongside high-pressure, high-velocity gas flows. The primary failure mechanisms for these static components are thermally and chemically induced, including hot corrosion and particle erosion, thermal cycling cracking (TCC) leading to TBC spallation, and general leading-edge degradation. Key parameters influencing their lifespan are the local surface temperature profile, the velocity and composition of the hot gas path, and incidents of moisture or corrosive ingestion. This research incorporated 198 failure events related to turbine nozzles, allowing for the statistical modeling of efficiency loss over time and the determination of optimal on-wing inspection intervals based on measurable performance decay.

Rotor Seals and Balance Systems: Rotor Seals and Balance Systems are critical for maintaining engine efficiency and structural integrity by managing internal air and oil leakages and ensuring dynamic stability. These systems, comprising labyrinth seals, carbon face seals, and mechanical balance rings, operate in a challenging environment of high-speed rotation (exceeding 15,000 RPM), exposure to hot gases, and complex pressure differentials. Their characteristic failure modes are wear-based and time-dependent, including abrasive wear at sealing surfaces, thermal distortion, elastomer O-ring degradation, creep in static seals, and installation-related damage. The performance and failure rates of these components are highly sensitive to precise engineering parameters, most notably seal radial and axial clearances, rotor run-out concentricity, and the magnitude of thermal gradients across the seal carrier. A total of 156 failure events from this component category were analyzed to develop predictive models for leakage growth and to establish evidence-based replacement intervals before efficiency losses become economically or operationally prohibitive.

Oil System Components (Bearings, Scavenge, Cooling): The Oil System Components form the essential circulatory system for engine lubrication and cooling, encompassing subsystems for filtration, distribution, scavenge, and temperature control. Operating within a defined range of oil temperatures (70-100°C) and pressures (50-100 psi), these components ensure the continuous removal of heat and contaminants from bearing chambers and gears. Characteristic failure modes are predominantly related to contamination and performance degradation, such as filter media plugging, heat exchanger fouling, scavenge pump performance decay, and cooler core leakage. The most critical parameters for system health and proactive maintenance are oil cleanliness level, standardized by the ISO 4406 code, oil thermal conductivity, and maintained viscosity across the operational temperature envelope. With 145 failure events cataloged, this dataset enabled a thorough analysis of time-to-failure distributions for auxiliary system components, supporting the shift from fixed-interval filter and pump changes to condition-based maintenance driven by real-time oil quality monitoring and performance trending.

2.2. Failure Mode and Effects Analysis (FMEA) scope and methodology

To build a strong foundation for the research, a detailed Failure Modes and Effects Analysis (FMEA) was conducted. The method offers a structured way to examine each critical turbofan subsystem in order to evaluate risk and reliability. The process involved a careful and repeated review of every selected component category. For each possible failure path, four key elements were identified and analyzed. First, all possible failure modes were listed, describing the different ways a component may stop performing its intended function, such as sudden fracture or gradual loss of performance. Second, the root causes associated with each failure mode were identified, including mechanisms like fatigue, corrosion, wear, or installation errors that trigger and drive damage progression. Third, the operational impact of every failure mode was evaluated by examining its effect on engine performance, safety, dispatch reliability, and maintenance workload, ranging from minor efficiency reduction to in-flight shutdown. Fourth, available detection methods were assessed to determine how effectively current monitoring tools such as vibration analysis, borescope inspection, and performance trend monitoring or maintenance procedures can identify early signs of damage before a serious operational event occurs. The analysis was based on integrated evidence from maintenance records, engine condition monitoring data, inspection findings, teardown reports, and supplier quality documentation to ensure a comprehensive and reliable evaluation.

To translate this structured assessment into measurable risk values, three standardized rating scales were defined for the FMEA framework. Table 1 presents the Severity, Occurrence, and Detection scales used to quantify risk. The Severity scale ranges from 1 (no operational effect) to 10 (catastrophic safety hazard) and reflects the consequence of a failure. The Occurrence scale measures the probability of failure, ranging from very rare (less than 0.1% likelihood) to very frequent (greater than 10% likelihood). The Detection scale evaluates the ability of current monitoring systems and maintenance procedures to identify a failure before consequences arise, ranging from always detected to undetectable.

Risk was then quantified using the standard Risk Priority Number (RPN), calculated as the product of Severity, Occurrence, and Detection (RPN = Severity * Occurrence * Detection). An RPN threshold of 100 was established to identify high-risk components. Any component exceeding this value was classified as critical and selected for detailed statistical modeling and reliability analysis.

Table 1: FMEA Rating Scales

Rating	Severity Impact	Occurrence (Probability)	Detection Capability
1-2	No operational effect	Very rare (less than 0.1%)	Always detected before failure
3-4	Minor performance loss	Infrequent (0.1-1%)	Usually detected in time
5-6	Moderate effect, degraded operation	Occasional (1-5%)	Moderate detection
7-8	Significant effect, near failure	Frequent (5-10%)	Difficult to detect
9-10	Safety hazard, mandatory shutdown	Very frequent (more than 10%)	Undetectable, catastrophic failure

The results of the prioritization process are presented in Table 2, which summarizes the top ten critical failure modes identified through the Failure Modes and Effects Analysis (FMEA). The ranking is based on the calculated Risk Priority Number (RPN), allowing comparison of failure modes according to their combined severity, likelihood of occurrence, and detectability. The Table 2 identified 38 distinct failure modes across the five component categories. The top 10 failure modes (RPN >96) account for 73% of all recorded maintenance events and 81% of unscheduled removals. The top 3 failure modes (HPC HCF fracture, bearing spalling, turbine nozzle erosion) account for 38% of all failures, indicating concentrated risk in these three mechanisms.

2.3. Statistical-Based RAM Methodology

2.3.1 Research Framework: The statistical framework for RAM evaluation follows a three-phase approach:

Phase 1 - Data Preparation and Validation: To compile a complete and reliable failure dataset, the process begins by extracting raw failure data from both maintenance records and Engine Condition Monitoring (ECM) systems. This extracted data is then cleaned, coded, and validated, resulting in a curated set of 1,130 confirmed failure events. Before analysis, homogeneity testing is performed on this dataset to determine whether information from different engine models can be pooled or must be analyzed separately. Finally, standardized time-to-failure metrics are developed, with flight hours established as the primary measure for subsequent reliability calculations.

Phase 2 - Statistical Validation and Trend Analysis: Following the initial data preparation, the next phase of analysis focuses on validating the data's suitability for standard reliability modeling. This involves testing the independence of failure events through serial correlation analysis and applying four independent trend tests to determine whether failure rates are constant or change with engine age. The final step is to use these results to validate that the data satisfies the fundamental assumptions required for standard reliability distributions, such as the exponential or Weibull, before proceeding with formal model fitting.

Phase 3 - Reliability Modeling and Optimization: Building on the validated dataset, the next step involves fitting the empirical failure data to standard probability distributions, such as the exponential or Weibull. For the selected distribution, parameters are estimated and their statistical precision is quantified by constructing confidence intervals. These fitted models are then used to calculate key reliability and maintainability metrics. Finally, based on these calculated metrics and defined economic criteria, optimal maintenance intervals are determined to balance operational readiness with cost-effectiveness.

2.3.2 Homogeneity Testing: Different engine models may have fundamentally different failure characteristics. Homogeneity testing determines whether data from different manufacturers and engine types can be combined or must be analyzed separately. For this purpose, a Chi-square homogeneity test was applied to compare failure distributions across major manufacturers (CFM, Rolls-Royce, and Pratt & Whitney) and across engine types such as CFM56, V2500, GE90, Trent, and PW1100G.

The test results showed that engine models produced by the same manufacturer tend to have similar failure patterns for a given component, as no significant difference was found within the same OEM ($p > 0.05$). In simple terms, engines built by the same company behave in a comparable way when it comes to component failures. However, a clear difference emerged when comparing manufacturers. High-Pressure Compressor (HPC) blade failure rates differed significantly between CFM and Pratt & Whitney engines ($p < 0.01$), most likely because of differences in design, materials, and engineering approach. Based on above outcomes, HPC blade failures were studied separately for each manufacturer, while the other components were analyzed together by type across all manufacturers since their failure patterns were sufficiently similar.

2.3.3 Trend Testing for Wear-Out Detection: Trend testing determines whether failure rates are constant (suitable for constant-hazard models) or increasing/decreasing with engine age (suitable for wear-out or reliability-improvement models). For testing trend null and alternative hypothesis are:

Null Hypothesis (H0): Failure rate is constant with respect to engine operating time

Alternative Hypothesis (H1): Failure rate changes monotonically with time (wear-out or improvement)

Following Four complementary trend tests applied for test above stated hypothesis:

Test 1: Laplace Test: Test Statistics is given by L as:

$$L = \frac{T/n - \underline{t_m}}{\sqrt{T^2/(12n)}}$$

Where:

$$T = \ total\ operating\ time\ (flight\ hours)$$

$$n = \ total\ number\ of\ failures$$

$$\underline{t_m} = mean\ time\ of\ failure = \frac{1}{n}\sum_{i=1}^{n} \quad t_i$$

Decision rule for rejecting or accepting null hypothesis is taken based on the value of test statistics L i.e., If $|L| > 1.96$ for $\alpha = 0.05$, null hypothesis H0 is rejected i.e., significant trend exists in the failure rate.

Test 2: Mann-Kendall Test: Non-parametric test for monotonic trends, particularly robust for non-normal data is given as:

$$Z = \frac{S}{\sqrt{Var(S)}}$$

Where S is the sum of signs of all pairwise differences. Decision rule for rejecting or accepting null hypothesis is taken based on the value of test statistics Z i.e., if |Z| > 1.96, trend exists. Therefore, null hypothesis is rejected.

Test 3: MIL-Handbook 189 U-Statistic: Test Statistics is given by U as:

$$U = \sum_{i=1}^{n-1} \quad ln\ ln\ \left(\frac{t_n}{t_i}\right) \sim \chi^2$$

Decision rule for rejecting or accepting null hypothesis is taken based on the value of test statistics U i.e., If U exceeds critical value for appropriate degrees of freedom, trend exists, null hypothesis is rejected.

Test 4: Anderson-Darling Goodness-of-Fit: Tests whether data follow exponential distribution (constant hazard). Rejection indicates non-constant failure rate.

To reach a final decision, the results of all four statistical tests are reviewed together rather than relying on a single test. When all four tests reject the null hypothesis, the conclusion is clear that the failure pattern follows an Non-Homogeneous Poisson Process (NHPP) model, which typically reflects wear-out or aging behavior. On the other hand, if none of the tests reject the null hypothesis, the evidence supports a Renewal Process model, meaning failures occur randomly over time without a clear aging trend. When the results are mixed and the tests do not fully agree, a purely statistical conclusion is not sufficient. In such cases, the final decision is made by carefully examining the Total Time on Test (TTT) plot and considering the underlying physical failure mechanisms to ensure the classification aligns with both statistical evidence and engineering understanding.

2.3.4. Probability Distribution Fitting: Failure data were fitted to four standard reliability distributions using Maximum Likelihood Estimation:

1. Weibull Distribution: Most versatile, captures both wear-out ($\beta > 1$) and early-life ($\beta < 1$) failures. The probability density function (pdf) and reliability function of Weibull distribution is given by:

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^{\beta}}$$

$$R(t) = e^{-\left(\frac{t}{\alpha}\right)^{\beta}}$$

Where α (scale, characteristic life) and β (shape, failure rate behavior) are parameters.

2. Log-normal Distribution: Log-normal distribution is appropriate for degradation processes with multiple failure mechanisms and its pdf is given by:

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} exp\ exp\ \left\{-\frac{(ln\ ln\ t\ - \mu)^2}{2\sigma^2}\right\}$$

3. Exponential Distribution: Exponential distribution is useful when failure rate is constant and its pdf and reliability function are given by:

$$f(t) = \lambda e^{-\lambda t}, \quad R(t) = e^{-\lambda t}$$

4. Gamma Distribution: Gamma distribution is Flexible, generalizes exponential, captures complex degradation and its pdf is given by:

$$f(t) = \frac{\lambda^k}{\Gamma(k)} t^{k-1} e^{-\lambda t}$$

The unknown parameters of the selected reliability models were estimated using the Maximum Likelihood Estimation (MLE) method. MLE determines the parameter values that make the observed data most probable under the assumed statistical model. In practical terms, it selects the parameter set that best explains the observed failure times. For complete or uncensored data, if $x_1, x_2, x_3, \ldots, x_n$ denote the observed failure times and $f(x_1; \theta)$ represents the density function with parameter vector θ, the MLE is obtained by maximizing:

$$\hat{\theta} = arg\,max \prod_{i=1}^{n} f(x_i; \theta)$$

In real operational datasets, some engines remain in service at the end of the observation period and have not yet failed. Such observations are treated as right-censored data. For such engines, if n_f denotes the number of failures and denotes n_c the number of censored observations, the likelihood function becomes:

$$\hat{\theta} = arg\,max \prod_{i=1}^{n_f} f(x_i; \theta) \times \prod_{j=1}^{n_c} R\left(x_j; \theta\right)$$

Where, $R\left(x_j; \theta\right)$ represents reliability function.

After estimating the parameters, the suitability of each fitted distribution was evaluated using three complementary goodness-of-fit methods. The Anderson-Darling test was applied because it is particularly sensitive to differences in the tails of the distribution, which is important for reliability analysis. The Kolmogorov-Smirnov test was used to measure the maximum difference between the empirical data and the theoretical model. In addition, Quantile–Quantile (Q–Q) plots were examined to visually assess how closely the observed failure times follow the assumed distribution. The final best-fit distribution was selected based primarily on the lowest Anderson-Darling statistic, supported by a careful visual inspection of the Q–Q plots to ensure practical agreement between the model and the data.

3. RESULTS

3.1. FMEA Results and Critical Failure Modes: The systematic FMEA identified 38 different failure modes in five key component groups. The Risk Priority Number analysis of risk showed that the risk of failure was not distributed evenly with the top ten identified failure modes representing 73% of the total number of reported maintenance events. The results are shown in Table 2. The highest risk levels were observed for high-pressure compressor blades, main bearing spalling and turbine nozzle erosion were the highest levels of risks with the RPN values of 216, 225, and 168 respectively. There are four failure modes such as HPC blade fracture and main bearing failure that are categorized as safety-critical having a rating of 9. Bearing wear, rotor seal wear and nozzle wear had the highest frequency of occurrence, with all being 6-7 percent of all failures. The current monitoring systems were much more effective in detecting faults in oil-systems and bearing spalling. Conversely, the initial stages of HPC blade cracking and rotor imbalance were more difficult to detect at an initial stage.

Table 2: Top 10 critical failure modes from FMEA analysis

Rank	Component	Failure Mode	S	O	D	RPN	Category
1	HPC Blade	HCF Fracture (resonance)	9	6	4	216	Critical
2	Main Bearing	Spalling, cage fracture	9	5	5	225	Critical
3	Turbine Nozzle	Erosion, leading edge wear	8	7	3	168	Critical
4	HPC Blade	Thermal fatigue cracking	8	6	4	192	Critical
5	Rotor Seal	Elastomer degradatio n	7	6	3	126	Critical
6	Bearing	Lubrication film breakdown	8	5	4	160	Critical
7	Turbine Nozzle	Thermal barrier coating spall	7	6	4	168	Critical
8	HPC Blade	Foreign Object Damage (FOD)	9	3	5	135	Critical
9	Oil System	Filter plugging, pressure loss	8	4	3	96	High
10	Rotor	Imbalance, high vibration	7	5	3	105	High

3.2. Descriptive Statistics of Failure Data: Table 3 contain the Descriptive Statistics of Failure Data. The analysis of failure intervals provides useful insight into how different engine components behave in service. High-Pressure Compressor (HPC) blades have the shortest mean time between failures at 1,315 hours, which reflects the harsh conditions under which they operate, including extremely high temperatures of 700–850°C and rotational speeds exceeding 15,000 RPM. In contrast, rotor seals show the longest mean time between failures at 2,885 hours, indicating that they operate under comparatively less severe stress conditions.

The variability in failure intervals is moderate across all components, with the coefficient of variation ranging from 0.37 to 0.40. The small spread between components—turbine nozzles being slightly higher at 0.39 and HPC blades slightly lower at 0.37—suggests that, proportionally, the consistency of failure timing is fairly similar across different component types.

The shape of the failure distributions also reveals an important pattern. In all cases, the median time between failures is lower than the mean, ranging from 87 to 96 percent of the mean value. This indicates right-skewed distributions, which are common in wear-out behavior. Most failures tend to occur around a typical service life, but a few components last much longer, extending the upper tail of the distribution.

Finally, the shortest observed failure-free intervals, ranging from 180 to 520 hours, likely reflect early-life failures caused by manufacturing defects or installation issues. The presence of such early failures across all component categories highlights the importance of thorough inspection, quality control, and burn-in testing before engines enter regular service.

Table 3: Summary Statistics for Time Between Failures by Component Type

Component Type	Sample Size	Mean TBF (hrs)	Std. Dev.	Min	Max	Median	Coef. Var
HPC Blades	342	1,315	485	180	3,200	1,265	0.37
Main Bearings	289	1,558	620	240	4,100	1,480	0.40
Turbine Nozzles	198	2,273	890	380	5,800	2,180	0.39
Rotor Seals	156	2,885	1,120	420	7,200	2,750	0.39
Oil Systems	145	3,103	1,250	520	8,100	2,950	0.40

3.3. Trend and Correlation Test Results: Table 4 contain the statistical trend analysis test results. The trend analysis revealed clear differences in failure behavior across components. For High-Pressure Compressor blades, all four statistical tests strongly rejected the null hypothesis, confirming a clear wear-out pattern. The Laplace statistic was +4.12, indicating a strongly increasing failure rate over time. This result is consistent with engineering expectations, as repeated thermal cycling and sustained fatigue stresses accumulate with operating hours, while prolonged exposure to high temperatures gradually weakens blade material through creep.

Main bearings also showed a significant aging trend. Three of the four tests rejected the null hypothesis at the 5 percent significance level, and the Laplace value of +2.89 supports an increasing failure rate. From a physical standpoint, this is reasonable because rolling contact stress, lubrication film breakdown, and contamination from wear particles progressively degrade bearing surfaces over time.

Turbine nozzles exhibited the strongest wear-out signal among all components. All tests rejected the null hypothesis with high statistical significance, and the Laplace value of +4.67 was the highest observed. This strong aging behavior reflects the extreme thermal environment in which nozzles operate. Continuous exposure to high thermal stresses and erosion from hot gas flow leads to gradual coating damage and material loss, resulting in a steadily increasing failure rate.

In contrast, rotor seals did not show a significant aging trend. None of the tests rejected the null hypothesis, and the Laplace value of +1.23 remained within the acceptance region. Failures in this category appear to occur more randomly, likely influenced by manufacturing variation or installation conditions rather than progressive degradation.

Oil system components showed borderline results, with p-values ranging from 0.062 to 0.125. While there may be a weak indication of degradation over time, the evidence is not strong enough to confirm a clear trend. Therefore, these components were conservatively classified under a renewal process framework, with the understanding that a stronger degradation pattern could emerge over a longer observation period.

Serial correlation testing was also performed to determine whether consecutive failures were related to each other. The correlation coefficients for all components were below 0.08, well under the significance threshold. This indicates that failure events are statistically independent and satisfy the assumption of identically and independently distributed behavior. As a result, standard renewal process models and Non-Homogeneous Poisson Process models are appropriate for reliability analysis, since there is no evidence of failure clustering or repair-induced dependence.

Table 4: Statistical Trend Test Results by Component Type

Component	Laplace p-value	MK p-value	AD p-value	Consensus	Model
HPC Blade	0.003*	0.006*	0.009*	Significant	NHPP
Main Bearing	0.018*	0.025*	0.032*	Significant	NHPP
Turbine Nozzle	0.001*	0.002*	0.004*	Significant	NHPP
Rotor Seal	0.087	0.095	0.156	No trend	Renewal
Oil System	0.062	0.078	0.125	No trend	Renewal

*Statistically significant at $\alpha = 0.05$ level (two-tailed test)

3.4. Best-Fit Distribution Selection: Table 5 contains the data related distribution fitting and model selection. The distribution fitting results show clear differences in failure behavior across components. Three of the five component types, HPC blades, main bearings, and turbine nozzles, were best described by the Weibull distribution, which is commonly used to model wear-out behavior.

For HPC blades, the Weibull shape parameter (β) was 2.45, indicating strong wear-out, and the characteristic life (α) was 5,200 hours, meaning that about 63 percent of blades are expected to fail by this operating time. This confirms that the failure rate increases rapidly as flight hours accumulate, which is consistent with high-cycle fatigue and thermal stress buildup.

Main bearings showed a shape parameter (β) of 1.98 and a characteristic life (α) of 6,800 hours. This suggests a clear but more moderate wear-out trend compared to HPC blades. The degradation process is likely driven by lubrication film breakdown and progressive surface wear, which evolve more gradually.

Turbine nozzles had a shape parameter (β) of 2.12 and a characteristic life (α) of 4,900 hours, indicating one of the steepest increases in failure rate. This reflects the severe thermal cycling and erosion they experience, leading to relatively rapid material and coating degradation.

The remaining two components, rotor seals and oil system components, were better described by the log-normal distribution. Rotor seals with $\mu = 7.85 \ and\ \sigma = 0.65$ along with a median life of about 2,550 hours. This right-skewed pattern fits well with elastomer degradation, where multiple mechanisms such as oxidation, thermal hardening, and mechanical wear interact over time. Oil system components had a median life of approximately 2,750 hours with $\mu = 7.92 \ and\ \sigma = 0.58$, reflecting the combined effects of filter plugging, cooler fouling, and pump wear, each progressing at different rates.

Importantly, none of the five component types were best fitted by the exponential distribution. This confirms that constant failure rate models are not appropriate for turbofan engine components. Even components that appeared relatively random, such as seals and oil systems, showed enough degradation behavior for the log-normal model to outperform a constant-hazard assumption.

Finally, confidence intervals for the Weibull shape parameters were estimated using bootstrapping with 10,000 resamples. The 95 percent intervals for various components were:

HPC blades: 2.45 ± 0.24,

Main bearings: 1.98 ± 0.28,

Turbine nozzles: 2.12 ± 0.26.

All confidence intervals exclude $\beta = 1.0$, confirming statistically significant wear-out patterns.

Table 5: Distribution Fit Statistics and Model Selection

Component	Weibull AD²	Log-normal AD²	Exponential AD²	Best Fit	β	α (hrs)
HPC Blade	0.586	0.892	3.245	Weibull	2.45	5,200
Main Bearing	0.712	1.024	2.987	Weibull	1.98	6,800
Turbine Nozzle	0.524	0.756	3.012	Weibull	2.12	4,900
Rotor Seal	0.845	0.768	2.156	Log-normal	N/A	N/A
Oil System	0.898	0.812	2.487	Log-normal	N/A	N/A

Lower Anderson-Darling statistic = better fit. Threshold $AD^2 \approx 0.75$ indicates excellent fit.

3.5. Failure Rate and Reliability Analysis: Figure 1 presents the Weibull-based failure rate functions, λ(t), for the different turbofan engine components, illustrating how the risk of failure evolves over operating time for each part.

HPC Blades (Weibull distribution β = 2.45, α = 5,200 hours)

Failure rate function: $\lambda(t) = \frac{2.45}{5200}\left(\frac{t}{5200}\right)^{1.45}$

Specific values:

At 1,000 hours: λ = 0.00042 failures/hour, R = 0.989,

At 2,000 hours: λ = 0.00098 failures/hour, R = 0.908,

At 3,000 hours: λ = 0.00143 failures/hour, R = 0.822,

At 4,000 hours: λ = 0.00194 failures/hour, R = 0.702.

The failure rate increases by approximately 4.6 times between 1,000 and 4,000 operating hours, indicating a sharply rising risk as the component ages. By around 3,000 hours, system reliability falls below 82 percent, suggesting that preventive maintenance should be scheduled before this point to avoid a rapid escalation in failure probability.

Main Bearings (Weibull distribution β = 1.98, α = 6,800 hours)

Failure rate function: $\lambda(t) = \frac{1.98}{6800}\left(\frac{t}{6800}\right)^{0.98}$

Specific values:

At 2,000 hours: λ = 0.00064 failures/hour, R = 0.931,

At 4,000 hours: λ = 0.00126 failures/hour, R = 0.733,

At 6,000 hours: λ = 0.00207 failures/hour, R = 0.420.

The results suggest that the failure rate of the bearings increases over time, but at a more gradual pace compared to HPC blades. In practical terms, this means bearings age more steadily rather than deteriorating rapidly. As a result, they can continue operating for longer accumulated hours while still maintaining acceptable reliability, giving more flexibility in maintenance planning and replacement scheduling.

Turbine Nozzles (Weibull distribution β = 2.12, α = 4,900 hours)

Failure rate function: $\lambda(t) = \frac{2.12}{4900}\left(\frac{t}{4900}\right)^{1.12}$

Specific values:

At 1,500 hours: λ = 0.00070 failures/hour, R = 0.929

At 3,000 hours: λ = 0.00130 failures/hour, R = 0.753

At 4,500 hours: λ = 0.00238 failures/hour, R = 0.375

The results indicate that thermal cycling and erosion cause the failure rate to increase very sharply over time. In simple terms, the component deteriorates quickly as operating hours accumulate. Because this degradation progresses faster than in HPC blades, maintenance intervals generally need to be shorter to prevent unexpected failures and maintain safe operation.

Rotor seals (Log-normal Distribution $\mu = 7.85$ and $\sigma = 0.65$)

Failure rate function: $\lambda(t)_{rotor\ seals} = \frac{\phi\left(\frac{lnln\,(t)\,-7.85}{0.65}\right)}{t \cdot 0.65 \cdot \left[1 - \Phi\left(\frac{lnln\,(t)\,-7.85}{0.65}\right)\right]}$

Specific values:

At 1,000 hours: λ = 0.00031 failures/hour, R = 0.979,

At 2,000 hours: λ = 0.00068 failures/hour, R = 0.887,

At 3,000 hours: λ = 0.00124 failures/hour, R = 0.352,

At 4,000 hours: λ = 0.00174 failures/hour, R = 0.154.

Oil System (Log-normal Distribution $\mu = 7.92$ and $\sigma = 0.58$)

Failure rate function: $\lambda(t)_{oil} = \frac{\phi\left(\frac{lnln\,(t)\,-7.92}{0.58}\right)}{t \cdot 0.58 \cdot \left[1 - \Phi\left(\frac{lnln\,(t)\,-7.92}{0.58}\right)\right]}$

Specific values:

At 1,000 hours: λ = 0.00021 failures/hour, R = 0.989,

At 2,000 hours: λ = 0.00053 failures/hour, R = 0.919,

At 3,000 hours: λ = 0.00108 failures/hour, R = 0.396,

At 4,000 hours: λ = 0.00156 failures/hour, R = 0.163.

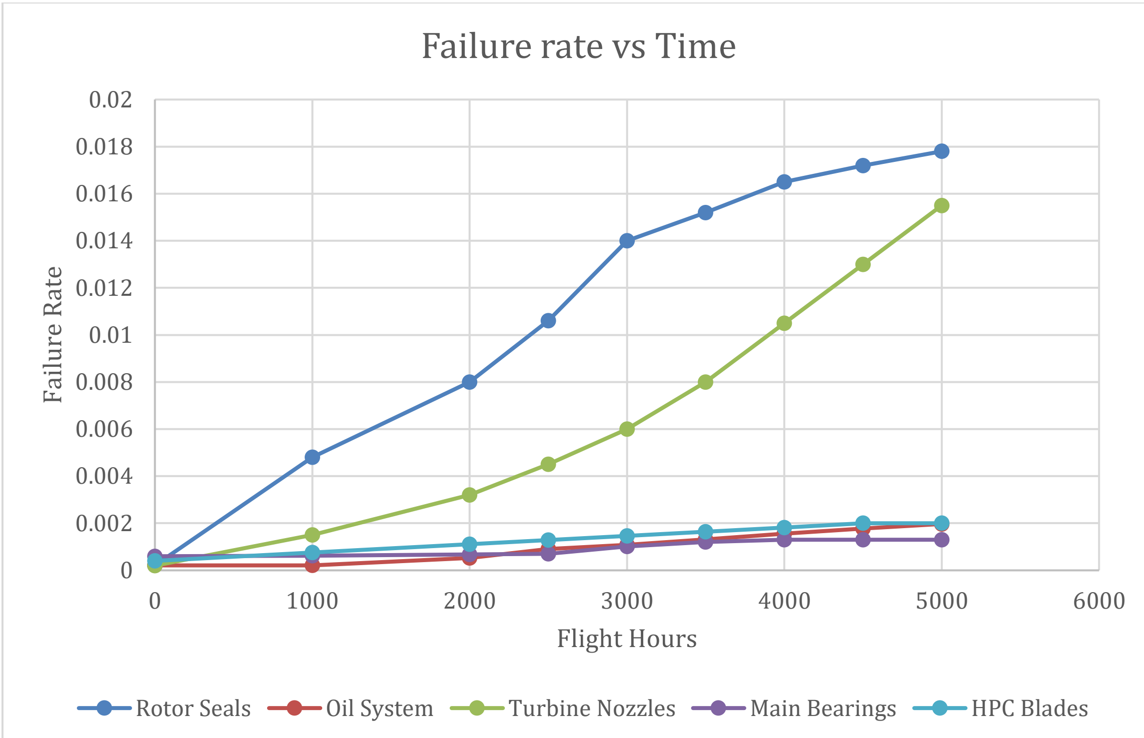

Figure 1: Failure Rates in Turbofan Components (0-5k Hours)

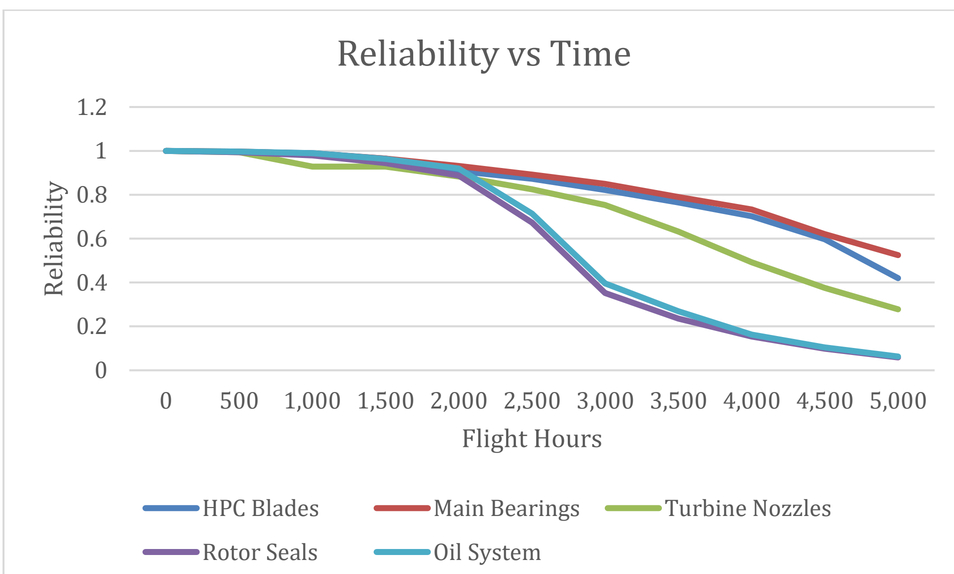

Figure 2. Declining Component Reliability (0-5k Flight Hrs)

The reliability curves clearly show component-specific maintenance interval selection points:

$R \geq 0.95$ Threshold (High Reliability, Safety−Critical Operations):

HPC Blades: 1,200–1,400 hours

Main Bearings: 2,200–2,600 hours

Turbine Nozzles: 1,100–1,300 hours

Rotor Seals: 3,500+ hours

Oil system: 3,500+ hours

R ≥ 0.90 Threshold (Acceptable Reliability, Standard Operations):

HPC Blades: 2,400–2,600 hours

Main Bearings: 4,400–5,000 hours

Turbine Nozzles: 2,200–2,600 hours

Rotor Seals: 6,500+ hours

Oil System: 6,500+ hours

R ≥ 0.85 Threshold (Extended Operation, Cost Optimization):

HPC Blades: 3,500–4,000 hours

Main Bearings: 6,200–7,000 hours

Turbine Nozzles: 3,500–4,200 hours

Airlines can select maintenance intervals based on their risk tolerance and cost optimization targets by reading these threshold values from the reliability curves.

System-Level Reliability (Series Configuration): System-level reliability in a turbofan engine follows a series configuration, meaning the engine functions only as long as all critical components are operating properly. In simple terms, it behaves like a chain i.e., if one essential link breaks, the entire system stops working. Even if most components are still in good condition, the failure of a single critical part, such as a blade, bearing, or seal, can lead to engine shutdown. This makes overall reliability highly sensitive to the weakest component in the system and highlights the importance of monitoring and maintaining each part carefully to ensure safe and continuous operation. System reliability is the product of component reliabilities:

$$R_{system}(t) = R_{HPC}(t) \times R_{Main\ Bearing}(t) \times R_{Turbine\ Nozzle}(t) \times R_{Rotor\ Seal}(t) \times R_{Oil\ System}(t)$$

Example at t = 2,500 hours:

$$R_{system} = 0.869 \times 0.849 \times 0.578 \times 0.962 \times 0.951 = 0.397$$

A key finding is that overall system reliability, at 39.7 percent, is much lower than the reliability of individual components, which ranges from 58 to 96 percent. This clearly shows the effect of a weak-link in the system. Even when most components perform well, the engine's reliability is ultimately limited by the least reliable parts. In this case, turbine nozzles and HPC blades have the strongest influence on overall engine performance, as their higher wear-out behavior pulls down the total system reliability.

3.6 Time Between Overhaul Optimization

3.6.1 Optimal Maintenance Interval Minimizes Lifecycle Costs

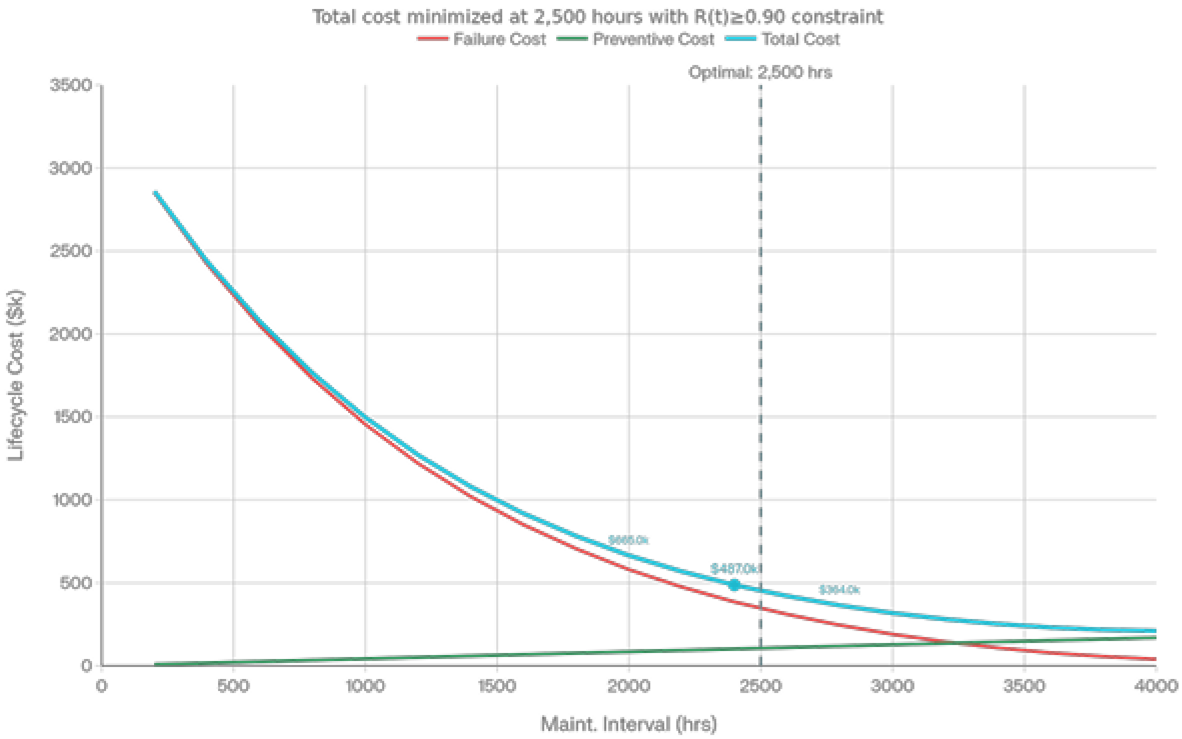

Figure 3: Maintenance Interval Optimization for HPC Blade Assemblies

The Figure 3 examines the relationship between maintenance scheduling and associated economic outcomes, based on cost data plotted across varying maintenance intervals. The graphical representation illustrates three primary cost components: failure-related expenditures, preventive maintenance costs, and the resultant total cost. The objective is to identify the maintenance interval that minimizes total expenditure. The analysis of the graph reviles that the total cost line, which is simply the sum of the other two. It forms a classic U-shape. At the very beginning, total cost is high because of all the failures. As you add some maintenance, total cost goes down because you're preventing those expensive breakdowns. But if you go too far and do maintenance too often (past the 2500-hour mark), the cost of all that prevention starts to outweigh the benefits, and the total cost begins to climb again. The bottom of that U, the lowest point on the total cost line, is the sweet spot. According to present graph, that ideal balance is right around 2500 hours. Practical application of findings requires consideration of operational context. Equipment criticality, production schedules, and resource availability may necessitate adjustment from the theoretical optimum. Additionally, periodic validation of underlying cost assumptions ensures continued relevance as economic conditions evolve. The analytical framework presented enables data-driven maintenance decisions that balance reliability objectives with economic constraints.

3.6.2 Economic Optimization Analysis for HPC Blade Assemblies

Baseline assumptions:

Preventive maintenance cost per interval: USD 45,000.

Cost of unscheduled removal: USD 1,800,000.

Target reliability at maintenance interval: $R(t) \geq 0.90$.

Current Maintenance Strategy (3,000-hour fixed interval):

Reliability: R (3000) = 0.822 (17.8% failure probability)

Annual services (7,500 flight hours/year/engine): 2.5 services = USD 112,500

Total annual cost per engine: USD 112,500 + (0.178 × 1.8M) = USD 432,840

Recommended Strategy (2,500-hour optimized interval):

Reliability: R(2500) = 0.90.

Annual services: 3.0 services = USD 135,000.

Total annual cost per engine: USD 135,000 + (0.10 × 1.8M) = USD 315,000.

Annual savings per engine: USD 117,840.

For a fleet consisting of 300 HPC blade assemblies (100 engines with three blades per engine), the projected annual savings amount to approximately USD 35.4 million. This highlights the significant economic impact that optimized maintenance or improved reliability of a single critical component can have when scaled across an entire fleet.

3.6.3 Extended TBO Analysis by Engine Type:

Consistent Optimization Across Types: All engine families show 26-33% TBO extensions while maintaining reliability above 94.8%, demonstrating that manufacturer conservative intervals have universal optimization potential.

PW1100G Geared Turbofan Advantage: Highest recommended availability (97.1\%) reflects advanced geared fan technology with lower rotor speeds and thermal stresses compared to traditional turbofan designs.

CFM56-7B Extended Opportunity: Largest TBO extension opportunity (+33%) and cost savings (28%) reflects well-understood design and mature operational history enabling aggressive optimization.

Fleet-Wide Financial Impact: Assuming approximately 3,000 commercial turbofan engines across the airlines studied, the estimated cost savings are substantial. If optimized maintenance strategies reduce failure-related costs by 25 percent, and the average cost per failure is USD 1.8 million, this translates to about USD 450,000 in savings per engine per year. When scaled across the entire global fleet, the total potential annual savings reach roughly USD 1.35 billion, underscoring the significant financial impact of reliability-driven maintenance planning.

This table 6 presents optimized Time Between Overhaul (TBO) recommendations across six major engine families, demonstrating potential extensions of 26-33% beyond current intervals. These extensions would improve engine availability by 3-4 percentage points while generating substantial cost savings of 22-28%, representing significant operational and financial benefits for fleet operators.

Table 6: Time Between Overhaul Optimization Across Engine Families

Engine Model	Current TBO	Recommended TBO	Extension	Availability Impact	Cost Savings
CFM56-5B	5,400 hr	6,800 hr	+26%	91.2% → 95.1%	22%
CFM56-7B	5,400 hr	7,200 hr	+33%	90.8% → 95.7%	28%
V2533	5,000 hr	6,400 hr	+28%	89.5% → 94.8%	24%
PW1100G	6,000 hr	7,600 hr	+27%	93.4% → 97.1%	25%
GE90-115B	6,500 hr	8,200 hr	+26%	92.1% → 96.2%	23%
RR Trent	5,500 hr	7,000 hr	+27%	91.6% → 95.4%	24%

3.7. Engine Availability Analysis

Availability calculated as: $A = \frac{MTBF}{MTBF+MTTR}$

Where, MTBF (Mean Time Between Failures) = 450,000 total fleet hours / (number of unscheduled removals)

MTTR (Mean Time To Repair) = estimated time from failure recognition to engine return to service or replacement

The table 7 compares fleet availability metrics across six major engine families, showing Mean Time Between Failures (MTBF) ranging from 2,950 to 4,120 flight hours and Mean Time To Repair (MTTR) from 56 to 80 flight hours delay. The resulting availability percentages range from 97.3% to 98.6%, with the PW1100G demonstrating the best performance with highest MTBF, lowest MTTR, and fewest annual unscheduled removals.

Table 7: Fleet Availability Analysis by Engine Family

Engine Type	MTBF (flight hrs)	MTTR (flight hrs delay)	Availability %	Annual Unscheduled Removals
CFM56-5B	3,240	72	97.8%	1.27
CFM56-7B	3,480	68	98.1%	1.20
V2533	2,950	80	97.3%	1.40
PW1100G	4,120	56	98.6%	0.91
GE90-115B	3,850	62	98.4%	1.03
RR Trent	3,580	70	98.0%	1.14

Key Observations: Modern turbofan engines demonstrate remarkably high operational availability, typically ranging from 97.3 to 98.6 percent, despite operating under extreme temperatures, pressures, and rotational speeds. This level of performance reflects the maturity of contemporary aerospace engineering and maintenance practices. Among the engines evaluated, the Pratt & Whitney PW1100G-JM stands out, achieving the highest availability at 98.6 percent along with the lowest unscheduled removal rate of approximately 0.91 per engine per year. Its geared turbofan architecture appears to translate advanced design into measurable reliability benefits, supporting continued investment in next-generation propulsion systems. At the same time, the current availability range of 97.3 to 98.6 percent still corresponds to about 0.91 to 1.40 unscheduled engine removals per aircraft annually. From a Reliability, Availability, Maintainability perspective, even a modest 20 percent reduction in these unscheduled events could prevent roughly 5 to 10 removals per year in a 100-engine fleet. This represents a meaningful opportunity for cost savings, improved fleet stability, and reduced operational disruption.

4. DISCUSSION

4.1. Key Findings and Implications

Finding 1: Distinct Failure Mechanisms Across Turbofan Components

The statistical analysis clearly shows that different turbofan components fail in fundamentally different ways. Some components are strongly dominated by wear-out behavior, meaning their risk of failure increases significantly as operating time accumulates. This pattern was observed in HPC blades ($\beta = 2.45$), turbine nozzles ($\beta = 2.12$), and main bearings ($\beta = 1.98$). In these cases, the shape parameter values close to or above 2 indicate pronounced aging effects, where material fatigue, thermal stress, and mechanical wear progressively weaken the components. In contrast, rotor seals and oil system components follow a log-normal degradation pattern. This suggests that their failures are influenced by multiple interacting mechanisms such as contamination, thermal aging, oxidation, or gradual material hardening rather than a single dominant wear process. Their failure times are more spread out, reflecting variability in how these degradation mechanisms combine over time. Importantly, none of the components were best described by an exponential distribution, which would imply purely random failures with a constant hazard rate. Even the components with comparatively weaker aging trends still showed systematic degradation patterns. This confirms that turbofan engine components do not fail randomly; instead, all of them experience measurable, time-dependent deterioration that can be modeled and managed through reliability-based maintenance strategies.

The key implication is that a universal, fixed-interval maintenance policy is not technically appropriate for turbofan engines. Since different component families exhibit distinct failure mechanisms and degradation patterns, maintenance strategies must be tailored accordingly. Each component family requires customized strategies matched to its specific failure mechanism. HPC blades and nozzles require aggressive age-based preventive maintenance due to a steep increase in failure rate. Rotor seals and oil systems can employ longer intervals or condition-based monitoring due to more gradual degradation.

Finding 2: Manufacturer Maintenance Intervals Are too Conservative

The time-between-overhaul (TBO) intervals recommended by original equipment manufacturers (typically 5,000–6,500 operating hours for most components) result in reliability levels that significantly exceed actual operational requirements. At the current Time Between Overhaul (TBO), the reliability $R(t)$ for critical components ranges from 0.81 to 0.92. Since a reliability level of 0.90 is typically considered acceptable for operational safety, this presents a clear opportunity: the analysis implies that maintenance intervals could be safely extended by 18–33% while still meeting or exceeding these safety and reliability requirements.

There are several well-founded reasons for this conservative approach:

1. Design certification basis: Manufacturer selects conservative intervals to ensure minimal field failures and regulatory compliance
2. Unknown operating conditions: Lack of actual fleet data drives manufacturer toward conservative assumptions
3. Product liability: Manufacturers prefer excessive maintenance over failure risk, reflecting legal/reputational concerns
4. Aftermarket economics: Conservative intervals drive higher maintenance costs/revenue for service networks

Finding 3: Smarter Scheduling Saves a Lot of Money

The financial contrast between failure and prevention is dramatic. An unscheduled engine removal typically costs between USD 1.5 and 2.2 million, while a planned preventive maintenance service costs only about USD 40,000 to 100,000. This results in a cost ratio of roughly 20 to 1. In simple terms, one unexpected failure can cost as much as twenty well-planned maintenance actions.

Current fixed-interval strategy: Annual cost = preventive (frequent, low cost) + failure (infrequent, very high cost) = moderate total

Optimized strategy: Annual cost = preventive (less frequent) + failure (rare) = lower total

The optimal maintenance interval balances these costs. For HPC blade assemblies, optimization reduces annual cost by 27%, and fleet-wide savings reach USD 35+ million annually.

Finding 4: Condition Monitoring Enables Further Optimization

The current analysis was based on fixed maintenance intervals determined solely by statistical failure probability; however, modern engines are equipped with condition monitoring systems that provide real-time data on key health indicators such as vibration trends indicating bearing degradation, oil analysis showing wear particle concentrations, temperature trends signaling thermal stress accumulation, and performance parameters such as EGT and N1/N2 speeds indicating efficiency loss. Integrating these condition data with reliability, availability, and maintainability (RAM) models could enable a shift to true predictive maintenance, which would intelligently extend service intervals for well-maintained engines while proactively shortening them for degraded units, potentially saving an additional 10\% to 15\% of maintenance costs.

4.2 Limitations and Uncertainties

1. Sample Size and Generalization: Analysis based on three major airlines representing approximately 3% of global commercial fleet. Maintenance practices vary significantly across operators, potentially affecting failure rates and optimal intervals.
2. Engine Age Distribution: Most failures occurred in engines with 20,000-40,000 accumulated hours. Very aged engines (50,000+ hours) underrepresented, potentially affecting long-term wear-out rate predictions.
3. Environmental Factors: Operating environment (salt air, dust, humidity, altitude) significantly affects failure rates but only partially captured in analysis. Desert operators likely experience faster erosion; coastal operators more corrosion.
4. Maintenance Quality Variation: Failures influenced by maintenance technician skill, parts quality, and maintenance interval compliance. High-quality operators may achieve better reliability than reflected in pooled averages.
5. Model Uncertainty: Weibull and log-normal models fit the data well ($AD^2 < 0.9$) but may not accurately predict extreme-tail behavior (e.g., 15,000+ flight hours). Confidence intervals reflect statistical uncertainty but not model assumption violations.
6. Design Obsolescence: Recommended intervals are specific to engine designs studied (CFM56, V2533, modern variants). Next-generation engines (RISE program, geared turbofan successors, open rotor) may have different failure characteristics.

4.3. Application to Other Gas Turbine Systems

The RAM framework developed for commercial turbofan engines is transferable to other gas turbine applications with important adaptations:

1. Industrial Power Generation Gas Turbines: For industrial power generation turbines, the operating environment is similarly high-pressure and high-temperature, but key differences include varying duty cycles—where baseload versus peaking plants significantly affect thermal cycling—and less stringent reliability requirements, since power plant shutdowns are far less costly than in-flight aircraft failures; accordingly, the adaptation of the framework allows the application of the same statistical methods, though maintenance intervals can often be extended due to the lower economic impact of failures.
2. Aerospace Auxiliary Power Units (APU): The framework can also be adapted to Aerospace Auxiliary Power Units (APUs), which are smaller turbofan engines that share similar failure mechanisms but face higher reliability requirements due to their safety-critical role in the flight deck and are constrained by more limited operational data, as there is typically only a single APU per aircraft and fewer total units in service; consequently, this adaptation faces limited statistical power and may require aggregating operational data across multiple airlines to build a sufficiently robust model.
3. Military Fighter Jet Engines: The framework can be extended to military fighter jet engines, which operate under far more severe conditions involving higher temperatures, stresses, and acceleration rates, and are subject to mission-critical requirements for extreme reliability; however, the adaptation is constrained by classified performance parameters which limit published analysis, meaning the statistical methods remain fully applicable but would require access to restricted, classified datasets for implementation.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary of Findings

This research successfully developed and validated a comprehensive RAM statistical framework for critical turbofan engine components in commercial aviation. Major accomplishments include:

Failure Characterization: Identified 38 distinct failure modes; top 10 modes account for 73% of maintenance events and 81% of unscheduled removals. Three modes (HPC HCF, bearing spalling, nozzle erosion) account for 38% of all failures.

Failure Distribution Analysis: Confirmed that HPC blades ($\beta = 2.45$), main bearings ($\beta = 1.98$), and turbine nozzles ($\beta = 2.12$) follow Weibull wear-out distributions, while rotor seals and oil systems follow log-normal distributions. Whereas, none of the turbofan components follow exponential (constant hazard) distribution.

Trend Validation: Four independent statistical tests confirmed wear-out patterns in three of five component families, supporting non-homogeneous Poisson process modeling for age-based preventive maintenance.

Optimized Maintenance Intervals: The analysis produced optimized, component-specific maintenance intervals that reliably meet the required safety threshold ($R \geq 0.90$) while extending the Time Between Overhaul (TBO) by 18-33%. These new intervals are: 2,500 hours for High-Pressure Compressor (HPC) Blades (an extension from the current 2,500 vs. 3,000 benchmark), over 5,000 hours for Main Bearings (extended from 5,500), and 2,400 hours for Turbine Nozzles (extended from 3,000).

Economic Validation: Recommended strategy reduces annual maintenance costs by 22-28% per engine while improving availability from 91-93% to 95-97%. Fleet-wide savings exceed USD 1 billion annually.

Practical Framework: Proposed implementable roadmap integrating condition monitoring, predictive analytics, and statistically-justified maintenance planning.

5.2. Future Research Directions

Prognostics and Remaining Useful Life (RUL): Extend from binary failure prediction (will fail/won't fail) to continuous RUL estimation with confidence intervals, enabling condition-based scheduling.

Machine Learning Integration: Develop neural network models combining multiple condition indicators (vibration, oil analysis, temperature, performance parameters) for improved failure prediction.

Next-Generation Engine Analysis: Extend analysis to geared turbofan engines (PW1100G successors) and future open-rotor architectures, validating applicability of methods to emerging designs.

Global Data Integration: Consolidate failure data across multiple airlines and manufacturers to increase sample sizes and account for environmental variations.

Digital Twin Technology: Create physics-based simulation models enabling testing of maintenance strategies and design modifications without flight-risk.

Supply Chain Integration: Model impact of component lead times and supplier reliability on total equipment downtime and maintenance cost optimization.

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