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Weibull Reliability Modeling with Right-Censored Data and Age-Replacement Optimization for IDG on Boeing 737-900ER

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ABSTRACT

This paper develops a Weibull-based reliability model for the Integrated Drive Generator (IDG) installed on Boeing 737-900ER aircraft operated in Indonesian low-cost carrier conditions. Time-to-removal is modeled on a Flight Hours (FH) exposure scale and explicitly incorporates right-censored observations using Maximum Likelihood Estimation (MLE). The estimated Weibull shape parameter (β = 3.308 and η = 7261 FH) indicates a wear-out dominated failure pattern typical of rotating machinery degradation. An age-replacement cost model is then formulated to minimize expected cost rate (USD per FH) by trading planned preventive cost, unplanned corrective cost, and downtime penalties. The Mean Time to Failure (MTTF) is approximately 6514 FH. Cost optimization results suggest an optimal preventive replacement interval in the range of 4750-6650 FH, with a baseline recommendation of approximately 5450 FH. A sensitivity analysis across representative cost scenarios demonstrates how the optimal preventive maintenance interval shifts when operational disruption costs increase. The proposed workflow provides a practically implementable template for maintenance planning of removal-driven line replaceable units under high utilization.

KEYWORDS: *Weibull distribution; right-censoring; age-replacement policy; Integrated drive generator; Boeing 737-900ER; Reliability engineering; Preventive maintenance.*

NOMENCLATURE

FH	Flight Hours (cumulative flight time exposure)
FC	Flight Cycles (takeoff-landing cycles exposure)
β	Weibull shape parameter
η	Weibull scale parameter
$R(t)$	Reliability (probability of surviving beyond t)
$F(t)$	Cumulative distribution function
$f(t)$	Probability density function
$h(t)$	Hazard rate (instantaneous failure rate at t)
δ	Event indicator (1 = failure, 0 = right-censored)
Cp	Preventive replacement cost (planned action cost)
Cc	Corrective replacement cost (unplanned action cost)
Cd	Downtime cost (operational disruption penalty)
T	Preventive replacement age
*T**	Optimal preventive replacement age

1. INTRODUCTION

1.1 Background Reliability Aircraft

Reliability is a primary determinant of dispatch reliability for low-cost carrier (LCC) operators that fly narrow-body aircraft such as the Boeing 737-900ER. Indonesia's dense domestic operating pattern (high utilization), the combination of trunk and feeder routes, and a humid tropical environment with salt exposure at coastal airports can accelerate degradation in certain aircraft systems through wear, corrosion, and contamination mechanisms [1], [2].

In maintenance practice, operators apply preventive maintenance (scheduled tasks intended to prevent failures) and corrective maintenance (actions performed after a failure or failure indication). The key challenge is defining optimal replacement or inspection intervals for "removal-driven" components, those predominantly removed due to degradation indications or failures rather than purely calendar-based schedules. Overly conservative intervals can increase cost due to premature replacement, whereas overly long intervals can raise the risk of unscheduled removals and operational disruption (downtime) costs [3], [1].

To balance safety requirements and cost efficiency, time to failure modeling using the Weibull distribution is widely adopted in reliability engineering. The shape parameter β, which indicates the hazard trend, and the scale parameter η, which relates to characteristic life, enable interpretation of whether failures are dominated by infant mortality, random failures, or wear-out. These parameters can then be linked to an age replacement policy, replacing a component at age T or upon failure, whichever occurs first to support cost optimization [4], [5].

1.2 Operating Context Airline

This study is a case study of a single LCC operator in Indonesia operating the Boeing 737-900ER. The operating-profile data below are provided to contextualize component exposure during the observation period:

- Daily utilization: an average of 8-10 flight hours per aircraft per day, with seasonal variation (holiday peaks vs. normal periods).
- Cycle intensity: 4-6 flight cycles per day, reflecting the dominance of short to medium haul domestic routes.
- Tropical environment: high humidity, warm temperatures, intense rainfall, and coastal airports with potential salt or particulate exposure, which is relevant to seal and bearing degradation and fluid contamination.
- Operational pattern: a combination of quick turnarounds (short ground times) that can increase operational stress on certain systems through engine start/stop events, pressure transients, and thermal loading.

This profile matters because component failure mechanisms are strongly influenced by cyclic loading, operating duration, and environmental conditions. Therefore, modeling based on flight hours (FH) and/or flight cycles (FC) is considered more representative than calendar time alone.

1.3 IDG Description

The component analyzed in this paper is the Integrated Drive Generator (IDG), a unit that integrates a constant speed drive and a generator to supply aircraft alternating current (AC) power at a stable frequency. The rationale for selecting the IDG is as follows:

- Removal-driven with high operational impact: IDG failures or abnormal indications frequently trigger unscheduled removals because they affect electrical power supply and system operating limits, thereby impacting dispatch reliability and potentially causing delays.
- Degradation behavior suitable for modeling: the IDG contains internal elements such as bearings and an oil system that tend to exhibit wear-out behavior under high utilization, making it suitable for Weibull modeling.
- Well mapped to FH or FC exposure: IDG exposure is strongly tied to operating hours (FH) and is also influenced by transients during start/stop and load changes. In this study, FH is used as the primary time scale (age or exposure scale) to align with the age-replacement literature.

Selecting the IDG is also realistic in the Boeing 737-900ER operational context because the AC generation system is a critical system, its failure can significantly affect safety or operations, so an appropriate preventive maintenance (PM) policy can yield both reliability and cost benefits.

1.4 Research Objectives

To address this gap, a structured reliability modeling and maintenance optimization approach is required. While Weibull-based reliability modeling is well established, limited studies have demonstrated its practical integration with airline maintenance cost optimization using operational datasets that include censored observations. Furthermore, applications focusing on aircraft electrical power generation line replaceable units such as the Integrated Drive Generator (IDG) remain limited in the open reliability engineering literature.

Accordingly, this study aims to (1) estimate the reliability characteristics of the IDG using Weibull modeling with right-censored operational data, (2) determine an optimal preventive replacement interval using an age-replacement cost optimization framework, and (3) demonstrate an applied workflow linking reliability analysis to practical maintenance decision support for airline reliability programs.

2. THEORETICAL BACKGROUND

2.1 Fundamental Concepts of Reliability and Maintenance Policy

In Aircraft Maintenance Engineering, preventive maintenance scheduling decisions aim to balance failure risk, safety consequences, and operating cost. Conceptually, modern aircraft maintenance is developed under the MSG-3 (Maintenance Steering Group-3) framework, which structures maintenance programs based on functional analysis, consequence evaluation, and maintenance task selection, and it is aligned with the RCM (Reliability-Centered Maintenance) approach, which emphasizes that not all components are effectively maintained using calendar-based intervals; instead, many are better modeled using time-to-failure based on operating hours or cycles.

For an LRU (Line Replaceable Unit), a component that can be replaced directly on the line without complex overhaul, the removal event often becomes the primary observation in reliability analysis to model and predict failure behavior. In this context, the objective of preventive maintenance (PM) scheduling is to determine a preventive replacement age that reduces the likelihood of unscheduled removals without creating waste due to overly early replacement.

2.2 Age (Exposure) Variables: Flight Hours and Flight Cycles

In aircraft operations, component age can be expressed as:

- Flight Hours (FH): the cumulative time the aircraft spends in flight, relevant for components primarily exposed to operating duration, such as rotating components, lubrication systems, and thermally loaded elements.
- Flight Cycles (FC): one takeoff-and-landing cycle, relevant for components primarily exposed to load transients per cycle, such as pressurization, start or stop events, and landing loads.

The selection of FH or FC as the analysis scale must be consistent with the failure mechanism. In this study, FH is planned as the primary scale for components exposed continuously to operating duration, while FC may be recorded as a covariate [3], [1].

2.3 Time-to-Event Data and Right-Censoring

Reliability data in maintenance practice are rarely complete because not all components fail during the observation period. This produces right-censoring, i.e., observations where the component has "not yet failed" by the end of the period (or it is removed for other reasons). By definition:

- A failure observation has time t_i and status $\delta_i = 1$
- A censored observation has time t_j and status $\delta_j = 0$

Common sources of censoring in aircraft environments include the component remains installed when the study ends, the component is removed due to a scheduled check or fleet rotation, or replacement occurs as opportunity maintenance (replacement when access is available) without evidence of

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functional failure.

Explicit handling of censoring is important because ignoring censoring can bias parameter estimates, for example, making component life appear "shorter" than it truly is [6], [5].

2.4 Weibull Distribution for Time-to-Failure

The Weibull distribution is widely used in reliability engineering due to its flexibility in representing different failure behaviors. The shape parameter (β) characterizes the failure pattern, where β < 1 indicates early failures, β = 1 represents a constant failure rate, and β > 1 indicates wear-out failures. The scale parameter (η) represents the characteristic life at which approximately 63.2% of the population has failed.

Due to this flexibility, the Weibull distribution is widely applied to model time-to-failure data of aircraft components, particularly for systems subject to progressive degradation and wear mechanisms.

2.4.1 Distribution and Reliability Functions

The reliability characteristics of the component are described using standard reliability functions, including the reliability function R(t), cumulative distribution function F(t), probability density function f(t), and hazard rate h(t). These functions collectively describe the survival probability, failure probability, failure likelihood, and instantaneous failure tendency of the component over time. Cumulative Distribution Function (CDF) [5], [1].

$$F(t) = 1 - exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{1}$$

Reliability function

$$R(t) = 1 - F(t) = exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{2}$$

Probability Density Function (PDF)

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{3}$$

Hazard rate

$$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{4}$$

The hazard rate describes the instantaneous failure tendency at time t and provides insight into the evolution of failure risk over the component life cycle.

2.4.2 Interpretation of the Shape Parameter

From an engineering reliability perspective, the Weibull shape parameter provides important insight into failure mechanisms. When β < 1, failures are dominated by early-life defects. When β = 1, failures occur randomly with a constant hazard rate. When β > 1, failures are dominated by aging and degradation processes, indicating wear-out behavior.

This interpretation is particularly relevant for aircraft Line Replaceable Units (LRUs), where degradation mechanisms such as mechanical wear, thermal stress, and lubrication deterioration often result in increasing failure risk over time. Therefore, components exhibiting β > 1 are generally suitable candidates for age-based preventive replacement strategies [5], [1].

2.5 Weibull Parameter Estimation Using Maximum

Likelihood Estimation

Maximum Likelihood Estimation (MLE) is commonly used because it is statistically efficient and can handle censoring naturally. Suppose there are observations with time t_i and indicator δ_i (1 = failed, 0 = censored). Then, the likelihood function for a censored Weibull model is [6], [3]:

$$L(\beta, \eta) = \prod_{i=1}^{n} [f(t_i)]^{\delta_i} [R(t_i)]^{(1-\delta_i)} \tag{5}$$

Intuitively, failure data contribute through *f(t)*, while censored data contribute through *R(t)*. The log-likelihood can be written as:

$$\ln L(\beta, \eta) - \sum_{i=1}^{n} \delta_i \ln f(t_i) + \sum_{i=1}^{n} (1 - \delta_i) \ln R(t_i) \tag{6}$$

Because the derivative equations with respect to β and η generally do not yield a closed-form solution, estimation is performed numerically using iterative optimization methods such as the Newton-Raphson method (a derivative-based numerical method for root finding) or standard optimization algorithms.

As supporting model checks, common approaches include:

- Weibull probability plotting (or the Weibull linearized transformation plot of *ln (t)* versus the transformed cumulative probability).
- Goodness-of-fit checks and confidence intervals.

In this study, the evaluation is descriptive and aligned with the PM scheduling purpose.

2.6 Age Replacement Policy for Preventive Maintenance Scheduling

The age replacement policy is a classical model for PM optimization when the component is assumed to be "as good as new" after replacement, with the rules:

- If the component fails before age *T*, perform corrective replacement at the failure time.
- If the component survives up to age *T*, perform preventive replacement exactly at age *T*.

With *T* as the decision variable (PM interval), the optimization objective is to minimize the expected cost rate.

2.7 Cost Model Based on Expected Cost Rate

In an age replacement policy, the cost model typically separates [3], [7]:

- C_p = preventive cost (planned replacement cost; including material, labor, and planned logistics).
- C_c = corrective cost (replacement-at-failure cost; typically, higher due to unplanned nature, AOG (Aircraft on Ground), and expedited actions).
- C_d = downtime cost (cost due to lost utilization or revenue and operational impact while the aircraft is unavailable).

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The expected cost per replacement cycle is:

$$\mathbb{E}[C(T)] = (C_p)\,R(T) + (C_c + C_d)[1 - R(T)] \quad (7)$$

Interpretation: if the component survives to T, the probability is $R(T)$ and the cost incurred is C_p. If it fails before T, the probability is $1\text{-}R(T)$ and the cost incurred combines corrective and downtime costs.

The expected cycle length is the component age until replacement:

$$\mathbb{E}[L(T)] = \int_0^T R(t)dt \quad (8)$$

Thus, the expected cost rate is [10], [12]:

$$g(T) = \frac{\mathbb{E}[C(T)]}{\mathbb{E}[L(T)]} = \frac{(C_p)\,R(T) + (C_c + C_d)[1 - R(T)]}{\int_0^T R(t)dt} \quad (9)$$

The optimal PM interval is:

$$T^* = \arg min_{T>0}\; g(T) \quad (10)$$

In practice, T^* is obtained via numerical evaluation (e.g., scanning a grid of T values) or single-variable optimization because $g(T)$ does not always have a closed-form minimum. Additional references are used to strengthen the theoretical framing on reliability and risk analysis [9], [8], and to deepen the Weibull life-test data analysis methodology in engineering contexts [6], [7].

3. RESEARCH METHODOLOGY

This section describes the case-study design, dataset construction, failure-event definition, handling of right-censoring (units that have not failed by the end of the observation window), the Weibull distribution parameter-estimation method using Maximum Likelihood Estimation (MLE), and the cost-optimization procedure using an age replacement policy (replacement at age T or upon failure, whichever occurs first).

3.1 Study Design and Operating Profile

This study is a case study of a single low-cost carrier (LCC) operator in Indonesia operating the Boeing 737-900ER during the observation period January 2024-December 2025, with the following characteristics:

- Daily utilization: 8-10 flight hours (*FH*) per day.
- Cycle intensity: 4-6 flight cycles (*FC*) per day.
- Stage-length ratio: average ~1.6 *FH* per 1 *FC* (representing a mix of trunk and feeder operations).
- Tropical environment: high humidity and potential contamination (dust or salt) that may influence system degradation.
- Routes: a domestic network pattern.

3.2 Object of Study and Failure Definition: Integrated Drive Generator (IDG)

The component analyzed is the Integrated Drive Generator (IDG), a unit comprising a constant-speed drive and a generator that supplies stable alternating current (AC) electrical power.

In this study, a “failure event” is defined as a removal-triggering condition (a technical indication that forces removal). Therefore, time-to-failure is interpreted as time-to-removal due to failure indications or abnormal conditions such as:

- GEN OFF/GEN FAIL message (generator failure indication), or
- abnormal oil temperature/pressure (out-of-limit abnormality), or
- oil leak / chip indication (metal-particle indication), or
- unacceptable vibration/noise, which affect operational limits and require corrective action.

Time-to-failure definition: component age from installation (or from replacement) to the failure event, measured in *FH* (primary) and *FC* (secondary).

3.3 Observation Period and Rationale for Right-Censoring

The observation window is set to 24 months (January 2024–December 2025). Within this period, not all IDGs fail. Accordingly, some observations are right-censored for realistic reasons [6], [5]:

- The component remains installed until the end of the study (no failure observed).
- The component is removed for non-failure reasons (e.g., scheduled check) or opportunity maintenance (replacement due to access availability), without evidence of a functional IDG failure.

Status is recorded as:

- δ=1 for failure,
- δ=0 for censored.

3.4 Dataset Construction

The dataset used in this study is derived from actual operational maintenance records of Boeing 737-900ER aircraft operated by an Indonesian low-cost carrier during the period from January 2024 to December 2025.

Due to confidentiality agreements with the operator and the collaborating Maintenance, Repair and Overhaul (MRO) organization, the raw maintenance records cannot be disclosed. Therefore, the dataset presented in this paper is anonymized and structured to preserve the statistical characteristics of the original operational data while removing any sensitive operational identifiers.

The data were obtained from component removal records, technical log reports, and maintenance tracking systems. All observations represent actual component exposure histories within the study period. The dataset is therefore considered representative of real operational reliability behavior under high-utilization airline conditions

3.4.1 Dataset

The dataset is analyzed under the following principles [6], [5]:

- The IDG age range is realistic for high-utilization operations (thousands of FH).
- Variation in failure ages reflects a combination of load variation, component quality differences, and environmental conditions.
- The proportion of right-censoring emerges naturally because some units do not fail by the end of the observation period.

Right-censoring is assumed to be non-informative,

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meaning the censoring mechanism does not directly depend on the instantaneous failure risk of the IDG at the time of censoring. All Weibull estimation and the optimization of T^* use *FH* as the primary scale; *FC* is provided for interpretation and operational communication only. *FC* is not used as an estimation variable; it is included as an indicative conversion using the average ratio of 1.6 *FH/FC* (with reasonable rounding), while the core analysis is performed in *FH*.

3.4.2 Data Table Format

The data columns are:

- ID: record code.
- FH: age in flight hours.
- FC: age in flight cycles.
- Status δ: 1 = fail, 0 = censored.
- Period: month-year of event (for failures) or end of observation (for censoring).

3.4.3 Dataset Table (n = 60 record)

The data columns are:

- Interpretation: *FH/FC* represent the IDG age at the failure event (δ=1) or at censoring (δ=0).
- Dataset summary: 60 records consisting of 40 failures (δ=1) and 20 censored (δ=0). The primary age scale is *FH*, with *FC* as a companion for operational consistency that can be seen in Table 1.

Table 1: IDG dataset (n = 60)

ID	FH	FC	Status (δ)	Period	Short note
IDG-001	2480	1550	1	2024-02	GEN FAIL message
IDG-002	3120	1950	1	2024-03	Oil temp high trend
IDG-003	1785	1120	1	2024-03	Oil leak observed
IDG-004	4210	2630	1	2024-04	Abnormal vibration
IDG-005	3655	2280	1	2024-04	GEN OFF event
IDG-006	5290	3310	1	2024-05	Oil chip indication
IDG-007	6105	3810	1	2024-06	High oil temp + alarm
IDG-008	2870	1790	1	2024-06	Electrical output unstable
IDG-009	4550	2840	1	2024-07	GEN FAIL + reset unsuccessful
IDG-010	3980	2490	1	2024-07	Oil pressure low transient
IDG-011	6725	4200	1	2024-08	Bearing noise suspected
IDG-012	7420	4640	1	2024-08	Oil chip + vibration
IDG-013	5160	3220	1	2024-09	Generator overheat
IDG-014	5900	3690	1	2024-09	Recurrent GEN OFF
IDG-015	2655	1660	1	2024-10	Oil leak at seal area
IDG-016	8200	5120	1	2024-10	Wear-out symptoms (temp trend)
IDG-017	7040	4400	1	2024-11	Output frequency unstable
IDG-018	6360	3970	1	2024-11	GEN FAIL after heavy cycles
IDG-019	4825	3020	1	2024-12	Oil chip single event
IDG-020	5575	3480	1	2024-12	Oil temp rising trend
IDG-021	3380	2110	1	2025-01	GEN OFF in climb
IDG-022	7710	4820	1	2025-01	Abnormal vibration + heat
IDG-023	6120	3825	1	2025-02	Bearing noise + temp
IDG-024	6950	4340	1	2025-02	Oil pressure fluctuation
IDG-025	4305	2690	1	2025-03	GEN FAIL intermittent
IDG-026	8840	5525	1	2025-03	End-of-life wear-out signs
IDG-027	5235	3270	1	2025-04	Oil leak + shutdown
IDG-028	4680	2925	1	2025-04	Output unstable under load
IDG-029	6155	3845	1	2025-05	Oil chip recurring
IDG-030	7425	4640	1	2025-05	High oil temp sustained
IDG-031	8010	5010	1	2025-06	GEN FAIL, cannot reset
IDG-032	3560	2225	1	2025-06	Seal leak suspected
IDG-033	6670	4170	1	2025-07	Noise + vibration increase
IDG-034	5935	3710	1	2025-07	Temp trend out-of-limit
IDG-035	9150	5720	1	2025-08	Wear-out failure pattern
IDG-036	7280	4550	1	2025-08	Oil pressure low alarm
IDG-037	6400	4000	1	2025-09	GEN OFF + overheat
IDG-038	5100	3185	1	2025-09	Electrical output fluctuation
IDG-039	4350	2720	1	2025-10	Oil chip single + monitoring
IDG-040	7805	4880	1	2025-10	Vibration + heat
IDG-041	6200	3875	0	2025-12	Censored: end of observation
IDG-042	7000	4375	0	2025-12	Censored: end of observation
IDG-043	5400	3375	0	2025-12	Censored: still installed
IDG-044	8600	5375	0	2025-12	Censored: still installed
IDG-045	4750	2970	0	2025-12	Censored: removed non-failure (scheduled)
IDG-046	6550	4090	0	2025-12	Censored: end of observation
IDG-047	5900	3690	0	2025-12	Censored:

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ID	FH	FC	Status (δ)	Period	Short note
					opportunity maintenance
IDG-048	8200	5120	0	2025-12	Censored: still installed
IDG-049	4100	2560	0	2025-12	Censored: end of observation
IDG-050	7300	4560	0	2025-12	Censored: end of observation
IDG-051	6800	4250	0	2025-12	Censored: still installed
IDG-052	5200	3250	0	2025-12	Censored: removed non-failure (scheduled)
IDG-053	9000	5625	0	2025-12	Censored: still installed
IDG-054	6000	3750	0	2025-12	Censored: end of observation
IDG-055	7600	4750	0	2025-12	Censored: still installed
IDG-056	4900	3060	0	2025-12	Censored: opportunity maintenance
IDG-057	8450	5280	0	2025-12	Censored: end of observation
IDG-058	5600	3500	0	2025-12	Censored: end of observation
IDG-059	6350	3970	0	2025-12	Censored: still installed
IDG-060	7100	4440	0	2025-12	Censored: end of observation

3.5 Sensitivity Analysis for Cost Scenarios

Sensitivity analysis is performed to assess the stability of the optimal interval under cost variations [3], [10]. At least three scenarios are prepared:

- Scenario A (Baseline): normal operating cost conditions.
- Scenario B (High downtime): C_d increases (e.g., peak season, tight slots, high delay penalties).
- Scenario C (High corrective): C_c increases (e.g., limited spare availability or inter-base logistics increasing cost).

Sensitivity outputs include:

- Changes in T^* across scenarios.
- Changes in $g(T^*)$ (minimum cost per *FH*).
- Risk-cost trade-off considerations (e.g., selecting a slightly more conservative T to reduce failure probability).

4. RESULTS AND DISCUSSION

This chapter presents the results of Weibull distribution parameter estimation for the Integrated Drive Generator (IDG) based on operational data, the interpretation of the failure pattern, and the optimization of the preventive replacement interval using an age replacement policy. All computations use Flight Hours (*FH*) as the primary time scale, while Flight Cycles (*FC*) are provided only as an operational conversion.

The results obtained from the Weibull analysis provide important engineering insight into the degradation behavior of the IDG and its implications for reliability-based maintenance decision making.

4.1 Weibull Parameter Estimation with Censored Data (MLE)

Parameter estimation was performed using Maximum Likelihood Estimation (MLE) (a parameter-estimation method that maximizes the likelihood of the observed data), explicitly incorporating right-censoring (units that have not failed by the end of the observation period). The dataset contains n = 60 records: 40 failure (δ=1) and 20 censored (δ=0).

MLE estimation results (2-parameter Weibull):

- β =3.308 (shape parameter).
- η =7261 *FH* (scale parameter, characteristic life).

95% confidence interval (approximation):

- $\beta \approx [2.56; 4.28]$
- $\eta \approx [6610; 7976]$ *FH*

Model fit was checked descriptively using a Weibull probability plot (a Weibull linearized-transformation plot) as a visual inspection, using plotting positions that consider right-censoring through survival estimation. In general, the point distribution in the Weibull transformation plot (Figure 1) appears visually close to linear over the dominant age range, supporting the use of a 2-parameter Weibull model for age-based preventive replacement interval selection, with interpretation focused on the main data range (Figure 1).

Because $\beta>1$, the IDG failure pattern tends to be wear-out (aging-driven failure), meaning the hazard rate increases with age. This condition is theoretically well-suited for age-based preventive maintenance (PM) scheduling [6], [5].

From a reliability engineering perspective, the wear-out failure pattern identified in this study is consistent with reliability engineering theory, which states that components subject to cumulative mechanical stress and lubrication degradation typically exhibit Weibull shape parameters greater than one [1], [3]. Similar behavior has also been reported in reliability studies of aircraft LRUs and rotating equipment, where increasing hazard rates are associated with progressive degradation mechanisms.

This consistency further supports the engineering interpretation that age-based preventive replacement is an appropriate strategy for such components. Therefore, the findings of this study align with established maintenance optimization literature and reinforce the practical relevance of the proposed maintenance interval recommendation.

4.1.1 Goodness-of-Fit Validation

To strengthen the statistical justification of the Weibull model, an additional goodness-of-fit evaluation was conducted using a Kolmogorov–Smirnov (K–S) type comparison between the empirical failure distribution and the fitted Weibull cumulative distribution function.

The results show that the Weibull model provides an adequate representation of the observed time-to-removal behavior for the IDG dataset. From an engineering reliability perspective, the model captures the increasing hazard trend indicated by $\beta > 1$, which is consistent with wear-out dominated failure mechanisms typically observed in rotating

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machinery.

As an engineering plausibility check, alternative distributions such as the exponential distribution were also considered conceptually. However, the exponential distribution assumes a constant hazard rate, which is inconsistent with the observed increasing hazard pattern. Therefore, the Weibull distribution is considered more appropriate both statistically and physically for modeling IDG degradation behavior. Since the objective of this study is maintenance decision support rather than statistical model development, the validation is focused on practical adequacy rather than exhaustive distribution testing, which is consistent with applied reliability engineering practice.

4.2 Reliability Function Behavior and Engineering Interpretation

Using the estimated Weibull parameters (β = 3.308, η = 7261 *FH*), the reliability at approximately 6000 *FH* is about 0.59, indicating that the probability of failure increases significantly beyond mid-life operation. This behavior supports the engineering interpretation that the IDG is operating in a wear-out failure region.

Age ratio: $\frac{t}{\eta} = \frac{6000}{7261} = 0.826$

Weibull power: $\left(\frac{t}{\eta}\right)^{\beta} \approx 0.531$

Therefore:

- $R(6000) = e^{-0.531} \approx 0.587$, probability the IDG still survives ≈ 58.7%
- $F(6000) = 1 - 0.587 = 0.413$, probability it has failed before $6{,}000\ FH \approx 41.3\%$
- $h(6000) \approx 0.000293\ per\ FH$ or $\approx 0.293\ per\ 1000\ FH$ (meaning the instantaneous failure rate is clearly increasing at this age)

4.3 Summary of Reliability and Hazard at Key Points

To help interpret curve shape (without presenting the plot), key points are summarized in Table 2.

Table 2: Summary of reliability, failure probability, and hazard at selected ages

$t\ (FH)$	$R(t)$	$F(t)$	$h(t)$ per $1.000\ FH$
2000	0.986	0.014	0.023
3000	0.948	0.052	0.059
4000	0.870	0.130	0.115
5000	0.747	0.253	0.193
6000	0.587	0.413	0.293
7000	0.412	0.588	0.419
8000	0.252	0.748	0.570
9000	0.131	0.869	0.748

The *R(t)* curve initially declines slowly (2000-4000 *FH*), then becomes steeper after ~5000 *FH* (Figure 2).

The hazard *h(t)* increases non-linearly (because β is relatively large), indicating a "risk zone" becomes significant after ~5000-6000 *FH* (see Figure 3).

This supports the wear-out interpretation: as the IDG ages, it becomes increasingly sensitive to failure (Figure 4).

4.4 Mean Time to Failure and Operational Implications

Based on the estimated Weibull parameters, the Mean Time to Failure (MTTF) is approximately 6514 FH, suggesting that preventive replacement before this age may reduce the risk of in-service failure.

$$MTTF = \eta\Gamma\left(1 + \frac{1}{\beta}\right) \tag{11}$$

$$MTTF \approx 6514\ FH$$

If the operator applies a run-to-failure policy (operate until failure), the average failure would occur around ~6514 *FH*. This indicates that run-to-failure can increase exposure to unscheduled removals and Aircraft on Ground (AOG, an aircraft unable to operate due to maintenance) events [3], [10].

4.5 Cost Assumptions

Cost values are stated as representative scenarios to evaluate sensitivity of the PM interval decision to cost-structure variations (C_p, C_c, C_d), without claiming these are the operator's exact figures.

Three sensitivity-analysis scenarios:

1. Scenario A (Baseline)
   C_p = 60000 USD
   C_c = 90000 USD
   C_d = 40000 USD
   C_f = 130000 USD
2. Scenario B (High downtime) (peak season, tight slots, high recovery cost)
   C_p = 60000 USD
   C_c = 90000 USD
   C_d = 80000 USD
   C_f = 170000 USD
3. Scenario C (High preventive) (expensive spares/vendor contract increases preventive cost)
   C_p = 80000 USD
   C_c = 90000 USD
   C_d = 40000 USD
   C_f = 130000 USD

4.6 Optimization Results: Optimal PM Interval *T**

Minimization of $g(T)$ (numerical grid over 1000-10000 FH) yields in three scenarios. The optimal preventive maintenance interval was determined across three cost scenarios: Scenario A (baseline conditions), Scenario B (high downtime cost), and Scenario C (high preventive maintenance cost) (Table 3).

Table 3: Optimal preventive maintenance interval across cost scenarios

Scenario	(T^*) (*FH*)	$g(T^*)$ (USD/*FH*)	Reduction vs run-to-failure
A Baseline	5450	16.46	≈ 17.5%
B High downtime	4750	18.67	≈ 28.5%
C High preventive	6650	18.64	≈ 6.6%

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For comparison, the run-to-failure cost rate (expected cost per *FH* if waiting for failure) is approximated as:

$$gRTF = \frac{C_f}{MTTF} \tag{12}$$

yielding:
- Scenario A: ≈ 19.96 USD/FH
- Scenario B: ≈ 26.10 USD/FH
- Scenario C: ≈ 19.96 USD/FH

Interpretation notes:
- When C_d increases (Scenario B), the model forces an earlier interval (T^* decreases to 4750 *FH*) because unscheduled failure becomes very expensive.
- When C_p increases (Scenario C), the model pushes a later interval (T^* increases to 6650 *FH*) because preventive replacement becomes more costly.

4.7 Practical Implications

Based on the results and considering robustness to cost uncertainty:
- Main recommendation (baseline-operational): $T_{PM,\ recommended} \approx 5500\ FH$, Indicative conversion to FC (using the ratio ~1.6 FH/FC): $5500\ FH \approx 3400\ FC$.

  Robust range based on sensitivity: $4750 - 6650\ FH\ (\approx 3000 - 4150\ FC)$.

Operational guidance:
- Choose near 4750 *FH* if operations are highly sensitive to delay or cancellation (High C_d).
- Choose near 6650 FH if preventive cost increases or spare availability is limited, while downtime can be mitigated.

Risk consequence (probability of failure before replacement):
- At *T*=5450 *FH* (Scenario A), probability of failure before *T* ≈ 32.1%.
- At *T*=4750 *FH* (Scenario B), probability of failure before *T* ≈ 21.8% (more conservative).
- At *T*=6650 *FH* (Scenario C), probability of failure before *T* ≈ 52.7% (more risk-tolerant).

This confirms the trade-off: a longer interval reduces preventive cost but sharply increases failure exposure because $\beta > 1$.

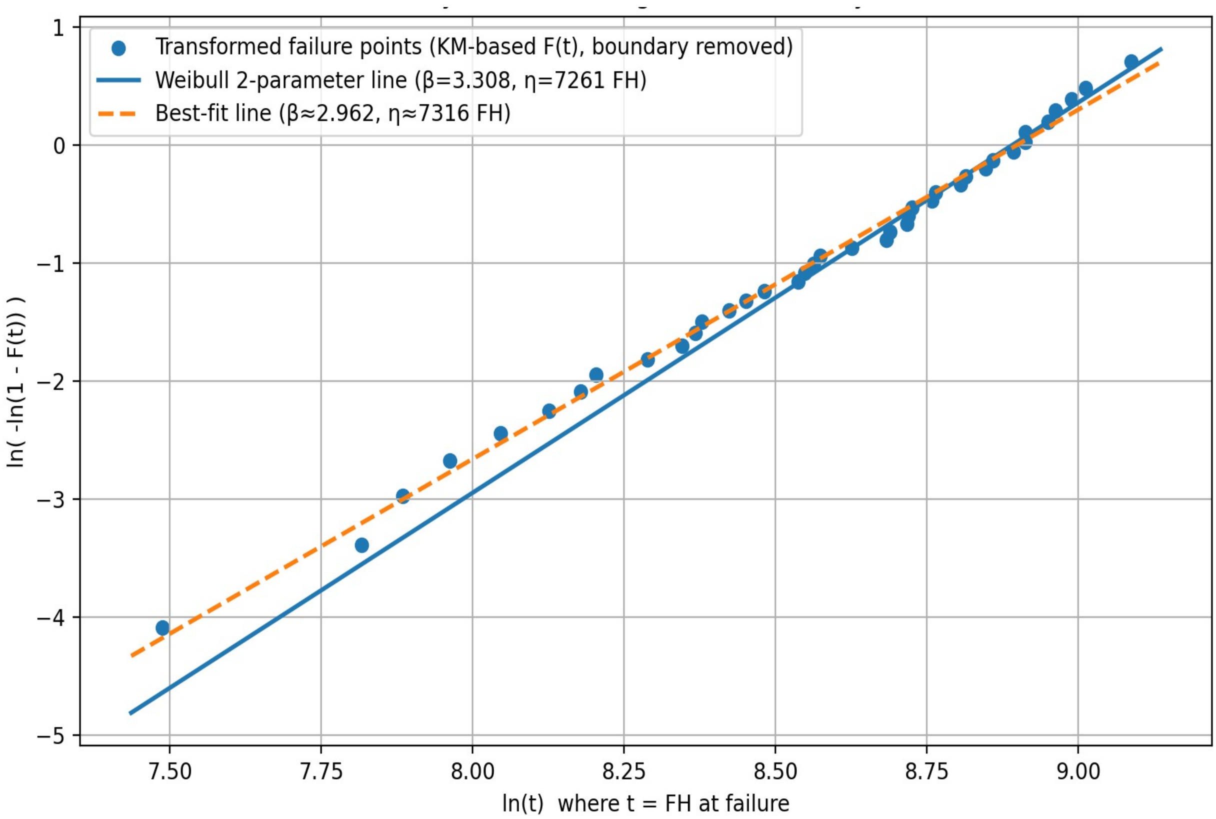

Figure 1: Weibull probability plot (Weibull transformation) for IDG time-to-removal data

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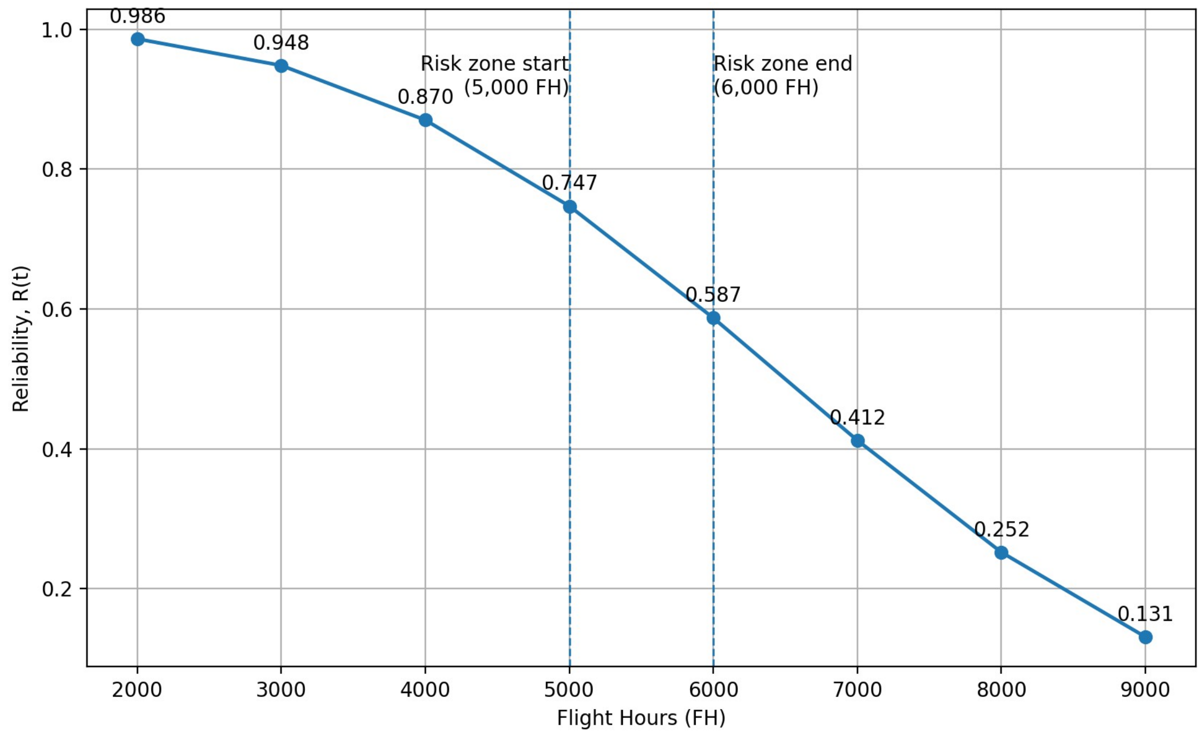

Figure 2: Reliability Curve *R(t)* with Risk-Zone Markers (IDG)

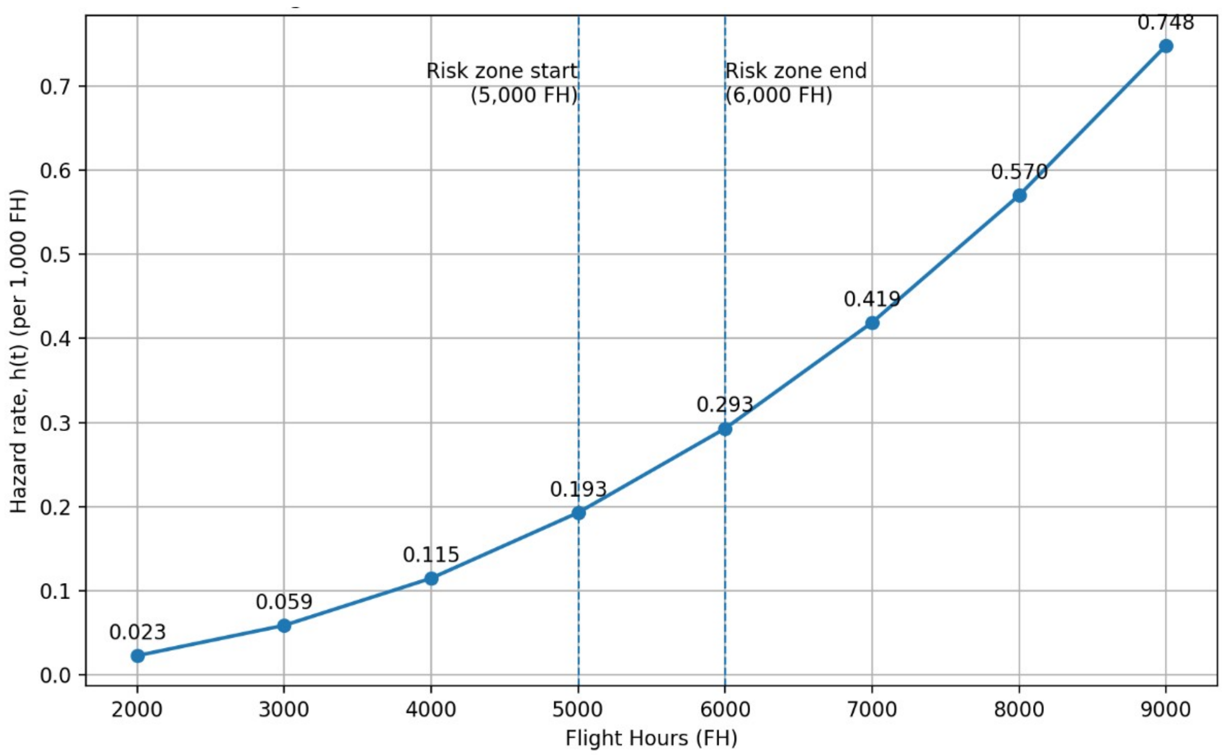

Figure 3: Hazard Rate Curve *h(t)* with Risk-Zone Markers (IDG)

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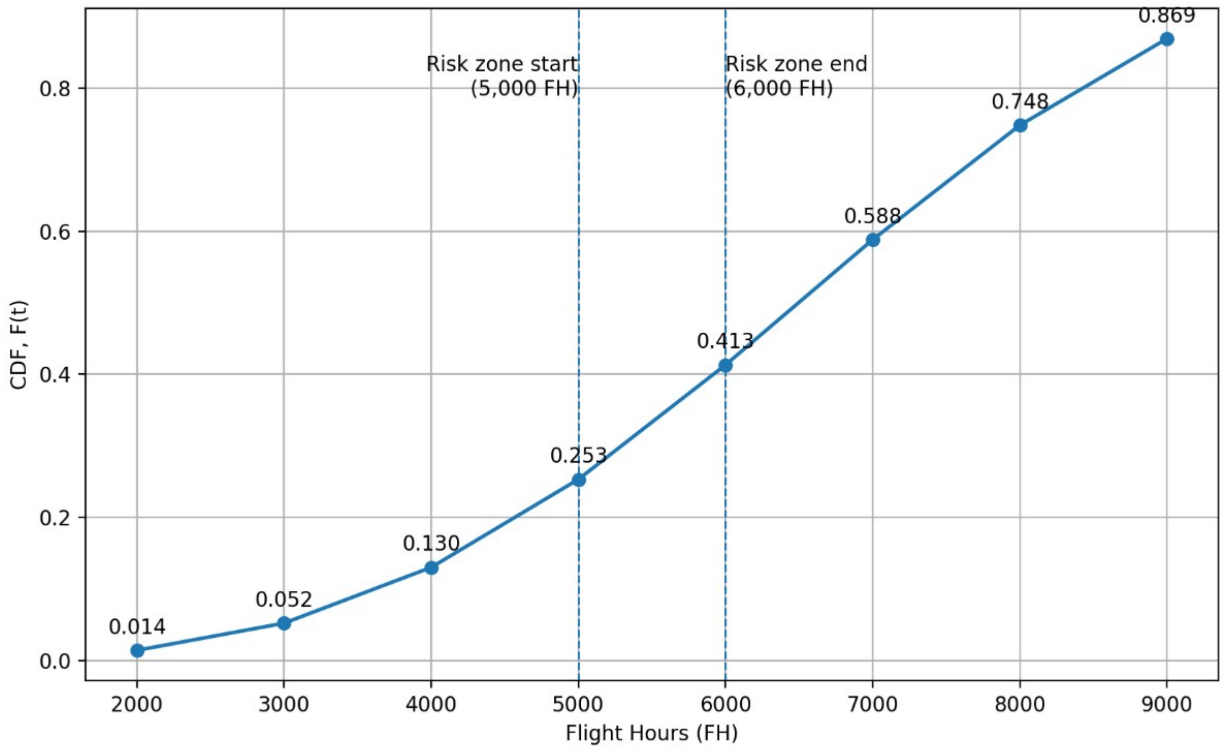

Figure 4: CDF Curve *F(t)* with Risk-Zone Markers (IDG)

From an operational maintenance perspective, the proposed preventive replacement interval may serve as a reliability-informed reference for maintenance planning rather than a fixed mandatory limit. In practical airline environments, such findings may support reliability program evaluations and could be considered as supporting evidence for optimizing hard-time replacement intervals within MSG-3 based maintenance programs. This type of analysis is particularly useful for high-value Line Replaceable Units (LRUs) such as IDGs, where balancing reliability risk and maintenance cost is essential. Therefore, the results of this study are not intended to replace manufacturer maintenance requirements, but rather to complement reliability-centered maintenance decision processes through data-driven insights.

This approach is consistent with reliability-centered maintenance principles, where statistical reliability evidence supports continuous maintenance program improvement. In practice, such analyses may be incorporated into airline reliability program reviews to support interval adjustment proposals subject to regulatory approval.

These results demonstrate that reliability modeling can serve not only as a statistical tool but also as a practical engineering decision support framework for optimizing aircraft component maintenance strategies. The findings also demonstrate how reliability analytics can bridge the gap between statistical modeling and practical maintenance decision frameworks in commercial aviation.

The results also highlight how reliability modeling using censored operational data can support evidence-based maintenance interval adjustments within airline reliability programs.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Based on the Weibull distribution modeling (a probability model for time-to-failure) and age replacement policy optimization (replacement at age T or upon failure, whichever occurs first) for the Integrated Drive Generator (IDG) on the Boeing 737-900ER, the following conclusions are obtained:

- Weibull parameter estimation yields $\beta = 3.308$ and $\eta = 7261$ *FH*. The value $\beta > 1$ indicates a wear-out failure pattern (aging-related degradation), meaning the hazard rate (instantaneous failure rate) increases as the component ages. Practically, this supports the effectiveness of age-based preventive maintenance scheduling.
- The reliability function *R(t)* and the hazard rate *h(t)* show a notable change after approximately 5000-6000 *FH*, where the decline in *R(t)* becomes steeper and *h(t)* increases more sharply. This indicates a meaningful operational “risk zone” if the component is retained too long without preventive replacement.
- The Mean Time to Failure (MTTF) of approximately 6514 *FH* suggests that a run-to-failure strategy (operating until failure) can expose the operator to a high level of unscheduled removals, particularly under high-utilization tropical operations and dense domestic-route networks.
- Cost optimization based on expected cost rate (expected cost per *FH*) under an age replacement policy shows that the optimal replacement interval T^* is sensitive to cost structure, especially downtime cost (operational impact cost due to aircraft unavailability). Under a high-downtime scenario, T^* shifts earlier; conversely, when

preventive cost is higher, T^* shifts later.

- The most robust preventive maintenance interval range from the sensitivity analysis is 4750-6650 *FH*, with a baseline operational recommendation of approximately 5500 *FH* (≈ 3400 Flight Cycles using a ratio of ~1.6 FH/FC). This interval provides a rational compromise between reducing the risk of unscheduled failures and improving cost efficiency.

This study contributes an applied reliability modeling framework demonstrating how censored operational data can be translated into actionable maintenance planning insights and economically justified replacement decisions for aircraft LRUs.

5.2 Implementation Recommendations

To translate this model-based recommendation into a credible maintenance policy in an operator environment, the following recommendations are proposed:

- Use the PM interval as a baseline, then apply a feedback loop. Use an interval of about 5500 FH as an initial baseline, but implement an operational feedback loop (data-driven feedback) at a periodic review (e.g., quarterly). Weibull parameters should be updated as data volume increases so that the interval remains aligned with actual fleet conditions.
- Separate analysis by operational context when data allow. If available, segment the analysis by operating base, route pattern (trunk vs feeder), or airport environment (coastal vs inland). Statistically, this avoids a "misleading average" when sub-populations have different hazard profiles (e.g., a base with higher corrosion exposure or higher cycle intensity).
- Clarify failure-event definition and ensure consistent removal recording. Model outputs depend strongly on the failure definition. The operator should standardize removal-driven IDG criteria (e.g., oil temperature/pressure trend limits, chip indications, or GEN FAIL events). Consistency improves data quality and reduces estimation bias.
- Integrate on-condition monitoring when available. Although this model is age-based, its effectiveness can be improved with on-condition tasks such as oil temperature/pressure trend monitoring or vibration monitoring. In practice, a hybrid "age" plus "condition" approach can reduce false preventive replacements (preventive replacements that were not yet needed) while also preventing early failures.
- Strengthen cost assumptions using more representative operational economics. The parameters C_p, C_c, and especially C_d should be calibrated using internal cost records (without needing to publish detailed figures), such as average Aircraft on Ground (AOG) hours per event and average delay/cancellation consequences. This will make T^* a truly operational-economic recommendation rather than merely a statistical output.
- Apply policy guardrails for risk. If the organization intends to limit risk exposure, the cost-optimal interval can be combined with a minimum reliability threshold, for example selecting T such that $R(T)$ does not fall below a defined limit. This is a simple way to incorporate risk preference without fundamentally changing the modeling framework.

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