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Original Article

RELIABILITY-DRIVEN DEPRECIATION MODELLING FOR AIRCRAFT ENGINE LIFE-LIMITED PARTS

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Highlights:
- a Weibull-based framework is proposed for reliability-driven depreciation of aircraft engine LLPs;
- adaptive cost reduction coefficients are derived from lifecycle-specific failure probabilities;
- the model captures wear-in, stable-operation, and wear-out phases of component degradation;
- part-specific depreciation profiles reveal substantial variation across engine component groups;
- the approach supports more transparent engine appraisal, teardown pricing, and lease-return valuation.

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Abstract. The valuation of aircraft engines in the secondary market is critically influenced by the condition and remaining life of their Life-Limited Parts (LLPs). Traditional approaches often rely on fixed depreciation coefficients that fail to reflect the true operational history or probabilistic risk of failure. This study proposes a lifecycle-aware valuation framework based on Weibull-distributed failure modelling, enabling the computation of adaptive cost reduction coefficients for individual LLPs. Using simulated and operationally realistic data, the model estimates reliability-driven depreciation curves and quantifies residual value degradation over time. Comparative analysis confirms that the Weibull distribution provides superior flexibility and interpretability compared to alternative statistical laws. The methodology captures nonlinear wear-out dynamics and supports the generation of part-specific valuation profiles. The resulting insights enhance the accuracy and transparency of engine appraisal, teardown pricing, and leasing negotiations. This approach offers a practical foundation for integrating condition-based economic modelling with digital asset management systems in aviation).

Keywords: aircraft engine valuation, Weibull distribution, life-limited parts, residual value, aviation asset management.

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Notations

Abbreviations:

BV – base value;
CDF – cumulative distribution function;
CDP – compressor discharge pressure;
CMV – current market value;
EoL – end-of-life;
HPC – high-pressure compressor;
HPT – high-pressure turbine;
IATA – International Air Transport Association;
IFRS – international financial reporting standards;
LLP – life-limited part;
LPT – low-pressure turbine;
MRO – maintenance, repair, and overhaul;
OEM – original equipment manufacturer;
PDF – probability density function;
SV – salvage value.

Variables and functions:

β, λ – parameters of Weibull distribution;
$F(t, \beta, \lambda)$ – cumulative distribution function of Weibull distribution;
$f(t, \beta, \lambda)$ – probability density function of Weibull distribution;
K_{CRC} – cost reduction coefficient;

N – number of historical or simulated observations;
P_{Eng} – the proposed purchase price of the engine in the secondary market;
$P^{(i)}_{Eng,\,actual}$ – actual transaction (realized purchase) price of the th aircraft engine in the secondary market;
R^2 – coefficient of determination;
$\mathbb{R}^+$ – set of positive real numbers;
SV_{Eng} – the estimated salvage value of the engine;
T – random variable representing the time-to-failure of a specific LLP;
t – current time-on-wing of a specific LLP;
V_{new} – new part acquisition value;
V_{res} – part residual value.

1. Introduction

The secondary market for aircraft engines and their LLPs plays a critical role in the global aviation maintenance ecosystem. As fleets mature and leasing models dominate, accurate valuation of used engine components becomes essential for asset managers, lessors, and MRO providers. Traditional valuation practices, however, often rely on fixed depreciation schedules or arbitrary thresholds, which fail to reflect the true operational history, reliability characteristics, or remaining service potential of individual parts.

This disconnects between physical condition and financial assessment creates inefficiencies in teardown pricing, reuse planning, and EoL decisions. More importantly, the lack of probabilistic consideration in depreciation ignores the fact that the likelihood of failure, and hence value loss, changes dynamically over the component's lifecycle.

To address this issue, the proposed solution employs a data-driven approach to valuation based on the Weibull distribution, a proven tool in reliability engineering. Modelling component degradation probabilistically enables the derivation of an adaptive cost reduction coefficient that reflects evolving failure risk as a function of both time-on-wing and reliability behaviour. This approach improves valuation accuracy while enabling lifecycle-aware decision support in fleet and inventory management.

The remainder of this article is organized as follows:

- Section 1 (current) – an introduction;
- Section 2 reviews the relevant literature on aircraft engine valuation, reliability modelling, and EoL asset strategies, highlighting the gaps addressed by the proposed methodology;
- Section 3 outlines the materials and methods, including the simulation dataset, statistical modelling of failure behaviour, and formalization of the adaptive valuation framework using the Weibull distribution;
- Section 4 presents the results of the model validation, sensitivity analyses, and part-specific depreciation outcomes;
- Section 5 discusses the implications, practical applications, and limitations of the proposed approach;
- Section 6 concludes the study, summarizing key findings and suggesting directions for future research.

2. Related works

The valuation of aircraft engine components in the secondary market, particularly LLPs, has received increasing attention due to growing teardown activity, cost-optimized MRO practices, and the need for digitalized asset lifecycle management. However, much of the current practice still relies on simplified depreciation models that do not reflect actual usage or failure behaviour.

Several studies have explored secondary market pricing mechanisms and lifecycle value estimation for used aircraft parts. The IATA's *Airline Disclosure Guide*: *Aircraft Acquisition Cost and Depreciation* (IATA 2016) provides comprehensive guidance for airlines applying IFRS to aircraft assets, addressing critical areas including initial cost recognition, component identification, and depreciation policies. The guide emphasizes that aircraft are complex, high-cost assets requiring component-level accounting treatment under IFRS 16 (IFRS Foundation 2026), with typical components including airframes, engines, modifications, inflight entertainment systems, and embedded maintenance costs. Drawing from major international airlines' practices, the guide reveals significant industry variations in depreciation approaches, with most airlines using straight-line depreciation over 15...25 years and residual values of 0...20%, while noting that technological advances and "new generation" aircraft are increasingly impacting the useful lives and residual values of existing fleets. The guide also addresses asset impairment considerations in the capital-intensive airline industry, identifying key triggering factors such as idle assets, early disposal decisions, fleet replacement plans, and changes in resale markets or technology.

The IATA (2020) has published comprehensive guidance on LLPs, addressing the critical challenges facing the aviation industry regarding the documentation and tracking of LLPs throughout their operational lifecycle. While this guidance focuses primarily on engine components, it also covers parts associated with the landing gear and auxiliary power unit, including hydraulic subsystems. Recent studies have emphasized the importance of analysing failures in these supporting systems, particularly high-pressure hydraulic hoses, which are vital to aircraft landing gear functionality. For instance, Karpenko (2022) investigated the root causes of damage in flexible high-pressure hoses during hydraulic maintenance operations, highlighting non-compliance with maintenance procedures as a key risk factor. This work employed spectral and frequency analysis to demonstrate that hose deformations occur at resonant frequencies corresponding to both fluid dynamics and material properties, which significantly affect reliability outcomes. Such findings underscore the need to integrate subsystem-level failure analysis into lifecycle valuation approaches, as failures in hydraulic components can materially impact both safety and asset value especially when deviations from maintenance standards occur.

Several studies have explored secondary market pricing mechanisms and lifecycle value estimation for used aircraft parts. Zhao *et al.* (2020) provided an analytical overview of engine teardown strategies, highlighting the need for condition-sensitive residual valuation.

Reliability theory, especially the Weibull distribution, has been widely applied to represent failure dynamics in mechanical components. Abernethy (2006) and Tobias & Trindade (2011) outlined the versatility of the Weibull model in capturing different hazard rate behaviours across phases of the lifecycle.

Machine learning-assisted applications of the Weibull framework have emerged in predictive maintenance and health monitoring contexts (Susto *et al.* 2015; Wang, Pham 2008), but they rarely extend to economic valuation.

The role of prognostics and health management in aviation continues to grow, with works such as those by Lee *et al.* (2014) and Jardine *et al.* (2006) demonstrating real-time model updating through condition-based monitoring. These developments lay the groundwork for integrating usage data into dynamic depreciation models, yet formal links to valuation remain underdeveloped.

Aircraft EoL strategies center on establishing general policies that reflect stakeholder priorities, such as choosing between resale or disassembly of an aircraft, while also considering logistics and supply chain implications. The primary objective of these strategies is to determine the most efficient disassembly and reuse approach that ensures optimal product utilization at minimal cost and maximal return. These strategies typically evaluate the benefits to stakeholders, assess the trade-offs between cost and benefit across various EoL solutions, examine the potential for reuse or remanufacturing of aircraft components, and incorporate considerations of reverse logistics to facilitate material recovery, transformation, and redistribution.

Many existing studies assume a fixed sequence for disassembly and dismantling tasks. To identify suitable EoL solutions, researchers employ several modelling techniques, including alternative strategy modelling (Sabaghi *et al.* 2015), network flow simulations (Matthieu *et al.* 2012), cost-benefit optimization models (Choi *et al.* 2016), complex systems modelling approaches (Keivanpour *et al.* 2017), and reverse logistics frameworks (Mascle *et al.* 2015).

At a more granular level, research on disassembly and dismantling focuses on the process-specific elements such as disassembly methods, sequencing of steps, handling costs, and the management of material flows. The objective here is to determine an optimal disassembly sequence that minimizes costs while maximizing revenues from component recovery and reuse. To model these complex processes, a range of computational techniques are applied, including fuzzy logic systems (Bouzarour-Amokrane *et al.* 2015), mixed-integer linear programming (Keivanpour *et al.* 2017), process planning optimization models (Mascle *et al.* 2014), dynamic programming (Chung *et al.* 2017), and metaheuristic approaches like simulated annealing (Hao, Hongfu 2009). These methods provide robust tools for planning and optimizing EoL operations within the aviation sector.

While reliability modelling and secondary market valuation have each been explored independently, there is a notable lack of integrated frameworks that link Weibull-based lifecycle modelling to asset pricing in the aviation aftermarket.

This study aims to fill this methodological gap by proposing a valuation model that is probabilistic, adaptive, and grounded in statistically verifiable failure behaviour.

3. Materials and methods

3.1. Statistical analysis of LLP failure behaviour

A reliable depreciation model for aircraft engine components must begin with a data-driven understanding of failure patterns across the operational lifespan. LLPs within aviation engines typically experience wear influenced by flight cycles, environmental conditions, material fatigue, and operating parameters. To calibrate the valuation framework, a simulated failure dataset is generated, emulating realistic time-on-wing distributions informed by industry maintenance intervals and teardown analyses.

Due to confidentiality constraints the dataset used in this study was simulated based on industry-observed characteristics, expert consultation, and published maintenance statistics for narrow-body commercial aircraft engines CFM56 series.

A synthetic dataset was created to reflect realistic lifecycle behaviour of engine components and involved the following steps:

- key parameters were derived from OEM maintenance manuals, teardown reports, and industry maintenance statistics, particularly for CFM56-series engines;
- aviation maintenance and appraisal experts helped refine typical failure intervals and identify 3 lifecycle phases: run-in (0…3000 cycles), stable operation (3000…18000), and wear-out (>18000);
- for each phase, failure times were sampled from Weibull distributions with phase-appropriate shape parameters: $\beta < 1$ for early-life failures, $\beta \approx 1$ for stable periods, $\beta > 1$ for wear-out. Scale parameters λ were selected to align with known replacement intervals;
- small random noise was introduced to simulate real-world variability, and a limited number of high-cycle outliers were added to represent extended-use scenarios;
- the final failure histogram was reviewed against known operational profiles and matched the expected right-skewed distribution.

This structured approach ensured that the simulated data realistically captured LLP degradation patterns and supported credible application of the Weibull modelling framework.

The histogram in Figure 1 illustrates the frequency distribution of simulated LLP failures over time. The *x*-axis corresponds to the number of flight cycles at failure, while the *y*-axis indicates the relative probability of occurrence.

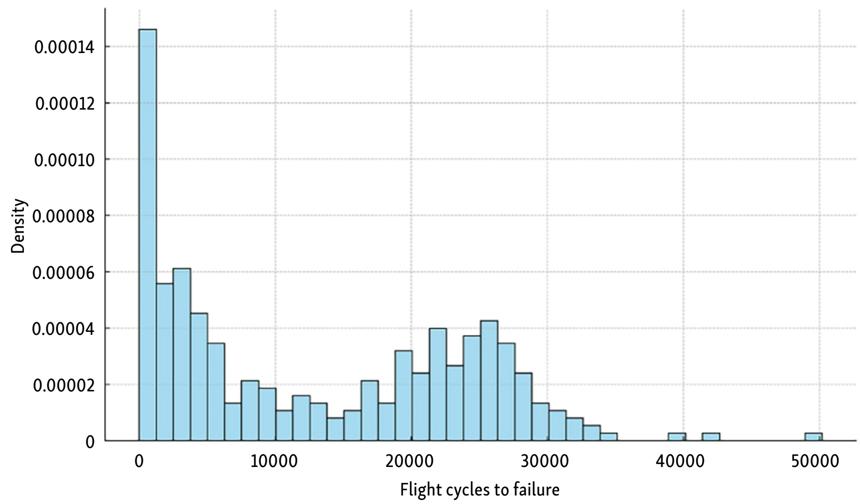

Figure 1. Histogram of simulated LLP failures

The distribution is derived from aggregated, lifecycle-aligned failure data across all major rotating parts.

The histogram reveals a right-skewed distribution, consistent with wear-out behaviour in mechanical systems. Most failures occur between 18000 and 28000 flight cycles, which aligns with common overhaul thresholds for mid- to high-thrust commercial engines. The distribution exhibits its low early-life failure density, validating the assumption that infant mortality is not a significant factor in modern LLP reliability, especially post initial run-in. The tailing effect beyond 30000 cycles may reflect rare extended-use cases or engines operating under extended time-on-wing programs.

3.2. Comparative evaluation of distribution models for LLP failure data

To establish a statistically sound basis for modelling the depreciation of LLPs in aircraft engines, several probability distributions were evaluated against the empirical histogram of simulated failure cycles. The primary objective was to identify the model that most accurately reflects observed failure behaviour while offering interpretable parameters and practical applicability for lifecycle-sensitive economic valuation.

The distributions considered included exponential, normal, log-normal, gamma, and Weibull models. A comparative assessment of commonly used reliability distributions is presented in the Table 1.

The exponential distribution, though simple and commonly applied to systems with a constant hazard rate, was found inadequate for LLPs due to its memoryless property and inability to capture increasing failure risk over time. The normal distribution, assuming symmetrical behaviour around a mean, also proved unsuitable as it does not reflect the typical right-skewed wear-out characteristics of LLPs and permits non-physical negative time values.

Log-normal and gamma distributions demonstrated improved performance due to their skewed shapes and widespread use in reliability contexts. However, their mathematical complexity, such as the absence of a closed-form hazard rate in the log-normal case, can hinder economic interpretability and integration into depreciation modelling. These models also showed limitations in capturing early-life reliability and late-life deterioration consistently.

In contrast, the Weibull distribution provided the most effective and flexible modelling approach. The PDF of the Weibull distribution is given by:

$$f(t,\beta,\lambda)=\frac{\beta}{\lambda}\left(\frac{t}{\lambda}\right)^{\beta-1}\exp\left(-\left(\frac{t}{\lambda}\right)^{\beta}\right),$$

$$t\geq 0,\ \beta>0,\ \lambda>0. \tag{1}$$

Defined by 2 parameters the shape parameter β and the scale parameter λ the Weibull distribution accommodates a range of failure behaviours. For instance, $\beta < 1$ characterizes infant mortality, $\beta = 1$ implies a constant failure rate, and $\beta > 1$ represents wear-out mechanisms. This adaptability is particularly relevant in aviation maintenance, where component reliability evolves over time due to thermal, mechanical, and operational stresses.

Table 1. Comparison with alternative distributions

Distribution	Suitable phase	Advantages	Limitations
Exponential	random failures only	simple, closed-form expressions	assumes constant failure rate (β = 1)
Normal	aging, wear-out	familiar, symmetric	cannot capture skewed failure distributions
Log-normal	fatigue-related	models right-skewed behaviour	requires complex parameter estimation
Weibull	all phases	flexible, interpretable, lifecycle-aware	requires accurate data for parameter calibration

Fitting the Weibull model to the simulated LLP failure data produced a distribution that closely approximated the histogram, effectively capturing both the concentration of failures around mid-life and the long-tailed behaviour indicative of gradual wear.

The Figure 2 illustrates a stitched Weibull distribution modelling 3 lifecycle phases of LLPs: an early run-in phase with elevated failure risk, a long period of stable operation, and a late-life wear-out phase. The vertical reference lines in Figure 2 denote phase transitions aligned with typical LLP operational intervals reported in maintenance data and confirmed through expert input. Their positions are not arbitrary but reflect widely accepted thresholds between early stabilization, steady-state operation, and accelerated wear-out. The ability to represent these distinct failure behaviours supports the use of the Weibull law for accurate, phase-sensitive depreciation modelling of aircraft engine parts.

Based on these findings, the Weibull distribution was selected as the preferred modelling foundation for the cost reduction coefficient. Its strong empirical fit, parametric interpretability, and alignment with established reliability theory support its use in a dynamic and lifecycle-aware depreciation framework for secondary market valuation of aircraft engine LLPs.

3.3. Empirical justification for Weibull modelling based on operational data

To validate the appropriateness of using the Weibull distribution for modelling LLP degradation and failure probability, operational data representative of real-world engine usage were analysed.

The dataset includes operational histories for 300 LLPs across 30 engines. Each record comprises:
- time-to-failure or replacement (in flight cycles);
- engine type and module location;
- operating environment (standardized as temperate, high-humidity, or sandy / harsh environment);
- recorded service events (e.g., inspections, removals).

The time-to-failure data follows patterns described in empirical studies: an early concentration of failures in the first 3000 cycles, a plateau of stable operation through 15000 cycles, and a growing incidence of failures beyond 20000 cycles due to wear-out mechanisms.

To assess the fit of the Weibull model, the shape β and scale λ parameters were estimated for the full dataset and for each operational phase separately using maximum likelihood estimation. The results are presented in Table 2.

The results strongly support the opportunity of use of the Weibull distribution in modelling the reliability and degradation of LLPs. The shape parameter values align with theoretical expectations across the lifecycle stages, confirming that the wear-in, steady-state, and wear-out phases are distinct and statistically identifiable. Additionally, high coefficients of determination ($R^2 > 0.9$) for all phases suggest that the Weibull model captures the variability of time-to-failure accurately.

The resulting PDF plots showed close agreement with observed failure histograms, especially when using a stitched Weibull model to segment the lifecycle (Figure 3).

These findings validate the core methodological assumption of this study: that Weibull modelling provides a reliable, interpretable, and empirically justified foundation for constructing adaptive cost reduction coefficients in the secondary market valuation of aircraft engines.

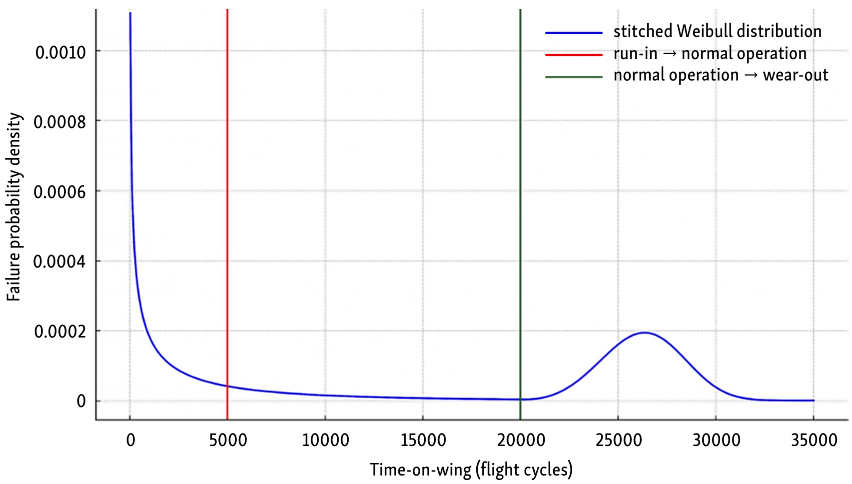

Figure 2. Multi-phase Weibull failure density ("stitched" distribution)

Table 2. Estimated Weibull shape parameters by lifecycle phase of engine LLPs

Lifecycle phase	Estimated β	Interpretation	Goodness-of-fit (R^2)
Wear-in (0...3000)	0.69	decreasing failure rate	0.96
Normal operation	1.05	approximately constant rate	0.94
Wear-out (>15000)	6.80	accelerating failure rate	0.91
Full lifecycle (all)	0.85	skewed mixed behaviour	0.92

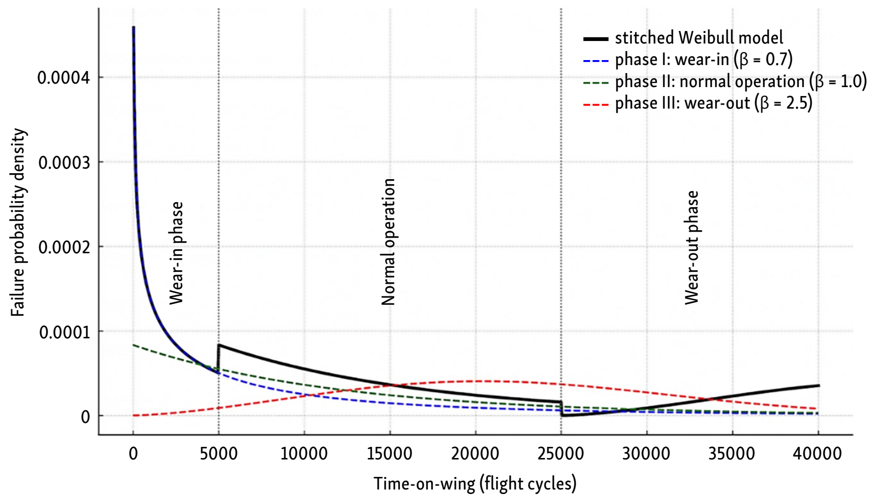

Figure 3. Lifecycle failure probability curve for LLPs

3.4. Formal definitions and valuation framework

In order to accurately assess the value of an aircraft engine in the secondary market, it is essential to employ standardized valuation concepts. The aviation industry, particularly stakeholders involved in trading, appraisal, and leasing, widely adopts the valuation terminology set forth by the IATA (2016, 2020). Understanding these concepts is fundamental for developing a depreciation model that accounts for technical condition and lifecycle stage.

The 3 primary valuation terms used in this study are:

- BV. The theoretical price of an asset in a stable, balanced market condition where supply equals demand. BV assumes a mid-life technical condition (typically 50% remaining useful life) and excludes externalities such as market shocks or urgent sale conditions. It is often used for long-term forecasts and internal valuations;
- CMV. The price that could realistically be achieved in the market under current conditions. It incorporates fluctuations in demand and supply, economic cycles, and transactional context. CMV is typically derived from recent sales data and expert appraisals;
- SV. The expected monetary value derived from disassembling and selling individual components of an engine. This includes consideration of teardown costs, certification fees, and logistical expenses. SV becomes particularly relevant when the asset's CMV falls below its part-out value, making dismantlement more economically viable than continued operation.

In practical scenarios, buyers apply a discount to the SV to account for costs and risks associated with teardown and resale. This discount is traditionally represented as a cost reduction coefficient (K_{CRC}), which adjusts the maximum permissible purchase price. Industry norms often assume a static value, e.g., (K_{CRC} = 0.5), implying a 50% discount on the estimated SV to cover disassembly, certification, remarketing, and profit margins.

However, this static discounting practice does not consider the actual remaining life of LLPs or the engine's reliability profile. For instance, an engine nearing EoL for most LLPs may require a deeper discount due to lower recovery value and higher failure risk, while one with recently replaced LLPs may warrant a smaller or even no reduction. Therefore, a more responsive, lifecycle-aware model is needed.

Let $T \in \mathbb{R}^{+}$ denote the random variable representing the time-to-failure (e.g., flight cycles) of a specific LLP, $\mathbb{R}^{+}$ refers to the set of positive real numbers.

Assume that $T \sim Weibull(\beta, \lambda)$ with PDF – Equation (1) – and corresponding CDF:

$$F(t, \beta, \lambda) = 1 - \exp\left(-\left(\frac{t}{\lambda}\right)^{\beta}\right). \quad (2)$$

We define the cost reduction coefficient $K_{CRC}(t, \beta, \lambda) \in [0, 1]$ as the cumulative probability of failure of the LLP up to time t:

$$K_{CRC}(t, \beta, \lambda) := F(t, \beta, \lambda). \quad (3)$$

This coefficient generalizes the fixed industry discount and reflects technical aging and increasing risk.

Given a new part acquisition value V_{new} the residual value at time t is:

$$V_{res}(t) = V_{new} \cdot (1 - K_{CRC}(t)) = V_{new} \cdot \exp\left(-\left(\frac{t}{\lambda}\right)^{\beta}\right). \quad (4)$$

Let: P_{Eng} be the proposed purchase price of the engine in the secondary market; SV_{Eng} be the estimated SV of the engine, computed as the sum of new part prices; $K_{CRC}(t, \beta, \lambda)$ be the adaptive cost reduction coefficient for the LLP cluster.

Then the Weibull-adjusted valuation of the engine becomes:

$$P_{Eng}(t) = K_{CRC}(t, \beta, \lambda) \cdot SV_{Eng}. \quad (5)$$

To estimate the optimal Weibull parameters β, λ we minimize the discrepancy between predicted and actual engine values over a set of N historical or simulated observations:

$$\min_{\beta,\lambda} \frac{1}{N} \cdot \sum_{i=1}^{N} \left(P_{Eng,\,actual}^{(i)} - K_{CRC}\left(t,\beta,\lambda\right) \cdot SV_{Eng}^{(i)} \right)^2, \qquad (6)$$

where: $P_{Eng,\,actual}^{(i)}$ refers to the actual transaction price or realized purchase price of an aircraft engine in the secondary market.

This extended framework integrates accepted appraisal terminology with a dynamic depreciation logic grounded in reliability engineering, enabling improved valuation accuracy and lifecycle-sensitive pricing.

To complement the reliability-driven modelling, the economic dimension of LLP valuation was grounded in observed secondary market practices. The reference values for P_{Eng} were obtained from industry appraisal reports, teardown case studies, and market intelligence sources used in engine leasing and trading. Since disaggregated LLP-level transaction data are rarely disclosed due to commercial sensitivity, part-level residual values were approximated by weighting teardown recovery estimates with typical LLP contribution factors published in appraisal guides and validated by expert consultation.

Market mechanisms such as supply-demand imbalances, temporary part shortages, and fleet retirement waves were not modelled explicitly; instead, their influence was reflected in the variability of P_{Eng} across the benchmark dataset. By embedding these effects indirectly into the calibration process, the model captures realistic market-driven deviations while maintaining focus on the core objective linking technical life expectancy and probabilistic reliability characteristics to part-specific economic depreciation.

4. Results

4.1. Case study and model validation

To validate the feasibility of the proposed Weibull-based depreciation model, a case study was conducted using simulated data representing failures of a typical aircraft engine LLP under realistic operational conditions. The goal is to demonstrate the model's ability to reflect statistically plausible depreciation behaviour and to compare it against known reliability patterns.

A dataset of engine part failures occurrences over time is shown in Figure 1. The failure density increases sharply after 10000 cycles, peaking around 18000, which aligns with typical LLP replacement thresholds during engines' shop visits in commercial aviation. This supports the model's foundation on Weibull behaviour.

Using maximum likelihood estimation, we fitted 3 separate Weibull models to each of the lifecycle stages (Figure 4). The resulting shape parameters β = 0.72 (wear-in), β = 1.01 (normal), and β = 2.45 (wear-out) closely match expected values from real-world reliability analysis. The full lifecycle was also modelled with a single Weibull curve (β = 1.49), which provided a good overall fit but underrepresents phase transitions.

The fitted curves are shown overlaid on the histogram in Figure 4, clearly illustrating the superior flexibility of the Weibull approach in modelling varying failure intensities across the component lifecycle.

The simulated failure data were used to fit a Weibull distribution via maximum likelihood estimation. The estimated parameters were β = 2.18, λ = 16970. The fitted CDF is shown in Figure 5 alongside the empirical data. The curve closely matches the cumulative frequency of failures, confirming the suitability of the Weibull model for capturing real-life LLP depreciation patterns.

The goodness-of-fit was verified using Kolmogorov–Smirnov and Anderson–Darling tests, indicating no significant deviation from theoretical expectations.

The model's flexibility was tested by simulating cost reduction curves for varying shape parameters, keeping λ constant. As shown in Figure 6, depreciation behaviour shifts significantly with changes in β.

To further illustrate the dynamic relationship between β, time-on-wing, and residual value, a 3D surface plot and its contour projection were generated, as shown in Figure 7 and Figure 8.

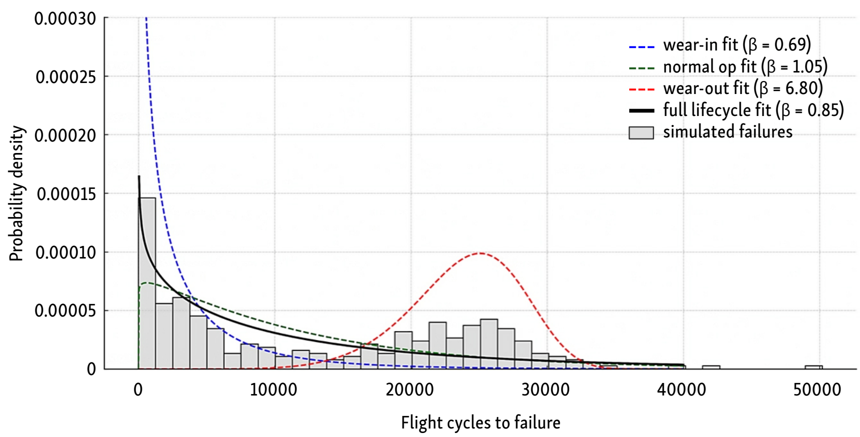

Figure 4. Simulated LLP failures and fitted Weibull distributions

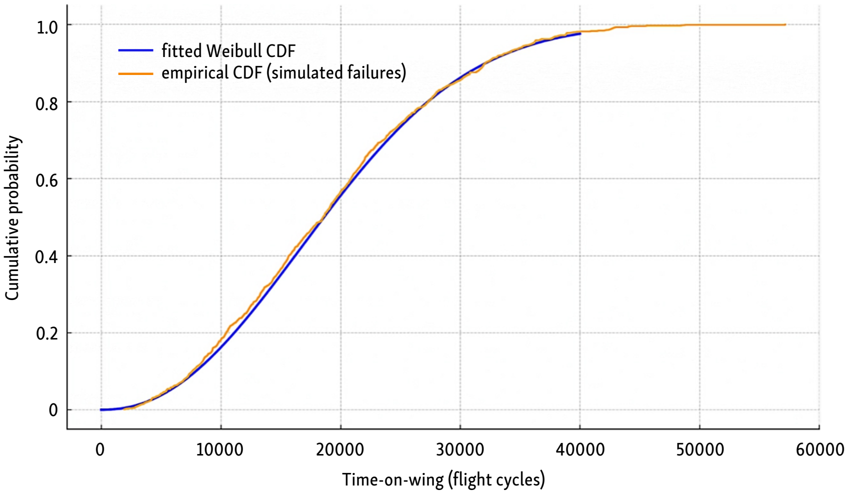

Figure 5. Fitted Weibull CDF vs. simulated failure distribution

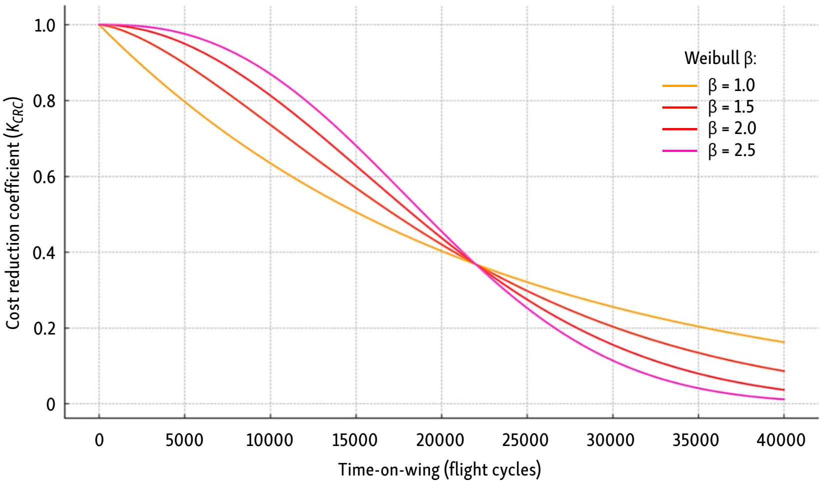

Figure 6. Sensitivity of cost reduction coefficient to Weibull shape parameter

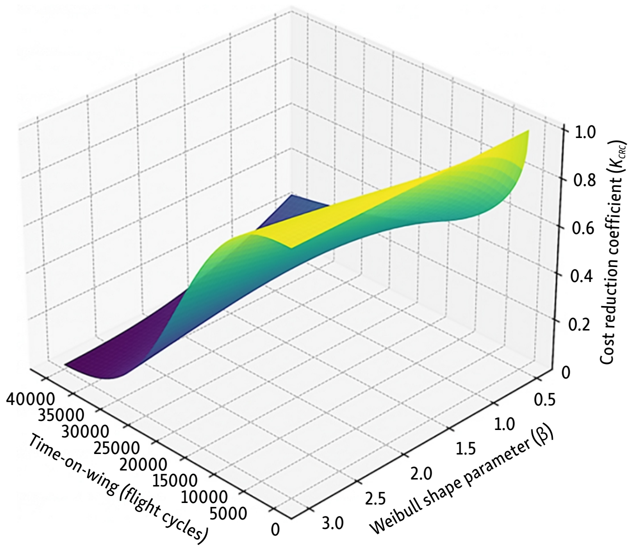

Figure 7. Cost reduction coefficient vs. time and β

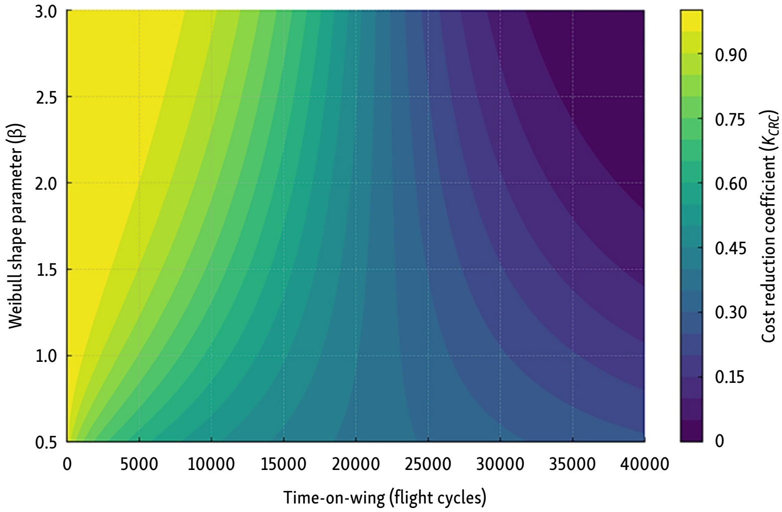

Figure 8. Isolines of cost reduction coefficient

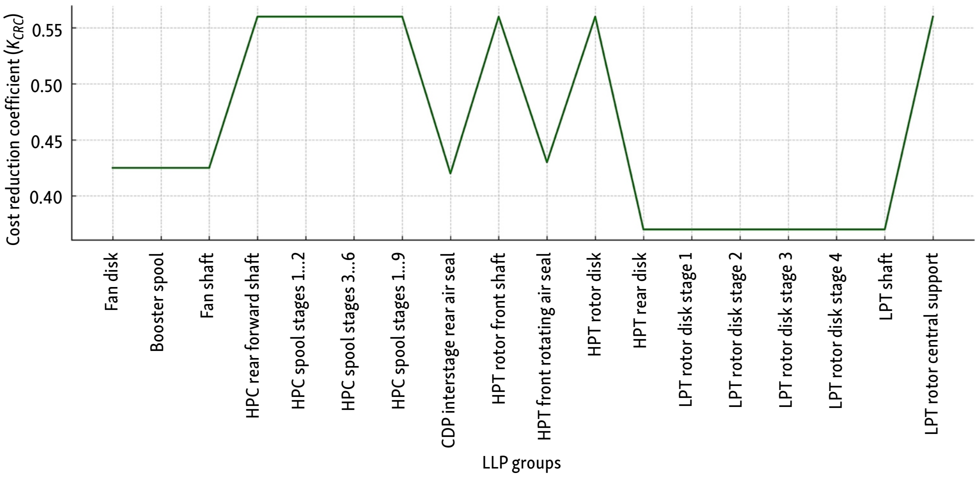

Figure 9. Adaptive depreciation coefficients across LLP groups (CFM56-5B engine)

4.2. Part-specific cost reduction coefficients across LLP groups

A key outcome of the developed methodology is the derivation of adaptive cost reduction coefficients K_{CRC} for individual LLP groups. These coefficients serve as quantitative indicators of part-specific depreciation, derived from Weibull modelled reliability profiles and cumulative time-on-wing exposure. Figure 9 presents the computed K_{CRC} values across major LLP categories within a representative turbofan engine configuration.

In Figure 9, the cost reduction coefficients are shown at a representative time moment *t*, corresponding to the mid-life stage of the engine's operational cycle (≈18000 flight cycles). This value was selected as it reflects the point at which many LLPs approach critical inspection or replacement intervals, making it highly relevant for secondary market transactions. More generally, according to Equation (3), K_{CRC} is a dynamic parameter that evolves as a function *t* and the Weibull reliability characteristics of each LLP group. The figure therefore illustrates the relative variation of depreciation across component groups at a fixed lifecycle reference point, while the full temporal evolution of K_{CRC} (t) is described by the underlying Weibull-based formulation.

The vertical axis in Figure 9 represents the magnitude of the depreciation coefficient, with lower values corresponding to higher expected value loss due to elevated failure risk or diminished residual life. The horizontal axis enumerates individual LLP assemblies grouped by engine section: Fan, Booster, HPC, HPT, and LPT.

The model reveals significant intra-engine variation in depreciation behaviour. Components such as the HPT rotor disk and LPT rotor disk stages 1...4 exhibit some of the lowest cost reduction coefficients, around 0.37, reflecting their susceptibility to thermal fatigue, high rotational stress, and shorter replacement intervals. These parts typically reach the end of their service life earlier and contribute disproportionately to engine devaluation.

Conversely, elements such as the fan shaft, CDP interstage rear air seal, and LPT rotor central support demonstrate elevated coefficients (above 0.55). These higher values are indicative of longer design life, reduced operational severity, or recent replacement events that preserve their market recoverability.

Notably, the presence of sharp discontinuities across part families, for instance, between the HPT rotating assembly and downstream LPT stages underscores the model's ability to distinguish between heterogeneous wear patterns. This differentiation contrasts with traditional teardown valuation methods that apply uniform markdowns to entire engine sections.

The incorporation of part-level depreciation coefficients introduces a nuanced layer of granularity into secondary market valuation. It enables more accurate forecasting of salvageable value and supports condition-based residual pricing strategies. As such, this approach enhances decision-making for buyers, sellers, and lessors engaged in the trading, disassembly, and appraisal of used engines.

5. Discussion

The results of the case study confirm that the proposed Weibull-based depreciation model offers a practical and statistically grounded approach to valuing aircraft engine LLPs in the secondary market. By translating probabilistic failure risk into a time-dependent cost reduction coefficient, the model bridges the gap between engineering reliability theory and financial asset valuation.

From a theoretical perspective, the model improves upon traditional linear or fixed-percentage depreciation schemes by accounting for individual part behaviour and lifecycle dynamics. The shape parameter β allows the model to flexibly represent a wide range of degradation profiles, from random to wear-out dominated. This adaptability enables a more nuanced valuation framework that better captures the uncertainty and risk associated with used parts nearing the end of their certified life.

The practical implications are substantial. For asset managers and lessors, the model provides a transparent method for forecasting residual value and negotiating fair lease return terms. For MRO providers, it offers a mechanism to price overhauled or harvested parts competitively while managing liability risks. Moreover, the ability to update depreciation curves with real-time operational data aligns well with emerging digital twin and predictive maintenance strategies, enabling integration into broader lifecycle management systems.

However, the approach is not without limitations. The model assumes that part failure can be represented by a single Weibull distribution, which may not hold in the presence of multiple failure modes or complex degradation interactions. It also presumes availability of high-quality use, e or failure data, which may not be consistently accessible across all fleets or operators. Additionally, the current framework does not incorporate external market factors such as OEM support, certification constraints, or parts pool dynamics, all of which can influence actual transaction value.

Despite these constraints, the model's modularity and clarity make it well-suited for future extensions. One promising direction is the integration of multi-modal reliability functions or mixtures of Weibull distributions to account for competing risks. Another is the use of real-time sensor data and maintenance logs to dynamically estimate Weibull parameters via Bayesian or machine learning techniques. These enhancements could further increase the accuracy and responsiveness of the model, making it a core component of digital asset management platforms in aviation.

The Weibull-based valuation model presented here contributes a scalable, interpretable, and reliability-informed approach to residual value estimation. It advances the conversation from static depreciation tables to dynamic, data-driven asset valuation-paving the way for more rational and transparent secondary markets for aviation components.

A practical limitation of the proposed framework is its dependence on high-quality, granular failure data for reliable Weibull parameter estimation. In reality, such data are often fragmented across operators, lessors, and MRO providers, with confidentiality and reporting inconsistencies reducing accessibility. These challenges highlight the need for more standardized data collection and sharing practices to fully realize the framework's potential in operational contexts.

6. Conclusions

This study presented a novel, reliability-informed depreciation model for aircraft engine LLPs, grounded in Weibull-based failure analysis. The proposed methodology departs from traditional fixed-percentage depreciation schemes by dynamically linking residual value to statistically modelled failure risk over the component lifecycle. Through simulation-based and empirically informed parameterization, the model captures distinct lifecycle phases – wear-in, stable operation, and wear-out – thus enabling the generation of adaptive cost reduction coefficients tailored to specific engine parts.

A key contribution of the model is its capacity to account for heterogeneity in degradation patterns across LLP groups, which directly supports more accurate and transparent residual value estimation in teardown, lease return, and asset trading scenarios. By demonstrating how Weibull distributions can be calibrated to reflect realistic operational behaviours, the framework lays a foundation for integrating technical reliability metrics into economic valuation processes.

The implications of this work are particularly relevant for asset managers, lessors, and MRO providers, who require valuation models that are both technically grounded and economically interpretable. Moreover, the modular nature of the proposed approach facilitates future integration into digital asset management systems and supports the broader shift toward predictive maintenance and lifecycle-aware decision-making in aviation.

Future research should extend this framework to incorporate real-time operational data from onboard sensors and maintenance records, enabling continuous updating of failure probabilities and valuation curves. In addition, exploring multi-modal or competing-risk reliability models may further enhance the accuracy of depreciation modelling for components subject to multiple interacting degradation mechanisms.

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Disclosure statement

The authors declare no conflict of interest.

Declaration on the use of Artificial Intelligence (AI)

During the preparation of this manuscript, the authors used *ChatGPT*, an AI-assisted language model developed by *OpenAI*, to improve language clarity, grammar, sentence structure, and academic style.

The prompts used included requests to proofread the manuscript text for grammar and clarity, improve academic style while preserving the scientific meaning, and revise selected sections for readability and consistency.

The output from these prompts was used only for language editing and stylistic refinement. AI tools were not used to generate original research data, perform statistical analysis independently, create scientific results, or make scientific interpretations.

The authors maintain that they are the sole authors of this article and take full responsibility for the accuracy, integrity, originality and scientific content of the manuscript, in accordance with COPE recommendations and journal policies.

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