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Probabilistic Reliability Modeling of Turbofan Degradation: Survival Analysis and Simulation

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ABSTRACT: Reliability analysis is essential for evaluating the safety, durability, and maintenance readiness of engineering systems that operate under uncertain degradation conditions. This study develops and empirically evaluates a probabilistic reliability framework that combines lifetime distribution fitting, survival estimation, failure-rate modeling, remaining-useful-life prediction, and Monte Carlo uncertainty simulation. The empirical case uses a public turbofan engine degradation benchmark containing run-to-failure training trajectories, incomplete test trajectories, operating-condition settings, sensor measurements, and true remaining-useful-life labels. The proposed framework first converts degradation trajectories into lifetime and remaining-useful-life indicators, then estimates reliability and cumulative failure probability using Weibull and empirical survival functions. A regularized prediction model links operating cycles and sensor behavior to remaining useful life, while bootstrap-based Monte Carlo simulation propagates uncertainty in the fitted lifetime distribution. The main single-condition, single-fault subset contains 100 complete training engines and 100 test engines. Its empirical mean lifetime was 206.31 cycles, and the Weibull model produced a shape parameter of 4.409 and a scale parameter of 225.026 cycles, indicating wear-out-dominated degradation. Estimated reliability declined from 0.846 at 150 cycles to 0.552 at 200 cycles. The prediction model achieved a root mean square error (RMSE) of 22.545 cycles in the main subset, with similar performance in the secondary robustness subsets. The findings show that probabilistic reliability modeling gives decision-makers more informative maintenance evidence than deterministic point estimates because it links degradation, failure probability, uncertainty intervals, and operational risk thresholds in one interpretable structure.

Keywords: reliability analysis; probability modeling; failure rate; Monte Carlo simulation; engineering systems.

I. INTRODUCTION

Reliability analysis is central to engineering and applied sciences because technical systems rarely fail under perfectly known or fixed conditions. Mechanical components, electrical networks, transport infrastructure, production equipment, and industrial processes face operational variability, material fatigue, environmental stress, imperfect monitoring, and hidden degradation. A deterministic evaluation may classify a system as acceptable or unacceptable at a single point in time, but it does not always show how failure likelihood changes across operating cycles or how much uncertainty surrounds a maintenance decision. This limitation matters especially for high-cost or safety-critical systems, where delayed maintenance can increase failure risk and overly early action can waste resources.

This study addresses the need to translate observable degradation evidence into probabilistic reliability information. Modern engineering systems produce continuous condition-monitoring records from sensors, cycle counters, operating settings, and inspection outputs. These records contain useful signs of degradation, but they are rarely complete. Some units may be observed until failure, while others may be censored before failure occurs. Operating conditions may differ across units, and noise may affect sensor behavior. In such

settings, reliability should be interpreted as a probability function rather than a fixed property. The decision-maker needs not only to know whether a system is functioning now; it also needs to estimate the probability that the system will continue functioning over a defined future horizon.

Probabilistic approaches provide a structured solution to this challenge. Lifetime distributions describe the statistical behavior of failure times. Survival functions estimate the probability that a system remains operational beyond a specified cycle or time point. Hazard functions show the changing rate of failure among units that have survived until a given point. Remaining-useful-life models connect current degradation evidence to the expected number of future cycles before failure. Monte Carlo simulation adds another layer by repeatedly sampling plausible reliability conditions so that uncertainty can be summarized as intervals rather than a single curve. Together, these tools make reliability analysis more transparent, interpretable, and useful for maintenance planning.

This study focuses on a public turbofan engine degradation benchmark because it provides a realistic engineering structure for reliability analysis. The data consist of multiple engine trajectories, operational settings, and sensor measurements recorded over operating cycles. In the complete training trajectories, each engine progresses toward failure, allowing us to construct lifetime distributions and remaining-useful-life labels. In the incomplete test trajectories, each engine stops before failure, making the task similar to real maintenance practice: the analyst must estimate remaining life from partial degradation evidence. The benchmark also includes simpler and more complex subsets, enabling both a clean main case and robustness checks under multiple conditions and fault modes.

The paper is organized as follows. The next section states the research aim and questions. The Literature Review summarizes studies from 2013 to 2022 only and places all reviewed studies in an evidence table. The Research Gap is presented separately from the review. The Proposed Method explains the probabilistic framework, followed by the Methodology section, which describes data structure, variables, preprocessing, reliability functions, prediction modeling, and simulation design. The Results section reports empirical findings, and the Discussion interprets their reliability and implications for maintenance. The final sections present theoretical contributions, practical implications, limitations, future research directions, and the conclusion.

II. RESEARCH AIM AND QUESTIONS

This study aims to develop and evaluate a probabilistic reliability framework to estimate time-dependent failure risk and remaining useful life in engineering systems under degradation uncertainty. The study uses turbofan degradation trajectories as an empirical case because they provide complete lifetime observations, partial test histories, operational settings, and sensor-based evidence of progressive deterioration.

The first research question asks how lifetime distributions can characterize the failure behavior of engineering systems using run-to-failure degradation evidence. The second research question asks how survival and hazard functions can translate degradation histories into time-dependent reliability probabilities. The third research question asks whether sensor-informed remaining-useful-life modeling produces useful predictive evidence for incomplete trajectories. The fourth research question asks how Monte Carlo simulation can quantify uncertainty in reliability estimates and support maintenance interpretation. The fifth research question asks whether findings from the main single-condition case remain directionally consistent in more complex subsets with additional operating conditions and fault modes.

III. LITERATURE REVIEW

The reviewed studies show three main directions in reliability and prognostics research. The first direction develops probabilistic reliability foundations such as Monte Carlo sampling, Bayesian networks, survival signatures, and multi-state reliability models. These studies matter because they frame reliability as a probabilistic problem under uncertainty rather than a deterministic pass-fail judgment. The second direction advances remaining-useful-life estimation from monitoring data, especially for rotating machinery and turbofan degradation benchmarks. These studies show that sequence information, degradation-sensitive features, and condition monitoring signals can improve failure prediction. The third direction focuses on uncertainty-aware prognostics, where the output is not only a point estimate but a distribution, interval, or

calibrated reliability measure. This direction is closest to the present study because maintenance decisions require both predicted life and confidence in that prediction.

In the reviewed evidence, turbofan degradation benchmarks first appear as dataset-aligned remaining-useful-life modeling, where aircraft engine histories link sensor trajectories to end-of-life prediction [1]. Sensor-based regression then provides an early data-driven foundation by showing how convolutional structures can estimate remaining useful life from degradation records [2]. Uncertainty-aware prediction extends this logic by emphasizing that prognostic outputs should communicate predictive uncertainty rather than only point estimates [3]. Bayesian-network reliability analysis further supports probabilistic representation for complex engineering systems, while probabilistic prognostic metrics clarify how to evaluate uncertainty in remaining-life estimates [4], [5]. Together, these studies justify treating reliability as an uncertainty-informed decision problem rather than a deterministic classification.

Computational sampling and survival-based reliability studies strengthen the framework's probabilistic foundation. Sampling-based structural reliability methods show why Monte Carlo procedures remain useful for estimating failure behavior under uncertainty [6]. Survival-signature analysis extends reliability interpretation to phased-mission systems and links component survival to system-level reliability [7]. Temporal convolutional memory networks and interpretable Bayesian remaining-life forecasting show that degradation histories can be modeled while still supporting transparent maintenance interpretation [8], [9]. Systematic machinery prognostics and convolutional sequence learning then link data acquisition, health indicators, and remaining-useful-life prediction into a coherent prognostic pipeline [10], [11].

Predictive-maintenance and probabilistic lifetime studies add the maintenance-oriented layer needed for applied engineering decisions. Dynamic predictive-maintenance modeling links monitoring data to failure prognostics and supports condition-based intervention logic [12]. Probabilistic deep-learning methodology for multi-component systems expands the output from a single remaining-life estimate to a distribution of possible lifetimes [13]. Turbofan prognosis using temporal and spatial feature fusion confirms the relevance of the empirical benchmark for aircraft engine degradation analysis [14]. Multi-state survival-signature work generalizes reliability evaluation to systems with multi-state components, while stochastic degradation and maintenance-timing models show how remaining-life estimates can support optimal intervention thresholds [15], [16]. Transfer and ensemble learning further indicate that robustness across operating conditions is an important requirement in remaining-useful-life prediction [17].

The final part of the alphabetically ordered review emphasizes residual learning, predictive-maintenance trends, multi-sensor sequence modeling, uncertainty quantification, and recurrent degradation modeling. Residual convolutional prognostics improve remaining-useful-life estimation by strengthening feature extraction from degradation records [18]. Broader predictive-maintenance reviews show that condition-based prognostics increasingly depend on data-driven monitoring, sensor interpretation, and maintenance planning [19]. Multi-sensor long short-term memory modeling confirms the value of fusing several sensor signals for remaining-life prediction [20]. Deep learning combined with nonstationary Gaussian processes shows how to report prediction accuracy alongside uncertainty intervals [21]. Recurrent sequence modeling further shows that temporal degradation information is essential for estimating remaining useful life from operating histories [22]. These studies confirm that current reliability research values not only prediction accuracy but also uncertainty communication and decision relevance.

Table 2. Literature-review studies included in the evidence table.

Study	Focus	Main contribution	Relevance
[1] Asif et al. (2022)	Turbofan RUL modeling	Predicted aircraft turbofan RUL using a degradation benchmark	Supports dataset-aligned validation
[2] Babu et al. (2016)	Sensor-based RUL regression	Proposed convolutional regression for degradation data	Supports sensor-to-RUL modeling
[3] Biggio et al. (2021)	Uncertainty-aware RUL	Evaluated uncertainty-aware RUL prediction for industrial assets	Supports uncertainty reporting
[4] Chen et al. (2017)	Bayesian network reliability	Applied Bayesian networks to complex engineering reliability	Supports uncertainty representation
[5] de Pater & Mitici (2022)	Probabilistic RUL metrics	Developed metrics for probabilistic RUL prognostics	Supports evaluation of uncertainty
[6] Huang et al. (2017)	Structural reliability sampling	Reviewed Monte Carlo and sampling reliability methods	Supports simulation component

Study	Focus	Main contribution	Relevance
[7] Huang et al. (2019)	Survival signature reliability	Modeled phased-mission reliability with survival signatures	Supports survival interpretation
[8] Jayasinghe et al. (2019)	Temporal memory networks	Modeled short- and long-term temporal degradation	Supports time-series evidence
[9] Kraus & Feuerriegel (2019)	Interpretable Bayesian RUL	Combined interpretability with Bayesian estimation	Supports transparent decisions
[10] Lei et al. (2018)	Machinery prognostics review	Connected data acquisition, indicators, and RUL prediction	Supports full prognostic pipeline
[11] Li et al. (2018)	Prognostic sequence learning	Estimated RUL from time-window sensor data	Supports degradation-sensitive features
[12] Nguyen & Medjaher (2019)	Dynamic predictive maintenance	Linked monitoring data with failure prognostics	Supports maintenance planning
[13] Nguyen et al. (2022)	Probabilistic lifetime prediction	Predicted RUL distributions for multi-component systems	Supports probabilistic outputs
[14] Peng et al. (2021)	Turbofan prognosis	Modeled turbofan RUL using temporal attention evidence	Supports empirical case relevance
[15] Qin & Coolen (2022)	Multi-state survival signature	Extended survival signature to multi-state reliability	Supports system reliability generalization
[16] Wang et al. (2021)	Gamma process maintenance timing	Connects stochastic degradation with optimal maintenance time	Supports probabilistic maintenance thresholds
[17] Wang et al. (2022)	Transfer and ensemble RUL	Combined transfer and ensemble learning for RUL prediction	Supports robustness across conditions
[18] Wen et al. (2019)	Residual prognostic modeling	Improved RUL estimation using residual convolutional structure	Supports benchmark comparison
[19] Wen et al. (2021)	Predictive-maintenance review	Summarized advances in condition-based prognostics	Supports field positioning
[20] Wu et al. (2020)	Multi-sensor RUL prediction	Fused multiple sensor signals for RUL estimation	Supports multivariate sensor use
[21] Xu et al. (2021)	RUL uncertainty quantification	Combined accurate prediction with uncertainty intervals	Supports interval-based reliability
[22] Zheng et al. (2017)	Sequential RUL estimation	Used temporal sequence learning for RUL prediction	Supports cycle-history modeling

IV. RESEARCH GAP

The reviewed studies provide strong evidence for reliability modeling, survival methods, and remaining-useful-life prediction, but several gaps remain. First, many studies emphasize predictive accuracy while paying less attention to the full reliability chain, from observed degradation to survival probability, hazard behavior, and uncertainty intervals. Second, several prognostic models report point estimates of remaining useful life without making the corresponding failure probability explicit for maintenance decision-making. Third, probabilistic reliability studies are often mathematically strong but may not show how the same framework can be applied to multivariate degradation trajectories. Fourth, benchmark studies frequently compare prediction models but give limited space to interpretable lifetime distributions and Monte Carlo reliability bands. This study addresses these gaps by integrating survival modeling, failure-rate estimation, sensor-informed remaining-life prediction, and simulation-based uncertainty propagation within one empirical framework.

V. PROPOSED METHOD

The proposed method is a secondary quantitative empirical design using benchmark degradation trajectories from engineering systems. The method is deliberately probabilistic because the goal is not simply to predict a single end-of-life value, but to estimate how reliability changes over time and how uncertainty affects maintenance interpretation. The framework has five stages: preparing degradation data, preprocessing reliability data, probabilistic lifetime modeling, simulation-based uncertainty propagation, and maintenance-oriented interpretation. Figure 1 summarizes the proposed framework.

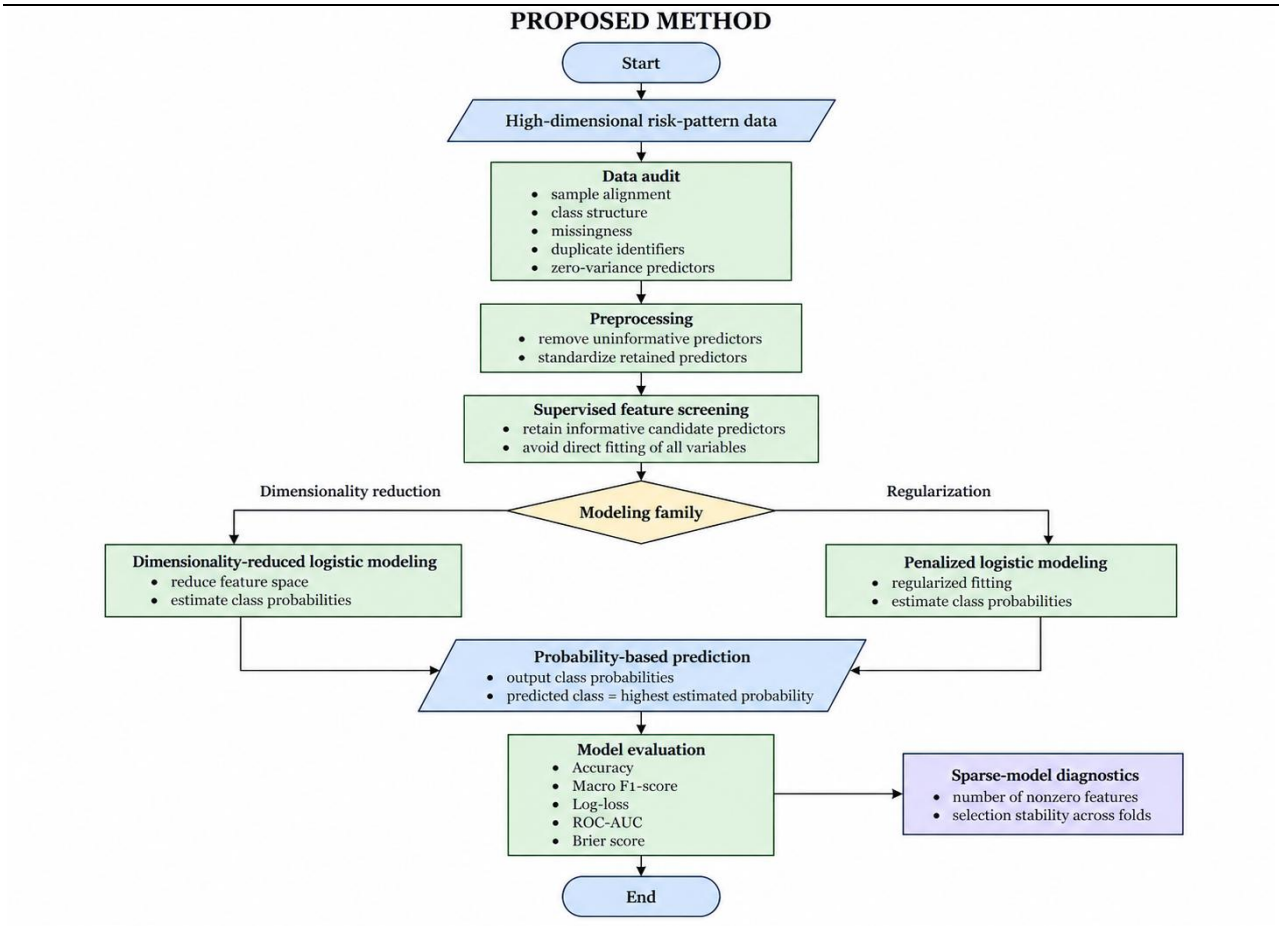


FIGURE 1. Proposed probabilistic reliability-analysis framework.

The framework begins with degradation trajectories that include cycle number, operational settings, and sensor measurements. It then constructs lifetime and remaining-useful-life indicators from complete run-to-failure histories. It estimates reliability using empirical survival and Weibull functions and interprets failure-rate behavior through the hazard function. We introduce simulation uncertainty by resampling lifetime observations and refitting the reliability distribution. The final stage converts the resulting reliability probabilities into maintenance evidence, such as the cycle range where failure risk becomes operationally significant.

VI. STUDY CONTRIBUTION

The study contributes methodologically and empirically. Methodologically, it proposes a compact reliability-analysis framework that integrates distribution fitting, survival estimation, hazard interpretation, remaining-useful-life prediction, and simulation-based uncertainty propagation. Empirically, it applies the framework to degradation trajectories and reports reliability curves, lifetime statistics, hazard behavior, remaining-life prediction accuracy, and simulation intervals. The study does not claim causal effects or universal transfer to all engineering systems. Instead, it shows how to extract probabilistic reliability evidence from degradation data and convert it into maintenance-relevant indicators.

VII.METHODOLOGY

1. RESEARCH DESIGN

The study uses a secondary quantitative design. The analysis is empirical because it uses observed degradation trajectories and true remaining-useful-life labels rather than a purely conceptual reliability example. It is also exploratory and association-based because the benchmark does not identify controlled interventions or causal maintenance policies. The analytical objective is to estimate reliability, failure probability, remaining useful life, and uncertainty intervals from degradation evidence.

2. DATA SOURCE AND ANALYTICAL SAMPLE

The empirical data consist of four benchmark turbofan degradation subsets. Each subset contains multiple engine units, operating cycles, three operational settings, and 21 sensor measurements. The training trajectories are complete run-to-failure histories, while the test trajectories stop before failure and are accompanied by true remaining-useful-life labels. The main analysis uses Subset A because it has one operating condition and one fault mode, allowing the clearest demonstration of the probabilistic framework. Subsets B, C, and D are retained as robustness cases because they introduce additional operating conditions and/or fault modes.

Table 3. Analytical data profile.

Subset	Train engines	Test engines	Train rows	Test rows	Conditions	Fault modes	Missing
A	100	100	20631	13096	one	one	0
B	260	259	53759	33991	six	one	0
C	100	100	24720	16596	one	two	0
D	249	248	61249	41214	six	two	0

3. VARIABLES AND OPERATIONAL DEFINITIONS

Table 4. Variables and operational definitions.

Variable	Meaning	Operationalization	Role
Engine unit	Individual system trajectory	Unit identifier	Grouping variable
Operating cycle	Elapsed operating time	Cycle count	Time index and lifetime measure
Operational settings	Operating-condition controls	Three numerical settings	Contextual covariates
Sensor signals	Condition-monitoring evidence	Twenty-one sensor measurements	Degradation indicators
Failure cycle	End of useful operating trajectory	Maximum cycle in complete trajectories	Lifetime outcome
Remaining useful life	Future operating cycles before failure	Failure cycle minus current cycle; true labels for test units	Prediction outcome
Reliability probability	Probability of survival beyond time t	Survival function R(t)	Main reliability indicator
Hazard rate	Instantaneous failure tendency among surviving units	h(t)=f(t)/R(t)	Failure-rate indicator

4. RELIABILITY FUNCTIONS AND EQUATIONS

Let T denote the time-to-failure random variable measured in operating cycles. Reliability is defined as the probability that the system survives beyond cycle t. The failure distribution is the complement of reliability, and the hazard rate describes the instantaneous tendency to fail conditional on survival until t.

$$R(t) = P(T > t) = 1 - F(t) (1)$$

$$h(t) = f(t)/R(t) (2)$$

We fitted the Weibull distribution to complete failure cycles because it can model increasing, decreasing, or approximately constant failure rates. In this study, the shape parameter beta indicates the failure-rate pattern, and the scale parameter eta gives the system's characteristic life.

$R(t) = exp[-(t/eta)^{beta}](3)$

$h(t) = (beta/eta)(t/eta)^(beta - 1)(4)$

Remaining useful life at cycle c for a complete trajectory is defined as the difference between the observed failure cycle and the current cycle. For incomplete test trajectories, the true remaining-life label is used only for validation.

$RUL_i(c) = T_i - c(5)$

We estimated Monte Carlo uncertainty by repeatedly resampling lifetime observations, refitting the Weibull parameters, and recalculating reliability across the operating-cycle grid.

$R_b(t) = exp\left[-(t/eta_b)^(beta_b)\right], b = 1, \ldots, B(6)$

5. ANALYTICAL PROCEDURE

The analysis followed six steps. First, we imported each subset and checked for missing values. Second, we converted complete training trajectories into failure-cycle and remaining-useful-life indicators. Third, descriptive lifetime statistics were estimated for all subsets. Fourth, we fitted the Weibull model to complete lifetime observations and compared it with the empirical survival curve in the main subset. Fifth, we trained a regularized prediction model using operating cycles, operational settings, and nonconstant sensor signals to estimate remaining useful life for incomplete test trajectories. Sixth, Monte Carlo resampling generated reliability uncertainty bands around the fitted survival curve. The robustness check repeated lifetime fitting and prediction evaluation across the more complex secondary subsets.

6. VALIDITY, RELIABILITY, AND ETHICS

We strengthened internal validity by using complete failure trajectories for distribution fitting and separate incomplete trajectories for remaining-life validation. Measurement reliability was supported by consistent variable definitions across all subsets and by a transparent preprocessing rule that removed only non-informative constant features. External validity is limited because the data represent a benchmark engineering degradation environment rather than direct field maintenance records. Ethical risk is minimal because the analysis uses non-human engineering data and does not involve personal or sensitive information.

VII. RESULTS

1. LIFETIME CHARACTERISTICS

The four subsets show clear run-to-failure variation. In the main subset, the minimum observed lifetime was 128 cycles, and the maximum was 362 cycles, with a mean of 206.31 cycles and a median of 199 cycles. The two more complex subsets with two fault modes had longer average lifetimes and greater dispersion. This suggests that reliability analysis should not rely on a single deterministic end-of-life threshold across all operating and fault conditions.

Table 5. Lifetime statistics by subset.

Subset	Min	Q1	Median	Q3	Max	Mean	SD
A	128	177.0	199.0	229.25	362	206.31	46.34
B	128	174.0	199.0	230.25	378	206.77	46.78
C	145	189.75	220.5	279.75	525	247.2	86.48
D	128	190.0	234.0	290.0	543	245.98	73.11

2. SURVIVAL AND RELIABILITY ESTIMATES

Figure 2 compares the empirical survival pattern of the main subset with the fitted Weibull survival curve. The model follows the overall decline of reliability and provides a smooth probability function for maintenance interpretation. The fitted curve estimates reliability at 0.846 after 150 cycles and 0.552 after 200 cycles. The corresponding cumulative failure probability at 200 cycles is 0.448, showing that the period around 200 cycles is a critical reliability transition zone in the main subset.

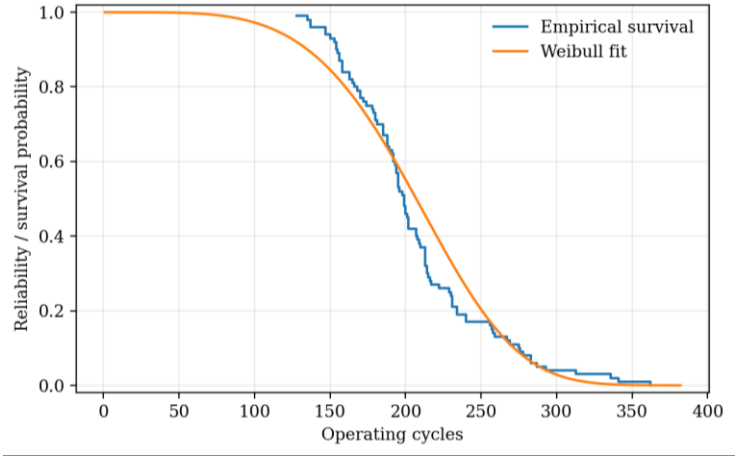


FIGURE 2. Survival pattern of engine lifetimes in the main subset.

3. WEIBULL RELIABILITY PARAMETERS AND HAZARD BEHAVIOR

The Weibull estimates support a wear-out interpretation. In the main subset, the shape parameter was 4.409, and the scale parameter was 225.026 cycles. Because the shape parameter is greater than one, the fitted hazard rate increases with operating cycles. The secondary subsets also show shape parameters greater than one, indicating increasing failure tendency as degradation accumulates. This pattern aligns with engineering wear-out behavior and supports maintenance thresholds that tighten as systems approach later operating cycles.

Table 6. Weibull lifetime-model estimates.

Subset	Shape beta	Scale eta	Empirical mean	Weibull mean	Log-likelihood
A	4.409	225.026	206.31	205.109	-530.749
B	4.388	225.664	206.765	205.635	-1382.32
C	2.929	276.818	247.2	246.938	-586.538
D	3.471	272.87	245.98	245.404	-1425.044

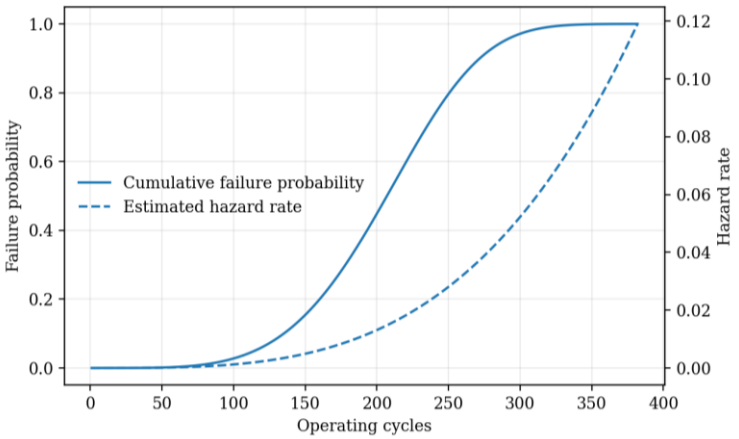


FIGURE 3. Failure probability and hazard rate from the Weibull model.

4. SENSOR EVIDENCE AND REMAINING-USEFUL-LIFE PREDICTION

The sensor-based prediction model provided useful remaining-life evidence for incomplete trajectories. In the main subset, the model used 18 informative features and achieved an RMSE of 22.545 cycles, an MAE of 17.780 cycles, and an R-squared value of 0.706. Performance was directionally stable across the secondary subsets, although error increased when additional operating conditions and multiple fault modes were present. This result supports reporting uncertainty alongside point predictions, especially when system conditions become more heterogeneous.

Table 7. Remaining-useful-life prediction performance.

Subset	Features	RMSE	MAE	R2	Mean residual	SD residual	95% coverage
A	18	22.545	17.78	0.706	-1.727	22.592	0.94
B	25	31.704	23.9	0.652	6.794	31.027	0.927
C	19	22.58	18.188	0.702	-7.526	21.396	0.94
D	25	34.745	27.886	0.594	5.165	34.428	0.935

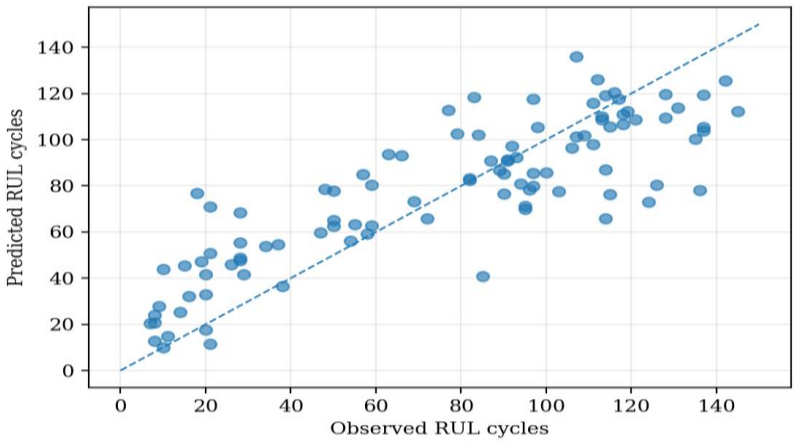


FIGURE 4. Observed and model-estimated remaining useful life.

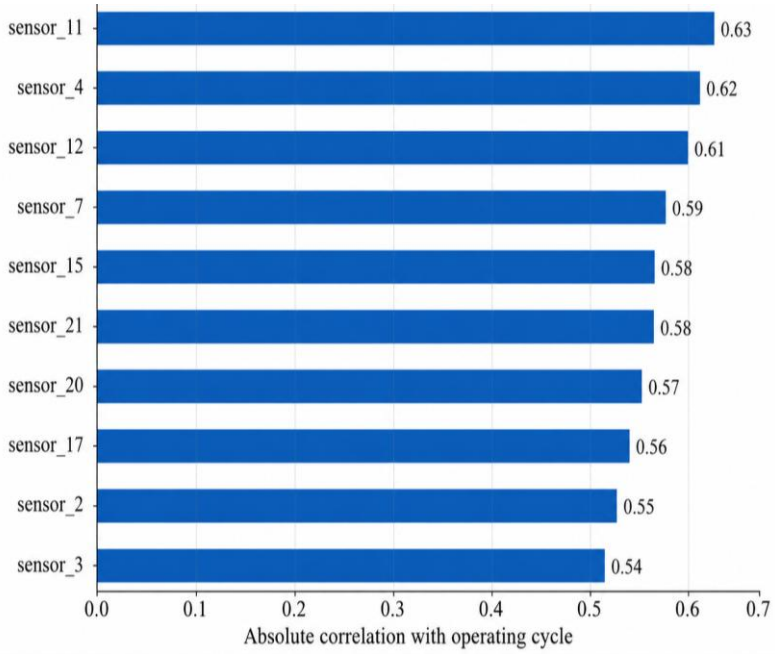


FIGURE 5. Most degradation-sensitive sensor signals in the main subset.

5. MONTE CARLO UNCERTAINTY SIMULATION

Monte Carlo resampling produced uncertainty bands around the reliability curve. For the main subset, the 95% bootstrap interval for the Weibull shape parameter ranged from 3.916 to 5.575, while the scale interval ranged from 213.733 to 235.320 cycles. The reliability band is narrow in early cycles, where nearly all units are expected to survive, and wider around the reliability transition zone, where maintenance decisions are most sensitive to uncertainty. This supports the value of simulation-based reliability reporting.

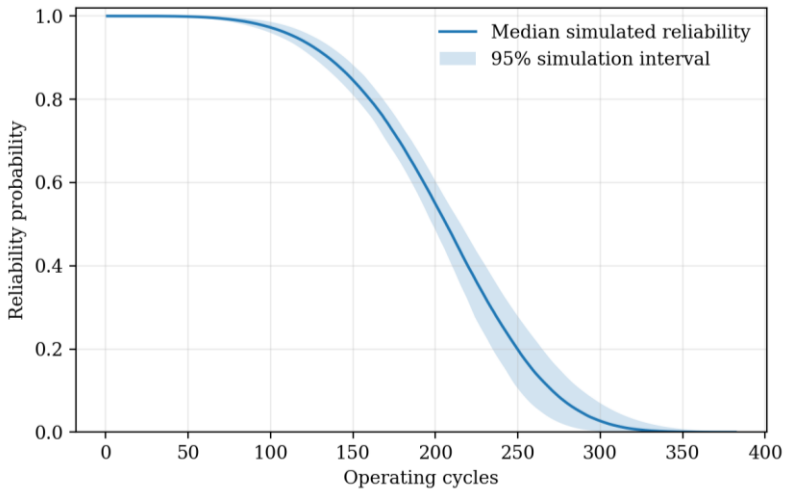


FIGURE 6. Monte Carlo uncertainty band for reliability estimate.

VIII. DISCUSSION

The findings support the central argument that reliability analysis becomes more informative when degradation evidence is converted into probabilistic survival, hazard, and remaining-life indicators. The main subset showed an empirical mean lifetime of 206.31 cycles and a median lifetime of 199 cycles, but these summary values alone are not enough for maintenance planning. A deterministic interpretation might use

the mean or median as a single replacement threshold, yet the survival curve shows that failure risk changes gradually and nonlinearly across cycles. The reliability estimate of 0.846 at 150 cycles suggests that most units are still expected to survive at that stage, while the estimate of 0.552 at 200 cycles indicates that the system has entered a much more uncertain transition region. This difference is operationally meaningful because it converts a descriptive lifetime average into a risk-aware maintenance horizon.

The Weibull estimates also provide important engineering interpretation. A shape parameter above one indicates an increasing hazard rate, and the main subset produced a shape value of 4.409. This pattern is consistent with wear-out behavior: the longer a unit operates, the greater the conditional tendency toward failure among surviving units. This does not mean that all engines fail near the same cycle, because the observed lifetime range extends from 128 to 362 cycles in the main subset. It does mean that the reliability function can help identify stages where monitoring should become more intensive and where preventive actions should be more strongly considered. In this sense, the hazard curve is not only a statistical output; it is a maintenance communication tool.

The results also show why remaining-useful-life prediction should be interpreted probabilistically. The prediction model performed well on the main subset, with an RMSE of 22.545 cycles and an MAE of 17.780 cycles. This level of error may be acceptable for broad planning, but it is not precise enough to justify a single exact failure date. The model is stronger when you combine its estimates with reliability probability and residual uncertainty. For example, treat a predicted remaining life near a risk threshold differently from a prediction far from the threshold. The same point estimate may mean different things for maintenance depending on the hazard rate, operating condition, and uncertainty interval.

The robustness subsets confirm the expected difficulty of reliability modeling under heterogeneous conditions. Subsets with multiple operating conditions or multiple fault modes showed higher prediction errors and wider lifetime dispersion. This result does not weaken the framework; rather, it demonstrates why probabilistic modeling is necessary. Deterministic methods are most attractive when the system is homogeneous and failure behavior is stable. Once condition variation and multiple degradation pathways enter the data, analysts need probability distributions, covariate-aware prediction, and simulation intervals to avoid overconfident decisions. Reliability analysis should therefore be adaptive to the complexity of the operating environment.

The Monte Carlo results add a further layer to this interpretation. The bootstrap intervals around the Weibull parameters show that reliability estimates themselves are uncertain because they depend on finite observed failure histories. The reliability band was most relevant in the transition region, where a moderate change in parameter estimates can alter the inferred probability of survival. This is exactly the region where maintenance decisions are often most difficult: early maintenance may waste remaining useful life, whereas delayed maintenance may increase risk. Simulation does not eliminate this trade-off, but it makes the trade-off visible and quantifiable.

The study also has implications for applied sciences beyond turbofan systems. Many applied systems produce degradation-like evidence even when their physical mechanisms differ. Infrastructure components accumulate wear, electrical devices experience thermal and load-related stress, and industrial processes experience component aging and environmental variability. Lifetime distributions and sensor features will differ across fields, but the proposed analytical logic remains transferable: define time-to-failure, estimate survival, model hazard, link current condition to remaining useful life, and propagate uncertainty. The framework is therefore not limited to one machine type, although its empirical estimates should not be generalized outside similar degradation contexts without validation.

A cautious interpretation is important. The analysis uses benchmark degradation trajectories rather than direct field-maintenance records. The results therefore demonstrate methodological applicability and empirical feasibility, not universal reliability thresholds. Treat the reported values as evidence for the analyzed benchmark, not as general aviation-maintenance standards. However, the study remains valuable because it shows how a researcher can build a transparent probabilistic reliability manuscript from degradation data using interpretable models, validation metrics, and simulation bands. This balance between empirical grounding and cautious generalization is necessary for publication-quality reliability research.

X. PRACTICAL IMPLICATIONS

For maintenance planners, the framework supports risk-based scheduling rather than fixed-cycle replacement alone. Reliability estimates can identify when a system moves from low-risk operation into a transition zone where inspection, part replacement, or operational restrictions become more defensible. For engineers, the sensor monotonicity and remaining-life results show which condition indicators deserve closer monitoring. For managers, the Monte Carlo uncertainty band provides a practical way to communicate risk without pretending that reliability predictions are exact. The framework can be adapted to mechanical, electrical, infrastructure, and process systems when comparable degradation and failure evidence is available.

XI. LIMITATIONS AND FUTURE RESEARCH

The study has several limitations. The data represent a benchmark degradation environment, not a direct industrial maintenance log. Operating conditions and fault modes are available in structured form, but detailed physical repair histories are not included. The prediction model is intentionally interpretable and regularized rather than optimized for maximum benchmark ranking. Future research can extend the framework by adding covariate-dependent survival models, Bayesian hierarchical reliability estimation, competing-risk models for multiple fault modes, and cost-sensitive maintenance optimization. Future studies should also test the framework using direct field data from industrial maintenance systems, infrastructure inspection records, or electrical-network reliability logs.

XII. CONCLUSION

This study developed and empirically evaluated a probabilistic reliability framework for engineering and applied science systems under degradation uncertainty. Using benchmark turbofan degradation trajectories, the analysis combined lifetime statistics, Weibull reliability modeling, empirical survival estimation, hazard interpretation, sensor-informed remaining-useful-life prediction, and Monte Carlo uncertainty simulation. The main subset showed a mean lifetime of 206.31 cycles and a Weibull shape parameter of 4.409, indicating increasing hazard and wear-out-dominated degradation. Reliability declined from 0.846 at 150 cycles to 0.552 at 200 cycles, showing that the area around 200 cycles is a meaningful risk-transition zone rather than a simple deterministic cutoff. The remaining-useful-life model performed well in the main subset, while more complex robustness subsets produced higher errors, confirming that operating heterogeneity increases uncertainty. Monte Carlo resampling further demonstrated that reliability estimates should be communicated with intervals, especially near maintenance thresholds. The study concludes that probabilistic approaches provide a stronger basis for reliability analysis than deterministic interpretation alone because they connect degradation evidence, survival probability, failure-rate behavior, prediction error, and uncertainty in one decision-oriented framework. The framework is suitable for adaptation to other engineering systems when comparable lifetime, sensor, and operating-condition data are available.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

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Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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