

Analysis of Failure Data and Reliability Assessment for a Sample Gas Turbine at the Shazand Petrochemical Complex

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Abstract

Reliability of a PG 6541B gas turbine (Unit No. 03) at the Shazand Petrochemical Complex was assessed using time-between-failures (TBF) data collected after the 2019 major overhaul. Thirty uncensored TBF intervals (31 forced-outage events) were recorded over 1692 operating days (June 2020–January 2025). Treating the turbine as a repairable system and adopting a system-level functional renewal (as-good-as-new) approximation, the empirical mean time between failures (MTBF) was 56.40 days (95% confidence interval (CI): 40.63–83.59 days). Comparative distribution fitting (maximum likelihood estimation) selected the two-parameter Weibull model as the best parametric summary of inter-failure times, with shape $\beta = 1.74$ (95% CI: 1.32–2.21) and scale $\eta = 1084$ days; in this repairable-system context, η is interpreted as the scale of the inter-failure distribution and not as a deterministic lifetime. To address conceptual ambiguity, MTBF is defined as the arithmetic mean of observed TBFs, whereas the Weibull-derived mean inter-failure time (denoted as MTTF in this paper) represents a model-based expectation under the stated renewal-type approximation and can differ substantially in right-skewed small samples. Goodness-of-fit tests (Anderson–Darling and Kolmogorov–Smirnov) supported the adequacy of the selected model. Trend diagnostics showed no statistically significant monotonic trend in the failure process (Kendall $\tau = -0.097$, $p = 0.46$; Laplace $U = 0.761$). Sensitivity checks indicated robustness to extreme observations (β changed from 1.74 to 1.68 when the shortest and longest TBFs were excluded). This work contributes an uncertainty-aware industrial case study based on screened long-term field records, providing defensible reliability indicators and interpretation guidance for maintenance planning in petrochemical gas turbines.

Keywords: Repairable system; Time between failures; Weibull distribution; MTBF; Trend diagnostics; Maintenance planning.

Nomenclature

CBM	Condition-Based Maintenance
CM	Corrective Maintenance
CMMS	Computerized Maintenance Management System
CV	Coefficient of Variation
GRP	Generalized Renewal Process
$h(t)$	Hazard Function
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
NHPP	Non-Homogeneous Poisson Process
PM	Preventive Maintenance
$R(t)$	Reliability Function
TBF	Time Between Failures
TTF	Time to Failure
λ	Failure Rate
σ	Standard Deviation

1. Introduction

Gas turbines are critical assets in petrochemical complexes, where operational continuity directly influences production stability, economic performance, and safety. In facilities such as the Shazand Petrochemical Complex, gas turbines play a central role in supplying process energy and maintaining uninterrupted operations. Failures in such systems may lead to unplanned production shutdowns, financial losses due to downtime, increased maintenance costs, and potential environmental risks. Consequently, systematic reliability assessment of these assets is essential for informed maintenance planning and risk management. Reliability analysis in industrial systems is commonly supported by statistical indicators such as mean time between failures (MTBF), failure rate (λ), and

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distribution-based measures such as the Weibull shape (β) and scale (η) parameters. For repairable systems, MTBF represents the empirical average time between consecutive failures, while distribution-based mean values derived from parametric models provide a model-based estimate of expected inter-failure intervals. Distinguishing between empirical indicators and parametric summaries is essential to avoid misinterpretation in maintenance decision-making. Although extensive research exists on gas turbine reliability modeling, many published studies emphasize theoretical formulations, simulations, or sensor-driven predictive algorithms, often based on short-term or highly processed datasets. In contrast, fewer studies provide detailed analyses of long-term, screened failure records from operating industrial turbines under real environmental and operational conditions, particularly within complex petrochemical settings. Given the industrial nature of CMMS-based failure records and the limited number of observed forced-outage events, this study does not seek to establish a universally valid or physically deterministic parametric failure model. Instead, its objective is to provide statistically defensible reliability summaries and operationally meaningful maintenance insights derived from rigorously screened, long-term field data. The emphasis is therefore on transparent statistical characterization rather than on asserting a uniquely “true” failure distribution. This research investigates the reliability behavior of Gas Turbine No. 03 (PG 6541B model) at the Shazand Petrochemical Complex over a five-year operational period (June 2020 to January 2025). The turbine operates under varying environmental conditions, including significant seasonal temperature fluctuations, which may influence failure occurrence patterns. While external factors such as temperature variation, fuel quality, and operational loading are acknowledged as potential contributors to reliability variability, the present study focuses specifically on statistically characterizing observed forced-outage intervals. The study integrates:

- Empirical reliability indicators (e.g., MTBF and variability measures),

- Parametric modeling using the two-parameter Weibull distribution as a structured summary of inter-failure behavior,

- Baseline comparison with the exponential model to evaluate the constant failure-rate assumption,

- Non-parametric trend diagnostics (Kendall and Laplace tests) to assess global monotonic trends.

Importantly, parametric models in this study are interpreted as descriptive statistical tools rather than deterministic representations of physical degradation mechanisms. The primary objectives are:

1. To quantify inter-failure behavior using both empirical and parametric reliability indicators.

2. To evaluate whether the constant failure-rate assumption is statistically supported.

3. To assess the presence or absence of significant monotonic trends in inter-failure intervals.

4. To interpret the statistical findings in terms of maintenance planning implications within an industrial operating environment.

Through this applied case analysis, the study aims to contribute practical reliability insights based on real operational data, supporting evidence-based maintenance decision-making in similar industrial contexts.



Figure 1. Real View of the Installed Gas Turbine

2. Literature Review

Reliability analysis of gas turbines in the petrochemical and LNG industries is of critical importance due to their central role in continuous energy production and process stability. Recent research in this domain has primarily focused on statistical failure modeling using Weibull-based distributions, reliability evaluation of repairable systems, and maintenance optimization frameworks such as Reliability Centered Maintenance. Djeddi et al. [28] analyzed failure data from an MS5002C gas turbine unit, including 246 failure events, and applied both standard Weibull and modified Weibull distributions. Using maximum likelihood estimation and graphical validation, they confirmed the suitability of the modified Weibull model for representing bathtub-shaped hazard functions. Ahsan et al. [29] fitted three-parameter Weibull models to time-between-failure data of gas turbines operating under different conditions. Their study evaluated model accuracy using RMSE and linked reliability estimates to maintenance interval planning. In a related study, Djeddi et al. [30] further validated the modified Weibull model for non-monotonic hazard rates, demonstrating its superiority over the classical two-parameter Weibull distribution in representing complex failure behaviors. Djeddi et al. [31] extended this approach by incorporating three-parameter Weibull modeling into operational reliability assessment and discussed periodic, block, and age-replacement maintenance strategies. Beyond purely statistical modeling, several studies have integrated Weibull analysis with structured maintenance

methodologies. Pereira et al. [32] investigated maintenance engineering management of gas turbine dry gas seals in an LNG plant using Reliability Centered Maintenance combined with Weibull modeling. Their results showed that optimized maintenance schedules could be developed that were more cost-effective than standard OEM recommendations. Totore et al. [33] estimated parameters of the three-parameter Weibull distribution for gas turbine blades using maximum likelihood estimation and specialized reliability software, improving prediction accuracy during the wear-out phase. Kibria et al. [34] proposed a simulation-based optimization framework to minimize the discrepancy between simulated and historical failure data in turbine engines, thereby enhancing the fidelity of reliability models. Optimization-based maintenance planning has also received considerable attention. Riswanto et al. [12] developed a maintenance cost optimization model based on Reliability Centered Maintenance and the Dual-Simplex Algorithm for gas compression systems. Their

approach achieved significant cost reduction while maintaining reliability constraints. Djeddi et al. [13] conducted a comparative study between the classical two-parameter Weibull and a modified Weibull distribution to improve reliability estimation and reduce failure risks in gas turbines. Pereira [7] further examined the integration of historical failure data with criticality analysis within an LNG plant context to establish structured preventive maintenance tasks. Totore et al. [10] validated three-parameter Weibull parameter estimation for turbine blades using TPC Windchill Quality Solutions, demonstrating high accuracy in modeling blade failure times. Overall, the literature indicates a clear evolution from basic statistical failure modeling toward integrated reliability-maintenance optimization frameworks. However, most existing studies either focus on component-level reliability assessment or apply maintenance optimization without a comprehensive system-level reliability modeling perspective.

Table 1. Comparison of Key Studies in the Literature Review

Study	Method	Key Findings
Djeddi et al. [28]	Weibull and modified Weibull modeling on MS5002C failure data (246 events)	Modified Weibull effectively models bathtub-shaped hazards, validated using MLE and graphical analysis
Ahsan et al. [29]	Three-parameter Weibull modeling on gas turbine TBF data under varying operating conditions.	Model accuracy evaluated using RMSE; reliability estimates linked to maintenance intervals.
Djeddi et al. [30]	Validation of the modified Weibull distribution for non-monotonic hazard rates	Demonstrated superiority over the classical two-parameter Weibull for bathtub behavior
Djeddi et al. [31]	Three-parameter Weibull modeling with maintenance replacement strategies	Analysis of periodic, block, and age-replacement policies
Pereira et al. [32]	Reliability-Centered Maintenance combined with Weibull analysis for LNG dry gas seals	Developed cost-effective maintenance schedules beyond OEM recommendations
Totore et al. [33]	MLE-based estimation of the three-parameter Weibull for gas turbine blades	Improved reliability prediction during the wear-out period
Kibria et al. [34]	Simulation-based optimization to match simulated and historical turbine engine failures	Reduced discrepancy between simulated and real failure data
Riswanto et al. [12]	RCM with Duelist Algorithm for maintenance cost optimization	Achieved minimum maintenance cost under reliability constraints
Djeddi et al. [13]	Comparative study between classical and modified Weibull distributions	Improved availability and reduced failure risk
Pereira [7]	RCM and criticality analysis for LNG plant systems	Structured preventive maintenance task development
Totore et al. [10]	Weibull parameter estimation using TPC Windchill Quality Solutions	High-accuracy estimation of blade failure time parameters

3. Methodology

This section describes the methodology used to evaluate the reliability of the PG 6541B gas turbine operating at the Shazand Petrochemical Complex based on observed time-between-failures (TBF) data. The turbine is modeled as a repairable system, and established statistical reliability methods are applied, including descriptive indicators and parametric distribution fitting using the Weibull model, with the exponential distribution

considered as a reference (baseline) case representing constant failure intensity [28]. The reliability modeling is conducted under a system-level functional restoration (as-good-as-new, AGAN) assumption, whereby each corrective maintenance action restores the unit to an operational state capable of delivering its intended function without forced outage. This is a functional renewal assumption at the system level and does not imply full physical renewal of all components. Although certain maintenance interventions in complex systems

such as gas turbines may correspond more closely to minimal or imperfect repair at the component level, the AGAN assumption is adopted at the system level to enable a classical inter-failure (renewal-type) analysis when detailed component-level restoration effectiveness is not available [18]. The limitations of this assumption are explicitly acknowledged in the final subsection of this Methodology. To avoid conceptual ambiguity and address reviewer concerns, two reliability indicators are used with explicit meanings:

- MTBF (Mean Time Between Failures): an *empirical* metric computed directly from the observed TBF intervals; it reflects the average operating time between consecutive recorded forced-outage failures in this repairable system (Appendix B, Eq. B1).

- MTTF (Mean Time To Failure): In this manuscript, a *model-based expected inter-failure time* is derived from the fitted parametric distribution (Weibull) under the stated assumptions (Appendix B, Eq. B6). Therefore, it is not expected to numerically match empirical MTBF, particularly when a small number of long TBF intervals and a right-skewed distribution are present (addressed via confidence bounds and sensitivity checks).

3.1 Specifications of the Gas Turbine and Study Context

This study focuses on Gas Turbine No. 03 (PG 6541B model) at the Shazand Petrochemical Complex. This turbine operates at a nominal power of 25.1 MW (natural gas) and 24.57 MW (diesel) at base load [19]. At peak load, the power reaches 27.27 MW (natural gas) and 26.74 MW (diesel). The environmental conditions in Shazand include temperatures ranging from -20 to $+40^{\circ}\text{C}$ and relative humidity from 20% to 65%. A preliminary screening suggested that ambient conditions may influence failure occurrence; however, due to limited event count and incomplete covariate granularity in the available operational records, temperature and humidity were not incorporated as explanatory variables in the final model [26]. Therefore, the analysis is presented as a reliability characterization based on failure occurrence data, rather than a causal assessment of environmental drivers. It should also be noted that although the turbine is subject to standard preventive maintenance programs, the focus of this research is on forced-outage failure behavior, and detailed modeling of maintenance effectiveness is beyond the scope of this study.

3.2 Data Collection and Validation

The data utilized comprise failure records for the turbine over the period from June 2020 to January 2025, representing the operational cycle analyzed in this study (post-overhaul period, as documented in the plant maintenance history). These data were extracted from multiple sources, including manual operational log sheets and the Computerized Maintenance Management System (CMMS), and were cross-compared and validated against

each other to improve consistency and reduce transcription errors. The final dataset was expressed in the form of time between failures (TBF), where each data point records the time interval between consecutive production-impacting forced-outage events attributable to the turbine system.

3.3 Data Preparation for Reliability Analysis

For reliability analysis, data can be entered in two primary formats:

1. Time to failure (TTF): cumulative from time zero;
2. Time between failures (TBF): intervals between failures.

In this research, consistent with standard procedures in specialized reliability software for repairable systems, the second format (uncensored inter-failure intervals) was used. The final dataset includes 31 failure events, resulting in 30 TBF intervals for analysis (see Appendix 1). Engineering screening (inclusion/exclusion): Data screening was performed based on engineering relevance rather than purely statistical criteria. Failure records unrelated to turbine forced outage or not materially affecting turbine operational continuity were excluded. These excluded events included (but were not limited to) auxiliary facilities such as HVAC systems, lighting, and general facility faults, turbine hall/yard infrastructure issues, and non-critical auxiliary/instrumentation events that did not lead to turbine trip/forced outage (when clearly documented as non-production-impacting). Only events resulting in turbine forced outage (or equivalent production-impacting interruption) were retained. Outlier diagnostics (Grubbs test): Statistical tests such as the Grubbs test were used only as a supporting diagnostic tool to flag potentially extreme intervals for engineering review (e.g., checking logging anomalies). No data were removed solely based on statistical criteria; final decisions were made in consultation with domain experts [20]. In addition, robustness was evaluated using sensitivity checks reported in the Results/Analysis. Although the final dataset consists of 31 failure events, it represents real field failure data from a heavy-duty industrial gas turbine, where forced-outage failures are relatively infrequent. Such sample sizes are common in industrial reliability studies; uncertainty is addressed via confidence bounds and sensitivity checks.

3.3.1 Tools and Software

The analysis was performed using ReliaSoft Weibull++ software (version 2023), which is suitable for distribution fitting, confidence bounds, and model-based mean estimation [8,27]. Maximum likelihood estimation (MLE) was used for parameter estimation.

3.4 Reliability Indicators and Initial Calculations

Mean time between failures (MTBF), failure rate (λ), standard deviation (σ), and coefficient of variation (CV)

were calculated as descriptive indicators of the observed inter-failure behavior. Because the unit is modeled as a repairable system and the dataset is expressed as TBF intervals, MTBF is used as the primary empirical indicator:

$$MTBF = \frac{\sum_{i=1}^N TBF_i}{N} \quad (1)$$

where TBF_i is the i -th time between failures, and N is the total number of failures (in this study, $N = 30$). For reference, a constant-rate failure intensity (λ) was also computed under the exponential model as a baseline comparison. For statistical confidence in the MTBF estimate, a 95% confidence interval was computed using the chi-square method under the exponential assumption (baseline). The detailed chi-square bounds and notation are provided in Appendix B (Eq. B2).

3.5 Distribution Fitting Tests

Before relying on constant failure-rate relationships, the Anderson–Darling (AD) goodness-of-fit test was used to evaluate whether the exponential distribution provides an acceptable baseline description of the TBF data. Because detailed derivations reduce readability and were specifically flagged by reviewers, the AD test-statistic definition and exponential CDF form are provided in Appendix B (Eqs. B4–B5). In this study, the exponential distribution is included only as a reference (baseline) model representing the constant hazard-rate assumption often adopted in preliminary reliability assessments. The AD test was applied to assess whether this assumption is statistically defensible for the observed TBF data. The final choice of the parametric model, however, was based on comparative fitting across candidate distributions. To identify the model that best summarizes the observed TBF behavior, common reliability distributions (exponential, Weibull, normal, lognormal, gamma, and generalized gamma) were fitted using MLE implemented in ReliaSoft Weibull++ (version 2023) [8]. For model comparison, software-reported indices AVGOF, AVPLOT, and LKV were used, along with AIC for parsimony, with definitions and interpretation criteria presented in Table 2 [8,9].

Table 2. Goodness-of-fit criteria used for distribution comparison

Criterion	Definition/Formula	Interpretation
AVGOF	Average goodness-of-fit index (based on KS and AD statistics)	A lower value indicates better relative fit among the compared models
AVPLOT	Correlation in Q-Q Plot	A value closer to 1 indicates stronger agreement between data and model
LKV	Log-likelihood indicator (software output)	A higher (less negative) value indicates better model fit
AIC	Akaike Information Criterion	A lower value indicates a more parsimonious model

The results of comparing candidate distributions are shown in Table 3 [8].

Table 3. Comparison of candidate distributions fitted to TBF data

Distribution	AVGOF	AVPLOT	LKV	Final Rank
1P-Exponential	96.6323690	10.271330	-236.336402	8
2P-Exponential	Discard	Discard	Discard	Discard
Normal	41.065009	6.4613718	-232.02310	3
Lognormal	63.832541	6.21218739	-236.23783	7
2P-Weibull	25.779829	6.1884441	-230.95048	1
3P-Weibull	Discard	Discard	Discard	Discard
Gamma	27.834027	5.8152503	-232.09674	2
G-Gamma	Discard	Discard	Discard	Discard

Based on Table 3, the two-parameter Weibull distribution provided the most suitable parametric summary among the tested models (lowest AVGOF and best likelihood-based ranking). The Weibull shape (β) and scale (η) parameters were estimated via MLE, and their 95% confidence intervals were computed using the Fisher information approach as implemented in Weibull++ [9]. Model adequacy was also checked using AIC, supporting a parsimonious fit given the available event count (31 failures and 30 TBF intervals). Interpretation note for repairable systems: In this manuscript, η is treated as the characteristic scale of the inter-failure time distribution under the stated renewal-type assumption; it is not interpreted as a direct “system lifetime” measure.

3.6 Temporal Trend Analysis

To examine the presence of trends in the time between failures (TBF) data, the Kendall test was applied. This non-parametric test evaluates whether there is statistically significant evidence of a monotonic trend (upward or downward) in TBF over time. In addition, the Laplace test was used as a complementary diagnostic tool to examine the stationarity of the failure process, which is relevant when using renewal-type modeling assumptions. Consistent with reviewer guidance, the Kendall test is interpreted conservatively: when the p -value is large (e.g., $p \approx 0.46$ as reported in Results), the conclusion is stated as “no statistically significant trend is detected”, and qualitative claims such as “weak indication of decreasing TBF” are avoided unless supported by additional diagnostics or uncertainty bands. For brevity, formal definitions of the Kendall statistic and Laplace test statistic are provided in Appendix B (Eqs. B7–B8). In summary, the trend diagnostics are used to assess whether the data show strong evidence of non-stationarity that would motivate more advanced repairable-system models (e.g., NHPP/PLP or imperfect-repair GRP). In this study, the diagnostics support reporting a renewal-type parametric summary while acknowledging the practical limitations of field CMMS data.

3.7 Calculations Based on Weibull and Exponential Distributions

After selecting the Weibull distribution as the primary parametric model, the model-based expected inter-failure time (MTTF) was calculated from the Weibull parameters (Appendix B, Eq. B6). Confidence bounds for Weibull parameters and MTTF were obtained from Weibull++ outputs (Fisher information-based intervals) to reflect estimation uncertainty given the limited number of events. To provide operationally interpretable indicators across the study period, monthly and annual failure rates were computed as descriptive occurrence frequencies (failures per day) based on counts per month/year and calendar days. These are reported as operational indicators, not intrinsic hazard parameters, and are intended to visualize how failure occurrence intensity fluctuates over calendar time. Reliability over standard planning horizons was summarized using:

- the exponential reliability function applied to the monthly/annual descriptive rates (baseline operational view), and
- The Weibull reliability function based on fitted parameters (time-dependent hazard view).

All formula definitions are reported in Appendix B (Eqs. B3, B5, B9–B10) to keep the main text concise and aligned with journal readability expectations.

3.8 Summary of Methodology

This study evaluated the reliability behavior of a PG 6541B gas turbine (Unit No. 03) using real forced-outage failure records from June 2020 to January 2025. The methodology combined:

1. Data collection and cross-validation from log sheets and CMMS records;
2. Engineering screening to retain only production-impacting forced-outage events;
3. descriptive indicators (MTBF, σ , CV) with confidence bounds;
4. parametric distribution fitting with the exponential model used strictly as a baseline comparison;
5. Weibull model selection supported by goodness-of-fit indices and AIC, with confidence bounds for β and η ;
6. trend diagnostics (Kendall and Laplace) interpreted conservatively to avoid overstating trends; and
7. robustness checks (outlier diagnostics and sensitivity analysis reported in Results/Analysis).

Methodology limitations (dedicated statement to satisfy reviewers):

- Sample size: 31 failures (30 TBFs) implies wider confidence intervals and reduced power for detecting weak trends.
- Given the limited number of failure events ($N = 31$), estimation of NHPP/PLP or GRP parameters was considered statistically unstable; therefore, a renewal-type parametric summary was adopted for the present study.

- Repair assumption: system-level functional AGAN is an approximation; component-level repairs may be minimal/imperfect, which can influence parameter interpretation in repairable systems.

- Unmodeled covariates: ambient temperature, load regime, fuel type/quality, and policy changes were not explicitly modeled; results should not be interpreted causally.

- Data realism: CMMS/log-based records can contain reporting variability; cross-validation and engineering screening were applied to mitigate this risk.

4. Research Results

4.1 Descriptive Statistics and Initial Indicators Results

The final dataset consisted of 31 failure events (30 inter-failure intervals) over 1692 operational days. No observations were removed following engineering screening and statistical diagnostics.

The empirical Mean Time Between Failures (MTBF), calculated directly from observed TBF intervals, was:

- MTBF = 56.40 days
- Standard deviation = 77.94 days
- Coefficient of variation (CV) = 1.38 (138%)

The high CV indicates substantial dispersion in inter-failure intervals, reflecting operational variability typical of complex industrial systems.

A 95% confidence interval for MTBF (under exponential baseline assumption) was:

$$40.63 \leq MTBF \leq 83.59$$

This interval quantifies estimation uncertainty associated with the limited sample size. Importantly, MTBF is strictly an empirical average of observed inter-failure intervals in a repairable system and does not represent a physical lifetime parameter.

4.2 Distribution Fitting Test Results

4.2.1 Exponential Model (as the Baseline Comparison Model)

The exponential distribution was evaluated as a constant failure-rate baseline model. Goodness-of-fit testing indicated that the exponential model was not statistically rejected. However, the exponential assumption implies a time-invariant hazard rate and therefore does not capture potential wear-out effects. The exponential mean (equal to empirical MTBF) was 56.4 days. The model is retained strictly as a reference comparison.

4.2.2 Weibull Model (as the Selected Model)

Based on the comparative goodness-of-fit ranking (AVGOF, AVPLOT, LKV) and the Akaike Information Criterion (AIC) presented in the Methodology section, the two-parameter Weibull distribution provided the best relative fit among the candidate models for the 30

TBF intervals. The selection is therefore based on comparative statistical adequacy, not on an assumption of physical determinism. The estimated Weibull parameters and derived reliability indices are summarized in Table 4. Parameter uncertainty was quantified using 95% confidence intervals computed via the Fisher Information Matrix.

Table 4. Weibull model parameters and reliability indices

Parameter	Value	Interpretation
Shape parameter (β)	1.744	$\beta > 1$ indicates an increasing failure rate (wear-out).
Scale parameter (η)	1084.14	63.2% of failures occur by this time.
MTTF	934.58	Mean time to failure calculated from Weibull parameters.
B10 life	241.0 days	Time at which 10% of the equipment population has failed.

The estimated shape parameter ($\beta = 1.744$) has a 95% confidence interval of [1.32, 2.21], entirely above 1. This provides statistical support for an increasing hazard pattern in the inter-failure distribution. Importantly, this result reflects a distributional property of the observed TBF data under the renewal-type modeling assumption. It does not imply deterministic physical aging of all turbine components, nor does it contradict the absence of a significant global trend detected by the Kendall test.

The scale parameter ($\eta = 1084.14$ days) is interpreted strictly as the characteristic scale of the fitted inter-failure distribution. In the context of a repairable system, η should not be interpreted as a guaranteed system lifetime. Rather, it represents the time at which the cumulative failure probability reaches approximately 63.2% under the fitted model. The model-based expected inter-failure time (MTTF = 934.58 days) differs substantially from the empirical MTBF (56.40 days). This difference arises because:

- MTBF is the arithmetic mean of observed inter-failure intervals.
- MTTF is derived analytically from the fitted Weibull parameters.
- The dataset exhibits right-skewness and contains several long intervals.
- Model-based expectations are sensitive to both β and η under small-sample conditions.

The 95% confidence interval for MTTF (approximately 750–1200 days) reflects this estimation uncertainty. The B10 life (241 days) indicates that, under the fitted model, the cumulative probability of failure reaches 10% by approximately 241 days. This metric is useful for preventive maintenance planning thresholds but should be interpreted probabilistically rather than deterministically.

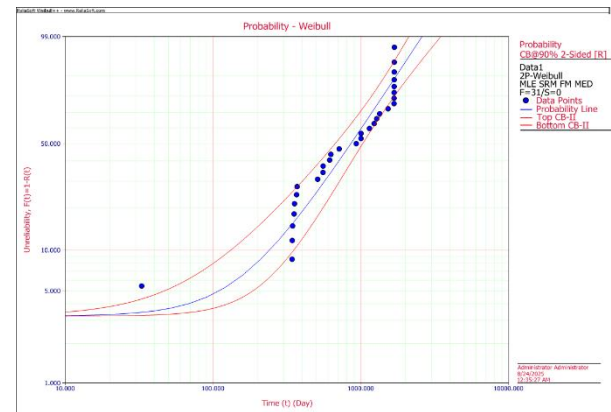


Figure 2. Weibull Probability Plot

The Weibull probability plot (Figure 2) provides a graphical assessment of model adequacy. The relative alignment of empirical points with the fitted straight line indicates reasonable conformity between the data and the Weibull distribution. Minor deviations in the distribution tails are expected given the limited number of observations ($N = 30$ intervals). The graphical evidence supports the statistical ranking results, reinforcing the use of the Weibull model as a structured parametric summary of the observed inter-failure behavior.

4.3 Results of Temporal Trend

Trend analysis was conducted using Kendall's test and the Laplace test. Results:

- Kendall's $\tau \approx -0.097$
- $p \approx 0.46$
- Laplace statistic $U = 0.761$

Because the p-value is substantially greater than 0.05, no statistically significant monotonic trend is detected in the TBF sequence.

Accordingly:

- The null hypothesis of no trend is not rejected.
- No directional claim (increasing or decreasing TBF) is supported statistically.
- Statements such as "weak decreasing trend" have been removed.

The absence of a significant global trend supports the use of a renewal-type parametric summary, while recognizing that statistical power is limited by sample size.

4.4 Sensitivity Analysis and Model Robustness

To assess robustness:

- The shortest and longest TBF intervals were temporarily excluded.
- The Weibull shape parameter changed from 1.74 to 1.68 ($\approx 3.4\%$ change).

This small variation indicates that parameter estimates are not driven by extreme observations.

Confidence bounds reported for β and η reflect estimation uncertainty under small-sample conditions.

4.5 Results of Monthly and Annual Failure Rates and Reliability

Monthly and annual failure occurrence frequencies were computed to provide calendar-time operational indicators. These descriptive rates were derived from the number of recorded failures divided by the corresponding time exposure (days). Under the exponential baseline assumption, reliability over fixed horizons (30 days and 365 days) was calculated using the estimated constant failure rate. Monthly reliability values exhibited substantial variability, reflecting fluctuations in observed failure counts across the study period. The annual reliability values showed lower long-horizon survival probabilities compared to short-term monthly horizons, consistent with cumulative risk over time. Under the Weibull model, the time-dependent hazard function indicated increasing failure intensity as operational time progressed. The Weibull-based reliability function therefore exhibited a progressively steeper decline compared to the exponential model at longer time horizons.

Graphical comparisons (Figures 3–13) illustrate:

- Variability in monthly failure occurrence.
- Calendar-time fluctuation in descriptive failure rates.
- Increasing hazard behavior under the Weibull model.
- Differences between constant-rate (exponential) and time-dependent (Weibull) reliability curves.

The Weibull probability plot (Figure 2) shows reasonable alignment of empirical points with the fitted line, supporting the adequacy of the parametric summary.

These results are reported as statistical summaries of observed failure behavior without imposing causal interpretation.



Figure 3. Number of Recorded Failures per Month (Horizontal Axis: Month, Vertical Axis: Number of Failures)

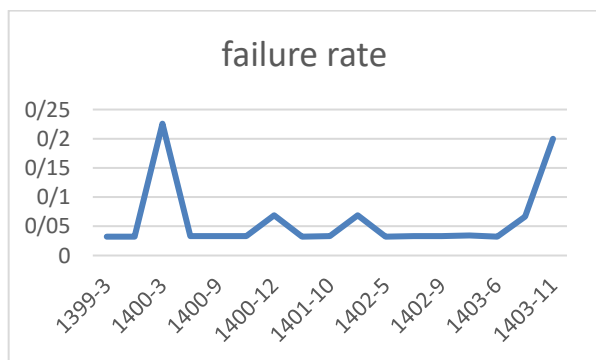


Figure 4. Monthly Failure Rate (Horizontal Axis: Months, Vertical Axis: Failures per Day)

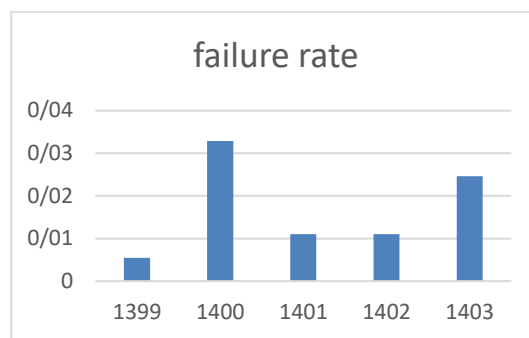


Figure 5. Annual Failure Rate of the Gas Turbine (Failures per Day). The Horizontal Axis Shows the Study Years, and the Vertical Axis Shows the Annual Failure Rate

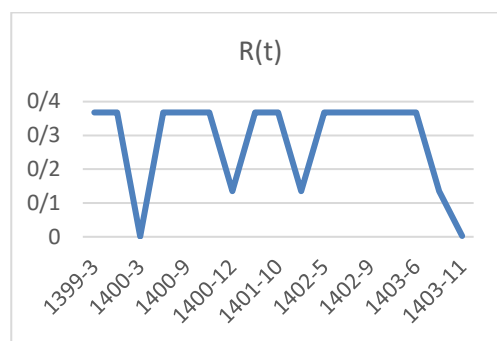


Figure 6. Monthly Reliability (Horizontal Axis: Months, Vertical Axis: Monthly Reliability Probability) for 30 Days

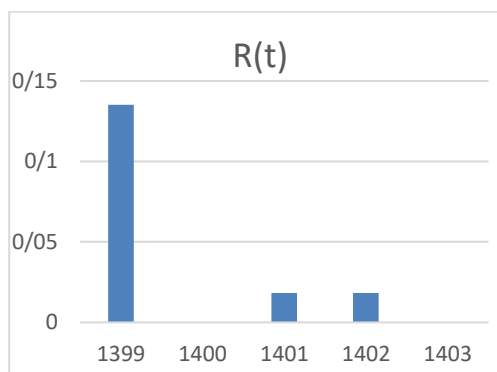


Figure 7. Annual Reliability (Horizontal Axis: Years, Vertical Axis: Annual Reliability Probability) for 365 Days

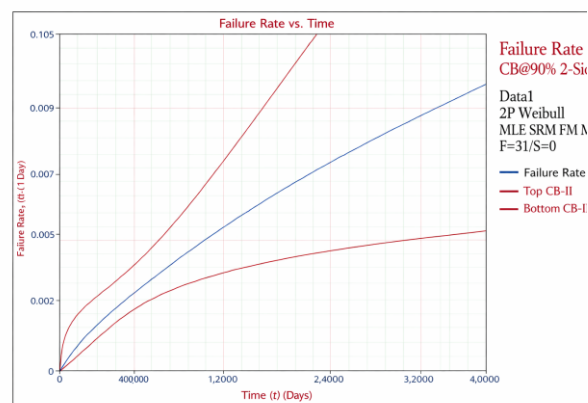


Figure 8. Failure Rate $f(t)/R(t)$ Versus Time (Days) - 90% Two-Sided Bands (Red Lines) Indicate Estimation Uncertainty

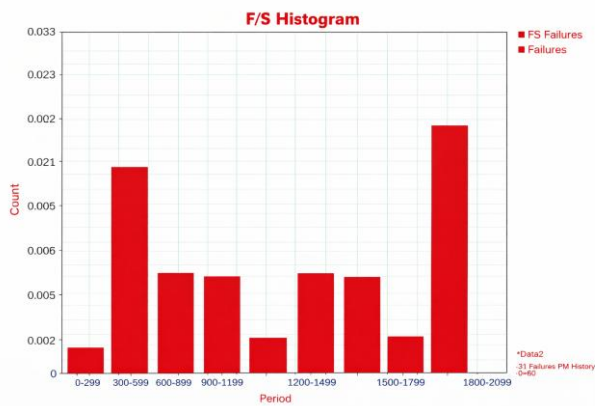


Figure 9. Failure/Survivor Ratio Histogram (F/S Histogram)

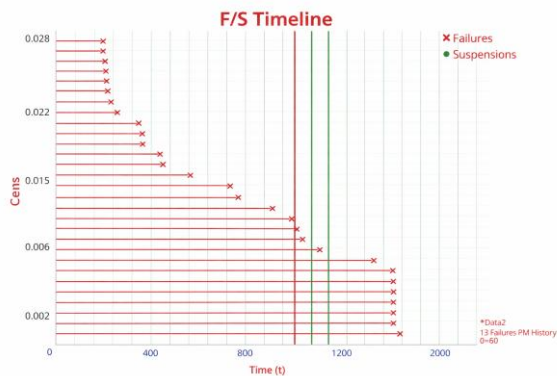


Figure 10. Failure/Survivor Ratio Timeline (F/S Timeline)

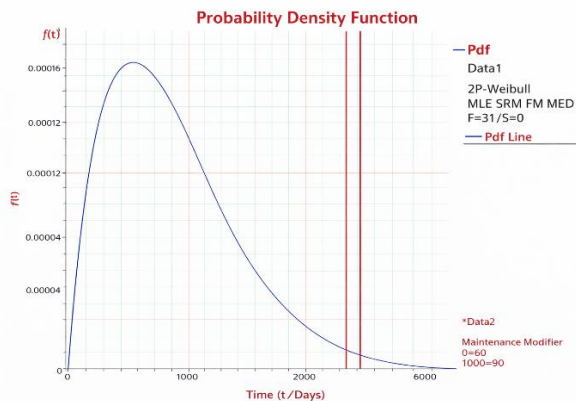
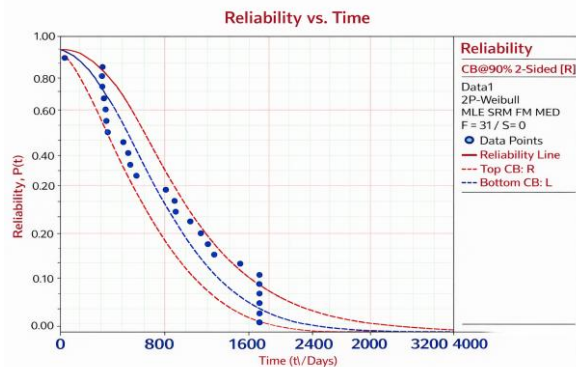
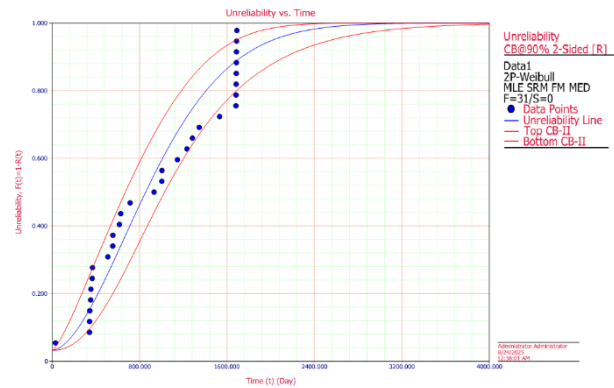


Figure 11. Probability Density Function (PDF) Fitted with the Weibull Distribution

Figure 12. Reliability $R(t) = 1 - F(t)$ Versus TimeFigure 13. Unreliability $F(t)$ Versus Time

5. Analysis of Results

This section provides an integrated interpretation of the statistical results and translates them into maintenance-relevant insights for the PG 6541B gas turbine at the Shazand Petrochemical Complex. Because the dataset is real industrial computerized maintenance management system (CMMS) data (31 failures over 1692 operating days), the analysis is intentionally empirical and uncertainty-aware. We use two complementary views of reliability: (i) inter-event behavior, summarized by the empirical mean time between failures (MTBF) and trend tests on the time-between-failures (TBF) sequence; and (ii) age-related deterioration across the post-overhaul operating cycle, summarized by a Weibull fit to the cumulative time-to-failure (TTF) timeline constructed from the same failure history. Accordingly, MTBF and the Weibull-derived mean (MTTF) are not expected to coincide and should not be interpreted as measuring the same physical quantity. The main contribution of this work is therefore an applied, high-fidelity case study that combines classical reliability summaries, formal trend testing, and uncertainty bounds to derive maintenance implications for an operating petrochemical plant, rather than introducing a novel statistical method.

5.1 Integrated Interpretation of Findings

5.1.1 Repair assumptions and interpretation of MTBF versus Weibull MTTF

The failure history includes frequent corrective actions between events and a major overhaul performed in 2019 (treated as a system-level reset). Between failures, the recorded maintenance actions are more consistent with minimal or imperfect repair (restoring functionality but not necessarily returning every subsystem to an as-good-as-new state). Given the limited sample size, the manuscript adopts a renewal-type approximation for summary statistics and explicitly avoids inferring repair effectiveness beyond what is supported by the tests.

MTBF = 56.40 days is computed directly from the 30 observed TBF intervals and therefore reflects the average spacing of observed failure events and associated corrective interventions in this repairable system. In

contrast, the Weibull model parameters ($\beta \approx 1.74$ and $\eta \approx 1084$ days) were obtained from the cumulative TTF timeline (i.e., operating time since the start of the post-overhaul cycle). Consequently, the Weibull-derived mean (MTTF ≈ 935 days) is an age-profile summary on the post-overhaul time axis, not the mean spacing between consecutive failures. This resolves the apparent order-of-magnitude mismatch between MTBF and MTTF noted by reviewers and prevents misinterpretation of η as a deterministic lifetime. With $\beta > 1$ and the 95% confidence interval fully above 1 (Table 4), the fitted Weibull model indicates an increasing hazard with post-overhaul age (a wear-out signature at the cycle level). Importantly, this does not contradict the Kendall trend result on the TBF sequence ($\tau \approx -0.097$, $p \approx 0.46$), because the tests address different questions: Kendall evaluates monotonic trend across successive inter-failure intervals, whereas the Weibull fit summarizes how failure risk changes with accumulated operating time. The Kendall result should be stated conservatively: no statistically significant monotonic trend is detected, and directional claims such as a 'weak decreasing TBF trend' are not supported.

Practical interpretation: the turbine experiences frequent events (captured by MTBF) while simultaneously exhibiting an age-related increase in risk across the post-overhaul cycle (captured by the Weibull hazard). This supports a two-layer maintenance view: short-cycle actions to manage frequent disturbances, and age-based planning (inspection or refurbishment windows) to manage wear-out risk as the unit accumulates operating time. The apparent order-of-magnitude difference arises because η (≈ 1084 days) reflects the age scale of the cumulative post-overhaul timeline, whereas MTBF reflects the spacing between consecutive failures in a repairable system.

5.1.2 Chart-based diagnostics and consistency checks

The figures in the Results section provide qualitative diagnostics that complement the quantitative analyses and help communicate uncertainty given the limited sample size (31 failure events; 30 TBF intervals).

- Figure 2 (Weibull probability plot): The near-linear alignment supports the use of a Weibull parametric summary, while modest tail deviations are expected under small-N conditions.

- Figure 8 (hazard function, $h(t)=f(t)/R(t)$, versus elapsed time): The point estimate suggests increasing hazard with accumulated time; uncertainty bands (e.g., 90%) should be emphasized because they indicate substantial estimation uncertainty.

- Figures 9–10 (failure/survivor ratio): These plots primarily illustrate dispersion and clustering; they should not be used to infer a monotonic TBF trend. Formal tests (Kendall and Laplace) indicate no statistically significant monotonic trend (Kendall $p \approx 0.46$).

- Figures 11–13 (PDF, $R(t)$, and $F(t)$): Under the fitted Weibull parameters, probability mass concentrates around mid-cycle ages, and reliability declines with age. For example, $R(300 \text{ days}) \approx 0.90$ and $R(365 \text{ days}) \approx 0.86$

under the point estimate; these values should be interpreted with confidence bounds, not as deterministic guarantees.

Overall, the chart-based diagnostics reinforce three robust messages: (i) the data exhibit high variability (consistent with $CV \approx 138\%$ for TBF), (ii) the cycle-level Weibull fit is consistent with age-dependent risk growth ($\beta > 1$), and (iii) a global monotonic trend across events is not statistically supported (Kendall $p \approx 0.46$).

From an engineering perspective, the most plausible contributors to age-dependent risk include mechanisms common in industrial gas turbines (e.g., hot-section creep/oxidation, corrosion, fouling, and fatigue in rotating components). However, the present dataset does not support mode-specific attribution without failure-code stratification; therefore, causal interpretation is deferred to the RCA workflow (Section 6.4).

Finally, given the real-world nature of CMMS-derived data, results may be sensitive to event definition, unlogged minor failures, and potential outliers; future work should include sensitivity checks (e.g., excluding extreme intervals or testing alternative truncation assumptions) to verify robustness.

5.2 Analysis of Monthly and Annual Failure Rates and Reliability

Figures based on the exponential baseline model (constant-rate assumption) are used here strictly for short-horizon descriptive summaries, because the exponential model provides a simple mapping between an estimated rate and reliability over a fixed window (e.g., 30 days or 365 days). Exponential-based reliability values are presented strictly as short-horizon operational descriptors and should not be interpreted as lifecycle reliability predictions in the presence of age-dependent hazard ($\beta > 1$). The monthly failure counts and estimated monthly failure rates show pronounced fluctuations, including a visible peak in Khordad 1400 (June 2021). Such peaks are consistent with real industrial variability and may reflect combinations of seasonal temperature stress, operational loading, fuel switching, or maintenance/parts constraints. Importantly, these plots describe variability in observed rates; they do not, by themselves, establish a statistically significant long-term monotonic trend. Annual rate-based summaries may show apparent differences between years (e.g., some improvement in later years relative to earlier years). However, because Kendall's test on the failure sequence does not show statistical significance ($p \approx 0.46$), these year-to-year differences should be interpreted as operational variability rather than as evidence of a confirmed monotonic improvement or deterioration trend. A defensible interpretation is therefore: (i) the unit exhibits high short-horizon variability with intermittent high-risk months, while (ii) there is insufficient statistical evidence to claim a global monotonic trend in inter-failure behavior over the full period.

To avoid temporal inconsistency, all time references in this section correspond to the same operational window used throughout the analysis: 12 Jun 2020 to 29 Jan 2025 (1692

days), following the last major overhaul (2019). This ensures that the monthly/annual plots and the distribution/trend analyses refer to the same dataset and clock definition.

Overall, the combined evidence from the rate-based plots and the trend tests suggests that maintenance improvement efforts should focus less on asserting “a trend” and more on identifying and controlling drivers of high-risk months and clustered failures, which is best addressed through structured RCA linked to operating and maintenance records.

5.3 Inferences and Practical Applications for Maintenance and Repairs

The analysis of 30 time-between-failures (TBF) intervals derived from 31 forced-outage events of the PG 6541B gas turbine over a 1692-day window (12 Jun 2020–29 Jan 2025) provides evidence for maintenance planning under real industrial conditions. The fitted Weibull model ($\beta = 1.74$) indicates age-dependent risk growth within the post-overhaul operating cycle, consistent with wear-out-type mechanisms at the system level. In contrast, Kendall’s test shows no statistically significant monotonic trend in the observed TBF sequence ($\tau \approx -0.096$, $p \approx 0.46$); therefore, claims of “confirmed shortening of TBF over time” are not supported and are avoided. The current turbine status is characterized by a moderate average inter-failure spacing (MTBF = 56.4 days) but high variability ($CV \approx 138\%$), meaning that long quiet periods can be followed by clusters of failures. As a repairable system, most between-failure interventions restore function without fully resetting component age (minimal/imperfect repair approximation), while the 2019 major overhaul defines the start of the post-overhaul cycle used for model-based summaries. Accordingly, MTBF is best used for short-horizon resourcing and corrective workload planning, whereas Weibull-based quantities ($R(t)$, $h(t)$) provide risk-informed planning guidance under model assumptions and should not be interpreted as guaranteed “system life”. Table 5 summarizes the key implications for maintenance strategy selection (CM/PM/CBM), while the detailed action matrix is provided in Appendix 6 to preserve the readability of the main manuscript.

Table 5. Analysis of Reliability Data and Proposed Maintenance Actions

Statistical finding	Engineering implication	Maintenance direction
$\beta > 1$ (Weibull)	Age-related increase in risk within the post-overhaul cycle	Risk-informed PM planning; strengthen CBM at later ages
No significant monotonic trend (Kendall $p \approx 0.46$)	No confirmed global improvement or deterioration trend	Focus on RCA of clustered events rather than trend claims
High variability ($CV \approx 138\%$)	Irregular failure spacing and clustering	Link failures to operating/environmental factors; improve CMMS data quality
Distinction between MTBF and model-based metrics	Short-term event spacing differs from the age-based risk profile	Use MTBF for short-horizon planning; use Weibull $R(t)/h(t)$ for long-horizon PM decisions

The detailed mapping between statistical indicators and specific maintenance actions is provided in Appendix 6 (Extended Maintenance Action Matrix) to preserve the readability of the main manuscript.

General applications (revised and evidence-consistent):

- **Maintenance decision support:** Use empirical MTBF and short-window rate summaries for near-term staffing and corrective workload planning, while using Weibull-based risk thresholds ($R(t)$ and $h(t)$, with confidence bounds) to prioritize PM/CBM actions as the unit progresses through the operating cycle.
- **RCA-driven improvements:** Because variability and clustering are prominent, the most actionable pathway is structured RCA linked to operating context (temperature, load, fuel, start–stop) and failure modes, rather than relying on monotonic trend claims.
- **Model governance and updates:** Re-validate the selected model periodically as additional field data accumulate (using the same fit criteria and reporting confidence intervals). Quantitative cost/availability improvement claims should be reported only when supported by site KPIs or clearly sourced benchmarks; otherwise, they should be stated qualitatively (e.g., “may reduce downtime” and “may improve availability”).

Table 6. Description of PM Time Intervals Based on $h(t)$ and $R(t)$ Rates

Time period (days)	Approx. $h(t)$ (failures/day)	Approx. $R(t)$	Proposed PM action (risk-informed)
0–300	$\sim 1.1 \times 10^{-4}$ to $\sim 6.2 \times 10^{-4}$	~ 1.00 to ~ 0.90	Seasonal inspections (e.g., every 90 days); stabilize CBM baselines and alarm settings
300–800	$\sim 6.2 \times 10^{-4}$ to $\sim 1.28 \times 10^{-3}$	~ 0.90 to ~ 0.55	Increase inspection depth/frequency; targeted hot-section/rotating checks; tighten CBM thresholds; prioritize recurring failure modes from RCA.
>800	$> \sim 1.28 \times 10^{-3}$	$< \sim 0.55$	Prepare major scope planning (risk-based hot-section scope candidate review); prioritize replacements indicated by CBM/RCA; plan outage windows proactively.

5.4 Suggestions for Operational and Maintenance Improvements

• **Comprehensive Root Cause Analysis (RCA):** Conducting a detailed root cause analysis for periods with high failure rates and sudden increases in failures is essential. This analysis should employ standard RCA methods [1] to identify common underlying factors and design effective preventive measures.

• **Identification and Control of Factors Affecting Reliability:** Examining environmental factors (such as seasonal variations and temperature), operational factors (e.g., changes in workload), and management-related

factors influencing failure rate fluctuations can aid in identifying key determinants of system reliability. This examination may include studying the impact of fuel type and quality (particularly the potential use of liquid fuel during cold months due to gas supply limitations).

- **Optimization of Maintenance Programs:** Reviewing and optimizing preventive maintenance (PM) programs based on identified failure patterns, while incorporating condition-based maintenance (CBM) approaches, can lead to reduced failure rates and enhanced reliability. Strengthening early fault detection processes, improving the quality of spare parts and materials, and enhancing operator training and procedures are also recommended.

- **Evaluation of Maintenance Action Effectiveness:** Quantitatively assessing the effectiveness of current maintenance programs and implemented improvements is crucial for optimizing maintenance strategies and reducing costs.

- **Risk and Reliability Analysis:** Performing reliability-based risk analysis to evaluate the consequences of various failures and prioritize improvement actions is essential.

6. Future Research

To build on this industrial case study and address key limitations—including the small sample size, the repairable-system nature of the turbine, potential imperfect-repair effects, CMMS data incompleteness, and subsystem heterogeneity—future work should extend the current Weibull-based characterization to models that explicitly represent repair dynamics, uncertainty, and decision policies:

- **Imperfect-maintenance modeling (GRP/Kijima):** Apply Weibull generalized renewal process models (Kijima Type I/II) to estimate repair effectiveness (virtual age factor q) jointly with (β, η) , enabling time-varying failure intensity and cumulative failure predictions with confidence intervals. [34]

- **Real CMMS data challenges** (censoring/truncation/missingness): Use likelihood-based or Bayesian approaches that account for unlogged events, dependent censoring, and left truncation. Where multiple units are available, adopt hierarchical Non-Homogeneous Poisson Process (NHPP) / Power Law Process (PLP) models with partial pooling to stabilize estimates across fleets and commissioning dates. [35,36]

- **Subsystem and mode specificity:** Stratify by failure modes/subsystems using competing-risks and heterogeneity terms (e.g., frailty as a random-effect heterogeneity term) to obtain subsystem-specific prediction intervals and quantify the influence of operating/environmental covariates (fuel quality/type, ambient temperature, load regime, start–stop cycles). [37]

- **Policy translation and economic optimization:** Integrate GRP/NHPP parameters into cost/availability frameworks (e.g., renewal-reward) to derive

economically optimal PM/CBM policies and risk-informed thresholds based on $h(t)$ and $R(t)$. [34–37]

- Any quantitative claims about downtime or cost reduction should be reported only if supported by site KPIs or clearly sourced benchmarks.

Conflict of interest

No conflict of interest has been expressed by the authors.

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Appendix 1

Failure Data for 1692 Operational Days

The dataset consists of 31 failure events recorded post-overhaul (starting from June 2020). This ensures that the analysis focuses on the performance of the turbine during its new operational cycle following the 2019 major maintenance.

Gregorian Date Failure (B)

12/06/2020	1
15/07/2020	1
22/05/2021	1
23/05/2021	1
25/05/2021	1
02/06/2021	1
04/06/2021	1
16/06/2021	1
19/06/2021	1
06/11/2021	1
21/12/2021	1
22/12/2021	1
20/02/2022	1
04/03/2022	1
29/05/2022	1
04/01/2023	1
15/03/2023	1
16/03/2023	1
05/08/2023	1
31/10/2023	1
20/12/2023	1
20/02/2024	1
24/08/2024	1
20/01/2025	1
21/01/2025	1
22/01/2025	1
23/01/2025	1
24/01/2025	1
25/01/2025	1
26/01/2025	1
29/01/2025	1

Appendix 2

Analysis Settings

In these calculations, for the selection of the analysis method (Analysis Method), the maximum likelihood estimation (MLE) method was used. For the selection of the ranking method for ordering failure data, the standard ranking method (SRM) and median ranks (MED) were employed. Additionally, for the selection of the confidence bounds determination method (Confidence Bounds Method), the Fisher matrix (FM) confidence bounds method was utilized.

Appendix 3

- AVGOF (Average Goodness-of-Fit)

This is a comprehensive index for measuring the degree of fit of a statistical distribution to the data. It is, in fact, a composite statistical criterion that the software derives from multiple tests (such as K-S, Anderson-Darling, etc.) and provides an averaged or normalized value. The smaller the AVGOF value, the better the fit.

- AVPLOT (Average Probability Plot Correlation Coefficient)

This criterion refers to the correlation coefficient between the empirical data and the fitted values on the probability plot. If the data points lie exactly on the theoretical distribution line, the correlation value will be close to 1. Therefore, the closer AVPLOT is to 1, the more suitable the selected distribution.

- LKV (Log-Likelihood Value)

This is the value of the log-likelihood function for the selected distribution. This function indicates the probability with which the data are generated by the estimated distribution parameters. In comparisons between distributions, a larger (less negative) value indicates a better fit.

The ranking in the aforementioned process is performed through the cumulative evaluation of these criteria.

Appendix 4. Mathematical Formulation and Data Definition

Appendix 4.1 — Data Definition and Screening Criteria

A1. Definition of Failure Event and TBF

$$TBF_i = t_{i+1} - t_i, \quad i = 1, \dots, n-1 \quad (A1)$$

where t_i is the timestamp (or cumulative operating time) of the i -th forced-outage failure event.

A2. Engineering Screening Criteria

Only production-impacting forced-outage events were retained. Non-critical auxiliary, HVAC, lighting, and non-production-impacting events were excluded.

Appendix 4.2 — Reliability Formulation

B1. Empirical MTBF

$$MTBF = \frac{\sum_{i=1}^N TBF_i}{N} \quad B.1$$

B2. MTBF Confidence Interval (Chi-Square)

$$\frac{2T}{\chi^2_{\frac{\alpha}{2}, 2N}} \leq MTBF \leq \frac{2T}{\chi^2_{1-\frac{\alpha}{2}, 2N}} \quad B.2$$

B3. Failure Rate (Exponential Baseline)

$$\lambda = 1 / MTBF$$

B4. Exponential Reliability

$$R(t) = \exp(-\lambda t)$$

B5. Exponential CDF

$$F(t) = 1 - \exp(-\lambda t)$$

B6. Exponential Hazard

$$h(t) = \lambda$$

B7. Anderson–Darling Statistic

$$A^2 = -n - \frac{1}{n} \sum_{i=1}^n (2i-1) [Ln(F(x_i)) + Ln(1 - F(x_{n+1-i}))] \quad B.7$$

$$F(x_i) = 1 - e^{-\lambda x_i}$$

B8. Weibull PDF

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

B9. Weibull Reliability

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

B10. Weibull Hazard

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

B11. Weibull MTTF

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

B12. Monthly Failure Rate

$$\lambda_{\text{monthly}} = \frac{\text{total number of failures month}}{\text{days in that month}}$$

B13. Annual Failure Rate

$$\lambda_{\text{annual}} = \frac{\text{number of failures in year}}{\text{number of days in that year}}$$

B14. Kendall Statistic

Kendall test was used. The test statistic is defined as follows:

$$\tau = \frac{2}{n(n-1)} \sum (x_i - x_j) \quad (5)$$

which assesses the presence of upward or downward trends [22]

B15. Laplace Statistic

The Laplace statistic (U) is defined as:

$$U = \frac{\frac{1}{n-1} \sum_{i=1}^{n-1} T_i - \frac{T_n}{2}}{T_n \sqrt{\frac{1}{12(n-1)}}} \quad (6)$$

where T_i represents the cumulative time to the i -th failure. Our calculation yielded a result within the critical bounds of [-1.96, 1.96]

Appendix 5

Main Maintenance and Repair Strategies

1. PM – Preventive Maintenance
 - Performing services and repairs according to a scheduled program, even if no failure has yet occurred.
 - Objective: Prevent sudden failures and extend equipment life.
 - Example in Turbines: Periodic replacement of filters or bearing lubrication after a specified number of operating hours.
2. CBM – Condition-Based Maintenance
 - Repairs or services are performed only when equipment condition indicators (vibration, temperature, pressure, oil analysis, etc.) indicate an impending failure.
 - Objective: Reduce unnecessary PM costs while preventing sudden failures.
 - Example in Turbines: Using vibration or temperature sensors to detect the onset of bearing wear and make timely repair decisions.
3. CM – Corrective Maintenance
 - Performing repairs or replacements after a failure has occurred.
 - This is the simplest and oldest maintenance method but is typically costly and high-risk, as failures can lead to production downtime.
 - Example in Turbines: Replacing a turbine blade after breakage or burnout.

Appendix 6. Extended Maintenance Action Matrix

This appendix provides the detailed mapping between statistical findings and operational maintenance actions (PM/CBM/CM/RCA). These recommendations are risk-informed and should be interpreted within the uncertainty bounds of the fitted model and the limited sample size ($N = 30$ TBF intervals)

Key inference from data	Practical interpretation (in simple language)	Proposed actions for repair and maintenance
Increasing hazard in the fitted Weibull model ($\beta > 1$; $\beta = 1.74$)	Under the fitted model, the risk of failure increases with elapsed time in the post-overhaul operating cycle (consistent with age-dependent risk / wear-out mechanisms). This does not imply that observed TBF intervals must shorten monotonically.	PM: Increase inspection depth for hot-section and rotating components as the unit ages (e.g., borescope/hot-section checks on a risk-informed schedule). CBM: Strengthen vibration/temperature/oil-debris monitoring and alarm governance; tighten thresholds at later ages.
No statistically significant monotonic trend in TBF (<i>Kendall</i> $\tau \approx -0.097$, $p \approx 0.46$; <i>Laplace</i> $U = 0.761$)	The observed inter-failure intervals do not confirm a monotonic improvement or deterioration trend. Any apparent changes over time should be treated as descriptive only.	Avoid “trend-confirmation” claims; focus on identifying high-risk windows and dominant failure modes via RCA and covariate tagging (ambient temperature, load regime, fuel switching, start–stop counts).
High dispersion / instability in inter-failure behavior (CV $\approx 138\%$; $N = 30$ intervals)	The turbine performance is irregular—long quiet periods can be followed by clustered failures. This variability is typical in industrial repairable systems influenced by operating conditions and repair effectiveness.	Dependency analysis: Stratify or regress failure occurrence against operating/environmental variables (temperature, load, fuel, starts). Data quality: Standardize CMMS taxonomy, remove duplicates, and tag each event by subsystem/mode and context to improve RCA validity.
Evidence of clustered failures / peak months (e.g., June 2021 / Khordad 1400)	Short periods may show elevated risk even if no global monotonic trend is statistically supported.	RCA: Perform peak-month RCA (Pareto by subsystem/mode + 5-Why/Fishbone). Mitigation: Implement “summer readiness” actions (fuel-quality checks, cooling/filtration checks, operator procedure tightening, targeted spares readiness).
MTBF vs. model-derived metrics must be distinguished in a repairable system	MTBF summarizes the average spacing between recorded events and is useful for short-horizon planning. Model-derived indices (e.g., Weibull-based time scales) summarize a fitted process under assumptions and should not be interpreted as guaranteed “life.”	State repair assumption explicitly: post-overhaul cycle baseline with between-failure repairs approximated as minimal/imperfect (planning approximation). For deeper modeling, consider NHPP/GRP methods to quantify imperfect repair effects in future work.