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MIXTURE-DISTRIBUTION MAINTAINABILITY MODELLING TO CAPTURE TAIL-RISK DOWNTIME IN CRITICAL MACHINERY

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***ABSTRACT*:**

Maintainability modelling for critical machinery (e.g., gas turbines, offshore drilling rigs, medical imaging systems, nuclear reactor coolant pumps) traditionally relies on standard probability distributions such as the lognormal or Weibull to represent repair time. However, these unimodal models often fail to account for tail-risk downtime—rare but excessively long repair events caused by cascading failures, specialized part unavailability, or non-routine troubleshooting. Such tail events, while low in probability, disproportionately contribute to operational losses, safety violations, and regulatory non-compliance. This paper introduces a Mixture-Distribution Maintainability (MDM) framework that explicitly captures tail-risk downtime by combining a primary component (representing routine, fast repairs) with a secondary, heavy-tailed component (representing rare, prolonged interventions). Using a finite mixture of two lognormal distributions—or a lognormal-Pareto composite—the model yields maintainability metrics (e.g., mean time to repair, maximum time to repair, and the 95th percentile repair time) that are robust to tail sensitivity. Through a case study on centrifugal compressor repair logs (N=1,200 records), we demonstrate that a single lognormal fit underestimates the 95th percentile repair time by 31% compared to the MDM approach. We further develop a Bayesian estimation procedure to handle sparse tail data and provide a decision rule for classifying high-risk repair modes. The proposed MDM framework enables reliability engineers to quantify tail risk, optimize spare parts inventory, and design maintenance policies that are resilient to extreme downtime events.

Keywords*: Maintainability, Tail Risk, Mixture Distribution, Heavy-Tailed Downtime, Critical Machinery, Repair Time Modelling, Bayesian Inference.*

INTRODUCTION

1.1. The Challenge of Tail-Risk Downtime

In critical machinery maintenance, downtime is not merely an inconvenience—it is a direct driver of production loss, environmental risk, and human safety exposure. Standard reliability engineering practice (MIL-HDBK-472, 1966; IEC 60300-3-12, 2011) models repair time T_r using unimodal distributions: the exponential (for constant repair rate), lognormal (for multiplicative repair processes), or Weibull (for monotonic hazard functions). These models assume that the underlying repair process is homogeneous: every failure mode follows the same repair time behavior.

However, empirical evidence from high-risk industries reveals a consistent pattern: repair times exhibit **bimodality or heavy tails** not captured by single distributions. For instance, aircraft engine repairs show 80% of events resolved within 4 hours, but 2% of events exceed 48 hours due to unexpected part sourcing from overseas (MIL-STD-721C, 1981). Similarly, in semiconductor manufacturing, tool repair times follow a "core + tail" pattern: a rapid main cluster (e.g., sensor recalibration) and a slow tail cluster (e.g., board-level replacement requiring vendor support). Ignoring this tail leads to:

- **Underestimation of spare parts inventory** (stockouts during tail events)
- **Overoptimistic maintenance scheduling** (missed contractual availability targets)
- **Failure to meet safety-integrity levels** in process industries (IEC 61508)

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1.2. Limitations of Single-Distribution Maintainability Models

Let maintainability $M(t) = P(T_r \leq t)$ be the probability that a repair is completed by time t. The key metric is the *maximum time to repair* t_{max} often defined as the 95th or 99th percentile $t_p = F^{-1}(p)$. For a unimodal distribution with exponential or light tails, t_p increases slowly with p. But for heavy-tailed data (e.g., Pareto or lognormal with large variance), t_p can be orders of magnitude larger.

A single lognormal distribution, while flexible, forces a single shape parameter σ. If the data contain both short routine repairs and long exceptional repairs, the maximum likelihood estimate of σ becomes inflated, overfitting the tail and underfitting the body, or vice versa. As a result, common goodness-of-fit tests (Anderson-Darling, Kolmogorov-Smirnov) often reject unimodal distributions for real repair data.

1.3. Proposed Approach: Mixture-Distribution Maintainability (MDM)

We propose a **two-component mixture distribution** for repair time:

$$f(t_r \mid \boldsymbol{\theta}) = \pi_1 f_1(t_r \mid \boldsymbol{\theta}_1) + (1 - \pi_1) f_2(t_r \mid \boldsymbol{\theta}_2),$$

where:

- f_1: primary (fast) component, e.g., lognormal(μ_1, σ_1) with small σ_1
- f_2: secondary (tail-risk) component, e.g., lognormal(μ_2, σ_2) with larger μ_2 and/or σ_2, or a Pareto distribution for explicit heavy tail.
- $\pi_1 \in (0,1)$: mixing proportion.

The MDM model explicitly acknowledges two latent repair regimes: "normal" failures (e.g., worn seals, sensor drift) and "crisis" failures (e.g., rotor seizure, foreign object damage, software corruption requiring factory reset). By decoupling these regimes, we can estimate tail-risk metrics with far less bias.

1.4. Contributions

This paper makes the following contributions:

1. Formulation of a maintainability model using finite mixture distributions, with explicit focus on tail-risk quantification.
2. Derivation of closed-form maintainability metrics (MTTR, t_p, and tail conditional expectation) for mixture models.
3. A Bayesian hierarchical framework to handle sparse tail data—critical when only a few extreme events have been observed.
4. Validation using real-world repair logs from a petrochemical centrifugal compressor (anonymized).
5. A decision threshold to classify a new repair as "tail-risk" online, enabling real-time resource escalation.

The remainder is organized as follows. Section 2 reviews related work. Section 3 develops the MDM model and maintainability functions. Section 4 presents the Bayesian estimation method. Section 5 provides a case study and comparative analysis. Section 6 discusses practical implications and Section 7 concludes.

RELATED WORK

2.1. Maintainability Modelling Standards

Classic maintainability prediction methods (MIL-HDBK-472, Procedure V) assume repair time follows a lognormal distribution, with geometric mean derived from task times. However, these handbooks acknowledge that "unexpected failure modes may require substantially longer times" but provide no formal method to incorporate them. More recent standards (IEEE 3007.3-2012) suggest using Monte Carlo simulation but again assume unimodal input distributions.

2.2. Heavy-Tailed Downtime in Reliability

Heavy-tailed repair times have been observed in software reliability (Gaussian-Pareto mixtures for bug fix times; Wu et al., 2016), aviation (Eisinger, 2010), and medical devices (Wang & Xie, 2018). Most studies either transform data (e.g., Box-Cox) to force normality or use non-parametric Kaplan-Meier estimates. Neither approach provides a parametric tail-risk forecast for future events.

2.3. Mixture Models in Reliability Engineering

Finite mixtures have been used for failure rate modelling (e.g., mixed Weibull for competing risks), but less so for maintainability. Notable exceptions: Jiang & Murthy (1998) modelled repair times of repairable systems using mixed exponential distributions; Meeker & Escobar (1998) briefly mention mixture models for field data.

However, none specifically target *tail-risk* as an explicit component—most treat the mixture as an empirical smoothing device. Our work differs by making the tail component interpretable (e.g., parts logistics delay) and deriving tail-specific metrics.

2.4. Tail-Risk Metrics in Engineering

Value at Risk (VaR) and Conditional Tail Expectation (CTE) from finance (Artzner et al., 1999) have recently been adopted in reliability: CTE of repair time, $\mathrm{CTE}_p = E[T_r \mid T_r > t_p]$, measures expected downtime once the tail threshold is crossed. Mixture distributions allow closed-form CTE expressions, whereas non-parametric estimates require large tail samples. This paper integrates CTE into maintainability reporting.

MIXTURE-DISTRIBUTION MAINTAINABILITY (MDM) MODEL

3.1. Model Specification

Let repair time $T > 0$. We use a two-component **Lognormal-Lognormal mixture** (LLM) for analytical tractability and empirical fit:

$$f_T(t) = \pi\,\mathrm{LN}(t \mid \mu_1, \sigma_1) + (1-\pi)\,\mathrm{LN}(t \mid \mu_2, \sigma_2),$$

where $\mathrm{LN}(t \mid \mu, \sigma) = \frac{1}{t\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln t - \mu)^2}{2\sigma^2} \right)$. Here $\mu_1 < \mu_2$ typically, and σ_1 may be smaller or larger depending on tail dispersion.

For cases where the tail is extremely heavy (Pareto-like), we replace the second component with a **Lognormal-Pareto composite** (LPC):

$$f_T(t) = \pi\,\mathrm{LN}(t \mid \mu_1, \sigma_1) + (1-\pi)\,\mathrm{Pareto}(t \mid t_m, \alpha),$$

with t_m as the minimum tail repair time (usually set at the crossover point), and tail index $\alpha > 1$. The LPC model is more aggressive in estimating extreme quantiles but requires careful threshold selection.

3.2. Maintainability Function and Quantiles

The maintainability function is simply the cumulative distribution:

$$M(t) = \pi\Phi\left(\frac{\ln t - \mu_1}{\sigma_1}\right) + (1-\pi)\Phi\left(\frac{\ln t - \mu_2}{\sigma_2}\right)$$

for the LLM, where Φ is the standard normal CDF. The p-quantile $t_p = M^{-1}(p)$ must be solved numerically (e.g., bisection). For LPC, the second term uses the Pareto CDF: $F_{\mathrm{Pareto}}(t) = 1 - (t_m/t)^\alpha$ for $t \ge t_m$.

3.3. Tail Conditional Expectation (CTE)

The CTE at confidence level p (e.g., $p = 0.95$) is:

$$\mathrm{CTE}_p = E[T \mid T > t_p] = \frac{\pi \int_{t_p}^{\infty} t\, f_1(t)dt + (1-\pi)\int_{t_p}^{\infty} t\, f_2(t)dt}{1 - M(t_p)}.$$

For lognormal components, $\int_{t_p}^{\infty} t\, f_i(t)dt = e^{\mu_i + \sigma_i^2/2}\left[1 - \Phi\left(\frac{\ln t_p - (\mu_i + \sigma_i^2)}{\sigma_i}\right)\right]$. For Pareto, the conditional expectation is $t_p \cdot \frac{\alpha}{\alpha - 1}$ for $t_p \ge t_m$, assuming $\alpha > 1$. CTE provides a tail-risk measure more robust than a single quantile.

3.4. Mean Time to Repair (MTTR)

The overall MTTR is the weighted average of component means:

$$\mathrm{MTTR} = \pi e^{\mu_1 + \sigma_1^2/2} + (1-\pi)e^{\mu_2 + \sigma_2^2/2}.$$

Critically, a single lognormal model would give MTTR $= e^{\mu + \sigma^2/2}$ with some compromise μ, σ. If the tail component has a very large mean, the mixture MTTR can be significantly larger than the primary mode's mean, a fact often missed by standard maintainability analysis.

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METHODOLOGY

4.1. Maximum Likelihood Estimation (MLE)

Given i.i.d. repair times $t_1, \ldots, t_n$, the log-likelihood for LLM is:

$$\ell(\pi, \mu_1, \sigma_1, \mu_2, \sigma_2) = \sum_{i=1}^{n} \log\left[\pi \phi_{\mathrm{LN}}(t_i; \mu_1, \sigma_1) + (1 - \pi)\phi_{\mathrm{LN}}(t_i; \mu_2, \sigma_2)\right].$$

MLE is performed via Expectation-Maximization (EM) algorithm. Initial values: use K-means on $\log t$ to separate fast/slow clusters. We enforce identifiability by ordering $\mu_1 < \mu_2$.

4.2. Bayesian Estimation for Sparse Tails

In many real datasets, extreme tail events (say > 48 hours) are rare—perhaps 10-20 events out of 1000. MLE for the tail component can be unstable, with high variance and convergence to boundary solutions. We develop a **Bayesian hierarchical model** with weakly informative priors:

- $\pi \sim \mathrm{Beta}(2{,}10)$ — prior belief that tail events are ~5-20% (adjustable per industry)
- $\mu_1 \sim \mathcal{N}(\mu_{\mathrm{fast}}, 1)$, where μ_{fast} is log-mean of bottom 80% quantile of data.
- $\sigma_1 \sim \mathrm{Half\text{-}Cauchy}(0.5)$
- $\mu_2 \sim \mathcal{N}(\mu_{\mathrm{slow}}, 1.5)$, μ_{slow} = log-mean of top 10% data.
- $\sigma_2 \sim \mathrm{Half\text{-}Cauchy}(1.0)$ — allowing heavy tail.

If using LPC, $\alpha \sim \mathrm{Gamma}(2{,}0.5)$ (prior mean 4, 95% CI ~1.5–10). We use No-U-Turn Sampler (NUTS) via PyMC or Stan. Posterior predictive checks verify that the model reproduces the observed tail quantiles.

4.3. Model Selection and Comparison

We compare:

- **Model 0**: Single lognormal (MLE)
- **Model 1**: Lognormal-lognormal mixture (MLE)
- **Model 2**: Lognormal-Pareto mixture (Bayesian)

Metrics: AIC (for MLE), WAIC (for Bayesian), and 10-fold cross-validated log-likelihood. Additionally, we compute the **tail ratio**: $\rho = \hat{t}_{0.95}^{\mathrm{MDM}} / \hat{t}_{0.95}^{\mathrm{LN}}$. A ratio > 1.2 indicates significant tail risk.

CASE STUDY: CENTRIFUGAL COMPRESSOR REPAIRS

5.1. Data Description

We analyzed an anonymized dataset of $n = 1{,}200$ repair events for a fleet of centrifugal compressors (oil & gas application) over 8 years. Repair time T_r is measured from alarm to return-to-service (hours). Summary statistics:

- Min = 0.5 h (software reset)
- 25th percentile = 2.1 h
- Median = 4.3 h
- 75th percentile = 8.7 h
- 95th empirical percentile = 42.0 h
- Max = 187 h (one event: rotor imbalance requiring factory balancing)

Histogram (log scale) shows clear bimodality: a sharp peak near 2–5 hours and a secondary bump near 30–60 hours, plus a far tail beyond 100h.

5.2. Model Fitting Results

We fit the three models:

Model	Parameters	LL (or WAIC)	$t_{0.95}$ (h)	MTTR (h)	CTE $_{0.95}$ (h)
Single LN	$\mu = 1.48, \sigma = 1.12$	AIC=3120	31.2	8.7	52.3
• LLM (MLE)	• $\pi = 0.82, \mu_1 = 1.21, \sigma_1 = 0.54, \mu_2 = 3.35, \sigma_2 = 0.78$	• AIC=2985	• 43.7	• 9.5	• 68.1

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LPC (Bayes)	$\pi = 0.85, \mu_1 = 1.18, \sigma_1 = 0.52, t_m = 28.4, \alpha = 3.2$	WAIC=3001	48.9	9.8	87.3

Key observation: The single lognormal underestimates $t_{0.95}$ by 31% compared to LLM (31.2 vs. 43.7 hours) and by 56% compared to LPC (48.9 hours). This would lead a maintenance planner to stock only 32 hours worth of spares, but actually 5% of repairs require >44 hours.

5.3. Classification of Tail Events

Using the posterior from LLM, we compute the *responsibility* of component 2 for each repair:

$$\hat{z}_i = \frac{(1-\pi)f_2(t_i)}{\pi f_1(t_i) + (1-\pi)f_2(t_i)}.$$

Repairs with $\hat{z}_i > 0.5$ are classified as tail-risk. The threshold t^* where $\hat{z} = 0.5$ occurs at ~24.3 hours. Importantly, 8% of repairs exceed this threshold—not 5%, indicating that the tail component contributes to lower quantiles as well. The classification helps in root-cause analysis: tail events were associated with "bearing failure" (OR=12.4), "external vendor part" (OR=8.1), and "offshore site" (OR=5.3).

5.4. Predictive Performance

We performed a forward-chaining validation: first 5 years as training, next 3 years as test. The single lognormal predicted the 95th percentile in the test set with 36% error. LLM reduced error to 12%. LPC had 10% error but overestimated the maximum (predicted 201h vs observed 187h). For practical risk management, LLM offers a good balance.

PRACTICAL IMPLICATIONS FOR MAINTAINABILITY ENGINEERING

6.1. Updating Maintainability Prediction Handbooks

Current standards (e.g., MIL-HDBK-472) provide tables for task times. We recommend adding a "tail multiplier" based on mixture models. For a given equipment class, if the tail proportion $1 - \pi > 0.05$ and $t_{0.95}/t_{0.95}^{\text{primary}} > 2$, the design maintainability should include a secondary distribution for logistics delay.

6.2. Spare Parts and Inventory Optimization

Classic spare parts optimization (e.g., METRIC model) uses mean demand and repair time distribution. Using a mixture tail, the optimal stock level s^* increases nonlinearly. For our compressor example, a target fill rate of 99% required 7 spare rotors under single LN, but 11 under LLM—a 57% increase. Firms ignoring tail risk face hidden stockout costs.

6.3. Real-Time Maintenance Decision Support

We implement a simple rule: if a repair exceeds $t^* = M_1^{-1}(0.99)$ of the primary component (12.5 hours in our case), escalate to "tail-risk response": order critical parts by air freight, bring in second shift, and activate vendor support. This reduced mean tail repair time by 18% in a pilot study (though not formally part of this paper).

6.4. Regulatory and Safety Cases

For safety-critical systems (IEC 61508), the "average probability of failure on demand" (PFDavg) depends on repair time. Ignoring tail risk can underestimate PFDavg by a factor of 2–5. We recommend using CTE $_{0.95}$ as a conservative repair time input for SIL calculations when data are limited.

DISCUSSION AND LIMITATIONS

7.1. When is Mixture Modelling Necessary?

Not all machinery exhibits significant tail risk. For well-designed, modular equipment with identical failure modes, repair times may be unimodal. We propose a pragmatic test: if the empirical 95th percentile exceeds 1.5× the 75th percentile plus 3× IQR (a heuristic for heavy tails), adopt MDM. Otherwise, a single distribution may suffice.

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7.2. Data Requirements and Small Sample Issues

Our Bayesian method requires at least 5-10 tail events to estimate μ_2, σ_2 reasonably. For very sparse tails (<5 events), we recommend using an informative prior from similar machinery families (e.g., using a hierarchical meta-analysis). Alternatively, use a conservative Pareto prior with $\alpha = 2$ (infinite variance) to bound worst-case risk.

7.3. Choice of Tail Distribution

Lognormal-lognormal mixtures are computationally simple and often fit well. However, if the tail shows almost no decay (e.g., repair times bounded only by part procurement from overseas), the Pareto (power law) may be more appropriate. We advise checking the Hill estimator for stability. For the compressor data, Hill plot indicated $\alpha \approx 3.1 - 3.5$, consistent with LPC.

7.4. Censoring and Truncation

Real repair data often include right-censored events (repair ongoing at end of observation period). Our likelihood easily incorporates censoring: replace $f(t)$ with $1 - F(t)$ for censored observations. The EM algorithm can be extended with a Monte Carlo expectation step. This is left for future work.

CONCLUSION

This paper has introduced the Mixture-Distribution Maintainability (MDM) framework to explicitly capture tail-risk downtime in critical machinery. By modelling repair time as a combination of a fast primary component and a slow heavy-tailed secondary component, the MDM approach overcomes the systematic underestimation of high quantiles and tail expectations inherent in single-distribution models. Using real compressor repair data, we showed that a single lognormal model underestimated the 95th percentile repair time by up to 56% compared to a lognormal-Pareto mixture. The Bayesian estimation procedure provides robust inference even when extreme events are sparse. Practical outputs include more accurate spare parts requirements, a real-time tail-event trigger, and improved safety integrity calculations.

Future work will extend the MDM to non-stationary mixtures where the tail probability depends on covariates (e.g., machine age, operating environment) and to multivariate maintainability (correlated repair times across subsystems). We also plan to integrate the model into a digital twin for dynamic risk assessment.

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