



CDM–Bayesian framework for multiscale fatigue life prediction of aircraft mechanisms with rigid–Flexible coupling

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ABSTRACT

Fatigue failure of aircraft mechanisms under complex multiaxial loading is a central challenge to structural safety. Conventional life prediction methods struggle to characterize nonlinear damage evolution, and material-level parameters are difficult to transfer to structural-scale applications. This study proposes a multiaxial fatigue life prediction method that integrates CDM and Bayesian inference, incorporating rigid–flexible coupling simulation to enable consistent cross-scale assessment from material to structure. A state-dependent continuum damage mechanics (CDM) model is developed within a two-scale framework coupling macroscopic elasticity and microscopic plasticity. Damage evolution is governed by stress triaxiality (η) and the normalized third invariant (ξ). Model parameters, calibrated via particle swarm optimization using 7050-T7451 multiaxial fatigue data, yield a 92.7 % hit rate within a factor-of-four error band. Bayesian posterior inference then quantifies parameter and model uncertainties, providing 95 % credible intervals for fatigue life prediction for use in reliability assessment. External validation on MIL-HDBK-5H (L/LT) shows twofold coverage of 90 % and 100 %. A test-validated rigid–flexible-coupled model provides multiaxial stress histories at critical locations. Material parameters are transferred across scales to hot spots in the cargo-door mechanism, yielding a deterministic life of 1.448×10^5 cycles and a 95 % reliability life of 7.319×10^4 cycles. Compared with the traditional S–N/Miner method, the Findley criterion, and the Brown–Miller method, the state-dependent CDM maintains comparable life magnitudes while capturing stress-state effects and damage-driving mechanisms. The approach enables integrated analysis across constitutive and material–structure scales, forming a closed loop from parameter calibration to engineering application. It provides a new pathway for fatigue evaluation and maintenance decision-making in complex aircraft mechanisms.

1. Introduction

The cargo door lifting mechanism is a critical moving component for aircraft cargo handling; during service it must withstand hundreds of thousands of load cycles, and any fatigue failure directly threatens flight safety. Engineering statistics indicate [1] that cargo-door system failures account for more than 15 % of aircraft ground-support delays, approximately 60 % of which are directly related to fatigue damage. As air transport shifts toward high-frequency, quick-turnaround operations, accurately predicting the fatigue life of cargo-door mechanisms is now a core technical requirement for ensuring safety and enhancing operational efficiency.

Accurate acquisition of complex in-service load histories is the foundation of fatigue life prediction. Rigid–flexible multibody dynamics

(RF-MBD) has been widely used for dynamic response analysis of complex mechanisms because it simultaneously and accurately captures structural deformation and inertial effects. Luo et al. [2] used a rigid–flexible coupling approach to analyze the influence of track structure on the dynamic stress of the metro bogie frame, demonstrating the importance of flexibility effects in fatigue risk assessment of rail vehicles. Xian et al. [3] integrated multibody dynamics and finite element analysis to develop a fatigue life prediction software system for an excavator swing platform, achieving an end-to-end workflow from load acquisition to life evaluation. Ma et al. [4] developed flexible multibody dynamic modeling techniques for satellite brush-type contactors, providing theoretical support for analyses of complex spacecraft mechanisms. Cheng et al. [5] analyzed the dynamic characteristics of a stratospheric airship's flexible propulsion system, validating the applicability of rigid–flexible coupling methods to aerospace flexible systems.

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Nomenclature			
σ	Cauchy stress tensor	$S_{0.33}, S_{0.0}$	Strength parameter in $S(\eta, \xi)$
S	Deviatoric stress tensor	X_i	The i th back-stress component
$\text{tr}(\sigma)$	Trace of the stress tensor	c_b, γ_i	Chaboche kinematic hardening parameters
$\det(S)$	Determinant of the deviatoric stress tensor	R_∞	Saturation value of isotropic hardening
p	Hydrostatic (mean) stress	b	Rate parameter of isotropic hardening
$\mathbf{X}$	Back-stress tensor (kinematic hardening)	θ	Vector of model parameters to be identified
$\bar{q}$	Equivalent deviatoric stress measure	N_{exp}	Experimental fatigue life
η	Stress triaxiality	N_{pred}	Predicted fatigue life
ξ	Normalized third invariant (Lode-related parameter)	$\mu(\theta)$	Model prediction in log-life domain
D	Scalar damage variable ($0 \leq D \leq 1$)	$J(\theta)$	Objective function for parameter identification
A_d	Damaged area	w_i	Weight for the i th data point
A_0	Initial (undamaged) area	σ^2	Variance of the log-life residuals
ε	Total strain tensor	$p(\theta)$	Prior distribution
ε^p	Plastic strain tensor	$p(\theta y)$	Posterior distribution
σ_0	Initial yield stress	$p(y^* y)$	Posterior predictive distribution
R	Isotropic hardening variable	N_f	Fatigue life (cycles to failure)
Y	Damage strain energy release rate	$R(N)$	Reliability function in cycle domain
$S(\eta, \xi)$	Stress-state-dependent damage-strength function	$N_{5\%}$	5th percentile life (approximately 95% reliability life)
		$N_{50\%}$	Median life
		$N_{95\%}$	95th percentile life

Wang et al. [6] constructed a rigid–flexible coupled dynamics model of a dumbbell-type spacecraft, providing a theoretical basis for the design of complex spacecraft structures. Handojo et al. [7] studied the effects of pre-design load alleviation on structural mass and fatigue in aircraft, demonstrating the effectiveness of load-alleviation strategies in achieving both weight reduction and life extension. Diltemiz et al. [8] analyzed the failure of a main-landing-gear cylinder bracket in an aircraft and, combining finite element analysis with fractographic observations, revealed the low-cycle fatigue mechanism caused by stress concentration and manufacturing defects. Korba et al. [9] conducted a fatigue life analysis of a brake component for a particular aircraft type, validating the effectiveness of coupled finite-element and fatigue-life methods. Nie et al. [10] established a fatigue life analysis model for a flexible-joint robot under impact loading, revealing the coupled effects of impact cycles and structural parameters on life evolution.

However, although methods based on S–N curves and Miner’s linear damage rule have seen wide use in engineering practice, they often fail to accurately characterize the nonlinear features of damage evolution under complex variable-amplitude loading. Li et al. [11] developed a Chaboche-based multiaxial damage model with a critical-plane parameter and SSI reliability for TC4 blades. Lang et al. [12] employed a damage-coupled cyclic plasticity model to accurately assess multiaxial ratcheting fatigue of pressurized pipe elbows. Chen et al. [13] formulated a nonlinear cumulative fatigue damage model under variable-amplitude loading by considering load-order effects, revealing the significant influence of load sequence on damage evolution. Liu et al. [14] proposed a nonlinear cumulative fatigue damage life-prediction model that accounts for load interaction, markedly improving prediction accuracy under complex loading. Zhang et al. [15] developed a damage–stress-based fatigue life prediction model on the basis of load interaction and, via a nonlinear damage evolution equation, effectively handled damage accumulation under alternating high–low load cycles. Chin et al. [16] proposed an effective-strain damage model that incorporates load-sequence effects for automotive coil springs, validating the engineering acceptability of nonlinear approaches. Kano et al. [17] integrated CAD–MDO with FSI and CDM-based damage tolerance for composite wings, identifying stiffness loss from fiber breakage as critical. Gao et al. [18] developed a critical-plane-based fatigue life damage model for multiaxial random loading, thereby incorporating load non-proportionality and randomness within a unified prediction framework. Shabani et al. [19] proposed a fatigue life prediction method for high-speed composite aircraft under impact loading based on

progressive fatigue damage modeling, effectively characterizing evolution under multiple failure modes. Gao et al. [20] achieved a unified representation of strength and stiffness degradation in composites using a unified fatigue damage model, significantly improving fatigue life prediction accuracy. Krüger et al. [21] proposed a physics-based in-plane fatigue damage model for fiber-reinforced plastics, revealing life-evolution laws under coupled multiple damage mechanisms. Guan et al. [22] modeled thermal-shock blade tests and proposed a modified Coffin–Manson life model, quantifying spray-cooling effects on thermal-fatigue life. These studies indicate that nonlinear cumulative damage theories offer significant advantages in describing fatigue behavior under complex loading and can more accurately reflect the physical nature of damage evolution.

In addition, material and geometric variability, initial defects, load fluctuations, and in-service degradation in real operation lead to scatter in life results, necessitating the incorporation of quantitative uncertainty characterization into the predictive closed loop. Wu et al. [23] used the Absolute Nodal Coordinate Formulation (ANCF) to establish an uncertain dynamics model of rigid–flexible mechanisms, revealing significant effects of geometric and material randomness on modal characteristics and fatigue reliability. Fei et al. [24,25] conducted research on the operational reliability of flexible mechanisms and applied interpretable neural networks to fatigue life prediction. Zhang et al. [26] combined response surface methodology with Monte Carlo simulation to conduct a fatigue reliability assessment of a bogie frame, showing that neglecting uncertainty systematically overestimates life. Miao et al. [27] applied the SCN-IHDMR method to address high-dimensional uncertainty in damage-tolerance analysis, achieving unified accuracy and efficiency. Deng et al. [28] integrated life prediction with failure mechanisms to establish a reliability assessment framework, thereby providing actionable safety margins for parameter and structural design.

In summary, fatigue life prediction for complex mechanisms still faces the following challenges in engineering applications: (1) Traditional rigid-body assumptions or quasi-static analyses struggle to capture stress concentration effects arising from contact, clearance, and flexibility coupling, whereas fully flexible modeling is computationally expensive and challenging for complex constraints; (2) Existing methods rely primarily on empirical criteria or local data calibration and lack a two-scale representation framework linking macroscopic structural response and microscopic plasticity, making it difficult to characterize nonlinear damage evolution under multiaxial loading, and parameter calibration lacks uniformity and reproducibility; (3) Most studies

provide only point estimates and lack quantitative characterization of model and parameter uncertainties as well as interval predictions, which limits support for risk-informed engineering decisions; (4) The cross-scale methodology from material-level parameter identification to structure-level life assessment remains incomplete and lacks a systematic validation framework. To clearly position the proposed method within the existing literature, Table 1 provides a concise comparative overview of representative approaches and the workflow proposed in this study.

Building on the gaps identified in Table 1, this study targets the aircraft cargo-door lifting mechanism and proposes a fatigue life prediction approach based on rigid-flexible multibody dynamics and a CDM-Bayesian framework. The main contributions are as follows: (1) A rigid-flexible-coupled model is constructed and validated through system-level tests to obtain multiaxial stress time histories at hot spots; (2) A state-dependent CDM model is established, within a two-scale constitutive description of macroscopic elasticity and microscopic plasticity to characterize damage driving and evolution; PSO achieves unified parameter calibration across multi-path datasets, and generalization capability is validated on independent external datasets; (3) Markov Chain Monte Carlo (MCMC)-based Bayesian posterior inference quantifies material and model scatter, providing life prediction intervals and reliability curves to support design decisions; (4) Material-level model parameters are transferred across scales to hot spots of the mechanism for engineering assessment, yielding deterministic and probabilistic lives, and results are compared with the S-N/Miner method, the Findley criterion, and the Brown-Miller method to verify methodological consistency and the advantage in characterizing stress-state effects.

The remainder of this paper is organized as follows: Section 2 outlines the theoretical methods and the overall research framework; Section 3 introduces the state-dependent CDM model and reports parameter calibration, Bayesian uncertainty quantification, and external validation; Section 4 develops a rigid-flexible multibody dynamics model and provides experimental validation; Section 5 performs deterministic evaluation of mechanism-level fatigue life and reliability (interval) prediction and presents method comparisons; Section 6 concludes the paper with conclusions and future prospects.

Table 1
Overview of related works and this study.

Reference	Load Acquisition	Damage & Constitutive Model	Uncertainty Treatment	Validation & Transferability
[2,10,23]	RF coupling	Structural dynamics	Deterministic or parameter variability	Numerical/prototype verification; No transfer chain
[3,9,26]	MBD-FE	S-N / Miner	Safety factors / RSM + Monte Carlo	Component/engineering case; limited level transfer
[11,12,18]	Prescribed multiaxial paths	Coupled CDM / cyclic plasticity / critical-plane	Reliability/Random loading	Mainly specimen or single-component level; mechanism implementation often absent
[28]	General	Mechanism-informed concept	General reliability framework	Conceptual demonstration
This work	RF-MBD + System Test	State-dependent CDM	Bayesian posterior + predictive	MIL-HDBK validation + cross-scale transfer

2. Theory and methods

2.1. Two-scale fatigue life model based on CDM

For complex mechanisms subjected to multiaxial and non-proportional cyclic loading, classical stress/strain criteria have difficulty accurately capturing the nonlinear accumulation of damage and stress-state effects. CDM [29] introduces internal damage variables in a thermodynamically consistent manner to describe the progressive degradation of materials from an intact state to failure, providing a physics-consistent modeling framework for full-life fatigue prediction.

The CDM approach characterizes degradation with a damage variable $D \in [0,1]$, defined as:

$$D = \frac{A_d}{A_0} \quad (1)$$

where A_d denotes the effective damage area, and A_0 is the initial cross-sectional area. Let D_c be the critical damage threshold, crack initiation is taken to occur when D reaches D_c . To characterize multiaxial stress states, consider the stress tensor σ and the deviatoric stress $S = \sigma - \text{tr}(\sigma)/3 \mathbf{I}$. Based on the effective stress concept and the relative deviatoric stress tensor, the equivalent deviatoric stress is defined as:

$$\begin{cases} \bar{q} = \sqrt{\frac{3}{2} \boldsymbol{\eta} : \boldsymbol{\eta}} \\ \boldsymbol{\eta} = \frac{\mathbf{S}}{1-D} - \mathbf{X} \end{cases} \quad (2)$$

To characterize the loading condition, the stress triaxiality η and the third invariant ξ are adopted, i.e.,

$$\begin{cases} \eta = \frac{\text{tr}(\sigma)}{3\bar{q}} \\ \xi = \frac{27 \det(\mathbf{S})}{2\bar{q}^3} \end{cases} \quad (3)$$

where η measures the relative weight between hydrostatic pressure and shear strength, and ξ distinguishes tension/compression-dominated versus shear-dominated deviatoric stress states; together they determine the dependence of the damage strength on the stress state.

A two-scale constitutive idea is adopted: the macroscopic level assumes elastic response, while the microscopic level employs the von Mises yield criterion with combined hardening [30]. In the deviatoric stress space, the yield function is taken as:

$$f = \sqrt{\frac{3}{2} \left\| \frac{\mathbf{S}}{1-D} - \mathbf{X} \right\|^2} - (\sigma_0 + R) = 0 \quad (4)$$

where $\mathbf{S}$ is the deviatoric stress tensor, $\mathbf{X}$ is the back-stress tensor defining the center of the yield surface, R is the isotropic hardening variable, and σ_0 is the initial yield strength. Plastic flow satisfies the associated flow rule:

$$d\epsilon^p = \frac{3}{2} \frac{\boldsymbol{\eta}}{1-D} d\lambda \quad (5)$$

and the Kuhn-Tucker conditions:

$$f \leq 0, \quad d\lambda \geq 0, \quad d\lambda f = 0 \quad (6)$$

where $d\lambda$ is the plastic multiplier. Kinematic hardening is described by the three-term Chaboche combined hardening model, and the total back stress is expressed as:

$$\mathbf{X} = \sum_{i=1}^3 \mathbf{X}_i \quad (7)$$

The stress evolution law is:

$$d\mathbf{X}_i = \begin{cases} \frac{2}{3}a_i\gamma_i d\epsilon^p - \gamma_i\mathbf{X}_i d\epsilon^p, & i = 1, 2, \\ a_3 d\epsilon^p, & i = 3 \end{cases} \quad (8)$$

where a_i and γ_i are the back-stress magnitude coefficients and the back-stress evolution parameters, respectively. For the isotropic hardening of the material behavior, the isotropic hardening evolution law is:

$$dR = b(R_\infty - R)d\epsilon^p \quad (9)$$

$$d\epsilon^p = \sqrt{\frac{2}{3}} \|d\epsilon^p\| = d\lambda \quad (10)$$

where R_∞ is the saturation value of isotropic hardening and b is the hardening evolution rate. This rule accounts for both the isotropic hardening limit and the hardening rate; these two material parameters capture the nonuniformity of isotropic hardening during loading cycles. Eq. (10) defines the increment of equivalent plastic strain, so that the evolution equations depend only on the scalar $d\epsilon^p$, which facilitates numerical integration.

Within the thermodynamically consistent framework of CDM, using Lemaitre's free-energy decomposition and the effective stress concept, the microscopic damage release rate (driving force) is:

$$Y = \frac{1}{(1-D)^2} \left(\frac{\bar{q}^2}{6G} + \frac{p^2}{2K} \right) \quad (11)$$

where G and K are the shear and bulk moduli. The incremental damage law is:

$$dD = \frac{1}{1-D} \left(\frac{Y}{S} \right)^s d\lambda \quad (12)$$

For metals, the damage exponent is taken as $s = 1$. The damage strength S is a function of the stress triaxiality η and the normalized third invariant ξ :

$$S(\eta, \xi) = \frac{S_{0.33}}{3|\eta| + \frac{S_{0.33}}{S_{0.0}}(1 - \xi^2)} \quad (13)$$

where $S_{0.33}$ and $S_{0.0}$ are calibrated from fully reversed tension-compression and pure shear tests, respectively. Unlike the conventional constant S , this form naturally distinguishes fatigue damage behavior under tension-compression, shear, and complex stress states, and multi-path data can be jointly used for endpoint parameter identification under a unified objective function.

In the numerical implementation, each load cycle is discretized into several time steps. Each step uses an operator-split implicit Euler scheme: an elastic predictor is followed, if the yield condition is met, by plastic return mapping; coupled with Chaboche combined hardening and Lemaitre's damage law, the system is solved and the internal variables $\Delta\lambda$, $\Delta\epsilon^p$, $\Delta\mathbf{X}_i$, ΔR , and ΔD are consistently updated via Newton-Raphson iterations. When the condition $D \geq D_c$ is first satisfied at any time step, microcrack initiation is assumed, and the corresponding cycle count is recorded as the numerical life N_{NUM} . The incremental update and life-determination procedure is shown in Fig. 1.

2.2. Parameter identification and uncertainty analysis based on PSO-Bayesian

To achieve unified calibration of the parameters of the damage-strength state function $S(\eta, \xi)$ on multiaxial high-cycle fatigue datasets, this study first employs Particle Swarm Optimization (PSO) [31] to perform a global search for a point estimate that minimizes the log-life residuals; it then constructs a Bayesian posterior in the log-life domain and applies MCMC sampling to quantify uncertainties in the parameters and life predictions; finally, the study evaluates extrapolation capability and interval calibration on independent external data.

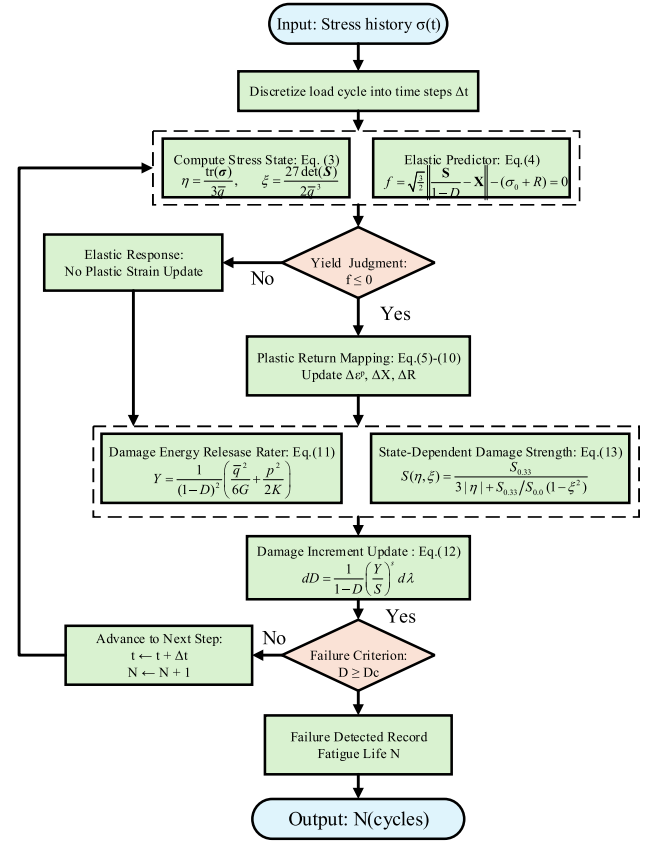


Fig. 1. Flowchart of incremental damage update and life determination.

The basic idea of PSO global optimization is to deploy a swarm of size N_p within the feasible parameter domain, where each particle carries a “position” (candidate parameters) and a “velocity” (search direction and step size). At each iteration, particles update their states by referencing both their personal best and the global best, thereby seeking an approximate global optimum on complex nonconvex objectives.

Let the parameter position and velocity of the i th particle at the k -th iteration be $\mathbf{x}_i^{(k)}$ and $\mathbf{v}_i^{(k)}$, with the personal best $\mathbf{p}_i^{(k)}$ and the global best $\mathbf{g}^{(k)}$. The standard PSO update equations are:

$$\mathbf{v}_i^{(k+1)} = \omega \mathbf{v}_i^{(k)} + c_1 r_1 (\mathbf{p}_i^{(k)} - \mathbf{x}_i^{(k)}) + c_2 r_2 (\mathbf{g}^{(k)} - \mathbf{x}_i^{(k)}) \quad (14)$$

$$\mathbf{x}_i^{(k+1)} = \mathbf{x}_i^{(k)} + \mathbf{v}_i^{(k+1)} \quad (15)$$

where ω is the inertia weight, c_1 and c_2 are learning factors, and $r_1, r_2 \sim U(0,1)$ are i.i.d. To ensure physical feasibility, positivity constraints $S_{0.33}, S_{0.0} > 0$ are imposed, and boundary truncation or velocity reflection is used to keep the search within the feasible domain. Considering that life exhibits order-of-magnitude scatter, a weighted least squares in the log domain is defined as the fitness function: for sample i , let the measured and predicted lives be $N_{\text{exp}, i}$ and $N_{\text{pred}, i}(\theta)$, then:

$$J(\theta) = \sum_{i=1}^n w_i [\log_{10} N_{\text{pred}, i}(\theta) - \log_{10} N_{\text{exp}, i}]^2 \quad (16)$$

where $n_{\text{path}}(i)$ is the sample count of the loading path (axial/torsion/proportional) to which sample i belongs, used to balance path proportions. PSO convergence yields the point estimate $\hat{\theta}_{\text{PSO}}$ and the minimum objective value J_{min} . A smaller objective $J(\theta)$ indicates better agreement between model predictions and test data.

After obtaining $\hat{\theta}_{\text{PSO}}$, a homoscedastic normal error model in log life is constructed and Bayesian posterior inference is performed [32,33]. Let

$$y_i = \log_{10} N_{\text{exp},i}, \mu_i(\theta) = \log_{10} N_{\text{pred},i}(\theta) \quad (17)$$

adopt the baseline model with homoscedastic Gaussian residuals

$$y_i | \theta, \sigma^2 \sim \mathcal{N}(\mu_i(\theta), \sigma^2), \quad i = 1, 2, \dots, n \quad (18)$$

to obtain the pooled likelihood

$$\mathcal{L}(\theta, \sigma^2 | \mathbf{y}) = (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n [y_i - \mu_i(\theta)]^2\right\} \quad (19)$$

To encode positivity and scale priors, weakly informative log-normal priors are assigned to $\{S_{0.33}, S_{0.0}\}$ (equivalently, their logarithms are normal), and an inverse-gamma prior is used for the observation variance; the joint posterior then satisfies

$$p(\theta, \sigma^2 | \mathbf{y}) \propto \mathcal{L}(\theta, \sigma^2 | \mathbf{y}) p(\theta) p(\sigma^2) \quad (20)$$

Because $\mu_i(\theta)$ requires nonlinear incremental solution, the posterior has no closed form. MCMC is used for posterior sampling with as the initial state and scale reference, combined with adaptive covariance and multi-chain diagnostics $\hat{R} < 1.05$. For any given loading condition $\mathbf{x}_\star$, the posterior predictive distribution of log life is

$$p(y_\star | \mathbf{y}) = \int \mathcal{N}(\mu_\star(\theta), \sigma^2) p(\theta, \sigma^2 | \mathbf{y}) d\theta d\sigma^2 \approx \frac{1}{M} \sum_{m=1}^M \mathcal{N}(\mu_\star(\theta^{(m)}), \sigma^{2(m)}) \quad (21)$$

where $\mu(\theta) = \log_{10} N_{\text{pred}}(\theta)$. Eq. (21) directly provides the 95 % prediction interval for life (including observation noise); if the mean response is of interest, letting $\sigma^2 \rightarrow 0$ yields a “posterior-mean” prediction interval as a supplement. This uncertainty characterization follows the common homoscedastic assumption in the log domain, aligns with the PSO objective in Eq. (21), and facilitates comparison of interval coverage and width across multiple paths and conditions.

After parameter identification and uncertainty quantification,

constant-amplitude axial ($R=-1$) smooth-specimen S-N curves from MIL-HDBK-5H with the same material series and orientations (L, LT) are selected as an independent external dataset. Without retraining on that dataset, N_{pred} and its prediction interval given by Eq. (21) are computed for the corresponding conditions using Eqs. (16)–(18) and posterior samples; point-wise comparison with the handbook curves is performed, and metrics including point-estimate error, coverage rate, and interval width are reported to assess extrapolation capability and the reliability of the uncertainty characterization on independent data. The algorithmic workflow is shown in Fig. 2.

2.3. Research framework

Building on the above theory, this study proposes a fatigue life prediction framework centered on damage mechanisms and integrating intelligent optimization techniques with rigid-flexible multibody dynamics, as shown in Fig. 3. First, a two-scale Continuum Damage Mechanics model is established: the macroscopic level adopts elastic response, the microscopic level introduces von Mises yielding and Chaboche combined hardening, and a state-dependent damage strength function is constructed using stress triaxiality η and the normalized third invariant ξ to provide a unified description of damage evolution under multiaxial stress. Subsequently, using material-level multiaxial fatigue test data, PSO enables unified calibration of model parameters, and Bayesian uncertainty inference is performed in the log-life domain to obtain probabilistic descriptions of the parameters and life predictions; in parallel, independent data from MIL-HDBK-5H are used for external validity testing to assess prediction accuracy and generalization capability, with SWT and the two-scale CDM set as baseline methods at the material level for comparison. Thereafter, a rigid-flexible multibody dynamics model of the cargo-door lifting mechanism is built and verified through system-level durability tests, and multiaxial stress histories at the crank hot spot are obtained as high-confidence inputs for structure-level assessment. Finally, the validated unified parameters are applied

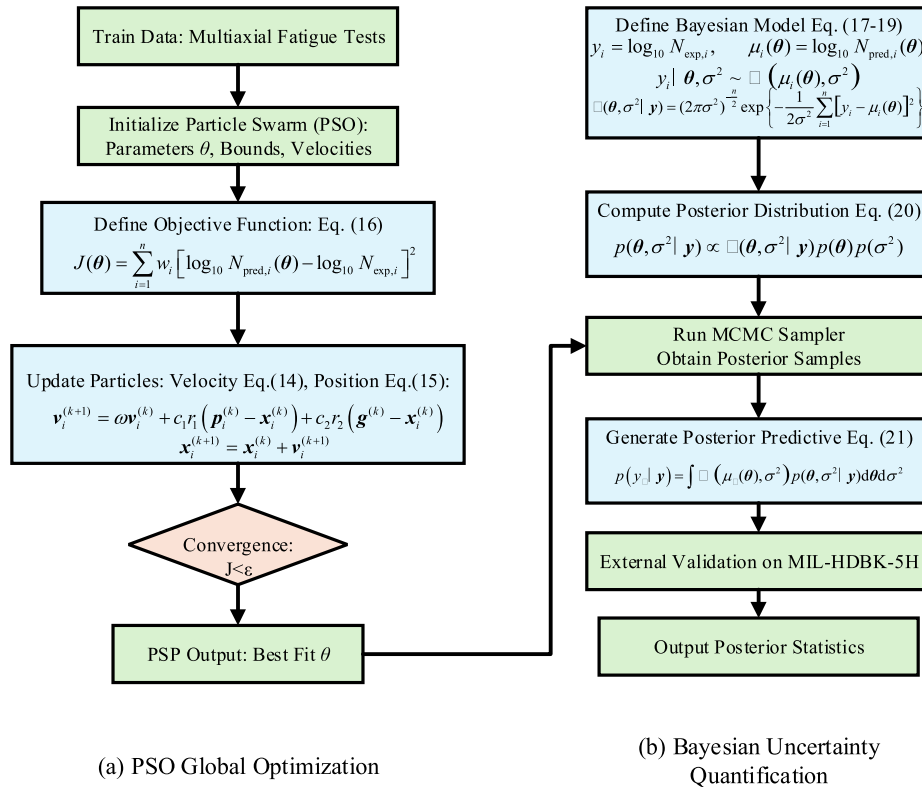


Fig. 2. Workflow of PSO optimization and Bayesian uncertainty analysis.

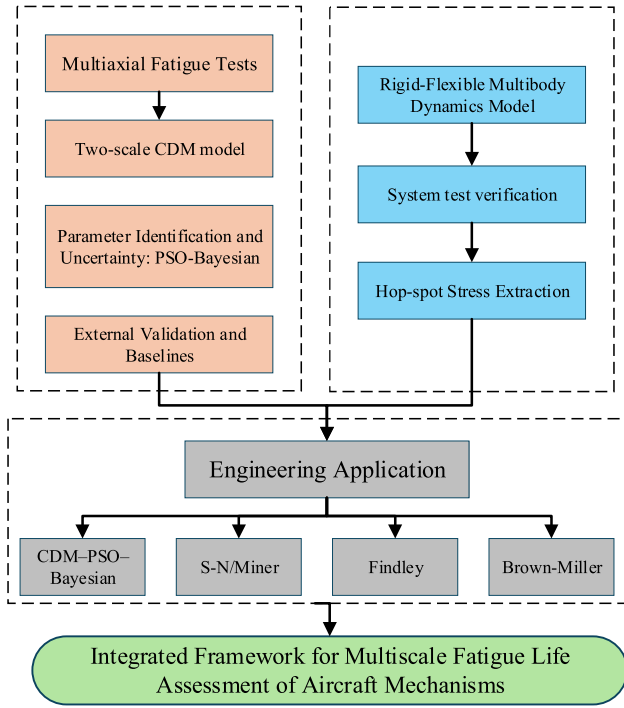


Fig. 3. Schematic of the mechanism fatigue life assessment framework.

across scales to the load spectrum at this hot spot, completing consistent propagation of point and interval estimates and conducting life–reliability assessment, followed by an engineering-level comparison with the S–N/Miner, the Findley, the Brown–Miller methods to form a closed loop from material data to engineering application.

3. Model parameter identification and validation

3.1. Parameter identification and uncertainty analysis

In the improved CDM framework, this section performs unified parameter identification on the publicly available multiaxial constant-amplitude fatigue data of 7050-T7451 aluminum alloy [34]. The dataset covers three loading paths: axial tension–compression (Path A), pure torsion (Path B), and biaxial proportional loading (Path C), as is shown in Fig. 4. Detailed data are given in Tables 2–4, covering a range of cycles and multiple stress-amplitude levels. For all data, stress triaxiality η and the normalized third invariant ξ are computed according to Eq. (3); for the proportional path, the phase-angle ratio is checked against the original test records; the correspondence between η and ξ is listed in Table 3.

In the $\log_{10}N$ domain, the path-weighted residual function given by (16) is minimized, and Particle Swarm Optimization (PSO) is used to

Table 2

Axial tension–compression fatigue data (Path A).

σ_a (MPa)	τ_a (MPa)	N_{EXP} (cycles)	σ_a (MPa)	τ_a (MPa)	N_{EXP} (cycles)
205.0	0.0	7.80×10^4	146.0	0.0	1.45×10^5
205.0	0.0	4.58×10^4	129.0	0.0	9.77×10^5
180.0	0.0	6.57×10^4	129.0	0.0	3.00×10^5
180.0	0.0	5.26×10^4	129.0	0.0	1.47×10^5
180.0	0.0	1.19×10^5	112.0	0.0	8.23×10^6
180.0	0.0	9.49×10^4	112.0	0.0	2.92×10^6
180.0	0.0	5.45×10^4	112.0	0.0	1.27×10^6
146.0	0.0	2.13×10^5	\	\	\

Table 3

Torsion fatigue data (Path B).

σ_a (MPa)	τ_a (MPa)	N_{EXP} (cycles)	σ_a (MPa)	τ_a (MPa)	N_{EXP} (cycles)
0.0	173.2	8.90×10^4	0.0	86.6	2.42×10^6
0.0	173.2	5.36×10^4	0.0	86.6	2.07×10^6
0.0	173.2	2.86×10^4	0.0	79.7	2.50×10^6
0.0	118.4	3.68×10^5	0.0	79.7	2.35×10^6
0.0	108.6	1.54×10^6	0.0	67.7	1.74×10^6
0.0	108.6	6.45×10^5	0.0	67.7	6.23×10^6
0.0	108.6	5.00×10^5	0.0	67.7	9.47×10^6
0.0	86.6	3.24×10^6	0.0	67.7	5.11×10^6
0.0	86.6	2.76×10^6	\	\	\

identify the parameters $\theta = \{S_{0.33}, S_{0.0}\}$; the algorithm settings are swarm size 30 and maximum iterations 60. The converged values are $S_{0.33} = 256.2$ MPa, $S_{0.0} = 633.7$ MPa.

Fig. 5 presents the $N_{pred} - N_{exp}$ comparison for the training set, where both axes use $\log_{10}N$; the solid line denotes the ideal identity, and the dashed/dash-dot lines indicate the $\pm 2/\pm 4$ factor-of-scatter bands. The statistical indicators of fitting accuracy are listed in Table 5. Overall, the predicted lives are distributed fairly symmetrically around the identity line, with no evident systematic overestimation or underestimation. Compared with the traditional fixed-endpoint scheme, this study avoids the abnormal increase of scatter for the proportional path; in the training plot, the distribution of Path C is more concentrated, reflecting the good adaptability of the state-dependent strength function $S(\eta, \xi)$ at intermediate stress states.

To more comprehensively evaluate model performance, this study compares the proposed PSO–CDM with the two-scale CDM in [34] and the Smith–Watson–Topper (SWT) criterion (Table 6). PSO–CDM achieves an overall F_4 of 92.7 %, exceeding the two-scale CDM (87.6 %) and matching the SWT method (92.7 %). Under pure torsion (Path B), PSO–CDM reaches 88.2 %, indicating good adaptability under compression- and shear-dominated loading.

To systematically assess parameter uncertainty and support reliability analysis, a Bayesian model is constructed in the $\log_{10}N$ domain, jointly estimating θ and the observational scatter parameter σ as unknowns. Assuming that $\log_{10}N$ residuals are approximately normal,

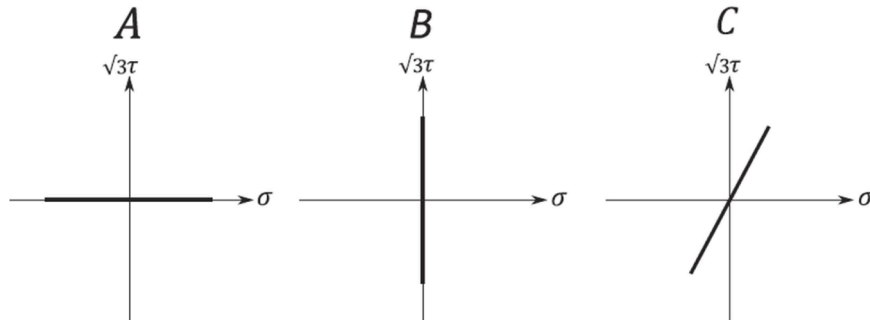
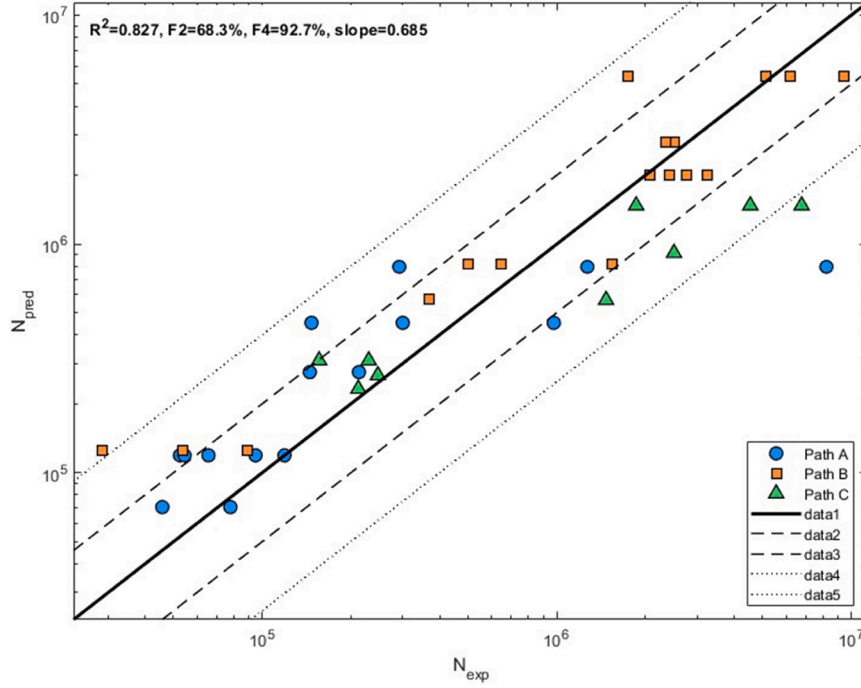


Fig. 4. Typical loading paths: (A) axial tension–compression; (B) pure torsion; (C) biaxial proportional.

Table 4

Biaxial proportional loading fatigue data (Path C).

σ_a (MPa)	τ_a (MPa)	λ	N_{EXP} (cycles)	σ_a (MPa)	τ_a (MPa)	λ	N_{EXP} (cycles)
121.9	61.0	$\sqrt{3}/2$	1.56×10^5	42.1	69.5	$33\sqrt{3}/20$	1.86×10^6
121.9	61.0	$\sqrt{3}/2$	2.30×10^5	42.1	69.5	$33\sqrt{3}/20$	4.54×10^6
64.6	106.6	$33\sqrt{3}/20$	2.47×10^5	42.1	69.5	$33\sqrt{3}/20$	6.78×10^6
53.5	88.2	$33\sqrt{3}/20$	1.47×10^6	57.5	115.0	$2\sqrt{3}$	2.12×10^5
47.5	78.3	$33\sqrt{3}/20$	2.50×10^6	\	\	\	\

**Fig. 5.** Training-set results of N_{pred} – N_{exp} .**Table 5**

Training-set statistics.

Path	Number	F_2 (%)	F_4 (%)
Path A	15	60.0	93.3
Path B	17	58.8	88.2
Path C	9	55.6	100.0
Overall	41	68.3	92.7

Table 6

Comparison of training-set statistics for the three methods.

Method	Path A F_2	Path A F_4	Path B F_2	Path B F_4	Path C F_2	Path C F_4	Global F_4
PSO–CDM	60.0	93.3	58.8	88.2 %	55.6	100.0	92.7 %
	%	%	%	%	%	%	%
CDM	73.3	86.7	76.5	100.0	44.4	66.7 %	87.6 %
	%	%	%	%	%	%	%
SWT	66.7	86.7	88.2	94.1 %	55.6	100.0	92.7 %
	%	%	%	%	%	%	%

Markov Chain Monte Carlo (MCMC) is used to draw samples in the log-parameter space, yielding the joint posterior $\{\log S_{0.33}, \log(S_{0.0}/S_{0.33}), \log \sigma\}$. The sampling settings are a burn-in of 1500, with 3000 retained samples, and a thinning factor of 2. The posterior statistics in original units are reported in Table 7.

For the results in Table 6, CrI denotes the credible interval, and CV denotes the coefficient of variation. Regressing posterior samples on the

Table 7

Posterior statistics of parameters.

Parameter	Mean	Standard Deviation	95 % CrI	CV(%)
$S_{0.33}$ (MPa)	263.0	54.7	[173.6385.3]	20.8
$S_{0.0}$ (MPa)	665.2	184.4	[381.3,1111.4]	27.7
$\sigma(\log_{10}N)$	0.360	0.108	[0.201,0.617]	30.0

training set yields an R^2 median of 0.820 [0.677, 0.837] and $F_2/F_4 = 0.579/0.890$. These results are consistent with the PSO point estimate, supporting the stability and statistical reliability of the model parameters. The posterior results indicate that, with the current data size (41 points), parameter estimates retain some statistical uncertainty, primarily due to the intrinsic scatter of fatigue data, the limited size of the training set, and structural errors introduced by model simplifications.

3.2. External validation of parameters

To assess the extrapolation capability and generalization performance of the calibrated parameters, this section employs constant-amplitude S–N data of 7050-T7451 aluminum alloy in L and LT orientations at a stress ratio $R=-1$ from MIL-HDBK-5H [35] as an independent validation set. For external validation, the identified parameter vector $\theta = \{S_{0.33}=256.2 \text{ MPa}, S_{0.0}=633.7 \text{ MPa}\}$ is used directly for life prediction. Figs. 6 and 7 respectively present the N_{pred} – N_{exp} comparisons for the L and LT orientations. The predictions are presented as the Bayesian-posterior median curve (solid line) together with the 95 %

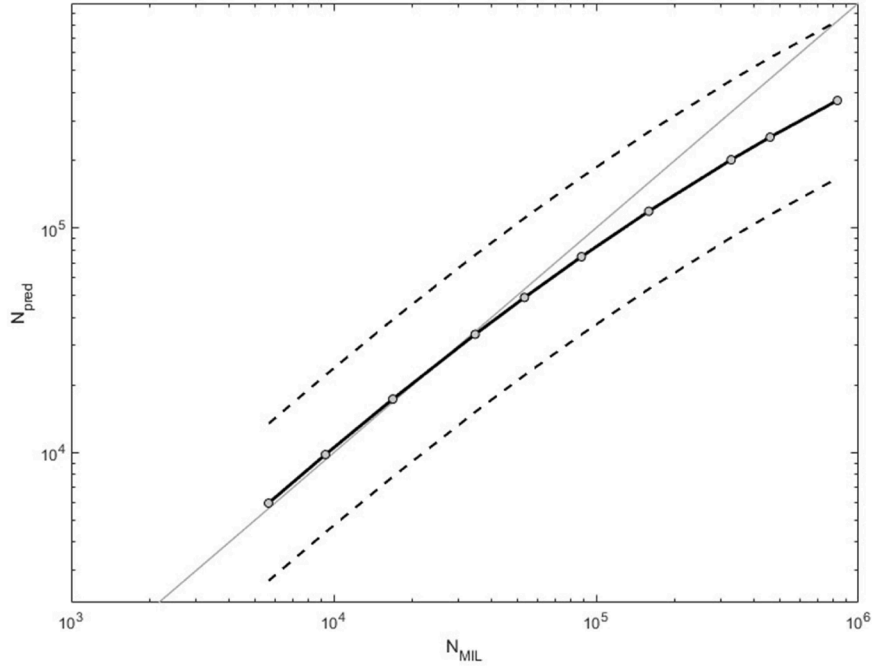


Fig. 6. Validation set (MIL-L orientation): $N_{\text{pred}}-N_{\text{exp}}$.

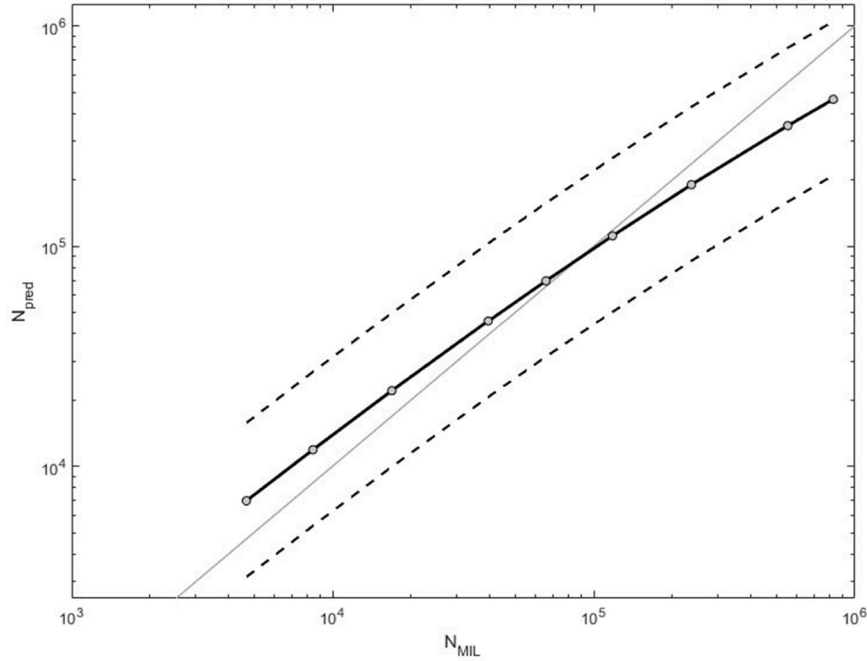


Fig. 7. Validation set (MIL-LT orientation): $N_{\text{pred}}-N_{\text{exp}}$.

prediction interval (dashed line), the latter reflecting the effect of parameter uncertainty propagating into the life prediction.

From Figs. 6 and 7, both validation datasets cluster around the identity line with no visible systematic bias, indicating good generalization and stability across L and LT orientations. Compared with the deterministic PSO fit, the posterior prediction bands reveal the propagation of parameter uncertainty more transparently. The band widths for the L and LT sets are similar, evidencing stable parameter transfer between material directions. The high coverage of the posterior intervals confirms that the state-dependent CDM parameters calibrated on the multiaxial training set are statistically consistent with the uniaxial

handbook data. Overall, the posterior-predictive validation indicates not only high average accuracy but also quantified uncertainty, enabling life estimates with credible intervals that provide statistically meaningful safety margins for reliability-based design and assessment.

4. Simulation and experimental validation

4.1. Rigid-flexible coupled dynamic simulation

The object of study is the lifting mechanism of an aircraft cargo door, which consists of a crank, the cargo door, a rocker, a support (bracket),

and a vertical drive shaft. The mechanism operates through opening and closing phases: during opening, a motor drives the vertical drive shaft to rotate about its axis via a gearbox; because the drive shaft is rigidly connected to the rocker, the shaft's rotation angle is directly transmitted to the rocker. However, the hinge points are constrained by the crank and the cargo door to move along arcs centered at their joints, so the spatial rotation of the rocker is transformed, via closed-loop geometric constraints, into the in-plane rotation of the cargo door, thereby accomplishing opening and closing. During this complex motion, the components are subjected to time-varying loads, and their stress distributions and fatigue characteristics become correspondingly complex; the closed and open states of the lifting mechanism are shown in Fig. 8.

The crank and cargo door are made of 7050 aluminum alloy, whereas the rocker, drive shaft, and other parts are made of high-strength steel (42CrMo4); detailed material parameters are listed in Table 8. Kinematic constraints in the simulation model are implemented using ideal pairs: hinge points connect adjacent components via revolute joints, and the drive shaft is rigidly connected to the rocker via a fixed joint. The driving input is implemented by prescribing a time-varying rotation angle on the drive shaft derived from the actual motor control curve.

The meshing strategy for flexible components directly affects the accuracy of stress computation. A hexahedral-dominant structured mesh is adopted, and the dynamic solution uses implicit time integration with adaptive substepping to adequately capture the system's dynamic response. To balance finite element simulation accuracy and computational efficiency, a systematic mesh-convergence study is performed for the crank model. Six element sizes of 16 mm, 12 mm, 10 mm, 8 mm, 6 mm, and 4 mm are used for mesh-independence verification, as shown in Table 9 and Fig. 9. The peak von Mises equivalent stress and peak equivalent strain are selected as convergence criteria, and the time-history maxima under the operating condition are extracted for comparison.

The simulation results in Table 9 show that, as mesh density increases, the maximum equivalent stress and equivalent strain exhibit monotonic convergence. When the element size is refined from 16 mm to 4 mm, the number of elements increases from 9485 to 83,140; the maximum equivalent stress converges to 228.14 MPa, and the maximum equivalent strain approaches 3.3798×10^{-3} . At the 6 mm mesh, relative changes in both metrics are each less than 0.1 % compared with the adjacent 8 mm level; after further refinement to 4 mm, the results lie within the mesh-independent regime. The convergence curves in Fig. 9 likewise show that, when mesh density reaches 8 mm, the stress-strain values enter a stable plateau, and the 6 mm mesh satisfies the strict convergence criterion ($<0.1\%$). Balancing accuracy and efficiency, a 6 mm element size is selected as the baseline for subsequent analyses.

Based on the validated 6 mm element-size scheme, a rigid-flexible coupled transient analysis is conducted for the full opening process of

Table 8

Material property parameters.

Parameters	7050	42CrMo4
Density(kg/m ³)	2821	7850
Young's Modulus(GPa)	69	197
Poisson's Ratio	0.33	0.32
Yield Strength(MPa)	465	1070
Tensile Strength(MPa)	584	1172

Table 9

Mesh convergence data.

Element size (mm)	Element number	Maximum Equivalent Stress(MPa)	Maximum Equivalent Strain
16	9485	217.17	3.0659×10^{-3}
12	12,221	225.31	3.2133×10^{-3}
10	16,544	227.43	3.3696×10^{-3}
8	18,316	227.93	3.3776×10^{-3}
6	31,115	228.10	3.3794×10^{-3}
4	83,140	228.14	3.3798×10^{-3}

the cargo-door lifting mechanism. Fig. 10 depicts the evolution of the von Mises equivalent stress distribution on the crank at key stages during the lifting process.

From the overall view of Fig. 10, the stress field of the flexible crank moves between the end-hole rim and the web as the configuration evolves during lifting, exhibiting a composite pattern of "stagewise" spatial migration. In the early stage of lifting, the overall stress level is low, with a maximum equivalent stress of about 38.6 MPa; as the motion progresses, the load path shifts from the hole rim to the hole-neck-web transition region, and the peak rises to 78.1 MPa. In the middle-to-late stage, redistribution occurs under the combined effects of contact and geometric nonlinearity, with the peak further increasing to 119.1 MPa and 167.7 MPa, and the extreme condition reaching 228.1 MPa. Based on the full-cycle stress field, the filleted transition zone around the pinhole is designated as the hot spot; throughout the motion cycle this location consistently exhibits coincident peaks of equivalent stress and maximum principal tensile stress, the steepest stress gradient, and governing geometric discontinuity, consistent with the precursor features of failure when in-plane bending dominates the component response.

To provide direct inputs for subsequent fatigue analysis, Fig. 11 presents the multiaxial stress history at the hot spot over a complete motion cycle. The local coordinate system takes the X-axis along the crank axis, the Z-axis in the plane of motion and orthogonal to X, and the Y-axis perpendicular to that plane. The results show that axial normal stress (σ_x), transverse normal stress (σ_z), and in-plane shear stress (τ_{xz})

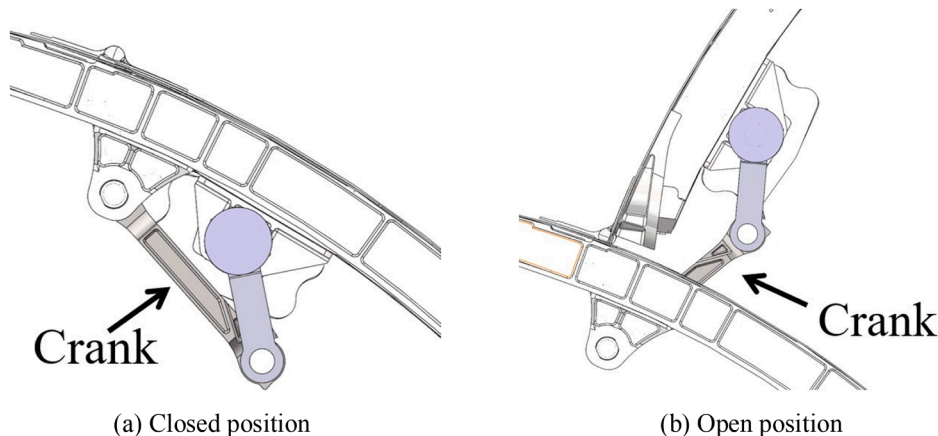


Fig. 8. Schematic of cargo-door closed and open states.

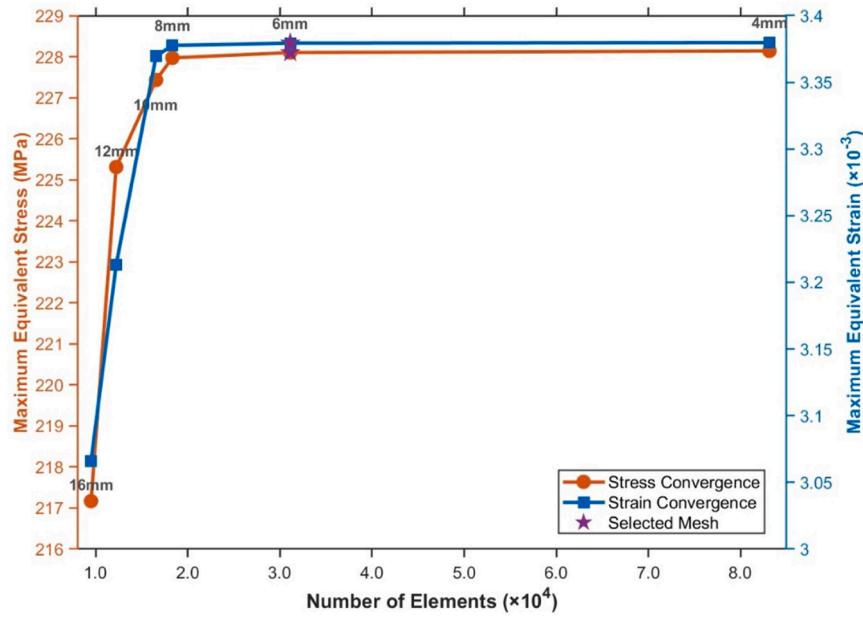


Fig. 9. Mesh convergence curves.

are the dominant components at this location, and the three components exhibit phase differences. The other three components, namely the through-thickness normal stress (σ_y) and the through-thickness shear stresses (τ_{xy} and τ_{yz}), remain near zero throughout the motion and can be neglected. For the crank, which approximates a beam-like member, the loading during motion occurs mainly within the plane of motion (the XZ plane), and the three out-of-plane stress components theoretically approach zero.

4.2. System-level durability testing

To validate the rigid-flexible coupled simulation model and obtain measured data required for fatigue damage analysis, a system-level test rig was constructed at a full (1:1) scale with the actual cargo-door lifting mechanism, as shown in Fig. 12. The test bench adopts a high-strength steel frame with sufficient stiffness to withstand the test loads without incurring deformations that would affect measurement accuracy. The drive system accurately reproduces the opening and closing trajectory of the cargo door, ensuring consistency between the test conditions and the simulation analysis.

As the lifting mechanism is designed with left-right symmetry, one crank on a single side is selected as the test object; four uniaxial strain gauges (P1–P4) are placed symmetrically at the centers of its four side faces, as shown in Fig. 13; each measurement point uses a uniaxial foil strain gauge oriented along the crank axis, with a gauge length of 3 mm and a nominal resistance of 120 Ω . Standard surface preparation and bonding procedures are used to ensure reliable attachment between the strain gauges and the crank surface, and moisture sealing is applied after the adhesive cures.

The data acquisition system uses a 24-bit high-precision A/D converter with a sampling frequency of 100 Hz, a dynamic range of $\pm 1000 \mu\epsilon$, and a resolution of 1 $\mu\epsilon$, meeting the requirements for high-precision strain measurement. The system supports a quarter-bridge configuration for 120 Ω strain gauges, with a bridge excitation voltage of 2.5 V. During testing, strain signals from all measurement points are synchronously recorded to form complete time-history data. Prior to acquisition, system calibration is performed, and signal quality is monitored in real time during acquisition to ensure data validity and continuity.

In addition, the main sources of measurement uncertainty include strain-gauge bonding/alignment and adhesive effects, temperature drift/self-heating, and electrical noise in the quarter-bridge acquisition

chain. To mitigate these effects, standard installation and curing procedures were followed, the symmetric layout (P1–P4) was adopted, and calibration/zeroing with shielding/grounding was performed prior to testing. The recorded strain histories were processed using consistent baseline correction and filtering for all channels to support a rigorous simulation-test comparison.

In the raw strain time-history data during the cargo-door opening process, significant high-frequency noise originating from mechanical vibrations and electromagnetic interference is present, and these raw data provide realistic inputs for subsequent processing and validation. To remove high-frequency noise while retaining the primary dynamic response of the mechanism, the test data are filtered using an eighth-order Butterworth low-pass filter with a cutoff frequency of 1.5 Hz. After processing, the experimental data from the four measurement points are compared with the simulated crank axial strain curves, as shown in Fig. 14.

Fig. 14 shows a simulation-experiment comparison of strain time histories at the four crank measurement points (P1–P4). The filtered experimental curves effectively suppress noise from the raw data and show good overall agreement with the simulation curves. Both simulation and experiment accurately capture the full single-cycle loading process, including the initial compression phase (0–50 s), the peak-loading phase (50–70 s), and the rebound recovery phase (70–120 s). Both curves exhibit a characteristic “U-shaped” strain evolution, consistent with the fundamental mechanical response of the crank mechanism under this operating condition. Local fluctuations observed in the experimental data reflect complex dynamic features of the real mechanism, including structural vibrations and material nonlinear effects; although the simulation has limitations in reproducing these fine-scale details, it demonstrates credible predictive capability for the primary response mechanisms of engineering interest.

5. Engineering application

5.1. Life prediction and uncertainty quantification

Based on the identified hot spot at the filleted transition of the crank pinhole and its multiaxial load history, the calibrated and externally validated unified parameter set θ is used to perform the fatigue life prediction of the cargo-door lifting mechanism. At this hot spot, the mission spectrum exhibits plane-stress dominance with periodic

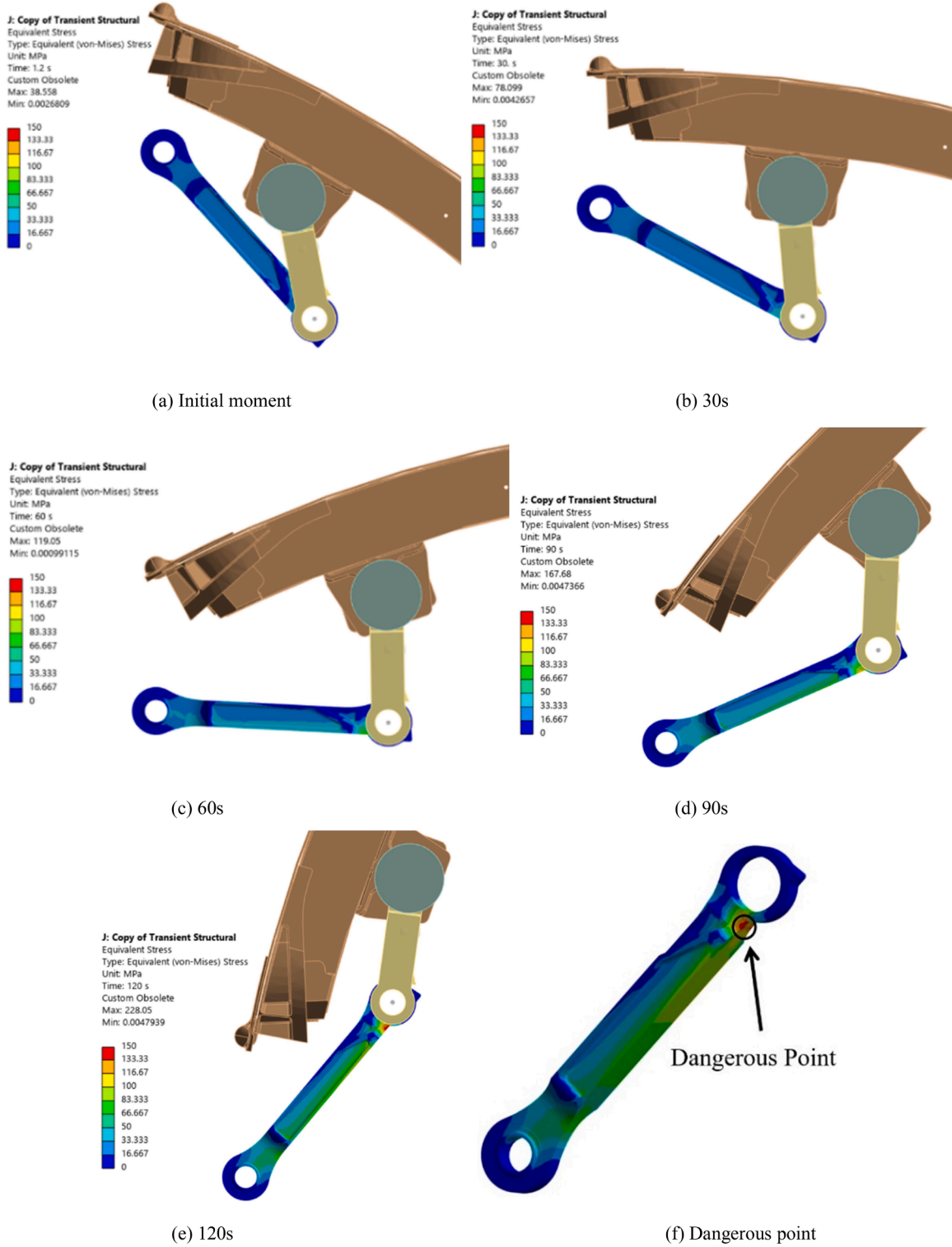


Fig. 10. Von Mises equivalent stress contours at key poses and hot-spot identification.

repetition; the dominant components are σ_x , σ_z , and τ_{xz} , whereas the through-thickness components σ_y , τ_{xy} , and τ_{yz} are negligible throughout the cycle. The Hilbert transform is applied to compute phase differences among the stress components; the phase offsets between σ_x and σ_z , between σ_x and τ_{xz} , and between σ_z and τ_{xz} are found to be 0.8° , 0.4° , and 0.4° , respectively, indicating nearly proportional loading.

Under a fixed-cycle assumption, the CDM numerical implementation in Section 2 is used to incrementally integrate damage over the

representative cycle within the mission period, yielding the per-cycle damage ΔD_{cyc} . First, the damage driving force Y is evaluated using Eq. (11), inserted into the damage evolution law in Eq. (12), and the state-dependent damage strength $S(\eta, \xi)$ from Eq. (13) is applied. With the critical threshold $D_c = 0.1$, the life is computed as $N_{\text{pred}} = D_c / \Delta D_{\text{cyc}}$.

Figs. 15 and 16 illustrate the evolution of CDM-based damage measures during a single cargo-door open–close duty cycle. Fig. 15 shows the damage-driving term $d(t)$, which directly follows the applied load

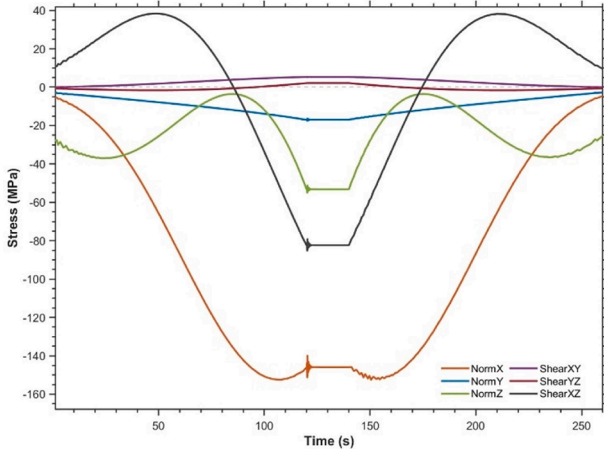


Fig. 11. Hot-spot load history.

history. As the door opens, the load increases and $d(t)$ rises to a maximum at approximately $t \approx 120$, corresponding to the fully opened configuration; during the closing stage, the load decreases and $d(t)$ decays accordingly. Since $d(t)$ represents an instantaneous driving quantity rather than an accumulated damage variable, it is not required to be monotonic and reflects load-induced fluctuations.

To represent the irreversible accumulation of fatigue degradation, the cumulative damage is obtained by time integration, $D(t) = \int_0^t d(\tau) d\tau$.

As shown in Fig. 16, the cumulative damage increases monotonically throughout the duty cycle and remains accumulated after each loading segment, which is consistent with the physical interpretation of damage in the CDM framework.

For a repeated and stable duty cycle, the per-cycle damage increment ΔD is defined as the cumulative damage accumulated over one cycle. In this study, ΔD is evaluated using the baseline peak-based procedure consistent with the adopted CDM formulation and calibration, giving

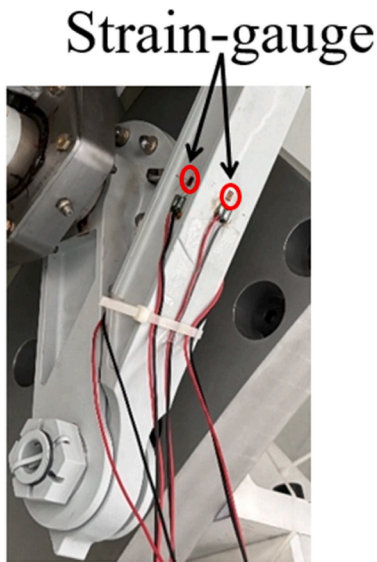


(a) Closed position

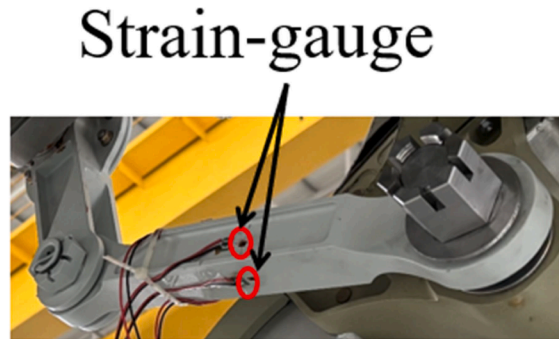


(b) Open position

Fig. 12. System-level cargo-door durability test rig.



(a) Initial position



(b) Final position

Fig. 13. Strain-gauge layout on the crank.

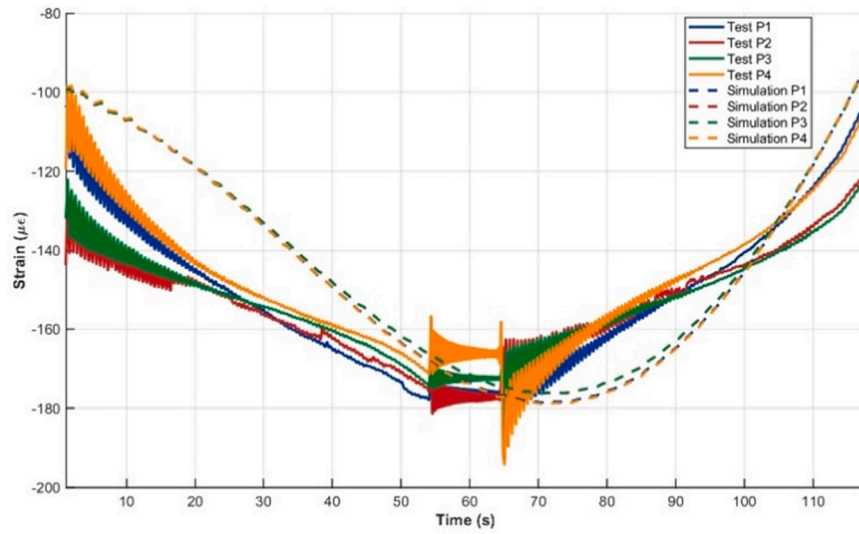


Fig. 14. Comparison of simulated and measured strain time histories at the measurement points.

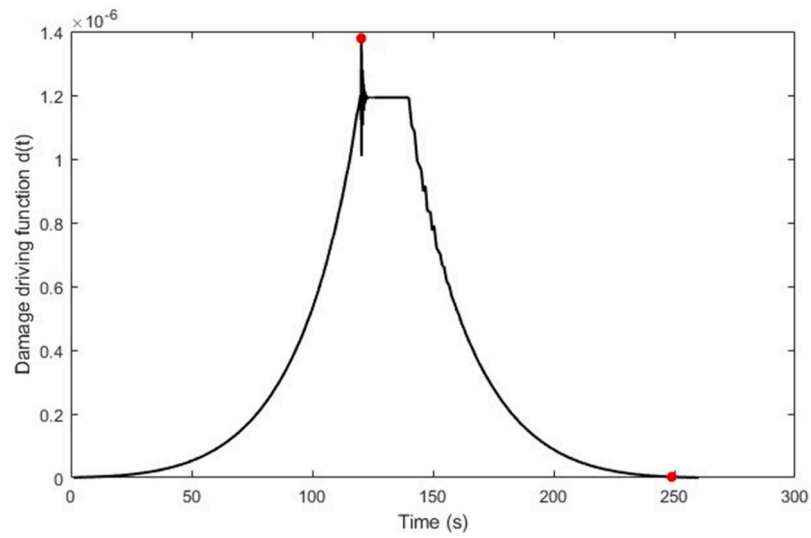


Fig. 15. Instantaneous damage-driving term $d(t)$ reflecting load-induced fluctuations.

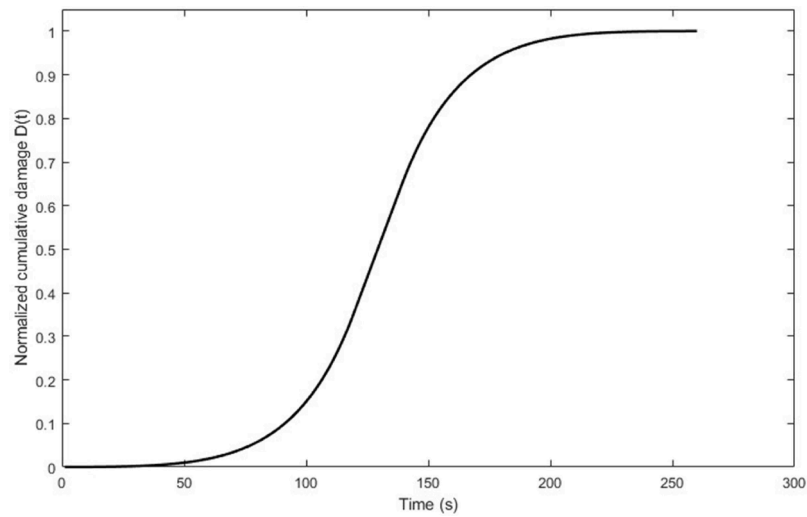


Fig. 16. Monotonic accumulation of cumulative damage $D(t)$ over a duty cycle.

$\Delta D = 6.90 \times 10^{-7}$. With the critical threshold $D_c = 0.1$, the corresponding deterministic fatigue life prediction is $N_{pred} = D_c / \Delta D = 1.448 \times 10^5$ cycles. The magnitude (and potential variability) of ΔD is primarily governed by the load level, duty-cycle shape, and multiaxial stress state; when these conditions are unchanged across cycles, ΔD can be treated as approximately constant.

To quantify the impact of material-parameter uncertainty on engineering life, the material-level posterior samples $\{\theta^{(m)}, \sigma^{2(m)}\}$ obtained in Section 3 are forward-propagated to the actual load spectrum of the cargo door, yielding the posterior predictive life distribution $\{N^{(m)}\}$. The posterior 5 % percentile is $N_{5\%} = 7.319 \times 10^4$ cycles, the posterior median is $N_{50\%} = 1.478 \times 10^5$ cycles, and the posterior 95 % percentile is $N_{95\%} = 2.917 \times 10^5$ cycles. For engineering application, it is recommended to use the posterior median $N_{50\%}$ as the baseline design value (corresponding to 50 % probability of failure) and to use the posterior 5th percentile $N_{5\%}$ as the conservative design value (corresponding to approximately 95 % reliability).

Based on the posterior samples, the reliability curve $R(N) = P(N_f > N)$ is constructed and shown in Fig. 17. From a reliability-analysis perspective, this posterior predictive formulation provides a direct evaluation of $R(N)$ by uncertainty propagation. Classical approaches such as FORM/SORM typically approximate failure probability through an explicit limit-state function and local linearization around the most probable point; such formulations can be viewed as complementary alternatives when a suitable limit-state representation is available. The curve shows a steep decline near $N \approx 10^5$ cycles, reflecting the combined effects of the concentration of the posterior life distribution and the periodicity of the loading. For high reliability with $R \geq 0.95$, the allowable design life is $N \leq 7.319 \times 10^4$ cycles; for very high reliability with $R \geq 0.99$, the design life should be limited to $N \leq 5.47 \times 10^4$ cycles.

5.2. Method comparison against classical criteria

To verify the soundness of the proposed fatigue life prediction method, three classical multiaxial fatigue assessment methods are selected for comparison. The S–N curve method uses the von Mises equivalent stress and employs Miner's linear accumulation, $D = \sum n_i / N_i$. The Findley critical-plane method scans candidate planes over 0° – 90° , computes the shear–normal stress interaction parameter, and maps it to the S–N curve. The Brown–Miller method adopts a critical-plane criterion based on strain parameters. The comparison results of the four methods are summarized in Table 10.

The three comparison methods exhibit good consistency with the

Table 10
Comparison of fatigue life prediction results.

Method	PSO–CDM	SN/Miner	Findley	Brown–Miller
Life	1.448×10^5	9.839×10^4	9.763×10^4	1.189×10^5

CDM results. The S–N and Findley predictions are very close, with ratios to the deterministic CDM life of 0.68 and 0.67, respectively, and the Brown–Miller ratio is 0.82. This consistency stems from the near-proportional loading characteristics of this case, dominated by compressive and shear components. A comprehensive analysis shows that the state-dependent strength function (η_s) in CDM maps stress-state effects into the damage process, with a clear physical mechanism, and additionally quantifies the damage-evolution pathway and reliability intervals, demonstrating stronger mechanistic interpretability and engineering applicability under complex stress conditions. Under near-proportional loading, classical engineering criteria and CDM predictions are highly consistent, mutually confirming the soundness of the predictions. In engineering practice, CDM can be used as the primary criterion together with Bayesian uncertainty quantification to provide design margins, while S–N, Findley, and Brown–Miller methods can be used for rapid cross-checks. Based on the posterior samples in this engineering application, the posterior 5th percentile $N_{5\%} = 7.319 \times 10^4$ cycles can serve as a reliable basis for conservative design, corresponding to approximately 95 % reliability.

6. Conclusions

This study targets the need for fatigue life prediction of aircraft mechanisms and introduces a CDM–Bayesian integrated approach for multiaxial fatigue life prediction. It combines rigid–flexible simulation and experimental validation to achieve cross-scale consistency assessment between material and structure.

- (1) A state-dependent Continuum Damage Mechanics (CDM) framework is constructed based on a two-scale constitutive theory. At the macroscopic level, the material exhibits elastic behavior, while at the microscopic level, von Mises yielding with cyclic characteristics is modeled using Chaboche combined hardening. The strength function $S(\eta, \xi)$, defined by stress triaxiality η and the normalized third invariant ξ , provides a unified description of damage initiation and evolution under multiaxial stress.

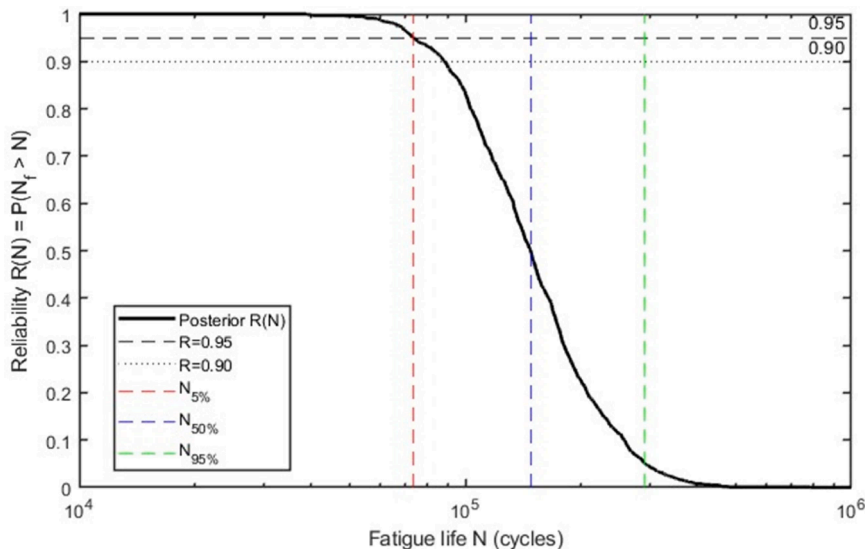


Fig. 17. Reliability curve $R(N)$ based on posterior samples.

- (2) The parameter set θ is uniformly calibrated using PSO on 7050–T7451 life-test data (factor-of-four hit rate 92.7 %). External validation is conducted with independent MIL-HDBK-5H data, and Bayesian inference quantifies parameter and model scatter, yielding probabilistic expressions for life and reliability.
- (3) A rigid–flexible multibody dynamics model is established and validated by experiment, yielding accurate multiaxial load histories at critical locations and ensuring high-fidelity inputs for structure-level assessment.
- (4) Material-level model parameters are applied across scales to life assessment at the hot spot of the cargo-door lifting mechanism, and the results are compared with the S–N/Miner, Findley, and Brown–Miller methods. The results show comparable life magnitudes among the three, whereas CDM simultaneously provides deterministic and reliability-based life and captures stress-state effects and damage-driving mechanisms, demonstrating its theoretical advantages and engineering applicability under complex stress conditions.
- (5) In this engineering application, the CDM deterministic life is 1.448×10^5 cycles, and the life corresponding to approximately 95 % reliability (posterior 5th percentile) is 7.319×10^4 cycles.

Future work will be expanded in the following directions: (1) incorporating modeling of variable-amplitude load sequence effects to enhance applicability under complex service spectra; (2) explicitly considering random factors such as geometric and material variability and load fluctuations to advance the framework's fatigue reliability assessment capability; (3) extending the proposed CDM–Bayesian multiscale workflow to other representative aeronautical mechanisms (e.g., landing gear and control-surface transmissions), and developing standardized workflows and material-parameter libraries; (4) extending the present scalar-damage formulation to more general multi-component or tensorial damage representations, and validating the framework under strongly non-proportional multiaxial loading when direction-resolved experimental evidence becomes available; (5) integrating digital twins with online monitoring to enable condition-based dynamic remaining-life assessment and to facilitate airworthiness certification applications.

CRedit authorship contribution statement

Yao-jia Han: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation.
Yi-pin Sun: Writing – review & editing, Methodology.
Cheng-wei Fei: Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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