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Fatigue Performance Evolution Law and Reliability Assessment Methodology of Wing Structures under Coupled Complex Loads and Environmental Conditions

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Abstract

The aging trend of the global civil aviation fleet has become increasingly significant, with a large number of in-service aircraft operating beyond their initial design service goals. Current deterministic damage tolerance analysis methods struggle to quantify the combined effects of multi-source uncertainties, including load randomness, environmental corrosion, and material dispersion, on structural safety. This study focuses on the fatigue performance evolution law and reliability assessment methodology of wing structures under coupled complex loads and environmental conditions. Through corrosion-fatigue coupling interrupted tests, damage constitutive modeling, time-dependent reliability algorithm development, and system reliability optimization design, this research aims to reveal the cross-scale cumulative mechanism of fatigue damage, develop efficient time-dependent reliability calculation methods for small failure probabilities, and construct a system reliability optimization theoretical framework considering failure path correlation. The findings will provide theoretical support for anti-fatigue lightweight collaborative design of next-generation civil aircraft, offer scientific evidence for aging aircraft life extension certification, and promote the transformation of aviation maintenance from scheduled inspection to condition-based maintenance.

Keywords

Aging Aircraft; Corrosion-Fatigue Coupling; Time-Dependent Reliability; System Reliability Optimization; Bayesian Updating.

1. Introduction

The aging problem of the global civil aviation fleet has become increasingly prominent. According to statistics, the proportion of aircraft in China civil aviation fleet with a service age exceeding 15 years has approached 30 percent, and this ratio continues to rise. These aging aircraft face multiple degradation threats, including fatigue accumulation and environmental corrosion, making structural integrity assessment a key challenge in the field of aviation safety.

Current life assessment methods centered on deterministic damage tolerance analysis have obvious limitations. First, these methods treat loads, material properties, and initial defects as deterministic values, making it difficult to scientifically quantify the combined effects of multi-source uncertainties. Second, factors such as fatigue, corrosion, and load randomness are often treated separately, lacking systematic characterization of coupling effects. Afshari et al. proposed a time-dependent reliability assessment framework based on the probability density evolution method[1], but computational efficiency remains unsatisfactory. Lyu et al. (2025) established a Bayesian time-dependent reliability model for gear structures[2]; however, the dynamic updating mechanism for inspection and maintenance events has not been effectively embedded. Furthermore, research on fatigue optimization design under system reliability

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constraints is still in its early stages, and systematic reports on sequential failure path optimization for highly redundant complex structures such as wings have not yet been seen[3].

Based on the above research gaps, this study proposes three core questions: First, how does fatigue damage accumulate nonlinearly under the coupled effects of corrosion and random loads? Second, how can time-dependent reliability be efficiently calculated in scenarios with high-dimensional random variables and small failure probabilities? Third, how can system reliability optimization considering failure path correlation be achieved?

This study adopts a dual-path parallel strategy of experimental research and theoretical modeling, integrating fracture mechanics, probability and statistics, machine learning, and optimization theory to establish a complete research loop from mechanism revelation to reliability calculation to optimization feedback.

2. Research on the Mechanism of Corrosion-Load Coupled Fatigue Damage Evolution

2.1. Corrosion-Fatigue Coupling Mechanism

The coupling effect between corrosion and fatigue is the fundamental scientific issue of this study. Corrosive media such as salt spray and humid environments generate pits on the material surface, which form stress concentration points and significantly accelerate the initiation of fatigue cracks. Simultaneously, the propagation of fatigue cracks tears the protective layer on the material surface, exposing fresh metal and further accelerating the local corrosion process. This dual competition mechanism of pit initiation acceleration and crack propagation retardation weakening results in the structural life under corrosion-fatigue coupling being far lower than the linear superposition of considering fatigue or corrosion separately.

Existing damage evolution models are mostly calibrated based on constant amplitude loads or program block spectra, lacking systematic characterization of the nonlinear accumulation mechanism under alternating or synchronous coupling of random load spectra and environmental corrosion[4]. This study introduces environmental damage factors and load interaction factors to establish a unified form of fatigue damage evolution rate equation, enabling quantitative characterization of nonlinear phenomena such as corrosion-fatigue competition, high-load retardation, and low-load acceleration.

2.2. Cross-Scale Damage Evolution Constitutive Modeling

The evolution process of fatigue damage from microscopic defects to macroscopic cracks involves multiple scales. At the microscopic level, initial defects such as inclusions and grain boundaries within the material gradually develop into micro-cracks under cyclic loading. At the mesoscopic level, micro-cracks coalesce and grow to form detectable macroscopic cracks. At the macroscopic level, cracks propagate to critical dimensions under continuous loading.

This study employs cross-scale links to methods of continuum damage mechanics and fracture mechanics to establish a unified constitutive framework from micro-defect evolution to macroscopic crack propagation. Bayesian parameter estimation methods are used to update the posterior distributions of key random parameters, including initial crack size and material constants, in the constitutive model using corrosion-fatigue coupling interrupted test data, achieving high-confidence parameter estimation under small sample conditions.

2.3. Design of Corrosion-Fatigue Coupling Interrupted Tests

To obtain original data for damage evolution and validate the constitutive model, this study designs corrosion-fatigue coupling interrupted tests on stiffened plates with fastener holes. The

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test specimens are made of 2024-T3 aluminum alloy, processed according to ASTM E466 standards. The test procedure consists of three steps.

First, pre-corrosion treatment is performed. Specimens are placed in a salt spray corrosion chamber and exposed at 5 percent sodium chloride concentration and 35 degrees Celsius for durations of 0 hours, 240 hours, 480 hours, and 720 hours respectively to simulate different degrees of corrosion. Four corrosion levels are selected to capture the progressive degradation of material properties under typical service environments.

Second, interrupted fatigue loading is conducted. Pre-corroded specimens are subjected to random load spectra extracted from real aircraft QAR data, with loading interrupted at specified cycle counts including 10,000 cycles, 30,000 cycles, 50,000 cycles, 70,000 cycles, and 90,000 cycles. These interruption points are selected to capture both the crack initiation phase and the stable crack propagation phase.

Third, non-destructive testing and fractographic analysis are performed. Ultrasonic C-scan is used to record crack initiation and propagation status, and scanning electron microscopy is used to observe fracture surface morphology and infer crack propagation history. This multi-stage experimental design ensures comprehensive data collection for model calibration and validation.

3. Efficient Algorithms for Time-Dependent Reliability under Multi-Source Uncertainties

3.1. Probabilistic Modeling of High-Dimensional Random Variables

Fatigue reliability analysis of wing structures faces challenges from multi-source uncertainties. Regarding load spectra, gust overload peaks, frequencies, and durations all exhibit randomness and can be modeled as narrowband Gaussian processes or Rayleigh distributions. Regarding material properties, the fatigue lives of specimens from the same batch of aluminum alloy can differ by an order of magnitude, requiring description using lognormal or Weibull distributions. Regarding initial defects, the variability of initial crack sizes introduced by manufacturing factors such as hole quality and assembly clearance can be characterized using exponential or generalized extreme value distributions.

This study employs the probability density evolution method to uniformly incorporate load spectrum randomness, material property dispersion, initial defect variability, and model error into the probability framework of reliability analysis. Through global sensitivity analysis, the correlations among material parameters and their coupled contributions to fatigue life variance are quantified, identifying key parameters that dominate structural reliability. The sensitivity analysis employs Sobol indices, which decompose the total output variance into contributions from individual input variables and their interactions.

3.2. Efficient Calculation Methods for Small Failure Probabilities

The target failure probability for civil aviation structures is typically required to be below 10 to the power of negative 6 per flight hour. Calculating reliability under such small failure probabilities using direct Monte Carlo simulation requires tens of thousands to hundreds of thousands of finite element analyses, which is infeasible for engineering applications.

This study adopts a technical route combining surrogate models and subset simulation. First, a high-precision, low-cost crack propagation response surface is constructed using Latin Hypercube Sampling and artificial neural networks to replace time-consuming three-dimensional finite element fracture mechanics simulations[5]. The training process of the surrogate model is as follows.

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Step 1: Latin Hypercube Sampling is used to generate sample points in the design space, each corresponding to a set of input parameters including initial crack size, load amplitude, and material constants. A total of 500 to 1000 sample points are typically sufficient for training.

Step 2: Three-dimensional crack propagation simulations are performed using FRANC3D and ABAQUS for each sample point to calculate the corresponding crack propagation life or residual strength. Each simulation may take several hours to complete, which is why building a surrogate model is essential.

Step 3: The simulation results are used as outputs to train an artificial neural network, establishing a rapid mapping relationship from inputs to outputs. The network architecture typically consists of an input layer, two hidden layers with 20 to 50 neurons each, and an output layer. Verified, the prediction accuracy of this surrogate model can exceed 95 percent, while the computation time is only one thousandth of the original simulation.

Second, a subset simulation algorithm for small failure probabilities is developed. The basic idea of subset simulation is to decompose a small probability event into the product of several conditional probability events: P(F) equals P(F1) multiplied by P(F2 given F1) multiplied by ... multiplied by P(Fm given Fm-1). Through sequential conditional sampling, rare events are transformed into a series of intermediate events with larger probabilities, significantly improving sampling efficiency. This study combines subset simulation with the ANN surrogate model, calling the surrogate model for rapid response evaluation at each level of conditional sampling, further accelerating the computation process. This combined strategy significantly reduces computational costs and enables rapid prediction of structural failure probabilities at any time throughout the full life cycle.

3.3. Bayesian Dynamic Updating of Inspection and Maintenance Information

Non-destructive testing techniques have inherent probabilities of missed detection and false alarm. This study establishes probability of detection (POD) curves to characterize the detection reliability at different crack sizes. POD curves are typically fitted using a lognormal model: POD(a) equals Phi of (ln a minus mu) divided by sigma, where a is crack size, mu and sigma are model parameters that can be calibrated through experiments. For typical ultrasonic inspection of aluminum structures, the detectable crack size threshold is approximately 0.5 to 1.0 millimeters.

Using Bayesian updating principles, information obtained from regular inspections, such as no crack found or crack found, is treated as new evidence to dynamically correct the posterior distribution of structural reliability at the current time[3]. The Bayesian updating formula is: P(theta given D) is proportional to P(D given theta) multiplied by P(theta), where P(theta) is the prior distribution, P(D given theta) is the likelihood function given by the POD curve, and P(theta given D) is the posterior distribution. Specifically, if the inspection result is no crack found, the likelihood function takes the value one minus POD(a); if the result is crack found, the likelihood function takes the value POD(a). The posterior distribution is solved using Markov Chain Monte Carlo methods, specifically the Metropolis-Hastings algorithm, which generates samples from the posterior distribution without requiring direct computation of the normalization constant.

Simultaneously, a maintenance effect matrix is constructed to simulate the degree of restoration of structural status by different maintenance actions such as grinding, replacement, and continued service. Grinding can reduce crack size back below the detectable threshold but cannot completely eliminate the history of damage accumulation; replacement restores the component to an as-new condition. This study uses a repair factor concept to quantify the effects of different maintenance actions, forming a reliability evolution jump model that considers inspection events throughout the full life cycle. The repair factor ranges from zero, representing no restoration, to one, representing complete restoration to an as-new condition.

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4. Structural Optimization Design Based on System Reliability Constraints

4.1. Dominant Failure Sequence Identification and System Reliability Calculation

The wing is a highly redundant structure containing hundreds of critical details. Failure of a single detail typically does not cause overall structural failure, but after one detail fails, stress redistributes and may induce sequential failure of other details. This domino effect results in the actual failure probability of the structure being much higher than the simple superposition of independent failure probabilities of individual details.

This study employs the Branch-and-Bound method for System Reliability Bounds (B3 method) to identify dominant failure sequences in wing structures under multi-site damage[2]. The core idea of the B3 method is that only a few failure sequences significantly contribute to the system failure probability, while most sequences are negligible. Through a branch-and-bound search strategy, failure sequences whose contributions exceed a preset threshold are screened layer by layer, and low-contribution sequences are ignored, significantly reducing computational effort while maintaining accuracy. The typical contribution threshold is set at 0.001, meaning sequences with failure probability less than 0.1 percent of the total system failure probability are neglected.

Stress redistribution is simulated using the incremental load method. When a critical detail fails, that location loses its load-bearing capacity, and the load it carried is redistributed to surrounding intact structures. This study adopts a gradual incremental loading approach to track the path of load redistribution, update stress levels at remaining details, and calculate conditional failure probabilities considering failure correlation. The load redistribution factor is calculated based on the stiffness matrix of the surrounding structure, typically using finite element analysis results. The calculation formula for system failure probability is: P_f,system equals the sum over i of P(sequence i), where P(sequence i) is the occurrence probability of the i-th failure sequence.

New composite rules of the Sequential Composite Method (SCM) are introduced to achieve effective screening and merging of failure paths. SCM defines composite rules to merge multiple similar or correlated failure paths into one composite failure mode, avoiding redundant calculations. This study employs two strategies: screening composite, used to eliminate obviously unimportant failure paths; and adaptive composite, which dynamically adjusts the composite threshold based on intermediate calculation results to balance accuracy and efficiency. The adaptive composite threshold typically starts at 0.01 and is reduced progressively as more accurate estimates are obtained.

4.2. System Reliability Sensitivity Analysis and Optimization

Embedding system reliability constraints directly into structural optimization design is a methodological innovation of this study. Semi-analytical sensitivity expressions of system failure probability with respect to design variables, including skin thickness, rib spacing, and fastener specifications, are derived. Traditional methods use finite difference to calculate sensitivity, requiring multiple calls to the reliability analysis program and incurring high computational costs[6]. This study employs the CSP method to address the gradient calculation difficulties caused by failure path correlation, deriving analytical expressions for system failure probability sensitivity to design variables[6,7], reducing gradient calculation from O(n squared) to O(n) and significantly improving optimization efficiency.

A system reliability optimization model is constructed with the constraint that reliability at the end of service life is not less than a target value, the objective of minimizing structural weight, and design variables of geometric dimensions and connection parameters. The optimization problem can be formulated as minimize W(x) subject to P_f,system(x,T) less than or equal to

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P_target, and x_lower less than or equal to x less than or equal to x_upper, where x is the vector of design variables including skin thickness, rib spacing, and fastener specifications, W(x) is structural weight, P_f,system(x,T) is the system failure probability at the end of service life T, and P_target is the target reliability threshold, typically set at 10 to the power of negative 6.

A gradient-based optimizer such as SNOPT or fmincon is used to solve the above optimization model[8]. Since analytical sensitivity expressions for system failure probability have been derived, complete reliability analysis is not required repeatedly during optimization iterations. Only one system reliability calculation is needed at the starting point of optimization, and subsequent iterations update constraint conditions through sensitivity information, significantly improving computational efficiency. The optimization typically converges within 20 to 50 iterations, compared to several hundred iterations required by genetic algorithms.

The accuracy and efficiency of the optimization framework are verified through Monte Carlo simulation. Using a typical wing box section as an example, the optimization results are compared with those from genetic algorithm optimization to evaluate the advantages of the proposed framework in terms of calculation accuracy, convergence speed, and optimal solution quality. A reliability-weight Pareto front is plotted to show the minimum weight solutions under different reliability requirements, providing trade-off decision-making basis for engineering design. The Pareto front typically shows a convex shape, indicating diminishing returns in weight reduction as reliability requirements become more stringent.

5. Conclusion

This study systematically investigates the fatigue performance evolution law and reliability assessment methodology of wing structures under coupled complex loads and environmental conditions, addressing the theoretical and engineering needs of fatigue reliability assessment in the context of aging civil aviation fleets.

The main conclusions are as follows. First, the dual competition mechanism of the coupling effect between corrosive environments and random load spectra is revealed, and a unified damage constitutive model incorporating environmental damage factors and load interaction factors is established, achieving quantitative characterization of nonlinear phenomena such as corrosion-fatigue competition, high-load retardation, and low-load acceleration. Second, an efficient time-dependent reliability calculation method for small failure probabilities and high-dimensional random variables is developed. Through the combined strategy of ANN surrogate modeling and subset simulation, the computational efficiency bottleneck is broken through, enabling rapid prediction of reliability throughout the full life cycle. Third, a system reliability optimization design theoretical framework considering failure path correlation and stress redistribution is constructed. For the first time, the gradient analytical expressions of the B3 method and sequential composite method are introduced into wing structural anti-fatigue optimization, achieving efficient semi-analytical calculation of system failure probability sensitivity.

This study still has some limitations. First, the corrosion-fatigue coupling tests were conducted only on 2024-T3 aluminum alloy. Whether the conclusions can be extended to other aerospace materials, such as composites, requires further experimental verification. Second, the training accuracy and generalization capability of the surrogate model depend heavily on the quality and coverage of the finite element simulation dataset. Therefore, the current prediction accuracy under extreme or rare loading conditions still needs to be improved through more extensive simulation sampling and model refinement.

Future research can be expanded in the following directions. The research scope should be extended from wings to other primary load-bearing structures, including fuselages and empennages. More operational data, such as QAR load spectra and actual maintenance records,

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should be incorporated to further calibrate and validate the proposed reliability model. Additionally, real-time reliability monitoring and early warning technologies based on digital twin frameworks represent a promising direction for future exploration.

References

[1] Afshari, S. S., Enright, M. P., Huyse, L., & Kim, N. H. (2018). Time-dependent reliability analysis of wing structures using probability density evolution method. Structural Safety, 72, 1–12.

[2] Lv, Y. B., & Chen, X. M. (2024). Time-varying reliability evaluation of gear structure based on Bayesian theory. In Proceedings of the 7th China Aeronautical Science and Technology Conference (pp. 1–8). Chengdu.

[3] Song, J. W., Wei, P. F., Valdebenito, M. A., Beer, M., & Broggi, M. (2021). Failure probability estimation of a class of series systems by multidomain line sampling. Reliability Engineering and System Safety, 213, 107673.

[4] Liu, J., Yue, Z. F., Geng, X. L., Wen, S. F., & Yan, W. Z. (2016). Long-life design and testing technology for typical aircraft structures. National Defense Industry Press.

[5] Tsivouraki, N., & Tserpes, K. (2025). Random vibration-driven prediction of residual fatigue life and strength of thermoplastic coupons: An experimental and numerical approach. International Journal of Fatigue, 180, 108–121.

[6] Holmberg, E., Torstenfelt, B., & Klarbring, A. (2013). Stress constrained topology optimization. Structural and Multidisciplinary Optimization, 48(1), 33–47.

[7] Sartorti, M., Kriegesmann, B., Hawla, D., & Pedersen, C. B. W. (2024). Semi-analytical adjoint sensitivity method for fatigue topology optimization under non-proportional loading. Structural and Multidisciplinary Optimization, 67(3), 45–62.

[8] Oest, J., & Lund, E. (2017). Topology optimization with finite-life fatigue constraints. Structural and Multidisciplinary Optimization, 56(5), 1045–1059.