Proceedings of the 4th International Conference on Functional Materials and Civil Engineering
DOI: 10.54254/2755-2721/2026.36952

Artificial Intelligence-Based Structural Health Monitoring and Predictive Maintenance for Civil Aircraft

Yizhe Lyu

College of Mechanical and Transportation Engineering, China University of Petroleum (Beijing), Beijing, China
13787167083@163.com

Abstract. Structural health monitoring (SHM) of civil aircraft is a critical enabler of aviation safety and operational reliability. Traditional SHM pipelines, which depend on physics-based mathematical models and rigidly scheduled maintenance, encounter two persistent bottlenecks: limited adaptability to complex, time-varying operating conditions, and insufficient throughput for the rapidly growing volume of multisource sensor data. Against this background, this paper presents a systematic review of aircraft SHM technologies organized around three pillars—probabilistic safety coefficient design, nano-modified advanced structural materials, and AI-driven predictive maintenance—with emphasis on the third. Specifically, this study examines how one-dimensional convolutional neural networks (1D-CNNs) automate fault feature extraction from raw vibration signals, how long short-term memory (LSTM) networks model long-range degradation trajectories for remaining useful life (RUL) estimation, and how reinforcement learning (RL) frameworks optimize maintenance scheduling under multi-objective constraints. It also benchmarks the open-source datasets most widely used in this field, including the CWRU bearing dataset and NASA C-MAPSS turbofan dataset. Reported results indicate that AI-based predictive maintenance can reduce unscheduled maintenance events by 35%–40% and lower overall MRO costs by 20%-30% while improving dispatch reliability. This study concludes that the integration of structural mechanics principles with data-driven AI models—particularly through physics-informed neural networks and edge-deployed lightweight models—represents the most promising direction for next-generation onboard intelligent health monitoring systems.

Keywords: structural health monitoring, predictive maintenance, convolutional neural network, civil aircraft, artificial intelligence

1. Introduction

The global civil aviation industry keeps expanding, making aircraft structural safety critical for passenger safety, efficiency, and confidence. Structural health monitoring (SHM) enables early damage detection and prevents in-flight failures. For decades the field rested on three pillars, safety coefficient design, advanced composites, and scheduled maintenance. Yet growing complexity and exploding sensor data now exceed conventional manual methods. AI offers a remedy: deep learning

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2026.36952

extracts fault features from raw signals and predictive maintenance forecasts degradation, shifting maintenance toward condition-based and predictive. This paper reviews aircraft SHM and how AI strengthens traditional approaches across techniques, datasets, challenges, and directions.

2. Safety coefficient assessment

2.1. Concept and evaluation process

The safety coefficient, the ratio of ultimate to limit load, is fundamental yet largely empirical, introducing subjectivity. The conventional 1.5 is a trade-off: too high adds weight and cost, too low compromises safety, so the right value balances safety against economics. Haftka related coefficients to distribution functions; Liu et al. and Jia et al. studied reliability-coefficient relations in composites; Wang integrated safety-coefficient, reliability, and robust design. Evaluating a composite coefficient follows an iterative seven-step loop (Figure 1) that discretizes load and strength distributions, computes cumulative failure probability, and adjusts the coefficient until the target index is met, yielding a safe yet economical result.

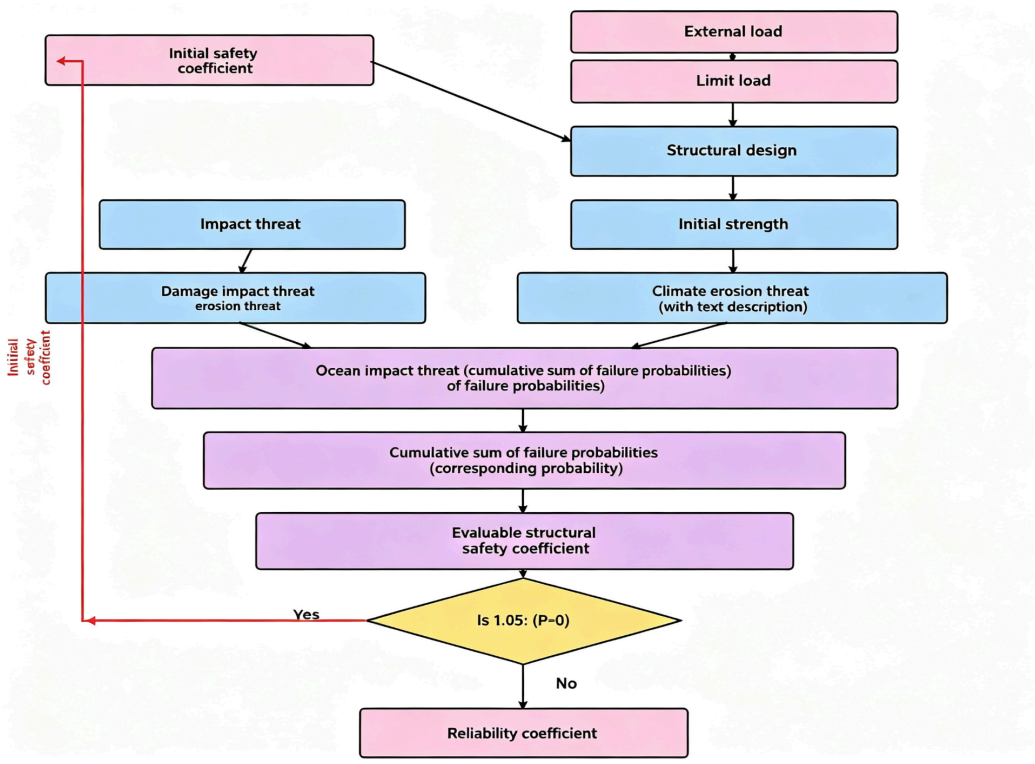

Figure 1. Safety coefficient evaluation process

2.2. Impact energy and failure probability

Impact damage is the primary cause of strength loss in composites, so impact energy must be handled carefully. Damage area, width, and dent depth relate quantifiably to impact energy; dent depth shows the cleanest one-to-one link and is most detectable by non-destructive testing, while damage area can be fitted experimentally. The stress-strength interference model captures failure probability: failure occurs when applied stress exceeds residual strength over the service life with

DOI: 10.54254/2755-2721/2026.36952

inspection and maintenance. As Figure 2 shows, overlapping density functions of residual strength and stress equal the failure probability, a framework widely used in aerospace design.

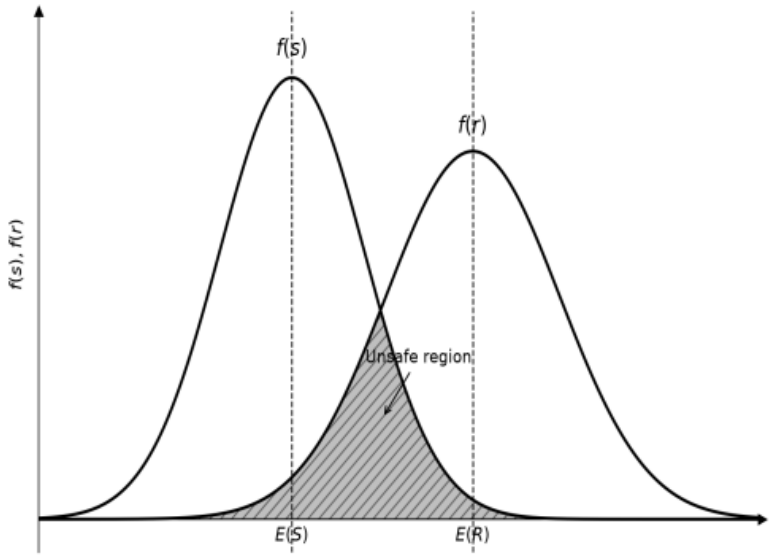

Figure 2. Stress-strength interference model

The safety coefficient has to be set so that failure probability stays below an acceptable threshold for the whole service life. The approach here treats external load, initial strength, and impact energy as probability distributions rather than fixed values, and uses the stress-strength interference model to compute the resulting failure probability. By iteratively comparing the result against the target failure probability index, an acceptable minimum safety coefficient emerges. This kind of optimization matters for cost reduction and weight optimization in aircraft design—it lets materials be used more efficiently without dropping the below required safety standards.

3. Advanced materials for aircraft structures

3.1. Nano-silica modified glass fiber composites

Alkali-free glass composite materials bring real benefits to aerospace structural applications, from aircraft and spacecraft components to automotive uses. Polymer matrix composites (PMCs) are particularly well-suited for aircraft structural applications, owing to their exceptional combination of properties: high corrosion resistance, superior specific strength, low density, excellent tensile performance, thermal stability, and relatively low manufacturing costs. These multifaceted attributes have positioned PMCs as an increasingly viable alternative to conventional metallic materials, enabling significant weight reduction and corresponding improvements in fuel efficiency. One new technique boosts the strength of 2D plain weave alkali-free glass fabric laminated composites by using CNC milling during compression molding and material cutting. Precise control over composite shapes and dimensions during manufacturing improves structural stability and gives better bonding performance. Adding nano-silica takes mechanical properties further still by strengthening the interfacial bond between fiber and matrix, producing composites with better strength, stiffness, and damage tolerance than conventional formulations. Table 1 summarizes the typical mechanical property gains from nano-silica modification of glass fiber reinforced epoxy composites. The improvements hold across multiple metrics: tensile strength goes up by 5.7%–24%,

DOI: 10.54254/2755-2721/2026.36952

and flexural strength can rise by as much as 39%, depending on nano-silica content and fiber architecture.

Table 1. Mechanical property improvement of nano-silica modified glass fiber/epoxy composites

Property	Improvement (%)	Typical Nano-Silica Content
Tensile strength	5.7-24	0.5-5 wt%
Tensile modulus	4.9-22	0.5-5 wt%
Flexural strength	22-39	1-3 wt%
Flexural modulus	28	1-3 wt%
Compressive strength	13	1-5 wt%
Shear strength	14	1-5 wt%
Impact strength	28	0.5-1 wt%
Fatigue life	Up to 60	0.5 vol%

3.2. Green corrosion inhibitors

Corrosion on metal surfaces is one of the toughest problems in aviation—aircraft operate in extreme climates and under demanding conditions that speed up degradation. Hexavalent chromium (Cr(VI))-based coatings have long offered effective corrosion protection at low cost, but they are toxic and carry serious environmental and health risks, which has led to regulatory restrictions in many parts of the world. To meet REACH regulations without giving up corrosion protection, research now focuses on coating systems that are both environmentally friendly and safe. These coatings need good adhesion, barrier performance, and rheological properties. The work centers on developing anti-corrosion, chromate-free coatings by modifying metal-based paint formulations. The main goal is to reduce environmental impact by using sustainable compounds or less toxic metals as corrosion inhibitors, while at the same time delivering better anti-corrosion performance and durability than existing systems.

4. Aircraft maintenance and AI-enabled predictive maintenance

4.1. Aviation maintenance concepts and processes

Maintenance keeps engineering systems in or restores them to their specified state. Aviation maintenance addresses fuselage, engines, and airborne systems to sustain reliability at minimum cost while preserving safety. Civil aircraft maintenance follows a standardized global process (Figure 3): Industry Steering Committees develop initial programs under MSG-3, published as Maintenance Review Board Reports; manufacturers add experience-based items into planning documents delivered to airlines, which adapt them into Operator Maintenance Programs; job cards and feedback loops drive continuous improvement.

DOI: 10.54254/2755-2721/2026.36952

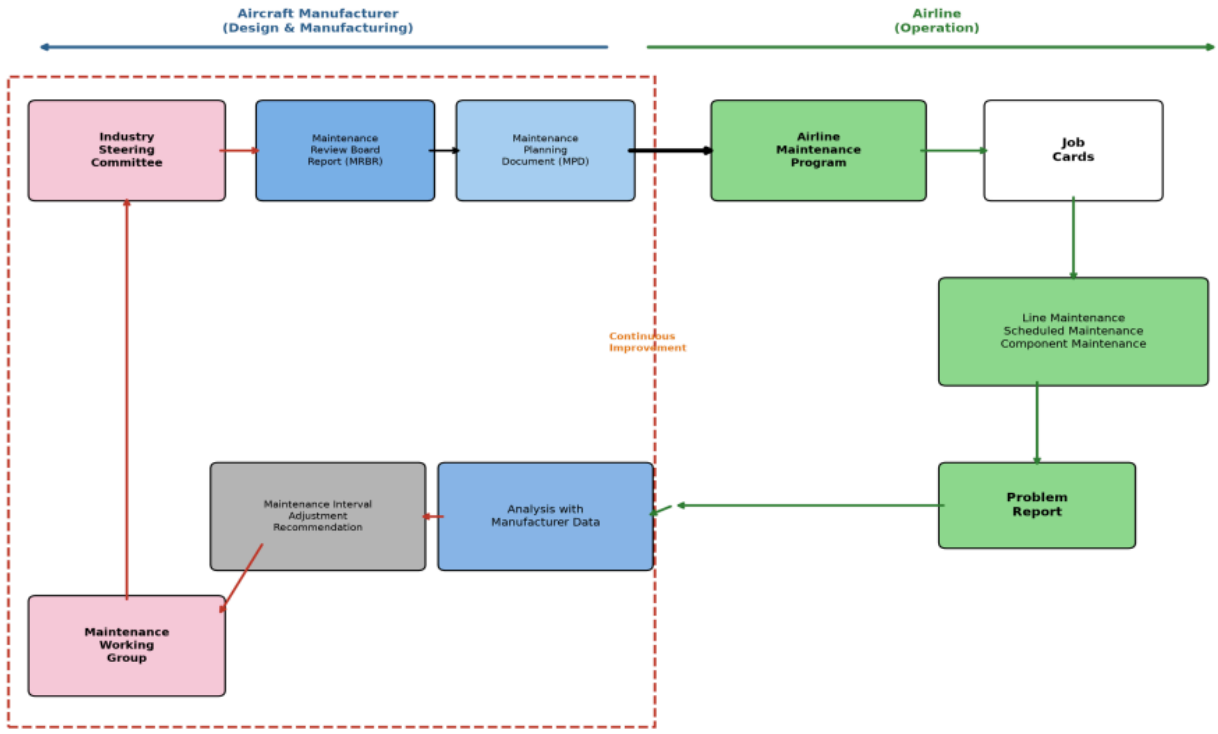

Figure 3. Schematic diagram of aircraft maintenance process

4.2. Machine learning for fault diagnosis

Industry 4.0 and intelligent manufacturing are pushing a fundamental shift away from scheduled and corrective maintenance toward predictive maintenance—predicting future equipment health through continuous monitoring and data analysis, so maintenance can be scheduled proactively before failures occur. The economic payoff is large, as Table 2 shows. AI-driven predictive maintenance cuts unscheduled maintenance events by 35%-40% and total MRO costs by 20%-30%, while lifting dispatch reliability from 97.5% to 99.2%. Paolanti et al. [1] demonstrated how effective machine learning-based predictive maintenance can be by analyzing industrial equipment sensor data to predict faults early in motors and other critical components.

Table 2. Benefits of AI-based predictive maintenance in commercial aviation

Metric	Traditional	AI Predictive	Improvement
Unscheduled Mx events	Baseline	Reduced	35-40% ↓
Total MRO cost	Baseline	Reduced	20-30% ↓
Dispatch reliability	97.5%	99.2%	+1.7 pp
AOG cost (per day)	$50K–$150K	Near zero	Eliminated
Annual savings/aircraft	-	$100K–$500K	-
ROI (per $1 invested)	-	$10–$30	12-18 mo payback

Machine learning-based fault diagnosis holds great promise for aircraft SHM. Unlike traditional methods relying on manual features and fixed thresholds, deep learning learns hierarchical features

DOI: 10.54254/2755-2721/2026.36952

automatically, improving adaptability. Qian et al. [2] proposed a relationship-transfer domain-generalization network for accurate diagnosis across operating conditions. Standardized datasets enable fair benchmarking: the CWRU bearing dataset [3] and NASA C-MAPSS turbofan dataset [4] are the standards for fault diagnosis and RUL prediction, with PHM Society challenges [5] supplying further benchmarks.

4.3. Deep learning models and decision support

Convolutional neural networks (CNNs) dominate mechanical fault diagnosis for their local feature extraction. One-dimensional CNNs learn multi-level fault features from raw vibration signals without manual engineering. Advanced variants, ResNet skip connections, attention mechanisms, and multi-scale convolutions, all surpass traditional methods. For remaining-useful-life (RUL) prediction, long short-term memory (LSTM) networks capture long-term degradation trends and are widely used for forecasting.

More recently, transformer architectures with self-attention model long-range dependencies efficiently for time-series tasks. Hybrid CNN-LSTM or CNN-transformer models exploit both spatial and temporal patterns for higher accuracy. For decision support, reinforcement learning optimizes maintenance timing and actions through interaction, multi-objective optimization yields Pareto trade-offs among cost, downtime, and reliability, and digital twins preview plans before deployment. AI also refines traditional safety-coefficient assessment by modeling impact energy and strength probabilistically [6], and edge computing enables compressed models on airborne systems for real-time warning.

5. Conclusion

This review has examined civil aircraft SHM from three complementary perspectives: probabilistic safety coefficient design, advanced material development, and AI-enabled predictive maintenance.

Three observations stand out. First, the mechanics-based toolkit (stress-strength interference, nano-silica composites, MSG-3 hierarchies) remains indispensable as the physical grounding that data-driven methods lack. Second, deep learning yields clear gains: 1D-CNNs remove manual feature engineering, LSTM and transformers capture nonlinear degradation beyond statistical RUL models, and RL-based support outperforms rule-based scheduling. Third, benchmarks such as CWRU and C-MAPSS drive progress, yet the lab-to-operation data gap is the largest barrier to deployment.

Four challenges remain before airworthiness certification. (1) Domain shift: models trained on clean bench data degrade on noisy in-flight streams, requiring domain adaptation. (2) Interpretability: black-box deep networks conflict with safety-critical traceability needs; physics-informed and attention-based methods help but are immature. (3) Onboard constraints: leading models exceed embedded memory and power budgets, needing compression, quantization, and edge co-design. (4) Data scarcity: large labeled aircraft-specific fault datasets are lacking, motivating synthetic augmentation and few-shot learning.

Building on these challenges, four priority directions for future work are identified: multi-modal sensor fusion integrating vibration, temperature, and acoustic emission signals for a more holistic health assessment, physics-informed deep learning that embeds structural mechanics constraints into network architectures to enhance generalization and certification potential, digital twin frameworks that enable virtual validation of maintenance strategies prior to physical implementation, and lightweight, edge-optimized AI models capable of real-time onboard inference. The convergence of

DOI: 10.54254/2755-2721/2026.36952

these directions—where mechanics provides the physics and AI provides the scalability—will define the next generation of aircraft health monitoring systems and contribute to safer, more sustainable civil aviation.

References

[1] Paolanti, M., Romeo, L., Felicetti, A., et al. (2019). Machine learning approach for predictive maintenance in Industry 4.0. *IEEE 14th International Conference on Emerging Technologies and Factory Automation (ETFA)*.

[2] Qian, Q., Zhou, J., & Qin, Y. (2023). Relationship transfer domain generalization network for rotating machinery fault diagnosis under different working conditions. *IEEE Transactions on Industrial Informatics, 19*(9), 9898–9908.

[3] Smith, W. A., & Randall, R. B. (2015). Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study. *Mechanical Systems and Signal Processing, 64–65*, 100–131.

[4] Saxena, A., Goebel, K., Simon, D., et al. (2008). Damage propagation modeling for aircraft engine run-to-failure simulation. *International Conference on Prognostics and Health Management*, 1–9.

[5] PHM Society. (2024). *PHM Conference Data Challenge Repository*. https://data.phmsociety.org/

[6] Zhang, X., Liu, Z., Chen, D., et al. (2024). A comprehensive survey on large language model compression for artificial intelligence applications in edge systems. *IEEE Access*.