Artificial Intelligence Applications in the Aviation Industry: From Design to Maintenance for Aircraft

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Abstract: Recently, the application of artificial intelligence in the aviation industry has received widespread attention. However, the existing literature review in this field remains fragmented and lacks a systematic and holistic approach. To fill this gap, this paper focuses on the whole life cycle of an aircraft, starting from the four key phases of design, manufacturing, operation, and maintenance, and systematically combs through the typical applications and representative technologies of AI in the aerospace industry, covering the optimization of deep learning in aerodynamic layout, the combination of digital twins and intelligent manufacturing, the intelligent analysis of flight operation data, and the predictive maintenance system and other key cases. Meanwhile, this paper also focuses on the core challenges of data quality, model credibility, system integration, and security faced in the current implementation process and proposes a preliminary outlook on future research directions such as credible AI, human-machine collaboration, and full-process data closure. As a review study, this paper builds a framework for aircraft life cycle by structurally organizing the existing results and practice cases, which provides a reference for promoting the deeper application of AI technology in the aviation field.

1 INTRODUCTION

Traditional engineering processes in the highly complex and safety-critical aviation industry are facing unprecedented challenges. The increasing technical sophistication of aircraft design structures, rising manufacturing costs, real-time operational scheduling requirements, and the trend toward precision in maintenance and assurance have made it difficult for traditional methods relying on experience-driven and linear processes to meet the combined requirements of efficiency, precision, and adaptability of modern aviation systems.

Artificial Intelligence (AI), as a technology with strong data processing, pattern recognition, and optimization capabilities, is gradually becoming an important driving force for the intelligent transformation of the aviation industry. In the design phase, AI technology can be used for aerodynamic layout optimization, structural topology reconstruction, and multi-objective decision support, effectively shortening the design cycle and improving design quality. In the manufacturing stage, by combining computer vision, digital twin technology, and intelligent robots, AI realizes efficient identification of defects in parts, real-time monitoring of equipment status, and optimal configuration of production processes. At the operation level, AI is widely used in route scheduling optimization, fuel consumption prediction, and flight data anomaly detection, helping airlines improve operational efficiency and reduce costs. In maintenance, the predictive maintenance system models and analyzes the remaining life, potential failures, and health status of equipment based on AI, realizing the transformation from “planned maintenance” to “dynamic maintenance based on status”, thus ensuring flight safety and reducing the waste of maintenance resources at the same time. This process reduces the waste of maintenance resources while ensuring flight safety.

Although AI has demonstrated its application value in several key nodes of aviation, most current research and practices still focus on a single link or a localized scenario and lack a systematic sorting and integration of the complete lifecycle of the aircraft. This fragmented application model not only limits the synergistic potential of AI technology but also does not help to evaluate its overall impact on efficiency, safety, and cost structure at the system level.

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Therefore, this paper will start from the four core phases of "design-manufacturing-operation-maintenance", systematically review the main application paths and key technologies of AI in the whole life cycle of aircraft, and deeply analyze the challenges faced during its actual deployment. It also analyzes the challenges faced in the actual deployment process, including the difficulties in data acquisition, low credibility of models, and the complexity of engineering system integration. At the same time, this paper will also explore the future development trends, such as the construction of the full-process digital twin system, the realization of the autonomous decision-making system, and the key role of Explainable AI in the aviation safety system. Through the systematic analysis of these issues, we aim to construct a set of prospective and sustainable AI application research frameworks for the field of aviation engineering and provide theoretical support and methodological guidance for subsequent academic research and industrial practice.

2 APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN AIRCRAFT DESIGN

Aircraft design is one of the most complex and critical aspects of aeronautical engineering, involving multiple perspectives of aerodynamics, structural mechanics, materials science, flight control system design, and comprehensive economic evaluation.

2.1 Deep Learning and Machine Learning Enabling Aerodynamic Layout Design

In aerodynamic layout design, AI has been widely used to quickly predict the aerodynamic characteristics of aircraft configurations. Although traditional Computational Fluid Dynamics (CFD) methods are highly accurate, they are expensive and time-consuming, making it difficult to meet the demand for efficient evaluation in the preliminary design stage.

Modern methods for aerodynamic data surrogacy modeling based on deep neural networks (DNN), support vector regression (SVR), and other models have been developed. Researchers have created a simpler model for changing Mach number unsteady flow using long short-term memory networks (LSTM), which can manage large amounts of training data. This model can accurately predict aerodynamic load characteristics across a wide range of Mach numbers. Through predictive experiments on the aerodynamic forces and aerodynamic elastic responses of the NACA 64A010 airfoil under transonic conditions, the results show that this DL model can accurately capture linear and nonlinear aerodynamic characteristics at different Mach numbers, vibration amplitudes, and frequencies, significantly improving the generalization performance and prediction accuracy of the model compared with traditional aerodynamic analysis methods (Zou & Sun, 2021). It is particularly noteworthy that the LSTM-ROM model reduces errors by 77% and improves computational efficiency by 90% in the prediction of transonic flutter in the NACA 64A010 airfoil. This DL-based method uses fewer computer resources than traditional computational fluid dynamics simulations while still providing more accurate models.

"Aerodynamic Intelligent Topology Design (AITD)-A Future Technology for Exploring the New Concept Configuration of Aircraft" proposes an AI-driven aerodynamic topology design method that combines topology parameterization with DL to break through the limitations of traditional empirical design and achieve efficient prediction of transonic flow fields (Liao et al., 2023).

In the AIAA Journal, Brunton et al. highlighted that using data-driven methods instead of detailed CFD models for quick estimates is a key way to enhance efficiency, particularly for modeling complex boundary layer behavior and predicting trans-Mach number issues (Brunton et al., 2021).

The application of DL algorithms has, to some extent, improved the efficiency and quality of the design of aircraft aerodynamics.

2.2 Application of Multi-Objective Optimization and Generative Design in Aircraft Configuration Exploration

The preliminary design stage of an aircraft requires a comprehensive evaluation of multiple performance objectives, such as aerodynamic efficiency, structural strength, weight, manufacturability, and cost. This process typically involves multi-objective, multi-constraint optimization problems. Traditional optimization methods are limited by computational resources and design space search capabilities, making it difficult to converge quickly on high-quality solutions under complex coupled conditions. With the introduction of artificial intelligence, especially the development of machine learning and generative modeling technologies, new opportunities have emerged for aircraft configuration exploration.

Multi-objective optimization (MOO) is a key component of design automation. Researchers have combined swarm intelligence algorithms such as genetic algorithms, particle swarm optimization, and Bayesian optimization with agent-based modeling to achieve more efficient design space search capabilities. For example, Zou and Sun summarized AI algorithms in the multidisciplinary design optimization of aircraft aerodynamics and structures, pointing out that AI is particularly suitable for nonlinear optimization problems with obvious conflicting objectives and can assist engineers in quickly providing feasible solutions by balancing lift-drag ratio, stability, and structural weight (Zou & Sun, 2021).

Generative design has also been a hot topic of research in the aviation industry in recent years. Its core idea is to use AI to automatically generate multiple design solutions based on objective functions and design constraints for engineers to select from. Unlike traditional parametric design, the generative method does not rely on manually set design templates and has strong divergent and innovative capabilities. On this basis, Liao et al. proposed the Aerodynamic Intelligent Topology Design (AITD) method, which combines topology optimization with DL to automatically generate configurations with novel structural features through multi-objective mapping learning of the configuration space, which can be used for high lift-to-drag ratio design exploration (Liao et al., 2023). AITD significantly expands the configuration search space and breaks through the limitations of human experience in the traditional design process.

2.3 Application of More Advanced Digital Prototyping Technology

In aircraft development, digital prototype (DP) technology is widely used to validate the manufacturability of structural, electrical, and assembly designs, particularly playing a critical role during the design phase of complex customized configurations. By constructing multi-dimensional product models, engineers can simulate production processes early in the design phase, identify potential assembly conflicts and manufacturing bottlenecks in advance, thereby reducing the cost of later modifications and improving design iteration efficiency.

Moenck et al. noted that in fields with significant customization requirements, such as aircraft interiors, DP supports the synchronized development of product configurations and manufacturing processes, breaking down traditional barriers between design and manufacturing (Moenck et al., 2023). Compared to document-based development methods, digital prototypes provide a visual, interactive design platform that enables different engineering departments to collaborate on optimizing design parameters and process paths within the same environment. Although this technology does not yet have real-time feedback and synchronized operational status capabilities, as a precursor to digital twin systems, it has laid an important foundation for the intelligent and closed-loop control of subsequent manufacturing processes.

3 APPLICATION OF AI IN AIRCRAFT MANUFACTURING

Currently, the international aviation industry is gradually introducing AI-driven systems to improve manufacturing efficiency, precision, and safety. AI has made the manufacturing process increasingly dependent on data-driven methods, enabling real-time status monitoring, predictive quality control, and comprehensive optimization of the production process.

3.1 Practical Application of Digital Twin Technology in Aircraft Manufacturing

The concept of digital twins was first proposed by NASA for the remote monitoring of their spacecraft. Recently, this technology has expanded from aerospace engineering to multiple fields such as industrial manufacturing, energy, and power. Digital twin technology has garnered significant attention in the aerospace manufacturing industry since the 21st century because it uniquely addresses three critical requirements: high complexity, high customization, and high reliability. With the synergistic development of hardware and software, this technology has evolved into a virtual mapping system spanning the entire product lifecycle, playing a pivotal role in driving intelligent transformation within aircraft manufacturing processes.

In “Digital Twins in Aircraft Production: Challenges and Opportunities”, Moenck et al. summarize several specific applications of digital twin technology in aerospace manufacturing, covering various stages such as assembly, logistics, and quality inspection. In flexible assembly scenarios, the digital twin system achieves path planning and dynamic guidance for aircraft cabin interior components through real-time modeling and on-site data fusion. For example, by combining with a laser projection system, operators can complete the installation of complex foam honeycomb structures based on virtual models, effectively improving the consistency and efficiency of human-robot collaborative assembly (Moenck et al., 2023).

In the production and supply chain process, the aviation manufacturing industry often faces challenges in identifying a large number of unlabeled, irregularly shaped components. Traditional methods relying on manual labor or physical labels are prone to failure in scenarios such as modification or refurbishment, and manual identification is costly and inefficient. Researchers have pointed out that AI training images can be synthesized using existing 3D models in digital twin systems to construct visual recognition models and achieve automatic recognition of unlabeled parts (Alexopoulos et al., 2020; Manettas et al., 2021; Schoepflin et al., 2021; Schoepflin et al., 2022). This method has shown excellent adaptability in production environments with a wide variety of parts and small batches with high variability, improving the flexibility and intelligence of aviation logistics.

Digital twin technology also plays a key role in the quality inspection process. Based on previous research, Moenck et al. combined key technologies such as multi-model databases (Koch et al., 2022), IoT platforms (Nițulescu & Korodi, 2020), and optical assistance systems to construct a "digital quality assurance twin" framework suitable for aviation manufacturing scenarios and introduced the "as-inspected twin" concept proposed by Kwon et al. as the theoretical basis for quality data modeling and closed-loop traceability (Kwon et al., 2020)

3.2 AI Intelligent Optimization System and Automated Production Case Study

In aircraft manufacturing, complex processes often require extremely high demands on process stability and precision control. Traditional production relies on empirical judgment and post-production testing, which not only results in delayed responses but also makes it difficult to promptly identify potential deviations. Brunton et al. pointed out that by integrating embedded sensors into the manufacturing system to collect real-time process data and combining it with ML models trained on historical production samples, predictions and early warnings can be made before deviations exceed specifications, thereby significantly improving the robustness (the ability of a system to maintain stable operation or achieve expected performance in the face of disturbances, uncertainties, or anomalies) and feedforward control capabilities of the production process (Brunton et al., 2021). This approach reduces reliance on manual quality inspections and provides a data foundation for intelligent adjustments in complex assembly processes, highlighting the critical role of AI technology in "pre-emptive prediction" and "process adaptation".

In addition, with the help of embedded sensors and data modeling technology, CNC machines can monitor their operating status in real time and use machine learning methods to predict tool wear trends, effectively reducing equipment failure rates and maintenance costs. Computer vision technology is also widely used in automatic thread laying and composite manufacturing processes, combining image recognition and thermal imaging methods to achieve online detection and intelligent classification of process defects. In the assembly process, researchers have also explored robotic systems that integrate visual feedback and path planning algorithms to improve automatic alignment accuracy and human-machine collaboration efficiency through dynamic recognition of the relative positions of parts and trajectory optimization. The integrated application of the above technologies is gradually promoting aviation manufacturing from an experience-driven process to a higher level of data-driven and intelligent manufacturing (Brunton et al., 2021).

4 APPLICATION OF ARTIFICIAL INTELLIGENCE IN AVIATION OPERATIONS AND MAINTENANCE

After an aircraft leaves the production line and is delivered, the focus of its lifecycle shifts to the dimensions of operation and maintenance. Every day, tens of thousands of flights take off and land worldwide, supported by complex air traffic control and flight scheduling systems, extensive health monitoring networks, and high-intensity maintenance and support mechanisms. Faced with ever-increasing aviation demand and safety standards, traditional methods are becoming increasingly inadequate in terms of efficiency, response speed, and accuracy. Against this backdrop, AI has begun to be used in key areas related to flight efficiency and safety, such as flight path optimization, flight status sensing, fault prediction, and maintenance strategies.

4.1 Route Optimization and Scheduling Decisions

Airlines face highly complex dynamic decision-making challenges at the scheduling level, requiring the simultaneous coordination of multiple resource constraints across dimensions such as route networks, fleet utilization, passenger demand, weather changes, and ground support. With the accumulation of data and improvements in computing power, AI, especially algorithms represented by Reinforcement Learning (RL) and DL, is gradually becoming an important tool for route planning and operational optimization. Tafur et al. pointed out that RL methods can effectively address airspace resource fluctuations and path congestion issues and, through continuous iterative training, obtain optimal route strategies, thereby improving route utilization and flight punctuality (Tafur et al., 2025).

In practical applications, the Operations Process Support and Decision Suite (OPSD) developed by Lufthansa has been deployed in operations. The system integrates flight schedules, weather data, maintenance status, and passenger information, with AI models generating scheduling plans for operational staff to adopt. The acceptance rate of its recommended plans exceeds 90%, demonstrating outstanding performance in improving resource allocation efficiency and system robustness (Lufthansa Group, 2023).

Qantas Airways has introduced a cloud-based flight path simulation system called Constellation for route optimization. The system was developed by Qantas in collaboration with the University of Sydney's Field Robotics Center over a period of five years. It can simulate thousands of possible routes based on millions of data points, such as weather and wind speed, and select the most fuel-efficient route. According to public statements by Qantas CEO Alan Joyce, the system saves the company approximately 40 million Australian dollars in fuel costs annually and reduces carbon emissions by approximately 50 million kilograms (Bice, 2013). The system has already achieved practical results on routes such as Sydney to San Diego, with fuel savings of up to one ton per flight. The full deployment of Constellation marks the large-scale application of AI in commercial aviation scheduling, and its concept of “pre-flight route optimization” also provides the industry with an innovative paradigm that combines energy conservation and profitability (Bice, 2013). This instance demonstrates that AI enhances aircraft operational efficiency while also exhibiting significant promise for energy sustainability and cost management. AI enhances the operational efficiency of flight scheduling and serves as a crucial tool for airlines to attain environmental protection objectives, save operating expenses, and augment revenues while maintaining safety.

At present, many international airports use AI-related technologies to assist in management, control, and decision-making. For instance, Singapore's air traffic control department uses a gradient boosting algorithm to optimize runway allocation, reducing takeoff delays by about 15%; Frankfurt Airport uses a DL model to predict airflow disturbances, helping flights adjust their flight paths in real time and significantly improving punctuality (Tafur et al., 2025).

In addition, AI has been used in Air Traffic Management (ATM) systems for critical tasks such as flight trajectory prediction and conflict avoidance. As mentioned in the literature, strategy models based on Markov Decision Processes (MDP) can dynamically select the optimal flight path, effectively alleviating scheduling pressure in high-density airspace (Tafur et al., 2025).

In summary, flight route optimization and scheduling decisions are gradually transitioning from rule- and experience-based manual processes to data-driven, model-assisted human-machine collaborative systems.

4.2 Flight Data Monitoring and Anomaly Identification

Modern aircraft generate vast amounts of operational data during each flight, such as flight altitude, speed, throttle position, engine vibration, and attitude angle changes. This data is continuously recorded by the Flight Data Recorder (FDR) and other sensor systems. Extracting meaningful information from this multidimensional, dynamic, and unstructured data has become one of the key challenges for flight safety monitoring and fault warning systems. Currently, researchers have begun to gradually introduce ML methods into flight data analysis, using models to learn “normal operating conditions” so that potential anomalies can be identified in real time during flight. Some algorithms use unsupervised learning strategies to extract “deviation from trajectory” patterns from historical data to provide early warnings of possible faults or manipulation errors (Tafur et al., 2025).

The primary application of such AI models lies in automatically identifying invisible trends and early failure signals from complex flight data, particularly excelling in engine health assessment and the identification of abnormal flight attitudes. For instance, research has utilized LSTM networks to model multiple time-series flight parameters, enabling effective prediction of risk states several minutes into the future and providing pilots with intelligent assistance. Additionally, convolutional neural networks (CNNs) and clustering methods have been applied to flight data visualization and multi-category fault classification, enhancing the system's sensitivity and response speed under complex operational conditions (Tafur et al., 2025).

With developments in modeling capabilities and real-time data processing technology, AI's role in flight data analysis is shifting from “post-event attribution” to “in-flight identification and prediction”, enabling more timely decision assistance for risk management.

4.3 Predictive Maintenance and Health Management

For aircraft with long operational cycles and complex structures, extending service life and reducing maintenance costs without compromising safety is a critical task in aviation operations. Compared with traditional periodic maintenance and post-accident repairs, Predictive Health Management (PHM) emphasizes continuous monitoring of equipment operating conditions and trend analysis so that interventions can be taken before failures occur. This method relies on large amounts of flight and sensor data and uses ML and statistical modeling methods to achieve a shift from “planned maintenance” to “condition-driven maintenance”.

NASA's public C-MAPSS engine dataset has become a benchmark testing platform in this field, with numerous studies using it as a basis for developing Remaining Useful Life (RUL) prediction models (NASA Ames Prognostics Data Repository, n.d.). For example, researchers have constructed a regression structure based on Convolutional Neural Networks (CNN) to extract temporal patterns from engine sensor data and predict the remaining operating cycles of the equipment in its current state (Dong et al., 2021); other methods utilize LSTM networks to model vibration and thermal data, enabling early identification of potential failures, with some models capable of issuing warnings 10 to 20 seconds before a failure occurs.

In addition to life prediction, condition diagnosis and root cause analysis are also critical components of PHM systems. Brunton et al. point out that health management should not only be able to predict “when problems will occur” but also explain “what problems will occur” and “why they will occur” (Brunton et al., 2021). They propose feeding the results of anomaly identification back into the design and manufacturing stages to form a cross-stage maintenance closed loop. This two-way path from data monitoring to design optimization is changing traditional maintenance logic, making aircraft operation and maintenance processes more transparent, efficient, and forward-looking.

5 CHALLENGES, LIMITATIONS, AND FUTURE PROSPECTS

Despite the extensive integration of artificial intelligence in the design, manufacture, and maintenance of airplanes, its comprehensive deployment continues to encounter several practical obstacles. AI must resolve several critical challenges, including the construction of trust mechanisms, data quality, model flexibility, and system integration, to attain persistent and profound use in this high-safety, high-dependence industry.

5.1 Reliable Foundations for AI in Aviation Systems

In fields such as aviation, where there is zero tolerance for safety issues, artificial intelligence must earn trust by simultaneously focusing on model transparency and engineering safeguards. Research indicates that “explainable artificial intelligence” (XAI) is one of the key pathways to establishing trust mechanisms. In recent years, various methods have been employed to enhance model reviewability, including feature weight analysis, visualization modules, and rule embedding (Kobayashi & Alam, 2022).

In current engineering practices, AI is more often embedded as a “recommendation system” rather than a direct controller. For example, in Lufthansa's OPSD system, AI provides flight scheduling recommendations, which are then adopted by human operators (Lufthansa Group, 2023); similarly, Qantas' Constellation system assists in pre-flight planning by simulating optimal flight paths, but the final decision remains with the pilot or control center (Bice, 2013). This "recommendation-first, human-in-the-loop" model effectively reduces the risk of loss of control caused by algorithmic misjudgment.

Additionally, the industry widely adopts technologies such as multi-model verification, fault-tolerant redundancy, and safety envelope design to enhance system stability and recovery capabilities in extreme scenarios (Kobayashi & Alam, 2022). AI is no longer a traditional "replacement" but rather a "third eye" capable of detecting subtle anomalies in advance, thereby improving the system's data fusion efficiency, operational organization capabilities, and forward-looking judgment.

5.2 Challenges Encountered: Multiple Constraints on Data, Models, and Systems

The implementation of AI in aviation still faces numerous practical challenges. First, high-quality labeled data is scarce, particularly in critical tasks such as engine fault prediction and PHM, where abnormal samples are extremely limited (Brunton et al., 2021). Second, the interpretability and stability of deep learning models still need improvement, making it difficult to completely replace traditional mechanisms in high-safety scenarios (Kobayashi & Alam, 2022).

In addition, AI systems must operate in conjunction with traditional aviation information architectures, facing engineering constraints such as system compatibility, real-time performance, and computing resources. In practical applications, data drift, input anomalies, or attacks can all pose systemic risks. These issues determine that the evolution of aviation AI requires multi-party collaboration covering algorithms, data, systems, and security, rather than just improving model accuracy.

5.3 Trend Outlook and Future Research Directions

As algorithms advance and aviation's digital infrastructure enhances, the function of AI in aviation is progressively transitioning from a "auxiliary tool" to a "system backbone". Future research will emphasize multi-source data fusion, continuous learning processes, and human-machine collaboration frameworks. Joint modeling that integrates sensor data, maintenance records, and flight logs is anticipated to improve the system's condition recognition skills and resilience.

At the same time, the verifiability and traceability of AI will become prerequisites for its in-depth application in mission-critical scenarios. AI will not only be a technical tool for improving efficiency but will also become a long-term driving force for the intelligent transformation of aviation systems in terms of system adaptability, operational resilience, and risk prevention and control.

6 CONCLUSIONS

AI is becoming increasingly embedded in the core processes of the aviation industry. From its initial role as an assisting tool, AI has gradually developed into an intelligent component in key areas such as design, manufacturing, operation, and maintenance. AI is no longer just a technical means of improving efficiency, but is also influencing the design concepts and engineering logic of aviation systems.

This article systematically reviews typical application paths for AI in aerodynamic design optimization, intelligent manufacturing systems, flight operation scheduling, predictive maintenance, and health management throughout the entire life cycle of aircraft. These technologies have already shown initial success in shortening development cycles, improving reliability, and reducing operating costs. At the same time, AI technology is also driving the industry toward higher levels of digitization, automation, and intelligence.

The in-depth application of AI in aviation is not limited to improving algorithm capabilities, but also depends on the systematic construction of its "reliability, transparency, and usability". Future technological advancements require the establishment of a complete closed-loop system in areas such as standardization, data governance, model validation, and system integration, driving AI from "black-box reasoning" toward "explainable decision-making" and from "support tools" toward "decision-making partners". This is not only a technical challenge but also necessitates the restructuring of engineering systems, organizational structures, and management mechanisms.

Artificial intelligence is not destined to be a short-term technological "stimulus" in the aviation revolution but rather a strategic partner deeply involved in the long term, continuously influencing the operational rules and value judgments of aviation systems. It will build a bridge of balance between efficiency and safety, establish a platform between complex machine systems and human intelligence, and gradually reshape the form and structure of the aviation industry. Future aviation engineering will no longer be a simple combination of mechanical and electronic systems but rather a cross-integration of human intelligence and AI. Building an efficient, reliable, intelligent, and controllable future aviation system is not only an exploration of technology itself but also a profound response to how humans can coexist and co-create with AI.

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