ENGINEER

international scientific journal

ISSUE 2, 2025 Vol. 3

E-ISSN
3030-3893

ISSN
3060-5172

A bridge between science and innovation

TOSHKENT DAVLAT TRANSPORT UNIVERSITETI

Tashkent state transport university

ENGINEER

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E-ISSN: 3030-3893

ISSN: 3060-5172

VOLUME 3, ISSUE 2

JUNE, 2025

engineer.tstu.uz

TASHKENT STATE TRANSPORT UNIVERSITY

ENGINEER

INTERNATIONAL SCIENTIFIC JOURNAL
VOLUME 3, ISSUE 2 JUNE, 2025

Founder of the international scientific journal “Engineer” – Tashkent State Transport University, 100167, Republic of Uzbekistan, Tashkent, Temiryo‘lchilar str., 1, office: 465, e-mail: publication@tstu.uz.

The “Engineer” publishes the most significant results of scientific and applied research carried out in universities of transport profile, as well as other higher educational institutions, research institutes, and centers of the Republic of Uzbekistan and foreign countries.

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Tashkent State Transport University had the opportunity to publish the international scientific journal “Engineer” based on the **Certificate No. 1183** of the Information and Mass Communications Agency under the Administration of the President of the Republic of Uzbekistan. **E-ISSN: 3030-3893, ISSN: 3060-5172.** Articles in the journal are published in English language.

Technology for improving the post-flight maintenance process of aircraft

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Abstract: Post-flight maintenance is a critical component of aviation safety, directly influencing the airworthiness, reliability, and operational readiness of aircraft. As aviation systems grow more complex, the industry faces the challenge of evolving from traditional reactive inspection methods to intelligent, data-driven maintenance strategies. This article explores current limitations in post-flight diagnostics, such as dependence on manual inspections, fragmented data systems, and a lack of integration across maintenance processes. It further highlights the transformative potential of emerging technologies including condition-based maintenance (CBM), prognostics and health management (PHM), and digital twins. These innovations enable real-time monitoring, predictive analytics, and proactive maintenance planning, ultimately reducing operational costs and minimizing unscheduled downtime. The study emphasizes the need for a shift towards integrated diagnostic infrastructures that combine AI, IoT, and advanced analytics to support timely decision-making and enhance flight safety. The paper also examines turnaround time optimization and addresses the human factor challenges in manual workflows. By proposing a framework for modernizing post-flight maintenance, the article contributes to the development of safer and more efficient aviation operations.

Keywords: Post-flight maintenance, aircraft safety, condition-based maintenance (CBM), prognostics and health management (PHM), digital twin, artificial intelligence (AI), diagnostics, operational readiness, turnaround time, aviation technology, predictive analytics, maintenance automation

1. Introduction

The Importance of Post-Flight Maintenance in Aviation

Post-flight maintenance plays a key role in ensuring the airworthiness, operational readiness, and safety of aircraft after each flight cycle. This stage includes a detailed inspection and assessment of critical aircraft systems such as engines, avionics, control surfaces, life support systems, and landing gear. The main objective is to detect and eliminate signs of wear or malfunctions before they escalate into critical issues that could compromise flight safety or cause costly operational disruptions.

Given the tight schedules in commercial aviation and the high utilization of aircraft, post-flight maintenance must be both thorough and efficient. The increasing complexity of onboard systems has driven the shift from traditional visual checks to automated diagnostic technologies that leverage sensor data, real-time analytics, and artificial intelligence (AI). These technologies enhance fault detection accuracy, reduce reliance on manual inspections, and enable condition-based maintenance (CBM) strategies, ultimately lowering lifecycle costs and improving both safety and efficiency. [1; 2].

Turnaround Time, Safety Assurance, and Operational Readiness

Minimizing aircraft turnaround time — the interval between landing and the next takeoff — is a key performance metric in commercial aviation, directly affecting airline schedules, profitability, and fleet utilization. Post-flight maintenance plays a critical role in this process as it involves mandatory inspections, technical assessments, and corrective actions that must be performed promptly without compromising regulatory compliance or safety standards.

While speed is important, it must not jeopardize the thoroughness and reliability of inspections. Undetected malfunctions can lead to in-flight incidents, regulatory violations, or Aircraft on Ground (AOG) situations, resulting in delays and financial losses. Therefore, a balanced approach that combines speed and diligence is essential.

Moreover, the operational readiness of an aircraft — the percentage of time it is fit for flight — directly depends on the efficiency of post-flight diagnostics. Modern technologies, including AI-driven analytics and integrated monitoring systems, improve fault detection accuracy and accelerate decision-making. This allows maintenance activities to be anticipated and resources to be optimized across the airline.

2. Research methodology

Limitations of Current Diagnostics and Workflow Automation

Despite technological advancements, post-flight diagnostics still often rely on reactive methods and manual operations. These include visual inspections by technicians, pilot reports, and the use of basic onboard systems based on threshold values. Such approaches have limited sensitivity to early-stage faults, especially if the faults are intermittent or progressive in nature.

Additionally, diagnostic data are often recorded in various formats and systems, making timely analysis difficult. Automation and integration among diagnostics, fault tracking, and maintenance planning are also insufficient. This results in inefficiencies in repair scheduling, parts logistics, and personnel allocation. Traditional systems rarely utilize historical and fleet-wide

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data, which could significantly enhance predictive accuracy. All this highlights the need for an intelligent, integrated, and data-driven diagnostic infrastructure to support proactive maintenance.

1. Traditional Post-Flight Checks: Manual Inspections and Fault Logging [4].

Conventional post-flight maintenance methods are primarily based on manual tasks and checklist execution. Technical personnel perform visual inspections of structural components, fluid levels, and system conditions according to the aircraft's Maintenance Planning Documents (MPD). Pilot remarks are recorded in the aircraft's technical logbook (Tech Log), which is then analyzed by ground staff. Diagnostic tools such as multimeters, borescopes, and thermal imagers are used when necessary.

Although effective for ensuring flight safety, these methods are labor-intensive, dependent on human factors, and limited in detecting hidden or early-stage faults. Furthermore, the reactive nature of these procedures means issues are addressed only after symptoms or failures occur, increasing operational risks and costs. This approach lacks the predictive capability necessary for supporting condition-based maintenance strategies.

2. Condition-Based Maintenance, PHM, and Digital Twin Technologies.

The aviation industry is transitioning from reactive and interval-based maintenance to intelligent, data-driven strategies such as Condition-Based Maintenance (CBM), Prognostics and Health Management (PHM), and digital twins. CBM relies on continuous monitoring of parameters like vibration, temperature, and pressure to assess the actual condition of components and perform maintenance only when wear indicators are detected. This reduces unnecessary work and extends the service life of parts.

PHM incorporates machine learning and statistical analysis methods to predict Remaining Useful Life (RUL) and assess failure probabilities based on current and historical data.

Digital twins are virtual models of real systems updated in real time. They integrate operational data, historical trends, and external conditions to simulate equipment behavior, enabling scenario testing, root cause analysis, and maintenance schedule optimization. In aviation, digital twins are already used for engines, hydraulic systems, landing gear, and even entire airframes. The integration of CBM, PHM, and digital twins enables more accurate diagnostics, better decision-making, and fosters a culture of proactive maintenance aligned with safety and cost-efficiency goals.

3. Modern Implementation of AI and Machine Learning in MRO.

The field of Maintenance, Repair, and Overhaul (MRO) is actively adopting Artificial Intelligence (AI) and Machine Learning (ML) technologies to enhance the efficiency and accuracy of processes. Major manufacturers and MRO providers are investing in AI-based platforms that analyze large volumes of data—from flight logs and telemetry to maintenance records. These systems allow the early identification of potential faults and the planning of maintenance before issues actually arise. Notable solutions include Airbus Skywise, Boeing AnalytX, and Rolls-Royce R2 Data Labs.

AI is also being applied in automatic defect recognition during non-destructive testing (NDT), as well as in natural language processing (NLP) for analyzing textual documents such as technical bulletins, logbooks, and reports. Reinforcement learning algorithms and adaptive AI models are being explored to dynamically update maintenance strategies based on operational conditions. These technologies support the shift from reactive maintenance to intelligent and predictive MRO infrastructures that enable real-time monitoring and fleet-wide optimization.[5]

4. AI Diagnostics in Aviation.

AI diagnostics involves applying AI techniques—such as supervised learning, deep learning, and statistical analysis—to detect, classify, and predict faults in complex aviation systems. Unlike traditional methods based on fixed thresholds or manual interpretation, AI models can process multidimensional, high-frequency data to uncover hidden or early signs of wear.

These systems are used to monitor critical components such as engines, avionics, hydraulics, and life support systems, providing failure probability assessments, anomaly detection, and predictive analytics. Their adaptive nature enables the models to improve as more data is collected. Furthermore, explainable AI (XAI) technologies—such as SHAP and LIME—are being integrated to improve transparency and trust among engineering personnel and regulators. (Figure 1).

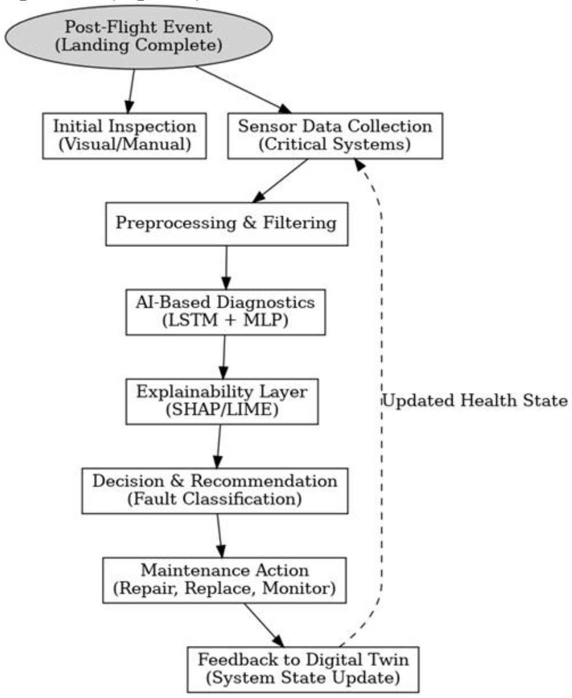

Fig. 1. Architecture of the Post-Flight AI Diagnostics Workflow

5. Methodology: LSTM-Based Supervised Learning for Critical Aircraft Systems.

The proposed diagnostic architecture is based on supervised learning methods using Long Short-Term Memory (LSTM) recurrent neural networks trained on telemetry time series from various aircraft systems. LSTM networks are well-suited for tasks with temporal dependencies, enabling effective identification of early wear patterns.

Input data include parameters from engines, hydraulic circuits, control surfaces, electrical and onboard systems. Prior to training, the data undergo noise filtering, normalization, and dimensionality reduction (e.g., using PCA). Ground truth labels are generated based on fault logs, MELs, and Aircraft Health Monitoring Systems (AHMS).

The model is trained using a 70/15/15 train-validation-test split and evaluated using metrics such as accuracy, recall, F1-score, and ROC-AUC. Additionally, a multilayer perceptron (MLP) is used for multiclass classification.[6]

The system supports integration with digital twins and MRO platforms, ensures interpretability via XAI, and is suitable for both ground-based and onboard deployment.

6. Challenges and Limitations.

Despite its potential, the implementation of AI in aviation diagnostics faces several challenges:

- Regulatory constraints. Compliance with standards (RTCA DO-178C, DO-330) is required, but the "black box" nature of many AI models complicates certification.
- Data availability and labeling. Fault data is rare, poorly structured, and labor-intensive to annotate.
- Integration with certified systems. Software changes often require full re-certification, which is costly and time-consuming.
- Cybersecurity and latency. Connected AI systems are vulnerable to cyber threats, while real-time requirements limit model complexity.

Solving these issues is critical to ensuring the reliable and safe deployment of AI in aviation diagnostics.[7]

3. Conclusion

Post-flight maintenance is not merely a procedural requirement but a vital pillar of aviation safety, operational efficiency, and cost management. As aircraft systems continue to grow in complexity, the limitations of traditional, reactive, and manual post-flight diagnostic practices become increasingly evident. The integration of modern technologies—particularly Artificial Intelligence (AI), Machine Learning (ML), Condition-Based Maintenance (CBM), Prognostics and Health Management (PHM), and digital twins—marks a significant transformation in how aviation maintenance is approached.

This article demonstrates that AI-driven diagnostic systems, such as those based on LSTM neural networks, offer advanced capabilities in early fault detection, predictive analytics, and intelligent decision-making. These systems not only reduce dependency on human error-prone methods but also allow maintenance planning to be more precise, timely, and cost-effective. Moreover, explainable AI techniques (XAI) enhance trust and transparency, which are critical for acceptance by regulatory bodies and engineering teams.

Nonetheless, the path to fully intelligent post-flight maintenance is not without its challenges. Regulatory hurdles, data scarcity, integration complexities, and cybersecurity risks pose real obstacles to widespread adoption. Addressing these challenges through standardization, collaborative data sharing, and robust AI governance will be crucial for the next generation of aviation diagnostics.

In conclusion, the evolution of post-flight maintenance into a data-driven, intelligent process will define the future of MRO operations. By leveraging the synergy of AI, digital infrastructures, and predictive methodologies, the aviation industry can achieve a higher standard of safety, reliability, and economic performance—essential in an era of rapidly advancing aerospace technologies.

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