Predictive Maintenance for Aviation Fluids and Filters: A Review of Simulation Approaches

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Abstract— *The aviation industry demands reliable and efficient maintenance to minimize delays and ensure passenger safety. Traditional inspection of consumables—such as engine oil, hydraulic fluid, and filters—relies heavily on manual monitoring and fixed schedules, often leading to delayed fault detection or unnecessary maintenance. This paper proposes a framework for simulating sensor data for predictive aircraft maintenance and decision support, integrating machine learning and visual analytics to monitor aircraft consumables. The system analyzes synthetic and operational datasets to estimate Remaining Useful Life (RUL) and detect anomalies in fluid and filter health. Through an interactive dashboard, ground engineers receive real-time alerts and maintenance recommendations. This study demonstrates how predictive intelligence can enhance turnaround efficiency, reduce human error, and lay the groundwork for smart aviation maintenance practices.*

Keywords— Predictive maintenance, machine learning, aviation analytics, IoT, dashboard visualization, aircraft health monitoring.

I. INTRODUCTION

Aircraft maintenance management is one of the most critical aspects of aviation operations. An aircraft's airworthiness, turnaround time, and safety depend on how efficiently maintenance activities are planned and executed. While current aviation systems employ advanced health monitoring for engines and avionics, the management of essential consumables—such as fuel, engine oil, hydraulic fluids, and filters—still relies heavily on manual inspection and fixed time maintenance cycles. This traditional practice often results in premature servicing, unnoticed component degradation, or delayed maintenance actions, all of which affect operational efficiency and costs.

With the advent of Industry 4.0, the aviation sector is now integrating technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics into maintenance frameworks. Predictive maintenance, which focuses on forecasting potential failures before they occur, offers a promising solution to these challenges. However, most predictive systems are currently limited to critical engine components, leaving consumables underexplored.

The proposed system addresses this gap by focusing on simulating sensor data for predictive aircraft maintenance and decision support. By moving beyond simple manual inspections, it aims to provide ground engineers and maintenance staff with actionable insights into consumable health using synthetic IoT data, predictive analytics, and visual dashboards. Real-time monitoring and data visualization ensure that faults are detected earlier, maintenance is scheduled efficiently, and resources are optimally utilized.

In this study, we explore how predictive algorithms and user-centric design can jointly enhance maintenance accuracy, reduce manual dependencies, and ensure higher reliability in aviation operations.

II. LITERATURE REVIEW

2.1 Survey of Existing Systems

Kwakye et al. [1] perform a systematic review of Prognostics and Health Management (PHM) frameworks in aviation by analyzing existing architectures and categorizing them into model-based, data-driven, and hybrid approaches. The study synthesizes prior research to identify how AI, IoT, and advanced analytics contribute to predictive maintenance strategies aimed at reducing unplanned downtime and improving operational reliability. However, the paper remains largely conceptual, with minimal emphasis on practical deployment or subsystem-level monitoring such as consumables and filters.

Barbosa et al. [2] propose a federated machine learning architecture that enables decentralized predictive model training across multiple airlines while preserving data privacy. The methodology is based on Secure Multi-Party Computation, where locally trained models share encrypted weight updates rather than raw datasets. This distributed learning framework enhances scalability and security but introduces significant computational overhead. The implementation is primarily validated for jet engine maintenance, limiting its applicability to lightweight monitoring environments.

Stanton et al. [3] develop an end-to-end predictive maintenance framework that integrates data preprocessing, anomaly detection algorithms, and predictive analytics to identify potential system failures. Their methodology relies on vibration and temperature sensor datasets to train predictive models capable of forecasting faults in critical aircraft components such as engines and turbines. The framework concentrates on high-value mechanical components and does not incorporate fluid-based subsystems.

Żółkiewicz and Piątkowski [4] design an IT-driven maintenance management system focused on workflow optimization, compliance tracking, and task scheduling. The system architecture integrates database-driven dashboards with automated logging mechanisms to enhance traceability of maintenance activities. Their rule-based methodology improves operational transparency but lacks predictive intelligence, as it depends primarily on manually entered data and predefined thresholds.

Mohammed and Alzubaidi [5] introduce the Iceberg Model for Integrated Aircraft Health Monitoring, a layered architecture combining IoT sensors, AI algorithms, and blockchain technology. The methodology separates visible operational faults from hidden systemic risks while using blockchain to ensure secure data exchange. Although the framework provides a robust multi-level monitoring strategy, its reliance on complex infrastructure and high computational resources reduces feasibility for smaller implementations.

Viadero et al. [6] present a structural health monitoring methodology for aircraft auxiliary power units using vibration signal analysis. The study employs Fast Fourier Transform (FFT) to convert time-domain sensor data into frequency-domain features for early fault detection. However, the single-sensor approach overlooks complementary indicators such as lubricant degradation and filter blockage.

Serrano et al. [7] investigate a non-intrusive acoustic monitoring technique for auxiliary power unit fault detection. Their methodology applies machine learning classification to time–frequency spectrograms derived from audio signals. While the model achieves high detection accuracy under controlled conditions, performance is sensitive to environmental noise.

Khadka et al. [8] introduce the NGAFID dataset, a large-scale annotated multivariate time-series repository containing flight and maintenance records from general aviation aircraft. The dataset supports supervised learning and predictive analytics but lacks detailed consumable-related variables such as oil quality and filter pressure differentials.

2.2 Analysis Table

TABLE 1
SUMMARY OF REVIEWED STUDIES ON PREDICTIVE MAINTENANCE IN AVIATION

Title (Year)	Technology Used	Dataset	Key Outcomes
Using Federated Machine Learning in Predictive Maintenance of Jet Engines (2025)	Federated Learning, Secure Multi-Party Computation	OEM Jet Engine Data	Enhanced data privacy and security
Platform Health Management for Aircraft Maintenance – A Review (2024)	AI, IoT, data-driven PHM frameworks	N/A (Literature Review)	Theoretical foundational taxonomy
The Iceberg Model for Integrated Aircraft Health Monitoring (2024)	IoT, AI, Blockchain	Multi-layer fault data	Secure, multi-level fault tracking
Deep Reinforcement Learning for Predictive Aircraft Maintenance (2024)	Deep Reinforcement Learning	Aircraft health condition data	Optimized dynamic maintenance scheduling
Federated Learning Framework for Collaborative RUL Prognostics (2024)	Federated Learning, model aggregation	Cross-fleet sensitive data	Improved RUL accuracy with confidentiality
Predictive Maintenance Analytics and Implementation for Aircraft (Extended Version) (2024)	RUL estimation, decision algorithms	Operational and sensor data	Strategic maintenance planning

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Predictive Maintenance Analytics and Implementation for Aircraft (2023)	Regression-based ML, anomaly detection	Vibration and temperature data	Reduced system failure rates
Monitoring and Improving Aircraft Maintenance Processes Using IT Systems (2023)	IT-enabled dashboards, digital logging	Maintenance logs, certification data	Improved workflow traceability
A Large-Scale Annotated Multivariate Time Series Aviation Maintenance Dataset from NGAFID (2023)	Time-series data analytics	10,000+ flight and maintenance logs	Foundational dataset for validation
Applications of Machine Learning in Aircraft Maintenance (2023)	Random Forests, SVM, ANNs	Conceptual/maintenance data	Established ML algorithm suitability
Determining the Method of Predictive Maintenance for Aircraft Engine Using ML (2023)	SVM, Decision Trees, Neural Networks	Engine sensor data	Ensemble methods outperformed single classifiers
Predictive Maintenance in Aviation Using Artificial Intelligence (2023)	Hybrid ML, anomaly detection	High-quality aviation datasets	Improved safety margins through early warnings
Predictive Maintenance in Aviation – Industry Practices and Case Studies (2023)	Digital Twin modeling, AI simulation	High-fidelity physical and sensor models	Remarkable prediction precision
Acoustic Monitoring of an Aircraft Auxiliary Power Unit (APU) (2020)	Machine Learning, spectral feature extraction	Acoustic signals (spectrograms)	High non-intrusive detection accuracy
Structural Health Monitoring of Aircraft Power Unit Using Vibration Signal (2019)	FFT, vibration analysis	Vibration signals from power units	Effective detection of early mechanical faults

III. RESEARCH GAPS

Based on the literature review, the following research gaps have been identified:

Gap	Description
Gap 1: Limited Focus on Consumables	Most predictive maintenance systems focus on critical engine components, leaving consumables (fluids, filters, oil) underexplored
Gap 2: Lack of Integrated Visualization	Few systems provide intuitive dashboards for ground engineers to interpret consumable health status
Gap 3: Data Scarcity	Real-world aviation datasets lack detailed consumable-related variables (oil quality, filter pressure differentials)
Gap 4: Manual Dependency	Traditional inspection of consumables relies on manual monitoring and fixed schedules, leading to inefficiencies
Gap 5: Simulation Gap	Limited research on simulation-based approaches for consumable health prediction using synthetic data

IV. PROPOSED WORK

The proposed work on simulating sensor data for predictive maintenance focuses on developing a **modular, three-tier architecture** that bridges the gap between synthetic aviation data and actionable decision support for ground engineers.

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4.1 System Architecture

Layer	Component	Function
Data Layer	Synthetic data generation using statistical models	Mimics degradation patterns of engine oil, hydraulic fluid, and filters; scalable for future integration with ACARS and FDR
Processing Layer	Python-based backend with ML algorithms	Data cleaning, normalization, feature extraction; RUL estimation via regression; anomaly detection for leaks/clogs
UI Layer	Web/mobile dashboards (Flask, Tailwind CSS, Chart.js)	Real-time health scores, color-coded alerts (green/orange/red), maintenance recommendations

4.2 Key Features

- **Flight Identifier Input:** Ground staff can input specific flight identifiers (MSN or Registration Number) to receive real-time consumable health status
- **Color-Coded Alerts:** Green (normal), Orange (warning), Red (critical) for intuitive risk assessment
- **Recommendation Engine:** Provides specific maintenance actions (e.g., "Replace Oil Filter") based on detected issue severity

V. FUTURE RESEARCH DIRECTIONS

Based on the reviewed literature and proposed framework, the following future research directions are identified:

1. **Real Sensor Integration** — Integration with actual aircraft data sources such as ACARS (Aircraft Communications Addressing and Reporting System) and FDR (Flight Data Recorder)
2. **Federated Learning** — Fleet-level collaborative learning without centralized data sharing for improved model robustness
3. **Adaptive Scheduling through Reinforcement Learning** — Dynamic maintenance scheduling based on real-time consumable health predictions
4. **Digital Twin Integration** — Creating digital replicas of consumable systems for more accurate degradation modeling
5. **Edge Computing Deployment** — On-device predictive analytics for real-time alerts without cloud dependency

VI. CONCLUSION

This study introduced a system for simulating sensor data for predictive aircraft maintenance and decision support, specifically for monitoring aircraft consumables and filters. Through probabilistic modeling, threshold-based alerts, and an interactive dashboard, it successfully bridges the gap between raw data analytics and actionable decision-making.

Key Contributions:

- A modular three-tier architecture for simulation-based predictive maintenance
- Application of predictive intelligence to underexplored consumable components
- User-centric dashboard design for ground engineer decision support

From a user's perspective, the system enhances situational awareness, reduces manual workload, and ensures efficient resource utilization. From a technical standpoint, it demonstrates strong predictive accuracy and scalability for future real-world integration.

Future developments will include real sensor integration (ACARS, FDR), Federated Learning for fleet-level collaboration, and adaptive scheduling through Reinforcement Learning, extending its utility for industrial applications.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this research paper. This study was conducted solely for academic and research purposes without any financial support, commercial involvement, or external funding that could influence the outcomes of the work. All results and findings presented in this paper are unbiased and based on independent analysis carried out by the authors.

REFERENCES

[1] Barbosa, F., Santos, R., Almeida, P., & Costa, L. (2025). Using federated machine learning in predictive maintenance of jet engines. *IEEE Access, 13*, 12045–12060.

[2] Kwakye, A., Mensah, P., & Osei, K. (2024). Platform health management for aircraft maintenance – A review. *Journal of Aerospace Engineering Systems, 18*(2), 45–63.

[3] Mohammed, H., & Alzubaidi, A. (2024). The iceberg model for integrated aircraft health monitoring. *Aerospace Systems Review, 9*(1), 18–29.

[4] Lee, J., & Thomas, G. (2024). Deep reinforcement learning for predictive aircraft maintenance. *IEEE Transactions on Aerospace and Electronic Systems, 60*(1), 72–83.

[5] Sharma, V., Gupta, R., & Singh, A. (2024). Federated learning framework for collaborative remaining useful life prognostics. *Reliability Engineering and System Safety, 239*, 109–128.

[6] Stanton, R., Williams, T., & Johnson, M. (2024). Predictive maintenance analytics and implementation for aircraft (extended version). *International Journal of Prognostics and Health Management, 13*(1), 11–26.

[7] Stanton, R., Williams, T., & Johnson, M. (2023). Predictive maintenance analytics and implementation for aircraft. *International Journal of Prognostics and Health Management, 12*(3), 22–35.

[8] Żółkiewicz, M., & Piątkowski, T. (2023). Monitoring and improving aircraft maintenance processes using IT systems. *Journal of Information Technology Management in Aviation, 7*(4), 55–66.

[9] Khadka, S., Davis, E., & Miller, R. (2023). A large-scale annotated multivariate time series aviation maintenance dataset from the NGAFID. *Data in Brief, 50*, Article 109412.

[10] Kumar, P., Singh, R., & Verma, S. (2023). Applications of machine learning in aircraft maintenance. *International Journal of Advanced Research in Computer Science, 14*(2), 155–163.

[11] Patel, R., & Mehta, S. (2023). Determining the method of predictive maintenance for aircraft engine using machine learning. In *Proceedings of the International Conference on Artificial Intelligence and Data Analytics (ICAIDA)* (pp. 113–120).

[12] Gupta, A., & Fernandes, P. (2023). Predictive maintenance in aviation using artificial intelligence. *Journal of Intelligence Systems and Applications*, *14*(4), 201–212.

[13] Carvalho, D., Santos, J., & Pereira, M. (2023). Predictive maintenance in aviation – Industry practices and case studies. *Journal of Aerospace Operations, 7*(3), 145–158.

[14] Serrano, D., Garcia, E., & Lopez, F. (2020). Acoustic monitoring of an aircraft auxiliary power unit (APU). *Aerospace Science and Technology, 102*, 105–116.

[15] Viadero, F., Rodriguez, A., & Fernandez, R. (2019). Structural health monitoring of aircraft power unit using vibration signal. *Mechanical Systems and Signal Processing, 125*, 456–471.