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The Iceberg Model for Integrated Aircraft Health Monitoring Based on AI, Blockchain, and Data Analytics

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Abstract: The increasing complexity of modern aircraft systems necessitates advanced monitoring solutions to ensure operational safety and efficiency. Traditional aircraft health monitoring systems (AHMS) often rely on reactive maintenance strategies, detecting only visible faults while leaving underlying issues unaddressed. This gap can lead to critical failures and unplanned downtime, resulting in significant operational costs. To address this issue, this paper proposes the integration of artificial intelligence (AI) and blockchain technologies within an enhanced AHMS, utilizing the iceberg model as a conceptual framework to illustrate both visible and hidden defects. The model highlights the importance of detecting and addressing issues at the earliest possible stages, ensuring that hidden defects are identified and mitigated before they evolve into significant failures. The rationale behind this approach lies in the need for a predictive maintenance system capable of identifying and mitigating hidden risks before they escalate. Key tasks completed in this study include: a comparative analysis of the proposed system with existing monitoring solutions, the selection of AI algorithms for fault prediction, and the development of a blockchain-based infrastructure for secure, transparent data sharing. The evolution of AHMS is discussed, emphasizing the shift from traditional monitoring to advanced, predictive, and prescriptive maintenance approaches. This integrated approach demonstrates the potential to significantly improve fault detection, optimize maintenance schedules, and enhance data security across the aviation industry.

Keywords: aircraft health monitoring systems; iceberg model; aviation health management; predictive maintenance; artificial intelligence; blockchain; federated learning; data analytics; prescriptive maintenance

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1. Introduction

The aviation industry is undergoing a technological transformation, driven by advancements in artificial intelligence (AI), blockchain, and advanced data analytics [1]. These technologies present a unique opportunity to enhance the performance and reliability of aircraft health monitoring systems (AHMS) [2]. Traditional approaches to aircraft health monitoring, which primarily focus on reactive or scheduled maintenance, are no longer sufficient in the face of modern aviation's increasing complexity.

The integration of AI and blockchain into AHMS represents a significant shift from conventional monitoring to a more proactive, predictive, and secure health management approach.

The research is guided by the following specific objectives:

- To explore how AI, particularly in the form of machine learning algorithms, can enhance the predictive capabilities of AHMS, allowing for early fault detection and the efficient scheduling of maintenance activities.
- To examine how blockchain technology can secure the transmission and storage of sensitive health monitoring data, ensuring data immutability, transparency, and trust among stakeholders in the aviation ecosystem.
- To propose the iceberg model as a conceptual framework for understanding the layered complexities of AHMS, emphasizing the importance of detecting hidden defects before they escalate into critical failures.

The purpose of this paper is to explore various aspects of the application of new technologies to shift the paradigm from aviation health monitoring to aviation health management.

Aircraft systems are critical components that require advanced maintenance strategies to ensure safety and control costs. Traditional routine maintenance is no longer sufficient, necessitating the implementation of more sophisticated approaches [3–5]. The development of data acquisition, transmission, storage, and processing technologies made condition-based and predictive maintenance more feasible [6]. These advancements enable more efficient detection of abnormal conditions from health monitoring data, such as pressure, flow rate, and temperature [7].

Health monitoring systems for critical aircraft systems were developed to ensure reliability. Examples include PlaneView (Gulfstream and Honeywell), Electronic Centralised Aircraft Monitor (Airbus), and the Engine Indicating and Crew Alerting System [8]. These systems demonstrate the powerful combination of sensor data and AI in effectively detecting and diagnosing fuel system failures.

Various approaches are applied to fuel system diagnostics. Knowledge-based reasoning methods, such as expert systems, are used for fault diagnosis in aircraft fuel systems [9–12]. These systems utilize rule bases built from manuals or expert knowledge to infer fault conditions. Aviation applications of fault diagnostic expert systems based on a fuzzy neural network are discussed in [13,14].

Model-based reasoning approaches were explored for fuel system diagnostics. These methods use qualitative or quantitative models to represent system behavior and diagnose faults [15–17]. While model-based approaches can provide deeper insights into system behavior, they may face challenges in computational complexity and model fidelity [18,19].

Machine learning techniques gained popularity in fuel system diagnostics due to their ability to handle high-dimensional data from complex systems [20–22]. Methods such as support vector machines and neural networks are applied to detect and diagnose faults in various fuel system components. However, the lack of interpretability in some of these approaches led to the exploration of explainable AI techniques to improve trust and understanding of diagnostic results [23–26].

Blockchain technology emerged as a potential solution to address many challenges faced by the aviation maintenance, repair, and overhaul (MRO) industry. The MRO sector is characterized by high complexity, multiple intermediaries, data sharing among various actors, and stringent security requirements [27,28].

In the context of MRO, blockchain could be used to store and manage maintenance records, creating a tamper-proof and easily accessible history of aircraft and component maintenance [29]. This could help address issues such as counterfeit parts, which compromise safety standards [30,31].

Blockchain could streamline record-keeping processes, reduce paperwork, and improve the efficiency of data retrieval and sharing among various stakeholders in the aviation ecosystem [31].

Organizational readiness for blockchain adoption in MRO is a critical factor [32]. The aviation sector is known for its cautious approach to new technologies due to its stringent safety requirements [33]. Further research and real-world implementations will be crucial in realizing the full potential of blockchain technology in aviation MRO.

Data analytics emerged as a powerful tool in the aerospace industry, offering significant benefits across various applications. In aircraft health monitoring, Jiao et al. [34] demonstrated a prognostic health management system using an aviation data mining platform based on the Hadoop cloud architecture. This system analyzed correlations among different tasks and system states to provide early warnings for potential faults. In space technology, data analytics is supporting various aspects of space missions and utilizing spaceborne data. Dong et al. [35] proposed a data-enabled architecture for supporting launches at rocket launch sites, incorporating elements such as mission planning, command support, and fault detection.

The increasing use of on-board sensor monitoring, and data-driven algorithms led to a shift towards data-driven maintenance for aircraft. This approach, referred to as data-driven predictive aircraft maintenance (PAM), utilizes sensor data and predictive algorithms to generate maintenance tasks only when needed [36–38]. Previous studies largely focused on challenges in traditional time-based maintenance [39,40]. However, since the European Aviation Safety Agency (EASA) integrated aircraft health monitoring into regulatory frameworks in 2018 [41], there has been some research conducted on the emerging challenges specific to data-driven PAM. To identify potential hazards associated with PAM, the researchers used an agent-based model of the aircraft maintenance process [38] where the data management team is a new agent specifically introduced to support the PAM process.

There is currently a gap in the aviation industry's approach to aircraft health monitoring and maintenance. While traditional systems focus on reactive or scheduled maintenance, there is a lack of a comprehensive, integrated framework that combines advanced technologies such as artificial intelligence, blockchain, and data analytics to enable a proactive, predictive, and prescriptive approach to aircraft health management.

Existing literature and systems primarily address individual aspects of aircraft monitoring or maintenance but fail to provide a holistic view that encompasses the entire spectrum from early defect detection to optimized maintenance strategies. The industry lacks a unified model that can represent the depth and complexity of modern aircraft health monitoring capabilities, from surface-level observations to deep, predictive insights.

This article aims to address this gap by proposing an advanced framework for aircraft health monitoring and management, leveraging cutting-edge technologies to shift the paradigm from simple monitoring to comprehensive health management. The purpose is to develop and present a model that integrates various aspects of modern AHMS, including predictive analytics, blockchain for data integrity, and federated learning for collaborative insights, thereby providing a more complete and effective approach to ensuring aircraft safety, reliability, and operational efficiency.

The structure of this article is as follows: Section 2 discusses the role of health monitoring systems in aviation, the iceberg model as a framework, and the methods employed in the study. Section 3 presents the findings on AI-based AHMS, future intelligent ecosystems, federated learning, the role of blockchain, and analytics in advanced health monitoring systems. Section 4 explores the shift from aviation health monitoring to health management on the base of modern AHMS, the development and utility of the iceberg model, mathematical interpretations, and the correlation between AHMS sophistication and maintenance levels. Section 5 summarizes the key findings and discusses the future implications for the aviation industry, emphasizing the transformative potential of advanced AHMS technologies.

2. Materials and Methods

2.1. The Role of Health Monitoring Systems in Enhancing the Reliability of Complex Aviation Systems

The aviation industry always prioritizes safety, performance, and reliability. As aircraft systems become increasingly complex, ensuring their reliability necessitates sophisticated approaches to maintenance and monitoring. One such approach is the deployment of advanced health monitoring systems, which play a critical role in identifying the origin of defects at their earliest stages. The ability to detect and address potential issues before they evolve into significant problems is crucial for maintaining the integrity of aviation systems.

The Figure 1 characterizes the typical development of failures in complex aviation systems. The failure progression curve is divided into distinct phases, each representing a different stage of degradation in an aircraft system: failure starts, potential failure detection, the beginning of degradation, pre-failure condition, and failure occurs. Each stage reflects a specific level of system deterioration, which corresponds to varying levels of detectability and necessary maintenance actions.

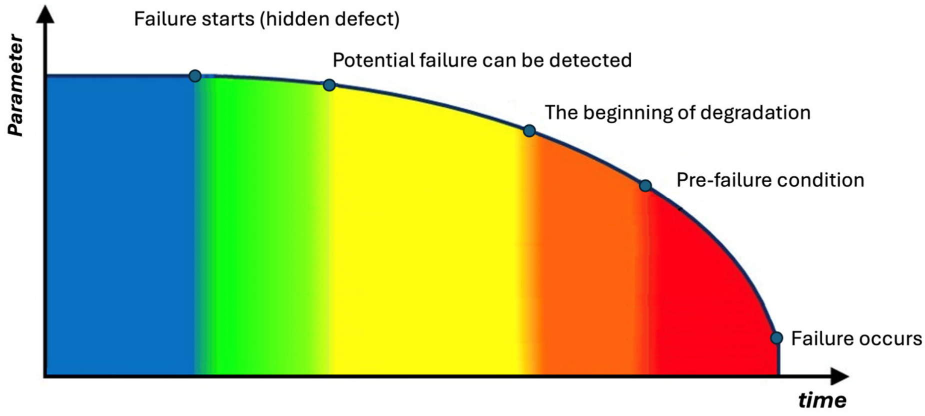

Figure 1. Typical development of failures in complex aviation systems.

Failure starts is characterized by the onset of a hidden defect. At this point, the defect is not detectable through standard operational checks or inspections. The system operates normally, and there are no immediate signs of impending failure.

As the defect progresses, it reaches a stage where it can be detected through advanced monitoring techniques. This is the phase where predictive maintenance becomes crucial. Technologies such as vibration analysis, ultrasonic testing, and oil debris analysis can identify potential issues before they manifest as operational problems.

At the stage of degradation beginning, the defect starts to affect the system's performance. It is now more apparent through monitoring tools, and the system shows early signs of degradation. This phase is critical for condition-based maintenance, where interventions are planned based on the actual condition of the equipment rather than on a fixed schedule.

In the pre-failure condition, the system is with noticeable performance deterioration. Immediate maintenance actions are required to prevent total failure. At this stage, maintenance is intensified to address the imminent risks.

If the defect is not addressed in the earlier stages, it leads to system failure. This phase requires corrective maintenance to restore the system to operational status. This is the most undesirable stage, as it often results in operational downtime and increased repair costs.

Health monitoring systems equipped with sophisticated sensors and analytical capabilities can identify these nascent defects. By detecting anomalies and deviations from normal operating parameters, these systems enable maintenance teams to intervene before the defects progress to more serious stages. This early detection is the cornerstone of prescriptive maintenance, which involves taking preventive actions based on the insights provided by the monitoring systems. The ability to address issues at this stage significantly reduces the likelihood of unexpected failures, thereby enhancing the overall reliability of the aircraft.

The effectiveness of health monitoring systems is largely determined by the depth of diagnostics and the breadth of coverage across all aviation systems. Comprehensive diagnostics involve not only the detection of defects, but also the precise identification of their origins and potential impact. This requires a robust network of sensors distributed throughout the aircraft, capable of monitoring various subsystems and components in real time.

For instance, engines, avionics, hydraulic systems, and structural components must all be integrated into the health monitoring framework. Each of these systems has unique characteristics and failure modes, necessitating specialized sensors and diagnostic algorithms. By covering a wide range of systems, health monitoring solutions ensure that no aspect of the aircraft is overlooked. This holistic approach to diagnostics enables maintenance teams to develop a complete picture of the aircraft's health, facilitating informed decision-making and targeted maintenance efforts.

AHMS plays a vital role in ensuring the safety, reliability, and efficiency of aircraft operations by continuously monitoring and diagnosing the health status of various aircraft components. The structure of a modern AHMS is illustrated in Figure 2.

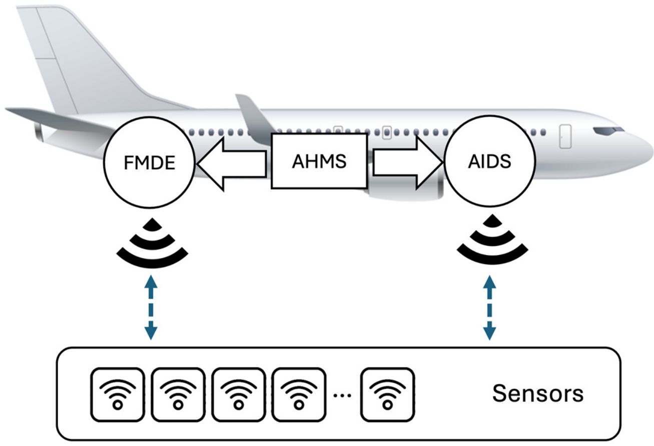

Figure 2. AHMS structure.

Sensors are the primary data collection points in an AHMS. These devices are strategically installed throughout the aircraft to monitor various parameters such as temperature, pressure, vibration, and structural integrity.

The Aircraft-Integrated Data System (AIDS) is responsible for aggregating data collected by the sensors. It acts as the central hub where all sensor data converge for initial processing.

AHMS processes the data received from AIDS. It employs sophisticated algorithms and machine learning techniques to analyze the data, detect anomalies, and predict potential failures.

The Fault Management and Diagnostics Engine (FMDE) is tasked with diagnosing faults and providing actionable insights based on the analysis performed by the AHMS. It generates alerts and recommendations for maintenance actions to prevent any potential issues from escalating. The FMDE interprets the data, identifies specific faults, and provides maintenance recommendations. This step is essential for decision-making and ensures that maintenance actions are timely and targeted, thereby enhancing the aircraft's reliability and operational efficiency.

2.2. Iceberg Model as a Framework for Aviation Health Monitoring Systems

The aviation industry is at the forefront of technological innovation, continually seeking to enhance the safety, reliability, and efficiency of aircraft operations. A critical aspect of this endeavor is the effective monitoring and maintenance of aircraft systems to preemptively address potential failures. One of the new useful frameworks for understanding and improving these processes can be the iceberg model, which provides a comprehensive visual and conceptual representation of the progression of aircraft defects from their hidden stages to complete failures (Figure 3).

The proposed iceberg model, similar to the widely known Swiss cheese model [42] used in safety analysis, illustrates how unseen defects can evolve over time, ultimately leading to significant failures if not properly managed. The iceberg model is particularly useful for aviation health monitoring systems (AHMS), as it underscores the importance of detecting and addressing issues at the earliest possible stages. By conceptualizing defects as an iceberg, where the majority of the structure lies hidden beneath the surface, the model highlights the necessity of advanced monitoring techniques to identify and mitigate these hidden risks. Just as an iceberg has a small visible portion above the water and a vast, hidden mass beneath, AHMS encompasses both obvious, surface-level indicators, and deep, often invisible processes that are crucial to aircraft safety and performance.

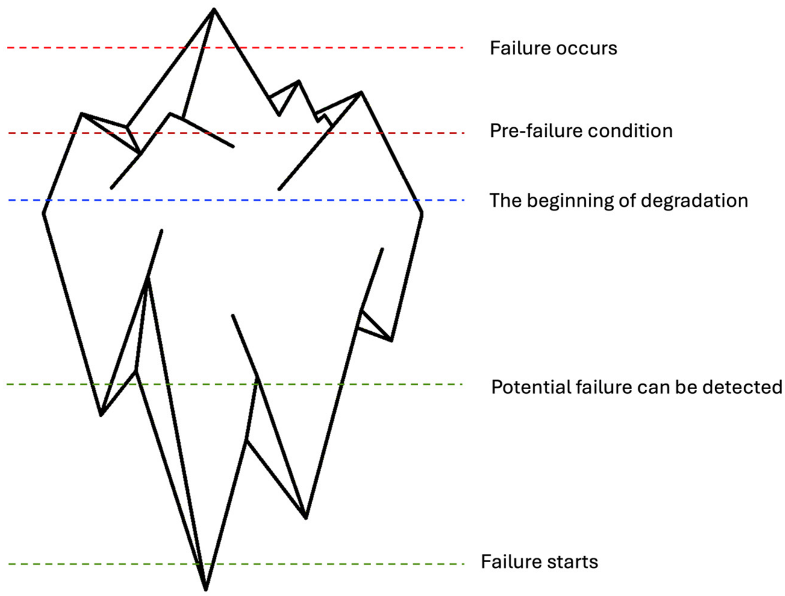

Figure 3. Iceberg model as a framework for AHMS.

At the tip of our metaphorical iceberg lie the most apparent and critical failure indicators: those visible malfunctions and alerts that demand immediate attention. These represent traditional monitoring systems that react to existing problems. However, the true power and potential of modern AHMS lie beneath this surface, in the larger, submerged portion of the iceberg.

As we descend through the layers of our iceberg, we encounter increasingly sophisticated levels of monitoring and analysis. The upper layers beneath the surface represent early warning systems and predictive maintenance capabilities. Deeper still, we find complex data analytics, machine learning algorithms, and artificial intelligence systems that can detect subtle anomalies and predict potential failures long before they manifest as visible issues.

The deepest layers of our iceberg model represent the cutting-edge of AHMS technology—systems that can analyze vast amounts of data from multiple sources, learn from global fleet performance, and even predict issues before they begin to form. These advanced systems delve into the very foundations of aircraft health, examining the conditions and factors that lead to the 'formation' of potential problems.

By viewing AHMS through the lens of the iceberg model, we gain a comprehensive understanding of how these systems evolved from simple, reactive tools to complex, predictive ecosystems. This model helps us appreciate the depth of information and analysis required for truly effective aircraft health monitoring, highlighting the journey from surface-level observations to deep, predictive insights.

As we explore the iceberg model of AHMS, we will uncover how each layer contributes to the overall goal of enhancing aviation safety and efficiency. From basic fault detection systems at the tip to advanced predictive analytics at the base, each level plays a crucial role in the comprehensive health monitoring of modern aircraft.

This framework not only allows us to understand the current state of AHMS, but also provides a roadmap for future developments. As technology continues to advance, we can anticipate even deeper layers of our iceberg, representing new frontiers in predictive maintenance, real-time analysis, and holistic aircraft health management.

2.3. Iceberg Model as Evolution of Aviation Health Monitoring Systems

The iceberg model serves as an excellent metaphor for understanding the evolution of aviation health monitoring systems. This evolution reflects a journey from surface-level observations to deep, predictive insights, mirroring our progression in detecting and managing aircraft failures at various stages of their development (Figure 4).

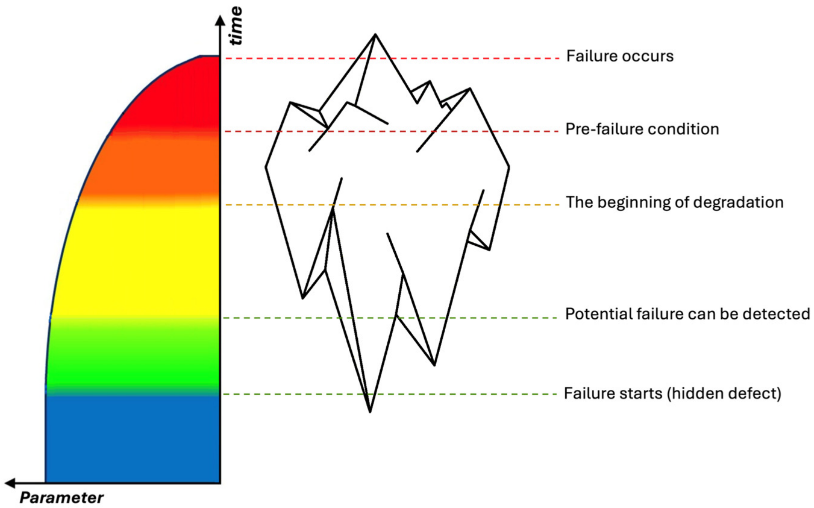

Figure 4. Iceberg model for failure evolution.

1. The Built-In Test Equipment (BITE) Era: Detecting the Peaks.

In the early stages of aviation health monitoring, BITE systems represented the industry standard. These systems, analogous to observing only the tip of the iceberg, were designed to detect and report obvious failures or malfunctions.

Characteristics of BITE systems:

- Limited to detecting failures that already occurred.
- Focused on individual component health.
- Provided basic go/no-go indicators.
- Data processing primarily on the ground after flights.
- Limited predictive capabilities.

BITE systems, while revolutionary for their time, were reactive in nature. They could identify when a failure occurred, but offered little insight into why it happened or how it could have been prevented.

2. Enhanced Monitoring: Seeing Below the Surface.

As technology advanced, aviation health monitoring systems began to peer slightly below the waterline of our metaphorical iceberg. This era saw the introduction of more sophisticated sensors and data collection methods with the next key advancements:

- Increased number of monitored parameters.
- Introduction of real-time data transmission to ground stations.
- Basic trend analysis capabilities.
- Integration of multiple systems for a more holistic view.

These systems allowed for some level of predictive maintenance, enabling airlines to address issues before they became critical failures. However, they were still limited by processing power and data transmission capabilities.

3. Big Data and Analytics: Exploring the Depths.

The advent of big data analytics marked a significant leap in aviation health monitoring. This phase corresponds to exploring the middle sections of our iceberg, where potential failures can be detected early.

Characteristics of this level:

- Massive increase in data collection points.
- Advanced algorithms for pattern recognition.
- Integration of historical data with real-time information.
- Improved predictive capabilities.

- Fleet-wide data analysis for identifying trends across multiple aircrafts.

These systems began to offer true predictive maintenance capabilities, allowing airlines to anticipate failures and schedule maintenance proactively. However, they were still primarily reliant on ground-based processing and analysis.

4. IoT and Edge Computing: Real-Time Insights.

The integration of Internet of Things (IoT) technologies and edge computing brought health monitoring capabilities directly into the aircraft. This development allowed for real-time processing of vast amounts of data, even during flight.

Key features:

- On-board processing of complex data sets.
- Real-time alerts and recommendations.
- Integration with flight operations for immediate action.
- Improved data transmission through advanced connectivity (e.g., satellite communications).

This phase represents a significant move towards the lower portions of the iceberg, enabling the detection of subtle anomalies that might indicate the early stages of a potential failure.

5. AI and Machine Learning: Predicting the Unseen.

The introduction of AI and machine learning (ML) marked a revolutionary step in aviation health monitoring. These technologies enable systems to not only detect, but also predict and understand failures at their earliest stages—the very bottom of our iceberg.

Advancements in this level:

- Complex pattern recognition across vast datasets.
- Predictive modeling of component lifecycles.
- Anomaly detection at microscopic levels.
- Self-learning systems that improve over time.
- Integration of non-traditional data sources (e.g., weather patterns, flight routes).

AI-powered systems can now detect the "birth of the iceberg", identifying potential issues long before they manifest as detectable problems through traditional means.

2.4. Selection Criteria for AI Algorithms in AHMS

The selection of appropriate AI algorithms for advanced AHMS is based on a comprehensive evaluation of various machine learning models. Our criteria for selection included:

- Predictive accuracy—the ability to accurately forecast potential failures and maintenance needs.
- Scalability—the capacity to handle large volumes of data from multiple aircraft systems.
- Interpretability—the extent to which the model's decisions can be explained, which is crucial for regulatory compliance and trust in the aviation industry.
- Computational efficiency—the ability to process data and make predictions in real time or near real time.
- Adaptability—the capacity to learn and improve from new data over time.

Based on these criteria the following key algorithms can be selected:

(a) Random forest for feature selection [43] due to its ability to handle high-dimensional data and provide feature importance rankings. This helps in identifying the most critical parameters for predicting aircraft health.

(b) Long short-term memory networks for time series prediction [44] for their ability to capture long-term dependencies in time series data, which is crucial for predicting future component failures based on historical sensor data.

(c) Gradient boosting machines for anomaly detection [45] for their high accuracy in classification tasks and ability to handle imbalanced datasets, which is common in fault detection scenarios.

(d) Federated learning framework [46] to enable collaborative learning across multiple aircraft and operators while maintaining data privacy. This was crucial for improving model performance without compromising sensitive operational data.

These algorithms can be optimized using techniques such as hyperparameter tuning via grid search and cross-validation and were validated using a hold-out test set to ensure generalizability.

3. Results

3.1. AI-Based AHMS as Intelligent Ecosystem

AI plays a crucial and expanding role in AHMS today, with even greater potential for the future. The Table 1 provides a concise overview of how AI's role in AHMS is expected to evolve, showing the transition from current applications focused on data analysis and predictive maintenance to future applications that encompass more autonomous, integrated, and sophisticated capabilities.

Table 1. Comparative analysis of current and future role of AI in AHMS.

Aspect	Current Role of AI in AHMS	Future Role of AI in AHMS
Data Analysis	Pattern recognition in sensor data	Advanced prognostics with longer-term predictions
Maintenance	Predictive maintenance scheduling	Autonomous decision-making for maintenance
Diagnostics	Fault diagnosis and repair recommendations	Enhanced digital twins for complex simulations
Data Processing	Data fusion from multiple sensors	Natural language processing of unstructured data
Optimization	Suggestion of optimal flight parameters	Adaptive learning systems for continuous improvement
System Integration	Limited to AHMS	Integration with broader airline systems
Manufacturing	Limited application	Anomaly detection in component manufacturing
Design	Not widely used	Predictive modeling for new aircraft designs
Human Interaction	Provides data for human decision-making	Enhanced human–AI collaboration
Computing Power	Traditional computing	Potential integration with quantum computing
Scope	Focused on individual aircraft	Fleet-wide learning and optimization
Autonomy	Limited autonomy	Increased autonomous capabilities
Time Horizon	Short- to medium-term predictions	Long-term health and performance forecasting

3.2. Future AHMS as Intelligent Ecosystem

The modern aircraft represents a pinnacle of intelligent systems in transportation, incorporating advanced technologies that enhance safety, efficiency, and performance. These flying machines evolved from purely mechanical devices to highly sophisticated, data-driven platforms that exemplify the concept of intelligent infrastructure. At the heart of these intelligent aircraft systems is the integration of sensors, computers, and automation. Modern planes are equipped with an array of sensors that continuously monitor everything from engine performance and fuel consumption to weather conditions and structural integrity. This constant stream of data is processed by onboard computers, which can make split-second decisions to optimize flight parameters.

As technology continues to advance, the future of AHMS is set to become more sophisticated, integrated, and intelligent too. Figure 5 encapsulates this vision, showcasing a complex yet streamlined ecosystem where data, analytics, and connectivity converge to enhance aircraft safety, efficiency, and maintenance practices. Figure 5 presents the key components and functionalities of future AHMS.

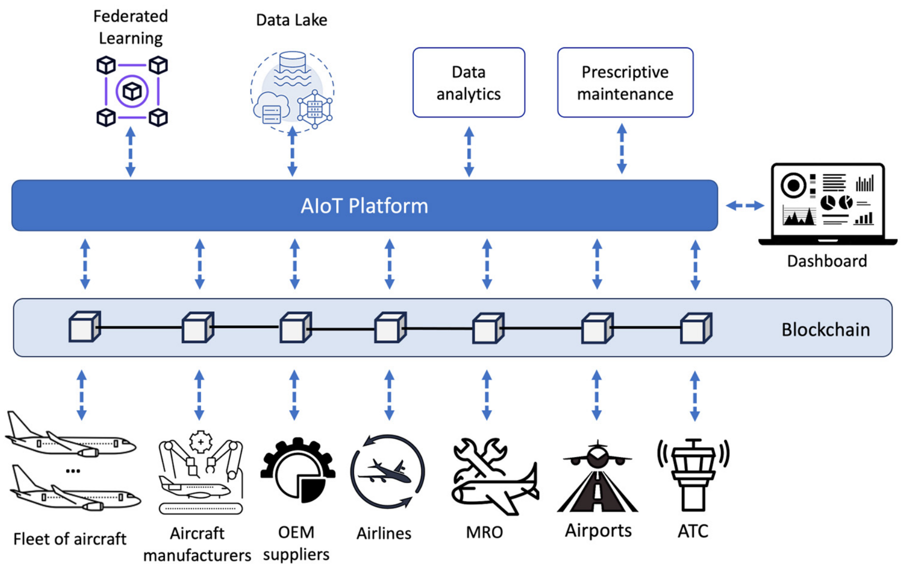

Figure 5. Structure of future AHMS.

At the foundation of this ecosystem is the fleet of aircrafts, each equipped with numerous sensors that continuously monitor various parameters related to the aircraft's health. These sensors collect critical data on aspects such as engine performance, structural integrity, and environmental conditions.

Figure 5 highlights the involvement of various stakeholders in the aviation industry, including aircraft manufacturers, original equipment manufacturer (OEM) suppliers, airlines, MRO providers, airports, and air traffic control (ATC). Each of these entities plays a crucial role in the data exchange and collaborative decision-making process.

Important component of the future AHMS is the use of blockchain technology. The blockchain network serves as the backbone of the aviation health management system, providing secure and transparent data storage and sharing capabilities:

- The network uses a consensus algorithm (e.g., proof of stake) to validate and add new data blocks to the chain.
- A distributed ledger ensures that all nodes in the network have an up-to-date copy of the data, providing redundancy and security.
- Smart contracts automate the validation and processing of data, triggering actions such as maintenance alerts or regulatory reporting based on predefined conditions.

Blockchain ensures secure, transparent, and immutable data exchange between all stakeholders. This decentralized ledger system enhances trust and accountability, allowing for seamless collaboration and data sharing across the aviation ecosystem.

The integration of AI and IoT technologies, termed AIoT, forms the core of the future AHMS. The AIoT platform serves as a central processing unit, where data from the fleet of aircrafts and other sources are aggregated, processed, and analyzed. This platform enables real-time monitoring, predictive analytics, and decision support.

Federated learning is an innovative approach that allows AI models to be trained across decentralized data sources while preserving data privacy. The federated learning framework consists of three components:

- Local model training. Each aircraft or organization trains a local machine learning model on its own data. This ensures that raw data never leave the local environment, preserving privacy.
- Model aggregation. The locally trained models are sent to a central server where they are aggregated to create a global model. This aggregated model benefits from the collective knowledge of the entire fleet without accessing the raw data.

- Model updates. The global model is periodically updated and redistributed to the local nodes, improving the predictive accuracy and robustness of the system over time.

In the future AHMS, federated learning enables the continuous improvement of predictive maintenance algorithms by using data from multiple aircrafts and stakeholders without compromising sensitive information.

A data lake is a centralized repository that stores vast amounts of structured and unstructured data at any scale. In the future AHMS, the data lake collects and stores all relevant data from various sources, providing a rich dataset for advanced analytics and machine learning applications.

The AIoT platform utilizes advanced data analytics to derive actionable insights from the collected data. Prescriptive maintenance goes beyond predictive maintenance by not only forecasting potential issues but also recommending specific actions to mitigate these issues. This proactive approach ensures optimal aircraft performance and reduces downtime.

The dashboard serves as the user interface for the future AHMS, providing real-time visualization and reporting of aircraft health status, maintenance recommendations, and operational metrics. It allows stakeholders to make informed decisions based on comprehensive data analysis.

The operational flow in the future AHMS begins with the sensors installed on the aircraft, which continuously monitor various health parameters. This data are transmitted to the AIoT platform, where it is securely stored in the data lake. Using federated learning, the AIoT platform enhances its predictive models by incorporating data from multiple sources while maintaining data privacy. The AIoT platform then performs advanced data analytics to identify potential issues and prescribe maintenance actions. These insights are presented on the dashboard, providing stakeholders with a clear view of the aircraft's health status and recommended actions. Blockchain technology ensures that all data exchanges and maintenance actions are transparent, secure, and immutable, fostering trust among all parties involved.

The future of AHMS is poised to revolutionize the aviation industry:

- By using real-time data and advanced analytics, future AHMS can detect and address potential issues before they escalate, significantly enhancing flight safety.
- The integration of AI and IoT technologies enables more accurate and timely maintenance actions, reducing aircraft downtime and improving operational efficiency.
- The use of blockchain and federated learning fosters a collaborative environment where all stakeholders can securely share data and insights, leading to more informed and effective decision-making.
- Proactive and prescriptive maintenance approaches reduce unexpected failures and associated costs, leading to significant savings for airlines and MRO providers.
- The extensive data collected and analyzed by the future AHMS provide valuable insights that can inform future aircraft design, maintenance practices, and operational strategies.

3.3. Federated Learning in Aviation AI-Based Health Monitoring System

The advent of AI and machine learning revolutionized the aviation domain by enabling predictive maintenance and real-time monitoring. However, the implementation of these technologies brings forth challenges related to data privacy and security.

Federated learning addresses the fundamental concern of data privacy and security in the aviation industry. Traditional centralized machine learning approaches require aggregating vast amounts of data in a central repository, posing significant risks of data breaches and unauthorized access. In contrast, federated learning ensures that raw data remain on local devices, such as aircraft and maintenance facilities, thus preserving data privacy.

Local data, including sensitive information about engine performance, fuel consumption, and structural integrity and the reliability of components and systems is encrypted and processed on-site. Only the model parameters (gradients or weights) are shared with a central server. This approach minimizes the risk of data exposure, ensuring compliance with stringent data protection regulations in the aviation sector.

One of the core functionalities of federated learning is the decentralized training of machine learning models. In the aviation health monitoring system, each aircraft or maintenance facility trains a local model using its own data. This localized training allows the model to learn specific patterns and insights pertinent to individual aircraft or operational scenarios.

By utilizing edge computing resources, federated learning leverages the computational power available on local devices. This not only reduces the dependency on central servers, but also enhances the responsiveness and efficiency of the system. The localized models are adept at capturing unique operational characteristics, contributing to more accurate and tailored predictions.

The process of federated learning involves aggregating locally trained models to create a global model. After local training, the models are encrypted and sent to a central aggregation server. Here, the server combines the parameters from all local models to update the global model. This aggregation process involves techniques such as federated averaging, which ensures that the global model benefits from the collective knowledge of all participating nodes.

The updated global model is then redistributed to the local nodes, replacing the previous versions. This iterative process of local training, aggregation, and global model updating leads to continuous improvement in model accuracy and performance. The system adapts to new data in real time, ensuring that the models remain relevant and up-to-date with the latest operational information.

Federated learning enhances the overall performance of the aviation health monitoring system through collaborative learning. By aggregating knowledge from diverse data sources across different aircraft and operational environments, the global model becomes more robust and comprehensive. This collaborative approach leads to improved predictive accuracy and reliability.

Real-time adaptation to new data ensures that the system can promptly respond to emerging issues. The enhanced global model can detect potential maintenance needs, predict failures, and identify anomalies across the fleet, thereby reducing downtime and preventing critical failures. This proactive maintenance capability significantly enhances the safety and operational efficiency of the aircraft.

The aviation industry is heavily regulated, with stringent requirements for data handling and reporting. Federated learning aligns with these regulatory requirements by ensuring data sovereignty and maintaining detailed audit trails. Data remain within their source location, complying with regulations that restrict data transfer across borders or to central repositories.

Audit trails of all model updates and training activities provide transparency and accountability. Regulatory bodies can access these records to verify compliance with safety and maintenance standards. This capability not only ensures adherence to regulations, but also builds trust with regulatory authorities and stakeholders.

Federated learning contributes to the operational efficiency of the aviation health monitoring system in several ways. Predictive maintenance, powered by accurate and up-to-date models, reduces unscheduled downtimes and optimizes maintenance schedules. This leads to significant cost savings and improved aircraft availability.

Anomaly detection capabilities enable early identification of potential issues, allowing for timely interventions. This proactive approach minimizes the risk of in-flight failures and enhances the overall safety of aircraft operations. Additionally, by decentralizing data processing and training, federated learning optimizes the use of computational resources, reducing the need for extensive data transfers and central processing.

Federated learning in an aviation AI-based health monitoring system involves several key steps to ensure effective model training, data privacy, and overall system efficiency:

- Step 1. Data collection and preprocessing. Each aircraft is equipped with various sensors that collect data on parameters such as engine performance, fuel levels, structural integrity, and environmental conditions. Data from maintenance facilities, including inspection reports and repair logs, are also collected. Raw data are cleaned to remove any noise or irrelevant information. Data are normalized to ensure consistency in format and scale. Relevant features are extracted and engineered from the raw data to improve model training.
- Step 2. Local model training. Each node (aircraft or maintenance facility) initializes its own local machine learning model. Initial parameters of the model are set, either randomly or based on a predefined configuration. The preprocessed data on each node are used to train the local model. The model is trained using standard machine learning algorithms, such as neural networks, decision trees, or regression models. The local model parameters are updated iteratively based on the training data.
- Step 3. Model encryption and transmission. The trained local model parameters are encrypted to ensure data security and privacy. A digital signature is added to verify the authenticity of the model parameters. The encrypted model parameters are uploaded to a central server or aggregation point. Secure transmission protocols, such as TLS/SSL, are used to prevent data breaches during transmission.
- Step 4. Model aggregation. The central server receives encrypted model parameters from multiple nodes. An aggregation algorithm, such as federated averaging, combines the parameters from all local models. This typically involves averaging the weights of the models to create a new global model. The aggregated parameters are used to update the global model. The updated global model is validated to ensure it meets performance and accuracy criteria.
- Step 5. Global model redistribution. The updated global model is encrypted for secure transmission. A digital signature is added to authenticate the global model. The encrypted global model is distributed back to all participating nodes. Secure transmission protocols are used to ensure the integrity and confidentiality of the model.
- Step 6. Local model update and retraining. Each node integrates the updated global model parameters into its local model. The local model parameters are updated with the new global parameters. The local model continues training on new incoming data, further refining its parameters. This step is repeated iteratively, with each cycle involving local training, aggregation, and redistribution, leading to continuous improvement of the global model.
- Step 7. Monitoring and evaluation. Each node monitors the performance of its local model, tracking metrics such as accuracy, precision, recall, and loss. The central server monitors the performance of the global model to ensure it meets the desired benchmarks. Feedback on model performance is collected from all nodes. Based on the feedback, adjustments are made to the model training process, aggregation methods, or feature engineering techniques.
- Step 8. Compliance and reporting. All training activities, model updates, and data transactions are logged to create an audit trail. These logs ensure transparency and accountability essential for regulatory compliance. Regulatory bodies can access the audit trails to verify compliance with aviation safety and maintenance standards. Regular reports are generated and submitted to regulatory authorities, detailing the health monitoring activities and model performance.

By decentralizing the training process and securely aggregating model parameters, federated learning leverages the collective knowledge of multiple data sources while maintaining the confidentiality of sensitive information.

3.4. The Role of Blockchain in the Future AHMS

Blockchain is a distributed ledger technology that records transactions across multiple computers in such a way that the registered transactions cannot be altered retroactively [47]. Each block in the chain contains a set of transactions, and each block is linked to the previous one through cryptographic hashes. This structure ensures that data are secure, transparent, and immutable.

In future AHMS, blockchain will serve as a decentralized platform for managing vast amounts of data generated by aircraft sensors and other sources. Each stakeholder, including airlines, aircraft manufacturers, OEM suppliers, MRO providers, airports, and ATC, will have access to the blockchain, enabling seamless data sharing and collaboration. This decentralized approach eliminates the need for a central authority, reducing the risk of data tampering and enhancing trust among stakeholders.

One of the most significant advantages of blockchain is its ability to ensure data integrity and security. Each transaction (or data entry) on the blockchain is time-stamped and linked to the previous entry, making it nearly impossible to alter or delete data without detection. In AHMS, this feature is crucial for maintaining accurate records of aircraft health data, maintenance actions, and operational logs. Blockchain's cryptographic security mechanisms protect sensitive information from unauthorized access and cyber-attacks.

Blockchain provides a transparent and traceable record of all transactions. In the context of AHMS, this means that every piece of data, from sensor readings to maintenance records, can be traced back to its origin. This transparency ensures accountability and enables stakeholders to verify the authenticity of data. For instance, if an aircraft component fails, the maintenance history recorded on the blockchain can be traced to identify when and where it was last serviced, ensuring that any discrepancies or lapses in maintenance are easily detectable.

Blockchain technology can streamline maintenance and supply chain processes by providing a unified platform for tracking parts and components. Each part can be assigned a unique digital identity on the blockchain, recording its entire lifecycle from manufacturing to installation and eventual replacement. This level of traceability helps in identifying counterfeit parts, ensuring compliance with safety standards, and optimizing inventory management. Additionally, smart contracts on the blockchain can automate various processes, such as ordering replacement parts or scheduling maintenance, based on predefined conditions.

The aviation industry involves multiple stakeholders who need to collaborate and share data efficiently. Blockchain facilitates this by providing a secure and transparent platform for data exchange. For example, aircraft manufacturers can share design and performance data with airlines and MRO providers, enabling them to perform more informed and accurate maintenance. Similarly, airlines can share operational data with airports and ATC to optimize flight schedules and enhance overall efficiency. Blockchain ensures that all shared data are reliable and up-to-date, fostering better collaboration and decision-making.

Compliance with regulatory standards is a critical aspect of aviation safety. Blockchain's immutable ledger provides a comprehensive and tamper-proof record of all transactions, making it easier for airlines and maintenance providers to demonstrate compliance with safety regulations. Regulators can access the blockchain to audit maintenance records, ensuring that all required inspections and repairs are performed. This level of auditability reduces the administrative burden on airlines and enhances regulatory oversight.

While the integration of blockchain into AHMS offers numerous benefits, it also presents certain challenges and considerations:

- Blockchain networks need to handle large volumes of data generated by aircraft sensors and other sources. Ensuring the scalability of the blockchain to accommodate these data is a critical challenge.
- The aviation industry involves various systems and technologies that need to work together seamlessly. Ensuring interoperability between blockchain and existing systems is essential for successful implementation.
- While blockchain enhances transparency, it is essential to ensure that sensitive data are protected and that privacy concerns are addressed. Implementing robust privacy measures, such as permissioned blockchains, can help mitigate these concerns.

- The adoption of blockchain technology in aviation will require regulatory acceptance and support. Engaging with regulators and demonstrating the benefits of blockchain for safety and compliance is crucial for widespread adoption.

Figure 6 illustrates the structural components and lifecycle of block creation within a blockchain, offering a detailed view of how various stakeholders in the aviation industry interact with the system and how data blocks are created and validated.

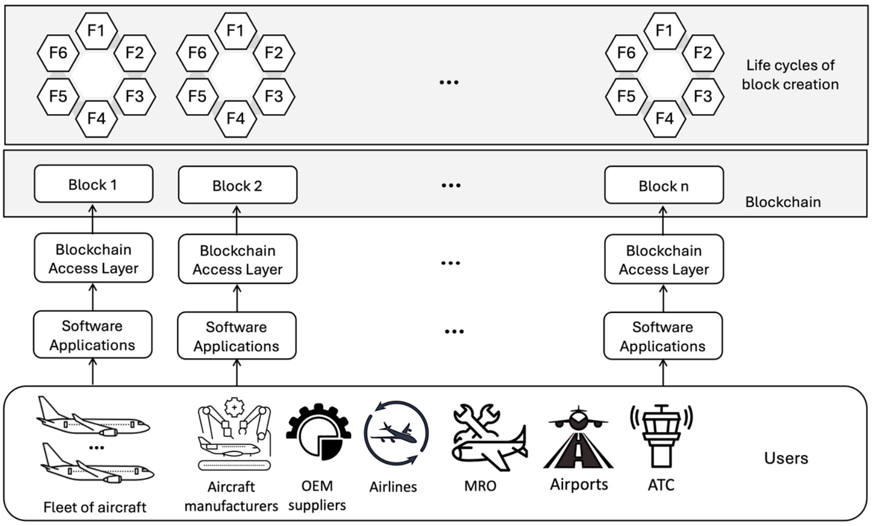

Figure 6. The structure of blockchain in AHMS.

Stakeholders in the aviation industry such as airlines, MRO providers, OEM suppliers, and aircraft manufacturers interact with the blockchain through specialized software applications designed for AHMS. These applications allow stakeholders to perform various actions such as initiating maintenance requests, querying the blockchain for aircraft health data, and participating in consensus mechanisms. Each user's interaction with the blockchain is mediated through these applications, providing a user-friendly way to access the system's capabilities.

Between the software applications and the blockchain itself lies the blockchain access layer. This layer acts as an intermediary that processes and formats the data from the software applications into a form that can be understood and utilized by the blockchain. It handles the communication between the stakeholders' applications and the underlying blockchain network, ensuring that data are transmitted securely and efficiently.

The core of the blockchain structure is a sequential series of blocks, starting from Block 1 and continuing to Block n. Each block contains a set of transactions or data entries that were validated and added to the blockchain. These transactions could include sensor data from aircraft, maintenance records, parts tracking, and other critical information. The blocks are linked together in a linear, chronological order, forming a continuous chain. This linkage is achieved through cryptographic hashes, where each block contains the hash of the previous block, ensuring the integrity and immutability of the blockchain.

The figure illustrates the life cycles of block creation, represented by hexagonal units labeled F1 to F6. These units symbolize the various stages and functions involved in the creation and validation of a new block within the AHMS context:

- Data gathering (F1). Data from various aircraft sensors and stakeholder inputs are gathered into a pool. These data entries contain details such as engine performance metrics, structural integrity checks, and environmental conditions.
- Verification (F2). The gathered data are verified for authenticity and correctness. This involves checking digital signatures and ensuring data consistency.

- Validation (F3). Verified data are validated according to the blockchain's consensus protocol. This could involve proof-of-work, proof-of-stake, or other consensus mechanisms that ensure the legitimacy of the data.
- Block assembly (F4). Validated data entries are assembled into a new block. This block includes a header containing metadata such as the timestamp, hash of the previous block, and a nonce (in the case of proof-of-work).
- Broadcasting (F5). The newly created block is broadcasted to the blockchain network, where it is shared with all participating nodes.
- Consensus and addition (F6). The network nodes reach a consensus on the validity of the new block. Once consensus is achieved, the block is added to the blockchain, and the process repeats for the next set of data entries.

By using blockchain's unique attributes, AHMS can ensure the integrity and reliability of aircraft health data, streamline maintenance processes, and foster better collaboration among stakeholders. While challenges exist, the potential benefits of blockchain for AHMS are substantial, paving the way for a safer, more efficient, and more reliable aviation industry. As technology continues to evolve, blockchain will undoubtedly play a pivotal role in shaping the future of aviation maintenance and operations.

The following steps outline the flow of data and their interaction with both AI algorithms and blockchain technology.

1 step. Data Collection and Validation.

- Sensor data are collected from various aircraft systems.
- Edge computing devices perform initial data validation and compression.
- Valid data points are packaged into transactions.

2 step. Block Creation.

- Transactions are grouped into blocks.
- Each block includes a timestamp, a unique identifier, and a hash of the previous block.
- A consensus mechanism (proof of authority in our implementation) validates the block.

3 step. Data Storage and Distribution.

- Validated blocks are added to the blockchain.
- The updated blockchain is distributed across the network of participating nodes (airlines, manufacturers, MRO providers).

4 step. Smart Contract Execution.

- Predefined smart contracts automatically execute based on blockchain data.
- These contracts can trigger maintenance alerts, parts orders, or compliance reports.

5 step. Access Control and Privacy.

- A permissioned blockchain structure ensures that only authorized parties can access sensitive data.
- Zero-knowledge proofs are used for data verification without revealing the underlying information.

6 step. Audit Trail.

- All transactions and smart contract executions are recorded, creating an immutable audit trail.
- This trail can be used for regulatory compliance and dispute resolution.

7 step. Data Retrieval and Analysis.

- Authorized users can query the blockchain for historical data.
- AI algorithms can access this data for training and prediction tasks.

This workflow ensures that all data in the AHMS are securely managed, validated, and accessible while maintaining the highest standards of data integrity and privacy.

3.5. Analytics in Advanced Health Monitoring Systems

Analytics in the context of AHMS and aircraft intelligent systems encompasses a broad spectrum of methodologies and techniques, ranging from basic statistical analysis to cutting-edge artificial intelligence and machine learning algorithms. These analytical approaches are applied to diverse data streams generated by an array of sensors, operational logs, maintenance records, and environmental inputs, creating a comprehensive picture of an aircraft's health, performance, and potential future states.

The primary goal of analytics in this domain is to shift the paradigm from reactive to proactive maintenance and operational strategies.

The application of analytics in AHMS and aircraft intelligent systems can be categorized into several key areas (Figure 7).

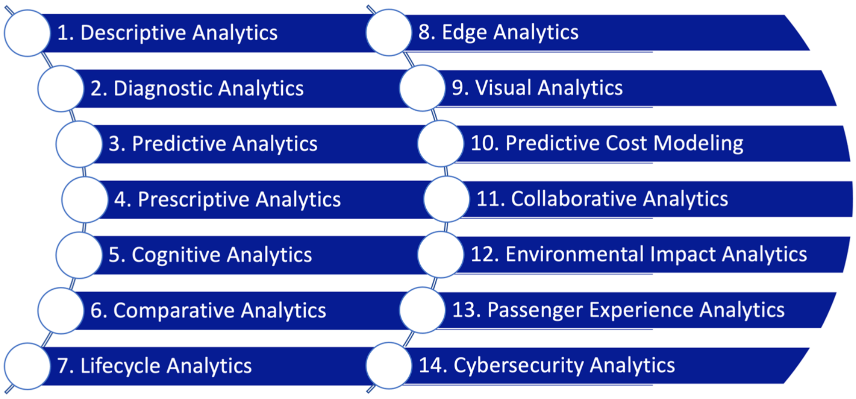

Figure 7. Analytics in advanced health monitoring systems.

At the heart of AHMS is descriptive analytics, which encompasses real-time monitoring, historical data analysis, performance metrics tracking, and condition reporting. Real-time monitoring continuously collects and analyzes data from various aircraft sensors, enabling immediate detection of abnormalities and ensuring optimal functioning of aircraft systems. Historical data analysis provides insights into long-term trends and patterns, helping to identify recurring issues and informing maintenance strategies. Performance metrics tracking involves monitoring key indicators such as engine efficiency, fuel consumption, and system reliability, while condition reporting generates comprehensive reports on the current state of the aircraft, detailing health status, recent maintenance actions, and any detected issues.

Diagnostic analytics plays a crucial role in fault detection, root cause analysis, anomaly detection, and pattern recognition. Fault detection identifies when and where faults occurred, enabling timely interventions. Root cause analysis delves deeper into these faults to determine their underlying causes, preventing future occurrences and improving maintenance strategies. Anomaly detection spots deviations from normal operating conditions, indicating potential problems that need preemptive attention. Pattern recognition helps diagnose problems more accurately and efficiently by identifying patterns in data indicative of specific faults or performance issues.

Predictive analytics, a cornerstone of future AHMS, involves failure prediction, remaining useful life estimation, performance degradation forecasting, and maintenance need prediction. By using historical and real-time data, predictive analytics forecasts potential failures, allowing maintenance teams to address issues before they lead to system breakdowns. Estimating the remaining useful life of components helps in planning maintenance activities, ensuring timely replacements. Forecasting performance degradation predicts how and when the performance of aircraft systems will decline, aiding in maintenance scheduling to restore optimal performance. Predicting maintenance needs ensures actions are performed based on actual conditions, optimizing resource use and reducing costs.

Prescriptive analytics enhances maintenance scheduling optimization, resource allocation recommendations, performance optimization suggestions, and risk mitigation strategies. It provides recommendations for optimizing maintenance schedules, minimizing operational disruptions while maintaining safety standards. By optimizing resource allocation, it ensures the right tools, parts, and personnel are available, reducing downtime and enhancing efficiency. Prescriptive analytics also offers suggestions for optimizing aircraft performance, such as adjusting operational parameters or upgrading components, and develops strategies to mitigate risks associated with aircraft operations and maintenance.

Cognitive analytics employs advanced techniques such as natural language processing (NLP), machine learning-based decision support, automated problem-solving, and context-aware analysis. NLP analyzes maintenance logs to extract valuable insights from textual data, identifying common issues and improving documentation. Machine learning algorithms provide decision support by analyzing data and suggesting optimal actions, enhancing the decision-making process. Automated problem-solving uses AI to diagnose and suggest solutions to detected issues, reducing reliance on human expertise, while context-aware analysis considers the operational context of the aircraft, ensuring relevant insights and recommendations.

Comparative analytics includes fleet-wide performance benchmarking, cross-aircraft type analysis, historical versus current performance comparison, and maintenance strategy effectiveness comparison. Benchmarking performance across the fleet identifies outliers and sets performance standards. Cross-aircraft type analysis helps understand performance differences, optimizing maintenance strategies. Comparing historical and current performance data identifies trends and improvements over time, assessing the effectiveness of maintenance actions. Comparing different maintenance strategies highlights the most effective approaches, improving overall practices.

Lifecycle analytics tracks cradle-to-grave performance, conducts lifecycle cost analysis, performs long-term trend analysis, and predicts and plans for end-of-life. It monitors performance from installation to end-of-life, ensuring optimal use and timely replacements. Lifecycle cost analysis optimizes budgets and reduces total ownership costs. Long-term trend analysis identifies trends affecting performance and maintenance needs over extended periods, aiding strategic planning. Predicting end-of-life ensures that aircraft systems remain reliable and safe.

Edge analytics processes data on-board the aircraft in real time, optimizing in-flight performance, detecting anomalies immediately, and preprocessing local data. Real-time processing allows for immediate responses to issues. Optimizing in-flight performance adjusts operational parameters based on real-time data. Immediate anomaly detection and response reduce the risk of in-flight failures. Local data preprocessing reduces the data transmitted to central servers, improving efficiency and reducing latency.

Visual analytics uses interactive dashboards, 3D visualization, augmented reality, and real-time performance visualization to present data effectively. Interactive dashboards provide real-time aircraft health data visualization, and 3D visualization aids in understanding spatial relationships and conditions of aircraft systems. Augmented reality assists maintenance personnel by overlaying digital information on physical components, improving accuracy and efficiency. Real-time performance visualization offers immediate insights into aircraft health, facilitating quick decision-making.

Predictive cost modeling forecasts maintenance and operational costs, analyzes ROI for maintenance strategies, and optimizes lifecycle costs. It helps in budget planning and optimization by forecasting maintenance costs. Predicting operational costs estimates expenses related to aircraft operations, aiding financial planning. ROI analysis for different maintenance strategies identifies the most cost-effective approaches. Lifecycle cost optimization ensures efficient resource use throughout the lifespan of aircraft components, reducing overall expenses.

Collaborative analytics enhances cross-airline data sharing and analysis, manufacturer–operator collaborative insights, global fleet performance analysis, and regulatory compliance analytics. Cross-airline data sharing allows airlines to benchmark their performance against peers and learn from each other's experiences. Manufacturer–operator collaboration ensures that insights from operational data are used to improve aircraft design and maintenance practices. Global fleet performance analysis aggregates data from multiple airlines to identify broader trends and insights. Regulatory compliance analytics ensures that all operations meet industry standards and regulations.

Environmental impact analytics focuses on emissions tracking and prediction, fuel efficiency optimization, noise pollution analysis, and sustainable operations planning. Tracking emissions helps airlines monitor their environmental footprint and comply with regulations. Fuel efficiency optimization identifies ways to reduce fuel consumption, benefiting both the environment and operational costs. Noise pollution analysis ensures that aircraft operations minimize noise impact on surrounding communities. Sustainable operations planning integrates environmental considerations into all aspects of aircraft operations and maintenance.

Passenger experience analytics enhances cabin environment optimization, ride comfort prediction and enhancement, in-flight service optimization, and correlating passenger satisfaction with aircraft health. Optimizing the cabin environment ensures passenger comfort and safety. Predicting and enhancing ride comfort addresses factors such as turbulence and vibration. In-flight service optimization uses data to improve services offered to passengers. Correlating passenger satisfaction with aircraft health provides insights into how maintenance and operational practices impact the passenger experience.

Cybersecurity analytics focuses on threat detection and prevention, data integrity verification, access pattern analysis, and resilience testing and enhancement. Detecting and preventing cybersecurity threats ensures the safety of onboard systems and data. Data integrity verification ensures that all collected and transmitted data are accurate and untampered. Access pattern analysis identifies unusual access patterns that may indicate security breaches. Resilience testing ensures that the system can withstand and quickly recover from cyberattacks.

The integration of advanced analytics into future aviation health monitoring systems promises to transform the aviation industry. By using a wide range of analytical approaches, AHMS can enhance safety, optimize maintenance schedules, reduce costs, and improve overall operational efficiency. This comprehensive framework for understanding the diverse applications and benefits of analytics in AHMS highlights the critical role these technologies will play in shaping the future of aircraft maintenance and operations.

The integration of these analytical approaches within AHMS and aircraft intelligent systems offers numerous benefits. It enables predictive maintenance strategies that reduce unscheduled downtime and extend the operational life of aircraft components. Real-time performance optimization enhances fuel efficiency and reduces environmental impact, improved safety through early detection of potential issues, and more informed decision-making at all levels of aircraft operation and management.

However, the implementation of advanced analytics in aviation also presents challenges. These include the need for robust data management systems to handle the vast amounts of data generated, ensuring data quality and consistency across diverse sources, and navigating the complex regulatory landscape of the aviation industry. Additionally, there is an ongoing need for skilled professionals who can develop, implement, and interpret these analytical systems effectively.

As we look to the future, the role of analytics in AHMS and aircraft intelligent systems is set to expand further. Emerging technologies such as quantum computing, advanced AI, and augmented reality promise to push the boundaries of what is possible in aircraft health monitoring and intelligent operations. The continued evolution of these analytical capabilities will play a crucial role in shaping the future of aviation, driving towards ever-higher levels of safety, efficiency, and performance.

4. Discussion

4.1. Comparative Analysis of Advanced AHMS with Existing Systems

To contextualize the proposed AHMS based on AI, blockchain, and advanced analytics, it is essential to compare its capabilities and features with the existing health monitoring systems that are currently employed in the aviation industry.

Several well-established health monitoring systems are currently in use within the aviation industry. The paper [48] presents a structured analysis of the management of system failures in modern transport aircraft. The authors review current AHMS used by various aircraft manufacturers, including Boeing 787, Airbus A380, Embraer ERJ 170/190, Bombardier C-Series, and Gulfstream G500. This paper highlights AHMS complexity, it also explores how they can form the foundation for future autonomous decision-support systems. Some additional information can be obtained at the website of AHMS producers, for example:

- PlaneView (Gulfstream and Honeywell) [49] focuses on delivering real-time health data from aircraft systems and offers some predictive capabilities. However, it largely relies on pre-defined thresholds and fails to fully leverage AI-driven predictive maintenance.
- Electronic Centralized Aircraft Monitor by Airbus [50] provides real-time alerts and displays system health information to pilots, facilitating reactive maintenance. While highly effective for immediate in-flight diagnostics, its ability to predict and prevent failures before they occur is limited.
- Engine Indicating and Crew Alerting System by Boeing [51] monitors engine and system performance, alerting the crew when faults occur. Similar to the Airbus system, it is excellent for real-time monitoring, but lacks advanced predictive capabilities that can help prevent faults before they escalate into significant issues.

These systems are primarily reactive, providing real-time alerts once a failure is detected. Their focus is on the immediate identification of issues that already occurred, and they rely on pre-configured rules to flag anomalies. As such, these systems are effective in detecting visible failures but offer limited insights into hidden or emerging defects that could be identified and addressed earlier.

In contrast to these traditional systems, the proposed AHMS integrates AI and blockchain technologies to address both visible and hidden defects within aircraft systems. Below is a more detailed comparison between the proposed system and existing solutions:

- The proposed system uses AI algorithms, including machine learning and deep learning models, to predict when and where failures are likely to occur. By analyzing historical and real-time data, the system can detect patterns that signify early stages of failure, which would remain unnoticed by traditional systems relying solely on rule-based approaches. This offers a clear advantage in terms of preventing faults rather than reacting to them after the fact.
- While traditional systems are often limited to a single aircraft or fleet, the proposed system uses federated learning techniques, allowing the sharing of insights across multiple aircraft without compromising data privacy. This enables a global approach to fleet-wide health management, offering improved diagnostics by learning from the operational history of multiple aircraft types and systems. Traditional systems do not offer this level of collaboration, often resulting in fragmented insights across fleets.
- One of the key differentiators of the proposed system is its use of blockchain technology to ensure the security and integrity of aircraft health data. Blockchain provides a decentralized and tamper-proof ledger for storing and sharing maintenance records. This ensures that all stakeholders (including airlines, manufacturers, and regulators) have access to transparent and immutable data regarding aircraft maintenance histories. Existing systems typically rely on centralized databases, which are vulnerable to tampering or unauthorized access.

- Traditional monitoring systems are designed primarily for small-scale operations, often focusing on single aircraft or individual fleets. The proposed AHMS is scalable and designed to function across entire fleets or even industry-wide, by using AI-driven insights and decentralized data sharing via blockchain. This makes it suitable for both small operators and large commercial airlines, providing the flexibility required to scale according to operational needs.
- By predicting failures before they happen and optimizing maintenance schedules, the proposed AHMS reduces the frequency and severity of unplanned downtime. This is a significant improvement over existing systems, which are primarily reactive and result in more frequent unplanned maintenance activities, leading to operational inefficiencies and higher costs.

Table 2 provides a comparison of key features across current AHMS technologies and the proposed system.

Table 2. Comparative Analysis of AHMS Technologies.

Feature	Traditional Systems	AI and Blockchain-Based AHMS
Maintenance Approach	Reactive, fault-based	Predictive, data-driven
Data Processing	Rule-based diagnostics	AI-powered analytics and learning
Data Sharing	Centralized databases	Decentralized, blockchain-based
Fleet-wide Insights	Isolated per aircraft	Collaborative, fleet-wide via federated learning
Failure Detection	Detects visible, present failures	Detects both visible and hidden failures
Security	Prone to data tampering	Blockchain-secured, immutable records
Scalability	Limited to individual aircraft	Scalable to fleets and entire industries

4.2. Roadmap for AHMS Practical Implementation

In order to facilitate the adoption of the proposed AHMS, it is crucial to provide a clear, step-by-step roadmap for its practical implementation. The roadmap in Table 3 highlights the key phases required to ensure smooth integration, scalability, and widespread adoption of AI and blockchain-based monitoring systems within the aviation industry. This table breaks down each phase of the implementation roadmap into key objectives, activities, and expected outcomes, making the roadmap easier to follow and understand.

Table 3. Roadmap for practical implementation of advanced AHMS.

Phase	Key Objectives	Key Activities	Expected Outcomes
Phase 1. Pilot Programs and Initial Integration	- Launch pilot projects with select airlines and manufacturers. - Test AI and blockchain integration with existing systems. - Ensure regulatory compliance.	- Integrate AI algorithms with real-time health data from aircraft sensors. - Implement blockchain infrastructure for secure data management. - Provide user training.	- Successful pilot projects demonstrating system feasibility. - Initial AI models deployed for predictive analytics. - Regulatory approval.
Phase 2. Data Collection, Model Refinement, and System Optimization	- Collect real-world data from pilots. - Refine AI models for enhanced predictive accuracy. - Expand blockchain infrastructure for secure data sharing.	- Gather large-scale operational data from aircraft sensors. - Refine machine learning algorithms. - Implement federated learning for privacy-preserving model training. - Scale blockchain infrastructure.	- Improved AI models for better failure detection. - Efficient blockchain system for multi-stakeholder data sharing. - Enhanced system optimization.

Table 3. *Cont.*

Phase	Key Objectives	Key Activities	Expected Outcomes
Phase 3. Industry-wide Integration and Scaling Across Fleets	- Scale the AHMS across entire fleets. - Ensure system interoperability with various platforms. - Establish industry standards for data sharing and interoperability.	- Deploy AHMS to monitor health data for large fleets. - Collaborate with industry stakeholders to standardize protocols and data formats. - Ensure compatibility across platforms.	- AHMS fully scaled for fleet-wide use. - Standardized data-sharing protocols. - Seamless integration with multiple aircraft types.
Phase 4. Continuous Improvement, Feedback Loop, and Evolution	- Establish continuous feedback loops for system improvement. - Incorporate technological advancements to keep the system updated. - Address operational challenges.	- Gather feedback from users and refine AI models based on real-world performance. - Regularly upgrade AI and blockchain infrastructure. - Monitor performance with KPIs and resolve issues.	- Continuously optimized AHMS. - Regular updates of AI models with increased accuracy. - Enhanced system performance and user satisfaction.

4.3. Scalability and Applicability of the Advanced AHMS

The advanced AHMS, which integrates AI and blockchain technology, is designed to be both scalable and highly applicable across a wide variety of aircraft types, operational environments, and fleet sizes.

One of the most significant strengths of the proposed AHMS is its ability to scale from small, individual implementations to large, multi-fleet deployments. The architecture of the system, leveraging AI and blockchain, allows for seamless scaling without compromising performance, data integrity, or security.

The blockchain technology underpinning the AHMS provides a decentralized data infrastructure, which is crucial for scalability. Traditional centralized systems often face bottlenecks as they expand, leading to slower performance, data overload, and security vulnerabilities. In contrast, the blockchain in the proposed system distributes data across multiple nodes, enabling the AHMS to handle increasing amounts of data as the number of monitored aircraft grows. The decentralized nature of blockchain also ensures that as new stakeholders—such as additional airlines, third-party maintenance teams, and regulatory bodies—join the network, the system can continue to function efficiently without creating single points of failure or security risks.

AI-driven data processing of the system is designed to process large volumes of real-time data from aircraft sensors, including engine health, hydraulic system performance, and flight control parameters. As the system scales to monitor more aircrafts, its AI algorithms can be adjusted to accommodate the increased data flow. Machine learning models can continuously be retrained on new data from various aircraft types and operational environments, ensuring that the system's predictive accuracy improves as it scales.

Federated learning for privacy-preserving scalability allows the AI models to be trained on data from multiple sources (i.e., different fleets or airlines) without requiring centralized data sharing. Instead of aggregating raw data, federated learning shares model updates, ensuring that sensitive operational data remain localized while still benefiting from insights drawn from the entire network. This enables scalability across fleets while maintaining compliance with privacy regulations and industry-specific data protection standards.

Cloud and edge computing are directly oriented on scalability. Cloud computing allows the system to store vast amounts of historical data and run complex AI algorithms at scale. Meanwhile, edge computing enables real-time data processing closer to the aircraft, ensuring that critical health data are analyzed instantly without the need for constant cloud connectivity. This hybrid approach ensures that the system can scale to monitor numerous aircraft without sacrificing performance or operational efficiency.

The modular design of the AHMS means that it can be scaled to fit operators with varying fleet sizes. For smaller airlines with a limited number of aircrafts, the system can be deployed at a minimal cost, focusing on key performance indicators for specific components. As the fleet grows, additional modules can be integrated to expand the system's monitoring capabilities, ensuring a cost-effective solution for operators of all sizes. The system's scalability ensures that even large commercial airlines, with hundreds of aircrafts, can benefit from the same predictive maintenance and data security features without performance degradation.

The AHMS is not limited to a specific type of aircraft or operational environment, making it highly applicable across a broad spectrum of aviation sectors.

The proposed AHMS can be applied to a wide range of aircrafts, from commercial airliners and cargo planes to private jets and military aircrafts. This makes the system highly adaptable to both domestic and international airlines that operate in diverse climates and regions, ensuring that it remains effective in different operational contexts.

Different regions and countries often have their own aviation safety regulations and maintenance standards, enforced by agencies such as the FAA, EASA, and ICAO. The proposed AHMS can be customized to ensure compliance with these varying regulatory requirements. The blockchain infrastructure can be tailored to meet specific data privacy and security laws, while the AI algorithms can be adjusted to prioritize the key maintenance indicators required by different regulatory bodies. This ensures that the system is applicable in diverse regulatory environments without compromising safety or compliance.

In addition to airlines and aircraft operators, the proposed AHMS is applicable to third-party MRO organizations. MROs play a critical role in ensuring the airworthiness of aircrafts through regular inspections and maintenance. By integrating the AHMS into their workflows, MROs can use AI-driven insights to prioritize maintenance tasks, identify potential failure points in advance, and optimize resource allocation. The blockchain component ensures transparency in maintenance records, providing MROs with verifiable data on the health of aircrafts they service.

4.4. Shift from Monitoring of Aviation Health Monitoring to Aviation Health Management

As technology continues to advance rapidly, the role of AHMS is evolving from simple monitoring to comprehensive management of aircraft health. This shift from monitoring to management signifies a transformative approach that integrates predictive and prescriptive analytics, real-time data processing, and advanced decision-making capabilities. The transition from monitoring to management presents numerous opportunities and benefits, enhancing safety, efficiency, and operational effectiveness. Table 4 highlights the key differences between aviation health monitoring and aviation health management, demonstrating how the shift to a more comprehensive management approach can lead to significant improvements in safety, efficiency, and overall operational effectiveness.

Traditionally, AHMS focused on monitoring the health status of aircraft components through continuous data collection and real-time reporting. This approach involves using sensors to gather information on parameters such as engine performance, structural integrity, and environmental conditions. The primary goal is to detect anomalies and faults as they occur, enabling timely interventions to maintain aircraft safety and reliability. However, the future of AHMS lies in transitioning from this reactive monitoring approach to a proactive and holistic management strategy. Aviation health management encompasses not only the detection of issues, but also the prediction, prevention, and optimization of maintenance and operational processes. This shift is driven by advancements in data analytics, machine learning, and AI, which provide the tools necessary for a more integrated and intelligent system.

Predictive and prescriptive analytics play a crucial role in this new paradigm. Predictive analytics uses historical and real-time data to forecast potential failures and maintenance needs. By identifying patterns and trends that precede equipment failures, predictive models enable proactive maintenance planning. Prescriptive analytics goes a step further by recommending specific actions to mitigate risks and optimize performance. This includes maintenance scheduling, resource allocation, and operational adjustments, ensuring that interventions are timely and effective.

Table 4. Comparative analysis of aviation health monitoring and aviation health management.

Aspect	Aviation Health Monitoring	Aviation Health Management
Approach	Reactive	Proactive
Primary Goal	Detection of anomalies and faults	Prediction, prevention, and optimization of maintenance and operations
Data Collection	Continuous, real-time data collection	Continuous, real-time data collection and integration with operational data
Data Processing	Centralized	Decentralized (edge computing for real-time processing)
Analytics Used	Descriptive and diagnostic analytics	Predictive, prescriptive, cognitive, collaborative, environmental impact, passenger experience, cybersecurity, comparative, lifecycle, and edge analytics
Response Time	Detection-based, slower response	Immediate, real-time response due to edge computing
Maintenance Strategy	Based on fixed intervals or detected issues	Data-driven, condition-based, and optimized maintenance schedules
Resource Allocation	Generalized and less optimized	Optimized and efficient allocation of resources
Predictive Capabilities	Limited	Advanced predictive analytics for failure prediction and remaining useful life estimation
Decision Support	Manual and semi-automated	Automated, AI-driven decision support
Integration with Operations	Limited	Full integration with flight and operational data
Safety Enhancement	Fault detection and anomaly alerts	Early detection, prediction, and proactive mitigation of risks
Operational Efficiency	Monitors performance, but less optimization	Optimizes flight parameters, fuel efficiency, and operational effectiveness
Regulatory Compliance	Provides maintenance records for compliance	Detailed, transparent records facilitating easier compliance and audits
Environmental Impact	Indirectly addressed	Directly addressed through emissions tracking and fuel optimization
Passenger Experience	Minimal impact	Enhanced through cabin environment optimization and comfort analytics
Cybersecurity	Basic security measures	Advanced threat detection, data integrity verification, and resilience testing
Cost Implications	Potentially higher due to reactive maintenance and downtime	Lower costs through optimized maintenance and resource allocation
Training and Adoption	Standard training for monitoring systems	Requires advanced training and change management for adoption of new technologies and processes

The incorporation of edge computing allows for real-time data processing on-board the aircraft. This enables immediate analysis and response to detect issues, minimizing latency and enhancing decision-making speed. Real-time data processing ensures that any deviations from normal operating conditions are addressed promptly, reducing the risk of in-flight failures and improving overall safety. Machine learning and AI algorithms further enhance the accuracy and reliability of diagnostics and prognostics. These technologies can analyze vast amounts of data to detect subtle patterns and anomalies that might be missed by traditional methods. AI-powered decision support systems provide maintenance crews and operators with actionable insights, improving the efficiency and effectiveness of maintenance actions.

Aviation health management integrates maintenance and operational data, providing a comprehensive view of the aircraft's health. This holistic approach ensures that maintenance decisions are informed by operational conditions and vice versa. For instance, flight data can be used to optimize maintenance schedules, while maintenance records can inform operational adjustments to enhance performance and reduce wear and tear.

The shift from monitoring to management offers numerous benefits. Enhanced safety is achieved by proactively addressing potential issues before they escalate. Predictive analytics and real-time data processing enable early detection and intervention, significantly reducing the risk of in-flight failures. Increased efficiency and reduced costs result from proactive maintenance planning and optimized resource allocation, which reduce unnecessary maintenance actions and minimize aircraft downtime. This leads to significant cost savings for airlines and maintenance organizations. Additionally, efficient maintenance practices extend the lifespan of aircraft components, further reducing costs.

Improved operational effectiveness is another key benefit. Integrating health management with operational data allows for better decision-making and performance optimization. Real-time insights enable operators to adjust flight parameters to improve fuel efficiency, reduce emissions, and enhance passenger comfort. This holistic approach ensures that aircrafts operate at peak efficiency, benefiting both airlines and passengers. Regulatory compliance and auditability are also enhanced, as aviation health management systems provide detailed records of maintenance actions, health status, and operational metrics. This transparency facilitates regulatory compliance and simplifies audits, ensuring that all operations meet industry standards and regulations.

Sustainability and environmental impact are critical considerations in modern aviation. By optimizing fuel efficiency and reducing unnecessary maintenance flights, aviation health management contributes to environmental sustainability. Emissions tracking and fuel optimization analytics help airlines reduce their carbon footprint, aligning with global sustainability goals.

While the transition to aviation health management offers numerous benefits, it also presents challenges that must be addressed. Integrating data from various sources, including sensors, maintenance records, and operational systems, requires robust data management and interoperability standards. Ensuring that these systems can communicate seamlessly is critical for effective health management.

4.5. Development of Iceberg Model as a Framework for Integrated AHMS

To comprehend the profound implications of transformation in aircraft health monitoring systems, we turn to an evolved version of the iceberg model, one that not only represents the depth of monitoring capabilities, but also the unique shape and lifecycle of each aircraft's health profile.

In this new paradigm, the iceberg model transcends its initial role. It now serves as a dynamic, multidimensional representation of an aircraft's digital twin, focused on reliability and health. Each iceberg in this model is as unique as the aircraft it represents, shaped by design specifics, operational history, and environmental factors (Figure 8).

At the visible tip of our iceberg lie the conventional monitoring systems: the reactive measures that respond to apparent issues. But it is beneath the surface where the true revolution unfolds. As we descend, we encounter layers of increasingly sophisticated technologies that not only monitor but predict and prevent potential failures.

To mathematically describe the possibility of using the iceberg shape as a metaphor for illustrating the evolution of AHMS, we can define the iceberg's shape as representing different levels of system awareness and failure prevention, corresponding to the visible and hidden parts of the iceberg.

Let us define the iceberg's visible portion as representing known and easily detectable issues, and the submerged portion as representing hidden or complex issues that are harder to detect but critical for the health of the aircraft.

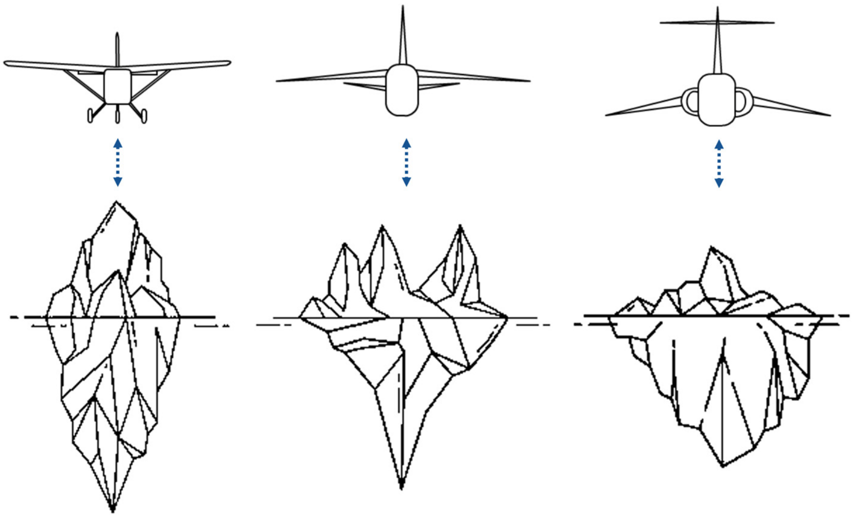

Figure 8. Iceberg model as analog of digital twin for aircraft reliability.

Assume the iceberg shape can be represented using a simple geometric model: the visible portion above the waterline represents reactive and obvious issues, which traditional monitoring systems can detect, and the submerged portion below the waterline represents potential future failures and early warning signs, only detectable with advanced AI-based and blockchain-integrated AHMS.

Let h_{total} represent the total height of the iceberg, $h_{visible}$ represent the portion of the iceberg above the surface (visible issues), and h_{hidden} represent the submerged part (hidden risks):

$$h_{total} = h_{visible} + h_{hidden}. \quad (1)$$

Let us denote ω_v as proportion of visible failures (or issues) that can be detected with traditional or basic monitoring systems, and ω_h represents the portion of issues that remain hidden without advanced diagnostic capabilities:

$$h_{visible} = \omega_v \times h_{total}; \quad h_{hidden} = \omega_h \times h_{total}\ . \quad (2)$$

These variables can be determined through:

- Analyzing historical maintenance and failure data can help identify the proportion of issues that are typically visible versus hidden.
- Subject matter experts can assess the complexity of specific aviation systems and estimate the proportion of visible versus hidden failures.
- Running simulations or real-world experiments on systems under varying diagnostic conditions can help refine these values.

Methods for determining these variables are described in known literature. For example, the book [52] discusses best practices for condition-based maintenance and how different monitoring techniques reveal varying proportions of detectable versus undetectable failures across industries, including aviation. The authors of book [53] explore how failures in engineering systems can be categorized into visible and hidden types, and how predictive maintenance technologies shift these ratios by improving early detection of failures. The paper [54] evaluates the application of condition-based maintenance in aviation, focusing on identifying challenges, limitations, and potential solutions for its wider adoption.

Define the probability of detecting system risks as a function of the depth of the defect within the iceberg. Let $P_{detection}(d)$ be the detection probability, where d is the relative depth below the waterline. When $d = 0$, the defect is at the surface (fully visible), when $d = 1$, the defect is at the deepest point (fully hidden). A simple detection probability function might be inversely proportional to the depth $0 \leq d \leq 1$:

$$P_{detection}(d) = 1 - d\ . \tag{3}$$

Thus, for surface-level defects (visible failures), the detection probability is near 1. For deeper, hidden defects, the detection probability decreases, illustrating the challenge of identifying hidden system faults without advanced technologies.

Let the severity of a defect or failure increase as it progresses deeper into the iceberg. Denote the severity of failure as $S(d)$:

$$S(d) = \alpha + \beta d\ \ , \tag{4}$$

where α is the base severity of a visible defect (at $d = 0$) and β represents the rate at which severity increases with depth. As defects go deeper into the hidden portion of the iceberg (with lower detection probability), the severity $S(d)$ increases, which illustrates the growing risk if hidden issues remain undetected.

To integrate this iceberg model with AHMS, let the capability of the system to monitor and detect hidden failures be represented by an advanced detection probability function $P_{advanced}(d)$, which depends on the level of technology (such as AI or blockchain integration):

$$P_{advanced}(d) = \gamma\left(1 - d^k\right)\ \ , \tag{5}$$

where $\gamma \in (0, 1]$ represents the effectiveness of the AHMS, k represents the sophistication of the monitoring system.

For $k > 1$, the system is more capable of detecting deeper, more hidden risks. For $k = 1$, the detection capability is linear, while for $k < 1$, the detection of deep defects is weak, resembling basic monitoring systems.

The overall reliability R of the aircraft system can be modeled as a function of how well-hidden defects are detected and mitigated by the AHMS. This can be expressed as the product of detection probability and the inverse of failure severity:

$$R(d) = P_{advanced}(d) \cdot \frac{1}{S(d)}\ . \tag{6}$$

Substituting into the (6) the expressions from (4) and (5), we obtain:

$$R(d) = \gamma\left(1 - d^k\right) \cdot \frac{1}{\alpha + \beta d}. \tag{7}$$

This equation models the system's reliability based on both the depth of potential defects and the effectiveness of the AHMS in detecting and addressing these defects.

To optimize the system's reliability, AHMS must be configured to maximize $R(d)$ across all possible defect depths $d \in [0,\ 1]$. The optimal performance of the AHMS can be achieved by increasing γ (the effectiveness of the system) and k (the capability to detect hidden failures) while minimizing the severity parameter β.

The objective is to minimize the total cost $C(T)$ over a time horizon T, which includes costs related to inspections, maintenance actions, downtime, and failures. Simultaneously, the system's reliability $R(d)$ should be maximized, which depends on the ability to detect and prevent failures.

The optimization problem can be defined as:

$$\min_{A(T)} C(T) = C_{ins}(T) + C_{main}(T) + C_{downtime}(T) + C_{failure}(T)\ , \tag{8}$$

where $C_{ins}(T)$ is the cost of inspections and monitoring over time T, $C_{main}(T)$ is the cost of performing maintenance (preventive or corrective), $C_{downtime}(T)$ is the cost due to operational downtime caused by maintenance or failures, $C_{failure}(T)$ is the cost associated with system failures, including repair or replacement, and $A(T)$ represents the set of actions (inspection, maintenance scheduling) over time TTT to minimize cost while ensuring system reliability and detection efficiency.

The objective is subject to maintaining system reliability and ensuring effective detection of failures.

The reliability of the system $R(d)$ is a function of the detection probability $P_{advanced}(d)$ and the severity of potential hidden failures $S(d)$. We aim to keep system reliability above a certain threshold R_{min} to ensure operational safety.

$$R(d) = P_{advanced}(d) \cdot \frac{1}{S(d)} \geq R_{min} \tag{9}$$

The total cost of AHMS maintenance and operation must stay within a predefined budget B:

$$C(T) \leq B. \tag{10}$$

The final optimization problem can be written as:

$$\min_{A(T)} C(T). \tag{11}$$

Subject to:

$$R(d) = \gamma\left(1 - d^k\right) \cdot \frac{1}{\alpha + \beta d} \geq R_{min} \ , \qquad C(T) \leq B. \tag{12}$$

The optimization of AHMS is a balancing act between minimizing operational and maintenance costs while ensuring that the system remains reliable and that potential failures are detected early. This formulation allows the system to adapt to different types of aviation systems, providing flexibility in adjusting detection capabilities and cost management.

The advent of federated learning and 6G technologies marks a quantum leap in our ability to understand and manage aircraft health. These technologies allow us to dive deeper into the iceberg than ever before, uncovering insights that were previously hidden from view. Federated learning enables shared insights across entire fleets and even between different airlines, all while maintaining strict data privacy. This collaborative approach creates a vast, interconnected network of knowledge, enhancing our predictive capabilities exponentially.

The implementation of 6G networks brings unprecedented speed and bandwidth to data transmission. This allows for real-time analysis of massive datasets, transforming the way we process and react to information.

But the true power of this new model lies in its ability to not just monitor, but to shape the very formation of the iceberg itself. Advanced materials with built-in sensing capabilities act as the building blocks of our iceberg, providing constant, real-time structural health monitoring. Blockchain technology ensures the integrity of maintenance records, creating an unalterable history of each aircraft's lifecycle.

Swarm intelligence takes this concept further, enabling collaborative diagnostics across multiple aircrafts. This interconnected approach allows for a more holistic understanding of fleet health, identifying patterns and potential issues that might be missed when looking at an aircraft in isolation.

The shape of each iceberg in this model is not static but evolves over time. It reflects the individual journey of each aircraft from design to retirement. By analyzing global fleet data, we can predict how new designs will perform over decades, tailoring maintenance schedules and operational parameters to optimize performance and longevity.

This individualized approach extends to real-time adaptations. For instance, the real environment of aircraft operation can be used to dynamically adjust maintenance schedules, accounting for the unique stresses each aircraft encounters in its specific operational environment.

In essence, this evolved iceberg model represents a paradigm shift in AHMS. We are no longer merely observers of aircraft health, reacting to issues as they arise. Instead, we become shapers of aircraft reliability, actively influencing the formation and evolution of each unique iceberg throughout its lifecycle.

This new model empowers us to not only predict failures before they occur, but to create conditions that prevent their very inception. It is a proactive, holistic approach that considers every factor, from global weather patterns to microscopic material stresses, in maintaining and optimizing aircraft health.

As we delve deeper into this model, we will explore how each layer of technology contributes to this comprehensive view of aircraft health. We will see how the integration of these advanced systems is reshaping not just maintenance practices, but the very way we conceive of aircraft reliability and performance.

The future of aviation health monitoring, as represented by this evolved iceberg model, is not just about seeing deeper beneath the surface; it is about understanding and shaping the unique profile of each aircraft's health journey, from the moment of design to the day of retirement. This is the new frontier of AHMS—a world where each aircraft's digital twin iceberg tells its own story, and where we have the tools to ensure that story is one of optimal performance, safety, and longevity.

4.6. The Iceberg Model as a Powerful Framework for Understanding and Advancing AHMS

The iceberg model, while a simplification of complex systems, offers significant utility in conceptualizing and advancing AHMS. Its value lies not just in its visual appeal, but in its ability to communicate complex ideas, guide strategic thinking, and foster innovation in the field of aviation safety and maintenance.

The iceberg model provides a clear, intuitive framework for understanding the layers of complexity in AHMS. By visually representing visible and hidden aspects of aircraft health, it helps stakeholders, from engineers to executives, grasp the full scope of monitoring needs and capabilities. This shared understanding facilitates better communication and alignment across different teams and disciplines involved in aircraft maintenance and safety.

The model naturally stratifies technologies and approaches based on their depth of insight. This stratification helps in categorizing existing technologies and identifying gaps where new solutions are needed. For instance, it clearly distinguishes between reactive measures (at the tip) and deep predictive analytics (at the base), guiding resource allocation and research priorities.

As an educational tool, the iceberg model excels in introducing new personnel to the complexities of AHMS. It provides a memorable, visual representation that can be easily grasped and expanded upon, making it valuable in training programs and academic settings.

For strategic planners, the model serves as a roadmap for future developments. By visualizing the progression from surface-level monitoring to deep, predictive analytics, it helps in planning long-term technological investments and research directions. It encourages thinking about not just current capabilities, but future possibilities in aircraft health monitoring.

The model aids in comprehensive risk assessment by highlighting that the most significant risks often lie beneath the surface. This perspective encourages a more thorough approach to risk management, pushing stakeholders to consider hidden or emerging risks that might be overlooked in traditional assessments.

By illustrating the vast, unexplored depths of potential monitoring capabilities, the iceberg model serves as a catalyst for innovation. It challenges engineers and researchers to think beyond current limitations and explore new technologies that can delve deeper into understanding aircraft health.

The model promotes a holistic view of aircraft health, emphasizing the interconnectedness of various systems and factors. This perspective is crucial in developing integrated AHMS that consider multiple data sources and their complex interactions.

As new technologies emerge, they can be easily incorporated into the existing framework of the iceberg model. This adaptability ensures the model remains relevant and useful as the field of AHMS evolves.

For communicating with non-technical stakeholders such as airline executives or regulatory bodies, the iceberg model provides an accessible way to explain the importance of investing in advanced AHMS technologies. It visually justifies the need for sophisticated (and often costly) monitoring systems by illustrating the depth of potential issues that can be addressed.

The model can serve as a benchmark for assessing the capability of different AHMS. By mapping a system's features to different levels of the iceberg, one can quickly gauge its depth of insight and predictive power. While developed for aviation, the principles of the iceberg model can be applied to health monitoring systems in other industries, fostering cross-sector learning and innovation.

The iceberg model, despite its simplicity, proves to be a versatile and powerful tool in the realm of AHMS. By providing a clear, adaptable framework for understanding the depths of aircraft health monitoring, it continues to play a crucial role in advancing aviation safety and efficiency. As AHMS technologies evolve, the iceberg model remains a valuable conceptual tool, guiding the industry towards more comprehensive, predictive, and integrated approaches to aircraft maintenance and safety.

4.7. Mathematical Interpretation of the Iceberg Model for AHMS

The iceberg model can be mathematically described as a framework for aviation health monitoring systems by representing the different stages of defect progression and their detection, prediction, and prescriptive maintenance actions.

Let us define the state of an aircraft system at time t as $S(t)$. The state can be categorized into different stages based on the iceberg model:

- Hidden defect stage S_h—defects are not detectable.
- Potential failure detection stage S_p—defects are detectable using advanced monitoring.
- Beginning of degradation stage S_d—defects start to impact performance.
- Pre-failure condition stage S_{pf}—performance degradation is noticeable.
- Failure stage S_f—complete failure occurs.

The transitions between these stages can be described using, for example, a Markov chain, where the probability of transitioning from one state to another depends on the current state and time. Let us denote the transition probability from state S_i to state S_j at time t as $P_{ij}(t)$:

$$P_{ij}(t) = P\{S(t+1) = S_i | S(t) = S_i\}. \tag{13}$$

The detection probability functions $D_i(t)$ represent the likelihood of detecting a defect in each stage. These functions depend on the effectiveness of the monitoring techniques employed:

- $D_h(t)$—probability of detecting a hidden defect.
- $D_p(t)$—probability of detecting a potential failure.
- $D_d(t)$—probability of detecting degradation.
- $D_{pf}(t)$—probability of detecting a pre-failure condition.

Predictive models use historical and real-time data to estimate the remaining useful life (RUL) of components and predict transitions between stages. Let $RUL(t)$ be the remaining useful life at time t.

The predictive model can be expressed as:

$$RUL(t) = f\{X(t), \theta\}, \tag{14}$$

where $X(t)$ represents the set of features (sensor data, operational parameters, etc.) and θ represents the model parameters.

Prescriptive actions $A(t)$ are recommendations based on the current state and predictions to optimize maintenance and operations. These actions can be represented as a function of the current state $S(t)$ and predicted RUL:

$$A(t) = g\{S(t), RUL(t)\}. \tag{15}$$

The overall cost of maintenance and failures can be modeled to optimize the maintenance strategy. Let $C(t)$ be the cost function, which includes costs for inspections, maintenance, downtime, and failures:

$$C(t) = C_i(t) + C_m(t) + C_d(t) + C_f(t), \tag{16}$$

where

$C_i(t)$ is the cost of inspections and monitoring.
$C_m(t)$ is the cost of maintenance actions.
$C_d(t)$ is the cost associated with degradation (e.g., fuel efficiency loss).
$C_f(t)$ is the cost of failure (e.g., repairs, downtime).

The goal is to minimize the total expected cost over a planning horizon T, considering the transition probabilities, detection functions, predictive models, and prescriptive actions:

$$\min_{A(t)} \sum_{t=0}^{T} E[S(t)]. \tag{17}$$

Subject to:

$$\begin{gathered} P_{ij}(t) \quad \forall i, j, t \\ D_i(t) \quad \forall i, t \\ RUL(t) = f\{X(t), \theta\} \\ A(t) = g\{S(t), RU \\ L(t)\}. \end{gathered}$$

4.8. The Relationship between the Level of AHMS and Aircraft Maintenance

Aircraft maintenance is traditionally classified into several levels, each representing different approaches and sophistication. Table 5 provides a comparative analysis of different maintenance types across various aspects such as definition, goal, approach, cost, downtime, resource utilization, reliability, and sustainability.

The level of AHMS directly influences the progression from corrective to prescriptive maintenance. The more sophisticated the AHMS, the higher the level of maintenance achievable.

- Basic AHMS capabilities include real-time monitoring and simple diagnostics. These systems enable a shift from purely reactive (corrective) maintenance to preventive maintenance. By monitoring key parameters, AHMS can identify when components are approaching their service limits, allowing maintenance to be scheduled at optimal intervals. This reduces the risk of unexpected failures and improves overall aircraft reliability.
- With intermediate AHMS, the maintenance strategy evolves to CBM. These systems not only monitor but also analyze data to assess the health of components continuously. Maintenance actions are based on the actual condition of the aircraft rather than predetermined schedules. This reduces unnecessary maintenance actions, extends component life, and lowers costs. The correlation between AHMS and maintenance level becomes evident as the precision of health assessments improves with more advanced data analytics capabilities.
- Advanced AHMS incorporate predictive analytics and machine learning algorithms to forecast future component conditions and potential failures. These systems leverage historical data and real-time inputs to provide accurate predictions of when and

where maintenance will be needed. Predictive maintenance minimizes downtime and prevents failures by addressing issues before they become critical. The correlation here is clear: as AHMS sophistication increases, the ability to predict and prevent failures enhances, leading to more proactive maintenance strategies.

- State-of-the-art AHMS is the most sophisticated AHMS, which integrate diagnostics, prognostics, and prescriptive analytics. These systems not only predict failures, but also provide recommendations for optimal maintenance actions considering various factors such as operational schedules, resource availability, and environmental impacts. Prescriptive maintenance represents the pinnacle of maintenance efficiency and effectiveness, made possible by the highest level of AHMS. The system's recommendations help to schedule maintenance activities in a way that minimizes disruptions and maximizes resource utilization.

Table 5. Types of aircraft maintenance.

Aspect	Corrective Maintenance	Preventive Maintenance	Condition-Based Maintenance (CBM)	Predictive Maintenance	Prescriptive Maintenance
Definition	Maintenance performed after a failure occurs	Maintenance performed at regular intervals to prevent failures	Maintenance based on the actual condition of the equipment	Maintenance that predicts future failures based on condition data	Maintenance that optimizes decisions based on predictions and ecosystem impacts
Goal	Restore functionality after failure	Prevent failures by regular checks and replacements	Detect and address issues before they lead to failure	Predict and prevent future failures	Optimize maintenance actions considering all relevant factors
Approach	Reactive	Proactive	Proactive	Proactive	Proactive
Monitoring	None	Time-based or usage-based intervals	Continuous condition monitoring	Continuous condition monitoring with failure predictions	Continuous condition monitoring with holistic decision-making
Cost	High due to unplanned downtimes and emergency repairs	Moderate due to regular maintenance activities	Moderate to low as maintenance is conducted only when necessary	Low to moderate by preventing failures and unplanned downtimes	Low due to optimized and well-planned maintenance actions
Downtime	High due to unplanned nature	Low to moderate depending on scheduling	Low as maintenance is performed based on condition	Low as future failures are predicted and prevented	Very low as maintenance is scheduled to minimize disruptions
Resource Utilization	Inefficient, resources are used unpredictably	Moderate, resources are used regularly	Efficient, resources are used only when needed	Efficient, resources are planned based on predictions	Highly efficient, resources are optimized across the ecosystem
Reliability	Low, as failures are unpredictable	High, as regular maintenance prevents most failures	High, as issues are addressed before failure	Very high, as future failures are predicted and prevented	Extremely high, as maintenance actions are optimized for all factors
Sustainability	Low, higher environmental impact due to emergency repairs	Moderate, as regular maintenance leads to waste	High, as unnecessary maintenance is avoided	Very high, as failures are minimized	Extremely high, as maintenance actions consider environmental impacts

The correlation between AHMS and maintenance levels has significant cost implications. While higher levels of AHMS require greater upfront investment, they can lead to long-term savings through optimized scheduling and reduced unnecessary part replacements. However, more sophisticated AHMS also requires increased investment in training for maintenance personnel. From a safety perspective, the positive correlation between AHMS levels and maintenance practices contributes to enhanced overall safety. Advanced AHMS can identify potential issues before they become critical safety concerns, provide a more holistic view of aircraft health, and offer data-backed insights for more informed safety-related decisions.

Despite the generally positive correlation, there are challenges to consider. Very advanced AHMS can produce vast amounts of data, potentially overwhelming maintenance teams. There is also a risk of becoming too dependent on AHMS, potentially neglecting traditional inspection methods. Additionally, implementing advanced AHMS in older aircrafts or across diverse fleets can be complex and challenging.

Looking to the future, the correlation between AHMS and maintenance levels is likely to strengthen further with technological advancements. Artificial intelligence and machine learning will enhance the predictive capabilities of AHMS, greater connectivity through IoT integration will allow for more comprehensive and real-time monitoring, and the use of digital twins will further optimize maintenance strategies.

As technology continues to evolve, the synergy between AHMS and maintenance practices will undoubtedly play a crucial role in shaping the future of aircraft maintenance and operations, requiring ongoing adaptation and innovation from all stakeholders in the aviation sector.

4.9. The Iceberg Model as a Unifying Framework

In addressing research questions regarding the enhancement of AHMS, the model of the integration of the iceberg model with AI-based systems and blockchain technology was selected after careful consideration of alternative frameworks and methodologies.

Several frameworks were analyzed for improving AHMS, including traditional reliability-centered maintenance (RCM), condition-based maintenance (CBM), and digital twin models. While each of these approaches offers certain advantages, they also have limitations. RCM, while effective for scheduled maintenance, lacks the predictive capabilities needed for modern, complex aircraft systems. CBM offers improvements over RCM, but often fails to capture the full depth of potential issues. Digital twins, though powerful for simulation, can be computationally intensive and may not fully capture the layered nature of aircraft health issues.

The iceberg model was selected as a primary framework due to its comprehensive representation of aircraft health issues, from easily observable symptoms to hidden, underlying causes. Its layered approach aligns well with the multi-faceted nature of aircraft systems, allowing for a structured approach to health monitoring at various levels of complexity. The model's scalability enables easy adaptation to incorporate new technologies and methodologies as they emerge. Additionally, its visual nature makes it an effective tool for communicating complex ideas to stakeholders across different levels of technical expertise.

The integration of AI-based systems with the iceberg model was driven by several factors. AI algorithms, particularly machine learning models, excel at identifying patterns and making predictions based on large datasets, which is crucial for detecting issues at the deeper levels of the iceberg model. The adaptability of AI systems allows the AHMS to continuously learn and improve over time. AI is uniquely suited to process and derive insights from the complex, high-dimensional data generated by modern aircrafts. Many AI algorithms can operate in real time, providing immediate insights crucial for aviation safety.

The addition of blockchain technology to the framework addresses several key challenges in current AHMS. Blockchain provides an immutable record of all maintenance actions and component lifecycles crucial for regulatory compliance and safety assurance. It offers a transparent and secure way to track aircraft parts, addressing the issue of counterfeit components. In a multi-stakeholder environment such as aviation, blockchain enables trusted collaboration without relying on a single centralized authority.

By combining the iceberg model, AI, and blockchain, a synergistic approach was created that addresses the multifaceted challenges of modern AHMS. The iceberg model provides the conceptual framework for understanding the depth and complexity of aircraft health issues. AI-based systems offer the analytical power to detect, predict, and address these issues at all levels of the model. Blockchain technology ensures the integrity, security, and traceability of all data and actions within the system.

It is important to note that the iceberg model does not exclude the use of other models or frameworks. It serves as an excellent complement to them, providing a visual and conceptual overlay that enhances our understanding of various AHMS processes. The iceberg model's strength lies in its ability to visualize many of the complex processes used in AI-based models that are often hidden from the end user.

For instance, while a neural network or a random forest algorithm might be working behind the scenes to process sensor data and make predictions, the iceberg model helps us conceptualize where these processes fit within the broader context of aircraft health management. It allows us to represent the visible outputs of these models at the "tip of the iceberg", while the underlying computations, data processing, and decision-making algorithms are visualized in the deeper, unseen layers.

This complementary approach enables the use of the strengths of various AI and data analysis techniques while maintaining a clear, intuitive framework for understanding the overall system. It bridges the gap between complex technical processes and the need for clear communication with stakeholders across different levels of expertise in the aviation industry.

By incorporating this perspective, the flexibility and applicability of the proposed AHMS framework was enhanced, allowing for the integration of diverse methodologies and technologies under a unifying conceptual model.

4.10. Limitations and Challenges of the Proposed Model

While an integrated approach using the iceberg model, AI, and blockchain technology offers significant advantages for AHMS, it is important to acknowledge its limitations and potential challenges.

The multi-layered nature of the model, while comprehensive, introduces considerable complexity. Implementing such a system across diverse aircraft fleets and integrating it with existing maintenance infrastructures poses significant technical and logistical challenges. The steep learning curve for maintenance personnel and the need for extensive retraining could lead to initial resistance and implementation delays.

The effectiveness of AI-based systems heavily relies on the quality and quantity of available data. In practice, obtaining consistent, high-quality data across all aircraft systems and from various operators can be challenging. Issues such as sensor failures, data gaps, or inconsistencies in data collection methods could impact the accuracy of predictive models.

The aviation industry is heavily regulated, and introducing new technologies, especially those involving AI and blockchain, may face regulatory scrutiny. Gaining approval from aviation authorities for such a comprehensive change in maintenance approaches could be a time-consuming process, potentially delaying widespread adoption.

The initial investment required for implementing the proposed system, including hardware upgrades, software development, and personnel training, could be substantial. While long-term cost savings is anticipated, the high upfront costs might be a barrier for smaller operators or those in financially constrained situations.

Ensuring seamless integration with existing systems and compatibility across different aircraft types and manufacturers presents a significant challenge. Standardization efforts will be crucial but may face resistance from stakeholders with proprietary systems.

While blockchain enhances data security, the need for data sharing across multiple stakeholders (airlines, manufacturers, and maintenance providers) raises privacy concerns. Striking the right balance between data accessibility for improved analytics and maintaining confidentiality of sensitive operational data remains a challenge.

There is a risk that overconfidence in AI-driven predictions could lead to complacency in human oversight. Maintaining a balance between technological assistance and human expertise in decision-making is crucial. At the same time, as AI systems become more autonomous in decision-making, ethical questions arise about responsibility and accountability in case of system failures or incorrect predictions leading to safety issues.

Future research and development efforts should focus on mitigating these challenges.

4.11. Future Directions of Research

The rapid evolution of AHMS and the shift towards comprehensive aviation health management open up several exciting avenues for future research. As quantum computing technology matures, investigating its potential applications in AHMS could lead to significant breakthroughs. Future studies should explore how quantum algorithms might enhance predictive analytics, optimize complex maintenance schedules, and process vast amounts of sensor data more efficiently. Concurrently, the development of smart materials with built-in sensing capabilities and the integration of nano sensors into aircraft structures present promising research opportunities. Studies on how these technologies can provide more granular and real-time health data, potentially reshaping the iceberg model's lower layers, would be valuable.

As AI systems become more integral to AHMS and maintenance decision-making, research into the ethical implications and development of frameworks for transparent, explainable AI in aviation contexts is crucial. This includes studying how to balance AI recommendations with human expertise in critical situations. Furthermore, while developed for aviation, the iceberg model could potentially be adapted for other complex systems. Research into how this model and the associated AHMS principles could be applied in industries such as maritime transport, nuclear power, or space exploration could yield valuable insights.

Optimizing the interaction between AI-driven AHMS and human maintenance crews is another critical area for future research. This includes studying how to present complex predictive data effectively, developing training methodologies for working with advanced AHMS, and exploring the psychological aspects of trusting AI-generated maintenance recommendations. As blockchain becomes more prevalent in AHMS, research into interoperability between different blockchain systems and the development of industry-wide standards for blockchain implementation in aviation will be crucial.

Environmental considerations should also drive future research, focusing on how advanced AHMS can contribute to reducing the aviation industry's environmental impact. This includes studying how predictive maintenance can optimize fuel efficiency, reduce emissions, and minimize waste in aircraft operations and maintenance. Additionally, as AHMS become more connected and data-driven, research into advanced cybersecurity measures specific to aviation systems is essential. This includes studying potential vulnerabilities in AI and blockchain implementations and developing robust security protocols.

Exploring how to effectively integrate external data sources such as global weather patterns, air traffic data, and even social media trends into AHMS could enhance predictive capabilities. Research in this area could lead to more comprehensive and accurate health management systems. Finally, developing models and methodologies for predicting aircraft health and performance over extended periods, potentially spanning the entire lifecycle of an aircraft, presents an interesting challenge for future research.

These future directions highlight the interdisciplinary nature of advanced AHMS, emphasizing the need for collaboration across various fields including computer science, materials engineering, ethics, and environmental studies. As the aviation industry continues to evolve, research in these areas will play a crucial role in shaping the future of aircraft health monitoring and management, ultimately contributing to safer, more efficient, and more sustainable air travel.

5. Conclusions

The evolution of AHMS from simple monitoring tools to comprehensive health management platforms represents a significant leap forward in aviation safety, efficiency, and sustainability. This transformation, driven by the integration of cutting-edge technologies such as artificial intelligence, blockchain, and advanced analytics, is reshaping the landscape of aircraft maintenance and operations.

The iceberg model, introduced as a conceptual framework in this paper, provides a powerful metaphor for understanding the depth and complexity of modern AHMS. It illustrates the progression from surface-level, reactive approaches to deep, predictive, and prescriptive strategies that can forecast and prevent potential issues before they manifest. This model not only aids in visualizing the current state of AHMS, but also serves as a roadmap for future developments in the field.

The shift from monitoring to management in aviation health systems marks a paradigm change in how the industry approaches aircraft maintenance and safety. By leveraging predictive and prescriptive analytics, real-time data processing, and advanced decision-making capabilities, aviation health management systems are enabling a proactive approach to maintenance that optimizes resource allocation, reduces downtime, and enhances overall operational efficiency.

The integration of blockchain technology in AHMS addresses critical issues of data integrity, security, and interoperability. By providing a secure and transparent platform for data exchange among various stakeholders, blockchain is fostering a new era of collaboration in the aviation ecosystem. This, coupled with the implementation of federated learning and advanced analytics, is paving the way for more informed decision-making and enhanced safety protocols.

The relationship between the sophistication of AHMS and the evolution of maintenance strategies, from corrective to preventive, condition-based, predictive, and finally prescriptive maintenance, underscores the transformative impact of these technologies on aviation practices. As AHMS continues to advance, the promise is to further optimize maintenance schedules, reduce costs, and improve aircraft reliability and safety.

However, the implementation of these advanced systems is not without challenges. Issues such as data management, regulatory compliance, and the need for skilled professionals to develop and operate these systems must be addressed. Moreover, the aviation industry must navigate the complexities of integrating these new technologies with existing systems and across diverse fleets.

Looking to the future, the continued evolution of AHMS will likely be shaped by emerging technologies such as quantum computing, advanced AI, and augmented reality. These developments promise to push the boundaries of what is possible in aircraft health monitoring and intelligent operations, potentially leading to even more sophisticated predictive and prescriptive capabilities.

The transition from aviation health monitoring to comprehensive health management represents a pivotal moment in the aviation industry. By embracing these advanced technologies and approaches, the industry is not only enhancing safety and efficiency, but also paving the way for more sustainable and environmentally friendly aviation practices.

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Abbreviations

AHMS	Aircraft Health Monitoring System
AI	Artificial Intelligence
AIDS	Aircraft Integrated Data System
AIOT	Artificial Intelligence of Things
ATC	Air Traffic Control
BITE	Built-In Test Equipment
CBM	Condition-Based Maintenance
EASA	European Aviation Safety Agency
FAA	Federal Aviation Administration
ICAO	International Civil Aviation Organization
IoT	Internet of Things
FMDE	Fault Management and Diagnostics Engine
ML	Machine Learning
MRO	Maintenance, Repair, and Overhaul
NLP	Natural Language Processing
OEM	Original Equipment Manufacturer
PAM	Predictive Aircraft Maintenance
RCM	Reliability-Centered Maintenance
RUL	Remaining Useful Life

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