VOL. 10 NO. 5,
NOVEMBER, 2025
E-ISSN 3027-1339
P-ISSN 3026-8257

African Scholar Publications & Research International
www.africanscholarpub.com

Journal of Systematic, Evaluation and Diversity Engr. (JSEDE)

Enhancing System Safety and Reliability in Aviation: A Hybrid Framework Combining Prognostics, Health Management, and Probabilistic Safety Analysis

Felix Isidore Ibanga[1]; Obinna Cosmas Nworie[2]; Christian Arerosuoghene Akpololohor[3]; Efeturi Fortune Eregare[4]; Rotimi Akinboboye[3]; Gospel Effiong Isangadighi[5]; & Blessing Ohinoreimen Ikhide[6]

[1]Department of Sustainability and Environmental Management, Faculty of Engineering, Environment and Computing, Coventry University, United Kingdom. [2]Department of Engineering Management, School of Engineering, University of Greater Manchester, United Kingdom. [3]Department of System Safety and Reliability Studies, Centre for Safety Management, Federal University, Felele, Lokoja, Nigeria. [4]Delta State Polytechnic Otefe-Oghara, Oghara, Delta, Nigeria. [5]HSSE UNIT, Department of Environmental Management and Toxicology, Federal University of Petroleum Resources, Effurun, Nigeria. [6]Department of Environmental Management and Toxicology, Federal University of Petroleum Resources, Effurun, Delta State, Nigeria

Corresponding Author: isangadighi.pub@gmail.com

DOI: https://doi.org/10.70382/ajsede.v10i5.022

Abstract

The growing complexity of modern aircraft systems has necessitated integrating predictive and probabilistic safety approaches to ensure continuous airworthiness and operational resilience. This review critically examines the hybridisation of Prognostics and Health Management (PHM) and Probabilistic Safety Analysis (PSA) as an emerging framework for enhancing system safety, reliability, and maintenance efficiency in aviation. The study aims to evaluate the state-of-the-art methodologies, identify integration challenges, and highlight future research and policy directions for PHM–PSA synergy. Methodologically,

an extensive review of recent peer-reviewed literature (2018–2026) was conducted, synthesising findings from key studies on Bayesian networks, digital twin architectures, dynamic risk modelling, and machine learning–based prognostics. Comparative analysis reveals that hybrid PHM–PSA models outperform conventional safety systems by enabling real-time risk estimation, adaptive maintenance scheduling, and lifecycle cost optimisation. Integrating probabilistic reasoning with predictive health indicators enhances early fault detection, reduces downtime by up to 40%, and supports regulatory compliance through data-driven safety assurance. However, the review identifies persistent challenges, including data heterogeneity, model interpretability, and certification barriers. It concludes that PHM–PSA integration marks a paradigm shift toward predictive, intelligent, and risk-aware aviation systems. The paper recommends establishing standardised data protocols, regulatory sandboxes, and digital twin infrastructures, alongside capacity-building initiatives to bridge the gap between innovation and certification. Collectively, these strategies will enable a globally harmonized, resilient, and proactive aviation safety ecosystem.

Keywords: Prognostics and Health Management (PHM), Probabilistic Safety Analysis (PSA), Aviation Safety, System Reliability, Digital Twin Integration, Bayesian Networks, Predictive Maintenance.

Introduction

The aviation industry is among the most safety-sensitive industries, and the dependability and integrity of its systems are of utmost importance. With the increasing complexity of modern aircraft and the incorporation of sophisticated avionics, digital control systems, and smart sensors, there is a growing challenge to ensure high safety standards while remaining cost-effective. Conventionally, aviation safety and maintenance strategies have been based on reactive and preventive maintenance tactics, in which aircraft failures are managed by fixing or replacing components according to a fixed timetable, regardless of the aircraft's actual state (Zhang *et al*., 2018). Nevertheless, such methods are sometimes ineffective and may cause unexpected downtime, high operating costs, and safety hazards arising from untested degradation. This changing environment has led to a paradigm shift favouring predictive and risk-based maintenance, which combines data-driven prognostics and probabilistic risk analysis to predict failures before they occur (Goebel *et al*., 2020; Chinedu *et al*., 2026; Orhuebor *et al*., 2026a and Orhuebor ety al., 2026b). Prognostics and Health Management (PHM) has emerged in recent years as a new approach for aviation systems, aiming to transform predictive maintenance. PHM is a continuous condition-sensing, diagnostics, and prognostics approach that estimates the Remaining Useful Life (RUL) of essential

parts to enable preventive measures (Saxena *et al*., 2022; Isangadighi & Ukudo, 2025). PHM supports real-time decision-making and improves asset availability and reliability through advanced data analytics, machine learning, and sensor fusion. However, PHM systems are primarily concerned with the health of the individual components. They can be limited in representing the system-level risk propagation and uncertainty-interaction among subsystems - both of which are important in the overall safety analysis (Galar *et al*., 2021; Isangadighi & udeh, 2023).

Concurrently with this progress, Probabilistic Safety Analysis (PSA) has found wide application in the aviation and nuclear industries to trace complex system interactions and quantify the probability of hazardous conditions (Ayyub, 2012). PSA represents causal interrelationships, identifies key failure pathways, and assesses overall system reliability under uncertainty using fault tree analysis (FTA), event tree analysis (ETA), and Bayesian networks. Nonetheless, PSA models typically rely on static data on system failures and do not adapt to real-time system health data, which limits their predictive performance under dynamic operating conditions (Li *et al*., 2022). A combination of PHM and PSA provides a hybrid that can overcome these constraints. PHM in this hybridised paradigm provides current degradation and health information, which continuously updates PSA models to indicate the current state of system reliability. This synergy of PHM and PSA enables dynamic risk assessment, design probability estimation, and adaptive maintenance decision-making, thereby transforming a general safety analysis into a dynamic risk model (Wang *et al*., 2022; Ahanor *et al*., 2025; Acha *et al*., 2025). This integration is also consistent with current trends in digital twins and Industry 4.0 social integration, in which system models continually learn and update as they incorporate operational data.

In aviation, given very high reliability requirements, such a hybrid structure can be used to enhance flight safety, minimise maintenance costs, and facilitate certification and compliance with international airworthiness standards. Although the research community is increasingly interested in PHM and PSA as separate fields, studies specifically addressing their integration remain incomplete. Existing research frequently focuses on either component-level health prognostics or system-level probabilistic risk modelling, with little material on data fusion procedures, computational frameworks, or validation guidelines for hybrid practices (Isangadighi *et al*., 2024; Isangadighi *et al*., 2025; Guo *et al*., 2023; Orhuebor *et al*., 2025; Essien *et al.,* 2025). This, consequently, demands a detailed analysis that integrates prior research and defines integration strategies, issues, and recommendations for the way forward. The purpose of the review is to critically analyse how PHM and PSA can be jointly used to enhance safety and reliability in the aviation industry, leveraging recent advances in data analytics, artificial intelligence, and reliability engineering. The review also addresses the development of techniques, case studies used in applications, gaps, and suggestions for establishing standardised hybrid safety schemes for next-generation aircraft systems.

Conceptual Foundations

Prognostics and Health Management (PHM)

PHM represents a paradigm shift in aviation maintenance toward a condition-based, predictive approach, as opposed to the former reactive and preventive strategies. PHM combines innovative sensor technologies, machine learning, and data-based modelling to continuously evaluate system health, perform fault diagnosis, and anticipate future failures, using real-time and historical data (Goebel *et al*., 2017; Acha *et al*., 2025). PHM has been adopted in Aircraft Health Monitoring Systems (AHMS) in the aviation industry to support decision-making regarding maintenance scheduling, mission planning, and safety assurance. The PHM architecture is typically three-process-based, comprising monitoring, diagnostics, and prognostics. The third stage is monitoring, in which data are continuously collected using onboard sensors, and parameters such as cyclic force, temperature, pressure, and strain are measured (Saxena *et al*., 2022). The existing faults or non-conformity to normal operating conditions are then diagnosed through the use of statistical, model-based or data-driven methods. Lastly, the prognostics step provides an initial estimate of the Remaining Useful Life (RUL) of components, enabling maintenance teams to perform corrective maintenance before failure (Galar *et al*., 2021). The process provides predictive information, enhancing operational consistency and minimising the likelihood of adverse outcomes. Some of the critical systems for which PHM can be used in the aviation industry include engines, avionics, landing gear, hydraulic systems, and flight control actuators. For example, turbofan engine prognostics employs hybrid models that integrate factor-based (degradation) models with machine learning to forecast turbine blade fatigue and bearing wear (Li *et al*., 2020). Similarly, the avionics health monitoring system employs anomaly detection algorithms to detect data communication errors in flight control networks (Huang *et al*., 2023). These programmes highlight the importance of PHM in improving maintenance efficiency, ensuring safety, and optimising lifecycle costs. Nonetheless, PHM is affected by several factors. To begin with, RUL estimation accuracy relies heavily on data quality, model calibration, and the capture of multi-source uncertainty. Second, PHM systems are typically component-level; we lack the capacity to model the impact of individual component degradation on system-level safety and risk propagation. Lastly, the absence of universal schemes for integrating PHM outputs into advanced risk assessment instruments constrains its scope of influence in probabilistic decision-making (Lee *et al*., 2022; Khan *et al.,* 2024). These difficulties reaffirm the need to connect PHM to other analysis chain models, such as Probabilistic Safety Analysis (PSA), to support risk-centric maintenance programs.

Probabilistic Safety Analysis (PSA)

Probabilistic Safety Analysis (PSA) is a quantitative risk assessment technique used to determine the probability and impact of failure modes in a system by conducting a system architecture analysis that accounts for interactions among system components and uncertainty propagation (Ayyub, 2012). The variability in component reliability, human performance, and

environmental conditions is explicitly accounted for in PSA, in contrast to deterministic analyses that rely on fixed failure thresholds. Another advantage of this probabilistic approach is that it allows decision-makers not only to quantify risk but also to identify key failure modes and to prioritise safety interventions, taking action grounded in statistical evidence rather than assumptions. In the aviation industry, PSA typically has three levels of analysis. Level PSA 1 PSA determines the rate of system or component failures through various methods, including fault tree analysis (FTA) and reliability block diagram (RBD) (Li *et al*., 2022). Level 2 PSA measures accident progression by examining sequences of events from the point at which the process begins with a failure (sequence modelling). Level 3 PSA considers potential impacts, such as aircraft loss, environmental harm, or fatalities (Wang *et al*., 2022). More recently, Bayesian networks have become a formidable probabilistic modelling tool for reliable assessments of network dynamics in the face of new information (Zhou *et al*., 2023). One of the significant advantages of PSA is its ability to manage intricate interdependencies among system components and to propagate uncertainty across hierarchical system structures. For example, in assessing flight control reliability, PSA models can estimate the likelihood of complete system failure arising from combinations of actuator, sensor, and software faults. Likewise, in the engine safety assessment of an aircraft, PSA integrates failure rates, sensor failure rates, and coordination time to estimate the probability of an engine shutdown within the aeroplane (Luo & Zhou, 2020). These lessons are invaluable for safety certification and compliance with standards, including FAA Advisory Circular AC 25.1309-1A and EASA CS-25. However, there are significant weaknesses in conventional PSA methods. The majority of them are based on inactive failure-rate data derived from historical records, which may not reflect the actual health of components in real time (Li *et al*., 2022). Furthermore, PSA models sometimes do not provide mechanisms for integrating degradation trends or sensor-based prognostic information, and thus are less adaptive under dynamic operating conditions. The result of such a static character may be a conservative assessment of risks and low maintenance efficiency. By combining PSA with PHM, in which probabilistic models are continuously updated with predictive health information, these shortcomings are mitigated through data-driven flexibility and real-time risk inference in safety analysis.

The Complementary Nature of PHM and PSA

PHM and PSA are closely linked. PHM is efficient at estimating the time to failure of a given component. In contrast, PSA is useful for estimating the consequences of component failures within the system and the probability of their occurrence, and combining the predictive properties of PHM with the risk quantification method of PSA in the construct of a dynamic reliability model in which real-time degradation data is used to correct system-level safety checks continuously (Zhang *et al*., 2024). Under this hybrid framework, likelihoods of the PHM (e.g., probability distributions of RUL) are fed into the PSA, which updates fault-tree probabilities or Bayesian nodes to reflect the current state of the system (Guo *et al*., 2023). This synergy will enable better, more timely decisions in maintenance, risk prioritisation, and

mission planning. The conceptual intersection of PHM and PSA, therefore, represents a significant advance in aviation safety management. It bridges the gap between predictive maintenance and probabilistic safety assurance, enabling real-time operational decision support based on risk. This is especially so as aviation systems transition to digital twin architectures, in which physical systems are represented by continuously updated virtual models that integrate prognostic, diagnostic, and risk information. In this regard, the hybrid PHM-PSA framework is a pillar of an intelligent, self-diagnostic, and self-healing aviation system.

Integration of PHM and PSA in Aviation Systems

Table 1: Integration of PHM and PSA in Aviation Systems

Integration Aspect	Description / Mechanism	Applications in Aviation Systems	Key Benefits	Limitations / Challenges	Representative Studies (APA)
Conceptual PHM–PSA Framework	PHM provides real-time degradation data (e.g., Remaining Useful Life), which updates PSA models such as fault trees or Bayesian networks to reflect evolving system reliability.	Applied in general aviation systems for dynamic risk updating and predictive maintenance.	Enables dynamic, real-time reliability assessment and risk-informed decisions.	Integration requires robust data pipelines and uncertainty management.	Wang *et al*. (2022); Guo *et al*. (2023); Li *et al*. (2021).
Bayesian PHM–PSA Fusion Models	Bayesian networks integrate PHM health indicators as evidence to update failure probabilities in PSA models dynamically.	Used in engine control and flight management systems.	Provides mathematically consistent uncertainty propagation and adaptability to new data.	Requires accurate prior distributions and continuous recalibration.	Zhou *et al*. (2023); Zhang *et al*. (2024).
Hybrid Monte Carlo / Markov Models	PHM degradation trajectories are simulated as probabilistic inputs to Monte Carlo or Markov models within PSA frameworks.	Commonly used in turbofan engine reliability modeling.	Captures time-dependent degradation and stochastic failure dynamics.	Computationally intensive; requires extensive simulation data.	Li *et al*. (2020); Hu & Liu (2022).
Digital Twin-Enabled Integration	Real-time PHM and PSA models are embedded in digital twin environments to simulate system performance and risk evolution.	Applied in aircraft propulsion and flight control systems.	Provides continuous system mirroring and predictive capability for early fault detection.	High model complexity and data synchronization challenges.	Huang *et al*. (2023); Lee *et al*. (2022).
Machine Learning-Augmented PSA Models	ML models (e.g., neural networks, Gaussian processes) map PHM indicators to PSA outcomes, acting as surrogate models for complex systems.	Used for avionics and sensor network reliability prediction.	Enables fast computation and captures nonlinear system interactions.	May lack interpretability and explainability for certification.	Lee *et al*. (2022); Zhang *et al*. (2024).
Integrated Decision Support Systems (IDSS)	PHM and PSA are embedded within risk-informed dashboards that visualize current health, failure probabilities, and recommended maintenance actions.	Implemented in maintenance planning and mission scheduling systems.	Supports condition-based maintenance and cost-effective decision-making.	Integration of multiple data sources may cause data heterogeneity and validation issues.	Guo *et al*. (2023); Wang *et al*. (2022).

Integration Aspect	Description / Mechanism	Applications in Aviation Systems	Key Benefits	Limitations / Challenges	Representative Studies (APA)
Aero-Engine Systems	PHM sensor data (temperature, vibration, efficiency) updates PSA fault trees to predict engine shutdown probability.	Turbofan and turboprop engines.	Reduces unplanned removals and enhances mission reliability.	Sensitive to sensor accuracy and data latency.	Li *et al*. (2020); Wang *et al*. (2022).
Avionics and Flight Control Systems	PHM detects software or sensor faults; PSA evaluates their propagation through redundant architectures.	Flight control computers and data buses.	Improves fault tolerance and supports redundancy validation.	Requires high computational synchronization between software and hardware layers.	Zhou *et al*. (2023); Huang *et al*. (2023).
Unmanned Aerial Vehicles (UAVs)	PHM health states of propulsion and navigation systems feed into PSA to estimate mission success probabilities.	Autonomous UAV operations under uncertainty.	Enhances mission planning reliability and real-time adaptation.	Data sparsity in UAV flight records limits model validation.	Huang *et al*. (2023); Li *et al*. (2021).
Hydraulic and Landing Gear Systems	Hydraulic pressure and actuator performance data are incorporated into PSA fault trees to assess system reliability.	Landing gear and brake systems.	Enables early detection of hydraulic leaks and component fatigue.	Complex system interdependencies complicate risk quantification.	Wang *et al*. (2022); Hu & Liu (2022).

Table 2: Integration of PHM and PSA in Aviation Systems

Integration Aspect	Description / Mechanism	Applications in Aviation Systems	Key Benefits	Limitations / Challenges	Representative Studies (APA)
Conceptual PHM–PSA Framework	PHM provides real-time degradation data (e.g., Remaining Useful Life), which updates PSA models such as fault trees or Bayesian networks to reflect evolving system reliability.	Applied in general aviation systems for dynamic risk updating and predictive maintenance.	Enables dynamic, real-time reliability assessment and risk-informed decisions.	Integration requires robust data pipelines and uncertainty management.	Wang *et al*. (2022); Guo *et al*. (2023); Li *et al*. (2021).
Bayesian PHM–PSA Fusion Models	Bayesian networks integrate PHM health indicators as evidence to update failure probabilities in PSA models dynamically.	Used in engine control and flight management systems.	Provides mathematically consistent uncertainty propagation and adaptability to new data.	Requires accurate prior distributions and continuous recalibration.	Zhou *et al*. (2023); Zhang *et al*. (2024).
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Digital Twin-Enabled Integration	Real-time PHM and PSA models are embedded in digital twin environments to simulate system performance and risk evolution.	Applied in aircraft propulsion and flight control systems.	Provides continuous system mirroring and predictive capability for early fault detection.	High model complexity and data synchronization challenges.	Huang *et al*. (2023); Lee *et al*. (2022).
Machine Learning-Augmented PSA Models	ML models (e.g., neural networks, Gaussian processes) map PHM indicators to PSA outcomes, acting as surrogate models for complex systems.	Used for avionics and sensor network reliability prediction.	Enables fast computation and captures nonlinear system interactions.	May lack interpretability and explainability for certification.	Lee *et al*. (2022); Zhang *et al*. (2024).
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Aero-Engine Systems	PHM sensor data (temperature, vibration, efficiency) updates PSA fault trees to predict engine shutdown probability.	Turbofan and turboprop engines.	Reduces unplanned removals and enhances mission reliability.	Sensitive to sensor accuracy and data latency.	Li *et al*. (2020); Wang *et al*. (2022).
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Table 3: Comparative review of representative PHM–PSA / related works (2018–2025)

Study	Focus / Domain	Methods / Integration Approach	Key findings	Limitations / Notes
Zio, E. (2022)	PHM conceptual & methodological review.	Comprehensive review of PHM methods (model-based, data-driven, hybrid) and decision layers.	Provides taxonomy of PHM approaches and discusses uncertainty, decision-support and ICT needs for PHM deployment.	High-level — limited coverage of explicit PHM–PSA fusion cases
Soualhi *et al*. (2022)	Survey of prognostic implementations.	Systematic survey of model-based, data-driven and hybrid prognostics; performance metrics and benchmarking.	Highlights trend to hybrid methods and ML adoption; emphasizes uncertainty quantification (PDF-of-RUL).	Emphasizes methods over system-level safety integration.
Mitici *et al*., (2023)	Dynamic predictive maintenance (turbofan engines).	CNN with Monte Carlo dropout to produce probabilistic RUL (PDF-of-RUL); Monte Carlo propagation to system risk.	Demonstrates viable PDF-of-RUL feeding into higher-level risk estimators for time-dependent maintenance.	Computational cost and need for realistic operation datasets.
Xiao *et al*. (2024)	Digital twin–driven PHM.	Review + case studies of DT integration with PHM (model + data fusion).	Digital twins improve PHM accuracy and provide a natural host for integrating PSA modules for live risk assessment.	Implementation complexity, data synchronization, and verification/validation challenges.
Kabashkin *et al*. (2024)	Digital twin framework for aircraft lifecycle.	Framework paper: data pipelines, models, twin lifecycle for maintenance & safety.	Shows DT as enabling infrastructure for continuous PHM–PSA updates across lifecycle.	Mostly framework-level; few empirically validated aircraft-scale deployments.
Bisanti *et al*. (2023)	Digital twins for aircraft maintenance/operation.	Systematic mapping of DT tech in aircraft maintenance (sensors, analytics, integration).	Recommends DT + PHM + risk models for predictive safety; documents early adopters.	Gaps in standardization and regulatory acceptance remain.
He, R. *et al*. (2022)	Real-time probabilistic risk assessment.	Dynamic Bayesian network (DBN) updating PSA using streaming data.	Demonstrates DBN can ingest online health signals to update system risk in near-real time.	Requires robust sensor fusion and validated conditional probability tables.
Zhou, Z. *et al*. (2022/2023)	Bayesian network for commercial aviation safety risk.	BN built from incident data; causal factor modeling for system-level risk.	BN effective for combining heterogeneous evidence (incident reports, sensors) to estimate safety risk.	BN construction reliant on quality of prior data and expert elicitation.
Peng, C. *et al*. (2022)	RUL prognostics for turbofan engines.	Deep learning + feature engineering (imSSAE + imESN) on C-MAPSS datasets.	High RUL accuracy on benchmark turbofan datasets — supports feeding probabilistic prognostics into downstream risk tools.	Benchmarks are simulated; real-field transferability limited.
Ensarioğlu, K. *et al*. (2023)	RUL estimation (applied ML).	1D-CNN-LSTM hybrid models for RUL prediction on turbofan data.	Confirms robust ML architectures and improvement in performance metrics (MAE, RMSE) vs older models.	Focus on algorithmic performance; few studies map outputs to PSA.

Study	Focus / Domain	Methods / Integration Approach	Key findings	Limitations / Notes
Scroggins, P. (2024)	Structured methodology for turbofan prognostics (practical workflow).	Methodology paper describing feature pipelines, validation and benchmarking for engine prognostics.	Offers reproducible pipeline recommendations for moving from prognostics to maintenance decisions.	Emphasizes engineering practice; does not fully close the PHM→PSA loop.
Review on Bayesian networks in reliability (various authors)	BN application in reliability evaluation.	BN as a bridge for probabilistic inference, evidence fusion, and dynamic updating.	BN is a prime candidate model for PHM→PSA integration because it natively accommodates uncertain evidence and updates.	Elicitation of priors and CPTs, and scaling to very large systems, are nontrivial.

Benefits and Implications of Integrating PHM and PSA in Aviation Systems

Enhanced Predictive Maintenance and Reduced Downtime

The most important advantage of PHM-PSA integration is the shift in the approaches towards the maintenance, i.e., the shift to proactive approaches. PHM systems, which have powerful diagnostics and prognostics, determine the Remaining Useful Life (RUL) of key parts like turbofan engines, avionics modules, and landing gear systems (Soualhi *et al*., 2022; Mitici *et al*., 2023). With these predictions added to probabilistic risk model, the maintenance schedule is dynamically adjusted on the basis of health degradation as well as failure probabilities. Research shows that such a hybrid solution can reduce unplanned maintenance costs by up to 3050 percent, enhance fleet availability, and reduce operational interruptions (Xiao *et al*., 2024; He *et al*., 2022). This predictive maintenance is fully in line with the philosophy of CVS now Condition-Based Maintenance Plus (CBM+) supported by NASA and EASA that can minimise the downtime and preserve or even enhance the reliability indices.

Better Reliability Test and Risk Measurement

The conventional PSA techniques use encoding using static fault tree or event tree, which assumed the failure rates to be constant. Nevertheless, by continuously updating its models with real-time PHM information, e.g. sensor-based measures of degradation or health index scores, the reliability measure becomes dynamic and situation-specific. The probabilistic models can use this integration to revise their probability of failure as operation data changes (Zhou *et al*., 2023). An example is that Bayesian networks are capable of combining live data on conditions to update conditional probabilities of failures in critical systems on flight (He *et al*., 2022). As a result, reliability measures including Mean Time to Failure (MTTF) and System Availability are dynamic and they would capture the true health of the system instead of setting assumptions during design. Through this dynamic reliability modelling, the decision confidence is improved especially in areas that are safety sensitive as in flights control and propulsion system.

Enhanced Safety Guarantee and Accident Prevention

The PHM–PSA hybrid model does not limit to maintenance but has a universal impact on the overall aviation safety assurance. Risk assessment becomes a more proactive safety paradigm by directly integrating prognostic indicators into safety models, turning the assessment of risk into more of a proactive activity (Kabashkin *et al*., 2024). This allows operators to determine the high risks situations before the failure of systems and some preventive mechanisms can be applied to reduce the cascading effects that could cause an accident. Probability of Loss of Mission (PLOM) or Probability of Loss of Aircraft (PLOA) can be re-calculated in real-time in response to deteriorating health states (Zio, 2022). It is implied as a step in the direction of the dynamic safety envelopes, with functional limits changing in response to the changing state of subsystems of aircraft. This has clearly been applicable to complex and integrated devices like unmanned aerial vehicles (UAVs) where decision-making under uncertainty is important.

Lifecycle Management and Cost Efficiency

Economic impacts are also very important. Combining PHM and PSA helps in optimization of lifecycle costs with a balanced approach between maintenance through reliability and risk-based asset management. By calculating the predicted cost of failure and probability of downtime, operators would be able to place priorities on maintenance activities that would have the greatest cost benefit ratio. Research indicates that these hybrid structures are potentially able to cut down the total cost of maintenance to 15-25 per cent with no impact on regulatory safety margins (Bisanti *et al*., 2023). Additionally, digital twin solutions, or the RIS in terms of PHM-PSA integration, allow to track the health of the aircraft in both cradle and grave (Xiao *et al*., 2024). Subsequently, the information provided by the resulting historical data can be utilised in fleet-level planning, logistics of spare parts and warranty because of the long-term sustainability of operations.

Policy/Certification/Regulatory Implications

The synergy between the PHM and the PSA presents opportunities and challenges in terms of an operational policy and regulatory aspect. Data-centric and safety management and continuous data on airworthiness becomes the focus of the increasing number of regulatory agencies like FAA, EASA, and ICAO. The hybrid framework offers an avenue to adhere to these emerging standards with measurable indicators, which are based on evidence (Kabashkin *et al*., 2024). Nonetheless, the certification of AI-based prognostic systems and probabilistic models is still complicated with the issue of transparency, traceability, and validation. Consequently, the explainable machine learning and the quantification of uncertainty need to be incorporated to be ready to be certified. Moreover, the purpose of the PHM-PSA fusion is that it enables to identify hazards and manage risks in a probabilistic context, which supports the objectives of the Safety Management Systems (SMS): in other words, it underpins the predictive functions of the current aviation safety supervision.

Difficulties, Limited Resources and Future Projections

Problems of Data Quality, Availability and Standardisation

Fidelity and continuity of operational data determines the performance of a PHM–PSA framework. Nevertheless, aviation systems are heterogeneous and, thus, generate disjointed and usually incomplete datasets (Mitici *et al*., 2023; Soualhi *et al*., 2022). Inconsistent definition of sensor calibration, sampling inconsistency in frequency, and record delays contribute to unreliability of prognostics generated. As an example, data on actual turbofan engine (or flight control system) degradation cannot always be available because of proprietary issues and regulatory secrecy, so researchers have to make extensive use of simulated data including the NASA C-MAPSS. Although such datasets are priceless to benchmark, they do not have all the stochastic variability or contextual dynamics of real aircrafts (Peng *et al*., 2022; Ensariooglu *et al*., 2023). Also, the PHM data formatting and interchange does not have any standard that makes it difficult to make models to work interoperatively. Various aircraft systems and manufacturers have different data structures, coding protocols and maintenance log systems. This means that a single probabilistic model would not be technically easy to integrate data of various aircraft type or fleets. The new directions to be taken must however focus on data harmonisation protocols including ISO 13374 (Condition Monitoring Data Processing and Communication) and creation of open-access PHM repositories in aviation. Standardisation of degradation parameter, fault mode and risk metric standard taxonomies would go a long way in improving model portability and model validation.

Modelling Uncertainty and Constraints of the Model

Both PHM and PSA have uncertainty as a factor of their nature, but the extent of uncertainty and its distribution throughout the hybrid interface is yet to be properly handled. PHM models (particularly machine learning-based models) tend to give deterministic results that only capture stochastic variation in degradation processes. Conversely, PSA models require clear probabilistic models of failure, e.g. failure probability models, post-factum risk models, or risk uncertainty bounds (Zio, 2022; He *et al*., 2022). To bridge such representations, it is important to have powerful uncertainty propagation algorithms to be able to map model confidence intervals of the PHM model to meaningful PSA specification parameters. There is also the problem of model validation and verification (V&V). The conventional safety evaluation techniques are based on the analytical transparency and traceability which are not inherent in most data-driven PHM algorithms. Black-box neural networks, which include the ones, have a high predictive power but nominal interpretability, so they are hard to certify by certification bodies like the FAA or EASA to the accepted safety assurance principles. Further studies must thus involve hybrid explainable AI (XAI) systems that combine physics-based degradation laws with learning systems that are more likely to happen (Kabashkin *et al*., 2024). Moreover, by developing uncertainty-sensitive prognostics, using Monte Carlo simulation or Bayesian

inference, it is possible to take the safety margins of both epistemic and aleatory uncertainty into consideration.

Real Time Integration and Computational Complexity

Computational scalability is a significant threat to real-time PHM-PSA integration. DBNs, Monte Carlo simulations, and digital twin synchronisation are extremely resource-intensive algorithms, particularly when used to analyse at a fleet scale or high-frequency sensor feeds (He *et al*., 2022; Xiao *et al*., 2024). These calculations may create a latency that could make the near-real-time nature of decisions impractical under high-stakes conditions in operations, e.g. in-flight risk estimation or fault detection during a mission. The frequency of model coupling is another aspect of this problem, which is deciding how frequently the PSA model is to be updated by PHM outputs. Regular coupling will make risk estimates more up-to-date, but also create an increase in the burden of calculation, and in extreme cases lead to risk of having outdated safety decisions. This trade-off could be reduced by conducting research on reduced-order probabilistic inference into surrogate modelling. Computational tasks can also be distributed through the leverage of the use of edge computing architectures and cloud-based digital twin platforms. Adaptive sampling and incremental learning approaches were identified to be prioritised in future research to maintain constant PHM-PSA updates with a small latency.

Issues in System Integration and Interoperability

The major limitation is integrating PHM and PSA into the systems of complex and multi-layered aviation. In contrast to single-component analyses, aircraft safety management is a situation where there are interactions between propulsion, avionics, environmental control, and structural systems. Technically speaking, it is still challenging to develop a unified hybrid framework to describe interdependencies between these subsystems (Bisanti *et al*., 2023; Kabashkin *et al*., 2024). The existing practises tend to provide local solutions, that is, PHM tools to plan maintenance and PSA models to quantify risks, and lack a flow of information between them. Interoperable digital architectures will be the key to the future of aviation safety management to establish system-level coherence. The developing digital twin paradigm promises an avenue, with being an integration point of both the health diagnostics and the probabilistic reasoning (Xiao *et al*., 2024). The interoperability can be obtained with the help of standardisation of communication protocols using Open System Architecture for Condition-Based Maintenance (OSA-CBM) and Aviation System Block Upgrades (ASBU). Besides, the holistic representation of the dependencies and feedback between the components of the system and ensuring the maintenance of the health indicators and risk models in the aircraft lifecycle is possible by utilising the model-based systems engineering (MBSE) frameworks.

Regulatory and Certification issues

The regulatory acceptance will continue to be one of the biggest challenges to the complete implementation of PHM-PSA frameworks. Aviation regulators are open to innovation but require traceable, transparent, and verifiable safety evidence to accept innovations for operational use (Zhou *et al*., 2023). The combination of AI-based prognostic systems and dynamic probabilistic models introduces interpretability issues that are incompatible with the deterministic validation culture historically applied in certification. There are numerous hybrid systems; consequently, some are at research or pilot stages, and a few are operational in commercial fleets. Future efforts to address this regulatory gap should focus on developing certification-ready methods that meet the DO-178C (certification of software) and ARP4754A (system development) standards. Certifiability can be improved by introducing explainability measures, probability confidence intervals and logs of the model. To establish the Aviation Safety Programme of NASA, as outlined in the EASA Artificial Intelligence Roadmap, and to develop relevant guidelines for the development of provisional probabilistic and ASD-based maintenance systems, collaboration among academia, industry, and regulators must be prioritised. The creation of a Regulatory Sandbox within PHM-PSA innovations, in the long term, could introduce a controlled environment for iterative testing and validation.

Future Directions

The way forward for the integration of aircraft Prognostics and Health Management (PHM) and Probabilistic Safety Assessment (PSA) is to develop transparent, data-driven, and regulation-consistent hybrid approaches. Another important research area includes the development of hybrid models, such as physics-informed neural networks (PINNs), and the integration of predictive uncertainty in probabilistic inference techniques, such as Bayesian deep learners, to enhance predictive performance and explainability of real-world behavior in complex systems. This synthesis helps models exploit physical laws and quantify uncertainty, thereby promoting safer and more explainable decisions. Another potential opportunity is federated and secure data sharing, which leverages blockchain or privacy-preserving federated learning to enable collaboration among aircraft fleets without compromising data confidentiality. With the help of such methods, distributed learning leads to better model generalisation and greater stakeholder trust. The concept of real-time risk visualisation is in the spotlight, and digital twins and augmented reality (AR) dashboards will provide pilots and engineers with an intuitive, real-time view of the safety envelope and system health. This real-time feedback is supporting proactive interventions and effective risk management. Moreover, the development of standardisation and ontologies would be necessary to ensure interoperability and enable the widespread exchange of data and consistent interpretation across PHM and PSA systems across various aircraft platforms. Finally, a mechanism to simulate regulatory frameworks must be developed to enable researchers and certification bodies to test PHM-PSA systems in synthetic testbeds and probabilistically verify compliance with the regulated conditions. Collectively, these new research opportunities constitute a

blueprint for building next-generation aviation safety architectures that are intelligent, secure, and certifiable.

Conclusion

The integration of Prognostics and Health Management (PHM) and Probabilistic Safety Analysis (PSA) represents a significant advance in aviation safety and reliability management, replacing reactive maintenance with predictive, evidence-based decision-making. By integrating PHM's capacity to predict component degradation with PSA's probabilistic approach to model system risks, aviation operators can achieve real-time dynamic reliability evaluation, streamlined maintenance scheduling, and the development of safety assurance. The literature surveys indicate that this type of hybrid structure provides high operational availability, reduces maintenance costs, and increases trust in safety-related decision-making through ongoing studies and adjustments. Nonetheless, there remain difficulties in data standardisation, model transparency, uncertainty quantification, and readiness to certify, which must be addressed to achieve widespread adoption. Overall, PHM-PSA synergy represents a new generation of the aviation safety paradigm, comprising more intelligent, resilient, risk-conscious systems that improve with each flight cycle to provide sustained airworthiness and long-term operational sustainability.

List of Abbreviations, Acronyms, and Symbols Used in the Study

Abbreviation / Symbol	Full Meaning / Description
>	Greater than
≤	Less than or equal to
≥	Greater than or equal to
AHMS	Aircraft Health Monitoring System
AI	Artificial Intelligence
ARP4754A	Guidelines for Development of Civil Aircraft and Systems
ASBU	Aviation System Block Upgrades
BN	Bayesian Network
CBM	Condition-Based Maintenance
CBM+	Condition-Based Maintenance Plus
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation (NASA)
CNN	Convolutional Neural Network
DBN	Dynamic Bayesian Network
DO-178C	Software Considerations in Airborne Systems and Equipment Certification
DT	Digital Twin
EASA	European Union Aviation Safety Agency
ETA	Event Tree Analysis
FAA	Federal Aviation Administration
FTA	Fault Tree Analysis
ICAO	International Civil Aviation Organization
ICT	Information and Communication Technology
IDSS	Integrated Decision Support System
ISO 13374	Condition Monitoring and Diagnostics of Machines – Data Processing, Communication and Presentation

Abbreviation / Symbol	Full Meaning / Description
LSTM	Long Short-Term Memory Network
MAE	Mean Absolute Error
MBSE	Model-Based Systems Engineering
ML	Machine Learning
MTTF	Mean Time to Failure
OSA-CBM	Open System Architecture for Condition-Based Maintenance
P(F)	Probability of failure
PDF-of-RUL	Probability Density Function of Remaining Useful Life
PHM	Prognostics and Health Management
PHM–PSA	Integrated Prognostics and Health Management and Probabilistic Safety Analysis framework
PINNs	Physics-Informed Neural Networks
PLOA	Probability of Loss of Aircraft
PLOM	Probability of Loss of Mission
PSA	Probabilistic Safety Analysis
R(t)	Reliability function
RBD	Reliability Block Diagram
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
SMS	Safety Management System
UAV	Unmanned Aerial Vehicle
V&V	Verification and Validation
XAI	Explainable Artificial Intelligence
λ	Failure rate

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