A Conceptual Framework to Integrate Prognostics and Health Management with Maintenance, Repair and Overhaul for a Hydrogen-Electric Aircraft Propulsion System

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ABSTRACT

This paper proposes a conceptual integration framework that maps Prognostics and Health Management (PHM) stages onto the Maintenance, Repair and Overhaul (MRO) process chain, motivated by a use case on Hydrogen-Electric Aircraft Propulsion System (HEAPS). Drawing on scientific literature, standards, and domain expertise, we identify failure modes, mechanisms, and sensor measurands for HEAPS, and examine maintenance considerations through PHM and MRO lenses. The framework reveals a fundamental asymmetry. From PHM to MRO, diagnostics is the only stage with operational links, feeding condition-based updates to the Aircraft Maintenance Programme (AMP) without altering its structure; prognostic capabilities show potential for planning the unscheduled at the Part 145 level, but beyond diagnostics PHM outputs remain underutilised due to missing certification pathways and because the schedule-driven AMP revision cycle can be slower than the dynamic decision-making advanced PHM promises. From MRO to PHM, Part 145 provides the ground-truth feedback essential to train and validate PHM models, yet structured end-to-end feedback pipelines remain a challenge in scale and architecture.

1. INTRODUCTION

Maintenance Engineering ensures asset reliability, availability, and performance over the operational lifecycle through systematic planning, execution, and control of maintenance activities (Garg & Deshmukh, 2006), balancing cost, availability, and safe operation (Parida & Kumar, 2006).

Prognostics and Health Management and **Maintenance, Repair and Overhaul** are prominent maintenance-related disciplines across different industries. Prognostics and Health Management (PHM) (Section 2.1) is a holistic and multidisciplinary information- and model-driven engineering discipline that aims to characterise current and future asset performance to support maintenance decisions (Zio, 2022). Maintenance, Repair and Overhaul (MRO) (Section 2.2) is a regulatory-institutional technical process, commonly framed as the set of actions that retain or restore an item so it can perform its required function, including not only technical work but also the managerial, administrative, and supervision actions (Esposito et al., 2019).

MRO and PHM have been converging through Industry 4.0 (Weiss et al., 2025), shifting from event- or routine-driven (reactive or schedule-based) maintenance towards **Condition-Based Maintenance (CBM)**, which accounts for the asset's condition (Candell, Karim & Söderholm, 2009). Building on this, advancements in predictive modelling and analytics have led to a further shift towards **Predictive Maintenance (PdM)** (Carvalho et al., 2019) and **Prescriptive Maintenance (PsM)** (Orošnjak, Saretzky & Kedziora, 2025), which provide valuable insights into the asset's health evolution and recommend strategic maintenance actions.

In the aviation industry, a heavily regulated maintenance environment (Hallensleben, Albers & Dewulf, 2025), MRO is the gold standard for maintenance management, accounting for 10–15% of an airline's annual operational costs (Sprong, Jiang & Polinder, 2019). PHM has been estimated to offer benefits on the order of €700 million per year for European aviation alone (Verhagen et al., 2023), motivating its integration into established MRO practice.

Despite these benefits, significant gaps impede PHM implementation in aviation. CBM is still treated as an extra monitoring layer rather than a certified component of the maintenance programme, and technical, organisational, and regulatory-economic barriers further hinder adoption (Verhagen et al., 2023). PHM success also depends on context-specific technology suitability; frameworks for selecting maintenance methods by ambition level, data type, and physics-based approach (Silveira, Meghoe & Tinga, 2024; Tiddens, Braaksma & Tinga, 2023) help assess maturity and facilitate the transition to PdM/PsM, yet scaling such solutions into reliable operational ecosystems remains an open challenge (Fu & Avdelidis, 2023).

A further challenge is the integration between MRO and PHM: MRO typically falls under operations and sustainment, tied to governance, compliance, and service delivery (Uhlmann, Bilz & Baumgarten, 2013), whereas PHM is often treated as an “add-on”, integrated only after system design and implementation (Hu et al., 2022). Existing work has examined CBM adoption barriers at the policy level (Verhagen et al., 2023), reviewed PHM algorithms for aircraft systems (Fu & Avdelidis, 2023), and surveyed predictive maintenance in defence aviation (Scott et al., 2022), but these contributions treat PHM as a *monolithic* capability and do not make explicit how its individual stages interface with specific MRO process steps. Understanding these relationships, including their synergies and bottlenecks, is the focus of this paper.

For this, we propose a *conceptual integration framework* (Section 4) that makes explicit key relationships between MRO and PHM, informed by scientific literature, standards, and structured consultation with practitioners at an integrated MRO organisation, and motivated by a use case on **Hydrogen-Electric Aircraft Propulsion System (HEAPS)**, a technology with the potential to reduce greenhouse gas emissions and help achieve net zero targets (Tiwari, Pekris & Doherty, 2024). This paper seeks to advance the development and certification of PHM technologies for MRO applications, serving readers from either domain seeking the complementary perspective, and engineers working on health management for hydrogen-powered vehicles.

Contributions. Our contributions are:

(i) A conceptual integration framework that maps PHM stages onto the regulated aviation MRO process chain, making the roles of the Continuing Airworthiness Management Organisation (CAMO), Part 21J, and Part 145 explicit.
(ii) An identification of failure modes, mechanisms, and sensor measurands relevant to Hydrogen-Electric Aircraft Propulsion System (HEAPS), examined through both PHM and MRO lenses.
(iii) An analysis revealing a fundamental *asymmetry*: PHM's influence on MRO is largely unrealized beyond diagnostics, while MRO defines the constraints and feedback that PHM depends on.

Outline. Section 2 provides background on PHM, MRO, and HEAPS. Section 3 presents our methodology. Section 4 introduces our framework, which is applied to a HEAPS in Section 5. Our discussion and future research directions are outlined in Section 6, with conclusions drawn in Section 7.

2. BACKGROUND

2.1. Prognostics and Health Management

Prognostics and Health Management (PHM) uses knowledge, information, and data from an asset to detect anomalies, isolate and diagnose faults, predict the evolution of system states, and support optimal maintenance and logistics decisions. The literature on PHM is rich; comprehensive reviews discussing modelling approaches, system architectures, sensing technologies, benefits, and open challenges, can be found in: Jouin et al. (2013); Lee et al. (2014); Xia et al. (2018); Tao et al. (2018); Zio (2022). PHM's building blocks are: **Physical and Edge Infrastructure** (i.e., measurement systems and digital interfaces) is the foundational hardware that acts as the direct interface between the asset and the digital system, encompassing sensors, data acquisition, embedded microprocessors, and communication networks.

Data gathering and processing connects physical assets to digital systems by capturing physical signatures through data acquisition hardware and communication protocols, cleaning raw data (e.g., removing noise, handling missing values), and applying signal processing algorithms to extract meaningful indicators and signatures.

Diagnostics answers: *what is happening now, and why?* It aims to identify the *current* system state, often in terms of health. It involves anomaly detection, classification (or fault types), root cause analysis, and quantification (associated with severity or degradation levels). More in Jardine, Lin and Banjevic (2006); Cerrada et al. (2018); Li et al. (2026). Diagnostic's outcomes support *condition assessment*, which in turn informs CBM decision-making.

Prognostics answers: *how long until an event or state is reached?* It focuses on assessing the *future* condition of an asset over an indexing unit, such as time or cycles, and enables *time-to-event* estimation. Main elements in a prognostics model are: system model, propagation model, prediction algorithm, and threshold event (Goebel et al., 2017). Prognostics support PdM decision-making and shares a methodological overlap with *time series forecasting* (B. Lim & Zohren, 2021).

Policy optimisation answers: *what should we do, and when?* It is typically framed as a *sequential decision-making prob-*

lem (Roijers et al., 2013) in operational research. A review on maintenance optimisation techniques can be found in Pinciroli, Baraldi and Zio (2023). Its primary goal is to determine the *optimal course of action* and *timing* to minimise long-term costs while maximising asset availability over a specified planning horizon, facilitating maintenance and logistics planning and resource allocation. The outcome of policy optimisation supports PsM decision-making, and ideally, should interface with both *diagnostics* and *prognostics* to create robust *state-aware* policies.

PHM design methods adopt a systems-engineering approach, prioritising validation and verification, with frameworks such as “5S” (Lee et al., 2014), “5C” (Lee, Bagheri & Kao, 2015), “DE^3” (Hu et al., 2022), and “DSS” (Abbate et al., 2024), and standards including ISO 13374 (Parts 1–4) (ISO, 2003, 2007, 2012, 2015), OSA-CBM (MIMOSA, 2006), ISO 13381-1 (ISO, 2025), ISO 17359 (ISO, 2018), and IEEE 1856-2017 (IEEE, 2017); reviews are provided in Vogl, Weiss and Donmez (2014). In the aviation industry, **Integrated Vehicle Health Management (IVHM)** (Benedettini et al., 2009) is a closely related discipline that strongly overlaps with PHM but places greater emphasis on integrated health management at the system and vehicle level.

2.2. Maintenance, Repair and Overhaul

The **Maintenance, Repair and Overhaul (MRO)** process in commercial aviation is embedded within a strict regulatory framework designed to guarantee continuous airworthiness throughout the aircraft lifecycle, dividing responsibilities across approved organisational entities, each contributing to the translation of engineering knowledge into regulated maintenance actions (Darli Rodrigues Vieira, 2016).

The aircraft manufacturer, acting as a **Part 21J** Design Organisation, most often together with an associated **Part 21G** Production Organisation, translates the **Maintenance Steering Group (MSG)-3** (Airlines for America, 2022) results into the **Maintenance Planning Document (MPD)**. Although comprehensive, the MPD as a whole is not legally binding; it reflects the recommendations for inspections by the **Original Equipment Manufacturer (OEM)**, functional checks, and component replacements needed to maintain safety and performance.

Transforming these recommendations into a legally enforceable maintenance regime is the responsibility of the **Continuing Airworthiness Management Organisation (CAMO)**. A CAMO may be internal to the airline or an external service provider. Its role is strategic and regulatory: CAMO develops the operator-specific **Aircraft Maintenance Programme (AMP)**, further defines an economical scheduling logic, and holds responsibility for the fleet and system reliability. Any version or revision of the AMP must be submitted to and approved by the aviation authority and is, after acceptance, legally binding. It describes the minimum required maintenance tasks. Every CAMO ultimately holds accountability for approved processes, including reliability monitoring, task escalation, review procedures, and more.

Maintenance execution is performed by the **Part 145 Maintenance Organisation**. A Part 145 organisation does not determine the applicable maintenance scope; instead, it ensures the accurate and compliant execution of approved tasks assigned by the CAMO. All actions follow approved maintenance data as outlined in job cards, work orders, and referenced manuals. Additionally, Part 145 organisations are responsible for production planning, assigning qualified personnel, and managing tooling, materials, and facility readiness.

Lufthansa Technik occupies an integrated position in this ecosystem, combining Part 145 maintenance, CAMO services, Part 21J design, Part 21G production, and Part 66 training organisations within a single structure. This enables efficient information flow across design, certification, and maintenance execution, supporting rapid feedback, strong compliance oversight, and streamlined maintenance programme development.

2.3. Hydrogen-Electric Aircraft Propulsion System

A **Hydrogen-Electric Aircraft Propulsion System (HEAPS)** is an integrated multi-subsystem architecture that converts the chemical energy of stored hydrogen directly into electrical power through an electrochemical process, which is subsequently converted into mechanical thrust by electromechanical propulsors. Relevant papers on HEAPS include Fard et al. (2022); Massaro et al. (2023) and Tiwari, Pekris and Doherty (2024).

In the general sense, the HEAPS architecture can be decomposed as in Figure 1. The **Hydrogen Fuel System**, comprising the **Hydrogen Storage System (HSS)** and the **Hydrogen Fuel Distribution and Conditioning System (HFD&CS)**, stores the onboard hydrogen and delivers it in a form suitable for the downstream power source; storage choice directly affects fuel distribution, conditioning, and thermal integration.

The **Power Generation System** converts hydrogen into useful onboard power through the **Fuel Cell System (FCS)**, which in some cases can also be achieved through Hydrogen Gas Turbine Systems, although these are outside the scope of this paper. Within the FCS, the **Fuel Cell Stack** performs the conversion, while the **Balance of Plant (BoP)** sustains it. The BoP relies on multiple sub-systems: the **Air Supply System** handles air and oxygen, the **Hydrogen Supply System** handles fuel delivery, the **Water Management System** balances water production and removal, and the **Thermal Management System** regulates operating temperatures.

The generated power is then handled by the **Electrical Power**

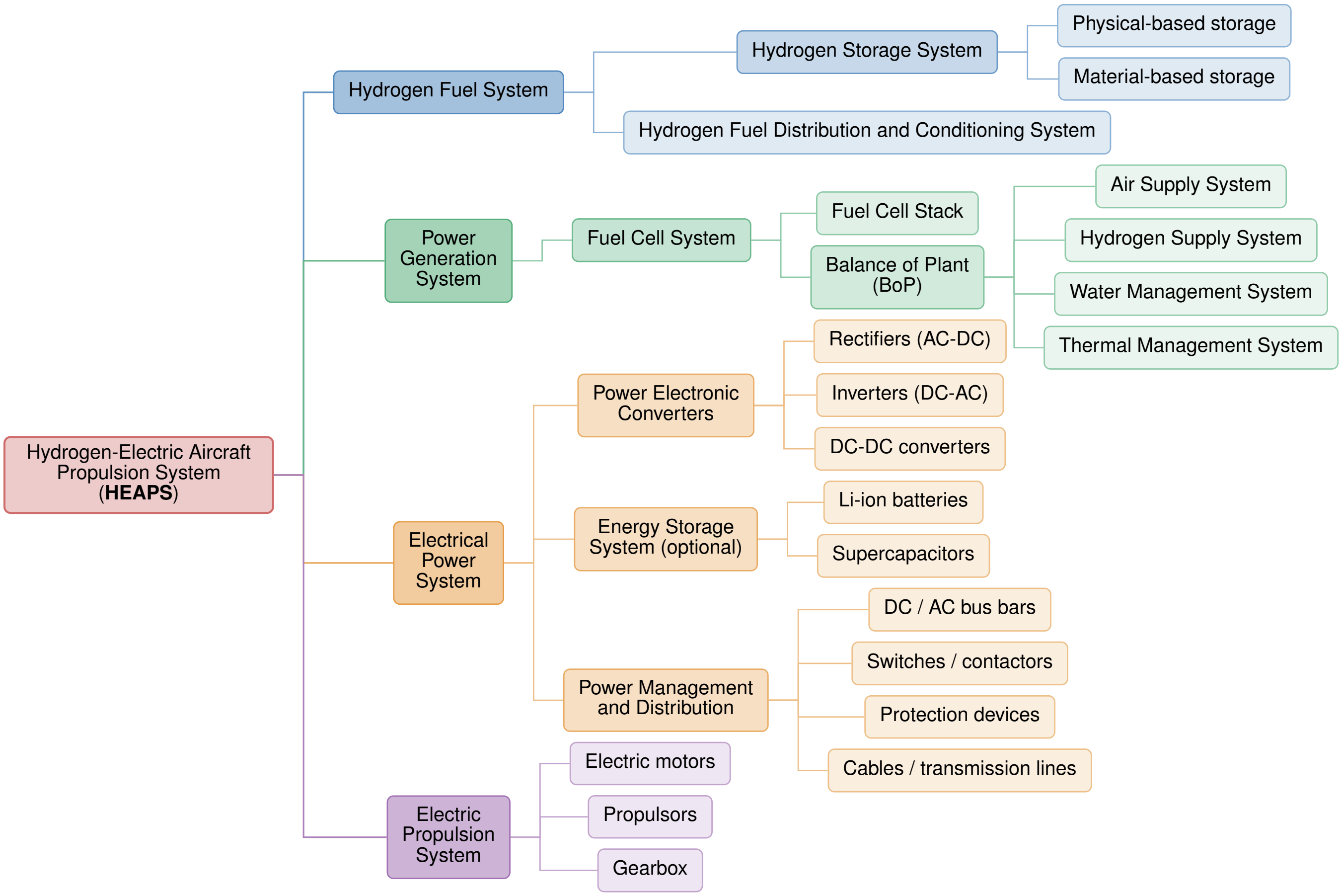

Figure 1. System-level architecture of a Hydrogen-Electric Aircraft Propulsion System (HEAPS).

System (EPS), which includes **Power Electronic Converters** for power transformation, the **Power Management and Distribution** network for electricity transmission, and an **Energy Storage System** pairing lithium-ion batteries and supercapacitors. Together, they condition, manage, and distribute power to the aircraft loads and propulsors.

Finally, the **Electric Propulsion System** converts delivered electrical power into thrust. Electric motors generate mechanical power, propulsors (distributed fans or propellers) generate thrust, and a gearbox is often integrated into the drivetrain to reduce high motor Revolutions Per Minute (RPM) for optimal aerodynamic efficiency.

3. METHODOLOGY

This study draws on PHM and MRO literature and domain expertise to answer: *What are key relations between MRO and PHM in the context of HEAPS?*

For this, we divided our strategy into three steps:

(1) We identify PHM, MRO, and HEAPS methodologies using scientific databases (e.g., Scopus) and domain expertise, summarised as background in Section 2.

(2) A common approach to initiate PHM and MRO design development involves identifying *failure modes* and *mechanisms* within a system, along with associated *sensor measurands*. To this end, we focused our literature search on studies discussing failure modes of HEAPS, with results presented in Section 5.1.

(3) We combine the above to assemble our framework (Section 4) and apply it to HEAPS (Section 5); emerging connections between PHM and MRO are discussed in Section 6.

Practitioner perspectives from co-authors at Lufthansa Technik AG, an integrated MRO organisation, contributed to the framework's treatment of the PHM–MRO interface.

4. PHM-MRO CONCEPTUAL INTEGRATION FRAMEWORK

Figure 2 illustrates our conceptual integration framework, which makes explicit key elements for understanding the interplay between PHM and MRO, as discussed in Section 6. The framework is intentionally designed as a conceptual mapping rather than a prescriptive decision procedure: its purpose is to surface and structure the implicit relationships between

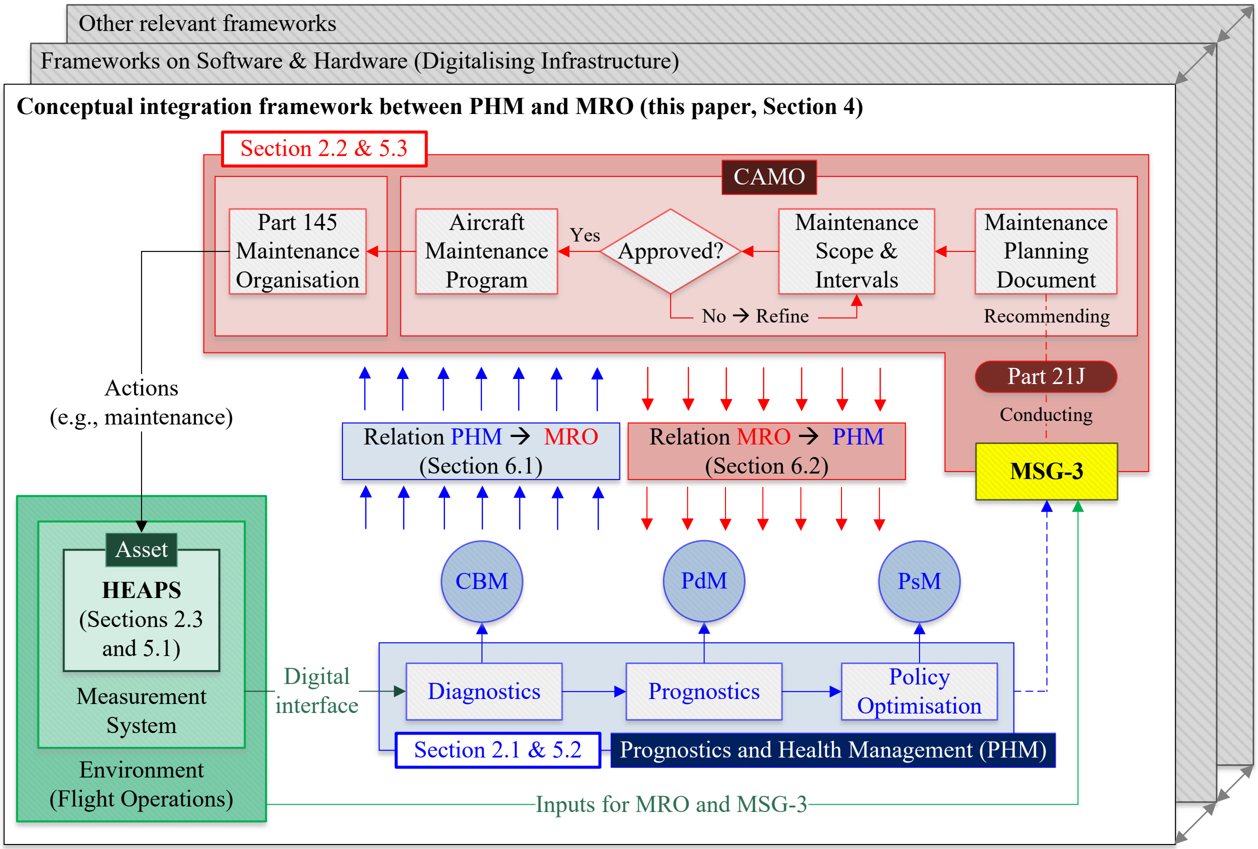

Figure 2. Conceptual integration framework of Prognostics and Health Management (PHM) and Maintenance, Repair and Overhaul (MRO) for health management of a Hydrogen-Electric Aircraft Propulsion System (HEAPS). Blue arrows (PHM → MRO) and red arrows (MRO → PHM) capture the bidirectional relationship analysed in Sections 6.1 and 6.2.

PHM stages and MRO process steps, enabling systematic analysis of their synergies and bottlenecks. While our context of application is a HEAPS, the framework is domain-agnostic by design; HEAPS serves as an illustrative case to populate and examine the mapping, but the identified relationships can be applied to other novel propulsion architectures or, more broadly, to other asset types in regulated industries. Our framework comprises three primary components:

1. **Asset and Environment**: The asset (here, a HEAPS) is situated within an environment (here, flight operations); the two influence each other. Relevant interactions (e.g., physical responses) are captured by a specialised hardware that digitalises the system's responses for subsequent stages.
2. **PHM methodology**: It uses information collected from the asset, together with mathematical pipelines and heuristics, to produce outcomes supporting CBM, PdM, and PsM (see Section 2.1). This includes examples such as CBM triggered by detected anomalies, PdM based on critical degradation profiles, and PsM adjusts operational conditions to ensure safe mission execution. The PHM process under the context of HEAPS is discussed in Section 5.2. These outcomes are essential at various levels of the Continuing Airworthiness Regulation.
3. **MRO methodology**: It is driven by an approved AMP issued by the CAMO (see Section 2.2). Its purpose is to generate the necessary technical and managerial actions that keep the asset operating safely and reliably, while also preserving its availability and quality. The process unfolds through several distinct stages, beginning with the MSG-3 analysis and concluding with Part-145 maintenance activities. The MRO process under the context of HEAPS is discussed in Section 5.3.

Other layers (e.g., hardware and software for digitalisation infrastructure) are beyond the scope of this paper; the *bidirectional relationship* between PHM and MRO captured by the framework is analysed in Sections 6.1 and 6.2.

5. CONCEPTUAL INTEGRATION OF PHM AND MRO APPLIED TO A HYDROGEN-ELECTRIC AIRCRAFT PROPULSION SYSTEM

We apply our framework (Section 4) to a relevant industrial application in aerospace, a HEAPS (Section 2.3). Rather than a traditional literature review, the following sections synthesise failure modes, mechanisms, and sensor measurands to populate the proposed conceptual integration framework. By mapping these HEAPS failure modes to corresponding PHM solutions and MRO procedures, we establish the practical engineering relevance of the framework.

5.1. Overview on failure modes, mechanisms, and sensor measurands in a Hydrogen-Electric Aircraft Propulsion System

Failure modes describe how a component or subsystem fails, **failure mechanisms** refer to the underlying physical processes, and **sensor measurands** are the observable variables used to monitor or infer such conditions. These three ingredients are foundational for PHM system design: failure mechanisms feed physics-informed modelling, e.g., Scientific Machine Learning (SciML) (Keith et al., 2025), while sensor measurands inform monitoring and digital interfaces. The overview below provides a grounded starting point for PHM development on HEAPS rather than an exhaustive review; Sections 5.2 and 5.3 draw on this material selectively. Well-established methods for system failure analysis include **FMEA** and **FMECA** (IEEE, 2017), **Physics-of-Failure (PoF)** (Pecht & Gu, 2009), and **Fault Tree Analysis** (Ruijters & Stoelinga, 2015).

5.1.1. Hydrogen Fuel System

In the **Hydrogen Storage System**, the primary failure modes are **reactant tank leakage** and **rupture**, exacerbated by material embrittlement and hydrogen permeation (Tiwari, Pekris & Doherty, 2024), leading to reactant loss and potentially dangerous external hydrogen reactions or fires (Miller, 2019). Cyclic stress and extreme storage pressures in compressed hydrogen introduce temperature rises and explosion risks (Massaro et al., 2023), while for liquid hydrogen, boil-off caused by heat transfer and ortho-to-para hydrogen conversion yields internal pressure rises and relief valve venting (Massaro et al., 2023).

The **Hydrogen Fuel Distribution and Conditioning System** is susceptible to **response hysteresis**, low supply efficiency, and viscous resistance (C. Zhang et al., 2023). Dead-end anode setups can accumulate liquid water and exhaust contaminants, leading to **hydrogen starvation** and irreversible catalyst degradation (C. Zhang et al., 2023). Component-level failures (**manual** and **solenoid valve failures**, **pressure regulator internal failures**, **recirculation pump failures**, **product water trap blockages**) result in **reactant loss**, **stack flooding**, and secondary hazards (Miller, 2019).

5.1.2. Power Generation System

The most pervasive **Fuel Cell Stack** failure mode is **water management imbalance** (**membrane drying** or **flooding**), caused by thermal and load transients and detectable via cell voltage monitoring (Miller, 2019). This imbalance exacerbates degradation across three key components:

- **Membrane**: **Chemical** and **mechanical degradation** (Whiteley, Dunnett & Jackson, 2016; C. Zhang et al., 2023), catalysed by bipolar corrosion; detectable via polarisation curves and linear sweep voltammetry (Whiteley, Dunnett & Jackson, 2016).
- **Catalyst Layer**: Active surface area loss from **particle detachment**, **growth/dissolution**, and **carbon support corrosion** during start-stop cycles (C. Zhang et al., 2023); tracked via electrochemical surface area and open-circuit voltage.
- **Gas Diffusion Layer (GDL) & Bipolar Plates (BPP)**: GDL **coating loss** through electrochemical oxidation (causing localised water blockage) and **fracture** under compressive stress; BPP develop **oxide films**, **corrode**, and **deform** under uneven thermal loads, increasing contact resistance (Whiteley, Dunnett & Jackson, 2016; C. Zhang et al., 2023).

System-level **cross-leaks** include hydrogen and oxygen entering the coolant (reactant loss), anode-to-cathode leaks from membrane degradation (voltage decay, hydrogen-oxygen reactions), and coolant entering reactant cavities (flooding or catalyst poisoning) (Miller, 2019). **Inert gas build-up** causes voltage decay, managed by correlating cell voltage and Amp-hour counting to schedule purges (Miller, 2019).

Within the **Balance of Plant**, the **Air Supply System** is susceptible to **compressor response lag**, **surging**, **clogged air filters**, and **improper oxygen-to-fuel ratios**, leading to catalyst poisoning or reverse cell polarity, typically detected as a voltage drop across cells (C. Zhang et al., 2023). The **Hydrogen Supply System** faces **response delays**, **low supply efficiency**, **backward water accumulation**, and **external hydrogen leaks** (C. Zhang et al., 2023); at the component level, recirculation pump degradation or stoppage can cause localised stack drying or flooding.

The **Water Management System** failure modes include water trap level switches **failing set** or **open** and drain solenoid valves **failing open**, **partly open**, or **closed** (Miller, 2019), leading to continuous reactant loss, hazardous air backflow, or severe stack flooding. Water traps and the product water tank are also susceptible to **external leaks**, **blocked drains**, **blocked inlets**, and **freeze damage** (Miller, 2019). The **Thermal Management System** failure modes include **coolant pump stoppages**, **heat exchanger (HEX) blockages**, and **coolant heater malfunctions** (Miller, 2019), causing stack overheating or freezing, monitored through coolant flow switches and temperature sensors.

5.1.3. Electrical Power System

Power electronic converters are susceptible to **single-event burnout (SEB)** and **single-event gate rupture (SEGR)**, causing permanent semiconductor damage, while cryogenic temperatures and high-frequency switching induce package degradation, capacitance decrease, and transient reflected voltage spikes or bearing currents that degrade downstream motor insulation (Fard et al., 2022). The power management and distribution network faces **partial discharges** causing progressive **insulation ageing** (Borghei & Ghassemi, 2021), **insulation breakdown**, the **corona effect**, and **surface discharges** (Hendricks et al., 2015; Fard et al., 2022), leading to electromagnetic interference and short circuits requiring rapid isolation by solid-state power controllers and fault current limiters. The energy storage system faces battery failure modes including **solid electrolyte interphase thickening**, **copper dissolution**, **aluminium corrosion**, and **internal short circuits** (Hendricks et al., 2015), causing capacity fade and thermal runaway.

5.1.4. Electrical Propulsion System

Electric motors are susceptible to **insulation degradation** and **breakdown** across stator windings, driven by transient surge voltage stresses from high-frequency switching in low-pressure environments, while continuous mechanical vibrations and excessive alternating current losses cause **thermal degradation** and **overheating** (Fard et al., 2022; Tiwari, Pekris & Doherty, 2024). Propulsors (distributed fans or propellers) are vulnerable to **sudden failure** or **complete thrust loss**, immediately creating hazardous flight conditions (Fard et al., 2022). Gearboxes, when integrated to reduce high motor RPM for aerodynamic efficiency, are susceptible to progressive **mechanical wear** and failure (Fard et al., 2022), adding weight and maintenance burden, which often motivates magnetically geared alternatives (Fard et al., 2022).

5.2. Prognostics and Health Management of a Hydrogen-Electric Aircraft Propulsion System

This section explores how PHM can support MRO in managing HEAPS failure modes through three applications: diagnostics (Section 5.2.1), prognostics (Section 5.2.2), and policy optimisation (Section 5.2.3), with relevant examples rather than a comprehensive review.

5.2.1. Diagnostics

Diagnostics supports CBM by assessing the system's *current* state at multiple levels: detection, classification, root-cause analysis, and quantification. Each level supports a different maintenance action: an anomaly detection may trigger an inspection, while a quantified severity estimate can justify component replacement. Comprehensive reviews of **Proton Exchange Membrane Fuel Cells (PEM-FCs)** diagnostics are provided in Wang et al. (2021) and C. Zhang et al. (2023).

Table 1 provides examples of diagnostic applications linked to various failure modes in HEAPS. **Anomaly detection** looks for significant deviations from nominal behaviour. Reported approaches include residual-generation methods such as **Artificial Neural Networks (ANNs)** (Dijoux et al., 2022) and **Gaussian-process regression** (Oh et al., 2020); threshold-based and statistical techniques (Dahmene et al., 2016); and in-situ testing (Abiru et al., 2024). MRO can exploit these methods to focus inspection effort on likely fault locations.

Classification assigns a specific fault label, enriching the information available for response planning. A combined **Long Short-Term Memory (LSTM)** and **Convolutional Neural Network (CNN)** model has been used to distinguish normal, flooding, and drying states (Kim et al., 2023); **Physics-Informed LSTMs** address the same problem (Pettorossi et al., 2025); and a **Support Vector Machine (SVM)** with selected features discriminates individual Thermal Management System faults (I. Lim et al., 2021). Such applications can help MRO initiate specific responses e.g., a leak detection can instantly dispatch the appropriate intervention team.

Quantification extends diagnostics by measuring condition severity and its evolution toward critical states. An **Adaptive Extended Kalman Filter (AEKF)** has been applied to estimate membrane water content (Lance, Leroy & Sery, 2024), and an SVM classifier has differentiated severity levels of pipe-gas leaks (Xiao, Hu & Li, 2019). MRO can exploit this information to tailor intervention; minor-severity issues demand different actions and resources than major ones.

Root Cause Analysis (e Oliveira, Miguéis & Borges, 2023) determines why an anomaly occurred and helps MRO map failure chains to responsible components; no strictly HEAPS-specific example was found at the time of this publication.

5.2.2. Prognostics

Prognostics supports PdM by evaluating the system's *future* condition, and enables *time-to-event* analyses. A common prognostic output is the **Remaining Useful Life (RUL)**, which quantifies the interval (e.g., calendar time or cycles) between the present moment and the expected occurrence of a failure or a performance-degrading state. The literature on PEM-FC prognostics is extensive; a review is provided in H. Liu et al. (2020). A growing trend combines physics-based modelling with data-driven techniques: incorporating physical knowledge (e.g., SciML) constrains Machine Learning (ML) models, improves interpretability, and helps capture degradation trends transferable across operating conditions. Table 2 summarises prognostics applications for HEAPS, which can improve MRO intervention planning (e.g., maintenance, inspection) and potentially enrich the *Maintenance Scope & Intervals* (see Section 6.1).

5.2.3. Policy Optimisation

Policy optimisation under the PsM framework (Orošnjak, Saretzky & Kedziora, 2025) seeks to guide optimal inspec-

Table 1. Examples of PHM **diagnostics** applications for Hydrogen-Electric Aircraft Propulsion System failure modes, illustrating PHM capabilities relevant to the diagnostics → MRO link in Figure 2.

Failure mode	Input	Approach	Output	Reference(s)
Anomaly detection				
Membrane drying and water flooding	Stack voltage, current, cathode pressure drop	ANN-based residual generation	Binary fault flag (detected / not detected)	Dijoux et al. (2022)
Hydrogen storage failure	AE; felicity ratio during pressurisation	Statistical analysis of AE parameters; threshold-based waveform pattern analysis	Accept / reject decision for vessel structural integrity	Dahmene et al. (2016)
Hydrogen embrittlement crack detection	ECT signals; hammering-test sound pressure signals	ECT detects large cracks; hammering test detects half-size cracks	Binary: crack detected / not detected	Abiru et al. (2024)
TMS fault (HEX fouling, pump degradation)	Stack and HEX temperatures, coolant flow rates, pump control signals	Linear and Gaussian-process regression for residual generation	Binary fault flag when residuals exceed thresholds	Oh et al. (2020)
Classification				
Water management faults	Cell/stack voltage, relative humidity, cell temperature (time-series)	Ensemble of DL models (LSTM and CNN)	Three classes: flooding, normal, drying	Kim et al. (2023)
Flooding, drying, combined faults	Stack voltage time-series (single signal)	Physics-guided LSTM; minimal sensor inputs	Multi-class label: flooding / drying / normal	Pettorossi et al. (2025)
TMS component faults	Temperatures, pressures, fan PWM control signals	SVM classifier on PCA-transformed residual features	Five classes: normal, pump degradation/disabled, fouling, tube clogging, fan disabled	I. Lim et al. (2021)
Quantification				
Pipeline gas leakage (severity)	Acoustic signals from leakage events	Wavelet feature extraction + SVM multi-class classification	Four severity levels: no leak, small, middle, large	Xiao, Hu and Li (2019)
Membrane water content (hydration level)	Cell voltage, current, anode/cathode pressures, mass flow rates, temperature	AEKF with adaptive covariance matrices	Continuous estimate of membrane water content; real-time capable	Lance, Leroy and Sery (2024)
Abnormal airflow / supply	Cathode and supply pressure, voltage, compressor speed, current	ST-SMO; nonlinear model-based	Continuous fault signal reconstruction (fault magnitude over time)	J. Liu et al. (2016)
Vessel damage evolution	Fibre optic sensors (distributed strain); internal pressure time-series	Strain residual analysis; spatial mapping along vessel length	Damage magnitude, spatial localisation, and evolution prior to failure	Karapanagiotis et al. (2025)
Air supply fault magnitude	Air compressor voltage; fuel cell stack current	LPV model from a 9th-order nonlinear formulation	Continuous fault magnitude estimate (e.g. mass flow deviation in kg/s)	Yang, Wang and Chen (2020)

Abbreviations: AE — Acoustic Emission; AEKF — Adaptive Extended Kalman Filter; ANN — Artificial Neural Network; CNN — Convolutional Neural Network; DL — Deep Learning; ECT — Eddy Current Testing; HEX — Heat EXchanger; LPV — Linear Parameter-Varying; LSTM — Long Short-Term Memory; PCA — Principal Component Analysis; PWM — Pulse-width modulation; ST-SMO — Super-twisting Sliding Mode Observer; SVM — Support Vector Machine; TMS — Thermal Management System.

tion, maintenance, and logistics decisions. Approaches range from **Reinforcement Learning (RL)** and its deep-learning variant **Deep Reinforcement Learning (DRL)**, which learn strategic policies through neural-network function approximators, to classical alternatives such as **Dynamic Linear Programming** and **Risk-Based Inspection (RBI)** methods.

In the context of HEAPS, Table 3 summarises how these techniques have been applied. RL/DRL approaches address real-time system control tasks such as dispatching hydrogen flow and preventing membrane dehydration or flooding (Dijoux et al., 2022). More conventional optimisation methods support longer-term planning activities, such as scheduling maintenance (Meng et al., 2026) and conducting inspections (Mahmoodzadeh et al., 2020).

5.3. Maintenance, Repair and Overhaul of a Hydrogen-Electric Aircraft Propulsion System

Creating an MRO plan for a HEAPS is challenging because no dedicated maintenance manuals or regulatory rules exist yet. Traditional aviation maintenance can offer a structural template, but it cannot be copied directly. Conventional aircraft only receive detailed manuals after certification, a stage HEAPS has not reached. Therefore, the first task is to lay out basic principles that can later become formal procedures and regulations, rather than trying to write specific “every x hours” checklists now.

A sensible way to begin is to break the aircraft into its core functions, similar to the MSG-3 approach used for existing aircraft. For each function we ask: *what could fail*, *how ser-*

Table 2. Examples of PHM **prognostics** applications for Hydrogen-Electric Aircraft Propulsion System failure modes, illustrating PHM capabilities relevant to the prognostics → MRO link in Figure 2.

Failure mode	Input	Approach	Output	Reference(s)
Data-driven				
PEM-FC overall voltage degradation	Stack voltage time-series (FCLAB dataset; constant and dynamic load profiles)	GRU neural network	RUL estimate (hours to failure threshold)	Long et al. (2022)
PEM-FC overall voltage degradation	Stack voltage and operational variables; features auto-selected via RF-RFE	RF + TCN, optimised with PSO	Degradation trend + RUL prediction	T. Zhang et al. (2025)
Cathode flooding and membrane drying (PEM-FC)	Cell voltage and current time-series from single-cell experiments	Bagging ensemble of LSTM and CNN models	Predicted flooding/drying state 30 s ahead	Kim et al. (2023)
Physics-based				
PEM-FC membrane dehydration	Operating conditions (current, temperature, pressure, etc.)	Analytical lumped model of membrane water transport dynamics	Membrane water content evolution prediction (real-time prognostics)	Sicilia et al. (2024)
IGBT module wire-bond and solder-joint fatigue	Collector–emitter on-state voltage, thermal resistance, case temperature under power cycling	Coffin–Manson strain-based and damage-based fatigue life models (review)	Cycles-to-failure estimation; RUL under thermomechanical cycling	Oh et al. (2015)
Hydrogen-assisted fatigue crack growth	Various pressures and load ratios	Correlating crack growth rate with stress, pressure, and load	Predicted crack growth rate as a function of stress and pressure	Amaro et al. (2018)
Hybrid				
PEM-FC overall voltage degradation	Stack voltage time-series, operating current, temperature	Multi-physical aging model + PF + extrapolation	RUL prediction with uncertainty bounds	Zhou et al. (2017)
PEM-FC membrane and catalyst degradation	Cell voltage, polarisation curves, resistance, ECSA measurements	Physics-based degradation mechanism model + PF	RUL prediction (hours); contribution analysis of degradation factors	Chen et al. (2022)
PEM-FC catalyst layer aging (ECSA loss)	Cell voltage, current load profile (cathode potential)	Physics-based catalyst degradation model + UKF	ECSA health state tracking + RUL prediction	X. Zhang and Pisu (2014)

Abbreviations: CNN — Convolutional Neural Network; ECSA — Electrochemically Active Surface Area; GRU — Gated Recurrent Unit; IGBT — Insulated-Gate Bipolar Transistor; LSTM — Long Short-Term Memory; PEM-FC — Proton Exchange Membrane Fuel Cell; PF — Particle Filter; PSO — Particle Swarm Optimisation; RF — Random Forest; RFE — Recursive Feature Elimination; RUL — Remaining Useful Life; TCN — Temporal Convolutional Network; UKF — Unscented Kalman Filter.

ious would the failure be, and *which other components are affected?* By describing the HEAPS in technology-neutral terms (e.g., "cryogenic hydrogen storage" instead of naming a particular tank) we build a functional map that any future design can fit into.

With that functional map, we can think about how to embed PHM from the start at a conceptual level. Examples include ANN-based residual analysis that flags membrane drying or water ingress from stack-voltage data (Dijoux et al., 2022), **Acoustic Emission** monitoring to catch structural degradation in storage vessels (Dahmene et al., 2016), and regression models that reveal HEX fouling (Oh et al., 2020). Projects such as HEROPS (European Commission, 2024) have shown that a "*function-first, task-later*" strategy yields a scalable framework that can be refined as the technology matures.

Hydrogen brings safety challenges not seen in conventional aircraft: cryogenic temperatures, invisible leaks, strict insulation, and handling a highly flammable gas within the aircraft's ventilation and sensor networks. PHM can inform inspection and service points, but these tools must first satisfy rigorous validation and certification, making regulatory acceptance the main hurdle. One way forward is to pair each identified hazard with a suitable PHM method, e.g., wavelet-based SVM classifiers for leak severity (Xiao, Hu & Li, 2019), sliding-mode observers for abnormal airflow (J. Liu et al., 2016), fibre-optic strain sensors for vessel degradation (Karapanagiotis et al., 2025), and embed this mapping in a *modular*, *technology-agnostic architecture* ready for future certification. At this stage, such mappings support methodological reasoning and architectural structuring, rather than defining certified maintenance tasks, thresholds, or intervals.

Although certified PHM-driven maintenance is not yet in place for HEAPS, current aviation practice illustrates how condition-based information can support operational de-

Table 3. Examples of PHM **policy optimisation** applications for Hydrogen-Electric Aircraft Propulsion System failure modes, illustrating PHM capabilities relevant to the policy optimisation → MRO link in Figure 2.

Failure mode	Input	Approach	Output	Reference(s)
Reinforcement learning				
Multi-component degradation in fuel cell systems	Real-time sensor data; historical maintenance records; degradation model	DRL agent balancing degradation rate against operational requirements	Optimal maintenance action recommendations; intervention timing	Meng et al. (2026)
Internal corrosion degradation of dry gas pipelines	Pipeline monitoring data; inspection history; environmental conditions	RL agent learning a CBM inspection and maintenance policy	Optimal inspection and maintenance scheduling policy	Mahmoodzadeh et al. (2020)
FC stack degradation and battery aging	Real-time FC voltage and current; battery SOC and SOH; load profile; hydrogen consumption	Deep Q-networks and actor–critic RL architectures	Real-time energy dispatch policy maximising hydrogen use	Taghizad-Tavana et al. (2025); Vellaiyan et al. (2026)
Membrane degradation	Degradation state and stack age; inspection and replacement costs; stochastic heterogeneity	PPO RL on an MDP formulation for preventive control limits and inspection intervals	Optimal replacement, threshold and inspection policy minimising cost	Zuo et al. (2025)
Optimisation-based planning				
Multi-component FC vehicle system degradation	Component failure rates; repair and replacement costs; system reliability models	Multi-objective optimisation: NSGA-II with fuzzy feasibility	Maintenance schedule balancing system reliability and total lifecycle cost	Mellal, Zio and Pecht (2023)
Catalyst layer aging	Voltage, current, and time-derived HI-RUL; hydrogen price; PEMFC price	Economic cost-evaluation for PEMFC replacement	Economically optimal PEMFC replacement date	Gibey et al. (2025)
Vessel structural failure	Strain measurements; internal pressure; damage state (dent size)	Reduced-basis digital twin with Bayesian inference and stress–life fatigue analysis	Statistical fatigue life prognosis; CBM schedule	Kang et al. (2025)
Hydrogen embrittlement	Material, environment and stress data; RBI standards	RBI review: ProF, CoF and damage-factor-based inspection planning	RBI-based inspection planning recommendations	Campari et al. (2023)
Real-time mitigation				
Cathode flooding and membrane dehydration	Cathode pressure-drop and cell-voltage signals; operating settings	ANN residual diagnosis with heuristic setpoint adjustment	Mitigation setpoints restoring healthy operation	Dijoux et al. (2022)
Reactant (air) starvation	Air-flow and pressure states; component fault estimates; oxygen stoichiometry	LPV-observer-based fault diagnosis with fault-tolerant air-supply control	State reconstruction and air-compressor voltage maximising net power	Yang, Wang and Chen (2020)

Abbreviations: ANN — Artificial Neural Network; CBM — Condition-Based Maintenance; CoF — Consequence of Failure; DRL — Deep Reinforcement Learning; FC — Fuel Cell; HI — Health Indicator; LPV — Linear Parameter-Varying; MDP — Markov Decision Process; NSGA-II — Non-dominated Sorting Genetic Algorithm II; PEMFC — Proton Exchange Membrane Fuel Cell; ProF — Probability of Failure; PPO — Proximal Policy Optimisation; RBI — Risk-Based Inspection; RL — Reinforcement Learning; RUL — Remaining Useful Life; SOC — State of Charge; SOH — State of Health.

cisions. Condition-based information can support operational extensions beyond scheduled intervals, based on in-the-moment health assessment combined with experience-based references across engine types. Whether to act on such information remains an operator decision, varying across operators and aircraft/engine types.

Beyond the aircraft itself, we must assess the maintenance environment: Technicians must be able to access hydrogen components and have specialised tools such as cryogenic-handling equipment, hydrogen-safe fire-suppression systems, and proper ventilation. Training and qualification programmes are essential. PHM can help at multiple levels: diagnostic tools locate faulty parts within the Thermal Management System (I. Lim et al., 2021), while RL policy optimisers can support *inspection scheduling* (Mahmoodzadeh et al., 2020) and optimal *part replacement* (Zuo et al., 2025), providing vital data for logistics planning and crew operations.

6. DISCUSSION

After outlining HEAPS's architecture (Section 2.3) and its failure modes (Section 5.1), we examined critical maintenance considerations through the lenses of PHM (Section 5.2) and MRO (Section 5.3). In this section we focus on the PHM–MRO relationship in HEAPS, beginning with a brief walkthrough that traces a single failure mode through the framework (Figure 2).

Illustrative walkthrough: **water management imbalance**. Stack voltage, cathode pressure drop, and relative humidity feed **diagnostics** (anomaly detection via ANN residuals (Dijoux et al., 2022), classification of flooding/drying states (Kim et al., 2023), membrane water content estimation (Lance, Leroy & Sery, 2024)), **prognostics** (RUL estimation via physics-based models with particle filtering (Zhou et al., 2017)), and **policy optimisation** (RL-based setpoint adjustment (Dijoux et al., 2022)). On the PHM-to-MRO side, diagnostic outputs give CAMO condition-based evidence to adjust inspection intervals within the AMP, and Part 145 executes and records the task. Prognostic RUL estimates could support planning at Part 145, but using them to extend AMP intervals requires formal authority justification, a heavier process than shortening. Policy optimisation outputs currently lack a regulatory entry point. On the MRO-to-PHM side, Part 145 findings provide ground-truth labels for model validation, MSG-3 supplies the failure-mode taxonomy, and the AMP defines the interval boundaries within which PHM operates. This walkthrough illustrates the asymmetry generalised in Sections 6.1 and 6.2: diagnostics has an operational pathway, prognostics faces regulatory friction, and policy optimisation remains disconnected.

6.1. Key relations: from PHM to MRO

PHM stages have the potential to inform and enable MRO process steps, but this potential is largely unrealised: outside diagnostics, PHM has not yet changed how the MRO process chain is structured, approved, or executed. The relationship is dominated by a structural *asymmetry*. PHM proposes performance- and condition-driven solutions to maintenance problems that MRO has defined, but implementing those solutions requires going through the very same regulatory process that PHM seeks to influence.

Diagnostics is the most established PHM stage with operational links to MRO. Its strongest relationship is with the AMP, where health monitoring data is already used to justify interval adjustments, extending or reducing inspections/maintenance according to the asset's condition (i.e., CBM), without altering the AMP structure itself. These practices exist today, though their systematic application can be further intensified. Even at this level, diagnostics outcomes are still seen as *complementary information*.

A practical asymmetry exists within this relationship. Because the AMP defines a minimum maintenance regime, intervening earlier than scheduled faces a lower regulatory threshold than extending intervals, which requires a formal justification procedure with the authority even when the technical case is strong. That said, neither direction is without cost: systematically shortening intervals increases operational burden, while the regulatory justification required to extend a maintenance interval based on prognostic evidence is substantially more demanding, potentially discouraging operators from pursuing deferral even when doing so would be more economically valuable. This asymmetry shapes which PHM outputs are most readily adopted in practice.

Prognostics has a partially realised relationship: at the Part 145 level, platforms such as **AVIATAR** (Witzig et al., 2023) demonstrate that prognostics outputs can enable "*planning the unscheduled*", allowing earlier allocation of personnel, tools, and spare parts ahead of predicted failures (i.e., PdM). PdM outcomes are also increasingly used as supporting evidence for Maintenance Scope & Intervals (MSI) and MPD updates, but they do not yet *drive* the formal revision cycle; the AMP structure and its schedule-driven approval logic remain the binding artefacts. In theory, accurate RUL predictions could justify longer intervals, feed reliability monitoring and AMP effectiveness assessments with predictive evidence, and eventually eliminate scheduled tasks. However, practical and regulatory barriers currently limit this: prognostic algorithms are not yet widely accepted as maintenance drivers, and CAMOs often lack a clear framework to incorporate prognostic evidence into the approval process. Even within the limits established by the AMP, the decision to act on PHM-derived information rests with the operator; therefore, PHM adoption depends not only on regulatory acceptance but also on the organisation's risk tolerance.

Policy optimisation has no realised relationship with any MRO process step, partly because PsM itself is still in its infancy, which hinders trust and adoption of the technology. The central tension with MRO is structural: conventional schedule-driven AMP logic requires preventive task execution at fixed intervals even when condition information indicates no technical necessity, directly counteracting the dynamic scheduling that optimisation would produce. As maintenance strategies become more condition-driven, the AMP revision and approval process (which CAMO must navigate) increasingly constrains their full implementation. The barrier is not only regulatory but also commercial: changes affecting type-certificate scope can be costly, and stakeholders may resist them even when the technical case is sound.

6.2. Key relations: from MRO to PHM

MRO process steps define, constrain, and validate PHM. They provide the starting point for PHM development: MSG-3 supplies the failure-mode taxonomy, and the MPD provides the baseline maintenance programme and documents life-limit values and related maintenance requirements where applicable. MRO also imposes constraints on how PHM may be applied. Because interval escalations must be justified to authorities without changing the AMP structure, PHM outputs must be auditable and evidence-based to support both regulatory approval arguments and reliability/AMP effectiveness assessments.

The MSI requires actionable condition indicators from diagnostics, demands that prognostic forecasts provide sufficient lead time before the next scheduled event, and delivers real-world operational boundaries for optimisation.

The AMP imposes a structural constraint: conventional schedule-driven logic requires preventive task execution at fixed intervals regardless of condition data, and its revision cycle is inherently slower than the dynamic decision-making that advanced PHM enables. This is not a hypothetical future barrier but a present-day constraint that actively limits prognostic and optimisation implementation.

Part 145 occupies a unique position as the primary provider of empirical feedback to all three PHM stages: ground-truth labels for diagnostics, time-to-failure verification for prognostics, and actual cost and downtime data for optimisation. Without this feedback, diagnostic models cannot be validated against confirmed faults, prognostic models cannot calibrate their RUL predictions, and optimisation models lack the real-world cost and downtime inputs needed to produce credible policies. This makes Part 145 not only the executor of maintenance actions but also the essential closing element of the PHM *learning loop*.

Yet establishing structured, end-to-end feedback pipelines from Part 145 back to PHM remains a challenge in scale and data architecture. Systematic feedback is crucial, as it builds *trust* with the technology and supports improved paths for regulation and standardisation. **Foundation Models** (Tsallis et al., 2026) could enhance these pipelines, e.g., enabling technicians to interact in plain language with interfaces that deliver PHM-based recommendations and capture feedback to improve the underlying models.

6.3. Research directions

Future research should address the key bottlenecks identified in this analysis. On the PHM-to-MRO side, regulatory pathways for accepting prognostic and optimisation outputs as valid maintenance drivers remain undefined; aligning PHM development with initiatives such as the **EASA AI Roadmap 2.0** (EASA, 2023) and **MLEAP** (Belkacem et al., 2024) is essential to establish certification frameworks for AI/ML-based maintenance technologies. The emerging **IEEE P1856.1** (Gullo & Sallade, 2026) represents a concrete step toward standardising PHM implementation, relevant to the certification gaps identified in this paper. PHM outputs can be ambiguous, and certification requires traceability of the reasoning chain; **eXplainable AI** (Ucar, Karakose & Kırımça, 2024) is therefore a research direction directly tied to regulatory acceptance, not only to model interpretability. 0n the MRO-to-PHM side, structured end-to-end feedback pipelines from Part 145 back to PHM models are critical for operational trust and continuous model improvement. The structural tension between condition-driven PHM strategies and the schedule-driven AMP revision cycle also warrants regulatory process innovation that accommodates faster, evidence-based programme updates without compromising safety assurance. Finally, this paper introduces a conceptual mapping of PHM stages onto the MRO process chain for hydrogen-electric propulsion, but a current limitation is the lack of empirical validation; future work should pursue quantitative comparisons and real-world case studies against traditional MRO approaches.

7. CONCLUSION

This paper investigates the interactions between Prognostics and Health Management (PHM) and Maintenance, Repair and Overhaul (MRO) for a Hydrogen-Electric Aircraft Propulsion System (HEAPS), drawing on literature, standards, and domain expertise. We present failure modes, mechanisms, and sensor measurands for HEAPS, examine maintenance considerations through both PHM and MRO lenses, and propose a conceptual integration framework that maps PHM stages onto the MRO process chain. The framework reveals a fundamental *asymmetry*: PHM currently adds value mainly through diagnostics, which feed condition-based updates to the Aircraft Maintenance Programme (AMP) without altering its structure, while emerging prognostic capabilities show potential for planning the unscheduled at the Part 145 level. Beyond diagnostics, PHM outputs remain underutilised due to missing certification pathways for prognostic and policy optimisation algorithms, and because the schedule-driven Aircraft Maintenance Programme revision cycle is slower than the dynamic decision-making advanced PHM enables. Conversely, MRO defines the failure-mode taxonomy, monitoring points, and life-limit values that constrain PHM system design, while Part 145 provides the ground-truth feedback to train and validate PHM models. A shift toward condition-driven, evidence-based maintenance governance is emerging but proceeds incrementally: each step requires the Continuing Airworthiness Management Organisation to carry PHM-derived evidence through the approval process, which remains the principal constraint on implementation.

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