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Built-In Prognostics and Health Management (BI-PHM): A novel concept for Prognostics and Health Management implementations in Aviation

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In the aviation industry, avoiding Aircraft on Ground (AOG) events is imperative for ensuring operational continuity, safety, and reduced lifecycle cost, and Prognostics and Health Management (PHM) has emerged as a key approach to this end by combining sensor measurements with mathematical models to comprehensively manage aircraft health. However, the effective deployment of PHM is hindered by several persistent obstacles: limited access to high-quality operational data, sparse failure events across fleets, the need for long time-series records, and a knowledge gap between operators, who often lack detailed system insight, and Original Equipment Manufacturers (OEMs), who are reluctant to share proprietary system knowledge for Intellectual Property (IP) reasons. To address these challenges, this paper proposes Built-In Prognostics and Health Management (BI-PHM), a novel concept in which predictive functionality is embedded directly into system components, extending the ubiquitous Built-In Test (BIT) functionality. Under BI-PHM, system OEMs develop and integrate the prognostic functionality within their own components, leveraging their system knowledge while sharing only vital, explainable health indicators with operators and maintenance organisations, thereby safeguarding their IP. The concept is structured around two complementary functionalities: onboard health management and offboard algorithm development and refinement. By restructuring the roles and data flows among stakeholders, BI-PHM offers a more effective path to PHM implementation, with the potential to reduce AOG incidents, lower lifecycle costs, and improve maintenance planning for the benefit of all parties in the aircraft maintenance ecosystem.

Keywords: Prognostics and Health Management, Maintenance Technology, Predictive Maintenance, Original Equipment Manufacturer, Edge Computing.

1. Introduction

Prognostics and Health Management (PHM) plays an important role in the improving maintainability, system reliability, supportability, availability, cost-effectiveness, and safety in aviation industry, by focusing on monitoring of critical systems components and continuously assessing the health and performance to detect potential issues and anomalies early on and predicts potential failures and degradation (Li, 2020). Application of PHM can result in significant cost savings for the aviation operators by planning and scheduling maintenance activities more efficiently and increasing the availability of the aircraft (Hongsheng, 2017). Since Remaining Useful Life (RUL) indicates how long a component is likely to operate before it requires repair or replacement and Failure Mode (FM) is the way it might break down, predicting the failures and degradation allows optimized spare parts inventory management (Tu, 2007). The growing complexity of modern engineering systems has made PHM vital for overall maintenance optimisation and safety, rather than merely an isolated addition to maintenance support as it was once perceived (Hu, 2022).

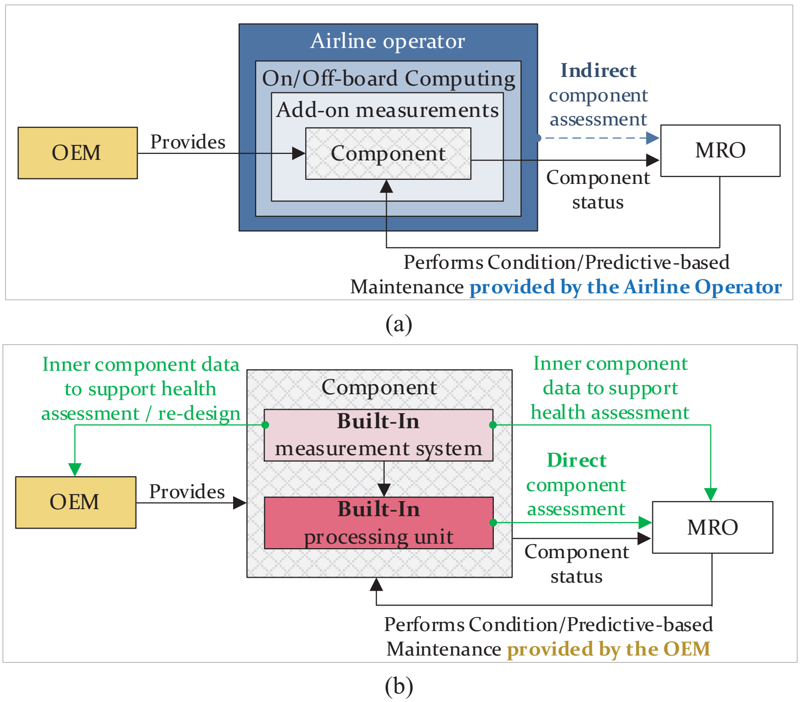

Figure 1 Comparison of maintenance architectures: (a) current operator-led PHM with indirect component assessment; (b) proposed BI-PHM with OEM-embedded direct component assessment.

In the past years, there have been a lot of interest and research in the development of PHM and its application in different scenarios (Hu, 2022). Although PHM offers an interesting opportunity in the aviation industry in analysing and modelling of the data and health in real time, prediction of degradation of system component is a challenge (Atamuradov, 2017). Atamuradov et al. (2017) has made an over-view of the PHM challenges including the data uncertainty, system and data complexity, and model compatibility among other challenges involved in the PHM steps. Rather than proposing a new algorithm or model, this paper presents a conceptual approach aimed at redefining the responsibilities of Original Equipment Manufacturer (OEM), operators, and maintenance organisations within the PHM ecosystem.

2. Current Challenges with PHM approach

The aviation industry has made numerous attempts to predict aircraft defects. The prevailing approach, illustrated in Figure 1(a), relies on the airline operator to analyse onboard data in order to predict defects: the OEM provides the component, while the operator is responsible for equipping it with add-on measurements and on/off-board computing to derive health information, which is then used by the MRO organisation to perform condition- or predictive-based maintenance. While this operator-led architecture has enabled meaningful progress in predictive maintenance, it also introduces several structural limitations related to data, system knowledge, and intellectual property.

Data - First of all, prognostics requires usage, maintenance and sensor data to (i) establish the condition of a system, (ii) predict the degradation of a system, and (iii) determine the most likely failure mode. Modern aircraft can provide a lot of sensor data, but it is often challenging to develop meaningful information and useful health indicators intended for diagnostics and prognostics from raw sensor data (Galanopoulos, 2021). As shown in Figure 1(a), the assessment of component health in the current approach is *indirect*: it relies on add-on measurements external to the component, rather than on data originating from within the component itself. Second, the operator must guarantee an uninterrupted flow of sensor and maintenance data, ensuring that the data is extracted from the aircraft and stored safely for later use. Lee et al., (2023) and Sezenoglu et al. (2026) discuss the challenges involved in data centred maintenance approaches and the consequence of sparse data is that important sensor data and maintenance data for predictive maintenance may be missing by design or as a result of the data retrieval and storage operations. Third, if the operator wishes to implement machine learning methods, the operator needs a large sample of failure event data, which requires data from a large fleet and a prolonged sampling period, before the operator can collect sufficient amounts of data to train the models.

System knowledge - Operators are often not involved in the design and development of onboard systems by the OEM. This means that they lack the insight and system level knowledge to implement PHM, making it difficult to apply model-based and hybrid prognostic approach (Atamuradov, 2017) (Vachtsevanos, 2006). This knowledge gap is inherent to the architecture depicted in Figure 1(a): because the operator sits outside the component boundary, health assessment must be inferred from externally observable data rather than from intrinsic component behaviour. A workaround would require serious investment to reverse-engineer models of these systems. This will always slow down the development of model-based prognostics and limit the number of Line Replaceable Units (LRUs) and systems that an operator can model. A possible alternative is the use of data-driven prognostics, where the investments for this approach are significantly less, as long as the operator can find the right sensor data efficiently. This, again requires proper system knowledge and an understanding of the information contained in the sensor data (Lee, 2023).

Intellectual property (IP) - Jennions et al. (2016) discuss the flow of information and data between OEMs, manufacturers, and suppliers and highlight the need to address the trust and IP concerns. Often, system OEMs are hesitant to share data for model-based and data-driven prognostics with operators, fearing that their knowledge and IP might leak outside the company. In general, operators cannot count on system OEMs for help with prognostics. Similarly, the operators are equally hesitant to share their data and knowledge with the OEM. As a consequence, the current architecture (Figure 1(a)) places the operator in the position of having to develop prognostic capabilities without direct OEM support, and concerns surrounding intellectual property hinder the open collaboration necessary for effective PHM implementation (Walthall, 2018).

3. Proposed concept - An Alternative Route

Based on the challenges with the current approach to implementing PHM in aviation discussed in the previous section, we propose an alternative route, a predictive maintenance functionality, built-in to the system. Much like the current **Built-In Test Equipment (BITE)**, this concept is not intended to only establish the current condition of a system, but rather intended to predict the future condition of a system. We refer to this concept as Built-In Prognostics Health Management (BI-PHM). BI-PHM (i) establishes the condition of a system, (ii) predicts the degradation of a system, and (iii) determines the most likely failure mode. The system communicates only these tiny bits of information to an onboard central health system, which aggregates the information into an aircraft health report for the operator.

The proposed BI-PHM architecture is illustrated in Figure 1(b). In contrast to the operator-led approach in Figure 1(a), both the measurement system and the processing unit are integrated directly within the component and fall under the responsibility of the system OEM. This enables a direct component assessment, with the resulting component status communicated to the MRO organisation, while inner component data remains available to the OEM to support health assessment and component re-design.

Data - A built-in predictive maintenance functionality has access to data at all times, it can generate the usage and sensor data it requires without having to rely on other systems. As shown in Figure 1(b), the measurement system resides within the component itself, so data quality is preserved because no external systems can tamper with it. In fact, if a system has built-in test functionalities, it is likely that it already collects much of the data needed for predictive maintenance. The consequence is that collecting usage and sensor data for BI-PHM is relatively straightforward for systems fitted with BITE. If we assume that am increasing number of systems will be electronically controlled and connected through the aircraft's data buses in the future, it will be possible to implement this concept on many onboard systems.

System knowledge - First, a built-in predictive maintenance functionality must be integrated by the system OEM. This is practical, because built-in test functionalities are standard fit by system OEMs in electronic, electro-mechanic and electro-hydraulic systems. Extending the built-in test functionality with a predictive maintenance functionality is thus a relatively small step. Second, this may work well for both the model-based prognostics and data-driven approaches too, if the usage and sensor data are stored within the system, and extracted during a shop visit. As indicated in Figure 1(b), inner component data can flow back to the OEM to support health assessment and component re-design. The data collected during shop visits can then be used to train models. And the trained models can be pushed to other LRUs via software updates, for example during shop visits.

Intellectual property - Now that the system OEMs can develop their own predictive maintenance functionality, they do not have to share their system knowledge with others. This is appealing for the system OEMs, because they can lower the life cycle costs of their systems, without having to share their system knowledge and intellectual property with operators and aircraft OEMs. As depicted in Figure 1(b), the only information shared externally with the MRO is the component status, for example, (i) the expected RUL, expressed in flight hours, flight cycles and calendar time, and (ii) the most likely failure mode communicated to an onboard central health system.

4. Opportunities along the alternative route

In the previous, we discussed the alternative to embed PHM at LRUs. This offers improvements in predictive maintenance, with better estimations of (i) the expected RUL, and (ii) the most likely failure mode. This, by itself, may prove a leap forward. However, if we continue along the same line of thinking, we are not limited to establishing the condition of the LRU as a whole, we can extend the concept to maintenance requirements. For this, we propose embedded Aircraft Health Management (AHM). AHM (according to MSG-3) is the use of data generated from specific aircraft systems to determine condition, reduced resistance to failure, or degradation of function for the purpose of timely scheduling maintenance actions (the use typically includes Sensing, Acquisition, Transfer, Analysis and Action 'SATAA')."

It is important to note that the benefits of BI-PHM, such as, improved RUL estimation and failure mode prediction are dependent on the quality and reliability of the embedded algorithms and processor. Health Indicators alone are insufficient for maintenance planning as the prognostics outputs must include the confidence levels and uncertainties. Future developments should emphasise on monitoring of the performance of algorithm, processing capabilities, uncertainty quantification, and continuous improvement as operational data accumulates.

Embedded AHM - AHM is an end-to-end system allowing credit to be taken to adjust intervals or completely replace a requirement. MSG-3 logic leads to scheduled maintenance tasks to be accomplished at specified intervals (so-called classic tasks). AHM logic may also lead to alternative procedures and/or actions and/or tasks, which make use of AHM capabilities. Thus, if we can replace a classic task on a LRU by making use of embedded AHM, we can reduce the number of classic tasks and replace them with an AHM Alternative that mitigates all failure cause(s) covered by a classic task. Since we are already implementing a system to monitor the condition of the LRU, it may be very effective and efficient to replace classic tasks with AHM Alternatives.

Analogous to an aircraft OEM, a system OEM can establish maintenance requirements during the design phase. MSG-3 logic sets the initial maintenance requirements based on the design alone. These requirements can be amended based on experience during the in-service phase. This means, that the system OEM can set maintenance requirements (either a classic task or an AHM Alternative) without any in-service experience or the need for extensive, in-service data collection. Note that the system OEM can gather data during the design process, which may help to substantiate design decisions. This means that systems with BI-PHM can utilise their predictive maintenance functionality from the day the design is approved.

The MSG-3 analyses for AHM focus on the aircraft. The analyses ensure no degradation of function in the case of failure. Typical solutions include redundant systems to avoid degradation of function if one system fails. This cannot be reflected in analyses at the LRU level. Therefore, AHM analyses at LRU level (i) must either be based on the worst-case scenario - for example without redundancy, or (ii) must be specific to an unique aircraft system configuration, or (iii) must cater for various aircraft system configurations.

5. Next steps and Guidelines

For successful implementation of BI-PHM, there are a few elements that need to be addressed (See Figure 2). The implementation of BI-PHM must be approached at the aircraft level, enabling all onboard systems to report to a centralised health management function. This requires clear value creation for aircraft original equipment manufacturers (OEMs). In addition, the successful deployment of BI-PHM depends on the active involvement of key system-level OEMs. These stakeholders must not only perceive tangible benefits from BI-PHM, but also commit to integrating PHM capabilities within their respective systems.

It is critical to have well defined implementation standards to ensure trustworthy health assessment across multiple aircraft systems. It is also critical to have a standardised communication protocols for aggregation of system level health indicators into a consolidated aircraft health report, to ensure interoperability between individual systems and the central onboard health management system. To lower the barrier for system OEMs to adopt BI-PHM, practical implementation solutions should be provided. These include: (i) on-component software for the acquisition and storage of usage and sensor data; (ii) embedded algorithms for computing health indicators;

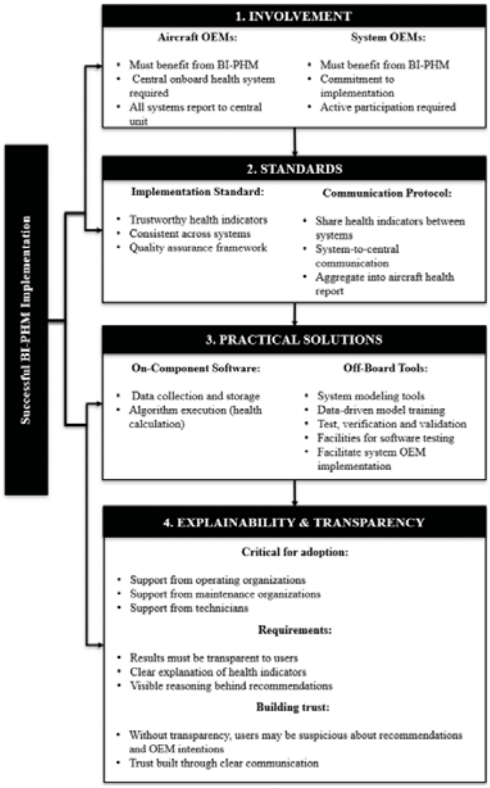

Figure 2. Important elements to be considered for a successful implementation of BI-PHM.

(iii) offboard tools for system modelling; (iv) offboard environments for training data-driven models; and (v) test, verification, and validation tools and facilities for embedded PHM software.

It is important to establish clear standardisation and certification framework for adoption of BI-PHM, that define what PHM functionalities must be embedded, how the health indicators should be computed and communicated, and how the embedded algorithms must be validated. However, when the OEMs lack in-house PHM development capabilities, the standardised interface can enable third-party PHM developers and R&D organisations to provide assistance with certified embedded solutions, without requiring to disclose proprietary system knowledge beyond what is needed for integration.

Finally, for BI-PHM to be accepted by operating organisations, maintenance organizations, and technicians, its outputs must be explainable and transparent. Health indicators and maintenance recommendations should be interpretable by end users; otherwise, a lack of transparency may lead to mistrust in the system outputs and in the intentions of system OEMs.

6. Discussion

BITE systems have been effective and valuable since their introduction, providing automated fault detection that has significantly reduced the troubleshooting time and aided maintenance decision making. BITE functionality has been particularly successful in isolating failures at the component level. However, as operational demands have shifted towards predictive rather than reactive maintenance, this shift presents an opportunity to extend BITE's diagnostic functionality with prognostic capabilities that can anticipate failures before they happen. Additionally, while BITE's component-focused architecture has served its purpose, cross-system integration presents potential for assessing degradation patterns across multiple subsystems.

There has been a significant advancement in maintenance decision making with the introduction of Integrated Vehicle Health Management (IVHM), demonstrating the advantages of having an integrated, multi-subsystem health monitoring system. Its holistic perspective has proven essential for complex system-level diagnostics. However, the predominant implementation of IVHM as a centralised, largely ground-based architecture presents its own challenges. Post-flight processing may introduce delays that may limit responsiveness to transient degradation events occurring during flight operations and there are always complications related to handling of the data. But this opens up opportunities as the advancement in the embedded processing capabilities can complement IVHM's centralized approach by enabling real-time monitoring during critical flight phases.

Current PHM systems have successfully extended health management into the domain of prognostics, demonstrating the feasibility and value of remaining useful life estimation and failure prediction. Their contributions to condition-based maintenance strategies are critically important. However, the typical implementation of PHM as an external system whether ground-based platforms or portable diagnostic tools presents an opportunities for architectural refinement. Dependence on post-flight data downloads necessitates batch processing rather than continuous assessment, and the separation from onboard systems limits integration with real-time operational decision-making.

Addressing the identified challenges and opportunities, BI-PHM can be perceived as a complementary architecture advancement rather than a replacement of existing systems. By having the prognostic capabilities embedded within Line Replaceable Units, BI-PHM can leverage advanced edge computing capabilities to enable continuous, component-level health assessment. This approach potentially reduces data transmission latency and enables autonomous component-level monitoring. Additionally, continuous operation during flight phases allows BI-PHM to capture transient anomalies and stress-induced degradation that may be missed by post-flight analysis. With respect to maintenance frameworks, BI-PHM design explicitly considers integration with established maintenance methodologies, particularly MSG-3, potentially facilitating industry adoption by providing prognostic intelligence within familiar regulatory and operational structures.

In summary, while acknowledging the substantial contributions of BITE, IVHM, and conventional PHM systems to aviation safety and maintenance capabilities, we propose that BI-PHM represents an architectural evolution. By embedding prognostic intelligence within aircraft systems, enabling real-time operational awareness, and integrating seamlessly with established maintenance frameworks, BI-PHM may offer complementary capabilities that address current challenges in predictive maintenance.

7. Conclusion

The aviation industry's desire to minimise Aircraft on Ground incidents while managing lifecycle costs demands innovative approaches to system health management. While PHM has emerged as a promising approach, its implementation faces fundamental hurdles such as limited access to operational data, sparse failure events across fleets, and an intellectual property induced knowledge gap between operators and OEMs.

This paper introduces Built-In Prognostics and Health Management (BI-PHM) as a paradigm shift that addresses these systemic challenges by embedding predictive capabilities directly into system components during the design phase. By enabling the OEMs with component-level PHM functionality, the concept leverages their inherent system knowledge while enabling them to share actionable, explainable health indicators with operators without compromising proprietary information. The architecture's division into onboard health management and offboard algorithm development functionalities creates a framework for continuous improvement while maintaining operational relevance.

The BI-PHM concept proposes a fundamental restructuring of responsibilities, data and information flow within the aircraft maintenance ecosystem. By resolving the data access and intellectual property hurdles that limit the implementation of PHM to its full potential, this approach paves the way toward more effective predictive maintenance implementation. The resulting benefits include a potential reduction in AOG incidents, optimised lifecycle costs, and enhanced maintenance planning capabilities, while addressing the needs of all stakeholders in the aircraft maintenance ecosystem.

Future work will focus on: (i) validating this concept through stakeholder analysis engaging system OMEs, aircraft OEMs, operators, MROs, and regulators to assess capability and willingness to adopt BI-PHM, (ii) case studies on BI-PHM embedded system components to validate the feasibility of having embedded PHM functionality within existing BITE architectures, (iii) development of frameworks compatible with MSG-3 and other methodologies, (iv) establishing industry guidelines for BI-PHM integration into certification process, including algorithm and hardware. The role of the third party PHM developers within this framework, and the associated IP and data governance arrangements will required attention in the future standardisation work.

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