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Integrating Prognostics and Health Management in the Design and Manufacturing of Future Aircraft

Marcia L. Baptista, Felipe Delgado, Nathan Eskue, Manuel Arias Chao, and Kai Goebel

Abstract Prognostics and Health Management (PHM) is a multidisciplinary framework that provides vital information to operators to ensure maximum system uptime and system safety. It does this by estimating the current and future condition (health) of engineering systems and providing decision support. In recent years, PHM has evolved from being a post hoc maintenance support tool to an essential system that should be integrated throughout all stages of the equipment lifecycle. This chapter describes the essential steps of how PHM can be used in the design and manufacturing of future aircraft. There are many benefits in adopting and evaluating PHM in the design stage. This includes a system that is ultimately easier to monitor and maintain, has better logistics, has reduced overall costs, and has less unplanned downtime. As such, it is argued here that PHM should be designed together with the aircraft. Therefore, this chapter proposes a methodology that includes PHM considerations at all stages of aircraft design. By promoting the integration of these disciplines − PHM, engineering design and manufacturing −, we hope to contribute to more reliable and

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safe aircraft that can achieve more cost-effective operations and a more sustainable future.

Keywords Aircraft · Prognostics and health management · Design · Manufacturing · Smart factory · Industry X.0

1 Introduction

The field of prognostics and health management (PHM) plays a role in ensuring the safety and reliability of engineering systems such as aircraft [109]. The PHM process involves monitoring [71] and evaluating the degradation condition of the systems to detect and predict failure [82]. In PHM, detection and prediction are fundamental activities that have evolved into two distinct disciplines: diagnostics and prognostics [99]. Diagnostics is the discipline focused on the detection and identification of faults and anomalies in a system [6]. Prognostics is the discipline concerned with the prediction of future states of a system, focusing on estimating the remaining useful life (RUL) [60]. Both disciplines involve real-time monitoring of system parameters and together enable other PHM strategies, such as the ability to plan maintenance activities accordingly.

Several authors, such as [48] and [107], consider the existence of four key areas in PHM: sensing, diagnostics, prognostics, and decision support (see Fig. 1). The sensing area has to do with the technologies used to monitor the system. Diagnostics and prognostics involve the study of the various modeling approaches that can accurately predict and identify system faults and failures. Decision support consists of optimizing maintenance tasks.

In this work, we argue that another important research area, of comparable importance to the typical four areas of PHM, is the integration of PHM in the design and manufacturing areas (see Fig. 1). Exploring how PHM can influence design decisions and manufacturing processes will result in more resilient and maintainable systems. This research reviews how to integrate PHM considerations early in the design phase, such as optimized sensor placement and improved data collection strategies.

Embedding prognostic capabilities into the initial design phase of these systems ensures that the components can generate the necessary data for accurate health monitoring. We also need to have standardized and certified design methodologies that incorporate prognostic requirements into the design specifications. Digital twins enable detailed simulations during the design phase, allowing virtual testing and validation of products before physical prototypes are built. Finally, it is necessary to quantify the cost and benefits of design and manufacturing choices on the longevity and performance of components.

PHM is an enabler of manufacturing efficiency and reduced costs. The idea is to capacitate machines with monitoring and prediction abilities that allow them not only to self-maintain and self-adjust. By self-maintain, we mean machines that can perform maintenance tasks autonomously. For example, a machine can lubricate

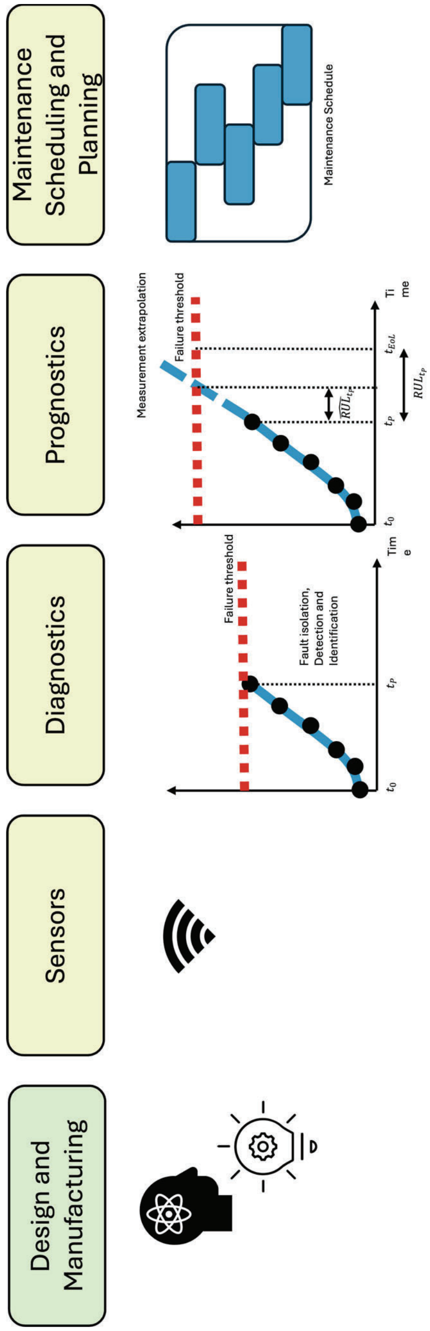

Fig. 1 The five areas of prognostics and health management

its moving parts or clean its sensors when it detects a decrease in performance. By self-adjust, we mean machines that adapt their operating parameters based on monitoring data. For example, if a machine detects that it is operating in a high-stress environment, it can reduce its speed or alter its process to prevent damage.

A challenge for future PHM systems is to predict system-wide failures instead of machine- and component-level failures. To achieve this goal, data from various machines need to be integrated to ensure interoperability and optimized PHM. In doing so, PHM can identify potential cascading effects and identify vulnerabilities that could lead to large system disruptions. Other challenges include adapting PHM to the manufacturing paradigms of sustainability, reconfigurability, and mass customization.

In this chapter, we focus on the application area of aviation because this has been a fundamental area for experimentation with PHM. Aircraft systems operate under stringent safety regulations, which makes them a suitable option for exploring design specifications and standards. Aircraft maintenance is also an expensive activity and an aircraft is a complex machine where an increase in performance could lead to significant benefits. The aerospace industry often leads in adopting new technologies. This has been the case for PHM and it is likely that aeronautics continues to push the boundaries of what is possible in system health management.

The remainder provides an overview of the fundamental concepts, history, as well as benefits and challenges faced (Sect. 2). We include a detailed analysis of the current state of research in aircraft PHM, focusing on the development of PHM systems (Sects. 2.3). We discuss the role of PHM in the design of future aircraft in detail in Sect. 3. In addition, current and future trends in manufacturing are discussed in Sect. 4. We conclude the chapter with a reflection in Sect. 5.

2 Background

This section provides an overview of the fundamentals of prognostics and health management (PHM). We begin by describing the concept of remaining useful life (RUL), which is often considered the ultimate goal of PHM [78]. We also describe and distinguish the disciplines of prognostics and diagnostics. Following this, we characterize the evolution of PHM, tracing its development and key milestones. We also explain the execution steps of a PHM solution. Finally, we explore the benefits of PHM as well as the challenges ahead.

2.1 Fundamental Concepts

A central concept in PHM (and prognostics in particular) is the remaining useful life (RUL). Figure 2 illustrates the concept graphically. We can start to predict the RUL from time t_1 (start time) to time t_P (current time). At the current time t_P we can

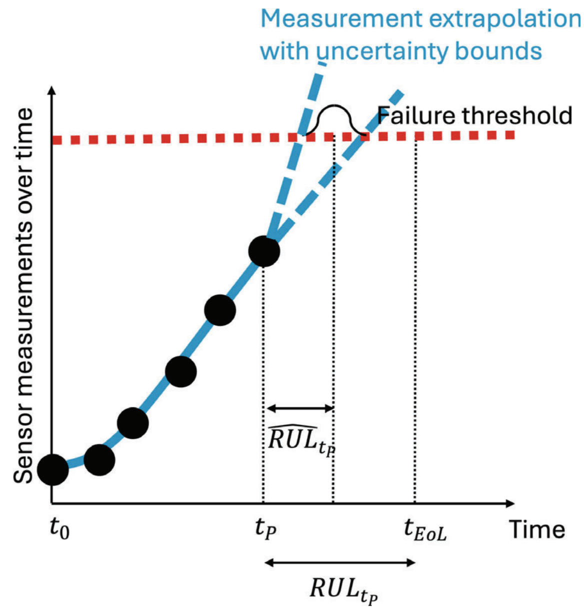

Fig. 2 Illustration of Remaining Useful Life (RUL) and End of Life (EoL) for a given current Time Point (t_P) with Uncertainty

predict the estimated RUL ($\hat{\mathrm{RUL}}_{t_P}$). This is the estimated time difference between the point of failure and the current time. The actual RUL is the ground truth (RUL_{t_P}) that varies linearly from the current time to the end of life point (t_{EoL}). The difference between these two values ($\hat{\mathrm{RUL}}_{t_P} - \mathrm{RUL}_{t_P}$) gives the estimation error in time t_P.

To predict a given RUL, real-time data analysis, and predictive modeling can be utilized [80]. In the example in Fig. 2, we use extrapolation curves to estimate the RUL value at t_P. A failure threshold is set to help determine the forecast distribution. It is possible to develop more complex models, but this illustration provides an idea of the basic prediction mechanism considering uncertainty. We indicate a reference to the book "Prognostics: The Science of Making Predictions" is a detailed description of these concepts [28].

Prognostics involves forecasting a future state and because of that it is the most complex discipline of PHM [85]. A related discipline is diagnostics, which concerns the identification and isolation of faults at the present time. Diagnostics consists of three tasks: fault detection, identification, and isolation [105]. Fault detection is the process of identifying that a fault has occurred in the system. Fault identification consists of determining the nature and cause of the detected fault. Fault isolation involves indicating the exact location or component where the fault has occurred within the system.

Decision support is another critical domain of PHM whose objective is to ensure that operators and maintenance personnel can make informed scheduling decisions based on data and prognostic outcomes [87]. Maintenance scheduling is a complex activity because it needs to quantify the effect of performing the three maintenance

Algorithm 1 Maintenance Scheduling Algorithm

Input: Set of equipment M, data D, maintenance slots MS
Output: Optimized maintenance schedule
for each equipment $m \in M$ **do**
    Predict failure probability $\mathrm{FP}_m(t)$ using prognostics model
    if $\mathrm{FP}_m(t) > \mathrm{Threshold}_m$ **then**
        Schedule maintenance within available MS_m
    end if
end for
Calculate total cost C and operational impact OI
Optimize schedule to minimize $C + OI$

strategies reactive, preventive, and predictive, at different time slots. Several factors can be considered, such as system criticality, maintenance resources and time involved in the maintenance task, costs, among others. In Algorithm 1 we describe the formalism of the scheduling problem.

2.2 History of Prognostics and Health Management

The roots of PHM and RUL estimation can be traced back to the development of reliability engineering during and after World War II, where the focus was on improving the reliability and maintenance of military equipment. This period saw the emergence of concepts such as mean time between failures (MTBF) and failure rate analysis [63, 68].

An important exploration of PHM was done in the Apollo program. Rigorous failure mode and effects analysis were used to identify potential faults and their risks during the design stage. In aviation, the A-7 single-engine fighter aircraft experienced problems and crashes in the 1970s. This motivated the instrumentation of the aircraft, which recorded around 50 parameters. The tapes were sent for analysis via courier and the results were reported back, a process that took several weeks. However, these recordings prevented several other losses related to engine issues.

What we consider today as PHM can also be related to the Joint Strike Fighter (JSF) program [36]. The JSF program, officially known as the F-35 Lightning II program, was a multinational effort to design and produce a family of single-seat, single-engine, multi-role fighters [67]. These novel aircraft designs included a PHM system that was integrated into the engineering framework. Importantly, the PHM system was conceived from the first day as a solution that could align well with the overall safety and logistics strategy. The JSF research papers [91] were among the first to propose the term "prognostics" to define the estimation of life use and the prediction of potential failures.

In the 1960s and 1970s, the shift towards predictive maintenance[1] [70] brought attention to PHM [86]. Advances in sensor technologies [90], data analysis techniques [108], and the development of sophisticated algorithms for prognostics helped the formal establishment of predictive maintenance and PHM in the early 2000s, especially with NASA Research Ames work on the prognostics of aerospace systems.

Since the 2000s, PHM has seen significant advances. Companies such as General Electric and Rolls-Royce have developed platforms using predictive algorithms for industrial equipment and aircraft engines. Siemens and Boeing have incorporated IoT sensors for real-time monitoring, while Airbus and Tesla have adopted digital twin technology to simulate and predict component performance. Improved user interfaces and visualization tools, such as the Honeywell Forge platform, assist technicians in maintenance tasks. Collaborative efforts by organizations such as the PHM Society, MFPT, SAE, NIST, ASME, and IEEE Reliability Society are also noteworthy.

Aviation and aerospace have played an important role in the history of PHM due to their stringent safety requirements, high operational costs, and complex systems. These industries pioneered PHM practices. The history of PHM in aviation [74] is one of technological evolution, where the ability to collect and analyze large volumes of data has enabled efficient and economical maintenance.

2.3 Framework of PHM Execution

The traditional framework for the execution of PHM is made up of six consecutive processing steps [62] (see Fig. 3). The process begins with the existing sensors and the data they collect [60]. At this stage, there is also usually an unclear understanding of what constitutes a good diagnosis or prognostic outcome for the specific system of interest. If a more effective design workflow was implemented, these issues could be addressed more efficiently [97].

During data acquisition, information is collected from various sensors and recorded for both real-time and historical analysis. Due to a disconnect between system designers and PHM developers, there is often a lack of sufficient knowledge about the system's data and domain-specific insights. This gap can limit the accuracy of diagnostic and prognostic models.

The acquired data undergo data processing, including signal processing to filter, normalize, and "baseline" [11] data, and also feature extraction to identify relevant indicators of system health and performance. When there is not enough data for machine learning algorithms, data augmentation [98] is used to generate synthetic data. A novel approach to feature engineering in PHM is to use post-processing interpretability techniques to assess and evaluate feature importance [3, 4]. Another direction is the development of a health indicator (or index) prior to modeling. A

[1] Often, predictive maintenance is referred as condition-based maintenance in the literature. We adopt the term predictive maintenance to emphasize the importance of predictive algorithms in achieving effective maintenance practices.

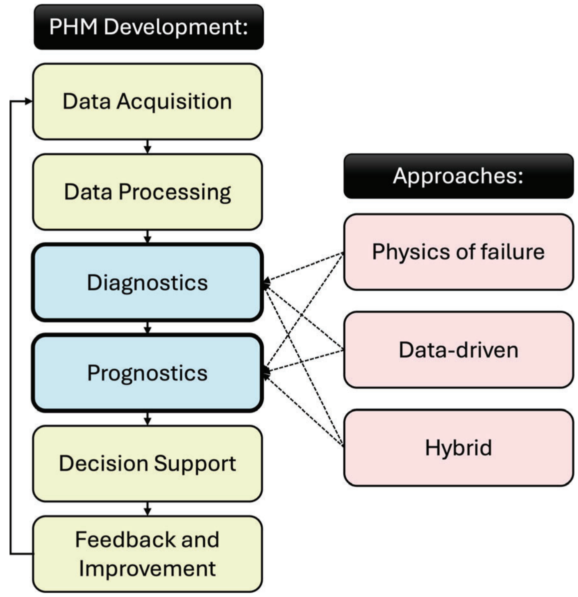

Fig. 3 Flowchart of Prognostics and Health Management (PHM)

health index is a unified measure that quantifies the overall health status of engineering equipment. A comprehensive work on health indicators is by [8].

Diagnostics is the step after data processing. This stage involves continuous monitoring to detect any anomalies and determine the root causes of these detected faults. The next step is prognostics, which estimates the remaining useful life and predicts the likelihood and timing of future failures. Sometimes, PHM workflows include only one of these two steps: diagnostics or prognostics. These two disciplines share the same methodological approaches in PHM: physics of failure, data-driven, and hybrid methods.

Physics of failure are models that rely extensively on physics knowledge [19]. Data-driven algorithms can be used to process large volumes of data and identify degradation patterns [56]. Hybrid models combine machine learning techniques and knowledge of physics [16]. These three groups of technologies are also important modeling approaches that should be used in all stages of the lifecycle of an aircraft, including design and manufacturing.

Decision support is another step of PHM, especially critical in aviation. It involves developing maintenance schedules and allocating the necessary resources for maintenance actions based on insights derived from diagnostics and prognostics [87]. For example, [55] described a dynamic airline maintenance scheduling problem which allows one to gradually shift many scheduled jobs to line maintenance, increasing fleet utilization efficiency.

Feedback and improvement is the final step, in which the system updates the diagnostics and prognostics models with new data to improve performance. This iterative step ensures that the system adapts and improves over time.

2.4 Benefits and Challenges

With regard to the benefits of PHM, the early detection of problems is one of the main advantages of PHM. By identifying anomalies or deviations from normal operational parameters, technicians can intervene before problems escalate. Also, airlines can better plan their operations, reduce delays, and increase passenger satisfaction [79]. Some helicopter manufacturers have fully adopted this concept and are offering certain models only with fully integrated health monitoring equipment.

Despite the promising results in the aviation sector [26, 106] with the implementation of PHM, there is still a gap to make the integration of these technologies more efficient in design and manufacturing. In the following sections, we describe this integration in more detail.

3 PHM in Aircraft Design

Aircraft design is a structured and systematic engineering workflow that involves conceptualization and development to meet a set of requirements [53]. The aircraft design process integrates multiple engineering disciplines and can be represented as a waterfall diagram (see Fig. 4) that involves the stages: requirement development, system functional analysis, design synthesis and integration, system verification and validation, and system maturation. This process framework is adapted from the work of [44].

Most PHM solutions today continue to be “retrofit” [41], meaning that PHM is integrated into the aircraft after the system has been operational. The incentive to implement PHM often arises from the inefficiencies and inconveniences associated with frequent and prolonged maintenance checks. Strategies, such as preventive maintenance and corrective repairs, can be costly and disruptive. However, choices about the PHM aspects of the system should be made early in the design stage when it is still possible to adapt the design of the aircraft system to gain a competitive edge in performance and reduce future maintenance costs [40].

Accurate implementation of PHM capabilities in a new system can be shown to result in greater reliability and greater performance [9, 14, 38, 40, 41, 84]. Traditionally, design uses simple reliability approaches, either by designing highly reliable components or by applying physical system redundancy. However, the question arises of whether we should instead rely on the projected operational PHM capabilities when designing the aircraft product. The consideration of PHM in the initial design rather than as a post hoc operational support system could naturally contribute to better aircraft configurations.

Reference [40] argue that PHM should not be perceived as an isolated discipline, but as an essential suite of technologies that should be adopted throughout the product lifecycle. The integration of such technologies should receive special attention during the design stage. Optimally, the design of the PHM aircraft and the support system should be carried out concurrently [40].

In the diagram of Fig. 4, we depict on the left the proposed aircraft design workflow inspired by the work of [44] and, on the right, the PHM lifecycle model of [22]. The aircraft operational and support goals are the initial high-level objectives (top left oval) together with the PHM business or mission goals (top right oval). The bottom ovals represent the ultimate results, a safe and reliable aircraft integrated with a PHM system, obtained by applying the outlined processes. We hereafter describe each of the stages of aircraft design and the PHM considerations.

3.1 Requirements Development

Requirement development is a crucial phase in the lifecycle of any system, particularly in aircraft systems with PHM. It involves identifying, documenting, and managing the needs and functionalities that systems must meet. Although some taxonomies of PHM requirements have been proposed [12, 83, 103], there is no widely accepted classification of the requirements that a system should adhere to in terms of its PHM capabilities. This complicates the design processes of aircraft with PHM systems.

There are, however, some significant efforts to systematize requirement development. For example, [103] construct an "ability" requirement framework for the PHM system around four groups: requirements for state supervision, fault diagnostics, the ability of fault pre-warning, and the ability of life prognostics. They give concrete examples for each group of abilities on how to measure and evaluate the PHM capability. For example, to measure fault isolation, the authors recommend evaluating the false alarm rate and the fault detection rate.

Reference [83] proposed a systematic approach to derive functional specifications for a PHM system from high-level requirements. The authors classify performance requirements into four groups: maximum allowable probability of failure (PoF) of the prognostic system, tolerable limits on proactive maintenance, lead time for advanced warning for actionable decisions, and required prognostics confidence. Importantly, the authors establish a formal method to translate requirements into performance quantities.

Reference [12] described a digital "hierarchy of needs" for PHM. The hierarchy encompasses five essential elements: data integration, which focuses on developing data pipelines for effective reporting; identification and documentation of data, which ensures system-level reporting and understanding of PHM data by differentiating faults and parametric data; characterization of PHM data capability, which involves fault detection/isolation analysis and the development of prognostics and trending; data science and machine learning, which provide advanced capabilities for early failure detection; and real-time operation for PHM, which implements verified algorithms for automated failure identification, ensuring comprehensive and proactive maintenance management.

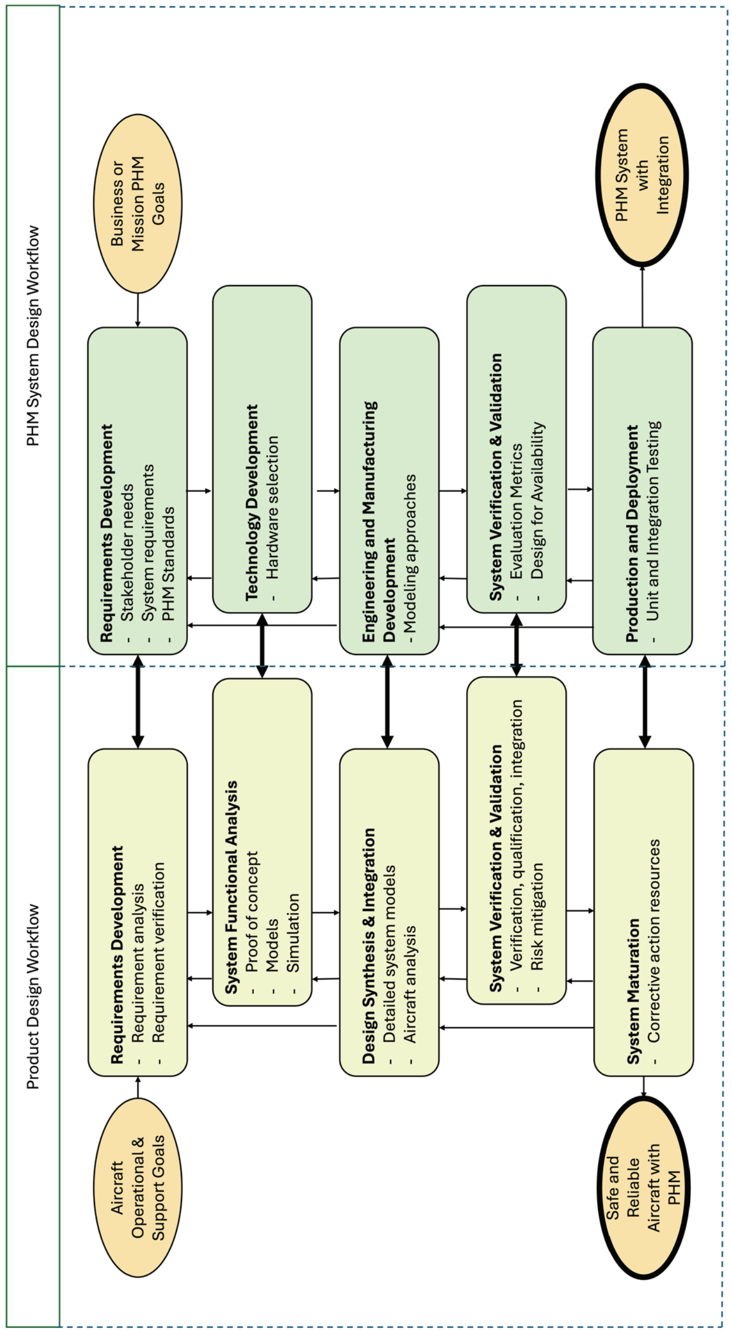

Fig. 4 Process of aircraft design. The aircraft design should be concurrent with the design of the prognostics and health management system

The previous contributions are important, but they are only partially complete. For example, [69] note that more attention should be paid to requirements that enhance the ability of the PHM system to respond to unforeseen events as well as changes in mission and operating conditions. The authors note the relevance of requirements that ensure that systems are adaptable to new failure modes and that enable architectures for system reconfiguration.

In general, obtaining design requirements is a difficult activity [42]. This is particularly true for PHM requirements, given the multidisciplinary nature of the field. There is no established methodology to capture this kind of requirements. Authors [41, 73] use the House of Quality (HoQ) method or the value-driven design to develop PHM requirements, each offering unique advantages. The HoQ method [35] facilitates the translation of customer needs into technical specifications, ensuring that all stakeholder requirements are systematically addressed and prioritized. This approach is a more user-centered design. On the other hand, value-driven design [21, 41] focuses on maximizing the overall value delivered by the system. This method integrates various disciplines and considers the trade-offs between different system attributes to achieve optimal performance and cost-effectiveness.

Regardless of the requirement methodology used, it is important to consider the effect of standards on requirement development. In aviation, organizations such as ICAO, IATA, RTCA and SAE establish the standards for best practices, covering data formats, transmission protocols, sensor calibration, and integrity measures that in turn can be used to satisfy FAA regulations for airworthiness. Standards in PHM are needed for the consistent terminology, systematization, and interoperability of the technologies used. Standards also provide guidance in the design and development of PHM techniques [33]. Fundamental standards such as ARINC 717 [92] specify the recording and transmission protocols for aircraft data, ensuring consistency between different types of aircraft and manufacturers. Furthermore, standards such as DO-178C [46] and DO-254 [37] require rigorous testing and verification processes for software and hardware development, mitigating the risks of system failures. Cybersecurity standards such as DO-326A [89] address concerns related to data security in aviation systems. Adherence to these standards not only improves safety, but also promotes efficiency and interoperability [29].

3.2 System Functional Analysis

The next stage after defining the aircraft requirements is functional analysis. This stage involves PHM considerations for sensor selection and placement, such as what parameters are to be monitored, the performance and reliability needs, the electrical and physical attributes of the sensors, and the costs. Not all sensor systems are suitable for the implementation of PHM [75]. The designer needs to understand the data acquisition requirements to make an appropriate choice.

If a monitoring solution is not designed properly, the final results of the implementation of PHM will not be good, regardless of the subsequent steps. For example, in recent years the number of sensors used in engine monitoring has been decreasing. This reduction has been mainly driven by weight and complexity considerations [54], but this reasoning can deteriorate the overall performance and reliability of PHM systems. As a result, this can affect the performance and effective operation of the aircraft.

PHM requires monitoring a large number of parameters which, depending on the product, can reach the level of thousands [18]. These parameters should include operational and environmental loads, as well as variables that describe the performance of the system. The selection of monitored parameters should be based on previous experience and field failure data for similar products or by laboratory tests. This selection should consider the relationship between parameters and safety, mission completeness, and overall availability. Parameter monitoring should preferably be considered during all stages of the life of the aircraft.

The use of systematic methods to assist the designer in understanding which faults to expect and therefore which faults would benefit from PHM solutions is absolutely paramount. For example, FMECA (Failure Modes, Effects, Criticality, and Analysis) is an essential tool that can help determine the parameters that need to be monitored [69].

Sensor systems for PHM must be themselves reliable [18]. High performance sensors are necessary to minimize possible adverse influences on system reliability and also to keep measurement uncertainty below a certain level [32]. To mitigate the risk of sensor failure, PHM designers must also evaluate the sensor's environmental and operating range to ensure that it is suitable for the specific application. In addition, the packaging of the sensor system is important, as it can protect the component from environmental effects such as humidity, chemicals, mechanical forces, and other conditions [75].

Emerging trends in sensor technology for PHM include miniaturization, low or no battery power consumption, and smart wireless networks [18, 75]. With the developments in micro and nano electromechanical systems, sensors will become smaller and lighter. The new sensors will offer significant advantages in fabrication, power consumption, and costs. It will also be easier to place these sensors as ultralow and battery-free devices can be considered for previously inaccessible and remote locations.

3.3 Design Synthesis and Integration

The next stage is the design synthesis and integration, where detailed models and aircraft analysis are performed. At this stage, analytical procedures and modeling approaches should be addressed. The analytical exercise is mostly attached to the data. Understanding the data and its characteristics should drive the development of PHM algorithms. The quality of the available data (temperature measurements, vibration or acoustic emissions, environmental conditions, etc.) and the characteristics of the data are fundamental for having a methodology with a suitable combination of algorithms [59].

Often, PHM developers face difficulties in accessing the volume and quality of the data required to design the PHM system [31, 100]. System design processes should take into account the data needs of the PHM system from the outset to make it easier to integrate and design the PHM system earlier in the design cycle. Possible data sources include formal design analysis, laboratory tests, legacy systems, and digital twins.

A crucial step to building an effective PHM system is the selection of diagnostic and prognostic algorithms. This selection should be based on both the data and the aircraft system itself. There are two options for this process: the selection can be performed manually based on the experience of the PHM designer [59] or it can be performed using a selection scheme to compare the suitability of each algorithmic solution such as automatic quality function deployment (QFD). Reference [15] describes how to transform engineering attributes and customer requirements into an algorithm ranking using a House of Quality (HoQ) procedure.

3.4 System Verification and Validation

To verify and validate PHM design solutions [81], we can use different sources of data. Ideally, the data should come from actual field data or accelerated mission testing. In these experiments, the operational conditions can be known and it might be possible to select the monitored parameters with more flexibility. If these more realistic data cannot be obtained, it is possible to perform component rig tests. In addition, digital twins [66] with different levels of fidelity can be used to simulate fault signatures and provide data. Digital twins are digital replicas of physical systems [47]. There are many benefits to simulation-based approaches such as digital twins, which explains the increase in interest and research on these methodologies [47].

3.5 System Maturation

What is missing from most aircraft design projects is the ability to determine in advance the expected performance of a PHM solution. Typically, the advantages of the proposed solution and monitoring parameters are only evaluated in production or compared to another similar maintenance solution. This evaluation should be performed early in the design stage to avoid the need to commit to expensive modeling efforts.

During the final stage of the design process, in system maturation, we should perform a cost-benefit analysis of the PHM systems that considers the impact of health monitoring technologies over the entire life of the system [10]. In the context of aircraft design, the TCO (total cost of ownership) calculation includes initial acquisition costs, operational costs, maintenance expenses, and end-of-life disposal costs. PHM costs can be classified as operational, maintenance, and end-of-life costs.

3.6 Future Trends and Innovations

Reference [40] analyzed the issues of integrated design and identified three major areas of improvement: requirements, operational performance, and decision support. The issue of "requirements" is related to the low maturity of the design methodology. A suitable methodology for requirement elicitation is necessary as well as a way to better assess alternative functional design solutions. The claims of "unstable operation" have to do with the inability of current systems to adapt to unexpected and unforeseen failure modes and operating conditions. The final area of "decision support" is related to the need to have better decision support tools to attest to the prognostic algorithms' capabilities.

4 PHM in Aircraft Manufacturing

PHM is an evolving field that plays a role in aircraft manufacturing [50, 58]. In the paradigm of the smart factory, machines and processes are advanced and increasingly difficult to manage and operate. This brings about the need to improve manufacturing maintenance. PHM is crucial to maintain the processes and machines of the factory in good condition [64]. We need efficient PHM policies that act at the individual machine level and also integrate different manufacturing paradigms such as mass customization, reconfigurability, and sustainability demands [2, 43].

The PHM framework is essential to create a paradigm shift from reactive and preventive fixed-interval schedules to predictive maintenance in the manufacturing industry [99]. An enabler of this vision is the use of real-time sensor networks to extract useful data to support maintenance decisions within manufacturing systems. Although PHM has the potential to cause a paradigm shift, more attention should be paid to this discipline [93] and maintenance should be considered more of a benefit than a net cost.

The smart factory consists of various advanced machines that degrade at different rates, which can cause unwanted breakdowns and production interruptions [88]. In the factory, there are processes that manage interconnected systems that establish the interface between physical assets and computational capabilities [65]. Importantly, manufacturing systems have both digital and physical capabilities as they are capable of sensing, communicating, and actuating in the industrial environment. PHM should help provide a systematic view of the condition of the machines involved in the various processes of the factory, and also should provide maintenance optimization and scheduling at the machine and system levels.

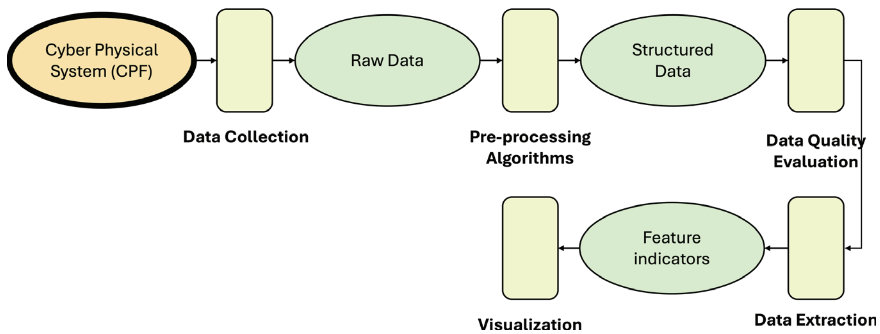

Fig. 5 Data workflow in manufacturing applications

In the following, we review PHM capabilities and best practices for manufacturing in the aviation sector. We focus on explaining how PHM can help evolve workflows into smarter processes that can realize the paradigm of self-maintenance and zero-defect manufacturing [77].

4.1 Data and Digitalization

The need exists to integrate, analyze, and process data during the life cycle of an aircraft system. Information from all dimensions of the factory should be monitored and digitalized so that the shop floor and physical cyberspace are in sync. The systems that operate within the smart factory must be reliable in predicting unexpected events, such as failures. PHM Methodologies are designed to improve efficiency by integrating data, diagnostics and prognostics and maintenance scheduling within manufacturing.

Most manufacturing systems have several sensors that generate large volumes of data on operational performance at both the machine level, answering "how well my manufacturing machine performs," and the process level, answering "how well the manufacturing process of a given product is doing." To effectively answer these questions and use the data, open access to the data and easy-to-use coding interfaces are required. In addition, quality data are necessary to make adequate decisions [49].

Reference [77] proposes a data workflow for manufacturing applications. Figure 5 illustrates the process and its modules of data collection, preprocessing, extraction, and visualization of feature indicators. The first step after data collection is data preprocessing which involves organizing the data in a structured format for efficient storage and access. The following steps include pre-processing, analysis, and storage. Challenges such as non-unified language messages and varying machine languages need to be addressed to ensure consistent data conversion.

Data-related issues are prevalent in the manufacturing industry. However, this problem is particularly critical when processes rely on manual methods for data collection. Although it is unavoidable to have some degree of manual processes, this approach can result in inconsistent descriptions of the same event, as each worker tends to record information in their own unique way. To address this problem, companies should standardize procedures and invest in automated data collection tools. If a manual process is indispensable, using data entry software with validation rules and integrating digital solutions can further enhance data consistency and accuracy.

New machines often lack established failure signatures, which are important for an effective PHM practise. Failure signatures are patterns or indicators that precede a machine's malfunction, and they are typically derived from historical data of past failures. For new machinery, these historical data are not yet available, making it challenging to manage maintenance. However, sensor data from new machines can provide information that goes beyond just failure events. Sensors continuously monitor various parameters such as temperature, vibration, pressure, and performance metrics, generating large volumes of data even in the absence of failures. This continuous stream of data can be analyzed to understand normal operating conditions and detect subtle anomalies that may indicate emerging problems long before they lead to failures.

4.2 PHM at Machine Level

Reference [96] performed a study on the benefits and challenges of maintenance for manufacturing and found that machine repair costs accounted for between 15% and 70% of the cost of the final goods. To address this, the approach followed so far is to rely on fixed time schedules optimized to reduce costs and downtime. Nevertheless, almost 50% of the scheduled interventions have been found to be unnecessary [99]. Adding to this, we still have unexpected downtime events that are very costly. In this context, PHM can enable condition monitoring and analysis of physical machines and functional processes [20]. PHM is the most suitable methodology to minimize the probability of undetected failures, reduce costs and downtime [52].

Importantly, the goal of PHM is not necessarily to capture failure. The objective is to provide decision support. This goes beyond the prediction of failures. The objective is to allow the machine to come up with recommendations and guide users toward a solution (or implement them where suitable). For example, if a machine is self-aware of its degradation state, it can adjust its production mechanisms to optimize production processes [57].

Based on machine prognostics models, the industry can develop maintenance schedules tailored to the specific wear and usage patterns of each machine. With PHM, it is possible to schedule maintenance activities based on the actual condition of the machinery rather than a fixed schedule.

4.3 PHM at System-Wide Level

Ideally, PHM is integrated at the machine level, and it also propagates information throughout the functional process to relate machines, manufacturing systems, and production lines. Here, a manufacturing system or cyberphysical system is a hierarchical structure of systems [39]. However, a challenge of PHM is that data acquisition is restricted to the machine level. This results in the absence of methodologies to support system-wide PHM [20]. In system-wide intelligence, machines are not isolated but spread information beyond their own limits so that the behavior of one component, such as failure, is connected to other components and produces system-wide effects.

It is possible to create methodologies for system-level manufacturing by focusing on established work in aerospace. For example, [104] propose a hierarchical model-based approach to testability modeling and analysis for PHM of aerospace systems. Reference [45] advance a hierarchical model control for real-time energy-optimized operation in aerospace. Reference [7] developed a distributed hierarchical framework for autonomous spacecraft control. More works in predictive model control are reviewed by [23].

Some works focus on system-level PHM for industrial settings. Reference [24, 30] propose a method to achieve PHM at the system level by propagating information through a fault tree structure. Reference [20] propose an adaptive multilevel PHM system for manufacturing robots. Reference [95] propose a system-level PHM considering component interactions and mission profile effects. Reference [94] also consider the effects of the interaction and mission profile, but include uncertainty in their study of system-level PHM.

In the existing literature, there are two maintenance policies that consider multi-componet systems: group maintenance policy and opportunistic maintenance policies [101]. The group maintenance policy focuses on intervening in a group of machines when a failure occurs [27]. In the opportunistic strategy, a critical failure that results in shut down is used to perform maintenance proactively in non-failed subsystems [72]. In both policies, it is possible to combine maintenance tasks for different machines based on expected or planned downtimes from the prognostics estimation.

4.4 Future Trends and Innovations

In the global market, mass customization is needed to deliver products and services that meet the exact needs of the final customer [25]. This paradigm has changed production from a "push" mode to a "pull" mode [76], where the customer drives the product requirements in a more personalized way. Major companies such as General Motors or Toyota have started to adopt this strategy. In aviation, this idea is slowly starting to take over in the military [13] and in the aerospace sector [61]. Several issues remain to adapt actual maintenance policies to the requirements of mass customization, such as the intractability of existing policies when the number of machines increases, the lack of a comprehensive study on the effects of increasing the intervals of preventive maintenance tasks, and the need for cost-effective scheduling at the system level in industrial companies with stochastic demands and complex production processes [17, 102].

Another concept that has been studied to manage varying product demands is that of reconfiguration [51]. Reconfigurable manufacturing systems (RMS) have been developed to allow dynamic adjustments in product functionality, but unlike traditional mass production, where system structures remain unchanged after the initial design, RMS can adapt to changing product demands through reconfigurable structures and machinery within a limited timeframe. The adaptable nature of RMS also presents challenges in system-level maintenance scheduling. Ensuring the healthy operation of RMS and its machines is critical for reconfigurable manufacturing. Changing requirements for capacity and functionality lead to various reconfigurations, dividing the production process into sequential stages with different system structures. This complexity makes maintenance scheduling difficult. Existing maintenance strategies, which focus on fixed system structures [5], need to be adjusted to the dynamic nature of reconfigurable systems.

With concerns about sustainability, industries have started to implement “green” manufacturing practices [34]. One of the aspects of sustainable manufacturing involves controlling energy consumption to comply with government regulations for green manufacturing [1]. Given the significant energy that manufacturing processes use on a global scale, the focus has been on reducing and balancing energy demands. Manufacturers must adopt new green and sustainable technologies to reduce industrial emissions. This includes developing a PHM methodology that considers machine deterioration, production characteristics, and energy interactions to avoid environmental taxes and penalties.

The challenges of manufacturing are expected to grow in importance in order to maintain industry competitiveness and personalization needs. This trend requires more targeted PHM methodologies, from both theoretical and practical points of view.

5 Conclusion

While most PHM solutions continue to be integrated after the aircraft system has been operational. The early incorporation of PHM considerations in the lifecycle of the aircraft system could bring several benefits, such as cost reduction, better aircraft design, and easier maintenance. In this chapter, we outline a process for aircraft design that includes PHM as an integral design flow (see Fig. 4). We also discuss how to obtain requirements and functional areas in the design.

The integration of advanced manufacturing techniques and PHM systems represents a significant advance for the aviation industry. These innovations not only enhance the efficiency and precision of aircraft production, but also ensure the reliability of the aircraft throughout its operational life. PHM plays a role in maintaining factory processes and machines, necessitating policies that operate at both the machine level and process level. The integration of PHM should consider the different manufacturing paradigms such as mass customization, reconfigurability, and modularity. The transition from reactive and preventive maintenance to predictive maintenance is key. This shift is essential to recognize maintenance and PHM as a beneficial investment rather than a cost.

The paradigm of integrating PHM into design and manufacturing could not only could improve safety, efficiency, and sustainability, but could also open new horizons for innovation and growth in the aerospace industry.

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