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Research paper

# Implementing PHM for legacy flight control actuators through operational aircraft data: Approach and lessons learned

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ABSTRACT

The prospect of optimizing fleet operations and streamlining maintenance processes has made Prognostic and Health Management (PHM) strategies valued in many engineering applications. However, implementing PHM for legacy equipment presents significant challenges, especially when existing monitoring frameworks were not designed for PHM. This paper presents a case study in which a data-driven PHM framework was developed for an Advanced Jet Trainer's flight control Electro-Hydraulic Actuator (EHA), relying solely on aircraft-level information. Rather than introducing new algorithms, this work documents the process, compromises, and adaptations necessary to extract actionable health and usage insights when ideal data conditions are not available. While PHM typically relies on monitoring equipment status signals to identify precursors of degradation, this approach is often impractical due to the absence or inadequacy of equipment-level data. The architecture described here was specifically designed to operate within these constraints, demonstrating how established PHM concepts can be tailored to real operational environments. The gained experience highlights both the opportunities and limitations of PHM in practice, offering practical guidance for similar efforts in aerospace and other domains where data quality and availability are major concerns. Through this study, we aim to provide a transparent account of the challenges faced, the solutions adopted, and the lessons learned, contributing to the broader understanding of PHM implementation in complex, data-limited settings.

## 1. Introduction

Prognostic and Health Management (PHM) strategies have gained significant popularity and attention in various engineering sectors. This is largely due to their potential to optimize fleet operations and streamline maintenance processes, making them a valuable resource in the industry, especially in those fields where availability is a fundamental driver and where down-time costs are substantial [1,2]. PHM is defined as a set of strategies which are able to monitor the health status of the systems and alert in advance before any fault may occur [3]. In this sense, the term prognosis is an evolution of the term diagnosis and, as such, prognosis is intended as a way to foresee the possible health state of the systems in the future and assign a probabilistic value to the predictions [4,5].

On this basis, the concepts of asset interconnection and fleet-wide monitoring are receiving increasing attention and interest, starting from Original Equipment Manufacturers (OEMs) which can offer tailored products to their customers, who benefit from an increased availability, customized maintenance, and an improved fleet awareness [6]. Against this backdrop, a strong interest towards digital-twin platforms is noted in the literature and in the industry [7,8]. In fact, PHM is one of those pivotal founding stones that are needed to create a seamless bi-univocal connection between the physical asset and a digital twin [9,10].

Adopting and integrating PHM strategies in a brand-new product is a demanding task where a wide range of divisions and business units must cooperate to reach a common end point [11]. These demanding tasks become even more ambitious when the PHM system is not envisioned along with the equipment itself, but, on the other hand, designed to operate on legacy equipment [12–14]. This opens to a completely new range of challenges and opportunities. In general, the pursuit of implementing PHM strategies on equipment for which there is currently no available data is a common challenge related to every System-of-Systems

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**Table 1**
List of relevant acronyms.

| Relevant Acronyms | Definitions |
|---|---|
| AJT | Advanced Jet Trainer |
| CF | Cumulative Feature |
| CI | Condition Index |
| CMT | Clustered Mission Type |
| DL | Deep Learning |
| EDA | Exploratory Data Analysis |
| ER | Equipment Register |
| EHA | Electro-Hydraulic Actuator |
| ETL | Extract, Transformation, and Load |
| FBW | Fly-By-Wire |
| FCS | Flight Control System |
| FD | Flight Duration |
| FH | Flight Hour |
| FP | Flight Parameters |
| HT | Horizontal Tail |
| HUMS | Health Usage Monitoring System |
| IPR | Intellectual Property Rights |
| IVHM | Integrated Vehicle Health Management |
| OH | Operating Hour |
| OEM | Original Equipment Manufacturer |
| PAS | Primary Actuation System |
| PDF | Probability Density Function |
| PN | Part Number |
| PoF | Probability of Failure |
| SHM | Structural Health Monitoring |
| SM | Statistical Moment |
| SN | Serial Number |
| SOM | Self-Organizing Map |
| STNR | Signal-to-Noise Ratio |
| TN | Tail Number |
| UR | Unscheduled Removal |

(SoS) and spreads through the operations of every asset [15,12]. In fact, if PHM engineers manage to design an architecture capable of integrating seamlessly with the existent asset management, the added value is consistent, and the return on investment is definitely justified [16].

Equipment PHM is typically performed through the analysis of signals at the equipment level to identify potential failure symptoms [17,4]. In other words, operating signals strictly related to or obtained from the monitored equipment are usually analyzed through advanced data mining techniques. The results are health indexes which represent the health status of the system [18,19]. Therefore, it is clear that the basis for the integration of these techniques is the availability of data likely coming from ad hoc sensors installed on the equipment under investigation. However, when applied in an operational scenario, these methodologies often encounter limitations stemming from a lack of available recorded equipment-level data or deficiencies in data quality [20,21,6]. The reasons of the lack of monitoring data can be varied: no sensors are mounted on the equipment itself, there are sensors but data is not logged, data is not available due to Intellectual Property Rights (IPR) issues, etc [22,23]. As a result, more often than not, the only available data are not strictly related to the equipment under study but are logged at a higher system level and hence preclude a straightforward and seamless calculation of equipment health through the plethora of signal analyses based on Deep Learning (DL) available in literature [24–26]. This is often the case of aerospace components. For reasons connected to equipment logistic reliability, weight, and complexity, a very limited number of sensors is often installed on single equipment by OEMs. This is particularly true for flight control actuators, where weight, safety, and reliability are the priorities. If equipment level data is often not logged, aircraft level data is often saved via Health Usage Monitoring Systems (HUMSs) or similar frameworks like Integrated Vehicle Health Management (IVHM) systems [27].

This paper addresses the complex yet rewarding task of deriving condition insights for aerospace components utilizing data at the aircraft level. The challenge lies in the transition from a holistic approach of monitoring the aircraft as a whole, to a more focused effort aimed at predicting the health of specific components. The methodology proposed in this paper is built around a specific pilot study, a flight control Electro Hydraulic Actuator (EHA), commonly used in aerospace applications for its high power density and safety properties [28], but the study may potentially cover a wide range of potential applications, creating a disruptive tool for different uses in several fields.

### 1.1. Key contributions

This work documents the practical experience of developing a data-driven PHM framework for legacy aerospace systems, specifically targeting EHAs. For reasons of clarity, Table 1 reports the list of the abbreviations and acronyms used in this document. The primary contributions of this study are as follows:

- **Demonstration of PHM Applicability with Limited Data:** We show that meaningful usage insights can be extracted even when only aircraft-level operational data are available, addressing the common reality of legacy platforms where equipment-level sensors and high-fidelity degradation data are absent.
- **Adaptation of Established PHM Concepts to Real Constraints:** The architecture presented was specifically tailored to operate within the severe data limitations of in-service aircraft, requiring methodological compromises and adaptations to established PHM strategies. This includes the use of indirect statistical indicators, such as cumulative moments, to infer degradation trends in the absence of direct physical measurements.
- **Transparent Account of Implementation Challenges:** Rather than proposing a new algorithm, this work provides a candid discussion of the practical hurdles, compromises, and validation strategies encountered in a real industrial context. The study highlights both the opportunities and the limitations of PHM when applied outside of idealized or simulated environments.
- **Validation with Extensive Real-World Data:** The framework was developed and tested using a comprehensive dataset obtained from the aircraft manufacturer (Leonardo S.p.A.), encompassing more than 20 aircraft, over 60 actuators, and as many as 25,000 flight hours. This unique access enabled the development and validation of the approach under authentic operational conditions.
- **Guidance for Future PHM Deployments:** By sharing lessons learned and the rationale behind key methodological choices, this study offers practical guidance for practitioners seeking to implement PHM in similarly constrained settings, facing data and instrumentation limitations.

## 2. Case study selection and related works

The equipment selected for this pilot study is an EHA, employed as a flight control Primary Actuation System (PAS). In particular, the actuator is responsible for the control of an Advanced Jet Trainer (AJT) all-moving Horizontal Tail (HT) (see Fig. 1).

HTs provide aircraft longitudinal control and stability and, in the case of all-moving HTs, the surface is responsible for stability, control, and trim. Most of the advanced general aviation, commercial, and advanced military aircraft are equipped with Fly-By-Wire (FBW) Flight Control Systems (FCSs) thanks to which the pilot input commands are translated into electronic low-power signals by transducers, transferred with wires to the actuator, and then handled by the actuator control logic which is responsible for the surface movement [29,30]. In particular, EHAs leverage hydraulic power provided by the hydraulic system to move the aerodynamic surfaces [28,31]. HTs, along with the other primary flight controls are classified as flight-critical and safety-critical equipment since their fault or failure would lead to catastrophic failure conditions.

The most commonly used types of EHAs include flapper-nozzle, jet-pipe, and Direct Drive Valve (DDV) powered EHAs [32]. In this case,

**Fig. 1.** The AJT considered in this study.

the AJT EHA is controlled by a DDV. The readers interested in a more detailed explanation of EHA functioning principles are encouraged to refer to Marè [28], as a comprehensive discussion of EHA designs is outside the scope of this paper.

As most advanced aircraft, the AJT records data through a parametric data acquisition and processing system, called HUMS [27]. This system collects, stores, and analyzes flight data coming from different sensors. HUMSs have been developed initially for rotary wing systems in the 1990s and their objectives are deeply intertwined with PHM and CBM concepts. The primary function of HUMSs is related to real-time/post-flight fault detection, obtained by preliminary analyzes on raw signals received during aircraft operation. In this way, HUMSs can be described as a basic elementary PHM framework at a very high abstraction level. The presence of a HUMS on-board is common for aircraft assets and, even if their functioning principles may vary slightly, the core capabilities are shared among platforms. For instance, one of the few publicly available information on military platforms involves the FACE system which is installed on board the Royal Netherland Air Force (RNLAF) F-16 [33].

However, legacy assets are often equipped with data logging modules especially optimized for the specific application they were designed for and under optimized for nowadays standards. In particular, the AJT HUMS has been designed to support Structural Health Monitoring (SHM) and fatigue management tracking [34]. The shift from HUMS to PHM is not seamless as it may seem. Kappas and Frith [35] highlighted very similar challenges to those encountered during the analysis of AJT HUMS data (i.e. low/variable data sampling, missing data, limited sensors, etc.), underscoring once again common issues when dealing with existing systems.

In this sense, this case study perfectly suits the intent of the paper: designing a PHM system leveraging asset operational data to forecast equipment health.

The selection of the HT EHA for the case study has been driven by two main reasons. On the one hand, after an in-house criticality and bad-actor analysis, the equipment has been selected to improve its performance by reducing the down times associated with the unscheduled unloading of the EHA [36]. On the other hand, a substantial research gap has been identified on PHM for flight controls EHAs, especially if designed leveraging operational and historical real-life data. If a solid base is retrieved for EHA diagnostic strategies leveraging system signals [37], a limited number of available studies involves the prognostic step.

The literature analysis reveals a limited and fragmented panorama concerning the studies conducted on EHA PHM leveraging operational and historical logistics data, as also highlighted by the Systematic Literature Review (SLR) carried out by the authors in [38]. The retrieved literature studies can be broadly divided into three main categories:

- Category 1: those studies which use asset operational and fleet data to assess the health status of systems which are however not strictly related to the case study (i.e., not EHAs)
- Category 2: those papers which focus specifically on EHAs but with equipment level data often not obtainable in operational scenarios (e.g., more sensors, laboratory tests, simulations, etc.)
- Category 3: those publications which developed PHM methodologies on EHAs with asset operational and fleet data.

### 2.1. Category 1

In the first category, two papers published in the context of the 2014 PHM Society Data Challenge have tried to address a similar problem underscoring the challenges of dealing with sparse and scattered data. The considered equipment was not related to EHAs but the available data in an industrial context presented some similarities with the pilot study data.

Rezvanizaniani et al. [39] highlights the difficulties to handle logistic and operational data coming from different sources and provide solutions based on Probabilistic Risk Assessments (PRA). The developed strategy is firmly grounded in statistical methods and leverages the very high number of Unscheduled Removals (URs) and detailed part removal data found in the data-set. Kim et al. [40], while addressing the same data-set, employed another statistical strategy based on an ensemble approach, which combines a part lifespan calculation and a set of usage classification methods. Unfortunately, the methodologies presented for the PHM Data Challenge are not applicable to our research project due to the much lower magnitude of data available and the lack of precise failure mode indications in our case.

If the aerospace field is considered, a CBM framework applied on the propeller and wheel brake assembly of a C-130J aircraft is presented by Schoenmakers in [41] using fleet and operational data. The results of applying several Machine Learning (ML) methodologies are however limited. The findings underscore once again a critical point: systematically gathering more data is essential in order to make reliable and grounded decisions.

### 2.2. Category 2

Another point of view to the problem is offered by the studies which focused specifically on EHAs, but using data hardly obtainable in real-life operations.

Some approaches employ advanced data processing methodologies, such as Particle Filtering (PF), a Bayesian methodology for fault detection and Remaining Useful Life (RUL) estimation [42,43]. With regard to EHAs, PF has been employed by Mornacchi et al. [44] and by Autin et al. [45]. Some variations around PF are also proposed by Guo ans Sui [46], which opted for the Minimum Hellinger Distance technique in conjunction with a PF application for EHAs. Predictions regarding the performance degradation of EHAs are presented in Liu et al. [47], firstly utilizing an Elman neural network observer, then a support vector regression (SVR), and finally a Gaussian Mixture Model (GMM). The research conducted by Soudbakhsh and Annaswamy [48], along with findings from Lu et al. [49], highlights significant advancements in fault detection methodologies and health monitoring strategies. Kordestanti et al. [50] developed a modular hybrid fault prognosis method that integrates distributed neural networks with a recursive Bayesian algorithm. In addition, Cui et al. [51] introduced a hybrid approach employing the Nonlinear Wiener Process (NWP) algorithm for the physics-based component and a data-driven Echo-State-Network (ESN) for the data-driven step. Another possibility is linked to the extraction of relevant features in the context of pre-flight checks and in-flight data [52]. Some other studies concentrate their effort towards specific EHA components. These studies present a range of solutions pertaining to fault detection and isolation (FDI) at the component level (e.g., seals), degradation models (e.g., leakage), and comprehensive PHM procedures for specific components. Mi and Huang [53] and Byington et al. [54] focus on servo valves, while Shanbhag et al. [55] examine cylinders. Additionally, Bertolino et al. [56] address leakage issues, whereas Chao et al. [57] investigate piston pumps. A multi-physics modeling of a faulty rod-end for EHAs is reported in [58], where the authors created a physics-based model of this often overlooked component in MATLAB/Simulink. Vianna and Malere [59] present a methodology for the identification of hydraulic system leakage detections as well as the service recommendation to reduce the Aircraft On Ground (AOG) risk. The developed strategy leverages three onboard sensors (a pressure transducer, a temperature transducer, and a quantity gauge), whose data are recorded in the Flight Data Recorder (FDR) unit for a fleet of EMBRAER regional jets. Zong et al. [60] developed a real-time monitoring system for the actuator mechanism of an aileron. This study is placed in the framework of SHM strategies and focuses on the comparison between different dynamic responses of the nominal and non-nominal system with a finite element software and simulations. The non-exhaustive list of papers reported in this paragraph provides the most relevant examples of studies on actuator parts and shows that a wide range of papers have been published on actuator internal components.

However, all these strategies require some kind of actuator level data to monitor the equipment health status. In this sense, it is important to acknowledge that there exist a significant number of records which focus on test benches approaches and synthetic data-sets or on specific fault modes monitoring [61,62], which are however not applicable to the authors' case study.

### 2.3. Category 3

Lastly, only one record has been identified for the final category. Kannemans and Jentink [63] focus on the flight control actuator of a HT of a fighter aircraft. The methodology is applied to the aircraft data obtained from the FACE measurement system (that is, a flight data recorder aimed at fatigue monitoring, maintenance, and safety) of an NLAF F-16 Falcon [33]. The authors tried to extract usage information from hinge moment data, however the results were limited and there are no additional updates available on the research project.

As discussed above, the literature review reveals a substantially sparse and limited body of research in this domain, which justifies and encourages further studies. This research gap becomes even more consistent considering that EHAs are responsible for controlling primary flight control surfaces in all current commercial aircraft and the majority of military aircraft. In fact, the scarcity of comprehensive studies is particularly remarkable given the crucial role these systems play in aviation safety and performance. Given these premises, this paper is positioned to cover a current gap in research literature aiming at providing a prognostic framework applied to real, currently flying, equipment based solely on the data currently available to the airframer.

## 3. Available standards and architecture rationale

The PHM framework has been developed in an industrial and operational scenario and the first part of the project has been devoted to the reconstruction of the data lineage. In fact, as stated in Jardine et al. [64], CBM encompasses three fundamental stages: data acquisition, data processing, and maintenance decision-making. These conceptual stages have been merged with the research group's experience in similar projects and the industrial know-how. Moreover, an extensive review of PHM standards across industries, with particular attention to aerospace applications has been conducted by Vogl et al. [65] and will be explained in the following paragraphs.

### 3.1. Available standards

The field has generated multiple standardization documents and implementation guidelines for PHM system development [66–68], including several specifically addressing aerospace requirements [69,70].

A wide range of standards related to CBM, Internet of Things (IoT), cyber physical systems or IT applications in systems engineering and aerospace suggest to delineate PHM architecture into integrated and modular layers.

The result of this preliminary analysis has been a workflow tailored to the specific constraints and requirements of the industrial environment and platform under consideration. By drawing inspiration from the existing projects and aligning them with industry requirements, the selected framework has been designed as a three-layer modular architecture. This adaptation was necessary to bridge the gap between theoretical frameworks and practical implementation challenges. The workflow design, data collection and pre-processing has been deeply analyzed in [71] and [72], while a broader overview of the research project has been published in [73].

### 3.2. Architecture rationale

In this sub section, the main framework underlying principles are explained. Even though every aspect of the methodology will be explained in detail in the following sections, this brief summary has to be intended as an executive summary of the methodology.

As already mentioned in Section 1, in PHM it is common practice to track one or more signals during operations, project them in the future with some probabilistic or ML based approaches and then compare the projected signals (or their residual with respect to a nominal baseline signal) with a hazard threshold, which can be dynamic or static, obtained through statistical or physics-based principles [74]. The signal trends in time underline an increasing damage and the residuals highlight when the damage reaches an alert zone. These strategies are particularly effective when a signal, which is representative of the equipment under study and selected through feature selection processes, is available and logged during operation. However, a thorough examination of HUMS records [71] showed that, since HUMS was designed for SHM, data are not logged with a constant high frequency and that no actuator level signals are logged in the AJT HUMS.

Given the lack of actuator level data and the low data sampling frequency, the authors selected an analytical approach based on the application of statistical functions to track the equipment usage from aircraft level data. The hypothesis of linking asset level usage and equipment health is justified by the intrinsic use of the AJT platform and the role of the PAS in the aircraft flight dynamics. In fact, the onset and progression of several of the most common EHA failure modes are linked to the amount and type of usage [63]. Typical prognosable [75] EHA failures such as internal leakage, backlash or friction are the result of the operating conditions. Moreover, being a trainer aircraft, the AJT is subjected to a wide however limited range of operating missions operated by student pilots. It is hence deemed reasonable and justified to link the health status of the actuator to how and how much the aircraft is used.

## 4. A layer perspective

As a result, inspired by the existing structures mentioned earlier in Section 3 and considering the industry requirements, a three-layer architecture has been selected with several working modules inside each functional layer. The data analysis framework has been implemented in Python version 3.8.18, utilizing Visual Studio Code within an Anaconda®-managed environment. Essential packages commonly employed for data analysis have been installed, alongside specialized libraries to facilitate customized operations. The overview of the framework layers and modules is reported in Fig. 2.

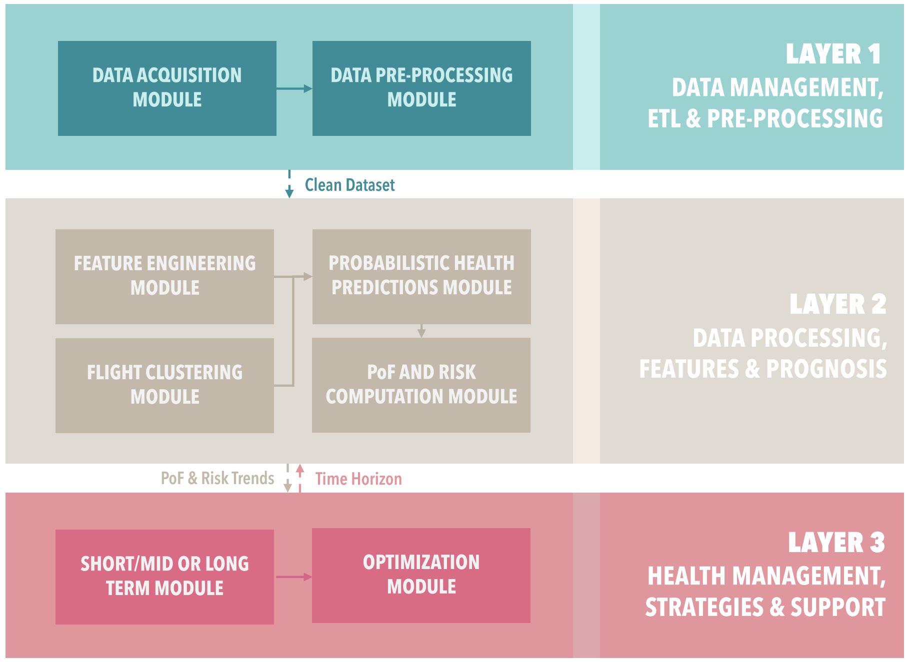



**Fig. 2.** PHM framework architecture overview.

- The first layer encompasses Data Management, ETL & Pre-Processing
- The second layer is responsible for Data Processing, Features & Prognosis
- The third layer involves Health Management, Strategies & Support.

### 4.1. *First layer: Data Management, ETL & Pre-Processing*

The first layer consists of two modules that prepare a clean dataset for the second layer. The Data Pre-Processing module then extracts flight information, cleans and structures the data, performs exploratory data analysis, and saves the processed data for future use.

### 4.2. *Second layer: Data Processing, Features & Prognosis*

After the pre-processing phase, the second layer processes the clean dataset to generate features, Probability of Failure (PoF), and Risk Trends by constructing probabilistic health models. A Feature Engineering Module identifies optimal Cumulative Features (CFs), while a Flight Clustering Module groups historical data into Clustered Mission Types (CMTs) to guide Monte-Carlo-based future projections of CFs. These simulations predict system health, deriving PoF and Risk Trends [76,77] in a different time horizon.

### 4.3. *Third layer: Health Management, Strategies & Support*

The third layer extracts management insights from risk trends and propose the structure for the integration into logistics and maintenance frameworks, shaping short- and long-term availability predictions. This layer is still in the development phase and is deeply influenced by the operational scenario, which cannot be disclosed due to confidentiality constraints. The Probabilistic Health Prediction Module customizable design supports tailored PHM solutions aligned with specific operator requirements and procedures. By simulating predefined CMTs in the short term, it forecasts increasing UR risk for specific mission sequences and aircraft, enabling informed decision-making on aircraft suitability; meanwhile, long-term "open-loop" CMT sequences based on historical data assess aircraft usage impacts, benefiting supply chain and warehouse management planning. The decision of the time horizon influences the process carried out in the previous module, this is indicated by the upwards arrow in Fig. 2.

In the next section, with the help of an exploded view of the layered architecture, each module is explained in detail.

## 5. A detailed overview

Fig. 3 shows a detailed view of the PHM architecture, focusing more closely on the modules and their interactions. Each layer, identified with the respective color, can be broken down into working modules, delineated by colored areas. Inside each module, several process blocks are linked together to create the data-to-strategy process. As already mentioned in Section 3 and 4, the overall architecture is inspired from several PHM modular architectures found in literature.

### 5.1. *First layer: Data Management, ETL & Pre-Processing*

#### 5.1.1. *Data Acquisition Module*

The first layer, divided into two modules, is reported on the left hand side of the graph: the Data Acquisition Module receives raw data in the form of HUMS Load Files, Flight Hours (FHs), Equipment Registers (ER) and Unscheduled Removals (URs).

1. HUMS Load files are the condition monitoring files where signals coming from aircraft systems are logged. Once decoded and transformed in engineering units, they are saved in txt files which can then be analyzed. A total of 256 signals from different on-board systems are saved in the HUMS Load files. A complete list of the recorded signals is reported in [71].
2. FHs consists in the register of the time flown by each aircraft of the fleet on a daily basis. This information can be obtained from an independent data source or directly from HUMS data by calculating the duration of each flight.
3. Equipment Registers are needed to guarantee the equipment traceability during its life-cycle. Aircraft equipments have been designed to be very maintainable and with the concept of Line Replaceable Unit (LRU) to ease maintenance operations and troubleshooting. As a result, equipments are swapped during service due to cannibalization/troubleshooting or operational/mission readiness requirements [78]. Furthermore, another reason is related to repair

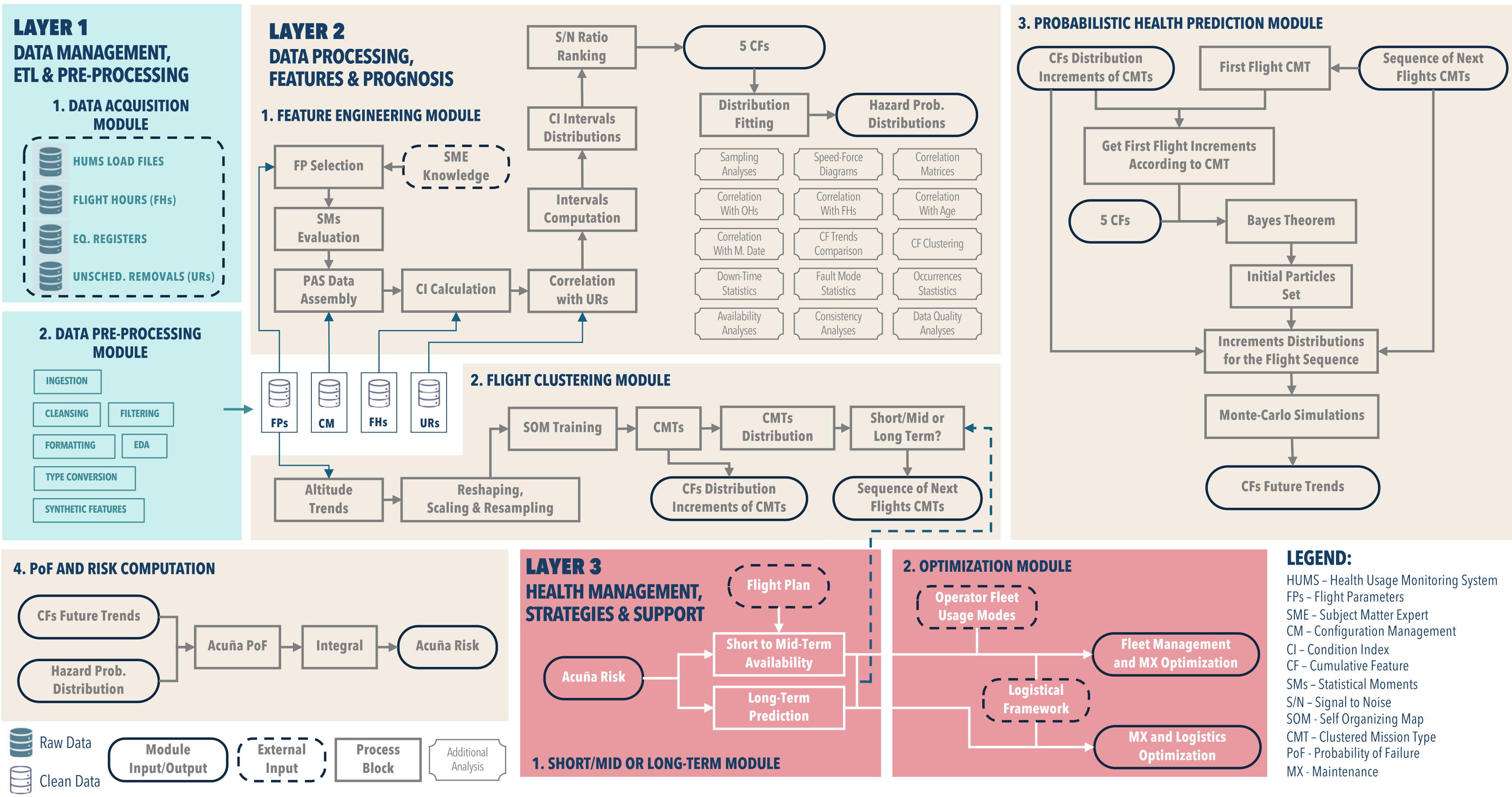



**Fig. 3.** PHM framework architecture detailed overview. Functional layers comprise operational modules characterized by process blocks.

management. When an aircraft component breaks down and is sent to the OEM for repair, the repaired component will regularly not be reinstalled on the same aircraft from which it was removed. Instead, it may be shipped to the general spare parts inventory and/or loaded on a different aircraft upon return from the OEM. Against this backdrop, tracking down the health of a specific equipment (identified by a Serial Number (SN)) differs from following the operational history of the aircraft (identified by a Tail Number (TN)) on which the equipment was firstly loaded on. This stresses that accurate and complete Equipment Registers, preferably digitized, is critical: without the SN-TN connection it is not possible to leverage aircraft operational data to forecast equipment future performance.
4. UR registers record information related to breakdowns or flight NO-GOs related to the equipment under investigation. Each piece of information to merge is however often scattered in different databases and they must be grouped, confronted and matched to obtain a single, coherent and as much informative data-set as possible.

### 5.1.2. Data Pre-Processing Module

The Data Pre-Processing Module inherits the operational data sources from the Data Acquisition Module and generates four cleaned data-sets. This is carried out thanks to ingestion processes, data cleaning and cleansing as well as filtering steps. The data is then formatted and converted to a coherent format and type. In this step, some additional synthetic signals can be added by elaborating the existing signals, leveraging on Subject Matter Experts (SMEs) [79], system knowledge or advanced data mining techniques. As a result, four main data sources are obtained: Flight Parameters (FPs) obtained from HUMS Load files, Configuration Management (CM) which contains the traceability information obtained from Equipment Registers, FHs and URs.

FP and FH pre-processing has involved removing outliers and spurious data entry as well as combining the data-sets into a single and coherent format. The authors published more details about this phase in [71].

The pre-processing of UR data focused on the integration and data merging from different files containing useful information and then the exclusion of a subset of UR which are deemed not related to prognosable failures. More specifically, only the URs which are deemed related to a degradation mode are considered. This selection has been carried out with the help of SMEs and by looking at the failure code written in the UR register (when reported). Moreover, URs which occurred less than 50 flights after the PAS loading have not been considered since those URs are probably linked to sudden failures (e.g., infant mortality) rather than degradations. This pre-processing step is pivotal since the URs are central to shape the PHM framework and considering UR which are not relatable to a component degradation would alter the analysis.

Along with CM, these four main data sources have to be integrated with a solid technical knowledge base on the equipment under study. This body of knowledge is often found in technical publications or reports as well as in engineering documentation. All of this has to be topped up with the specific Part Numbers (PNs), SNs and TNs of the system, equipment and aircraft fleet under study.

## 5.2. Second layer: Data Processing, Features & Prognosis

### 5.2.1. Feature Engineering Module

The Feature Engineering Module, contained within the Data Processing, Features & Prognosis Layer, takes as input the FPs, performs a selection on the most representative FPs based on SME knowledge, calculates statistical metrics and produces two outputs: the 5 Cumulative Features (CFs) and the hazard distributions.

Through FP selection, among the 256 signals logged in the HUMS system, 50 have been chosen via physical reasoning. Four other signals have been created ad hoc combining some of the 50 existing signals. In particular, the actuators mechanical works have been calculated starting from the actuator position and the structural moment. The complete list of the 54 selected FPs can be found in a previous paper [71]. In the SMs Evaluation phase, the statistical metrics are applied. The first four main Statistical Moments (SMs), selected to better represent the statistical relevance of each signal for each flight, have been calculated on the already pre-processed data-set.

The first four SMs are: mean, variance, skewness and kurtosis.

1. The mean value is associated with the central tendency of the data.
2. A high variance within a specific FP time series indicates that the aircraft has experienced values that are significantly different from the average. For example, a high variance in work values may suggest that the PAS jack has undergone a wide range of movements and positions. The authors in [80] used variance analyses on cumulative signals in a inverter fault detection study.
3. Skewness indicates the extent to which a data-set deviates from symmetry. It has been widely utilized in PHM and diagnostic applications for rotating mechanical equipment [81,82]. In this context, high skewness may identify values that are consistently distant from the mean within the load spectrum, thereby underscoring their significance.
4. Kurtosis serves as a measure of the degree of peakedness or flatness in a distribution, evaluating the concentration of data in the distribution tails in relation to its center. Traditionally, kurtosis has been a widely utilized statistical measure in PHM approaches for rotating equipment and bearings [83,82]. Moreover, the authors in [84] applied kurtosis for EHAs PHM, proving the approach robustness.

As a result, after the SM calculation operation, a total of 216 potential features are created. Each SM is applied on the data distribution pertaining to one flight; therefore one flight is characterized by 216 values.

The next step involves the data assembly for each PAS. As mentioned before, not only actuators are unloaded when a fault is detected, but equipment is also commonly swapped during operations due to logistical and readiness requirements [41]. In this context, monitoring the health of specific equipment identified by its SN is distinctly different from reviewing the operational history of the aircraft identified by its TN on which the equipment was initially installed. However, FPs are tracked by aircraft; therefore elaborating the PAS operational life consists in assembling relevant FP trends coming from the aircraft TNs on which they were loaded on through CM files.

After completing this operation, the cumulative CIs can be calculated by combining the actuator-level FPs with the FHs information. The cumulative calculation is straightforward: for each flight each SM value is multiplied by the flight duration (FD), and the resulting increment is then added to the previous cumulative value. In other words, CIs have been calculated by integrating the SM over time, specifically by multiplying the FP SMs by the FD to produce a trend that reflects the actual usage of the equipment under study (i.e. HT PAS). Each flight is hence characterized by a series of CI increments. This method, analogous to a finite difference integral operation, has been applied to each PAS and each SM and can be mathematically formulated as in Eq. (1).

$$CI_{i,j}(f) = \sum_{k=1}^{f} SM_{i,j}(k) \cdot FD(k) \tag{1}$$

$CI_{i,j}(f)$ represents the CI at flight $f$ of $SM_{i,j}$. $SM_{i,j}(k)$ represents the SM $i$ applied on the FP $j$ relative to the flight $k$. $i$ can be “mean”, “variance”, “skewness” or “kurtosis” and $j$ ranges from 1 to 54, underscoring the various FPs. For example, $CI_{mean,1}(k)$ indicates the CI value obtained using the SM “mean” on the FP number 1 related to the flight $k$. $FD(k)$ is the flight duration of the flight $k$.

The creation of a cumulative trend has already been used in the context of PHM and fault detection in [80] where the fourth statistical moment is considered as well as in [85], where the authors applied a cumulative of the fourth moment to identify working regimes. The

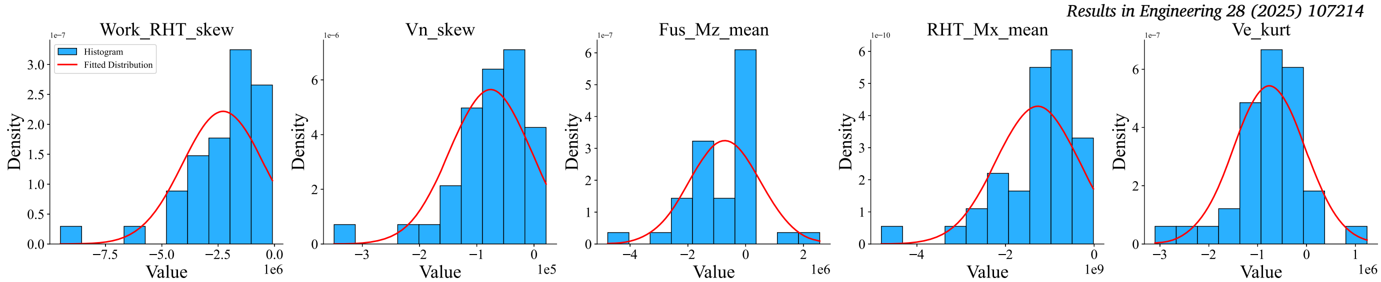



**Fig. 4.** Distribution of the CFs: values computed at URs. Example of feature distribution fitting for the calculation of the signal-to-noise ratio. For consistency, all features are fitted with a normal distribution to obtain the mean and variance required for ranking purposes.

result is a set of 216 cumulative CI, which characterize the life of the actuator both in terms of what happened during each flight (thanks to the information contained in the SM) and the duration of each flight (thanks to the duration FD).

Once the trends have been computed, their evolution in time is considered together with the URs saved in the UR register after the preprocessing step. Through the analysis of the CI trends with the URs, it is possible to evaluate the magnitude difference between one UR and the next one (or between the first flight and the first UR). After performing these operations, bar plot representations have been employed to visually illustrate the distribution of the obtained intervals. These intervals reflect the fluctuations in the value of a specific CI over time, providing valuable insights for identifying the most significant CIs, which are defined as CFs. Further insight on this part of the framework can be found in [71], where the authors detailed this phase.

CI distribution of values at UR are pivotal for two key reasons:

1. Identifying Periodicity: The bar plots showing the intervals between URs help identify features that show periodic behavior and rise of a somewhat constant value between two URs. Ideally, the best CI would be one that changes by a consistent magnitude between URs, represented by a single histogram bin. Each histogram is accompanied by a normal Probability Density Function (PDF) curve, which is characterized by a mean value and a standard deviation. This allows for the calculation of a normalized Signal-to-Noise Ratio (STNR), which is used to rank the features based on their informativeness. Specifically, the desired ones are those with the highest STNR ratio and narrowest histograms. A total of the best 5 CIs was selected to characterize the PAS health: the skewness applied to the mechanical work on the right actuator, the skewness on the north speed component $V_n$, the mean of the last section of the fuselage $M_z$ moment, the mean of the $M_x$ moment applied on the right HT and the kurtosis the east speed component $V_e$. These are the five CFs.
2. Hazard Distribution Representation: Histograms also play a crucial role in the subsequent analysis steps. Not only they help identify the most relevant features but also represent the hazard distribution. If the histogram distribution indicates a change in magnitude between two URs, it suggests that reaching this change increases the likelihood of a UR occurring. Consequently, when fitted with a custom PDF, histograms illustrate the distribution of hazard thresholds. According to [74], one approach to defining a threshold function is through the analysis of post-mortem statistical data collected from a fleet of operational equipment. Utilizing the values of these condition indicators at documented failure instances, it is possible to develop either a parametric or non-parametric hazard function by examining the cumulative function derived from the obtained PDF.

Fig. 4 shows the CF distribution of values at URs, with the normal PDF plot on top in red. As explained in the bullet points, these histograms have been selected after a S/N ranking. It has to be noted that, despite being the best CI distributions, the variance of CF histograms is fairly high, hence producing a wide hazard threshold distribution, which definitely hampers the PoF and risk prediction in the next phases. It now becomes even more clear why the exclusion of non-prognosable URs is pivotal for the algorithm prediction accuracy. These kinds of failures cannot be predicted due to the absence of an underlying degradation mode and must be removed from the analysis since their presence would dramatically alter the hazard distribution shape with substantial consequences for the PoF calculation algorithm, which relies on the comparison of the system state with the hazard threshold distribution. Finally, it is important to clarify that the normal distribution fits shown in Fig. 4 are used solely for the computation of the STNR. This metric requires the extraction of a mean and variance, and therefore the same distribution model must be applied uniformly to all features to ensure a fair comparison. While this step provides a consistent basis for feature ranking, it is not intended to reflect the true underlying distribution of each feature. In the subsequent sampling stage, the CF distributions are instead fitted using a more refined and feature-specific approach. Specifically, the distfit Python package is employed to evaluate over 90 parametric probability models and select the one that best represents each CF distribution according to the Residual Sum of Squares (RSS). The considered potential parametric PDF function ranges from simple (e.g., Weibull, Gamma, Cauchy) to advanced formulations (e.g., Loggamma, Johnson SU, t-Student). In other words, this approach allows for the selection of a specific parametric PDF function for each CMT, ensuring a high level of customization and accuracy.

Within layer two, an extensive range of supporting and secondary data studies have been carried out, as shown in Fig. 3. For instance, sampling analysis, correlation matrices, CF clustering, fault mode statistics and other exploration analyses, which have not been reported in this paper for reasons of brevity, helped to guide the choice of the adopted strategy.

Some insights have been drawn by analyzing the UR timing across the whole PAS fleet. Fig. 5 shows the relative occurrence of PAS UR in function of the Operating Hours (OH) at which a UR was recorded. The relative occurrence was needed as the number of UR occurred at a specific OH value had to be scaled according to the actual number of PAS that reached that OH value. Otherwise, the analysis would have been biased by the fact that only a few PAS SN reached a high amount of OHs. The graph shows a clear descending trend, resembling the decreasing path typical of the initial phase of a bath-tube curve, highlighting that the majority of the so far recorded URs occur at the beginning of the actuator life-cycle. Bath-tub curves [86] are often employed in reliability studies to represent the trend of the equipment failure rate compared to the equipment usage. During the initial phase of the bath-tub curve, often referred to as the “burn-in period”, the failure rate is not constant and experiences a decline due to a wide range factors often associated with the equipment infant mortality. As a result, these failures are not linked to a degradation affecting the equipment but rather to unexpected and not prognosable breakdowns. This analysis highlights that the framework outputs may be more reliable as the fleet accumulates FHs and a more solid statistical base will be achieved.

Finally, it has to be noted that most of the excluded URs were located in the first bin, highlighting that those URs were probably caused by impromptu failures linked to infant mortality, loading issues, etc. This

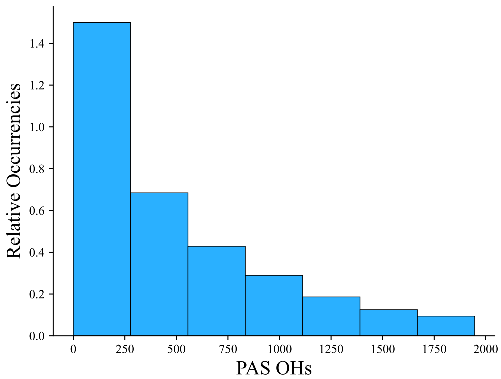



**Fig. 5.** Occurrences of UR events in function of the OHs reached at the UR event.

kind of failures cannot be predicted due to the absence of an underlying degradation mode and hence have been excluded from the analysis.

#### 5.2.2. Flight Clustering Module

The Flight Clustering Module uses the altitude trends from the cleaned Flight Parameters to obtain a set flight clusters, called CMTs. A univariate clustering analysis has been selected given the high amount of data to be processed. Altitude has been selected as the analysis main parameter for three key reasons: altitude trend presents a solid link with the Horizontal Tail effect in the longitudinal plane, mission profiles are often described using altitude graphs and altitude makes this analysis very intuitive and easy to understand [87]. In particular, the HT actuator is directly responsible for managing the aircraft pitch attitude, which in turn influences and adjusts the aircraft altitude throughout the mission. Consequently, the altitude profile during a mission is a direct result of actuator activity. For this reason, altitude is a practical and representative parameter for clustering flights based on horizontal tail actuator usage. By grouping missions according to their altitude trends, we can effectively capture variations in actuator workload patterns associated with different operational phases and mission types. This approach also enhances operational clarity, as altitude is an intuitive and commonly used descriptor of mission profiles, easily understood by engineers, operators, and maintenance personnel. A training subset of more than 3000 flights has been selected to reduce computational burden. After the application of a custom pre-processing technique specific for this analysis (i.e. reshaping, scaling, and resampling) altitude trends are given as input to a Self-Organizing Map (SOM).

The literature panorama of time-series clustering shows a limited number of alternatives [88] and the unavailability for this study of clear labeled information on the type of mission that had been performed during each flight has led to the selection of unsupervised clustering techniques. The choice of employing SOMs has been driven by the lower computational cost, the ease of implementation and the extreme interpretability of the results thanks to the high data dimensionality reduction power of SOMs. SOMs (also known as Kohonen maps) are unsupervised ML strategies which employ competitive learning to cluster data into bi-dimensional maps [89]. Classical SOM metrics have been used to quantify the clustering results and the choice of the network hyperparameters. The way SOMs are built enables a one-to-one relationship between map cells and clusters. As a result, 100 clusters corresponding to 100 cells have been selected and identified. Fig. 6 shows the 100 clusters with the altitude trends. The final values of optimized hyperparameters are $\sigma = 1.3$ and learning rate $\lambda = 0.4$. The similarity observed among certain CMTs should not be regarded as an error. Instead, it indicates that, with the 10-by-10 optimized network topology informed by the hyper-parameter tuning phase, these profiles are quite common and involve multiple CMTs with only minor variations.

It is challenging from the mission profiles displayed in Fig. 6 to associate typical labeled mission. The AJT under investigation is a lead-in to fighter training aircraft which therefore is characterized by recurring mission agenda, yet the flight trends can vary drastically between flights of the same mission type. Nevertheless, general considerations can be made. Steady high-altitude trends could be representative of basic navigation missions yet could also be indicative of dog fighting scenarios. Lower altitude trends before landing could likely be associated to approach missions. Low-altitude trends could lastly be representative of air-to-surface situations. Finally, several altitude variations during single flights could be indicative of formation flights or otherwise tactical missions. It should be at last mentioned that single flights often combine several of the many mission types that compose a full pilot training syllabus.

The identification of CMTs through a SOM has a twofold relevance.

- As mentioned in Section 5.2.1, each flight is characterized by a set of 5 CF increments (i.e. one for each CF) which describes how that flight impacts the CF trends. Once a CMT is assigned to each flight, it is possible to group the CFs increments of the flights with the same CMT label. By grouping CFs increments for each CMT, it is possible to develop a set of increments distributions specific to each CMT. In other words, by clustering flight increments for each CMT, a set of 5 CFs increments distributions that capture the unique characteristics of that sortie type is created. A best fitting parametric PDF is used to approximate each distribution. A CMT is hence described by a set of 5 increments distributions which characterize how that specific CMT impacts the increase of the CFs. As mentioned in Section 5.2.1, a custom parametric PDF is fitted to each CMT CF distribution to statistically characterize its trend. Once the sequence of next CMTs is decided, it is possible to simulate the CFs trend by sampling from the increments distributions of each CMT.
- The assignment of a CMT to each flight contained in the set used for training leads to the definition of a statistical CMTs occurrence distribution, which highlights those CMTs which appear more often and those which are less common. This historical distribution can be utilized to generate simulations of long-term future CMTs through sampling.

The two modules outputs are hence the CFs increments PDFs for each CMT and the sequence of the next flights CMTs. In particular, each CF distribution is fitted using the distfit Python package, which systematically tests over 90 parametric probability models and selects the one that best represents the observed data. The future CMTs sequence can be created based on two paradigms: short to mid and long-term.

In the case where the short to mid-term is selected, the sequence is decided based on the flight planning of the next days or weeks. In fact, once the flight planning is known, the planned sorties can be reconducted to the CMTs and a sequence of CMTs can be constructed. The application of unsupervised clustering approaches was necessary due to the lack of labeled mission data. However, if labeled data become available, the Flight Clustering Module can be modified by employing supervised techniques, which would significantly improve the module accuracy and facilitate the implementation of the short- to mid-term approach. In fact, if the fleet manager wants to simulate a set of specific missions, the connection between those missions and the labeled CMT will be clearly defined.

On the other hand, if a long-term simulation is desired, the sequence of CMTs can be sampled by the CMT occurrence distribution. The choice between the two strategies is placed in the Health Management, Strategies & Support Layer and that is why a dotted arrow bridges the two layers. Further explanation involving the short to mid and long-term simulation is reported in Section 5.3, where the third layer is presented in detail.

#### 5.2.3. Probabilistic Health Prediction Module

The Probabilistic Health Prediction Module represents the framework core, where the CFs are projected in the future according to CFs

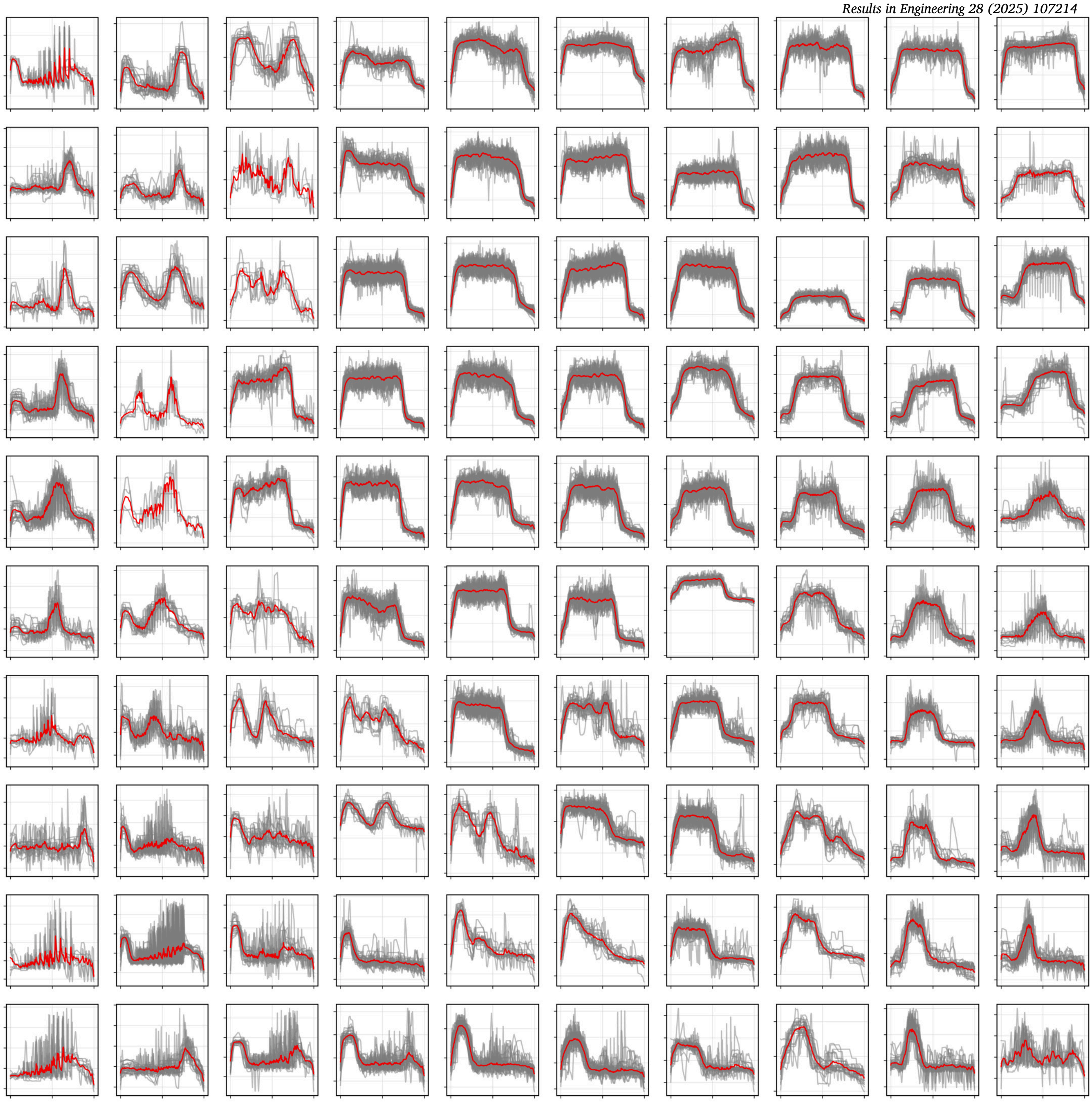


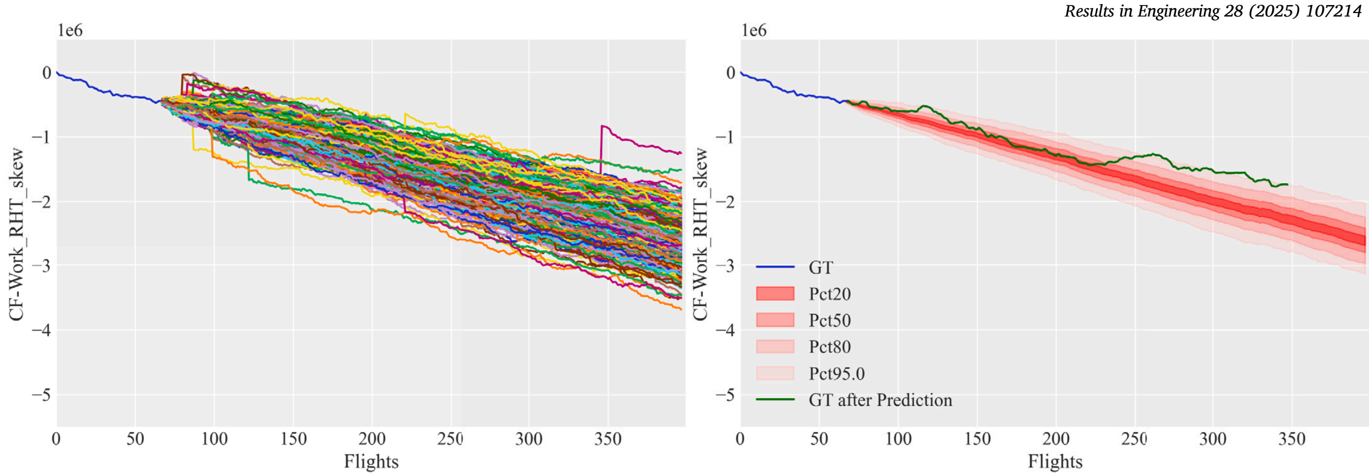
**Fig. 6.** CMT clusters with altitude trends. The gray trends denote the aggregate trends within each CMT, whereas the red trend indicates the representative trend for that specific CMT.

increments custom fitted PDFs and the sequence of next flights CMTs (Fig. 7a and 7b).

For the sake of clarity, let us take into consideration one CF (e.g., the skewness on the right HT work); the methodology can similarly be applied to other CFs without requiring modifications. While the framework is not explicitly based on PF techniques, the concept of particles can still be effectively utilized in this study as it makes the explanation clearer. Particles are defined as discrete samples that represent possible states of the system (i.e., of the CFs trends).

The first step has involved the creation of the initial particle set. Initially, particles have been generated based on the Bayes theorem, since little prior information about the system state is known. Bayes theorem is the cornerstone of Bayesian statistics and it provides a mathematical formulation for the probability estimation of a state given an a-priori knowledge of the system (i.e., the prior distribution) and a likelihood distribution. The prior distribution is typically determined based on an understanding of the physical system, and it may take on a Gaussian shaped PDF or another custom PDF if the physical insights offer relevant information.

In this analysis, the prior distribution represents the increments of the CFs across all PASs. This selection has leveraged the a-priori knowledge, which has been derived from the known historical trends of all PASs. The reason to consider all PASs lies in the fact that some PAS SN may have a longer history than others and considering only the increments related to that specific PAS SN, while adding some value in term of precision for some PAS SN, may hinder the overall framework ac-




(a) MC traces whose particles have been initially generated via Bayes theorem.

(b) Comparison between simulations and ground truth.

**Fig. 7.** Examples of CF projections in the future through Monte-Carlo simulations for PAS SN 9.

curacy. In fact, some PAS SN may have an historical record consisting of an extremely limited number of flights and generating the particle relying on a PDF based on a limited number of samples may lead to inaccuracies. This is particularly true since the generation of particles is extremely important for the overall framework accuracy as the initial particles represent the first points of CF traces and an inaccurate initialization may lead to consistent inaccuracies during the simulation phases. The prior distributions have been represented with a t-student PDF which has been selected as the best-fit PDF.

In the context of Bayes' theorem, likelihood denotes the conditional probability of the observed evidence given a particular hypothesis. It is central for the process of updating prior beliefs about the hypothesis in light of new data or information. In this case, the likelihood is selected as the increment distribution of the first CMT in the sequence. In fact, the observed evidence can be traced back to the fact that the first flight CMT in the future CMT sequence is known.

Thanks to these distributions and the application of the Bayes theorem, the initial particle set (1000 particles) is generated. Once projected into the future, each particle position will be updated for each flight according to the increment guided by the CMT sequence. The resulting trace (created by connecting the particle positions in time) will represent a possible evolution of the CF. This process is carried out in parallel for each single particle and, in the end, a total of 1000 possible traces will represent a statistical basis on how the CF can evolve. These traces, each representing a possible trend of the CF in time, are built according to the CMT sequence through Monte-Carlo simulations.

Monte Carlo simulation is a mathematical technique that is often used to predict a range of possible outcomes for uncertain events by employing repeated random sampling [90]. In fact, once the particles have been generated through Bayes theorem, the process is repeated for each new flight contained in the future flight sequence.

A new flight is identified by its CMT and each CMT is linked to the specific increments distribution. The process involves the sampling of a value from the CMT increment distribution for each particle trace and this operation is repeated until the end of the CMT sequence. This process can be repeated for every CFs. Figs. 7a and 7b show the simulations carried out for PAS SN 9, involving 1000 particles and 330 CMT simulation in the future. The CF "Work_RHT_Skew" is considered and plotted against the PAS flight number. The prediction flight $k_p$ was set as flight number 70 and the final prediction flight at 400. In particular Fig. 7a reports the single traces, whereas Fig. 7b show the percentiles of the MC simulations along with the ground truth signal, highlighting an excellent prediction ability even in the mid-term. Further details along with the methodology evaluation are reported in Section 6. Fig. 8 shows the simulation process at four different values of $k_p$. More specifically, Fig. 8 is related to a different SN than the one considered before to demonstrate the framework effectiveness across multiple SNs, as better shown in Section 6 where the strategy validation is reported.

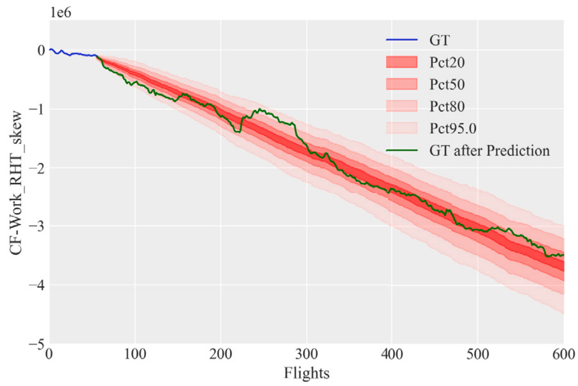
The forward looking design of this module facilitates the shift from a short to mid to a long-term perspective since the only change needed lies in the next flight CMT sequence; the health prediction routine remains unchanged, as explained in Section 5.2.4. The only output of the Probabilistic Health Prediction Module is represented by the CFs future traces.

### 5.2.4. Probability of Failure & Risk Computation Module

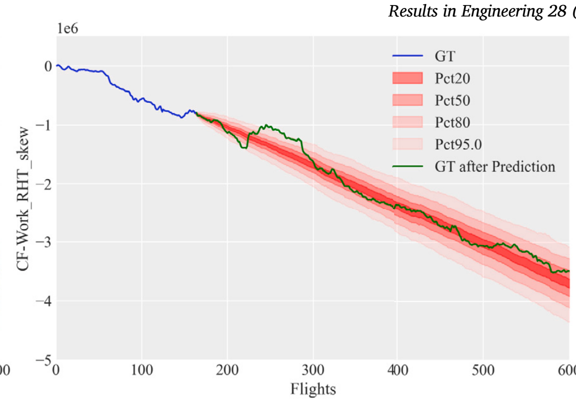
The Probability of Failure and Risk Computation Module leverages the CFs future traces inherited by the Probabilistic Health Prediction Module and compares the CFs trends with the hazard threshold distribution obtained from the Feature Engineering Module. The classical definition and mathematical formulation of PoF presented in [76,77] cannot be applied in this context since the hazard distribution can be defined as an "uncertain event" bandwidth as presented in the paper by Orchard et al. [74]. In fact, the threshold is not represented by a value but by a distribution, as often happens in real-life operational scenarios.

The PoF is hence calculated using the mathematical formulation reported in [74] and called Acuña PoF. Once the PoF trend is obtained, the risk trend can be computed by the integration of the PoF trend in time, resulting in a curve which has a 0 to 100 range. From both a mathematical and management standpoint, incorporating risk values into decision-making processes is considered as the most effective approach for managing uncertainty. Risk quantifies the likelihood of an UR occurring, and when risk reaches a value of 100 percent, it signifies absolute certainty of that event having occurred. The user has the option to select their desired risk level [91]; in the rest of the paper the risk target value is set as 99 per cent. The Acuña risk trend is then passed to the Health Management, Strategies & Support Layer.

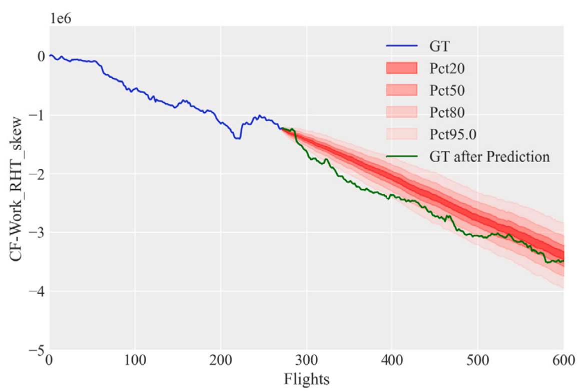
An example is provided in Fig. 9, where the results of the Probability of Failure and Risk Computation Module are reported. The same CF "Work_RHT_Skew" is considered and plotted against the PAS flight number. The PAS, SN 47, had already suffered one UR at flight 291 and a prediction is performed a few flights after the first UR ($k_p = 296$). The results of the MC simulations are reported and highlight an excellent simulation ability, noticeable by comparing the distributions in the blue "fanchart" with the GT after $k_p$. The second UR happened at flight 451, as highlighted by the vertical thick orange line. The green trend represents the PoF density, while the red curve trend represents the risk. It should be noted that the risk reaches a high percentage before the



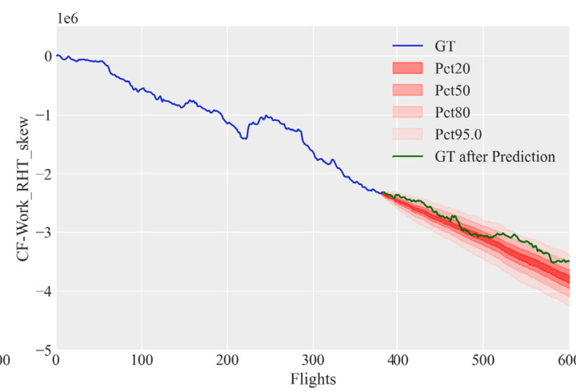

(a) Simulation with $k_p$ set to 56.




(b) Simulation with $k_p$ set to 164.




(c) Simulation with $k_p$ set to 272.




(d) Simulation with $k_p$ set to 380.

**Fig. 8.** MC simulations and results for PAS SN 56 with 1000 particles at four evenly spaced values of $k_p$ with a final flight set to 600. The GT evolution is inside the prediction cone, marked by the 95 percentile.

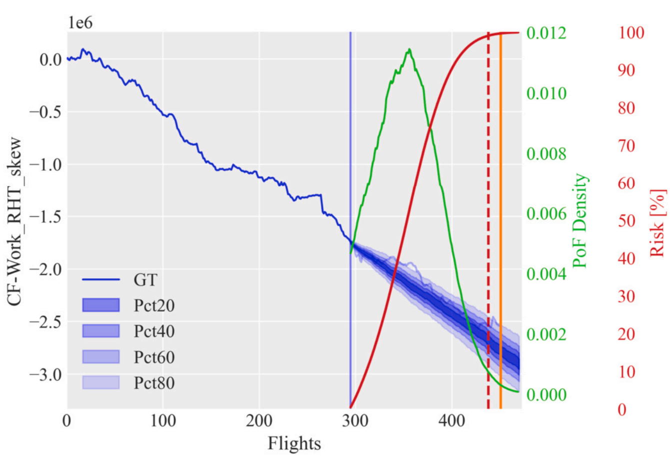



**Fig. 9.** MC simulations and PoF/Risk results with 1000 particles for as many as 200 simulated flights starting at flight $k_p = 297$. The GT after $k_p$ is reported and it is inside the prediction "cone", marked by the 80 percentile. The PAS SN already suffered one UR at 291 flights and the second UR occurred at flight 451, as shown by the vertical orange line. A sharp increase in risk can be noted due to the fact that, at $k_p$, the PoF is already near its peak. The prediction associated with 99 per cent risk is highlighted by the vertical dotted red line.

actual UR occurred which implies that, although precision can be improved with more data, failure is not missed (or underestimated), thus raising confidence in the CF processing. A red dotted line is reported when risk reaches 99 per cent, indicating a good estimate of the possible next UR. Further details involving the evaluation through a literature established metric are reported in Section 6.

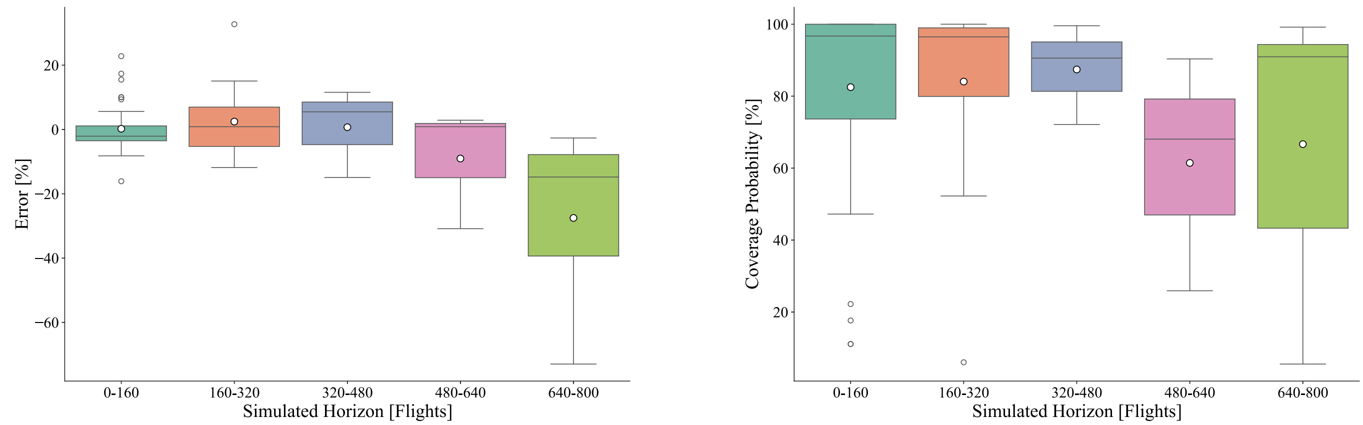
### 5.3. Third layer: Health Management, Strategies & Support

As already mentioned in Section 5.2.3, the design of the Probabilistic Health Prediction Module facilitates the operation of the Health Management, Strategies & Support Layer enabling the possibility of both short to mid and long-term optimization strategies stemming from the same risk evaluation pipeline, hence providing tailored solutions that adapt to specific customer needs.

#### 5.3.1. Short to mid-term methodologies

In the short to mid-term scenario, the module simulates a set of predefined CMTs to assess the increasing risk of URs. This capability allows for forecasting specific mission sequences and evaluating how different CMT sequences impact a specific PAS SN health loaded on a particular aircraft. Of course, there is the need of knowing the flight plan for the next set of missions. Once the set of next CMTs is identified, the Probabilistic Health Prediction Module can be run. This loop back is reported in the diagram of Fig. 3 by a dotted arrow, which starts from the Health Management, Strategies & Support Layer. The insights gained from these analyses can be integrated into a decision-making framework, offering customized recommendations on the most suitable aircraft for specific missions while considering the risk of potential URs.

The potential for developing such systems across a broad spectrum of components is disruptive, as it would provide comprehensive aircraft health status reporting, thereby facilitating the selection of the most appropriate aircraft tail number for a given mission based on the operational condition of the monitored systems without adding any new sensors.




(a) Mean relative error between the CFs future trends simulations and the GT.

(b) Coverage probability inside the 95-th percentile.

**Fig. 10.** Box plot results of the metrics for the Probabilistic Health Predictions Module evaluated at different simulation horizons across the whole PAS fleet. The median is represented with the horizontal line inside the box, whereas the white dot inside the box represents the mean. Both the mean relative error and the coverage probability highlight the capability of this module in predicting the CF trend, with better performance in the medium term.

*5.3.2. Long-term methodologies*

On the other hand, a long-term perspective can be envisioned by providing "open-loop" CMT sequence, with their distributions informed by and sampled from statistical distributions of CMT historical data. In this way, the impact of a long-term aircraft usage could be evaluated and estimated, yielding positive outcomes on maintenance optimization and spare parts/storage organization. Logistics framework (e.g. availability of the number of spares, maintenance technicians, free hangar slots, etc.) can then be integrated providing more precise decision-making support depending on the real situation on the ground.

The specific actions of the Health Management, Strategies & Support Layer have to be designed according to how the AJT operator manages and operates his fleet and may focus on the exploitation of risk trends in relation to the way the fleet schedule and missions are organized. A possible implementation would be easily carried out by creating a direct link between the CMTs and the syllabus missions performed by pilots during the training: in this way the fleet manager can specifically simulate the effect of a set of pre-defined missions on the equipment health. Given the high confidentiality and customization level, a detailed description of the risk exploitation phase is not reported in this study, since the methodology is currently being customized and tailored to the specific application.

## 6. Metrics & discussion

A typical challenge related to the development and acceptance of PHM results is linked to the wide range of applicable validation metrics. To make the analysis more grounded and demonstrate the framework solidity and future potential, the authors decided to split the evaluation phase into two parts: the first linked to the Probability Health Prediction Module to evaluate how well the predictions compare to the GT and the second part which assesses the PoF and Risk Computation Module performance.

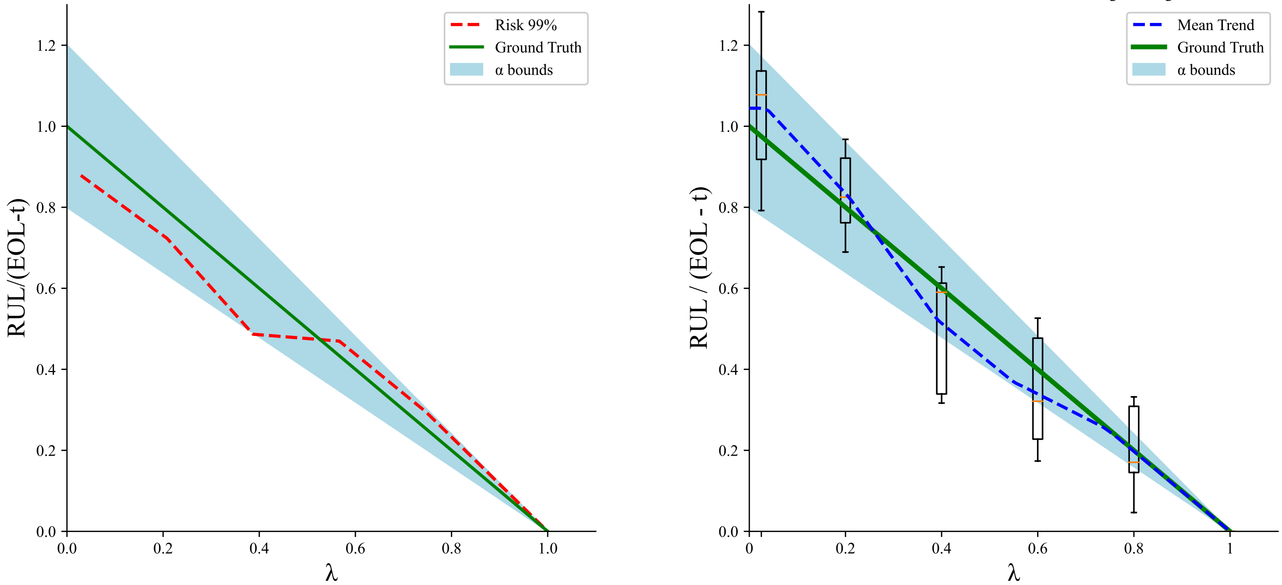
### *6.1. Probabilistic health prediction module performance evaluation*

Figs. 10a and 10b show the statistics of the evaluation metrics chosen for the Probabilistic Health Prediction Module, performed across the whole PAS fleet at different simulated horizons. In particular, Fig. 10a reports the box plot of the mean relative error calculated between the mean of the probability cone and the GT and shows a prediction performance with limited relative errors within acceptability margins defined by the OEM, especially in the mid term. When the simulations are carried out for more than 640 flights the mean of the error, despite being higher, still is lower than 20 per cent. Fig. 10b shows the probability that the 95th percentile cone captures the actual GT. The results show extremely promising performance in the short and mid horizon. In the 0-160 flight band the presence of some outliers can be noted. This is due to the fact that the prediction horizon is short and the probability that the GT is outside of the cone is higher since the cone is very narrow. However, the error in the same horizon band confirms that the GT does not differ much from the prediction. These metrics confirm the Probabilistic Health Predictions Module ability to simulate Cumulative Features (CFs) behavior.

### *6.2. PoF and Risk Computation Module performance evaluation*

The next paragraphs report the evaluation metrics for the Probability of Failure and Risk Computation Module. The validation metric is calculated using a validation subset of URs that meet two criteria: they must have occurred in the latter part of the recorded data-set, and their reported causes must be directly related to prognosable failures (in accordance with the information provided). These criteria exclude older records, where data storing was not performed systematically and failures due to unprognosable/unknown events (e.g., no information reported, vibration, actuator locked, external leakage, etc.). Moreover, the predictions were performed by excluding the final CF value associated with each UR from its respective threshold distribution. This method is similar to cross-validation, preventing contamination between training and testing phases.

Multiple studies have tried to standardize the metrics panorama and a possible solution is represented by the widely recognized $\alpha - \lambda$ curves, as explained in Saxena et al. in [92,93]. $\alpha - \lambda$ curves compare the actual RUL against the predicted RUL. $\alpha$ refers to the acceptance bound of the uncertainty cone (typically set at 20%), while $\lambda$ indicates the normalized time scale defined as $\lambda = \frac{k}{k_f}$ where $k$ is the present time and $k_f$ indicates the time-to-failure. $\lambda$ is hence plotted on the x-axis. When $\lambda$ equals one, the equipment has reached the UR. A normalized version is often selected to compare different traces in a single graph: in this case various SN with different age. Fig. 11a shows an example of $\alpha - \lambda$ for a specific SN, whereas Fig. 11b shows the $\alpha - \lambda$ plot obtained for a set of 12 predictions in the validation subset. The mean value is reported in blue along with the uncertainty indication in a box-plot fashion at specific values of $\lambda$.




(a) $\alpha - \lambda$ plot for PAS 57 when risk reaches 99 per cent.

(b) $\alpha - \lambda$ plot across the subset of prognosable URs with uncertainty quantification in a box-plot fashion.

**Fig. 11.** Metric for the Probability of Failure and Risk Computation Module: $\alpha - \lambda$ plots calculated when risk reaches 99 per cent.

Despite the wide threshold PDF variance, Fig. 11b shows promising results as the mean is always inside the prediction cone. The system does converge for the RUL estimation and, although suboptimal in terms of precision, provides useful information from a maintenance perspective. This is consistent with the primary objective of the framework: offering a reasonable time horizon for maintenance personnel, rather than seeking the exact point of failure to perform just-in-time maintenance. Moreover, it has to be noted that in most of the cases, the framework is underestimating the actual RUL, showing to be conservative. This underlines once again that the methodology is robust and is able to track degradation patters: it is hence deemed that, once new data is logged and the threshold PDF is more precise, the methodology will provide even better results, thus reducing the variance and the linked inter quartile range especially at $\lambda$ of 0.8 and higher.

### 6.3. Discussion

The developed methodology has been envisioned to comply with an operational challenging scenario in which data scarcity and quality issues hamper the full potential of the PHM strategy, a concern already identified by Lukens et al. [21].

As a consequence, the requirement of relying on the available dataset shaped and informed the framework design in various ways. In this specific case, while the high safety standards in the aerospace field have luckily made actuator failures rare and characterized by a "few-shot" scenario, a limited number of occurrences hinders the establishment of a solid and robust statistical base. The number of Unscheduled Removals (URs) for the Advanced Jet Trainer (AJT) Primary Actuation System (PAS) is limited and only one PAS SN has suffered more than two URs, with the others that suffered two, one or none. Moreover, as discussed in Section 3, the lack of equipment level data prohibited popular signal analyses which are often performed for EHAs and PHM application in general, leading to the development of a completely different strategy based on SMs. On top of that, the information related to the UR failure modes is not always indicated in the records, therefore not allowing the possibility of failure mode-specific degradation models and predictions nor a precise exclusion of UR which were not considered to be caused by known degradation modes. Finally, storing and management of the early flights recording were performed according to non standardized, consolidated, and grounded operational practices, resulting in the possibility that the HUMS file were not saved correctly. These first phases of PASs operational life are hence less reliable.

The adoption of a risk-based approach to analyze the RUL output was chosen to allow future integration of the proposed tool within current and future fleet management policies, allowing maintenance technicians and fleet managers to make decisions based on global tolerance to risk rather than solely on the PoF distribution as the risk threshold can be customized.

Another point of view is offered by UR timing analyses. In fact, the analyses of the UR timing have indicated that all the so far recorded failures may be attributed to the initial phase of a failure rate bath-tub curve, typical of mechanical equipment. This suggests that the framework effectiveness will increase as more FHs and URs are registered. In fact, the methodology has been developed during the initial phase of the AJT operational life cycle and it is expected to enhance its effectiveness as new data, both in terms of quantity and quality, becomes available. The acquisition of new data will contribute to the framework perspective in several ways. On the one hand, new operative data may improve the overall representativeness of a wide range of operations and operational scenarios, climate, missions, and usage. On the other hand, it is likely that additional data would contribute to a more grounded and robust statistical base, improving the knowledge base of the threshold distributions, so far defined through a sub-optimal number of failure instances. In fact, if the MC simulations perform well and give a manageable level of uncertainty, the same cannot be said for the hazard threshold distributions, which are excessively spread due to the few URs and the lack of punctual failure mode information.

Not only can the development of frameworks such as the one proposed in this paper improve the platform availability, but they can also provide useful loopbacks on aircraft design and management for future projects or aircraft versions. In this case, useful feedback involves the need of standardized and digitalized data storing and management as well as evaluate the possibility of logging new signals which could improve the health status assessment (e.g. actuator level data already transferred through avionic buses). It is finally worth noting that the proposed approach lends itself naturally to future upgrades as more data, and potentially more signals in future aircraft systems updates, are provided.

## 7. Conclusions

Developing PHM systems able to track down abnormal behaviors and improve maintenance management along the asset life cycle is a rewarding but challenging task. This paper presented a case study focused on extracting equipment health information from aircraft-level data of an AJT's EHA, without relying on dedicated sensors or additional electronics. The PHM architecture was designed with layered functional modules and adapted to the limited and low-frequency data typical of in-service aerospace assets. The main contributions of this work are the development of a PHM framework based on real industrial data and demonstrating that prognostic strategies can be applied to real aerospace cases even without local signals. The goal is not to define new algorithms or prove one method superior to another, but to provide an example of how a prognostic system can be developed and used in an operational environment.

All the design choices were made to comply with the available data and infrastructure, dealing with a legacy platform to create a robust and grounded system which could be seamlessly adopted by fleet operators without retrofits and changes in data management pipelines. By processing raw operational data into useful statistical features and projecting their future behavior using Monte Carlo simulations and clustering techniques, the framework provides probabilistic estimates of failure timeframes and risk trends. Although the validation results show conservative predictions with some uncertainty, mainly due to limited data and incomplete failure mode information, the results still offer valuable insights for maintenance planning in real-world scenarios. In fact, while the current performance is limited by data availability and quality, the system is expected to improve as more operational data become available over the aircraft's life cycle, increasing prediction accuracy and reliability.

Although demonstrated on a military training aircraft with predictable mission profiles, this approach can be applied more broadly and may be even more effectively in civil aviation, where data volumes and operational consistency tend to be higher.

In summary, this paper offers both a tested PHM framework for legacy aerospace systems and a clear account of the challenges and compromises involved. It provides practical guidance for implementing PHM in complex environments where data are limited, which is common in aerospace and other industries. Given that these limitations are fairly common in the aeronautics industry, where the typical lifespan of a platform extends over several decades and necessitates new certification cycles after design modifications, the work presented in this paper offers a validated and potential pathway for the development of predictive maintenance tools.

## CRediT authorship contribution statement

**Leonardo Baldo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea De Martin:** Writing – review & editing, Methodology, Conceptualization. **Mathieu Terner:** Writing – review & editing, Resources, Funding acquisition. **Giovanni Jacazio:** Supervision, Project administration, Conceptualization. **Massimo Sorli:** Supervision, Project administration, Funding acquisition.

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## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Leonardo Baldo reports financial support was provided by Leonardo Aircraft Division. Mathieu Terner reports financial support was provided by Leonardo Aircraft Division. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The data that has been used is confidential.

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