The Journey Towards Condition-Based Maintenance: a Framework for the Horizontal Tail Actuator of an Advanced Jet Trainer Aircraft

THE JOURNEY TOWARDS CONDITION-BASED MAINTENANCE: A FRAMEWORK FOR THE HORIZONTAL TAIL ACTUATOR OF AN ADVANCED JET TRAINER AIRCRAFT

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Abstract

The emphasis on innovative maintenance strategies is driving the industry towards the analyses of operational and historical data from a new perspective. Condition-Based Maintenance (CBM) and Prognostic and Health Management (PHM) strategies can benefit every stakeholder along assets life cycles in assessing systems health status and limiting unexpected breakdowns, hence enabling optimized planning of maintenance actions, better availability and lower operative costs. This consideration holds particularly true for the aerospace industry as aircraft maintenance costs can account for significant portions of Life Cycle Costs (LCC). Stored in-service operational data, initially collected for other purposes such as Structural Health Monitoring (SHM), could hold significant value when used as comprehensive datasets for the construction of PHM frameworks. On the other hand, unique challenges arise when implementing PHM logics for legacy and operational platforms due to data availability, quality, consistency and the complexity of integrating data from a multitude of sources and formats into a single framework. This paper underscores once again the high-effort high-reward scenario of developing PHM strategies on equipment in operation and highlights the challenges and trade-offs required to deal with an In-Service dataset. A data-driven approach which relies on operational and historical data for an Advanced Jet Trainer (AJT) is reported in this paper. The research project has been tailored to address a specific subsystem: the Horizontal Tail (HT) flight control actuator, which has been thoroughly analyzed starting from design documents and performance values to operational flight and maintenance/logistics data acquired from an actual fleet of as much as 22 aircrafts, reaching more than 25000 flight hours. Following the overview of the available data repository, the customized methodological workflow is shown. After conducting analyses on data quality and sampling, a statistical approach based on cumulative features (CF) has been adopted. The first four statistical moments have been employed as predictors to extract lumped data statistical characteristics. This methodology has been selected to assess whether the available data exhibits predictive significance in regards to the designated subsystem. Finally the main results and next steps of the research project are reported.

Keywords: Prognostics and Health Management, Condition-Based Maintenance, Advanced Jet Trainer, Flight Controls, Electro-Hydraulic Actuators

1. Introduction

Two decades have passed since the first studies on aircraft systems health monitoring [1] and a concept that was once just a mere industry buzzword is now seamlessly integrated into manifold engineering ventures. After their introduction, PHM strategies sparked interest across various disciplines focusing on methods for monitoring the health of components and subsystems, thus becoming a significant area of study in its own right.
As a matter of fact, the emerging PHM thread capable of estimating a system health status, when combined with higher level decisional framework, can provide decision makers with fleet situational

awareness, fleet management opportunities as well as the potential development of disruptive technologies such as the so-called Digital Twins (DT). Back in the days, the PHM vision included Enhanced Diagnostics, Health Management and Prognostics [1, 2, 3].

Time passed but the rationale behind PHM strategies has not changed significantly [4, 5]. What has changed however is the fact that now PHM routines are no longer perceived as niche experimental projects but rather as the backbone of logistic support strategies and maintenance programs in many sectors.

Among the paradigms which flourished, laying their roots on the PHM concept, CBM and predictive maintenance (PDM) strategies are steadily but surely changing the way assets are managed, thus enabling the possibility of optimized and strategically allocated maintenance activities, with positive outcomes on logistic support and overall platform availability. In particular, CBM systems assist maintenance organizations in identifying and overseeing the health status of aircraft components. These very systems enable timely intervention and necessary maintenance procedures as and when required, based on observable indicators. One of the results of this cross-the-board interest in CBM is that many industries are trying to adapt already operational platforms to bring them on-line and to enhance their readiness leveraging data [6].

This is particularly relevant for the aerospace field, where availability, reliability and mission readiness are key success factors in creating value and confidence [7].

1.1 PHM/CBM Framework Challenges

The development of such innovative strategies requires, among others, an in-depth understanding of the selected system, a substantial amount of high-quality raw data, a well-structured data-flow, customized PHM routines, platform specific CBM logics, just to name a few. The development of PHM systems continues to present challenges due to their inherent interconnected nature [8]: information coming from design engineering, systems engineering, logistic engineering, quality, MRO and customer support units must be integrated to develop a single but multifaceted and optimized product.

The already challenging conditions related to the development of such frameworks from scratches are much more apparent when they are designed for already operational platforms (legacy aircrafts) [9, 10]. In fact, in this latter case, PHM engineers have to face the challenges of an already built and assembled system, not designed with PHM applications in mind (e.g., data quality, sub-optimal number of sensors, limited built-in sensing capability, low sampling rates, siloed data-bases, non-coherent data formats, missing data, extreme data heterogeneity, etc). On top of that, extreme care must be taken when selecting the case study since the system must be prognosable [11, 12] and the business value of the PHM endeavor must be verified and justified.

In this paper, a data driven approach towards a comprehensive CBM framework for a specific aircraft subsystem is presented. The selected case study is the Horizontal Tail (HT) Primary Actuation System (PAS) of an Advanced Jet Trainer Aircraft (AJT) [13, 14], a twin-engine tandem-seat training platform with fully digital flight controls and avionics.

1.2 State of the art

As better explained in section 3.2, the HT PAS is an Electro Hydraulic Actuator (EHA), as commonly found in most commercial and military aircrafts. The literature analysis highlights a very scarce and scattered panorama of the studies performed on operational data for the selected subsystem.

It has to be noted that there is a substantial body of literature available regarding individual actuator components leveraging modelled or laboratory data. These studies provide a variety of solutions relating to fault detection and isolation (FDI) at the component level, degradation models, and comprehensive PHM procedures but for individual parts: servo valves have been addressed by the authors in [15, 16, 17, 18] while Shanbhag et al. [19] studied cylinders, the authors in [20, 21] provide research approaches for leakages and piston pumps are studied by Chao et al. [22].

However, these solutions require detailed data from actuator signals, which are not logged in operative scenarios.

Some EHA level studies address only the diagnostic part, excluding the PHM steps as reported in [23]. Significantly, these methodologies present a gap in addressing EHA level PHM, which, to the best of the authors' knowledge, is only tackled by a limited range of strategies. EHA performance degradation predictions are provided in [24], exploiting Elman neural network observer, support vector regression (SVR) and Gaussian Mixture Model (GMM). The studies conducted by Soudbakhsh and Annaswamy [25] as well as in Lu et al. [26] demonstrate advancements in fault detection methodology and health monitoring strategies. The authors in [27] introduced the Minimum Hellinger Distance technique in conjunction with a Particle Filtering (PF) application. This PF-based solution has been integrated into another Prognostics and Health Management (PHM) framework alongside high-fidelity models developed by Autin et al. in [28] and by De Martin et al. [29].

In the study conducted by the authors in [30], a modular hybrid fault prognosis method was developed, utilizing distributed neural networks in conjunction with a recursive Bayesian algorithm. Similarly, the authors in [31] presented a hybrid approach in which the Nonlinear Wiener Process (NWP) algorithm was applied for the physics-based component, while a data-driven Echo-State-Network (ESN) was utilized for the data-driven part.

While these studies provide valuable insights, their applicability to existing legacy systems in operation can be limited due to the lack of detailed monitoring of low-level subsystem data and the absence of logged control signals within the Flight Control Computer (FCC) control loop.

As a result, there is a scarcity of approaches that utilize operational data from real-world scenarios, with only a few studies offering limited insights [32, 33]. In particular, the authors in [32] propose a CBM framework for selected subsystems of the C-130J aircraft (propeller and the wheel brake assembly) using neural network approaches and operational data from a fleet of aircrafts. The results highlight the importance of collecting additional data in order to make informed and actionable CBM decisions.

On the other hand, the authors in [33] presented a technique to extract insights regarding the usage of the hydraulic actuators based on data collected during the flight. In this case, more high frequency signals were available from the flight data and an hinge moment model has been developed. No further updates on the research project can be found in literature.

This research gap, along with the industry's growing interest in advanced maintenance strategies, highlights the importance of further research in this specialized field.

2. Adopted Workflow

As highlighted by Jardine et al. [34], CBM requires three steps: Data Acquisition, Data Processing and Maintenance Decision Making. These concise and abstract phases can be further expanded in operational guidelines.

In order to envision a coherent workflow and methodology, an evaluation of key PHM standards within the aerospace industry, as well as others, has been conducted [8]. As a result, there are numerous standards and guidelines available for the development of PHM systems [35, 36], with some of which specifically tailored to the aerospace industry [37, 38]. These documents, along with the research group experience in managing similar projects, ahs provided the authors with the required workflow which, however, had to be further adapted to the industrial reality, environment and platform. The final diagram, reported in Figure 1 shows the most important steps. It has to be noted that the feedback loops shown in the lower section of the figure can improve the quality and robustness of the approach and can provide additional value through multiple iterations, if the necessity arises. Each phase is now analyzed more in detail in the next sections.

3. Domain Understanding

The Domain Understanding phase has provided insightful information concerning case study, the system and problem understanding, an overview of the system and platform architecture as well as the available data sources. Each bullet point is now further discussed.

3.1 Aircraft & Case Study Identification

As stated before, the selected case study is the AJT HT PAS, chosen to improve its operational performance and to fill a consistent research gap in literature. This selection has been guided by criticality analyses among various aircraft components and it is deemed to bring improvements to the platform availability and maintenance processes.

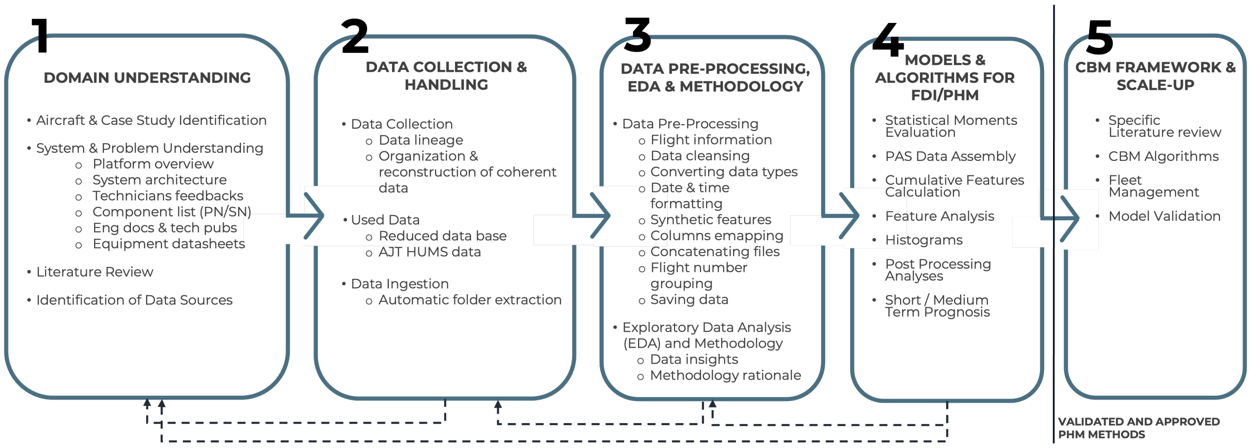

Figure 1 – Research project workflow.

3.2 System & Problem Understanding

Flight controls are essential components of aircraft subsystems and play a crucial role in ensuring safety as they allow for the movement of aerodynamic surfaces [39]. Primary flight controls, such as ailerons, rudder, and elevators, typically use EHA to convert hydraulic power into movement, which is controlled by electronic signals from the Flight Control Computer (FCC). In terms of longitudinal control, the selected platform employs an all-moving HT. This design combines the stabilizer and elevator into a single moving surface, known as a stabilator [40]. This configuration offers improved control effectiveness and reduced drag. Each stabilator is operated by an independent EHA (in this case a tandem Direct-Drive-Valve (DDV) controlled actuator) integrated with the aircraft main hydraulic system through a control module which ensures system redundancy. In this phase, some in depth studies and analyses have been performed on engineering documents and technical publications, available on the industry engineering portal, providing data to better understand the problem being analysed.

The comprehensive compilation of data sheets and technical documentation has been categorized and indexed. Face to face interactions, characterized by in-depth discussions and hands-on data and information exchanges, have been conducted with maintenance technicians engaged in aircraft operations and tasked with executing maintenance checks, thereby enriching the overall knowledge. Furthermore, the list of the main assembly and sub-assemblies Part Number (PN) and Serial Number (SN) constitutes the ground base for in depth analyses in the industry databases.

3.3 Literature Review

In this initial phase a literature review has been carried out in order to understand the state-of-the-art of PHM for EHAs and the common strategies employed. The results have already been reported in the Section 1.2.

3.4 Identification of Data Sources

On the one hand, technical publications, technical drawings, equipment data sheets as well as any other document describing the system overall architecture are central for the comprehension of the platform working principles and the subsystem operation in relation with other ones. On the other hand, operational data, such as flight data as well maintenance reports and activities, represent the main data set to develop algorithms and methods.

As advised by the aforementioned guidelines provided, a preliminary list of the data required to successfully develop a CBM scheme for the actuator under analysis has been identified.

As a result, the study of all related engineering and operational documents provides the base for the identification of potential data sources needed for the next steps: the design and data handling phase.

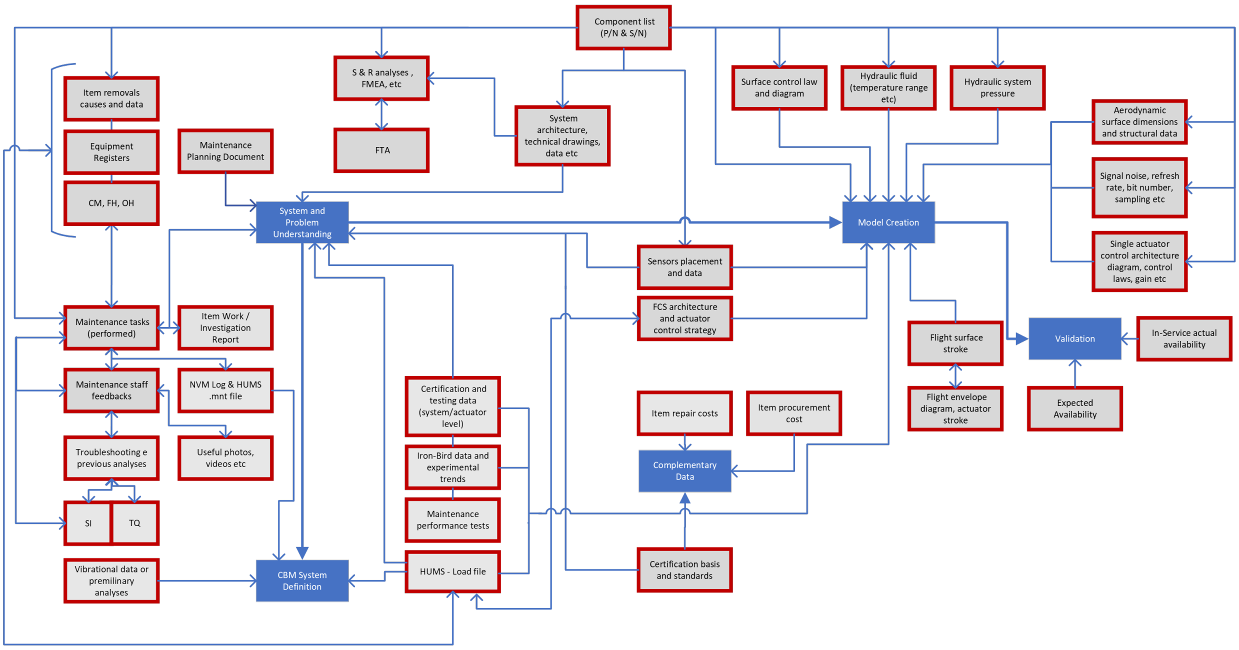

Figure 2 – Data organization overview.

4. Data Collection & Handling

4.1 Data Collection

The data collection & handling phase leveraged the findings obtained in the previous step and has been central to precisely organize data sources and formats so that they could be integrated in a data organization diagram. In this phase, data collection (data lineage, data organization and classification) has been carried out providing extended value from a methodological point of view. Such data have been obtained through an in-depth analysis of the case-study and have been organized in the graphical scheme of Figure 2.
The diagram in Figure 2 depicts the main phases of the process (in blue boxes): the initial phase involves the understanding of the system and problem, subsequently leading to the definition of the CBM system and potential model creation. Following this, the validation phase is also addressed. Complimentary data sources can be used to supplement the research project with additional information.
Figure 2 is now analyzed in details from top to bottom in the following paragraphs.
The PN and SN for the selected subsystem and aircrafts have been pivotal to delineate the system architecture and to reference a wide range of data blocks. Safety and Reliability (S & R) analyses, as well as (Failure Modes Effect and Criticality Analysis) FMEAs and (Fault Tree Analysis) FTAs, have been useful to understand the main critical modes and the magnitude of the problem being investigated. For the same reasons, the block "System architecture, technical drawings, data, etc" includes an extensive range of engineering documents, central for the System and Problem Understanding. Component replacement causes and data have been grouped up with operational equipment registers, Configuration Management (CM) and FH and OH data. This information has been linked with Health Usage Monitoring System (HUMS) Load files, containing time-series flight data (see subsection 4.2.2 for additional details on HUMS data). The maintenance planning document provides the scheduled tasks for the selected case study. Maintenance performed tasks, grouped with work reports and maintenance staff feedback, useful photos and videos, troubleshooting and previous analyses have been aggregated with vibrational data or preliminary analyses SI (Segnalazione Inconvenienti – Occurrence Reporting) & TQ (Technical Queries), FCC Non-Volatile Memory Logs & HUMS Fault and Alert (F&A) files contributing to the CBM system definition. SIs and TQs are two of the possible ways a customer can ask for additional support from the engineering division via formal communication with the engineering units. HUMS (F&A) files include systems level faults and alerts logged during flights. NVM logs, which record FCC fault codes, are downloaded from the aircraft only

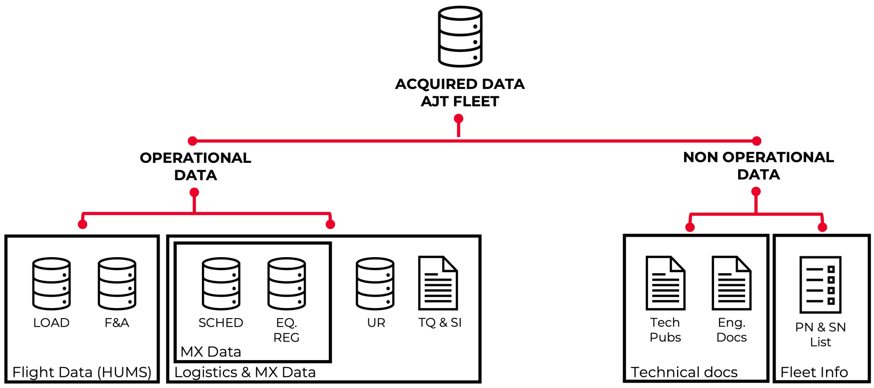

Figure 3 – Reduced database overview.

on special occasions and, when accessible, can provide additional information on occurred faults along with the appropriate (F&A) files. Maintenance performance tests and iron bird test data have been grouped together with certification test data.
If needed, some data can be used as model parameters for high fidelity or low fidelity physical models (e.g. sensor placement, surface control laws and FCC algorithms, hydraulic fluid and system characteristics, aerodynamic surface dimensions and structural data, FCS architecture, control architecture diagram, flight surface and actuator stroke, flight envelope diagram etc). Availability data can be employed for the PHM/CBM system validation while among complementary data there are item costs information, certification basis and standards.
Additional operational data sources, commonly utilized in the creation of PHM strategies for legacy and operational equipment, may involve the Crash Survival Memory Unit (CSMU) or the Digital Video and Data Recorder (DVDR). However, these sources were not included in the study due to inconsistent data retrieval processes that are triggered only by specific events, rather than occurring consistently.
The reported data organization scheme has been central to delineate data requests inside the industry as well as visualizing the data interactions in such a complex system and operational environment.

4.2 Methodology and Used Data

Considering the nature of the subsystem under examination and the complex data organization, thanks to the information gained in the first steps, the analysis has prioritized a thorough examination of operational data, to extract comprehensive insights into the system performance and behavior.

4.2.1 Reduced Database

After the Data Collection step, the research project focused on the elaboration of a Reduced Database (RD) to extract data-driven insights on the subsystem operation. The RD is a subset of the overall data repository and a scheme is reported in Figure 3, where the data is divided into Operational Data (OD) and Non Operational Data (NOD), offering a more functional view of the data obtained and employed in the following analysis.
Operational Data (OD) can be categorized into two main groups: Flight Data and Logistics and Maintenance Data (LMX). Flight data encompasses in-service data collected from HUMS.
As already mentioned, HUMS data retrieved from the aircraft is segmented into Load files and Faults and Alerts (F&A) (see subsection 4.2.2 for additional details on HUMS data). Scheduled maintenance, unscheduled removals, equipment registers, technical queries and inconvenience reports are contained in the LMX category.
Conversely, NOD covers all technical details related to the design, performance, process, and configuration of aircraft components and subsystems, such as PN and SN.
In the context of this analysis, 22 aircraft and 60 PAS have been identified and taken into consideration in the following analyses.

4.2.2 AJT HUMS

In order to envision a tailored methodology, a detailed analysis of HUMS Load data, which is the main operational data source, is required.
The AJT is equipped with a Health and Usage Monitoring System (HUMS) [41], a parametric data acquisition and processing system that gathers, stores, and analyzes flight data. For the aircraft under consideration, HUMS is design for the purpose of supporting Structural Health Monitoring (SHM) and fatigue management initiatives. HUMSs have been developed in conjunction with the concepts of CBM and PHM since their initial introduction for rotary wing systems in the 1990s. Currently, the objectives of HUMSs are deeply intertwined with these aforementioned concepts. Primarily, HUMSs perform elementary functions in fault detection by analyzing raw signals received from sensors during aircraft troubleshooting and post-flight inspections. Consequently, these sensors and signal processing techniques offer valuable insights into the condition of various systems structures, thus enabling informed maintenance decisions. In this way, HUMS can be seen as a rudimentary PHM framework at a very high level.
The HUMS airborne segment comprehensively leverages all operational data, encompassing data obtained during ground activities, in-flight operations, and subsequent to landing. After the landing, data, grouped in two distinct files (.str and .mnt) are elaborated in the HUMS land segment, through a GSS (Ground Support System).

- The .str file provides information on the structural health state of the aircraft. The AJT HUMS logs data obtained from strain gauge sensors as well as system level data (e.g weight-on-wheel, flight surface deflections, etc), structural ones (forces, moments, buffeting coefficients, etc) and general flight data (airspeed, angles, angular speeds, etc), for a total of 256 outputs. While these data were originally designed to be used only for fatigue life reporting (SHM), they could also potentially hold valuable information for system and component prognostics. The system employs a peak and valley acquisition strategy: the system monitors and checks the exceedance of some of the main flight parameters. The .str file is coded and written in binary format and, on the ground, is converted into an intelligible format. At the same time, additional values are synthetically calculated using raw signals, obtaining an elaborated .str file, called Load file, which is used in the selected methodology.
- The .mnt file includes information on maintenance actions to be carried out and/or anomalies registered during the flight and in this paper is hence called (F&A) register for reasons of clarity.

4.3 Data Ingestion

A single LOAD txt file is generated for each flight by the HUMS and data has been organized in folders: a folder containing all txt files for each aircraft is created as reported in Figure 4.
Each txt file is labeled with the date, whereas data in each file are organized in a comma delimited structure with some initial lines providing flight and pilot information.

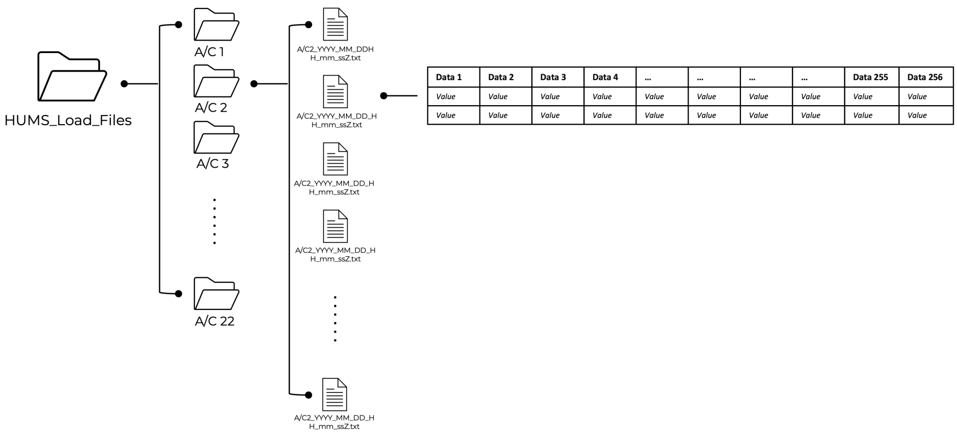

Figure 4 – Folder organization.

All data analyses have been performed in Python 3.8.18, utilizing VSCode in an Anaconda® powered environment.
In order to efficiently process HUMS data, an automatic file ingestion framework has been created. Thanks to this process, each folder is opened, then each file contained is loaded and the information is extracted through Pandas and Numpy Python packages. Then, data is passed to the Pre-Processing routine to be cleaned, elaborated and formatted.

5. Pre-Processing, EDA & Methodology

5.1 Pre-Processing

After the ingestion phase, data is pre-processed according to common pre-processing pipelines to handle missing or inconsistent data.
Configuration Management (CM) information and URs have been transcribed and converted into a single .csv file.
HUMS pre-processing phase is more intensive and involves several steps which are needed to prepare the data for further analyses:

- Flight Information Processing. Each flight number and date is extracted from the first rows of each HUMS file and saved.
- Dimensionality reduction. An essential step involves the dataset dimensionality reduction: this is done during each file importing process not to overload the memory with superfluous data and to store only essential data. Among the 256 signals, a total of 50 is selected through physical reasoning, along with complementary information (i.e. Flight ID, UTC Date & Time, etc). The 50 signals are selected as potential feature candidates whose physical meaning can be linked to the HT health status. For instance, the aircraft variables in the longitudinal plane, the mobile surfaces positions, the forces on the tail and on the HT, etc. Correlation matrices have also been used in this step.
- Data cleansing: Non flight rows. The rows in the Load file are designated as either "ground" or "flight" rows, indicating whether the data was collected while the aircraft's systems were operating while on the tarmac or while in flight. Ground rows have been thus excluded.
- Data cleansing: NaN and zeros. Rows containing NaN (Not-a-Number) and zeros have been excluded from the analysis.
- Conversion of data types into coherent conventions. During the data ingestion phase, careful consideration has been given to the establishment of a coherent data structure and formats in order to facilitate the subsequent analyses.
- Date & Time formatting. Date and time of each flight as well as the time of each recording (i.e. row) have been formatted in date-time object as well as in Unix TimeStamps (seconds from 01-01-1970), a popular format for saving time values.
- Addition of work related features. In this analysis an additional group of 4 signals (position differences and mechanical work on the actuator) have been added to increase the potential feature space. Mechanical work for the right HT for the "i-th" row has been obtained as follows:

  $$Work_{i,Right_{HT}} = M_x \cdot \frac{\Delta\alpha_{i,Right_{HT}}}{b} \tag{1}$$

  where

  $$\Delta\alpha_{i,Right_{HT}} = \alpha_i - \alpha_{i-1} \tag{2}$$

  $\Delta\alpha_{i,Right_{HT}}$ is the difference of the HT position, calculated for each time step by subtracting the value in the row before (*i-1*)and the value in the current row (*i*). *b* is a constant arm value of 1 meter.
- Column remapping. Column have been remapped and renamed.

Number	Flight Parameter (FP)	Notes
a	Mode	Flight/Ground
b	Flight ID	Increasing Number on each FCC power up
c	Counter	Increasing counter
d	UTC Date & Time	DD_MM_YYYY – hh_mm_ss
1	Weight	[kg]
2,3,4,5,6,7	LHT Fx, Fy, Fz, Mx, My, Mz	Six load components acting on the left HT. [N or Nm]
8,9,10,11,12,13	RHT Fx, Fy, Fz, Mx, My, Mz	Six load components acting on the right HT. [N or Nm]
14,15,16,17,18,19	Tail Fx, Fy, Fz, Mx, My, Mz	Six load components acting on the last fuselage section. [N or Nm]
20,21,22	Nx, Ny, Nz	z, y, x axes accelerations [g]
23,24,25,26	Buffet Coefficients	-
27,28,29	p, q, r,	Roll, pitch and yaw rate [deg/s]
30,31,32	p, q, r dot	Roll, pitch and yaw acceleration [rad/s^2]
33,34,35	V (NEU)	Speed North, East, Up [ft/s]
36,37	AoA, AoS	Attack and sideslip angles [deg]
38	LEF Deflection	Leading Edge Flap Position [deg]
39,40	Stick Position (long, lat)	Longitudinal and lateral stick position [mm]
41,42	LHT, RHT deflection	Left and right HT position [deg]
43	Pedal position	[mm]
44	Flap position	Trailing Edge Flap position [deg]
45	Pressure Altitude	[ft]
46	TAS	True Air Speed [Knots]
47	Mach	Mach number
48,49	Left and right throttle	[%]
50	Static air temperature	[°C]
51,52	LHT, RHT deflection variations	Left and right HT position difference with the previous value [deg]
53,54	LHT, RHT Work	Mechanical work of the actuators

Figure 5 – List of complementary information (a,b,c,d) and flight parameters (1-54) Flight dynamics, loads and aircraft level signals are logged as indicated by [41].

- Flight number grouping. An additional column has been added containing the increasing flight number so that each file can be easily found in the database.
- File Concatenation. The files have been concatenated in a single data frame
- Saving in dictionary. Each data frame has been then saved both locally in the computer memory for easy access and in a Python dictionary.

Figure 5 shows the final set of 54 Flight Parameters.
Finally data have been saved in several data structures which contains HUMS data for each aircraft. As a result, 22 data structures (one for each aircraft) have been created and saved in a Python dictionary, with the tail numbers of each aircraft used as the dictionary keys.

5.2 EDA and Methodology

5.2.1 Data Insights

Exploratory Data Analysis (EDA) [42] refers to the important process of conducting initial investigations on data in order to uncover patterns, assess data quality, and explore relationships between data sources with simple representations.

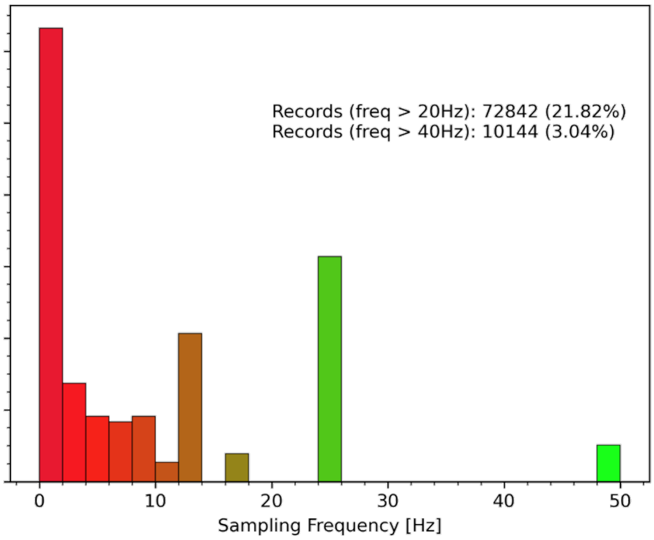

Figure 6 – Sampling analysis for one aircraft.

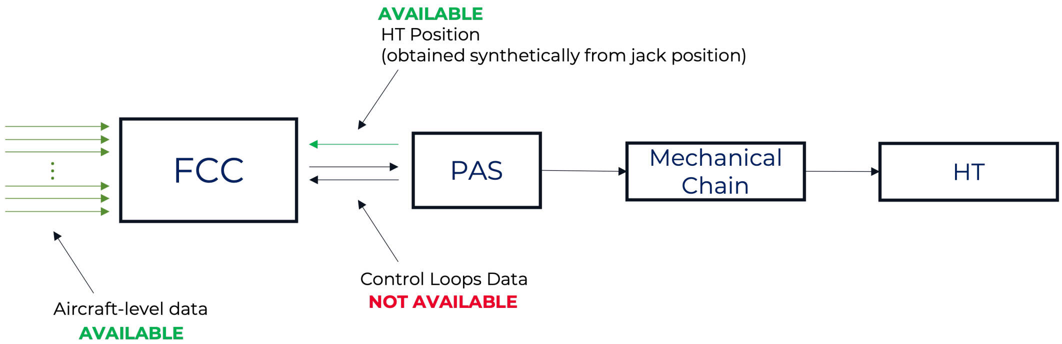

Figure 7 – Block diagram with available data along the HT control flow.

In this section, some considerations about the load file data sampling frequency and signal analysis are reported. These factors have been paramount in determining the appropriate methodology.
A sampling analysis has been carried out for 4 aircrafts.
The results are comparable for all analysed aircrafts and, hence, can be extended for the whole fleet since the recording equipment, training flights and overall subsystem infrastructure are shared across the whole fleet.
An example for a single aircraft is reported in Figure 6. The performed sampling analysis highlights an extremely variable frequency with few (at most 22%) irregular and sparse batches of high frequency data, whereas most of the samplings are acquired at frequencies below 5 Hz. It has to be noted that HUMS was not designed for PHM applications but for SHM and, as such, high frequency sampling was not required.
As it can be seen from Figure 7, no actuator level data is saved in the HUMS load file apart from the HT position, logged by the FCC but obtained synthetically from the jack position.
After an in depth evaluation of the selected parameters and signals, a general methodology has been envisioned.

5.2.2 Methodology Rationale

At the current state, component analyses as reported in the literature review cannot be applied for the selected case study as component level signals are not logged. On top of that, the low frequency sampling adds an additional difficulty layer not enabling dynamic analyses on the components (which are characterized by much higher frequencies).
Therefore, according to EDA results and insights, a methodology has been envisioned in order to extract potential value from the operational data set. The adopted approach involves the central role

of the first four Statistical Moments (SMs), which serve as lumped statistical properties indicators. SMs are a typical way to characterize distributions, as they allow to accurately describe the properties of the distribution with a limited number of parameters. Moreover, there has been a strong literature base supporting the applications of SM for PHM applications especially for mechanical components [43, 44, 45, 46].
This approach has been chosen to highlight possible correlations between stored fleet usage data and the HT PAS URs. The SMs are assembled in a cumulative fashion to discover pattern in data. A similar approach of cumulative feature assessment has been used by the authors in [47] for inverter fault detection and diagnosis. Cumulative features are employed in [48] and in [49] to carry out fault detection and remaining useful life (RUL) prediction for bearings. The resulting workflow for the selected statistical approach is reported in Figure 8.

6. Models & Algorithms for FDI/PHM

The inputs and pre-processing steps have been already examined in the previous sections. The processing phase involves two main steps: Feature Creation and Feature Analysis.

6.1 Feature Creation

In the feature creation step, three main tasks can be found: Statistical Moments (SM) Evaluation, PAS Data Assembly and Cumulative Feature (CF) Calculation.

6.1.1 SM Evaluation

In the SMs Evaluation phase, the four main SMs have been applied to the already pre-processed data-set. In this step, for each aircraft, flight data is concatenated one after the other. A total of 22 data frames (one for each aircraft) with variable length according to the total number of flights has hence been elaborated.
The first four statistical moments have been selected to better represent the statistical content of each signal for each flight. In fact, thanks to the column highlighting the flight number (added in the pre-processing step), each flight data is analyzed separately from the others. As a result, the four values represent the main properties of each signal for each flight.
The first four statistical moments are: mean, skewness, kurtosis and variance.

- First Statistical Moment: Mean.

  Mean value is linked to the central tendency of the data and highlights if the aircraft or actuator is subjected to a high or low load baseline [46]. The formula is here reported:

  $$\text{mean} = \mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

  where n is the total number of samples, and x_i is the single sample.

- Second Statistical Moment: Variance

  The concept of variance involves the examination of the distribution of data points around their mean value. It correlates with the magnitude of deviation of individual data points from the average value. A higher variance indicates a wider dispersion of data points from the mean, resulting in greater variability in the measurements.

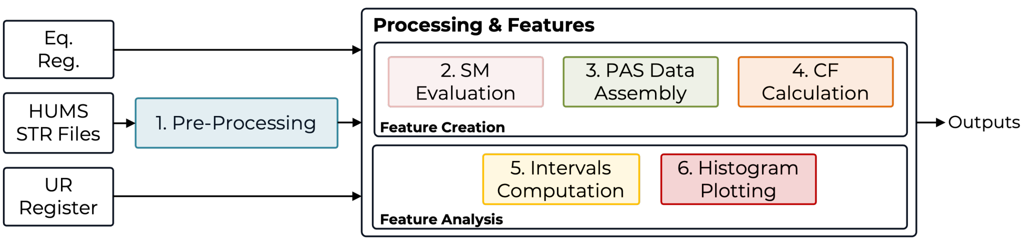

Figure 8 – Statistical methodology work flow.

In the specific case study discussed, a high variance within a particular feature time series indicates that the aircraft has experienced values significantly divergent from the average. Variance is also used as a possible condition indicator in PHM applications as highlighted in [47]. For instance, a high variance on work values may underline that the PAS jack has been subjected to a wide range of movements and positions.

$$\text{variance} = \sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2 \tag{4}$$

- Third Statistical Moment: Skewness

  Skewness measures the asymmetry of the probability distribution of a variable. In physical terms, skewness reflects the departure of a dataset from symmetry (Figure 9). Skewness has been used extensively in PHM and diagnostics application for rotating mechanical equipment [50, 45] and highlights peaks distant from the mean value. Skewness has been calculated according to the following formula:

$$\text{skewness} = s = \frac{1}{n}\frac{\sum_{i=1}^{n}(x_i - \mu)^3}{\sigma^3} \tag{5}$$

- Fourth Statistical Moment: Kurtosis

  If skewness quantifies the extent of asymmetry within a distribution, kurtosis quantifies the degree of peakedness or flatness. Kurtosis is the fourth central statistical moment and indicates the degree of concentrations of a distribution in its tails with respect to to the distribution center. A high kurtosis suggests that the distribution may have heavier tails, indicating a greater occurrence of high values if compared to a standard normal distribution (Figure 9). Kurtosis has been traditionally one of the most used statistical measure for PHM approaches for rotating equipment and bearings [51, 53].

  In practical terms, kurtosis is a statistical measure used to assess the likelihood of very high values occurring in a dataset. It indicates the distribution of observations within the dataset, focusing on the frequency of deviations towards the tails of the distribution rather than remaining centered around the mean. the formula used is here reported:

$$\text{kurtosis} = k = \frac{1}{n}\frac{\sum_{i=1}^{n}(x_i - \mu)^4}{\sigma^4} \tag{6}$$

6.1.2 PAS Data Assembly

Once the SMs have been calculated following the aircraft operational life, the PAS Data Assembly phase has been carried out in order to recreate the operational time history of each PAS, which is reconstructed by assembling the time windows from each aircraft on which the PAS was loaded on. This process is essential to track down and follow a possible increasing degradation of a specific PAS SN which, during its operational life, has been loaded on different aircrafts. This information would have been lost if data had been analyzed following aircraft operational life.
An example of a PAS data assembly phase is reported in Figure 10

Figure 9 – Differences between the effect of positive or negative kurtosis and skewness on a distribution.

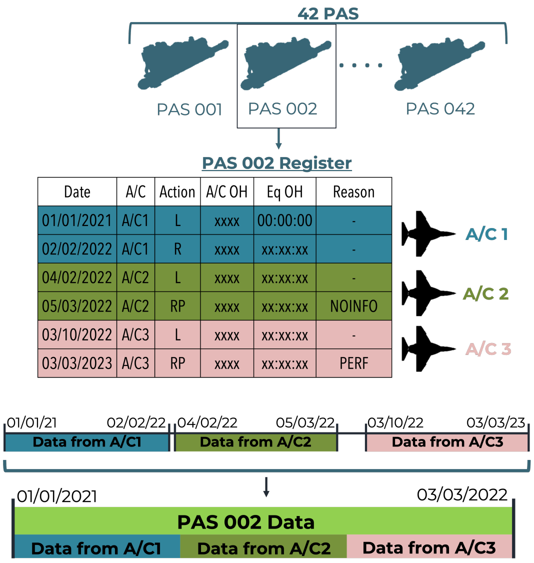

Figure 10 – PAS data assembly phase. PAS 002 data is assembled with data from aircraft 1, 2 and 3 according to the loading (L) and unloading (R or RP) dates. The reasons for the equipment unloading is sometimes reported (PERF - Performance test Failed).

6.1.3 CF Calculation

Once PAS operational life data have been assembled, the next phase has involved the calculation of CFs. CFs have been obtained by integrating the SMs in time (multiplying the FP SMs by the flight duration (FD)) to replicate a time degradation tailored to the effective aircraft usage [48]. FD is obtained from the starting and ending time of each Load file flight recording. This process, similar to a finite difference integral operation, has been carried out for each PAS and for each SM. The results provided 216 cumulative trends which have been analysed merging the information from URs in the next steps.

If a specific PAS SN is taken into consideration, each point of the CF, linked to a specific flight *f* can be obtained following Equation 7:

$$CF_{i,j}(f) = \sum_{k=1}^{f} SM_{i,j}(k) \cdot FD(k) \tag{7}$$

where $CF_{i,j}(f)$ is the CF at flight f of $SM_{i,j}$. $SM_{i,j}(k)$ is the statistical moment *i* applied on the FP *j* for the flight *k*. *i* is equal to "mean", "variance", "skewness" or "kurtosis" and *j* ranges from 1 to 56, highlighting the different FPs. For instance, $CF_{mean,1}(k)$ refers to the value of the CF obtained using the statistical moment "mean" on the FP number 1 for the flight *k*. Finally, $FD(k)$ is the flight duration of the flight *k*.

If the entire $\overrightarrow{CF_{i,j}}$ vector is considered, a vectorized formula can be defined, as shown in Equation 9:

$$\overrightarrow{CF_{i,j}} = cumsum(\overrightarrow{FP_{i,j}} \cdot \overrightarrow{FD}) \tag{8}$$

where $\overrightarrow{CF_{i,j}}$ is the CF of $\overrightarrow{FP_{i,j}}$. $\overrightarrow{FP_{i,j}}$ is the vector containing all concatenated FP *i* using the SM *j*, $\overrightarrow{FD}$ is the vector containing all flight durations.

6.2 Feature Analysis

The Feature Analysis involves the interval computation and histogram plotting phases. In this step the number of analysed PAS has been reduced from 60 to 42 due to data unavailability or absence of URs for a specific PAS SN.

6.2.1 Intervals Computation

Once the 216 CFs have been obtained at a PAS level, the variations of the CF between two URs of each PAS can be calculated.

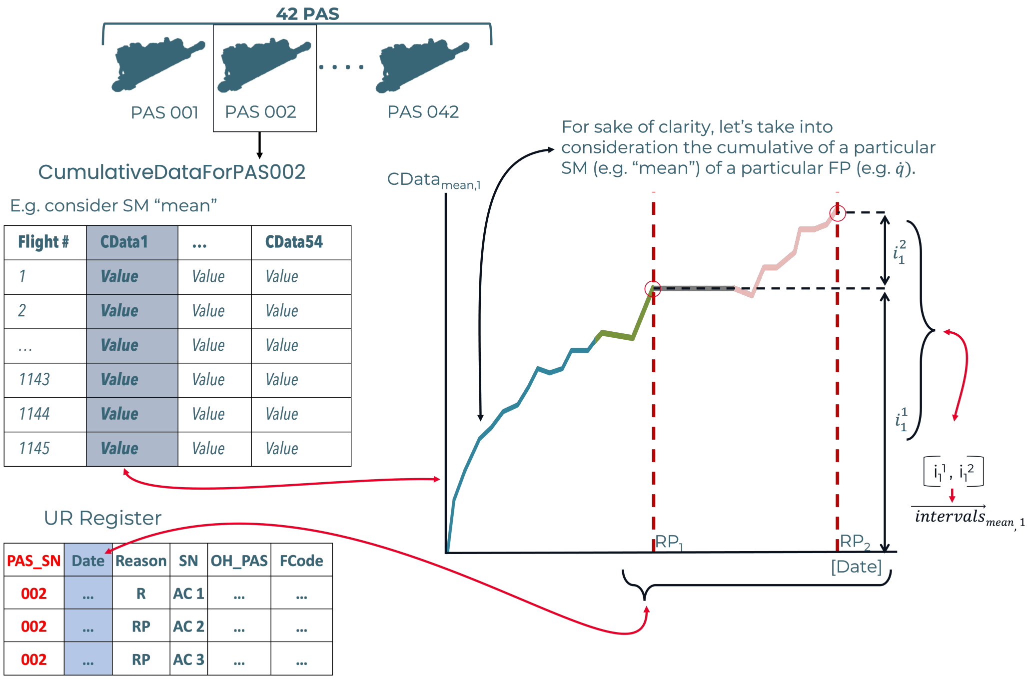

Figure 11 – Interval calculation for one selected PAS.

Figure 11 shows this process for one actuator. PAS 002 is selected for this example. In the graph on the right hand side a specific cumulative feature (e.g. the mean of $CF_{mean,1}$) is reported with a color code assigned to the aircraft on which the PAS was loaded on in function of the date. This information is taken from the previous step and already shown in Figure 10. The data presented in the table located in the upper right section of the figure indicates that this particular PAS has been utilized for a total of 1145 flights. Similar data can be extracted from all 216 CFs for comparison.
The CF is intersected by some vertical red dotted lines which are the removals that the PAS 002 suffered from. The variation between the beginning of the actuator operational life and the first UR or between two URs are then calculated and inserted in a vector. It is important to highlight that PAS 002 encountered three URs, with only two of them attributed to failures (labeled as "RP" for Repair), while the initial UR was simply a Removal (R) necessitated by logistical considerations to transfer the component from one aircraft to another.
This process has been carried out automatically for each CF and for each PAS. The variations are then grouped inside a single vector $\overrightarrow{intervals}_{i,j}$ and analyzed in the next phase.

6.2.2 Histogram Plotting & Ranking

Histogram representations have been utilized to visually display the distribution of the obtained intervals. A total of 37 intervals has been computed during the preceding phases. These intervals depict the fluctuations in value of a particular CF over time, offering insights into identifying the most meaningful CFs.
A histogram has been generated for each of the 216 CFs, complete with a fitted Kernel Density Estimation (KDE) curve [54]. From this curve, a normalized Signal to Noise ratio (SN Ratio) has been calculated to rank the features as shown in the following formula:

$$S/N_{norm} = \frac{norm(m)}{\Sigma} \tag{9}$$

where m and Σ are the mean and standard deviation of the KDE.
The results show that the most informative CFs are:

- the skewness applied to the work on the right actuator
- the skewness applied to the north speed component

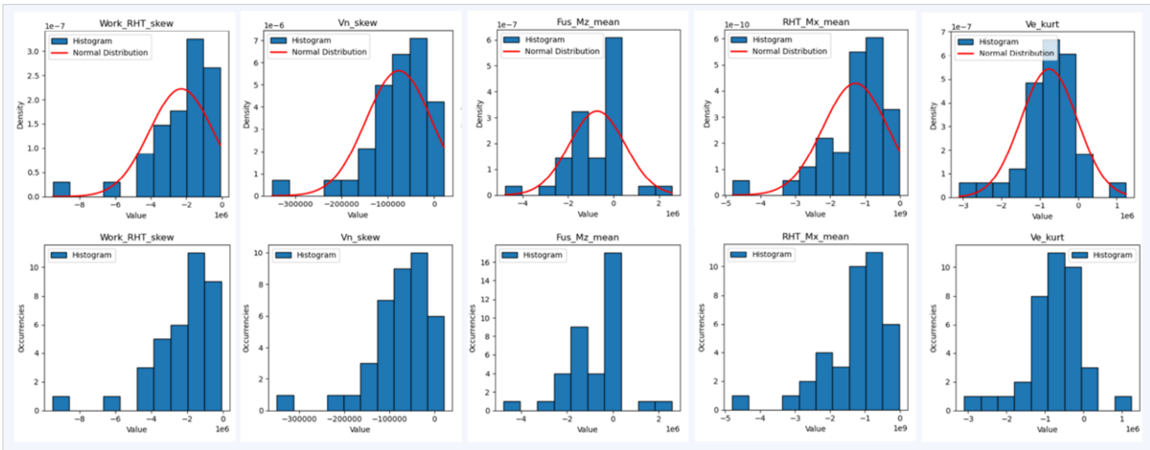

Figure 12 – Histograms for the "Top 5" most informative CFs according to signal to noise ratio. The first row shows the distribution along with the KDE curve, while the second row reports the occurrences.

- the mean of the M_z moment applied to the last section of the fuselage
- the mean of the M_x moment applied on the right HT
- the kurtosis applied to the east speed component

Histograms for the top 5 CFs are reported in Figure 12.
It can be noted that all the most informative CFs are physically linked to the mechanical behaviours of the HT and the related effect on the AJT flight mechanics. Moreover the prevalence of skewness, mean and kurtosis indications and the absence of variance may highlight a more relevant effect of higher loads with respect to the mean value.
These results are significant from two points of view: on the one hand, this analysis has provided an objective and mathematically sound way to identify the most informative CFs from flight data. On the other hand, for each CF a threshold distribution has been characterized, delineating a way to statistically allocate a possible UR in time. In other words, when a CF is subjected to an increase comparable to the values reported in the histograms, a possible warning can be raised as proposed in the next paragraph.

7. Post Processing and Prognosis

Post processing studies and data mining steps are currently being carried out to enhance the statistical analysis, highlighting undiscovered patterns and correlations in data or identifying additional way to treat features. These steps can be useful to handle the high uncertainty found in in-service data and to reduce data volatility.
For instance, multivariate analyses in the feature space (e.g. clustering strategies) are to be performed to discover patterns between different CFs. At the same time, similarity studies between Load file time series can provide ways to aggregate different flight behaviours. Finally, the assessment of maintenance intervals according to the known failure conditions and the CF trends between two URs can allow for more precise tuning of refined CF calculation.
The combination of CFs analyses and post processing results can represent the founding stone for the next step of the CBM framework: prognosis.
In this way, using the information contained in the last flight Load file, prognosis can be intended as a twofold process: short-term prognosis and long-term prognosis (Figure 13).
On the one hand, a short-term prediction can be calculated from Load files. In fact, the AJT, being a trainer aircraft, can be considered as it is subjected to a standard range of flight missions, regimes or manoeuvres. Following this hypothesis, flight data from the Load files contained in the RD can be categorized with time series clustering or other machine learning techniques into a set of Clustered Mission Types (CMT). The new Load file can be classified according to the various CMTs contained

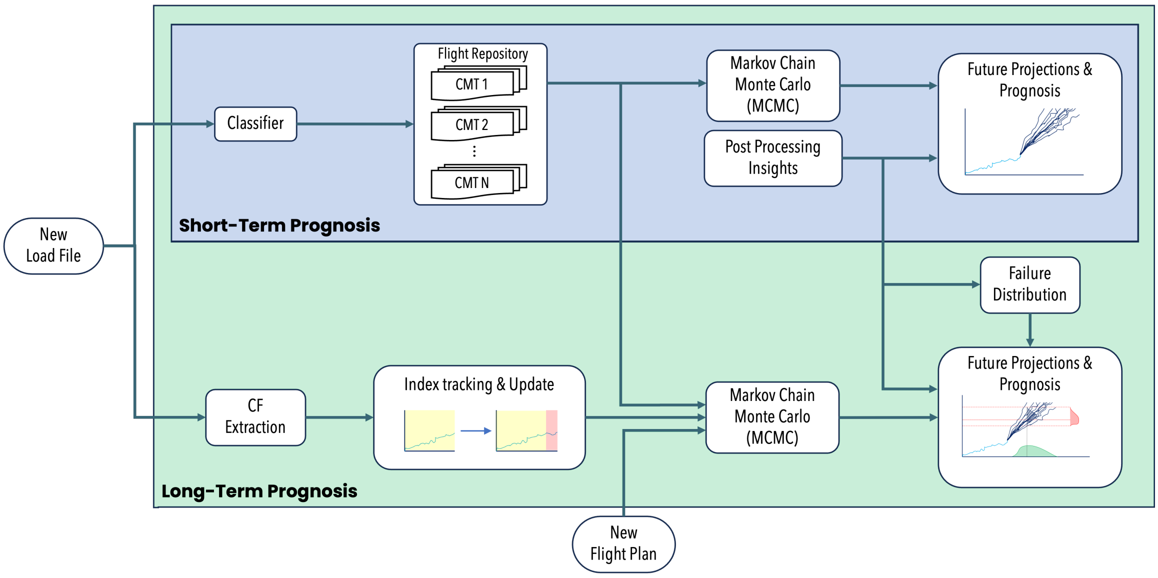

Figure 13 – Prognosis envisioned flowchart. Short-term prognosis can provide prompt information on the near future, whereas long-term prognosis can allow for more precise and comprehensive indication in the long term.

in the flight repository. In this way, the specific PAS SN history is compared with other SNs with similar operational history.
Operational history can then be projected in the near future via Markov Chain Monte Carlo (MCMC) analyses driven by the labeled historical historical flight repository. Moreover, considerations on the number of URs, the UR reasons (if available) or the intervals magnitude trends can provide useful and actionable data for a short term prognosis.
On the other hand, long-term prognosis methodology can be designed, providing a more comprehensive information, leveraging more data. Once a new Load file is downloaded and processed, CF can be extracted and the relative trend can be updated. After that, according to the flight plan for a potential new flight, the selected refined CFs can be projected in the future by assigning the probability of matching with one or more CMTs via MCMC analyses. In this way, the CFs can be projected in the future with a certain probability distribution.
The CF probability distribution can be then compared with the failure threshold distribution obtained from the histograms, obtaining a RUL distribution in time. Information previously gained from post processing steps can help to reduce the volatility of the failure distribution and increase the overall analysis robustness. As a result, a solid methodology to statistically allocate failure distribution probability can be envisioned.

8. Conclusions

This paper has accomplished the complex and challenging task of integrating in-service data from an operational scenario into a CBM methodology bringing additional value to the logistical chain and maintenance scheduling.
The findings and methodological strategies have significant implications from several perspectives. Firstly, the analysis has offered an objective and mathematically rigorous method for determining the most informative features from flight data. Secondly, a threshold distribution has been developed for each contributing factor, establishing a statistical framework ground base for the temporal allocation of URs.
The presented methodologies, developed on real life operational data from a fleet of assets, can be hardly found in literature due to intellectual properties issues and can provide useful insights and directions for maintenance organization and operators in better managing their assets.
Especially in the aerospace field and in the flight control realm, studies such as the one presented in this paper are very rare and can offer field tested PHM and CBM solutions for legacy equipment that can be modified and applied for a wider range of equipment, thus delineating a operational flow-chart.

PHM strategies are significantly transforming and improving the way aircraft and industrial assets are managed. Although this is certainly true for newly design products where PHM is (or should be) integrated in the design loop; the proven value of PHM solutions goes well beyond that, offering maintenance practitioners, final end users and Original Equipment Manufacturer (OEMs) the possibility of enhancing asset readiness and availability of already operational systems, facing a high commitment but also a high reward scenario.

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11. Copyright Statement

References

[1] Smith G, Schroeder JB, Navarro S and Haldeman D, Development of a Prognostics and Health Management Capability for the Joint Strike Fighter. *IEEE Autotestcon IEEE Systems Readiness Technology Conference. Systems Readiness Supporting Global Needs and Awareness in the 21st Century*, Anaheim, CA, USA, pp 676–682, 1997.

[2] Hess A, and Fila L. The Joint Strike Fighter (JSF) PHM concept: Potential impact on aging aircraft problems. *IEEE Aerospace Conference*, Big Sky, MT, USA, pp 6–6, 2002.

[3] Brown ER, McCollom NN, Moore EE and Hess A. Prognostics and Health Management A Data-Driven Approach to Supporting the F-35 Lightning II. *2007 IEEE Aerospace Conference*, pp 1–12, 2007.

[4] Fu S and Avdelidis NP. Prognostic and Health Management of Critical Aircraft Systems and Components: An Overview. *Sensors*, Vol. 23, No. 19, pp 8124, 2023.

[5] Zio E. Prognostics and Health Management (PHM): Where are we and where do we (need to) go in theory and practice. *Reliability Engineering & System Safety*, Vol. 218, pp 108119, 2022.

[6] Berri PC, Dalla Vedova MDL and Mainini L. Computational framework for real-time diagnostics and prognostics of aircraft actuation systems. *Computers in Industry*, Vol. 132, pp 103523, 2021;132.

[7] Scott MJ, Verhagen WJC, Bieber MT and Marzocca P. A Systematic Literature Review of Predictive Maintenance for Defence Fixed-Wing Aircraft Sustainment and Operations. *Sensors*, Vol. 22, No. 18, pp 7070, 2022.

[8] Vogl G, Weiss B and Donmez MA. Standards for Prognostics and Health Management (PHM) Techniques within Manufacturing Operations. *Annual Conference of the PHM Society*, Fort Worth, TX, USA, Vol 6, No. 1, 2014.

[9] Esperon-Miguez M, John P and Jennions IK. A review of Integrated Vehicle Health Management tools for legacy platforms: Challenges and opportunities. *Progress in Aerospace Sciences.* Vol. 56, pp 19-34, 2013.

[10] Esperon-Miguez M, Jennions IK and John P. Implementing IVHM on Legacy Aircraft: Progress Towards Identifying an Optimal Combination of Technologies. *8th World Congress on Engineering Asset Management (WCEAM 2013)*, Hong Kong, 2015.

[11] Gu X and Shi X. A Review of Research on Diagnosability of Control Systems Based on Structural Analysis. *Applied Sciences*. Vol. 13, No. 22, pp 12241, 2023.

[12] Vignolles A, Chanthery E, Ribot P. An overview on diagnosability and prognosability for system monitoring. *PHM Society European Conference*, Virtual, Online. Vol. 5, No. 1, pp 11-11, 2020.

[13] Baldo L, De Martin, A, Sorli, M and Terner M. Condition-based-maintenance for fleet management. *Aerospace science and engineering - iii aerospace phd-days*, Bertinoro, Italy, pp. 57–60, 2023.

[14] Baldo L. Development of a Data-driven Condition-Based Maintenance Methodology Framework for an Advanced Jet Trainer. *PHM Society European Conference- Doctoral Symposium*, Prague, Czech Republic, Camera ready for production, 2024.

[15] Mi J and Huang G. Dynamic Prediction of Performance Degradation Characteristics of Direct-Drive Electro-Hydraulic Servo Valves. *Applied Sciences*, Vol. 13, No. 12, pp 7231, 2023.

[16] Byington CS, Watson M and Edwards D. Data-driven neural network methodology to remaining life predictions for aircraft actuator components. *IEEE Aerospace Conference Proceedings*, Big Sky, MT, USA, Vol 6. pp 3581-3589, 2004.

[17] Zong W, Wan F and Wei Y. Real-time monitoring for the actuator mechanism of the aileron. 2017 Prognostics and System Health Management Conference, Harbin, China. pp 1-5, 2017.

[18] Baldo L, Caredda E, Quattrocchi Q, Dalla Vedova MDL and Maggiore P, Simplified Modeling of a Flapper-Nozzle Servo Valve for Electro-Hydraulic Actuators: Genetic Algorithms and Neural Networks. *2023 Prognostics and Health Management Conference*, Paris, France, pp 207-212, 2023.

[19] Shanbhag VV, Meyer TJJ, Caspers LW and Schlanbusch R. Failure Monitoring and Predictive Maintenance of Hydraulic Cylinder—State-of-the-Art Review. *IEEE/ASME Transactions on Mechatronics*. Vol. 26, No. 6, pp 3087-3103, 2021.

[20] Vianna WOL and Malere JPP. Aircraft Hydraulic System Leakage Detection and Servicing Recommendations Method. *Annual Conference of the PHM Society*, Fort Worth, TX, USA, Vol 6, 2014.

[21] Bertolino AC, Gentile R, Jacazio G, Marino F and Sorli M. EHSA Primary Flight Controls Seals Wear Degradation Model. *ASME 2018 International Mechanical Engineering Congress and Exposition*, Pittsburgh, Pennsylvania, USA, Vol. 1, 2019.

[22] Chao Q, Shao Y, Liu C and Yang X. Health evaluation of axial piston pumps based on density weighted support vector data description. *Reliability Engineering System Safety*. Vol. 237, pp 109354, 2023.

[23] Iyaghigba SD, Ali F and Jennions IK. A Review of Diagnostic Methods for Hydraulically Powered Flight Control Actuation Systems. *Machines*. Vol. 11, No, 2, pp 165, 2023

[24] Liu H, Zhang J and Lu C. Performance degradation prediction for a hydraulic servo system based on Elman network observer and GMM–SVR. *Applied Mathematical Modelling*. Vol. 39, No. 19, pp 5882-5895, 2015.

[25] Soudbakhsh D and Annaswamy AM. Prognostics and Health Monitoring of Electro-Hydraulic Systems. *ASME 2017 Dynamic Systems and Control Conference*, Tysons, Virginia, USA, Vol. 2, 2017.

[26] Lu C, Yuan H and Ma J. Fault detection, diagnosis, and performance assessment scheme for multiple redundancy aileron actuator. *Mechanical Systems and Signal Processing*. Vol. 113, pp 199-221, 2018.

[27] Guo Y, Cunbao M and Zhengdong. A Hybrid Health Monitoring Approach for Aircraft Flight Control Systems With System-Level Degradation. *IEEE Transactions on Industrial Electronics* Vol. 70, No. 7, pp 7438-7448, 2022

[28] Autin S, Martin AD, Jacazio G, Socheleau J and Vachtsevanos G. Results of a Feasibility Study of a Prognostic System for Electro-Hydraulic Flight Control Actuators. *International Journal of Prognostics and Health Management*. Vol. 12, No. 3, 2021.

[29] De Martin A, Jacazio G, Sorli M and Vitrani G. A Simulation Survey on the Effects of Progressing Faults Within the SCAS of a Flight Control Actuator for Helicopters. *ASME/BATH 2021 Symposium on Fluid Power and Motion Control*, Virtual, Online, 2021.

[30] Kordestani M, Samadi MF, Saif M. A New Hybrid Fault Prognosis Method for MFS Systems Based on Distributed Neural Networks and Recursive Bayesian Algorithm. *IEEE Systems Journal*. Vol. 14, No. 4, pp 5407-5416, 2020.

[31] Cui Z, Jing B, Jiao X, Huang Y and Wang S. The Integrated-Servo-Actuator Degradation Prognosis Based on the Physical Model Combined With Data-Driven Approach. *IEEE Sensors Journal*. Vol. 23, No. 9, pp 9370-9381, 2023.

[32] Schoenmakers L. Condition-Based Maintenance for the RNLAF C-130H(-30) Hercules. *MS Thesis Eindhoven University of Technology*, 2020.

[33] Kannemans H and Jentink HW. A Method to Derive the Usage of Hydraulic Actuators From Flight Data. *ICAS 2002 International Congress of Aeronautical Sciences*, Toronto, Canada, 2002.

[34] Jardine AKS, Lin D and Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*. Vol. 20, No. 7, pp 1483-1510, 2006.

[35] ISO 17359:2018 *Condition monitoring and diagnostics of machines — General guidelines*. 3rd edition, 2018.

[36] ISO 13374-1:2003 *Condition monitoring and diagnostics of machines — Data processing, communication*

and presentation Part 1: General guidelines. 1st Edition, 2003.

[37] ADS-79E-HDBK *Condition Based Maintenance System for US Army Aircraft*, 2016.

[38] SAE-AIR-8012 *Prognostics and Health Management Guidelines for Electro-Mechanical Actuators*, 2020.

[39] Maré JC. *Aerospace Actuators 1: Needs, Reliability and Hydraulic Power Solutions.* John Wiley Sons, 2016.

[40] Frumusa M, and Vaccaro V. Investigation on the Effects of Control Surface Freeplay on the Aerolastic Characteristics of a Trainer Aircraft and Extension of Limits in Support of Maintenance Tasks. *International Forum on Aeroelasticity and Structural Dynamics IFASD*, Savannah, Georgia, USA, 2019.

[41] S5000F - *International specification for in- service data feedback.* Vol. Issue No. 3.1; Tech. Rep. No. S5000F-B6865-05000-00, 2023.

[42] Zaman N, Jun YJ and Chan D, Exploratory Data Analysis for Failure Detection and Isolation in Complex Systems. *2024 Annual Reliability and Maintainability Symposium (RAMS)*, Albuquerque, NM, USA, pp 1-5, 2024.

[43] Zhu J, Nostrand T, Spiegel C, and Morton B. Survey of Condition Indicators for Condition Monitoring Systems. *Annual Conference of the PHM Society*, Fort Worth, Texas, USA, Vol. 6, No. 1, 2014.

[44] Das S, Hall R, Herzog S, Harrison G, Bodkin M and Martin L. Essential steps in prognostic health management. In 2011 *IEEE Conference on Prognostics and Health Management*, Denver, CO, USA, pp 1-9, 2011.

[45] Atamuradov V, Medjaher K, Camci F, Zerhouni N, Dersin P and Lamoureux B. Machine Health Indicator Construction Framework for Failure Diagnostics and Prognostics. *J Sign Process Syst* Vol. 92, pp 591–609, 2020.

[46] Kosasih BY, Caesarendra W, Tieu K, Widodo A, Moodie CAS and Tieu AK. Degradation Trend Estimation and Prognosis of Large Low Speed Slewing Bearing Lifetime. *Applied Mechanics and Materials.* Vol. 493, pp 343–48, 2014.

[47] Baghli M, Delpha C, Diallo D, and Hallouche A. Three-Level Inverter Fault Detection and Diagnosis Using Current-Based Statistical Analysis. *2018 Prognostics and System Health Management Conference*, Chongqing, China, pp 686-691, 2018.

[48] Li Z, Xu P and Wang XB. Online anomaly detection and remaining useful life prediction of rotating machinery based on cumulative summation features. *Measurement and Control*. Vol. 56 No. 3-4, pp 615-629, 2023.

[49] Duan L, Zhao F, Wang J, Wang N, Zhang J, An Integrated Cumulative Transformation and Feature Fusion Approach for Bearing Degradation Prognostics, *Shock and Vibration*, Vol. 2018, pp 15, 2018.

[50] Caesarendra W, Tjahjowidodo T, Kosasih B and Tieu AK. Integrated Condition Monitoring and Prognosis Method for Incipient Defect Detection and Remaining Life Prediction of Low Speed Slew Bearings. *Machines* Vol. 5, No. 2, pp 11.

[51] Wang Y, Xiang J, Markert R, Liang M. Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications. *Mechanical Systems and Signal Processing*, Vol. 66, pp 679-698, 2016.

[52] Zhong J, Wang D, Guo J, Cabrera D and Li D. Theoretical Investigations on Kurtosis and Entropy and Their Improvements for System Health Monitoring. *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp 1-10, 2021.

[53] Zhong J, Wang D and Li C. A nonparametric health index and its statistical threshold for machine condition monitoring. *Measurement*, Vol. 167, pp 108290, 2021.

[54] Węglarczyk S, Kernel density estimation and its application. *ITM web of conferences. EDP Sciences* Vol. 3, No. 37, 2018.