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Development of a Data-driven Condition-Based Maintenance Methodology Framework for an Advanced Jet Trainer

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ABSTRACT

Since their introduction more than 20 years ago, PHM strategies for aerospace equipment have gone a long way, enabling operators and Original Equipment Manufacturers (OEM) to monitor their assets, track down abnormal behaviors and plan maintenance action in advance. On the other hand, the transition from PHM strategies using simulated data to solutions utilizing real-life operational data is consistently prone to significant challenges and demands. This doctoral thesis aims to develop a PHM/CBM framework applied to a Electro-Hydraulic Actuators (EHAs) leveraging real in-service fleet data. In this paper, the first steps of the research project are presented.

1. INTRODUCTION

In the end of the 90s, the Joint Strike Fighter (JSF) Autonomic Logistics (AL) system began to take shape in the minds of forward-looking analysts and engineers with one mission: conceiving a revolutionary way to assist assets along their life cycle, hence enabling enlightened operational processes, innovative maintenance strategies and progressive logistic solutions (Smith, Schroeder, Navarro, & Haldeman, 1997; Hess & Fila, 2002). The AL framework core is encapsulated within Prognostic and Health Management (PHM) solutions which, as a consequence, have been defined as key enabling technologies for the development of reliable Performance Based Logistics (PBL) frameworks.
The creation of more available, dependable and resilient assets is especially important in the military aircraft sector, where the availability and reliability of assets are crucial for defense administrations to foster trust and guarantee mission readiness. Since the introduction of PHM strategies in the industrial and aerospace sector, in fact, many systems have been the scope of research in order to develop tailored prognostic strategies. It may then seem trivial that, along with other pivotal subsystems, the Flight Control System (FCS) is being gradually more covered by these approaches. However, this is only true to some extents.
While the constantly growing interest buildup involving the More Electric Aircraft (MEA) concept has led many prognostic research activities related to Electro-Mechanical Actuators (EMAs), applications on the widespread hydraulic actuators have somewhat lagged behind in terms of PHM. The challenges linked to the lack of precise and extensive data as well as the major difficulties in understanding and modeling failure mechanisms add one more difficulty layer to an already demanding task, which however deserves attention and can prove to generate extensive savings (Rodrigues, Yoneyama, & Nascimento Jr, 2012).

2. NOVELTY AND SIGNIFICANCE

The sharp contrast between the popularity of EHAs in both commercial and military aircraft and the scarcity of PHM related published studies focused on these actuators highlight a significant research gap - a gap that deserves attention.
The development of PHM solutions and strategies for such pivotal widespread systems holds substantial operational and economic potential for every stakeholder in the MRO sector. With the military MRO sector valued at around 37 billion USD in 2024, the demand for digital transformation initiatives and advanced MRO services is expected to undergo a substantial growth in the coming years, motivated by the necessity to maintain aging fleets and incorporate technological advancements for legacy equipment.
One way to address these performance requirements is focusing on the operations. The adoption of condition-based maintenance (CBM) and predictive maintenance (PDM) strategies falls within this enlightened vision which, thanks to the benefits offered by PHM analyses, provides decision makers with extended situational awareness of fleet operations. Some of the main components of a FCS are the actuators, which control the aerodynamic surfaces. Primary flight controls actuators are extremely safety critical elements within aircraft FCS

and, at the current state, they exploit mostly EHAs or Electro-Hydro-Static Actuators (EHSAs). Sure enough, found in most commercial and military aircraft, EHAs represent to date the backbone of actuation mechanisms for flight controls.

3. State of the Art

A solid literature base exists for individual actuator components. These studies have developed a wide range of solutions related to component-level fault detection and isolation (FDI), degradation models, and comprehensive PHM routines for individual parts: (Mi & Huang, 2023; Byington, Watson, & Edwards, 2004; Zhong et al., 2023) for servo valves, (Shanbhag, Meyer, Caspers, & Schlanbusch, 2021) for cylinders, (Vianna & Malere, 2014; Bertolino, Gentile, Jacazio, Marino, & Sorli, 2018) for leakages, (Chao, Shao, Liu, & Yang, 2023) for piston pumps. Additionally, some works have concentrated on the construction of custom test benches (Chiavaroli, De Martin, Evangelista, Jacazio, & Sorli, 2018) and the development of models (Iyaghigba, Petrunin, & Avdelidis, 2024), aiming at the generation of custom datasets. Moreover, some PHM strategies at the FCS level have been envisioned (Kosova & Unver, 2023; Shen & Zhao, 2023). Finally, most of the EHA level approaches found in literature primarily focus on the sole diagnostics (Iyaghigba, Ali, & Jennions, 2023). Notably, these approaches leave a consistent gap for EHA level PHM, which, to the best of the author knowledge, is approached with a limited number of strategies. In (Liu, Zhang, & Lu, 2015), the author developed EHA performance degradation predictions leveraging Elman neural network observer, support vector regression (SVR) and Gaussian Mixture Model (GMM). The research carried out in (Soudbakhsh & Annaswamy, 2017) and (Lu, Yuan, & Ma, 2018) shows the development of both a fault detection technique and a health monitoring approach. (Guo & Sui, 2020) presented an application of the Minimum Hellinger Distance on top of a Particle Filtering (PF). This PF-based solution is adopted by another PHM framework which combines also high-fidelity models (Autin, De Martin, Jacazio, Socheleau, & Vachtsevanos, 2021; De Martin, Jacazio, & Sorli, 2022). A modular hybrid fault prognosis method is developed in (Kordestani, Samadi, & Saif, 2020), where the author leveraged distributed neural networks and recursive Bayesian algorithm. In (Cui, Jing, Jiao, Huang, & Wang, 2023) the author approached a hybrid method: the nonlinear Wiener process (NWP) algorithm is used for the physics based section while the data-driven echo-state-network (ESN) is employed for the data driven one. In summary, the exhaustive yet limited number of studies mentioned above lay its roots on detailed actuator level data obtained from test benches and laboratory tests. Although highly valuable, the results of such studies hardly transfer to actual in-service legacy systems as detailed monitoring of low-level subsystem data is often not carried out and the control signals remain inside the FCC control loop without being saved or logged. On the other hand, the approaches that leverage operational data collected from real-world operational scenario are scarce and the few published studies provide constrained findings (Schoenmakers, 2020; Kannemans & Jentink, 2002).

In conclusion, if creating these frameworks was not an already challenging task, designing them for legacy and already operational platforms, definitely does not make the process easier. In this scenario, PHM engineers face obstacles related to working with pre-existing systems that were not originally designed for PHM applications (e.g low and/or variable sampling rates, limited built-in sensing/testing capability, no subsystem level sensors, hand written records, siloed databases, etc) as well as a vertical functional organization in the industry (Vogl, Weiss, & Donmez, 2014; Esperon-Miguez, John, & Jennions, 2013).

4. Approach and Work in Progress

This paper presents the initial steps towards implementing a comprehensive CBM framework for a specific aircraft subsystem. Precisely, the horizontal tail (HT) flight control Primary Actuation System (PAS) of an Advanced Jet Trainer (AJT), a twin-engine lead-in fighter training platform equipped with fully digital flight controls and avionics, is considered as a proof of concept (Baldo, De Martin, Sorli, & Terner, 2023). Through an in-depth analysis of design documents and operational procedures, relevant data have been identified and categorized. The AJT HT flight control PAS can be categorized as an EHA controlled by a tandem configuration Direct-Drive-Valve (DDV). The HT assembly is configured as an all-moving tail, a very popular solution when a good trade-off between control effectiveness, aerodynamic efficiency and operational complexity is desired. This solution has been adopted in various high-performance platforms (e.g. F16 Fighting Falcon, F22 Raptor) providing excellent maneuvering and flying qualities. On the other hand, DDVs are established solutions for flight controls and the adopted crank-connecting rod mechanism is widely accepted among mechanical solutions for longitudinal control.

The workflow employed for this research is reported in Figure 1. The most time demanding step so far has been represented by the domain understanding phase where the platform and data knowledge acquisition has been carried out. During this phase, significant effort has been devoted to acquiring comprehensive knowledge about the platform and gathering data. Leveraging the research group experience and expertise, both from the OEM and the University, the author created a data organization overview with the requested data for the first steps along with importance and priority indications. In this way, the author managed to reconstruct the data lineage and the data flow from the operative base to the info logistic systems and to the project data repository (DR). This first phase has been pivotal to plan ahead and understand which possible

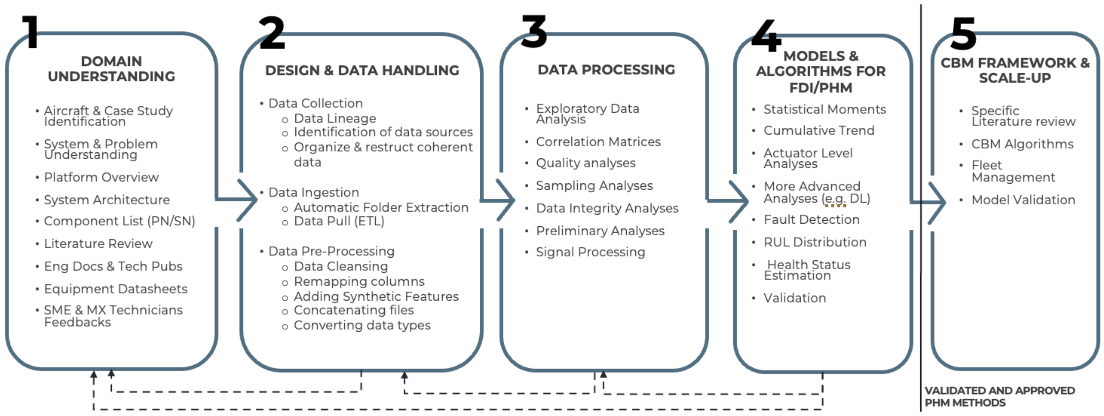

Figure 1. Research project workflow. Note the loopbacks to enhance the data processing with various iterations if necessary.

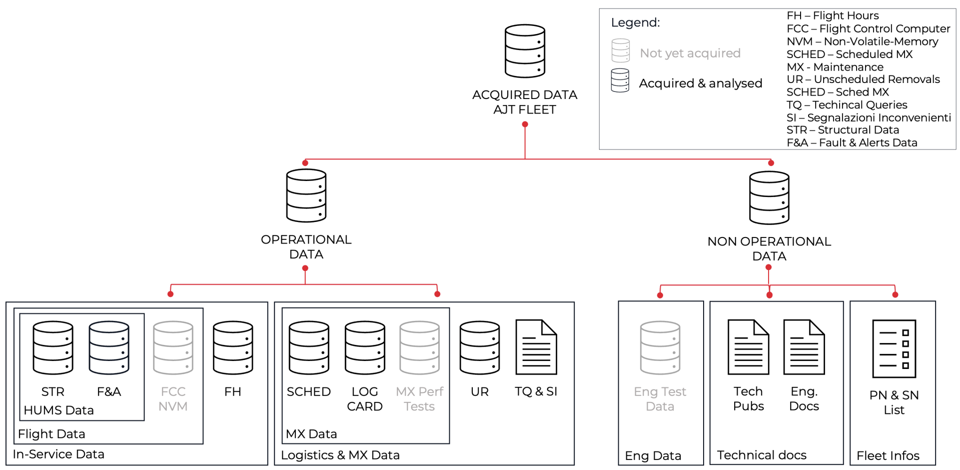

Figure 2. Data repository divided in categories.

strategic and methodological options could be approached, based on the available data. The current DR, encompassing more than 25000 Flight Hours (FH), is illustrated in Figure 2 where a clear distinction between operational (OD) and non-operational data (NOD) has been carried out to streamline the data classification process. LMX include Scheduled MX, unscheduled removals, log cards, technical queries, inconvenience reports and MX performance tests.

OD can be divided into In-Service Data (ISD) and Logistics & Maintenance Data (LMX). ISD includes all the data obtained from the aircraft itself after the sorties (FH register, Health Usage Monitoring System (HUMS) data and the Non-Volatile Memory of the FCC). In particular, HUMS data downloaded from the aircraft (S5000F, 2023) is divided in structural related data (STR) and Faults & Alerts (F&A).

Other potential operational data sources, which are often employed in the development of PHM strategies for legacy equipment, could include the Crash Survival Memory Unit (CSMU) or the Digital Video and Data Recorder. However, these latter sources were excluded from the study due to unreliable data download processes that occur only on an occurrence basis rather than consistently.

On the other hand, NOD encompass all technical information involving design, performance, process and configuration of aircraft components and subsystems (e.g. PAS PN and SN).

Following the domain understanding, the design and data handling and the data processing steps, the research is currently approaching the models and algorithm phase. This first steps focused on data derived from STR HUMS, Log Cards and UR. A total of 54 flight parameters (FP) has been selected through physical reasoning from the STR file. Given the lack of component-level signals that can accurately describe actuator health, relevant indicators were selected based on their potential to represent mechanical wear processes or possible flight anomalies (e.g. mechanical work). The selected FPs include:

- load components (forces and moments) acting on the HT and fuselage
- yaw, pitch and roll rates and accelerations
- body angles

- north, east, up speed components
- mobile surfaces deflections
- stick, pedals and throttle commands
- true air speed, Mach
- timestamps and complementary data
- 4 additional indirect signals (difference between two consecutive HT positions and the mechanical work carried out by the actuator obtained multiplying the position difference with the moment acting on the HT)

It is important to underscore once again that, by design, no actuator level data is recorded, including the actuator command produced by the FCC which would greatly benefit usage monitoring. FPs are saved in the form of time-series data with variable frequency. HUMS was not designed for PHM applications, thereby only a few irregular and sparse batches of high frequency data can be found in data records while most of the samplings are acquired at frequencies below 5 Hz. At the current state, this irregular low frequency sampling does not enable low level dynamic analyses of the actuator (whose dynamics is characterised by much higher frequencies) or the adoption of literature strategies based on high frequency actuator signals.
Following data quality and sampling analyses, the author thus decided to adopt a statistical approach based on cumulative features (CF). This approach has been chosen to determine if the data at hand demonstrates prognostic value in relation to the selected subsystem. CFs are currently being obtained from the merging of operational data sources and are the scope of current activities as reported in Figure 3. The four main statistical moments (SM) are calculated from the time series data of each flight for each FP. Then, CF are created by integrating these SMs in time (multiplying the FP SMs by the flight time) to replicate a time degradation tailored to the effective aircraft usage. Subsequently, the CF variations between two unscheduled removals are calculated and visualized using histograms representations. Histograms are then analysed and a signal-to-noise ratio ranking is performed to discern the most informative CF for further analyses and model development.

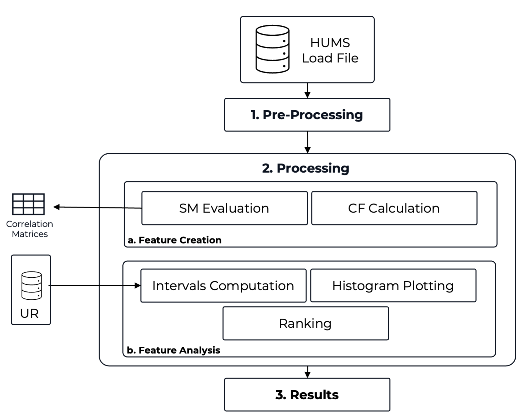

Figure 3. Statistical methodology overview.

The model and algorithm phase for diagnosis and PHM is currently being investigated and the calculations are currently being carried out. These results, if positive, would allow the author to statistically allocate a failure probability distribution in time leading to the next steps of the research project: conceiving a maintenance framework for fleet management leveraging a selected PHM strategy to support CBM. Otherwise, a custom actuator model will be needed to integrate in-service time series signals.

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