Condition-based-maintenance for fleet management

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Abstract. New "enlightened" and holistic maintenance strategies are shaping the industrial world from the inside, providing intelligent and focused solutions where high availability, reliability and safety are required. Maintenance planning and scheduling is an extremely daunting and multi-faceted task which involves competences from fairly different fields: customer support, quality, engineering, production, RAMS, cost estimation etc. In the aerospace sector, a significant percentage of Life Cycle Costs (LCCs) and, in particular, operating costs, are determined by Maintenance, Repair and Overhaul (MRO) activities and the relative asset unavailability due to down-time or turn-around-time [1,2]. This is the reason why currently there is an ongoing intense effort in the research community and in the industry towards new maintenance strategies which could overcome the limitations of preventive maintenance thus streamlining operations, without jeopardizing mission safety. This research project is hence spot on and focuses on the development of optimized maintenance strategies, built around the system health status.

Introduction

Preventive maintenance employs a very simple approach where the component is replaced after a number of cycles or hours. This approach is definitely safe (as significant safety margins and factors are applied) but it is beyond any doubt inefficient for both the Original Equipment Manufacturer (OEM) and the operator, which have to replace working parts. On top of that, the Integrated Logistic Support (ILS) chain must be somehow oversized to guarantee component readiness.

A plethora of maintenance solutions have hence engendered to pitch in these scenarios, bolstered by the parallel growth in sensors technologies and Industry 4.0: starting from Opportunistic Maintenance (OM), passing through Condition-Based Maintenance (CBM) and even approaching predictive maintenance. If OM proposes an intelligent regrouping of maintenance activities, CBM and predictive maintenance [3] tries to plan maintenance actions according to the real component/subsystem health status. If the idea behind the CBM concept is, at least, quite straightforward, the implementation is anything but simple. This requires the complex interaction of several entities which must be integrated in a single holistic framework to enable the vision of customized, pinpointing and tailored planning [1].

In fact, CBM involves different steps: data collection, data analysis, forecasting and acting. The selected component or subsystem must be monitored by appropriate sensors which transmit data that are logged and analyzed in a Prognostic and Health Management (PHM) perspective. Meaningful features that can successfully track down possible failures are extracted and examined through different algorithms. A central step is represented by Remaining Useful Life (RUL) predictions: leveraging on sophisticated algorithms, a probabilistic approach is often employed [4]. After that, a maintenance plan can be derived from RUL predictions, the relative confidence levels and many other factors (e.g. hangar slots and availability, maintenance task flexible regrouping, criticality of the potential failure, regulations, etc.).

Before the algorithm could be employed, an extended off-line activity must be carried out with historical data to train the algorithms and verify the accuracy and confidence levels of the overall prognostic framework [4].

The goal of this Ph.D research project co-financed by Leonardo S.p.A. and Politecnico di Torino is to develop a CBM framework which could support Leonardo's customers and, at the same time, bringing the current state-of-the-art of maintenance strategies a step forward, employing cutting edge algorithms to real-life operational data. Furthermore, it has to be noted that interaction with an industrial partner is then pivotal to have a real-life feedback of the solution feasibility.

If in the civil aviation sector, the development of PBL (Performance Based Logistics) and CBM logics is difficult due to safety and reliability concerns, in the defence field all of this is compounded by additional complexities. Disruptive routines, alteration (or absence) of flight schedules and routes, 24-hour-a-day activities, excessive structural stresses, extended flight envelopes require an even more flexible maintenance planning, which should take into consideration specific mission profiles and requirements.

Material and Methods

Starting from a candidate aircraft for the analysis and the general overview of its subsystems architecture, the research is focused on algorithms and solutions which integrate PHM strategies with Remaining Useful Life (RUL) predictions in more complex frameworks for maintenance scheduling and planning [5].

Among different possible subsystems, the research will focus on primary flight control actuation systems and the relative non-linearities (e.g. friction, free-play [6] etc). To this end, a literature review is currently being carried out to highlight the potential PHM strategies applied to Electro-Hydraulic servo actuators for primary flight control [7], starting from diagnostic applications [8].

The first step of any PHM related activity starts with the analysis of the system architecture along with the RAMS-T industry department. A series of data ranging from technical publications to historical failure events as well as maintenance, operative and flight performances are currently being examined to identify possible opportunities and threats.

The central objective is to identify and assess the correlations that may exist between the operational data gathered from flight operations, maintenance reports, historical data, and the real-time data obtained from onboard sensors (downloaded on ground after landing or in the future potentially transferred live during flight). This research will encompass mapping out and defining these correlations with the aim of comprehending the frequency, types, severity, and occurrence of failures. Leveraging on engineering and logistics resources, algorithms will be designed and developed for CBM purposes of selected critical systems/items in view of optimizing fleet management. After appropriate simulations with developed models aimed at forecasting operation in nominal and degraded conditions, the final step will include the framework validation with real-life data, in order to assess the strategy performance in terms of prognostic capability and positive effects on the fleet availability.

Enabling technologies could range from Digital Twins (DT) [9,10,11] to high and low fidelity models which could predict the component behavior. Data-driven, model-based as well as hybrid solutions will be taken into consideration with specific literature reviews to select appropriate Machine Learning (ML) methodologies and computational approaches. Promising strategies include particle filtering, Long Short-Term Memory (LSTM) [12] or even Physics Informed Neural Networks (PNN) combined with classification algorithms like Support Vector Machines (SVMs) or random forests. Moreover, the approaches should take into consideration the "fewshot" phenomenon, which lead to the substantially unbalanced healthy-unhealthy datasets typical of PHM tasks [12,13]. During the development phase there will be an extensive use of modelling techniques based on physical laws and experimental data: thanks to high and low fidelity models, the expected component behavior can be outlined and compared with the actual trends. In this direction, even the initial steps towards the creation of components and subsystem DTs or reasoning models will be considered, exploiting CAD and physics-of-failure representation.

Since the selected aerospace application is extremely safety-critical, particular attention will be paid to the method traceability, explainability and interpretability selecting, if possible, Explainable Artificial Intelligence (ExAI) methods. In this way, operators and maintenance crews can interpret the results and understand why a particular decision has been taken, providing useful feedbacks and contributing to decision-making.

Results & Conclusion

The expected result is a tight integration between academia and industry, computational analyses and on-site experience, technical design and customer support, maintenance planning and prognostic results, enhanced by cutting edge data science methods. CBM and predictive maintenance are here to stay and this project is perfectly spot on with the research community, giving its own contribution to make the aviation world more efficient, safer and, at the same time, assuring top-notch asset performance.

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