Advanced data analytics and digital technologies for smart and sustainable maintenance

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Abstract: Maintenance optimization has been of high interest in recent years for both the industry and the knowledge institutions. For example, tens of billions of dollars are spent on annual aviation Maintenance, Repair and Overhaul (MRO) activities. At the same time, the attention also grows in the direction of the advances in data analytics and digital technologies which can enable the next step in maintenance transition from preventive to predictive. The integration and operational deployment of physics-based (domain knowledge) and data-driven (AI, digital twin) innovative technologies can enhance the optimization of lifecycles and processes. Main objectives are the reduction of aircraft downtime and costs as well as a minimal waste in terms of materials and energy.

Keywords: Data analytics, AI, digital twins, predictive maintenance, sustainability

1. Introduction

Optimization of aviation Maintenance, Repair and Overhaul (MRO) operations has been of high interest in recent years for both the knowledge institutions and the industrial community as a total of approximately $70 billion has been spent on MRO activities in 2018 which represents around 10% of an airline's annual operational cost (IATA, 2019). Moreover, the aircraft MRO tasks vary from routine inspections to heavy overhauls and are typically characterized by unpredictable process times and material requirements. Especially nowadays due to the unprecedent COVID-19 crisis, the aviation sector is facing significant challenges and the MRO companies strive to strengthen their competitive position and respond to the increasing demand for more efficient, cost-effective, and sustainable processes.

Currently, most maintenance strategies employ preventive maintenance as an industrial standard, which is based on fixed and predetermined schedules. Preventive maintenance is a long-time preferred strategy, due to increased flight safety and relatively simple implementation (Phillips et al., 2010). However, its main drawback stems from the fact that the actual time of failure and the replacement interval of a component are hard to predict resulting in an inevitable suboptimal utilization of material and labour. This has two repercussions: First, the reduced availability of assets, the reduced capacity of maintenance facilities and the increased costs for both the MRO provider and the operator. Second, the increased waste from

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an environmental standpoint, as the suboptimal use of assets, is also associated with wasted remaining lifetime for aircraft parts which are replaced while this isn't yet necessary (e.g., Nguyen et al., 2019).

The recently introduced, condition-based maintenance (CBM) and predictive maintenance (PdM) data-driven strategies aim to reduce maintenance costs, maximize availability, and contribute to sustainable operations by offering tailored programs that can potentially result in optimally planned, just-in-time maintenance meaning reduction in material waste and unneeded inspections.

2. The Predictive Maintenance Approach and Building Blocks

As the MRO providers try to address the complexity and uncertainty of the aircraft maintenance processes, the use of data-driven methods can provide meaningful information and insights into the way aircraft systems and components are operated and maintained. The rise of the so-called Industry 4.0 and the leverage of enabling technologies such as the Internet of Things (IoT) and the Artificial Intelligence have allowed the transition to a data-driven, proactive approach, the so-called predictive maintenance (PdM) strategy.

In literature, PdM and CBM are applied interchangeably or linked implicitly. These approaches rely both on collected data and have a lot of commonalities, however they are focusing on different aspects: CBM in the actual condition while PdM is deploying prognostics (i.e., remaining useful life - RUL) to support the maintenance decision making (e.g., Tinga & Loendersloot, 2014). Most authors agree on five required components to deploy a predictive maintenance approach, as illustrated in Figure 1:

1. Hardware: sensors installed or retrofitted in physical assets or systems or components.
2. Data acquisition: data-capturing and transfer between the monitored asset and the data storage and data transformation so data can be stored in a useful form.
3. Data storage and management: platform on premises or in the cloud to ensure data storage, availability, and efficient transfer processes.
4. Data analytics: data pre-processing, so algorithms are fed with the right input and development of prognostic algorithms and models (e.g., Machine Learning and AI) to identify patterns or other useful information (RUL, degradation).
5. Decision support: tools used (e.g., Digital Twins) to determine actions based on the provided information.

Overall, added value is created by transforming the acquired data into predictions about the system condition and other relevant, meaningful information so that maintenance can be carried out when and where needed. However currently, in most cases, a few of the components or building blocks of the predictive maintenance process are in place so that developed solutions focus on these individual components and not in operationally deploy the full cycle.

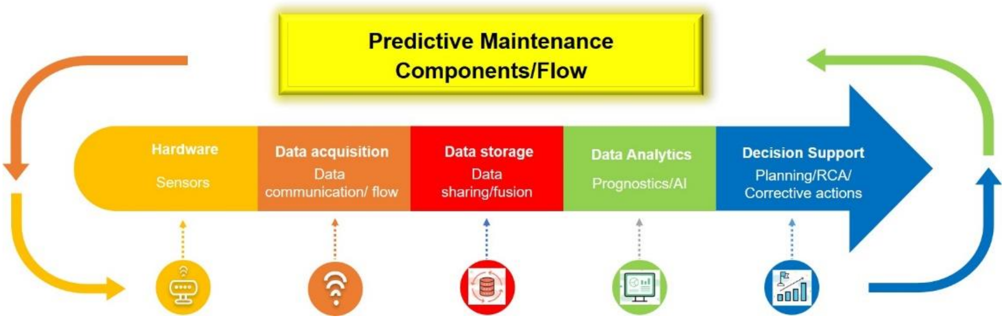

Fig.1. Components and flow chart of PdM (Own edition)

3. Big Data Management

In recent decades, as every new generation of civil aircraft creates more on-wing data and fleets gradually become more connected with the ground, a lot of barriers have been removed and an increased number of opportunities can be identified for more effective MRO operations. Today, data volumes are growing exponentially, e.g., an Airbus A350 generates and archives 50 times more data than an Airbus A320 i.e. from 12000 parameters and 8.3TB to over 670000 parameters and 450TB (Daily & Peterson, 2017). Therefore, data is increasingly becoming an asset for aircraft manufacturers, operators and maintainers.

At the same time, the MRO providers underutilize their data, mainly due to data protection and focus on compliance. Other typical issues include the limited availability and low quality of historical data and the limited options in combining datasets from different operators of the same aircraft type. In addition, the availability of external data from airline operators, suppliers and manufacturers is hampered by confidentiality and ownership issues. Last, time-consuming data preparation work is often needed to make the data quality acceptable (Pelt et al., 2019a, b).

Several new data capturing, manipulation and sharing technologies are currently being developed, with the potential to change the landscape in data management. For example, data can now be organized effectively with the use of modern Big Data technologies. However, the availability, sharing and combination of data is still an issue that has technical and legal challenges. A promising solution is the Federated Analytics (FA, aka Federated Learning) architecture which can be employed and act to combine and analyse datasets and algorithms located in different geographical locations, without compromising confidentiality or ownership

(Nilsson et al., 2018 and Li et al., 2020). The FA can provide an efficient data exchange environment to MRO end users without risking unauthorized exposure of their data.

4. Data Analytics and Algorithmic Methods

The key to unleash data potential and deliver meaningful insights lies in data analytics. Further, the inherent advantage of the data-driven methodologies is that they are not dependent on in-depth domain knowledge. Nevertheless, in practice, domain knowledge is required to establish what matters. Before starting the analysis and dive into specific methods and techniques, it is important to define the goal and the precise research question(s). For example, is the objective to detect abnormal behaviour of an aircraft system or to predict the remaining useful life of a component? Defining first the data analysis goal helps to determine the KPIs and the variables, i.e., the input and target variables (Pelt et al., 2019a, b).

There are numerous schemes in the literature (e.g., Han et al., 2012) that can be used to classify the data analytics & algorithmic methods. In terms of technical complexity, a method can be one or any combination of the following (Apostolidis, Pelt & Stamoulis, 2020):

1. Fairly simple, making use of visualization techniques can be used for descriptive, exploration, monitoring and communication purposes.
2. Simple to moderate, consisting of a wide range of statistical data mining techniques such as correlation to identify patterns and meaningful information from large pools of data
3. Complex, using sophisticated, high-fidelity machine learning and AI algorithms for prognostics and recommendations for decision-support systems.

Overall, added value is created by transforming the acquired data into knowledge, reasoning, predictions, and ultimately, decisions and actions. Nevertheless, each problem must be approached with the appropriate, feasible and relevant method. Then, it can be determined if the benefits outweigh the investment taking also under consideration that the increased complexity is not necessarily an advantage. For example, complex and not transparent AI methods can create reduced confidence and certification issues while simpler methods, more relevant with the standard practices and engineering logic might be more attractive in certain cases.

5. Digital Twins

Digital Twins (DT) are currently considered as a promising approach to address the problem of unpredictability in MRO operations. A DT is the combination of multiple state-of-the-art technologies embedded in three distinctive components, which are the physical entities, the virtual models, and the data that tie the physical and virtual entities, as illustrated in Figure 2. However, DT is not a fundamentally new concept, as it is rooted in a wide range of conventional system simulation methodologies (Glaessgen & Stargel, 2012). Nevertheless, a conventional simulation can typically provide only a snapshot of the entity's behaviour while a DT can extend that simulation process and yield an accurate description over time.

In literature, it is generally agreed that a DT can be considered as a detailed digital representation of the physical components of an aircraft system with the use of relevant data from various sources, such as real-time sensor data and historical maintenance data, a combination that can describe, optimize and predict the performance behaviour and the Remaining Useful Life (URL) of an aircraft system or an MRO process with the use of simulation, prognostics, diagnostics, and analytics (Liu et al., 2018). This digital representation provides information about the current operational status of an aircraft component, with the benefit of exploring and investigating different operational and maintenance scenarios before their execution (Li et al., 2017).

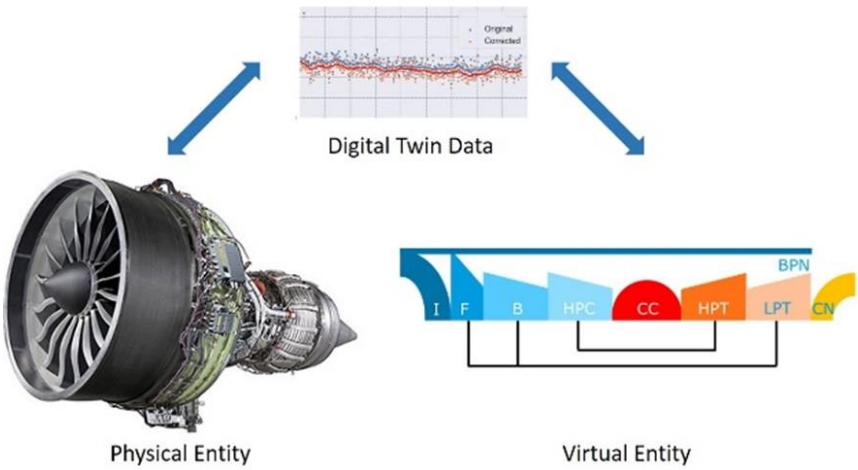

Fig.2. An example of a Digital Twin (Apostolidis & Stamoulis, 2021)

A Digital Twin enables operators to understand, predict, and optimize the performance of their physical assets or analyse the behaviour of a device after a failure or a technical issue (Apostolidis & Stamoulis, 2021). In addition, simulation models can play a crucial role in designing new maintenance practices for systems and assets which can be assessed in the virtual environment and deployed in the physical one. This way, an MRO provider can run experiments that will lead to an optimal operation of their assets. Nevertheless, various technical limitations complicated the development of effective Digital Twins, as it required technical maturity from a group of necessary enablers, such as the data-related and the Internet of Things (IoT) infrastructure for effective communication between the physical and the virtual entities (Wright & Davidson, 2020).

6. Decision Support Tools

The ultimate building block of a predictive maintenance flow is the application of the data analysis output into recommendations for decision making and actions to improve the MRO efficiency. The operational deployment of predictive analytics can significantly reduce downtime, waste and costs through labour, inventory and material management and processes optimization without any compromise in quality and safety.

Individual case studies conducted with the use of a wide range of Aviation data and analytics proved to be successful in delivering better information and prognostics e.g. in Baptista et al., 2018, Pelt, Stamoulis & Apostolidis, 2019b, Nguyen et al., 2019, Deng, Santos & Curran, 2020, Stamoulis & Apostolidis, 2022, as follows:

1. Aircraft data with the use of sensors technology and effective data transfer and analytics can reveal the real-time physical status of the corresponding aircraft systems.
2. MRO-specific, AI algorithms and simulation techniques enable faster diagnostics and prognostics, e.g., detection and assessment of hazards/defects/damages and Remaining Useful Life (RUL) estimation.
3. Data-driven, scheduling tools can optimize fleet maintenance scheduling by determining maintenance tasks optimal slots and facilitating the decision-making.

7. Conclusion

There are a number of challenges that the aviation MRO industry is confronted with, not the least of which are related to a pressing demand for optimization in maintenance operations as well as an urgent sustainability agenda.

The operational deployment of proactive-type strategies and efficient, digital maintenance tools as discussed in the previous sections can ensure:

– Less unneeded maintenance and reduced waste of materials, which are currently replaced while still having remaining useful life.
– Fewer operational disruptions, shorter lead times and overall decreased downtimes.
– Less deteriorated aircraft engines and systems that can operate at a higher efficiency, requiring less energy, which is translated to a better fuel consumption.

Nevertheless, the current degree of operational adoption of the aforementioned enabling technologies and novel approaches in the MRO landscape, is relatively low. Currently, there remain several technical and operational challenges including data challenges and human and organisational factors to be addressed to exploit the full potential of the data-driven predictive strategies and decision support tools. Moreover, as aviation is a safety-critical and highly regulated industry (e.g., in RCM based MSG-3 standard), it is necessary to develop certification standards for the AI-based aircraft systems applications and ultimately, certifiable PdM models to render these technologies and methodologies suitable for operational deployment and real-life applications.

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