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Author(s)
Apostolidis, Asteris; Pelt, Maurice; Stamoulis, Konstantinos P.

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Aviation Data Analytics in MRO Operations: Prospects and Pitfalls

Asteris Apostolidis, PhD, KLM Royal Dutch Airlines
Maurice Pelt, Amsterdam University of Applied Sciences
Konstantinos P. Stamoulis, PhD, Amsterdam University of Applied Sciences

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SUMMARY & CONCLUSIONS

As every new generation of civil aircraft creates more on-wing data and fleets gradually become more connected with the ground, an increased number of opportunities can be identified for more effective Maintenance, Repair and Overhaul (MRO) operations. Data are becoming a valuable asset for aircraft operators. Sensors measure and record thousands of parameters in increased sampling rates. However, data do not serve any purpose per se. It is the analysis that unleashes their value. Data analytics methods can be simple, making use of visualizations, or more complex, with the use of sophisticated statistics and Artificial Intelligence algorithms. Every problem needs to be approached with the most suitable and less complex method. In MRO operations, two major categories of on-wing data analytics problems can be identified. The first one requires the identification of patterns, which enable the classification and optimization of different maintenance and overhaul processes. The second category of problems requires the identification of rare events, such as the unexpected failure of parts. This cluster of problems relies on the detection of meaningful outliers in large data sets. Different Machine Learning methods can be suggested here, such as Isolation Forest and Logistic Regression. In general, the use of data analytics for maintenance or failure prediction is a scientific field with a great potentiality. Due to its complex nature, the opportunities for aviation Data Analytics in MRO operations are numerous. As MRO services focus increasingly in long term contracts, maintenance organizations with the right forecasting methods will have an advantage. Data accessibility and data quality are two key-factors. At the same time, numerous technical developments related to data transfer and data processing can be promising for the future.

1 INTRODUCTION

The introduction of data recording in aircraft was first envisioned as a measure for increased safety. The introduction of mandatory FDRs was implemented gradually during the 1950s in various countries [1], with safety again as the primary aim. The idea was that the technical details of an accident could lead to improved designs and prevent further accidents. Recorders' technology has improved significantly from analogue, capable of storing only four parameters, to digital on tape and then to solid state, able to record over 3000 parameters.

Nevertheless, the scope of flight data recording remained relatively unchanged for decades. During these years, the MRO of aircraft components was based on Corrective Maintenance in the early days or Preventive Maintenance later, with fixed-time or -cycle intervals, regular inspections and high safety margins [2]. That was indeed the right way to go -and it still is in many cases. However, it is associated with a major disadvantage: it is financially, environmentally and operationally unsustainable. Preventive maintenance means that aircraft parts will always be replaced prematurely, leading to wasted remaining useful life. Indeed, this type of maintenance implies increased material costs [3]. Within many large-scale organizations, maintenance costs can account for as much as 40% of the operational budget [4]. It also means that the environmental penalties to manufacture and recycle a part correspond to a shorter-than-designed life-cycle. Lastly, hard limits impose operational challenges, as parts need to be replaced independently of the operational situation. So, the main question deriving from those deficiencies is:

"*What if the performance of a part could be monitored, so the necessary maintenance takes place* ***exactly*** *when needed?"*

In more details, this article will address the following general sub-questions, by using suitable examples and case-studies:

"What is the current state-of-the-art in Data Analytics for Aviation MRO, its range of applications and opportunities? What are the limitations and how data can be used more effectively? How can the methods and applications be classified?"

This article started with a historical overview of the development of aviation data recording and MRO data analytics and it passed to current technical developments. The classification of stakeholders follows, along with method classification. Data quality and legal aspects are subsequently discussed, followed by the distinction between two generic problem categories: Classification and Identification of rare events. Conclusions is the latest section discussed.

2 DATA ANALYTICS IN MRO: AN OVERVIEW

An interesting point is that the various control systems of modern fly-by-wire aircraft, such as the FADEC (Full Authority Digital Engine Control) require sensor inputs, in order to effectively control the operating point of an engine.

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However, the limited capabilities in computer performance, data storage and transfer speeds of the 1980s and 1990s were not favorable for the effective introduction of Data Analytics in aviation and MRO at the time.

It was not until the early years of the 21st century that computers and networks started offering sufficient performance for the processing of big amounts of data. At the same time, a large number of data algorithms was developed, improved, tested and put into production [5]. This development brought a revolution in the MRO domain, enhancing the evolution of Predictive Maintenance [6,7]. Predictive Maintenance of aircraft systems is based on sensor inputs for determining the actual health of an aircraft component. The fact that installed sensors pre-existed for control and reporting reasons facilitated the development of such a technology [8]. At the same time, as new aircraft are developed with predictive MRO technologies in place, new enablers for additional capabilities are developed. To name a few, increased data sampling rates are now the norm. New data transfer technologies enabled such a development.

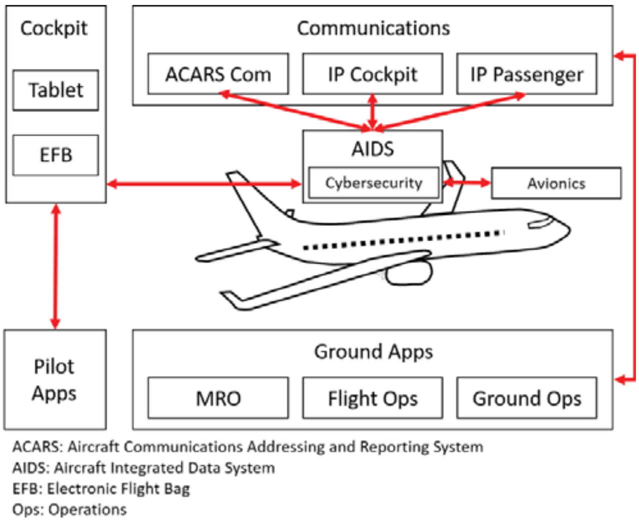


Figure 1: Aircraft connectivity systems and applications

It is important to note here that there is still a long way to go, in order to fully exploit the new data transfer capabilities. Increased sampling rates and data transfer speeds only make sense if the data contain useful information for the operator and the MRO provider. As an example, processes that evolve gradually, such as component degradation do not require continuous data streaming. On the other hand, if the dynamic behavior of a system needs to be under scrutiny, continuous data is the only way to do so.

In general, either snapshot or continuous data may contain very useful information and the only way to unleash this potential is with the development and use of suitable algorithms. As every new generation of civil aircraft creates more on-wing data and fleets gradually become more connected with the ground, an increased number of opportunities can be identified for more effective MRO operations. Today, numerous OEMs, operators and research organizations are active in this field.

Data are becoming a valuable asset for aircraft operators. "*Data is the new oil*" [9, 10], as many experts suggest, making a parallelism between the two resources. Real-time data transmission via satellite or ground data transfer via Wi-Fi or cellular networks becomes increasingly common (Fig. 1). MRO providers try to capitalize this market, directly competing with the OEMs of airframes, engines and systems. Each category has their own strategic advantages:

- Traditional MRO providers can be more independent in their services, eventually selecting the tools and methods they use from multiple providers and provide services to products manufactured by different OEMs. Accessibility to data and large-scale operations can act as pitfalls here, which puts traditional MRO providers under pressure with the introduction of Data Analytics.
- MRO providers who are at the same time aircraft operators are a separate category. Examples of this class are Delta Tech Ops, Lufthansa Technik and Air France Industries KLM Engineering & Maintenance. The competitive advantage of those organizations is that as MRO providers are benefited from the operational data of their airline businesses. In other words, they have access to large data pools, which can be used for modelling and training their analytics models, which can then sell to their customers. Here, data accessibility and ownership is a complex issue.
- The third category is OEMs. Usually, they have a better understanding of the technical aspects of their own products, but they do not operate aircraft commercially. As a result, they rely on their customers to access operational data, a process that faces reluctance from the airlines. Airlines see the risk of providing data to the OEMs that may be used to train models for the totality of their customer base. Therefore, operators see the danger that their data will also benefit competition indirectly. As a result, complex legal agreements are usually needed, making data accessibility challenging. On the other hand, as customers of the main OEMs are spread across the globe, the data samples can be more complete.

There are numerous ways that data analytics methods for MRO can be classified. In terms of technical complexity, Data Analytics can be fairly simple, making use of visualizations and conventional statistics in one side of the spectrum, or complex, making use of sophisticated Artificial Intelligence algorithms, on the other side (Fig. 2). However, it is recommended to approach every problem with the most suitable and less complex method needed, that serves the purpose of the original research question. In other words, a complex method does not necessarily imply increased fidelity. On the other hand, there are complex technical problems that can only be approached with high fidelity methods, as the hidden data patterns to be identified are equally complex [11]. The ultimate goal in every case is improved reliability and maintainability for the system.

MRO providers increasingly analyze on-wing data, produced by the aircraft while flying. A key-parameter for the capabilities of such methods is the type of data made available, as installed sensors are always limited compared with the mechanical complexity of a system or component. Also, priority is put on components with sufficient number of sensors installed, with known reliability issues or with relatively expensive maintenance in terms of costs and operational penalties.

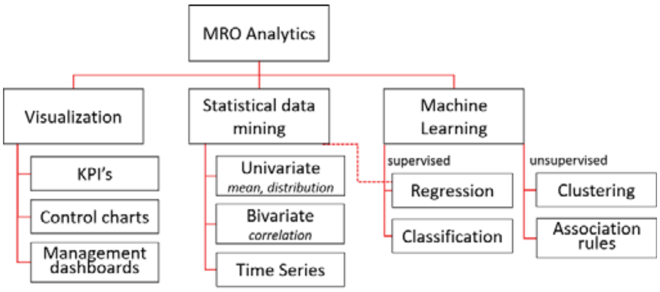


Figure 2: MRO Analytics classification

A necessary distinction needs to be made here. The first category requires the identification of large-scale patterns, which enable the classification and optimization of different maintenance and overhaul processes. This way, the operation of an aircraft system can be compared against a large pool of historical operational and maintenance data and its condition to be assessed. It is generally used for work scope forecasting. The second category of problems requires the identification of rare events, such as the unexpected failure of parts. This cluster of problems requires the identification of meaningful outliers in large data sets. These outliers act as flags for irregular system performance, due to specific degradation and wear modes. This way, an imminent failure can be identified and prevented.

Apart from flight technical data, ground maintenance data are used and analyzed, in order to produce forecasts for the optimization and planning of maintenance operations. As an example, an aircraft engine consists of several thousand piece-parts. During an overhaul and depending on the nature and level of maintenance, the engine will be disassembled in modules and furtherly on a piece-part level. Following, each one of the composing parts will be inspected and either stored, repaired or scrapped. The optimization this problem makes it a very interesting and complex case. There are three overall variables to be optimized: cost, time and quality. The link between the MRO operations and the maintenance Key Performance Indicators (KPIs) derives from the nature of data to be analyzed. Maintenance procedures, type of repairs, availability of machinery equipment, time, workforce, punctuality of external vendors and other parameters can act as inputs to different methods. It is important to mention here that as the Turn Around Time (TAT) of an overhaul project is minimized, the benefit is threefold: First, it results in the reduction of direct costs, related labor and machinery. Second, it results in better reputation in the clientele. Third and usually most importantly, it also results in additional capacity for an MRO provider, enabling the accommodation of additional maintenance projects.

In any case, there is a common denominator in any MRO data problem: *Data quality* [12]. Data quality is a separate research item on its own, but the important point here is that any prediction is as good as the data it relies on. So, datasets with missing values, data noise, high dimensionality or lack of balance will result in poor forecasting quality.

In case of flight technical data, the possibility of sensor malfunctions, recording issues, procedural changes or data accessibility due to contractual complexions are present. In case of MRO operational data, quality issues can also be encountered. They are mainly related to erroneous or incomplete registration of tasks, the existence of multiple registration systems, inconsistencies in recorded parameters in historical datasets and the lack of information regarding the performance of external maintenance organizations.

Another important contributor to effective forecasting in MRO operations is the legal aspects of data ownership. This is also a field of complex agreements and reduced clarity. A point of dispute was always the answer to the question *"Who owns the data?"* The operator normally has a claim to the data produced by its own equipment. However, OEMs claim data ownership as well, since they need to use them for continuous airworthiness. In addition, accessibility to various parameters is a matter of contractual agreement between the OEM and the operator, as there might be different levels of installed sensors, or service agreements. As a result, there might be encoded non-critical parameters that are not part of the data accessed by the operator. However, the detection of a critical failure is not always straightforward and it might only be achieved with a combination of features. To make things more complex, operators might have individual contracts with MRO providers regarding data accessibility. Maintenance organizations who offer power-by-the-hour contracts might require access to different data streams, as part of their services. And different contracts with different MRO providers in parallel with contracts with OEMs can well be the case for an operator. In addition, the operator might not be the owner of the equipment, which can be owned by a lessor.

This complex field of bipartite agreements can be an area of legal disputes and leads to limitations in the exploitation of the full value of data. Possible solutions can derive from structured data exchange systems, such as the Digital data Marketplace (DDM), as explained in [13].

3 CLASSIFICATION AND OPTIMIZATION

As discussed in paragraph 2, Data Analytics problems in MRO operations can be separated in two categories. Starting with the first type of problems, this is currently the most widely applied in the MRO domain. The main reason is that classification is a commonly encountered problem, usually related to the forecasting of maintenance processes, work scopes or overhaul optimization. By pursuing the identification of large-scale patterns, the operation of an aircraft system can be compared against a large pool of historical operational and maintenance data and its condition can be assessed. The needed MRO work can then be predicted. The benefits of such an approach are multiple:

- Better maintenance planning and fleet management.
- Better cost prediction for one-off or long-term maintenance contracts.
- Proactivity concerning the repair material needed and resource allocation.

- Fewer disruptions in the operation of repair shops.

Examples of descriptive and optimization problems are the ones requiring either simple calculations or linear programming, in order to forecast possible scenarios concerning the maintenance processes. Some examples of fundamental questions in this category are the following:

- *"Does a part require light, standard or heavy maintenance?"* Each class is predefined, based on a set of maintenance rules.
- *"What type of repair (if needed) is suitable for a specific part, operated under specific conditions?"*
- *"Which aircraft inspection scheme results in an optimum fleet availability and resource efficiency?"*
- *"What is the best labor and machinery schedule to meet the MRO workload?"*
- *"How can operational decisions be supported with the use of suitable visualizations?"* For example, illustration of various KPIs, such as scheduled vs. real maintenance times, correlations between flight hours and/or cycles vs. maintenance work scopes, labor workload, etc.

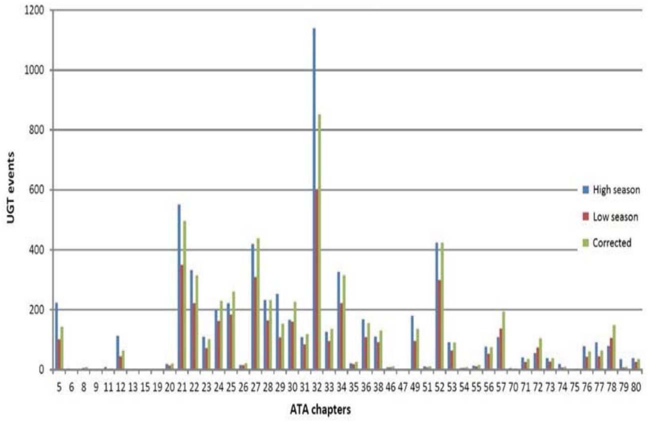


Figure 3: Unscheduled Ground Time events per ATA chapter and season

An example of classification problem for an MRO provider was the observation of a significant and unexplained decrease in fleet availability during the high season of an aircraft operator [14]. It is evident that a decrease in fleet availability results in lost revenue and damage in reputation. The research question in this case was the following: *"Can Data Analytics determine what problems occur more frequently during the high season, in order to explain the drop in fleet availability during this period?"*

To answer this question, the number of Unscheduled Ground Time (UGT) events were visualized in the high and low seasons per ATA chapter (Fig. 3). ATA chapters, also called "ATA 100 System Codes", are a way of categorizing the various aircraft systems, originally created by the Air Transport Association in 1956. In this case study ATA 32 (Landing Gear), ATA 29 (Hydraulic Power), ATA 21 (Air Conditioning), ATA 49 (Airborne Auxiliary Power), ATA 76 (Engine Control) and ATA 77 (Engine) were selected for further analysis. As the high season lasts longer than the low season, a data set corrected for the period has been added to find the differences between high and low season. These are the ATA chapters where a higher number of hours and events still occur in the high season than in the corrected low season.

To find the exact reason for the observed discrepancies between the low and high seasons, the UGT events were plotted against the sub-chapters of the aforementioned ATA chapters. Support Vector Machine (SVM) analysis was used, to see whether an operation-disturbing ATA chapter could be predicted based on parameters such as air temperature and humidity, as long as performed cycles. The analysis revealed that a major cause of unplanned ground time was the replacement of coalescers. And this event was found to be correlated with air temperature and humidity, an evident seasonal effect. Based on these insights, a new maintenance schedule for coalescers was proposed to the MRO provider.

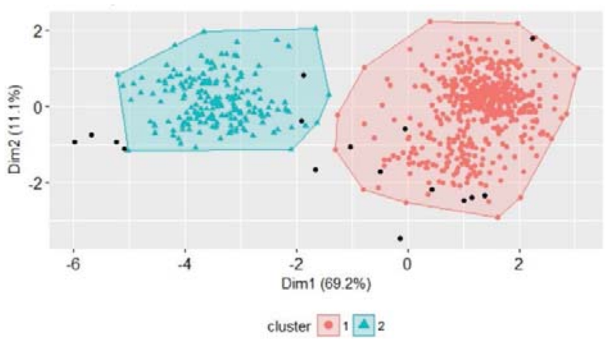


Figure 4: Clustering of take-off phase of a legacy aircraft

Another example of clustering problem for an MRO provider was the forecasting of unplanned maintenance for legacy aircraft [14]. In this case study the main research question can be expressed as follows:

"Can unscheduled maintenance and operational disruption costs be optimized, by using a combination of flight data, maintenance records and/or airworthiness records of legacy aircraft?"

An important point here is that in this specific case, sensitive flight data had to be excluded from the analysis and be replaced by data deriving from public domain sources. The two main challenges in this case were Data confidentiality and the unpredictable nature of legacy aircraft.

The first challenge was tackled by focusing on Automatic Dependent Surveillance-Broadcast (ADS-B) and weather data, obtained from open domain flight-tracking platforms. The second challenge was tackled by the nature of the developed model: Predicted aircraft failures were based on anomalous flights. For example, a hard landing might eventually result in landing gear failure and can be considered as an anomalous case. Two different clustering algorithms were used in order to identify the nature of the anomalous flights with the use of aircraft flight data: Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and k-means clustering. Continuing, the anomalous flights were corresponded to maintenance data, to identify whether the anomalies resulted in failures and discover possible correlations. Fig. 4 illustrates a clustering example of the take-off phase of a legacy aircraft for two dimensions, Dim1 and Dim2. The black dots represent outliers that do not fit in the criteria.

There are numerous other examples of applications of similar methods to MRO operations. Each case has different particularities and patterns in the datasets. This is the reason that an algorithm that provides satisfactory results for a specific problem is not necessarily replicable for a similar one.

Overall, classification, clustering and optimization methods are becoming increasingly popular in MRO operations. The accuracy of these methods depends on the nature and complexity of the problem, the suitability of the selected algorithm, the right selection of features for the training of the forecasting method, the quality of the data and how these data were pre-processed.

4 IDENTIFICATION OF RARE EVENTS

A technical dataset can also be used for the identification of slowly evolving processes, such as component degradation. However, a natural follow-up question is: *"Can an algorithm identify an imminent failure?"* Such cases can occur when degraded parts have reached their life limit, either as a result of a design flaw, or due to particular operating conditions. In other words, they can be considered as **rare** events.

Data Science has always been interested in identifying rare events. There are numerous applications in other sectors too, such as in finance and health sciences. The underlying principles remain the same, as the objective in every case is to identify outliers that can possibly indicate abnormalities in large datasets. An interesting point here is that the datasets to be analyzed in this case are the same as in classification and optimization problems. They consist of readings from sensors installed on aircraft, but the aim of the research is different. The algorithms are trained to identify combinations of feature values that are associated with specific failure modes.

A simplified example is the observation of a sharp increase in vibrations and reduced isentropic efficiency in a rotating component, the last based on inlet and outlet temperatures and pressures. Such an observation might indicate a possible material loss. As a result, if the specific component has a history of similar failures, then the possibility of identifying the same problem is relatively high. However, in reality things are more complex. The number of sensors installed on a specific aircraft component is small, compared to the number of its piece-parts. Thus, predictions cannot be usually part-specific.

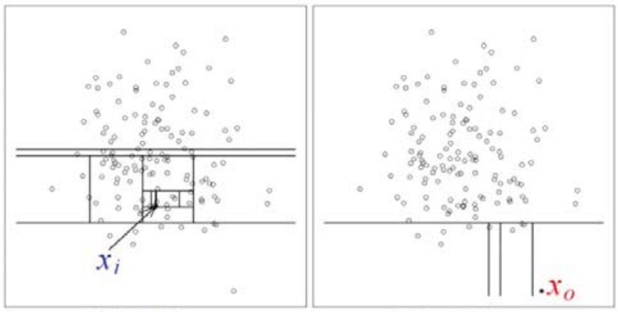
The best alternative way is the examination of a larger set of input features. The assumption is that an imminent failure will have a specific footprint to a combination of parameters, which can be unique for a specific failure mode and it can only be encountered prior to this failure. This assumption is case-dependent and it is a function of the used features, the algorithm, the piece-part design, the associated failure mode and it can only be approached as such. In other words, a method can be developed for a single failure mode of a specific part.

But even if this combination exists indeed, a Machine Learning algorithm needs to be trained, in order to be able to identify similar failures in the future. The training requires the availability of historical data which contain sufficient encounters of the same problem in the past. This number depends on the nature of the problem, but in general a new or relatively new failure mode cannot be predicted, as there are not enough data available. On the other hand, if a problem is well known, corrective actions can be implemented before the development of the predictive method, turning it obsolete.

Another aspect of the problem is related to the method's accuracy. According to the authors' experience, even in cases with high fidelity, such predictions can result to a number of either false positive or false negative results. The main issues with such predictions are the cost and the operational challenges. Two different questions can be asked at this point:

- *"If the method predicts an imminent failure, shall the aircraft be grounded immediately and performed inspections? What if the prediction is a false positive?"*
- *"If the method does not predict an imminent failure, shall we completely rely on it, risking an expensive shop visit in case this is a false negative?"*

As aircraft are used in operational environments and excessive grounding times should be avoided, the validation of such forecasts requires trust in the method and additional costs.



(a) Isolating x_i (b) Isolating x_o

Figure 5: Isolation Forest: (a) A normal point requires twelve random partitions to be isolated; (b) an anomaly requires only four partitions to be isolated.

It is important to note here that attention needs to be paid in the selection of forecasting features and their relevance. As correlation does not imply causation, there might be features that seem to be important for the prediction of a specific failure mode, but in reality there is no physical explanation for it. Therefore, the accuracy of the prediction can be compromised when new cases occur. As a result, expert input regarding the selection of predictors is essential. In the case of the aforementioned rotating component, pressure, temperature or vibrations make sense from a physics point of view. On the other hand, unrelated features might appear to contribute as well in a failure prediction and it is a matter of expertise to distinguish between a related and an unrelated parameter.

There are different algorithms that are being used for the solution of such problems. A very interesting case of algorithm is *Isolation Forest*, aiming in data anomaly detection [15]. According to Isolation Forest, the algorithm divides the space where a parameter belongs and tries to find the outliers, by random partitioning (Fig. 5). An outlier X_o in the dataset will require less partitions than a normal point X_i. Isolation Forest has the benefit of not requiring the presence of relevant outliers in the training set of the Machine Learning algorithm.

Another interesting example of a suitable algorithm is Logistic Regression [16], a method that is used to model the probability of a certain binary event, such as fail/not fail for an aircraft part. Generally, logistic regression is well suited for describing and testing hypotheses about relationships between a categorical outcome variable and one or more categorical or continuous predictor variables.

As a general comment, anomaly detection for failure prediction in Data Analytics for MRO is in an early maturity stage, despite the high potentiality. The efforts should be put in understanding the physical phenomena, their footprint in the machine behavior and how this is captured by a set of sensors.

5 CONCLUSIONS AND DISCUSSION

Data Analytics is undoubtedly one of the most active areas in aviation MRO today. In many cases, the technical infrastructure for data collection was already in place, as sensors were used for control or safety reasons in aircraft components and systems. MRO data were also generated within the premises of MRO providers, by registering maintenance operations. However, when the technology in data transfer, processing and storage became mature, the development of this domain was sharp and sometimes chaotic. For example, the realization of the value of data led to increased complexity in legal agreements among operators, MRO providers and OEMs.

Nevertheless, the storage of raw technical data does not have value per se. It is the developments in algorithms that facilitated the formation of Predictive Maintenance. Predictive Maintenance is the MRO practice where the decision for the maintenance of an aircraft component is educated due to the analysis of relevant data. As a result, the repair of parts can be optimal in time, cost and resources, but also with the minimum environmental penalties. However, Predictive Maintenance is not a general practice yet, as there are still many challenges ahead: Limited numbers and types of sensors installed, vast combinations of degradation/failure modes for different parts of the same component and complexity in the algorithmic domain. Data quality is also a very fundamental factor that is not always in place. Consequently, data Analytics in MRO are in a phase of quick development, but still not completely mature, despite the technical advancements in sampling rates, transfer speeds and computational capabilities.

Data Analytics do not necessarily need to be complex. There are many cases where a simple data visualization deck or simple statistics are sufficient for decision making support by an MRO provider. On the other side of the complexity spectrum, sophisticated Artificial Intelligence methods might be necessary for specific forecasting models. In any case, a complex method does not necessarily imply increased fidelity, while a simpler method can be more suitable.

Two main categories in Data Analytics can be recognized: First, the problems that aim at the identification of large-scale patterns, which enable the classification, clustering and optimization of different maintenance and overhaul processes. Second, the problems that aim to the prediction of rare events, such as the unexpected failure of parts. Typically, the penetration of the first category is higher, as results are easier to be achieved. However, the second category is very interesting as well, as it aims in reducing sudden incidents for the operator, with many direct or indirect costs involved.

As MRO services focus increasingly in long term contracts, maintenance organizations with the right forecasting methods will have an advantage over traditional ones, where the risks of wrong cost estimations can have a significant effect over the course of long periods. The right prediction of any maintenance requirements of large fleets is a key point, which can determine the survival chances of an MRO business.

It is justified then that data ownership and data quality are two very important factors. MRO providers will keep pushing for higher data accessibility with the promise of more cost-efficient maintenance. OEMs will also push towards the same direction for their MRO businesses, with the additional point of increased safety and early detection of possible technical issues that have the potentiality of becoming operationally challenging, if not detected. Last, aircraft operators with their own MRO businesses have many reasons not to share data with external parties, as they can rely on those data to provide better services.

The common denominator in all three cases is the capability in developing suitable and accurate Data Analytics methods. The competition in this field is already intense, where the demand for skilled Data Scientists becomes increasingly higher. However, the engineering knowledge is also essential and needs to be combined with the data science to provide meaningful results, as seen in various examples.

At the same time, numerous technical developments can be promising for the future. The most obvious are related to the ever-increasing data transfer speeds via satellites, which can provide faster diagnostics or prognostics. Other emerging technologies, such as Edge Computing [17], compete with this philosophy and promote the processing of data onboard the aircraft, which then transmits directly the results to the ground. Last, as the conflicts in legal aspects of data ownership will intensify, initiatives such as the Digital Data Marketplace [13] will be increasingly popular in the future, in order to set clear sets of rules and trust among the participating parties.

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BIOGRAPHIES

Asteris Apostolidis, PhD
Strategy & Technology Office
Air France-KLM Group
Tupolevlaan 2-12A
1119 NX Schiphol-Rijk
The Netherlands

e-mail: asteris.apostolidis@klm.com

Asteris Apostolidis is currently a Technology Innovation Manager at the Technology Office of Air France-KLM Group. Asteris holds a PhD in Computational Aerothermodynamics and an MSc in Aerospace Propulsion, both from Cranfield University (UK) and a Diploma in Mechanical Engineering from Aristotle University of Thessaloniki (Greece). He has worked for KLM Engineering & Maintenance in the areas of Predictive Maintenance, Data Analytics, Prognostics & Diagnostics. He was awarded with various research and academic grants from organizations such as the German Aerospace Center (DLR), Rolls Royce Plc. and Cranfield University.

Maurice Pelt, MSc
Aviation Academy, Faculty of Technology
Amsterdam University of Applied Sciences
Weesperzijde 190
1097 DZ Amsterdam
The Netherlands

m.m.j.m.pelt@hva.nl

Maurice Pelt is senior lecturer at the Amsterdam University of Applied Sciences (AUAS). He is responsible for the curriculum of the Industrial Management program. His current research focusses on the application of data science in the maintenance field. Furthermore he is research data steward for the Faculty of Technology. He holds a MSc degree Mechanical Engineering from Delft University of Technology (Netherlands).

Konstantinos P. Stamoulis, PhD
Aviation Academy, Faculty of Technology
Amsterdam University of Applied Sciences
Weesperzijde 190
1097 DZ Amsterdam
The Netherlands

e-mail: k.stamoulis@hva.nl

Konstantinos P. Stamoulis is currently an Associate Professor of Aviation Maintenance Engineering at the Amsterdam University of Applied Sciences (AUAS). He holds a PhD in Structural Analysis from University of Thessaly (Greece), where he was a research assistant at the Laboratory for Strength of Materials and Micromechanics. He also holds an MSc in Materials Science and Engineering (MIT, US) and an MSc in Applied Mechanics (National Technical University of Athens, Greece). Konstantinos was formerly a senior officer in the Hellenic Air Force (HAF), having served as an aeronautical engineer for 25 years. He has worked as research assistant at the Technology Laboratory for Advanced Materials and Structures (MIT, US) and he has broad, part-time teaching experience, at both the undergraduate and graduate level since 2004. In 2018, he was appointed full-time Associate Professor at the AUAS.