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A REVIEW OF SMART RESOURCE PLANNING IN MAINTENANCE, REPAIR AND OVERHAUL.

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With an estimated market value of 3.2$ trillion between 2021 and 2030, aerospace customer support and services play a key role in the lifecycle and costs of an Aircraft. The 70% of this market corresponds to maintenance, repair and overhaul activities (MRO). The digitalization and use of smart prediction systems in MRO could maximize operational efficiencies by improving the availability of in-service aircraft, as well as optimizing the resources required for it. Forecasting of preventive maintenance activities is generally based on estimated aircraft flying hours and impacts the MRO centre capacity, tools availability and inventory levels. The aim of this paper is to analyse the impact of new Artificial Intelligence prediction systems on the improvement of maintenance activities and resource planning in the MRO industry.

Keywords: MRO; Aerospace; Machine Learning; Planning; Capacity.

REVISIÓN A LA PLANIFICACIÓN DE RECURSOS INTELIGENTE EN MANTENIMIENTO, REPARACIÓN Y OVERHAUL.

Con un valor de mercado estimado de 3.2 trillones de dolares entre los años 2031 y 2030, la industria aeroespacial de soporte a cliente y servicios juega un papel esencial en el ciclo de vida y costes de una aeronave. El 70% de este mercado se corresponde con actividades de mantenimiento, reparación y overhaul (MRO). La digitalización y uso de sistemas de predicción inteligentes en MRO puede maximizar la eficiencia operacional mediante la mejora de la disponibilidad de las aeronaves en servicio, así como optimizar los recursos requeridos para ello. La previsión de actividades de mantenimiento preventivo se basa generalmente en estimaciones de horas de vuelo e impacta la capacidad del centro de mantenimiento, la dispobilidad de herramientas y los niveles de inventario. El objetivo de esta publicación es analizar el impacto de nuevos sistemas de predicción basados en Inteligencia Artificial para la mejora de las actividades de mantenimiento y la planificación de recursos en la industria MRO.

Palabras clave: MRO; Aeroespacial; Inteligencia Artificial; Planificación; Capacidad.

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1. Introduction

Aerospace customer support and services play a key role in the lifecycle of an aircraft. With an estimated market value of 3.2$ trillion between years 2021 and 2030 (Boeing, 2021), the 70% of this market corresponds to Maintenance Repair and Overhaul (MRO) operations, which aims to improve life expectancy, reliability, and availability of maintained aircrafts.

Carrying out MRO operations requires an efficient planning of maintenance resources and activities. The estimation of maintenance resources is obtained by forecasting, which can be classified in short-term (days to weeks), intermediate-term (weeks to months) and long-term (months to years). Forecasting of future maintenance resources is used for capacity planning, which determines the allocation of resources into the different maintenance activities (Al-Fares & Duffuaa, 2009). Examples of maintenance resources are manpower, tools, or spare parts.

Efficient MRO services will reduce aircraft downtime and costs by minimizing the required maintenance. Data has become a strategic maintenance asset due to the digitalization of the industry and advances in data analysis tools, allowing the transition into data-driven maintenance organizations.

2. Objectives

The aim of this paper is to analyse the impact of new Artificial Intelligence (AI) prediction systems towards the improvement of maintenance activities and resources planning in the MRO industry. Clustering and optimization of maintenance processes and prediction of anomalies, like unexpected failure of parts, are identified by Apostolidis, Pelt, and Stamoulis, (2020) as data analytics approaches utilised in aerospace maintenance activities.

Falling under this latter classification, some of the following areas of interest can be identified, like aircraft Prognosis and Health Management (PHM), forecasting, supply chain or spare parts/tools management. Those areas can be strongly benefitted with the application of data analytics and relevant articles have been selected to illustrate their impact on aircraft maintenance and data-driven maintenance operations. Public databases are frequently used as source data due to the limited availability of aircraft sensor and maintenance operational data. This review is focused on the use of Machine Learning (ML) techniques in aircraft PHM applications, identifying relevant case of study that provides a general overview of the impact of ML techniques on the MRO industry.

3. Methodology

Literature review was performed on IEEE Xplore, SpringerLink and ScienceDirect databases. The search was limited to publications from the year 2017 of journal, books and conference proceedings that includes real cases of use of data analysis in the MRO industry or that can benefit aircraft maintenance operations.

For this, the keyword *MRO* had been combined with the keywords *data analytics* or *artificial intelligence*. A first classification had been done for identifying relevant articles based on their title and abstract. After that, a full text analysis had been performed for identifying relevant cases of use of data analytics applied to MRO operations. During this review, *Remaining Useful Life, RUL,* and *anomaly detection* keywords used for PHM applications were identified and combined with the keyword *MRO*, so additional relevant literature could be integrated in the original search.

It is worth mentioning that this review aims to present a general overview of the use of Artificial Intelligence applications in the MRO industry, not an in-depth review of all cases of use available in the literature. For example, due to the availability of public engine life datasets, several articles of PHM applications over Turbofan engines that can benefit MRO operations were identified, but only the most relevant ones which present different analysis methods are presented in this review.

4. Results

4.1. Aircraft Prognostics and Health Management

Maintenance is the process of ensuring that a system performs its required functions. It can be classified as scheduled or unscheduled. One example of unscheduled maintenance is corrective maintenance, which is carried out after a failure and intends to restore the maintained asset functionality.

Safety is critical in aviation, and therefore proactive maintenance strategies are implemented, like preventive and predictive maintenance. Preventive maintenance organizes intervals of maintenance activities to reduce the asset probability of failure. Predictive maintenance activities are adaptively determined based on the asset condition and reliability estimates. Predictive maintenance is classified by Kothamasu, Huang, and VerDuin, (2009) as follows:

- Condition based maintenance (CBM). The condition of the system and its components determines the necessity of maintenance operations. This condition is determined by continuously monitored parameters, like vibration, noise, lubricant, or temperature.
- Reliability centred maintenance (RCM). Reliability estimates of the system are used to schedule cost-effective maintenance operations, analysing failure modes and the impact of maintenance activities on reliability, which is normally estimated from the asset time to failure.

Aircraft health data is a key factor for transitioning from corrective and preventive maintenance into predictive-based maintenance operations, improving the planning of maintenance activities and optimising aircraft availability. The use of Aircraft health data combined with Machine Learning analysis can be used to create Maintenance Decision Support Systems to find the optimal maintenance policy (Azar & Naderkhani, 2020).

Aircraft health data is acquired and process using the Health and Usage Monitoring System (HUMS), which collects data from aircraft sensors, like vibration, temperature, pressure, or rotating speed of critical systems. Generally, aircraft data is stored in compact flash memories for post-flight analysis. Nonetheless, on-board analysis and monitoring of specific components are performed, such us the monitoring of engine vibrations for warning purposes. Current aircraft HUMS monitor critical systems with known failure modes, mainly based on vibration, temperature, or pressure measurements.

Big data platforms for managing real-time health status have been proposed (Zhang et al., 2015) and are commercially available for aircraft operators. One example is Skywise Health

Monitoring data platform (Airbus, 2017), developed by Airbus in partnership with Palantir for A320, A330, A350 and A380 fleets. Flight data analytics could be used for monitoring pilot behaviour or traffic flow dynamics, detecting safety risks, flight operations improvement strategies or Aircraft health condition (Zhao et al., 2021).

The use of big data platforms that integrate operator aircraft data along with PHM and aircraft system analysis (Li, Verhagen & Curran, 2020) could be used to improve future aircraft designs, enabling condition-based maintenance in a broader number of systems.

Due to the availability of public datasets and the criticality of the system, aircraft PHM research and applications are usually focused on engines (Mathew et al., 2017) and auxiliary power units (L. Liu et al. 2019), along with studies covering flight control electromechanical actuators (Berri, Vedova, & Mainini, 2021), hydraulic system (Yan et al., 2019), or landing gear system (Haider, 2019).

Some of the PHM limitations are described by Zio (2022): quality of the data, which may be scarce, incomplete, unlabelled, and noisy; lack of interpretability, that reduces the trust of the results; and security of PHM models in safety critical applications, which may require to include built-in forensic capabilities to identify intrusion detection and prevent maliciously introduced input data.

Current aircraft health management applications are focused on maintenance and logistic improvement. However, they are expected to be exceeded and expanded upon in the future and become an essential component in autonomous and safety-critical aerospace systems. Some examples of these new capabilities are the cognitive evaluation of the human operator to adjust mission autonomy, replanning of mission activities based on failure detection and mission performance, system adaptability to different failure modes and available sensor data or the improvement in accuracy and reliability (Ranasinghe et al., 2022).

Generally, a complete PHM framework includes a first phase of data acquisition and storage, followed by a fault detection phase to identify early signs of wear and damage and a final step to estimate the Remaining Useful Life (RUL) of the system. Fault detection and RUL are normally estimated in post-flight analysis due to computational requirements.

Anomaly detection

Anomaly detection is the process of finding unexpected events and items in an observation. An unexpected behaviour will not necessarily cause a failure in a system, but its identification can represent an early fault or degradation of a component that needs to be evaluated.

One of the main challenges of anomaly detection in the aerospace industry is the detection of rarely reported events, as the datasets used for training are extremely imbalanced. Apart from this, false negatives can incur in safety critical situations and false positives in bad MRO resource planification. The use of Deep Reinforcement Learning (DRL) techniques is proposed by Dangut et al. (2022) to tackle the imbalance ratio of the datasets, detecting extremely rare failure problems in complex systems. Proposed models are based on Deep Q-networks (DQN) and State Action Reward State Action (SARSA) adaptations with Prioritized Experience Replay (PER) memory. These models are validated with A320 and A330 Aircraft Central Maintenance System (ACMS) datasets, proving that extremely rare failures can be effectively predicted with low false-positive and false-negative rates using DRL. Those methods include a reward function that allows the model to alter its own behaviour in response to it.

Anomaly detection can represent an alternative to the traditional RUL estimation. Baptista, Henriques and Prendinger, (2021) present binary classification models used in RUL estimations. Proposed classification provides useful information for industry experts to decide if a maintenance action is required. In order to do this, several Machine Learning models are compared and tested using two real case studies, the first one relates to a gas turbine engine and the second one to a valve-subsystem of the engine. Models evaluated are K-Nearest Neighbours (KNN), Random Forests (RF), Naïve Bayes (NB), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP) and Deep Learning methods, such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). Comparing the performance of the proposed methods, Deep Learning ones obtain better results, followed by the RF algorithm. Traditional classifiers like KNN, NB, SVM and MLP do not seem to be suited for these prognosis tasks.

The hydraulic system plays a vital role in an aircraft and provides power to critical systems, like flight controls, brakes, doors or landing gear actuators. It includes a variety of components, such as reservoirs, pumps, hydraulic pipes, filters, actuators, valves, etc. Anomaly detection of complex systems is challenging and generally requires the use of multi parameters that represents its behaviour.

A semi-supervised autoencoder anomaly detection model is proposed by Yan et al. (2019) for analysing aircraft hydraulic systems using Quick Access Recorder (QAR) flight data. A total of 334 flights are analysed along with the aircraft maintenance records, identifying the health state of the hydraulic system during each flight. A total of eight monitoring parameters of the hydraulic system are used, including oil volume and pressure. Results obtained have better performance in anomaly detection compared to benchmark methods. Wang, Zhang and Wang, (2020), analyse the hydraulic system using the unsupervised K-Means clustering algorithm, identifying health statuses: health, sub-health, and non-health. The model is trained using previous low-pressure fault alarms occurred in 338 flights.

A data-driven architecture for semi-supervised anomaly detection combining LSTM networks and one-class Support Vector Machine (SVM) classifiers is proposed by Vos et al. (2022). The model is validated with an Airbus Helicopters' gearbox dataset and obtains good results given its simplicity. Although the model can detect anomalous behaviour in the deterministic components of the signal, weaker changes in the random components are not detected. To tackle this, a new architecture in two steps is proposed, using a LSTM regressor trained with healthy signals, enabling an increase in the identification of these components with the one-class SVM.

Remaining Useful Life

The remaining useful life is defined as the period in which an asset or system is expected to be usable for its purpose and is one of the key factors in Condition Based Maintenance (Si et al., 2011). The objective of PHM research is to estimate the RUL in advance of the system failure and allocate the necessary resources and materials for an optimum maintenance strategy.

Data-based RUL methods can identify hidden features contained in the raw data but heavily depend on performance parameters and training data. To improve accuracy, data-based methods can be combined with traditional physical degradation models, which can improve accuracy and stability of RUL predictions (X. Liu et al., 2020).

The acquisition process can produce large amounts of data that cannot be processed on-board. To tackle this issue, a real-time methodology based on Support Vector Machines (SVM) for real-time fault detection and prognosis is proposed by Berri et al. (2021). The model is validated using flight control system's Electromechanical Actuator (EMA) data and combines real physics behaviour with Machine Learning techniques, reducing the computational requirement by compressing the monitoring signals with Self-Organizing Maps (SOM) and Proper Orthogonal Decomposition (POD). A compression map is generated offline and applied for onboard PHM analysis, reducing the computation requirements.

The auxiliary power unit (APU) can be started using the aircraft battery(s) and provides bleed air for cabin conditioning during ground operations and main engine start capability, as well as an additional source of electrical power. Generally, exhaust gas temperature (EGT) is acknowledged as the most important parameter for estimating the remaining useful life of APUs, although it can be combined with other on-wing sensing data to improve performance and stability in the predictions. L. Liu et al. (2019) propose a data-driven approach based on Gaussian Process Regression (GPR) to predict the APU RUL.

Different Machine Learning models are evaluated by Mathew et al. (2017) for the RUL estimation of Turbofans using sensor measurements from degrading engines and obtaining the best results with the Random Forest algorithm. A PHM framework that includes condition assessment, fault classification and RUL estimations combining multiple deep learning algorithms is proposed by Che et al. (2019). The model is validated using NASA C-MAPSS data sets (turbofan engine) and has more accurate prediction compared to traditional models. The framework uses various stages composed by Deep Belief Networks (DBN), Back Propagation neural network (BP), and LSTM.

A method based on Generative Adversarial Networks (GANs) is proposed by Fu et al. (2019) for generating condition monitoring data of aircraft engines, compensating for the lack of monitoring data samples and allowing accurate predictions.

4.2. Machine Learning methods in MRO

Machine learning (ML) is defined as "a set of methods that can automatically detect patterns in data, and then used the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty" (Murphy, 2012).

The use of ML models in MRO PHM applications is presented in the Table 1.

Table 1. Machine Learning models in MRO PHM applications

Reference	Source	Analysis	Models	Performance Metrics
(Azar & Naderkhani, 2020)	Engine	PHM	Clustering: K-Means. Classification: RF, KNN, SVM, and NB	Train accuracy, SD of train accuracy, Test accuracy

(Baptista, Henriques & Prendinger, 2021)	Engine	PHM	Classification: RF, KNN, SVM, NB, MLP and deep RNNs (LSTM, standard RNN, GRU)	AUC, F-Score
(Dangut et al., 2022)	ACMS	Failure Prediction	Deep Q-network, Double Deep SARSA-Learning, Double Deep Q-Network	G-Mean, FPR, FNR
(Vos et al., 2022)	Gearbox vibration	Anomaly Detection	LSTM, SVM	Accuracy, precision, recall, F1
(Yan et al., 2019)	Hydraulic System	Anomaly Detection	Deep Stacked Auto-Encoder (DSAE)	Accuracy, precision, recall, F1
(Wang, Zhang & Wang, 2020)	Hydraulic System	PHM	K-Means	-
(Fu et al., 2019)	Engine	PHM hazard model	GANs	Generated data correlation
(X. Liu et al., 2020).	APU	RUL	Hybrid LSTM combined with physical degradation model (Wiener)	Mean absolute error, root mean square error
(Che et al., 2019)	Engine	PHM	LSTM, DBN, BP	Accuracy
(Mathew et al., 2017)	Engine	RUL	Decision Trees (DT), SVM, RF, KNN, K-Means, Gradient Boosting Method (GBM), AdaBoost, Deep Learning, Anova	Root mean square error
(Berri et al., 2021).	Flight control EMA	PHM	SVM and SOM for signal compression	Root mean squared error, uncertainty intervals
(L. Liu et al., 2019)	APU	RUL	GPR	Mean absolute error, root mean square error

There is a wide variety of ML methods and are usually classified into the following main categories: supervised, unsupervised, semi-supervised and reinforcement learning. The objective of supervised learning is to map labelled inputs and outputs, such as classification and regression methods. Unsupervised learning tries to find patterns in unlabelled data, like the clustering of input data into groups and dimensionality reduction. Semi-supervised models are used when a higher number of unlabelled features is present in a dataset. Finally, reinforcement learning models does not use a fixed dataset and explores the environment by trial and error during training; their experience becomes part of the dataset, and a reward function is used for evaluating the learning outcomes.

Supervised models' performance is generally evaluated using a confusion matrix, which records correctly and incorrectly predicted values. A confusion matrix for binary classification includes the following items: true positives (*tp)*, false positives *(fp)*, false negatives *(fn)* and true negatives (*tn)*. Built from those values, accuracy, precision, recall, F-Score, AUC or ROC measures are traditionally used for performance evaluation (Sokolova, Japkowicz & Szpakowicz, 2006).

Relevant articles are classified considering the data source, objectives of the analysis, ML models, and performance metrics used for evaluation. Failure prediction, anomaly detection or RUL estimations have been classified as such, although can be classified as PHM analysis. Classified as PHM studies generally include anomaly detection and RUL phases.

Maintenance activities could benefit from the use of data analytics but are limited by the parameters monitored. The integration of PHM in the Aircraft lifecycle management is challenging and requires the assessment of eligible systems whose health and failure modes can be monitored and analysed. Identified aircraft systems or components that can be benefited with aircraft PHM are focused on engines, APUs, gearbox and rotary parts, EMA or the hydraulic system. The lack of public datasets and knowledge over failure modes and representative monitored parameters limits the analysis on a wider number of aircraft systems.

In anomaly detection for aircraft PHM applications, labelled data is not widely available and if exists, generally corresponds to operational system condition. Therefore, semi-supervised and unsupervised models are commonly used, although supervised models can be used as well for anomaly detection.

Different approaches interesting for aircraft maintenance have been identified. Firstly, early fault detection models can be used to identify abnormal behaviour of aircraft systems and evaluate if maintenance activities are required. Secondly, clusters representing health status can be identified and the classification of monitoring data into these health clusters is used for determining maintenance necessities.

For the remaining useful life estimation, supervised regression models are widely used. Apart from regression models that determine the life expectancy of a system, other approaches have been explored for RUL estimation. The classification at a particular time interval on the necessity of performing maintenance operations in the next interval is proposed by Baptista, Henriques and Prendinger, (2021), using far from end-of-life and close to end-of-life statuses. Aircraft spare parts can have long lead times and accurate RUL estimation can be used for planning maintenance resources and managing inventory levels, reducing aircraft downtime.

Compared to RF models, traditional classifiers like KNN, NB, SVM and MLP do not obtain good performance results for engine PHM applications. Baptista, Henriques and Prendinger, (2021) analyse performance metrics of various methods used for Engine PHM applications and compares them to baseline classifiers. For example, the random classifier obtains a F-Score of 18.14% in the first analysed dataset, higher than the obtained with KNN (17.11%), NB (17.38%), MLP (17.63%) and GSVM (18.04%). This baseline F-Score is improved using RF classifier (18.38%), as well as deep learning methods, like LSTM (25.72%), RNN (33.19%) and GRU (32.88%). With regards to the second dataset analysed, the random classifier obtains an F-Score of 48.37%, higher than the obtained by NB (39.82%), KNN (40.28%), MLP (40.78%), RF (43.01%) and GSVM (43.63%) classifiers. Again, deep learning methods obtains the better classification performance: RNN (49.40%), GRU (55.04%) and LSTM (55.09%).

Deep Learning, Generative Adversarial Network and Deep Gaussian Process models used for reliability and safety applications are gaining popularity due to their advantages over other types of ML (Xu & Saleh, 2021). Deep Learning consists of organised connected multiple layers and can be used in supervised, unsupervised, semi-supervised and reinforcement learning. DL is capable of handling high dimensional data and learning more complex functions, outperforming shallow ML methods in reliability and safety applications. GANs models consist of two neural networks, generator and discriminator, competing in a classification task.

5. Conclusions

Data can be used for improving MRO operations and has become a strategic maintenance asset with the advance in analysis tools and the digitalization of the industry. Data-driven maintenance decisions can reduce human bias, improve aircraft safety and reduce overall maintenance costs.

Machine Learning can be applied to several areas of MRO industry, such as asset health management or maintenance process improvement. Regarding aircraft health management, ML models can be used for aircraft anomaly detection, classification into known failure modes or remaining life estimations of aircraft systems. These analysis in turn, can be used for maintenance resource planning and the selection of optimal time frames for performing maintenance operations. With regards to the optimization of MRO processes, examples of spare parts classification, demand forecasting and inventory management (Bhalla et al., 2021) or capacity forecasting (Dinis, Barbosa-Póvoa & Teixeira, 2022) can be found. Analysis of ML applications in the MRO industry for maintenance processes optimization is not included in the scope of this publication and is proposed as a future work.

Given the variety of data generated in the MRO industry, different data sources can be used for addressing the same problem. For example, spare parts management of an aircraft component can be approached both by RUL estimation and the analysis of the aircraft component procurement data. No publications have been found in this review that evaluate possible synergies or compare the impact of using different data sources for approaching the same problem. For example, Yan et al. (2019) and Wang et al. (2020) address the life monitoring of the Hydraulic system of an aircraft using airborne sensors measurements, like oil pressure or oil quantity. Anomalies detected in hydraulic sensors can be used for planning appropriate inspections and allocate required maintenance resources. Apart from this, a different approach based on the analysis of procurement datasets of specific parts of the Hydraulic system, like oil pumps, could be useful for identifying trends or inspection requirements, which would potentially improve or complement the estimations obtained with the PHM analysis. Would the results obtained from an aircraft-life-oriented dataset be better than the obtained from a procurement-oriented one? And the results obtained from a model that combines both? Identified literature is focused on model performance, but the possibility of combining complementary datasets is not evaluated. Apart from this, cannibalization of interchangeable parts fleetwide for improving fleet serviceability suggests that there might be benefits in addressing spare parts management at fleet level.

The nature of aircraft and MRO operational datasets makes some ML models more suitable than others. For example, PHM training data used for failure detection is generally imbalanced, as system failures rarely occurs, and the datasets will be biased towards the normal operational conditions. Moreover, the complexity of aircraft systems might require high dimensional input data and appropriate models need to be selected to handle it.

Applications of ML in aircraft maintenance present some limitations that need to be addressed. Given the variety of datasets and applications, appropriate model selection can be a challenging task. The comparison of analysis models for identifying the most suitable one given a data source requires the use of common performance metrics. Reviews like the one presented by Baptista, Henriques and Prendinger, (2021) or Mathew et al. (2017) are very useful for this task, as different models are evaluated. However, as can be identified in Table 1, there is a lack of standardization in performance metrics utilised for analysing proposed model performance. For example, the performance of engine PHM models is measured by Baptista, Henriques and Prendinger, (2021) with the AUC and F-Score metrics, but Azar and Naderkhani (2020) or Che et al. (2019) evaluates the performance exclusively using the accuracy for a similar analysis. With regards to the performance of PHM applications that can benefit MRO operations, false positives can incur in inefficient MRO resource planning and false negatives in undetected unsafety situations. Accuracy only measures the percentage of correct predictions, so it could be considered insufficient for identifying the suitability of a particular model used in MRO applications, whereas the F-Score and AUC provide more information. Apart from this, other ML limitations are the quality of the data, lack of interpretability that reduces the trust over obtained results and models security in critical applications. Aircraft online computing limitations with a rising number of monitored parameters need to be addressed, and reducing misclassification is paramount for the use of ML in MRO applications.

Condition Based maintenance using aircraft health data cannot be applied over all aircraft systems, as might not be feasible to evaluate all possible failure modes using aircraft sensors. Future studies in aircraft systems failure modes, monitoring signals and analysis models can be used for improving future aircraft designs.

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Communication aligned with the Sustainable Development Objectives