Predictive Maintenance Analytics and Implementation for Aircraft: Challenges and Opportunities

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Abstract

The increase in available data from sensors embedded in industrial equipment has led to a recent rise in the use of industrial predictive maintenance. In the aircraft industry predictive maintenance has become an essential tool for optimising maintenance schedules, reducing aircraft downtime and identifying unexpected faults. Despite this there is currently no comprehensive survey of predictive maintenance applications and techniques solely devoted to the aircraft manufacturing industry. This article is an in-depth state-of-the-art systematic literature review of the different data types, applications, projects, and opportunities for predictive maintenance in this industry. The goal of this review is to identify, and highlight the challenges and opportunities for future research in this field. This review found that the current focus of research is too biased towards aircraft engines due to a lack of publicly available data sets, and that greater automation is an important step to optimise aircraft maintenance to its full potential.

Keywords: Aircraft maintenance, Predictive maintenance, Machine learning, Deep learning, Big Data Analytics

1. Introduction

All engineered objects are inherently unreliable as they degrade with age and use, and will ultimately fail if unmaintained [1]. Regular maintenance is important to extend the operational lifetime of industrial equipment and reduce the loss in revenue caused by its downtime. This is particularly important for aircraft, where airlines and customer have high expectations for aircraft to be flight ready, and the high loss in revenue induced from out of service aircraft. In 2018 around $69 billion was spent by airlines globally on conducting maintenance, repairs and overhaul, consisting of 9% of their total operational costs [2]. Between 2009 and 2019 there was a 183% increase in scheduled passengers on airlines globally [3], and between 2019-2039 the size of aircraft fleets globally is predicted to almost double [4]. As older models of aircraft with fewer sensors are retired and replaced, both the maintenance requirements of aircraft systems and the recorded data will greatly increase across this time frame, requiring more .

The various maintenance strategies used across different industries can be broadly split between reactive and proactive methodologies, for rectifying equipment failures immediately and preventing them from occurring respectively. Corrective maintenance (CM) is a reactive methodology where maintenance is unscheduled and performed immediately after an asset fails. This is the oldest method that best utilises the maximum lifetime of components and is the easiest strategy to implement for technicians. Preventative Maintenance (PM) is a proactive methodology where maintenance is scheduled and performed at predefined intervals to reduce the probability of failure in the future. Interval periods for PM are generated by following maintenance programs, such as the Maintenance Review Board Report [5], where engineers use their experience to perform experiments and collect data to determine the most appropriate length of maintenance intervals.

Predictive maintenance (PdM) is where the system is regularly monitored, and maintenance action is only triggered by a pre-defined condition of the system. PdM can exploit networks of sensors to gather data which can be analysed to identify the health and degradation of a given system. By analysing a systems physical parameters such as temperature, pressures or vibration using either trend analysis, pattern recognition or statistical analysis, it is possible to predict the condition of the system at which failure is imminent. Therefore, before the degradation level reaches this threshold, the system that is about to fail can be replaced. PdM is not a perfect strategy. Performing a combination of the different maintenance strategies is still the most reliable approach for maintaining aircraft effectively.

The increase in available data recorded from on board sensors across different aircraft systems, has driven greater use of data-driven PdM. The data collected from an aircraft can be analysed using statistical models to determine relationships and generate predictions of measured parameters. There are three main use cases for PdM in the aerospace industry; real-time diagnostics, real-time flight assistance and prognostics [6]. Real-time diagnostics allows for faults detected in flight to be recorded for immediate repair on landing, and real time fight assistance can provide guidance for the pilot. Prognostics is responsible for predicting the degradation of a system by interpreting the operational and environmental condition to estimate the systems remaining useful lifetime (RUL) [7] or its end-of-life (EOL). These metrics can be used to help determine the optimal maintenance schedules for replacing and repairing aircraft components to maximise their lifespan. Without effectively utilising this data for PdM, terabytes of available data are effectively wasted where it could be used to save money, time, and manpower.

1.1. Contributions

Contribution of this paper: There are several state-of-the-art reviews for different industrial predictive maintenance techniques [8][9][10], ML methods for PdM [11] and PdM for specific aircraft components [12]. To our knowledge, there does not exist an exhaustive evaluation of the current state-of-the-art focused on PdM for all available aircraft systems. This paper compiles and compares the current demographic of publications in the field of aircraft maintenance, to support readers and future research. The documents collected can be used to identify areas where predictive maintenance has and could be applied, which datasets and predictive models that have been used to compare results against, and the challenges and new opportunities the field contains.

1.2. Paper Organisation

This paper follows the review structure outlined in Figure 1 to provide a thorough literature review and provide detailed discussion on future opportunities for new researchers to this field. It starts with an extensive review of available academic literature regarding which data types can be used for prognostics in section 2, and what benchmark datasets are used for replicating results. This is expanded by identifying which models and tools have been applied to these datasets and other in different PdM applications in section 3. Section 4 outline different projects and industrial services for PdM, to highlight the growth within academia and industry. Section 5 reviews the challenges researchers in this field will encounter, as well as opportunities afforded by new technologies. Section 6 concludes the main points, summarizing the trends from the most impactful papers from the literature review, and identifying key research areas in the future.

2. Data Types and Benchmark Datasets

Due to the explosion in new data sources and prognostic techniques, greater use of data-driven prognostics is being used alongside traditional maintenance techniques for aircraft systems. Raw sensor data collected from aircraft components can be interpreted to assess the health of an aircraft and detect patterns and measurements that indicate health degradation and performance loss. Coupled with the growing availability of publicly available datasets for different engineered systems [13], experimentation in the field of industrial PdM has risen in recent years. The following section examines the different data types that have been used for PdM in recent publications. The most used benchmark datasets that have been used for PdM have also been identified, providing datasets as comparators between papers of similar applications. These benchmark datasets were selected for their aerospace focus and consistent use within 10 or more state-of-art-papers in the past 5 years.

2.1. Data Types

There are three main data types for aircraft maintenance data, time series, natural language and graphical data. The source, use and papers where this data has been used for aircraft are displayed in Table 1. The number of time series datasets greatly outnumber the others due to the ease in collecting and processing the data compared to natural language processing (NLP) and computer vision required for language and graphical data respectively. NLP could provide a suitable redundancy for identifying indicators of problems with aircraft, however widespread application of NLP is doubtful due to integration problems. There will be inconsistencies between airline reporting protocols and the written language that pilots use around the world, producing inconsistent data that will be more difficult to accurately process. Graphical data has rarely been used for aircraft PdM so far, but its greatest use is for technician inspecting aircraft bodies, and since 1998 it has been proposed that much of this work could be offloaded to robots [14]. This can be performed by gathering graphical data consisting of photos using robotics systems. One such approach recorded aircraft fuselage images taken by drone Aircraft by Airbus for automated fuselage inspection, reducing inspection times from 2 hours to 10-15 minutes [15].

2.2. Benchmark Datasets

There are datasets that have been released to encourage research in the field and enable greater cross comparison between work. Many of these dataset have been available online by in a Data Repository operated by NASA [13], but only one has been used in the field of aircraft maintenance.

The Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) is a transient simulation of a large commercial turbofan jet engine, with a realistic engine control system developed by NASA [19]. It has been used frequently in publications to generate multivariate time series engine datasets for developing novel prognostics and health management models. The most commonly used example is a set of run-to-failure datasets [20] which have been used in at least 68 publications [21]. Each dataset

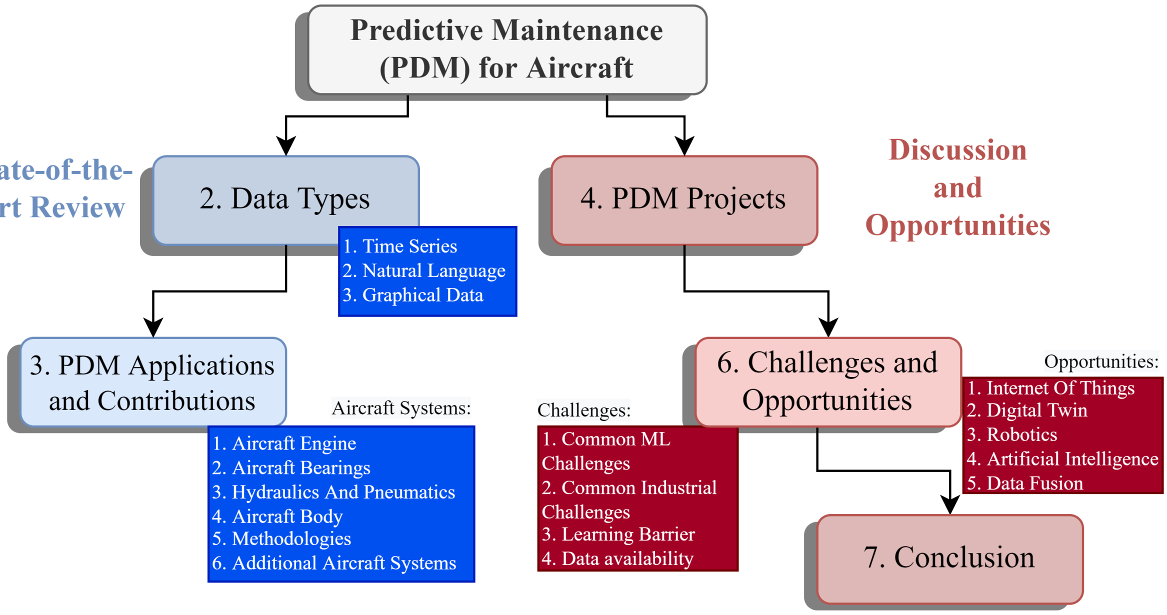

Figure 1: Review structure for this state-of-the-art review

contains 100 different engines, and the multivariate time series is split into 26 fields ranging between engine identifier, cycle time and 21 different sensor measurements. These example datasets have been used frequently in aircraft PdM papers as shown in section 3.1, and are suitable for comparing models between similar datasets. While allowing for easier comparison of models against similarly structured simulated datasets, there are drawbacks to over reliance from researchers using these datasets. As the most used dataset, applications investigated are skewed towards turbofan engine models, with significantly fewer academic papers dedicated to other vital components such as hydraulics and bearings which require different sensors and models to process effectively.

Starting in 2008, the Prognostics and Health Management (PHM) society has organized an annual data challenge competitions for attracting attention to address PdM problems within different industries. A new dataset from a different industrial field has been released each year with a different prognostics goal. This data reflects covers a couple of additional topics such as Anemometer [22] and Gearboxes [23]. Two of the datasets generated for these challenges have been generated using C-MAPSS [24]. Besides the C-MAPSS dataset, there is a general lack of publicly available dataset, or similar simulation tools to build datasets for aircraft-specific components. Some aircraft components such as the PRONOSTIA ball bearings dataset [25] and batteries [26] can be translated from other industries where the datasets are available, and are considered as transferable systems in this review.

3. Predictive Maintenance Applications and Contributions

Strategies for performing PdM are being applied to a wide range of different industrial fields and applications, with many novel methods developed in recent years. Many authors have applied different methods to applications, using a mix of data analytics and machine learning. A number of papers have summarised and compared different machine-learning algorithms for predictive maintenance in the general industry already [8][27]. This section identifies the key state-of-the-art methods published in journals in recent years. This section highlights the paper's key features, the highest performing models for each appellation, and the future work proposed by each paper to encourage future innovations.

Of the papers highlighted in this section, different traditional and ML models were applied. These are shown in Table 2, with their respective strengths and weaknesses. What follows is a review of the different PdM applications that have been addressed within the aircraft industry specifically and the publications that represent the current state-of-the-art. Figure 4 shows a treeline diagram of all the papers that were highlighted by this review, both for aircraft specifically, and transferable industries.

There were three primary criteria for the selection of these publications; being aerospace focused where there are papers available, having been published in the last 5 years to be considered state-of-the-art, and being well cited respective to their release date. Where no aerospace examples exist, transferable industrial systems have been used instead. The papers were searched for in respected

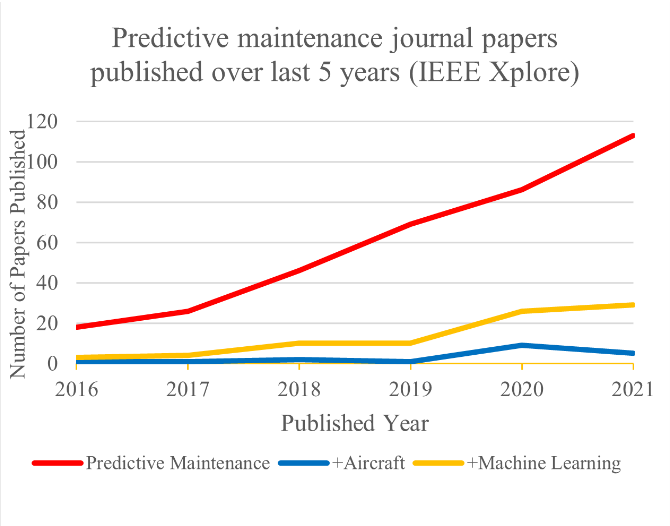

Figure 2: PdM Journal Papers Published Over last 5 years available from IEEE Xplore

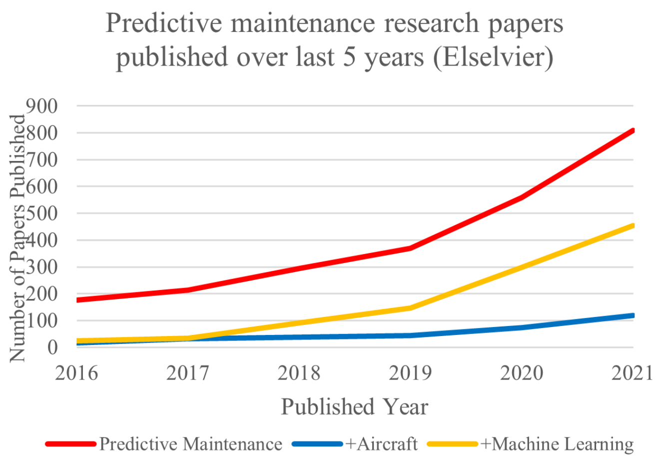

Figure 3: PdM Journal Papers Published Over last 5 years available from ScienceDirect (Elselvier).

research databases IEEE Xplore and Elsevier, using keywords that have grown in popularity as the field has grown, as shown in Figures 2 and 3 respectively. These figures highlight the growth in research in predictive maintenance, and to a slower extent the focus of aircraft and machine learning.

3.1. Aircraft Engine

Aircraft engines are complex and require regular maintenance, making up 35%-40% of the total aircraft maintenance expenses from an operator [43]. Turbofan engines can contain large suites of sensors that record values such as fan inlet temperature and pressure, and physical fan speed [44]. C-MAPSS generated datasets have been found to be used most frequently in publications, particularly the datasets released for the PHM 2008 data challenge [20] which has cemented itself as an established benchmark for new approaches.

State-of-the-art reviews have already been conducted investigating aircraft engines. Due to the time series nature of most engine data, it was suggested that machine learning models will be used more frequently, specifically LSTMs [12]. However, this paper only highlights LSTM examples which are hydraulics focussed. Another paper also supports a move towards LSTMs, however, also highlights random forests as a powerful traditional model [45]. For this section, we have looked at the paper that both fit within these trends, and those that defy them. Table 3 contains a list of the papers covering PdM for aircraft engines that were investigated as part of this review.

Published papers in the scope of the proposed research methodology support these identified trends. Long Short-Term Memory Networks have been used frequently for time series data. LSTMs have been used to identify features in time series data despite no clear trends existing in the dataset [42]. Three Bi-directional LSTMs (BLSTM) have been applied to a C-MAPSS dataset to extract features, learn higher features, and generate target outputs respectively, outperforming other deep learning models [46]. In a comparison between multiple traditional and deep learning models against a C-MAPSS dataset, random forest model attained the highest performance, and an LSTM outperformed.

Some papers published in the last 5 years don't fit these trends as well. While still moving towards machine learning, CNNs have been used to success for performing PdM. A novel Deep Convolutional Neural Networks (DCNN) utilizing a time window approach to improve feature extraction had significant cross-paper performance and outperformed an LSTM network [40]. Hybrid models are only briefly touched upon in previous reviews, and in the last couple of years have been used successfully against C-MAPSS generated datasets. A hybrid Maintenance Decision Support System for prognostics using unsupervised and supervised techniques[47] coupling Cox Proportional Hazards Model and K-means clustering to labels unlabelled data. Supervised multi-class classification is then applied to optimize the PdM predictions using several different supervised models, with SVMS, KNN and Random Forest consistently achieving accuracies of over 95%. LSTMS have been used in hybrid models [28], and when coupled with DCNN for handling fine-grain data and exploring different, LSTM cells and optimization functions can fine-tune the performance as suggested by [42].

3.2. Aircraft Bearings

Bearings are components that reduce friction between moving parts moving relative to one desired axis. In aircraft they are commonly found in engines, landing gear, hydraulic fuel pumps, doors, and cockpit controls. The reliability of a bearing is paramount, as a single bearing failure can potentially jeopardize hundreds of lives [48]. Measuring the quality of bearing directly with sensors can

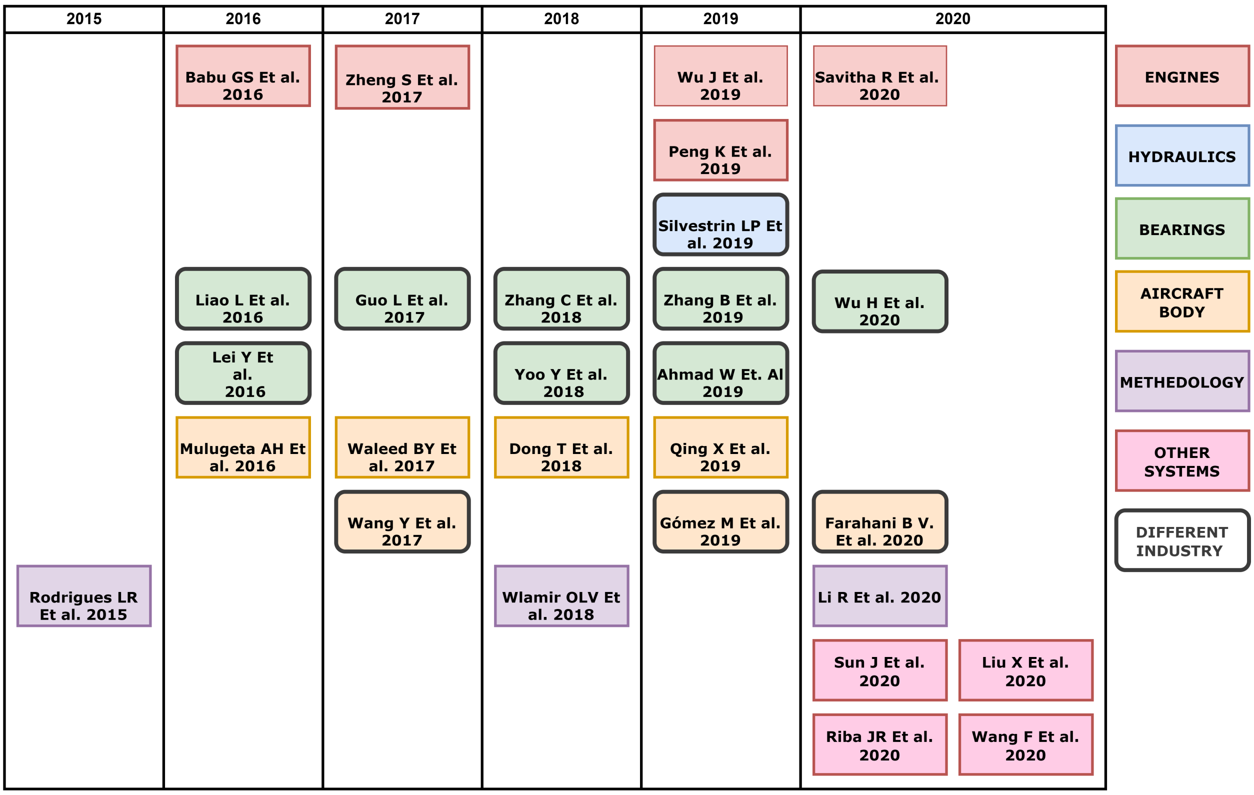

Figure 4: Treeline diagram of all the papers highlighted by this review, by year.

be difficult with no direct measurements possible, therefore measurements for temperature, vibration, and acoustics are used to assess their health.

There are no publications that propose PdM methods for bearings tested against data sourced from aircraft or respective simulations that could be found for this review. There have been many papers that have used the motor bearing dataset for the 2012 PHM data challenge, which contains temperature and vibration signals that could be translated to aircraft systems. Since its original release, the employed models have shifted from traditional ML methods such as RBM [17] and particle filtering [33] and standard RNN [49], to more commonly use deep learning. Most notably a proposed LSTM method that outperformed a CNN and sparse auto-encoder [50]. However this was not compared against non-ML methods, or even proposed models from other publications against the same dataset. Despite this, DL models are being more commonly used in recent years, with LSTMs [51][50] and CNNs [52] at the forefront. Table 4 contains a list of the papers covering PdM for bearings that were investigated as part of this review.

3.3. Hydraulics and Pneumatics

Hydraulics are a mechanical function that operates through the force of liquid pressure. In hydraulics-based systems, mechanical movement is produced by a contained pumped liquid, typically through cylinders moving pistons. They are commonly found in construction, automotive engineering and in aircraft, which exploit the larger amount of power that can be generated compared to pneumatics. Hydraulic systems are used in many different areas of an aircraft such as in landing gear, fuels lines and for engine driven pumps. Despite this importance, there are no publicly available aircraft hydraulics data sets or publications that could be found for this review.

A comparison of many state-of-the-art machine learning algorithms was performed by testing against hydraulic system sensor data [27]. They found that the traditional methods with feature engineering outperformed deep learning models likely due to the small dataset size which deep models struggle more with. Table 5 contains a list of the papers covering PdM for hydraulics and pneumatic's that were investigated as part of this review.

3.4. Body

The fuselage and frame of an aircraft is just as vital a component as the engine and is liable to damage from bird strikes, lightning strikes, and degradation over time. In recent years particle filters[31], and Kalman filters [32] have been used to estimate and predict the size of flaws and cracks in the aircrafts frame and wing leading to significant cost reduction. For a more thorough monitoring structural health monitoring has been used to assess the condition of engineered systems. It is conducted by observing and analysing the sensor measurements of a system to assess the health of the structure. An overview of piezoelectric transducer-based SHM system technology for aircraft addresses some of the challenges of applying SHM to aircraft, but suggests that the field is expanding from diagnostics, to prognostics, using data-driven methods yo predict the life and performance of the aircraft structure [54]. It has been suggested that the aviation industry is unable to exploit SHM-based inspections as it is not cost effective, and the weight of sensors systems must first be reduced [55]. SHM has been used in other industries already, some elements of which could be reapplied to future SHM for aircraft when these challenges have been addressed. In recent years it has been used to identify defects in wind turbine blades [56] and detecting defects in railway tunnel structure and [57]. Table 6 contains a list of the papers covering PdM for the aircraft body, and transferable papers covering SHM that were investigated as part of this review.

3.5. Methodologies

The applications of PdM in aircraft are not the only innovations in recent years, as several publications have focused on the methodologies implemented alongside them. A methodology to estimate overall systems-level RUL, with the goal of interpreting component level RUL to make replacements that will benefit the system RUL was proposed [58]. Despite some existing state-of-the-art methodologies, one major drawback is the lack of a rigorous process for defining requirements and proposed a systematic derivation for system requirements for the further development of PHM systems [59]. Table 7 contains a list of the papers covering maintenance methodologies that were investigated as part of this review.

3.6. Additional Aircraft Systems

There are other specific aircraft systems that have been optimised using PdM. The Auxiliary power unit is an essential piece of equipment for an aircraft; however, it has a non-linear degradation process. Data-driven and physics models alone make poor predictions on these, so a hybrid of the two was proposed, feeding exhaust gas temperature data into an LSTM to generate the RUL [16]. Random forest has been used to assess the performance and predict the RUL of an aircraft auxiliary power unit [29]. Using random forest and Bayesian dynamic models to quantify degradation, achieving a prediction error rate of less than 4%. It was tested against a multivariate ACMS report from a commercial aircraft fleet covering values such as pressures and temperatures for air, bleed, and oil. Low-pressure environments are more prone to corona and arc tracking, and three methods were proposed to monitor them [61]. This includes an example of graphical data used by UV imaging sensors to detect arcs. These methods allow for on-line monitoring of this activity and are compatible with predictive maintenance approaches. Table 8 contains a list of the papers covering PdM for the additional aircraft systems that were investigated as part of this review.

4. Predictive Maintenance Projects

Predictive maintenance needs are growing in this industry as data collection and greater development of data-driven prognosis tools enable greater exploitation of it. In parallel, greater funding and awareness is required to ensure tools are developed and new researchers are educated and inspired. This section provides insight into what projects and services the industry is investing in, to help guide research towards methods and tools that are beneficial and in demand by airlines and manufacturers.

Table 9 outlines the PdM projects that have been received in recent years, both by governments and within the industry. Although only one project was identified outside of the scope of the last 5 years, DAMEs goal to aid diagnostics differs from the joint goals of the remaining projects to advance PdM and problem forecasting technologies. Prognostics to forecast problems is a primary focus of PdM research, which is supported by the number of RUL estimation techniques proposed in recent years. Funded research will likely continue to focus on prognostics, real-time diagnostics or other uses of PdM .

As well as the grants afforded to academic research and universities, companies are developing services to handle and process the growing available data to enable more optimized maintenance. The largest of these services are shown in Table 10. All the tools provide the benefit of reducing aircraft downtime, return to service time, operational which highlight these as the key needs for airlines. Collecting and consolidating data is another key goal of these systems, due to the increase in available data harvested from aircraft in more recent years.

This research field is fast-growing, with more PhD opportunities listed by universities and laboratories around the world in recent years. The CRAN research laboratory focusing on novel methods for data-driven PdM, at the Delft University of Technology researching optimisation approaches for PdM maintenance planning [74] and at Cranfield University researching the optimisation of UAV maintenance paradigms using artificial intelligence [75]. Universities have received greater support from the industry, with sponsored PhD's in this field, such as the University of Southampton, working alongside GE to advance optical fibre sensor technology for PdM application in aircraft [76]. The last of these also highlights the future of research in this industry, implementing greater use of automation and AI for greater optimisation and accessibility.

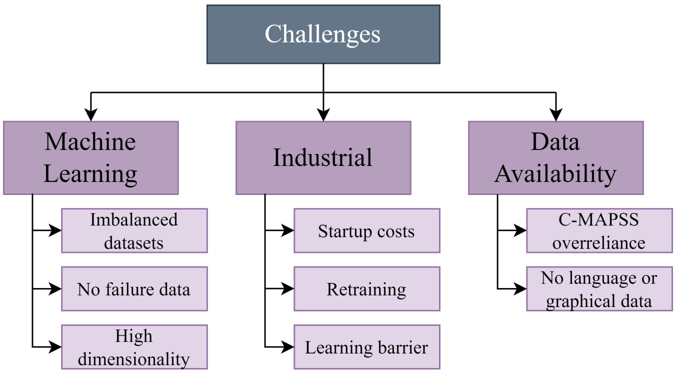

Figure 5: Challenges for Predictive Maintenance(PdM) research for aircraft.

5. Discussion: Challenges and Opportunities

There are a number of challenges that researchers will face, summarised in Figure 5. This section outlines the challenges that researchers in this field will need to overcome to enable widespread and effective use of PdM for aircraft. New technologies that can be exploited to provide valuable opportunities to expand research in this field are also highlighted.

5.1. Challenges

PdM tools utilizing ML architectures must navigate the same challenges and pitfalls that all ML tools for predictive analytics face. This section discusses the larger challenges and potential solutions for the implementation and distribution of these techniques within the aircraft industry.

5.1.1. Common Machine Learning Challenges

Machine learning, particularly deep learning, is being used more often in recent years for PdM for aircraft problems. The same challenges that appear in many other industries are just as rel event to aircraft. A systematic review of AI-based prognostics was performed by [77], who highlighted several notable diagnostic challenges, such as noisy sensor readings, difficulties in accurately modelling the physical process of systems [78] and health degradation trends [79]. The datasets used to train ML models are commonly imbalanced, as faults are generally uncommon in aircraft, and data is skewed towards normal operation. This leads to the model struggling to learn the minority class of failed systems, and requires methods such as those summarized by [80] to counteract the imbalance. In many cases, there is no failure data at all, as preventive maintenance schedules encourage replacing faulty components before they reach failure. Finally, with huge numbers of embedded sensors available in aircraft, there can be a high dimensionality in the data collected, risking the curse of dimensionality, where the higher the dimension space, the denser the data samples are required [17]. The reliability of maintenance predictions may vary between aircraft systems which these problems, making aircraft wide health diagnosis difficult to ascertain.

5.1.2. Common Industrial Challenges

Starting a new PdM scheme requires the purchase of new sensors, software, and tools. Companies that lack these resources and the required data for training will have to invest money to build up their resources, as well as time to collect data and train technicians to use the new tools. These costs increase when applied to large and complex engineered objects such as aircraft, which require more intensive sensor networks and specialised knowledge to install and utilise. PdM can be the most optimised maintenance strategy, but not for every problem or system and these high start-up costs can discourage companies looking to invest in PdM solutions These tools have a learning barrier for inexperienced programmers, whereas Domain specialists and technicians who are less likely to possess this experience may have the most to contribute to its tuning. New technologies such as AI-driven automation could be implemented to select parameters, and analytic models and interpret results with limited coding experience required. This could help to de-skill the process and allow greater use within manufacturers and airlines in the future.

5.1.3. Data Availability

While the availability of data. There are several datasets available for performing PdM, many supplied by the PHM society. However, over the course of this review, no public datasets beyond those generated using C-MAPSS, or specifically the PHM were identified. Natural language and graphical datasets in particular are rare and underused in PdM research. This is a major problem, as there is an obvious bias in the aircraft systems that PdM solutions are being researched for as demonstrated by the skew in engine-focused papers. The aircraft manufacturers who benefit from this research are unable to publish the proprietary aircraft data that belongs to the airlines, limiting the scope of potential research outside of the industry. Research covering other engineered systems, such as bearings and hydraulics, may be possible to translate to some aircraft problems as they share the same physical properties, and collected data types. For more aircraft specific research however the simulation or acquisition of more aircraft maintenance data is vital to broaden the breadth of future research in this field.

5.2. Opportunities

New technologies could enhance and automate the PdM process, allowing for greater optimisation of industrial systems. While some of these technologies are still in their infancy, some are well developed and merely have yet to be reapplied to the field. The following is a list of technologies that could provide opportunities to enhance PdM for aircraft in the future.

5.2.1. Internet Of Things

The Internet of things (IoT) defined as a world where physical objects are seemingly integrated into the information network [81], has widespread industrial applications for physical systems containing sensors. There are proposals for coupling this technology with aircraft systems for making aircraft maintenance more autonomous [82][83][84] to apply this to commercial aircraft components. They are a prime candidate with a greater number of embedded sensors in recent years for overseeing the performance of equipment.

5.2.2. Digital Twin

A Digital twin is the virtual representation that serves as the real-time digital counterpart of a physical object or process. Infosys services build digital twins of critical aircraft systems, such as engines and landing gear, and apply analytical solutions to the various aircraft system and sources [85]. Unlike many other tools, there is a keen focus on text analysis over raw sensor data, analysing maintenance logs and visualising analytics on a smart dashboard alongside other analytics. Recently a paradigm hybrid system of combining multi physical modelling with data-driven analytics was proposed [84]. Using a digital twin, the system would continually adapt to operational changes using collected sensor data of industrial equipment in real-time to increase autonomy. It has the potential to revolutionise the relationship between engineers and aircraft systems in terms of speed, autonomy and required programming experience to operate.

5.2.3. Robotics

Acquiring data is vital for performing accurate PdM, and automation provided by robotics systems allows for more automated data acquisition. Aerial drones are already being deployed for performing near-autonomous inspections to assist technicians, further automating the data collection process for conducting maintenance. In 2018, Rolls Royce revealed they are working with the University of Nottingham and Harvard University to develop cockroach inspired robots, with the intention to mount them with cameras for performing inspections inside aircraft engines [86]. Collecting more data improves the performance of data-driven methods and deep learning, so every opportunity to automate the data collection process will improve the efficiency and accuracy. Network of robots working in unison could greatly optimise data collection and fault identification, such as the network of drones and climbing robots for wind turbine global inspections [87]. Like aircraft maintenance, wind turbine maintenance is manual and operates across a large structure. Climbing robots could be applied for aircraft fuselage inspection, especially during weather conditions that disable drone inspection.

5.2.4. Artificial Intelligence

Artificial intelligence (AI) is the attempt of machines to learn independently and emulate natural intelligence and forms the field in which both machine and deep learning belong to. An intelligent PdM framework was proposed that utilises multiple features of the 4th revolution, with data generated by cyber-physical systems, transmitted and processed using the IoT, and providing early alerts by Internet of Service [88]. This all centres around autonomous systems working together with a strong focus on AI. They recognise that elements such as feature selection are currently performed manually by experienced engineers. This is labour intensive and costlier but could be replaced by proposed deep learning methods to automatically extract features. A systematic review of AI prognostics theories and architectures has been conducted, which is primarily situated in the field of deep learning [77]. The focus of their research is to lead to the development of an "overall solution with several interacting components" but questions both the costs of the development of deep learning tools against the benefits they propose and the lack of consistent high-quality data in the field. As computational power and data collection capacity increase these concerns will be mitigated, and the use of a single automated system appears to be a common goal for those in the industry. Automated machine learning (Auto-ML) could also be applied to build complex DL systems with minimal human assistance required. Tools like Auto-Keras can be used to build DL models for regression, classification, and time forecasting problems, which has applications for predicting aircraft system deterioration.

5.2.5. Data Fusion

While system deterioration can be predicted from single data sources, data fusion can integrate data from multiple sources. This improves the accuracy of the prediction of deterioration, and better utilises the abundance of recorded data. A data-level data fusion method for early detection of incipient faults and achieved a lower variance before the occurrence of incipient faults when tested of a C-MAPSS generated dataset [89]. It can also be used at a decision-level, such as for predicting the RUL of an aircraft engineering by interpreting as a convex optimisation problem instead of the traditional linear regression problem and outperforming preliminary decisions using individual sensors. Datasets generated using C-MAPSS have been used as they provide up to 21 parameters. There is room to improve on this work, either by integrating a greater number of parameters and applying the method to real-time prognostics.

6. Conclusion

State-of-the-art Predictive maintenance techniques can be applied to a wide range of aircraft maintenance applications for optimising maintenance. This paper serves as a state-of-the-art review to identify the novel solutions that are being applied to PdM problems and plot the current landscape of the field. PdM can be more optimised than alternative maintenance strategies for maximising the RUL of aircraft components. By applying prognostic methods to the growing number of available benchmark datasets, it is more possible than ever to develop novel PdM methods. Further development of PdM is inevitable, given the rising number of novel methods and potential applications in the field. The enhancements afforded by new technologies such as robotics and AI will further optimise and automate these procedures. Greater use of it has the potential to greatly reduce maintenance costs for aircraft manufacturers and operators.

In the current landscape, PdM is performed by data engineers and researchers in academia but is inaccessible to in-experienced users who could benefit from it most. Even easily accessible tools such as Microsoft AZURE, which possess predictive maintenance guides using C-MAPSS data [90], requires some level of domain knowledge and programming experience to understand and use effectively. Dedicated predictive maintenance tools that utilise new technologies such as AI and Auto-ML to provide greater automation would enable a wider user base. Automated tools will enable a greater number of people to build predictive maintenance models on aircraft data. Greater research into automated tools in this field will encourage both more development and use in the industry, leading to greater savings and safety afforded to in-service aircraft.

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Data Type	Source
Time Series	Turbofan Engines [16]), landing gear hydraulics and bearings [17]
Natural Language	Pilot complaints, equipment failure logs [18] and post flight reports
Graphical Data	Imaging of Aircraft fuselage and wing

Table 1: Most common data types for aircraft maintenance data.

Architecture	Operation	Strengths	Limitations	Applications and References
SVM	Generates an optimal line/ hyperplane to separates data into different classes for classification or regression problems.	Very effective in high dimensional spaces where number of dimensions exceed number features and samples.	Unsuitable for large datasets. Sensitive to noisy data, missing values, and outliers and under performs where number of features exceeds dimensions	RUL Estimation [28]
K-Nearest Neighbour	Classifies new data based on a similarity measure between the new data point and several of the nearest existing data points.	Faster as there is no training period. Easy to add new data to the datasets without impacting accuracy. Simple and easy to implement.	Unsuitable for large datasets. sensitive to noisy data, missing values, and outliers and cannot handle high dimensional well. Requires feature scaling.	RUL Estimation [28]
Random Forest	An algorithm consisting of multiple uncorrelated decision trees, to more accurately predict by committee than an individual tree	Reduces overfitting in decision trees while improving accuracy. Works well with both categorical and continuous data.	Computationally intensive. Long training times. Struggles to determine the significance of parameters.	RUL Estimation [28][29]
Particle Filter	Solve filtering problems for a Markov process by calculating the posterior distributions of the states and applying a Monte Carlo algorithm.	Simple to implement for many different problems, can work with high dimensional data and scales well.	Computationally expensive, difficult to measure performance and non-deterministic.	Fatigue estimation [30][31][32] Bearing RUL estimation [33]
Autoencoders (AE)	ANN that replicates data at output from input through a smaller encoder layer, reducing the dimensionality but keeping maximum input data variance.	Can identify features from the data and doesn't require labelled data (Unsupervised learning).	Extracted resources not necessarily specific to problem. Loses temporal relation input data are raw sensor data. Leads to overfitting.	Calculating RUL of Aircraft Engine [34][35]
Restricted Boltzmann Machine (RBM)	Similar operation to autoencoder, consisting of simplified Boltzmann machines. Learns the probability distributions of data.	Extract meaningful features from input data, maintain spatial representation in the new space	Fails to maintain data variance in new space and difficult to model complex systems with only one layer in model.	RUL prediction for ball bearings [17], Aircraft health prediction from time series sensor data [36]
Deep Belief Networks (DBN)	Deep ANN, successive stack of RBMs that learn to probabilistically reproduce the input at the output with the RBN layers.	Same as RBM and can classify faults from frequency distributions	Requires pre-processing, tends to overfit and cannot model temporal relaxations.	Health diagnosis of aircraft engine [37], RUL prediction of C-MAPSS degradation datasets [38]
Convolutional Neural Networks (CNN)	Deep ANN consisting of layers of receptive fields here features are convolved by applying kernels.	Exploits neighbourhoods, can reduce training time and data required by weight sharing, prevent overfitting using dropout.	Slower training than other deep ANNs and can't model long-term dependencies.	RUL prediction from raw time series sensor signal [39] and [40], Internal pump leakage prediction of Hydraulic system [27]
Recurrent Neural Networks (RNN)	ANN that reuses information from the past network using a feedback connection from the hidden or output layers back to the preceding layers	Can model the temporal relationship of time series data and capable of self-learning.	Suffers the vanishing gradient problem, cannot model long-term dependencies, and requires more resources than AE and CNN for training.	Prediction of bearing defect propagation [41](
Long Short-Term Memory Network (LSTM)	Deep ANN variant of RNN, similar structure but with additional gates to model longer term dependencies.	Same as RNN but can model longer term dependencies.	Long training time and high computational requirements.	RUL prediction from raw time series sensor data [42] and [27], Hoogendoorn and Koole, 2019)

Table 2: List of predictive models that have been used in the highlighted papers in this review.

References	Method	Features	Future Work
Zheng S, Ristovski K, Farahat A, Gupta C [42]	LSTM	RUL estimation. Identifies hidden patterns. Outperformed traditional model and CNN.	Implement detection degradation point. Investigate alternate LSTM structures. Add a CNN layer to reduce frequency and noise.
Li X, Ding Q, Sun JQ [40]	Deep CNN (DCNN)	RUL estimation. Uses time window approach to improve feature extraction.	Include the scoring function in the loss function of the neural network.
Huang CG, Huang HZ, Li YF [46]	Bidirectional LSTM (BLSTM)	RUL estimation. Integrates multiple sensors data with operational conditions data.	Address the issue of limited training data and combining the proposed method with model-based prognostic approaches to expand the potential prognostic application scenarios.
Azar K, Naderkhani F [47]	Hybrid Maintenance Decision Support System	Fault diagnostic and prognostics. Infers and fuses high-dimensional/multi-modal data sources. Recommends optimal maintenance decisions without human intervention	None Stated
Chen C, Lu N, Jiang B, Wang C [28]	Hybrid LSTM-SVR	RUL estimation. Employs degradation feature selection. Obtain crucial features reflecting the system degradation.	Apply the proposed method to other engineering systems and investigating systems with multiple failure modes.

Table 3: Publications employing state-of-the-art PdM for Aircraft Engines

References	Method	Features	Future Work
Liao L, Jin W, Pavel R [17]	RBM	RUL estimation. Employed a novel regularization term to maximise trendability. Automatically generate features suitable	Employ a deep structure of RBMs.
Lei Y, Li N, Lin J [33]	Stochastic process model/Kalman Particle Filtering	RUL Estimation. Validated against PHM 2012 dataset. Compared with and outperformed 4 methods.	Investigate how to acquire the initial model parameters for this model.
Guo L, Li N, Jia F, Lei Y, Lin J [49]	RNN	RUL estimation. Overcome common drawbacks of health indicators.	Investigate new RUL models: Conditional three-parameter capacity degradation model and stochastic degradation model.
Yoo Y, Baek J-G [52]	Continuous Wavelet Transforms and CNN	Compress feature extraction, selection, and fusion into a single algorithm. Validated against PRONOSTIA dataset.	Overcome limitations of proposed method. Larger training data. Improve reliability for health indication
Ahmad W, Khan SA, Islam MMM, Kim JM [53]	Regression	RUL estimation. Infer RUL from a dimensionless health indicator.	Extensive studies with greater number of different applications and datasets for validation.
Zhang B, Zhang S, Li W [50]	LSTM	Assess the degradation of bearings. Utilize the fault propagation information. Validated on simulation model based on vibration response mechanism.	Investigate two problems: 1) The difficulties simulating random mutation of degradation process. 2) How the degradation process is split into stages by time.
Wu H, Huang A, Sutherland JW [51]	LSTM	Predict health of a manufacturing system. Superior classification of critical states than SVM	Increase the accuracy on early stages by employing parameter tuning within the architecture of the RNN.

Table 4: Publications employing state-of-the-art PdM for bearings

References	Method	Features	Future Work
Silvestrin LP, Hoogendoorn M, Koole G [27]	Temporal CNN (TCNN)	RUL Estimation. Comparison of different traditional ML and DL models. Validated against a hydraulics dataset	Apply the algorithm to more PdM datasets. Increase the dataset size to confirm the proposed method outperform traditional methods utilising feature engineering.

Table 5: Publications employing state-of-the-art PdM for hydraulics and pneumatics

References	Method	Features	Future Work
Haile MA, Riddick JC, Assefa AH [30]	Particle Filter	Integrated diagnostic framework. Fatigue life estimation of critical rotorcraft structures"	None Stated
Yousuf W Bin, Khan T, Ali T [31]	Particle Filter	Predict posterior probability density . Estimate flaw size for aircraft wings. Applied to Airbus A310 data.	Incorporating alternative life distributions or mechanical fatigue models.
Dong T, Kim NH [55]	N/A	Reviews sensor types for aircraft SHM. Highlight costs saved by SHM outweighed by added sensors weight.	Repeat study with considerations to sensor reliability.
Wang Y Et al. [32]	Extended Kalman Filter	Estimate fatigue crack size in airframe. Predict future crack size/ distribution. Significant cost reduction	None Stated
Qing X Et al. [54]	N/A	Overview of piezoelectric transducer-based for aircraft SHM. Identifies challenges for SHM of aircraft.	Extensive study in individual highlighted challenges.
Gómez Muñoz CQ Et al. [56]	N/A	Identify defects in wind turbine blades. Utilise ultrasonic sensors	None Stated
Farahani B V. Et al. [57]	None (Employs computer vision)	Detect defects in railway tunnel structure. Utilise monitoring of railway tunnel's 3D geometry	None Stated

Table 6: Publications employing state-of-the-art PdM for aircraft bodies and transferable engineered systems.

References	Features	Future Work
Rodrigues LR Et al. [58]	Estimate overall systems-level RUL of aircraft. Combine systems architecture information and the RUL estimations across all the aircraft systems available.	Use a larger dataset for further experimentation and testing
Li R, Verhagen WJC, Curran R [59]	Systematic derivation of system requirements for prognostics and health management system development. Defines detailed processes for requirements definition.	None stated
Vianna WOL, Yoneyama T [60]	Methodology for predictive line maintenance. Optimisation of redundant aeronautical systems	Incorporate troubleshooting tasks to the planning optimization process.

Table 7: Publications proposing state-of-the-art methodologies for PdM.

References	Method	Features	Future Work
Liu X, Liu L, Liu D, Wang L, Guo Q, Peng X [16]	Hybrid LSTM	RUL estimation of Auxiliary power unit. Use non-linear degradation data	Study optimisation method to determine the dimension of generated data. Improve stability/accuracy of RUL predictions.
Wang F, Sun J, Liu X, Liu C [29]	Random Forrest	RUL estimation of Auxiliary power unit. Uses four performance baseline models to improve accuracy. Validated on 22 auxiliary power units of a commercial aircraft fleet.	None Stated
Riba JR, Gomez-Pau A, Moreno-Eguilaz M [61]	N/A	Detect arc tracking in low-pressure environment. Evaluate three low-cost and small-size sensing methods.	None Stated
Sun J, Wang F, Ning S [62]	Dynamic Linear Model	Novel Bayesian failure prognostics approach. Uses Aircraft Condition Monitoring System (ACMS) data.	Reapply method to medium and short-ranged aircraft fleets.

Table 8: Publications employing state-of-the-art PdM for additional aircraft systems.

Project	Recipients	Goal	Grant Amount
Distributed Aircraft Maintenance Environment (DAME) [63]	Rolls Royce, Data Systems and Solutions and Cybula, and the universities of York, Oxford, Leeds, and Sheffield	To build a Grid testbed for Distributed Diagnostics	£3,096,172 from the U.K. Engineering and Physical Research Council
Overall Management Architecture for Health Analysis (OMAHA) [64]	Lufthansa Industry solutions	Overall Management Architecture for Health Analysis to develop forecast models and standardized system of monitoring airplane conditions	Unknown amount from German Federal Ministry for Economic Affairs and Energy's aviation research program
UPTIME [65]	11 European-based contributors	To build a unified framework for PdM strategy	€6,248,367.50 from the EU, Horizon 2020 programme
Unnamed [66]	University of South Carolina (UofSC) college of Engineering and Computing	To further advances in the fields of robotics, combustion and PdM	$5.7 million from NASA

Table 9: Grants awarded to projects focusing on PdM around the world

Tool name	Company	Features	Benefits	Application and Customers
Amazon Web Services [6]	Amazon	Report maintenance problems in real-time both to the pilot and maintenance staff for detecting and preparing maintenance for problems	Detecting and preparing maintenance for problems	Optimises predicting and preempting fleet maintenance (Korean Air) [67]
Aircraft Health analysis and Diagnosis (AHEAD) [68]	Embraer	An integrated tool consolidating aircraft data to Optimize maintenance activities	Advanced notification for unscheduled events, faster support and Reduce return to service time	Realtime Aircraft fault alerts (JetBlue and US Airways) [69]
Airbus Real Time Health Monitoring Service (AiRTHM) [70]	Airbus	Provides real-time remote access to aircraft data parameters, allowing for optimised maintenance and real-time troubleshooting actions	Reduces aircraft down time, maintenance costs and enables anticipated unscheduled maintenance	Provide components for PdM Support (Sichuan Airlines) [71]
AnalytX [72]	Boeing	Predictive analytics service providing Digital Solutions, Analytics Consulting Services and Self-Service Analytics [72]	Apply predictive analytics to increase time to evaluate, plan and manage solutions	Real-time maintenance and engineering support (Air Peace and EnterAir) and accessing real-time maintenance data (Amber, Go2Sky, Landry's, and Metrojet) [73]

Table 10: Identified PdM services and tools provided by members of the industry.