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REVIEW ARTICLE

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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 optimizing 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 optimize aircraft maintenance to its full potential.

KEYWORDS

aircraft maintenance, Big Data analytics, deep learning, machine learning, predictive maintenance

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 customers 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 and 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 utilizes the maximum lifetime of components and is the easiest strategy to implement for technicians, however, is the most expensive, and while common, no industry would use widespread run-to-failure methodology [5]. 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 [6], where engineers use their experience to perform experiments and collect data to determine the most appropriate length of maintenance intervals.

There are many definitions for predictive maintenance (PdM), but the common thread is that PdM is to review the data from the mechanical conditions, operating efficiency and similar indicators of the condition of a mechanical device, to make appropriate maintenance decisions as to maximize the interval between repairs [5]. PdM is where the system is regularly monitored, and maintenance action is only triggered by a predefined condition of the system. PdM can exploit networks of sensors to gather data that can be analyzed to identify the health and degradation of a given system. By analyzing 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.

Aircrafts are more capable than ever of recording vast amounts of sensor data across almost all of their components in flight, with an Airbus A380 having up to 25,000 sensors [7]. This increase in data has driven greater use of data-driven PdM, that is to build and train PdM algorithms using data rather than domain experience. The data collected from an aircraft can be analyzed 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 [8]. Real-time diagnostics allow 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 system's remaining useful lifetime (RUL) [9] 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 maximize their lifespan. Without effectively utilizing 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

There are several state-of-the-art reviews for PdM; however, 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 in future research. The documents collected can be used to identify areas where predictive maintenance has and could be applied, which datasets and predictive models have been used to compare results against, what tools the industry has been developing to aid in these problems for customers, and the challenges and new opportunities the field contains.

1.2 | Paper organization

This paper follows the review structure outlined in Figure 1 to provide a thorough literature review and provide a detailed discussion of future opportunities for new researchers in 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 others in different PdM applications in Section 3. Section 4 outlines 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 | RESEARCH METHODOLOGY AND BIBLIOMETRIC ANALYSIS

2.1 | Research methodology

The purpose of a literature review is to gather the available sources on the topic being researched and perform a thorough evaluation to identify research gaps, trends, and so forth. To conduct an effective literature review then, a methodology is required to structure the research toward the goal of conducting a thorough review. This research methodology consists of three main parts as follows, establishing the research questions this review intends to answer, conducting a bibliometric analysis, and a thorough review of the material to identify trends and research gaps. A diagram for the methodology can be seen in Figure 2. The scope of this review will only extend to 2015, as only the state-of-the-art techniques are being evaluated by this review.

2.1.1 | Research questions

This paper will attempt to answer the following research questions to provide an effective review of this field.

1. Who and what are the most significant people, journals, organizations, and countries that are leading in this field?
2. What are the primary applications of the aircraft industry that state-of-the-art PdM is being applied to?
3. What are the biggest challenges the field faces, and what potential opportunities are afforded by new technologies to mitigate them?

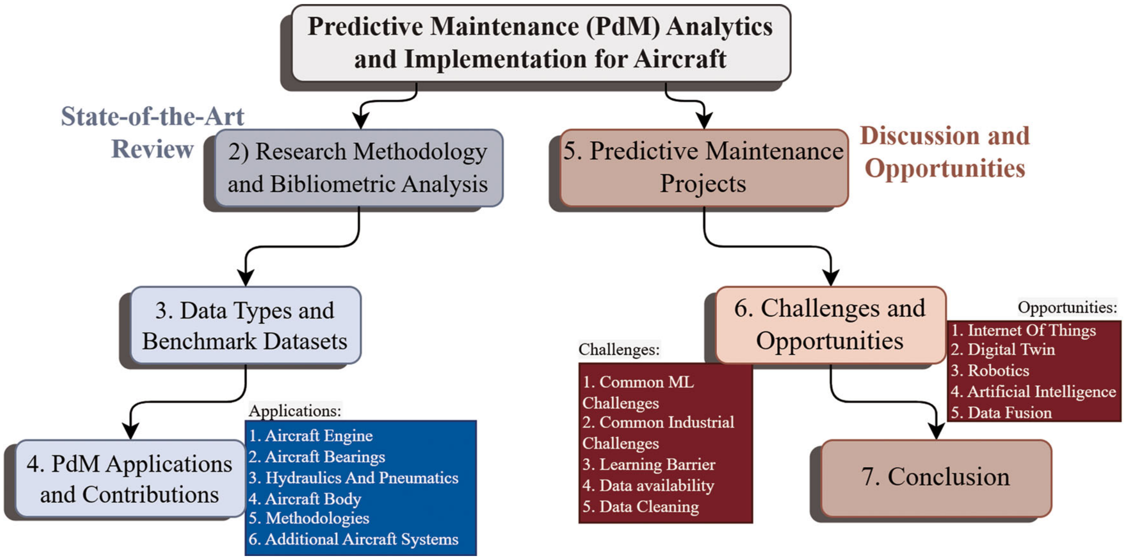

FIGURE 1 Review structure for this state-of-the-art review

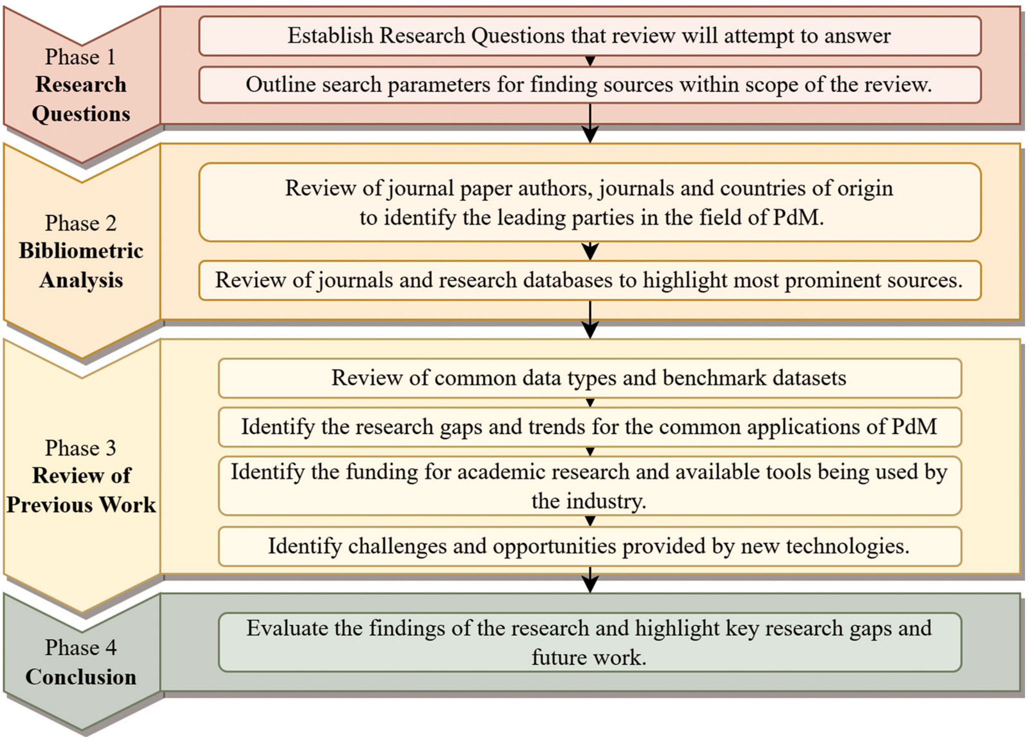

FIGURE 2 A diagram outlining the research methodology that was adhered to for this review

2.1.2 | Search parameters

There were three primary search criteria for the selection of the publications used in Section 4; being aerospace focused where there are papers available, having been published since 2015 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 research databases IEEE Xplore and Elsevier, using keywords that have grown in popularity as the field has grown, as shown in Figures 3 and 4, respectively. These figures highlight the growth in research in PdM and to a slower extent the focus on aircraft and machine learning.

2.1.3 | Existing literature review papers for predictive maintenance

There have been several reviews for PdM in the last decade, with some references to the aircraft industry. Hashemian et al.[10] discussed the advantages and limitations of three categories of time-based PdM.

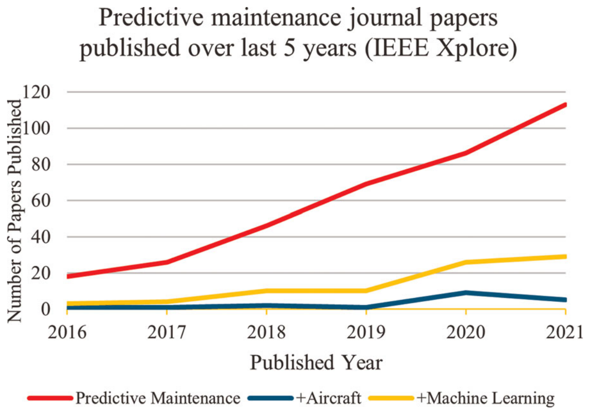

FIGURE 3 PdM Journal Papers Published over the last 5 years available from IEEE Xplore

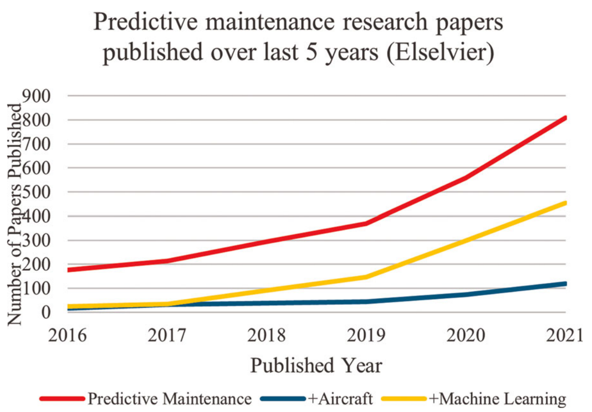

FIGURE 4 PdM Journal Papers Published over the last 5 years available from ScienceDirect (Elsevier)

The reviewed methods originate from methods used in industrial and nuclear plants, and they conclude that ongoing research into these three technologies improves the efficiency and safety of the technology moving forward. Another review by Montero et al. [11] looks at the current trends in diagnostics and prognostics and investigates opportunities and challenges of multimodel approaches to PdM applications. They list the available single- and multimodel approaches for PdM, as well as different machine learning models that can be and have been used for PdM. Only small references to aircraft and Jet Engines are made in examples of safety-critical systems. Carvalho et al. [12] provide a systematic review of different ML methods and public datasets for PdM applications, highlighting those specific approaches that address specifying PdM problems and equipment under maintenance. This review provides the most exhaustive look into machine learning models available to this industry, but again has no focus or mentions of aircraft.

Two reviews were found to have a more direct focus on aircraft. Wen et al. [13] conducted a review of data-driven prognostic algorithms, for conventional and deep learning models. Aircrafts were highlighted as a major application of PdM, and they dedicated a subsection to reviewing recent papers applying different models to a group of aircraft equipment. Finally, [14] reviewed the trends and challenges for PdM of aircraft engines and hydraulics specifically. It reviews different prognostic methods that have been used for aircraft engines and hydraulics in recent years, followed by a case study using data from an aircraft's hydraulics system using a support vector machine (SVM).

Of the available reviews, there was only one directly focused on just two aircraft systems. There are far more aircraft systems than those covered in these reviews, and no paper found delves too deeply into the aircraft industry, and what tools are used within it. Therefore, this state-of-the-art review will be the first exhaustive review solely focused on aircraft in both academia and the aircraft industry, and identify the challenges

2.2 | Bibliometric analysis

To answer the first research question, the papers that were highlighted as within the scope of the outlined search parameters were analyzed based on different parameters. The authors, journals, and county of origin can be key indicators to identify who the key players are, and where this research is flourishing the most. The journal papers have been analyzed to establish any patterns or concentration of research. These can be used to help future researchers identify key journals and authors more easily for their research. For this review, journal papers were reviewed for Sections 3 and 4 for the more academic-focused parts of the review, whereas for Sections 5 and 6, new articles, and blogs for the industrial side. Therefore, this analysis will only cover the journal papers mentioned in sections A and B to reflect the state of research in academia.

2.2.1 | Analysis of authors

An analysis of the lead authors of every journal found that no author appeared more than once in the papers that were reviewed. For this reason, our findings cannot suggest any leading authors in this field based on the papers we have reviewed that were published since 2015.

2.2.2 | Analysis of journals

An analysis of the journals, the papers we found were published in, was conducted, and the top 10 journals can be seen in Table 1. Four of these were from journals belonging to the Institute of Electrical and Electronics Engineers (IEEE), with 10 papers just within the top 10. IEEE can, therefore, be considered a reliable source for papers in this field in the future.

2.2.3 | Analysis of countries

The countries that these journals originate from were also analyzed to identify which countries are producing the most papers in this field. The top eight countries and their respective paper counts can be seen

TABLE 1 The top eight journal of journal papers in this review

Journal	Number of papers
IEEE Transactions on Instrumentation and Measurement	4
Chinese Journal of Aeronautics	3
Reliability Engineering and System Safety	3
Aerospace	2
IEEE Sensors Journal	2
IEEE Transactions on Industrial Electronics	2
IEEE Transactions on Reliability	2
Neurocomputing	2

TABLE 2 The top eight countries of journal papers in this review

Authors country	Number of papers
China	16
USA	9
Brazil	3
Spain	3
France	2
Germany	2
India	2
South Korea	2

in Table 2. China numbered highest on this list, in stark contrast to the most popular journals of choice that originate from IEEE journals, which are based in the United States. It is clear that China and the United States are producing the greatest quantity of papers in this field.

3 | DATA TYPES AND BENCHMARK DATASETS

Due to the explosion in new data sources and prognostic techniques, data-driven prognostics is a now more accessible approach 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 [15], experimentation in the field of industrial PdM has grown 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.

TABLE 3 Most common data types for aircraft maintenance data

Data type	Source
Time series	Turbofan engines [19], landing gear hydraulics and bearings [20]
Natural language	Pilot complaints, equipment failure logs, [21] and post flight reports
Graphical data	Imaging of aircraft fuselage and wing [22]

3.1 | 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 3. The number of time series datasets greatly outnumbers 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 as a major challenge of NLP is language barriers and maintaining the meaning of sentences [16]. Logically, 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 have rarely been used for aircraft PdM so far, but its greatest use is for technicians inspecting aircraft bodies, and since 1998, it has been proposed that much of this work could be offloaded to robots [17]. 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 h to 10–15 min [18].

3.2 | 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 datasets have been available online in a Data Repository operated by NASA [15], 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 [23]. It has been used frequently in publications to generate multivariate time series engine datasets for developing novel prognostics and health management (PHM) models. The most commonly used example is a set of run-to-failure datasets, [24] which have been used in at least 68 publications [25]. Each dataset 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 PHM society has organized annual data challenge competitions for attracting attention to address PdM problems within different industries [26]. A new dataset from a different industrial field has been released each year with a different prognostic goal. This data reflects cover a couple of additional topics such as Anemometer [27] and Gearboxes [28]. Two of the datasets generated for these challenges have been generated using C-MAPSS [29]. 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 [30] and batteries [31] can be translated from other industries where the datasets are available, and are considered as transferable systems in this review.

4 | 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 summarized and compared different machine-learning algorithms for PdM in the general industry already [10,32]. This section identifies the key state-of-the-art methods published in journals in recent years for specific applications. 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. In doing so, this section works to answer our second research question.

Of the papers highlighted in this section, different traditional and ML models were applied. These are shown in Table 4, 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 5 shows a table of all the papers that were highlighted by this review, both for aircraft specifically, and transferable industries.

4.1 | Aircraft engine

Aircraft engines are complex and require regular maintenance, making up 35–40% of the total aircraft maintenance expenses from an operator [48]. Turbofan engines can contain large suites of sensors that record values such as fan inlet temperature and pressure, and physical fan speed [49]. C-MAPSS generated datasets have been found to be used most frequently in publications, particularly the datasets released for the PHM 2008 data challenge, [24] 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 Long Short-Term Memory Networks (LSTMs) [14]. However, this paper only highlights LSTM examples that are hydraulics focussed. Another paper also supports a move towards LSTMs; however, also highlighting Random Forests as a powerful traditional model [50]. For this section, we have looked at the paper that both fit within these trends and those that defy them. Table 5 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. LSTMs 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 [47]. 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 [51]. 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 do not 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 Network (DCNN) utilizing a time window approach to improve feature extraction had significant cross-paper performance and outperformed an LSTM network [45]. 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 [52] coupling Cox Proportional Hazards Model and K-means clustering to labels unlabeled data. Supervised multiclass 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 [33], 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 Zheng et al [47].

4.2 | 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 [53]. Measuring the quality of bearing directly with sensors can be difficult with no direct

TABLE 4 List of predictive models that have been used in the highlighted papers in this review

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 [33]
K-Nearest Neighbor	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 [33]
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 [33,34]
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 nondeterministic.	Fatigue estimation [35–37] Bearing RUL estimation [38]
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 does not require labeled 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 [39,40]
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 [20], aircraft health prediction from time series sensor data [41]
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 preprocessing, tends to overfit and cannot model temporal relaxations.	Health diagnosis of aircraft engine [42], RUL prediction of C-MAPSS degradation datasets [43]
Convolutional Neural Networks (CNN)	Deep ANN consisting of layers of receptive fields here features are convolved by applying kernels.	Exploits neighborhoods, can reduce training time and data required by weight sharing, prevent overfitting using dropout.	Slower training than other deep ANNs and cannot model long-term dependencies.	RUL prediction from raw time series sensor signal, [44,45] Internal pump leakage prediction of hydraulic system [32]

(Continues)

TABLE 4 (Continued)

Architecture	Operation	Strengths	Limitations	Applications and references
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 [46]
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 [32,47]

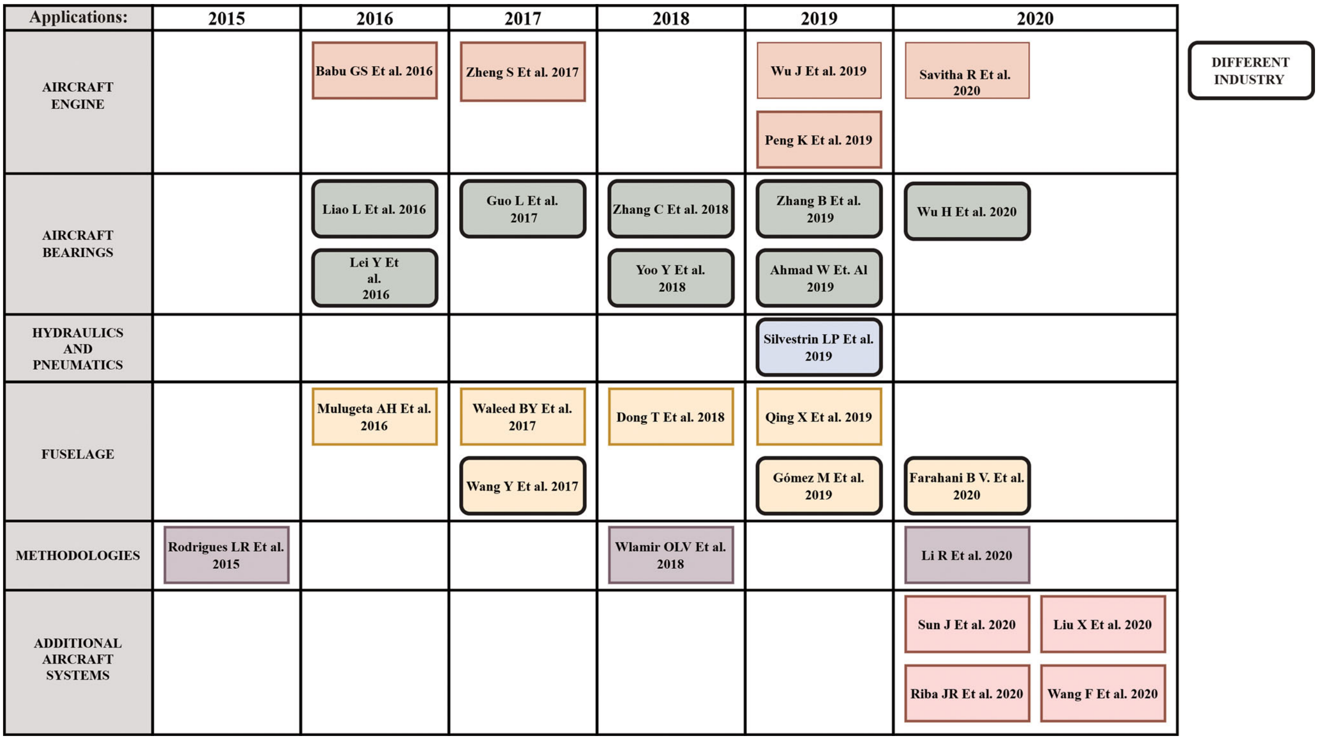

FIGURE 5 Table of all the papers highlighted by this review, ordered by applications and year of release

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 [20] and particle filtering [38] and standard RNN [54], to more commonly use deep learning. Most notably a proposed LSTM method that outperformed a CNN and sparse auto-encoder [55]. 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 [5655] and CNNs [57] at the forefront. Table 6 contains a list of the papers covering PdM for bearings that were investigated as part of this review.

4.3 | Hydraulics and pneumatics

Hydraulics is a mechanical function that operates through the force of liquid pressure. In hydraulics-based systems, mechanical movement

TABLE 5 Publications employing state-of-the-art PdM for aircraft engines

References	Method	Features	Future Work
Zheng et al. [47]	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 et al. [45]	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 et al. [51]	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 and Naderkhani [52]	Hybrid Maintenance Decision Support System	Fault diagnostic and prognostics. Infers and fuses high-dimensional/multimodal data sources. Recommends optimal maintenance decisions without human intervention	None stated
Chen et al. [33]	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.

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, fuel 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 [32]. 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 7 contains a list of the papers covering PdM for hydraulics and pneumatic's that were investigated as part of this review.

4.4 | Fuselage

The fuselage and frame of an aircraft are just as vital a component as the engine and are liable to damage from bird strikes, lightning strikes, and degradation over time. In recent years, particle[36] and Kalman filters [37] have been used to estimate and predict the size of flaws and cracks in the frame and wing of the aircraft 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 analyzing 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 to predict the life and performance of the

TABLE 6 Publications employing state-of-the-art PdM for bearings

References	Method	Features	Future work
Liao et al. [20]	RBM	RUL estimation. Employed a novel regularization term to maximize trendability. Automatically generate features suitable.	Employ a deep structure of RBMs.
Lei et al. [38]	Stochastic Process Model/Kalman Particle Filtering	RUL estimation. Validated against PHM 2012 dataset. Compared with and outperformed four methods.	Investigate how to acquire the initial model parameters for this model.
Guo et al. [54]	RNN	RUL estimation. Overcome common drawbacks of health indicators.	Investigate new RUL models: conditional three-parameter capacity degradation model and stochastic degradation model.
Yoo and Baek[57]	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 et al. [58]	Regression	RUL estimation. Infer RUL from a dimensionless health indicator.	Extensive studies with greater number of different applications and datasets for validation.
Zhang et al. [55]	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 et al. [56]	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.

aircraft structure [59]. 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 the sensor's systems must first be reduced [60]. 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 [61] and railway tunnel structures [62]. Table 8 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.

TABLE 7 Publications employing state-of-the-art PdM for hydraulics and pneumatics

References	Method	Features	Future work
Silvestrin et al. [32]	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 utilizing feature engineering.

TABLE 8 Publications employing state-of-the-art PdM for aircraft bodies and transferable engineered systems

References	Method	Features	Future work
Haile et al. [35]	Particle Filter	Integrated diagnostic framework. Fatigue life estimation of critical rotorcraft structures”	None stated
Yousuf et al. [36]	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 and Kim[60]	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 et al. [37]	Extended Kalman Filter	Estimate fatigue crack size in airframe. Predict future crack size/distribution. Significant cost reduction.	None stated
Qing et al. [59]	N/A	Overview of piezoelectric transducer-based for aircraft SHM. Identifies challenges for SHM of aircraft.	Extensive study in individual highlighted challenges.
Muñoz et al. [61]	N/A	Identify defects in wind turbine blades. Utilize ultrasonic sensors.	None stated
Farahani et al. [62]	None (Employs computer vision)	Detect defects in railway tunnel structure. Utilize monitoring of railway tunnel’s 3D geometry.	None stated

4.5 | 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 [63]. 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 [64]. Table 9 contains a list of the papers covering maintenance methodologies that were investigated as part of this review.

4.6 | Additional aircraft systems

There are other specific aircraft systems that have been optimized using PdM. The Auxiliary power unit is an essential piece of equipment for an aircraft; however, it has a nonlinear degradation process.

TABLE 9 Publications proposing state-of-the-art methodologies for PdM

References	Features	Future work
Rodrigues et al.[63]	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 et al. [64]	Systematic derivation of system requirements for prognostics and health management system development. Defines detailed processes for requirements definition.	None stated
Vianna and Yoneyama [65]	Methodology for predictive line maintenance. Optimization of redundant aeronautical systems.	Incorporate troubleshooting tasks to the planning optimization 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 [19]. Random Forest has been used to assess the performance and predict the RUL of an aircraft auxiliary power unit [34]. 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 [66]. This includes an example of graphical data used by UV imaging sensors to detect arcs. These methods allow for online monitoring of this activity and are compatible with PdM approaches. Table 10 contains a list of the papers covering PdM for the additional aircraft systems that were investigated as part of this review.

5 | PREDICTIVE MAINTENANCE PROJECTS

PdM needs are growing in this industry as data collection and greater development of data-driven prognosis tools enables greater exploitation of it. In parallel, greater funding and awareness are required to ensure that 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 toward methods and tools that are beneficial and in demand by airlines and manufacturers.

Table 11 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 most popular of these services are shown in Table 12, organized by year of release. Most of the tools provide the benefits of reducing aircraft downtime and return to service time, which highlights these as the key needs for airlines. The features each of these services provide are displayed in Table 13, which displays the main features displayed by the companies themselves. Features that can be assumed to be in all or most of them such as generic data analysis, RUL Prediction, and anomaly detection have not been included. The most common features are possessing user-friendly applications, real-time monitoring of aircraft, and data management, which emphasize the features airlines and manufacturers most desire from these services. Other features such as internet of things (IoT) integration, automated data analysis, and physics-based modeling are less commonly displayed as prime features but have appeared in tools released more recently. This suggests that these three areas may be where the industry is heading, with a greater amount of IoT compatible sensors, automated PdM tools, and digital twin usage, respectively. A timeline of the release year for each service is shown in Figure 6, which shows a steady growth of services over time in the last 15 years, and these services will only grow in number or quality in years to come.

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 focuses on novel methods for data-driven PdM, at the Delft University of Technology researching optimization approaches for PdM maintenance planning [89] and at Cranfield University researching the optimization of UAV maintenance paradigms using artificial intelligence (AI) [90]. Universities have received greater support from the industry, with sponsored PhD's in

TABLE 10 Publications employing state-of-the-art PdM for additional aircraft systems

References	Method	Features	Future Work
Liu et al. [19]	Hybrid LSTM	RUL estimation of Auxiliary power unit. Use nonlinear degradation data.	Study optimization method to determine the dimension of generated data. Improve stability/accuracy of RUL predictions.
Wang et al. [34]	Random Forest	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 et al. [66]	N/A	Detect arc tracking in low-pressure environment. Evaluate three low-cost and small-size sensing methods.	None stated
Sun et al. [67]	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 11 Grants awarded to projects focusing on PdM around the world

Project	Recipients	Goal	Grant amount
Distributed Aircraft Maintenance Environment (DAME) [68]	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	£3096,172 from the U.K. Engineering and Physical Research Council.
Overall Management Architecture for Health Analysis (OMAHA) [69]	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 [70]	11 European-based contributors	To build a unified framework for PdM strategy.	€6248,367.50 from the EU, Horizon 2020 programme.
Unnamed [71]	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.

this field, such as the University of Southampton, working alongside GE to advance optical fiber sensor technology for PdM application in aircraft [91]. The last of these also highlights the future of research in this industry, implementing greater use of automation and AI for greater optimization and accessibility.

6 | DISCUSSION: CHALLENGES AND OPPORTUNITIES

There are a number of challenges that researchers will face, summarized in Figure 7. This section outlines the challenges that researchers

TABLE 12 Identified PdM services and tools provided by key members of the industry

Service name	Company	Year	Benefits	Real-world application
Amazon Web Services [8]	Amazon	2006	Detecting and preparing maintenance for problems.	Predict health of aircraft engine bleed valve using Sagemaker (Korean Air [72]).
Aircraft Health analysis and Diagnosis (AHEAD) [73]	Embraer	2007	Advanced notification for unscheduled events, faster support, and reduce return to service time.	Storing/transmitting fault data to ground when landing, to provide a information to mechanics (JetBlue and US Airways [74]).
PROGNOS [75]	AirFrance—MRO Lab	2015	Increased operational reliability, flight safety, and reduced costs and flight delays/cancellations.	Performance monitoring and alert solution for systems aboard A380s and Boeing 747/787s, and data analysis and failure prediction for engines such as the CFM56 (Air France [76]).
Airbus Real Time Health Monitoring Service (AiRTHM) [77]	Airbus	2017	Reduces aircraft down time, maintenance costs, and enables anticipated unscheduled maintenance.	Provide components and predictive maintenance support for a fleet of four A350 XWBs (Sichuan Airlines [78]).
AVIATAR [79]	Lufthansa - Technik	2017	Provides recommendations and notifications, enabling customers to make faster and better decisions.	Technical Logbooks to replace paper-based issue capture, to enable capturing of technical issues with aircraft during flight/on ground, with real-time data availability (Wizz Air [11] and Vietjet [80]).
AnalytX [81]	Boeing	2018	Apply predictive analytics to increase time to evaluate, plan, and manage solutions.	Real-time maintenance and engineering support (Air Peace and EnterAir), and optimizing crew management (Cathay Pacific Group) and cockpit solutions (Interglobe Aviation). [82]
EngineLife—Health Monitoring [83]	Safran	2018	Provide maintenance recommendations, more tailored to customer's fleet requirements.	Track engine life parameters, implement PdM actions, and provide automatic Engine Power Checks for 36 H120 helicopters (HeliDax [83]).
SAS Platform [84]	Lockheed Martin	2019	Reduce data cleanup times, aircraft downtime, and customer costs.	Application of intelligent diagnostics related to spare parts optimization for 20 aircraft, saving 1400 h of downtime in 3 months (unnamed C-130J operator [84]).
Ascentia [85]	Collins Aerospace	2020	Decrease in potential delays and unscheduled maintenance.	Applying advanced data management and analytics services to reduce potential delays and cancellations related to components and systems monitored on the Boeing 787 fleet by 30% [85].
Smart Link Plus [86]	Bombardier	2020	Streamline customer service relationships and efficiently dispatch, troubleshoot and track aircraft service needs.	None found yet
Insight Accelerator [87]	Boeing	2021	Improved efficiency for predictive analytics, faster insights into issues, and simplified data analytics.	None found yet

in this field will need to overcome to enable the 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. The investigation of these works answers our third research question.

6.1 | Challenges

Few papers that we found suggested that their solution addressed the exact challenges faced by the field, rather than providing novel models to increase the performance of PdM for a given application. Given the

TABLE 13 Available features presented online for respective PdM services and tools

Service name	User-friendly app	Real-time monitoring	Data management	Automated analysis	Available expert help	Big Data analytics	Cloud-based	Internet of Things integration	Physics-based modeling
AWS [8]	✓	✓	✓	✓			✓		
AHEAD [73]	✓	✓		✓	✓				
PROGNOS [75]			✓			✓			
AiRTHM [77]	✓	✓				✓			
AVIATAR [79]	✓						✓		
AnalytX [81]	✓	✓							
EngineLife—Health Monitoring [83]	✓	✓	✓	✓	✓				
SAS Platform [84]		✓	✓	✓				✓	
Ascentia [85]	✓		✓		✓				✓
Smart Link Plus [88]	✓	✓							
Insight Accelerator [87]	✓	✓		✓		✓			

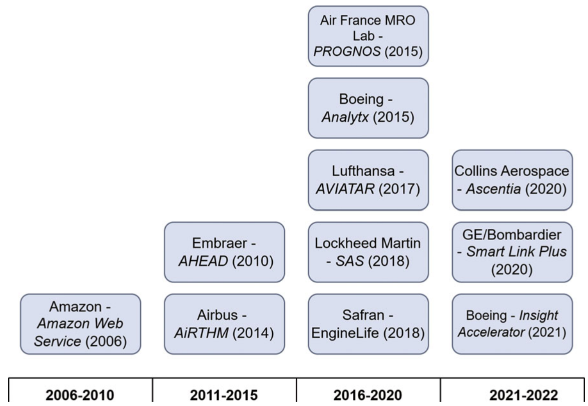

FIGURE 6 Timeline of PdM Services provided by major companies

use of PdM in other industries such as automotive, construction, and manufacturing industry, it will suffer from the same challenges found in similar fields. There were no challenges highlighted in this review that could be considered aircraft specific, or that would not appear in similar industries. This section outlines the five major groups of challenges that were identified by this review.

6.1.1 | 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 relevant to aircraft. A systematic review of AI-based prognostics was performed by Khan and Yairi [92], who highlighted several notable diagnostic challenges, such as noisy sensor readings, difficulties in accurately modeling the physical process of systems [93], and health degradation trends [94]. The datasets used to train ML models are commonly imbalanced, as faults are generally uncommon in aircraft, and data are skewed towards the normal operation. This leads to the model struggling to learn the minority class of failed systems and requires methods such as those summarized by Dangut et al.[95] 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 [20]. The reliability of maintenance predictions may vary between aircraft systems which these problems, making aircraft-wide health diagnosis difficult to ascertain.

6.1.2 | 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,

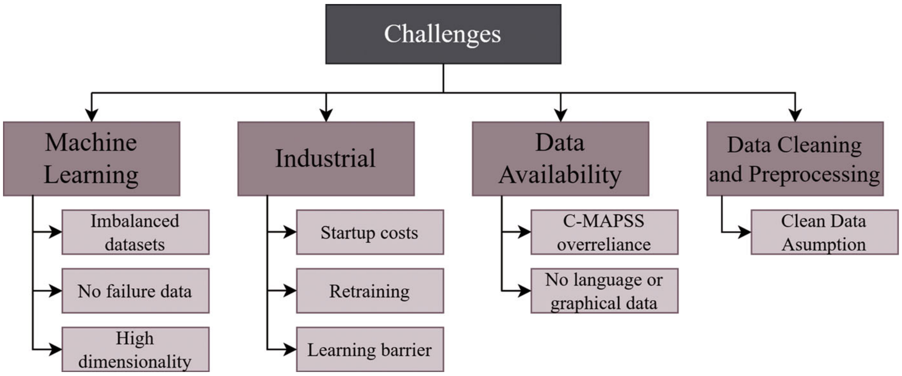

FIGURE 7 Challenges for Predictive Maintenance (PdM) research for aircraft

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 specialized knowledge to install and utilize. PdM can be the most optimized 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.

6.1.3 | Data availability

While 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. The lack of diversity in available dataset types also limits the number of techniques that can be tested and expanded in future research. NLP and computer vision could potentially provide new insights for text-based data (e.g., Pilot logs, ACMS reports, etc.) and photographs (e.g., Fuselage inspections, component monitoring, etc.), respectively. The lack of available public datasets severely limits the number of researchers who can explore these options. For more aircraft-specific research, the simulation or acquisition of more aircraft maintenance data is vital to broadening the breadth of future research in this field.

6.1.4 | Data cleaning and preprocessing

Data cleaning is seldom mentioned in the journal articles discussed as part of this review. There is a common assumption in these papers that the data being used in these examples are already clean, and in cases of using publicly available datasets such as the C-MAPSS dataset, this is the case. However, from a practical standing, the data will not always be clean and across fleets of aircraft, anomalies, noise, and mistakes will make analyzing the data more difficult. Aircraft data is noisy as it is being recorded and must be filtered before being stored. Clean data allow for more efficient, reliable, and accurate analysis of the data, and given the volume, traditional data cleansing is not an effective option.

6.2 | Opportunities

New technologies could enhance and automate the PdM process, allowing for greater optimization 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.

6.2.1 | Internet of things

The IoT defined as a world where physical objects are seemingly integrated into the information network [96], 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 [97–99] 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.

6.2.2 | Digital twin

A Digital twin is the virtual representation that serves as the real-time digital counterpart of a physical object or process. Unlike many other tools, there is a keen focus on text analysis over raw sensor data, analyzing maintenance logs, and visualizing analytics on a smart dashboard alongside other analytics. Recently, a paradigm hybrid system of combining multiphysical modeling with data-driven analytics was proposed [99]. 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 revolutionize the relationship between engineers and aircraft systems in terms of speed, autonomy, and required programming experience to operate.

Digital twin services are being used for aircraft by companies such as Airbus for aircraft using MATLAB and Simulink [100], and Rolls Royce for aero-engines with InteligentEngine [101]. Companies like Infosys services build digital twin of critical aircraft systems, such as engines and landing gear, and apply analytical solutions to the various aircraft system and sources [102]. Universities are also developing digital twin for aircraft applications, with Cranfield University proposing using digital twin and AI to create a "conscious aircraft," [90] and Wichita State University, which is developing digital twin of both a UH-50 Blackhawk helicopter and B-1 Rockwell bomber [103].There are limitations in using DT with complex aircraft components, however, as they require a definite, physical model. Data-driven methods have been identified to mitigate these challenges by mining connections between variables with no prior knowledge or experience required, Data-driven and deep learning technologies were used by Xiong et al. to develop an aero engine DT from sensors and historical operation data and use an LSTM model for RUL prediction with better RSME than similar experimental schemes [104].

6.2.3 | 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 that 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 [105]. Collecting more data improves the performance of data-driven methods and deep learning, so every opportunity to automate the data collection process will improve efficiency and accuracy. A network of robots working in unison could greatly optimize data collection and fault identification, such as the network of drones and climbing robots for wind turbine global inspections [106]. 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.

6.2.4 | 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 utilizes 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 [107]. This all centers around autonomous systems working together with a strong focus on AI. They recognize that elements such as feature selection are currently performed manually by experienced engineers. This is labor-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 [92]. 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 have applications for predicting aircraft system deterioration.

6.2.5 | 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 utilizes 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 [108]. It can also be used at a decision level, such as for predicting the RUL of an aircraft by interpreting it as a convex optimization 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 or applying the method to real-time prognostics.

7 | CONCLUSION

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 optimized than alternative maintenance strategies for maximizing 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 optimize 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 in the industry and researchers in academia, but it is inaccessible to in-experienced users who could benefit from it most. Even easily accessible tools such as Microsoft Azure, which possess PdM guides using C-MAPSS data [109], require some level of domain knowledge and programming experience to understand and use effectively. Dedicated PdM tools that utilize 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 PdM 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.

There is an abundant new technology that will provide opportunities to optimize and automate this work in the future. Many of these will directly mitigate the challenges highlighted in this review, but will these require the integration of physical new technology into the industry, which will be a slow process to normalize amongst large fleets. Using AI and Auto-ML to provide greater automation could mitigate many of these challenges and enable a wider user base. Automated tools will enable a greater number of people to build PdM models on aircraft data. Greater research into the integration of AI in this field will encourage both more development and greater use in the industry, leading to greater savings and safety afforded to in-service aircraft.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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