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An Analysis of Barriers Preventing the Widespread Adoption of Predictive and Prescriptive Maintenance in Aviation

Christopher Teubert
National Aeronautics and Space Administration

Ahmad Ali Pohya
German Aerospace Center (DLR) Institute of Maintenance, Repair, and Overhaul

George Gorospe
National Aeronautics and Space Administration

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National Aeronautics and
Space Administration

Ames Research Center
Moffett Field, CA 94043

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Summary

The aviation industry has long recognized the potential benefits of predictive maintenance, a maintenance strategy that leverages sensor and operational data to predict the future degradation of components. Prescriptive maintenance takes this a step further and considers the entire aviation ecosystem to schedule maintenance actions optimally. With the ability to reduce maintenance costs by up to 30%, as reported by the Department of Energy, these maintenance strategies have been identified to be an important investment to reduce a airline costs. However, despite great interest and technological advances in areas such as diagnostics, prognostics, sensing, computation, and machine learning, the adoption of predictive and prescriptive maintenance has not been widely applied in aviation.

To shed light on this issue, we conducted an analysis of the barriers preventing or limiting the adoption of predictive and prescriptive maintenance in aviation. Through discussions with subject matter experts across industry, academia, standards bodies, and government, we identified five key challenges: complexity of prediction; validation, safety assurance, and regulatory challenges; cost of adoption; difficulty in quantifying impact and informing decisions; and data availability, quality, and ownership challenges. This study provides a detailed overview of these barriers and areas where stakeholders could invest to overcome them, aiming to support the scaled adoption of predictive and prescriptive maintenance in aviation.

Abbreviations

AHM Aircraft Health Management
CAA Civilian Aviation Authority
CBM Condition Based Maintenance
CBM+ Condition Based Maintenance Plus
DoE Department of Energy
FAA Federal Aviation Administration
HUMS Health and Usage Monitoring System
IMRBPB International Maintenance Review Board Policy Board
OEM Original Equipment Manufacturer
MEL Minimum Equipment List
MRB Maintenance Review Board
MRBR Maintenance Review Board Report
MRO Maintenance, Repair, and Overhaul
MPIG Maintenance Programs Industry Group
PdM Predictive Maintenance
PHM Prognostics and Health Management
PIML Physics Informed Machine Learning
RCM Reliability-Centered Maintenance
SME Subject Matter Experts

1 Background

1.1 Maintenance Strategies

At a high level, airlines and operators craft maintenance policies to minimize costs while ensuring a required level of safety. A spectrum of different maintenance policies can be applied to achieve these goals. An operator's maintenance policy frequently consists of some combination of strategies according to data availability, failure risk, and consequence of failure.

Maintenance policies generally fall into two overarching categories: corrective and preventative (Ref. 1). For **corrective maintenance** (also called reactive maintenance), a failure triggers maintenance. This is common for non-safety critical systems where the consequence of failure is low (e.g., a coffee machine). This is occasionally referred to as run to failure. Alternatively, **preventative maintenance** strategies are designed to schedule maintenance before a failure occurs.

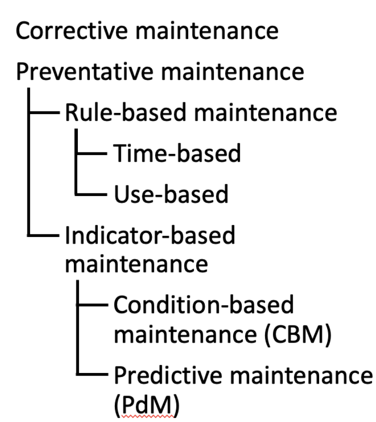

Figure 1.—Hierarchy of Maintenance Strategies

Preventative maintenance strategies are further divided into two categories: rule-based and indicator-based. In **rule-based maintenance**, pre-defined rules trigger maintenance based on time, usage, or risk. Generally, these rules are defined using a reliability analysis, called Reliability-Centered Maintenance (RCM), where a distribution of failure times is determined experimentally as a function of time, usage, or risk. A distribution percentile is selected based on the program's risk tolerance. For example, choosing the first percentile indicates a willingness to accept a 1% risk of failure. Maintenance will then be performed on the selected fixed interval. Most modern maintenance programs can be categorized as some form of RCM (Ref. 2).

Rule-based approaches naturally result in unnecessary maintenance. The amount of unnecessary maintenance is dependent on the operator's risk tolerance. A lower accepted risk of failure results in lower costs from line (i.e., gate) maintenance and associated downtime at the cost of greater unnecessary base (i.e., in-hangar) maintenance costs.

To illustrate, consider a simplified example from (Ref. 3): In a reliability study, an example centrifugal pump failed at the frequencies depicted in Figure 2.

A user scheduling maintenance that accepts a 1% probability of failure would perform maintenance and rebuild the pump after 17 months of operation. Actual wear on the pump depends on the operational loading and environment during its lifetime. The result is that for 99% of pumps, maintenance is performed prematurely, resulting in increased maintenance costs.

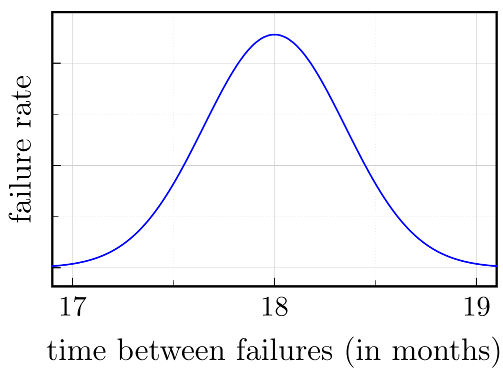

Figure 2.—Example Centrifugal Pump Failure Frequency

Alternatively, **indicator-based maintenance** strategies leverage indicators of a system's condition to anticipate its maintenance needs. Indicator-based strategies can either be **Condition Based Maintenance (CBM)** or **Predictive Maintenance (PdM)**. CBM is triggered by some measurement, inspection, or estimate of the system state. PdM strategies combine measurement or estimation of system state produced from operational data with a model of degradation and future loading estimate to predict how a system will degrade with time (Ref. 3–5). This prediction is then used to improve maintenance scheduling. **Prescriptive Maintenance** takes this one step further by using the prediction to suggest optimized maintenance actions considering the entire ecosystem of aviation.

PdM relies on an assessment of a component's state and health as well as a prediction of how these will evolve with time. A component's state and health are estimated using state estimation diagnostics or fault detection algorithms and models. Fault detection determines if there is anomalous behavior present in a system, while diagnostics isolates the specific cause of the fault and estimates its severity. Prognostics algorithms and models produce a prediction of how the system's state and health evolve with time and when the system will eventually fail, with uncertainty. Diagnostic and prognostics models can be physics-based, data-driven, knowledge-based, or some combination of these. PdM algorithms leverage this information to schedule maintenance and inspection activities, illustrated in Figure 3.

PdM is not appropriate for all systems. Some systems either have failure modes that cannot be predicted effectively or where the frequency or consequence of failure are low enough that a CBM or rule-based approach is adequate. But for systems where PdM is appropriate, there is a significant potential for impact. The Department of Energy (DoE) estimated that a well-designed PdM program can reduce maintenance costs by 30% (Ref. 6). Maintenance costs currently account

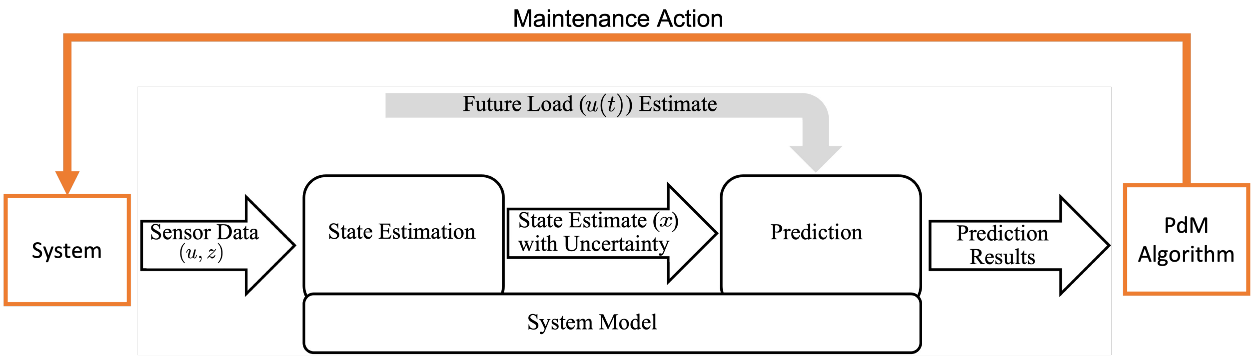

Figure 3.—Architecture of PdM and Prognostics and Health Management (PHM)

for around 13% of total airline operation costs (Ref. 7). Independent aviation consulting firm ICF estimates that savings to airlines from aircraft health management and predictive maintenance could be as much as $3 Billion (Ref. 8). Most manufacturing companies expect PdM will increase their assets uptime (Ref. 9). The US Congress identified that ”If performed effectively, predictive maintenance can reduce. . . system downtime, ensure adequate supply of needed parts, and decrease costs.” (Ref. 10) Army and Navy officials have identified predictive maintenance technologies as possibly preventing accidents on aircraft such as the AH-64 Apache and the F/A-18 Super Hornet and in trucking, preventative maintenance has reduced breakdowns by 20% and maintenance costs by $2-12.5k per truck per year (Ref. 11).

1.2 Maintenance Programs

The maintenance program for an aircraft type is a typically developed via the Maintenance Review Board (MRB) process, using the MSG methodology from the Maintenance Programs Industry Group (MPIG). MSG is a methodology used to determine cost-effective maintenance tasks and intervals for commercial aircraft (Ref. 12). This MRB process is based on the analysis of aircraft fleet data and feedback from operators’ experience, maintenance providers and manufacturers. However, it does not currently incorporate the benefits of PdM.

The process starts with the collection and analysis of aircraft fleet data, including flight hours, cycles, and maintenance events. This data is used to identify patterns and trends in aircraft performance and maintenance requirements. Next, the team, which is composed of representatives from the aircraft manufacturer, airlines, and maintenance providers, review and evaluate the data in combination with a failure mode and effect analysis to develop maintenance tasks and intervals that are most cost-effective for the specific aircraft type.

The MRB process is a collaborative effort between the industry and the regulatory authorities (e.g., FAA), with the goal of providing safe, reliable, and efficient maintenance programs. The MRB results in the development of a Maintenance Review Board Report (MRBR) which is then reviewed by the regulatory authorities and becomes the basis for the Minimum Equipment List (MEL) and the maintenance program of the aircraft type.

The International Maintenance Review Board Policy Board (IMRBPB) is a group consisting of representatives from 10 global National Airworthiness Authorities (including FAA Flight Standards in the US) and the MPIG. They ensure that maintenance guidance is applied uniformly across the world, reconciling differences between nations airworthiness authorities.

1.3 Current State of Adoption

PdM strategies have been investigated for years and have recently seen some success in non-aviation fields such as wind turbines or the oil and gas industry. Compared to aviation, these applications operate in a more repeatable, understood, and controlled environment.

Several efforts are working to unlock the potential of PdM, including Airbus Skywise, Boeing Analytx, Collins Ascentia, Embraer Ikon, GE Predix, Honeywell Forge, KLM Prognos, Lufthansa AVIATAR, and Rolls-Royce Intelligent Engine. Furthermore, there has been limited success in the Helicopter Health and Usage Monitoring System (HUMS) (Ref. 13, 14) and military Condition Based Maintenance Plus (CBM+) communities (Ref. 11). Despite this, with a few exceptions, current aircraft maintenance strategies are primarily some combination of corrective and rule-based with a few CBM applications.

One notable exception is jet engine maintenance. A significant amount of research has been put into PdM strategies for engines by General Electric (Ref. 15–17)[Abhinav Saxena, GE Aerospace Research, 2022][Kimon Abu-Taa, Rolls-Royce Germany, 2023] and others. Unlike manufacturers of many other aircraft systems, the Original Equipment Manufacturer (OEM) for engines typically is responsible for maintenance at a fixed price (per flight hour) [Ravi Rajamani, IDCA President]. This creates an economic incentive to develop and adopt PdM technologies to minimize maintenance costs.

Some claim to be utilizing PdM. With a few exceptions, most of these PdM approaches are rudimentary PdM approaches such as trending. In some cases, there is a mislabeling of CBM techniques. Price Waterhouse Cooper found that “companies plans and ambitions regarding PdM have not yet resulted in a noticeable increase in its use among companies” (Ref. 9)

In 2022, the FAA issued guidance on how to develop an Integrated Aircraft Health Management (AHM) System (Ref. 18). This follows earlier guidance from the IMRBPB (Ref. 19). This action has encouraged airlines to put more effort into developing and exploring the adoption of PdM and other AHM technologies (Ref. 20).

Stakeholders in NASA, industry, and academia have been dissatisfied with the scale of adoption of PdM strategies. There is universal recognition of the advantages of PdM, but it true potential has yet to be unlocked.

2 Approach

In order to better understand why PdM has not been adopted en masse, we collected and examined data from aviation industry experts on the barriers they faced in adopting predictive maintenance strategies. The goal was to understand the barriers preventing scale adoptions, and the most impactful work that academia, industry, and research organizations such as NASA could do to address those barriers.

Data collection was conducted via a literature survey and discussions with 24 Subject Matter Experts (SME)’s from academia, industry, and government, as well as ad-hoc discussions at the PHM Society and other industry conferences.

In an attempt to attain comprehensive data, we tried to cover the majority of stakeholders:

- Operators (e.g., Airlines)
- Regulatory Organizations (e.g., FAA)
- Standard Bodies (e.g., SAE, IEEE)

- Aircraft Manufacturers (e.g., Boeing)
- OEMs (e.g., GE)
- Independent Maintenance, Repair, and Overhaul (MRO) Organizations (e.g., Rolls-Royce Germany)
- Professional Societies (e.g., PHM Society, IEEE)
- Research Institutions (e.g., Universities)

Note that in this document input from these discussions are referenced using the following format: [Name, Affiliation, Year]. Some contributors preferred not to be indicated by name, in which case it is replaced with position. Others preferred not to have their affiliation revealed, in which case they referred to using their industry category (e.g., Airline or OEM).

The key barriers are summarized in the following sections. For each barrier some potential investments are identified. These investments are areas where industry, academia, or government should invest resources (time, people, money) to resolve the barrier. Note that this list is not exhaustive, and NASA is not always the appropriate organization to contribute to the resolution of every barrier.

It should be noted that the barriers are interconnected, as Figure 5 shows, indicating the general complexity that the widespread adoption of PdM is facing. The italic annotations between the barriers are just one out of many mentionable connections. Further details and cross-references can be found in the respective sections.

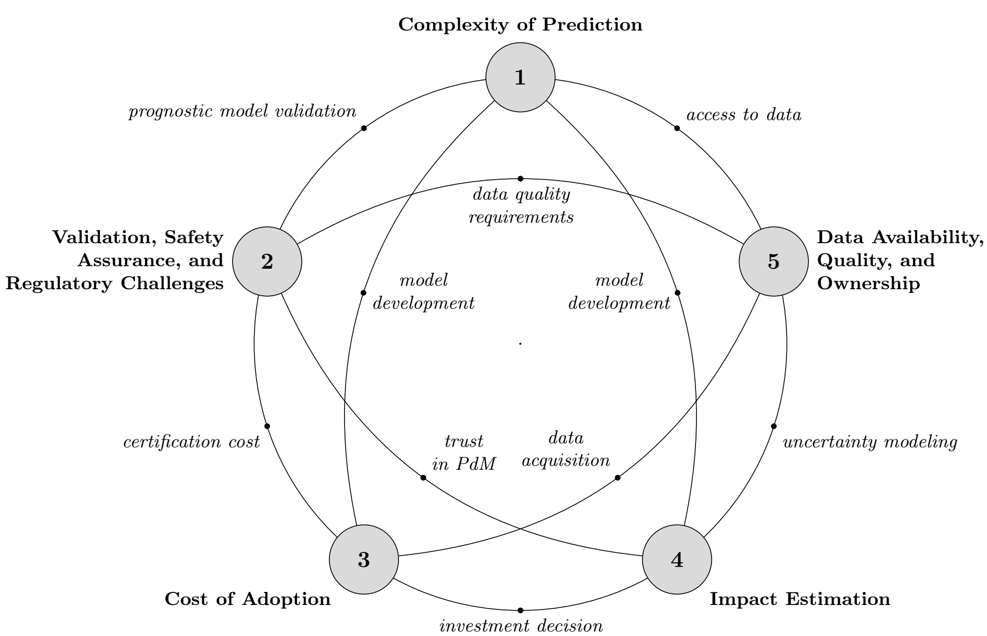

Figure 4.—Key Barriers Limiting the Full-Scale Adoption of PdM

3 Barrier 1: Complexity of Prediction

An overarching theme that we encountered was that prognostics of operational aircraft systems is a difficult problem (Ref. 21). Furthermore, aircraft are complex and that aircraft components are affected by the performance and states of other systems in difficult-to-model ways. Aircraft are operated in various conditions and environments and degradation is highly dependent on the operational environment and operational history [Mark Roboff, SkyThread CEO, 2023][Darren Macer, Boeing, 2023]. Often times, a prognostics model will perform well in a controlled lab environment but poorly in operation [Kai Goebel, PARC, 2022].

An SME from an airline indicated they are "unable to truly simulate degradation in operation" due to this complexity [Airline SME, 2022]. Okeoma Moronu, Aviation and Regulatory Lead at Zipline, explains how "It's one thing to create a product that works the way it's supposed to every time. It's another thing to create an operation that works the way it's supposed to every time." (Ref. 22) Much of the technical barrier in adopting predictive maintenance strategies is the ability to produce quality predictions that can account for the myriad operational complexities.

3.1 Challenges

The widespread adoption of PdM in commercial aviation faces several significant challenges in the domain of complexity. This section explores these challenges, categorized into (a) System Complexity, (b) Modeling and Implementation, and (c) Contractual, Logistical, and Process Complexity.

3.1.1 System Complexity

Commercial aviation is a highly complex field where numerous systems interact, and understanding their behavior is essential for accurately predicting degradation, required for PdM. In this context, the inherent complexity of these systems include:

1. **Inter-System Interactions** Diagnostics and prognostics are frequently thought of as applying to an individual component (e.g., valve or bearing). However, aircraft are a complex interconnection of many systems that work together to allow the aircraft to operate safely. Frequently, a system's state and faults depend on these complex inter-system interactions [Kai Goebel, PARC, 2022] (Ref. 23). A SME from a commercial aircraft engine manufacturer said (translated from German) "Despite (partial) access to data, modeling the entire lifecycle of engines and their components is a difficult endeavor. Especially degradation behaviors and the interaction of (partially) degraded components in a system of systems poses a challenge" [Kimon Abu-Taa, Rolls-Royce Deutschland, 2023].

2. **Operational Environment Complexity** Aircraft operate in complex operational environments. The loads on systems depend on the atmospheric conditions (turbulence, temperature, precipitation, etc.) and how the aircraft is controlled. These conditions are difficult to predict, and can vary greatly, introducing uncertainty into prediction. [Mark Roboff, SkyThread, 2023]

3. **Behavior Variation with Replacement and Repair** Over the lifetime of an aircraft, individual components will be replaced and repaired many times. There are slight variations in the behavior and performance after maintenance and replacement (e.g., natural variation

between systems or imperfect maintenance due to human factors). This variation adds additional uncertainty into state estimation and prediction [Mark Roboff, SkyThread, 2023] (Ref. 23).

3.1.2 Modeling and Implementation

Engineers and maintenance professionals face a range of modeling and implementation challenges when attempting to develop, deploy, and operationalize PdM solutions that can meet the needs of complex and dynamic aircraft systems. These include:

1. **Noise and Uncertainty** Any prediction or state estimate used to inform PdM is uncertain. Uncertainty can come from a variety of sources, including sensor noise, model uncertainty, model parameter uncertainty, approximations made by an algorithm (e.g., discretization in simulation or distribution representation), uncertainty in future loading, etc. These complicated uncertainty sources combine to create an uncertain state estimate and prediction. It is very challenging to estimate the uncertainty and to use an uncertain estimate or prediction effectively in a PdM strategy (Ref. 24). Effective prognostics must be able to quantify, propagate, and effectively handle this uncertainty.

2. **Computational Complexity** Prognostics of a complex system can be very computationally expensive (Ref. 25, 26). Frequently, prognostics utilize a sample-based Monte Carlo approach to predict a distribution of possible states forward. Performing an accurate prediction of future states within the risk tolerances required for aviation can require many samples, sometimes measured in the hundreds of thousands or higher. When this is repeated for many inter-connected systems, the result is large computational loads, which are frequently untenable. This is especially true for users that wish to use prognostics in decision-making, which often requires repeated predictions with different future loading profiles, frequently in the inner optimization loop. This is not possible for many current prognostic approaches.

3.1.3 Contractual, Logistical, and Process Complexity

Commercial aviation is a well-established field which relies on a complex system of logistics, processes, and contracts. As these systems pre-date PdM, PdM's incorporation into them is a challenging endeavor. For example, the contractual framework between airlines and maintenance service providers can be highly individual and an introduction of PdM can increase that complexity, especially considering service level agreements and warranties. Furthermore, it is challenging to ensure the necessary logistics, including the availability of maintenance crews, spare parts and required tools, especially in remote airports. Any changes from the long-established processes between various stakeholders will be difficult. This is a barrier that complicates and delays the adoption of PdM.

3.2 Investments Needed

To overcome these challenges, significant investments are needed. This section discusses some potential areas, organized into (a) Development and Improvement of Tools for System Modeling, (b) Development and Improvement of Tools for Prediction, and (c) Other Fields of Investments.

3.2.1 Development and Improvement of Tools for System Modeling

The following investment areas focus on overcoming the challenge of modeling complex aviation systems.

1. **Tools and Approaches for Modeling Complex Systems** Modeling aviation systems is challenging, and once an individual system's complexity is understood, their interactions with other systems need to be modeled [Abhinav Saxena, GE Aerospace Research, 2022]. There is a real need for a set of tools to support and enable the modeling of complex systems. Ideally, this is done in a collaborative, open-source manner, resulting in a shared set of tools for modeling components, systems, and system-of-systems (e.g., ProgPy (Ref. 27). These tools must be able to accurately and efficiently representing complex component behavior, including system-of-systems interactions and noise.

2. **Approaches for Handling Variation in Operational Behavior** There needs to be methods and best practices for transferring models that are developed in a laboratory environment to be used in operation [Brian Tucker, Bell, 2022]. Furthermore, the variation of the operational behavior after repair and replacement needs to be addressed with appropriate methods. These include:

   (a) **Online transfer learning or meta learning:** These technologies can "transfer" or "adapt" general models to describe the behavior of a specific system after maintenance or replacement, improving the model's ability to predict degradation accurately. [Mark Roboff, SkyThread, 2023]

   (b) **Online parameter estimation for physics-based and hybrid models:** Parameterized physics-based models use parameters to configure the model to match the component's behavior. Often, parameters for a specific component type (e.g., Valve with model number ABC123) are estimated experimentally. This generalizes away variation in behavior between specific systems and after maintenance. Online parameter estimation updates those parameters post-maintenance or repair, in operation, without experimental parameter estimation, improving the model's ability to predict degradation accurately.

3. **New Modeling Approaches** There is a need for continuous development of new modeling approaches such as the hybrid and Physics Informed Machine Learning (PIML). These combine physics-based and data-driven modeling approaches. Leveraging the strengths of both, hybrid and PIML approaches can provide more accurate and robust predictions (Ref. 28, 29).

4. **Algorithms Approaches for Reducing Computational Complexity in Models** High-fidelity prognostic models are needed for some applications. However, they are sometimes prohibitively computationally expensive or contain unnecessarily details for the application. In computationally constrained environments or scenarios that require repeated execution (e.g., optimization), it may be impossible to use high-fidelity models. In these cases, multi-fidelity and surrogate modeling techniques and tools could help. Surrogate modeling techniques will generate a surrogate or replacement that approximates the behavior of the original model at a fraction of the runtime, often with a more limited scope specific to the systems current conditions and expected operational environment. Generally, surrogacy is a tradeoff between

accuracy and runtime. There is a need for new techniques and technologies for model surrogacy, especially with configurable runtime and accuracy, including publishing guidance on when/how to use it, developing and publishing new approaches, and building and releasing surrogate tools (e.g., in ProgPy).

3.2.2 Development and Improvement of Tools for Prediction

There is a need for developing and improving tools for the prediction of future states and dealing with uncertainty, including:

1. **Strategies for Improved Prediction of Future Conditions** Environmental conditions impact on how the system degrades. Better predictions of future conditions (both environmental and operational) that the aircraft and its systems will encounter improve prediction accuracy and reduce uncertainty.

2. **Tools for Prognostic Uncertainty Management** This includes tools for quantifying and propagating, and analyzing uncertainty in prediction and state estimation. All uncertainty sources (e.g., sensors, models, discretization, etc.) should be considered. For an efficient allocation of uncertainty quantification and reduction efforts, global sensitivity analyses should be readily available in these tools.

3. **Tools for Reducing Computational Complexity in Prediction** In computationally constrained environments or scenarios that require repeated execution (e.g., optimization), it may be impossible to use current predictive approaches. Research is needed into improved prediction algorithms for computationally constrained environments. Additionally, research is needed into effectively leveraging alternative computational architectures like neuromorphic computing, tensor processing units, or even emerging quantum computing technologies.

3.2.3 Other Fields of Investments

This last set of suggestions lists points that are less computationally driven, but rather focus on collaboration and soft-skills.

1. **Interdisciplinary Collaboration** Predictive maintenance requires expertise from a range of disciplines, including engineering, data science, and maintenance professionals. Interdisciplinary collaboration between these groups could help overcome the complexity of commercial aviation systems and develop effective predictive maintenance solutions, taking into account different resources and mutual influences.

2. **Update Logistics, Contracting Mechanisms, and Processes** update logistics, contracting mechanisms, and processes to take advantage of prognostics/PdM information. These include contracts, logistics, and processes for spare part maintenance, MRO contracts, information sharing (see Barrier 5), etc.

3. **Focus on Usability** It is essential that prognostic information can be used effectively by human or automated decision makers. Additionally, providing user feedback during use can help with identifying potential problems and improving the overall user experience.

4. **Specific Training and Education Efforts** These efforts should focus on enhancing the understanding of engineers and scientists regarding aviation systems, PdM, and other supporting technologies, including advanced modeling approaches and modern software tools. The training should also include hands-on experience in using these tools, applying appropriate modeling techniques to various aviation system domains, and interpreting the results. Furthermore, collaboration between academia and industry could be established to offer relevant training courses and internships to bridge the gap between theoretical knowledge and practical application. Additionally, publicly released supporting tools such as software, examples, and labeled datasets (see Barrier 5) can help the research and education community significantly.

4 Barrier 2: Validation, Safety Assurance, and Regulatory Challenges

Adopters of PdM technologies and regulatory agencies (e.g., FAA and other Civilian Aviation Authority (CAA)'s) are dedicated to maintaining aviation safety and reliability. Towards that goal, any new technology or approach, such as PdM, must be demonstrated to maintain or improve aviation safety levels. In the case of PdM, this typically means demonstrating that a combination of a PdM strategy and supporting prognostic technologies does not increase the likelihood of failure and still meet regulators requirements and acceptable means of compliance - an issue that has not yet been solved [Kai Goebel, PARC, 2022][Kai Wicke, DLR, 2022][Brian Tucker, Bell, 2022][Madhav Mishra, RISE, 2023] (Ref. 30). This is especially true for data-driven or hybrid (e.g., PIML) prognostics models.

4.1 Challenges

The challenges in this barrier can be summarized as follows.

1. **Shortage of Standards and Regulations** The absence of industry-wide standard methods, guidelines, and regulations for the development, testing, and deployment of predictive maintenance technologies and strategies is a significant challenge. The lack thereof can lead to inconsistent validation approaches, different interpretations of requirements, and varying levels of rigor in safety assessment, which ultimately leads to regulatory agencies such as the FAA being hesitant to approve of predictive maintenance strategies. Establishing such standards and certification procedures, in some cases, requires updating FAA regulations or the management via Certification Review and Action Items. Doing this will require demonstrating to FAA that PdM policies and supporting technologies are safe [Abhinav Saxena, GE Aerospace Research, 2022] [Kai Goebel, PARC, 2022] [Kai Wicke, DLR, 2022]. **The route to widespread PdM approval by the FAA and other regulators is not fully clear**, but there have been significant recent work in this area by regulatory authorities, both in rotorcraft and fixed-wing aircraft. Nonetheless, it is expected to be a lengthy and difficult process due to the high safety requirements in aviation.

2. **Ensuring the Reliability and Accuracy of PdM Algorithms** It is important to ensure that the algorithms used to make predictions and decisions are reliable and accurate to avoid safety hazards or unnecessary maintenance actions. This requires a thorough evaluation

and validation process to ensure that the algorithms are reliable and accurate under a wide range of operating conditions. The evaluation should consider factors such as the quality and quantity of the data used to train the algorithm, the suitability of the algorithm to the system and operating conditions, and the ability of the algorithm to handle uncertainty and variability. The evaluation should also consider the impact of any changes to the algorithm or system, such as the introduction of new components or changes in operating conditions, on the reliability and accuracy of the algorithms. Validation of AI/ML based PdM algorithms is especially challenging.

3. **Ensuring Properly Calibrated Trust in PdM Algorithms** Closely related to the reliability and accuracy is trust. Trust is the confidence that human decision makers (e.g., maintainers) have in a technology. Even if a PdM technology is accurate, if it's not trusted, then the results are going to be ignored and it will not have an impact (Ref. 31). Conversely, trusting a PdM approach beyond it's capabilities can result in unexpected failures and increased downtime.

4. **Training and Education** Implementing PdM systems is challenging and requires special skills. It is important that engineers working on these systems have the right skills to create and validate robust and accurate PdM technologies.

5. **Limited Data Quality** The quality of data used to train predictive maintenance models can be limited (see Barrier 5). This can result in models that are inaccurate or unreliable. Poor data quality can be caused by a variety of factors, such as faulty sensors, incomplete data sets, and inconsistent data formats. Regulatory agencies may require extensive and costly testing and validation to ensure that models trained on such data are safe and effective.

4.2 Investments Needed

The development and widespread adoption of PdM require significant investments in technology, infrastructure, and personnel. Some of the investments needed include:

1. **Develop and Mature PdM Validation Standards, Procedures, and Guides** This can help to ensure comparable quality assurance of PdM systems, algorithms, and models. This should be done in collaboration with standard committees such as the SAE HM-1 and IEEE P1856.1, and other stakeholders. Special attention is required into validation of PdM algorithms relying on machine learning [Madhav Misra, RISE, 2023]. In addition, prognostic model cards (borrowed from the AI/ML community) could be used to communicate the capabilities, requirements, and limitations of a model. Standardizing these is essential to enabling the responsible sharing and use of models in PdM. [Rodney Martin, NASA, 2022]

2. **Update Infrastructure and Mature Infrastructure Certification Processes** PdM requires a robust and secure technology infrastructure, including hardware, software, and networks. This infrastructure must be scalable, reliable, and capable of supporting a large number of devices and sensors. The underlying data management infrastructure could, depending on the implementation, require high-performance computing resources, large-scale data storage and processing, and advanced analytic tools. Due to the high safety standards of regulatory authorities, this infrastructure will have to be tested rigorously in order to be certified.

3. **Develop Supporting Technologies** Investing in the development of technologies supporting the evaluation of PdM technology quality will help support validation and assurance. This may include visual representations of prediction quality, interpretable metrics, automatic validation tools, data quality analysis tools, and other aspects. These tools could be provided open-source in a common industry tool such as ProgPy, or offered by an independent organization providing certification and/or validation services. Additionally, new technologies such as explainable prognostics could help address the lack of interpretability of some machine learning models.

5 Barrier 3: Cost of Adoption

Designing and implementing any predictive technology is a costly and time-consuming endeavor. A strong, well-validated, and comprehensive degradation model can often take years of work. Occasionally, the expense of creating these technologies is deemed prohibitively expensive [Madhav Misra, RISE, 2023].

5.1 Challenges

These costs challenges can be categorized into (a) Implementation and (b) Operational Costs.

5.1.1 Implementation Costs

The implementation costs tend to be non-recurring in nature but can make up a large portion of the cost of adoption. They include:

1. **Initial Investment** Predictive maintenance technologies require significant initial investments in research and development, manufacturing, procurement, and implementation. These costs include the development and validation of models and algorithms, the design and production of sensors and data collection systems, as well as the installation and integration of PdM systems into existing infrastructure. It is not unusual for the process of building a robust and complete prognostic component to take years of work by experts with specialized and rare expertise for a single component. Finally, legacy hardware and software increase the difficulty and cost of deploying PdM [Madhav Misra, RISE, 2023].

2. **Cost of Data Collection and Quality Control** PdM systems rely on large amounts of high-quality data to function properly (see Barrier 5). Collecting, processing, and ensuring the quality of data can be a costly and time-consuming process. This includes the cost of sensor installation, calibration, and maintenance, as well as the cost of labor for data collection and quality control. Data transfer and storage can also be quite costly, depending on the specific solution (e.g., using cloud services).

5.1.2 Operational Costs

The costs for the operation of PdM include:

1. **Labor Costs** PdM systems require skilled personnel for operation, maintenance, and analysis. These personnel may need to be trained in the use of new technologies, which can be time-consuming and expensive [Wes Ryan, Former FAA, 2023][Madhav Misra, RISE, 2023].

2. **Integration with Existing Systems** Integrating PdM systems with existing infrastructure (see Section 3.1.3) and legacy systems can be a complex and costly process. This includes the cost of upgrading or replacing existing hardware and software, as well as the cost of integrating new systems with legacy systems.

3. **Validation and Certification** PdM systems must be validated and certified to ensure their reliability and accuracy. This process can be expensive and time-consuming, requiring extensive testing and validation to meet regulatory requirements (see Barrier 2).

4. **Cost of Downtime** Downtime in industrial settings can be extremely costly, and predictive maintenance systems must be able to minimize downtime by accurately predicting when maintenance is required. If a predictive maintenance system is not accurate or reliable, it can result in increased downtime and associated costs.

5.2 Investments Needed

The suggested investments are multifold and address all stakeholders, including research and academia. They are listed below.

1. **Industry-level Collaboration and Discussions** For PdM to be successful, industry stakeholders must discuss and work collectively to develop standards, technologies, and approaches to address the challenges. [Amy O'Dell, United, 2023]

2. **Build and Maintain Foundational Software Packages** Many disciplines have foundational software packages that support research and development in these areas. Examples include TensorFlow or PyTorch in Machine Learning, Pandas in Data Science, or OpenMDAO in design optimization. These packages implement their discipline's common elements in an efficient, robust manner and include tools to help developers and researchers. They lift the entire discipline by reducing the effort required to perform research or build a functional solution. They also improve the quality of solutions by providing robust tools that have been thoroughly validated by a large user base. Finally, they enable the sharing of solutions, since solutions are built to common interfaces and patterns. The wider community should collaborate in building a robust set of tools (e.g., NASA's ProgPy (Ref. 27)) and software frameworks to support PdM.

3. **Develop and Mature Digital Thread Approaches and Technologies** Develop tools for reusing information from the design of a system (e.g., CAD models, requirements, etc.) in the development of new PdM technologies. These approaches could provide a good starting point for developing predictive models, and reduces duplicated work. [Brian Tucker, Bell, 2022][Anupa Bajwa, NASA, 2022][Abhinav Saxena, GE Aerospace Research, 2022]

4. **Support Training of the Next Generation of PdM Engineers** Multiple stakeholders had identified a talent shortage as a contributor to the high cost of adoption. NASA and Industry should invest in training the next generation of PdM engineers through internships, lectures and professional society involvement, partnerships with universities, and university grants. Additionally, NASA and Industry can help develop tools (e.g., ProgPy) and datasets (see Barrier 5) that support students in their education.[Madhav Misra, RISE, 2023][Wes Ryan, Former FAA, 2023]

5. **Develop New Intelligent Maintenance Strategies and Methods** NASA, Industry, and Academia should invest in developing advanced maintenance strategies and methods such as those based on proximity (e.g., when a pump is maintained, consider maintaining adjacent valve). This goes hand in hand with Barrier 4, as we would need methods to estimate the effectiveness of maintenance strategies.

6. **Develop Standards and Guidelines for Effective Communication of Prognostic Information** NASA, Industry, and Academia should develop recommendations and standards for effectively displaying and communicating prognostic information with uncertainty to best inform PdM decisions by automated and human maintainers.

7. **Methods to Reduce Testing Required for Validation** New technologies and techniques are needed to reduce the investment required to validate a PdM technology (see Barrier 2) while still maintaining a high level of safety [Brian Tucker, Bell, 2022][Abhinav Saxena, GE Aerospace Research, 2022]. These can be technologies like analysis tools, methods for minimizing the number of units required to test, automated testing technologies, or other validation tools.

8. **Design for Prognostics**, incorporate decisions on sensor placement and prognostics applications early in design process, from the beginning for new systems. [Wes Ryan, Former FAA, 2023][Kai Goebel, PARC, 2022]

9. **Update Legacy Hardware and Software**

6 Barrier 4: Impact Estimation

Any decision to adopt new technologies is preceded by a comprehensive cost-benefit analysis. In the case of predictive maintenance and other intelligent maintenance technologies, airlines, OEMs, MROs, and other stakeholders have to compare the cost of adoption (Barrier 3) against the benefits such a program could provide. This Section deals with the estimation of the latter.

6.1 Challenges

Estimating the impact of predictive maintenance in commercial aviation is a complex endeavor. Challenges that stakeholders identified include:

1. **Life Cycle Cost Modeling** There is a lack of accurate and reliable life cycle cost and risk modeling (Ref. 11, 32). [Darren Macer, Boeing, 2023][Kai Goebel, PARC, 2022][Brian Tucker, Bell, 2022][Kai Wicke, DLR, 2022][Wes Ryan, Former FAA, 2023] Life cycle costs include acquisition, operation, maintenance, and expected future repair and replacement. Life cycle cost modeling help airlines understand the impact of PdM and assess if its cost are worth the benefits of reduced downtime and reduction of unforeseen repairs. 63% of companies not working on implementing PdM indicate that their reason for not doing so was because of their inability to quantify the impact/business case (Ref. 9). Without this data, it is difficult for OEMs to tailor aircraft component design (including sensor integration) and manufacturing to reduce maintenance costs. Risk modeling examines how maintenance techniques may affect aircraft safety and dependability. Without proper comprehension of the potential risks and the likelihood of their occurrence, airlines are hindered in making informed decisions regarding

optimal maintenance strategies. To this date, there exists neither a standardized methodology for the simulation of an aircraft's life cycle, nor a widely used standardized methodology for the estimation of their life cycle cost [Aircraft OEM, 2022]. Some best practices, although rather general in nature, can be found in SAE ARP 4293 and SAE AIR 1939.

2. **Uncertainty Modeling** Uncertainty in the life cycle simulation (including, but not limited to, future price developments, expected demands, and the environment) leads to inaccurate predictions and reduced trust in the overall benefit of predictive maintenance [Kai Wicke, DLR, 2022][Kai Goebel, PARC, 2022]. These uncertainties can be of aleatory nature (i.e., not reducible, as it stems from the system's natural randomness) or of epistemic nature (i.e., potentially reducible, as it stems from a lack of knowledge). Difficulties include the many uncertain sources, lack of data to properly quantify them, lack of methods to combine and propagate them, and a lack of understanding when it comes to result interpretation. Overall speaking, there is a lack of comprehensive life cycle simulation uncertainty management, which, especially considering the nature of PdM, is a significant challenge for innovation.

3. **Economic Competition** OEMs, independent MROs, and airlines compete in the aftermarket. This competition arises because MROs and airlines seek to reduce costs while maintaining the required level of reliability and safety. However, OEMs have a competitive advantage in the aftermarket due to their access to the original equipment design and engineering data. In contrast, independent MROs and airlines have to rely on reverse engineering, which can be costly and time-consuming. To maintain their market position, OEMs often restrict access to their proprietary data, making it difficult for MROs and airlines to develop and apply PdM technologies. This lack of access hinders the ability of MROs and airlines to provide accurate impact estimates and can limit the effectiveness of PdM programs [Kai Wicke, DLR, 2022]. This point is related to the data ownership, described in Barrier 5.

4. **Operational Complexity** The variety with which different airlines operate their fleet can make it difficult to generalize the impact of PdM to the entire industry [Kai Wicke, DLR, 2022]. This includes not only the operational complexity mentioned in Barrier 1, but also fleet-wide decisions such as when and how to cluster maintenance events, or decisions regarding phase-outs and acquisitions of new aircraft [Airline SME, 2022].

These challenges need to be faced and solved in order to inform design and operational decisions, e.g. if, when, and how to deploy predictive maintenance [Kai Goebel, PARC, 2022].

6.2 Investments Needed

To overcome the previously mentioned challenges, we have identified the following two potential solutions: Creating a standardized methodology for life cycle simulations and a standardized methodology for incorporating uncertainties in the predictions.

6.2.1 Standardized Methodology for Life Cycle Simulations

By developing a standardized methodology for the simulation of aircraft and component life cycles, it will be possible to comprehensibly estimate the impact of PdM measures by simulating (at least) two cases: (a) a reference case, which imitates the current operation, and (b) a study case, where the technology in question is activated, and its repercussions are thoroughly monitored.

The technology's benefit can be isolated and quantified in terms of availability and downtime as well as operating costs. Feeding these insights back to the OEMs enables optimizing design for maintenance, prognostics, and, ultimately, life cycle cost. A thorough review and subsequent modeling of each stakeholder's operation is required for this methodology to be standardized. This includes, but is not limited to, the airline's rotational and maintenance planning, the MRO's line and base maintenance operation, and the interactions between the aircraft's operational environment and the component's health. Ideally, such a methodology is modular and modifiable, allowing (de)activating and customizing specific aspects of the simulation. Recent developments indicate a high potential of discrete event or agent-based approaches.

6.2.2 Standardized Methodology for the Incorporation of Uncertainty in Impact Estimation

A standardized methodology for a comprehensive uncertainty-enabled simulation of aircraft and component life cycles would help practitioners navigate the vast field of uncertainty quantification techniques, helping them choose the best techniques at the right time. This can help guide future uncertainty reduction efforts as well as aid in the interpretation of uncertainty when presented to stakeholders and decision-makers. Recognizing, quantifying, combining, propagating, and portraying all sources of uncertainty that may affect impact estimation is complete uncertainty management. In addition, recent techniques such as sensitivity analysis or non-probabilistic modeling should be investigated and employed where suitable. Sensitivity analysis examines how input factors affect model output to determine which variables cause the most uncertainty. When data is insufficient and expert elicitation is needed, non-probabilistic methods may prove useful.

7 Barrier 5: Data Availability, Quality, and Ownership

The success of predictive maintenance systems and technologies heavily relies on data, which is essential for training, validating, and improving machine learning models. However, there are several challenges that arise in the context of data availability, quality, and ownership. These challenges include issues related to the collection, labeling, cleaning, and sharing of data, as well as concerns around data privacy and security. In this section, we will discuss these challenges in more detail and explore potential solutions to overcome them.

7.1 Challenges

1. **The Right Data** The first challenge is getting the right data for prognostics [Kai Goebel, PARC, 2022][Darren Macer, Boeing, 2023]. Prognostics requires the specific data that can be used to detect degradation and degradation trends at high enough frequencies and precision. As Darren Macer from Boeing said, "we're woefully undersensed". Sometimes, the sensing technologies required to collect this information does not exist. Other times, these needs are not considered in the design phase, so systems are not designed to include the required sensors (Design for Prognostics). Finally, sometimes the cost of integrating a sensor is not deemed acceptable for the capabilities it provides [Darren Macer, Boeing, 2023] (see also Barrier 3).

2. **Getting the Data** Even if the data exists, frequently it is not possible to get the data off of the aircraft (Ref. 8, 16, 31) [Wes Ryan, Former FAA, 2023]. Bandwidth constraints from satellite connectivity limit the ability to stream data in flight. Additionally, cost and logistical

constraints frequently prevent aircraft from installing systems to offload data at the gate or hangar [Mark Roboff, SkyThread CEO, 2023].

3. **Record Digitization** Beyond the sensor data, development, evaluation, and application of predictive maintenance requires maintenance record digitization. Many records, and even current maintenance operations are still recorded on physical forms (Ref. 8), which are usually not structured and are thus difficult to use in an automated manner [Kimon Abu-Taa, Rolls-Royce Deutschland, 2023]. Digitizing and standardizing these forms and maintenance records processes is a big task. Additionally, maintenance records frequently include errors [Mark Roboff, SkyThread CEO, 2023].

4. **Data Ownership** In addition to data availability and quality, there is some question about data ownership. Many OEMs restrict access to operational data for airlines and MROs (Ref. 16, 33). Finally, pilot unions sometimes negotiate limitations on how the data can be used or requirements to anonymize data [Amy O'Dell, United, 2023]. Conversely, it can also be difficult for the Engine OEM to get access to operator's essential data (e.g. data regarding EHM, flight connections, on-wing maintenance etc.). These data limitations or data anonymizations sometimes make it difficult to use the data for predictive maintenance.

Finally, labeled relevant degradation datasets are essential for model building and validation in academia and industry. This can be seen in the impact of existing datasets like the CMAPSS datasets (Ref. 34, 35).

7.2 Investments Needed

A few contributions that could help close this barrier are described below. They are clustered into those that aid in accessing more data and those that improve the way data is dealt with.

7.2.1 Accessing more Data

1. **Develop New Sensing Technologies** New sensing technologies (e.g., embedded or printed sensors or active sensing techniques) can help generate data relevant for prognostics that may not exist now. [Darren Macer, Boeing, 2023]

2. **Data Export from Aircraft** There is ongoing discussion and first approaches among some airlines and airports to explore technologies and methods for exporting data from aircraft (e.g., gate link and satellite) to secure and accessible storage. Further work is needed in order to make use of the data for predictive maintenance operations, model building, and tool validation. [Mark Roboff, SkyThread, 2023][Amy O'Dell, United, 2023][Madhav Misra, RISE, 2023]

3. **Digitize Maintenance Records** Already underway by many airlines and MROs, maintenance records should be standardized, digitized, and parameterised (for machine readability) so they can be available for predictive maintenance model building and validation. [Madhav Misra, RISE, 2023][Marc Roboff, SkyThread, 2022][Kimon Abu-Taa, Rolls-Royce Deutschland, 2023]

4. **Develop and Mature Methods and Technologies for Automated Inspection** Mature at-gate or in-hangar ("Hangar of the future") automated inspection techniques. This would

provide additional sources of information in an environment with fewer bandwidth constraints. Considering that many modeling and validation efforts for PdM depend on geometrical data (which can essentially be obtained in MRO facilities), an automated collection and parameterization of the component's geometry (for machine readability) would be a significant step forward in the realization of PdM.

5. **Develop and Mature Methods for Incorporating Textual Information** Develop tools and approaches to incorporate unstructured and textual data into PdM.

7.2.2 Improving Data Accessibility

1. **Data Standardization** Stakeholders could work with the SAE HM-1, IEEE P1856.1, the Independent Data Consortium for Aviation (IDCA), and other standards teams to standardize data collection and sharing formats and procedures. Standardized format must protect pilot privacy while still containing the information necessary to inform predictive maintenance operations and research. [Madhav Misra, RISE, 2023]

2. **Publicly Releasing Labeled Component-level Datasets** Generate or collect and publicly release relevant labeled degradation datasets for individual components. This would provide valuable data for model building and validation. This data could be generated through construction of a testbed that is able to load the system of interest while collecting data, perhaps while emulating a fault of interest or with an already faulty system. [Darren Macer, Boeing, 2023][Madhav Misra, RISE, 2023]

3. **Publicly Releasing Labeled Operational Datasets** Develop, anonymize, and release a large dataset of operation data. For example this could be sensor, operational, and environmental data and maintenance records from a single aircraft over one year time, anonymized and labeled. This dataset would help support and enable research in predictive maintenance technologies and validation of new technologies. [Darren Macer, Boeing, 2023][Madhav Misra, RISE, 2023][Kai Wicke, DLR, 2023]

4. **Support Data Sharing** Develop, mature, and support technologies and organizations supporting data sharing, such as the ICDA.

8 Conclusions

Everyone in this study recognized the potential for PdM and agreed that there was inadequate adoption. According to the Department of Energy, predictive maintenance program can reduce maintenance costs by as much as 30% (Ref. 6) or $3 Billion (Ref. 8). With input from SMEs and published sources, the authors identified five barriers preventing the full-scale adoption of predictive maintenance technologies. Targeted investments to address these barriers, such as those outlined in this document, will ultimately help break down these barriers and enable progress toward the full-scale adoption of predictive maintenance technologies and strategies in aviation.

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