MACHINE LEARNING REQUIREMENTS FOR THE AIRWORTHINESS OF STRUCTURAL HEALTH MONITORING SYSTEMS IN AIRCRAFT

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Abstract:
In the evolving realm of airworthiness and aircraft maintenance task scheduling, the introduction of data-driven Predictive Maintenance (PdM) and Structural Health Monitoring (SHM) has prompted a paradigm shift, which underscores the profound implications of innovative sensing techniques within damage and operational monitoring. Concurrently, the role of avionics in data acquisition and processing has drawn renewed focus, with machine learning (ML) algorithms facilitating pattern recognition, trend analysis, and anomaly detection. This paper discusses the diagnostic sequence in SHM systems, the necessity for damage information, and delves into active and passive sensing techniques within damage and operational monitoring. The role of avionics is also emphasized, especially in data acquisition and processing for operational monitoring. The utilization of ML algorithms for efficient use within SHM is explored, alongside supervised and unsupervised learning methods. The paper underlines how integrating ML in aircraft systems applications can optimize maintenance schedules and lay a solid foundation for SHM integration in aircraft health systems. The study also covers the application of ML techniques for detection, localization, and assessment of structural damage. It reviews research implementations using ML, statistical, and hybrid approaches in monitoring and predicting aircraft damage. The incorporation of non-exclusive ML in SHM to minimize environmental feature uncertainty and enable trackable model behaviour is illustrated. Lastly, the paper discusses evolving regulatory requirements and standards for ML application in aviation SHM, provided by authorities and workgroups like EASA and the SAE G-34 AI in Aviation Committee, respectively, and concludes with an overview of the future trends and standards in this dynamic domain. The aim is to spotlight the transformative potential of PdM and SHM, and their critical roles in boosting the operational efficiency of the aviation industry.

Keywords: Structural Health Monitoring, Predictive Maintenance, data-driven models, Machine Learning assurance, avionics systems

INTRODUCTION

As we traverse the innovative landscape of the aviation industry, it is essential to highlight the data-centric shift in maintenance practices as part of the emerging Industry 4.0, led by Predictive Maintenance (PdM). The adoption of PdM, driven by the growing accessibility of aircraft-generated data and the demand for enhanced efficiency in asset management, aims to pre-emptively address maintenance challenges through precise failure predictions. Simultaneously, Structural Health Monitoring (SHM), a progression from Non-Destructive Testing (NDT), has the potential to facilitate real-time, comprehensive structural integrity insights. The integration of machine learning (ML) algorithms within structural health monitoring (SHM) systems has unlocked new possibilities for detecting, localizing, and classifying damage in aircraft components. This conference paper explores the synergies between ML and SHM, highlighting their relevance in the rapidly evolving landscape of aircraft maintenance.

As we delve into the different types of ML techniques employed in SHM, such as supervised and unsupervised algorithms, we discuss their respective advantages and limitations in relation to the evolving guidelines and regulations from certification bodies and relevant standards development organisations for engineers—the European union Aviation Safety Agency (EASA) and the Society for Automotive Engineers (SAE) G-34 respectively—which are critical for the safe and effective implementation of ML in aircraft systems. In addition, we underscore the importance of various assurance institutional ML publications in shaping these guidelines. Despite the scarcity of open-access research in this niche, our paper explores diverse SHM applications employing physics and data-driven approaches for aircraft structural components. We focus on research implementations using ML and statistical methods for monitoring and predicting damage progression in stress-prone structures like aircraft wings and rotorcraft structures. Exploring hybrid SHM approaches that merge ML models helps reduce environmental feature uncertainty and track model behaviour.

This paper finally underscores the vital need for regulatory standards in implementing ML along SHM, ensuring safety when integrating ML, transparency, and accountability, and anticipating future trends in the regulatory landscape for ML in aviation systems. By doing so, we aim to provide a comprehensive understanding of the evolving dynamics of ML application in SHM, keeping our readers abreast of the latest advancements and prospects in this crucial field.

THE EMERGENCE OF DATA-BASED PREDICTIVE MAINTENANCE IN THE AVIATION INDUSTRY

PdM: optimising aircraft maintenance with prognostics and Condition-based Maintenance

The aircraft operations industry has in recent years experienced a shift towards PdM, a crucial component in cost-effective and efficient management of resources for aircraft components maintenance and increased systems availability. Interdependent with Prognostics and Health Management (PHM) in the realm of asset management, it serves to monitor an asset's condition and report imminent faults, be it through knowledge-based, physics-based, data-driven models of implementation, or a combination of the prior, in order to utilize insights gleaned from collected data and recommend timely and appropriate maintenance actions [1], [2]. Under the same fault detection and analysis umbrella, Condition-based Maintenance (CBM), a diagnostics-focused maintenance concept, is referenced when maintenance activities are initiated in response to the outcomes derived from monitoring the condition of a system or equipment via Condition Monitoring (CM). CM exclusively covers the real-time analysis of sensor data such as vibration or temperature exceedances from a component's normal operating conditions to detect anomalies and anticipate short-term failures [3]. While CBM is more effective than conventional predetermined maintenance (also referred to as preventative, cycle-based, or time-based maintenance) in considering equipment usage conditions, it is limited by the uncertainty of failure occurrence dates and the inconsideration of the indirect system variables which are not explicitly monitored by CM but can influence the failure or performance of the monitored component. This issue is addressed by PdM through forecasting equipment failures using the analysis and evaluation of significant degradation parameters that cause the imminent inadequacy of a component in a system to perform as expected within safe limits [4]. PdM allows for projecting the equipment's current state into the future, estimating its operational duration until predicted failure, and adjusting maintenance schedules accordingly. Thus, by incorporating PdM, the aviation industry can optimize equipment lifecycle management and make evidence-supported informed decisions regarding maintenance and operations.

Growth of data-driven PdM in aviation and stakeholder roles

An increasingly large amount of data is being generated by aircraft with relatively newer avionics equipment, allowing for a more seamless transportation and recording of data, as well as a larger number of sensors onboard the aircraft. Such enabled aircraft are estimated to reach 45% of operational fleets by 2025, according to Richard Brown, former principal at ICF's aerospace consulting practice [5]. Brown estimates a potential of $3 billion in maintenance savings alone, when implementing data-driven PdM. This emergent approach for maintenance is dependent on data owned by three major industry stakeholders: Original Equipment Manufacturers (OEMs), aircraft operators, and Maintenance, Repair, and Operations shops (MROs), all of whom have access to their own proprietary data that they individually generate along the life of an aircraft before and in-service. Data from the OEMs' design and test programmes is first used to populate monitoring and predictive systems, where they typically provide flight-hour support throughout the first third of an aircraft's life; however, airline operating data from aircraft operators is gradually added to or replaces this data, where large integrators' flight-hour programmes become more significant. Many OEM's will also provide flight-hour (or power-by-the-hour/total care) throughout the asset's life, dependant on the aircraft component being monitored. Global airline MROs are making inroads into the predictive market. Their strategy differs from OEM's in that they concentrate on particular reliability or cost concerns brought on by certain components rather than employing big data to analyse vast data sets. The most relevant information for PdM comes from operational and maintenance data, but fault logic for a system or component is also crucial [6].

Challenges in adopting PdM

PdM has shown significant potential in the aviation industry, helping airlines optimize their maintenance processes and reduce costs. Nonetheless, its widespread implementation faces several obstacles. A primary challenge lies in data sharing, as MROs, OEMs, and operators are often unwilling to share crucial data that is necessary for predictive algorithms [7]. This reluctance hampers access to vital operational data, and when accessible, some stakeholders worry that sharing it with third-party MRO providers could advantage their competitors. In this case, applying ML to datasets from multiple operators allows for the development of ML algorithms without directly accessing another operator's data, as explained by Rik van Lieshout, digital products and services manager for Air France Industries KLM Engineering & Maintenance [8]. An example of such algorithms is Federated Learning (FL), which offers a potential solution to these data-sharing concerns. FL allows for ML across distributed data sources without centralizing the data, addressing privacy and data governance challenges. In an FL environment, data controllers not only establish their governance processes and privacy policies but also maintain control over data access and revocation during both training and validation phases. A requirement for viable FL to be adopted is that, when comparing models with identical architectures, the performance of the model developed through FL, as assessed by evaluation metrics such as test accuracy, should surpass that of a model developed through local training [9]. This approach enables new opportunities such as large-scale, cross-party validation or research on rare events where individual parties have insufficient data [10]. Furthermore, to fully embrace PdM, airlines must be willing to remove serviceable components based on algorithmic predictions, even if it means incurring a higher cost or downtime in the short term. Such proactive actions can significantly reduce long-term expenses [11].

Use cases demonstrating the value of PdM

In the realm of independent maintenance providers in the aircraft industry, Lufthansa Technik's (LHT) AVIATAR platform helps avoid up to 30% of unscheduled removals by leveraging new predictors developed for various aircraft systems [8], [12]. Another instance is AFI KLM E&M's PROGNOS for aircraft, which utilizes continuous aircraft sensor data to calculate health metrics of A380s and 747/787s, and analyses engine data for failure prediction of CFM engines onboard aircraft [13]. By incorporating pattern recognition and historical operational data, PROGNOS can recognize unhealthy behaviour, alert the end user, and enable proactive maintenance planning [14]. Such PdM tools have been successful in optimizing inventory planning and troubleshooting times and averting unplanned ground time for fleets.

STRUCTURAL HEALTH MONITORING SYSTEMS AND THEIR RELEVANCE TO AIRCRAFT MAINTENANCE

Advancements and challenges in SHM

SHM systems, which assess damage; a system's change in structural composure or properties negatively affecting its expected performance [15], play a crucial role in providing real-time information on the structural integrity of an aircraft, enabling more efficient resource allocation compared to scheduled maintenance conducted as a precautionary measure. As inferred by [3], [16]–[20], SHM, specifically its active sensing component, is a progression of Non-destructive testing (NDT) methods, enabling the continuous monitoring of a structural property by means of sensors installed onboard the structure. Therefore, instead of schedule-driven inspections which were reliant on NDT techniques, SHM enables CBM, and consequentially, with added prognostics, PdM (The reader may refer to [3], [4] for an in-depth comparison of the aforementioned health management terms). Given the concurrent use of terms such as SHM, PdM, CBM, and PHM in various resources, the authors of this paper deemed it essential to clarify their intention when using the term SHM. In this context, SHM is defined as a subfunction of PdM. To further elucidate, in alignment with SAE's ARP6461A guidelines [21] and Farrar and Worden's definition [22], a health monitoring system that incorporates damage detection, quantification, and prognostics is considered an SHM system and can also be referred to as a PdM system. However, the reverse is not true, as PdM may encompass, apart from prognostics, other aspects beyond those covered by SHM, such as aircraft bearing health management and aircraft engine fault detection, which are both distinguished from aircraft fuselage and structural damage detection, the focus of SHM in aircraft.

With inspection and maintenance costs accounting for over 27% of an aircraft's lifecycle, SHM systems offer an attractive solution for concurrently reducing costs and detecting damage as or prior to its occurrence, although the optimized selection and placement of a sensor configuration where cost is saved when compared to costs incurred during scheduled maintenance downtime has not been feasible to this date [23]. Gaps in the research include the necessity for the validation of proposed SHM systems on non-oversimplified physical structures, and the use of data-driven approaches to complement sensor readings, in order to reduce the amount of sensors required pending that current sensor configurations are optimised, or newer cost-efficient sensor technologies emerge [2], [23]–[25]. Within this context, diagnostics—evaluating the presence and extent of damage in a system—involves addressing a sequence of interdependent questions. Firstly, Is there damage? If so, where is it located? To what extent is the damage propagated? What type of damage is it? And finally, how severe is the damage [26]? Thus, completing the diagnostic sequence. It is vital to remember that not all damage can be measured by sensors. To transform sensor data into damage information, feature extraction through signal processing and statistical classification is required [27]. In modern aircraft, particularly for primary structures with multiple load paths, the Damage Tolerance approach is often utilized. This approach involves recognizing, inspecting, and managing fatigue cracks, requiring the selection of materials that exhibit a manageable crack growth rate and possess fracture toughness that allows operation up to limit load with detectable cracks during scheduled inspections, thus preventing catastrophic failures.

Sensing and monitoring techniques in SHM

Drawing upon the diagnostic queries outlined in the preceding section, the process of accruing damage information organizes itself into a hierarchical four-tier structure: damage detection, localization, characterization, and quantification. Subsequently, the prognostics stage takes place, where the damage is assessed within the context of a comprehensive plan, considering its relation to replacement timings and the degradation rate of the component or structure w.r.t other affecting factors [22]. The inputs for

SHM are obtained from sensors onboard the aircraft, which can be used for SHM purposes and/or for the benefit of other aircraft health monitoring techniques e.g., CM or PHM. As defined by [21] for the implementation of SHM on aircraft, these inputs facilitate Operational and Damage Monitoring through various sub-functions, such as Fatigue Monitoring, Exceedance Monitoring, and Environmental Monitoring.

Damage Monitoring involves direct measurement methods, such as active and passive sensing, that detect damages in the structure, including damage localization and size characterization. Sensors are generally installed in or near targeted areas, and the output can either be equivalent to an inspection report or an advisory indication that helps improve repair planning. If the inspection requirements cannot be met, damage monitoring could complement the inspection program of an aircraft.
Active and passive sensing, which are methods of sensing in Damage Monitoring and can also be used simultaneously, are differentiated as follows:

- Passive sensing refers to the process of collecting data on a structure without the use of actuators. It involves sensors that continuously detect and receive any alterations or disturbances within the structure, such as strain or acoustic emissions, which may indicate hidden damage. Passive sensing is generally less intrusive and less complex than active sensing but may be more susceptible to noise and signal interpretation difficulties due to its sensing sources' inability to accurately include external factors affecting damage, such as environmental and temperature differences, which contribute to the component's dynamic response [28], [29]. Examples of sensors used include strain gauges, FBG sensors, and accelerometers.
- Active sensing involves the use of actuators and/or receivers to actively interrogate the structure. Actuators generate waves or signals that propagate through the structure, and the receivers capture the response. By analysing these responses, one can detect and potentially locate damage within the structure. Active sensing can provide more detailed information about damage but may be more complex and require more resources compared to passive sensing [30]. Examples of sensors used include ultrasonic and electro-mechanical impedance piezoelectric sensors for measuring local damage [20], [31].

In contrast, Operational Monitoring encompasses all indirect measurement methods that contribute to the evaluation of an aircraft structure's condition or its utilisation. Its parameters can be derived from damage tolerance and fatigue evaluation of the structure, taken from flight data monitoring (FDM) parameters and/or loads in-service, depending on the sub-function. Its output can be an advisory indication or structural usage evaluation. This output can lead to modifying inspection intervals based on aircraft use [21]. It is important to note that this method of monitoring does not explicitly require the installation of sensors other than those that already feed data into the aircraft's avionics systems.

- Exceedance monitoring, an aspect of operational monitoring, identifies instances when in-service loads exceed the design criteria, detecting abnormal loads on the structure (e.g., hard landing or severe gust). By utilizing load-related parameters such as flight parameters or strain measurements, exceedance monitoring can reduce the rate of false negative and false positive indications related to these instances. Its output consists of advisory indications that can trigger maintenance actions. Examples of such monitoring includes Boeing's landing loads estimation model aimed at helping reduce false-positive hard landing announcements [32].

THE ROLE OF AVIONICS IN HEALTH MANAGEMENT SYSTEMS

Avionics systems play a crucial role in the PdM processes of aircraft, as they are responsible for collecting, processing, filtering, and transmitting the vast amounts of data generated by the SHM subsystems. By integrating this data with other information from the aircraft's systems, avionics serve as a primary pillar to providing a comprehensive understanding of the aircraft's health, allowing for the implementation of timely and targeted maintenance actions.

Data Acquisition Example for Operational Monitoring

PdM programs and/or models receive their input from avionics systems through a series of data transfers and conversions, which involve components such as sensors, data buses, and data management units. It is important to note that different aircraft may have different data sources e.g. A320 data originating from an Aeronautical Radio Incorporated (ARINC) 429 bus. Additionally, the type of data collection equipment at the receiving end depends on the operator's preferences. E.g., for an A320 with specified avionics fit:

1. Data acquisition begins with sensors installed on the aircraft. These sensors measure various parameters such as temperature, pressure, acceleration, radio altitude, and aircraft heading.

2. The sensor data is then sent to data buses, such as ARINC 429, which are communication systems responsible for transmitting the data between different avionics components. The ARINC 429 bus is a widely used data bus in the aviation industry, standardized for the transfer of digital information between avionics systems.

3. The Data Management Unit (DMU) or Flight Data Interface Management Unit (FDIMU) receives the data from the ARINC 429 bus. The DMU is the central processing unit responsible for managing and recording aircraft data. It can also be referred to as a data acquisition unit.

4. After receiving the data, the DMU processes it and packages it into ARINC 717 format. The ARINC 717 is a standard data format specifically designed for flight data recording systems, such as Digital Aircraft Condition Monitoring system (ACMS) Recorders (DAR), Quick Access Recorders (QAR), and Smart ACMS Recorders (SAR) data frames. DAR, QAR, and SAR are nowadays virtual units within a single DMU, responsible for recording different types of data [33]:
    - DAR: Collects and stores data from the aircraft's systems for maintenance and analysis purposes. Operators can configure their own data frame by adapting the default data frame, adding parameters, and changing the recording frequency.
    - QAR: QAR may record a richer set of data than the Flight Data Recorder (FDR) for various purposes, including Flight Data Monitoring (FDM) and other operational analyses. The QAR data has started to move more towards uses resembling FDM, as it provides more detailed information compared to the FDR, which is primarily designed for accident investigation purposes. The QAR's primary benefit is its storage of data on a removable flash memory card or transferred via cellular network.
    - SAR: Utilizing the SAR feature, an airline can establish distinct data recording channels that activate in response to specific system events. This enables maintenance, system assessment, trend analysis, and problem-solving requirements to be addressed more effectively.

5. Once the data is recorded in the appropriate format (e.g., ARINC 717), it is stored on the DMU card as either individual files per flight or a single file for the entire flight, depending on the avionics fit of the aircraft.

6. The raw binary data (ARINC 717 stream) is then taken by software such as Aerobytes or Airphase for data conversion and storage in a proprietary format within the database of that software. The data may then be exported for analysis, when used for research applications.

PdM models may then utilize algorithms and data analytics to identify patterns, trends, and anomalies in the extracted data for the purposes of Operational Monitoring from the above example, as well as from various custom-fitted system outputs. These insights can then be used to predict the remaining useful life of critical aircraft components, optimize maintenance schedules, and ultimately, enhance the overall safety and reliability of the aircraft. The effectiveness of SHM systems largely depends on the quality and accuracy of the data provided by the sensors embedded within the aircraft structure e.g., sampling rate, method of sampling, and the bit depth of the Analog to Digital Converter (ADC). Modern avionics systems are increasingly incorporating a wide array of sensors to monitor the health of various structural components in real-time. SHM systems may now be used much more widely thanks to the development of health management capabilities as well as significant advancements in processing power, memory storage, data transmission rates, and analytical methodologies. Furthermore, the role of health management in decision-making is anticipated to become much more tightly integrated with control functions as a result of the issues posed by unmanned vehicles in the future [34].

STRUCTURAL HEALTH MONITORING AND MACHINE LEARNING

Why ML is interlinked with SHM

According to Farrar and Worden [22], there are two main categories of approaches to SHM: the model-based approach, which involves building a physics-based model of the structure, and the data-driven approach, which relies on ML algorithms as one of the tools for pattern recognition. Review papers covering diagnostics and prognostics models [2], [35] explicitly introduce two more categories: knowledge-based, and multi-model, or hybrid approaches (which are combinations of the data, knowledge, and physics-based approaches), emphasizing that hybrid approaches can lead to more efficient diagnosis and prognosis of faults. The data-driven approach for an SHM system, which encompasses statistical, stochastic, and machine learning models, consists of four main sequential procedures: operational evaluation, data acquisition, feature selection, and statistical modelling for feature discrimination [36]. In operational evaluation—the first step—the system being monitored is evaluated based on its operational mode and directly affecting features, specifying initial assumptions for data collection requirements. This process includes determining sensor types, configuration needs, sensing objectives, and considered operational and environmental conditions. Once these specifications are met, and in the second step, sensors are placed, data collection takes place, class labels are assigned, and the output is pre-processed for use in pattern recognition via dimensionality, noise, and outlier reduction and/or removal. The output of this data acquisition is also the form in which benchmark datasets exist, which are used extensively in research, due to their ease of access. Thirdly, with the integration of engineering knowledge or data transformation techniques, critical indicators of potential damage are identified and selected. Subsequently, the data may undergo additional refinement processes such as compression, normalization, or fusion as required. Fourthly, An algorithm determines the damage state, applying one or more techniques: assigning a discrete class label such as damaged or undamaged, locating damage and estimating its size, and identifying new or anomalous observations [19]. The final output data can be analysed, and if needed, decisions can be made regarding remedial actions for the identified damages. Data filtering methods, the types of sensors for data collection, sensor selection and placement, and damage detection techniques for SHM in aircraft are not covered in detail due to them being out of the scope of this paper. The reader may refer to [20] for a more detailed review on these topics. The authors chose to cover the final or fourth aspect of machine learning used in SHM, namely statistical modelling for feature discrimination, or pattern recognition.

ML in Data-driven SHM

The usage of data-driven approaches in SHM is encouraged due to its alternative—the model-based approach—having stringent material property and physical performance requirements which pose a major problem for the modeller, as the extent of replicability of the modelled structure's performance and output depends on the accuracy of its model. In addition to the optimisation of sensor placement along the component [24], ML enhances statistical pattern detection and decision-making, which are its key functions when used in SHM systems. The concept of ML primarily comes into play in the areas of feature selection and statistical modelling, addressing the question: 'what type of damage is it?', as it facilitates the establishment of a relationship between the features derived from the collected data and the condition of the damaged structure [22], [37]. To establish this relationship, ML techniques utilize either supervised, unsupervised, or semi-supervised learning methods, depending on the availability of class labels (adequate labelled damaged samples) in the training data. Moreover, although ML techniques primarily rely on data-driven approaches, they can also incorporate physics-based modelling for SHM, and therefore be part of a hybrid-based approach, where even more datapoints may be generated. To safely reach the stage of automation, a certain confidence in the prediction of the ML algorithm and its level of explainability is necessary [38]. This ultimately lessens the requirement for human intervention and leads to autonomous damage localisation, which focuses on detecting damage that will lead to failure if not corrected. The identification problem in SHM can be further represented as a hierarchical structure consisting of detection, localization, classification, assessment, and prediction. The classification approach to SHM is based on pattern recognition, which assigns a class label to a sample of measured data. This process requires examples of data or features corresponding to each class for higher levels of identification [22]. This brings us back to the several learning types of ML used in SHM, most of which are supervised, unsupervised, and the emerging semi-supervised learning method.

ML solutions

Since it needs information from an adequate and representative amount of damage situations, supervised learning can be challenging. In the case of SHM applications, experimentation and physics-based modelling such as finite element analysis are two potential sources of this information. Both sources, nevertheless, have their limitations. Modelling, for instance, may be difficult for geometrically or physically complicated structures, whereas experimenting may not be practical for expensive sources of structural information such as aircraft components. An alternative solution in this scenario is unsupervised learning, which can be used for damage detection and localization, depending on the use case. Unsupervised learning methods extract training data from the structure or system's typical working conditions as input, and label this data as within a set threshold, outside of which the outlying data points would be omitted and representative of a fault mode [39]. This approach is thereby known as outlier or novelty detection. Such an approach of unsupervised learning mitigates the training requirement of each type of fault in the case of supervised ML. This method therefore streamlines the procedure and does away with the necessity to cause damage to the structure in question. Combining both methods, semi-supervised learning takes as input partially labelled damage data on the same structure. As Eltouny et al. describe [40], although more practical than supervised learning for damage detection in structures, it faces limitations such as engineering experience being used for threshold placement when selecting parameters, due to only using healthy structure samples for training, which leads to human judgement being a factor and major source of error in training these models. Supervised learning methods have a higher certainty rate due to the existence of solid fault examples to be trained on, as demonstrated in [41] where damage is classified in a Carbon-Fibre Reinforced Polymer plate and aluminium plates via several types of Self-Organizing Maps (SOMs). In their comparison, supervised SOMs result in a higher accuracy of fault prediction. Additional problems include environmental changes causing a change in the features used for training [42], leading to the ineffective performance of unsupervised models due to their inconsideration of the effects of external influences on the signal of the input sensors [43]. Thus emerges the benefit of hybrid approaches to SHM, as demonstrated in [44] where the integration of physics-based healthy and damaged structural performance data of a bridge structure in various environmental conditions from Finite Element Modelling (FEM) allowed for the incorporation of external environmental influences and thus the improvement of ML outputs resulting from it being trained by sensor-based data exclusively, that did not incorporate environmental condition effects on the structure.

The usage of ML in SHM on Aircraft

Key areas of focus in the application of SHM to aircraft primarily revolve around identifying damage, such as fatigue cracks in an aircraft's structure. Moreover, they involve understanding the potential impact of such damage on structural properties, pinpointing damage location, and assessing its severity in line with the Damage Tolerance approach. However, it is noteworthy that open-access research within this subject area, particularly in terms of tangible implementations, remains limited. The authors have therefore resorted to SHM applications using physics and data-driven implementations for aircraft structural components, and those most relevant to this area, such as rotorcraft.

Considering the susceptibility of aircraft wings to stress due to recurring flight cycles, Yousuf et al. [45] addressed the challenges associated with monitoring and predicting the initiation and progression of damage, particularly around rivets. The countersink rivet hole (CSK) is a common site for damage growth, which often transforms into a three-dimensional entity over time. NDT personnel conduct regular monitoring and analysis of these pits, providing insights into whether preventive measures are necessary. Predicting flaw size based on these NDT measurements presents an intricate inverse problem given the stochastic nature of crack growth and inherent noise in NDT measurements. To tackle these complexities, their study considered the adoption of statistical methods such as Bayes' techniques. Among these, the Particle Filter (PF) method garnered specific attention due to its suitability with non-linear state transition models and non-Gaussian noise probability density functions (PDFs), where they predicted damage progression on the rivet holes over time.

In their similarly focused aircraft wing rib-joints damage research, Lin et al. [46] employed aerodynamic loads analogous to those experienced during flight—consistent with the limit load requirements across an aircraft's necessary flight phases—on composite wings. Conceptualizing the process of identifying and characterizing damage, the team suggested the use of a passive damage monitoring fastener replacing a rivet. Positioned at high-strain locations—specifically, skin-rib joints on the wing during flight manoeuvres—this fastener offers the potential for effective in-situ damage monitoring [47]. The process of modelling the wings, in the form of an FEM, was facilitated by a simplified yet physically compliant and efficient aircraft geometric model based on aircraft design requirements. The strain measurements resulting from these loads were then utilized to train a Convolutional Neural Network, thereby forming a hybrid modelling approach, incorporating strain output data from the physics-based FEM simulation.

As has been demonstrated in the previous examples, in the realm of aerospace, the longevity and reliability of airframe structures are gradually compromised due to slow progressing damages like fatigue cracks, delamination, and corrosion. These afflictions increase both the operational risk and maintenance cost. Notwithstanding the progress made in the field, accurate and reliable detection and quantification of fatigue crack growth, especially in rotorcrafts, remains challenging. To tackle this challenge, research by Mulugeta et al. [48] presented an integrated method to improve the accuracy of crack growth estimation in rotorcraft structures. This method combines sensor readings with physical damage models utilizing a PF approach. The PF ML algorithm assigns a probability distribution to the unobserved or unknown crack size based on the prediction of physical damage model, subsequently updated with sensor data through sequential Monte Carlo sampling. This approach is especially applicable for structures of rotorcrafts which endure highly complex, random, and vibratory flight load spectrums and are therefore susceptible to cracks. A series of experiments were performed on representative rotorcraft structural components to test this approach. Their experiments involved the use of aerospace-grade aluminium alloy angle-plates, fastened together to form a nested-angle assembly, subjected to fatigue tests under various flight loads. The detection of cracks utilized the widely applied non-destructive technique of Ultrasonic Testing. Current physical damage models, like the Paris–Erdogan model or NASGRO equation, primarily designed for uniform loads of fixed-wing platforms, are unsuitable for rotorcraft application. Therefore, an integrated diagnostic framework combining the predictions of a physical damage model and evidence from real-time diagnostic sensor data was developed and validated through experimental data. This approach, significantly reducing the prediction error and the uncertainty bounds of the Most Probable Crack Size, is set to make a substantial contribution to the field of rotorcraft health monitoring by providing accurate damage size estimation, thus directly impacting risk management, availability, and maintenance cost. A comparison of the data used in these aforementioned SHM applications incorporating ML may be found in Table 1.

Table 1: A range of representative SHM applications and their sources of data

SHM Application	**Data used**	**ML type**
Aircraft wing CSK rivet hole damage profile [45]	Historical in-service damage readings at set load intervals	Particle Filters
Joint damage localisation on a physics-based composite wing through fasteners [46]	Image-based strain distribution output of a FEM skin-rib joint aircraft wing	CNN
Fatigue Crack Growth prediction in rotorcraft structures [48]	Ultrasonic sensor readings, experimental crack growth data from fatigue tests of rotorcraft structures, Paris–Erdogan physical damage models	Particle Filters

Implementing ML non-exclusively

Merging ML models with other categories of SHM approaches contributes to reducing environmental feature uncertainty and enables the tracking of the model's behaviour in a quantifiable manner from inception to completion in some cases.

As previously mentioned, when considering the data-driven approach, statistical and stochastic methods that are prevalently used in conjunction with ML models should also be considered. A prime example of this can be found in a study on aircraft engine degradation modelling [49]. The research employed ensemble learning techniques; combining multiple base ML models, including statistical and stochastic models into a single, more accurate predictive model for the degradation modelling and remaining useful life (RUL) prediction of aircraft engines. This demonstrates the value and effectiveness of using such methods as part of data-driven approaches in SHM. It is also an example of the dominant nature of hybrid approaches being used to diagnose and predict faults during the life of an aircraft component most effectively. Figure 1 adapted from the text in [2], [19], serves to highlight the most common forms of ML methods used in SHM, as well as the types of data-driven models most prevalent in PdM, which are used concurrently or as a part of a larger model where the output of a certain data-driven model serves as an input for another [50], to fulfil either all or one of the damage diagnostics and prognostics techniques in SHM (damage detection, localization, characterization, quantification, and prognostics). In the previously cited paper, fault detection and characterisation are addressed via the correlation of failure modes to a physical component, using comparable data that exhibits a recognized malfunction mode to diagnose the condition of a jet engine, via the use of kernel density estimation (KDE); a statistical non-parametric model, to obtain the probability density function from the outputs of a Kohonen maps neural network (NN); an unsupervised ML model and a category of SOMs. Obtaining the PDF results with a visualisation of the most probable fault types (characterisation) and the number of faults contained within each of them, whereas the NN detects degradation patterns in the time-series input. As achieved in the aforementioned examples, using several data-driven models in conjunction serves to reduce the uncertainty of each of the outputs of those models if used separately, and reduces the need for human intervention through the automation of the fault detection process from beginning to end. Combining physics-based and data-driven models is another method reducing uncertainty, on the condition that these physics-based models are built on trustworthy and validated data. Demonstrated in [51], a Relevance Vector ML model is used in conjunction with a FE model to predict RUL of aluminium plates under fatigue.

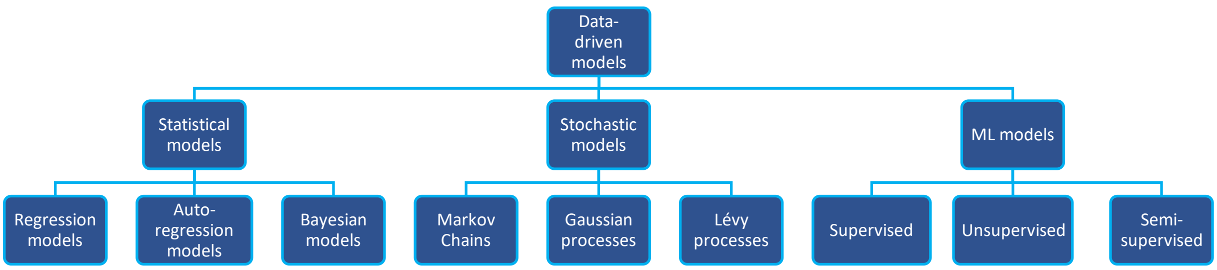

Figure 1: data-driven models predominantly used for PdM

Regulatory Compliance for ML in Aviation Structural Health Monitoring

The adoption of ML techniques in SHM has presented promising results for aircraft maintenance and reliability. However, for them to be implemented in aircraft systems, these methods must align with specific regulatory standards, such as those provided by the European Union Aviation Safety Agency (EASA) and SAE G-34, to ensure safety of usage, transparency, and accountability in the aviation industry. The SAE G-34 AI in Aviation Committee, formed by the Society of Automotive Engineers, in conjunction with EUROCAE, are developing standards for safe, efficient, and accountable AI use in aviation. In a parallel initiative, EASA has a team focusing on providing guidelines for ML deployment, emphasizing robustness, reliability, explainability, adaptability, documentation, rigorous performance assessment, and continuous monitoring. These initiatives play a critical role in driving the responsible integration of AI and ML in the aviation industry.

Regarding supervised learning, EASA mandates that any ML method should be thoroughly tested and validated to ensure its performance and safety [52]. Supervised learning excels in this aspect, as it relies on pre-labelled data sets and offers predictable and explainable outcomes (for the data scientist). However, the acquisition of representative labelled training data for adequate possible failure scenarios poses a challenge. To comply with these regulatory requirements, efforts should be dedicated towards generating extensive and diverse datasets that reflect realistic failure scenarios in the aviation industry. On the other hand, unsupervised learning has shown potential for damage detection and localization without requiring explicit damage examples for training. This feature aligns well with SAE G-34's emphasis on the autonomy and resilience of AI systems in diverse and unforeseen situations. However, the unsupervised approach's lack of human interpretability could become a limitation when considering EASA's stipulations on the explainability and transparency of AI systems. A challenge, therefore, lies in the development of techniques that enhance the interpretability of unsupervised learning methods while preserving their autonomous detection capabilities.

Moreover, EASA and SAE G-34 both emphasize the importance of robustness to environmental changes in aviation systems. In this regard, ML techniques in SHM need to account for the possible impacts of external influences on sensor data. This could be achieved through enhanced data pre-processing techniques and the incorporation of environmental parameters into learning algorithms. The standards also stress on the need for regular revalidation and recalibration of ML algorithms to maintain their performance and reliability over time, thus pushing for continuous learning strategies within SHM systems.

Evolving Regulatory Landscape for ML in Aviation Systems

EASA have made significant strides by issuing the most prominent and inclusive documents including the evolving "Artificial Intelligence Roadmap 2.0" and preliminary guidance for cognitively assisting ML applications via their “EASA Concept paper: First usable guidance for Level 1 Machine Learning applications” and its proposed revisions in progress. These documents stem from their "SC-AI-01 Trustworthiness of Machine Learning based Systems" standard, an auxiliary airworthiness standard specifically tailored for AI/ML-driven applications in the aviation domain, as a transition towards covering ML involved applications, which are not covered in the CS25 and CS23 standards. Simultaneously, the cooperative venture between SAE and European organisation for Civil Aviation Equipment (EUROCAE), facilitated through the international committee WG-114 / G-34, has published their “Artificial Intelligence in Aeronautical Systems: Statement of Concerns” AIR6988 information report, and is fostering the development of the AS6983 standard, reliant on the initial definitions of areas in which current equipment-level standards and system/sub-system level standards would need change or addition with regards to their readiness for incorporation of ML applications. The AS6983 standard is to be designed to streamline the creation and certification procedures for ML-integrated safety-oriented aeronautical products, by introducing a ML development lifecycle through the comparison of learning assurance objectives and means of compliance definitions that were set by published documents including but not limited to those released by EASA (those mentioned prior in this paragraph, stemming from a standards issuer and regulator), the University of York’s Assuring Autonomy International Programme group (an educational and research institution), and Laboratorie National de Metrologie et d’Essais (a French commercial institution providing third-party certifications, including a specialized standard for machine learning systems). The joint workgroup thereby set a baseline consisting of the ML requirement process, the model’s design process, and its data management process, in each of the documents they reviewed, in order to set their own improved ML lifecycle definitions [53]. The integration of these nascent regulations and standards into the established EASA regulatory framework is still a subject under discussion, with AS6983 remaining in the development phase. Nevertheless, extrapolating from existing norms, it is anticipated that AS6983 will comfortably fit alongside system/sub-system level standards such as ARP4754, and equipment-level standards like DO-178 and DO-254. This configuration facilitates the co-existence of the new ML standard with traditional, non-ML based aviation developments, thereby fostering an environment that leverages the potency of AI whilst upholding safety and reliability.

CONCLUSION AND RESEARCH AIMS

This paper has meticulously analysed the role of data-driven predictive maintenance strategies, avionics systems, and Machine Learning (ML) integration in aircraft health management, highlighting their transformative potential in revolutionizing the aviation industry. However, inherent challenges persist, and future research directions need to address these challenges to maximize the utility of these promising technologies.

One notable challenge concerns the explainability of ML algorithms. While the mechanics of these algorithms are often understandable for data scientists, their interpretability for the end user remains limited. Future work should, therefore, focus on translating the intricacies of ML algorithms into a format comprehensible to the end users, thereby ensuring that insights derived from these techniques can be effectively utilized for maintenance decision-making.

Moreover, the integration of ML with Structural Health Monitoring (SHM) carries various impacts and consequences. ML algorithms, when employed with SHM, have the potential to enhance fault detection, prediction accuracy, and facilitate efficient resource allocation, thus reducing maintenance costs and operational risk. However, the successful application of ML in SHM must navigate challenges such as environmental feature uncertainty, issues related to data acquisition for supervised learning, and the lack of interpretability in unsupervised learning.

In light of the identified challenges, the role of maturity and assurance becomes paramount. These pillars are critical for achieving the stage at which Technology Readiness Level (TRL) requirements are adequately met, and therefore warrant significant attention in future research endeavours. To this end, efforts should be directed towards developing robust ML models that align with regulatory standards, improving data acquisition, processing, and interpretability, and cultivating an ecosystem that encourages innovation and safe application of these transformative maintenance strategies.

A key recommendation for future research is to facilitate a loopback mechanism for inspection outcomes into the ML training cycle. This feedback mechanism can potentially enhance the adaptability of ML algorithms and improve their diagnostic and prognostic efficacy. A framework should be developed where ML algorithms are equipped to revisit the scenario being evaluated by re-evaluating their results. This will facilitate a continuous learning process, enabling the ML models to refine their predictions based on real-world feedback.

In conclusion, the integration of data-based predictive maintenance strategies, avionics systems, and ML techniques represents a significant stride towards an advanced, autonomous, and cost-efficient aviation industry. However, realizing the full potential of these technologies will hinge upon dedicated efforts to address existing challenges, enhance the maturity and assurance of ML methods, improve algorithmic explainability, and establish an effective feedback mechanism into the ML training cycle. Continued research in these areas promises to yield substantial improvements in aircraft health monitoring systems, maintaining safety and reducing maintenance and operational costs.

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