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Platform health management for aircraft maintenance – a review

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Abstract

Aircraft health management has been researched at both component and system levels. In instances of certain aircraft faults, like the Boeing 777 fuel icing problem, there is evidence suggesting that a platform approach using an Integrated Vehicle Health Management (IVHM) system could have helped detect faults and their interaction effects earlier, before they became catastrophic. This paper reviews aircraft health management from the aircraft maintenance point of view. It emphasizes the potential of a platform solution to diagnose faults, and their interaction effects, at an early stage. The paper conducts a thorough analysis of existing literature concerning maintenance and its evolution, delves into the application of Artificial Intelligence (AI) techniques in maintenance, explains the rationale behind their employment, and illustrates how AI implementation can enhance fault detection using platform sensor data. Further, it discusses how computational severity and criticality indexes (health indexes) can potentially be complementary to the use of AI for the provision of maintenance information on aircraft components, for assisting operational decisions.

Keywords

Artificial intelligence, maintenance repair and overhaul, integrated vehicle health management, platform health management, aircraft health management, maintenance

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Introduction

Aircraft component failure has the potential to cause the destruction of life and property,[1] so maintenance of these components is necessary.[2] Aircraft downtimes which result from unplanned maintenance, especially with commercial aircraft, can be costly for airlines, judging from the fact that direct maintenance costs about $234 million per airline and $3.67 million per aircraft, as reported for the thirty-seven 37 Maintenance Cost Technical Group (MCTG) airlines.[3] Aircraft maintenance is significant in ensuring the reliability of aircraft components, by identifying and mitigating potential hazards, thereby preventing accidents and enhancing overall flight operations. It contributes to increased availability, reducing unplanned downtimes and operational disruptions. Adhering to regulatory standards set by aviation authorities is contingent upon rigorous maintenance, which also extends an aircraft's lifecycle and optimizes cost-efficiency by averting major breakdowns. Furthermore, well-documented maintenance history positively influences an aircraft's resale value because it demonstrates that it has been consistently cared for and maintained in accordance with manufacturer recommendations and regulatory requirements.[4] Maintenance strategies have been applied to manage the health of aircraft components, from reactive maintenance[5] up to condition-based maintenance.[5] In that, subsequent development like approaching health management from a component level or system level has been explored. Further, justification for a vehicle-level approach has been given, particularly, with Framework For Aerospace Reasoning (FAVER),[6] which covers how beneficial it is to consider the relationship that exist between aircraft systems to enable faults and cascading effects detection. It does so by relying on the individual systems' diagnostics. Due to this, in a scenario where a system's diagnostic is not available, faults and cascading effects detection is impossible. This has presented an opportunity to consider a platform solution, which will not rely on systems' diagnostics, but sensor data from the systems to monitor their health. With the help of Artificial Intelligence (AI), a platform diagnostic that can ensure

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a quicker fault and interaction effect can be developed. This will fill the gap of not depending on systems' diagnostics for faults and interaction effects detection. Airlines have invested significantly in major aircraft maintenance programs to improve efficiencies. They continue to invest in emerging technologies, with Artificial Intelligence (AI) being a crucial part of it.[6] This is evidenced by an increase in investments in Data Exchange Technologies (XML) as well as AI programs.[6] There is evidence that applying AI techniques in maintenance can produce effective solutions in aircraft health management, to help airline operators avoid unexpected interruptions that occur due to aircraft component failure.[7] This paper covers the relationship between maintenance and AI in aircraft component health management at the platform level, and how AI techniques like machine learning can be applied to platform sensor data to generate insights that can support operational decisions. Tasks for replacing and repairing failing components are usually handled by Maintenance, Repair and Overhaul Organisations (MROs).[8] Maintenance has been approached in various ways, but in recent times airline MROs adopt Integrated Vehicle Health Management (IVHM) in maintaining complex aircraft components.[9] This approach gives MROs the advantage of looking at physical assets as a whole and considering their interacting components at the same time.[10] Implementing IVHM is usually supplemented with AI due to AI's ability to create methodologies that utilize the decision-making capabilities of AI techniques, such as deep learning (DL) and machine learning (ML), to develop fault diagnostics and prognostics systems.[11] To provide decision support to both maintainers and operators, at the platform level of health management, the health of components can be ascertained and propagated through its corresponding subsystems and systems,[12] while providing health information at every level.

This paper is organized into six different sections including the present one. The sections that follow will discuss the history of maintenance until the present day, and cover the Maintenance, Repair, and Overhaul (MRO) business, the key handler of maintenance activities, as it significantly influences the delivery of aircraft maintenance solutions. The next parts covers how MRO businesses have evolved, and the synergy between MRO businesses and IVHM. IVHM and its implementation across industries is also discussed. The fifth segment discusses health management from a platform level, with AI as an enabler and some of its techniques that have been applied in maintenance. The sixth section discusses health index computation and criticality index, as a supplement to maintenance information on components, for making operational decisions. The final section provides a conclusion to this paper.

A brief history of maintenance

Maintenance has to do with basic servicing procedures on regular timescales, to preserve, as well as keep vehicles lubricated and counteractive maintenance to restore them when they have broken down.[13] In past times, maintenance was easier to perform due to the simple nature of the physical assets and how the resources for making parts that could be replaced were easily accessible. This was the case until the industrial revolution when more powerful machines were made, and manual efforts reduced.[13] The Wright Brothers were the first to fly a plane in 1903, in Kitty Hawk.[14] Maintenance was a craft learned through experience and not often examined analytically.[15] Its costs grew as designers reached for higher performance leading to increasingly complex equipment. Also, aviation maintenance was unregulated, and most maintenance activities were undocumented until the Air Commerce Act of 1925 was introduced.[16] The Act came along with licensing standards by the International Civil Aviation Organization (ICAO) in 1948.[16] By the late 1950s, the magnitude of maintenance costs in the airline industry had reached a level that demanded a new approach to maintenance.[16] Boeing adopted a bottom-up approach[17] as it looked to invent new ways to troubleshoot after it launched the first 747 aircraft in 1969.[16] Aircraft had started using built-in-test equipment (BITE) by this time.[18] The method was restricted by how the indicators that were placed in the system were because they failed to account for everything that could potentially malfunction.[18] Nowlan and Heap[15] in their revolutionary approach to maintenance, established Reliability-Centered Maintenance (RCM) to realize the equipment's inherent reliability capability. The maintenance program for the Boeing 747 was the first effort to implement this approach.[15] After this came the Maintenance Steering Group (MSG-3) method, which took an up-bottom approach, used in the design of the B757 and B767, and is now a mainstream maintenance method for aircraft maintenance. In 1992, NASA introduced Integrated Vehicle Health Management (IVHM) to deliver an integrated platform capability that ensured the reliable capture of the health status of the overall aerospace system and helps to prevent its degradation or failure by providing reliable information about faults.[19] Approaches like the Aircraft Structural Integrity Program (ASIP) and Engine Structural Integrity Program (ENSIP) played crucial roles in the military aviation industry by ensuring the structural integrity of aircraft and engine components, respectively. Every subsequent development in aircraft maintenance thereafter can be attributed to technological innovation[20] or technology enablers.[13]

Maintenance evolution timeline

Every physical asset undergoes wear and tear, and this is more noticeable when it breaks down. When this happens, it is rational to restore it to its functional state except the asset was meant to be used once and disposed of.[21] The reason for a maintenance strategy can be traced across industries to the need for increased availability and a reduced maintenance cost of physical assets.[22–24] Also, as assets have evolved into modern, multi-technological systems, they should be handled with appropriate engineering methods, enhanced processes, and a set of maintenance procedures that make sure the asset can operate at full capacity.[25] The techniques used to increase availability, cut costs, and restore assets to a functional state gave rise to maintenance strategy.[26] A maintenance strategy is coined out of five major pillars – reactive maintenance, regularly scheduled preventative maintenance, inspection, backup equipment, and equipment upgrades.[22] These factors serve as a foundation for determining a maintenance mix, which depends on the facility, the equipment that must be maintained, and the maintenance aim.[22] When maintenance activities are carried out and what measures are included are influenced by the maintenance strategy.[27]

Technological advancement in how maintenance is approached in the aviation industry is what has accounted for its evolution,[28] as shown in Table 1. Kobbacy et al.[28] see it as a path that begins when an asset does not need maintenance to a point where the asset is performing self-maintenance,[21] Ledet[29] suggests that it began with Reactive Maintenance, and Jin et al.[30] propose that it has developed through Reactive Maintenance (RM), Preventive Maintenance (PM), to Condition-based Maintenance (CBM).[30]

The purpose of Reactive Maintenance (RM) is to fix the asset when it is broken.[31] Machines tend to break down without warning, and it is essential to get them back working when this happens.[13] As shown in Table 1, reactive maintenance was emphasized in earlier times,[13] and with it, no prior data on the asset is required. Although the manpower and the amount of money spent on equipment maintenance are reduced, the drawbacks of this strategy include unpredictable and fluctuating production capacity and higher total maintenance costs.[32] For instance, unscheduled maintenance contributes about 15% to 60% to the production cost.[33] RM is usually characterized by a low failure severity and frequency, like repairing a fan blade of an aircraft after a bird strike.[30] When a life-critical system like an aircraft is in play, estimating its dysfunction before it happens is necessary. As a result, there is justification to turn to the Preventive Maintenance (PM) approach.

With Preventive Maintenance (PM), replacement and overhauling are done at certain stipulated time frames, irrespective of the status of the asset at that time to minimize unexpected breakdowns.[30] Wang[34] classifies preventive maintenance as a long-term maintenance policy that takes a record of breakdowns to plan preventive interventions. Maintenance times for assets in PM policy focusses on the assets' age. The underlining idea is that for whichever comes first – the age or failure of the unit – it is then fixed or changed.[35,36] This is carried out by applying techniques that extract from historical data of behaviour of assets, indices like Mean Time Between Failure (MTBF), and Mean Time To Repair (MTTR).[32] Preventive replacements can help minimize the number of random failures, but it can also waste resources. It is best to synchronize maintenance and inventory management strategies[27] because even an effective preventive maintenance plan that increases equipment availability suffers from these flaws:

1. Time-based or operation count-based PM programs lead to possible under-maintained or over-maintained equipment, especially in instances when the PM interval is predetermined without considering various operation regime shifts. For instance, it was found in the case of gearboxes for helicopters that although approximately half of the parts were in a convincingly functional condition, they were taken out for repairs.[28]
2. Replacing the component before it fails limits how much information can be learned from the equipment's lifecycle.[30] Figure 1 depicts the difference between reactive and preventive (proactive) maintenance. PM is not the most cost-effective program choice because of these challenges. Hence, more efficient maintenance methods such as predictive maintenance (PdM) are sought.

Predictive Maintenance (PdM) is the 'right on time' strategy. It can be grouped into reliability-centred maintenance and condition-based maintenance (CBM). In most cases, it has been implemented as CBM as its performance indicators are either measured periodically[37,38] or observed continuously.[39] PdM makes pre-sets on failure rate and or any other reliability indicator of the asset so that maintenance is rolled out only when the pre-set rates or indicators are reached or triggered. Integration is the strength of PdM as it merges data with reasoning methods, and considers physical factors and known engineering constraints, so that it can diagnose a problem before it happens.[33] This approach varies from preventative maintenance such that the requirement for repair is determined by the asset's actual

Table 1. Maintenance strategy evolution.

Evolution	Strategy	Data	Aeon	IVHM feature
Prescriptive	CBM What can you do when a failure occurs?	Big data	21st century	Prognostics
Predictive	CBM Which machine health scenarios could result in a future failure and when?	Real-time data	1980s	Diagnostics
Preventive	RCM What is the present health of the asset?	Historic data	1950s	Statistical (data driven) Prognostics
Reactive	How can we fix the failure that has occurred?	No data		

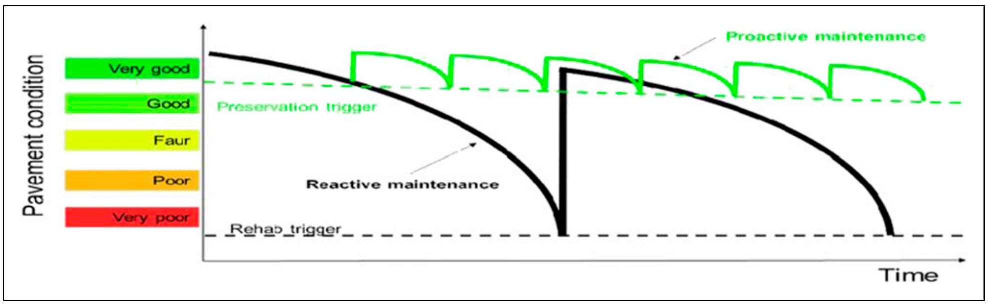

Figure 1. Preventive (proactive) and reactive maintenance approach.[33]

state rather than a pre-determined schedule. It uses technologies to monitor the state of the asset to detect issues sooner and intervene with higher accuracy.[32] PdM has proven benefits such that Rao[40] reports that a CBM investment of $10,000 to $20,000 translates into a $500,000 yearly savings. The timeline depicted in Table 1 highlights various ways maintenance can be approached, but the question of when maintenance should take place remains. The Potential Failure – Functional Failure (P–F) curve throws light on this.

P–F interval impact on maintenance strategy

The P–F curve shows the time between an asset's potential failure and its predicted functional failure. It informs asset owners of when it is 'right' to perform maintenance.[13] Initially, the state of the system or component is in good condition, but over time it begins to deteriorate. Figure 1 demonstrates the progression of failure, starting with the beginning stages and worsening until it is noticeable. This is when potential failure is detected (point P, in Figure 2). The deterioration continues until the point of functional breakdown (point F, in Figure 2). The P–F time interval provides the amount of time that a monitoring system could detect the deterioration and allow for maintenance to be performed. This interval must be long enough to make maintenance feasible and the monitoring effective. The remaining useful life (RUL) refers to the amount of time until functional failure as the deterioration moves away from point P. Figure 2 displays the RUL at any given moment, represented by point A on the curve. The P–F interval must be long enough to enable for maintenance to be performed in order for any action to be feasible and for the monitoring to have been effective. Although Jennions[13] explains how crucial this is for any organization that uses high-value assets in the P–F Curve, Figueiredo-Pinto[41] asserts that Predictive maintenance is only practicable if the deterioration pattern depicted in the P–F curve is generally constant, and a consistent gradient profile is seen for every part's cycle of operating life. According to Refs 13,33,42 the P-F curve shown in Figure 1 aids in measuring performance per time (or usage), and not just that but it also offers the ability to monitor degradation such that action (maintenance) is taken when the depletion is more perceptible before it reaches a point of functional failure. As a result, it measures the remaining useful life (RUL) of the asset for maintenance decisions. Failures are approached differently based on the categories they fall in. Failures that are seen to impact health and safety, or that affect business operation are deemed urgent, and hence receive immediate maintenance. However, other failures that are not necessarily affecting functionality or interrupting operations, although their degradation is noticeable, are less likely to be tackled in the same swift manner.[13]

Maintenance has evolved into Prescriptive Maintenance (PxM). It is a layer or a step above Predictive Maintenance. It draws from developing systems that can intelligently observe, predict, and augment their functional ability.[43] It leverages embedded systems that have been built into the assets, focussing on finding out the source of faults, and not just the signs. After this, it will feed the information gathered back to the system so that maintenance can be done where it is needed. Prescriptive maintenance is distinctive in the sense that not only does it forecast asset failure like Predictive Maintenance does but it also provides consequence-based suggestions for processes and maintenance from prescriptive analytics.[44] PxM is driven by the capability to have varied scenarios and simulations outside of the reality of happenings to allow maintenance teams to have a more exhaustive approach to the condition of the asset. Prescriptive maintenance heavily depends on huge data collected from sensors placed on different points of assets and manipulated or evaluated using various data analytic tools to provide information on the condition of assets.[44]

In the future, maintenance strategy in aviation will gravitate towards a Conscious Aircraft[45] or self-maintenance.[21] Complex assets like aircraft will assume consciousness like a human would in observing health states and forecasting with precision, the remaining useful life of components, subsystems, and systems. At this stage, it will have the ability to monitor faults, diagnose faults, judge faults and plan repairs, as well as improve and self-learn on its own. A typical example is what is being done in F-35 airplanes,[46] where the Autonomic Logistics Information System (ALIS); a comprehensive system that serves as the central nervous system of the F-35 fleet, is used to manage and analyse vast amounts of data generated by the aircraft's various systems during operations. ALIS provides real-time health and diagnostic information to maintainers, support personnel, operators, and enables

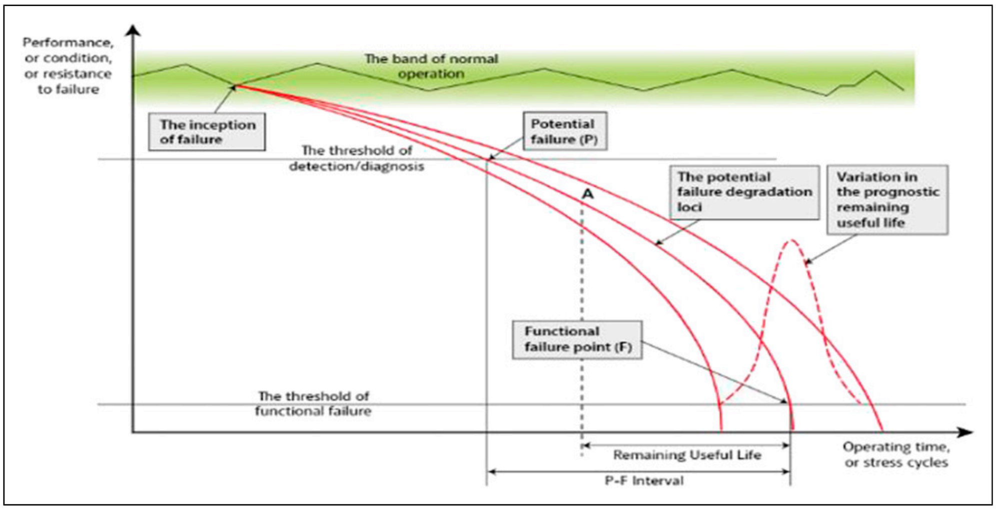

Figure 2. The P–F interval.[14]

efficient maintenance. The timelines depicted in Figure 2 are like what was proposed by Ledet[29] that is, reactive maintenance, planned maintenance, predictive maintenance, reliability maintenance, and enterprise maintenance. Gallimore et al.[22] suggest that organizations, in this case MROs, should find the most appropriate maintenance strategy based on the facility, the equipment, and the maintenance aim.

MROs and their role in maintenance

MROs are the branch of the aviation business that is largely responsible for maintaining or restoring aircraft parts to a functional state.[47] This includes all technical, administrative, management, and supervisory responsibilities.[8] For instance, Hawker Pacific Aerospace (HPA) specializes in the repair and overhaul of landing gear (in airplanes and helicopters), hydromechanical components, wheels, brakes and braking systems, and the distribution and sales of new and overhauled aerospace spares.[8,48–50] classify MROs by organizational structure, by placing them under independent or third-party MROs, and airline-operated-and-owned MROs. MROs have developed from when most MRO tasks were only performed by airline-operated-and-owned MROs.[47] After the deregulation of the airline industry in 1978 in the USA,[51] several new airlines did not have established MRO facilities or spare parts inventory to serve their fleet.[52] The increase in the number of low-cost carriers urged the entry of independent MRO sources that provided low-cost services ranging from line maintenance to inventory control.[8] The smaller airline carriers opted to outsource MRO activities to third parties because of the capital-intensive nature of establishing an airline MRO.[8] On the other hand, the larger airline operators were inclined to retain a presence in this line of work as it meant they could offer MRO-type services to other airlines.[53] AAR Corporation, whose operations include aircraft and engine support, engineering, and logistics is another example of an independent MRO organization.[54] In contrast, an example of an airline-operated-and-owned MRO is Lufthansa Technik, a subsidiary of Lufthansa. The joint venture between Air France Industries and KLM Engineering & Maintenance which has seen remarkable development in terms of its MRO capabilities is another example of an airline-operated-and-owned MRO organization.[8] MRO business must pay attention to the flow of value from one organization to another to decide on what brings the most benefits to it.[55] This facilitates long-lasting connections with clients, deliver more customization and superior quality, decrease inefficient use of resource and labour, and get feedback from using it, to be put back into the design and manufacturing phase.[56] In this way, whether the business is Product-oriented or Service-oriented,[55] it will be able to make a good Return on Investment (ROI). Since MRO organisations are largely responsible for maintenance, it is feasible to link it to IVHM because it helps them detect faults quicker before they happen. Maintainers want to know when a component should be replaced or if it should be replaced and an efficient way of coming to such a conclusion is implementing IVHM, which relies heavily on digitally enabled on-condition maintenance.[13]

Synergy between MROs and IVHM

It is a difficult task for an aerospace platform to deliver an autonomous, well-timed, and exact evaluation of vehicle health for both vehicle operations and maintenance.[57] NASA established IVHM on the strength of communications technology, Decision Support Systems (DSS) engineering, and sensor integration, to deliver a snapshot of the health of systems and components, by providing information on faults for spacecraft.[13] Previously, IVHM had been referred to by several other names such as Fault Detection, Isolation and Reconfiguration (FDIR), Vehicle Health Monitoring (VHM), Systems Health Management (SHM), and Vehicle Health Management (VHM).[58] There is no definition of IVHM that is universal yet, by comparing the various definitions in Table 2, the concept can

Table 2. Definitions of IVHM.

Author	Definition
Benedettini et al.[10]	'IVHM is a collection of data relevant to the present and future performance of a vehicle system and its transformation into information can be used to support operational decisions'.
Esperon-Miguez et al.[122]	'IVHM comprises a set of tools, technologies, and techniques for automated detection, diagnosis, and prognosis of faults to support platforms more efficiently'.
Rajamani et al.[123]	'IVHM describes a set of capabilities that enable sustainable and safe operation of components and subsystems within aerospace platforms'.
Jennions et al.[68]	'IVHM describes a set of capabilities that enable effective and efficient maintenance and operation of the target vehicle. It accounts for the collecting of data, conducting analysis, and supporting the decision-making process for sustainment and operation'.
Jakovljevic et al.[19]	'IVHM ensures the reliable capture of the "health status" of the overall aerospace system and helps to prevent its degradation or failure by providing reliable information about problems and faults'.

be generalized as the holistic approach of evaluating the present or subsequent health state of components, subsystems, or systems in a unified way such that it provides a suitable framework to make use of resources to address the health state.[59] IVHM's objectives in the aerospace sector include lowering MRO costs and increasing aircraft availability by providing comprehensive health monitoring and support for CBM.[60] IVHM's framework for understanding how complex systems, such as aircraft or other vehicles, can be made more reliable is the 'Sense-Acquire-Transfer-Analyse-Act' (SATAA).[13] 'Sense' involves using sensors and other monitoring systems to collect data on the performance and health of the system. 'Acquire' involves transferring the data collected by the sensors to a central location where it can be accessed and analysed. 'Transfer' involves transmitting the data from the system to a central location, either wirelessly or through a physical connection. 'Analyse' involves using algorithms and other tools to manipulate the data and identify any problems or potential issues with the system. 'Act' involves taking action based on the results of the analysis, such as scheduling maintenance or repairs.[13] In the SATAA process, the stages are generally sequential, but it is important to note that the process is not necessarily a linear one, and some stages may be repeated or may occur concurrently with other stages.[13] The SATAA process is an ongoing process, and the steps may be repeated multiple times in order to continuously monitor the health and performance of the system.[61] The IVHM system typically relies on cutting-edge machine learning techniques and Artificial Intelligence (AI) to diagnose faults and estimate the remaining useful life of physical assets.[62] There is a close relationship between IVHM and MRO organizations, as the data collected through IVHM can be used by MRO organizations to improve their maintenance and repair processes. For example, if an IVHM system detects a problem with a component on an aircraft, it can alert the MRO organization to the issue, allowing them to schedule maintenance or repairs before the problem becomes more serious.[13]

IVHM and its implementation across industries

IVHM is seen as a capability to support condition-based maintenance,[63] allowing intelligent and suitable decisions to be made based on present and future vehicle conditions.[10] It has been applied in four primary areas across the aerospace industry[57]: diagnostics, prognostics, automated inspections, and anomaly detection.[58] Some of the practical applications of IVHM in organizations are shown in Table 3. There have been huge advantages that have come from the application of IVHM systems. Some of these benefits are the early identification of failure and replacement of critical units on mission operations before accidents are caused by their malfunctioning,[64] a minimized human input which can translate into increased reliability and maintainability[65,66], and improved responsiveness for support operations.[67] Despite these benefits, adopting IVHM has its own considerable economic and cultural barriers, with the main challenges being its acceptance[13] and the cost of hardware and software required to execute IVHM tasks.[68–70] This cost covers the improvement and implementation of sensors and software for processing data, as well as penalties for additional weight, power, and computing resources.[10] A cultural shift is required for every user of an IVHM system to accept the weakness of IVHM induced faults, such as false alarms and sensor failure, especially in cases where integration is fairly easy (for instance with Skywise)[60] and additional systems like sensors are not necessary or the already existing ones can be relied upon. This system should facilitate the detection of the health status of various components and their effect on other units by using the data gathered from the units.[60] This can be achieved when supporting technologies like sensor technology, and Artificial Intelligence (AI)[60] are developed. It should be noted that certification and airworthiness regulations represent one of the main difficulties IVHM encounters because modifications to hardware and software can have a negative impact on an aircraft's ability to fly safely[19]. Any system placed on an aircraft is covered by these regulations for design, manufacturing, integration, and installation. To

Table 3. Examples of IVHM applications in organizations.

Organization	Description	Link
Rolls Royce	Rolls Royce has combined with Microsoft to enable predictive maintenance of their Trent XWB turbofan jet engines, by employing data from historical feeds and real-time monitoring.	124
US DoD	The 'JSF' is being developed by the US Department of Defense (DoD). The aircraft's health management capabilities are being 'built in' and incorporated into an integrated maintenance and logistics system.	125
The boeing company	Boeing has on a commercial scale, and AHM system that leverages remote analysis of real-time airplane data to support airlines and operators with personalized maintenance decisions.	126
NASA	NASA is working on several IVHM systems for the next generation of reusable launch vehicles, as well as personnel and cargo transport. IVHM technology will be employed to offer real-time information, allowing for better decision-making and maintenance.	127
Lockheed Martin	The US marine corps has ordered an 'Enhanced Platform Logistics System' from Lockheed Martin. This will provide marine corps ground vehicles with the capacity to track their performance and offer predictive data, allowing for CBM, enhanced logistical support, and more efficient fleet management.	10
US navy	On its ships, the US Navy is deploying an integrated condition assessment system (ICAS) that interfaces with distant support to enable system-l[64,65] l supervision and performance trends for CBM.	10

make room for new sensors, it is frequently required to alter the component being monitored, which creates additional certification issues[20]. If this could be prevented, certification may be quite simple as long as the hardware utilised on a new health monitoring system employs components similar to already approved devices available on the market or even using the same devices (for instance, using the same installed sensors instead of new ones). The focus of IVHM was at the LRU level until it gravitated towards the subsystems/systems level.[71] There has been a shift towards the vehicle level,[72,73] where the advantage over component level diagnostics is evident. Ezhilarasu and Jennions[74] tackled health management at the vehicle level, using digital twins and a reasoning layer, to detect faults, their origin as well as their interaction effects. This approach is instrumental in the early detection of faults like the left main bus malfunction in the Cessna 680, in September 2010, where the crew experienced an uncommanded transfer of fuel from the right to the left fuel tank after following the checklist procedures for a left main electrical bus fault indication. The aircraft subsequently became left wing heavy and exceeded the lateral imbalance limits. It returned to Luton Airport where a flapless landing was completed without further incident. The investigation established that the isolation of the left main bus had caused a false fuel cross-feed command which resulted in the uncommanded fuel transfer.[1] Aircraft component faults of this nature require IVHM systems that might not necessarily prevent the faults but enable early detection for operational actions to be taken quickly to avert further catastrophes.[60] A way forward is using the foundation laid down in Ezhilarasu and Jennions[74] to tackle health management from a platform view.

Health management from the platform view

Aircraft health management can be approached from different levels. This paper has categorised it into four levels: component, subsystem, system, and platform levels. At the component level, what is considered is the most 'basic' unit that faults can be traced. For example, heat exchanger, air cycle machine, and a control valve. The subsystem level consists of a combination of elements form the component level. For example, a pump, a fuel tank, or a Passenger Air Conditioner (PACK), which is made up of several parts including the above-mentioned components. In the same way, at the system level, it consists of a combination of elements from the subsystem level. For example, the aircraft fuel system, or the environmental control system, which is made of several subsystems like the PACK and the mixing manifold. At the platform level, which can also be referred to as the vehicle level, health management has to do with the entire vehicle (aircraft). The name platform is as a result of the nature in which health is managed. In this paper, platform refers to taking sensor data from the component level and propagating it through the subsystem and system levels up to the vehicle level. Figure 3 embodies the inputs needed to manage health from the platform. Health data that will be collected will help provide maintenance information to help answer the questions posed by various levels (i.e. component, subsystem, system, and platform). This information, however, will not answer operational decisions, but it will help provide inputs that can assist in making operational decisions. Operational decisions refer to the decisions that are made during the operation of an aircraft, such as decisions related to flight planning and maintenance.[75] For instance, for an operational decision like 'can we fly,' at the platform level, the maintenance information from the platform health management can tell the health status of the aircraft components but will not be concerned with making the decision of whether to fly or not. At the platform level of health management, the health of the asset is determined by considering the health state and the interaction effect of the components, subsystems, and systems,[76] giving it an advantage over the component or system level approaches. The Boeing 777 engine rollback at Heathrow Airport in 2008 is an example of a real-world incident.[77] The cause of the engine rollback, according to an investigation into the occurrence, was

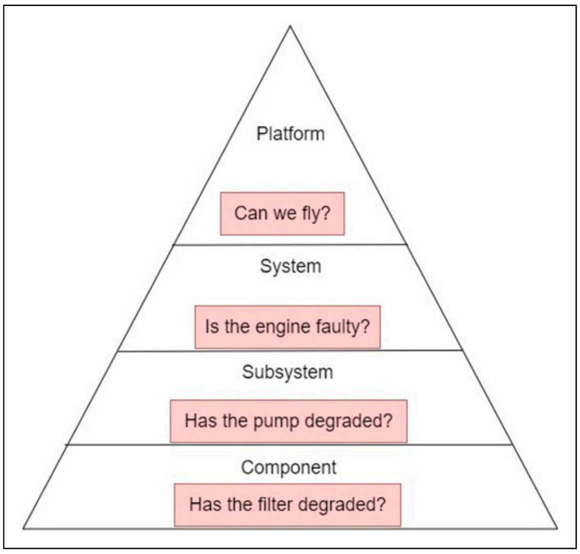

Figure 3. Health management pyramid.

a decrease in thrust brought on by a limited fuel supply to both engines. Further inquiry into the root cause found that the fuel developed ice as a result of prolonged exposure to a temperature of less than −70°C. The fuel feed pipe was then damaged by this ice, which later burst, clogging the fuel oil heat exchanger and other fuel lines. Another example is the 2008 emergency evacuation of an Embraer 195 because of smoke in the cabin[78] where, after an inquiry into the incident, it was determined that both ACMs had suffered Stage 2 turbine blade failures. The resultant imbalance had resulted in contact between the turbine blade tips and the ACM casings, producing hot, finely divided, metallic particles that were released into the cabin air system, creating the reported symptoms of smoke and fumes inside the aircraft. Diagnosing faults in scenarios like the abovementioned incidents, where failure in one component cascades into another component, and eventually into another system, requires a system that can detect faults as well as any interaction effects between components and systems.[79] This can be achieved by adopting a platform solution. Further, to support operational decisions, faults and interaction effect detection could be supplemented with information on the health index and criticality of the components.[80] This is because not all component failures affect the functionality of the aircraft, so immediate attention should be given to ones that are crucial.[81] This presents various questions to be answered in order to provide operational decisions, as shown in Figure 3. In this vein, it is important to lay down the dependencies that exist among the components, subsystems, and systems as it was applied in damage propagation modelling for aircraft engine by Abhinav,[82] and Roemer,[83] and Roemer[12] in developing a hierarchical reasoning structure for aerospace IVHM, where distinctions between independent relationships, serial dependencies, and parallel dependencies were made uses a parent–child approach to establish this relationship for a health index framework for condition monitoring. From a platform view, answering the questions at the base of the pyramid in Figure 3 help to answer the one at the apex, when the dependencies that exist among them are established.

AI as an enabler for health management

The approaches that have been applied to manage the health of complex assets and fall under: Data-Driven, Model-Based and Expert Systems approaches.[93] Data-driven diagnostic methods rely on data collected from sensors that are placed at strategic areas of the system.[77,94,95] For instance, Skywise, which is designed by Airbus to handle integrations of commercial and operational systems, processing large volumes of data such as time-series data coming from aircraft sensors, structured data from operational and maintenance data and unstructured data such as technical documents.[96] Model-based methods use a physics model of the system or component to conduct the analysis on its health, by developing a virtual representation of the actual asset to mimic its behaviour. Its application can be found in the use of digital twins to mimic the behaviour of systems or components to simulate what-if scenarios of actual systems. For examples, as discussed in Liu et al.[85] and applied on an automotive brake pad for predictive maintenance in Rajesh et al.[86] In an extended approach, there can be a hybrid of data-driven and model-based techniques. For instance, digital twins of systems can be developed, then used to produce data, which could be processed to derive insights into fault modes in the actual systems, as done with aircraft systems in Ezhilarasu et al.[74] An expert system is derived from two fundamental concepts.[97] First, that it contains specific knowledge about a particular field, component, or system. This knowledge is a fusion of existing facts from human experts and documentation within that field. Although the system closely models the human expert, it is not a replacement for the human expert, but an assistant.[98] Rolls Royce's KBO Environment, which allows the company to capture its knowledge base, as well as best practice and performance, manufacturing, and cost criteria into a simulated model to help engineers precisely explore and try multiple "what ifs" against all identified constraints, is an example of an expert system. Another example is RuleSentry™ which has been used by Lockheed Martin to simplify system behaviour modification and operational decision making to save time and effort (*RuleSentry TM Configurable Decision Support*, 2013). Platform level decisions are typically concerned with efficiency matters like prioritizing component failure modes. These health management decisions typically rely on the use of technologies like artificial intelligence. To add to that, data is increasing in relevance and size. With reference to a report by the International Data Corporation (IDC), the global data sphere was to grow from 33 zettabytes in 2018 to 175 zettabytes by 2025. These figures are noteworthy when compared to the global total of 3 exabytes in 1986. Aircrafts produce huge data. The Boeing 787 creates nearly half a terabyte on a single trip, while the Airbus A380-1000 generates approximately eight terabytes daily . A General Electric (GE) jet engine creates about 20 terabytes of information per engine data per hour. For two engines on an average six-hour cross-country flight from New York to Los Angeles, the data generated is approximately 240 terabytes. The effective utilization of the vast volume of generated data demands the integration of key technologies like AI. These synergistic technologies are instrumental in facilitating continuous communication, robust data storage, and clever data analysis, to optimize data exploitation.

The term Artificial Intelligence (AI) originated from the belief that all facets of intelligence, including learning, can be precisely defined, and programmed into a machine to simulate them.[93] The word 'artificial intelligence' is used to describe the development of tools that are intended to conduct tasks that ordinarily call for human intellect. Unlike how human intelligence develops naturally, these tools are made by a combination of algorithms, computer programmes, and other technologies. In other words, the intelligence exhibited by AI systems is not something that happens naturally; rather, it is something that the tool's designers intentionally manufactured and encoded into the device. The difference between human and machine intelligence is further brought out by the 'artificial' character of AI. Human intelligence is the outcome of a complex interaction between heredity, environment, and experience, whereas artificial intelligence (AI) is created using mathematical models and algorithms that are intended to conduct specific tasks. This artificial intelligence is neither sentient or self-aware; rather, it functions according to the rules and logic established by its designers. Functioning in this way would be called intelligent if it were displayed by a person, thus the name artificial intelligence.[94] Over the years, the evolution of AI in aircraft maintenance has followed a clear trajectory from rule-based methods to machine learning and, ultimately, deep learning paradigms. Initially, rule-based systems were employed to detect and diagnose maintenance issues. However, the inherent complexity of aircraft systems and the limitations of rule-based approaches led to a transition towards machine learning techniques. Machine learning models, with their ability to autonomously learn patterns and adapt, offered enhanced predictive maintenance capabilities. In recent years, deep learning, a subset of machine learning, has taken centre stage due to its proficiency in handling vast and intricate datasets. The neural networks used in deep learning excel in recognizing intricate patterns and anomalies, thus revolutionizing aircraft maintenance by providing more accurate and proactive insights into equipment health and performance. This shift towards deep learning signifies a significant advancement in AI-driven aircraft maintenance, promising greater efficiency and safety in aviation operations. The definitions of AI, highlighted in Table 4, dovetail towards a purpose of assisting with decision-making in the real world. AI has three primary types of assistance in maintenance: prescriptive, predictive, and descriptive AI.[95] AI has transformed aircraft health management by facilitating advanced data analytics, predictive maintenance, and fault detection. Current trends in this field encompass the application of cutting-edge AI algorithms capable of processing vast datasets from aircraft systems. For instance, commercial fleet monitoring tools like Boeing's AnalytX platform utilizes AI and machine learning to monitor aircraft health in real-time, enabling proactive maintenance actions based on data-driven insights. Prognostics and remaining useful life (RUL) estimation have also improved significantly, with companies like Lufthansa Technik implementing AI-based RUL prediction models for critical components, allowing for more efficient maintenance planning. AI monitoring techniques, including those based on vibration, which have been used for anomaly detection in unmanned aircraft, and acoustic emissions, which have been used for diagnostics in auxiliary power unit, have been developed. In some cases, natural language processing has been employed, as done in Duan et al., where mechanical monitoring readings were treated as natural language sequences and inputted into a transformer for extracting health indexes that reflect the health status components. Recent approaches feature an integration of AI with other technologies like the internet of things (IoT) and edge computing, as done in Hsu et al., for RUL prediction on aircraft engines and digital twins (DT) as done in Ezhilarasu et al., for fault diagnostics in aircraft. Furthermore, explainable AI (XAI) models have become essential for critical aviation applications. Explainable AI techniques are employed to ensure that the decision-making process of AI algorithms can be understood and validated by human operators as demonstrated in Zeldam et al. XAI has become essential to maintenance and potentially holds the key to speed up AI adoption and certification in aircraft health management. This is because it creates an avenue to explain, validate, and improve results from the application of AI techniques. In that, the focus is being directed at how to consistently measure the success of XAI models under criteria like depth of explanation, stability , predictive accuracy, privacy and model coverage. These trends collectively showcase the significant impact of AI in enhancing aircraft health management and will continually be, especially with the onset of a conscious aircraft.

AI techniques in maintenance

The application of AI techniques to optimize maintenance has seen significant success after AI came to the scene in the 1960s.[91] After a considerable amount of time in development, the use of AI in maintenance has been continuously increasing, and current developments in machine learning and other AI technologies have sparked a rise in its usage in areas such as condition-based monitoring and predictive maintenance. This is evident in the last 5 years; in that airlines have committed significant investment to AI programs.[97] Over time, applying AI in maintenance has expanded to include several AI approaches, as shown in Table 5, because of the uniqueness of each approach.[91] For example, techniques such as Genetic Algorithms (GAs) and Neural Networks (NNs) can be used with Explainable AI (XAI), which seeks to overcome the limitation of 'black box' approaches. This has helped to extend their use to tasks such as scheduling and fault diagnosis.[91] The Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Deep Convolutional Neural Network (DCNN) mainly concentrate on using deep neural networks for complex pattern recognition and image classification. These networks can be used to identify and categorize anomalies in images, such as cracks or distortions in aircraft parts.[98] Long Short-Term Memory (LSTM) is particularly suitable for dealing with the issue of vanishing gradients that arise during backpropagation, as it was used in Eldali and Kumar.[99] Fuzzy Logic is used as a way of addressing uncertainty through the notion of degrees of truth instead of binary values. For example, it has been applied to determine fault severity in rotating machines.[100] Naïve Bayes (NB) relies on the probability of an event happening, considering the occurrence of other events. For instance, in a fault tree analysis, how probable it is for a Passenger Air Conditioner (PACK) to malfunction, given that the primary heat exchanger develops a fault. NB has been used for system-level fault propagation analysis.[101] SVR, RF, and LR techniques model the connection between an independent variable and one or more dependent variables. Every physical asset begins deteriorating at the start of its usage (See Figure 1). Monitoring this deterioration throughout the asset's useful lifecycle helps to effectively diagnose failure, to prevent major asset downtime.[13] In the field of artificial

Table 4. Definitions of AI.

Author(s)	Academic field	Definition
Baranov et al.[128]	Psychology	Artificial intelligence (AI) is the sum of a computer's functional skills for solving human issues.
Kaplan and Haenlein[129]	Business	Artificial intelligence (AI) is described as a system's capacity to accurately understand external input, learn from it, and use what it has learned to achieve specified objectives and tasks through flexible adaptation (p. 15).
Ransbotham et al.[130]	Business and management	Artificial intelligence (AI) is the study and development of computer systems that can do activities that would ordinarily require human intellect, such as visual perception, speech recognition, decision-making, and language translation (Oxford dictionary p. 2).
Russell and Norvig[131]	Computer science	AI is the study and development of rational agents that operate in accordance with given inputs to attain the best possible results or goals (p. 7).
Wahl et al.[132]	Health	Artificial intelligence (AI) is an area of computer science concerned with the emulation of intelligent behaviour in computers (p. 1).
Weber and Schütte[133]	Big data and cognitive computing	AI is the study of attempting to teach robots to utilise language, develop abstractions and concepts, and solve issues that are currently reserved for humans (p. 3).

Table 5. AI techniques applied in maintenance.

Author(s)	AI technique	Health management level	Output
Daniyan et al.[134]	ANN	Component level	RUL
Dallapiccola et al.[135]	ANN, LSTM	Component level	Fault diagnosis
Akpudo et al.[136]	NN	Component level	RUL
Silva et al.[137]	NN	Component level	Fault diagnosis
Frank et al.[138]	FL	Component level	Fault diagnosis
Philips et al.[139]	KBS	Component level	Fault diagnosis
Adhikari et al.[140]	SVM, KNN, RVM	Component level	RUL
Kavana et al.[141]	ANN	Component level	Fault classification
Ozkat[142]	SVM	Component level	Fault diagnosis
Patil et al.[143]	SVR, RF, MLP	Component level	RUL
Chazhoor et al.[144]	KNN, LR, RF	Component level	RUL
Davari et al.[145]	DL	System level	Fault diagnosis
Hermawan et al.[146]	CNN, LSTM	System level	RUL
Putra et al.[73]	ML	Vehicle level	RUL
Markridis et al.[72]	ML	Vehicle level	Fault diagnosis
Chen et al.[147]	DCNN, NB	Vehicle level	Fault diagnosis
Ezhilirasu and Jennions[74]	ML	Vehicle level	Fault diagnosis

intelligence (AI), the selection of AI techniques should be based on the desired outcomes. It is crucial to think about the intended results and select the AI techniques that are most likely to achieve them in order to successfully apply AI in maintenance.[92] As shown in Table 5, several AI techniques have been applied in maintenance to achieve different results, although in some cases, some of the techniques can be applied to achieve more than one maintenance results. Applying AI techniques for maintenance at the platform level requires a system that builds on health results obtained from prior levels.[83] In this way, from Figure 3, the health of components will be propagated to the subsystem level, the system level, and then to the platform. Health results reflect the health state of components and are typically referred to as health index as it was used in Kamtsiuris[12] for developing a health index framework, Khan et al.[79] for health index behaviour based on vehicle level reasoning, and Yin et al.[103] for constructing a health index for aircraft ECS. The potential to apply AI in a platform solution can be seen in how it has, for example, through the application of Physics-Informed Neural Networks (PINNs); which belong to a group of neural networks that, in both their design and training, take into account physical principles and limitations, been applied in areas like modelling cumulative damage (fatigue crack) in airplanes[104] and machine degradation assessment.[105] Further, in Li et al.,[105] PINNs were used to generate a health indicator to check the health of components. This approach can be applied in Figure 3.

Health index (HI) for operational decisions

As a complementary information to the insight that will be derived from applying AI techniques to sensor data, HI can be beneficial to aircraft maintenance. It is helpful to be able to tell if a fault has been detected in a component, but it is more efficient to know the extent of that failure and its effects.[13] This paper proposes that for a platform approach to health management, computing health indexes alongside insights from applying AI could be more efficient for providing maintenance information to support operational decisions. Health index computations are rooted in finding faults and their effect on components, along with their cascading effects on other components.[80] Built-In Test Equipment (BITE) has been used as both in-field maintenance and to indicate the health state of a system.[106] In the 1950s, BITE was used to ensure uninterrupted availability and fault-free operation of critical weapons systems (Minutemen I and II missiles) and aerospace equipment (Saturn, Apollo).[106,107] Similar techniques for estimating a health index have emerged after BIT.[108] For example, Automatic Test Equipment (ATE),[109] and Embedded Diagnostics/Prognostics (ED/EP).[110] While it is common to conceive of damage as an issue that increases monotonically, the domain in which damage is assessed could have non-monotonic characteristics. These may be external effects, such as partial maintenance activities, or inherent characteristics (such as recovery effects in the capacity of batteries or semiconductors). It may be required to consider specific damage propagation models for various failure types since damage propagation may display different symptoms depending on the fault mode.[111] In a bottom-up approach (components level to platform level), the health of components can be disguised by the overall health at the platform level.[83] By generating a health index to offer details on the health state of components, subsystems, and systems, a top-down (platform to components) method can effectively disclose the health of components (for maintenance decision) at the platform level. This maintenance decision can eventually be used to assist operational decisions. Managing the health of physical assets, like in the approaches mentioned Table 5, provides useful information for maintenance, but to assist an operational decision, the IVHM system might need a high-level reasoner to deduce that system's criticality to the functioning of the entire asset.[63] Establishing the health of systems can be categorised under: (1) system health index-based, (2) integration of components' remaining useful life (RUL), (3) influenced component-based, and (4) multiple failure modes approaches.[112] The health index (HI) of a component can be defined by the 'functional availability' of that component to execute the intended purpose for which it was made.[83,113] Abhinav[82] proposed a component level estimation method in calculating a health index. This method determines critical parameters that point to the performance of the system from the data gathered, by computing how distant a component's present health parameter is from certain operational boundaries. By calculating the difference between the present system state and predetermined limits, these health indexes can be estimated. Each of these health indexes is then normalised to the interval [0, 1], where one (1) indicates a healthy component and zero (0) indicates an unhealthy component. It is important to determine the critical parameters because, in specific situations, not all parameters carry the same weight of importance. For example, Abhinav[82] identified efficiency and flow as critical parameters to identify the health of an aircraft engine's compressor and turbine. Diagle et al.[114] adopt the estimation of the end of useful life (EOL) of a system in a distributed manner by decomposing it into replaceable units, based on the concept of structural model decomposition. The distributed framework computes the health of components, which then feeds into their corresponding systems to estimate the health of these systems. One strength of this approach, which can help component health index propagation, is how it provides a tool (structural model decomposition) to merge local prognostics results into a system-level result. In the case of Chang et al.,[115] a health index (Remaining useful life (RUL)) was computed based on a multi-input neural network, using long short-term memory (LSTM) for RUL prediction, and the previous monitoring data and the future operational condition settings. These two data streams are manipulated and combined to predict the RUL of the examined components. Wang et al.[116] applied a strategy in a similar manner to estimate the system health of aero engines by taking into consideration several operating conditions. At the platform level, it may be required to propagate health states from preceding levels. Roemer[113] proposes a reasoning architecture to propagate aggregated component health indexes up to the system level, in Unmanned Aerial Vehicles (UAVs). This propagation is done by quantifying the remaining functionality at every point, in three separate levels. At the lowest level, the diagnostic reasoning starts with the raw sensor data and attempts to categorise hidden failure mode symptoms. The mid-level of the reasoning architecture is used to ascertain the overall functional availability of the subsystems that make up the whole, that is, what effects do the failure modes that have been recognised have on the functional availability of the subsystem? The challenge of determining and measuring functional availability, but from a system-wide viewpoint, is present at the system-level reasoning, the highest level of onboard reasoning. At this level, the system's capacity to carry out planned activities is determined using the functional availability evaluations, or condition indicators, from all of the underlying components. This architecture has a connection to the approach in Roemer,[83] where a hierarchical reasoning is designed to support IVHM to provide real-time health state and information on remaining available functionality from various levels of functionality; LRU, assembly, subsystem, and overall system or vehicle. After computing the health indexes at the component level, a successive process rolls up the effects to the subsystem level. The process in Roemer[83] distinguishes between independent relationships, serial dependencies, and parallel dependencies among the functional areas. This can be instrumental in making operational decisions because the nature of the relationship that exists between the components can provide information on how crucial they are to the asset's functionality at the platform level. The methods in these approaches can be applied to Figure 3 to aggregate the health results from the component, subsystem, and system levels to the platform. Kamtsiuris et al.[12] tackle health estimation of physical assets by employing an inheritance mechanism. The authors describe a system as a set of subsystems, components, or parts that are connected structurally and functionally in a hierarchy.[117] With this hierarchy, a parent–child relationship is established between components, subsystems, and the system. Individual components that make up a subsystem are referred to as a 'child' of that subsystem, while that subsystem is the 'parent.' In the same vein, individual subsystems that make up a system are referred to as a 'child' of that system, while the system itself is the 'parent.' That is, every 'parent' inherits its health state from its 'children'. The estimation of health indexes can be rolled up to the platform level by computing the health state of a 'parent' at every point and propagating it to the next level in the hierarchy (i.e. from component to subsystem, to system, and to the platform levels). For example, following the structure of Figure 3, a low efficiency in an Air Cycle Machine (ACM) and Heat Exchanger fouling, at the component level, can be propagated to the Passenger Air Conditioner (PACK) at the subsystem level, and then to the ECS at the system level to be seen at the platform level. Tamssaouet et al.[118] approaches health index propagation in a slightly different way. Once a fault is detected, based on the system's functional architecture, its estimated health state is propagated into the future to determine its system remaining useful life (SRUL). The input–output model, as it is referred to, is a unified model for system degradation, which considers interdependencies between components, mission profile, and inner component degradations. The taxonomy it considers for a physical asset is a components-system classification. Each component has its own failure mode that leads to degradation and this degradation impacts other related components. A component fails when it reaches a supposed threshold and the degradation of a system is characterised by its inoperability, which includes its components' inoperability. The input data needed to implement this approach at the system level is the failure threshold of the systems' components, architecture, the online health indicator value of the system's components and the degradation trends of the system's components with their uncertainty. Shigang et al.[119] identify the task of hierarchical health assessment as being able to analyse the effect of faults at different levels of health management, given a determined health status at the lower level. This falls in line with the questions that will be faced in making operational decisions, as shown in the pyramid in Figure 3. Shigang[119] adopts a multi-layer Bayesian network for hierarchical health assessment, by assigning probabilities to fault statuses at lower levels and propagating it to higher levels. A similar application of the Bayesian networks is seen in Barua and Khorasani,[120,121] where a Component Dependency Model (CDM) for hierarchical fault diagnosis is developed to facilitate a systematic diagnosis of faults at different health management levels of satellites. This can inform maintainers of the probability of a fault getting worse if that fault can potentially affect the overall functioning of the physical asset. In a nutshell, this section shows how employing a HI to supplement the application of AI to diagnose faults has the tendency to improve maintenance information to support operational decisions.

Summary and conclusions

This paper attempts to report the relationship between AI and maintenance, for tackling aircraft component health management from the platform-level. To that effect, it reviews how maintenance has evolved over time, up to where Prescriptive Maintenance (PM) is being done to support CBM, the role of MROs and why they typically adopt IVHM for maintenance. It also touches on how the level of health management has been at the component or system levels and how due to the nature of certain aircraft faults, these approaches might not be able to detect the faults in time. Hence, justifying why a platform level approach can be useful, as it will be able to detect faults and the interaction effects of components quickly. Further, it touches on what might be needed when handling aircraft component health from a platform view - providing information to answer the questions posed by Figure 3, for assisting operational decision. It reviews work on health index computation and suggests that an IVHM system might need a reasoner that can output a criticality index of the components to assist in making an operational decision.

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References

1. Air Accidents Investigation Branch (AAIB). *Annual Safety Report*. New Delhi, India: AAIB, 2015.
2. Saltoǀlu R, Humaira N and Inalhan G. Aircraft scheduled airframe maintenance and downtime integrated cost model. *Adv Oper Res*. 2016; 2016(1): 1–12. DOI: 10.1155/2016/2576825.
3. International Air Transport Association (IATA). *Airline maintenance cost executive commentary*. Montreal, QC: IATA, 2020.
4. Ezhilarasu Mattuvarkuzhali C, Skaf Z and Jennions K. I. Progress towards a framework for aerospace vehicle reasoning (FAVER). *Annual Conf Prog Health Manag Soc*. 2019; 11(1). DOI:10.36001/phmconf.2019.v11i1.887.
5. Mohsen A. Mohsen A. Condition based maintenance. 2017. [Online], https://www.researchgate.net/publication/319290229. *Condition based maintenance*, 2017, [Online]. https://www.researchgate.net/publication/319290229
6. Société Internationale de Télécommunications Aéronautiques (SITA). *Air transport IT insights*. Geneva, Switzerland: SITA, 2021.
7. Nagaraja Rao BK. The role of artificial intelligence (AI) in condition monitoring and diagnostic engineering management (COMADEM): a literature survey. *American Jour Arti Intel*. 2021; 5(1): 17. DOI: 10.11648/j.ajai.20210501.12.
8. Ayeni P, Baines T, Lightfoot H, et al. State-of-the-art of 'lean' in the aviation maintenance, repair, and overhaul industry. *Proc Inst Mech Eng*. 2011; 225(11): 2108–2123. DOI: 10.1177/0954405411407122.
9. Zhang G. A integrated vehicle health management framework for aircraft - a preliminary report. *2015 IEEE conference on prognostics and health management: enhancing safety, efficiency, availability, and effectiveness of systems through PHAf technology and application*. Austin, TX: PHM, September 2015. DOI: 10.1109/ICPHM.2015.7245034.
10. Benedettini O, Baines TS, Lightfoot HW, et al. State-of-the-art in integrated vehicle health management. *Proc Inst Mech Eng G J Aerosp Eng*. 2009; 223(2): 157–170. DOI: 10.1243/09544100JAERO446.
11. Roemer MJ, Byington CS and Schoeller MS. Selected artificial intelligence methods applied within an integrated vehicle health management system. *AAAI Fall Symposium: Artificial Intelligence for Prognostics*. 2007; 88–96. https://cdn.aaai.org/Symposia/Fall/2007/FS-07-02/FS07-02-013.pdf
12. Kamtsiuris AA, Raddatz F and Wende G. *A health index framework for condition monitoring and health prediction*. 1st ed.. Turin, Italy: PHM Society European Conference, 2022, 7, pp. 231–238.
13. Jennions IK. *Integrated vehicle health management perspectives on an emerging field*. SAE International, 2011.
14. Fred H. *Wilbur and Orville. A biography of the Wright Brothers*. Chelmsford, MA: Chelmsford, MA, 2013.
15. Bengtsson M. *Condition based maintenance systems: an investigation of technical constituents and organizational aspects*. Eskilstuna, Sweden: Mälardalen University, 2004.
16. North Central Institute. *The evolution of aviation maintenance*. Clarksville, TN: North Central Institute, 2020. https://nci.edu/2020/12/09/the-evolution-of-aviation-maintenance/ (accessed 12 Nov 2021).
17. Anthony KM. *Maintenance planning optimisation for the Boeing 737 next generation*. Delft University of Technology, 2002.
18. Kay HL. Bite in aircraft electric power systems. *IEEE Trans Aero Electron Syst*. 1966; 2(4): 286–289. DOI: 10.1109/TAES.1966.4501852.
19. Jakovljevic M and Artner M. Protocol-Level System Health Monitoring and Redundancy Management for Integrated Vehicle Health Management, 2006 ieee/aiaa 25TH Digital Avionics Systems Conference, Portland, OR, USA, 2006, pp. 1-7. DOI: 10.1109/DASC.2006.313723
20. Omdec A. History of CBM (condition based maintenance). 2021. https://www.omdec.com/moxie/Technical/Reliability/a-history-of-cbm.shtml (accessedNov. 20 2021).
21. Takata S, Kirnura F and van Houten FJAM. Maintenance: changing role in life cycle management. *CIRP annals*. 2004; 53(2): 643–655.
22. Gallimore KF and Penlesky RJ. A framework for developing maintenance strategies. *Prod Inventory Manag J*. 1988; 29(1).
23. Ahmed NU. An analytical decision model for resource allocation in highway maintenance management. *Transport Res Gen*. 1983; 17(2): 133–138. DOI: 10.1016/0191-2607(83)90067-5.
24. Shahin MY and Kohn SD. *Pavement maintenance management for roads and parking lots*, 1981. https://apps.dtic.mil/sti/citations/ADA110296
25. Montero Jimenez JJ, Schwartz S, Vingerhoeds R, et al. Towards multi-model approaches to predictive maintenance: a systematic literature survey on diagnostics and prognostics. *J Manuf Syst*. 2020; 56: 539–557. DOI: 10.1016/j.jmsy.2020.07.008.
26. Kelly A. *Maintenance strategy: Business centred maintenance*. Oxford, UK: Butterworth-Heinemann, 1997.
27. Gallego-García S, Gejo-García J and García-García M. Development of a maintenance and spare parts distribution model for increasing aircraft efficiency. *Appl Sci*. 2021; 11(3): 1333. DOI: 10.3390/APP11031333
28. Kobbacy KA, Prabhakar Murthy DN, (eds). *Springer series in reliability engineering*. London, UK: Springer, 2008. https://link.springer.com/book/10.1007/978-1-84800-011-7
29. Alain LB. Engaging the entire organization key to improving reliability. SIRF Roundtables *Blog* 2019; 13. accessed 13 Nov 2021. https://www.sirfrt.com/blog/maintenance-maturity-and-the-importan t-role-of-predictive-maintenance
30. Jin X. The present status and future growth of maintenance in US manufacturing: results from a pilot survey.

Manufac Rev. 2016; 3: 10. DOI: 10.1051/mfreview/2016005.
31. Eduardo Afonso Pereira B, Fernando TMTMA and Wlamir OLV. Aircraft routing problem model for fractional fleets using fault prognostics. *Journal of Quality in Maintenance Engineering*. 2021; 27(3): 517–536. DOI: 10.1108/JQME-06-2020-0053.
32. Afolalu SA, Ikumapayi OM, Okwilagwe O, et al. Evaluation of effective maintenance and reliability operation management: a review. *E3S Web of Conferences*. 2021; 309. DOI: 10.1051/e3sconf/202130, https://www.proquest.com/docview/2583082990?fromopenview=true&pq-origsite=gscholar
33. Mobley Keith R. *An introduction to predictive maintenance*. Oxford, UK: Butterworth-Heinemann, 2002. https://www.irantpm.ir/wp-content/uploads/2008/02/an-introduction-to-predictivemaintenance.pdf
34. Wang H. A survey of maintenance policies of deteriorating systems. *European Journal of Operational Research*. 2001; 139(3): 469–489.
35. Badía F and Campos CA. Reliability Engineering & System Safety. *Reliability Engineering & System Safety*. 2002; 78(2): 157–163.
36. Mijailovic V. Probabilistic method for planning of maintenance activities of substation components. *Electric Power Systems Research*. 2003; 64(1): 53–58.
37. Barbera F, Schneider H and Kelle P. A condition based maintenance model with exponential failures and fixed inspection intervals. *J Oper Res Soc*. 2017; 47(8): 1037–1045. DOI: 10.1057/JORS.1996.130
38. Chen D and Trivedi KS. Closed-form analytical results for condition-based maintenance. *Reliability Engineering & System Safety*. 2002; 76(1): 43–51.
39. Marseguerra M, Zio E and Podofillini L. Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation. *Reliability Engineering & System Safety*. 2002; 77(2): 151–165.
40. Rao BKN. *Handbook of condition monitoring*. 1st ed.. Oxford UK: Elsevier Advanced Technology, 1996.
41. Figueiredo-Pinto DG, Teixeira F, Abrahão M, et al. An operational availability optimization model based on the integration of predictive and scheduled maintenance. *PHM Society European Conference*. 2021; 6(1): 11–11. DOI: 10.36001/PHME.2021.V6I1.2816.
42. Shafiee M and Sørensen JD. Maintenance optimization and inspection planning of wind energy assets: models, methods and strategies. *Reliability Engineering & System Safety*. 2019; 192: 105993. DOI: 10.1016/j.ress.2017.10.025.
43. Donghan W, Wei T, Xiangyu D, et al. Applications and analysis of digital twin in prognostic and health management. 2021 IEEE 11th international conference on electronics information and emergency communication (ICEIEC), Beijing, China, 18200-20203 June 2021, pp. –. DOI: 10.1109/iceiec51955.2021.9463843.
44. Kennedy S. What is prescriptive maintenance? 2020. https://www.plantservices.comm
45. Jennions S. *Introduction to conscious aircraft*. Cranfield, UK: Cranfield University, United Kingdom - YouTube. https://www.youtube.com/watch?v=MZ_c3YXTmcM (accessed 21 Nov 2021).
46. Brown ER, McCollom NN, Moore E-E, et al. Prognostics and health management a data-driven approach to supporting the F-35 lightning II. 2007 IEEE Aerospace Conference (2007): 1–12.
47. Al-kaabi H, Potter A and Naim M. An outsourcing decision model for airlines' MRO activities. *J Qual Mainten Eng*. 2007; 13(3): 217–227. DOI: 10.1108/13552510710780258/FULL/PDF
48. Michaels K. Air transport MRO market outlook. *Aviation MRO conference and exhibition, aeroStrategy*. Manila, Philippines: AeroStrategy, 2007.
49. Ayeni P, Ball P and Baines T. Towards the strategic adoption of lean in aviation maintenance repair and overhaul (MRO) industry an empirical study into the industry's lean status. *Jnl of Manu Tech Mnagmnt*. 2016; 27(1): 38–61. DOI: 10.1108/JMTM-04-2015-0025
50. Cohen MA and Willie JH. *Implications for service parts management in the rapidly changing aviation MRO market*. Helmutt Schmidt University, 2006, pp. 1–7. https://www.semanticscholar.org/paper/Implications-for-Service-Parts-Management-in-the-Cohen/de28fa9215540e4b1aa99bbe9525264861b93000
51. Freeman JW. State regulation of airlines and the airline deregulation Act of 1978. *J Air Law Commer*. 1979; 44(4).
52. Almeida C. *Low cost maintenance, repair and overhaul providers: an optimum balance to capture the low cost carriers market. MSc Thesis*. Department of Air Transport School of Engineerin. Cranfield University, 2005.
53. Kilpi J and Vepsäläinen APJ. Pooling of spare components between airlines. *J Air Transp Manag*. 2004; 10(2): 137–146. DOI: 10.1016/J.JAIRTRAMAN.2003.09.001
54. Keles B. *Data-Driven Modeling, Planning and Scheduling MRO Operations in Aviation Industry. Data-driven modeling, planning and scheduling MRO operations in aviation industry. Doctoral dissertation*. University of Miami, 2019.
55. Jennions IK. *Integrated vehicle health management: business case theory and practice*. Warrendale, PA: SAE International, 2012.
56. Zhu H, Gao J, Li D, et al. A web-based product service system for aerospace maintenance, repair and overhaul services. *Comput Ind*. 2012; 63(4): 338–348. DOI: 10.1016/j.compind.2012.02.016.
57. Ofsthun S. Integrated vehicle health management for aerospace platforms. *IEEE Instrum Meas Mag*. 2002; 5(3): 21–24. DOI: 10.1109/MIM.2002.1028368.
58. Baroth E, Powers W, Fox J, et al. IVHM (integrated vehicle health management) techniques for future space vehicles. 37th joint propulsion conference and exhibit, Salt Lake City, UT, 8–11 July 2001. DOI: 10.2514/6.2001-3523.
59. Ezhilarasu CM, Skaf Z and Jennions IK. *Understanding the role of digital twin in integrated vehicle health management (IVHM). IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, October 2019.
60. Ezhilarasu CM, Skaf Z and Jennions IK. The application of reasoning to aerospace integrated vehicle health management (IVHM): challenges and opportunities. *Progress in Aerospace Sciences*. 2019; 105: 60–73. DOI: 10.1016/j.paerosci.2019.01.001.
61. Jennions IK. Society of Automotive Engineers. Integrated vehicle health management. The technology. *SAE International*. 2013.
62. Ochella S, Shafiee M and Sansom C. Adopting machine learning and condition monitoring P-F curves in determining and prioritizing high-value assets for life extension. *Expert Syst Appl*. 2021; 176: 114897. DOI: 10.1016/J.ESWA.2021.114897.

63. Schoeller MH, Roemer MJ, Leonard MS, et al. Embedded reasoning supporting aerospace IVHM. 2007 *conference and exhibit*, Rohnert Park, CA, 7–10 May 2007.
64. Fox JJ and Glass BJ. Impact of integrated vehicle health management (IVHM) technologies on ground operations for reusable launch vehicles (RLVs) and spacecraft. *IEEE Aerospace Conference Proceedings*. 2000; 2: 179–186. DOI: 10.1109/AERO.2000.878223.
65. Zuniga FA, Maclise DC, Romano DJ, et al. Integrated systems health management for exploration systems. *1st Space Exploration Conference: Continuing the Voyage of Discovery*. 2005. DOI: 10.2514/6.2005-2586.
66. Byer B, Hess A and Fila L. Writing a convincing cost benefit analysis to substantiate autonomic logistics. *IEEE Aeros Conf Proc*. 2001; 6: 63095–63103. DOI: 10.1109/AERO.2001.931327.
67. Hess A, Calvello G and Dabney T. PHM a key enabler for the JSF autonomie logistics support concept. *IEEE Aero Conf Proc*. 2004; 6: 3543–4549. DOI: 10.1109/AERO.2004.1368171.
68. Jennions IK, Niculita O and Esperon-Miguez M. Integrating IVHM and asset design. *Int J Prognostics Health Manag*. 2016; 7(2): 28. DOI: 10.36001/IJPHM.2016.V7I2.2404.
69. Company T. Benefits of IVHM. an analytical approach. *IEEE Aero Conf Proc*. 2006; 2006. DOI: 10.1109/AERO.2006.1656072.
70. Banks J, Reichard K, Crow E, et al. How engineers can conduct cost-benefit analysis for PHM systems. 2005 IEEE Aerospace Conference, Big Sky, MT, 5–12 March 2005, pp. 3958–3967. DOI: 10.1109/AERO.2005.1559701.
71. Ezhilarasu CM, Skaf Z and Jennions IK. A generalised methodology for the diagnosis of aircraft systems. *IEEE Acc*. 2021; 9: 11437–11454. DOI: 10.1109/ACCESS.2021.3050877.
72. Makridis G, Kyriazis D and Plitsos S. *Predictive maintenance leveraging machine learning for time-series forecasting in the maritime industry*. In: 2020 IEEE 23rd international conference on intelligent transportation systems, ITSC, Rhodes, Greece, 20–23 September 2020. DOI: 10.1109/ITSC45102.2020.9294450.
73. Putra HGP, Supangkat SH, Nugraha IGBB, et al. Designing machine learning model for predictive maintenance of railway vehicle. In: 8th international conference on ICT for smart society: digital twin for smart society. ICISS 2021 - proceeding, Bandung, Indonesia, 2–4 August 2021. DOI: 10.1109/ICISS53185.2021.9533201.
74. Ezhilarasu CM and Jennions IK. Development and implementation of a framework for aerospace vehicle reasoning (FAVER). *IEEE Acc*. 2021; 9: 108028–108048. DOI: 10.1109/access.2021.3100865
75. Papakostas N, Papachatzakis P, Xanthakis V, et al. An approach to operational aircraft maintenance planning. *Decis Support Syst*. 2010; 48(4): 604–612. DOI: 10.1016/J.DSS.2009.11.010
76. Kossiakoff A, William NS, Samuel JS, et al. *Systems engineering principles and practice*. 2nd ed. New York, NY: Wiley, 2011.
77. Sleight PA and Carter RDG. 2010. *Aircraft accident report 1/2010. Department for Transport (Air Accidents Investigation Branch)*, 2010.
78. Air Accidents Investigation Branch (AAIB). *Aviation accidents report 287*. UK: Department of Transport, 2010. https://assets.publishing.service.gov.uk/media/5422f3dbe5274a1314000495/1-2010_G-YMMM.pdf
79. Khan F, Eker OF, Sreenuch T, et al. Multi-domain modeling and simulation of an aircraft system for advanced vehicle-level reasoning research and development. 2014. [Online]. Available: https://www.ijacsa.thesai.org
80. Crespo Márquez A, Serra Parajes J, de la Fuente Carmona A, et al. Integrating complex asset health modelling techniques with continuous time simulation modelling: a practical tool for maintenance and capital investments analysis. *Comput Ind*. 2021; 133: 103507. DOI: 10.1016/J.COMPIND.2021.103507.
81. Rodrigues LR, Gomes JPP, Ferri FAS, et al. Use of PHM information and system architecture for optimized aircraft maintenance planning. *IEEE Syst J*. 2015; 9(4): 1197–1207. DOI: 10.1109/JSYST.2014.2343752.
82. Saxena A, Goebel K and Simon D, et al. Damage propagation modeling for aircraft engine run-to-failure simulation, 2008 *International Conference on Prognostics and Health Management*, Denver, CO, USA, 2008, pp. 1–9, DOI: 10.1109/PHM.2008.4711414. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=4711414&casa_token=yHhq5xgQPpwAAAAA:owsHKieqFtzMzeNOKF3wHtN5VPmvB8kjPRyrJz1iL3wVSKSVR5R-stxg0UNwE3CFr6JoCZWH&tag=1
83. Roemer M. A hierarchical reasoning structure to support aerospace IVHM. *SAE Int J Aerosp*; 4(2): 1176–1183. DOI: 10.4271/2011-01-2665.
84. Skliros C, Esperon Miguez M, Fakhre A, et al. A review of model based and data driven methods targeting hardware systems diagnostics. *Diagnostyka*. 2019; 20: 3–21. DOI: 10.29354/diag/99603.
85. Liu Z, Meyendorf N and Mrad N. The role of data fusion in predictive maintenance using digital twin. *AIP Conf Proc*. 2018; 1949(1). DOI: 10.1063/1.5031520.
86. Rajesh PK, Manikandan N, Ramshankar CS, et al. Digital twin of an automotive brake pad for predictive maintenance. *Procedia Comput Sci*. 2019; 165: 18–24. DOI: 10.1016/j.procs.2020.01.061.
87. Airbus. *Airbus launches skywise – aviation's open data platform Airbus*. 2017. https://www.airbus.com/en/newsroom/press-releases/2017-06-airbus-launches-skywise-aviations-open-data-platform (accessed 30 Nov 2022).
88. Ferguson GR. *Aircraft maintenance expert systems*, 1983. https://apps.dtic.mil/sti/citations/ADA138373
89. Emerald Insight. *Rolls-Royce plc invests in knowledge-based design software*. Bingley, UK: Emerald Group Publishing Limited, 2000. DOI: 10.1108/aeat.2000.12772fab.015 (accessed 28 Dec 2021).
90. RuleSentry™ configurable decision support. 2013. https://www.lockheedmartin.com/content/dam/lockheed-martin/rms/documents/c4isr-situational-awareness-tools/RuleSentry-brochure.pdf (Accessed: 11 Feb 2023)
91. Kobbacy KAH. Artificial intelligence in maintenance. *Springer Series in Reliability Engineering*. 2008; 8: 209–231. DOI: 10.1007/978-1-84800-011-7_9.
92. Ochella S, Shafiee M and Dinmohammadi F. Artificial intelligence in prognostics and health management of engineering systems. *Eng Appl Artif Intell*. 2022; 108: 104552. DOI: 10.1016/j.engappai.2021.104552.
93. McCarthy J, Minsky ML, Rochester N, et al. A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI Mag*. 2006; 27(4): 12–12. DOI: 10.1609/AIMAG.V27I4.1904.

94. Simmons AB and Chappell SG. Artificial intelligence-definition and practice. *IEEE J Ocean Eng*. 1988; 13(2): 14–42. DOI: 10.1109/48.551.
95. Keleko AT, Kamsu-Foguem B, Raymond HN, et al. Artificial intelligence and real-time predictive maintenance in industry 4.0: A bibliometric analysis. *AI and Ethics*. 2022; 2(4): 553–577. DOI: 10.1007/s43681-021-00132-6.
96. Vedran V. Control-M…As an application management platform. *Imaves -. BMC*. 2014. https://www.doc-developpement-durable.org/file/Projets-informatiques/cours-&-manuels-informatiques/control-m/Control-M%20for%20Hadoop.pdf
97. Société Internationale de Télécommunications Aéronautiques (SITA). *IT insights*. Brussels, Belgium: SITA, 2021.
98. Xu L, Yuan S, Chen J, et al. Deep learning based fatigue crack diagnosis of aircraft structures. 7th Asia-Pacific workshop on structural health monitoring,, Hongkong, China, 12–15 November 2018. https://www.ndt.net/article/apwshm2018/papers/120.pdf (Accessed: 9 Feb 2023).
99. Eldali M and Kumar KD. Fault diagnosis and prognosis of aerospace systems using growing recurrent neural networks and LSTM. IEEE Aerospace Conference Proceedings, 2021; 2021-March. DOI: 10.1109/AERO50100.2021.9438432.
100. Islam MS and Chong U. Fault detection and severity classification based on adaptive filter and fuzzy logic. *SN Appl Sci*. 2019; 1(12): 1632. DOI: 10.1007/s42452-019-1680-0
101. Guo RX and Wang ZH. A fault propagation model based on bayesian network. Proceedings - international conference on control science and electric power systems, CSEPS 2021, Shanghai, China, 28152–30156 May 2021, pp. –. DOI: 10.1109/CSEPS53726.2021.00037.
102. Khan F, Eker OF, Sreenuch T, et al. Health index and behaviour based vehicle level reasoning system. *2015 IEEE conference on prognostics and health management: enhancing safety, efficiency, availability, and effectiveness of systems through PHAf technology and application*. Austin, TX, September 2015, pp. 22–25. DOI: 10.1109/ICPHM.2015.7245042
103. Yin X, Li Y, Zhang Y, et al. Construction of health index for aircraft air-conditioning system health prediction. In: *2020 global reliability and prognostics and health management*, Shanghai, China, 16–18 October 2020. DOI: 10.1109/PHM-Shanghai49105.2020.9280933
104. Nascimento RG and Viana FAC. Fleet prognosis with physics-informed recurrent neural networks. Structural health monitoring 2019: enabling intelligent life-cycle health management for industry internet of things (IIOT). proceedings of the 12th international workshop on structural health monitoring, January 2019, pp. 1740–1747. DOI: 10.48550/arxiv.1901.05512.
105. Li P, Jia X, Feng J, et al. A novel scalable method for machine degradation assessment using deep convolutional neural network. *Measurement*. 2020; 151: 107106. DOI: 10.1016/J.MEASUREMENT.2019.107106
106. Pecht M, Dube M, Natishan M, et al. Evaluation of built-in test. IEEE. 2001; 37(1): 266–271. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=913684&casa_token=B7KHfRcKL-wAAAAA:lpKc6c0Tg9yZf5QJVzsWmXz7vML6b_CnDiwlbEpx2tVj6ivw50O7ZmQbe6euueFD4E6jYruf
107. Goodman DM. *Automation in electronic test equipment*, v. 3–5, 1967. https://www.amazon.es/Automation-Electronic-Test-Equipment-3-5/dp/034009401X (accessed 17 Oct. 2022).
108. Yarnall WH, Moore CR and Dussault PL. *BIT/BITE/ED/EP/IVHM and ATE in da*. Baltimore, MD: AUTOTESTCON (Proceedings, September 2011, pp. 1287–1591. DOI: 10.1109/AUTEST.2011.6058763.
109. Dorsch J. *A brief history of test*. 2017. https://semiengineering.com/a-brief-history-of-test/ (accessed 17 Oct. 2022).
110. Chen ZS, Yang YM and Hu Z. complex mechanical systems in prognostics and health management systems. *IEEE Trans Reliab*. 2012; 61(2): 314–322. DOI: 10.1109/TR.2012.2196171.
111. Jennions IK. *Integrated vehicle health management: the technology: essential reading*. Warrendale, PA: SAE eBooks. IEEE Xplore, 2013. https://ieeexplore.ieee.org/book/8505006 (accessed 12 Oct. 2022).
112. Kim S, Choi JH and Kim NH. Challenges and opportunities of system-level prognostics. *Sensors*. 2021; 21(22). DOI: 10.3390/s21227655.
113. Roemer MJ and Tang L. *Integrated vehicle health and fault contingency management for UAVs*. Berlin, Germany: Springer Netherlands, 2015. DOI: 10.1007/978-90-481-9707-1.
114. Daigle M., Bregon A. and Roychoudhury I. A Distributed Approach to System-Level Prognostics. *Annual Conference of the PHM Society*. 2012; 4(1). DOI: 10.36001/phmconf.2012.v4i1.2112.
115. Chang L, Lin YH and Zio E. Remaining useful life prediction for complex systems considering varying future operational conditions. *Qual Reliab Eng Int*. 2022; 38(1): 516–531. DOI: 10.1002/qre.2997.
116. Wang C, Zhu Z, Lu N, et al. A data-driven degradation prognostic strategy for aero-engine under various operational conditions. *Neurocomputing*. 2021; 462: 195–207. DOI: 10.1016/J.NEUCOM.2021.07.080.
117. Kossiakoff A, Seymour SJ, Flanigan DA, et al. *Systems engineering: principles and practice*, 2020. https://www.wiley.com/en-ie/Systems+Engineering+Principles+and+Practice%2C+3rd+Edition-p-9781119516668 (Accessed: 5 Sep, 2022)
118. Tamssaouet F, Nguyen KTP, Medjaher K, et al. A fresh new look on system-level prognostic: handling multi-component interactions, mission profile impacts, and uncertainty quantification. *Int J Prognostics Health Manag*. 2021; 12(2). DOI: 10.36001/IJPHM.2021.V12I2.2777.
119. Shigang Z, Xu L, Lei L, et al. Hierarchical health assessment of equipment with uncertain fault diagnosis result. 2019 Prognostics and system health management conference (PHM-Qingdao), Qingdao, China. *IEEE. October.* 2019; 25–27.
120. Barua A and Khorasani K. Hierarchical fault diagnosis and health monitoring in satellites formation flight. *IEEE Trans Syst Man Cybern C*. 2011; 41(2): 223–239. DOI: 10.1109/TSMCC.2010.2049994.
121. Zofka A. Proactive pavement asset management with climate change aspects. *IOP Conference Series: Materials Science and Engineering*. 2018; 356(1). DOI: 10.1088/1757-899X/356/1/012005.
122. Esperon-Miguez M, John P and Jennions IK. A review of integrated vehicle health management tools for legacy platforms: challenges and opportunities. *Prog Aero Sci*. 2013; 56: 19–34. DOI: 10.1016/J.PAEROSCI.2012.04.003.
123. Rajamani R, Saxena A., Kramer F, et al. Developing IVHM requirements for aerospace systems. *SAE Technical Paper*. 2013. https://ntrs.nasa.gov/api/citations/20140010620/downloads/20140010620.pdf
124. Floyd S. Rolls-Royce intelligent jet engine steals the show at Hannover Messe 2016. *MicrosoftIndustry Blogs*, 2016. https://

cloudblogs.microsoft.com/industry-blog/manufacturing/2016/05/25/rolls-royce-intelligentjet-engine-steals-the-show-at-hannover-messe-2016/ (accessed 29 Nov, 2022)
125. Martin L. Autonomic logistics information system (ALIS). 2022. https://www.lockheedmartin.com/en-us/products/autonomic-logistics-information-system-alis.html (accessed 29 Nov 2022)
126. Boeing. AERO. *A quaterly publication*. 2008; (Q307). https://www.boeing.com/commercial/aeromagazine/articles/qtr_3_07/AERO_Q307.pdf
127. Ranasinghe K, Sabatini R, Gardi A, et al. Advances in integrated system health management for mission-essential and safety-critical aerospace applications. *Prog Aero Sci*. 2022; 128: 100758. DOI: 10.1016/J.PAEROSCI.2021.100758.
128. Baranov PP, Mamychev AY, Plotnikov AA, et al. Problems of legal regulation of robotics and artificial intelligence from the psychological perspective. *PyR*. 2020; 8(2): 511. DOI: 10.20511/PYR2020.V8N2.511.
129. Kaplan A, Haenlein M and Siri S. My hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus Horiz*. 2019; 62(1): 15–25. DOI: 10.1016/J.BUSHOR.2018.08.004.
130. Ransbotham S, Kiron D, Gerbert P, et al. Reshaping business with artificial intelligence. Closing the gap between ambition and action. *MIT Sloan Management Review*. 2017; 59(1). https://www.proquest.com/docview/1950374030?pq-origsite=gscholar&fromopenview=true
131. Russel S and Norvig P. *Artificial intelligence a modern approach*. London, UK: Pearson Education, Inc, 2010.
132. Wahl B, Cossy-Gantner A, Germann S, et al. Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings? *BMJ Glob Health*. 2018; 3(4): e000798. DOI: 10.1136/BMJGH-2018-000798.
133. Weber F and Schütte R. A domain-oriented analysis of the impact of machine learning—the case of retailing. *Big Data and Cog Comp*. 2019; 3: 11. DOI: 10.3390/BDCC3010011.
134. Daniyan I, Mpofu K, Oyesola M, et al. Artificial intelligence for predictive maintenance in the railcar learning factories. *Procedia Manuf.* 2020; 45: 13–18. DOI: 10.1016/j.promfg.2020.04.032.
135. Dallapiccola D and Ilin A. Predictive maintenance of centrifugal pumps: a neural network approach. *Doctoral dissertation, ETSI_Informatica*. 2020. https://oa.upm.es/66271/1/TFM_DAMIANO_DALL APICCOLA.pdf
136. Akpudo UE and Hur JW. A ceemdan–assisted deep learning model for the rul estimation of solenoid pumps. *Electronics*. 2021; 10: 2054. DOI: 10.3390/electronics10172054.
137. Silva JC, Saxena A, Balaban E, et al. A knowledge-based system approach for sensor fault modeling, detection and mitigation. *Expert Syst Appl*. 2012; 39(12): 10977–10989. DOI: 10.1016/J.ESWA.2012.03.026.
138. Frank PM and Ki3ppen-Seliger B. *New developments using*. AI in fault diagnosis, 1997.
139. Phillips P and Diston D. A knowledge driven approach to aerospace condition monitoring. *Knowl Base Syst*. 2011; 24(6): 915–927. DOI: 10.1016/j.knosys.2011.04.008
140. Adhikari P and Rao HG and Buderath D-IM. Machine learning based data driven diagnostics & prognostics framework for aircraft predictive maintenance. *In Proceedings of the 10th International Symposium on NDT in Aerospace*. 2018; 24–26.
141. Kavana V and Neethi M. *International conference on electrical, electronics, communication, computer, and optimization techniques (ICEECCOT)*. IEEE, 2018.
142. Özkat EC. Makine öğrenmesi metodolojisi kullanılarak yüksek hızlı rulmanlarda sağlık göstergesinin belirlenmesi. *European Jour Sci and Techn*. 2021; 22: 176–183. DOI: 10.31590/ejosat.843465.
143. Patil SS, Bewoor AK, Kumar R, et al. Development of optimized maintenance program for a steam boiler system using reliability-centered maintenance approach. *Sustainability.* 2022; 14: 1–16. DOI: 10.3390/su141610073.
144. Chazhoor A, Mounika Y, Vergin Raja Sarobin M, et al. Predictive maintenance using machine learning based classification models. *IOP Conf Ser: Mater Sci Eng*. 2020; 954: 012001. DOI: 10.1088/1757-899X/954/1/012001.
145. Davari N, Veloso B, Ribeiro RP, et al. Predictive maintenance based on anomaly detection using deep learning for air production unit in the railway industry. *IEEE 8th international conference on data science and advanced analytics DSAA*. Porto, Portugal: 2021, October 2021, pp. 6–9. DOI: 10.1109/DSAA53316.2021.9564181.
146. Hermawan AP, Kim DS and Lee JM. Predictive maintenance of aircraft engine using deep learning technique. *International conference on ICT convergence, Jeju, Korea*. October; 2020: 211296–231298. DOI: 10.1109/ICTC49870.2020.9289466.
147. Chen C, Liu Y, Sun X, et al. Automobile maintenance prediction using deep learning with GIS data. *Procedia CIRP.* 2019; 81: 447–452. DOI: 10.1016/j.procir.2019.03.077.

Appendix

ANN	Artificial neural network
LSTM	Long short-term memory
NN	Neural network
FL	Fuzzy logic
KBS	Knowledge-based systems
KNN	K-nearest neighbours
RVM	Relevance vector machines
SVM	Support vector machine
SVR	Support vector regression
RF	Random forest
MLP	Multilayer perceptron
LR	Logistic regression
DL	Deep learning
CNN	Convolutional neural network
ML	Machine learning
DCNN	Deep convolutional neural network
NB	Naïve Bayes

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Platform health management for aircraft þÿ m a i n t e n a n c e   a r e v i e w

Kwakye, Andrews Darfour

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