Thorough Analysis of Predictive Maintenance for the Operation and Maintenance of Military Aircraft

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The increasing digitisation of aircraft operations and support in recent years have made it possible to monitor, assess, and predict the health of aircraft structures, systems, and components more often. Different activities fed into what is called condition-based maintenance (CBM) strategy,[1] is believed to offer significant benefits in terms of both cost and time. These activities are typically summarised using terms like predictive maintenance, prognostics and health management (PHM), integrated vehicle health management (IVHM), or aircraft health management (AHM).[2]

In order to achieve high accuracy and precision as well as to avert worse catastrophes (failures), predictive maintenance on airplanes has been widely used but in recent times the adoption of Artificial Learning (AI) and Machine Learning (ML) across predictive maintenance has transformed the process of Predictive Maintenance. The fundamental goal of AI-based predictive maintenance strategies and processes is to repair and detect faults in time and give aircraft enough space to repair on-time while operations. Attaining targets for aircraft availability and operating expenses must coexist with ensuring continuing airworthiness in order to assure the effective use

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of aircraft. In military settings, current maintenance programmes mostly employ 'fixed-time-interval and preventive maintenance programmes, which often leads to unexpected maintenance activities, comprehensive inspections and unnecessary replacement of undamaged parts'. It is in this context, this commentary argues for the need of AI-based Predictive Maintenance across Military aircraft and even highlights different models or strategies used globally for the aircraft maintenance.

Predictive Maintenance: Future for Aircraft Maintenance

The concept of predictive maintenance has gained significant appeal in recent years as 'big data' and machine-learning algorithms have gained popularity. The armed services do not often replace parts or components even as per predictive maintenance projections, despite the fact that they have started testing predictive maintenance programmes on various weapon systems adopting Machine Learning algorithms. These days different armed forces assets are being equipped with sensors that gather information that usually notify maintainers when a component is wearing out and how it might fail.

For instance, defence forces across the world have started employing 3D digital designs for predictive maintenance of their fighter aircraft and are considering ways to use Artificial Intelligence (AI) for such processes. To improve the capabilities process, models like Digital twins are adopted to accurately anticipate the component fatigue life. For this, digital engineering footprint of the design elements is created via stress modelling and physics-based modelling.[3]

The conventional method of estimating maintenance intervals has been based on experience and statistical failure analysis.[4] However, the operational efficiency of the assets can be improved significantly when the maintenance is performed in a more dynamic manner, that is, by taking the variations in usage and operating environment into account. But this predictive maintenance approach is only possible when first, the relation between the degradation rate and the operational conditions can be quantified, and second, the variations in these conditions are monitored.[5]

Therefore, to an extent adopting physical failure models that quantitatively describe the damage rates as a function of system usage can satisfy the first requirement. Failure models are already accessible for the majority of typical failure modes, including as wear, corrosion and fatigue. The monitoring of the right use parameter and its conversion into the proper internal load is the key to using these models in a predictive maintenance concept. Hence, it can be said that the predictive maintenance offers definite advantages over the conventional static technique.

Dimensions of AI-based Predictive Maintenance Process

The objective of an automated AI-based predictive maintenance system is to maintain and enhance the functionality of crucial fighter jets, which may lead to a decrease in failures, reduction in downtime, an increase in productivity, and enhanced in-air time safety. But flight problems and unscheduled downtime can be avoided with an automated AI-based predictive maintenance system. It links the physical assets to digital systems and further to an analytics platform, which can examine the intricate machine data to forecast breakdowns and avoid unscheduled downtime. Therefore, to alert maintenance and reliability specialists for the maintenance requirements of various equipment sets, the AI-based system examines machine output data, which includes historical performance and real-time contextual data.

Predictive diagnostic engineering is a crucial component of the predictive maintenance process. Currently, sensors on propulsion, auxiliary and fighting systems already provide data to computerised consoles, which trigger an alarm when the engine speeds or fuel-oil temperatures are affected. But predictive diagnostic engineering gathers and examines such sensor data from all fighter planes, either onboard or through a shared data network. Here, the AI looks for abnormalities by comparing the data from the aircraft with the general trends. Even when the sensor readings on the consoles aren't yet changing, it may discover, for instance, the decay pattern of a specific system or engine.

To predict when the aircraft system would eventually fail, AI also considers other factors with equally fast decays, such as temperature, durability, etc. Therefore, to produce a better quality estimate, the AI uses contextual data in addition to maintenance-sensor data. It may also consider the craft's exposure to atmospheric factors, such as temperature and humidity, and consider how those conditions have historically accelerated or slowed down decay trends. AI also takes into account the craft's maintenance history, for instance, prior repairs to the fuel-oil system and their historical effects on related other systems.

In modern times, due to the multiple roles of combat aircraft, these jets have been loaded with several digitalisation frameworks to change how they operate. Because of the development of digital technology, maintenance professionals now have access to vast volumes of data, and they have been searching for tools and processes that can make it simpler to draw insights from that data in order to put in use. The most advanced tool developed to date has the capacity to sift through massive amounts of complex machine data and give vital information to improve maintenance operations. When applied properly, it has the ability to identify even subtle changes in machine performance and carry out root cause analysis to avert equipment breakdowns and unscheduled downtime.

The true value of AI lies in its capacity to analyse vast quantities and various types of data, together with intricate machine operations and practical applications, to better comprehend the general state and performance of industrial assets. In order to deliver real-time insights on machine health, it generally evaluates various types of machine-generated data using Machine Learning algorithms and thus it helps flight data to be utilised by one or more AI algorithms to characterise engine performance and condition, failures, maintenance methods, environment impact, etc. So, using the information at hand, this AI technique creates a mathematical model of the complex system and its interactions.

Hence, the way the data is built up makes it possible to forecast a dependent 'target' variable that in this case describes the condition of the flight components and its remaining lifespan, etc. The major intention for the model is to output a status, forecast, etc., after receiving new data.

Common Methods Adopted for Predictive Maintenance

Approach 1

A quantifiable relationship of factors between the deterioration rate and the operating parameters, along with monitoring of possible fluctuations, are necessary for a predictive maintenance approach. A large collection of failure data can be used to estimate the average degradation rate, therefore, the precise relationship with operational conditions is difficult to come by. Therefore, as shown in Figure 1, it is crucial to comprehend the physical failure mechanisms.

Figure 1 shows that by only taking into account the underlying physical failure mechanisms and accompanying stresses, one can determine the quantitative relationship between a system's utilisation and remaining life.

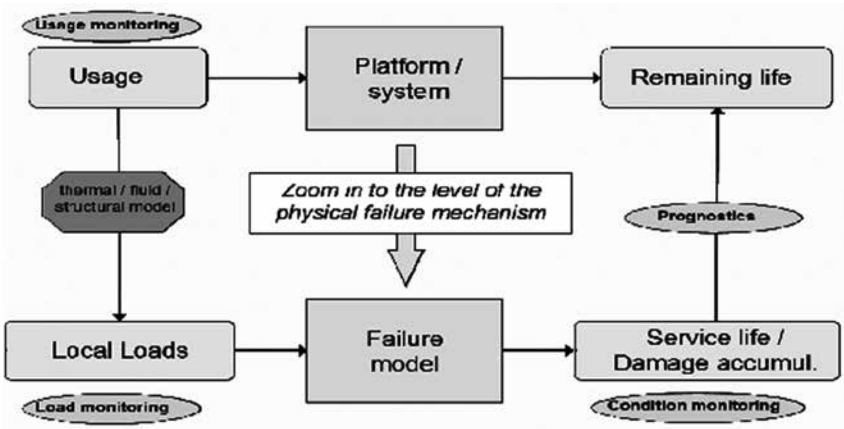

Figure 1 Relationship between systems or component's utilisation, loads, and service life consumption.

Source: https://www.researchgate.net/figure/Relation-usage-loads-and-service-life-consumption-of-a-system-or-component_fig1_269401922

Approach 2

Monitoring is the second need for a predictive maintenance strategy. Finding the parameter that is most pertinent to the failure mechanism is a difficult task. For instance, if a fatigue failure is taken into account, the service life consumption is determined not by the number of running hours but rather by the number of start stops of a (spinning) system (which defines the number of load cycles). Therefore, choosing the correct parameter to monitor only becomes possible with knowledge of the physical mechanics. However, it is not possible to apply the proposed strategy to all components and failure modes.

Current Challenges and Future Aspects

Issue Remote and AI-based Predictive Maintenance

Using AI or remote processes for predictive maintenance involves several acknowledged drawbacks, including data quality and availability issues, security and privacy, interpretation and analysis, and adoption and implementation. These drawbacks are particularly noticeable while using these methods to develop and maintain military and defence aircraft. Therefore, reliable and consistent data collection, storage, and integration from a centralised source are required. Also, sensitive and secret data requires the adoption of an indigenous encryption mechanism, like in the case of military aircraft. To guarantee synchronisation of data obtained from ON or OFF flight sets, more effective communication, cooperation, and change management is the need of the hour. Future facility upgrades may be made possible by the fast-developing area of AI for predictive maintenance. However, edge computing, the Internet of Things (IoT), Augmented Reality (AR), virtual reality (VR), and digital twins are some of the new trends and innovations that can make data sets easier to handle and analyse different flight degradation aspects more quickly and effectively at the source rather than at a centralised place.

Although the likelihood of a data breach increases as more devices and sensors connect to the internet via the IoT, at the same time more data can be gathered and shared between the aircraft equipment and devices, which ultimately can improve the predictive maintenance procedures. By enhancing the interaction and visualisation of data from aircraft and equipment, AR and VR can create immersive, lifelike experiences for preventative maintenance. With the use of digital twins, actual assets and systems may be virtually replicated, enabling experimentation, optimisation, and simulation of various situations and circumstances, but the larger issues remains about the transfer of crucial in-link and out-link data between aircraft and the server.

Conclusion

Even with the progress of this field study, many issues remain unanswered. A common problem with these kinds of questions remains about the methods, as these are tailored to solve a single piece of technology or equipment rather than a common series of machineries, the responses are specialised rather than all-encompassing. Furthermore, the solutions do not consider the cascading effects of one component's degradation on the others. The cause of the failure and the interaction between the parts are not modelled using different risk metrics or models like Dynamic Fault Trees (DFT).[6]

On the other hand, Machine Learning methods are capable of representing highly heterogeneous and non-linear models. But, the challenge across the data-driven methodologies and processes has restricted the process. This requires a lot of data, which could train specific machine learning models and develop a high computational analysis.

Notes

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