A general Bayesian predictive maintenance methodology

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Abstract

The development of new and the improvement of existing Health and Usage Monitoring Systems remains an active and multi-disciplinary area of research. Applications of these systems span numerous applications including Defence assets, infrastructure, utilities, aviation and transportation; sharing the common aim of improving our understanding of overall condition or 'health' of the application using data. Systems can be developed on the basis of empirical data, theoretical formulae or machine learning algorithms and may also include elements of reasoning abstracted from human psychology. The present work provides a methodology which can be applied to create a Bayesian predictive maintenance system for a general component. The methodology incorporates any number of faults or failure scenarios and produces a discrete set of outcomes which are human-readable and actionable.
Considering that maintenance is a decision taken in the context of uncertainty, or 'risk', the methodology describes how sensor data can be transformed using a Bayesian machine learning algorithm and integrated with a multi-attribute utility value system to produce these outcomes. A predictive maintenance system developed using this framework is expected to deliver the greatest impact when supporting high-value applications such as those within the aerospace and Defence industries; where investment in maintenance is needed to achieve high reliability requirements and prevent often extreme consequences of failure. A theoretical application to the hull of a Reusable Launch Vehicle is presented as it is anticipated that predictive maintenance will play a role in Australia's future as an emerging Space power. By presenting this methodology, it is intended that future research develops and evaluates its value and accuracy toward improving our understanding of equipment health and function.

Keywords: Bayesian, maintenance, predictive, risk, Reusable Launch Vehicle, rocket.

Introduction

Data-driven maintenance, applied as a Health and Usage Monitoring System, is driven by the desire to understand, how a piece of equipment is functioning. This understanding is based upon the widespread understanding that failure mechanisms as well as maintenance can impact equipment health, which was formalised as Reliability-Centered Maintenance [1]. New insights in this area can also be gained though applications of Artificial Intelligence [2], the Internet of Things [3] and Industry 4.0 [4, 5] concepts, as well as through the development of a Digital Twin [6].
In principle, applications of data-driven maintenance can lead to improved asset reliability. While this is beneficial in any industry, high-value assets in Defence stand to benefit the most since typically high through-life sustainment costs can be reduced [7].
Space is a Defence domain. It is currently an expensive, technically challenging and time-consuming endeavour for a vehicle, manned or unmanned, to travel there. It is common for equipment failure or non-ideal conditions to delay or prevent a launch. It is less common, though

expected that an unknown external factor (such as debris impact) or failure will destroy or damage a vehicle mid-flight. When these failures occur, engineers must investigate the event using a formalised process such as Failure Modes, Effects and Criticality Analysis (FMECA) [8, 9], and apply remedial actions. Varying degrees of data are available to support these investigations, and in some cases, previously unknown factors must be discovered and analysed to prevent the future occurrence of the same, however unlikely event. Beyond asset reliability, data-driven maintenance methodologies can also improve the safety of launch vehicles through the delivery of diagnostic or predictive data.

For the purposes of this paper, an RLV is defined as a space launch vehicle that is employed in entirety or most part in more than one launch beyond the Karman line (100 km above the Earth's surface [10]) to deliver a payload, before returning in entirety or most part to earth. Considering the time and expense involved in the event diagnosis process outlined above, restricted launch windows and conditions, pre-flight verification and routine maintenance – it is not surprising that RLV technologies are developing. The first RLV was the "Space Shuttle", which was constructed by NASA as part of the Apollo Program, although its construction was only officially supported by the US Government 1972 [11]. Since then, established programs in the European Union [12] and Russia [13], as well others in Japan, China and India [14] have been competing for a presence in Space. In 2019, Space Exploration Technologies Corporation (SpaceX) successfully recovered and landed its Falcon 9 boosters. Currently, SpaceX is developing the reusable "Starship" launch vehicle for missions to Low Earth Orbit and Mars [15]. RLVs will deliver improved access to Space by decreasing launch cost and increasing launch frequency. Availability and reliability are necessary to achieve this and can in turn be improved using data-driven maintenance.
One data-driven maintenance approach applied to an RLV has been identified as simulated opportunistic maintenance scheduling applied to a reusable rocket engine [16]. Other research identified included a discussion of Reliability-Centred Maintenance [17] and several review articles [18, 19, 20]. Due to limited research in this area, the present paper expands upon a Bayesian approach demonstrated in the naval domain [21].

Methodology

This paper describes how a general Bayesian method for predictive maintenance of a general component can be conducted and demonstrates this framework using a theoretical case study covering the hull of an RLV. The present general Bayesian methodology can be potentially applied within any phase of operation and characterised by eight key stages and key questions within each. An explanation and example of each stage follows as part of a theoretical case study in the next section.

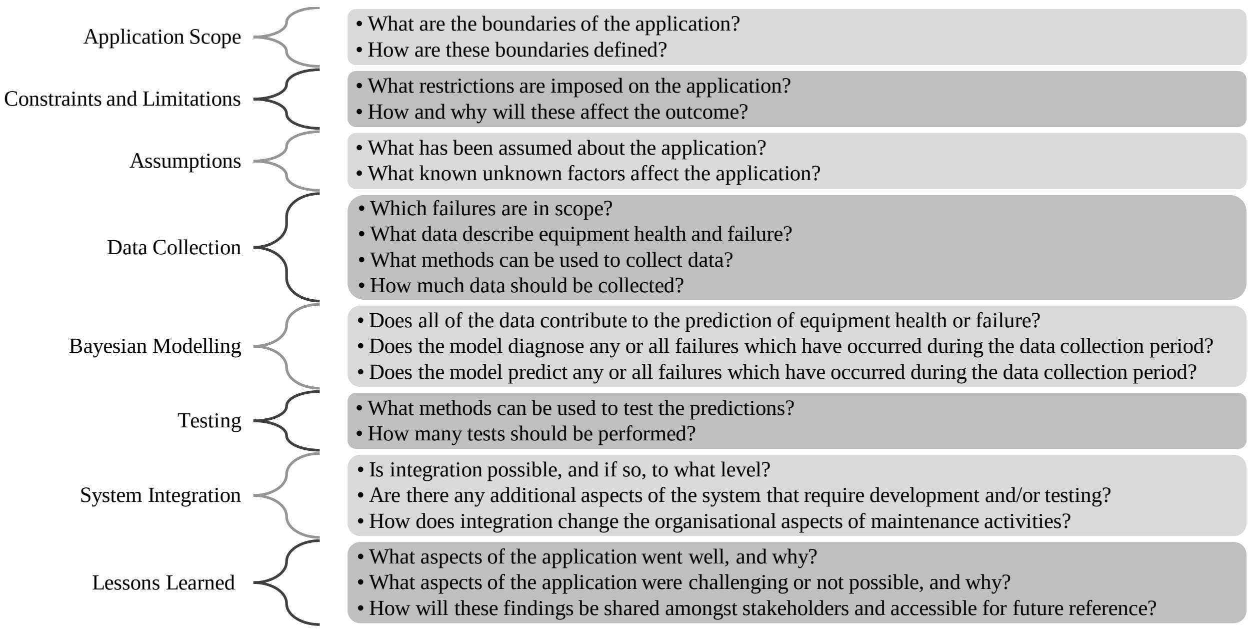

Figure 1: Methodology and Key Questions

Case Study

Application Scope, Constraints, Limitations and Assumptions

The boundary of the application in the present paper is restricted to the exterior hull of an RLV – the SpaceX Super Heavy Booster, or 'first stage' of the reusable Starship launch vehicle. The boundary is defined as the physical size of the exterior hull – surface area and depth. The Super Heavy booster is 69m in length, and 9m in diameter, and burns cryogenic liquid methane and liquid oxygen fuel [15]. Based on these measurements, the Super Heavy Booster has a surface area of approximately 2078m^2. The thickness of the hull is not known. The hull has been constructed from a 301 stainless steel variant to minimise cost and weight [22].
Though not applicable to the present theoretical discussion, it is anticipated that cost and time constraints will affect a real application. These factors will limit the quality of the results produced, such that an ideal level of availability (e.g., 90%) may not be possible. Cost and time limitations will affect data volume and quality which in turn affect predictive accuracy. It is assumed that: the hull does not have the double-walled design discussed by Elon Musk in the previous reference; the hull is covered in tiles made of 301 stainless steel; hull tiles are coated to improve heat resistance and aerodynamic efficiency; joints between tiles are of a similar composition to 301 stainless steel and lastly that the tiles as well as their joints must withstand a number of launches. Known unknowns are expected to include launch day weather conditions and the possibility of collisions with other space objects during ascent or payload deployment.

Data Collection

The present theoretical application discusses only failure of a hull tile due to surface or internal crack formation and propagation. The key functions of the hull tiles include: protecting inner components, retaining physical, chemical and other material properties, as well as resisting atmospheric loads and debris impacts. The ability of a tile to perform these functions can be correlated with its shape and surface roughness, measured against initial values. Shape is defined as the ideal length, width and thickness of the hull material. Surface roughness is a surface property of the hull material, which occurs due to how tiles are manufactured, finished or coated. Differences in these values will occur due to operation of the vehicle and may indicate crack initiation and propagation.

As it would not be cost effective to destructively test any of the tiles not requiring maintenance within the real application, in-situ non-destructive inspection methods should be investigated. It is suggested that a launch facility drone, and a drone deployed from the vehicle while in space are used during the pre-launch and payload phases of operation respectively to perform inspections. Each drone would inspect the entire hull using an optical imaging method, following the most efficient, pre-planned route. These drones could then transmit data to the launch facility which catalogues and analyses the inspection data for maintenance recommendations.

A suitable optical imaging method may prove to be Phase Measuring Deflectometry [23] which works well on reflective surfaces. The precise requirements for surface roughness measurements and shape changes will require the application of experimentation mimicking flight conditions and subsequent analysis. It may also be desirable to develop experiments which study ideal conditions, and increasingly step toward failure to track the progression of these conditions more precisely.

Data are also required which describe the shape and surface roughness of the hull in operational or functional condition. Lastly, a third set of data should also be collected from hull tiles of active launch vehicles.

Given constraints and limitations, as much data as possible should be collected. It is suggested that at least ten measurements should be taken describing shape and surface roughness per failure condition or operational condition. A minimum of ten measurements will reduce the impact of any measurement errors which occur, while minimising the cost and time taken for data collection. An appropriate processing method must then be developed which ensures that key features of data can be identified, such as peak values of depth or shape distortion.

Bayesian Modelling

Feature selection [24] or statistical methods [25] can then be applied to the data to ensure that each feature contributes to model quality. A Bayesian classifier can then be trained for each failure and operational class and used to estimate posterior probabilities of failure. Bayesian Classifiers can be combined with decision support or decision-making tools to produce maintenance action recommendations. At this stage, a diagnostic system exists. The predictive system can then be developed by extracting each classes' discriminant function [26] and comparing their values over time. The Bayesian predictive system can then be used to predict failures based on the active vehicle dataset, and the accuracy of predictions determined.

Testing, Systems Integration and Lessons Learned

Further testing of the Bayesian predictive system should include: the collection and analysis of a larger active vehicle dataset and a controlled trial which involves conducting maintenance according to system predictions. Discussion of systems integration activities requires more information than the present author was able to obtain, though such information should be obtained and answer the key questions posed in Figure 1 in a real application. Recording and sharing both positive and negative lessons learned will enable an organisation to develop further applications or investigate alternatives. It is anticipated that key lessons learned will include tools, methods and processes which worked well or alternatively should be avoided.

Conclusions

Advancement in aerospace engineering, space exploration and maintenance practises mandate the best use of enabling technologies to date. There are many avenues for innovation, such as the integration of advanced sensors, novel optical imaging algorithms, autonomous systems and predictive machine learning, described within this paper as a potential Bayesian system. The component systems and technologies needed to efficiently maintain RLVs exist and should be applied.

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