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Downtime Uncertainty Reduction Through the Correct Implementation of Health Monitoring Tools

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Abstract

The objective of Integrated Vehicle Health Management (IVHM) is to increase platform availability and reduce maintenance times and costs through the use of health monitoring on key systems. The information generated using condition monitoring algorithms can be used to reduce maintenance times, improve the management of the support process and operate the fleet more efficiently. This paper discusses the effect of advanced health monitoring tools on the uncertainty of predicted downtimes and costs for vehicles and fleets and how they affect the management of the asset. If a health monitoring tool is to be installed it is critical to keep in mind that the objective is to maximise the use of the asset, not just reduce the average downtime. An improvement of the availability might not translate in a significant increase of effective active time since operational planning normally involves working with conservative estimations for the maintenance time. Thus, algorithms that result in a higher average downtime but present lower uncertainty can be more effective at maximising the use of a given vehicle. Most Cost Benefit Analyses (CBAs) focus on calculating the difference between the current average downtime and the expected downtime to determine the benefit of using algorithms to diagnose or predict a fault. Calculating the variation of these uncertainties with the introduction of health monitoring tools is critical to assess what the real impact on the downtime is going to be. The benefits of the approach presented in this paper are: (1) a better understanding of how uncertainties play a role in the downtime and maintenance cost of the asset, (2) being able to differentiate between improving the availability of the asset and its active operational time and (3) an improvement in the viability of CBAs for health monitoring tools.

1 Introduction

Integrated Vehicle Health Management (IVHM) comprises tools and procedures to monitor the condition of multiple components in order to improve the management of the support system of a given fleet and increase its availability. This can only be achieved through the use of diagnostic tools, which detect faults and their sources faster and more accurately than conventional techniques; and/or prognostic tools, which estimate the Remaining Useful Life (RUL) of certain components to schedule their replacement when the impact on operations is the lowest possible. This information can then be used by other computer-based tools to assist in the improvement of the management of logistics, maintenance and operations. The topic of this paper is focused on the effect diagnostic and prognostic tools have on vehicles and the fleets they belong to.

While intuition dictates that the wider the coverage of a health monitoring system the more significant the improvement on availability will be, it is not practical, or even possible, to monitor the condition of all the elements of a vehicle. Cost Benefit Analyses (CBAs) are essential to determine which components are to be monitored and by which tools. Some authors propose the use of FMECAs as a basis for the design of IVHM tools and perform CBAs [1-3]. However, the need for accurate estimations of the changes in maintenance costs and times as well as their uncertainties calls for a different approach. Event Tree Analysis (ETA) has been used to determine the operational consequences of a failure [4] and to develop quantitative methods to determine the changes in maintenance cost and platform downtime based on the performance of individual IVHM tools [5].

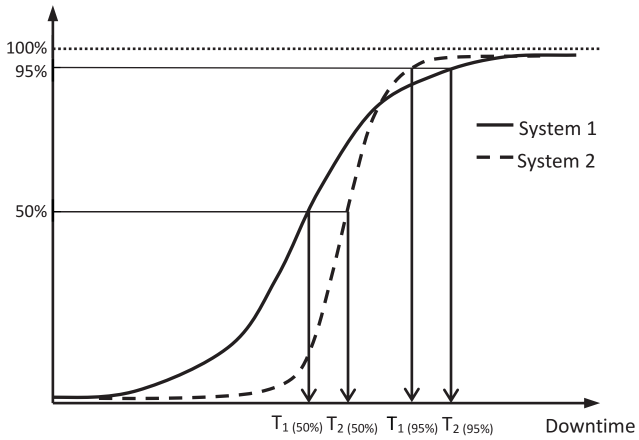

Figure 1: CPF of the expected downtime with two different IVHM systems. System 2, which has a lower average downtime, is more reliable for a confidence level of 95%.

However, choosing those tools which simply reduce the average maintenance cost and downtime by a greater amount without taking into account how their standard deviation is affected can have serious consequences. Not only can the use average values underestimate the final maintenance cost and time, but also it overlooks the importance of consistency for operational planning. Additionally, a combination with higher average cost and downtime can be cheaper and more efficient for a given confidence level (Figure 1). Understanding that increasing the availability may not result in more operating hours and the role uncertainty plays in this issue is essential to implement the correct combination of health monitoring tools on a vehicle. In the following sections the different aspects of this problem are discussed in more detail.

2 Uncertainty and health monitoring

During the design of any system engineers often work with average values which have either been recorded in the past or estimated. In most cases the standard deviations are negligible, especially if safety margins apply. For example, while the stress limit of a certain material can be different between two samples, the variation is negligible when compared to other uncertainties in the design and the safety margin. However, the standard deviation of most parameters involved in the maintenance of an asset cannot be neglected.

The sources of uncertainty can be divided into two main categories. Aleatoric or statistical uncertainties are those caused by the random variation of parameters over time. Recurring costs, time spent on different activities, delays and the performance of health monitoring tools are the most prominent. While the amount a supplier charges for a part can be fairly constant (this does not apply to expensive components with low failure rates and low stock), shipping and storage costs can vary considerably. The same can be said about the time dedicated to maintenance tasks, whose variability is related to the complexity of the task. The uncertainty of the performance of IVHM tools has been well documented. Lopez & Sarigul-Klijn [6], showed how the reliability of an IVHM tool varies depending on the characteristics of the fault, which are different on every occasion, and this translates into uncertainty about its performance. Furthermore, Saxena et al. [7] also analysed how the accuracy of prognostic algorithms evolves with time, with the RUL becoming more accurate as the component approaches its point of failure.

The second group comprises the sources of epistemic or systematic uncertainty, which are caused by inaccuracies in the measurement, recording or modelling of a given parameter. These are the kind of uncertainties which affect the accuracy of maintenance records. To begin with, recorded times are never perfectly accurate but rounded to the nearest multiple of five, ten or fifteen minutes. Additionally, while the total maintenance time spent on each component is often recorded, this is not always the case for the different steps involved (e.g.: preparation, diagnosis, check-out, etc.) or the delays. Even in those few cases when records include this information values are most likely approximations written down after the work has been completed.

Characterizing these probability distributions is a major problem in itself in which second order uncertainties might need to be considered. It would seem as if defining the confidence on the probability distributions of recorded parameters (e.g.: maintenance costs and times) is easy to determine based on the size of the dataset. However, epistemic uncertainties affect these parameters the most and cannot be ignored. Additionally, the uncertainty affecting the performance of health monitoring tools is also difficult to characterise without testing them in operational conditions. Since this can require a significant amount of time and resources, engineers are left with lab-based estimations during the conceptual design stage. In any case, the standard deviations caused by aleatoric and epistemic uncertainties are difficult to quantify and interviewing the maintenance team and the team in charge of the development of each tool is essential to estimate them.

3 Quantifying uncertainty

In order to compare different combinations of IVHM tools and carry out an accurate and reliable CBA the standard deviation of maintenance time and cost must be quantified. Feldman et al. [8] managed to obtain the probability distribution of the ROI using Monte Carlo simulations. Discrete even simulations of the full maintenance process can also be used. However, while these methods can generate very useful additional data for CBAs, they are also time consuming and are not practical to generate a quick estimate of costs and downtimes. It is possible to obtain analytical equations to calculate them using ETA [5] by defining the different possible outcomes of implementing diagnostic and prognostic tools.

Diagnostic tools reduce the time dedicated to detect and isolate faults and have the potential to reduce the time necessary to replace the component being monitored provided administrative, technical and logistic delays are not too long. Maintenance is still carried out on a reactive manner, which does not allow for more efficient scheduling and can result in secondary damage of other components. If the algorithm is too sensitive to the reading of some signals these tools can produce false positives (a.k.a. false alarms) which can result in more time dedicated to check the condition of the component and, in some cases, to the replacements of healthy parts to minimise risks. False negatives can also occur, having the same consequences as not having any diagnostic tool monitoring the component.

Prognostic tools estimate the RUL of the part based on the readings of certain parameters. This estimation becomes more accurate as the component approaches its point of failure. Consequently, prognostic tools can be divided into two categories. Long-term prognostic tools are capable of generating an accurate estimation of the RUL with enough anticipation to defer the replacement of the part until the next scheduled maintenance stop. Short-term prognostic tools, on the other hand, can only be used to inform maintenance personnel of the need to replace the component between missions. Depending on the time necessary to replace the part this can affect the availability of the vehicle. The RUL estimated by both long and short-term tools is not perfectly accurate and components could fail before they are replaced.

As shown in Figure 2, there are six maintenance scenarios with different maintenance times and costs depending on whether the tools that monitor a certain component perform their function correctly or not. The diagram has two starting points: one defined by the probability of failure of the component per flying hour, P_F, and a second in which the component is healthy. The diagram illustrates how, in case a long-term prognostic algorithm fails to provide an accurate prediction, there is still the possibility of a short-term algorithm generating a correct, yet shorter, prognosis. If the component still fails before it was replaced, a diagnostic tool can help to detect and isolate the fault.

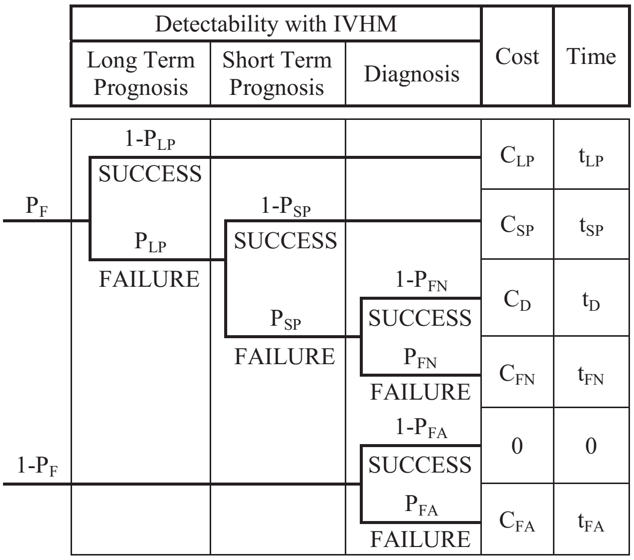

Figure 2: Event tree for the health monitoring of a single component and the possible outcomes of using different IVHM tools.

The probabilities of the component failing before it is replaced based on the indications of long-term and short-term prognostic tools are P_{LP} and P_{SP} respectively. The probabilities of false alarms, P_{FA}, and false negatives, P_{FN}, are also included. This diagram does not reflect the sequence in which health monitoring algorithms work, but the order in which the information they generate affects the conditions maintenance is going to be carried out in.

Using this diagram as a starting point is very easy to define analytical equations for the maintenance cost and time per flying hour spent on a given component. Equations (1) and (2) can then be used to determine their probability distributions based on the variances of their variables.

$$C = P_F\left[(1 - P_{LP})C_{LP} + P_{LP}\left[(1 - P_{SP})C_{SP} + P_{SP}\left[(1-P_{FN})C_D + P_{FN}C_{FN}\right]\right]\right] + (1 - P_F)P_{FA}C_{FA} \quad (1)$$

$$T = P_F\left[(1 - P_{LP})t_{LP} + P_{LP}\left[(1 - P_{SP})t_{SP} + P_{SP}\left[(1-P_{FN})t_D + P_{FN}t_{FN}\right]\right]\right] + (1 - P_F)P_{FA}t_{FA} \quad (2)$$

It is important to note that the criticalities of different costs and maintenance operations vary for each stakeholder [9] and depend on whether the vehicle is operated in a civilian or a military environment [10]. Therefore, a correct estimation of the uncertainty requires identifying which costs and benefits are allocated to each stakeholder. Techniques necessary to calculate some of these parameters have been described by Leao et al. [11], as well as Prabhakar and Sandborn [12].

4 Good performers vs. Consistent performers

The use of IVHM technology has two counteracting effects. On one hand, maintenance costs and times become more consistent (lower standard deviation) because the detection and isolation of a fault is automatized (diagnostic tools) or tasks can be scheduled to avoid major delays (prognostic tools). On the other hand, the inaccuracy of these tools increases the uncertainty. That is because by implementing a given health monitoring tool on a component, maintenance is shifted from an original scenario in which the cost and time of the repair have a certain probability distribution to a combination of scenarios which result in different probability distributions for the maintenance cost and time (Figure 3). Therefore, the accuracy of a health monitoring tool should not be regarded as the only measurement of its performance; it is the final distributions of the maintenance costs and times that should be used to compare their effectiveness.

As a consequence of the randomness of the factors involved, the comparison between different options cannot be based on the use of average values, nor can the CBA. A confidence level has to be defined in order to compare them. This confidence level is equal to the probability of the parameter used in the comparison being equal of lower than a certain value. This also reflects how operators scheduled assignments assuming conservative maintenance times to avoid changes in their plans.

The confidence level used to compare different options should be the same used later in the CBA to avoid confusions. Therefore, the confidence level must be conservative enough to ensure the outcome is equal or better than expected without reducing the expected Return on Investment (ROI) so much that the project becomes unviable from a financial point of view.

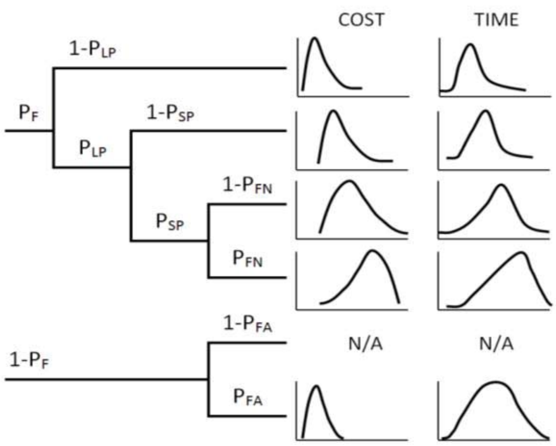

Figure 3: The result of implementing IVHM technology can be seen as combining the PDF of maintenance cost and time of different scenarios.

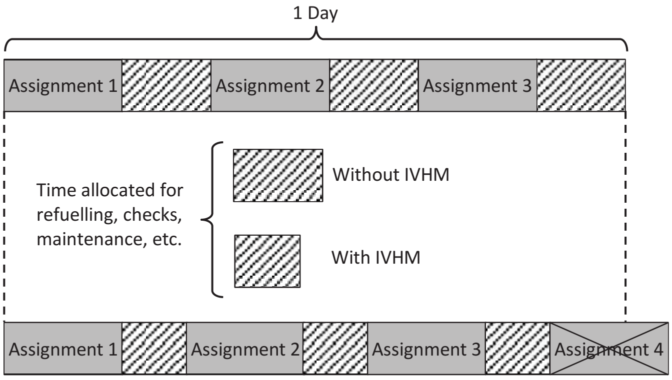

Figure 4: Example of how reducing the time allocated for maintenance can result in no operational gains if additional assignments cannot be scheduled.

CBAs normally focus on the reduction of maintenance costs and increase of availability as the main factors to justify the implementation of IVHM technology. These are perfectly valid arguments if the operator, maintainer and investor are part of the same company. However, if the operator outsources the maintenance of its fleet, the use of this technology can only be justified if it translates in an increase in the use of its assets. While the effectiveness of the tools is directly related to its availability, there is not a continuous correlation between the latter and the real use of the vehicle because assignments have minimum duration (Figure 4.)

From an operational perspective, implementing an IVHM system is only justifiable if additional assignments can be scheduled, which is achievable by reducing the time spent on maintenance and/or reducing its standard deviation. If the maintenance is outsourced, service providers must engage with operators to avoid investing on health monitoring technology that will not improve the service they provide to their clients and, therefore, will not increase their revenue. Any improvement on availability that does not translate into an increase in operating time will only help to reduce maintenance labour costs. Since the availability can only be improved by investing on more effective and expensive technology, the return on investment will diminish quickly without an increase of revenue.

Figure 5 shows the result of comparing two different diagnostic tools to monitor de condition of a component of an aircraft. Each has different false positives and false negative rates. The reason for the discrepancies in the standard deviations of both tools lies in the fact that, in this example, tool 1 operates with a sensitive algorithm that generated a significant number of false alarms which result in a long, but consistent, maintenance time. Tool 2, on the other hand, produced more false negatives requiring conventional fault identification and isolation, the duration of which is very variable. Additionally, while the probability of tool 1 producing false alarms had a low standard deviation, the performance of tool 2 was more capricious.

This example illustrates how different tools can have a significant effect on the standard deviation of the maintenance

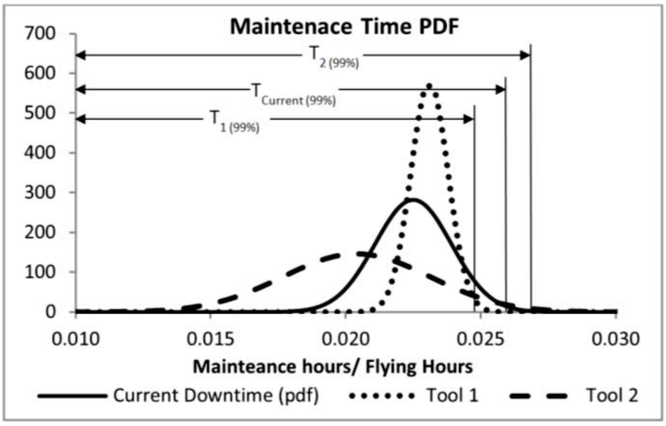

Figure 5: Comparison of maintenance time PDFs and their 99% confidence intervals.

time dedicated to a given component. Furthermore, this example also shows how a tool that increase the average maintenance compared to a non-monitored component can still be useful if the uncertainty is reduced enough.

5 Combining IVHM tools to tackle uncertainty

Basic on-board diagnostic tools have been used in aircraft for several years with mixed results. Built In Test Equipment (BITE) normally produces simple indications as to whether an electronic component is working correctly. Normally the interface is limited to a binary display of the condition of the component. In modern vehicles some parameters are monitored by a condition monitoring module during every flight. If any of them exceeds their predefined threshold an error code is generated in order for ground personnel to analyse the data and evaluate the condition of the asset. While most of these tools have proven to be very reliable, false negatives and false positives can be a problem in some cases. Given the inclination towards safety in aerospace industry, sometimes these tools can generate a significant number of false alarms.

This problem is usually tackled by improving the algorithm used by the BITE or even removing this capability completely. However, it is possible to combine the existing systems with additional health monitoring tools to maximise the use of the asset. This presents the advantage of avoiding modifications of existing hardware which can result very expensive in those cases when re-certification is required.

Sometimes, the inaccuracy of the BITE is not caused by the algorithm it is based on, but by the lack of precision of the signals it receives. Such problem can have its origin in the lack of accuracy, precision or resolution of the sensors; broadband limitations; or noise. Consequently, the only way to achieve major improvements with a new diagnostic tool requires hardware modifications which, as explained, can become financially unviable due to certification costs.

The example Figure 6 shows the improvement achieved by retrofitting a long-term prognostic tool to monitor a component which already counts with diagnostic capabilities.

The design requirements in this example were a reduction of 15% in maintenance cost and 40% in maintenance time (with 95% confidence). An interesting phenomenon brought to light in this example is the possibility to reduce the uncertainty of one of the factors (maintenance cost in this case) while the standard deviation of the second is increased.

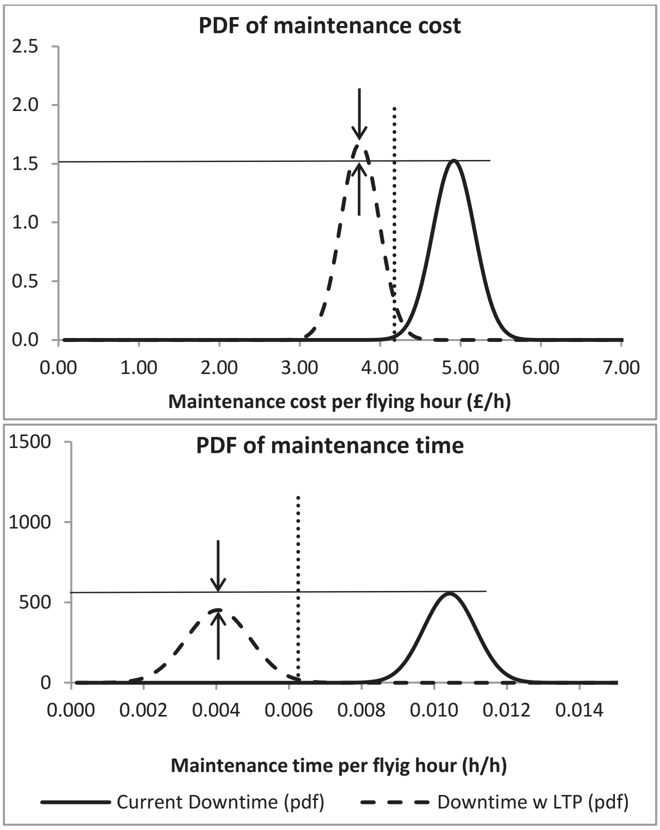

Figure 6: Improvement on a vehicle with BITE by installing a prognostic tool. Vertical lines indicate the required reduction in cost and downtime by 15% and 40% respectively.

6 Conclusions

Uncertainty of maintenance cost and downtime are key to ensure the objectives set for IVHM technology are met. However, improvements in maintenance time will only translate in an increase in the use of the vehicle as long as operational planners can schedule additional assignments. This can only occur in a discrete progression while repair times diminish continuously.

CBAs must acknowledge that it is the operators who are interested in the potential of IVHM technology to maximise the use of their fleets. If the cost of investing in health monitoring tools cannot be transmitted to the final user, the only use for this technology is the reduction maintenance costs.

As it has been shown in this article, improvements in the standard deviation of maintenance costs do not necessarily translate in a reduction in the uncertainty of downtimes and vice versa. Consequently, the probability distributions of both factors must be calculated, even if the aim is to reduce only one of them, to avoid undesired results.

The examples shown in this paper illustrate how maintenance cost and time for individual can be improved. However, analysing maintenance times at vehicle or fleet level is much more complex because maintenance actions can be performed in parallel. Computer-based model are essential to determine the effect IVHM tools have on the probability distribution of the final downtime. The principles explained in this article, however, are applicable to component, vehicle and fleet level.

It can be inferred that accurate CBAs require a significant amount of reliability data which can be difficult to obtain. Maintenance logs available for legacy platforms put them in and advantaged position compared to new designs, especially regarding the trustworthiness of the CBA.

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