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Uncertainty of performance requirements for IVHM tools according to business targets

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ABSTRACT

Operators and maintainers are faced with the task of selecting which health monitoring tools are to be acquired or developed in order to increase the availability and reduce operational costs of a vehicle. Since these decisions will affect the strength of the business case, choices must be based on a cost benefit analysis. The methodology presented here takes advantage of the historical maintenance data available for legacy platforms to determine the performance requirements for diagnostic and prognostic tools to achieve a certain reduction in maintenance costs and time. The effect of these tools on the maintenance process is studied using Event Tree Analysis, from which the equations are derived. However, many of the parameters included in the formulas are not constant and tend to vary randomly around a mean value (e.g.: shipping costs of parts, repair times), introducing uncertainties in the results. As a consequence the equations are modified to take into account the variance of all variables. Additionally, the reliability of the information generated using diagnostic and prognostic tools can be affected by multiple characteristics of the fault, which are never exactly the same, meaning the performance of these tools might not be constant either. To tackle this issue, formulas to determine the acceptable variance in the performance of a health monitoring tool are derived under the assumption that the variables considered follow Gaussian distributions. An example of the application of this methodology using synthetic data is included.

1. INTRODUCTION

The objective of Integrated Vehicle Health Management (IVHM) is to increase platform availability and reduce maintenance 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. Although IVHM can include the use of tools to improve the management of logistics, maintenance and operations (Khalak & Tierno, 2006), this methodology focuses on diagnostic and prognostic tools.

In order to run the algorithms it is necessary to read a set of parameters with a given accuracy and enough resolution to generate trustworthy information for the maintainer. Additionally, the data generated by sensors has to be transmitted, postprocessed, stored and analyzed. Although it is possible to carry out part of this process off-board, legacy vehicles rarely have the sensors, data buses, memory or computer power still required on-board. However, legacy platforms are expensive to modify to accommodate new hardware, especially if the modifications have to be certified. Therefore, it is not always possible to use the best hardware available for every tool and its performance will not reach its full potential. Furthermore, the implementation of the new health monitoring tools must have the lowest impact possible on the normal operation of the fleet, a problem not found in vehicles which are still being designed or manufactured. Thus, health monitoring tools for legacy platforms have a lower performance, a higher cost and a shorter payback period than if they were used on new vehicles.

On the other hand, the historical maintenance data generated by fleets provide information that can be used to select the components to retrofit health monitoring tools on, validate diagnostic and prognostic algorithms, and carry out Cost-Benefit Analyses (CBA). This is an important advantage since the expectations regarding the performance of the tool and their impact on the operational costs and availability are much more accurate for legacy platforms. Additionally, FMECAs, which are widely used for the design of health monitoring tools and perform CBAs (Banks, Reichard, Crow and Nickell, 2009; Kacprzynski, Roemer, and Hess, 2002; Ashby & Byer, 2002) become easier to populate and more precise. Even the experience of maintenance personnel and operators on qualitative aspects has a huge value for the development of IVHM tools.

This information can be used to define the performance requirements of any diagnostic or prognostic tool. Since the main objective of retrofitting IVHM is the reduction of maintenance cost and time, these are the constraints used in the methodology presented here. Teams in charge of developing health monitoring algorithms need to know not only the performance expected from their tools, but also the budget constraints to make them profitable. This data can be used to calculate the performance expected from a diagnostic or prognostic tool if it is to achieve a certain reduction of the cost and downtime associated with the maintenance of component it monitors. It is important to note that the criticalities of different costs and maintenance operations vary for each stakeholder (Wheeler, Kurtoglu and Poll, 2009) and depend on whether the vehicle is operated in a civilian or a military environment (Williams, 2006).

In some cases it is possible to generate mathematical expressions to relate the return on investment with certain design parameters (Kacprzynski et al., 2002; Hoyle, Mehr, Turner, and Chen, 2007; Banks & Merenich, 2007), but this approach restricts major changes in the design and the equations are not applicable to other monitoring systems.

Working with historical maintenance data involves using average values of many recorded parameters which are really random variables. Therefore, there is a certain degree of uncertainty in any calculation of the performance requirements which must be taken into account to avoid arriving at overconfident results. Furthermore, 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 (Lopez & Sarigul-Klijn, 2010). As a result, the acceptable standard deviations of the performance parameters of each tool have to be calculated to ensure the targets are met.

2. Performance of IVHM tools

IVHM is enabled by the use of sensors to gather data of a component and those systems that interact with it in order to detect malfunctions – diagnostic tools – or to predict the failure of the part – prognostic tools. Diagnostic tools help to identify the component responsible for the malfunction of a system, reducing the diagnosis and localization times. Additionally, they can prevent the vehicle to continue running with an unnoticed fault.

If a diagnostic tool is too sensitive it can trigger false alarms which could result in unnecessary checks, waste of resources and, in some cases, aborting the mission. On the other hand, if the sensitivity is too low and faults are not detected, the investment on the tool will not produce any benefits. Therefore, the main performance parameters of a diagnostic tool in an analysis of its effect on maintenance cost and time are the probability of triggering a false alarm, P_{FA}, and the probability of producing a false negative, P_{FN}.

Prognostic tools calculate the RUL of a component at a given moment providing maintainers with a lead time to accommodate the replacement or repair of that part in the future. If the lead time is long and accurate enough, the maintenance of the component can be carried out along with other scheduled tasks (long-term prognosis). Otherwise, the part will have to be replaced between missions (short-term prognosis), but this approach is still safer, cheaper and less time-consuming than running the component until failure. While long-term prognostic tools enable the deferral of the maintenance action until the next scheduled service, short-term prognostic tools can affect the availability of the vehicle if the time available for maintenance between missions is shorter that the time necessary to repair the fault.

The performance of a prognostic tool is determined by the reliability of the information it provides and how it is used, in other words, by the probability of the component failing before it was planned to be replaced (P_{LP} for long-term tools and P_{SP} for short-term tools). As shown in Figure 1, it is necessary to define a maximum admissible probability of failure, P_{max}, to determine how long the component can remain in service, t_{max}. This requires choosing a degradation curve from those generated by the prognostic tool from which t_{max} is estimated. The probability of the component failing is a function of the average life of the components removed, t_m, which depends on the period between scheduled services (long-term tools) or the mean time between missions (short-term tools).

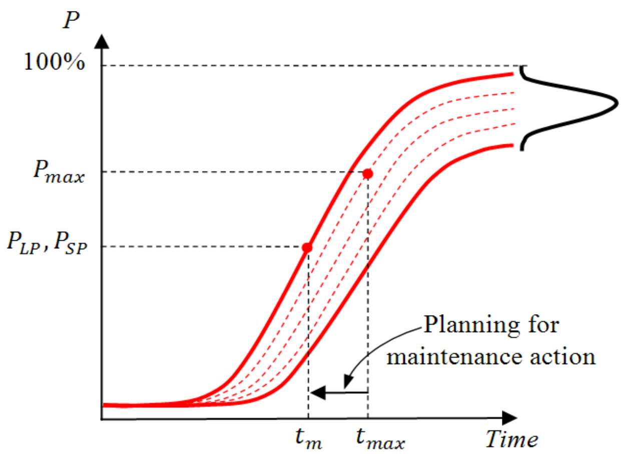


Figure 1. Degradation curves generated by a prognostic tool used to estimate the probability of failure of a component before it has been replaced.

3. Event Tree Analysis

The failure of a component has a different cost and repair time depending on whether an IVHM tools has performed its function correctly or not. This can be studied using Event Tree Analysis (ETA) where the probability of the failure of the component, P_F, is the triggering event and each tool introduces a fork in the diagram as shown in Figure 2. A correct prognosis prevents the need for a diagnosis and, if it is incorrect, a diagnostic tool can still be used. For the same reason long-term prognostic tools are further to the left on the diagram than short-term tools. It is important to remark that this is not a representation of the way the algorithms work, but how the performance of each tool leads to different outcomes.

In case a component presents different failure modes that need to be monitored by different tools, costs and downtimes need to be estimated independently for each mode. This is not a problem since most algorithms for diagnostic and prognostic tools track specific failure modes.

The tree shows six possible outcomes or maintenance scenarios, including the lack of need to replace a healthy component. Maintenance cost and time are calculated for each scenario according to how the use (or malfunction) of a health monitoring tool affects maintenance process. In case a prognostic tool is used, it is necessary to take into account factors such as the reduction of the delays, the value of the RUL of the component, the lower operational for costs on scheduled operations, and the avoidance of secondary failures. The use of diagnostic tools can help to reduce the maintenance time as well as the use of resources and personnel since searching for the cause of the malfunction is no longer necessary. However, false alarms, or false positives, can lead to unnecessary checks or even the removal of healthy components which could be disposed of (Trichy, Sandborn, Raghavan and Sahasrabudhe, 2001). Techniques necessary to calculate some of these parameters were described by Leao, Fitzgibbon, Puttini and de Melo (2008) as well as Prabhakar and Sandborn (2010.)

Since the event tree can be used to calculate the probability of each outcome, the resulting total maintenance cost, C, and time, T, can be calculated using the following expressions:

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

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

These polynomial functions can be used to calculate the sensitivities of the maintenance cost and time to the performance of health monitoring tools. Additionally, it must be noted that the data used to calculate the cost and downtime of each scenario are not constant and vary around average values (e.g.: time to repair or shipping costs), and these equations can be used as the basis to calculate the standard deviation of the resulting maintenance costs and times.

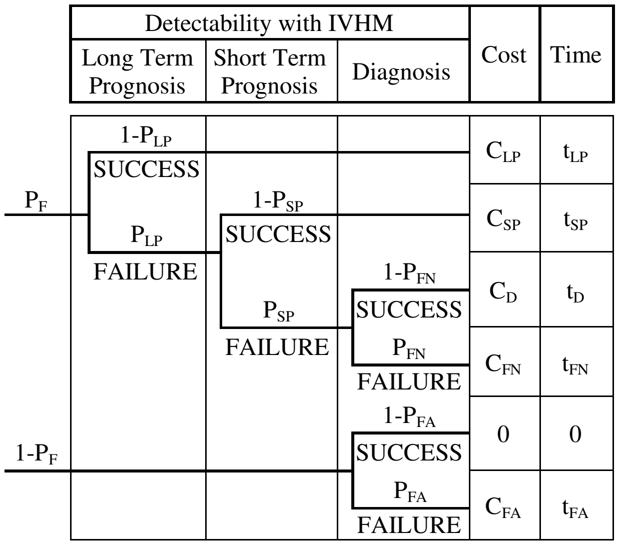


Figure 2. ETA for the use of health monitoring tools on a single component.

4. Performance Requirements with Exact Data

The performance of an IVHM tool must guarantee that the maintenance cost and time associated with the component it monitors are below C* and T* respectively.

Prognostic tools can be used to monitor a system which already has some diagnostic capability in order to combine the benefits from estimating its RUL and being able to identify the source of a malfunction if the component fails before it was expected. However, it is difficult to imagine developing a diagnostic algorithm for a part which is no longer run until failure thanks to the use of prognostics. Therefore, the equations for the probability of false negative and false alarm only take into consideration the parameters of scenarios in which diagnostic tools are used.

$$C^* \leq P_F\left((1-P_{FN})C_D + P_{FN}C_{FN}\right) + (1-P_F)P_{FA}C_{FA} \quad (3)$$

$$T^* \leq P_F\left((1-P_{FN})t_D + P_{FN}t_{FN}\right) + (1-P_F)P_{FA}t_{FA} \quad (4)$$

$$P_{FA} \geq 0\ ;\ P_{FN} \geq 0 \quad (5;6)$$

$$P_{FA} \leq \frac{C^* - P_F\left((1-P_{FN})C_D + P_{FN}C_{FN}\right)}{(1-P_F)C_{FA}} \quad (7)$$

$$P_{FA} \leq \frac{T^* - P_F\left((1-P_{FN})t_D + P_{FN}t_{FN}\right)}{(1-P_F)t_{FA}} \quad (8)$$

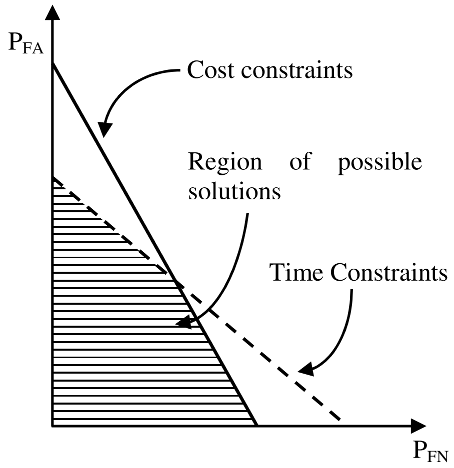


Figure 3. Region of acceptable performance of a diagnostic tool

Equations (5-8) define a space which encloses all the possible solutions that comply with the requirements. This space can be represented as sown in Figure 3.

The following expressions can be used to determine the probability of failure of a long-term prognostic tool given time and cost constraints. The equations for short-term tool are obtained the same way.

$$C^* \leq P_F\left((1-P_{LP})C_{LP} + P_{LP}\big((1-P_{FN})C_D + P_{FN}\,C_{FN}\big)\right) + (1-P_F)P_{FA}C_{FA} \tag{9}$$

$$T^* \leq P_F\left((1-P_{LP})t_{LP} + P_{LP}\big((1-P_{FN})t_D + P_{FN}\,t_{FN}\big)\right) + (1-P_F)P_{FA}t_{FA} \tag{10}$$

$$P_{LP} \geq 0 \tag{11}$$

$$P_{LP} \leq \frac{\dfrac{C^*-(1-P_F)P_{FA}C_{FA}}{P_F} - C_{LP}}{(1-P_{FN})C_D + P_{FN}\,C_{FN} - C_{LP}} \tag{12}$$

$$P_{LP} \leq \frac{\dfrac{T^*-(1-P_F)P_{FA}t_{FA}}{P_F} - t_{LP}}{(1-P_{FN})t_D + P_{FN}\,t_{FN} - t_{LP}} \tag{13}$$

Since the system is overdetermined the most stringent solution must be selected.

5. Uncertainty

Most parameters used to perform a CBA are not constant since the conditions under which each job is carried out are different. Costs of personnel and parts can change depending on the location or the shift. Active maintenance times, delays and the time dedicated to the diagnosis and localization of a fault are never exactly the same. Consequently, the variables used to define a maintenance activity are approximated to average values. This also affects the frequency of failure of the component, which is approximated to the Mean Time Between Failures (MTBF) for most quantitative analyses despite being extremely variable for those components that can benefit the most from IVHM. Additionally, the performance of health monitoring tools over a fixed period can also vary, increasing the uncertainty of the cost and downtime calculated in the previous sections.

Although the total maintenance time dedicated to a single component can be broken down into several steps including delays, repair time and checkout time (British Standard, 1991), they tend to be poorly recorded. Since the whole process involves different teams, it is difficult to keep track of the exact amount of time dedicated to each component (especially for delays and diagnosis). In addition, technicians tend to focus on the task in hand and register approximate values once the job is finished.

Therefore, there are uncertainties associated with the results from a CBA and this affects the definition of the performance requirements for IVHM tools. To avoid overstating the benefits from using diagnostic and prognostic tools it is necessary to include the standard deviation of every parameter that does not remain constant. It is also necessary to determine the acceptable standard deviation for the performance of the algorithms to ensure the maintenance costs and times will remain below acceptable levels.

Taking into account the effects of uncertainties means that for every performance parameter aforementioned an additional variable has to be calculated. At the same time, it is necessary to define the probability of the maintenance cost and downtime being bellow the limits imposed; in other words: how confident we are that the costs and times will remain below limits. As a consequence, two additional constraints are introduced: confidence to comply with cost requirements, R_C; and confidence to comply with time requirements, R_T.

The maintenance costs and times of different scenarios can be considered independent since numerous factors included in their calculation are random and uncorrelated. These assumptions allows for analytical expression to be formulated using the standard deviation of such random factors. In order to simplify mathematical operations variance is used instead of standard deviation. Therefore, the following properties apply:

$$Var\,(XY) = \hat{X}\,Var(Y) + \hat{Y}\,Var(X) + Var(X)Var(Y) \tag{14}$$

$$Var\,(aX + bY) = a^2\,Var(X) + b^2 Var(Y) \tag{15}$$

Since the variations in costs and maintenance times are due to numerous random factors, it has been assumed that both the total maintenance time and total maintenance cost per component follow Gaussian distributions.

Diagnostic tools are now defined by four parameters: probability of false alarm, P_{FA}; probability of false negative, PFN; and their variances, Var(P_{FA}) and Var(P_{FN}) respectively. The limits of these variables are defined by the following functions:

$$R_C \le \frac{1}{2}\left(1 + erf\left(\frac{C^* - \hat{C}}{\sqrt{2Var(C)}}\right)\right) \quad (16)$$

$$R_T \le \frac{1}{2}\left(1 + erf\left(\frac{T^* - \hat{T}}{\sqrt{2Var(T)}}\right)\right) \quad (17)$$

$$P_{FA} \ge 0 \;\&\; P_{FN} \ge 0 \quad (18)$$

Where

$$\hat{C} = \widehat{P_{FN}}\widehat{P_F}\ \left(\widehat{C_{FN}} - \widehat{C_D}\right) + \widehat{P_F}\,\widehat{C_D} + \widehat{P_{FA}}(1 - \widehat{P_F})\widehat{C_{FA}} \quad (19)$$

$$\hat{T} = \widehat{P_{FN}}\widehat{P_F}\ (\widehat{t_{FN}} - \widehat{t_D}) + \widehat{P_F}\,\widehat{t_D} + \widehat{P_{FA}}(1 - \widehat{P_F})\widehat{t_{FA}} \quad (20)$$

$$\begin{aligned} Var(C) &= Var\big(P_{FN}P_F\,(C_{FN} - C_D)\big) + Var(P_F\,C_D) \\ &\quad + Var(P_{FA}(1 - P_F)C_{FA}) \end{aligned} \quad (21)$$

$$\begin{aligned} Var(T) &= Var(P_{FN}P_F\,(t_{FN} - t_D)) + Var(P_F\,t_D) \\ &\quad + Var(\,P_{FA}(1 - P_F)t_{FA}) \end{aligned} \quad (22)$$

From equation (16)

$$Var(C) \le \frac{\left(C^* - \hat{C}\right)^2}{2(erf^{-1}(2R_C - 1))^2} \quad (23)$$

Additionally

$$Var(C) = K_1 Var(P_{FN}) + K_2 Var(P_{FA}) + K_3 \quad (24)$$

where

$$K_1 = \widehat{P_F}^{\,2}\left(\widehat{C_{FN}} - \widehat{C_D}\right)^2 + Var\big(P_F\,(C_{FN} - C_D)\big) \quad (25)$$

$$K_2 = \left(1 - \widehat{P_F}\right)^2 \widehat{C_{FA}}^{\,2} + Var\big((1 - P_F)C_{FA}\big) \quad (26)$$

$$\begin{aligned} K_3 &= \widehat{P_{FN}}^{\,2} Var\big(P_F\,(C_{FN} - C_D)\big) \\ &\quad + \widehat{P_{FA}}^{\,2} Var\big((1 - P_F)C_{FA}\big) + Var(P_F\,C_D) \end{aligned} \quad (27)$$

As a result

$$\begin{aligned} &K_1 Var(P_{FN}) + K_2 Var(P_{FA}) \\ &\le \frac{\left(C^* - \widehat{P_{FN}}\widehat{P_F}\ \left(\widehat{C_{FN}} - \widehat{C_D}\right) + \widehat{P_F}\,\widehat{C_D} + \widehat{P_{FA}}(1 - \widehat{P_F})\widehat{C_{FA}}\right)^2}{2(erf^{-1}(2R_C - 1))^2} - K_3 \end{aligned} \quad (28)$$

Following the same steps for the maintenance time requirements from equation (17), the second condition is

$$\begin{aligned} &K_4 Var(P_{FN}) + K_5 Var(P_{FA}) \\ &\le \frac{\left(C^* - \widehat{P_{FN}}\widehat{P_F}\ (\widehat{t_{FN}} - \widehat{t_D}) + \widehat{P_F}\,\widehat{t_D} + \widehat{P_{FA}}(1 - \widehat{P_F})\widehat{t_{FA}}\right)^2}{2(erf^{-1}(2R_T - 1))^2} - K_6 \end{aligned} \quad (29)$$

where

$$K_4 = \widehat{P_F}^{\,2}(\widehat{t_{FN}} - \widehat{t_D})^2 + Var\big(P_F\,(t_{FN} - t_D)\big) \quad (30)$$

$$K_5 = \left(1 - \widehat{P_F}\right)^2 \widehat{t_{FA}}^{\,2} + Var\big((1 - P_F)t_{FA}\big) \quad (31)$$

$$\begin{aligned} K_6 &= \widehat{P_{FN}}^{\,2} Var\big(P_F\,(t_{FN} - t_D)\big) + \widehat{P_{FA}}^{\,2} Var\big((1 - P_F)t_{FA}\big) \\ &\quad + Var(P_F\,t_D) \end{aligned} \quad (32)$$

Therefore, any diagnostic tool that satisfies the requirements and can generate the projected savings with the expected accuracy must comply with equations (18), (28), and (29).

Prognostic tools are now defined by the probability of the component failing before it is replaced and its variance. The following formulas define the constraints for a prognostic tool to comply with the cost and support requirements. To keep the equations manageable, the parameters of diagnostic tools are not included. In case they were necessary the full equations can be obtained in a similar manner. As for diagnostic tools:

$$R_C \le \frac{1}{2}\left(1 + erf\left(\frac{C^* - \hat{C}}{\sqrt{2Var(C)}}\right)\right) \quad (33)$$

$$R_T \le \frac{1}{2}\left(1 + erf\left(\frac{T^* - \hat{T}}{\sqrt{2Var(T)}}\right)\right) \quad (34)$$

The difference being

$$P_{LP} \ge 0 \quad (35)$$

$$\hat{C} = \widehat{P_{LP}}\widehat{P_F}\left(\widehat{C_{FN}} - \widehat{C_{LP}}\right) + \widehat{P_F}\,\widehat{C_{LP}} \quad (36)$$

$$\hat{T} = \widehat{P_{LP}}\widehat{P_F}\,(\widehat{t_{FN}} - \widehat{t_{LP}}\,) + \widehat{P_F}\,\widehat{t_{LP}} \quad (37)$$

$$Var(C) = Var\big(P_{LP}P_F\,(C_{FN} - C_{LP})\big) + Var(P_F\,C_{LP}) \quad (38)$$

$$Var(T) = Var\big(P_{LP}P_F\,(t_{FN} - t_{LP}\,)\big) + Var(P_F\,t_{LP}) \quad (39)$$

From equation (33)

$$Var(C) \le \frac{\left(C^* - \hat{C}\right)^2}{2(erf^{-1}(2R_C - 1))^2} \quad (40)$$

Combining equations (37), (38) and (40)

$$\begin{aligned} &Var\big(P_{LP}P_F\,(C_{FN} - C_{LP})\big) \\ &\le \frac{\left(C^* - \widehat{P_F}\,\widehat{P_{LP}}\left(\widehat{C_{FN}} - \widehat{C_{LP}}\right) + \widehat{P_F}\,\widehat{C_{LP}}\right)^2}{2(erf^{-1}(2R_C - 1))^2} - Var(P_F\,C_{LP}) \end{aligned} \quad (41)$$

Using the properties described in equations (14) and (15) and following the same steps with the equations for maintenance time constraints the results are:

$$Var(P_{LP}) \leq \frac{\dfrac{\left(C^{*} - \widehat{P_F}\,\widehat{P_{LP}}\left(\widehat{C_{FN}} - \widehat{C_{LP}}\right) + \widehat{P_F}\,\widehat{C_{LP}}\right)^2}{2(erf^{-1}(2R_C - 1))^2} - Var(P_F\,C_{LP}) - \widehat{P_{LP}}^{\,2} Var\left(P_F\,(C_{FN} - C_{LP})\right)}{\left(\widehat{P_F}^{\,2}\left(\widehat{C_{FN}} - \widehat{C_{LP}}\right)^2 + Var\left(P_F\,(C_{FN} - C_{LP})\right)\right)} \quad (42)$$

$$Var(P_{LP}) \leq \frac{\dfrac{\left(T^{*} - \widehat{P_F}\,\widehat{P_{LP}}(\widehat{t_{FN}} - \widehat{t_{LP}}) + \widehat{P_F}\,\widehat{t_{LP}}\right)^2}{2(erf^{-1}(2R_T - 1))^2} - Var(P_F\,t_{LP}) - \widehat{P_{LP}}^{\,2} Var\left(P_F\,(t_{FN} - t_{LP})\right)}{\left(\widehat{P_F}^{\,2}(\widehat{t_{FN}} - \widehat{t_{LP}})^2 + Var\left(P_F\,(t_{FN} - t_{LP})\right)\right)} \quad (43)$$

These parabolas define the limits for the performance requirements of any prognostic tool as shown in Figure 4. These expressions are for long-term prognostic tools. To obtain the formulas for short term tools replace C_{LP} and t_{LP} by C_{ST} and t_{LP} respectively.

These formulas can be applied to any component of a vehicle to quantify the performance requirements for continuous monitoring tools. These requirements will be then communicated to the internal teams in charge of developing IVHM tools, the supplier of the component, independent developers of health monitoring technology or even can be used to call an open tender. Since the performance parameters are determined based on economic objectives, it is possible to calculate the maximum acceptable cost for each tool based on the remaining useful life of the fleet.

Additionally, this set of equations presents a framework to include risk analysis on a CBA and strengthen the business case for installing IVHM on the aircraft.

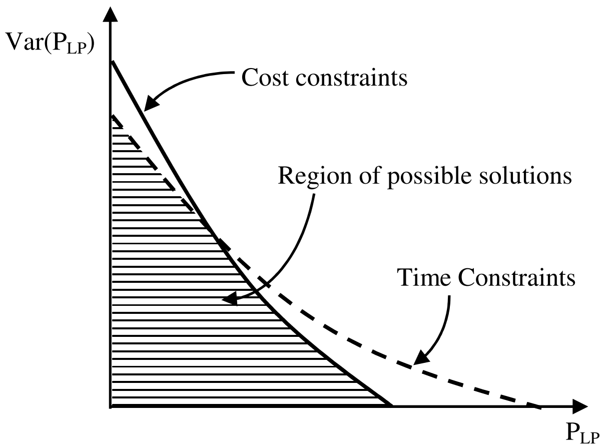


Figure 4. Region of acceptable performance and variance of performance of a long-term prognostic tool

6. CASE STUDY

The following example is based on synthetic data for a generic component that fails every 250 flying hours. Although the values chosen for the parameters used in this case do not belong to a specific real component, they are representative of the costs and maintenance times of many parts currently run until failure. All the factors taken into account to calculate the maintenance cost and time of each scenario, as well as their values, are listed in Table 1. Standards deviations were chosen to ensure the uncertainties would vary between ±5% and ±20% (assuming all parameters follow Gaussian distributions so 99.7% of the outcomes are within ±3σ from the mean). The results for each scenario are shown in Figure 5.

The objective is to reduce the maintenance costs per flying hour for this component by 15% and the maintenance time by 40%. These goals must be met with, at least, 95% confidence. As a result the performance requirements for long and short term prognostic tools are shown in Figure 6.

Since the performance of diagnostic tools is described by four variables it is not possible to represent the limits of the requirements. To provide some guidance, the graphs for diagnostic tools shown in Figure 6c represent the relation between the probability of false alarm and the probability of false negative, assuming there is no uncertainty about the performance of the tool (i.e.: zero variance). To check if the performance of a given tool complies with the requirements it is necessary to use the equations previously shown.

	Detectability with IVHM			Cost (£)	Time (h)
	L-T Prognosis	S-T Prognosis	Diagnosis		
P_F	$1-P_{LP}$ S			773.5 [2.95E+02]	1.35 [9.00E-04]
P_F	P_{LP} F	$1-P_{SP}$ S		906.1 [1.88E+02]	1.35 [9.00E-04]
P_F	P_{LP} F	P_{SP} F	$1-P_{FN}$ S	1021.7 [1.86E+02]	1.35 [3.16E-03]
P_F	P_{LP} F	P_{SP} F	P_{FN} F	1319.825 [3.10E+02]	3.375 [6.46E-03]
$1-P_F$			$1-P_{FA}$ S	0	0
$1-P_F$			P_{FA} F	330 [3.03E+01]	2 [2.27E-03]
			Total	5.279 [6.82E-02]	0.0135 [5.17E-07]

Figure 5. Costs, times and their variances (in brackets) for each maintenance scenario.

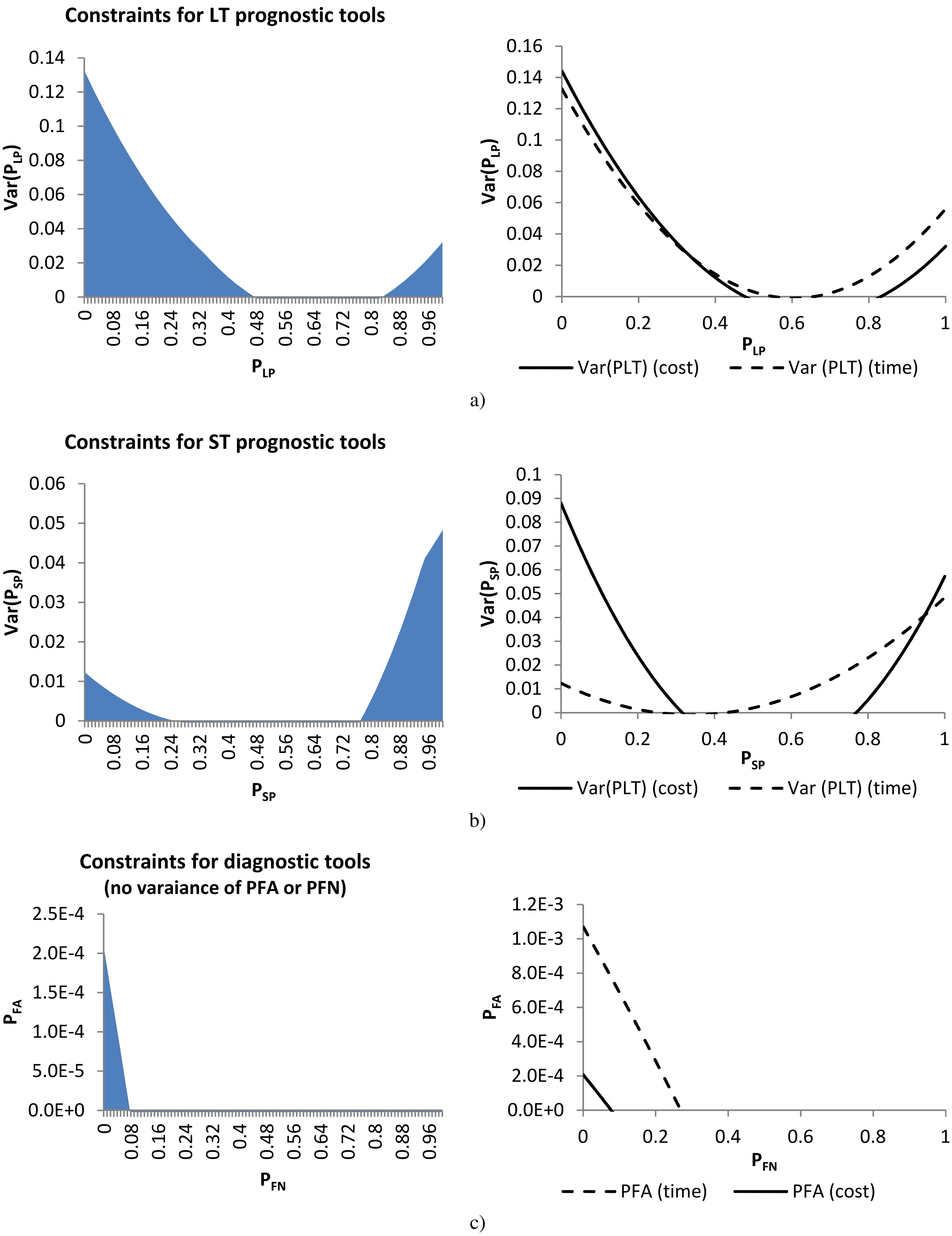
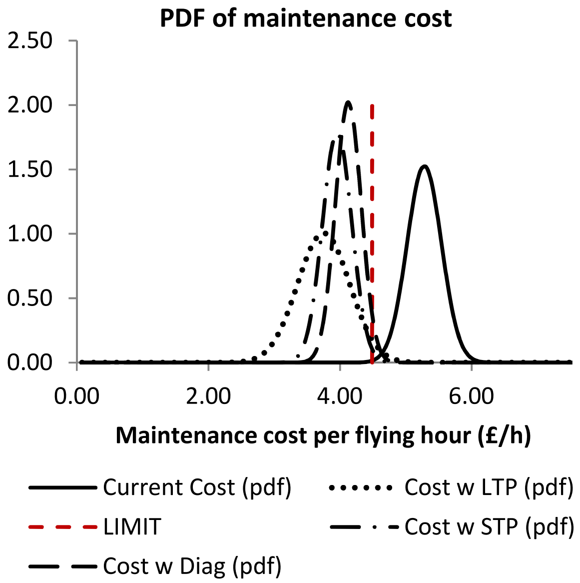
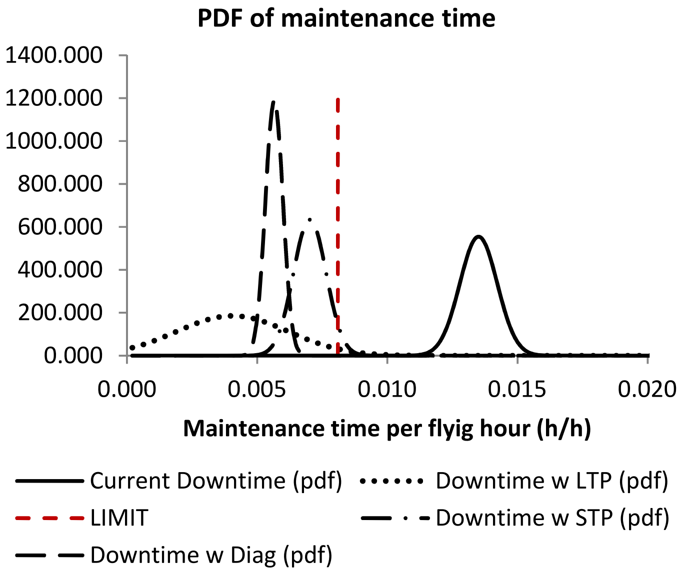


Figure 6. Graphs for possible solutions for a) long-term and b) short term prognostic tools and c) diagnostic tools.



a)



b)

Figure 7. PDF of maintenance a) cost and b) time for the different IVHM tools proposed.

The probability density functions (PDFs) of the new maintenance cost and time are calculated and compared to the targets to verify if a diagnostic tool with a given performance is capable of achieving the necessary improvements. Figure 7 shows the PDF for three possible IVHM tools (one of each kind) that reach the targets compared to the original distributions. It also illustrates how changing the probabilities of different maintenance scenarios, with different variances, affects the standard deviation of the final maintenance cost and time, which can be reduced (diagnostic tool) or increased (long term prognostic tool.)

Only the shaded area on left side of the graphs comprises those tools that achieve the expected reduction in cost and downtime. The area on the right is for those which match the requirements with a confidence complimentary to what is expected (i.e.: 5%) as illustrated in Figure 8.

The requirements for diagnostic and short term prognostic tools illustrate an interesting phenomenon: in some cases one of the targets can result in any possible solution overperforming in other areas. In this example a diagnostic tool that barely reaches the expected cost reduction will improve maintenance times by much more than it is required. The opposite happens to short term prognostic tools.

P_F		0.004
Cost of component (£)	Scheduled M.	525
	Unscheduled M.	628.9
	False Alarm	65
Cost of Labor (£)	Scheduled M.	90
	Unscheduled M.	132.5
Value of RUL (£)	Long Term Prog	68.5
	Short Term Prog	12.2
Other costs (£)	Compensation	0
	Secondary damage	127.8
	Flight Test	0
	Loss Income	0
Warranty	Parts (%)	0
	Labor (%)	0
Time (h)	MTTR	2
	Check-out	0.25
	MTTD	2
	Localization	0.25
	Technical delay	0.33
	Administrative delay	1
	Logistic delay	0

Table 1. List of parameters used in case study and their values.

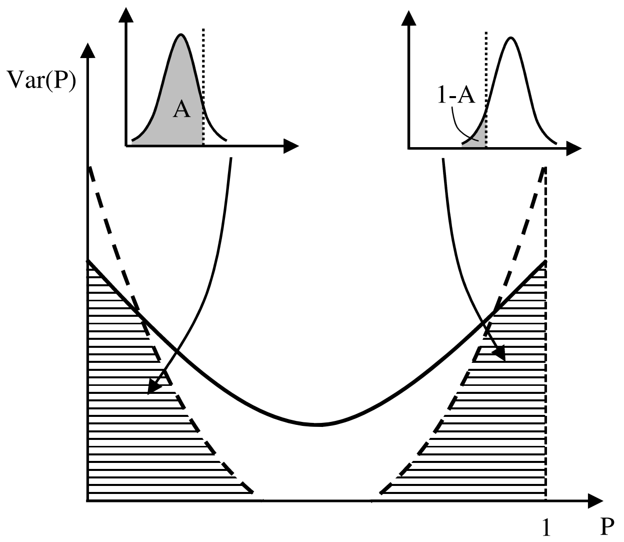


Figure 8. Region of acceptable performance and variance of performance of a long-term prognostic tool

7. Conclusions

This methodology represents a reliable way to define the requirements of individual tools based on the expectations of improving the maintenance of specific components and the uncertainty of the available data. Since the equations allow to carry out a quantitative risk analysis, business cases that use this methodology are more robust and less likely to overstate the benefits of installing the selected combination of IVHM tools.

It is not always possible to obtain reliable data to determine the standard deviation or variance of some of the variables used to calculate the costs or maintenance times. In some cases these variables are poorly recorded or not recorded at all. To tackle this problem, personnel with experience maintaining the aircraft should be interviewed to get approximated values. This will always be a better option than ignoring the effect of these uncertainties.

Quantifying the uncertainty of the expected revenue is critical to estimate the present value of an investment on IVHM technology given its long return period. For that purpose, techniques like real options can be combined with the methodology presented here.

IVHM tools can affect the uncertainty, or standard deviation, of the resulting maintenance costs and times significantly, either reducing it or increasing it. Since the predictability of these factors is sometime as important as decreasing their value, this effect must be analyzed carefully in a CBA.

Further work is necessary to study how the diagnoses and prognoses from several algorithms interact. If this new information enables grouping maintenance activities the total downtime can be reduced, increasing the availability of the vehicle and generating additional savings.

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Nomenclature

C	*Maintenance cost of component per flying hour*
C^*	*Target cost per flying hour*
C_D	*Maintenance cost of an effective automated diagnosis*
C_{FA}	*Maintenance cost of a false alarm*
C_{FN}	*Maintenance cost of a false negative*
C_{LP}	*Maintenance cost of an effective long term prognosis*
C_{SP}	*Maintenance cost of an effective short term prognosis*
P_F	*Probability of failure of the component per flying hour*
P_{FA}	*Probability of false alarm*
P_{FN}	*Probability of false negative*
P_{LP}	*Probability of long term prognosis being ineffective*
P_{SP}	*Probability of short term prognosis being ineffective*
R_C	*Expected confidence to comply with cost requirements*
R_T	*Expected confidence to comply with time requirements*
T	*Maintenance time of component per flying hour*
T^*	*Target maintenance time per flying hour*
t_D	*Maintenance time of an effective automated diagnosis*
t_{FA}	*Maintenance time of a false alarm*
t_{FN}	*Maintenance time of a false negative*
t_{LP}	*Maintenance time of an effective long term prognosis*
t_m	*Average life of components replaced following the indication of a prognostic tool*
t_{max}	*Maximum time a component is run before its probability of failure reaches a predetermined limit*
t_{SP}	*Maintenance time of an effective short term prognosis*

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BIOGRAPHIES

Manuel Esperon-Miguez has been researching on retrofitting IVHM tools on legacy platforms at Cranfield IVHM Centre since 2010. Manuel has also worked on R&D for high energy storage devices and their implementation on land vehicles. He holds a Master in Mechanical Engineering from Madrid Polytechnic University, Spain, and an MSc in Aerospace Engineering from Brunel University, UK. He is currently pursuing a PhD in IVHM at Cranfield University.

Philip John is the Head of the School of Engineering at Cranfield University in the UK and has been the University's Professor of Systems Engineering since joining in 1999. Following his PhD at Imperial College, London he spent 18 years in industry, holding a wide range of systems engineering and management roles, including Head of Systems Engineering for a major multinational company. His experience and responsibilities in industry encompassed the whole scope of systems engineering, including Requirements Engineering, System Design, ILS, ARM, Human Factors, Safety, Systems Proving & Simulation and Modelling. He is a member of several National Advisory Committees and Industrial Steering Boards and served as the President of the International Council on Systems Engineering (INCOSE) in the UK from 2003 to 2004. His research interests include: Understanding Complex Systems and Systems of Systems (SoS); Managing Complex Systems Projects and Risks; Through Life Capability Management; and Coping with Uncertainty and Change in Systems

Ian K. Jennions. Ian's career spans over 30 years, working mostly for a variety of gas turbine companies. He has a Mechanical Engineering degree and a PhD in CFD both from Imperial College, London. He has worked for Rolls-Royce (twice), General Electric and Alstom in a number of technical roles, gaining experience in aerodynamics, heat transfer, fluid systems, mechanical design, combustion, services and IVHM. He moved to Cranfield in July 2008 as Professor and Director of the newly formed IVHM Centre. The Centre is funded by a number of industrial companies, including Boeing, BAe Systems, Rolls-Royce, Thales, Meggitt, MOD and Alstom Transport. He has led the development and growth of the Centre, in research and education, over the last three years. The Centre offers a short course in IVHM and the world's first IVHM MSc, begun in 2011.

Ian is on the editorial Board for the International Journal of Condition Monitoring, a Director of the PHM Society, contributing member of the SAE IVHM Steering Group and HM-1 IVHM committee, a Fellow of IMechE, RAeS and ASME. He is the editor of the recent SAE book: IVHM – Perspectives on an Emerging Field.

Uncertainty of performance requirements for IVHM tools according to business targets

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PHM Society

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