CRANFIELD UNIVERSITY

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FINANCIAL AND RISK ASSESSMENT AND SELECTION OF HEALTH MONITORING SYSTEM DESIGN OPTIONS FOR LEGACY AIRCRAFT

SHOOL OF ENGINEERING

PhD Thesis
Academic Year: 2012 - 2013

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ABSTRACT

Aircraft operators demand an ever increasing availability of their fleets with constant reduction of their operational costs. With the age of many fleets measured in decades, the options to face these challenges are limited. Integrated Vehicle Health Management (IVHM) uses data gathered through sensors in the aircraft to assess the condition of components to detect and isolate faults or even estimate their Remaining Useful Life (RUL). This information can then be used to improve the planning of maintenance operations and even logistics and operational planning, resulting in shorter maintenance stops and lower cost. Retrofitting health monitoring technology onto legacy aircraft has the capability to deliver what operators and maintainers demand, but working on aging platforms presents numerous challenges. This thesis presents a novel methodology to select the combination of diagnostic and prognostic tools for legacy aircraft that best suits the stakeholders' needs based on economic return and financial risk. The methodology is comprised of different steps in which a series of quantitative analyses are carried out to reach an objective solution. Beginning with the identification of which components could bring higher reduction of maintenance cost and time if monitored, the methodology also provides a method to define the requirements for diagnostic and prognostic tools capable of monitoring these components. It then continues to analyse how combining these tools affects the economic return and financial risk. Each possible combination is analysed to identify which of them should be retrofitted. Whilst computer models of maintenance operations can be used to analyse the effect of retrofitting IVHM technology on a legacy fleet, the number of possible combinations of diagnostic and prognostic tools is too big for this approach to be practicable. Nevertheless, computer models can go beyond the economic analysis performed thus far and simulations are used as part of the methodology to get an insight of other effects or retrofitting the chosen toolset.

Keywords: IVHM, technology insertion, requirements definition, uncertainty analysis, error propagation.

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LIST OF ABBREVIATIONS

AEPHM: Advanced Electrical Power Health Management.
AFTCS: Active Fault Tolerant Control Systems.
AL: Autonomic Logistics.
ALIS: Automatic Logistics Information System.
ANN: Artificial Neural Networks.
APU: Auxiliary Power Units.
BITE: Built-In Test Equipment.
BN: Bayesian Networks.
CBA: Cost Benefit Analysis.
CBM: Condition Based Maintenance.
CBS: Case-Based Reasoning.
CI: Condition Indicators.
CMMS: Computerised Maintenance Management Systems.
CND: Can Not Duplicate.
DBN: Dynamic Bayesian Networks.
DES: Discrete Event Simulators.
EFDC: Early Fault Detection Cell.
ETA: Event Tree Analysis.
FDD: Fault Detection and Diagnosis.
FDIR: Fault Detection Isolation and Recovery.
FMECA: Failure Mode Effects and Criticality Analysis.
FTA: Fault Tree Analysis.
FTCS: Fault Tolerant Control Systems.
GS: Global Sustainment.
HAZOP: HAZard and OPerability study.
HMM: Hidden Markov Models.
HUMS: Health and Usage Monitoring Systems.
IDVTB: Integrated Diagnostics Virtual Test Bench.
ISHM: Integrated Systems Health Management.
IVHM: Integrated Vehicle Health Management.
JSF: Joint Strike Fighter.
KDD: Knowledge Discovery from Data.
KF: Kalman Filters.
LIS: Logistics Information System.
LRU: Line Replaceable Unit.
MDP: Magnetic Detector Plug. ; Maintenance Data Panel.
MIG: Materials Integrity Group.
MIMOSA: Machinery Information Management Open Systems Alliance.
MoD: UK’s Ministry of Defence.
MTBA: Meat Time Between Arisals.
MTF: Maintenance Test Flights.
MTTR: Mean Time To Repair/Replace.
NFF: No Fault Found.
OCCAHM: Ownership Cost Calculator for Aerospace Health Management.
OEMs: Original Equipment Manufacturers.
OSA CBM: Open System Architecture for Condition Based Maintenance.

PFTCS: Passive Fault Tolerant Control Systems.
PMDS: Portable Maintenance Data Stores.
PTF: Partial Test Flights.
RCFIS: Reconfigurable Control and Fault Identification System.
RIU: Remote Interface Unit.
ROI: Return on Investment.
RTB: Rotor Track and Balancing.
RUL: Remaining Useful Life.
SHM: Structural Health Monitoring.
SOAP: Spectrometric Oil Analysis Programme.
SPN: Stochastic Petri Nets.
TFPG: Time Failure Propagation Graphs.
UML: Unified Modelling Language.
VCC: Vibration Control Cells.
WDM: Wear Debris Monitoring.
WDMS: Wear Debris Management System.

1 Introduction

Organizations invest in technological assets to deliver a certain capability and expect to be able use them as often as they require. At the same time, they are constantly seeking for ways to reduce operational costs. Improving maintenance operation can have a positive effect on both cost and downtime.

Integrated Vehicle Health Management (IVHM) is aimed at maximising the use of technological assets through the use of diagnostic and prognostic tools to produce information on the present and/or future condition of components. This information is then used to manage maintenance operations in a more efficient way. This results in lower maintenance cost and higher operational availability.

Diagnostic tools can detect and isolate faults faster than trained personnel, resulting in a reduction of the active maintenance time dedicated to the replacement of the components they monitor. Prognostic tools measure different parameters to assess the current condition of a component and then use algorithms to infer its Remaining Useful Life (RUL). Based on the prognostic window (a.k.a. lead time) provided and the accuracy of the algorithm, maintainers can schedule the replacement of the part at the moment and location which have the lowest possible impact on normal operations.

The capabilities of IVHM are especially useful for the aerospace industry. Aircraft are comprised of completely different systems whose interactions result in complex failure modes that are difficult to diagnose or predict. Additionally, the high operational needs of civilian and military organizations put pressure on maintainers to reduce down times to a minimum.

In an industry with aging fleets, the need to retrofit this technology on legacy aircraft has increased as the retirement of aircraft is constantly differed. As civilian and military operators are left with aircraft that are no longer being manufactured, they have to face additional challenges regarding the maintenance of aircraft with aging technology and decreasing support of the Original Equipment Manufacturers (OEMs.)

Whilst there have been cases of successful implementations of individual diagnostic or prognostic tools on legacy aircraft, they cannot deliver the capability necessary to produce a significant impact on maintenance operations. This can only be achieved by retrofitting fully working IVHM systems with substantial coverage.

The challenge resides in finding the best combination of diagnostic and prognostic tools that can deliver the benefits operators and maintainers expect. The substantial investment and the fact that many of these tools are still in R&D phase presents a significant risk for investors.

This thesis presents a methodology to find the combination of diagnostic and prognostic tools capable of producing the best economic return for a legacy aircraft taking into consideration the financial risk involved. Starting with a legacy aircraft with little or none health monitoring capability, this methodology identifies which components should be monitored and by which diagnostic and prognostic tools. The result includes a prediction of the expected Return on Investment (ROI) and the financial risk undertaken.

This contribution to the current knowledge of IVHM design should underpin the design of larger and more complex IVHM systems to be retrofitted on legacy aircraft. The focus on producing an economic benefit with a financial risk acceptable for the investors helps to go beyond the technical capabilities of this technology to help to produce a solid business case.

1.1 Important concepts and definitions

There are a series of terms and concepts that will appear repeatedly throughout this thesis. Some of the terminology used in the field of IVHM is not universally agreed upon. To avoid confusion on the meaning given to some of these terms, a list of definitions is provided.

- **Diagnostic and prognostic tools**: The terms tool, IVHM tool, and health monitoring tool have been used as synonyms of diagnostic and prognostic tools. They refer to the pieces of hardware and software that deliver this capability.

- **IVHM system**: Combination of diagnostic and prognostic tools put together to deliver a certain degree of health monitoring capability. This includes all the hardware and software necessary both on-board and off-board to deliver this capability. “IVHM system” and “IVHM toolset” (or just “toolset”) are used as synonyms throughout this thesis.
- **Component/Part**: Indications provided by IVHM tools result in items being removed from an aircraft to be repaired or replaced. These items can be isolated components, but sometimes whole subsystems are replaced. The term Line Replaceable Unit (LRU) is often used to refer to modular components designed to be replaced, but this term does not apply to all the instances when components are replaced as a group. In that sense, the terms “component”, “part” and “LRU” are used interchangeably to mean the smallest unit that would be replaced in case of a fault, a scheduled replacement or an indication of imminent failure.
- **Maintenance times and delays**:

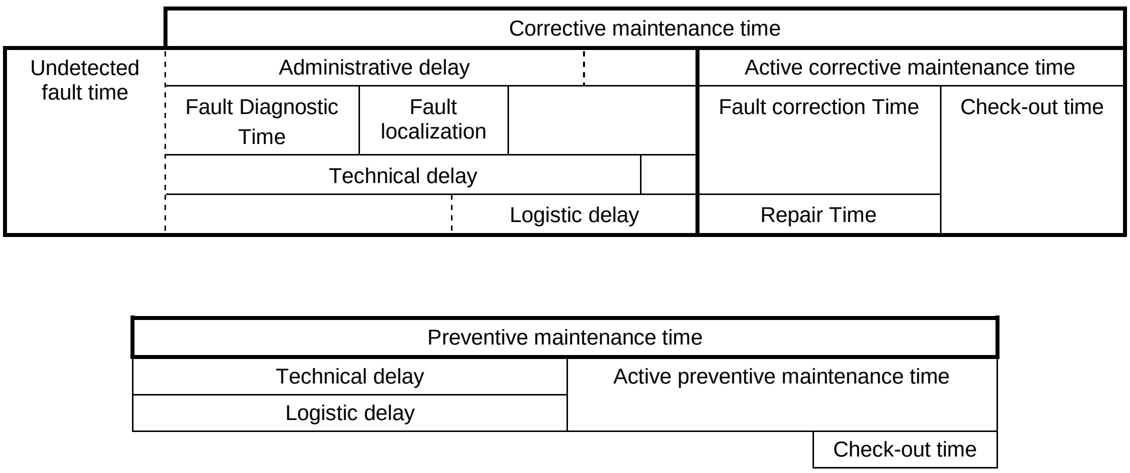

Figure 1-1 Maintenance times according to BS 4778-3.1 [1]**.**

- **Operational availability, A_O**: This parameter is used to evaluate the probability an item will operate satisfactory at a given point in time taking into account the effect of maintenance activities. It is calculated using the following formula:

$$A_O = \frac{Mean\ Time\ Between\ Failures}{Mean\ Time\ Between\ Failures + Mean\ Down\ Time} = \frac{MTBF}{MTBF + MDT}$$

In this thesis operational availability is often referred to as simply "availability". Unless stated otherwise, "availability" always refers to A_O and not to any other type of availability.

2 Literature review

"Where is the wisdom we have lost in knowledge?
Where is the knowledge we have lost in information?"
- T. S. Eliot

This chapter is dedicated to study the literature on the development and implementation of IVHM as well as all aspects that affect these processes such as justifying the financial viability of IVHM systems or the numerous technical challenges faced*. The findings from this chapter are essential to identify the gaps in the knowledge this thesis tries to fill and which will be discussed in chapter 3.

On one hand, given the multidisciplinary nature of IVHM, it is not possible to produce a comprehensive study of the relevant literature if the search is limited to those articles that make specific reference to this topic. On the other hand, it is not practical, or even practicable, to study the literature available for some disciplines which affect IVHM in excessive depth (e.g.: the discussion on use of Markov chains to develop health monitoring algorithms would not benefit from an in-depth analysis of the mathematical theory behind them.)

The topics that will be covered are:

- The state of the art of health monitoring technology (section 2.1)
- Current methods to perform Cost Benefit Analysis (CBA) for IVHM technology (section 2.2)
- Challenges faced by the insertion of IVHM technology (section 2.3)

The reader is reminded that IVHM is sometimes referred to using different denominations (e.g.: PHM). As a consequence, some of the publications that will be referenced in the following sections do not use the term IVHM, despite the fact that they make reference to the same set of technologies. To facilitate

* The findings from the literature review were published in a peer-reviewed journal as a review paper (included in Appendix C):
Esperon-Miguez, M., John, P., Jennions, I.K., 2012, A review of Integrated Vehicle Health Management tools for legacy platforms: challenges and opportunities, January 2013, Progress in Aerospace Sciences, Vol.56, Pages 19–34

the discussion of their content, whichever term they happen to use will be replaced by “IVHM” when reference is made to their findings and conclusions.

2.1 State of the art of health monitoring applications

IVHM systems are based on their capability to gather data on the systems they monitor to transform them into information that can be of use for the management of maintenance activities, logistics and even fleet operations. Diagnostic and prognostic tools underpin this process by detecting and isolating faults or estimating the RUL of components whose degradation they monitor respectively.

Diagnostic and prognostic tools are usually classified according to how the data available are analysed and conclusions reached. Vachtsevanos *et al.* [2] have proposed a classification of health monitoring tools (now widely used in the literature) by which they are divided into two main groups (see section 2.1.1):

- Data-driven methods: developed finding patterns in data to identify and predict faults. Some authors propose subdividing data-driven methods into knowledge-based methods, artificial intelligence methods and statistical methods [3].
- Model-based methods: based on an understanding of the physics of that drive a given failure mode.

To maximize the benefit of implanting diagnostic and prognostic tools, the management of logistics and maintenance operations has to evolve to be able to put to good use the new information provided by health monitoring systems. There have been significant improvements in these areas in the last decades, although not necessarily related to IVHM. Latest developments in logistics and maintenance management that can be integrated with IVHM are discussed in section 2.1.2

Besides using health monitoring tools to reduce the cost of operating a fleet whilst increasing its availability, information regarding the condition of a component and its capability to perform its task can be very useful to adapt control systems and counteract the effects of a fault to ensure the safety of the crew, passengers and cargo. Dynamic control systems, which are analysed in section 2.1.3, have the potential to improve mission completion rates and increase safety. These systems rely on the accuracy of the information produced by the health monitoring system for a correct reconfiguration and therefore, can only be implemented once the diagnostic and prognostic tools have been thoroughly tested.

2.1.1 Diagnostic and prognostic tools

2.1.1.1 Data-driven methods

Thanks to the numerous sensors used to operate an aircraft it is possible to produce data on the performance on different systems. Using data-mining techniques these data can be analysed to detect patterns to determine which component or module is causing a system to fail (diagnostic data-driven methods), or to estimate the RUL of a component (prognostic data-driven methods). Models developed with these techniques are not based on an understanding of the physics behind a certain failure mechanism, but on correlations found between different variables that give an indication of the condition of the part.

Some authors believe these techniques lack the precision and accuracy physics-based models provide [4; 5]. However, studying the literature available on the latest developments on health monitoring algorithms revealed that most published works focus on data-driven methods. This is not to say physics-based models have not become part of numerous IVHM systems or been the subject of research and development in the recent years, as discussed in detail in next section. The reason behind this bias seems to be the capability of data-driven methods to develop diagnostic and prognostic algorithms for systems whose failure mechanisms are too complex to be studied analytically using physics.

Experienced-based models are a subcategory of data-driven methods (sometimes considered as in a class of their own) which use conventional statistical analysis (as opposed to data-driven techniques) to develop degradation models. Traditional preventive maintenance is based on these methods. They use historical maintenance data with statistically significant failures which can be correlated to time or other measurable parameter. By adjusting a statistical distribution to the recorded information available it is possible to obtain a function to relate its RUL to a monitoring parameter. The failure distribution of most components can be approximated to at least one commonly used probability distribution, such as Weibull, Poisson, exponential, and normal distributions. Weibull distribution has been applied successfully for decades to mechanical components since it is especially suited for elements that get worn, besides, it can be adjusted for those parts that present infant mortality and follow a bathtub curve.

According to Atlas *et al.* [6], since the health curve of a component is created using statistical data, the model to which every component is compared is just an average and is a function of time or the number of cycles. Due to the variability during the manufacturing process (across and within manufacturers), age disparity across the fleet, differences in parts replaced on each aircraft and repairs carried out, the behaviour of each aircraft under certain conditions may vary, making components degrade at a different pace across the fleet. Consequently, these models tend to be conservative to avoid unpredicted failures, resulting in many components being replaced despite have a long RUL.

Whilst it is not difficult to correlate the probability of failure of many mechanical and electrical components with the time and loads under which they have been operated, it is often quite difficult to record the conditions or the exact period they have been working. Therefore, trying to correlate their failure rate with the hours of use of the aircraft or the number of landings is not necessarily a good approach.

The probability of failure of electronic components is also quite difficult to estimate using experience-based techniques. Their faults are more likely to be caused by environmental effects than by prolonged periods of operation, such as the faults due to cosmic radiation mentioned by Dyer et al. [7].

Data mining techniques have been used for many years for all sorts of applications. Fayyad et al. [8] and Skormin et al. [9] refer to these methods as

Knowledge Discovery from Data (KDD) technology. Fayad et al. [8] divide the process of applying data mining to a dataset into:

1. Identifying the domain in which the problem is framed and identifying the goal of the analysis; selecting the dataset to be analysed
2. Cleaning and pre-processing the data
3. Reducing and transforming the data
4. Selecting the appropriate data mining method
5. Performing the data mining
6. Checking the results
7. Applying the newly acquired knowledge for the purpose it was intended for

The most common problems faced when using data mining are noise, gaps and data corruption. Several techniques have been developed to tackle these problems [10-12], as well as reducing the dimensions to facilitate processing large amounts of information [13; 14]. However, in some cases, the transformation of data is not carried out to reduce the calculation cost, but because the data are stored using variables that do not represent the information in a useful manner. Such is the case of structural vibration monitoring, in which modal analysis requires data to be studied in the frequency domain whilst raw data is in time domain. After all the pre-processes have been finished the developer must have a set of training data to be used by the data mining algorithm and a test set to check the results [8; 9].

Whilst KDD processes can be used to verify the user's hypotheses the use of data mining to develop IVHM tools tends to focus on letting the system discover patterns autonomously. Both diagnostic and prognostic tools can be developed using data mining, but the goal of the analysis influences which method is to be chosen. A proposed method to divide data mining techniques uses the following six groups [8]:

- Classification: Classes are predefined by the user and the dataset is partitioned according to the patterns found.

- Regression: The variables of the dataset are analysed to detect correlations between them and produce a mathematical function to describe the behaviour of the system.
- Clustering: Different categories or clusters are identified within the data set. Clusters can be mutually exclusive, overlapping or use hierarchical categories. Unlike classification methods, clusters do not use previous knowledge to define the groups data are sorted in.
- Summarization: Data are divided into groups which are analysed to find a simple description of the information contained in them in ways such as statistical properties, relationship between variables, etc.
- Dependency modelling or association rule learning: Relationships between different subcategories are found and association rules are obtained from the use of these methods. These methods are limited to large databases to obtain statistically sound associations [15].
- Change and deviation detection: Changes in data gathered in different moments are detected using these techniques.

Finally, the findings from data mining must be validated using the test set of data previously defined. The developer focuses on the accuracy of the results obtained from running the model on the test set as well as on the consistency of its performance when different test sets are used. The model must also provide relevant information, since the patterns detected by data mining might not be useful for health monitoring.

Artificial Intelligence (AI) techniques and knowledge-based methods have been used for the development of both diagnostic and prognostic techniques in aerospace industry and have been successful in several applications thanks to their learning capability. Artificial Neural Networks (ANN), Bayesian Networks

(BN), Evolutionary Algorithms (EA) and Stochastic Petri Nets (SPN) are some of the most common techniques used [5]. One of the main limitations of these methods is the need of large datasets to train the system and these are seldom available [16].

ANN mimic the structure of a biological neural network by interconnecting individual nodes or neurons and allowing them to transfer information to each other. Each neuron has several input signals, each of which is multiplied by its synaptic weight before they are all summated and fed to the activation function. Since the activation functions can be non-linear (e.g. tangent hyperbolic) ANN are well suited for non-linear applications [17]. Multilayer feed-forward ANN (which are the most commonly used in IVHM) organise neurons in layers in which neurons belonging to a layer only receive information from neurons of the previous layer and their output is only fed to the next layer. The network has to undergo a learning process in which the weights of the inputs are adjusted. Supervised learning algorithms use data which have been analysed previously and include known faults, whilst unsupervised learning is carried using new information. The latter still has to be proven successful in health monitoring. ANN have been tested on identifying simultaneous faults [18] and even detecting faults in the sensors used to obtain the data [19]. Using a gas turbine performance model to generate the required data, Joly *et al.* [20] proposed a diagnostic tool using ANN for a Rolls Royce engine with which the components were analysed in pairs obtaining mixed performances for different components. Besides diagnoses, ANN have been used successfully to obtain prognoses in Auxiliary Power Units (APU) and hydraulics systems [21]; jet engines [22]; and actuators [23].

BN are probabilistic graphical models in which the variables that are analysed are represented as nodes and their causal relations as arrows connecting them. These variables can be of different nature (numerical, logic, etc.) according to the way the component degrades. Predefined causal relations can be obtained from a Failure Mode Effects and Criticality Analysis (FMECA), a HAZard and OPerability study (HAZOP) or from consulting an expert on the system.

However, best results are obtained when the structure and parameters are learnt. Dynamic Bayesian Networks (DBNs) are a development of conventional BN in which time evolution of variables is taken into account. DBN are basically conventional BN in which the graphic representation includes two static BN, one at time t and another t+1. This requires the definition of dynamic relations linking variables that belong to different time slices and which represent the degradation that takes place in the system. DBN have become very popular for the development of prognostic tools with diverse applications such as chemical processes, ball bearings or manufacturing, to cite a few [4; 5; 24; 25]. Kalman Filters (KF) and Hidden Markov Models (HMM) are the two of the simplest forms of DBN [26] and are widely used in the development of health monitoring tools.

Although data-driven methods include a diverse range of techniques besides ANN and BN, these two approaches seem to dominate the literature. However, there are some examples in which other AI techniques have been proven successful. For example, Dutuit *et al.* [27] used SPN and Montecarlo simulation to study the reliability of electronic equipment obtaining better results than following a Markovian approach. EA have also been applied successfully, having performed better for the diagnosis of faults in power transformers than ANN, fuzzy systems and even IEC/IEEE standards [28]. However, none of the approaches mentioned has been proved to be the best as a generic tool for the development of diagnostic or prognostic tools.

Finding 1: Data-driven methods have numerous examples of successful applications when there is little understanding of the failure modes and degradation mechanisms involved. However, no specific data-driven method has been proven to perform better than the others for all possible applications, which means that a case by case analysis is still required.

2.1.1.2 **Model-based methods**

Model-based methods, also known as physics-based methods, have been the traditional choice to develop health monitoring tools when rich data gathered by sensors was available and there was a good understanding of the behaviour of the system under healthy and faulty conditions. Diagnostic and prognostic systems based on using models can be produced using two different approaches: failure propagation models, which focus on how each failure affects the system and propagates producing symptoms and affecting each component or function; and performance models, which use mathematical functions to reproduce the behaviour of the component under both normal and failed operation. The latter are much more precise, but also much more expensive to develop (more man-hours and experimental equipment). Although Medjaher et al. [5] claim that one of the disadvantages of model-based health monitoring is its case by case approach, Ofsthun and Wilmering [29] showed how blocks developed to model components and subsystems can be reused to build up models of larger systems.

Time Failure Propagation Graphs (TFPGs) are used to diagnose failures based on which components or functions have been working out of range (or failing), in which order and at what time. Analysing this information it is possible to generate a set of possible explanations and, in some cases, even predict which components or functions will experience problems in the near future and in which time interval [30]. The fault propagation model is based on a simplified model of the system dynamics in which nodes represent failure modes. Some of these nodes can be grouped attending to which function or component they belong (e.g. pump or electric generation). Failure modes are linked according to how they can propagate. Each link is defined by its probability of occurring and a time interval in which the predecessor failure mode can affect its successor. Monitors represent sensors or alarms which are present in the real system and help to distinguish between the real state of the system and what the health monitoring system can actually detect. Some failure modes are connected to the failed state of a specific component, making it possible to determine the source of the problem [30; 31]. When one or more monitors detect that some failure modes are active a diagnosis process is followed to determine to more plausible explanation. First, a set of hypotheses are generated; then, they are evaluated according to which alarms have been triggered and the plausibility, robustness and frequency of each hypothesis; after comparing the results a diagnosis is obtained, although it can consist of a probability ranking of the hypotheses rather than simply pinpointing a single explanation [31]. Examples of the algorithms used for hypothesis generation, hypothesis evaluation and diagnostic reasoning can found in [32-34]. TFPGs are easy to develop as long as the interrelations among functions in the system and how faults affect them are well understood, that is why this method is especially suited for systems in which mass and/or energy are being exchanged, such as power generation [30] or aircraft fuel systems [31].

Performance models generate a set of residuals or fault indicators which represent the difference between the signals from the sensors and the expected values obtained from the model. Under normal operation the residuals are nearly zero, but once the components starts degrading or a fault appears their value changes, providing information to the health monitoring system. Therefore, the reliability of the diagnoses and prognoses generated with these methods are very sensitive to the accuracy of the model.

To develop the model some authors have suggested the use bond graphs modelling techniques since they have already been proven successful in several engineering disciplines [35-39]. A bond graph of a system is a graphic model in which dynamic properties are represented using basic elements which exchange energy in different forms and, since the models are energy-oriented, it is possible to use them to analyse the dynamics across different energy domains (i.e. mechanical, electrical, hydraulic, thermal, etc). The graphic representation can be used to obtain a set of state equations which describe the model and, once solved, permit obtaining the time response. Furthermore, Beez *et al.* [35] have developed a program capable of generating the diagrams automatically using object-oriented computer aided engineering tools, although their work focuses on process plants. An example of this kind of models would be the work done by Wong *et al.* [36] to simulate electrical systems or by Mosterman [37] to take into account discontinuities in physical systems. To consider the uncertainties of some parameters in the model it has been proposed to use bond graph elements [38]. To study the accuracy of a model developed using bond graphs Djerziri *et al.* [39] tested and validated the option of characterizing the uncertainties using Linear Fraction Transformation (LFT).

In many aerospace applications data-based methods have not been able to produce diagnoses that are accurate enough to be useful for maintenance teams, therefore it has been proposed to combine them with model-based models. This has led to the use of expert systems in which the knowledge base of the system is combined with an inference engine which analyses data gathered by sensors. The knowledge base is often programmed as a set of rules that define the possible states of the system under both healthy and faulty conditions [40]. To define this set of rules systematic methods to study the effect and causes of faults like Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) are common practice. Expert systems have been used for diagnostic systems such as structural damage [41], power electronics [42], fuel systems [40] or embedded electronics [43].

Finding 2: Model-based methods require a good knowledge of the degradation and failure mechanisms that affect the component being monitored and, since many models are often generated during the development phase of components, the implementation of monitoring techniques based on this approach can be much easier to develop than other methods. However, in the case of components installed on legacy aircraft, these methods can be too expensive to implement if there is not comprehensive documentation to base the models on.

2.1.2 Maintenance and logistics management

The use of diagnostic and prognostic tools generates new information regarding the use of components, aircraft and the whole fleet. This new data, already in digital format, can be used to make better informed decisions regarding maintenance management and, up to a certain point, reduce the need of human intervention to produce maintenance orders. Davies *et al.* [44] carried out a survey to investigate the effectiveness of using maintenance information systems already available. They concluded that users are very satisfied with the performance of Computerised Maintenance Management Systems (CMMS), but less enthusiastic about information support systems. Although the majority agreed that the downtime was reduced thanks to the use of these tools, they also believed that they still need to be improved.

Using information and communication technologies E-maintenance is a maintenance support system through which expertise on every step of the maintenance and logistics processes can be shared and many activities automated [45-47]. These tools help to improve the efficiency of maintenance orders processing, tool logistics, human resources planning, spare parts logistics and inventory management. However, it is necessary to ensure that the information generated on every stage of the process is formatted to be easily shared and understood. Using Case-Based Reasoning (CBS) it is possible to translate the structure of the maintenance process into a decision model [48]. A framework for developing e-maintenance systems with enabled proactive maintenance including prognosis, remote diagnosis and fault-recovery can be found in [49]. Rasovska *et al.* [48] tested the use of decision support systems working with incomplete information and Muller *et al.* [4] demonstrated, by experimenting on an industrial system, the feasibility of implementing a DBN-based prognostic tool on an e-maintenance architecture. Saint-Voirin *et al.* [50] established a set of modelling principles to develop e-maintenance models using multi-agent systems and Petri nets.

For the development of different tools that can be applied to the maintenance system of the Joint Strike Fighter (JSF) the Integrated Diagnostics Virtual Test Bench (IDVTB) was developed. It uses models and simulations to foresee how upgrades and updates will interact with the platform. However, this still presents some difficulties, especially concerning the compliance with the Model and Simulation Office High-Level Architecture [51].

Logistics have a high potential for improvement since this discipline has been highly automated in manufacturing and transport industries for decades, making it easy to adopt these techniques once the information they require is available. For those parts that are replaced according to a predictive maintenance approach, the use of prognostic tools enables a logistic system focused on supplying components based on the immediate need instead of following a fixed schedule.

Taking into account the worldwide distribution of the aerospace industry Hess *et al.* [52] propose implementing a Global Sustainment (GS) solution to provide support through a common platform. This requires a long term business case analysis taking into account the uncertainty of the performance of new health monitoring tools combined with the changes in contract conditions as the project evolves, especially if a price improvement policy based on performance is applied.

Since IVHM capability was among the design requirements for JSF from early in its development. The Autonomic Logistics (AL) system has been proposed to automate the logistics environment and, reduce human intervention. The health monitoring system transmits the information wirelessly so the maintenance actions can be decided on the ground and personnel and materiel can be ready by the time the aircraft has landed [51]. The information is exchanged between the stakeholders using the Automatic Logistics Information System (ALIS) which collects and analyses data and is used for decision support and action tracking [53]. Provided the system is proved successful it is planned to retrofit the on-board data capture capability to the F-22, F-18/F and the V-22 [51].

Finding 3: From the information available in the literature, it can be said that IVHM can benefit from the maintenance and logistics technology already developed for other industries with very little modifications required to reach full capability, provided the information from diagnostic and prognostic tools is reliable enough.

2.1.3 Dynamic control systems

The evolution of Fault Detection and Diagnosis (FDD) tools has made it possible to develop control systems capable of dealing with the abnormal behaviour of a system. Fault Tolerant Control Systems (FTCS) can be passive (PFTCS), which are designed to remain effective after a fault appears without any modification; and active (AFTCS), if their internal logic is reconfigured according to the state of certain components [54].

Since PFTCS (also known as robust systems) are not informed of the existence of a fault, they need to be designed to work under some faulty conditions. Robust systems have been used successfully in many engineering applications over the decades, and they perform very efficiently when dealing with a small number of faults; although their performance drops significantly as the number of scenarios increases. Unlike AFTCS, PFTCS do not benefit from the use of continuous health monitoring and, therefore, are not affected by the implementation of IVHM technology. AFTCS can use techniques to react to the detection of an unexpected fault (fault accommodation techniques) [55], use dynamic models of the system (model predictive control techniques) [56], or monitor the state of a system and readjust the controller continuously (adaptive control techniques) [57]. The latter can be developed for systems with no diagnostic capability, but only perform well as long as the variations of the parameters of the system are small and slow. Similarly, model predictive controls perform poorly when the fault of the system too severe [41]. Model predictive control approaches are capable of dealing with complex and non-linear systems, but they require considerable computing power [56].

Most AFTCS are developed under the assumption that an ideal FDD tool is available whilst most FDD systems are designed without taking into account the close-loop effect of its interaction with a dynamic control system. Although some papers have been published regarding the integration of both systems [58-60], the effect of the uncertainty of diagnosis is an issue that is widely disregarded. Additionally, neither the detection of a fault nor the reconfiguration of the control system is immediate, an important factor in time-critical control systems. To improve the overall performance the reconfiguration is carried out by a combination of adaptive, switching or following mechanisms with optimization or matching techniques. Although changes in AFTCS can be limited to their parameters (reconfigurable control systems) it is also possible to change aspects of their structure such as the order, type and number of controllers they use (restructurable control systems) [55]. The first approach, although simpler to apply, reduces the capability of the control system to deal with severe faults.

In many applications, as long as a fault produces small variations of those parameters of the systems relevant for its control, it is possible to apply linear systems control theory for the design of the AFTCS. Sometimes, in order to provide a solution to deal with a fault, even if it is not optimal, linearity is considered an acceptable simplification if no better alternative is found. To deal with non-linear systems the use of artificial intelligence tools to adjust the control parameters has been considered for several years, including neural networks, fuzzy logic, Bayesian probability, machine learning and many others [61]. Since software redundancy has become critical by the introduction of fly-by-wire, AFTCS must be designed to deal with information that might become contradictive. For complex applications the use of expert systems has been proposed [62].

Dynamic control systems have been tested successfully on several experimental platforms such as NASA's F-15S TOL/MTD (a modified version of the fighter jet with additional control surfaces) as well as Boeing UAVs X-36 X-40A, X-45, and T-33 [63; 64]. Tailless airplane control was tested successfully on a VISTA F-16, a modified version by General Dynamics, which used an indirect adaptive scheme [65]. These projects have focused on keeping the aircraft under control once the damage of a component affects its dynamic behaviour. A step further has been proposed using the Structural Health Monitoring (SHM) system developed for Eurofighter Typhoon, which has been tested and validated [66; 67], by using the flight control system to prevent the pilot from pushing the aircraft beyond its structural limits – these limits would change in case a damage in the structure is detected. Similarly, Stewart Hughes Limited (now part of GE Aviation) has worked on a carefree handling system for helicopters. This system would help the pilot to control operational parameters to avoid exceeding the limits defined the structure, the aerodynamic conditions and control capabilities reducing the pilot's workload. The system used neural network to predict the value of parameters (e.g. torque) and use them to predict future envelope exceedances and produce cues for the pilot [68].

Finding 4: Since dynamic control systems are underpinned by reliable health monitoring tools, they still have limited capabilities, although they have a high potential to reduce the number of flights cut short due to failures that can be dealt with on-board, increasing the effectiveness of the fleet.

2.2 Financial viability of IVHM technology

It comes as no surprise that justifying the economic advantages of investing on IVHM technology is essential to apply it. However, whilst diagnostic and prognostic tools have been developed for decades, IVHM entails a level of complexity that has made engineers focus on the technical side rather than on justifying the economic viability of the technology.

This is not to say there is not a significant amount of work published on the aimed at justifying the investment on IVHM in financial terms. After studying the literature on this topic, three main themes have been identified (they correspond to the following subsections).

A good part of the literature analyses the impact of switching from conventional maintenance schemes to predictive maintenance using IVHM. This is an essential step to demonstrate the potential of health monitoring to have a positive and significant impact on maintenance and all other activities it affects.

The second category focuses on the study of the optimization of maintenance management using information generated with IVHM systems. The reason research in this area is of importance for the economics of health monitoring technology is the fact it involves a significant amount of work on what are the real benefits stakeholders expect and how to maximize them.

Finally, the third group is comprised of the work published on performing CBA for IVHM systems. This includes specific examples of CBA performed for specific applications and methodologies developed to conduct such analyses.

2.2.1 IVHM-enabled maintenance

The lack of health monitoring systems makes it quite difficult to find published studies on the profitability of IVHM technology. This is due to the relative youth of this technology, whose benefits are acknowledged by most, but for which there is little evidence.

Luckily, Health and Usage Monitoring Systems (HUMS) has been used in helicopters for a period long enough, allowing Scanff et al. [69] to compare the life cycle cost of unscheduled and fixed-interval maintenance of helicopter avionics to having a PHM system using a stochastic model. They concluded the modern health monitoring system could result in a reduction of life cycle costs of up to 10% compared to fixed-interval maintenance and up to 22% compared to unscheduled maintenance. However, Sumner [70] studied the economic benefits experimented by the UK military thanks to the introduction of HUMS in the 1980s and concluded that, despite the clear potential to improve maintenance operations it is still not in widespread use.

In one of the few examples of a system level studies on the profitability of health monitoring technology MacConnel [71] analysed the design related benefits of an ideal Integrated Systems Health Management system (ISHM) by assembling experts from the industry and academia. This study helped to determine the needs linked to specific benefits and scenarios. The article cites specific reductions and improvements in maintenance cost and downtimes “reported by a number of sources”, but does not specify which sources, to which aircraft they correspond or how they were calculated.

To be able to conduct this kind of analysis in the future in a systematic and faster manner Berdinyazov et al. [72] have developed a mathematical tool capable of comparing the benefits of corrective maintenance, preventive maintenance and condition based maintenance that includes the use of sensitivity analysis.

One of the main limitations of most economic analyses on the profitability of IVHM is the excessive focus on maintenance cost, not taking into account the impact it can have on other areas. Wang [73] conducted a survey of different maintenance policies for deteriorating systems. He found that most optimal maintenance models focus on minimizing system maintenance cost, rather than system reliability performance. He concluded that for multicomponent systems an optimal maintenance policy must consider both maintenance cost and reliability measures simultaneously. To tackle this problem Marais and Saleh [74] propose a method to determine the value of maintenance as opposed to traditional approaches that focus on cost reduction.

Another issue often ignored it the fact that, despite the savings generated by IVHM systems, their profitability depends also on their development and implementation cost. Marquez et al. [75] studied the effect remote condition monitoring can have on the life cycle cost of railways. In their article the show how, since there is an expenditure associated with the implementation of health monitoring systems, the cumulative net benefit will depend on the use of the asset during its remaining life.

Finally, few address the numerous uncertainties regarding maintenance times and how IVHM affects, and is affected by them. An exception is the work carried out by Williams [76] who studied the benefits to stakeholders of using IVHM on military aircraft, but only on a qualitative manner.

Finding 5: Whilst the capability of IVHM to reduce maintenance cost and time has been clearly demonstrated, its profitability also depends on the cost of the system and the new recurring costs it generates.

2.2.2 Optimization of maintenance management using IVHM

The work on optimization of maintenance based on the information generated by IVHM systems focuses on determining the best moment to replace a given component to extract as much use from it as possible (there is a certain value associated with using each part as long as possible) whilst the probability of the part failing before said action taken remains low.

Bucher and Frangopol [77] go even further in the chase to reduce maintenance cost. They analyse the possibility of violating safety and condition thresholds to achieve greater reduction with either preventive or predictive maintenance. They conclude that “a trade-off between maintenance cost and failure cost can be achieved”. Whilst this may make economic sense it is difficult to imagine a case in the aerospace sector in which operators and maintainers would accept a decrease in the reliability of a system knowingly to reduce maintenance cost.

Most methods are much more conservative and focus on the replacement of a component or LRU keeping the probability of failure low. Deloux et al. [78] propose a maintenance decision method for a structural component monitored using a degradation model and a model to detect sudden failures due to shock. Andersen and Rasmussen [79] proposed a method to schedule replacements in the short-term based on an analysis of the cost and risk of the different options. This approach is, once again, limited to individual components or LRUs

One of the main problems regarding the optimization of maintenance tasks scheduling using IVHM is the uncertainty of the information it generates (diagnostic tools can trigger false alarms and prognostic tools only provide a probability distribution of the RUL). In [80] Haddad et al. propose using real options to make maintenance decisions based on the information provided by prognostic tool. A technique inherited from financial analysis, real options analyse the opportunity costs of making a certain choice at a given point in time.

Whilst a lot of work has been done to optimise maintenance to reduce cost, downtime reduction has also been addressed. Jing et al. [81] studied inspection interval of structures and how they impact maintenance cost. They considered variable inspection intervals and the possibility of imperfect inspections, but considered the duration of inspections negligible. This limits their method to a tool to determine the best inspection interval for Condition Based Maintenance (CBM) inspections

As mentioned before, maintenance cost and time reduction are not the only benefits one can expect from IVHM. Hess et al. [52] point out the potential of prognostic tools to enable performance based logistics and the generation of new business practices. Khalak and Tierno [82] have studied how PHM affects the logistics supply focusing on the level of safety stock. In their analysis they acknowledge the risk of early faults with prognostic tools and the cost associated with them. Their work provides a mathematical formulation to express the cost of supply chain storage as a function of the lead time given by a PHM system as well as for the total supportability cost.

Finding 6: The work on the optimization of maintenance management tends to focus on the reduction of maintenance cost and does not take into account the complexities involved in the IVHM-enabled maintenance of multiple components from different systems.

2.2.3 CBA for IVHM

Since those involved in the development and implementation of IVHM systems have realised the importance of being able to prove their financial viability multiple techniques have been proposed to conduct CBAs. Due to the complexity of the task most methodologies are discussed at a qualitative level without much detail as to how quantitative steps should be undertaken.

In [80] Sandborn describes the different aspects involved in the estimation of the ROI of an IVHM system, but does not explain in detail how multi-component IVHM systems can be analysed. Similarly Wanling et al. [83] researched the economic benefits of PHM systems focusing on the impact such systems would have by monitoring individual components or LRUs. Leao et al. [84] present one of the few works specific for legacy aircraft. However, like the rest of CBA methods mentioned here, theirs does not take into account how the combination of several health monitoring tools affects the expected ROI.

Banks et al. [85] propose a methodology to estimate the ROI of a PHM system applicable to different platforms in which FMEACA is used to evaluate the potential benefit of PHM on each component. Their method focuses on maximizing the asset's availability and does not take into account whether there are other factors that should be taken into account (i.e.: cost). They do not provide equations to specify how their method works.

Wilmering and Ramesh [86] described a tool developed by the Boeing Company called Ownership Cost Calculator for Aerospace Health Management

(OCCAHM) which has been used for several years to compare alternative IVHM solutions. This tool provides information on the probability of cost avoidance on different components using detailed representation of failure behaviour, maintenance and logistic processes particular to IVHM and the effect of IVHM on them.

Prabhakar and Sanborn [87] have developed a total cost of ownership model which includes the part support mode, the assembly model (for the recurring costs) and the field failure model. The main purpose of this particular model is to analyse the effect discontinued parts on the life cycle costs, which is particularly problematic for electronics given the short production life of many components.

Kavussanos and Bitros [88] present a maintenance modelling approach that considers maintenance cost as a factor that affects the operating revenue. It also takes into account the remaining value of the asset to define the optimum maintenance cost to maximize the return.

Some work has been done on CBA for IVHM systems for space aplications, such as Kurien and Moreno [89] have developed a method to carry out a CBA for diagnostic tools for space applications in which the value is based on the days of operation (equivalent to asset availability). However, given the needs and cost spacecraft, they do not take into account economic factors and focus mostly on improving the robustness of the system.

Banks and Merenich [90] carried out a CBA for battery prognostics using trade space analysis which allowed them to examine the correlation between several variables. They propose an iterative conduct said CBA, but the only benefit considered is maintenance time reduction and development costs are estimated based on the volume of the production of the asset in question.

Hoyle at al. [91] present one of the few analysis of the economic impact of IVHM to take into account the risk in financial terms, but their work is focused on diagnostic tools and revenue is a function of availability. Another important simplification in the method proposed by them is estimating the development cost of a diagnostic system based on the number of sensors it uses which is not proven to be correct.

One of the problems faced by engineers trying to carry out a CBA for an IVHM system is the numerous uncertainness involving factors such as part cost, shipping cost, etc. (Feldman et al. [92] provide a detailed list and classification of the different costs involved in any financial analysis for health monitoring technology). Gutche [93] analysed how the forces of the market situation affect the demand for factors such as asset availability. The article study how the volatility of the market affects the profitability of PHM systems according to the changes experimented by recurring costs.

As mentioned in the previous section, sometimes the complexity of the maintenance operations themselves introduce additional complexities to the problem generating additional uncertainties. Ashby and Bayer [94] have developed a CBA method for engines that use PHM technology which takes into account different possible maintenance process and how they affect the profitability of the system.

Whilst it is important to be able to prove a given IVHM system is a good investment, it would be useful to be able to design IVHM systems with this ultimate goal in mind from the very beginning. Kacprzynski and Hess [95] have developed one of the few design methods for IVHM with cost/benefit optimization as the main goal. As with other methods they propose using modified FMECA which includes failure mode symptoms to link failure modes with characteristics of health monitoring systems. The cost/benefit optimization assigns dollar values to all aspects of the system, but no indication is provided as to how to do it. Another limitation of this method is the rather simplistic evaluation of some cost.

Finding 7: Whilst there are multiple CBA techniques proposed for IVHM systems none of them seem to combine a capability to study the effect of implementing several diagnostic and prognostic tools on an aircraft and a clear quantitative underpinning that takes into account the multiple uncertainties involved.

2.3 Technology insertion and its challenges

Given the current state of the art of most monitoring techniques, their application on legacy platforms faces some of the same challenges as in newly design aircraft. Although legacy aircraft present the advantage of having historical maintenance data generated after years of service, the cost of making modifications on pre-existing vehicles is too high in most cases. This means that diagnoses and prognoses have to be carried out using information obtained through hardware that was chosen for purposes different from health monitoring. Technical challenges can be divided into those related to the characteristics of the health monitoring tool, those related to the platform, and the problems that arise during implementation. In the literature, organizational problems are considered to have been the cause of the failure of some projects. Most organizational problems are common for new and existing aircraft, but those regarding changes in a predefined support system are exclusive of the latter.

2.3.1 Technical challenges

A classification of most common technical challenges face when retrofitting IVHM can be seen in Figure 2-1

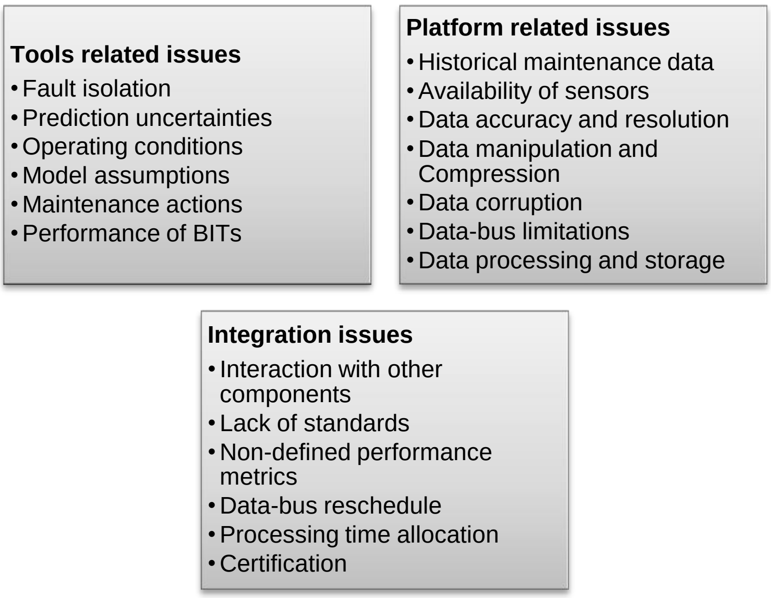

Figure 2-1 Classification of most common technical issues on retrofitting IVHM

2.3.1.1 Limitations of health monitoring tools

Uncertainty

Any diagnostic and prognostic tool has a limited accuracy and, therefore, to determine to what extent the information it provides is useful, it is necessary to find out the uncertainty of the results. This subject is often found in the literature, either related to a specific tool, or as research topic itself [41; 96-98]. Whilst the uncertainty of a diagnosis means that it is not possible to pinpoint a single component or module as the cause of a fault, in a prognosis it means that the exact RUL of a part cannot be determined because of the variance of the prediction. Due to the presence of a nearly constant segment in the degradation curve of many parameters, determining the exact position on the curve becomes extremely difficult when factors such as sensors' resolution and precision are taken into account (Figure 2-2). The variance of the prediction must be small enough to be able to make an accurate forecast. If the variance is excessively high, only short term predictions will be accurate enough to be useful for maintenance tasks. A possible solution to this problem proposed by Atlas *et al.* [6] is to contrast the information from the prognostics system to the life usage model of the component, but that requires that a proven model has to be available.

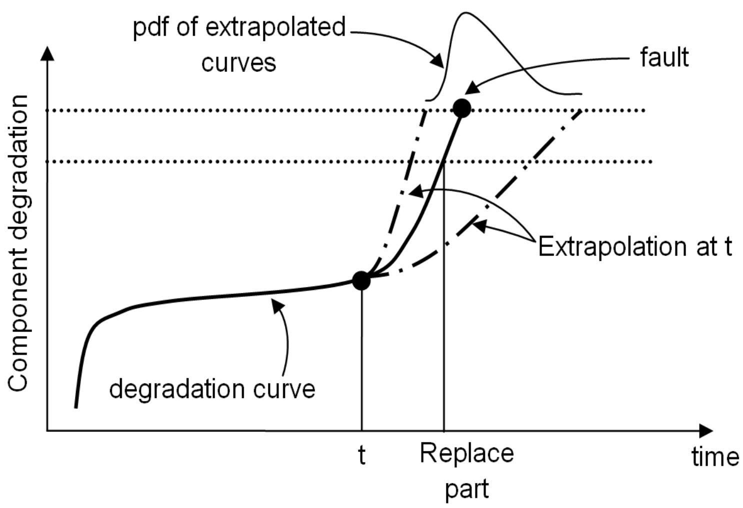

Figure 2-2 Prediction variance by extrapolating at time t.

Lopez *et al.* [41] have divided the sources of uncertainty into environmental and operational uncertainties (e.g. weather, loading conditions); scenario abstractions (e.g. subjective decisions, lack of knowledge); system uncertainties (e.g. non-linearity, boundary conditions, complexity); signal processing uncertainties (e.g. sensors, data fusion, decision making); and model uncertainties (e.g. form, parameters). Walley [98] proposes a classification splits uncertainties into two groups: random uncertainties, which are those that can be described using a probability density function or some deterministic approach; and epistemic uncertainty for those that cannot, mainly because of lack of information or knowledge. Sometimes random uncertainty is also called variability, irreducible uncertainty, stochastic uncertainty or random uncertainty; and to epistemic uncertainty can sometimes be found as subjective uncertainty, state-of-knowledge uncertainty or irreducible uncertainty.

Several techniques have been developed to quantify and describe different types of uncertainties, of which the most important are [29]:

- Probability-based methods
- Possibility-based methods
- Set-theoretical methods
- Evaluation and measures
- Epistemological concepts (verification, validation and usability)

Assumptions

Developing models involves assuming certain simplifications either because they improve their performance, or because it is not possible to obtain information about a parameter that otherwise would help to assess the state of the component. This introduces additional uncertainties that are difficult to evaluate and, during the development phase, can only be assessed in a qualitative manner by the engineer since they vary significantly from one application to another. In a good example of this problem Li *et al.* [99] demonstrated through numerical simulation and testing how a model-based prognostic tool for bearings required to have very precisely adjusted parameters to be able to produce satisfactory results.

Effect of operating conditions

Several diagnostic and prognostic techniques monitor parameters that can be directly affected by variations of the operating conditions of the vehicle such as accelerations, temperatures, current and many more. Stander *et al*. [100] attempted to transform the variables which are used in diagnostic tools when working on gear faults by averaging the accelerations to the speed of the shaft, this is synchronously averaging the signals with the parameter they are related to and which varies with the operating conditions. McFadden [101], on the other hand, transforms the variables to work on the frequency domain. For prognosis Lee *et al.* [102] proposed the use of clustering methods and a feature normalization technique. However, it is still necessary to validate any of these methods under real operational conditions and this has not been done for any of the health monitoring systems found in the literature.

Effect of maintenance actions

The fact that a component has been replaced or repaired does not guaranty a return to the starting point for the estimation of its RUL. Carrying out a maintenance action involves a certain amount of risk of introducing a new fault in the system, which is difficult to evaluate, especially since it is difficult to identify some of the faults that can be caused by the inappropriate execution of a maintenance task. Obviously, this kind of faults cannot be predicted and, usually, are not frequent enough to justify the development of a specific diagnostic tool. However, their interaction with other diagnostic and prognostic systems should be addressed. Even more critical is the evaluation of how the deterioration rate changes on repaired components. Monga and Zuo [103] have proposed the use of deterioration factors whilst Bloch-Mercier [104] believes the best approach is to use Markov models in which the component would evolve from one state to another with every repair.

False positives or false alarms

Several years ago suppliers started to install in their systems Built-In Test Equipment (BITE) or some other form of diagnostic tool. These tools have been very successful reducing the time required to detect faults and identify the source of the problem. However, these systems have faced problems like false alarms, ‘Can Not Duplicate’ (CND) and ‘No Fault Found’ (NFF) that have fed the scepticism regarding the use of automatic health monitoring tools [105]. Although there has been significant improvement in the reliability of these tools, reducing the false alarm rate remains a basically a case-by-case activity [106].

Finding 8: The information used to develop health monitoring tools and that is used by their algorithms plays a key role in the reliability of the diagnoses and prognoses they produce. It is necessary to understand how its limitations affect the accuracy of the results in order to avoid encountering problems too late into their development.

2.3.1.2 Problems caused by the platform

Data acquisition

Data-based methods rely on the analysis of recorded maintenance data obtained from components run to failure, which in the aerospace industry tends to be problematic to obtain for both technical and organizational reasons. On one hand, parts tend to be replaced when they are believed to show the first signs of an imminent fault, although it is common to remove components whose RUL is longer than the time they have been used [107]. Therefore, the data available only provides information regarding how long parts have been running successfully in what is known as suspended or censored data. Although some prognostic models use it to produce an estimation of the RUL, the resulting algorithm is too conservative. Heng *et al.* [108] have started to investigate how the omission of censored data produces even worse results and finding the optimum way of using these data has started to be investigated.

On the other hand, given the sensitivity of some of the data required to develop predictive models it can be extremely difficult (if not impossible) to convince the operator to release it. Additionally, this problem worsens when the health of a component has to be inferred through indirect methods that require extracting signals from modules manufactured by subcontractors, who might not want to share information concerning the internal logic of their products.

Condition monitoring data is usually automatically collected requiring minimal or no human intervention whilst event data normally has to be input manually and tend to be incomplete and more error-prone. Therefore, it is very common to find much more information available regarding the parameters measured in a system than events to correlate all that data against. This problem is even acuter when the monitoring system is already in operation and the condition indicators seem to be well adjusted since it becomes more difficult to persuade personnel of the importance of this information. Jarding *et al.* [16] propose using automated even data collection, but identifying the nature of the event, especially in components with multiple failure modes, can be a complex task that introduces additional uncertainty.

Sensors availability and resolution

The quality of the data used to assess the state of a system depends on the characteristics of the sensors used to measure the different parameters used by the algorithm. In many cases, engineers are forced to measure certain variables indirectly through different parameters measured by other sensors [109]. This is because when a monitoring tool is being developed for an aircraft that is already operative or whose design is in an advanced state, designers have to rely on the sensors already installed. In those situations most sensors have been installed for other purposes (e.g. control). Even if a sensor measures a parameter useful to monitor the system, its characteristics might be different for those required to infer the state of component.

Data manipulation and compression

Given the architecture of monitoring systems, it is relatively common to capture unnecessary or even redundant information. By compressing data and reducing their dimensions data analysis can be carried out more effectively and accurately whilst computational effort and memory requirements remain within practicable limits. Obviously, truncating and compressing data increases the uncertainty of the results and this must be addressed carefully. On the other hand, it is important to remember that when data classifiers are used, although increasing the dimensions of the data available reduces the error at the beginning, the error can soar if dimensions are increased carelessly: this is known as the “peaking phenomenon” or “curse of dimensionality” [13; 14; 110; 111]. Therefore, developers must find the correct balance by understanding the interrelationships between datasets.

In many cases, time-related data is transformed to extract information such as modal properties (which is frequency-related) in structural health monitoring [41]. However, transferring data to a frequency domain usually requires removing data from the extremes which are affected by error propagation. In other cases, signals are transformed into a simple parameter that indicates the state of the components like Condition Indicators (CI) [66; 67].

Data corruption

Due to problems during the capture, transmission or storage of data it is possible that part of the information is either lost or contaminated with values different from those really measured. If this problems are not detected these data can be used by a health monitoring algorithm producing wrong diagnoses or prognoses. Data corruption can be either continuous or sporadic, the latter being the most difficult to detect.

Since many sensors operate at a very low voltage, small changes in their electrical properties or noise can affect the measures significantly. Failure in compensation mechanisms for pressure, temperature and other environmental factors are behind many of the problems related to sensors’ accuracy. Fuzzy logic has been proven successful to detect data corruption as shown by Wakefield et al. [10] with an application for off-board post-analysis of the data which was included as a part of a larger tool for structural health analysis.

Data buses limitations

Modern airplanes use several sensors which are connected to different computers through data buses, and they have a limited capacity. Monitoring systems normally require data with very high resolution and, usually, in a nearly constant flow. These requirements can exceed the maximum capacity of the buses which is rarely available due to the normal flow of data between systems required to fly the aircraft. Retrofitting modern buses would offer higher performance, but they might not be compatible with all the subsystems already in place. Increasing the wiring also increases weight and the risk of a faulty wire or connector. Besides, both options are nearly impossible to be applied on legacy platforms unless they are carried out during a major upgrade. Even when the internal communication system is not upgraded, the use of new health monitoring tools requires bus scheduling reprogramming.

Nowadays, the standard bus used in commercial aviation is the ARINC 429 or Mark 33. ARINC 659 is an evolution of the original ARINC 429 already installed successfully on the Boeing 777 [112]. Many US military airplanes have used the 1553 data bus since it was introduced in 1973 and has since been upgraded by the use of optic fibre in what is known as the 1773 data bus [113]. Computer buses like VME have been used on numerous military applications.

In order to increase the capacity of the buses and, at the same time, reduce the wiring, it has been proposed to use wireless communication. Dusndon and Harringdon [114] describe a Remote Interface Unit (RIU) that can be installed next to the sensors and collates and digitises up to 200 signals which are then sent wirelessly to the health monitoring system.

On-board/off-board applications

It is impractical to process all data on a ground stations since it would require a huge amount of on-board memory (increasing weight and cost) and a long time to download all the information. Once the data have been compressed they can be transferred to the ground station using either a wireless connection or a smaller and lighter memory cartridge [105; 115; 116]. Therefore, when an IVHM system is developed for an aircraft it is necessary to define to what extent the analysis is going to be carried out on-board and what will be left to be finished in a ground station.

On the other hand, carrying out all the analyses on-board is nearly impossible since it would require significant computer power on-board and some of the data required for prognosis is only available on the ground. Increasing processing capacity means increasing weight and cost. Furthermore, the certification of additional on-board software packages can be very expensive [116].

To find an optimum solution it is necessary to find and equilibrium between both extremes. Swearingen and Keller [105; 116] propose to carry out the data acquisition, data manipulation, state detection and health assessment on-board and leave ground based modules take care of prognosis and decision support. Health assessment can be implemented on both platforms and even divided between them. The final decision will depend on the compromise between the weight of the on-board systems and the compression of the data.

<u>Data processing and storage</u>

As explained by Keller *et al.* [117], most health monitoring algorithms are too demanding for current on-board master computers and upgrading on-board computers can be extremely complex and expensive, specially taking into account the certification process.

Off-board analysis, on the other hand, avoids the need of modifying key hardware components, but it means that the information must be stored during the flight to be then downloaded. It is possible to use the data stored on the crash survivable memory for further analysis, but the information recorded might not comply with the requirements of some health analysis tools. Most modern aircraft use additional storage systems for maintenance purposes, but as demand for data increases with new diagnostic and prognostic tools their capacity will have to be increased [117].

Finding 9: Working with legacy platforms implies having to work with hardware originally installed for purposes different from health monitoring. Upgrading the hardware is very expensive and, therefore, the data fed to the health monitoring algorithms might not suit the requirements of the tool to generate reliable results.

2.3.1.3 Implementation issues

Standardization

The lack of a common architecture for developing IVHM tools has limited the development of the technology by forcing engineers to design health monitoring systems compatible with specific vehicles, increasing the cost of industry-wide compatible tools. Driver *et al.* [118] insist on the need to establish a set of standards which allow subsystem suppliers to increase the potential market for diagnostic and prognostic systems and ensure those who integrate those subsystems that the ensemble will operate correctly.

The industry is starting to follow the Open System Architecture for Condition Based Maintenance (OSA CBM). OSA was originated by Boeing under the Navy Dual Use Science and Technology program [115]. Later, the standard was supported by the Machinery Information Management Open Systems Alliance (MIMOSA) [102; 115]. The will to establish standards for IVHM technology boosted the development of a communications standard for transducers specific for health monitoring (IEEE 1451) and even standards for condition monitoring and diagnosis of machines (ISO 13374) [102; 114; 116].

OSA CBM is a layered architecture formed by seven different levels and each of these layers represents a group of similar functions and tasks. The architecture works in such way that any module of any layer can communicate with any other module belonging to any other layer. These layers are [29; 105; 115]:

1. Data acquisition
2. Data manipulation
3. State detection

4. Health assessment
5. Prognosis assessment
6. Decision support
7. Presentation

OSA CBM uses the Unified Modelling Language (UML) in order to be able to used different programming languages. Dunsdon and Harringodn [114; 116] have mapped UML for C++ and Swearingen *et al.* [114; 116] have developed it to use XML [114; 116]. The latter is especially useful for those developers who work on portable maintenance solutions since it is quite easy to apply to web services. Additionally, since the experts who can develop diagnosis and prognosis tools generally aren't software experts, a library of Simulink blocks has been developed. They chose this platform because many developers are familiar with it and it is capable of generating embedded C code.

OSA CBM has been used for the development of tools for the NAVAIR DUS&T Reconfigurable Control and Fault Identification System (RCFIS) and for the US Air Force DUS&T Advanced Electrical Power Health Management (AEPHM) program [115]. However, it has not been implemented yet and is not applicable to legacy platforms without major modifications.

Performance metrics

One to the main difficulties of finding a suitable diagnostic or prognostic tool is the lack of information regarding the performance of the different solutions available in the literature. Although sometimes values for some widespread metrics such as fault detection percentages, fault identification percentages, failure ambiguity groups, and false alarm rates can be found, these variables are not comprehensive enough to fully describe the performance of a monitoring tool. Furthermore, there is not a standard defining these parameters which leads to ambiguous and inconsistent interpretations [52]. Saxena *et al.* [119] propose classifying the metrics based on either the end user requirements (operating, engineering and regulatory) or the function they represent (algorithm performance, computational performance, cost-benefit-risk).

Datta *et al.* [120] used an ETA to parameterise the performance of different IVHM tools based on the probabilities of different outcomes of several steps in the support process. Saxena *et al.* [121] have also proposed a comprehensive set of metrics for prognostics concerning accuracy, precision, robustness and cost/benefit, but their definition is still far from being standardized across the aerospace industry.

Systems integration and IVHM

Traditionally, aircraft's systems have been installed following a federated approach, with health monitoring systems being developed for specific subsystems. Many of them have a similar structure and even use some common data. Monitoring systems developed for different systems usually have different providers, each of them with its own architecture and ground equipment, which means that personnel have to be trained to operate all these modules. Furthermore, they could generate contradictory results very easily, making it necessary to check the components using traditional methods, eliminating any advantage of installing the monitoring systems in the first place [114]. To reduce cost and contradictory results, companies are developing unified systems in which data from all the sensors can be analysed by a vehicle-wide single monitoring system [114; 122].

Certification

Airworthiness regulations represent one of the main challenges that IVHM faces since modifications of hardware and software whose failure can affect the safe flight and landing of the aircraft or reduce the ability of the aircraft or the crew to fly under adverse conditions [123; 124]. These regulations cover design, manufacturing, integration and installation of any system installed on an aircraft.

In many cases it is necessary to modify the component being monitored to accommodate new sensors and this represents additional certification problems [125]. If this could be avoided, as long as the hardware used on a new health monitoring system uses components similar to existing certified products available in the market, certification can be relatively straightforward

The cost of software certification depends on the functions implemented since different functions require different certification levels. Taking into account that audio, visual and physical clues can be very distracting, a malfunctioning diagnostic or prognostic program can affect operations significantly. It is possible to take advantage of this progressive certification levels to introduce IVHM capabilities gradually reducing costs significantly. Azzam *et al*. [125] proposed the use of a certified architecture (including the timing scheduler to organize the execution of all processes) which would make the implementation of each new program a standalone task.

Finding 10: The lack of a standard platform for the development and implementation of IVHM increases development costs significantly, since putting into service the technology is limited to a case-by-case activity with high certification costs. This has the additional disadvantage of increasing the probability of integration problems appearing.

2.3.2 Organisational challenges

Since IVHM requires a commitment of the whole organisation to be put into service successfully, organisational issues play a key role from the development to the implementation of the tools. The problems that have to be faced by those involved in the design of IVHM technology are both structural and cultural, the latter being more difficult to tackle. The classification of most common organisational challenges face when retrofitting IVHM can be seen in Figure 2-3.

	Development	Implementation
Cultural	• Lack of compromise • Unwillingness to share information • Focus only on technical criteria • Low attention on keeping exhaustive records • Scepticism leads to little resources allocated to IVHM	• Resistance to shift from traditional maintenance procedures • Little benefit perceived despite significant improvement reached • Unwillingness to share information
Structural	• Lack of specific development tools • Use previous designs (with pre-existing problems) • Ambiguity of goals • Several organizations per project • Lack of accountability	• Uncertainties at the start of projects are not updated • Cost of case-by-case implementation • Lack of design reviews to check if integration requirements are met

Figure 2-3 Classification of most common organisational challenges regarding retrofitting IVHM.

2.3.2.1 Development

<u>Program planning</u>

Aircraft manufacturers often lack the expertise necessary to understand the potential of certain technologies and, therefore, tend to avoid health monitoring techniques that are not fully matured, limiting the development of IVHM technology [52]. Additionally, the scepticism based on previous failures to meet expectations has made it difficult to justify the development of some diagnostic of prognostic tools.

Developing a fully operational prognostic tool is a very long process. In most cases a successful diagnostic tool is necessary before attempting the development of a prognostic tool. However, presupposing a set of BITEs and Fault Detection Isolation and Recovery (FDIR) techniques based on previous designs often leads to removing and adding features several times, increasing the development cost [126]. Additionally, according to Hess *et al.* [109], maturation time can become very long and this must be taken into account when the development program is planned, especially for those cases where the roots of the fault are random or the physics of the degradation are not well understood.

Deviations from the original development plan are very common, especially among incoming managers who didn't take part in the original planning and who also refuse to abide by agreements made by their predecessors [126], producing as a result a lack of accountability which increases the chances of repeating the same mistakes.

Ambiguity when the goals are defined during the initial stages of the design of a new tool often result in unsatisfactory results. Tsang [127] mentions how in the past it was very common to have objectives such as "minimize the costs" or "maximize the availability".

The development cost of IVHM tools is usually too high for a single platform program and should be divided among different programs [109], but this introduces new organisational problems when different teams, with different priorities and dynamics, have to work on the same product. When different companies are involved in the same project this problem aggravates [122].

It is easy to find in the literature different strategies for the design process, although they remain relatively vague. Tsang [127], being one of the few with specific solutions, proposed a decision tree for classifying failure modes and determine the best applicable solution. Wilmering *et al.* [86] followed a systems engineering approach which consisted of five stages: requirements development, system/functional analysis, design synthesis and integration, system test and evaluation and system maturation. Beshears *et al.* [128] have developed a closed loop design methodology to implement health monitoring in some of Raytheon's products which also consists of five stages: requirements analysis, analysis/design influence, resting, reasoned development and fielding.

Resources

Since there are no standards established for IVHM technology, engineers often start from scratch or use pre-existing tools as a base for further development. This means that there are very few design tools specifically developed for designing monitoring systems and in many occasions teams have to develop their own [122]. Although Boeing has developed some programs such as the Diagnostic Tool Suit (DTS) or AutoTEST they are specific for their fleet and do not take into account all the aspects involved in IVHM [29].

According to Hess *et al.* [109], given the little popularity of health monitoring techniques when compared to other programs in the aerospace industry, funding cuts tend to be more severe for them and this should be foreseen by preparing specific benefit justifications.

Aircraft manufacturers act many times as system integrators, therefore subsystems suppliers are required to design their products with health monitoring capability or even retrofit it. This can eventually cascade down to component suppliers who normally do not have the technical expertise, tools or capacity to deliver these capabilities, meaning that knowledge, resources and costs need to be shared [52].

<u>Information</u>

Information regarding failure modes, maintenance procedures and cost is indispensible to develop new diagnostic and prognostic tools. However, given the large number of different players in the overall support process, obtaining the necessary data can be extremely difficult. Economic parameters, essential for a cost-benefit analysis are the most difficult to obtain. According to Hess *et al.* [109], lead-time interval, or the time between an accurate prediction is generated and the moment the component has to be replaced, is key for the designer. To determine the optimum value of this parameter it is necessary to analyse the effect on the overall maintenance process of different lead-times. This information is rarely available and the designer tends to focus on optimising the accuracy of the tool if no economic criterion is available.

The lack of information is not always related to the unwillingness to share it, but to the fact that sometimes, records of some parameters are not kept. In order to automate part of maintenance and logistics it is necessary to carry out an analysis of these processes. Since many times processes emerge from history, they are not well documented, making it difficult to be understood by people not involved in them. Additionally, if a process is unstable and is executed differently each time, it becomes impossible to model. A lack of stability means that the structure of the process changes depending on the situation whilst flexible process can still be modelled as long as their structure remains unchanged. Therefore, and as stated by Hausladen *et al.* [45], only processes with a certain level of complexity and a significant volume of activities generate value by being automated.

Finding 11: Previous problems with the development of IVHM tools have created certain scepticism within organizations which eventually diminishes the interest of some of the people involved in their design. This lack of commitment can make it difficult to obtain the resources and information necessary to reach the objectives.

2.3.1 Implementation

The introduction of IVHM faces important cultural challenges within the organisations involved that include breaking with tradition and shifting mission operations and ground operations paradigm. It is very common that, even in those cases in which a new tool has worked successfully throughout its first development phases, it fails to perform as expected when it is integrated with other systems.

Traditionally, monitoring systems where installed on a case-by-cases basis, with different modules for different systems. The installation of these modules required a lot of time, reducing the availability of the aircraft increasing the costs even further [114]. Inadequate program management has created situations in which many subsystems worked according to the specifications, but the whole system didn't meet the costumer's expectations [126].

The uncertainties at the beginning of any project can lead to erroneous conclusions regarding the economic and organisational benefits of implementing a monitoring system. To tackle this problem Hess et al. [52] propose using a spiral development strategy to carry out the business case analysis to incorporate more detailed qualitative information as different elements are re-evaluated.

Surprisingly, Scandura *et al.* [126] report that one of the reasons so many problems are encountered during the implementation phase is the lack or misuse of design reviews. This creates situations in which the design of the monitoring systems does not comply with the specifications originally defined.

Finding 12: For a long time, IVHM has been relegated to projects focused on implementing isolated applications undermining the development of a strategy for implementing a comprehensive IVHM program. The complexity of retrofitting several tools remains an unexplored area, undermining the chances of success of future projects.

2.4 Conclusions

From the study of the literature regarding the state of the art of the technology underpinning IVHM it can be said that both diagnostic and prognostic tools have reached a level of development that leaves no doubt as to their capability to deliver the information necessary to improve maintenance management with the speed and accuracy required. Combining diagnostic and prognostic tools in integrated health monitoring system is still in its infancy but it has the potential to reduce development, implementation and recurring costs.

In regards to the optimization of maintenance using IVHM technology there seems to be an excessive focus on either reducing maintenance cost or downtime. Given the complexity of the contracts on aircraft maintenance services, a deeper understanding on how different stakeholders is essential and it should be taken into account in the optimization of maintenance activities.

The numerous technical and organizational challenges faced by IVHM as a discipline which have to be acknowledge from the very early stages of any project for the design of an IVHM system. Strengthening the business case with a robust quantitative underpinning seems the best way to ensure stakeholders stay involved and supportive throughout the project.

3 Research Questions and Methodology

"He who seeks for methods without having a definite problem in mind seeks in the most part in vain."

- *David Hilbert*

Following the findings from the study of the literature, this chapter aims to explain how these findings are transformed into a set of research questions which this thesis attempts to answer. The following sections explain the process through which these research questions were framed and the characteristics of the methodology followed to answer them.

In order to understand what would be the real contribution to knowledge if these research questions were answered, one first needs to know which are the gaps in the current knowledge that affect the development and implementation of IVHM technology. The existence of these gaps, which are listed in section 3.1, is justified by the findings from the literature review.

Filling these gaps has been the goal of the research project on which this thesis is based. As with any other project, aims and objectives were defined to be able to plan the necessary work and track progress (section 0). The reader will find easy to understand how these objectives were then transformed into specific research questions, as explained in section 3.3.

In regards to the methodology followed, like with any other research project aimed at developing a methodology itself, section 3.4 focuses on the techniques that were considered to be best suited to tackle specific problems identified by the research questions.

3.1 Gaps in the knowledge

The literature review has covered three main areas that affect IVHM as a field of knowledge or technical discipline: the state of the art of IVHM technology, the challenges faced when trying to justify its economic and operational benefits, and the challenges regarding the insertion of IVHM technology.

One of the main conclusions is that, as a discipline, IVHM (or PHM or any other term that denotes the family of technologies that have the functionalities included in the definition of IVHM given at the beginning of this thesis) is relatively young and, as such, there is a lack of experience regarding its development, implementation and exploitation. Some people may say that IVHM is, however, comprised of numerous disciplines that are well established and which have underpinned the development of technology and businesses for decades (e.g.: mechanical degradation, data mining, operational analysis, etc.), but the idea of integrating of all these technologies to deliver the capabilities IVHM promises is relatively new, and this where the main problem resides. As different health monitoring tools are combined to produce information that is supposed to affect maintenance, logistics and operations, the complexity of the problem increases exponentially. This problem is not exclusive to legacy platforms and affects any system on which IVHM could be implemented.

The question is not understanding how IVHM can improve maintenance operations and, subsequently, all the activities it affects and by which it is affected. The problem is being able to design an IVHM system with specific capabilities in mind for a certain platform taking into account all the technical and operational constraints a system of these characteristics will face.

This does not mean that it is not possible to design a viable and useful IVHM system. Nothing would be further from the truth. After all there are numerous examples of successful businesses based on the use of some kind of IVHM toolset. However, all these cases are the consequence of we could call a *reactive*, rather than *proactive*, approach to the development of IVHM technology (Findings 10 and 12 of the literature review).

IVHM systems are developed in a reactive way in that they are the result putting together a set of diagnostic and/or prognostic tools, each of which was developed solely on the basis that the benefits of monitoring that particular part outweighed the costs and the risk of development and implementation. This is normally happens as a result of a breakthrough in the understanding of the physics of failure of the part in question or by analysing data gathered by pre-existing sensors which allows to develop a model to correlate the degradation of the part with some parameters.

A proactive development of an IVHM system would involve setting a set of goals regarding the improvements expected from the use of such system (essentially improvements of maintenance costs and availability) and designing a toolset comprised of diagnostic and prognostic tools taking into account all interactions and how these affect the final result. Following this approach does not only result in better integrated health monitoring systems that can share hardware and information, but also takes into account the complexity of maintenance operations and how changing the frequency with which different parts are repaired or replaced eventually affects the availability of the fleet.

Some techniques for the design of IVHM systems have been proposed, as mentioned in the literature review, but they lack the quantitative underpinning necessary to make sure the system resulting from following any of these guidelines is the best of all possible solutions (Findings 5 to 7). The main reason is the difficulty of comparing the cost of developing a tool to monitor a component or improving its reliability by modifying its design, specially trying to correlate the improvement in reliability with the amount of money invested. In the case of legacy platforms this becomes much simpler because of the astronomical cost modifying parts means it is rarely an alternative to IVHM, since it can involve certification, retooling, problems with obsolescence, etc.

The lack of a quantitative approach to the problem means that it is almost impossible to battle the existing scepticism faced by IVHM technology (Finding 11). To get the support of the organizations the will implement, use, and ultimately benefit from an IVHM system one must prove quantitatively its financial viability.

As individual tools are combined into an IVHM system, the interactions between them add complexity to the problem. These interactions are not limited to the hardware and software. The most important effect of combining IVHM tools is the effect they produce as a whole in the decision making of maintenance operations. The information from all diagnostic and prognostic tools is used to improve maintenance schedules. Consequently, the total improvement in maintenance cost and time is not the sum of the contributions of each individual tool.

The conclusion of this analysis is the identification of an important gap in the current knowledge on the design of IVHM systems:

The field of IVHM is in need for a quantitative methodology to determine the best possible combination of technologies to monitor the condition of the components of legacy aircraft in order to produce an economic benefit.

The first problem faced in the design of an IVHM system for a given aircraft is choosing which components should be monitored. At first glance it would seem quite easy: simply focus on those parts that have higher maintenance cost per operating hour or are responsible for the longest downtimes. However, this has little to do with the degree to which IVHM can diminish the impact maintaining certain component has on maintenance costs and availability. To illustrate this problem imagine a valve of the hydraulic system of an aircraft which would take five hours to replace because it is very difficult to access and involves partially draining the system. Imagine now that, for a particular failure mode, the MTTD using conventional methods is ten minutes and the remaining time is dedicated to replacing the valve. Using a diagnostic tool would have a nearly negligible impact on the total downtime of the aircraft, not to mention the potential to cause problems by .producing false positives or false negatives. Therefore:

There is a need for a technique capable of identify which components present the highest potential to improve maintenance operations using IVHM technology.

In order to develop an IVHM system for an aircraft diagnostic and prognostic tools suitable for the selected components have to be found. From the literature we see that there are all kinds of organizations developing health monitoring technology, from OEMs to academic institutions. What is more important is to notice that there is not a single organization capable of developing a wide variety of tools on its own. The final IVHM system is, therefore, most likely be comprised of tools developed by and acquired from different companies.

Criteria for determining which tools can deliver the desired improvements in maintenance cost and time is key, not only to filter out those existing health monitoring tools that do not suit our needs, but also to establish design guidelines for tools that are still under development, but we might want to consider. The performance requirements for IVHM tools define the benefit they can generate and therefore must be calculated to attending to the need to improve maintenance time and cost. With this we identify another important gap in the current knowledge on the design of IVHM systems:

There is a need for a technique to determine the performance requirements for diagnostic and prognostic tools to achieve the desired improvements in maintenance cost and time of the components they monitor.

However, one must not forget that another issue that undermines quantitative analysis for IVHM systems is the numerous uncertainties that affect the variables involved. Since retrofitting IVHM on legacy aircraft sometimes imposes working with older hardware, the inaccuracy of the data fed to IVHM algorithms result in greater uncertainties (Findings 8 and 9). Working with legacy aircraft means basing CBAs on historical maintenance data which is not 100% accurate as will be discussed further on (after all no dataset can be 100% accurate). All this contributes to errors in any calculation one desires to carry out to design an IVHM system. Whilst the existence of uncertainties is known and accepted among the IVHM community –especially regarding the accuracy of prediction and diagnoses– design methodologies presented so far do not account for this problem. Therefore:

Design methodologies for IVHM lack the mathematical underpinning to include the effect of uncertainties on the resulting improvements in maintenance operations.

As with the rest of the discussions and findings in this thesis, the reader is reminded that these gaps are specific for legacy aircraft, although they could also be applied to other systems.

Having identified a series of gaps in the current knowledge on the design of IVHM systems, the next section present a list of aim and objectives for the research project on which this thesis is based.

3.2 Aim and objectives

The gaps mentioned in the previous section informed the decision as to what would be interesting to achieve in a research project that would make a significant contribution to the IVHM community. Justifying the investment on this technology and dealing with the complexity of larger and more integrated IVHM systems lead to the conclusion that what the aim of the project has to be:

Develop a methodology to obtain the combination of diagnostic and prognostic tools that will deliver the best possible financial return taking into account the effect of uncertainties.

In order to reach this goal the research project was given the following specific objectives:

- Develop a technique capable to identify the best components to be monitored IVHM technology in order to improve maintenance time and cost on a legacy aircraft.
- Develop a technique to calculate the performance requirements for diagnostic and prognostic tools to achieve the desired improvements in maintenance cost and time on a legacy aircraft.
- Develop a method to analyse the effect of interactions between IVHM tools on the financial viability of IVHM toolsets for legacy aircraft.

Project planning consisted in defining specific tasks to accomplish these goals in three years. Progress was monitored and assessed according to the degree to which objectives were being reached.

3.3 Research questions

The previous aim and objectives can be used as the base to define the research questions that have to be answered in this thesis. Since accomplishing the goal of the project involves reaching a set of objectives, the decision was made to set a main research question followed by a set of secondary research question.

The main research question that has driven this thesis is:

How can the optimal combination of diagnostic and prognostic tools for a legacy aircraft be chosen according to its economic merits taking into consideration the effect of uncertainties in the analysis?

The secondary questions are more specific and resulted in specific steps of the methodology developed for this thesis. For the selection of components:

How can the components of a legacy aircraft be selected according to their potential to improve maintenance cost and time using health monitoring technology taking into consideration the effect of uncertainties in the analysis?

Regarding the technical specifications of diagnostic and prognostic tools:

How can the requirements for diagnostic and prognostic tools be defined to produce a specific improvement in the maintenance cost and time of the component being motored?

Finally, the analysis of the interactions between tools requires answering the following question:

How does combining IVHM tools affect the economic return and the financial risk of investing on a given toolset?

The answers to these questions can be found in chapters 4 to 10 of this thesis.

Specifying the research questions helps to define the research methodology that need to be followed in order to find appropriate answers. The next section enumerates the different techniques that form the research methodology applied throughout this thesis.

3.4 Research methodology

The ultimate goal of the research project on which this thesis is based was the development of a methodology to configure IVHM systems. Consequently, the approach to arriving to a solution revolved around using different techniques to tackle independent parts of the problem. Since the idea is to estimate the economic return of a combination of diagnostic and prognostic tools, the methodology must focus on using quantitative techniques.

The first step involves understanding how the outcomes of faults change after the implementation of IVHM technology. The best way to conduct this analysis is using Event Tree Analysis (ETA). This technique helps to obtain analytical equations based on the probability of different outcomes of a given event. Subsequent events can be included resulting in a list of possible outcomes, each of which is given a probability. Since we are interested in understanding how maintenance times and cost are affected by IVHM systems, this technique proves to be helpful in generating equations to quantify the change.

As explained before, one of the main problems that affect any quantitative approach to designing IVHM systems is dealing with the multiple uncertainties present in the data used as inputs and assumption made by designers. Consequently, error propagation or propagation of uncertainty must be taken into consideration to understand how this will affect the accuracy of the result. Error propagation is a well-established field of statistics (see [129; 130]) and commonly used in experimental research. In this thesis the approach to error propagation consists in obtaining equation capable of characterising the probability distributions of the results.

The analysis of combinations of IVHM tools can be very complex, but if the aim is to determine how interactions between tools affect the ROI of the final system, it is not too much of a stretch of the imagination to analyse this problem from a financial perspective. Portfolio risk analysis has been used for many years to assess the risk of investing on different combinations of assets [131-133]. Whilst conventional portfolio analysis techniques proved not to be sufficient to analyse all the complexities of combining health monitoring tools, they provided a good basis for developing a mathematical tool capable of achieving this goal (mode details in chapter 8.)

The complexity of maintenance operations means it is not possible to parameterise aspects like operational availability of the effect of logistics using just analytical expressions. This calls for using computer simulations. Computer simulations of maintenance operations dates back to the 70s [134] and has been successfully used in industry and academia. The tendency in recent publications is to use Discrete Event Simulators (DES) to analyse complex maintenance operations. DES allows modelling the effect of implementing IVHM on a legacy fleet building models from the bottom up, focussing on the effect of monitoring individual components on a fleet of aircraft. There has been some work published on using DES to analyse the effect of IVHM on maintenance. For example, Szczerbicki and White [135], developed a model to be used a support tool for condition-monitoring service groups and Horning et al. [136] simulated using DES how the implementation of prognostic tools can affect the operational readiness of military aircraft (more examples are discussed in chapter 8). Whilst the examples of models found in the literature are not sufficiently developed to conduct the kind of analyses necessary to determine the financial outcome of implementing an IVHM system, they do provide a solid base to choose DES as modelling technique.

As the reader will discover, a lot of the work described in this thesis is centred on the development of a mathematical framework to provide the quantitative tools of a design methodology. These techniques provide the tools necessary to analyse the problem at hand and reach a solution for the problems stated in the research questions.

3.5 Conclusions

The literature review has helped to identify a series of gaps in the current knowledge of IVHM design that needed to be filled for the discipline to progress beyond its current situation. The need for a methodology to configure IVHM systems for legacy aircraft with an economic return as the ultimate goal has been identified as a key issue.

In order to develop this methodology the problem has been broken down into a series of objectives that, when completed, present a framework of quantitative methods to arrive at the desired solution.

The different techniques listed in the discussion on the research methodology will be described in further detail as the results they produced are commented in the relevant chapters.

Chapter 4 will describe the main aspects of the methodology proposed as a result of the research carried out. The different steps the methodology consists of will be discussed in subsequent chapters.

4 Methodology for the selection of IVHM tools

"What saves a man is to take a step. Then another step."
- Antoine de Saint-Exupery

The most important decision made at the beginning of in any engineering project is to define the aims and objectives. In most cases, engineers work with a set of technical requirements for a given budget. This budget is calculated based on an estimation of how much clients can be charged for a product with certain technical capabilities. However, in the case of IVHM, the final goal is to provide a service, not just deliver a product, making this process more complicated than usual.

It is evident that IVHM presents both economic and operational benefits. The relative importance of each factor depends on the operational needs. However, there is always a way to transform the availability of the vehicle into an economic return: operators can operate their fleet for longer periods and maintainers who charge based on the availability of the vehicles would also see their income rise. Therefore, the focus of this methodology will be to configure an IVHM system so the ROI is maximised.

The methodology described in this thesis[*] can be applied by any stakeholder interested in exploiting or selling IVHM technology. Developers of IVHM technology can use it to design IVHM systems for maintainers and operators. This methodology can also be used by operators of aging fleets to define the configuration of an IVHM system whose final design can be subcontracted to an engineering company. Maintainers can also use it to design an IVHM system that enables them to increase their profitability.

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[*] A summary of the steps of this methodology has been published as a conference paper (included in Appendix C):
Esperon-Miguez, M., John, P., Jennions, I. K., 2012, Implementing IVHM on Legacy Aircraft: Progress towards identifying an Optimal Combination of Technologies. 8th World Congress on Engineering Asset Management, October 2013, Hong Kong

In any case, it is essential to understand how the design and implementation is going to be funded (and by whom). Whilst there are still operators that remain in control of the servicing of their fleet, subcontracting has become widespread. From the supply of components to frontline maintenance, it is not unusual to find out these activities have been externalised.

Subcontractors can charge per activity (similar to any car garage) or based on the availability they provide. Normally the agreement between operators and subcontractors are a combination of both and include clauses for penalties and bonuses based on the quality of the service. This means that there are nearly as many different ways to charge operators for these services as there are contracts between them and the subcontractors.

This will be discussed in further detail in the following chapter. Suffices to say at this point that the key to estimating the ROI of an IVHM system is to understand how it is ultimately going to be financed and by whom.

Given the complexity of the problem and the fact that the profitability of an IVHM system depends on the effect it has on maintenance activities, it would seem obvious that the best way to design it would involve using some kind of computer simulation of maintenance activities. However, this is not as simple as it may seem. In the following sections we will discuss to what extent a computer model can be a useful tool and what are its limitations; why is there a need for a methodology capable of tackling these issues; and how such methodology works.

4.1 Computer simulations: advantages and limitations

Calculating the effect a set of diagnostic and prognostic tools on maintenance cost is a simple (if sometimes tedious) task because it is just a matter of comparing previous costs with the summation of the new labour and parts costs, and both can be estimated analytically. Conversely, the availability of a vehicle is much more complicated to determine because maintenance can be performed in parallel. Furthermore, maintenance tasks performed in parallel do not necessarily star at the same time and can be interrupted for various reasons and resumed later. Consequently, it is not possible to predict analytically the effect IVHM will have on the downtime of a vehicle.

Computer simulations of maintenance activities can be used to find a solution to this problem. Models can simulate the failure of components of a vehicle by working with random variables and the PDF of components' failure rates. They can then compare the resources available at any given time (e.g.: personnel and auxiliary equipment) with those necessary to perform any repairs and determine how long the aircraft will be grounded.

IVHM can affect the Mean Time To Repair/Replace (MTTR) and the frequency with which a component has to be replaced or repaired (by shifting from reactive/preventive maintenance to predictive maintenance). Analysing the benefits of using a certain IVHM system would only be a matter of modelling how the fleet's availability would change with these new parameters.

Simulating maintenance operations presents further advantages regarding the preparation of CBAs for IVHM systems. To begin with, they can also simulate the effect a health monitoring system can have on the stock of components and the logistic chain. Performing sensitivity analyses is also a straight forward task once a model is available, although it can be computationally demanding. Probably one the main advantages of a computer model is the possibility to work with random variables which helps to account for the multiple uncertainties involved in the process.

There are, however, limitations to what simulations can achieve, especially regarding the preparation of CBAs for IVHM systems. The ROI is measured as a percentage and is a relatively low number (ROIs are normally 10-20% per year) meaning the accuracy of the model has to be high enough to ensure the estimation of the ROI is trustworthy.

The Achilles' heel of modelling maintenance activities is data. These models need significant amounts of historical maintenance data to determine the PDFs of the numerous variables they use. The accuracy of these data is difficult to estimate which undermines the credibility of the results. This problem is not exclusive to computer models and affects anybody working with historical maintenance data (this will be discussed in further detail in chapter [insert cross reference]). What can undermine the development of a computer model is the difficulty to obtain data to develop and validate such model. Failure rates, cost and availability are normally very sensitive pieces of information and organizations are very reluctant to share them.

Above all, the main reason behind the need to develop an alternative to computer models to configure an IVHM system is the impossibility to simulate the effect all possible combinations of diagnostic and prognostic tools. For example, choosing 10 tools among 50 possible options results in more than 10 billion possible combinations. Whilst it is possible that there are several combinations that are not feasible for different technical reasons (e.g.: data bus limitations, need for computer power or geometric constraints) it is impossible to analyse them one by one. Therefore, there is a need for a methodology capable of comparing multiple combinations of IVHM tools according to their expected ROIs in an efficient and accurate manner.

However, despite their limitations computer models can provide all sorts of additional information that make the effort necessary to develop and validate them worthwhilst. They can be used at different stages in the design of an IVHM system (as discussed in the following sections) and we will discuss their use in chapter **Error! Reference source not found.**.

4.2 Assumptions to enable the selection of IVHM tools for legacy aircraft

The main idea behind this methodology is that it is possible to develop a mathematical framework to study different combinations of diagnostic and prognostic tools for legacy aircraft. As with any other mathematical problem, this involves setting a set of boundary conditions or constraints within which the problem is to be solved. Essentially, this involves regarding certain parameters as constants instead of variables.

The first question one should ask when given consideration to the implementation of IVHM would be: Is it worth developing, installing and supporting a tool to monitor a certain component when its reliability could be improved by modifying its design? Unfortunately it is not possible to give a definite answer to this question because it is impossible to correlate the cost of redesigning a part and its new reliability and maintainability with enough accuracy to make a direct comparison with IVHM technology based on the profitability of each option.

Whilst one might find interesting the idea of improving the reliability and maintainability of a component whilst the aircraft is still on the drawing board, matters become much more complicated once the aircraft has entered service, not to mention once it is no longer in production. Any modification to a component would require recertification, which can be too expensive to justify the savings on a single part. Furthermore, new components would have to be manufactured, incurring in the extra expense of modifying lines of production or even setting new ones from scratch if production has ceased. Although stocks of old part would not be rendered completely useless, their value would drop, which represents an additional cost.

Up to this point, the possibility of modifying components has been regarded as an economic problem, which would apply if the organization analysing the possibility of implementing an IVHM system was the OEM of such components. Operator and maintainer are unlikely to have the capability to undertake such task. Even subcontracting the redesign and production of the parts (a costly endeavour indeed) might not be possible due to intellectual property conflicts.

In summary, do we need an IVHM system at all? For legacy aircraft the answer to this question is: yes. Since the characteristic of components are not to change their reliability and maintainability can be considered constant. As a result, parameters such as failure rates are to be considered constant and delays, MTTRs and MTTDs can only change thanks to the information provided by IVHM tools.

This leads us to the next major assumption made in the development of this methodology. Analysing the effect health monitoring tools have on the support of a fleet requires a good understanding of how aircraft are maintained. In other words: reliability and maintainability data. To estimate if a given tool will produce a significant improvement on the maintenance cost and time spent on a certain component we first need to know what the original costs and times were.

Aircraft are designed taking maintainability into account from the very early stages of the design, but reliability and maintainability parameters cannot be estimated accurately enough once the design of components has reached a certain point. This does not mean that the data must be perfectly accurate. It means data, and ways of estimating their uncertainty, must be available. Legacy aircraft have been operated for thousands of hours and have maintenance records from which reliability and maintainability data can be obtained. The second major assumption would be that sufficient historical maintenance data for all of the aircraft's components can be produced.

Obviously, these boundary conditions define under which circumstances this methodology can be used. This is not to say that all the tools described in this thesis are rendered useless if these conditions are not met. But, overall, the main assumptions just described must be applicable to the problem at hand to be able to trust the results obtained.

Legacy aircraft satisfy these conditions, but so do other legacy systems. This methodology can be used to configure an IVHM toolset for any system (vehicle, machine or any item that is comprised of multiple components that have to maintained) whose design cannot be modified and for which there is plenty of reliability and maintainability data. Examples of system that satisfy these conditions would be military land vehicles, large ships or manufacturing machinery.

4.3 Methodology

The discussion in this section describes the methodology at a high level (Figure 4-1). Details regarding the necessary steps to perform all the actions described hare are included in the following chapters.

The starting point is an aircraft (or a fleet comprised of the same model of aircraft) and the first step is to gather as much information regarding the reliability and maintainability of its components as possible. Further details in chapter 10.

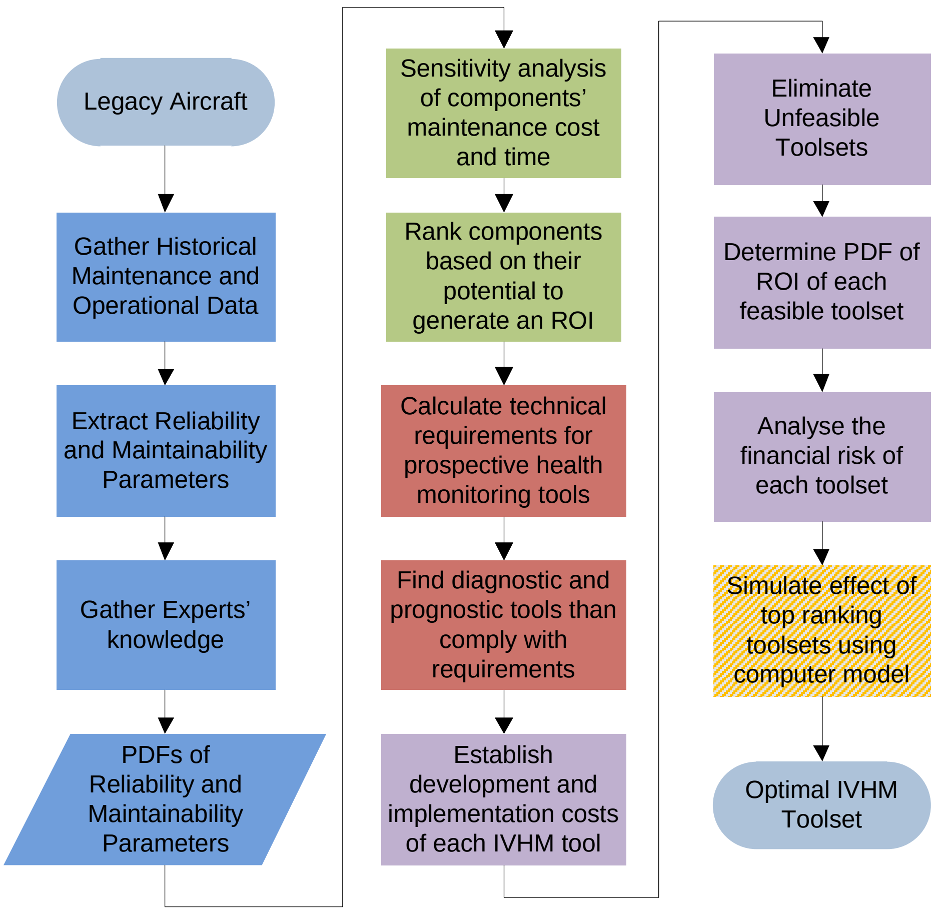

Figure 4-1 Flowchart of methodology to configure an IVHM system for a legacy vehicle. Details on the different processes can be found in chapter 6 (green boxes), chapter 7 (red), chapter 8 (purple), chapter 9 (orange) and chapter 10 (blue).

Once the PDFs of all necessary variables have been determined we proceed to identify which components should be monitored. The best way to do so would be to rank components according the sensitivity of the final ROI to the implementation of diagnostic and prognostic tools. However, at this stage it is not possible to estimate the ROI because it is a function of the platform's availability which, as explained before, cannot be calculated analytically. Consequently, components are ranked based on the sensitivity of maintenance cost and time associated to each of them to the performance of prospective diagnostic and prognostic tools. Further details in chapter 6.

The next step is to find health monitoring tools suitable for each of those components selected in the previous step. Technical requirements regarding the performance of diagnostic and prognostic tools are defined in this step to determine which tools of those available or under development can be used. Those in charge of designing the IVHM system can contact in-house departments or other developers of health monitoring technology to find which tools comply with these requirements.

These requirements are not just performance parameters of IVHM tools, but also their acceptable standard deviation. To this effect the analysis will not just revolve around reliability and maintainability parameters and will take into account their uncertainty.

Ideally, there will be several diagnostic and/or prognostic tools that can be used for each component. The number of tools and components being considered at this point has to be greater than the number of tools that will be included in the final IVHM system. The reason is to allow for as many combinations as possible to ensure the configuration of the IVHM system is optimal. Further details in chapter 7.

The final step compares the financial risk of the different possible configurations. The ROI to be expected from each tool is a random variable that can be defined by a PDF. As tools are combined there are multiple ways of sharing development and implementation costs. As a result of this, the ROI of each combination is a function that has to be calculated taking these savings into account (costs are no longer just the summation of the cost of each tool). Defining the PDF of each combination requires taking into account error propagation. Finally, all possible IVHM toolsets are ranked according the financial risk they represent. In doing so the IVHM toolset that represents the soundest investment is identified. Further details in chapter 8.

As discussed before, whilst maximising the ROI is the ultimate goal of investing in IVHM technology, there are multiple factors that affect the decision of which is the optimal configuration of an IVHM toolset. Whilst this methodology helps to identify which combination is optimal from a financial perspective, stakeholders would be interested in comparing those toolsets ranked highest using a computer simulation of maintenance activities. Having reduced the number of possible combinations from billions to a handful, the problem becomes much more manageable. Further details in chapter 9.

5 Economic Benefits of IVHM and role of stakeholders

"If it be now, 'tis not to come. If it be not to come, it will be now. If it be not now, yet it will come—the readiness is all."

- William Shakespeare

Health monitoring tools provide information that helps to make better informed decisions on the management of maintenance operations. This results in shorter downtimes, fewer unexpected maintenance stops and potential improvements –and cost cuts- in other activities such as operational management or the logistics and stock management of replacement parts. The viability of an IVHM system depends on finding a manner to translate these benefits into services or products to finance it.

The intention of the methodology described in chapter 4 (whose steps are explained in detail in chapters 6 to 9) compares IVHM toolsets based on their financial viability. It is crucial to understand the different ways in which retrofitting IVHM can result in savings and even new sources of revenue.

Besides the improvements in the management of the maintenance of a legacy fleet, the use of IVHM can result in additional savings in other areas (e.g.: personnel training, enforcement of quality policies, etc.). These secondary benefits must be taken into account in the comparison of the financial viability of different IVHM toolsets.

There are, however, external factors that limit the profitability of certain health monitoring tools that are not related to their technical limitations. Standards and regulations impose a series of constraints on what can be changed in regards to maintenance operations.

All these topics are studied in this chapter to provide a better understanding regarding the financial viability of IVHM toolsets for legacy aircraft. The contributions included in this chapter are:

- Discussion on the financing of IVHM technology for legacy platforms (section 5.1)

- Analysis of the impact of secondary benefits and case study (section 5.2)
- Analysis of the impact of standard and regulations and case study (section 5.3)

The initial expected benefits expected from each tool are to be calculated following the indication from this chapter*. The findings from this chapter are essential to put in practice the methodology described in the following chapters.

5.1 Financing IVHM technology

The benefits of using tools capable of detecting a failure and identifying the faulty component or even predicting the failure of a component are self-evident. Developing a structured business plan to specify how an IVHM system is to be financed, on the other hand, can be more complicated than originally anticipated.

The needs of different stakeholders are usually taken into account in business analysis methodology developed for IVHM (e.g.: Fan et al. [137]), but since the methodology presented here follow a bottom-up approach we are concerned about how stakeholders define the profitability of IVHM systems.

The difficulty resides in the fact that the support and operation of a fleet of aircraft involves multiple stakeholders, some of which would benefit from the use of this technology, but in different ways. Operators will enjoy an increase in availability. Maintainers will see some of their cost diminish. Providers of spare parts could reduce the stock of components they keep and improve their supply chain.

Traditionally, some organizations would play several of these roles at the same time. Military organizations used to be in charge of every aspect from the acquisition to the disposal of the aircraft. Airlines used to own maintenance divisions in capable of maintaining their fleets. Outsourcing has atomised the

* Both case studies, which are the results of conducting these analyses for military aircraft operated by the MoD, were published in a conference paper (included in Appendix C):
Esperon-Miguez, M., John, P., Jennions, I. K., 2012, The Effect of Current Military Maintenance Practices and Regulations on the Implementation of IVHM Technology. IFAC Workshop A-MEST, 2012, Seville

division of responsibilities into a chain of subcontractors. Whilst there are some airlines that still maintain their own aircraft and air forces still keep full control of the support and operation of some squadrons, these are the exception rather than the rule.

Fan and Jennions [138], produced a list of IVHM stakeholders including all aspects besides the economic:

- Pilot
- Operator
- Technician
- Other aircraft
- Systems engineers
- Maintenance engineers
- Legislators
- Vendors/OEM
- General Public
- Finance managers

Whilst this list includes individuals rather than organizations they can be extrapolated. For an analysis of the main financial benefits of IVHM the relevant roles are:

- IVHM developer
- Operator
- Maintainer

The developer will just focus on the design of IVHM toolsets for operators, maintainers, or both. From his perspective, IVHM technology has to be sold for a profit to a user. The financial analysis can be carried out by the developer to pitch a health monitoring system to an end user, or by the end user to determine whether they should contact with a developer of IVHM technology. Said developer can be the original manufacturer of the aircraft, manufacturers of aircraft systems, independent developers of health monitoring technology, or even the operator or maintainer if they have the technical capability to undertake such project.

Although it is possible to enumerate the multiple advantages and disadvantages of installing health monitoring tools on an aircraft, it is necessary to determine which are really relevant for each platform. Evidently there are major differences in the way stakeholders perceive these issues for different vehicles, specially taking into account how the goals change from civilian to military platforms [76].

However, before each benefit can be allocated to a specific stakeholder we must find a way to calculate how these can be turned into profits. As explained in chapter 2, performing CBA for IVHM is an active area of research. There are numerous publications which divide maintenance cost and times into different elements to study how IVHM affects each of them (see [84; 139]). However, analysing the changes experimented by each of these variables by each tool is a time consuming task.

Analysing the potential effect of diagnostic and prognostic tools of all the components of an aircraft requires focusing on those aspects that are more likely to be substantially changed by the implementation of this technology. For this purpose, the main economic benefits of implementing IVHM have been divided into:

- Increase of availability: For the operator this can mean more flights over the same period. If the fleet is maintained using an availability based contract this can result in the maintainer receiving a bonus from the operator.
- Reduce maintenance cost: These savings are generated through the reduction of time to isolate faults and a better management of maintenance tasks thanks to the foresight provided by prognostic tools.

There are other economic benefits as a result of the improvements in maintenance operations and the information generated with health monitoring tools. Improvements in the allocation of resources and personnel time can come as a result of implementing an IVHM system. These secondary benefits are not necessarily the main reason a health monitoring tool was originally conceived, but can be significant in regards to the overall profitability of the tool. These secondary benefits and the way they should be analysed are discussed in the next section of this chapter.

IVHM can also result in all sorts of intangible effects that, whist real, are impossible to quantify. This is the case of the competitive advantage of maintainers that can guarantee a higher availability thanks to IVHM. Another example would be the increase in safety if an aircrew could be informed of the specific nature of a minor technical problem instead of deviating their attention to diagnosing it themselves. However, since it is not possible to assign an economic value to these benefits a priori, they cannot be considered in a CBA and therefore not included on the calculations of the expected profits generated by individual tools.

5.1.1 Increase of availability

The increase of availability has to be given a monetary value to determine the profitability of an IVHM system. This economic value will depend from which stakeholders' perspective the profitability is analysed.

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 and maintainer 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. Whilst 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 5-1.)

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 ROI will diminish without an increase of revenue.

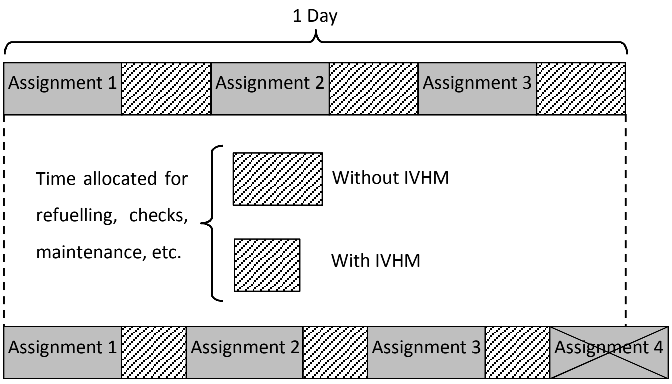

Figure 5-1 Example of how reducing the time allocated for maintenance can result in no operational gains if additional assignments cannot be scheduled.

If the organization interested in investing on an IVHM system is the maintainer (and it is not part of the same organization as the operator) the increase of availability can result in an increase of revenue if the maintenance of the fleet is regulated by an availability-based contract. Whilst there are possibly as many varieties of availability based contracts, clauses to incentivise improvements in availability by paying bonuses are common practice. These bonuses are normally established for discrete increases in operational availability, not on a continuous basis. The result is similar to the problem described from the operator's perspective and the profits from an IVHM system will depend on its availability to make improvements in operational availability that are significant enough to generate an increase in income.

If the maintainer does not have an economic incentive to improve the availability of the aircraft –either because it is not operating under an availability contract or because bonuses are not contemplated–, this operational benefit cannot be taken into consideration.

5.1.2 Reduction of maintenance costs

Diagnostic and prognostic tools perform different functions that are aimed at producing the same outcome: reduce maintenance cost and time. The way each groups achieves this objective, however, is quite different.

From a purely monetary perspective modern diagnostic tools present two main advantages over conventional methods to detect and isolate faults: shorter diagnostic time, resulting in lower personnel; and higher accuracy, meaning fewer false positives and cannot-duplicates. Obviously, this is not always the case since diagnostic tools are never 100% accurate, but any diagnostic device whose inaccuracy makes it a worse option than whichever method is being used at the moment should not be part any IVHM toolset.

Prognostic tools, which are normally praised for helping to avoid the failure of components in service resulting on a higher availability, also have an impact on the normalised maintenance cost of the components they monitor. To begin with, there is no need to diagnose a fault, which reduces labour costs. Additionally, the hourly labour cost is lower for preventive and predictive maintenance time than for reactive maintenance because the replacement of parts is scheduled trying to avoid the need for overtimes or night shifts if these are more expensive. Last, but not least, scheduling maintenance tasks in advance results in fewer and shorted delays and a better use of auxiliary equipment resulting in a smoother operation and lower costs.

The calculation of these changes in maintenance costs are discussed in more detail in section 6.1.2 as part of the identification of critical components for the use of health monitoring tools. The potential changes of maintenance policies enabled can produce further benefits [140], but since these changes are hypothetical their effect should be ignore to ensure the benefits of IVHM are not overestimated.

It is important to note that, unlike the additional income perceived thanks to an increase of availability, the benefits of shorter or better scheduled maintenance actions are not reflected in an increase of revenue. The result is cost avoidance

[92; 141]. The consequence of this dichotomy is that the perception of the beneficial effects of an IVHM system can be undervalued, for no extra income will be received and the benefit of parts “not failing” thanks to prognostic tools can only be appreciated in the long term.

In any case, the reduction of maintenance cost will benefit mostly the maintainer of the fleet who will see its margins increase. This means that regardless of whether the support of the fleet is defined by an availability-based contract or not, the savings on their own can enough of a justification to invest on this technology. From the operator’s perspective, the reduction of maintenance cost is only beneficial in the degree to which it will be able to renegotiate maintenance fees. This is not a problem for the numerous organizations that operate and maintain their own aircraft.

5.2 Impact of secondary benefits

The information generated using IVHM systems can produce benefits beyond shortening maintenance times and delays. Whilst these may be the main reasons to justify the investment on a health monitoring system, there is a potential to improve other aspects of the support and operation of a legacy fleet.

These tools can be used to, among other things, enforce quality policies [142], to reduce costs in manufacturing, testing and certification phases [126; 143], to react automatically to a fault [144]; and to generate all sort of benefits for stakeholders that are not directly involved in manufacturing, supporting or operating the vehicle [145]. It is important to realise that some of these secondary benefits can be used to develop new business practices with the potential to reshape the way cash flows through the aerospace sector [146].

The challenge resides in quantifying these benefits and allocate them to specific diagnostic and prognostic tools so different IVHM toolsets can be compared. This is not always possible for all the secondary benefits listed in the literature either due to the complexity of estimating said benefits, or due to the lack of data to quantify the benefits that should be expected from new business practices underpinned by IVHM.

Nevertheless, it is still possible to study the potential improvements and savings on the following areas:

- Flight tests
- Personnel training
- Administrative tasks
- Auditing
- Quality policies
- Logistic Information Services
- Data transfer

The improvements IVHM can bring to these factors are discussed in the following subsections. The results of a case study to analyse these potential benefits for a military fast jet are discussed in section 5.2.9.

5.2.1 Test Flights

Most CBAs focus on the how computer aided diagnoses improve the efficiency of maintenance jobs by reducing the time necessary to identify and isolate a fault. If a prognostic tool is being considered, the deferral of the job until it can be carried out at more convenient time is regarded as the main benefit. In some cases the increase in the number of missions completed successfully is also taken into account in the analysis. However, the effect of test flights is rarely mentioned in the literature and is missing from most comprehensive quantitative CBAs.

Test flights are common practice for diagnosing problems or for checking that a job on some critical system was completed correctly. The decision to use a health monitoring tool on a certain component is normally based on the frequency of failure of the component, the time necessary to repair it and its cost. However, test flights can be necessary on cheap reliable components which are not normally regarded as candidates for the use of IVHM. Perkins [147] showed how the cost of replacing a rotor bearing on a Chinook is largely driven by the cost of the test flight, which is several orders of magnitude higher than the cost of replacing the part. If the maintenance of the vehicle is outsourced, the cost or loss of availability due to a test flight might not be considered critical by the maintainer, but it still affects the operator.

Whilst the cost of a flight test can be easily calculated, the allocation of the cost and the analysis of the effect of the test on the availability of the vehicle might not be that simple. Depending on the requirements the test can be carried as part of a routine flight (known as Partial Test Flights, PTFs) or it might need a specific maintenance flight (known as Maintenance Test Flights, MTFs). It is not uncommon for test flights to be repeated because additional work or adjustments need to be made (e.g.: helicopter rotor balancing). Diagnostic and prognostic tools have the potential to reduce the duration of certain test flights or even eliminate them, but computer models which simulate both maintenance operations and fleet management are necessary to quantify the improvement on availability.

5.2.2 Personnel Training

It is often claimed that the use of computer based diagnosis and electronic documentation can help to reduce the amount of time personnel dedicate to training. Whilst this claim is evidently true, it was not clear to what extent this would produce a significant improvement in personnel availability and productivity. This will depend on the proportion of time personnel dedicate to training activities.

5.2.3 Administrative tasks

Theoretically, the information generated automatically by diagnostic and prognostic tools can be used to automate all sorts of administrative tasks. Form placing orders for components to the generation of maintenance reports, using IVHM tools in combination to the appropriate IT systems has the potential to save time and money. Furthermore, maintenance organizations dedicate time to analysing ways to improve their processes, an activity that could be assisted by IVHM.

To determine if these savings are worth considering in a CBA, the key variables are the proportion of time personnel dedicate to administrative tasks and what portion of said time they spend on each type of task.

5.2.4 Auditing

Maintenance practices of legacy aircraft must be reviewed to take into account any unforeseen changes in the way they are operated, their components degrade or the way they impact the support systems of other platforms. Structural, systems and propulsion audits are carried out to verify the airworthiness of the aircraft and that the operational and maintenance costs are under control.

These audits are exhaustive and can take years to complete resulting in a significant expense. The analysis of historical maintenance data is the core activity of these audits and requires going through numerous documents to put the information together before any kind of analysis can be performed. Health monitoring tools can store the same information in digital format making it accessible at any time much faster than it used to be. Additionally, they allow for much more component-specific information to be stored, improving the detail of the analyses that can be carried out. Furthermore, data mining techniques can be used to detect trend hidden in the data that would be missed in a conventional audit.

5.2.5 Quality policies

Most maintenance organizations that work on the support of military aircraft, either subcontractors or ministries of defence, meet the basic requirements of ISO 9001. This quality policy is to be applied to both fixed and rotary wing aircraft.

In case an issue regarding the quality of any of the activities or systems involved is detected it must be reported immediately through the generation of an occurrence report. The quality of an activity is considered to be compromised when normal fault reporting cannot be applied, problems with the technical information have been detected, problems regarding the information contained in reports are found or when there is suspicion of a deficiency in the management of the quality policy [148; 149].

Time is normally an important factor when these occurrences are investigated since most organizations expect that the report must have been received, the matter must be studied, and subsequent action recommended, within 7 working days.

Health monitoring tools can help on two main areas regarding this matter. First, they provide additional data that can help to better understand the issue in a format that allows for all sort of computer-based analyses to be carried out. Second, they are time-saving tools that accelerate the generation of occurrence reports and investigation of the problem. And third, a comprehensive health monitoring system implemented on the whole fleet can be used as the basis to partially automate the detection of deviations from the quality policy by detecting abnormal fault rates.

5.2.6 Logistics

A Logistics Information System (LIS) comprises electronic information tools used for the management of the logistics operations capable of performing any combination of the following functions [150]:

- Administrative
- Financial
- Asset management
- Maintenance management

Using the information generated with an IVHM system in combination with a LIS can result in major savings in maintenance cost and a reduction in delays. However, whilst these benefits are possible in theory, the real value IVHM can bring will depend on the capabilities of the LIS, which will have to be studied on a case by case basis.

5.2.7 Data transfer and management

Most health monitoring systems currently in use, such as HUMS (standard in all modern helicopters) or Typhoon's Integrated Monitoring and Recording System (IMRS), rely on some sort of Portable Maintenance Data Stores (PMDS) to download the data. PMDSs are memory cards that are removed after each flight and then taken to a ground station. Although sometimes it is possible to read the arisings onboard through some kind of Maintenance Data Panel (MDP) installed on board of some aircraft, it is still necessary to download the information from the PMDS to carry out an analysis with enough depth.

All the steps involved in this part of the process can take several minutes, especially in those cases in which the data are first sent to a centralised system and then they have to be requested from the ground station again, increasing the amount of time wasted. This must be acknowledge in the CBA to make sure the time gained through installing an IVHM tools does not end up wasted transferring the data.

5.2.8 Gathering data through questionnaires

Some of the information than needs to be gathered to conduct these analyses is also relevant to conduct computer simulations of maintenance operations. The information generated using these models can be useful to compare reduced numbers of IVHM toolsets and a recommended step of the methodology described in this thesis (this topic is discussed in further detail in chapter **Error! Reference source not found.**). Therefore, dedicating resources to this task is justifiable.

Questionnaires distributed among maintenance experts are the best option to collect this kind of information. Maintenance organizations collect most of these data for their daily operations and they should be readily available. For this purpose, a generic questionnaire was developed (see Appendix A.)

5.2.9 Analysis of potential secondary benefits on a maintenance organization

A questionnaire was prepared and distributed within a maintenance organization belonging to BAE Systems to carry out a case study. The answers to the questionnaire helped to shed some light on the potential of new diagnostic and prognostic tools to generate additional benefits to those discussed in section 5.1. Answers correspond to the support of a military fast jet.

According to the answers to the questionnaire, approximately only 10% of test flights are MTFs, which can lead experts to believe that analysing the potential of IVHM to improve costs and downtimes in this area is not worth the effort. However, the answers also showed that about 70% of PTFs are not carried out in combination with a routine flight, effectively having the same impact as an MTF. This shows that operational demands play a major role in the way test flights are planned.

Regarding personnel training, it is estimated that, over a year, nearly 10% of the total man-hours are spent on training, 50% of which are dedicated to learning on check, damage evaluation and failure diagnosis. Therefore, the gain of man-hours due to a reduction in training by the use of diagnostic tools would be, at best, 5%. Nevertheless, there is potential to make important savings if less experienced personnel (with lower salaries) can be dedicated to more complex tasks thanks to the use of IVHM.

As for personnel working in the technical offices, it is estimated that 30% of their total man-hours are spent on administrative tasks and logistics, meaning that the use of automated decision making tools could help to reduce not only the delays, but also the fixed costs of personnel. Currently, less than 25% of the time left is dedicated to activities aimed at improving the efficiency of the maintenance process, part of which is spent analysing historical maintenance data, something that could be significantly reduced if IVHM data-based tools are implemented.

The questionnaire helped to shed some light on the effect administrative task have on the availability of personnel with hands on the aircraft. Of all the delays affecting maintenance tasks between 10% and 15% are delayed because the necessary personnel are not available. Most of the delays come as result of the maintenance tasks requiring more time than that available between missions. Therefore, little improvement can be expected from focusing on micromanaging workers, given the complexity of such task, compared to what can be achieved by using IVHM to improve the performance on logistics and administrative tasks. Especially taking into account that approximately between 10% and 15% of maintenance personnel’s time is dedicated to administrative tasks, a proportion that can be reduced as the different IVHM tools become more integrated with logistics.

The potential to integrate a health monitoring system with the existing military LIS was found to be limited. Although there are LISs already in place to a higher or lesser degree in most modern air forces in NATO, currently they are normally limited to electronic tracking of orders and stock, with no automation based on the information from IVHM systems.

The rest of the work consisted in studying the potential of IVHM to help to conduct quality audits. According to the UK’s Ministry of Defence (MoD) quality standards the first set of audits starts 15 years after the aircraft was declared in service or at 50% of its expected operational life. In most air forces these audits are to be repeated every 10 years.

The integration of logistics with the use of health monitoring tools is key to ensure the success of an IVHM system, but it is important to keep in mind that, according to the answers received to the questionnaire, about 10% of the times an aircraft is not available for a mission the cause is a logistics or administrative delay. Although this shows that an improvement in the management of logistics can have a noteworthy impact on the availability of the aircraft, it is necessary to keep in mind that the cost of developing and implementing these technologies is high and might not justify an increase in availability that might not reach 10%.

A study based on the same structure and using in the same questionnaire should be conducted to ensure all significant benefits are taking into account in the CBA of an IVHM system. However, standards and regulations can limit the reach of health monitoring systems and undermine some of the benefits here discussed. This is the topic of the next section.

5.3 Limiting effect of standards and regulations on economic benefits

The first two sections of this chapter cover the different sources of revenue and mechanisms to reduce maintenance cost that justify the investment on health monitoring tools. Understanding these concepts is essential to estimate the profitability of individual tools and will prove to be critical in future chapters. The reader is reminded that many of these benefits imply changes in current maintenance practices.

Maintenance activities in the aerospace sector –both civilian and military– are subjected to stringent regulation and controls. Standards and regulations are put in place to ensure the airworthiness of the aircraft is guaranteed. Sometimes, the by-product of imposing these regulations is limiting the implementation of health monitoring tools.

The problem lies in the fact that CBM has been used to different degrees for long enough to become part of the regulations. It is not uncommon for regulations to impose the use of some condition monitoring procedure or device to assess the condition of a component. Installing a tool to monitor the degradation of the same component would be redundant.

This leads to two possible scenarios. Sometimes a specific procedure or tool must be used with a certain frequency to determine the state of a part, but the decision on how to act based on this information is not strictly defined in the regulation. This leaves the door open to the use a more accurate prognostic tool in parallel. The improvement in accuracy must result in savings that justify the cost of implementing and running the new tool as well as continue using whichever method the regulation imposes.

The worst scenario is that in which the only information on which maintainers can act is that produced by the method or tool referred to in the regulation. In this case, implementing a new health monitoring device will only result in an expense.

From and R&D perspective, using a prognostic tool along an existing condition monitoring tool or process can be seen as a viable validation method. This can lead to experimental results that prove the advantages of the new tool and, eventually, a modification of the regulations. However, this is too speculative to be taken seriously in any CBA.

These problems were considered in a case study that is described in the following subsection. This study was conducted on current maintenance regulations imposed by NATO and the MoD.

5.3.1 Case study

A study of maintenance regulations and standards was carried out as part of a viability analysis of IVHM technology for military aircraft. The analysis covered those procedures that are imposed on all MoD aircraft. There are additional maintenance procedures specific for each aircraft that were beyond the scope of this analysis.

The MoD has put in place a set of procedures for the use of information generated by the use of health monitoring tools. In order to assess the development and implementation of new diagnostic and prognostic tools and systems related to them the MoD has prepared the Equipment Usage Condition Monitoring and Management Strategy (EUCAMS). However, despite EUCAMS, regulations still impose limitations on the benefits that can be expected from some health monitoring tools.

After studying MoD and NATO maintenance standards, three applications for which CBM is already regulated were identified:

- Vibration control in helicopter transmissions
- Wear debris monitoring

- Hydraulic fluid monitoring

Any IVHM tool focused on these issues is unlikely to be justifiable from an economic point of view.

5.3.1.1 Vibration Control

HUMS is standard on all MoD's helicopters [151] and additional monitoring techniques are continuously being developed. Vibration monitoring is a widespread method to assess the health of all sorts of rotating equipment and it is used by the MoD on aircraft engines, transmissions and even structures. Vibration sensing is also used as part of the standard procedure for Rotor Track and Balancing (RTB) and propeller balancing.

Forward maintenance organizations (first line maintainers of the MoD) must measure the vibrations after maintenance activities such as rectification, fitting major assemblies, events that may have affected the natural frequency of some systems (e.g., heavy landing, bird strike) or if the crew reports an abnormal vibration in the aircraft. Vibration Control Cells (VCCs) gather the data and provide technical assistance to the operating units.

5.3.1.2 Wear Debris Monitoring

Those systems that use some sort of lubricant can be subjected to debris monitoring to detect excessive friction or abnormal loading that, eventually, can lead to the failure of the system. Wear Debris Monitoring (WDM) is especially suited for rotating machinery and hydraulic systems in which the content of metallic particles in the oil can very useful for the detection or prediction of faults [152]. Any analysis using WDM must take into account the operational and maintenance history of the system.

Data from WDM can be used to put in place alarms to detect significant increases in the concentration of particles and even trended it using historical data. The MoD uses two approved WDM methods:

- Spectrometric Oil Analysis Programme (SOAP): Based on testing oil samples, this method is very precise for fine debris, but fails to detect larger particles such as those produced by phenomena like surface fatigue.
- Magnetic Detector Plug (MDP) and filter debris assessment: This method is capable of detecting larger particles which can be further analysed (along with smaller ones) to determine the material composition for more accurate wear assessments.

The Wear Debris Management System (WDMS) is used to submit, analyse and report the findings from debris samples. The system is web-based allows the exchange of information among different operators and other interested parties.

5.3.1.3 Hydraulic Fluid Monitoring

The cleanliness of hydraulic fluid is defined by NATO standards [153] (ratified by the MoD [154]) and must be monitored regularly. Particles, water and other contaminants must be monitored to ensure the integrity of the hydraulic system is not compromised by the use of inadequate fluid. The different techniques approved by the MoD are:

- CM20 particle counter: Using a sample of fluid the size and concentration of particles is counted electronically. The counter can be installed in-line avoiding the need of extracting samples and the risk of contamination of the samples.
- Patch testing: Using a porous membrane the particles are separated from the fluid which decolorizes once the particles are removed and can be compared against master membranes to determine the level of contamination.
- Compar testing: A sample of the fluid is used to prepare a slide which is then compared against master slides.
- HIAC particle counter: Samples are sent to an Early Fault Detection Cell (EFDC) which uses very precise electronic equipment to test them.
- Chlorine monitoring: The combination of chlorine with water can produce hydrochloric acid that can corrode components of the hydraulic system. If

the forward organization suspects this problem may appear, a sample must be sent to Qinetiq for testing.

- Water monitoring: Contamination with water can be noticed as it produces certain “cloudiness” in the sample. CM20 counters can also detect the presence of water in the fluid.
- Filter Examination: Filters are to be sent to the Materials Integrity Group (MIG) for analysing the debris collected on them.

5.3.1.4 Observations on the case study

HUMS presents a great opportunity to develop algorithms use the information gathered with this system and generate indications on the conditions of components of helicopter transmissions. There seems to be a significant amount of data already gathered which could be combined with historical maintenance data and operational data to test the accuracy of tools developed for this purpose. This should compensate for the limitations of being forced to work within the limits of the existing system.

As for WDM and hydraulic fluid monitoring they undermine the implementation of more advanced and efficient ways to obtain the same information. However, there is no obligation to use the information gathered the existing procedures. This leaves the door open for the development of prognostic tools to track the degradation of mechanical parts, provided the benefit they generate compensates for running redundant inspections until confidence in the new prognostic tool results in a change in the regulation.

5.4 Conclusions

The ultimate goal of the methodology described in this thesis is to compare the financial viability of different combinations of diagnostic and prognostic tools to reach an optimal solution from a financial point of view. This requires understanding which are the economic benefits of individual tools and IVHM systems. The role of this chapter is to provide the reader with an understanding of the way IVHM can be seen as a profitable investment for different stakeholders and therefore a viable business for those interested in developing IVHM systems.

The contributions included in this chapter are:

- The main benefits that should be expected from an IVHM system are new revenue through improved availability and maintenance cost avoidance. Their impact on the profitability of the system will depend on the agreements between stakeholders.
- A method to analyses secondary benefits has been presented and a case study described. Some of these secondary benefits, like the reduction of test flights' cost can be more significant than the main benefits of implementing an IVHM system.
- Standards and regulations can undermine the otherwise promising beneficial effect of some diagnostic and prognostic tools. Their effect on the expected profitability of these tools has be taken into account to avoid investing on technologies that cannot deliver a profit for reasons other than technical.

Having identified the bases of the financial viability of IVHM tools, the next chapter will concentrate on comparing the components of an aircraft based on their potential to improve the availability and support cost of the aircraft they belong to through the use of different health monitoring tools. This will be the first step towards finding an optimal combination of IVHM tools from a financial perspective.

6 Sensitivity of maintenance cost and time to the performance of IVHM tools

"Time is a waste of money"

- *Oscar Wilde*

Aircraft are comprised of thousands of components. A methodology to design IVHM –regardless of whether it focuses on legacy aircraft or state of the art designs– must include a systematic method to determine which components should be covered by said health monitoring system. If this selection is to be carried out at the very early stages of the design, the characteristics of the IVHM system would not be defined yet. One may argue then, that without knowing which diagnostic or prognostic tools will be used to monitor each part (and how accurate they are), it is not possible to infer what the consequences of choosing one component over another will be. Consequently, one could be lead to believe that trying to make a selection of components at this point is a futile effort.

However, if one could determine the sensitivity of the maintenance cost and time associated with each part or LRU to being monitored by a diagnostic or prognostic tool, it would be possible to rank all the components of an aircraft in order of criticality for an eventual IVHM system. This chapter presents a method that enables designers to obtain these sensitivities using maintainability and reliability data.

Focusing on maintenance cost and time helps to guide the design of the IVHM system to achieve its ultimate goal of improving the profitability of the fleet. Other technical considerations will be taken into account, but they will determine whether it is viable to monitor a certain part rather than how important it is to monitor it.

To obtain the equation to calculate these sensitivities the method uses Event Tree Analysis (ETA) in which the initial event is the failure of the part (section 6.1). This helps to obtain analytical equations to determine the maintenance cost and time associated with each part as a function of the potential role played by different IVHM tools (section 6.2). These represent the first steps of the methodology that are not related to data gathering* (Figure 6-1.)

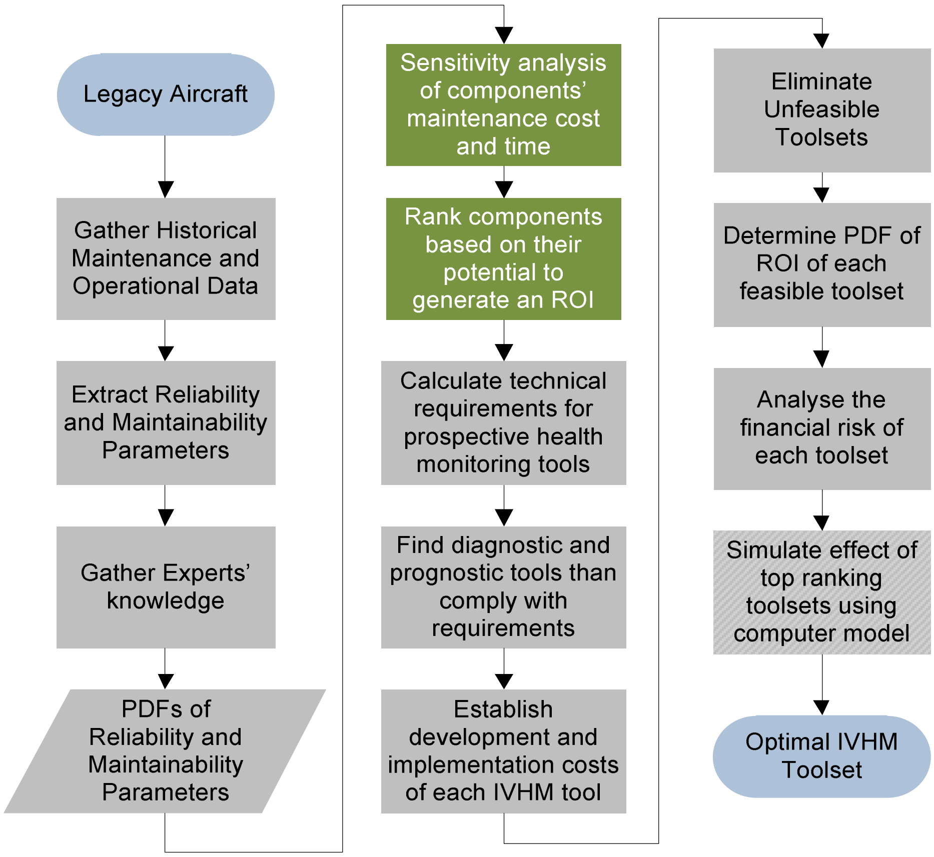

Figure 6-1 Flowchart of methodology to configure an IVHM system for a legacy vehicle highlighting the steps covered in this chapter in green.

ETA has been used to quantify the requirements for IVHM tools applied to aerospace platforms [120] and to analyse the operational consequences of a failure [155]. The method described here represents a step further, obtaining mathematical expressions to calculate the cost of maintenance and downtime per part and their sensitivity to the implementation of diagnostic and prognostic tools.

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* This method has been described in a paper submitted to the Aerospace Science and Technology Journal which is still under review. The submitted copy is included in Appendix C.
Esperon-Miguez, M., John, P., Jennions, I.K., 2013, Selection of Health Monitoring Tools Based on Sensitivity Analysis of Maintenance Parameters. Submitted to the Aerospace Science and Technology Journal on March 2013

Banks et al. [85] presented an alternative method to identify critical components for IVHM. They described the key drivers to determine on which assets prognostic tools should be installed, but did not develop a complete methodology to calculate costs or the effect health monitoring tools on downtimes.

FMECAs are widely used in the design of IVHM tools and can be used to identify critical components [94; 95; 156], but this method focuses on the criticality of failure rather than on the potential of IVHM to improve maintenance operations. These are completely separate issues. To illustrate this point imagine a component whose fault normally takes 10 minutes to diagnose and results in the aircraft being grounded 10 hours to be repaired. Whilst FMECA would indicate that the failure of this component causes major disturbances to normal operations, it would fail to notice that the impact of using a diagnostic tool would be negligible.

There have been other attempts to focus the design of IVHM systems on the economic benefits they bring. Saxena et al. [121] presented a comprehensive list of parameters to analyse the cost-benefit of prognostic tools, but did not specify how some of them should be calculated or include parameters for diagnostic tools. Kurien et al. [89] described how to estimate the net value of implementing model-based diagnosis considering the costs of operational outcomes and Leão et al. [84] proposed a set of equation to calculate the costs and benefits of implementing PHM. The method presented in this chapter goes further in two main aspects: it does not presuppose a given configuration for the health monitoring system and takes into account the possibility of using different health monitoring tools simultaneously. It also provides analytical expressions to calculate the sensitivity of the results to the performance of these tools.

The contributions of the method described in this chapter are:

- Analytical equations to estimate maintenance cost and downtime for each part of the aircraft as functions of the performance of health monitoring tools.

- Analytical equations to determine the sensitivity of the maintenance cost and downtime for each part to the use of different health monitoring tools. These equations allow ranking components according to their criticality for an IVHM system.
- Include in the analysis the possibility of improving existing health monitoring capabilities or abandoning preventive maintenance to use IVHM.

To illustrate how this method can be put in practice a case study is discussed in section 6.3.

6.1 Description of the method

6.1.1 Event Tree

The diagram shown in Figure 6-2 illustrates how the use of different health monitoring tools can lead to outcomes with different maintenance costs and times. The ETA starts with two initial events which correspond to the two possible states of the component: faulty or healthy. The first case is given a probability per flying hour, P_F, and the second, evidently, $1-P_F$. After that, the diagram continues bifurcating based whether health monitoring tools succeed in providing the correct prognosis or diagnosis (highlighted in blue). The ETA continues expanding based on the effect the failure may have on the vehicle, the flight, the performance of the aircraft, and, finally, its availability (highlighted in red). The result is 22 possible scenarios or outcomes with different operational impacts (green), each of which can be associated to an individual maintenance cost and time, as will be demonstrated later on.

It is important to take into account that this analysis can be carried out for components that have failed completely or which have degraded to their replacement point. The only requisite is that, as a consequence of the change in the state of the part, a maintenance action has to be undertaken. Additionally, the failure of a component can be the result of different failure modes with different probabilities, all of which should be analysed independently.

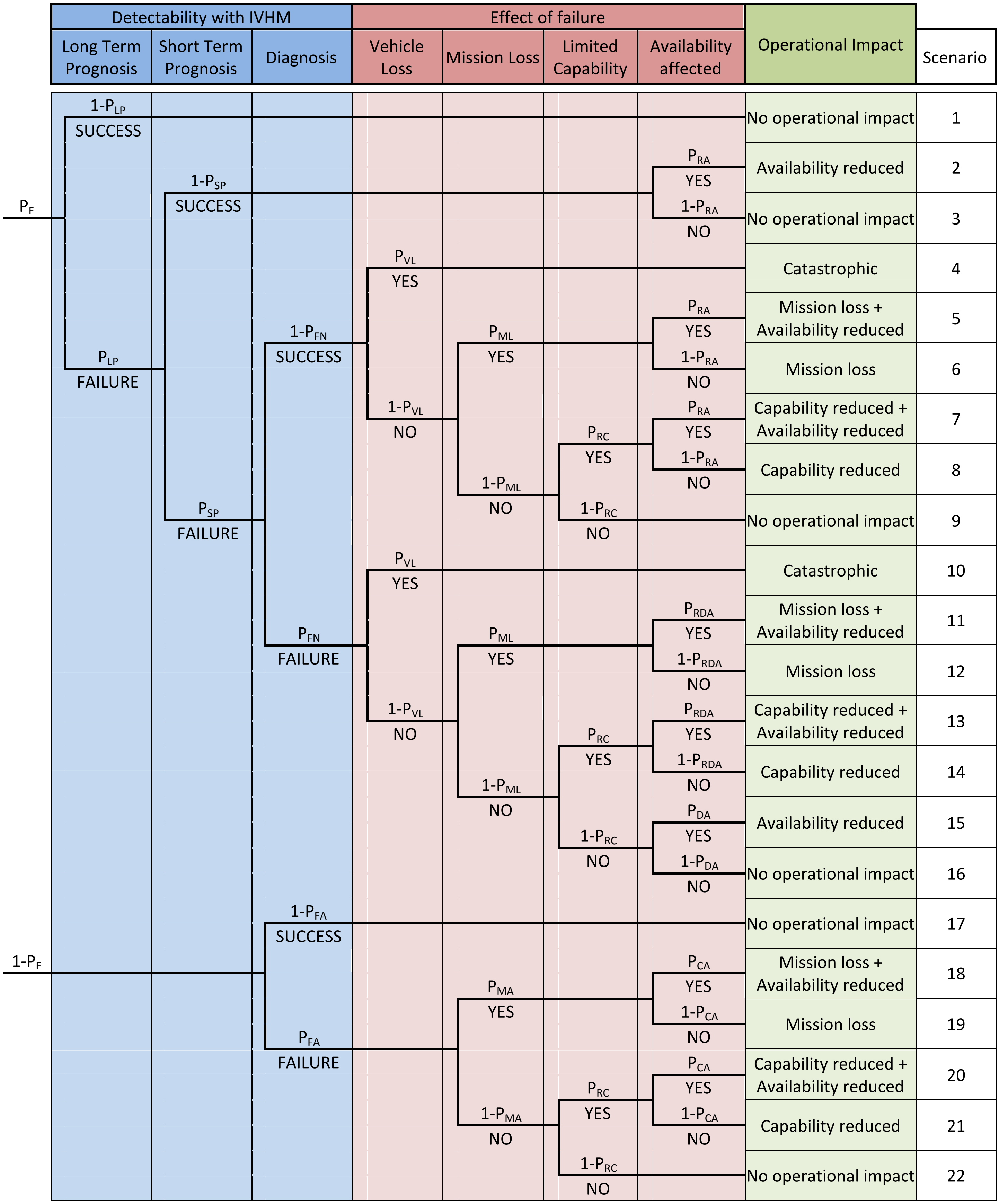


Figure 6-2 Event Tree Analysis of Aircraft with Health Monitoring Capabilities.

Health monitoring tools have been divided into three different categories according to the information they can produce: long term prognosis, short term prognosis and diagnosis. The first group is capable of predicting the failure of the components with enough anticipation to have it replaced or repaired during the next scheduled maintenance stop. The second group can only make predictions that avoid running the part until it fails, but still require an unscheduled maintenance operation. The third group includes those tools that help maintenance personnel either to identify the component responsible for a malfunction whose origin is not obvious, or to flag a failure that would otherwise be unnoticed.

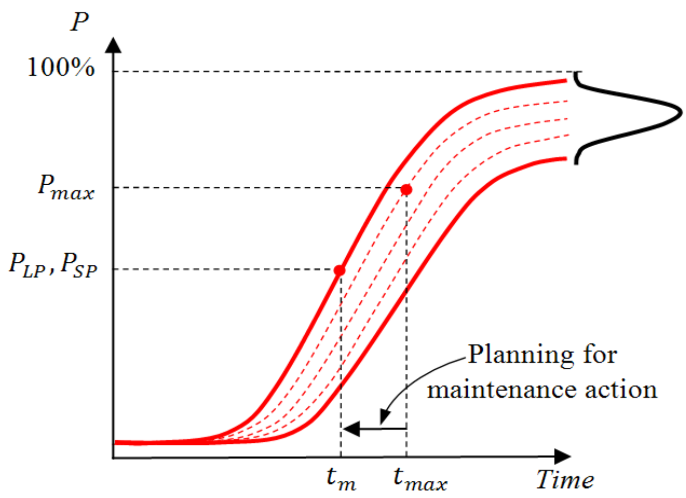


Figure 6-3 Degradation curves generated by a prognostic tool used to estimate the probability of failure of a component before it has been replaced.

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 [41]. The performance of a prognostic tool is determined by the reliability of the information it provides, 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 6-3, it is necessary to define a maximum admissible probability of failure, P_{max}, to determine how long the component can remain in service. This requires choosing a degradation curve from those generated by the prognostic tool. 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).

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 [143]. 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}.

The order in which these tools produce a new pair of outcomes does not reflect the way prognosis and diagnosis algorithms work, but how the performance of each tool affects maintenance costs and downtime. If a long term prognostic tool works properly and generates a correct prognosis, there is no need to use another health monitoring tool. However, if the prediction is erroneous, or no long term prognostic tool is being used, the information provided by a short term prognostic tool becomes relevant. In a similar way, diagnostic tools are only used when either the prognoses have been mistaken and the component has failed anyway, or prognostic tools are not being used. The lack of a prognostic tool can be reflected in the ETA by giving it a 100% probability of failure. In case no diagnostic tool is being used, its probability of triggering a false alarm or false positive (indication of a non-existing failure) would be 0% and the probability of giving a false negative (failure to detect a fault) would be 100%.

The branches of the different outcomes of using health monitoring tools are then divided according to the operational effects of the failure (highlighted in red in Figure 6-2). If the component fails during a flight, it can make the vehicle uncontrollable and impossible to land on a safe location. The outcome of such scenario would be a catastrophic accident. The probability of a vehicle loss (P_{VL}) must comply with flight safety regulations.

If the failure is not critical, it still can be serious enough to force the pilot to abort the mission. The probability of this happening is P_{ML}. In case none of the two previous outcomes occur, the performance of the vehicle can still be affected whilst still allowing it to complete its mission (e.g., clogged fuel pipes could reduce the power of an engine limiting the speed of the airplane and still allow the flight to reach its destination). The probability of suffering a reduction in capability is accounted for in the ETA by P_{RC}.

These options are given probabilities on the ETA which in many cases will be either 0% or 100% (e.g., the failure of the engines will always be critical). However, the component might not be used on every flight (e.g., external fuel tanks) or its criticality might depend on the mission (e.g., weapons systems are only relevant for combat and some training exercises). Additionally, the probability of aborting a mission or having the performance of the aircraft affected depends on the information provided by the health monitoring system to the pilot and to what extent it is possible to perceive the malfunction during the flight without the help of electronic aids. This problem is analysed in the following scenarios:

- If the failure of the component is key for the success of the mission, the pilot should notice the problem whether the diagnostic tool informs of the failure or not. Therefore, the probability of losing the mission would be the same with a correct diagnosis or a false negative. However, if a false alarm is reported to the pilot the mission would be aborted whilst if it the diagnostic tool does not communicate with the instruments the mission would continue.
- If the failure of the components means a limitation in the capability of the aircraft, again the probability would be the same after a correct diagnosis or a false negative since the pilot would notice the problem. This changes when a false alarm is triggered, because this information could be used by an Active Fault Tolerant Control System (AFTCS) which would modify the response of the vehicle, or it could misinform the pilot who could start flying the aircraft bellow its capability. If the false alarm is not reported then the aircraft will be flown as normal.

The failure of a component that has no consequences on the completion of a mission or the performance of the aircraft is assumed to be deferred until the component can be replaced with no disruption to normal operations. In that case, the effect on the availability depends on the time required to detect the fault (in case the diagnostic tool gives a false negative) or the time necessary to confirm the part is healthy (in case of a false positive).

Twenty two different outcomes are possible as a result of including all this aspects into the ETA, each of them with an overall operational impact. This impact can be one, or a combination, of the following:

- Catastrophic
- Mission loss
- Capability reduced
- Availability reduced
- No operational impact

Note that this method includes the possibility of studying the potential effect of enhancing existing health monitoring capabilities. If the component already uses some sort of BITE or is replaced regularly following a preventive maintenance schedule (which has the same effect on the ETA as a prognostic tool), the reliability of the current system can be included in the calculations. As a result, this method can also identify components which have a significant sensitivity to an improvement in the performance of a diagnostic tool or abandoning preventive maintenance for CBM.

6.1.2 Costs and increase of downtime

Numerous factors affect the maintenance cost and time associated with each replaceable element of a vehicle and the values of many of the parameters that intervene in this calculation depend on the probabilities of different situations or events (e.g.: need to ship component to different locations, variations of the availability of personnel or auxiliary equipment over time, etc.)

For each case it is possible to calculate the maintenance cost and the downtime. In order to do so, they are divided into parameters that are easy to calculate and that simply have to be added up to determine the economic and managerial impact of each scenario.

To calculate the cost associated with each case it is necessary to calculate both the expenditure and the income (in case the failure of the part is covered by a warranty) of each scenario. The example shown in Figure 6-4 includes all possible factors to be taken into account, although in some of them might not be relevant for some components. Maintenance cost can be calculated as the sum of the cost of the part, C_P including acquisition, shipping and storage; cost of labour, $C_{L\,,}$ which is affected by the time necessary to diagnose and repair each fault; cost of test, C_T:, which accounts mainly for expensive tests such as test flights; cost of RUL, C_R, or the remaining value of components replaced before they have failed; cost of secondary failure, C_{SF}, in case other components are damaged as a consequence of the original fault; loss of income, C_{LI}, due to the aircraft being grounded; and finally the compensations, C_C, in case the maintainer is expected to pay penalties if availability expectations are not met.

If the failure of the part is covered by a warranty, it might include the cost of the component, W_P, and the labour, W_L. These warranties would be executed in case the component failed before the period specified according to a preventive maintenance plan.

Regarding maintenance times, it is possible to focus solely on the time spent on each scenario or try to infer how faults may affect the availability of the aircraft. Whilst the availability of an aircraft depends on multiple factors that make it impossible to calculate analytically how it is affected by tools monitoring individual components, maintenance time can be replaced by the difference between the time necessary to replace the component and the average time available for maintenance between flights.

	Cost							Warranty		Time		
Scenario	Parts, C_P	Labour, C_L	Test, C_T	RUL, C_R	Secondary failure, C_{SF}	Loss of income, C_{LI}	Compensation, C_C	Parts, W_P	Labour, W_L	Check and Repair time, t_R	Delays, t_D	Increase of Downtime, Δt
1	$C_{P,1}$	$C_{L,1}$	$C_{T,1}$	$C_{R,1}$	0	0	0	0	0	0	0	0
2	$C_{P,2}$	$C_{L,2}$	$C_{T,2}$	$C_{R,2}$	0	$C_{LI,2}$	0	0	0	$t_{R,2}$	$t_{D,2}$	Δt_2
3	$C_{P,3}$	$C_{L,3}$	$C_{T,3}$	$C_{R,3}$	0	0	0	0	0	0	0	0
4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
5	$C_{P,5}$	$C_{L,5}$	$C_{T,5}$	0	$C_{SF,5}$	$C_{LI,5}$	$C_{C,5}$	$W_{P,5}$	$W_{L,5}$	$t_{R,5}$	$t_{D,5}$	Δt_5
6	$C_{P,6}$	$C_{L,6}$	$C_{T,6}$	0	$C_{SF,6}$	0	$C_{C,6}$	$W_{P,6}$	$W_{L,6}$	0	0	0
7	$C_{P,7}$	$C_{L,7}$	$C_{T,7}$	0	$C_{SF,7}$	$C_{LI,7}$	$C_{C,7}$	$W_{P,7}$	$W_{L,7}$	$t_{R,7}$	$t_{D,7}$	Δt_7
8	$C_{P,8}$	$C_{L,8}$	$C_{T,8}$	0	$C_{SF,8}$	0	$C_{C,8}$	$W_{P,8}$	$W_{L,8}$	0	0	0
9	$C_{P,9}$	$C_{L,9}$	$C_{T,9}$	0	$C_{SF,9}$	0	0	$W_{P,9}$	$W_{L,9}$	0	0	0
10	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
11	$C_{P,11}$	$C_{L,11}$	$C_{T,11}$	0	$C_{SF,11}$	$C_{LI,11}$	$C_{C,11}$	$W_{P,11}$	$W_{L,11}$	$t_{R,11}$	$t_{D,11}$	Δt_{11}
12	$C_{P,12}$	$C_{L,12}$	$C_{T,12}$	0	$C_{SF,12}$	0	$C_{C,12}$	$W_{P,12}$	$W_{L,12}$	0	0	0
13	$C_{P,13}$	$C_{L,13}$	$C_{T,13}$	0	$C_{SF,13}$	$C_{LI,13}$	$C_{C,13}$	$W_{P,13}$	$W_{L,13}$	$t_{R,13}$	$t_{D,13}$	Δt_{13}
14	$C_{P,14}$	$C_{L,14}$	$C_{T,14}$	0	$C_{SF,14}$	0	$C_{C,14}$	$W_{P,14}$	$W_{L,14}$	0	0	0
15	$C_{P,15}$	$C_{L,15}$	$C_{T,15}$	0	$C_{SF,15}$	$C_{LI,15}$	0	$W_{P,15}$	$W_{L,15}$	$t_{R,15}$	$t_{D,15}$	Δt
16	$C_{P,16}$	$C_{L,16}$	$C_{T,16}$	0	$C_{SF,16}$	0	0	$W_{P,16}$	$W_{L,16}$	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0
18	$C_{P,18}$	$C_{L,18}$	$C_{T,18}$	0	0	$C_{LI,18}$	$C_{C,18}$	$W_{P,18}$	$W_{L,18}$	$t_{R,18}$	$t_{D,18}$	Δt_{18}
19	$C_{P,19}$	$C_{L,19}$	$C_{T,19}$	0	0	0	$C_{C,19}$	$W_{P,19}$	$W_{L,19}$	0	0	0
20	$C_{P,20}$	$C_{L,20}$	$C_{T,20}$	0	0	$C_{LI,20}$	$C_{C,20}$	$W_{P,20}$	$W_{L,20}$	$t_{R,20}$	$t_{D,20}$	Δt_{20}
21	$C_{P,21}$	$C_{L,21}$	$C_{T,21}$	0	0	0	$C_{C,21}$	$W_{P,21}$	$W_{L,21}$	0	0	0
22	$C_{P,22}$	$C_{L,22}$	$C_{T,22}$	0	0	0	0	$W_{P,22}$	$W_{L,22}$	0	0	0

Figure 6-4 Costs and increases of downtime for the scenarios obtained from the ETA.

The time available for maintenance between missions can change significantly and can be approximated by a probability density function, $f_{AV}(t)$, with an average time available between missions, t_{bm} (Figure 6-5). This curve is defined by the operator since it is directly related to mission planning. The odds of affecting the availability can be obtained using this function. It should be noted that the time available for maintenance is shorter than the total time between flights due to factors such as taxing, loading/unloading cargo and passengers, pre-flight checking, etc.

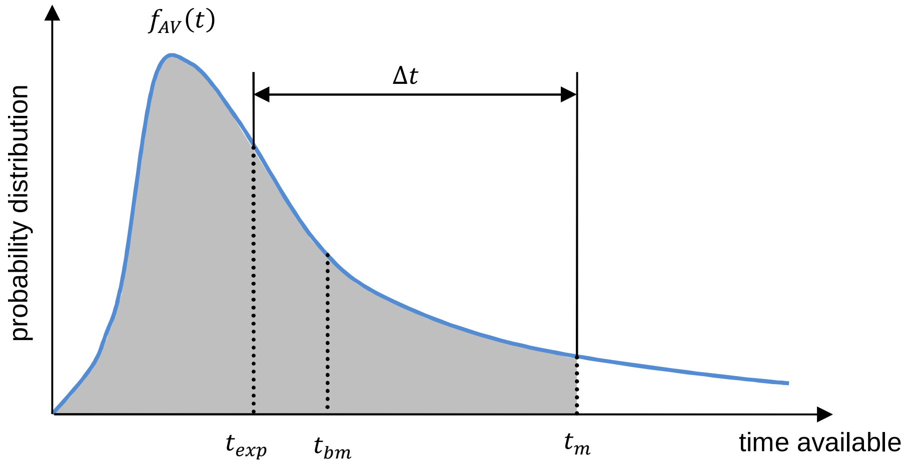


Figure 6-5 Probability distribution of time available between missions for maintenance tasks.

The effect on availability is represented in the ETA as two different cases:

- The availability of the platform is affected. The probability of this case, P_{AV}, is calculated using Eq. 6-1.
- The availability of the platform is not affected. The probability of this case is complementary to the previous.

Since P_{AV} has different values in different scenarios it is indicated in the ETA as P_{RA}, P_{RDA}, P_{DA} and P_{CA}, all of which can be calculated using Eq. 6-1.

$$P_{AV} = P(t \geq t_m) = 1 - \int_0^{t_m} f_{AV}(t)dt \qquad \textbf{6-1}$$

where t_m is the total time necessary to complete the maintenance task.

If the inherent availability is affected, it is necessary to calculate the average increase of downtime, Δt. This is given by the difference between the maintenance time and the average time available. However, in these scenarios, the time available for maintenance must be between 0 and t_m (a higher value would mean the availability is not compromised), which means that the new expected value will be lower than the average time available between missions calculated for the previous time range, t_{bm}. Therefore, the increase of downtime can be calculated as the difference between the repair time and the expected value of the probability distribution of the available time for maintenance for the new time range, t_{exp}.

$$\Delta t = t_m - t_{exp} = t_m - E(f_{AV}(t)) = t_m - \int_0^{t_m} t f_{AV}(t) dt \qquad \textbf{6-2}$$

This method can applied using either the maintenance time dedicated of each scenario or the increase of downtime. In the rest of the chapter equations will make reference to the increase of downtime, but the reader is reminded that they would work in the exact same way should they prefer to focus on maintenance time.

6.2 Simplified event tree, equations and sensitivities

Whilst the effect a failure has on a flight and the performance of the aircraft must be taken into account, the objective is to analyse the effect of IVHM tools on maintenance costs and times. Focusing only on the performance of the health monitoring tools, the ETA can be compressed and the 22 original scenarios can be grouped into 6 branches, each of which is associated to a cost and an increase of downtime (Figure 6-6). The values of the cost and increase of downtime corresponding to each branch of the simplified ETA are calculated using the following expressions:

$$C_{k,m} = \sum_{i=k}^{m} P_i \left(C_{P,i} + C_{L,i} + C_{T,i} + C_{R,i} + C_{SF,i} + C_{LI,i} + C_{C,i} - W_{P,i} - W_{L,i} \right) \qquad \textbf{6-3}$$

$$\Delta t_{k,m} = \sum_{i=k}^{m} P_i \, \Delta t_i \qquad \textbf{6-4}$$

where

for Long Term Prognostic Tools: $C_{LP} \rightarrow k = m = 1$

for Short Term Prognostic Tools: $C_{SP} \rightarrow k = 2,\ m = 2$

for Diagnostic Tools: $C_D \rightarrow k = 4, m = 9$

for False Negatives: $C_{FN} \rightarrow k = 10, m = 16$

for False Alarms: $C_{FA} \rightarrow k = 18, m = 22$

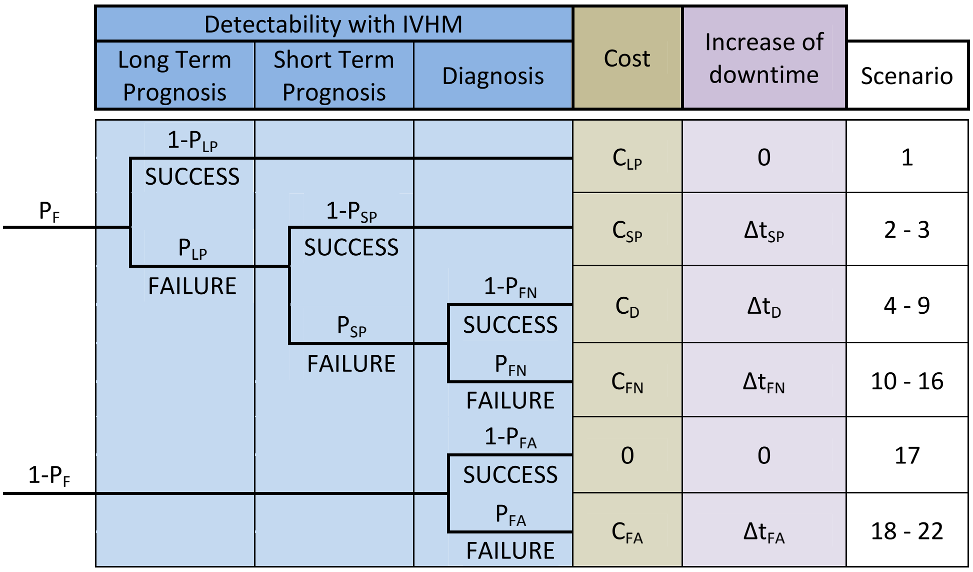


Figure 6-6 Simplified ETA with branches for diagnostic and prognostic tools only.

This way, it is possible to express the cost and the increase of downtime using polynomial expressions whose variables are the performance of the health monitoring tools (Eqs. 6-5 and 6-6).

$$C = P_F\left((1 - P_{LP})C_{LP} + P_{LP}\left((1 - P_{SP})C_{SP} + P_{SP}\left((1 - P_{FN})C_D + P_{FN}\,C_{FN}\right)\right)\right) + (1 - P_F)P_{FA}C_{FA} \qquad \textbf{6-5}$$

$$\Delta T = P_F\,P_{LP}\left((1 - P_{SP})\Delta t_{SP} + P_{SP}\left((1 - P_{FN})\Delta t_D + P_{FN}\Delta\, t_{FN}\right)\right) + (1 - P_F)P_{FA}\Delta t_{FA} \qquad \textbf{6-6}$$

These expressions can be differentiated to obtain their sensitivity to the performance of the tools, as shown in equations Eqs. 6-7 to 6-14:

$$\frac{dC}{dP_{LP}} = P_F \left((1 - P_{LP})\frac{dC_{LP}}{dP_{LP}} - C_{LP} + \left((1 - P_{SP})C_{SP} + P_{SP}\left((1 - P_{FN})C_D + P_{FN}\, C_{FN} \right) \right) \right) \tag{6-7}$$

$$\frac{d\Delta T}{dP_{LP}} = P_F \left((1 - P_{SP})\Delta t_{SP} + P_{SP}\left((1 - P_{FN})\Delta t_D + P_{FN}\, \Delta t_{FN} \right) \right) \tag{6-8}$$

$$\frac{dC}{dP_{SP}} = P_F\, P_{LP} \left((1 - P_{SP})\frac{dC_{SP}}{dP_{LP}} - C_{SP} + \left((1 - P_{FN})C_D + P_{FN}\, C_{FN} \right) \right) \tag{6-9}$$

$$\frac{d\Delta T}{dP_{SP}} = P_F\, P_{LP} \left(\left((1 - P_{FN})\Delta t_D + P_{FN}\, \Delta t_{FN} \right) - \Delta t_{SP} \right) \tag{6-10}$$

$$\frac{dC}{dP_{FN}} = P_F\, P_{LP} P_{SP} (C_{FN} - C_D) \tag{6-11}$$

$$\frac{d\Delta T}{dP_{FN}} = P_F\, P_{LP} P_{SP} (\Delta t_{FN} - \Delta t_D) \tag{6-12}$$

$$\frac{dC}{dP_{FA}} = (1 - P_F)C_{FA} \tag{6-13}$$

$$\frac{d\Delta T}{dP_{FA}} = (1 - P_F)\Delta t_{FA} \frac{dC}{dP_{FA}} = (1 - P_F)C_{FA} \tag{6-14}$$

For prognostic tools there is a cost associated to the residual value of every component that is replaced before it reaches its point of failure. Essentially, components monitored with prognostic tools will be replaced more frequently than if they were run until they failed and a larger number of them will have to be purchased during the life of the aircraft. This residual cost of the RUL of a component is related to the moment chosen to remove it from the vehicle, which also determines the probability of that part failing before that instant or, for the purpose of this analysis, the probability of failure of the prognostic tool (P_{LT} and P_{ST}). Therefore, in order to calculate these sensitivities, the derivative of the cost of the RUL to the probability of failure of the prognostic tool has to be calculated.

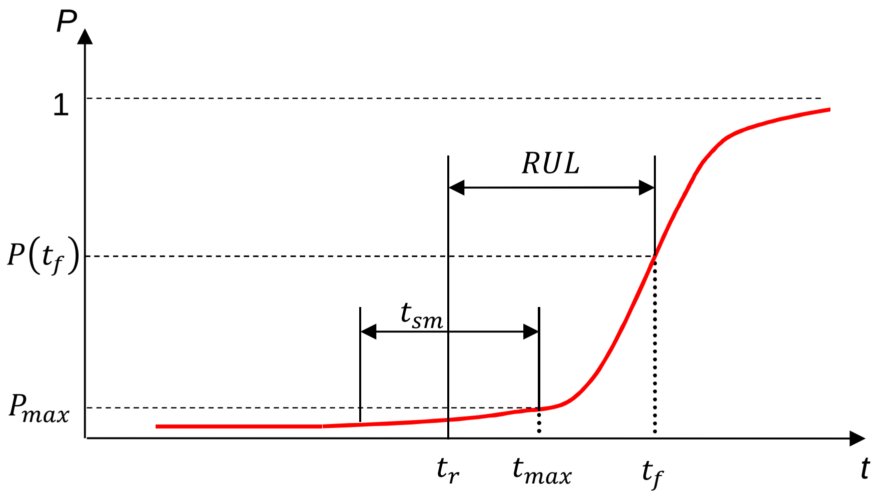


Figure 6-7 Probability function of the failure of a component as a function of the time it has been operated.

The cost of the RUL of the components is directly proportional to the difference between the average life of the parts when they fail, t_f, and their average life when they are removed, t_r (Figure 6-7). Since prognostic tools determine the moment the probability of failure of a part will reach the maximum level allowed, P_{max}, it must be replaced before this limit is reached. Therefore, the average RUL of the removed components must be shorter than the life corresponding to the limit of the probability of failure, t_{max}. Maintenance stops are scheduled with a determined periodicity, t_{sm}, thus the soonest a part can be replaced is t_{max} – t_{sm} and the latest is t_{max}. Consequently, the average RUL can be calculated (Eq. 6-15 and the cost associated with it obtained (Eq.6-16).

$$t_r = t_{max} - \frac{t_{sm}}{2} \qquad \textbf{6-15}$$

$$RUL = t_f - t_r = t_f - t_{max} + \frac{t_{sm}}{2} \qquad \textbf{6-16}$$

$$C_R = C_P \frac{RUL}{t_f} = C_P \frac{t_f - t_{max} + \frac{t_{sm}}{2}}{t_f} = C_P \left(1 - \frac{t_{max} - \frac{t_{sm}}{2}}{t_f} \right) \frac{dT}{dP_{FA}} \qquad \textbf{6-17}$$

$$= (1 - P_F)\Delta t_{FA} \frac{dC}{dP_{FA}} = (1 - P_F)C_{FA}$$

$$\frac{dC_R}{dP} = \frac{d}{dP}\left(C_P \frac{RUL}{t_f}\right) = \frac{d}{dP}\left(C_P \frac{t_f - t}{t_f}\right) = C_P \frac{-\frac{dt}{dP}}{t_f} = -\frac{C_P}{t_f} \frac{1}{\frac{dP(t)}{dt}} \qquad \textbf{6-18}$$

Degradation models employed by prognostic tools are not completely accurate and they provide a range of probability functions for the failure of the component. In this analysis, the function represented in Figure 6-7 is assumed to have the same confidence level as the curve used by the maintenance team to choose the moment to remove the component.

The degradation of a component can be approximated to an explicit expression defined by the probability distribution which best matches the empirical data gathered. Mechanical components tend to fit a Weibull distribution and the failure of many electronic devices can be modelled using normal distributions. Therefore, the derivative of the cost of RUL can be calculated analytically since it is a function of time (Eq. 6-18).

In case of a Weibull distribution:

$$P(x) = 1 - e^{-\left(\frac{x}{\lambda}\right)^k} \qquad \textbf{6-19}$$

$$\frac{dP(t)}{dt} = \frac{d}{dt}\left(1 - e^{-\left(\frac{t}{\lambda}\right)^k}\right) = -e^{-\left(\frac{t}{\lambda}\right)^k}\left(-k\left(\frac{t}{\lambda}\right)^{k-1}\right)\frac{1}{\lambda} = \frac{kt^{k-1}}{\lambda^k}\frac{1}{e^{\left(\frac{t}{\lambda}\right)^k}} \qquad \textbf{6-20}$$

$$\frac{dC_R}{dP} = -\frac{C_P}{t_f}\frac{\lambda^k e^{\left(\frac{t}{\lambda}\right)^k}}{kt^{k-1}} \qquad \textbf{6-21}$$

By combining Eq. 6-21 with Eqs. 6-7 and 6-9 the final analytical expressions of the sensitivity of the cost using a Weibull distribution for the degradation of the component are:

$$\frac{dC}{dP_{LP}} = P_F \left((P_{LP} - 1\,) \frac{C_P}{t_f} \frac{\lambda^k e^{\left(\frac{t}{\lambda}\right)^k}}{kt^{k-1}} - C_{LP} \right. \tag{6-22}$$

$$\left. + \left((1 - P_{SP}\,)C_{SP} + P_{SP}\left((1{-}P_{FN}\,)C_D + P_{FN}\,C_{FN}\,\right)\right) \right)$$

$$\frac{dC}{dP_{SP}} = P_F\,P_{LP} \left((P_{SP} - 1\,) \frac{C_P}{t_f} \frac{\lambda^k e^{\left(\frac{t}{\lambda}\right)^k}}{kt^{k-1}} - C_{SP} + \left((1{-}P_{FN}\,)C_D + P_{FN}\,C_{FN}\,\right) \right) \tag{6-23}$$

Sometimes, the probability of failure of a component is best described using a Normal or Gaussian distribution. The failure of electronic components, for example, tends to fit this kind of probability curves. In that case:

$$P(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\,dt = \frac{1}{2}\left(1 + erf\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right) \tag{6-24}$$

$$\frac{dP(t)}{dt} = \frac{d}{dt}\left(\frac{1}{2}\left(1 + erf\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)\right)\right) = \frac{1}{\sqrt{2\sigma^2}} \frac{d}{dt}\left(erf\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)\right) \tag{6-25}$$

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}\,dt \rightarrow \frac{derf(x)}{dx} = \frac{2}{\sqrt{\pi}} e^{-x^2} \tag{6-26}$$

$$\frac{dP(t)}{dt} = \frac{1}{\sqrt{2\sigma^2}} \frac{2}{\sqrt{\pi}} e^{-\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} = \sqrt{\frac{2}{\pi\sigma^2}}\, e^{-\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} \tag{6-27}$$

$$\frac{dC_R}{dP} = -\frac{C_P}{t_f} \sqrt{\frac{\pi\sigma^2}{2}}\, e^{\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} \tag{6-28}$$

By combining Eq. 6-28 with Eqs. 6-7 and 6-9 the final analytical expressions of the sensitivity of the cost using a normal distribution for the degradation of the component are:

$$\frac{dC}{dP_{LP}} = P_F \left((P_{LP} - 1) \frac{C_P}{t_f} \sqrt{\frac{\pi\sigma^2}{2}} e^{\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} - C_{LP} \right. \qquad \textbf{6-29}$$
$$\left. + \left((1 - P_{SP}) C_{SP} + P_{SP} \left((1 - P_{FN}) C_D + P_{FN} C_{FN} \right) \right) \right)$$

$$\frac{dC}{dP_{SP}} = P_F \, P_{LP} \left((P_{SP} - 1) \frac{C_P}{t_f} \sqrt{\frac{\pi\sigma^2}{2}} e^{\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} - C_{SP} \right. \qquad \textbf{6-30}$$
$$\left. + \left((1 - P_{FN}) C_D + P_{FN} \, C_{FN} \right) \right)$$

These analytical expressions relate the sensitivity of the cost and downtime to the performance of health monitoring tools. If they are combined with Eqs. 6-7 and 6-9 it is possible to identify which components would benefit the most from installing IVHM tools and which kind of tools should implemented.

Other probability distributions for the degradation of components can be used to obtain the derivative *dP(t)/dt* to use with Eqs. 6-7 and 6-9. Another possibility is to use historical maintenance data to determine the reliability of the component and the value of *dP(t)/dt*.

The functions listed in this section form the basis for the ranking of aircraft components based on their potential to reduce maintenance cost and time if their condition was to be monitored using diagnostic or prognostic tools. To illustrate how this analysis can be carried out, the next section describes a case study that convers a comprehensive list of aircraft components with different types of reliability functions.

6.3 Case study

The case study focuses on 2300 components, 1335 of which degraded following a Weibull distribution and the failure of the remaining 965 was modelled using Gaussian probability distributions. The aim was to define two sets of approximately 100 components (according cost and time criteria respectively) to start the basic design of an IVHM system for the aircraft. The analysis does not account for the false positives and negatives that may occur during routine checks or a result of using BITE.

The cost of each component included shipping and storage costs and the cost associated with the value of the RUL of components removed before they fail ranged between 2% and 20% of the total cost of the part. This cost was only taken into account in scenarios 1 to 3, where prognostic tools are involved. Labour costs per hour were also different for unscheduled maintenance tasks because sometimes they are carried out during night shifts or require overtime, resulting in a higher average labour costs. To account for this phenomenon, labour cost per hour of unscheduled maintenance tasks were assumed to be 15% higher than the labour cost for prognostic tools. Finally, the costs of secondary failures, which affect 18 components, ranged from £580 to £24,579 and included parts and labour.

To estimate the effect of IVHM tools on the inherent availability of the vehicle we need to calculate the increase of downtime as shown in Eq. 6-2. To solve this equation the time available for maintenance between missions was modelled using an exponential distribution with an average of 3 hours. Each component was assigned an active maintenance time, a diagnostic time and an average delay. The latter was not taken into account with prognostic tools and the average diagnostic time only affected false negatives and false alarms (remember that components without any diagnostic capability are equivalent to using a diagnostic tool with 100% probability of false negative).

The sensitivities of downtimes are shown in Figure 6-8 where components that show higher sensitivities are more prone to reduce downtimes than those with lower sensitivities if they were monitored by a health monitoring tool with the same accuracy. The analysis showed how long term prognostic tools are more likely to produce a sharper decrease on a larger number of components. Not surprisingly, diagnostic tools, whilst still capable of improving aircraft availability, cannot produce the same results.

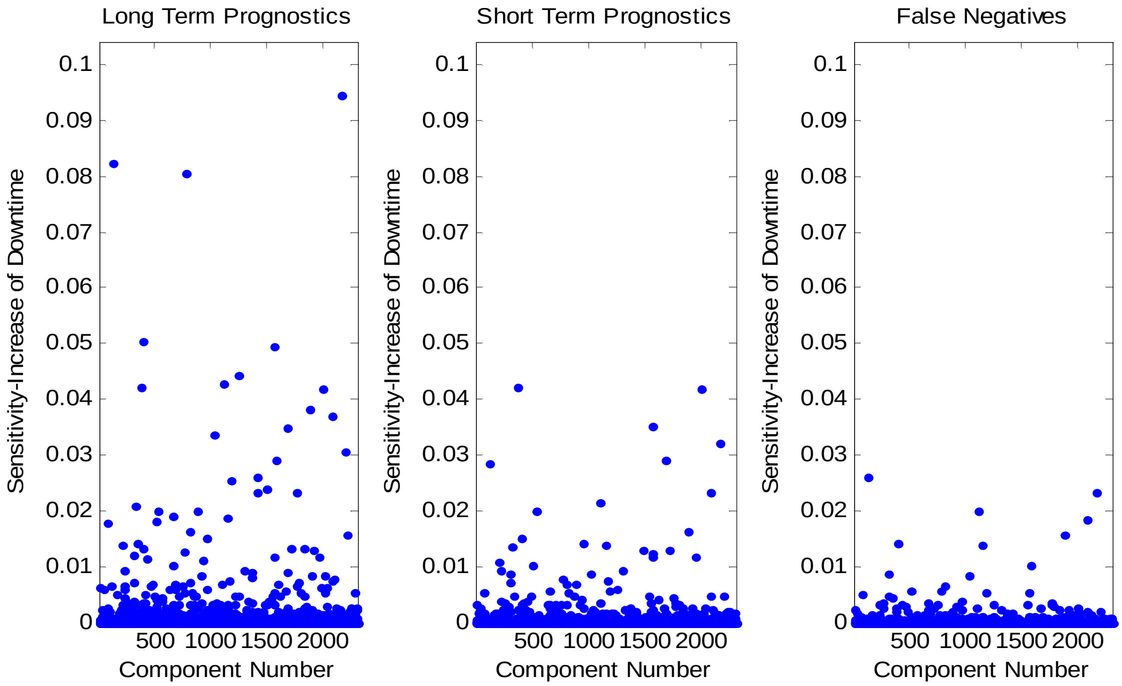


Figure 6-8 Sensitivities of increases of downtime to the performance of long term prognostic tools (left), short term prognostic tools (centre) and diagnostic tools (right).

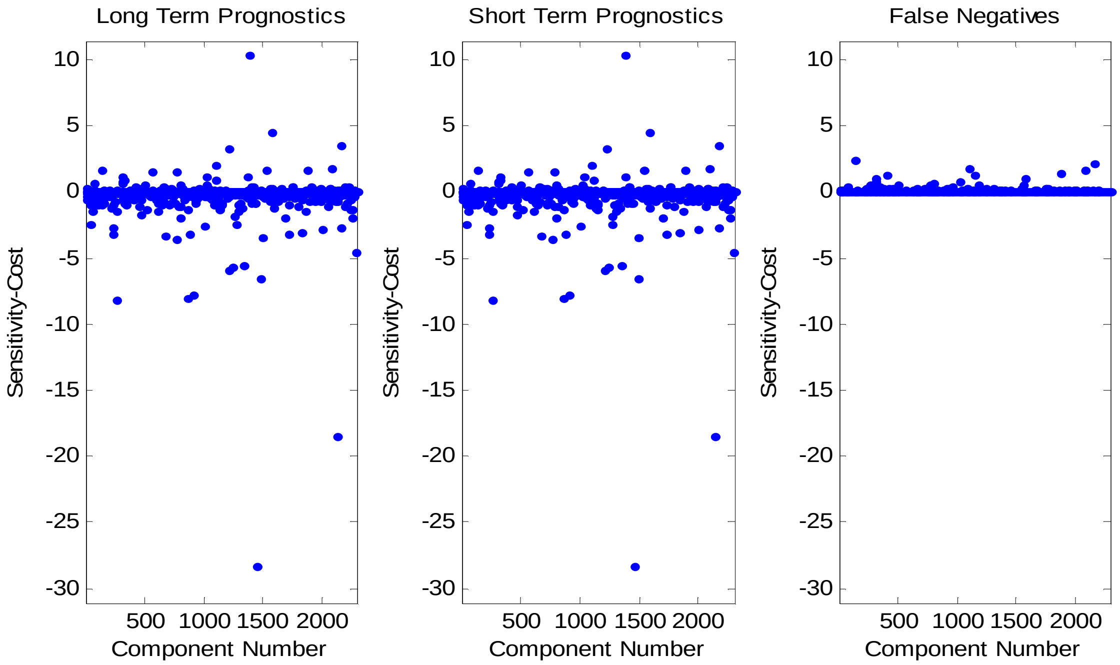


Figure 6-9 Sensitivities of maintenance costs to the performance of long term prognostic tools (left), short term prognostic tools (centre) and diagnostic tools (right).

Shifting attention to the sensitivities of costs we find that prognostic tools can have two opposite effects (Figure 6-9). In most cases, replacing components before they fail instead of following a reactive maintenance approach results in a higher number of components being replaced over a given time period. Lower labour costs and not spending time diagnosing faults do not compensate for the additional cost associated with the RUL at replacement. Consequently, the sensitivity of maintenance costs to the implementation of prognostic tools is negative in most cases. Figure 6-9 shows how in some extreme cases in which the cost of the part is high and the prognostic window long, installing a prognostic tool could result in a steep rise in costs. This shows how this method, besides helping to identify the best candidates among all the components of the vehicle, can also help to avoid focusing on certain parts which would have seem good options given their high value.

However, preventive maintenance can result in significant savings when the failure of a part causes further damage. Avoiding secondary failures, lower average cost of labour and not spending time diagnosing faults mean that the sensitivity of the maintenance cost of some components to the implementation of prognostic tools can be positive. Thanks to this effect 49.52% of components would see their maintenance costs reduced if their degradation was monitored.

Table 6-1 Number of tools unique to each ranking list corresponding to the different performance parameters of IVHM tools.

Sensitivity to	Ranking criteria	
	$d\Delta T$	dC
Long Term Prognostic tools (P_{LP})	100	100
Short Term Prognostic Tools (P_{SP})	24	0
Diagnostic Tools (P_{FN})	19	37
Total	143	137
False Alarms (P_{FA})	33	34
Total (final)	110	103

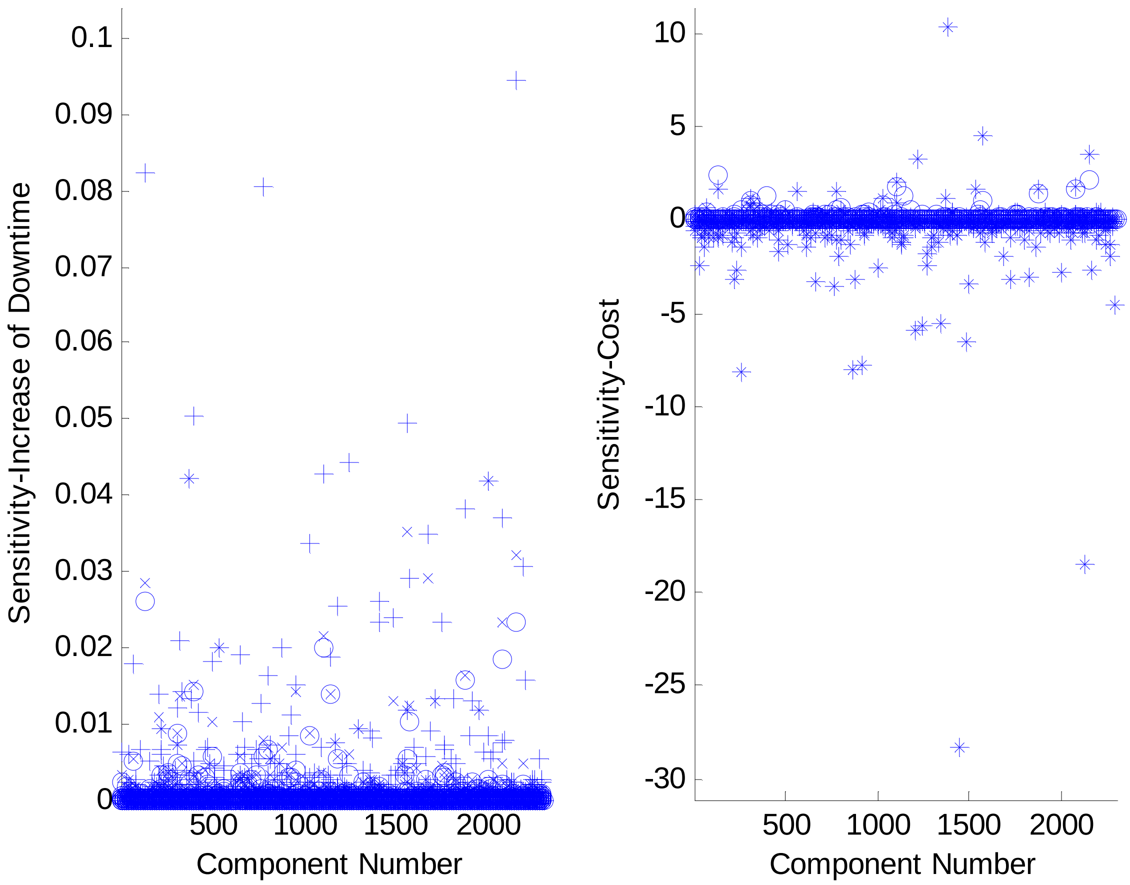


Figure 6-10 Comparison of the sensitivities of increases of downtime (left) and maintenance costs (right) to the use of long term prognostic tools (+), short term prognostic tools (x) and diagnostic tools (o).

Components were ranked according to the sensitivity of downtimes to the performance of long term prognostic tools, short term prognostic tools and diagnostic tools. Another way of identifying critical parts to be monitored is by ranking them based on the sensitivity of their maintenance costs to the use of prognostic and diagnostic tools. The top 100 components with the highest sensitivities were included in independent lists which were later compared to remove those parts that appeared more than one time (Table 6-1). The sensitivities of maintenance costs with long and short term prognostic tools, are exactly the same due to the choice of parameters to calculate them (Figure 6-10). These results show that, whilst the majority of components selected for prognostic and diagnostic tools are the same, focusing on just one group of

IVHM tools can leave 37% of critical components out of the analysis without any justification.

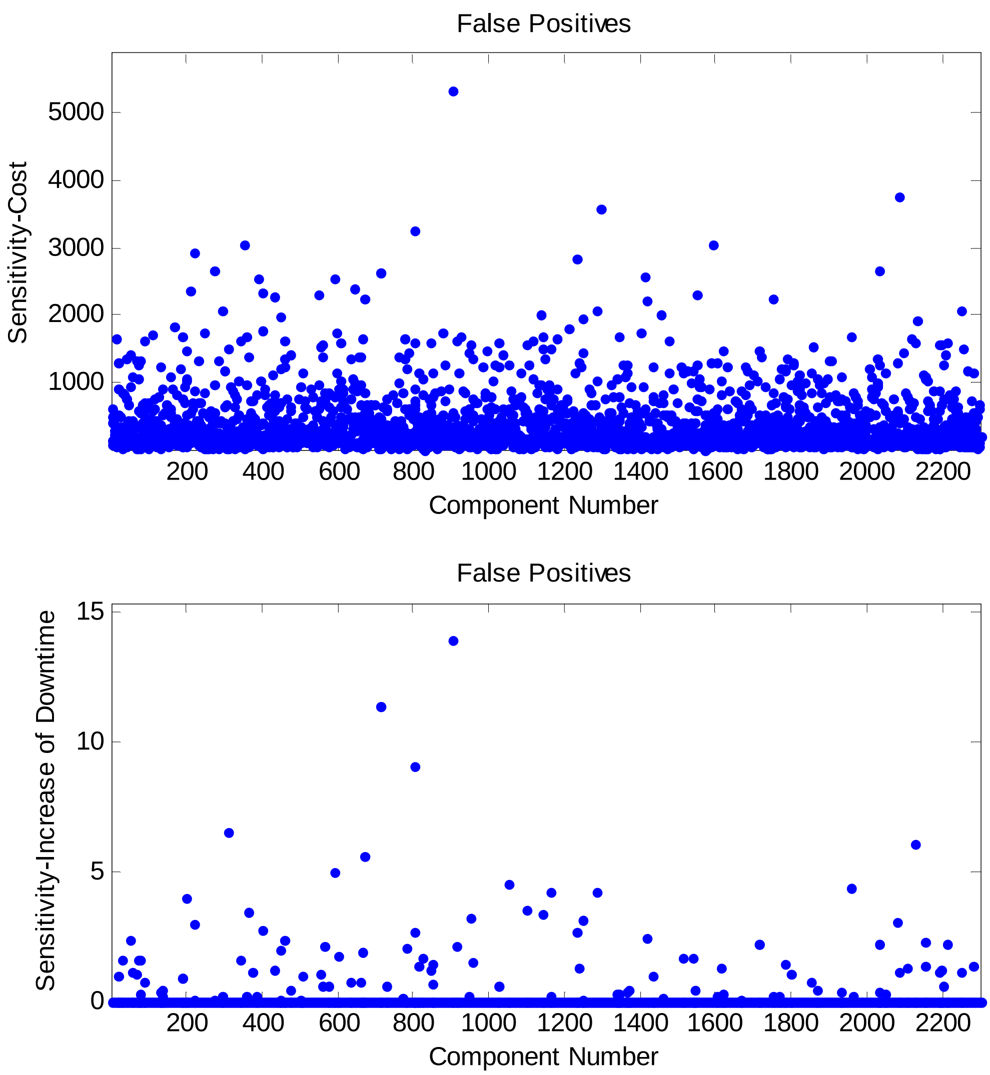


Figure 6-11.- Sensitivities of maintenance costs (top) and increases of downtime (bottom) to the probability of false alarms.

False alarms normally result in shorter downtimes and lower costs than any other possible scenario because it was assumed that false positives were detected and therefore healthy parts were not replaced. Provided the data is available, it is possible to define a component cost specific for false alarms which would be the average expense on new components and repairs undertaken. However, regardless of the values of costs and downtimes, the impact of false alarms in comparison to other scenarios is magnified by the fact that the initial condition, a healthy component, has a much higher probability (Figure 6-6). Consequently, the sensitivity to a variation of the probability of false alarms is much higher than for any other parameter, as shown in Figure 6-11.

The disproportionate sensitivity to false alarms provides little information for the selection of components. However, being able to identify which components are more sensitive to false positives is very useful from a risk management perspective. Since at this point the performance of the health monitoring tools that will be used is unknown designer must consider the possibility that the false alarm rate of a diagnostic tool can be increased by multiple factors (e.g.: low sensor accuracy, signal noise, etc.), which could result in higher maintenance costs and longer downtimes.

To avoid developing IVHM system to monitor components too sensitive to false alarms these components can be removed from the list of those preselected attending to the rankings of sensitivities to prognostics or diagnostic tools (see Table 6-1). In doing so, we generate a list with components that present a higher potential to reach the desired reduction in maintenance costs and increase in availability, whilst avoiding those which could have the opposite effect if the performance of the diagnostic tool that monitored them was worse than originally planned. Additionally, with this risk-avoidance step we ended up with two lists which were close enough to our original objective of 100 components.

6.4 Conclusions

The use of a quantitative comparative approach to the selection of components to be monitored by either diagnostic or prognostic tools is essential to ensure the decision is based on objective information avoiding any personal bias. By focusing on maintenance costs and times and their sensitivities to the performance of health monitoring tools, the results of this method are useful to any stakeholder regardless of the maintenance scheme under which the aircraft operates. Depending on who (and how) is going to pay for this technology, focus will be placed on costs, times or both.

The sensitivity analyses that can be performed with the analytical expressions proposed here not only help to determine on which components or subsystems it would be beneficial to install health monitoring capabilities, but also help to decide whether improving the performance of some of the tools already in place could be useful too.

However, components that would rank higher according to the sensitivity of their maintenance cost and time might not necessarily be “monitorable”. For diagnostic tools this means failures producing clear symptoms that can help to detect and isolate faults. For prognostic tools failure mechanisms must be traceable, either because the physics of failure that govern them are well understood, or because data mining techniques have led to the discovery of correlations between the degradation of the component and some known parameters. In any case, there must be a way to read the parameters necessary to run the health monitoring algorithm, condition the signal, and store or transmit the data. Designers of IVHM systems must revise the list of components they obtain following this method and perform a sanity check to avoid wasting time on component that do not comply with these requirements.

The reader is also reminded that in order to obtain the equations included in this chapter, the following assumptions and simplifications have been made:

- Parameters such as costs and times are considered constant despite the fact that they are not. The different steps involved in any maintenance task never have the exact same duration and many of the costs are subjected to fluctuations over time.
- Maintenance cost and time are considered at a component level trying to infer what will be the effect of individual IVHM tools. Whilst this is a valid assumption to identify critical component it is no longer valid to determine the effect of the interactions among the different tools of which an IVHM system is comprised.

These limitations, which do not invalidate the results obtained using this method, are addressed in chapters 7 and 8. Chapter 7 will focus on defining the technical requirements for each of the components selected using the method described in this chapter taking into account the effect of the uncertainties of times, costs, and the performance of health monitoring tools.

The effect of the interactions between health monitoring tools on the expected ROI of the overall IVHM system will be studied in chapter 8. As for their effect on the availability of a fleet, that problem has to be solved using computer simulations which are discussed in chapter 9.

7 Defining performance requirements for IVHM tools

"In these matters the only certainty is that nothing is certain."
- Pliny the Elder

The method described in the previous chapter shows how components can be ranked according to the sensitivity of their individual maintenance cost and time to the performance of diagnostic or prognostics tools, which helps to identify which parts are more likely to produce the desired reduction in maintenance cost and time if monitored by an IVHM system. This chapter focuses on calculating the performance requirements for health monitoring tools so as to produce the expected improvements in maintenance operations* (Figure 7-1.)

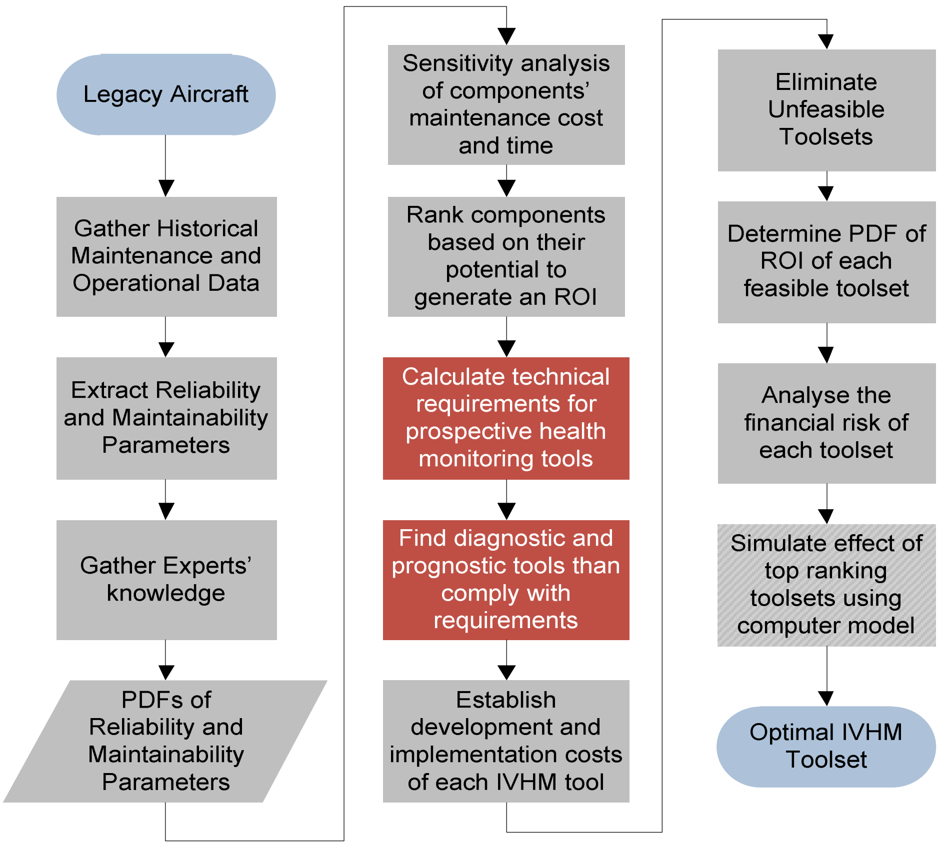


Figure 7-1 Flowchart of methodology to configure an IVHM system for a legacy vehicle highlighting the steps covered in this chapter in red.

* Different parts of this method were published in two conference papers (included in Appendix C):
•Esperon-Miguez, M., John, P., Jennions, I. K., 2012, Uncertainty of Performance Metrics for IVHM Tools According to Business Targets. PHM Conference Europe, July 2012, Dresden.
•Esperon-Miguez, M., John, P., Jennions, I. K., 2012, Downtime uncertainty reduction through correct implementation of health monitoring tools. IET Asset Management Conference, November 2012, London

Knowing the minimum performance requirements to monitor specific components provides those in charge of designing an IVHM system with the basic information to compile a list of tools to compare. Diagnostic and prognostic tools can be developed by in-house technical departments, but also acquired from independent developers of IVHM technology or other companies willing to sell health monitoring technology.

The method is based on the use of the simplified ETA described in the previous chapter. As explained in section 6.2, the maintenance cost and time associated with each component can be expressed as analytical functions of the performance of diagnostic and prognostic tools. These same equations can be used to calculate the minimum performance requirements by defining the new cost and downtime for each part that are expected to achieve using IVHM (section 7.1). It is important to note that the criticalities of different costs and maintenance operations vary for each stakeholder [145] and depend on whether the vehicle is operated in a civilian or military environment [76].

At this stage one must consider the numerous uncertainties at play: the variability of the duration of the multiple stages of maintenance jobs (tasks never take the exact same amount of time), fluctuations in recurring and non-recurring costs, and the fact that health monitoring tools are not 100% accurate (a factor already reflected in the ETA used in the previous chapter). Consequently, rather than assuming performance requirements can be defined just using scalars, this chapter describes how the probability distributions of said requirements can be calculated taking into account the standard deviations of all variables involved (the effect of uncertainties is discussed in section 7.2.)

By taking uncertainties into account, it is possible to include tools that are already available and whose performance is well documented and tools that still under development. Obviously, the higher uncertainty of the accuracy of untested tools will have to be reflected in the decision process, but this problem is tackled in chapter 8. For now, it suffices to say that the more options designers have to choose from, the better.

Not much work has been done in the pursuit of a method to calculate the performance requirement for health monitoring tools. Datta and Squires [120] also used to quantify IVHM requirements using ETA. In their approach, IVHM systems are considered to be comprised of diagnostic tools and requirements are calculated attending to maintenance cost and safety.

Xu et al. [158] listed the main performance requirements for diagnostic, prewarning and prognostic capabilities of a PHM system as well as a method to validate them. Whilst they provide a descriptive explanation as to how to validate the design, they do not provide a quantitative method to calculate these requirements.

The method proposed by Luna [159] can be used to define the performance requirements of a complete PHM system based on availability and reliability expectations. This method, however, cannot be used to specify the requirements of individual diagnostic or prognostic tools.

Some research has been done on obtaining mathematical expressions that relate the ROI of IVHM systems to specific design parameters [90; 91; 95], but these are specific to certain technical characteristics rather than the overall performance of the tools. They also imply a very stringent configuration for the health monitoring system for each case, making it impossible to obtain generalised expressions to define performance requirements.

The contributions of the method described in this chapter are:

- Analytical equations to define the performance requirements of diagnostic and prognostic tools to achieve specific reductions in maintenance cost and time.
- Include the effect of the standard deviation of the variables involved to ensure the required improvements in maintenance times and cost are reached with a given degree of confidence.
- Define performance requirements as probability functions instead of fix scalars,

To illustrate how this method can be put in practice a case study is discussed in section 7.3.

7.1 Initial analysis of performance requirements

The mathematical basis on which this method is based is the same as described in the previous chapter. It uses the same event tree to obtain the polynomial equations that define the maintenance cost and time of each component as a function of the reliability of diagnostic and prognostic tools. Figure 7-2 is included here as a reminder and so are equations 7-1 and 7-2.

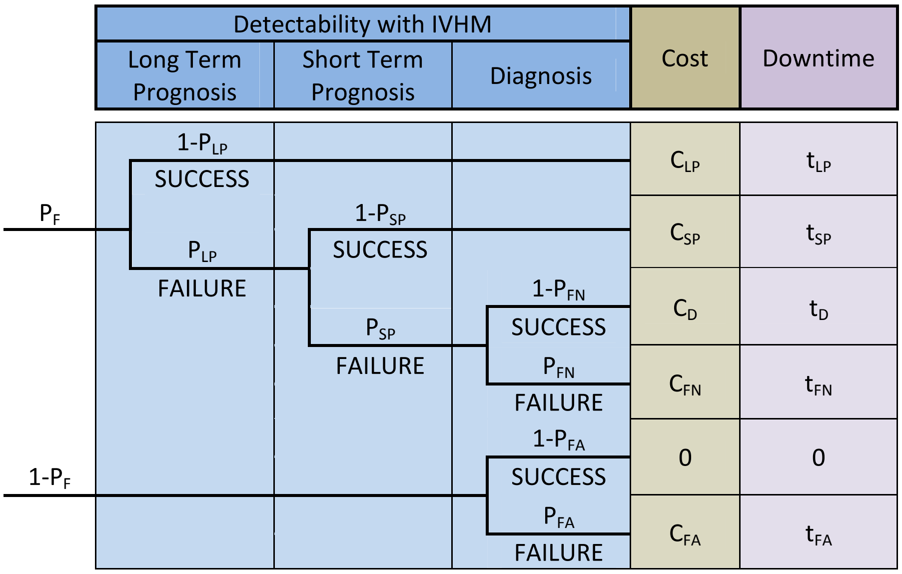


Figure 7-2 ETA for the use of health monitoring tools on a single component.

$$C = P_F \left((1 - P_{LP})C_{LP} + P_{LP} \left((1 - P_{SP})C_{SP} + P_{SP} \left((1-P_{FN})C_D + P_{FN}\, C_{FN} \right) \right) \right) + (1 - P_F)P_{FA}C_{FA} \tag{7-1}$$

$$T = P_F \left((1 - P_{LP})t_{LP} + P_{LP} \left((1 - P_{SP})t_{SP} + P_{SP} \left((1-P_{FN})t_D + P_{FN}\, t_{FN} \right) \right) \right) + (1 - P_F)P_{FA}t_{FA} \tag{7-2}$$

Remember that 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.

A detail list of the parameters used to calculate the maintenance cost and time of each scenario can be found in section 6.1.2, although it also possible to calculate some of them using the techniques described in [84; 160].

In regards to the performance requirements, 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 would not make sense to develop 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.

$$C^* \leq P_F\left((1-P_{FN})C_D + P_{FN}\,C_{FN}\right) + (1-P_F)P_{FA}C_{FA} \qquad \textbf{7-3}$$

$$T^* \leq P_F\left((1-P_{FN})t_D + P_{FN}\,t_{FN}\right) + (1-P_F)P_{FA}t_{FA} \qquad \textbf{7-4}$$

$$P_{FA} \geq 0\,;\; P_{FN} \geq 0 \qquad \textbf{7-5, 7-6}$$

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

$$P_{FA} \leq \frac{T^* - P_F\left((1-P_{FN})t_D + P_{FN}\,t_{FN}\right)}{(1-P_F)t_{FA}} \qquad \textbf{7-8}$$

Equations 7-5, 7-6, 7-7 and 7-8 define a space which encloses all the possible solutions that comply with the requirements. This space can be represented as shown in Figure 7-3.

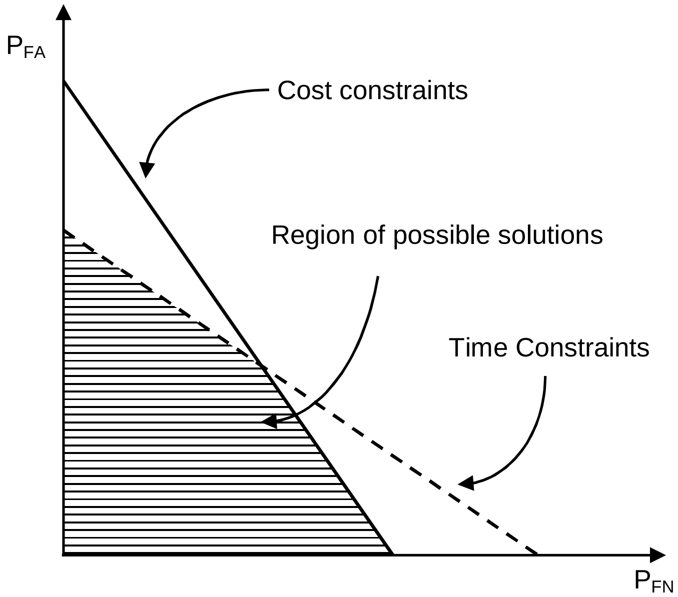


Figure 7-3.- Region of acceptable performance of a diagnostic tool

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.

$$C^* \leq P_F \left((1 - P_{LP})C_{LP} + P_{LP}\left((1 - P_{FN})C_D + P_{FN}\, C_{FN}\right)\right) + (1 - P_F)P_{FA}C_{FA} \qquad \textbf{7-9}$$

$$T^* \leq P_F \left((1 - P_{LP})t_{LP} + P_{LP}\left((1 - P_{FN})t_D + P_{FN}\, t_{FN}\right)\right) + (1 - P_F)P_{FA}t_{FA} \qquad \textbf{7-10}$$

$$P_{LP} \geq 0 \qquad \textbf{7-11}$$

$$P_{LP} \leq \frac{\dfrac{C^* - (1 - P_F)P_{FA}C_{FA}}{P_F} - C_{LP}}{(1 - P_{FN})C_D + P_{FN}\, C_{FN} - C_{LP}} \qquad \textbf{7-12}$$

$$P_{LP} \leq \frac{\dfrac{T^* - (1 - P_F)P_{FA}t_{FA}}{P_F} - t_{LP}}{(1 - P_{FN})t_D + P_{FN}\, t_{FN} - t_{LP}} \qquad \textbf{7-13}$$

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

7.2 Effect of uncertainties

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 [1], 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:

$$Var\,(XY) = \hat{X}\,Var(Y) + \hat{Y}\,Var(X) + Var(X)Var(Y) \quad \textbf{7-14}$$

$$Var\,(aX + bY) = a^2\,Var(X) + b^2 Var(Y) \quad \textbf{7-15}$$

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, P_{FN}; and their variances, var(P_{FA}) and var(P_{FN}) respectively. The limits of these variables are defined by the following functions:

$$R_C \leq \frac{1}{2}\left(1 + erf\left(\frac{C^* - \hat{C}}{\sqrt{2Var(C)}}\right)\right) \quad \textbf{7-16}$$

$$R_T \leq \frac{1}{2}\left(1 + erf\left(\frac{T^* - \hat{T}}{\sqrt{2Var(T)}}\right)\right) \quad \textbf{7-17}$$

$$P_{FA} \geq 0 \;\&\; P_{FN} \geq 0 \quad \textbf{7-18, 7-19}$$

where

$$\hat{C} = \widehat{P_{FN}}\widehat{P_F}\left(\widehat{C_{FN}} - \widehat{C_D}\right) + \widehat{P_F}\,\widehat{C_D} + \widehat{P_{FA}}(1 - \widehat{P_F})\widehat{C_{FA}} \quad \textbf{7-20}$$

$$\hat{T} = \widehat{P_{FN}}\widehat{P_F}\,(\widehat{t_{FN}} - \widehat{t_D}) + \widehat{P_F}\,\widehat{t_D} + \widehat{P_{FA}}(1 - \widehat{P_F})\widehat{t_{FA}} \quad \textbf{7-21}$$

$$Var(C) = Var\big(P_{FN}P_F\,(C_{FN} - C_D)\big) + Var(P_F\,C_D) + Var(P_{FA}(1 - P_F)C_{FA}) \quad \textbf{7-22}$$

$$Var(T) = Var(P_{FN}P_F\,(t_{FN} - t_D)) + Var(P_F\,t_D) + Var(\,P_{FA}(1 - P_F)t_{FA}) \quad \textbf{7-23}$$

From equation 7-16

$$Var(C) \leq \frac{\left(C^{*} - \hat{C}\right)^{2}}{2(erf^{-1}(2R_{C} - 1))^{2}} \qquad \textbf{7-24}$$

Additionally

$$\begin{aligned} Var(C) = {} & Var(P_{FN})\left(\widehat{P_{F}}^{2}\left(\widehat{C_{FN}} - \widehat{C_{D}}\right)^{2} + Var\left(P_{F}\,(C_{FN} - C_{D})\right)\right) \\ & + \widehat{P_{FN}}^{2} Var\left(P_{F}\,(C_{FN} - C_{D})\right) \\ & + Var(P_{FA})\left(\left(1 - \widehat{P_{F}}\right)^{2}\widehat{C_{FA}}^{2} + Var\left((1 - P_{F})C_{FA}\right)\right) \\ & + \widehat{P_{FA}}^{2} Var\left((1 - P_{F})C_{FA}\right) + Var(P_{F}\,C_{D}) \end{aligned} \qquad \textbf{7-25}$$

This expression can be rewritten as follows

$$Var(C) = K_{1}Var(P_{FN}) + K_{2}Var(P_{FA}) + K_{3} \qquad \textbf{7-26}$$

where

$$K_{1} = \widehat{P_{F}}^{2}\left(\widehat{C_{FN}} - \widehat{C_{D}}\right)^{2} + Var\left(P_{F}\,(C_{FN} - C_{D})\right) \qquad \textbf{7-27}$$

$$K_{2} = \left(1 - \widehat{P_{F}}\right)^{2}\widehat{C_{FA}}^{2} + Var\left((1 - P_{F})C_{FA}\right) \qquad \textbf{7-28}$$

$$K_{3} = \widehat{P_{FN}}^{2} Var\left(P_{F}\,(C_{FN} - C_{D})\right) + \widehat{P_{FA}}^{2} Var\left((1 - P_{F})C_{FA}\right) + Var(P_{F}\,C_{D}) \qquad \textbf{7-29}$$

As a result

$$K_{1}Var(P_{FN}) + K_{2}Var(P_{FA}) \leq \frac{\left(C^{*} - \widehat{P_{FN}}\widehat{P_{F}}\left(\widehat{C_{FN}} - \widehat{C_{D}}\right) + \widehat{P_{F}}\,\widehat{C_{D}} + \widehat{P_{FA}}(1 - \widehat{P_{F}})\widehat{C_{FA}}\right)^{2}}{2(erf^{-1}(2R_{C} - 1))^{2}} - K_{3} \qquad \textbf{7-30}$$

Following the same steps for the maintenance time requirements from equation 7-17, the second condition is

$$K_{4}Var(P_{FN}) + K_{5}Var(P_{FA}) \leq \frac{\left(C^{*} - \widehat{P_{FN}}\widehat{P_{F}}\,(\widehat{t_{FN}} - \widehat{t_{D}}) + \widehat{P_{F}}\,\widehat{t_{D}} + \widehat{P_{FA}}(1 - \widehat{P_{F}})\widehat{t_{FA}}\right)^{2}}{2(erf^{-1}(2R_{T} - 1))^{2}} - K_{6} \qquad \textbf{7-31}$$

where

$$K_4 = \widehat{P_F}^2(\widehat{t_{FN}} - \widehat{t_D})^2 + Var\big(P_F\,(t_{FN} - t_D)\big) \quad \textbf{7-32}$$

$$K_5 = \big(1 - \widehat{P_F}\big)^2\widehat{t_{FA}}^2 + Var\big((1 - P_F)t_{FA}\big) \quad \textbf{7-33}$$

$$K_6 = \widehat{P_{FN}}^2 Var\big(P_F\,(t_{FN} - t_D)\big) + \widehat{P_{FA}}^2 Var\big((1 - P_F)t_{FA}\big) + Var(P_F\,t_D) \quad \textbf{7-34}$$

Therefore, any diagnostic tool that satisfies the requirements and can generate the projected savings with the expected accuracy must comply with equations 7-18, 7-19, 7-30 and 7-31.

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:

$$R_C \leq \frac{1}{2}\left(1 + erf\left(\frac{C^* - \hat{C}}{\sqrt{2Var(C)}}\right)\right) \quad \textbf{7-35}$$

$$R_T \leq \frac{1}{2}\left(1 + erf\left(\frac{T^* - \hat{T}}{\sqrt{2Var(T)}}\right)\right) \quad \textbf{7-36}$$

The difference being

$$P_{LP} \geq 0 \quad \textbf{7-37}$$

$$\hat{C} = \widehat{P_{LP}}\widehat{P_F}\left(\widehat{C_{FN}} - \widehat{C_{LP}}\right) + \widehat{P_F}\,\widehat{C_{LP}} \quad \textbf{7-38}$$

$$\hat{T} = \widehat{P_{LP}}\widehat{P_F}\,(\widehat{t_{FN}} - \widehat{t_{LP}}\,) + \widehat{P_F}\,\widehat{t_{LP}} \quad \textbf{7-39}$$

$$Var(C) = Var\big(P_{LP}P_F\,(C_{FN} - C_{LP})\big) + Var(P_F\,C_{LP}) \quad \textbf{7-40}$$

$$Var(T) = Var\big(P_{LP}P_F\,(t_{FN} - t_{LP}\,)\big) + Var(P_F\,t_{LP}) \qquad \textbf{7-41}$$

From equation 7-35

$$Var(C) \leq \frac{\left(C^* - \hat{C}\right)^2}{2(erf^{-1}(2R_C - 1))^2} \qquad \textbf{7-42}$$

Combining equations 7-40 and 7-42

$$Var\big(P_{LP}P_F\,(C_{FN} - C_{LP})\big) \leq \frac{\left(C^* - \widehat{P_F}\,\widehat{P_{LP}}\big(\widehat{C_{FN}} - \widehat{C_{LP}}\big) + \widehat{P_F}\,\widehat{C_{LP}}\right)^2}{2(erf^{-1}(2R_C - 1))^2} - Var(P_F\,C_{LP}) \qquad \textbf{7-43}$$

$$Var(P_{LP}) \leq \frac{\dfrac{\left(C^* - \widehat{P_F}\,\widehat{P_{LP}}\big(\widehat{C_{FN}} - \widehat{C_{LP}}\big) + \widehat{P_F}\,\widehat{C_{LP}}\right)^2}{2(erf^{-1}(2R_C - 1))^2} - Var(P_F\,C_{LP}) - \widehat{P_{LP}}^{\,2} Var\big(P_F\,(C_{FN} - C_{LP})\big)}{\left(\widehat{P_F}^{\,2}\big(\widehat{C_{FN}} - \widehat{C_{LP}}\big)^2 + Var\big(P_F\,(C_{FN} - C_{LP})\big)\right)} \qquad \textbf{7-44}$$

Following the same steps with the equations for maintenance time constraints the result is:

$$Var(P_{LP}) \leq \frac{\dfrac{\left(T^* - \widehat{P_F}\,\widehat{P_{LP}}(\widehat{t_{FN}} - \widehat{t_{LP}}) + \widehat{P_F}\,\widehat{t_{LP}}\right)^2}{2(erf^{-1}(2R_T - 1))^2} - Var(P_F\,t_{LP}) - \widehat{P_{LP}}^{\,2} Var\big(P_F\,(t_{FN} - t_{LP})\big)}{\left(\widehat{P_F}^{\,2}(\widehat{t_{FN}} - \widehat{t_{LP}})^2 + Var\big(P_F\,(t_{FN} - t_{LP})\big)\right)} \qquad \textbf{7-45}$$

These parabolas define the limits for the performance requirements of any prognostic tool as shown in Figure 7-4. 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.

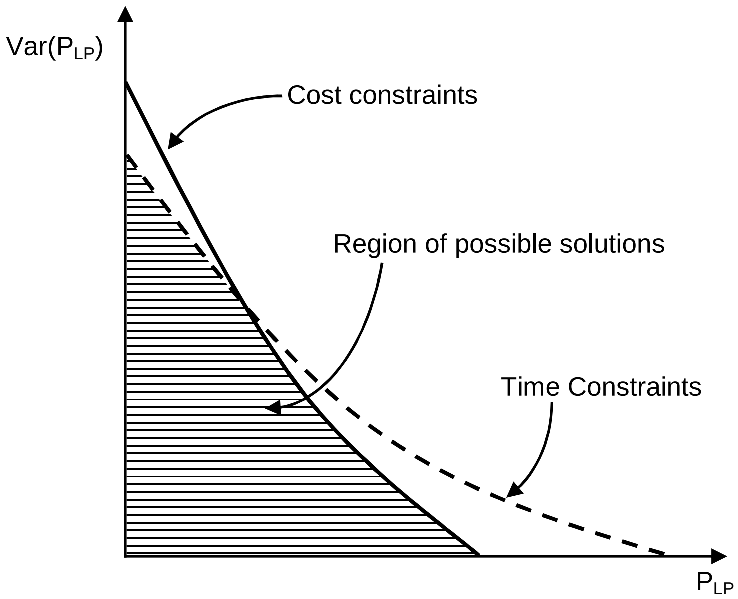


Figure 7-4.- Region of acceptable performance and variance of performance of a long-term prognostic tool

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.

7.3 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 till 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 7-1. 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 7-5.

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 7-6.

Table 7-1.- List of parameters used in case study and their values.

P_F		0.004
Cost of component (£)	Schedulled M.	525
	Unschedulled M.	628.9
	Flase Alarm	65
Cost of Labour (£)	Shcedulled M.	90
	Unschedulled 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
	Labour (%)	0
Time (h)	MTTR	2
	Check-out	0.25
	MTTD	2
	Localization	0.25
	Technical delay	0.33
	Administrative delay	1
	Logistic delay	0

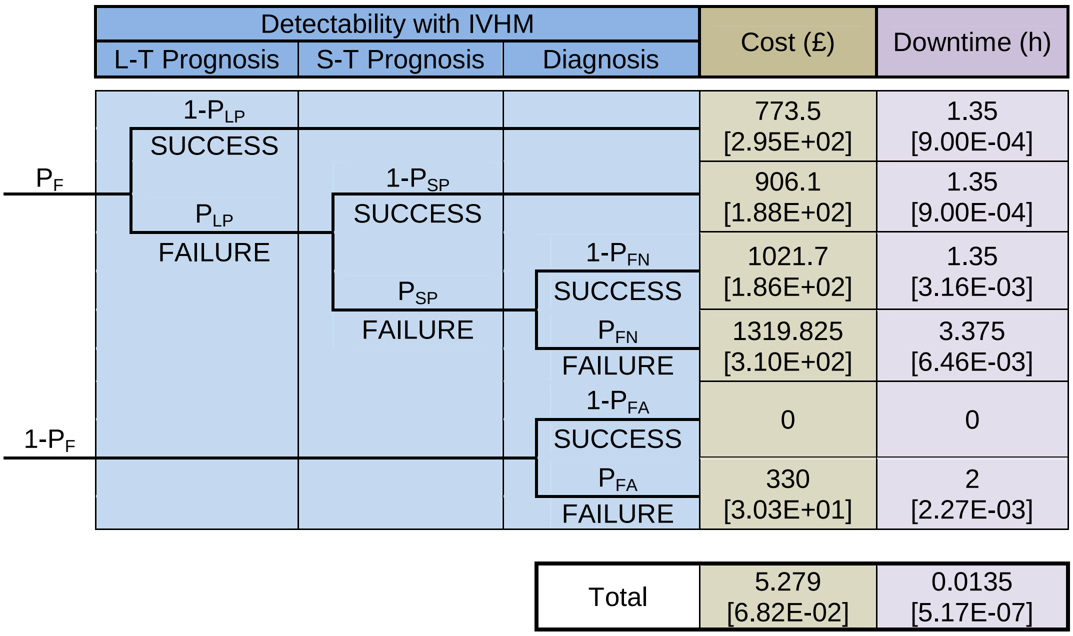


Figure 7-5.- Costs, times and their variances (in brackets) for each maintenance scenario.

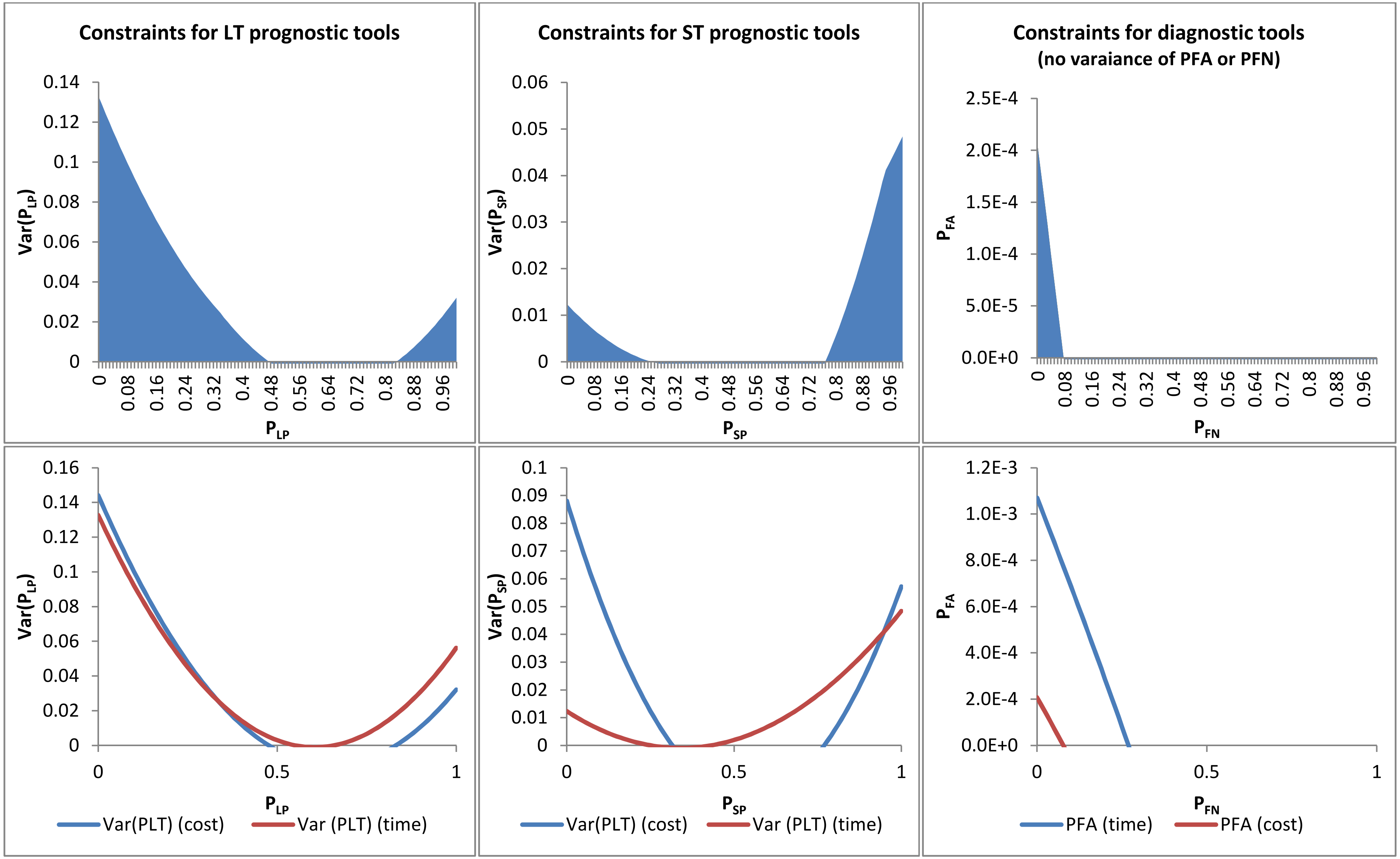


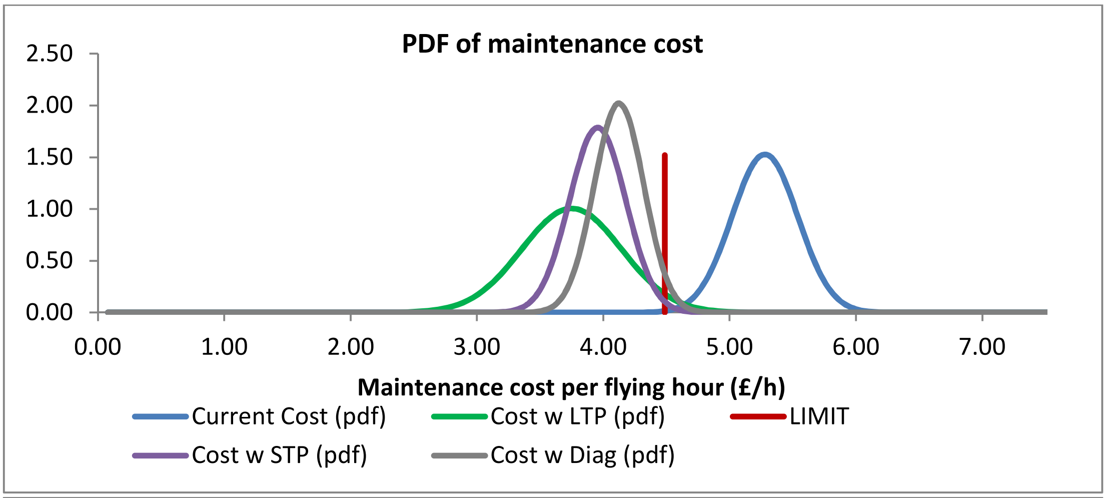
Figure 7-6.- Graphs representing the possible solutions for long-term and short term prognostic tools and diagnostic tools

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 7-6 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.

The probability density functions (pdf) 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 7-7 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 7-8.

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.



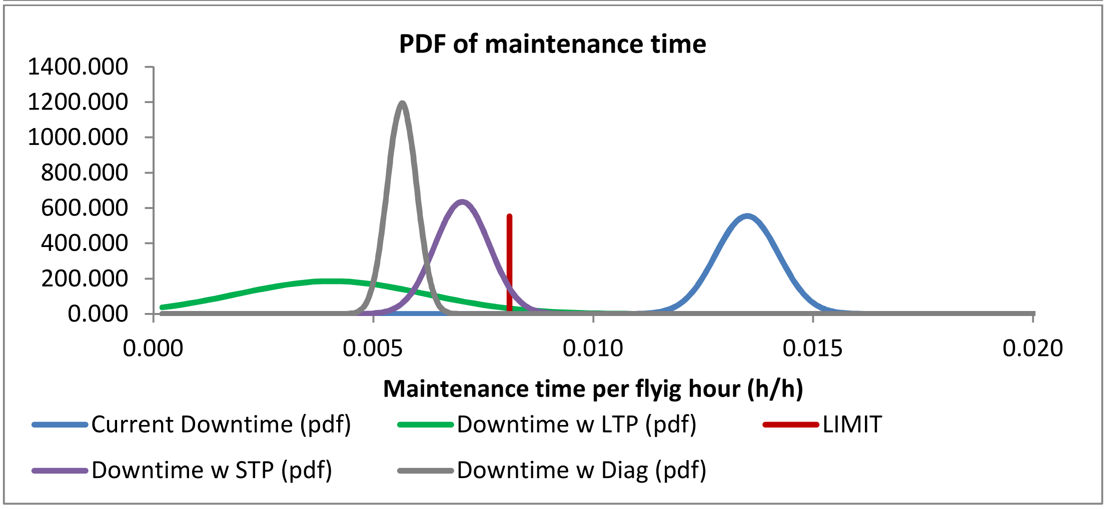


Figure 7-7 PDF of maintenance cost & time for the different IVHM tools proposed.

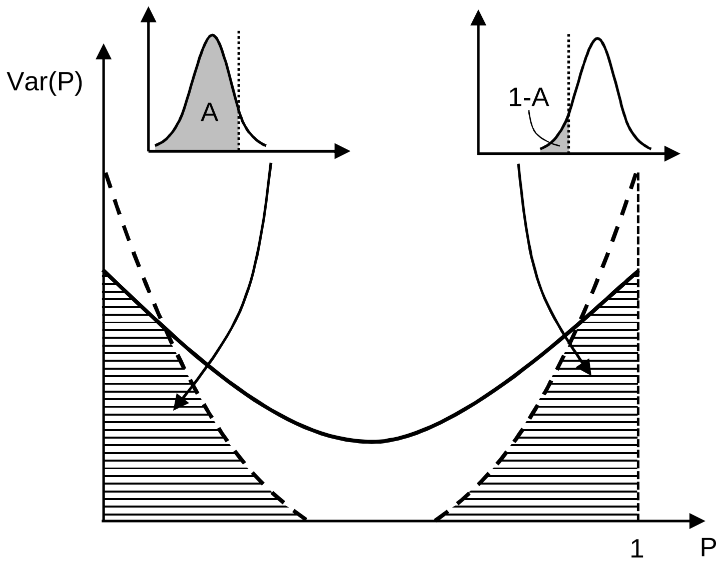


Figure 7-8 Region of acceptable performance and variance of performance of a long-term prognostic tool. Regions highlighted on the righ side of contraints plots correspond to the complementary probabilty of acceptable performance.

7.4 Conclusions

This method represents a reliable way to define the requirements of individual diagnostic and prognostic tools based on the expectations of improving the maintenance of specific components and the uncertainty of the available data. Since the equations provide the possibility to carry out a quantitative risk analysis, the results they provide can be used to make sure business cases are more robust and less likely to overstate the benefits of installing the selected combination of IVHM tools. This possibility will be explored in more detail in chapter 8.

As in chapter 6, this method works on individual parts or LRUs, setting requirements for improvements that are to be achieved at component level. The effect of interactions between tools and the complexity of maintenance operations will be studied in chapters 8 and 9 respectively.

Next chapter will compare all the possible combinations of the tools that comply with the performance requirements calculated using the equations from this chapter. The more tools are found that comply with these requirements, the larger the number of possible combinations. By having a large number of candidates designers can rest assured sure that they have examined all options and that the final configuration chosen for the IVHM is the most advantageous.

A look at the effect IVHM tools can have on the standard deviations of the probability distributions of maintenance costs and times shows that they can either reducing them or increasing them. Since the predictability of these factors is sometime as important as decreasing their value, this shows that such effect must be analysed carefully in the CBA of the final design of the IVHM system.

From now on uncertainties will play a major role in all steps taken in the rest of the methodology described in this thesis. Therefore it is necessary to take into account that it may not always be 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 on the aircraft should be interviewed to get approximated values. This will always be a better option than ignoring the effect of these uncertainties.

8 Risk analysis on the investment on different combinations of IVHM tools

"Our doubts are traitors,
And make us lose the good we oft might win
By fearing to attempt."
- *William Shakespeare*

The steps of the methodology discussed up to this point have focused on identifying critical components (chapter 6) and defining the requirements for health monitoring tools that could achieve the desired effect by monitoring said components (chapter 7). In this chapter the discussion will focus on the effect of combining different health monitoring tools to form an IVHM system and how the optimal combination in economic terms can be identified* (see Figure 8-1).

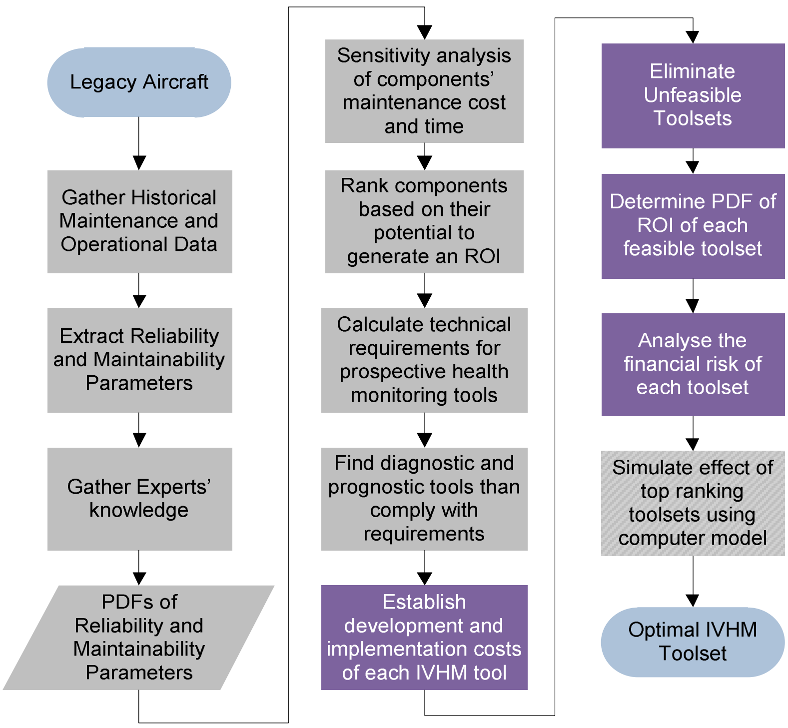


Figure 8-1 Flowchart of methodology to configure an IVHM system for a legacy vehicle highlighting the steps covered in this chapter in purple.

* This method is part of an article submitted to the Journal of Mechanical Design, included in Appendix C. Esperon-Miguez, M., John, P., Jennions, I.K., 2013, Configuring IVHM Toolsets for legacy platforms according to economic risk analysis at the preliminary design stage. Submitted to the Journal of Mechanical Design (ASME) on May 2013

One of the most important characteristics of a health monitoring system is the level to which the different diagnostic and prognostic tools it is comprised of are integrated. A completely federated system would consist of independent devices, each of which would receive the signal from the sensors that monitor a specific component. Each device would then postprocess and analyse the data to diagnose faults or estimate the RUL of the component. They would use their own hardware and would not exchange any information with other tools that are part of the IVHM system.

Conversely, a fully integrated system would combine all diagnostic and prognostic tools in a single device which would receive the signals of all sensors used to monitor the condition of multiple components. All data would be stored on the same memory unit and diagnostic and prognostic algorithms run in the same computer. Since data are accessible to all tools, integrated systems allow for interactions between components (and their failures/degradation) to be taken into account. This is of utmost importance for the development of health monitoring algorithms for failure modes in which several components are involved. (i.e.: secondary failures caused by the failure of other parts.)

Needless to say, fully integrated systems are, so far, just part of the long-term objectives of the IVHM community. There are some examples of health monitoring systems which postprocess data to a certain degree and store it in a common memory device (e.g.: HUMS), but they cannot run diagnostic or prognostic algorithms. At best, they can indicate if a certain parameter has exceeded some predetermined boundaries, but that barely qualifies them as monitoring systems, not IVHM systems. Furthermore, systems that monitor multiple components tend to focus on specific aircraft systems (e.g.: engines, structure) and do not exchange of information on the condition of components that belong to different systems.

Whist the advantages of developing integrated IVHM systems are clear, the fact that most health monitoring systems are, for the most part, nearly completely federated is not due to a lack of understanding or vision. The numerous impediments faced by those trying to implement this technology has resulted in health monitoring systems that have been developed in incremental steps, with tools being developed by independent teams, during different time periods and usually for components whose failure mechanisms are not related –which limits the benefits of an integrated system.

The analytical method described in this chapter has been developed to tackle these problems by focusing on the financial aspects of combining IVHM tools (this is discussed in more detail in sections 8.1 and 8.2). The contributions of this method are:

- Eliminate from the analysis combinations of tools that are not viable due to technical limitations (section 8.3.)
- Provide an analytical approach to identify the best IVHM toolset according to its economic return and the financial risk it represents (section 8.4.)
- Provide criteria to focus on a handful of combinations of tools, rather than thousands or millions, in case further analyses are to be conducted using DES or any other sort of computer simulation of maintenance operations (section 8.4.)

As an example of applying this method to multiple potential combinations of IVHM tools, a case study is discussed in section 8.5.

8.1 Technical and economic consequences of combining diagnostic and prognostic tools

From a maintenance perspective it is essential that the selection of components to be monitored takes into account their failure/replacement frequency, replacement time, delays and how IVHM can affect them. Given the complexity of maintenance operations this problem must be studied using computer-based simulations of maintenance activities. This can result in health monitoring systems that improve the maintenance time and/or cost of individual components, but have a negligible effect on the maintenance of the fleet.

From an implementation perspective, the interactions between tools can result in unforseen problems with the hardware and/or the software. Therefore, implementing and IVHM system that comprises diagnostic and prognostic tools to monitor several components becomes an engineering project that requires a significant investment and involves great uncertainty.

Some methodologies to approach this problem do exist, but they normally focus on individual parts or a limited number of components or subsystems. It has been proposed to FMECA as the main basis for the design of full IVHM systems [85; 94; 95]. However, these methodologies, whilst applicable to a limited number of components, are not suitable for the analysis of a complete aircraft since it would be impractical to carry out an FMECA for each individual part, not to mention to analyse all possible interactions between components and between their potential monitoring tools. In their CBA to study the use of PHM on legacy commercial aircraft Leao et al. [84] presented a comprehensive set of equations that can be used both by aircraft manufacturers and operators, but did not acknowledge the interactions between tools and how this affects the resulting platform availability.

However, in the case of legacy aircraft, their unique combinations of abundant historical maintenance data and constraints that rule out significant modifications of their systems, allow for a series of quantitative analyses that can lead to an optimal combination of diagnostic and prognostic tools. Computer simulations of maintenance activities which take into account the use of diagnostic and prognostic tools are essential to quantify the effect of implementing this technology.

Ideally, once the maintenance model has been developed and validated, different combinations of diagnostic and prognostic tools can be tested. However, whilst a computer essential to carry out a solid CBA, it is not practical, or even possible, to simulate the effect of all potential combinations of health monitoring tools. Taking into account that aircraft are comprised of thousands of components, a comprehensive analysis of all options should consider, at least, the possibility of monitoring a few dozen components, even if the final number of tools implemented may be lower. For example, if designers have to choose 10 tools out of 50 possible options, this represents more than 10 billion combinations. Even taking into account incompatibilities between tools due to conflicts caused by their hardware or software, it is unlikely that the total number of toolsets is reduced significantly enough so all combinations can be studied and compared thoroughly.

The method described in this chapter analyses the financial risk incurred by investing on different combinations of IVHM tools. The financial risk is determined by calculating the variance of the expected ROI for each toolset. This allows ranking toolsets according to the probability of their ROI falling below a given threshold (normally the cost of money). Those toolsets that present a lower financial risk can then be analyse thoroughly using computer models.

8.2 IVHM tools as financial assets

Each diagnostic and prognostic tool is essentially an investment from which a return is expected. This return is the result of avoiding certain maintenance costs and, if contemplated in the agreement between operator and maintainer, increasing the availability of the asset. From this point of view diagnostic tools are equivalent to financial assets.

Comparing toolsets must take into account the possibility of sharing resources between tools in their design, testing, manufacturing, implementation and operation. In other words, tools can share -among others- sensors, memory, flight test expenses, recurring costs, etc. This translates to a reduction in the investment necessary to put a certain group of tools in service. Consequently, the ROI of each toolset is not the weighted average of the ROIs of those tools it comprises, but the ratio between the sum of their expected profits and the total cost of developing, implementing and operating the complete IVHM system.

In mathematical terms, for a toolset with n tools in which the project budget for each tool has been divided into m phases or parts this can expressed as:

$$ROI = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} C_i} = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} \sum_{j}^{m} c_{ij}/\alpha_{ij}} \qquad \textbf{8-1}$$

where

P_i = Expected profit from tool i

C_i = Total cost of tool i

c_{ij} = Cost of tool i for part j of its budget

α_{ij} = Number of tools with which c_{ij} is shared

However, sharing resources means that a deviation in their cost can effectively raise the cost of several tools. For example, if algorithms are processed in a centralised unit whose costs exceeds the original budget this will also impact the cost of each individual health monitoring tool. A federated IVHM system with algorithms run in individual processing units may be more expensive, but its total cost is less vulnerable to this kind of problems.

Comparing toolsets becomes even more complicated when options include tools that are under development and not fully proven. Mature diagnostic and prognostic tools are less likely to present problems and have significant variations in their cost, but their performance can be lower than tools that are still being developed and employ the latest hardware and software. The cost of the latter however is more likely to deviate from the original budget.

This resembles a classic financial investment problem in which investors must select the optimal combination of assets to maximise the return of their portfolio whilst keeping risk within reasonable limits. As in the problem described in this chapter, financial assets have some degree of correlation and this must be carefully studied to avoid situations in which an investor can be severely affected by fluctuations in the market (e.g.: stock prices of logistic companies are affected by the fluctuation of oil prices in commodity markets, gold prices and the USD are normally inversely correlated, etc.)

There are all sorts of financial analysis tools that can be applied to solve this problem [131-133], but there is an important part of this financial analysis tools ignore: the variation of the ROI of each health monitoring tool depending on how it is combined with others. This is due to the fact that the return on a financial product is not affected by how much one invests in other assets. Figure 8-2.a shows an example of using conventional financial risk analysis to compare combinations of a generic set of IVHM tools. As toolsets include larger numbers of diagnostic and prognostic tools the risk decreases because deviations in the cost of individual tools have a smaller impact on the total investment. However, the ROI tends to the average ROI of all possible options because the savings are not taken into account. Figure 8-2.b shows how the ROI can increase significantly if IVHM tools are combined appropriately taking into account Eq. 8-1.

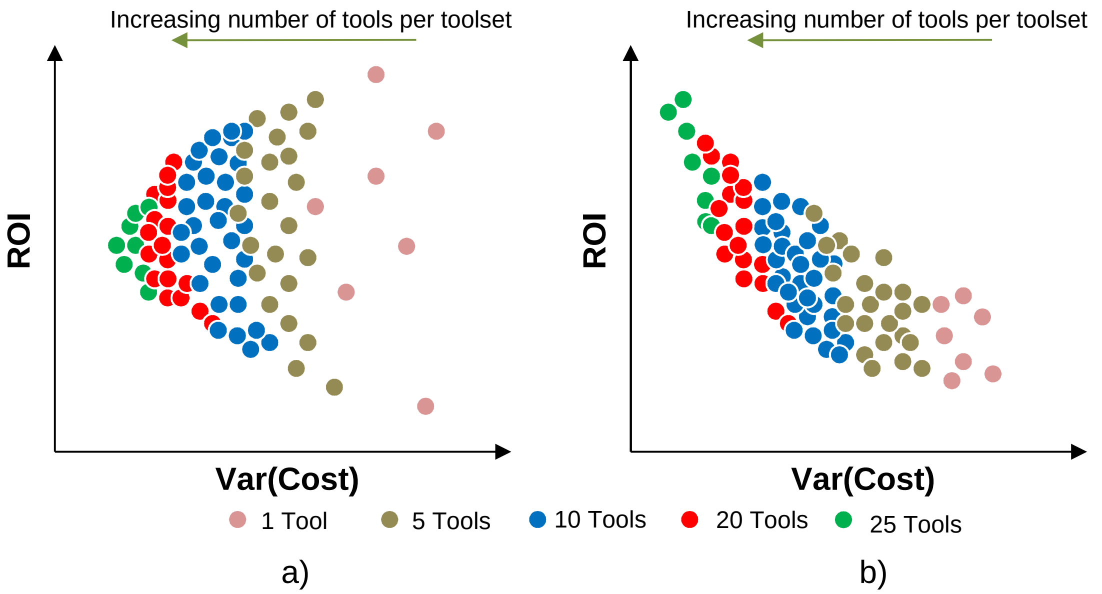


Figure 8-2 Comparison of the plots of ROI and variance of the cost of IVHM toolsets based using financial analysis (a) and including cost sharing (b).

8.3 Removing incompatible combinations

The starting point for the comparison of different combinations of health monitoring tools is a list of diagnostic and prognostic tools. However, designers would be interested in analysing more than one possible tool for each component which means that some of the them cannot be combined in the same toolset (i.e.: there is no reason to monitor the condition of a component with more than one tool). Furthermore, incompatibilities between tools can also be caused by technical factors such as geometric constraints or incompatible communication protocols. Therefore, it is essential to identify and remove any toolset that includes tools that are incompatible. This also helps to run the risk analysis algorithm faster thanks to the reduction in the number of combinations that need to be analysed.

For an original list with a total of *t* health monitoring tools, incompatibilities between each pair of tools are included in the symmetrical matrix ***I*** in which the values of the diagonal are all zeros:

$$\boldsymbol{I} = \begin{bmatrix} 0 & i_{12} & \cdots & i_{1t} \\ i_{21} & 0 & \cdots & i_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ i_{t1} & i_{t2} & \cdots & 0 \end{bmatrix}_{t\times t}$$

$$i_{ij} = i_{ij} \quad \& \quad i_{ij} \in \mathbb{N}, [0,1]$$

where:

if tools *i* and *j* are compatible $i_{ij} = 0$

if tools *i* and *j* are incompatible $i_{ij} = 1$

For a given combination of tools defined by vector ***t*** (where t_n is the position of each tool on the list), the viability of each combination will be determined by the value of *k*:

$$k = \boldsymbol{l}_n \cdot \boldsymbol{I}(\boldsymbol{t},\boldsymbol{t}) \cdot \boldsymbol{l}_n^T \qquad \textbf{8-2}$$

where $\boldsymbol{l}_n=[1,\ldots,1]_n$ and:

if all tools included in ***t*** are compatible $k = 0$

if any pair of tools included in ***t*** are incompatible $k \neq 0$

There is no difficulty in identifying which tools cannot be part of the same toolset because they would monitor the same component. However, to be able to include all other technical incompatibilities at this stage, experts on each tool and in systems engineering should be consulted.

8.4 Comparison of Toolsets

As mentioned in the introduction, toolsets are to be compared based on the risk they represent from a financial point of view. Knowing the ROI and its variance for each viable combination of health monitoring tools is not enough to identify which toolset represents a sounder investment. Both parameters need to be transformed into a single metric that can gives a clear indication of which is the best option available.

There are numerous ways of doing this in financial analysis, such as the Value at Risk or the Expected Shortfall, but those are more suitable for portfolio analysis. Another way of parameterising the risk of an investment is to determine the likelihood of their ROIs falling below the cost of money used by the organization, C_m. The less likely a toolset is to produce a lower profit than a generic investment within the organization the higher it appears in the ranking. The formula to calculate this probability is:

$$\Pr(ROI \leq C_m) = \int_0^{C_m} f(x)dx \tag{8-3}$$

All these methods rely on knowing the shape of the probability distribution of the ROI, *f(x)*. In this section we will demonstrate how to calculate the function of this distribution applying statistics to information obtained using conventional risk analysis methods.

8.4.1 Using moments to characterise probability distributions

Moments can be used to characterise the shape of any probability distribution. Moments are a quantitative measure of the shape of a set of points. The nth moment of a probability distribution *f(x)* about the value a is:

$$\mu_n' = \int_{-\infty}^{\infty} (x-a)^n f(x)dx \tag{8-4}$$

The first order moment taken about 0 is known as the expected value of the probability distribution, *E[X]*, and is equal to the mean of the distribution.

$$\bar{x} = E[X] = \int_{-\infty}^{\infty} x f(x) dx \qquad \textbf{8-5}$$

When moments are taken about the mean of the distribution they are known as central moments

$$\mu_n = E[(X - E[X])^n] = \int_{-\infty}^{\infty} (x - \bar{x})^n f(x) dx \qquad \textbf{8-6}$$

The second central moment of a probability distribution is equal to its variance, σ^2, the third is its skewness, γ_1, and the fourth its kourtosis, β_2. The skewness provides a measurement of the asymmetry of the distribution (Figure 8-3), whilst the kurtosis is a measurement of the "peakedness" of the distribution (Figure 8-4). The kurtosis can also be interpreted as an indication of the heaviness of the tails of the distribution.

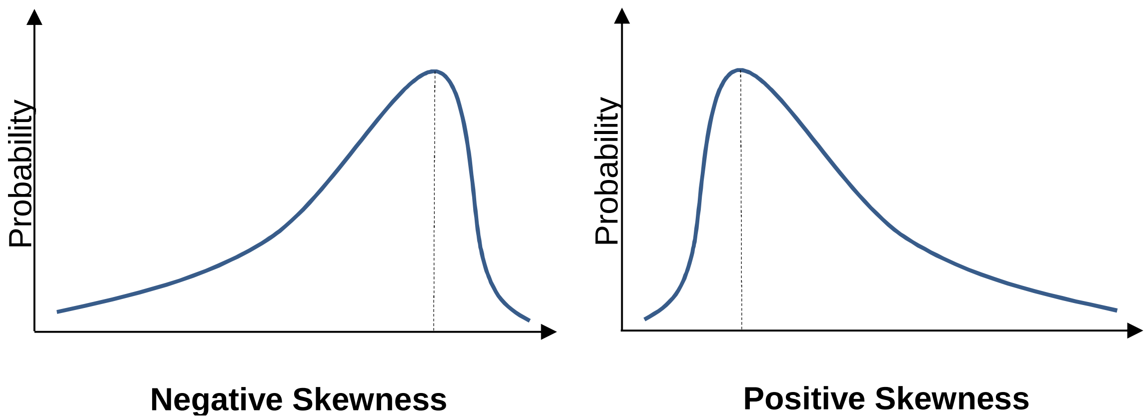


Figure 8-3 Examples of negative (left and positive (right) skewness.

When working with probabilities it is much more common to use the excess of kurtosis, γ_2, rather than the "classic" kurtosis, β_2 (eq. 8-7). In essence, the excess of kurtosis defines "peakedness" of a distribution in comparison to a normal distribution, whose kurtosis is always 0 (Figure 8-4). Distributions with positive excess of kurtosis have "heavier tails" than the normal distribution and are called leptokurtic distributions ("lepto-"="slender"), conversely, those that have a negative of kurtosis are called platykurtic ("platy-"="broad"). The reader might be interested to know that the coin toss is the most platykurtic distribution, with γ_2=-2.

$$\gamma_2 = \beta_2 - 3 \tag{8-7}$$

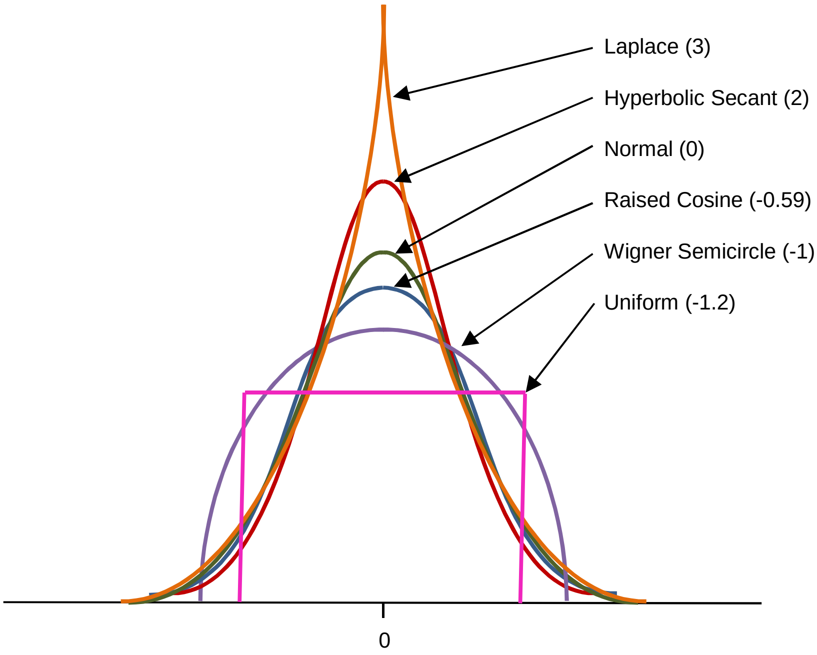


Figure 8-4 Excess kurtosis of various common statistical distributions

The more moments used, the more precise the estimation of the probability distribution. However, in this case it is not possible to calculate them using eq. 8-6 because the objective is to calculate *f(x)* which is unknown at this point. The next sections describe how to calculate the first four moments of the ROI based on the information available regarding the cost and expected profit of each combination of tools.

8.4.2 Probability distributions of cost and profit

The ROI is the ratio of two random variables: the cost and expected profit of each toolset. The cost of each toolset is equal to the summation of multiple expenses. Similarly, the profit is the difference between the summation of future savings and incomes produced by the use of the IVHM system minus its cost.

In risk analysis costs are normally estimated by providing an estimated average cost and a lower and upper boundary [161; 162], which means using triangular probability distributions. Detailed methods for elicitation in cost analysis can be found in [161; 163; 164]. The same process can be followed to estimate the savings and incomes the IVHM system will generate since they will be based on information gathered using experts' opinion. The variance of the profit can be estimated taking into account the variance of: maintenance costs, maintenance times and the performance of health monitoring tools [165; 166].

The Central Limit Theorem (CLT) states that the sum of independent and identically distributed random variables can be approximated to a normally distributed function (see [167; 168]). However, the probability distributions of the different estimated costs and profits are not identically distributed (they have different means, variances, and shapes). Nevertheless, these random variables do not need to be identical as long as they comply with Lindeberg's condition [167], which, for every ε>0, requires:

$$\lim_{n\to\infty} \frac{\sum_{i=1}^{n} \int_{\{|X_i - E[X_i]| > \varepsilon s_n\}} E[|X_i - E[X_i]|^2]}{s_n^2} = 0 \qquad \textbf{8-8}$$

where $s_n^2 = \sum_{i=1}^{n} \sigma_i^2$.

Since the triangular probability distribution complies with Lindeberg's condition, the CLT can be applied and the total cost and profit produced by each toolset can be considered normally distributed.

Characterizing the ROI becomes much simpler because the central moments of random Gaussian variables are:

$$\begin{cases} \mu_{2n} = \dfrac{(2n)!}{n!\,2^n}\sigma^{2n} \\ \mu_{2n+1} = 0 \end{cases} \qquad \textbf{8-9}$$

This means that the only parameters necessary to carry out this risk analysis are the mean and the variance of the cost and expected profit of each combination of tools (μ_c and σ_c, and μ_p and σ_p respectively). The next section explains how the first four moments of the ROI can be calculated using just these four inputs.

8.4.3 Calculating the moments of the ROI

8.4.3.1 Mean

Since the ROI is a ratio between two random variables its mean does not necessarily correspond to the ratio between their averages. The new mean can be estimated using Taylor expansions for the first moment of random variables:

$$E\left[\frac{x}{y}\right] \approx f(E[\boldsymbol{x}]) + \frac{1}{2}f''(E[\boldsymbol{x}])var\big(f(E[\boldsymbol{x}])\big) \qquad \textbf{8-10}$$

For the ratio of two random variables:

$$E\left[\frac{x}{y}\right] \approx \frac{\bar{x}}{\bar{y}} + \frac{\bar{x}}{\bar{y}^3}\sigma_y - \frac{\sigma_{x,y}}{\bar{y}^2} \qquad \textbf{8-11}$$

where $\sigma_y = var(y)$ and $\sigma_{x,y} = cov(x,y)$.

Intuitively, it might seem as if the cost of an IVHM system and the savings it will eventually produce should be connected: investing on a system that is more expensive because it is capable of detecting and predicting faults more accurately should result in bigger savings. However, this particular point of the analysis is not about comparing different configurations of an IVHM system. Instead, it focuses on evaluating how unforeseeable events (e.g.: miscalculated project cost and time, technical problems, reallocation of resources to projects with higher priority, etc.) that could deviate costs from the original budget affect the risk of the investment. In other words: is any deviation from the original budget correlated with the accuracy of the IVHM system and, therefore, correlated with its effect on maintenance costs and the availability of the fleet? It is not difficult to see that problems encountered during the design, installation and testing of an IVHM system can result in modifications that improve, worsen or leave unaffected its performance. Therefore, it is safe to say that the cost of the system and the savings it produces are independent and $cov(C, P)=0$.

Consequently, applying eq. 8-1 to eq. 8-11 we obtain the mean (a.k.a. expected value) of the ROI:

$$E[ROI] \approx \frac{\bar{P}}{\bar{C}} + \frac{\bar{P}}{\bar{C}^3}\sigma_C \qquad \textbf{8-12}$$

8.4.3.2 Variance

The delta method [169]can be used to estimate confidence intervals of a random variables. It uses Taylor expansions to approximate the variance of random variables (a.k.a.: second central moment). The formula for a multivariate function is:

$$var\big(f(\boldsymbol{x})\big) \approx \nabla f(E[\boldsymbol{x}])^T var(\bar{x}) \nabla f(E[\boldsymbol{x}]) \qquad \textbf{8-13}$$

Since the ROI is a fraction we are interested in the following expression:

$$var\left(\frac{x}{y}\right) \approx \frac{\sigma_x}{\bar{y}^2} + \bar{x}^2\frac{\sigma_y}{\bar{y}^4} - \frac{2\bar{x}}{\bar{y}^3}\sigma_{x,y} \qquad \textbf{8-14}$$

Since profits and costs can be considered independent the variance of the ROI is:

$$var(ROI) = var\left(\frac{P}{C}\right) \approx \frac{\bar{C}^2\sigma_P + \bar{P}^2\sigma_C}{\bar{C}^4} \qquad \textbf{8-15}$$

8.4.3.3 Skewness and kurtosis

Anderson and Mattson [170] have obtained the formulas for the propagating skewness and kurtosis for monovariate functions using Taylor expansions to characterise PDFs in rolling manufacturing processes. This is the first time these expressions are used for financial analysis or in relation to IVHM.

Assuming *y=f(x),*the skewness as a function of the central moments of *x* is:

$$\gamma_1 = E\left[\left(\frac{y-\bar{y}}{\sigma}\right)^3\right] = \frac{E[(y-\bar{y})^3]}{(E[(y-\bar{y})^2])^{1.5}} \approx \frac{\begin{bmatrix} \mu_3 \\ \frac{3}{2}(\mu_4 - \mu_2^2) \\ \left(\frac{3}{4}\mu_5 - \frac{3}{2}\mu_2\mu_3\right) \\ \left(\frac{1}{4}\mu_2^3 - \frac{3}{8}\mu_2\mu_4 + \frac{1}{8}\mu_6\right) \end{bmatrix} \begin{bmatrix} \partial_1^3 \\ \partial_1^2\partial_2 \\ \partial_1\partial_2^2 \\ \partial_2^3 \end{bmatrix}}{\left[\mu_2\partial_1^2 + \mu_3\partial_1\partial_2 + \frac{1}{4}(\mu_4 - \mu_2^2)\partial_2^2\right]^{1.5}} \qquad \textbf{8-16}$$

where $\partial_1 = \frac{\partial f}{\partial x}$, $\partial_2 = \frac{\partial^2 f}{\partial x^2}$ and μ_i is the *ith* central moment of *x*.

For the kurtosis the formula for monovariate functions is [170]:

$$\beta_2 = E\left[\left(\frac{y-\bar{y}}{\sigma}\right)^4\right] = \frac{E[(y-\bar{y})^4]}{(E[(y-\bar{y})^2])^2} \approx \frac{\begin{bmatrix} \mu_4 \\ 2(\mu_5 - \mu_2\mu_3) \\ \frac{3}{2}(\mu_2^3 - 2\mu_2\mu_4 + \mu_6) \\ \frac{3}{2}\left(\mu_2^2\mu_3 - \mu_2\mu_5 + \frac{1}{3}\mu_7\right) \\ \frac{1}{16}(6\mu_2^2\mu_4 - 3\mu_2^4 - 4\mu_2\mu_6 + \mu_8) \end{bmatrix} \begin{bmatrix} \partial_1^4 \\ \partial_1^3\partial_2 \\ \partial_1^2\partial_2^2 \\ \partial_1\partial_2^3 \\ \partial_2^4 \end{bmatrix}}{\left[\mu_2\partial_1^2 + \mu_3\partial_1\partial_2 + \frac{1}{4}(\mu_4 - \mu_2^2)\partial_2^2\right]^2} \qquad \textbf{8-17}$$

The reader is reminded that *E([y-E[y]]*^{2}*)* is the second moment or variance of the ROI which has already been calculated for each toolset using eq. 8-15. Therefore, we only need to find the numerators of eq. 8-16 and 8-17.

Since *f(x)=f(C,P)*, the next step is to find a way to calculate the central moments of the cost and profit for each toolset. From eq. 8-9 we know that $\mu_3=\mu_5=\mu_7=0$, $\mu_4=3\sigma^4$, $\mu_6=15\sigma^6$, $\mu_8=105\sigma^8$, resulting in:

$$\gamma_1 \approx \frac{3\sigma_x\partial_1^2\partial_2 + \sigma_x^3\partial_2^3}{\left(\partial_1^2 + \frac{1}{2}\partial_2^2\sigma_x^2\right)^{1.5}} = \frac{3\sigma_x\partial_1^2\partial_2 + \sigma_x^3\partial_2^3}{\sigma_y^3} \qquad \textbf{8-18}$$

$$\beta_2 \approx \frac{3\sigma_x^4\partial_1^4 + 15\sigma_x^6\partial_1^2\partial_2^2 + \frac{15}{4}\sigma_x^8\partial_2^4}{\sigma_y^4} \qquad \textbf{8-19}$$

The problem at hand involves working with multivariate functions, transforming eq. 8-18 and 8-19 into:

$$\gamma_1 \approx \frac{1}{\sigma_y^3}\left(\sum_{j=1}^{n}\sum_{i=1}^{n} 3\sigma_{i,j}\left(\frac{\partial f}{\partial x_i}\right)^2\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right) + \sigma_{i,j}^3\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^3\right) \quad \textbf{8-20}$$

$$\beta_2 \approx \frac{1}{\sigma_y^4}\sum_{i=1}^{n}\left[3\sigma_i^4\left(\frac{\partial f}{\partial x_i}\right)^4 + \sum_{j=1}^{n} 15\sigma_{i,j}^6\left(\frac{\partial f}{\partial x_i}\right)^2\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^2 + \frac{15}{4}\sigma_{i,j}^8\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^4\right] \quad \textbf{8-21}$$

Since for every toolset its cost and profit are considered independent $\sigma_{C,P}=0$. As for the derivatives of *f(C,P)*:

$$\begin{cases} \dfrac{\partial f}{\partial P} = \dfrac{1}{C} \\ \dfrac{\partial f}{\partial C} = -\dfrac{P}{C^2} \\ \dfrac{\partial^2 f}{\partial P^2} = 0 \\ \dfrac{\partial^2 f}{\partial C^2} = 2\dfrac{P}{C^3} \\ \dfrac{\partial^2 f}{\partial P \partial C} = -\dfrac{1}{C^2} \end{cases} \quad \textbf{8-22}$$

Applying eq. 8-22 to eq. 8-20 and 8-21 results in the final equations to calculate the skewness and kurtosis of the probability distribution of the ROI:

$$\gamma_1(ROI) \approx \frac{8\sigma_C^3\dfrac{\bar{P}^3}{\bar{C}^9} + 6\sigma_C\dfrac{\bar{P}^4}{\bar{C}^7}}{\left(\dfrac{\bar{C}^2\sigma_P^2 + \bar{P}^2\sigma_C^2}{\bar{C}^4}\right)^{1.5}} \quad \textbf{8-23}$$

$$\beta_2(ROI) \approx \frac{3\sigma_P^4\dfrac{1}{\bar{C}^4} + 3\sigma_C^4\dfrac{\bar{P}^4}{\bar{C}^8} + 60\sigma_C^6\dfrac{\bar{P}^4}{\bar{C}^{10}} + \dfrac{15}{4}\sigma_C^8\dfrac{\bar{P}^4}{\bar{C}^{12}}}{\left(\dfrac{\bar{C}^2\sigma_P^2 + \bar{P}^2\sigma_C^2}{\bar{C}^4}\right)^2} \quad \textbf{8-24}$$

Now, armed with the mean, variance, skewness and kurtosis of the ROI designers can compare the risk of investing in different IVHM toolsets.

However, before eq. 8-11, 8-12, 8-23 and 8-24 can be solved, the mean and standard deviations of the cost and expected profit of each combination of tools have to be calculated.

Since the mean and variance of the ROI are always positive, looking at eq. 8-23 is easy to see that the probability distribution of the ROI will always present positive skewness.

As explained before, profits are essentially a summation of different incomes. Since the different costs avoided and other sources of revenue can be considered independent $\sigma_P = \sum_{k=1}^{n} var(P_i)$. However, this is not so straightforward for costs due to the sharing of expenses. The next section describes how the mean and variance can be calculated based on which costs are shared.

8.4.4 Correlation of costs and its effect on the risk

Sharing costs results in correlations that affect the way errors propagate, increasing the difficulty of calculating the standard deviation of the cost of each combination of health monitoring tools. The budget for each tool includes all the expenses necessary to develop, test, manufacture and install each tool. This budget can be divided in as many parts or steps as desired, but keeping in mind that as these divisions become more detailed, it will be more difficult to estimate the expenses incurred in each of them. These costs can include (but are not limited to) the cost of components, cost of hardware modifications, cost of tests, etc. For a total number of tools t, with project budgets divided into p elements, each of these costs, denoted by b_{ij}, are included in the Budget Matrix $\boldsymbol{B}_{txp}$.

$$\boldsymbol{B} = \begin{bmatrix} b_{11} & \cdots & b_{1p} \\ \vdots & \ddots & \vdots \\ b_{t1} & \cdots & b_{tp} \end{bmatrix}$$

Once the different costs can be quantified experts on each tool and systems engineers have to be consulted to determine which of them can be shared by which tools. Each shared cost is to be included in the Share Tensor, $\boldsymbol{S}$.

$$\boldsymbol{S} = \begin{bmatrix} 1 & s_{12x} & \cdots & s_{1tx} \\ s_{21x} & 1 & \cdots & s_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ s_{t1x} & s_{t2x} & \cdots & 1 \end{bmatrix}_{t \times t \times p}$$

$$s_{ijx} = s_{ijx} \ \forall\, x \in \mathbb{N} \quad \& \quad s_{ij} \in \mathbb{N}\,, [0,1]$$

where:

if tools *i* and *j* share cost *k* then $s_{ijk} = 1$

if tools *i* and *j* do not share cost *k* then $s_{ijk} = 0$

For a toolset with *n* tools matrix ***A*** defines which fraction of each cost is allocated to each tool. This matrix is a function of the Share Tensor and the Budget Matrix. The newly calculated costs incurred in implementing the toolset are defined by the elements of the Toolset Budget Matrix, ***B*.*** This matrix is essential to calculate vector of the final cost of each tool, ***c***, and eventually the total cost of the toolset, *C* as shown in eq. 8-26 and 8-27

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1p} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{np} \end{bmatrix}_{n \times p}$$

$$\boldsymbol{A} = f(\boldsymbol{B}_{n \times p}\ ,\ \ \boldsymbol{S}_{n \times n \times p}) \qquad \textbf{8-25}$$

$$\boldsymbol{B}^{*} = \begin{bmatrix} a_{11}b_{11} & \cdots & a_{1p}b_{1p} \\ \vdots & \ddots & \vdots \\ a_{n1}b_{n1} & \cdots & a_{np}b_{np} \end{bmatrix}_{n \times p}$$

$$\boldsymbol{c} = \boldsymbol{B}^{*} \cdot \boldsymbol{l}_p^T \qquad \textbf{8-26}$$

$$C = \boldsymbol{l}_n \cdot \boldsymbol{c} = \boldsymbol{l}_n \cdot \boldsymbol{B}^{*}\boldsymbol{l}_p^T \qquad \textbf{8-27}$$

where $\boldsymbol{l}_p = [1,\ldots,1]_p$ and $\boldsymbol{l}_n = [1,\ldots,1]_n$

The simplest way to allocate each cost is to divide it evenly amongst those tools that share it as shown in Eq.8-28, but other formulas can be applied.

$$a_{ij} = \frac{1}{\sum_{k=1}^{n} s_{ikj}} \qquad \textbf{8-28}$$

The variance of the cost of a given combination of diagnostic and prognostic tools can be calculated with the following expression:

$$\sigma_C = \boldsymbol{w} \cdot \boldsymbol{Cov}(\boldsymbol{c}) \cdot \boldsymbol{w}^T \qquad \textbf{8-29}$$

where ***w*** is the vector with the weighed cost of each tools included in the toolset in which

$$w_i = \frac{q_i}{\sum_{j=1}^{n} q_j} \qquad \textbf{8-30}$$

and ***Cov(c)*** is the covariance matrix of ***c***

$$\boldsymbol{Cov}(\boldsymbol{c}) = \begin{bmatrix} var(c_1) & Cov(c_1, c_2) & \cdots & Cov(c_1, c_n) \\ Cov(c_2, c_1) & var(c_2) & \cdots & Cov(c_2, c_n) \\ \vdots & \vdots & \ddots & \vdots \\ Cov(c_n, c_1) & Cov(c_n, c_2) & \cdots & var(c_n) \end{bmatrix}_{n \times n}$$

The elements of ***Cov***(***c***) are the covariances of the sum of the costs of each tool, whose covariances are easy to calculate since they are first grade polynomial expressions.

$$\begin{aligned} Cov(c_i, c_j) &= Cov\left(\sum_{k=1}^{p} b_{ik}^*, \sum_{k=1}^{p} b_{jk}^*\right) = \sum_{k=1}^{p} \sum_{m=1}^{p} Cov(b_{ik}^*, b_{jm}^*) \\ &= \sum_{k=1}^{p} \sum_{m=1}^{p} Cov(a_{ik} b_{ik}, a_{jm} b_{jm}) \end{aligned} \qquad \textbf{8-31}$$

Only those costs or budget elements that are in the same category can be correlated and consequently:

$$\sum_{k=1}^{p} Cov(a_{ik} b_{ik}, a_{jk} b_{jk}) = \sum_{k=1}^{p} a_{ik} a_{jk} Cov(b_{ik}, b_{jk}) \qquad \textbf{8-32}$$

$$Cov(c_i, c_j) = \sum_{k=1}^{p} a_{ik} a_{jk} var(b_{ik}) \qquad \textbf{8-33}$$

It must be noted that as ***A*** and ***B***, ***Cov***(***c***) has to be recalculated for each combination of health monitoring tools.

Using Eq. 8-33 to solve eq. 8-29 provides the last part necessary to carry out the risk analysis. In essence, we have transformed the variances of individual items of the budget into the variance of the cost of each toolset. This is the used in eq. 8-12, 8-23 and 8-24, along with eq. 8-11 for the mean, to determine the shape of the probability distribution of the ROI of each combination of tools.

Whilst the analysis of the development costs of IVHM tools is widely covered in literature on CBA for IVHM, this is the first time the covariance of costs has been considered.

8.4.5 Characterising the ROI using moments

Having shown how the moments of the ROI can be calculated the final step is to use them to obtain a mathematical expression of its probability distribution. There are multiple probability distributions that are defined by four parameters that can be used to estimate the ROI. Whilst there are differences between their shapes, given the accuracy achieved by using four moments to adjust the curve of the probability and the lack of further information to infer which would be closer to real values, one should work with the distribution with simpler analytical expressions and/or requires less computational power.

Among all probabilities distributions that use four parameters the most commonly used are the Pearson, Johnson and Generalised Lambda distributions. These distributions have been widely used to fit probability curves to statistical data. However, whilst all of them are defined by four different shape parameters, in the case of Johnson and Generalised Lambda distribution, said parameters cannot be calculated analytically using the moments of the distribution. They could be calculated using numerical methods, but that would result in too long a computational time to estimate the distribution of the ROI for all possible combinations of health monitoring tools.

In contrast, the shape parameters of Pearson distributions can be calculated using moments. Pearson distributions with an average μ satisfy the following differential equation:

$$\frac{f'(x)}{f(x)} = \frac{(x-\mu) - b_1}{b_2(x-\mu)^2 + b_1(x-\mu) + b_0} \quad \textbf{8-34}$$

where

$$b_0 = \frac{4\beta_2 - 3\gamma_1^2}{10\beta_2 - 12\gamma_1^2 - 18}\mu_2 \quad \textbf{8-35}$$

$$b_0 = \frac{4\beta_2 - 3\gamma_1^2}{10\beta_2 - 12\gamma_1^2 - 18}\mu_2 \quad \textbf{8-36}$$

$$b_2 = \frac{2\beta_2 - 3\gamma_1^2 - 6}{10\beta_2 - 12\gamma_1^2 - 18} \quad \textbf{8-37}$$

There are different solutions for eq 8-34 depending on the value of $K = b_1^2/(4b_0b_2)$. For *K<0* the roots of the denominator of eq 8-34 are real and the distribution is known as a Pearson type-I or beta distribution. If *0<K<1* roots are complex and the solution of the differential equation is a Pearson type-IV distribution. Finally, if *K>1* the distribution is known as type-VII.

Another approach is to fit a ratio distribution using the parameters of the probability distributions of the expected profit and cost of each toolset. However, that means not taking into account the values of the skewness and kurtosis which reduces the accuracy of the risk analysis.

This presents for the first time an analytical approach to estimate the financial risk of a combination of health monitoring tools. Unlike conventional CBA for IVHM technology that are limited to rough estimations of the ROI, this method provides a PDF for the ROI parameterised up to the fourth moment. Whilst this method is shown as part of a methodology focused on working with legacy aircraft, it could be applied to analyse combinations of IVHM tools of newer aircraft as well because the data required does not depend on the type of vehicle. The same principles apply as long as it is possible to estimate the profitability of each tool, their costs, and get information on which costs can be shared.

As explained before, to determine which toolset is safer from a financial standpoint all we need is to set a threshold for the ROI below which the investment would not be considered safe (normally the cost of money for the organization or the interest rates of long term deposits). Much more complex financial analyses can now be carried out thanks to heaving obtained the PDF, but that is beyond the scope of this research.

To demonstrate how these principles can be applied and the types of results this method generates, the next section describes a case study conducted using synthetic data.

8.5 Case study

The following example illustrates what kind of results can be obtained from the use of this method. Figure 8-5 shows the expected ROI and the risk (or variance of the ROI) over 7 years of each possible combination of 20 health monitoring tools with a maximum of 11 tools per toolset. As an average, each health monitoring tool was incompatible with 20% of the remaining 19 tools. As a result of these incompatibilities the total number of viable toolsets decreases as their size increases (see Figure 8-6).

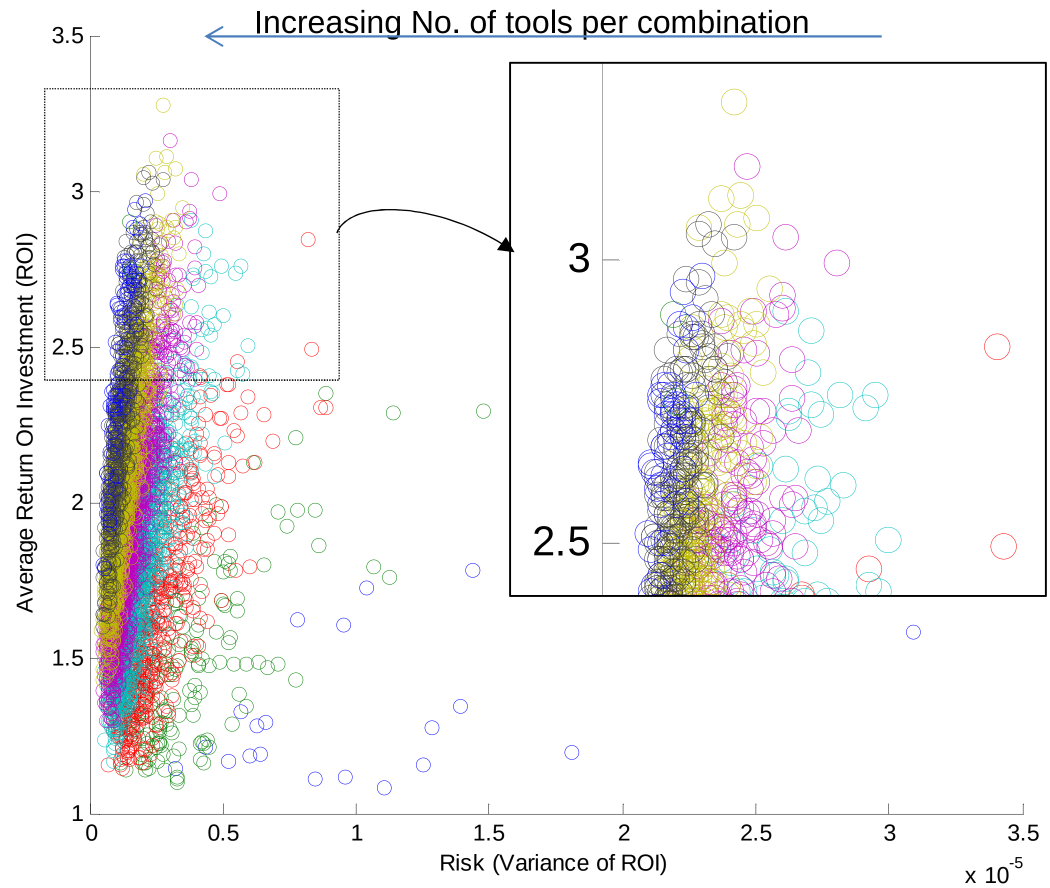


Figure 8-5 ROI VS Risk for combinations with different numbers of diagnostic and prognostic tools. Dots with the same colour represent toolsets with the same number of tools.

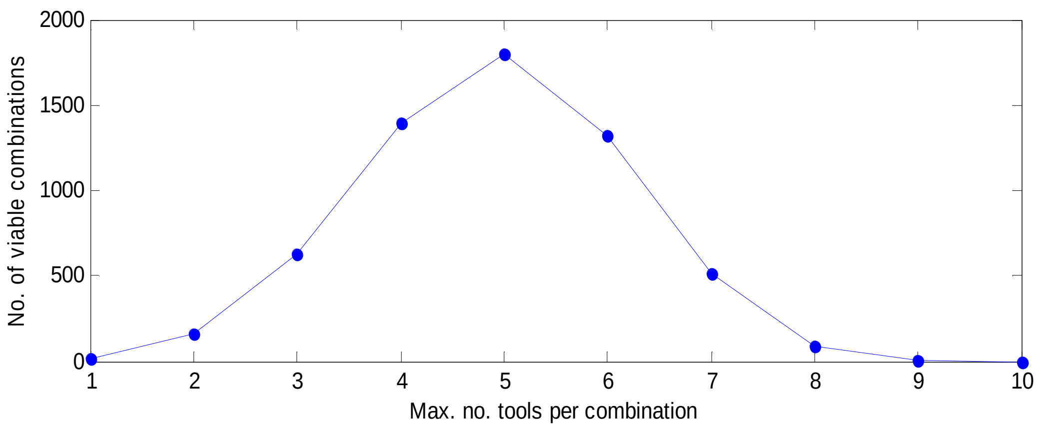


Figure 8-6 Maximum number of combinations of health monitoring tools taking into account the incompatibilities between them.

The results show how increasing the size of the toolset increases the ROI thanks to the savings generated by sharing costs among more tools. However, this effect is counteracted by the increase of uncertainty as errors propagate. Therefore, toolsets were compared according to the risk of their return falling below the cost of the money of the organization, which for this particular case was 8.5% per year. Based on this condition, the best toolset presented an average ROI of 378% over 7 years (equivalent to 20.8% per year) with a probability distribution as shown in Figure 8-7.

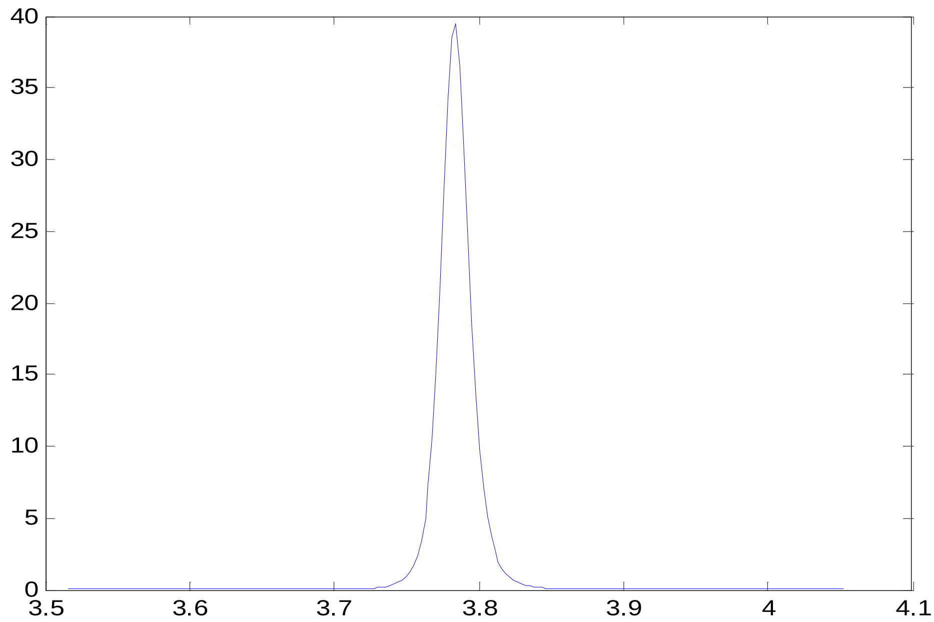


Figure 8-7 Probability distribution of the best possible combination of IVHM tools according to economic objectives and risk analysis.

As shown in Figure 8-8, increasing the number of tool does not necessarily translate into a higher ROI, but it narrows the margin between the riskier and safer combination of tools. In other words, in case of not having enough information to populate the matrices described in the previous section we can at least know that as we increase the size of toolsets they probability of making a poor choice diminishes. However, as show at the bottom of Figure 8-8, this can result in a significant penalty in future revenues. Furthermore, it also shows that increasing the number of tools can result a reduction of the ROI. Consequently, given the wide variation of possible ROIs it is recommendable to make every effort necessary to obtain all the data necessary to apply the method described in this chapter.

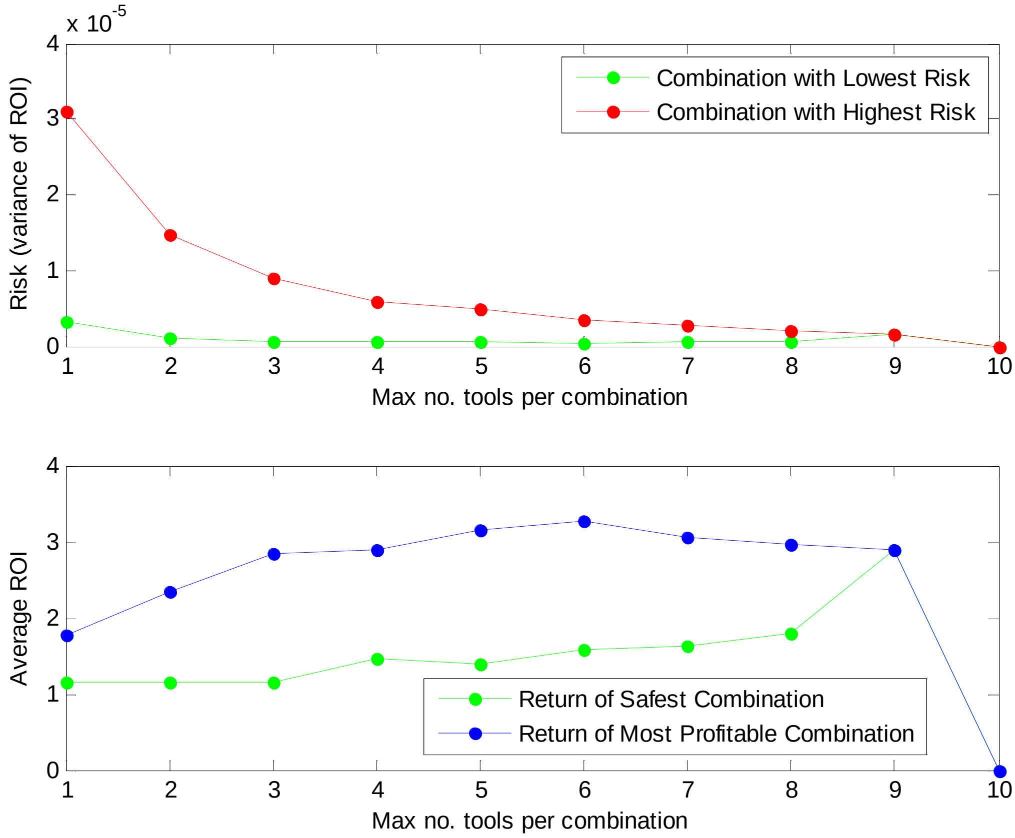


Figure 8-8 Evolution of the risk (top) and ROI (bottom) of the combinations of health monitoring tools with the lowest and highest variance of ROI for a given number of health monitoring tools.

8.6 Conclusions

In this chapter the reader has been shown a method through which it is possible to conduct an objective comparison of large numbers of IVHM toolsets. This method focuses on the ultimate goal of any product: generate an economic return. The rest of the published work available follows a bottom-up approach to estimate the ROI of IVHM systems once the characteristics of the tools they are comprised of are known. Following the steps enumerated here allows for a top-down design of IVHM systems.

Let’s revisit the contributions of the method described in this chapter:

- Provide a systematic and quick manner of analysing technical incompatibilities between tools to eliminate unviable toolsets from the analysis, saving time and ensuring the chosen combinations of tools is technically practicable.
- Provide the mathematical tools necessary to analyse the effect of combining diagnostic and prognostic tools on the profitability of IVHM toolsets. By accounting for error propagation financial risk is also considered. The result is identifying the best IVHM toolset for an aircraft according the needs of the investor, or
- provide ranking tool so further analyses conducted using computer simulations can focus on a limited number of IVHM toolsets. This circumvents the problem of having too large a number of possible combinations to study.

The capability to provide a measurement of the risk incurred by choosing a certain combination of tools can be very useful to battle the scepticism that normally undermines the acceptance of IVHM within organizations.

The benefits of this approach are not limited to providing the capability to compare toolsets. It also shows how the probability distribution of the ROI can be characterised. Having a mathematical function to describe the ROI can be very useful to conduct financial analyses with a level of complexity and detail that is beyond the scope of this thesis.

Probably one of the most important findings described in these pages is the fact that it is possible to have an optimal number of tools, meaning that the idea of “the larger the coverage, the larger the benefit” is not necessarily true. Further research on this topic should prove quite fruitful for the development of design methodologies for IVHM systems.

There is still room to optimise the equation presented to make the algorithm more efficient. Setting thresholds for the maximum and minimum number of tools per toolset or setting boundaries for the expected ROI and initial investment should prove useful.

Further work is necessary to adapt this method to those cases in which the combination of certain tools produces an increase in the total cost instead of savings. This can be due to tools interfering with each other and resulting in further modifications.

9 Assessing IVHM Benefits Through Modelling Aircraft Maintenance

"Don't let us forget that the causes of human actions are usually immeasurably more complex and varied than our subsequent explanations of them."
- Fyodor Dostoyevsky

The methodology presented in this thesis includes all the steps necessary to compare a large number of viable IVHM toolsets to reach a solution to maximize economic profits, whether they come in the form of maintenance cost avoidance or an increase in the availability of the fleet. In order to compare the benefits of each tool the expected benefit of putting it into service must be calculated attending to the way the IVHM system is going to be financed and the role played by each stakeholder (this was discussed in detail in Chapter 5). However, the use of health monitoring systems is likely to have a significant impact on activities related to the maintenance of the aircraft which might not be under the responsibility of the same organizations (e.g.: logistics, stock of parts, etc.). Even if we are not responsible for these activities and feel that any change in their costs will not affect our profitability, it is of the upmost importance to understand the externalities of IVHM. Whilst any increase in cost for other stakeholders might not have an immediate effect on the organizations that benefit from the use of IVHM, those whose condition is worsened will be forced to renegotiate their contracts and said costs will eventually emerge, increasing the support and operational cot of the fleet.

Given the complexity of maintenance activities it is not possible to analyse the externalities of using an IVHM system in an analytical manner. Maintenance tasks can be performed in parallel, their duration is affected by multiple uncertainties and they involve the use of resources whose availability depends on the way maintenance operations are conducted as well as external factors. The only way these complexities can be studied through computer simulations.

Another important application of the model is to validate the results obtained with the risk analysis described in chapter 8. Thanks to this method, the number of toolset that would have to be simulated is considerably smaller. From millions of combinations, designers can now simulate only a handful of them by focusing on those that ranked at the top after performing a financial risk analysis. This represents the last step of the methodology presented in this thesis (Figure 9-1.)

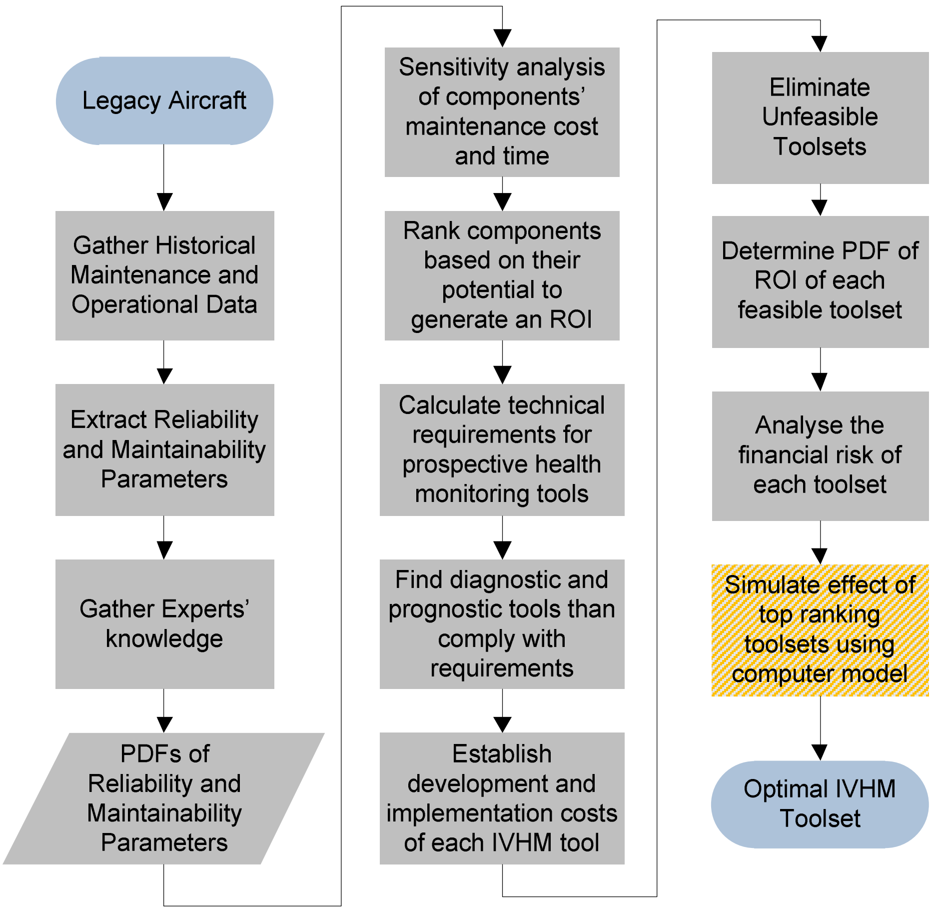


Figure 9-1 Flowchart of methodology to configure an IVHM system for a legacy vehicle highlighting the step covered in this chapter in orange.

The idea of developing computer models of maintenance operations is not new. Sarma et al. [134] used queuing models back in the 70s to study the effect of uncertainties in operations and repair on the operational availability of a fleet and determine the optimal repair-depot capability. Preston White and Ingalls [171] provide a concise, and yet comprehensive, introduction to simulation that covers all the principles relevant for the development of a model of maintenance activities.

Recent work tends to focus on Discrete Event Simulators (DES) to analyse complex maintenance operations, but other approaches have been considered. Stranjak et al. [172] used agent-based simulation to optimise both prediction and scheduling practices for aero engines overhauls. Agent-based simulation allows them to optimise the decision making process with a better understanding of all activities affected by maintenance such as operations or logistics.

DES allows for a better understanding of transient stages in the light of the condition of individual components which is very useful to study the effectiveness of individual health monitoring tools. As an example the reader can study the work of Szczerbicki and White [135], who developed a model to be used a support tool for condition-monitoring service groups. They used a commercial DES modelling environment. This model, which focused on the impact of inspections rather than the repair or replacement of parts, helps to optimise the use of resources (staff and data collection equipment) to conduct inspections on multiple locations. Sharda and Bury [173] present three case studies in which they used DES to study the effect of failures in a plant and identify critical components; analyse the viability of a capital expansion; and a third case to verify its production capacity.

Duffuaa et al. [174] propose a generic conceptual stochastic model of maintenance systems to examine maintenance policies. Whilst this model takes into account both planned and unplanned maintenance actions, it does not include the role played by the information generated by health monitoring tools and its effect on the decision making. This problem is very common among models of maintenance systems. The use of models to study the benefits of health monitoring tools is normally focused on prognostics and does not analyse the possibility of combining it with diagnostics.

An example of this phenomenon is the online simulation framework proposed by Teixiera et al. [175] that is based on closed-loop control systems to study the potential of prognostic tools to enable Product-Service Systems (PSS). This model is oriented towards short-term operational decisions in response to online inputs as opposed to the long-term strategy followed in most models for the analysis of the viability of IVHM systems. Also, Horning et al. [136] simulated using DES how the implementation of prognostic tools can affect the operational readiness of military aircraft.

Most work on modelling of maintenance revolves around the optimization of decision making rather than the implementation of new technology. Volovoi et al. [176] studied the grouping of preventive maintenance actions for gas turbines using a component-based approach that allowed them to account for the interactions between components as they degrade and fail. Manivannan and Zimer [177] modelled aircraft offloading operations in an air cargo HUB to determine the best operating rules and study strategic changes.

Due to the complexity and size some of these models reach, parallel or distributed computing can be necessary. This was the case of the air traffic model developed by Blair et al. [178].

This chapter describes the work undertaken to develop a computer model capable of analysing the effect of implementing IVHM technology on an existing maintenance organization. The objectives set for the model of maintenance activities are described in section 9.1. The contributions of the work described in this chapter are:

- Identify the requirements of a computer model to study the effect of implementing IVHM on a legacy fleet (section 9.2), including:
    - The functionalities of the model
    - The requirements for inputs and outputs
- Define the validation requirements for the model (section 9.4).

A model was implemented using a discrete event simulation program called Simul8™. The details of this work are discussed in section 9.3.

9.1 Objectives

The use of a computer model enables the validation of the results obtained from the risk-based comparison of toolsets, and the improvement of our understanding of the externalities of implementing different IVHM systems. The simulation of maintenance activities must produce all the necessary information to conduct both analyses.

In order to verify the estimated financial risk of choosing a certain combination of diagnostic and prognostic tools, the model should provide the following information:

- Probability distribution of maintenance costs per flying hour before and after the implementation of the IVHM system.
- Probability distribution of maintenance times per flying hour before and after the implementation of the IVHM system.
- Probability distribution of the operational availability before and after the implementation of the IVHM system.

Besides validating the financial risk comparison of toolsets, this information can be used for other purposes. If the model is developed with the capability to perform sensitivity analyses, these can shed some light on the potential of different toolsets to be upgraded in the future. Whilst this is not a key aspect to compare toolsets (after all the shorter remaining operational life a legacy fleet might not justify upgrading the IVHM system), it can be useful to make a choice if the best toolset according to the financial risk analysis are very close. In order to compare the potential to upgrade different IVHM system the model has to be able to calculate the following parameters:

- Sensitivity of costs, total downtime and availability to the performance of health monitoring tools. Obviously, the higher the accuracy the more expensive the tool and more costs and downtimes are reduced. The optimum solution is going to be determined by the curve of diminishing returns. The sensitivity of total costs and availability to the performance of individual and groups of tools needs to be calculated for different cases.
- Sensitivity of costs, total downtime and availability to the coverage of health monitoring tools. By changing the number of components being monitored by either diagnostic or prognostic tools the support process is

affected. It is necessary to determine to what extent the IVHM technology should focus on improving its accuracy rather than monitor a large number of components. The curve of diminishing returns has to be obtained to determine the maximum number of components that should be monitored.

- Effect on the standard deviation of costs, total downtime and availability of the coverage and performance of health monitoring tools. Apart from the effect IVHM has on reducing the average values of critical parameters of the support process, it is necessary to determine the effect this technology has on their probability distributions.

If the model has the capability to conduct sensitivity analyses on the parameters it uses, there will not be any need for extra work to be able to calculate these sensitivities. This is likely to affect the choice of modelling software rather than the time and resources allocated to the development of the model.

As for the analysis of the externalities of implementing a health monitoring system, the model must take into account how the information provided by a new IVHM system affects the management of maintenance operations and, consequently, any other activities affected by them. In that regard, the model must take into account the interactions of maintenance tasks with:

- Logistics and how they affect delays and the availability of components to replace failed parts.
- The management of the stock of components on how it is affected by both logistics and the information provided by prognostic tools
- Operations planning based on the improvement in the availability of the fleet.
- Availability of personnel and auxiliary equipment. These are probably the easiest to simulate but are essential to study the possibility to optimise resources thanks to the use of IVHM.

Obviously, these effects can be simulated with a wide range of detail. Some of them involve very complex interactions that can be very laborious to simulate.

The degree to which the maintenance model should account for the complexity of these external factors is discussed in further detail in section 9.2.3.

With these objectives in mind it is possible to define the requirements for the modelling of maintenance activities.

9.2 Model requirements

This section describes the requirements for a computer model of maintenance operations to analyse the effect of implementing IVHM on a fleet of legacy aircraft. The definition of these requirements is the result of the work conducted developing a model capable of reaching the goals set for said model and the multiple revisions to which it was subjected. The description of the requirements has been divided into:

- Functionalities
- Data exchange: Outputs & inputs
- Scalability of the model

9.2.1 Functionalities of the model

The model must focus on those activities put in place to keep aircraft airworthy. These involve both scheduled and unscheduled stops to replace components and conduct inspections. Components can be replaced because they have failed, they are due to be replaced following a preventive maintenance schedule, or as result of a false alarm misrepresenting the condition of the part. Inspections can be necessary to isolate a fault, determine the condition of a component subjected to predictive maintenance, or to verify an indication of a diagnostic tool.

The model has to simulate all these activities as well as any other steps taken to ensure these activities can be conducted. There are other factors that affect the time aircraft have to spend on the ground between missions (e.g.: taxing, refuelling, etc.) This effect can be implemented as a delay in the model.

The functions of the model must comply also with the objectives described in the previous section. Said functions must produce the data necessary to conduct the analyse for which the model is developed.

The full functional diagram is shown in Figure 9-2. For those functions that are more complex, functional diagrams corresponding to the second level have been provided in Appendix B. The final structure of the model depends on the capabilities and limitations of the software chosen to implement the model. However, the logic and functionalities of the program match those described in these functional diagrams. The following paragraphs describe the role played by each function.

0. Mission n: Each mission is defined by its duration and any parameters that could affect the degradation of different components. Those factors are to be used in different states of the simulation to compute the degradation, probability of failure and probability of detecting the fault of different parts.
1. Faults and degradation of components: In this stage the state of all components is updated according to the characteristics of the last mission. For those components whose condition is monitored by measuring some physical parameter (e.g., maximum current through an electric motor) the values of this parameter must also be updated. Then, using a random numbers generator and probability distribution of the failure of each part, the model determines which components have failed during the mission.
2. Update status of aircraft's components.
3. Update the status of auxiliary components: This function affects elements that are not used on every mission and might not be always used on the same aircraft such as the fuel pump of external tanks.
4. Fault detection through conventional methods: Each fault presents symptoms which can be noticed by the pilot, ground personnel or during routine checks, but without the use of any health monitoring tool. This can be simulated assuming there is a certain probability of detecting each failure. In many cases this probability is either 100% or 0. The

outcome of this function updates the perceived health of the components, not the real condition. This way it is possible to simulate errors in the diagnosis and prognosis of failures. This function also contemplates the possibility of further testing being necessary which will be performed later.

5. Transfer of data: This function is included to simulate the problems that may occur during the transmission of information including bus overloading and data corruption. The possibility to use software to tackle these problems is also included as one of the sub-functions.
6. IVHM prognosis: This function updates the RUL of those components that use some sort of prognostic tool.
7. IVHM diagnostics: This function updates the perceived condition of those parts monitored by some diagnostic tool. As in function 4 this does not represent the real state of the components being checked. Also as in function 4 the information provided by the diagnostic algorithm may be inconclusive and require further testing.
8. Calculate resources required: In this function the simulation calculates the resources necessary to repair or replace all those components that have failed or whose RUL is lower than the next scheduled major maintenance stop. It also calculates the resources necessary for each test and for those repairs that may be necessary as a result of what is found on every test.
9. Plan mission n+1: In parallel to functions 1 to 8 it is necessary to generate through random number generators the characteristics of the next mission. This is necessary to prioritize activities (function 10) based on the time available before the next mission and how the aircraft is going to be operated.
10. Prioritization of activities: Criticality levels are assigned to all tasks (including to those differed on previous cycles of the simulation) to determine which could be deferred in case the time available is not enough to complete all repairs. Once the deferred tasks are identified, those that have to be completed before the next mission are arranged to

optimise the use of resources and minimise the time spent on maintenance. The outcomes of the tests are also simulated by this function. In case there is any time left before the next mission it may be allocated to previously differed tasks.

11. Produce work orders: In this function the register of the work performed is generated as well as updating the stock of components and the total maintenance costs of the fleet.
12. Update maintenance schedule: Deferred tasks and those whose RUL can be estimated are included in the maintenance scheduled.
13. Update aircraft's status: The status of the components of the aircraft is update according to the maintenance performed.
14. Update auxiliary components' status: As in function 13
15. Logistics: This function simulates the state of the stock of components based on the maintenance scheduled and the time necessary for components to be delivered, including all sort of delays that may affect this process.
16. Generate new configuration of the aircraft: Based on the description of the next mission a new set of auxiliary components is assigned to the aircraft.

By now the reader must be wondering if it is possible to implement these functions and obtain a model capable of accounting for the differences between scheduled and unscheduled maintenance stops.

From a modelling perspective, whilst the reason that triggers the replacement of a component under one or the other may be different, the actions that take place are exactly the same. In the real world, reactive maintenance involves an extra step to diagnose the fault and predictive maintenance requires conducting inspections, none of which affect parts replaced following a preventive maintenance scheme. But, in the model it is possible to account for all these steps and then assume that no time was spent diagnosing a fault that did not occur (nor produced false positives) or inspecting the condition of a part for which predictive maintenance is not an option.

In the model, the main difference lies in the fact that scheduled tasks can be grouped, components purchased in advance, and personnel and auxiliary equipment prepared so the time the aircraft spends grounded is minimised. Thus, whilst the steps taken to repair or replace a component on a scheduled or unscheduled basis may be the same, the duration of each step is not, especially for those that can be affected by delays. Waiting for components to be shipped or having to squeeze an extra maintenance task in a busy maintenance facility are among the many reasons why replacing a part in a reactive manner takes longer.

Having shown that the functional diagram described here includes the necessary functionalities to model maintenance activities and how they may be affected by the implementation of IVHM technology, it is necessary to define the data that will be used as inputs to run the model and the data that is expected to be produced by it. Both are discussed in the next subsection.

9.2.2 Data exchange

The ultimate goal of the model to produce results designers can interpret easily to make an informed decision on which combination of diagnostic and prognostic tools suits their needs better. This information must be comprehensive to ensure any aspect of maintenance operations can be analysed. At the same time the model has to be based on real maintenance facilities, and therefore, needs to be able to read input data to characterise how performance tasks are performed. Input data is also essential to characterise the IVHM systems that are to be studied in the simulations.

Evidently, the model will have to use many more variables than those included among the inputs and outputs, but this will depend more on the characteristics of the software being used than on any other factor. To ensure that the use of the model does not represent a steep learning curve, all modifications necessary to compare different IVHM configurations should be made through simple changes in the input data. The recommended strategy is to configure the model so it can read spreadsheets or text files in which the input data is stored.

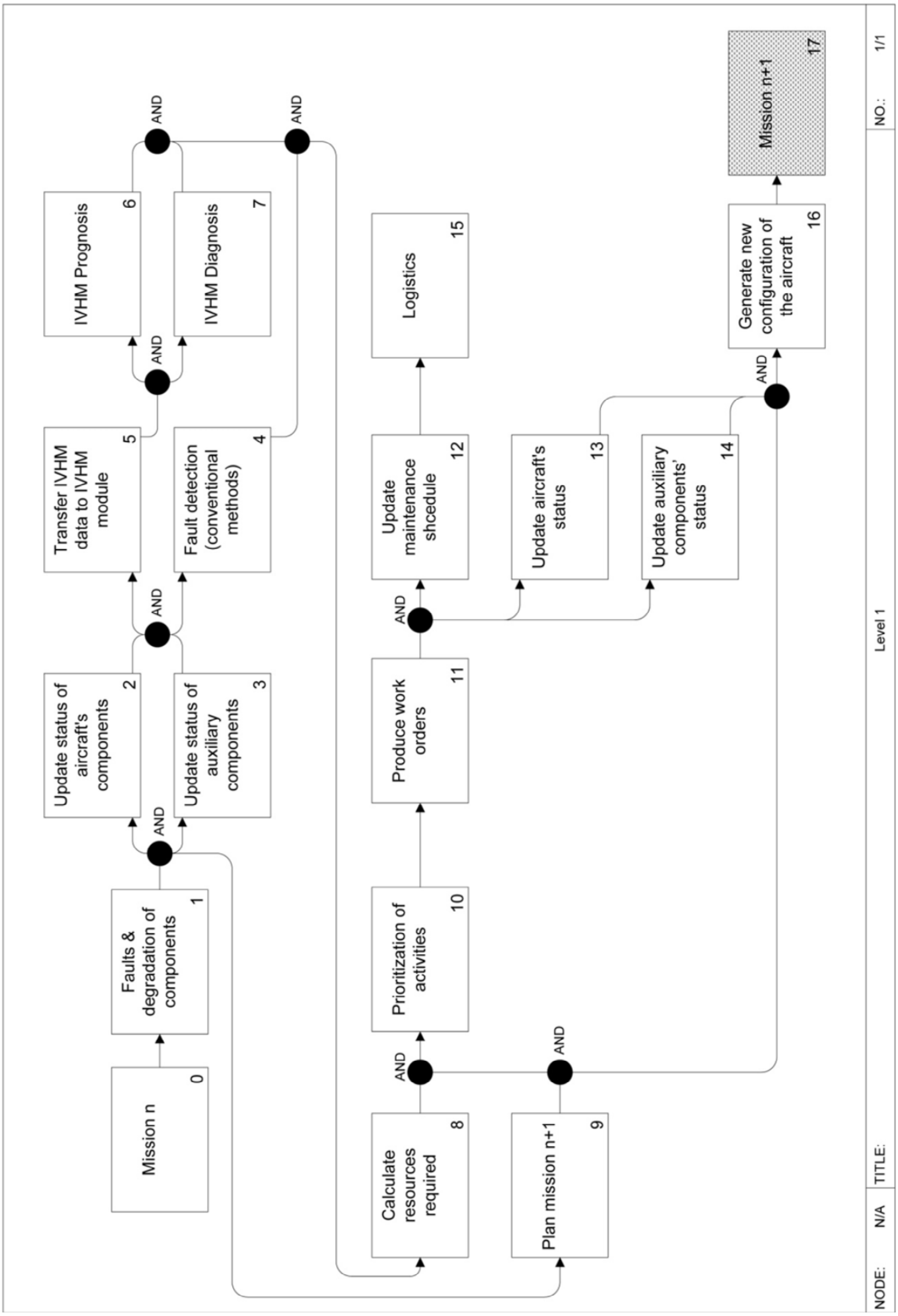


Figure 9-2 Functional diagram of the computer model to simulate the maintenance of a legacy fleet and the effect of retrofitting IVHM.

Results should also be stored on a spreadsheet. This way, it is not necessary to acquire licenses of modelling software just so the results of the model can be read and interpreted.

9.2.2.1 Outputs

The best way to present the outputs of the model is in a manner that is easily interpreted by experts on maintenance so they can assess the impact of implementing IVHM. Additionally, the outputs should include the most basic maintenance variables and information on the characteristics of each flight. Any parameter that can be derived from them should be excluded. This is because simulations can cover years of operation, generating an immense amount of data. Anything that can be obtained by postprocessing the outputs of the model will save memory and computational time.

With these requisites in mind, the output of the model should be a list of all the relevant parameters that define each maintenance job a log of all flights. For each maintenance facility (keep in mind aircraft can be maintained at multiple facilities which can be modelled by replicating the same structure described in this chapter) the model has to produce a list of all jobs and for each of them:

- Aircraft tail number
- Component’s number
- Component’s name
- Date and time the maintenance job started
- Diagnostic Time
- Inspection TIme
- Active Maintenance Time in hours
- Duration of delays, including logistic, administrative and technical delays
- Total Maintenance time dedicated to the tasks
- Average number of personnel dedicated to the job (the number of workes dedicated to a job may vary whilst it is conducted).
- Cost of the part (including acquisitoin, shipping and storage).

- Cost of labour –cost of labour per hour can evolve over time, hence the need to include this value despite the fact that the duration of the job can easyliy be calculated from other parameters.
- Total Cost –including part, labour and any other cost that the model accounts for.
- Flying hours of the aircraft at the time the job started.
- Number of flights flown by the aircraft at the time the job started.
- Date the component was first installed on an aircraft –this information is essential to keep track of the aging of components that are cannibalised from one aircraft to another.
- Flying hours of the component at the time the job started.
- Number of flights flown by the component at the time the job started.

The best way to present this informaiton is in the form of a maintnenance and mission logs. The results stored in these logs can the be used to calculate maintainability and reliability paramters estimated with the model to analyse the effect of retrofiting certain health monitoring tools or to compare them with real life values (model validation is discussed in detail in section 9.4). An extract of the mission log spreadsheet generated by the model implemented using Simul8™ is shown in Figure 9-3. The details of this implemenation are discussed in section 9.3.

	A	B	C	D	E	F	G	H	I	J	K
1	Aircraft	Component Number	Component Name	Starting time	Active Maintenance Time	Delay	Total Maintenance Time	Personnel	Cost Part	Cost Labour	Total Cost
2	4	56	T2150104	1022.58795	2.896	0	2.896	1.19	4007.46	289.6004	4297.05611
3	3	56	T2150104	1067.58877	2.94124	0	2.94124	1.19	4007.46	294.1242	4301.5799
4	5	56	T2150104	1069.08777	2.70643	0	2.70643	1.19	4007.46	270.64313	4278.09883
5	6	56	T2150104	1095.67121	2.88548	0	2.88548	1.19	4007.46	288.54764	4296.00335
6	1	56	T2150104	1187.69049	2.76518	0	2.76518	1.19	4007.46	276.51779	4283.97349
7	2	56	T2150104	1192.0903	2.90546	0	2.90546	1.19	4007.46	290.54581	4298.00151
8	3	56	T2150104	2128.24886	2.92431	0	2.92431	1.19	4007.46	292.43143	4299.88714
9	5	142	T2730009	2192.5	8.40634	0	8.40634	1.16	772.751	840.6344	1613.3857
10	2	142	T2730009	2192.5	8.51775	0	8.51775	1.16	772.751	851.77545	1624.52675

Figure 9-3 Partial sample of the information stored in the maintenance log spreadsheet generated by the model implemented using Simul8™.

Information on each flight can be relatively basic, with the main paramters being the time each flight or mission started and it duration. If the model accounts for different speeds of degradation of each component dependinf ond the nature of the mission, this must also be included in the flight log. However, limitations in the information available to model this phenomenom (i.e.: lacking of knowledge or data on how the nature of the misson affects degradtaion mechanisms) mean this might not be possible or practicable. Nevertheless, any infromation on simulated missions should be stored in a spreadsheet with the mission log as shown in Figure 9-4.

1	Aircraft	Mission Start	Flying Time	Mission Type
17	1	13/06/2011 10:05	1.03491	A
18	6	13/06/2011 10:05	1.08478	A
19	4	13/06/2011 10:09	1.65061	D
20	2	13/06/2011 10:53	1.137	D
21	3	13/06/2011 11:33	0.9284	B
22	5	13/06/2011 11:15	1.26416	B
23	1	13/06/2011 11:37	0.94507	C

Figure 9-4 Partial sample of the information stored in the mission log spreadsheet generated by the model implemented using Simul8™.

Examples of the information that can be extracted from combining the data from the mission log and the maintenance log is the evolution of the maintenance cost per flying hour of the fleet or its average maintenance time per flying hour (see Figure 9-5).

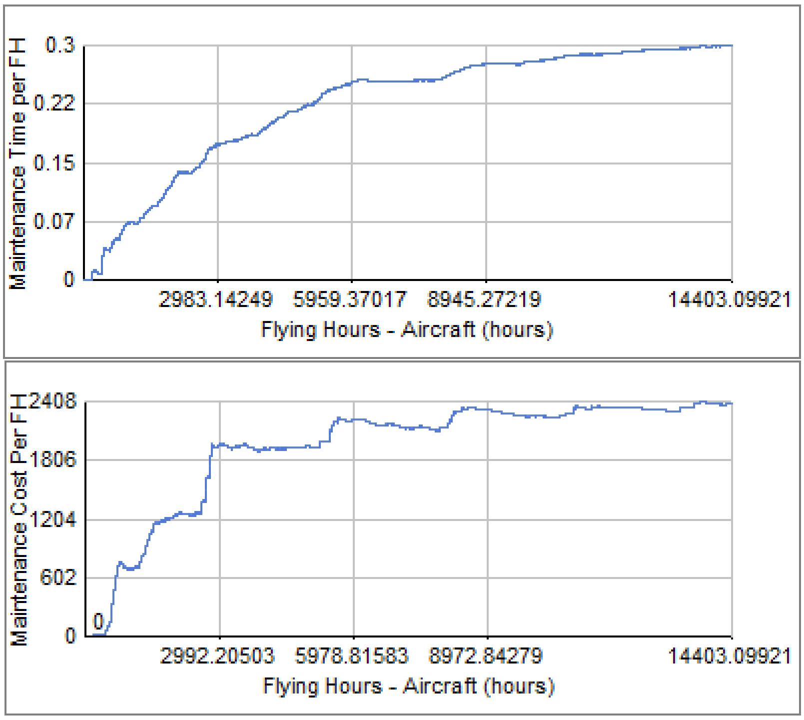


Figure 9-5 Examples of a single run of a simulation of a fleet of 6 aircraft over a period of 21 years using the model implemented on Simul8™. Maintenance time per flying hour (top) and average maintenance cost per flying hour (USD) for each aircraft (bottom.)

Although many of the variables listed are random, the values stored in the output files are integers. Their values will change according to the different probability distributions used by the model, but in each instance they will have an exact value. However, to interpret these results it will be necessary to study the distributions of these outputs since the implementation of IVHM affects both the average and the standard deviations of the results. Furthermore, although according to the Central Limit Theorem the outputs can be expected to follow Gaussian distributions under normal circumstances, it is important to keep in mind that the use of health monitoring tools introduces additional uncertainties that could change the shape of the PDFs of some parameters. A detailed discussion on the uncertainty of all these parameters can be found in chapter 10.

Each run of the model generates a single set of results. To account for the randomness in the process a Monte Carlo analysis must be performed. Figure 9-6 shows the evolution of the maintenance cost per flying hour of 60 simulations in which all random parameters have been allowed to vary according to predefined PDFs. The jumps that appear in the graph despite the randomness of the process correspond to expensive components run until failure which tend to fail in a narrow time window. This results in sharp increases of the average maintenance cost, especially in the early stages of the simulation when the total number of flying hours is lower.

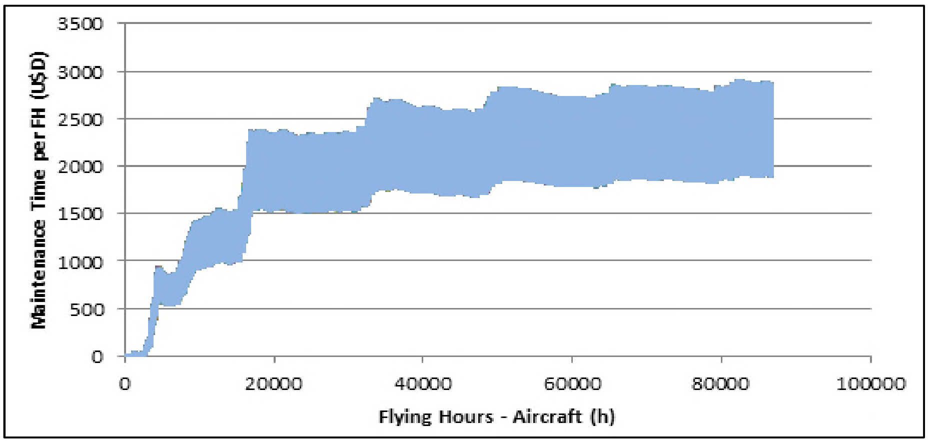


Figure 9-6 Example of the maintenance cost per flying hour (USD) generated by 60 runs of a simulation of a fleet of 7 aircraft over a period of 15 years using the model implemented on Simul8^{TM}.

The accuracy of these outputs depends as much on the characteristics of the model as on the variables used as inputs. The next section defines the minimum set of inputs to run this type of simulations.

9.2.2.2 Inputs

Inputs are used to configure the model so it behaves as a real support system for aircraft. The essential information is to be stored in spreadsheets or text files from which the model will extract the data necessary to run. Unlike outputs, that are a list of the defining characteristics of each maintenance job performed during the period simulated with the model, inputs are permanent and only need to be read when the simulation starts.

Inputs can be divided into two main groups: the maintainability parameters of all components and the technical characteristics of the health monitoring tools that are to be analysed. The maintainability parameters can be obtained the data gathered over years of maintaining a legacy aircraft. The information that can be extracted from maintenance logs should be processed to provide the following parameters as inputs for the model:

- Component's number
- Component's name.
- Probability distribution of the time between failures –this is normally defined by the MTBF and its standard deviation if it follows a symmetrical probability distribution. More data will be needed to characterise asymmetrical distributions
- Probability distribution of the time necessary to repair/replace the component –normally defined by MTTR and its standard deviation.
- Personnel dedicated to complete the task –whilst in an ideal case this would be broken down into the amount of personnel dedicated to each task of the job (diagnosis, removal, etc.) this information is not normally available and an average value for the whole task.
- Probability distribution of the component's purchase cost –this PDF is rarely available and in most cases the model will have to use the average.

- Probability distribution of the component’s shipping cost
- Probability distribution of the component’s storage cost
- Probability distribution of logistic delays.
- Probability distribution of technical delays.
- Probability distribution of administrative delays.
- Probability distribution of false negatives per flying hour –this corresponds to those occasions when conventional methods (without IVHM) fail to detect and isolate the failure of the component.
- Probability distribution of false positives or false alarms per flying hour.

The characteristics of the IVHM system are loaded by the model at the start of the simulation, but they will only affect the management of maintenance operations at a predetermined date to simulate the change the health monitoring system will induce in the maintenance of the fleet. Different tools can be given different implementation dates to account for the fact that the installation can be carried out in multiple stages. This also allows o simulate having some sort of original health monitoring capability (e.g.: BITE) that can be enhanced (or replaced) with new diagnostic and prognostic tools.

The information the model needs to simulate an IVHM tool is the changes is induced in the maintainability of the component being monitored. For prognostic tools this includes:

- Component’s number –used to define which component is being monitored.
- Probability distribution of the component’s RUL at removal/repair –this cannot be defined by a fix value because of the variability in the performance of prognostic tools.
- New probability distribution of the component’s purchase cost
- New probability distribution of the component’s shipping cost
- New probability distribution of the component’s storage cost

As for diagnostic tools, the model needs the following inputs:

- Component’s number

- New probability distribution of the time necessary to repair/replace the component
- New amount of personnel dedicated to complete the task
- New probability distribution of the component’s shipping cost
- New probability distribution of the component’s storage cost
- New probability distribution of technical delays.
- New Probability distribution of administrative delays.
- New probability distribution of false negatives per flying hour –specific of the diagnostic tool
- New probability distribution of false positives or false alarms per flying hour.

This completes the set of parameters the model needs to simulate maintenance operations. However, there are other parameters that will affect the potential of the model to be expanded or to merge with models to study more accurately how the use of IVHM affects activities such as logistics of operational planning. All this is discussed in the next section.

9.2.3 Scalability of the model

Since the aims of using a computer model are to validate the financial risk analysis and study the externalities of implementing IVHM, it is not difficult to see how this can easily become a very arduous task. On top of all the challenges of simulating the maintenance of an asset as complex as an aircraft, the model must acknowledge the role played by logistics, stock of parts, operations planning, personnel training, regulations, etc. They influence the planning and running of maintenance operations and are also affected by them, creating a closed loop effect.

The level to which these external factors need to be included in the model depends on the degree to which they can be affected by the introduction of IVHM, which is not known a priori. A simplistic, but laborious, approach would be to simulate all of them with as much detail as possible. However, this is not realistic and a compromise must be reached between the coverage and complexity of the model.

The simulation of some of these activities, such as logistics or the planning of operations, is common practice in industry and academia [134; 176; 177]. It is possible to develop a model of maintenance activities that can be merged with others in case higher precision is needed. This way, the model can focus on simulating one or several maintenance facilities and include some simple functions to simulate the effect of these external activities.

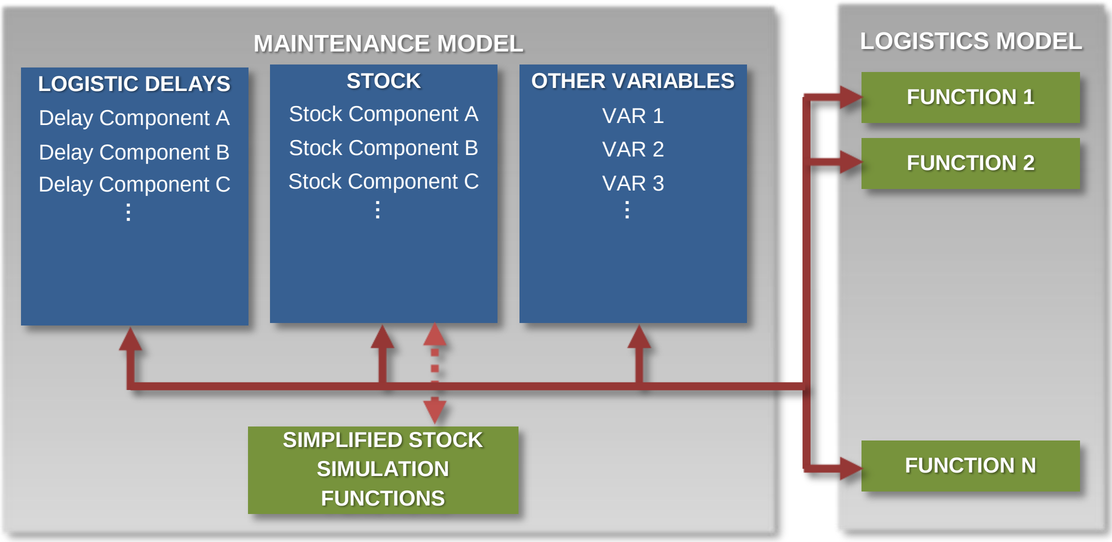


Figure 9-7 Example of scalability of the maintenance model by merging it with a logistics model.

As a result, the variables that are common to both activities have to be included in the simulation of maintenance operations (for an illustration of scalability with a logistics model see Figure 9-7). Some of these variables can be considered independent of any other factors in the maintenance model. For example, logistics delays or the duration of each flight can be simulated as random variables with a certain average and standard deviation. Other parameters can depend on the state of the model at each moment and some simple functions will have to be included in the model. This is the case of the stock of parts, which can be given a threshold below which the stock is replenished to a predetermined number of parts. The functions that govern the evolution of these variables change once the maintenance model is merged with another model with more detailed and accurate rules (see Figure 9-7).

In summary, regardless of the complexity of the maintenance model and the accuracy with which it accounts for all activities that are not directly involved in the maintenance of the aircraft, the model must allow for scalability to merge with other models to improve and increase its capabilities.

9.3 Implementation of the model

The model has been implemented according to the requirements listed in the previous section and following the functional diagrams included in Appendix B. The software chosen was Simul8™, which is a discrete event simulation package that fulfilled all the needs to model maintenance operations including the use of random variables and being capable of performing sensitivity analyses on any variable of the model. The functions described in the previous section can be implemented using other off-the-shelf discreet event simulation software packages or even programmed using more generic programming platforms such as Matlab or C++.

In Simul8 objects (aircraft in this particular case) are simulated using "Work Items" which are characterised by parameters defined by the user. These parameters are called "Labels" and can change to simulate how the state of each Work Item changes during the simulation. Work Items are generated in Work Entry Points and the values of their Labels can be modified in Work Centres.

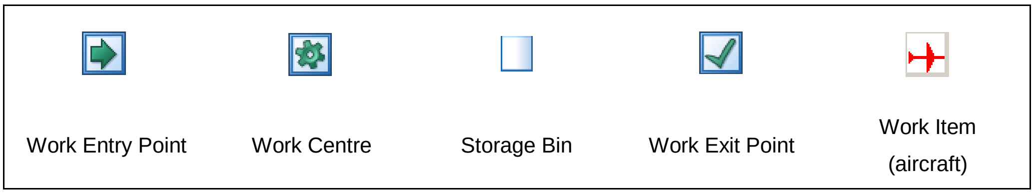


Figure 9-8 Building Blocks used in SImul8

The time each object spends on each Work Centre or moving between Work Centres can be defined using random or deterministic variables. Shifts can be defined for each Work Centre so it can be active only during predefined periods.

Work Items can be stored in Storage Bins, where they can remain undisturbed as long as necessary, and can be disposed of using Work Exit Points.

Besides Labels, it is possible to define five types of global variables: numbers, text strings, time stamps, spreadsheets and multidimensional arrays. These global variables can be modified at any time during the simulation. Additionally, Simul8 can use random global variables known as “Distributions” which will take different values each time they are used during a simulation.

It is possible to program functions using a tool called Visual Logic (VL). These functions can be programmed to be executed when a Work item is loaded in a Work Centre or at specific times (e.g.: start of simulation, after each reset, etc.).

Simul8 models can include personnel and other resources to simulate how their availability affects the process as Work Centres demand them to perform different tasks. In this particular model, the demand of personnel is simulated using global variables rather than using this built-in tool for programming reasons.

Input files are loaded every time the simulation is reset. Input files are spreadsheets with Coma Separated Values (CSV) format and each of them is copied on a different global Spreadsheet in Simul8. The outputs from the model are the mission log and the maintenance log and are stored using the same format. All parameters can be extracted from the variables recorded in these files. Whilst there are other files generated as outputs the information they contain is based on the mission and maintenance logs and their only purpose is to produce data that can be turned into graphs more easily.

9.3.1 Structure

The structure of the model uses the same closed-loop principle used by Teixira et al. [175], but the structure is complete different given its aim at analysing long-term effects and including both prognostic and diagnostic tools. As the model presented by Volovoi et al. [176], this model follows a bottom-up process in which aircraft are the modelled as the grouping of components that degrade and fail based as the simulation progresses.

The model consists of two main sets of Building Blocks as shown in Figure 9-9. The first set (on the top) comprises a Work Entry Point and two Work Centres and generates the desired number of aircraft at the beginning of each simulation. The second set of Work Centres forms a close loop in which the aircraft will circulate as different functions are executed. This set is in charge of simulating maintenance operations, mission planning and mission execution.

The functions performed by each Work Centre are programmed using Visual Logic and are executed every time an aircraft is loaded or leaves a Work Centre. The specifics of all functions are not discussed here to avoid unnecesary detail.

9.3.2 Implementation of functions in Work Centres

Each Work Centre performs a small number of simple tasks which helps to understand what the model is doing at any given time. Work Centres are used to change the value of some variables or to make sure an aircraft remains in it for a given period to simulate delays, maintenance of flights.

The following descriptions correspond to each of the Work Centres shown in Figure 9-9:

- *Assign Tail Number*: A code is assigned to each aircraft so it can be identified. Aircraft are numbered consecutively starting from 1.
- *Define Initial Condition of Components*: The RUL of the components of each aircraft is recorded in a spreadsheet called Condition of Components. At the start of each simulation all aircraft go through this Work Centre and the RUL is reset. The initial RULs are determined based on a Gaussian distribution of the MTBF from a list with the characteristics of each component.
- *Mission*: Aircraft stay in this Work Centre whilst they are supposed to be flying. The duration of each flight is random and defined by the distribution called “Mission Time”. The mission log is updated when the aircraft leaves this Work Centre. It is possible to specify shifts to limit the number of hours a fleet can fly per working day.

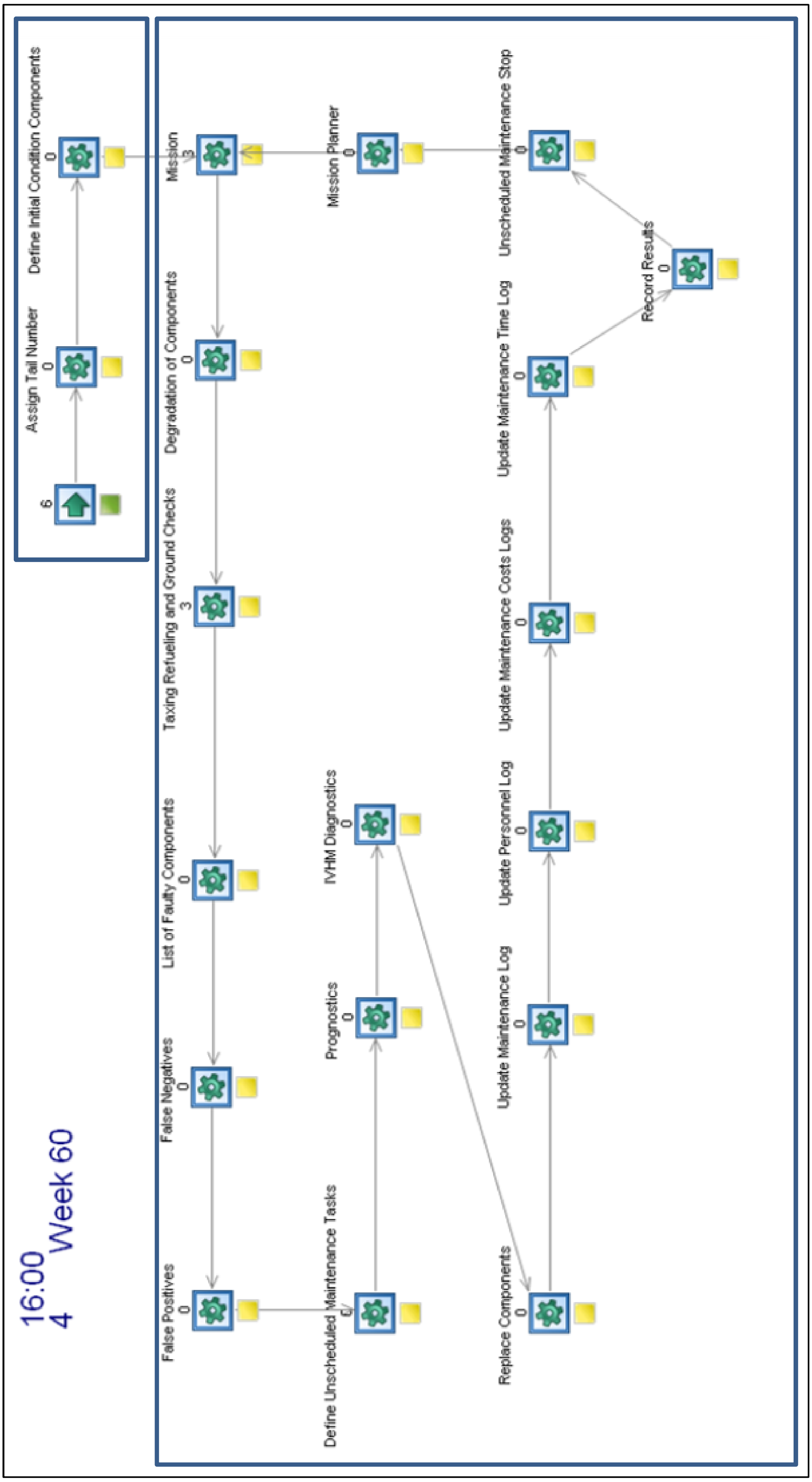


Figure 9-9 Model implemented on Simul8.

- *Degradation of Components*: The RUL of each component is reduced by the same amount as the duration of the last mission.
- *Taxing Refuelling and Ground Checks*: As the Work Centre Mission, this work centre introduces a delay equivalent to the time spent after each flight on taxing refuelling and ground checks The duration of the delay is determined by the random variable called "Taxing, Refuelling and Ground Checks"
- *List of Faulty Components*: This Work Centre checks the spreadsheet with the condition of all the aircraft's components and generates a new list with all those parts whose RUL is equal or lower than zero. This list is stored in a spreadsheet called "Faulty Components".
- *False Negatives* and *False Positives*: These Work Centres can modify the content of the list of faulty components (adding or removing components) based on the characteristics of the diagnostic tools and procedures being used. Using probability distributions the
- *Define Unscheduled Maintenance Tasks*: Based on the list of faulty components this Work Centre produces a list with all the maintenance tasks that have be performed on the aircraft which includes the MTTR (average and standard deviation), the personnel necessary, the cost of the part and delays (average and standard deviation). This new list is stored in a separate spreadsheet called "Maintenance Tasks".
- *Prognostics*: Using the list of prognostic tools available the RULs of all components monitored by these tools. Those that fall below their threshold are added to the list of Maintenance Tasks.
- *IVHM Diagnostics*: Performs the same tasks as the previous Work Centre, but for diagnostic tools.
- *Replace Components*: The RUL of the components included in the Maintenance Tasks list is reset. The new RUL is assigned using a random variable called "RUL at Replacement" based on the average and standard deviation of the MTTR read from the Component Characteristics spreadsheet.

- *Update Maintenance Log*: The list of maintenance tasks performed is added to the maintenance log which is stored in the spreadsheet named "Maintenance Log". The duration of the tasks and delays, which are random, are calculated in this step.
- *Update Personnel Log*, *Update Maintenance Costs Log* and *Update Maintenance Time Log*: The spreadsheets in which these logs are recorded are updated.
- *Record Results*: The files in which the outputs are recorded are updated to include the changes made in all the logs.
- *Unscheduled Maintenance Stop*: The aircraft is delayed for the duration of the unscheduled maintenance stop which is defined by the distribution Unscheduled Maintenance Time whose parameters were calculated in Update Maintenance Log. A shift is specified for this Work Centre so maintenance will only be carried out during normal working hours.
- *Mission Planner*: This Work Centre calculates the duration of the next mission the aircraft is going to fly. As long as the aircraft is available and the working shift is not finished the aircraft takes off.

This structure allows simulating the evolution of relevant parameters for the analysis of the financial viability of using IVHM. Using historical data from facilities in charge of maintaining the fleet being considered for retrofitting IVHM these models can reproduce the economic and operational changes faced with different health monitoring systems. Once the model is implemented, it has to be validated using these real data to ensure the results obtained are reliable. The process to validate the model is described in the next section.

9.4 Validation process

The need for validation arises as a result of simplifications of complex maintenance activities into programmable functions so they can be modelled. Additionally, the historical maintenance data used to define the parameters that govern the execution of each task simulated in the model cannot be 100% accurate (this is discussed in more detail in chapter 10). These factors act as sources of errors and uncertainties that result in the model producing result that can deviate from reality.

Since the model is used to make predictions as to how IVHM will influence the support of legacy platforms, inaccuracies become especially problematic. Whilst it is not possible to corroborate the veracity of predictions, it is possible –and desirable– to make sure that the model reproduces the same maintenance times and costs that are being experienced in the same maintenance facilities from which the data it uses was gathered.

For the validation of the model, a Monte Carlo analysis has to be run to obtain the probability distributions of those parameters that are to be compared. The sources of variability in the model will be the randomness of some of the inputs (e.g.: duration of tasks.)

The validation process must accomplish the following objectives:

- For average values:
    - Ensure the average values of maintenance costs for the fleet or individual aircraft match those of real aircraft operated under standard conditions.
    - Ensure the average values of maintenance downtime for the fleet or individual aircraft match those of real aircraft operated under standard conditions.
    - Ensure the average operational availability over a given period (which will depend on the characteristics of the data available) matches for the fleet or individual aircraft match those of real aircraft operated under standard conditions.
- For standard deviations:
    - Ensure the standard deviation of maintenance costs for the fleet or individual aircraft match those of real aircraft operated under standard conditions.
    - Ensure the standard deviation of maintenance downtime for the fleet or individual aircraft match those of real aircraft operated under standard conditions.

- Ensure the standard deviation of the operational availability over a given period (which will depend on the characteristics of the data available) matches for the fleet or individual aircraft match those of real aircraft operated under standard conditions.

The reason the focus is made on average values and standard deviations rather and on comparing all the parameters that can define the shape of the probability distributions is because these are rarely available. According to the central limit theorem maintenance cost and time (and consequently the availability) are the result of adding multiple variables with different probability distributions and therefore are likely to present a Gaussian distribution. Since Gaussian distributions are symmetrical averages and standard deviations are sufficient to validate the results.

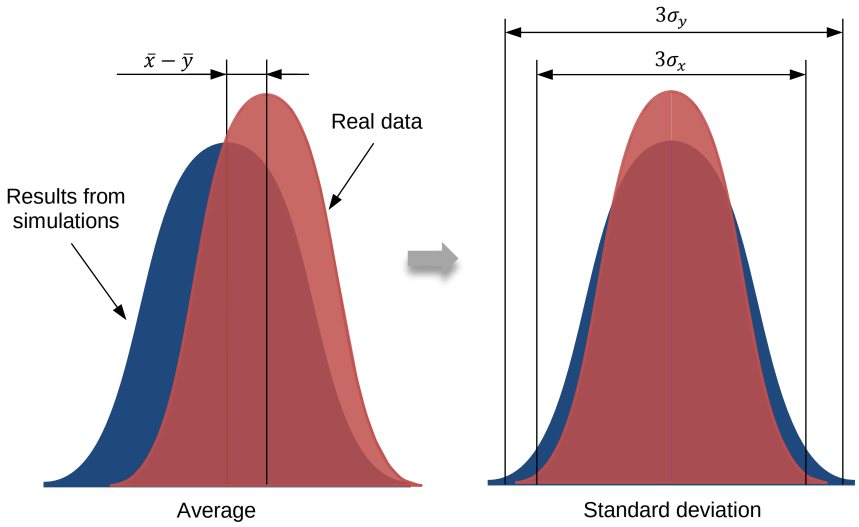


Figure 9-10 Illustration of comparing of differences in the average (left) and standard deviation (right) between real values (red) and those obtained from simulations (blue).

Evidently, if there is enough information available to accurately compare the shapes of real and simulated probability distributions of maintenance cost, downtime and availability, this comparison should be made (Figure 9-11). This can be done by calculating the error in higher moments of the distributions (skweness and kurtosis.)

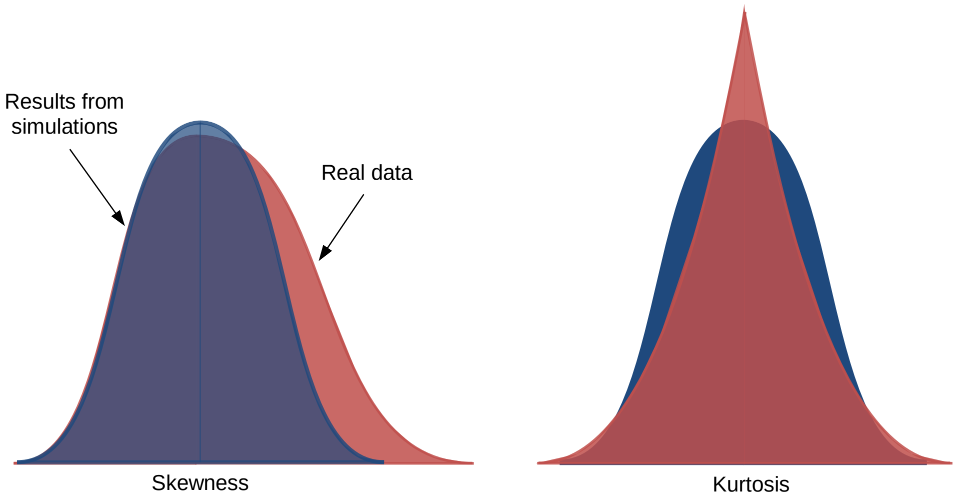


Figure 9-11 Illustration of comparing of differences in the skweness (left) and kurtosis (right) between real values (red) and those obtained from simulations (blue).

It is important to keep in mind the difference in the calculation of moments of probability distributions and how they affect the acceptable deviations of simulated results from real values. As explained in section 8.4.1, the nth moment of a probability distribution $f(x)$ about its average is calculated using the following formula:

$$\mu_n' = \int_{-\infty}^{\infty} (x - \bar{x})^n f(x) dx \qquad \textbf{9-1}$$

Each increase in the order of the moment corresponds to an equivalent increase in the power of the difference between the average, $\bar{x}$, and the values of the sample, x. Therefore, it is not reasonable to expect the same relative error for moments of different orders.

Imagine a case in which the acceptable relative error of the averages was 1%. Requiring a relative error of the skweness or kurtosis (second and third moments) of 1% also would not account for the fact that deviations are now elevated to the power of three and four. The result is an acceptable skweness of 3.03% ($1.01^3 = 1.0303$) and 4.06% for the kurtosis ($1.01^4 = 1.0406$). The choice of a specific acceptable value for the relative errors for higher moments must take this factor into account.

The acceptable relative deviations of the averages are marked by the magnitude of the desired improvement in each metric. The annual profitability of investments is measured as a percentage and is normally between 5-25%. This means that variations of 1% are significant for the comparison of IVHM toolsets. Errors in the model can result in maintenance costs being underestimated or overestimated. This can make health monitoring tools seam more or less profitable than they really are, but it is not possible to know a priori if these deviations are of the same sign and magnitude for all combinations of tools. Therefore, the maximum deviation of maintenance costs that should be allowed is 1%. A limit of the same magnitude should be imposed for the operational availability, but the value should be adjusted taking into account the availability before IVHM and the expected improvement. In any cases deviations larger than 5% are not acceptable. The acceptable deviation of the maintenance time per flying hour depends on the values without IVHM and the impact said systems may have as well, but it should not exceed 25 minutes (approximately 5% of an 8h shift) in any case.

Horning et al. [136] considered acceptable for the validation of their model – which was developed to study the effect of IVHM on operational readiness– deviations of up to 10%. They achieved an accuracy of 2-7% for availability, 2-10% for the use of personnel, and 7% for the downtime.

The degree to which the model can be validated and adjusted will depend on the datasets available for this task. Datasets are never perfectly accurate and might not cover all the parameters included in the model which means that compromises have to be made.

9.4.1 Data

The validation of the model is underpinned by the use of data to run the model and compare results. However, only a few stakeholders gather the necessary data and due to security or intellectual property concerns they might be reluctant to share it.

The criticality of data for the success of the simulation is no secret. As for the quality of a simulation, Sadowski and Grabau [179] identify the main problems with data as: too little, too much, and having to understand it. Andel [180] says that data management is what ends up taking most of the time, since getting the data, running it, and analysing it are very time-consuming. Brunner et al. [181] also cite data capturing and analysis as major challenges for simulation.

Real uncensored data obtained from maintenance logs of a fleet of aircraft represents the best option since it can provide all sorts of additional information that might be missing under other circumstances. The validation process and the run of simulations are faster with this kind of data since the accuracy of the values is not questioned. Additional unforeseen experiments can be run based on the trustworthiness of this data if considered necessary.

Sanitised data represents the second best option to run the experiments and the only option left for validation if a complete dataset of historical maintenance data is not available. This kind of datasets might hide the nature of the component each value is related to or they can have modified values to avoid the disclosure of critical information. The latter is not valid for the validation of the model since the results obtained with them cannot match the real values no matter how accurate the model is. Nevertheless, these datasets are good enough for running simulations of fleets to extrapolate conclusions to a generic fleet of aircraft.

Synthetic data can be used to run simulations once the model has been validated. These values are obtained using a random number generator. These simulations will not provide any insight on concrete improvements on a specific fleet, but can be used to extract some generic conclusion as to the effect of implementing IVHM on a generic fleet. The nature of such fleet will define the ranges given to the randomly generated parameters. Parameters such as maintenance time, cost, personnel requirements and others can be given constraints to avoid producing datasets that represent completely unrealistic scenarios. However, problems to understand the results from simulations may arise as a consequence of some of these parameters having an unrealistic value. These problems can be solved by checking the values of the dataset, but these results in less time available to run simulations from which conclusions can be extracted.

9.4.2 Initial validation of model for academic study

The validation of the model proved to be by far the most difficult stage of developing the model. In order to adjust all the parameters of the model real reliability, maintainability and operational data would be used as inputs and the results of the model compared with real life recorded maintenance times and costs. Some of the problems faced in this research project can be avoided in the future if the designers of the IVHM system make sure that the access to data is guaranteed at the beginning as indicated in the flowchart of the methodology.

Obtaining the input data proved to be challenging taking three times as long as developing the model itself. A sanitised dataset was eventually obtained. This dataset consisted in reliability and maintainability data of 1,237 components of a single engine subsonic jet trainer. Due to gaps in the dataset, information on 873 components was eventually used. The final list included components from all main aircraft systems. The dataset contained, for each component:

- Meat Time Between Arisals (MTBA)
- MTBF
- MTTR
- Average amount of personnel needed for its replacement.
- Cost

Values were representative for a squadron of 6 aircraft. Standard deviations where not available, but the advice from the organization that provided the datasets was to assume standard deviations so ±3σ represented ±15% of all parameters. The failure frequency of mechanical and electrical components were simulated using Weibull distributions whilst Gaussian distributions were used for electronic components

The simultaneous failure of multiple components had proven to be rare personnel availability was assumed to be 100% at any time in single maintenance and flying shift of 8 hours.

The average duration of flights was 1 hour with taxying with standard deviation 6.6 minutes. Refuelling and ground check taking an average of 30 minutes and a standard deviation of 3.3 minutes. Both parameters were simulated using Gaussian probability distributions.

This information was formatted to be read as normal inputs of the model and a Monte Carlo simulation conducted. The results of these simulations provided information on the evolution of maintenance costs, times and availability over a period of 21 years. The results of the simulations are shown in Figure 9-12.

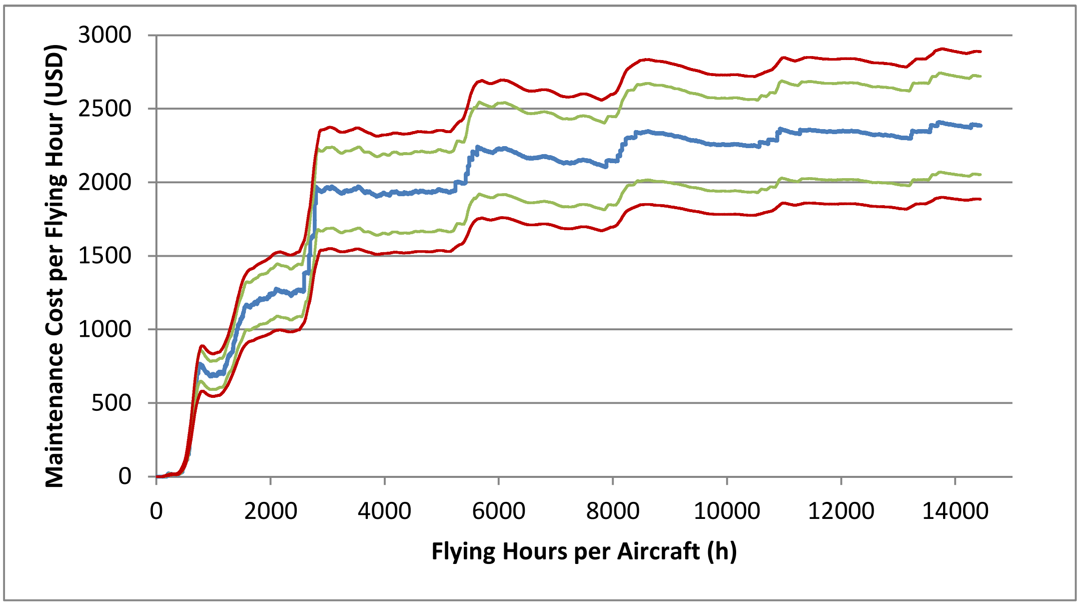


Figure 9-12 Evolution of the average maintenance cost per flying hour (blue) of a squadron of 6 jet trainers over 21 years corresponding to 60 simulation runs. Green and red lines mark the ranges of ±2σ and ±3σ respectively.

Whilst this provided enough information to run simulations, it was no possible to data on maintenance cost, time or availability. Consequently, it was not possible to validate the results.

To achieve some degree of validation, data on similar aircraft was used. Data on availability and maintenance time of equivalent fleets was not available.

Fortunately, there is abundant information on operational costs per flying hour of multiple aircraft. Operational costs include the cost of fuel, operational panning and aircrew.

The decision was made to compare the costs predicted by the model with those of aircraft of similar characteristics and complexity. Two groups of aircraft were chose to conduct this comparison: legacy fighter jets with similar capabilities and complexity (Table 9-1), and business jets (Table 9-2)

Table 9-1 Operational costs per flying hour of military jets operated by the US Navy and the US Air Force [182]. The original costs date from 1984 and have been adjusted based on data from the US Bureau of Labour Statistics [183].

Aircraft	Operational Cost per Flying Hour (USD)	
	1984	Inflation Adjusted
F4-J	2250	5062
P-3A/B	1318	2965.5
A-7 Corsair	1229	2765.25
A-6E Intruder	1876	4221
S-3A Viking	1452	3267

For the comparison with business jets it was decided to focus on category 5 jets (TOW above 41,000pounds) for presenting similar complexity and powertrains.

Table 9-2 Operational costs per flying hour of business jets [184].

Aircraft	Operational Cost per Flying Hour (USD)
Dassault Falcon 2000S	2216
Dassailt Falcon 2000LX	2204
Gulfstream G350	3099
Gulfstream G450	3116
Dassault Falcon 900	2372
Gulfstream G500	2778
Dassault Falcon 7X	2678
Embraer Lineage 1000	4371

The model predicted an average maintenance cost of $2385.4 per flying hour after 21 years and 14,000 hours of operation. The cost of the fuel per flying hour of the jet trainer being considered was estimated at approximately $900 per hour. Assuming the hourly cost of aircrew (pilot) and operational planning can be considered negligible, the approximate operational cost of the modelled fleet is $3285.4. This would place it between category 5 business jets and legacy fighter jets. This is consistent with the fact that the complexity of the systems of the jet trainer is slightly higher that business jets', and close to combat ready fighters. The cost estimation of the model seems to be reliable enough to produce accurate predictions of maintenance costs if the data necessary to adjust it becomes available.

The lack of data on maintenance hours per flying hour or availability prevented a more accurate assessment of the accuracy of the model. However, lessons learned in the attempt to achieve a more accurate validation of the model resulted in modifications to the flowchart of the methodology, with emphasis on data gathering being shifted to the first steps of the methodology. This should avoid any waste of time and resources trying to design and IVHM system for an aircraft for the necessary datasets are not available. A detailed discussion on the sources of data is included in chapter 10.

9.5 Conclusions

Using a computer model of maintenance operations to complement the other methods described in this thesis can be a useful tool to extract additional information that can be used to analyse other factors beyond the choice of the financially optimal IVHM toolset. The study of the literature showed that, whilst modelling maintenance operations is not new, it was necessary to develop a model capable of simulating the disrupting effect of implementing diagnostic and prognostic tools.

The main contributions of the work described in this chapter are:

- The requirements of the model have been defined. The functionalities, and outputs and inputs of the model have been specified.

- Validation requirements have also been specified

As an example, of the application of these principles, the model was implemented using Simul8^{TM}.

The importance of data for the development of this kind of modes has also been established. The next chapter will discuss this topic in more detail and will shed some light on what specific problems will be encountered when gathering these data.

The findings from conducting analyses with a model like the one described in this pages produces information that is relevant for many –if not all– stakeholders. Therefore, one should remember the importance of ensuring the message one is trying to convey gets through. In the words of Sadowski and Grabau [179]: “Wonderful simulation work, advanced analysis and eye-grabbing animation, all completed on-time still are of no value if they aren’t delivered to the right person in the right context.”

10 Data and their role in the quantitative analyses of the methodology

"It is a capital mistake to theorize before one has data."
- *Arthur Conan Doyle*

Throughout the methodology described in these pages the assumption has been made that data on the reliability and maintainability of an aircraft and its components is available. Legacy fleets present the advantage of having years of operation and maintenance which should be recorded in one way or another.

One must compile as much data as possible from the very beginning and extract all significant statistic parameters that define the probability distributions of all relevant parameters for every single component. There are, however, some issues that affect the access to these data and our capability to extract useful information from them.

Reliability and maintainability information of a legacy fleet provides a very detailed understanding of how its aircraft are operated and kept airworthy. Regardless of whether we are working with a civilian or military organization, this information is extremely sensitive and the owners of the data should be reluctant to share it. This is not necessarily a problem if the organization interested in implementing IVHM plays the roles of operator and maintainer, but in a world where outsourcing has become commonplace this is rarely the case. If the organization in charge of designing IVHM systems wants to pitch a particular toolset to a maintainer or and operator it will have problems trying to obtain the data necessary to present an accurate business case. The problem can be aggravated if the maintenance of the engine(s) –or any other system for that matter– is carried out by a different company from the one that maintains the rest of the aircraft.

Even if the access to these data is granted, extracting the necessary information from them can require a significant amount of manhours. The reasons are diverse. Large fleets can be maintained in multiple facilities meaning maintenance records can be scattered over multiple sites and for legacy aircraft the choice of maintenance facilities may have changed over time, making it even more difficult to track old maintenance records.

Maintenance logs record the details of individual maintenance tasks, meaning that to obtain the information in a format that is useful a statistical analysis has to be carried out. This brings us to one of the major challenges for legacy aircraft: extracting data from maintenance logs kept on paper records or outdated databases. Fortunately, in most cases, the maintenance of legacy aircraft has transitioned to some sort of digital recording. For large fleets, even the records of a few years can be sufficient to obtain the necessary parameters.

Getting the historical maintenance data is not the end. The next problem comes from the challenge of characterising uncertainties. As explained in the literature review, uncertainties can be divided into aleatoric or statistical uncertainties, and epistemic or systematic uncertainties [185; 186]. The former are uncertainties caused by the random nature of some of the phenomena we are working with, such as the variability of the time it takes to replace a part or the fact that the price of spare parts can be renegotiated, resulting in a fluctuation of costs. The latter refers to uncertainties produced as a result of inaccuracies in the records. These are caused by missing data in the records (e.g.: sometimes just the total active maintenance times is recorded whilst other time delays are included) and rounding up numbers. The result is second order uncertainties or “uncertainty of uncertainties” which can be difficult to quantify. However, since second order uncertainties are not considered in the risk analysis of this methodology and, therefore, are not a matter of consideration.

This chapter is aimed at shedding some light on the critical role of data in this methodology. In essence, the contributions of the work described in this chapter are:

- Specify the data that is necessary on each step of the methodology presented in this thesis (section 10.1)
- Identify the main causes of uncertainty on data obtained from maintenance, operation, and IVHM design organizations (section 10.2).

10.1 Data and the methodology

The data used in this methodology can be divided into:

- Data on reliability and maintainability of components as well as their delivery and storage.
- Data on maintenance facilities
- Data on operations.
- Data on the performance and cost of prospective IVHM tools, and the interactions between them.

The first two groups of data can be obtained from historical maintenance and operational data. Whilst the first has to be gathered for each component, data on operations affects the aircraft as a whole.

Data on the prospective diagnostic and prognostic tools can come from two sources: in-house departments involved in developing IVHM tools or independent providers of IVHM tools.

In many cases it will not be possible to obtain records with sufficient detail to obtain all this information. Gathering experts' opinion is the second best option and in most cases the only alternative. Whilst it is not an ideal solution, it is a better option than removing a component from the list for lack of data. If a component for which data was obtained in this manner was flagged as good potential candidate to be monitored, maintenance data can be gathered a posteriori to ensure the result is correct.

Whilst the data on reliability and maintainability of components and the data on operations are necessary in the very first quantitative analysis, information on the performance of IVHM tools only becomes relevant after the requirements have been defined and toolsets are to be compared.

The use of each group of data in each corresponding step of the methodology can be seen in Figure 10-1.

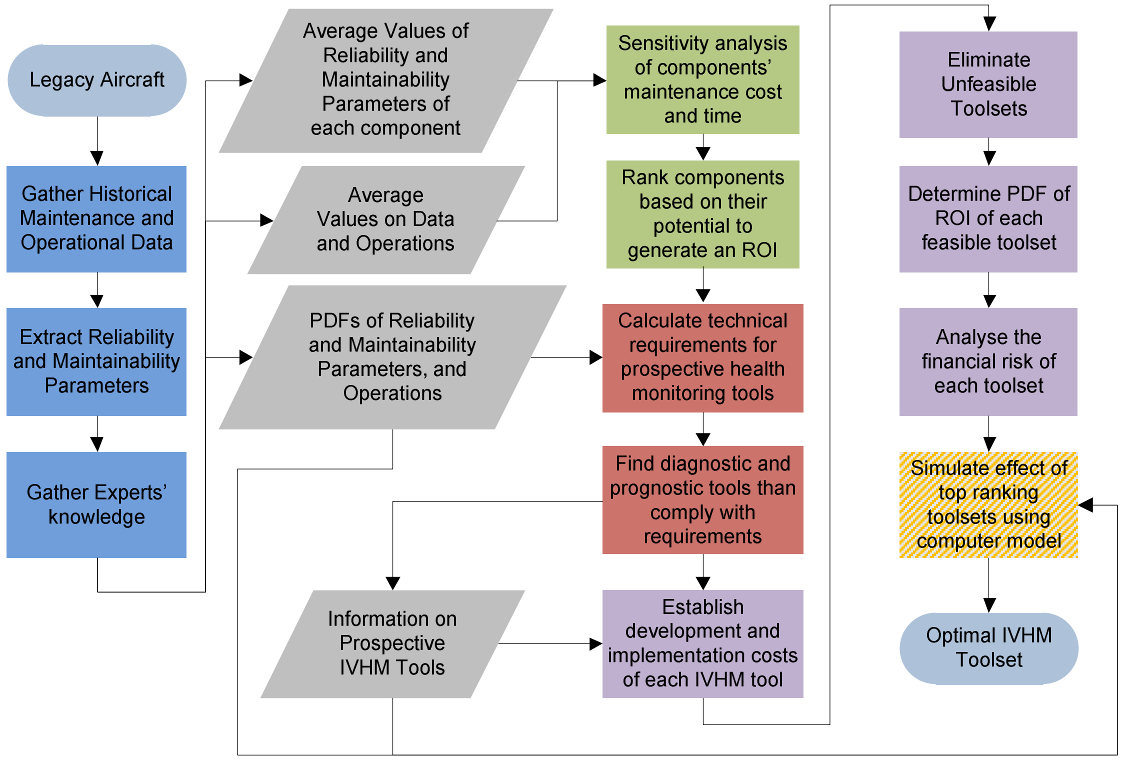


Figure 10-1 Expanded flowchart of methodology with the used of different data on each corresponding step (in grey.)

10.1.1 Data on reliability and maintainability of components

Gathering historical maintenance data represents the first step of the methodology since they are essential to conduct the subsequent quantitative analyses. Not all the data gathered is used in every single step. The analysis of the sensitivity of the maintenance cost and time of each component to the use of IVHM, which is the first quantitative analysis of the methodology, does not require the use of probability distributions. The reason data is supposed to be gathered and processed from the beginning is to ensure all necessary parameters are ready and avoid delays.

Ideally, maintenance logs should provide enough information to parameterise the probability distributions of all the parameters that characterise any corrective or preventive maintenance task (see Figure 10-2 as a reminder). Whilst active corrective and preventive maintenance times are always recorded, other times are not always included in the logs. Given the fact that the analyses conducted in this methodology do not require all these variables some simplifications can be made.

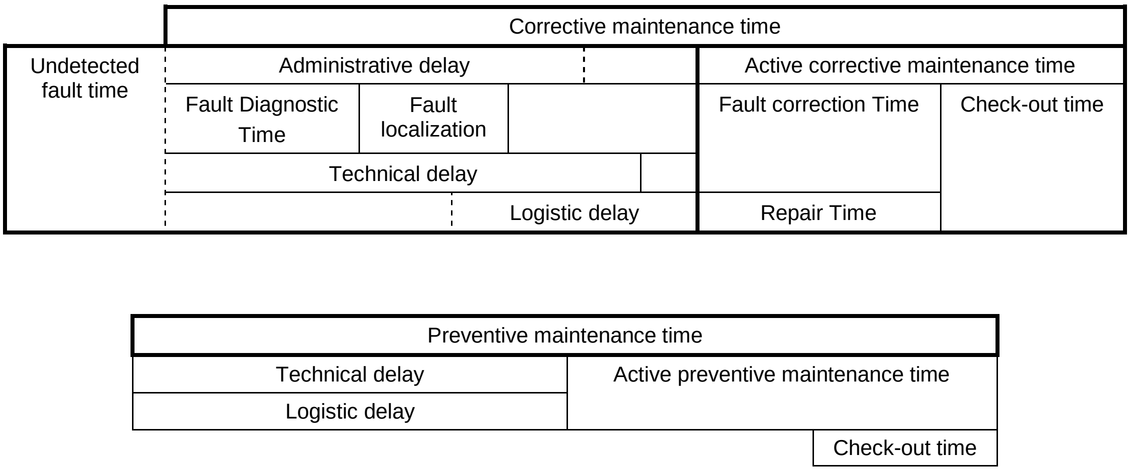


Figure 10-2 Maintenance times according to BS 4778-3.1 [1]**.**

We are interested in comparing the time dedicated to diagnose and localise a fault before and after the implementation of a diagnostic tool, therefore, there is no need to distinguish between both as long as we can estimate the sum.

The sub-steps in which the active corrective maintenance time is divided are of no interest for us either. The use of diagnostic and prognostic times does not affect the time to complete the active maintenance task, for it is defined by the steps that need to be taken to replace the part.

Obtaining maintenance records with detailed delays is almost impossible since that would require administrative, technical and logistics personnel to keep track of the starting and finishing times of every single task they are given and correlate it to a specific maintenance task. Instead, for logistic delays it is possible to obtain their duration from comparing purchase orders to stock logs. Technical delays can be traced for auxiliary equipment that requires authorisation or leaves some other kind of paper trail. Administrative delays are almost impossible to trace, especially if the intention is to determine their probability distribution. However, analysing the independent component of delay is only relevant to extract information on logistics and the use of auxiliary equipment from the DES as discussed in chapter 10.

The stock of components is essential to model correctly the influence of logistics on maintenance and vice versa. There is a threshold below which a the stock of each component has to be replenished to a predetermined amount. Both values have to be defined for every component.

The rest of the steps of the methodology only take into account the fact that corrective maintenance actions can become part of preventive maintenance, eliminating delays. Only the total delays suffered in the replacement of a component is relevant for this comparison. Total delays are sometimes included in maintenance logs. If there was not enough information to characterise the PDF of the total delays experience for each component, a viable assumption is to use the logistic delay as the total sum of delays given the fact that it tend to be considerably longer than technical and administrative delays.

Needless to say, the undetected fault time is not important to estimate the economic benefits of an IVHM system (although the safety benefits are obvious). However, this is related to a very important set of parameters: false negative rates and false positive rates. Aircraft maintainers can become aware of a fault thanks to symptoms noticed by the pilot, regular checks or BITE; but neither of these methods are infallible. Neither are IVHM tools, but the changes they produce on these two parameters are important, as it was discussed in chapters 6 and 7. Since maintenance logs tend to differentiate between arisals and failures, both parameters can be easily calculated.

10.1.2 Data on maintenance facilities

The DES must take into account the constrains faced by maintenance facilities. These constraints are defined by the resources of each maintenance facility in which the aircraft can be maintained. The relevant parameters to model maintenance operations with the detail required in this methodology are (for each facility):

- Duration of shifts
- Calendar of shifts
- Personnel available on each shift

- Amount of auxiliary equipment available (different components needs different pieces of special equipment and many need none)

Flying time between facilities is also important as it will determine the probability of addition failures or false positives.

The stock levels and thresholds can be different depending on the facility. This should be reflected in the model as well.

10.1.3 Operational data

Operational data can include all sorts of parameters to characterise both missions and ground operations, but for the purpose of this methodology the only two essential variables are:

- PDF of the duration of flights
- PDF of the frequency of flights
- PDF of time spent on non-maintenance related ground operations (e.g.: refuelling, loading and downloading cargo/passengers, taxing)

Other parameters that could help the DES to be more precise would be the frequency of each type of flight or missions. This is only relevant if the failure rate of components can be modelled to change depending on the characteristics of the flight (e.g.: for military aircraft the degradation suffered by part during a combat mission will be completely different from what they experiment during a reconnaissance mission). Obviously, whilst desirable, this is not essential and probably will not be available for most components.

10.1.4 Data on prospective diagnostic and prognostic tools

The last set of data that has to be gathered does not involve maintainers or operators, but developers of IVHM technology. These can include the organization in charge of designing the IVHM system or independent contractors capable of supplying diagnostic or prognostic tools.

The performance diagnostic tools is defined by the PDF of false positives and false positives. The performance parameter of prognostic tools relevant for a financial analysis is the probability of a component failing before it is replaced based on the indicated degradation. This can be calculated using the PDF of the RUL provided by the prognostic tool as degradation progresses and the PDF of the frequency of maintenance stops (for more details see chapter 6.)

The costs of each tool has to be divided into different parts to allow designers to analyse which can be shared as tools are combined (for more details see chapter 8). The analysis of which costs can be shared relies on asking experts to fill in the Share Tensor, ***S***. Similarly, the identification of incompatibilities between tools requires the expertise of engineers familiar with the technical characteristics of each tool and the aircraft.

With these last dataset the remaining steps of the methodology can be completed. Data will be generated by the quantitative analyses and the DES, but these results will be affected by the variance of the data used as inputs. Understanding some of causes of this variance can help to better understand the results we obtain.

10.2 Data uncertainty

The previous section described the different sources from which data can be obtained and, in some cases, the assumptions that have to be made due to the scarcity of information on some variables. The uncertainty introduced by these assumptions must be acknowledged and their effect on the results of each step of the methodology assessed before progressing to the following step. This is true regardless of the source of the information.

The aleatoric uncertainties have been described in chapters 7 and 8. This section explains the main sources of epistemic uncertainty caused by working with legacy fleets.

10.2.1 Uncertainty of data on the reliability and maintainability of components

Working with historical maintenance data presents problems regarding the accuracy of the information extracted from them. This results in two main sources of epistemic uncertainty:

- Gaps in the data: Historical records can be incomplete in that logs can be missing or because relevant data might have not been recorded in the first place. This is especially problematic for components with very low failure rates, but with a repair/replacement cost high enough to be interesting from an IVHM perspective. This tends to affect the records of delays, and diagnostic and isolation times.
- Lack of precision in the records: Records rely on the precision and accuracy of the information written down by maintenance personnel. It is inevitable for workers to round the duration of the tasks stated on maintenance logs. The magnitude of this rounding will depend on each worker and on the duration of the task. Consequently, it is very difficult to estimate the error introduced and the second order uncertainty that results from it.

10.2.2 Uncertainty of data on maintenance facilities

Luckily, the information on maintenance facilities is not affected by randomness as much as other factors. Duration of working shifts and the amount of personnel in them is constant (if we ignore absence for illness or other causes.)

However, information on the facilities where legacy platforms were maintained can disappear over the years. In that case the best option is to try to find information on facilities that serviced a similar amount of similar aircraft to tray to infer these parameters.

10.2.3 Uncertainty on operational data

Operational data suffers the same problems as historical maintenance data, but to a lesser degree. Every single flight is recorded by a civilian or military authority so the PDF of the frequency of flights can be calculated very accurately. Rounding values also affects the records of the duration of flights, but these tend to be much more accurate than maintenance times. After all, a transatlantic flight can be timed to the nearest minute, but a maintenance task that spans over several hours is likely to be rounded to the nearest 30 minutes, at best.

Records on the time spent on non-maintenance related ground operations are more uncommon, but operators need to estimate this time to manage their fleet and should be easy to obtain and accurate enough for the purposes of the DES.

10.2.4 Uncertainty of information on prospective diagnostic and prognostic tools

Working with health monitoring systems in the aerospace industry presents major challenges for engineers to test the accuracy of these tools, especially since it would involve running several components until failure, which would be prohibitively expensive. Tests are conducted using special rigs to try to recreate the condition in which parts will degrade and fail. These tests are the only viable alternative, but will never produce the same results as real flight conditions, meaning the estimated performance suffers from some degree of epistemic uncertainty.

The major problem is when among the toolsets that are to be compared using this methodology we find tools that are still being developed. The reason we might be interested in included tools that have not been properly tested is that health monitoring tools are scarce and in most cases have be developed, or at least tailored, for specific aircraft. Obviously, this means that the predicted performance of these tools depends on their level of development. However, the higher variance in performance of these tools is accounted for in the risk-based comparison in chapter 10. The challenge is to estimate the variance of the performance parameters in a way that satisfies those putting together the IVHM toolset. This can only be achieved by working together with the team that develops each tool.

10.3 Conclusions

Data remains one the major sources of problems for the IVHM community. From getting access to sensitive information to deciphering old databases, extracting the necessary information to conduct any kind of viability analysis for IVHM systems remains the main challenge.

The contributions of the work described in this chapter are:

- Enumerate the problems that are to be faced trying to obtain the different datasets necessary to reach a design solution using the methodology described in this thesis. Identify the main causes of uncertainty on data obtained from maintenance, operation, and IVHM design organizations.
- Identify the sources of uncertainty embedded in the datasets that have to be interrogated in order to carry out the quantitative analyses of this methodology and run the DES to raise awareness and help to understand their effect on the final result.

11 Discussion and conclusions

"Every achievement is a servitude. It compels us to a higher achievement."
- Albert Camus

Reaching the end of the thesis calls for revising the progress made and determine if the objectives set have been achieved. The analysis of the state of the art of IVHM technology and the literature on the topic lead to framing a specific research question:

How can the optimal combination of diagnostic and prognostic tools for a legacy aircraft be chosen according to its economic merits taking into consideration the effect of uncertainties in the analysis?

The succession of chapters of which this thesis is comprised describe a methodology that can help designers if IVHM determine the best possible combination of diagnostic and prognostic tools to produce an economic return with an acceptable risk. The answer to the main research question is the whole methodology described from chapter 4 to chapter 10.

As the reader probably remembers, there was also a list of secondary research questions. These questions are:

- *How can the components of a legacy aircraft be selected according to their potential to improve maintenance cost and time using health monitoring technology taking into consideration the effect of uncertainties in the analysis?*
- *How can the requirements for diagnostic and prognostic tools be defined to produce a specific improvement in the maintenance cost and time of the component being motored?*
- *How does combining IVHM tools affect the economic return and the financial risk of investing on a given toolset?*

The answers to the secondary research questions correspond to the steps of the methodology described in chapters 6, 7, and 8 respectively.

The following pages will cover the work presented in this thesis and which conclusions can be extracted from it. Whilst the conclusion of individual pieces of work can be found at the end of each chapter, this chapter will focus on the overall result of the thesis.

There are some unexplored areas of research that have appeared as a result of developing new methods to conduct the quantitative analyses that form this methodology. Although they might not be essential to answer the research question defined at the beginning of this research, they do present interesting challenges worth pursuing. A list of future research work is included in the last section of this chapter.

11.1 Summary

Chapter 2: The literature review discussed the current state of the art of IVHM technology, the financial viability of IVHM systems, and the challenges of implementing it. The findings of the literature review helped to recognise the need for a design methodology of IVHM systems for legacy aircraft with focus on financial returns and risk analysis.

Chapter 3: This chapter identifies specific research questions that were to be answered with the findings of this thesis. The research methodology is comprised of a series of quantitative techniques to assist in the development of the design methodology that was to answer these questions. These techniques include ETA, error propagation analysis, portfolio risk analysis and DES.

Chapter 4: The first description of the methodology is provided in this chapter with an explanation of the main assumptions made in its development. The steps of the methodology can be summarised as:

1. Gathering the necessary data
2. Analyse the potential benefits of monitoring each component of the aircraft.
3. Calculate the performance requirements of diagnostic and prognostic tools to monitor top ranking components from the analysis conducted in the previous step.

4. Conduct a comparison based on the financial risk of different combination of IHVM tools to identify the best possible solutions attending to the requirements of the users.
5. Perform further analyses on economic and non-economic aspects of retrofitting a given IVHM toolset using DES.

The details of these steps are discussed in subsequent chapters.

Chapter 5: A description of the relative importance of the different economic benefits expected from an IVHM system is provided. This is necessary to understand how to quantify the benefits of individual tools. This is essential to rank components according to their potential to generate an economic return as described in chapter 6. This chapter also includes case studies on the impact of secondary benefits and regulations.

Chapter 6: This chapter demonstrates a quantitative method to determine which components should be monitored to see maintenance time and cost reduced. The analysis is based on the equations obtained using ETA of the possible outcomes of a fault with and without diagnostic and prognostic tools. Components are ranked according to the sensitivity of their maintenance cost and time to the accuracy of IVHM tools. A case study is included.

Chapter 7: This chapter demonstrates a quantitative method to determine the technical requirements of diagnostic and prognostic tools. This is necessary to find diagnostic and prognostic tools capable of producing the necessary improvement in maintenance costs and times. This method accounts for the uncertainties present in the analysis and defines the performance requirements of IVHM tools as PDFs to account for the variance of their accuracy. A case study is included.

Chapter 8: The risk-based comparison of IVHM toolsets is described in this chapter. The risk of the financial return is calculated as a function the savings produced by combining multiple diagnostic and prognostic tools and the variances of the expected costs. The result is a quantitative method to characterise the PDFs of the ROI of multiple IVHM toolsets without having to run an impracticable number of computer simulations. A case study is included.

Chapter 9: This is the last chapter that discusses as specific step of the methodology. It includes: a description of the requirements of DES models of aircraft maintenance operations capable of conducting the analysis necessary to compare the benefits of different IVHM toolsets; definition of the structure of the model with an example of the implementation on Simul8™; a discussion on the validation requirements and a description of the high level validation performed on the Simul8™ model.

Chapter 10: This chapter provides an understanding of which datasets are needed on each step of the methodology, the information that each dataset should contain, and what are the best sources of information available. Additionally, the sources of uncertainty that affect these data are discussed to raise awareness of which problems can arise and how they affect the propagation of errors.

11.2 Conclusions

The result of the research described in this thesis has been the development of a methodology to identify the combination of diagnostic and prognostic tools for a legacy fleet that brings the best combination of economic return and financial risk. The methodology starts by ranking components according to their capability to improve maintenance operations. The search for diagnostic and prognostic tools for top ranking components is initiated by defining their performance requirements. Once the list of tools is completed, the viable combinations are compared according their ROI and the financial risk they represent. Whilst it is possible to select a specific combination based on this result, DES can be used to analyse in more detail the effect of retrofitting a handful of different IVHM toolsets. This answers the main and secondary research questions.

Whilst the methodology requires following a series of specific steps to arrive to a solution, the different methods it is comprised of can be put to use individually.

The identification of critical components as candidates to be monitored can also be used to analyse the potential benefits of shifting some components to CBM or some sort of preventive maintenance scheme. The equations to obtain the performance requirements for IVHM tools can be used to determine the needs of individual tools according to business needs regardless of the reasons behind the choice of the components.

Besides describing the individual steps of the methodology, additional research was conducted on the areas of economic benefits of IVHM and on sources of data and the uncertainty they introduce into quantitative analyses. Findings in both areas are relevant for other topics of research apart from that of this thesis. Identifying sources of revenue, the importance of secondary benefits and the limit role of regulations affects both legacy and new aircraft and the same approach described in chapter 5 can be applied. Similarly, the need of data to conduct CBAs and means that the problems caused by data uncertainty identified in chapter 10 can be of use to other areas of research.

The merits of this methodology are not limited to assisting in the design of an IVHM system. By making financial viability the priority and by taking into consideration the risk of investing on an IVHM system, supporters of this technology can present and stronger case to those more sceptic about the capabilities of IVHM systems. As discussed in the literature review, this is still one of the main obstacles for current application of health monitoring systems. If we are to reach the levels of coverage and complexity necessary to produce significant gains, the capability to present a strong business cannot be underestimated.

11.3 Future research

The results from this thesis, besides providing answers to the research questions, have brought to like some additional issues that should be explored in the future. Carrying out this work would increase the accuracy and scope of the methodology here presented. The main areas of future research that have been identified are:

- The questionnaire on the economic impact of secondary benefits was conducted on a single organization. Similarly, the study of maintenance regulations focused on NATO and the British MoD. Distributing the questionnaire among more organizations and studying maintenance regulations more broadly should help to understand the impact of these issues on a greater number and variety of organizations.
- The risk-based comparison assumes combining IVHM tools produces savings as resources are brought together. Combining tools could result in higher costs if their combined needs resulted in more expensive hardware, testing or operations. This could be used to include in the comparison combinations of tools that are now considered incompatible if said incompatibility could be replaced by an increase in the cost of installing both tools.
- The financial risk comparison of IVHM toolsets relies on the PDF of the ROI calculated for each possible combination of tools. There are multiple financial risk analysis techniques that could use this information to produce an even stronger business case for the chosen solution. Including these techniques into the methodology would take it from providing a design recommendation to generating all the data necessary for a business case.
- The validation of the DES model implemented on Simul8™ was undermined for the lack of data to conduct a proper validation. The model includes all relevant parameters that need to be adjusted to simulate maintenance operations for a legacy fleet. Getting access to comprehensive historical maintenance data and operational data is essential to achieve the level of accuracy required. The validation of the model has to be repeated for each fleet subjected to the analyses of this methodology to ensure the accuracy of results is maintained.
- Uncertainties play a major role in the comparison of different IVHM toolsets. These uncertainties, which are the basis of the financial risk analysis, need to be quantified. Some of them, like the PDFs of tools'

performance or the PDFs of reliability variables, can be obtained from tests or statistical analysis of data. There are, however, second order uncertainties or "uncertainties of uncertainties" caused by lack of accuracy of maintenance records or assumptions and errors in tests. Including the effect of second order uncertainties would add to the accuracy of this methodology.

- This methodology enables designing complex IVHM systems with a larger coverage than those implemented so far on legacy aircraft. This presents a problem: there is not a real case to compare the predicted ROI and the real impact of retrofitting a system with these characteristics. The continuing advancements in health monitoring technology and the need to extract more flying hours from aging fleets mean that sooner or later full IVHM systems will be retrofitted. This will generate data on the economic impact of retrofitting IVHM which can be used to validate the predictions made using the quantitative tools of this methodology. Hopefully, this will provide ultimate proof of the validity of this method.

Exploring these areas should add accuracy to the methodology and confidence on the results it produces. However, it must be taken into account that carrying out some of this extra work will depend on external factors such as additional data becoming available. Hopefully, the result from this thesis will be compelling enough to convince all stakeholders of the importance of dedicating the necessary resources to make progress in this field.

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APPENDICES

Appendix A Questionnaire to gather data on secondary benefits of IVHM systems

QUESTIONNAIRE

Please answer the following questions to the best of your knowledge by marking or highlighting the option you believe to be correct. If you can provide an answer more accurate than the options given or if none of the options correspond to the value you consider correct, write an alternative answer on the given space. If you believe the answer to be in a range of values, please, either select the upper and lower range of the interval from the options provided or specify it on the space available for other possible answers. When maintenance personnel are mentioned in the following questions it refers to those workers who perform depth maintenance activities. If you wish to elaborate on some of the answers, please do it on the space given for comments at the end of this document.

1. Shifts:

1.1. Do all the shifts have the same amount of maintenance personnel?

YES NO

1.2. If not, what is the ratio between the man-hours of the less active and those of the busiest approximately?

0.9 0.8 0.7 0.6 other:_____

1.3. Considering a typical 24 hour period, what is approximately the ratio between the man-hours spent by personnel with hands on the aircraft and the man-hours of technical and administrative personnel?

0.9 0.8 0.7 0.6 other:_____

1.4. What is the efficiency of maintenance personnel on a normal shift (i.e.: the ratio between the real man-hours and those available on an average shift)?

0.9 0.8 0.7 0.6 other:_____

1.5. What is the proportion of man-hours that personnel with hands on the aircraft spend on administrative tasks (e.g.: documenting activities) compared to working on the vehicle?

0.1 0.2 0.3 0.4 other:_____

1.6. Of all the delays affecting maintenance tasks, what is the proportion of maintenance tasks that have to be delayed because the required personnel is not available?

0.1 0.2 0.3 0.4 other:_____

2. Personnel training

2.1. What is the proportion of man-hours maintenance personnel spend on training over a year approximately? (not taking into account the initial training phase before they start performing maintenance tasks)

0.1 0.2 0.3 0.4 other:_____

2.2. What is the proportion between the time spent training to perform checks, evaluate damages or diagnose failures and the time spent training to perform maintenance activities (i.e.: replace and repair components)?

0.1 0.2 0.3 0.4 other:_____

3. Office Personnel

3.1. Considering only the personnel working in the technical office, what is the ratio between the man-hours dedicated to administrative and logistic tasks and the man-hours spent on engineering tasks such as providing technical assistance to maintenance workers?

0.1 0.2 0.3 0.4 other:_____

3.2. Of all the man-hours dedicated in the technical office on engineering tasks, what is the ratio between the time spent on improving the efficiency of the maintenance tasks (e.g.: analysing historical maintenance data, studying alternative maintenance procedures) and the time spent managing the daily operations of the fleet?

0.1 0.2 0.3 0.4 other:_____

3.3. Is the previous parameter measured in any way? If the answer is yes, please describe how this is done how the benefits are assessed in the comments section at the end of this document.

YES NO

4. <u>Auxiliary equipment</u>

4.1. Of all the delays affecting maintenance tasks, what is the proportion of maintenance tasks that have to be delayed because auxiliary equipment is not available?

0.1 0.2 0.3 0.4 other:_____

4.2. What is ratio between the cost per man-hour of auxiliary equipment and cost per man-hour of maintenance personnel?

0.1 0.2 0.3 0.4 other:_____

5. <u>Maintenance and tests</u>

5.1. Considering a normal use of the aircraft over a year, what is the ratio between the man-hours dedicated to corrective maintenance and the man-hours spent on preventive maintenance (including checks and replacing components)?

0.1 0.2 0.3 0.4 other:_____

5.2. Of all the times an aircraft has not been available for a mission because of maintenance, what is the ratio between the times the delay was caused by logistics or administrative delays and the times the delay came as a result of the maintenance tasks requiring more time that that available between missions?

0.1 0.2 0.3 0.4 other:_____

5.3. Regarding those maintenance tasks that require a test flight and the typical operation of the fleet over a year, what is the ratio between the flying hours dedicated to Maintenance Test Flights (MTFs) and Partial Test Flights (PTFs)?

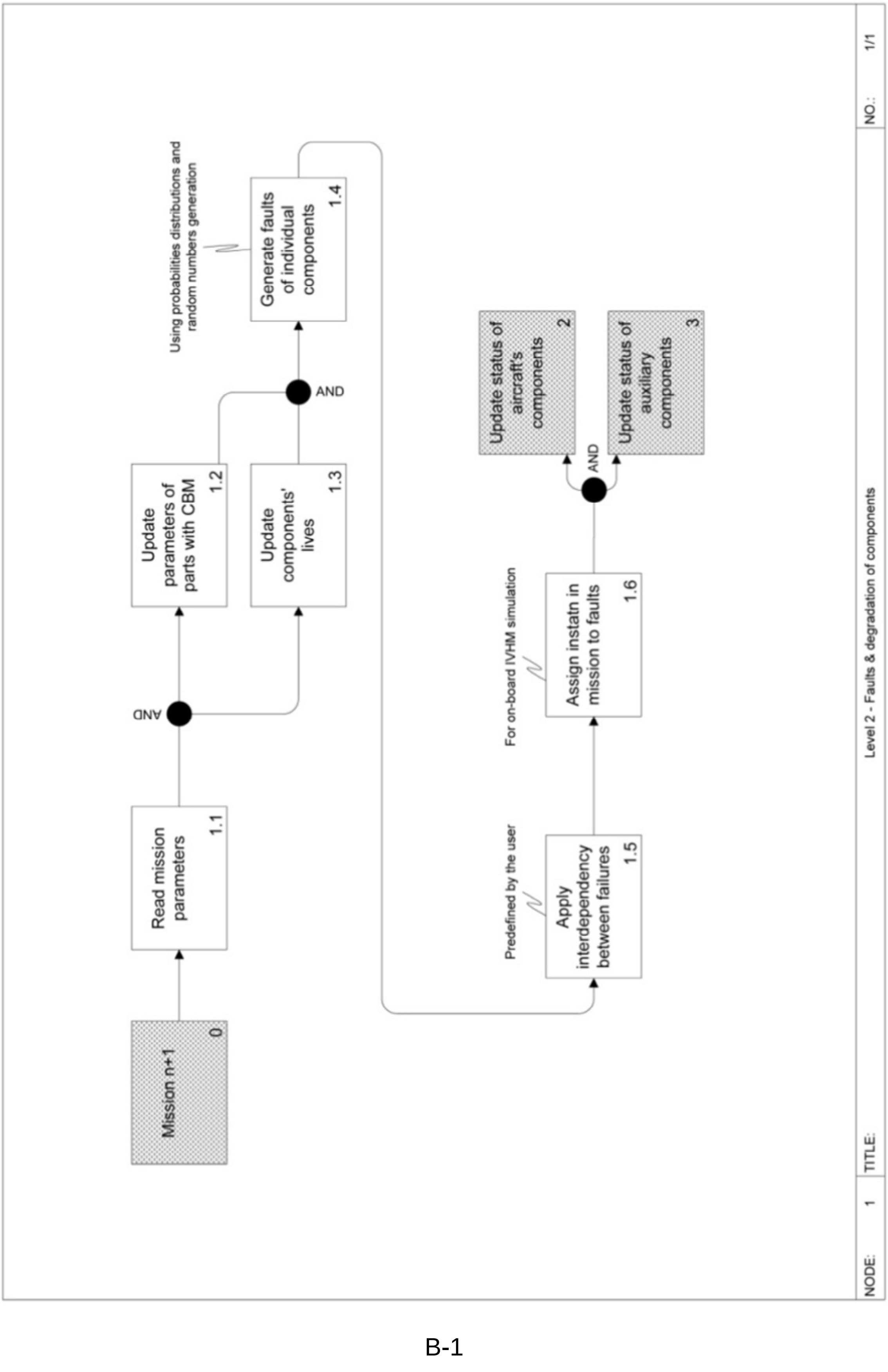
0.1 0.2 0.3 0.4 other:_____

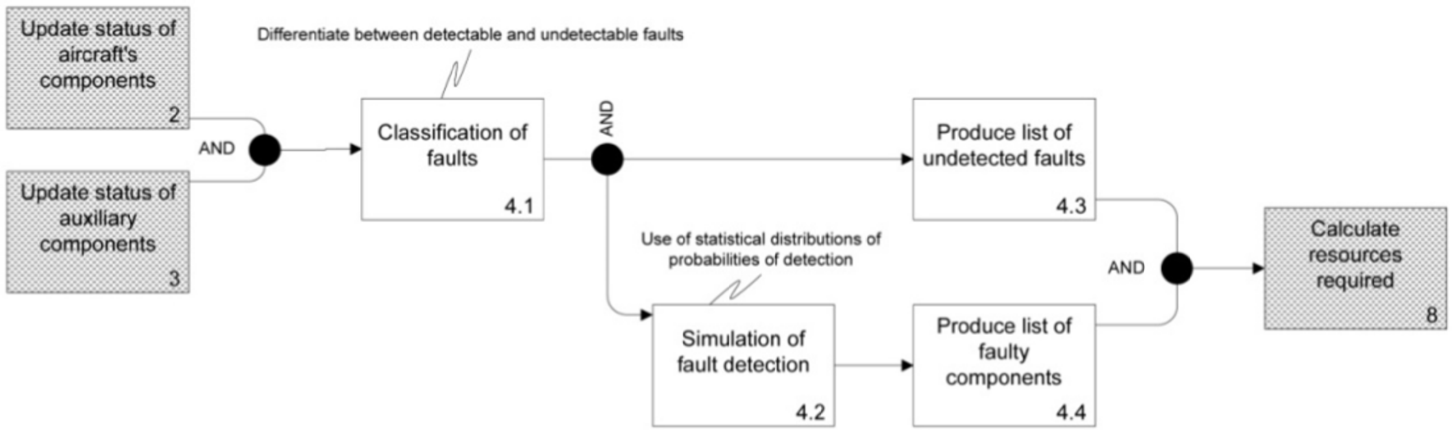
5.4. What is the ratio between the flying hours of those PFTs conducted during a routine flight and the flying hours of those flights whose only purpose was to carry out a PFT?

0.1 0.2 0.3 0.4 other:_____

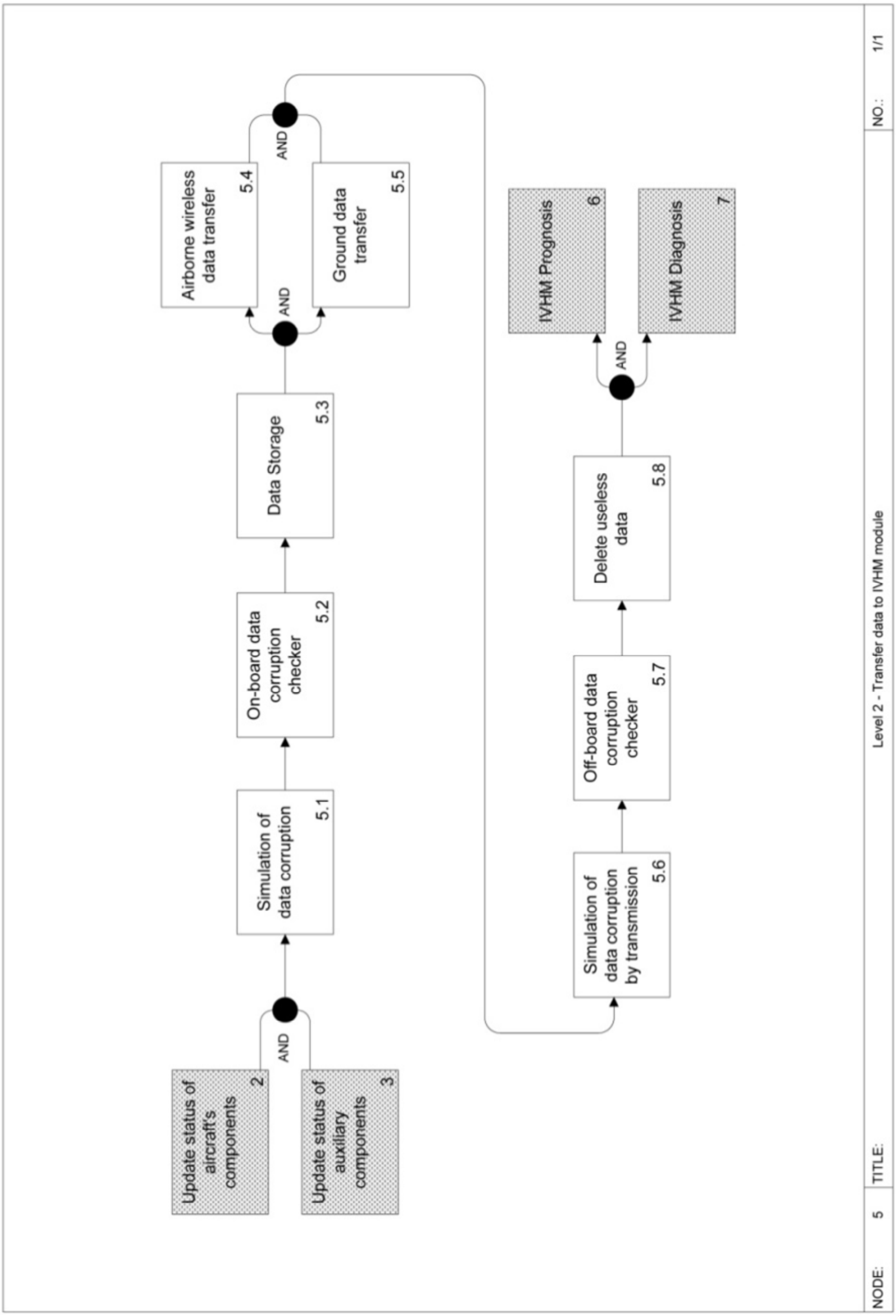
Comments:

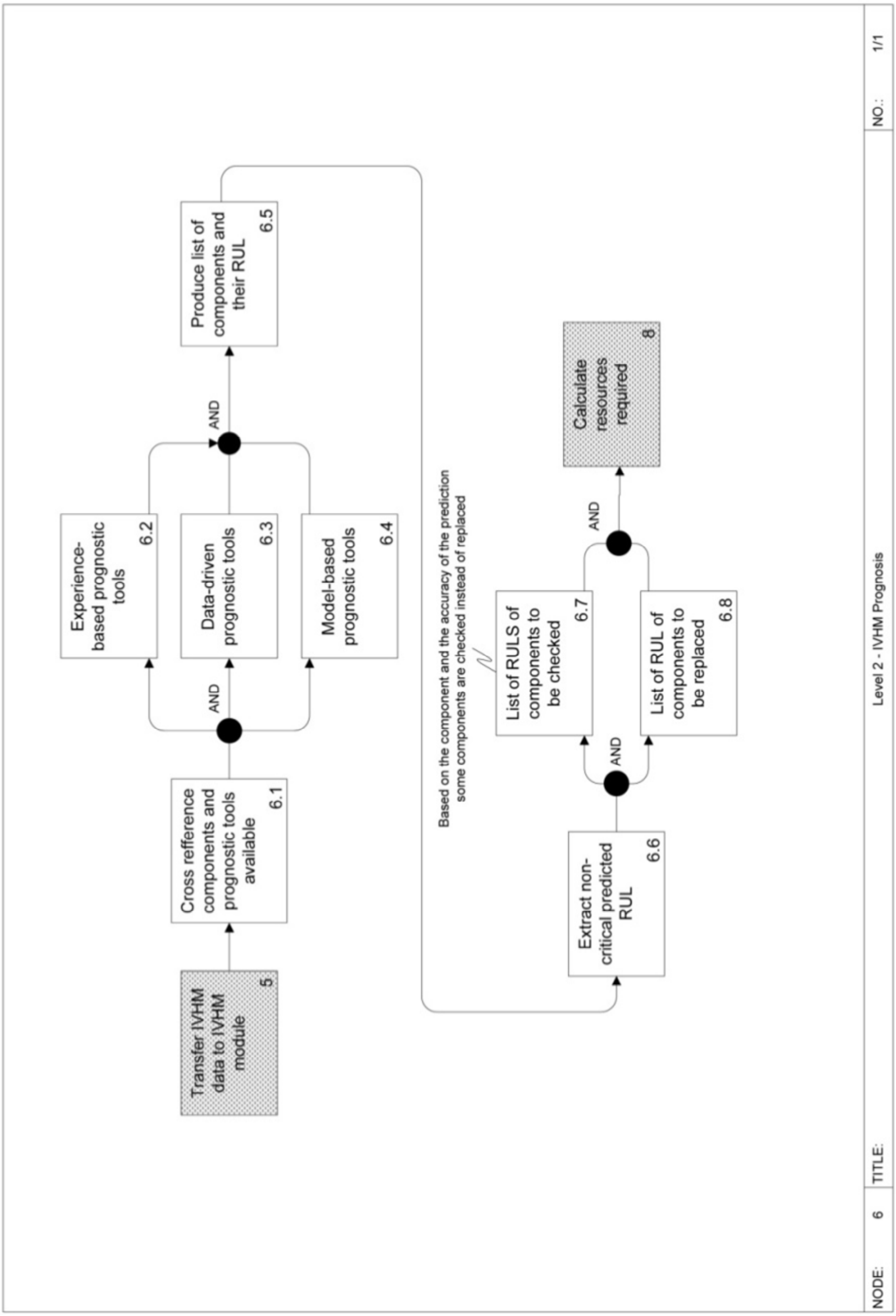
Appendix B Subfunctions of the computer model of maintenance operations

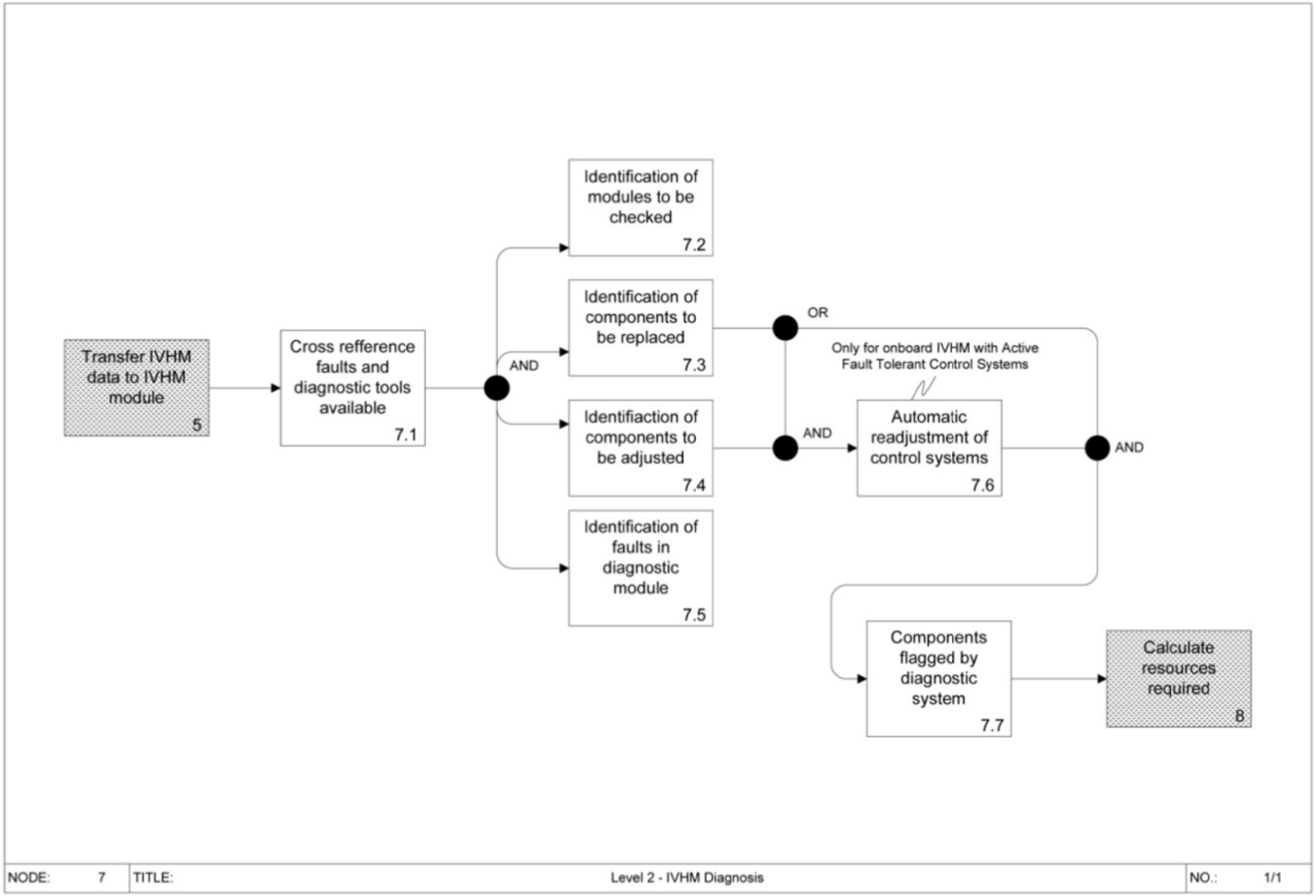


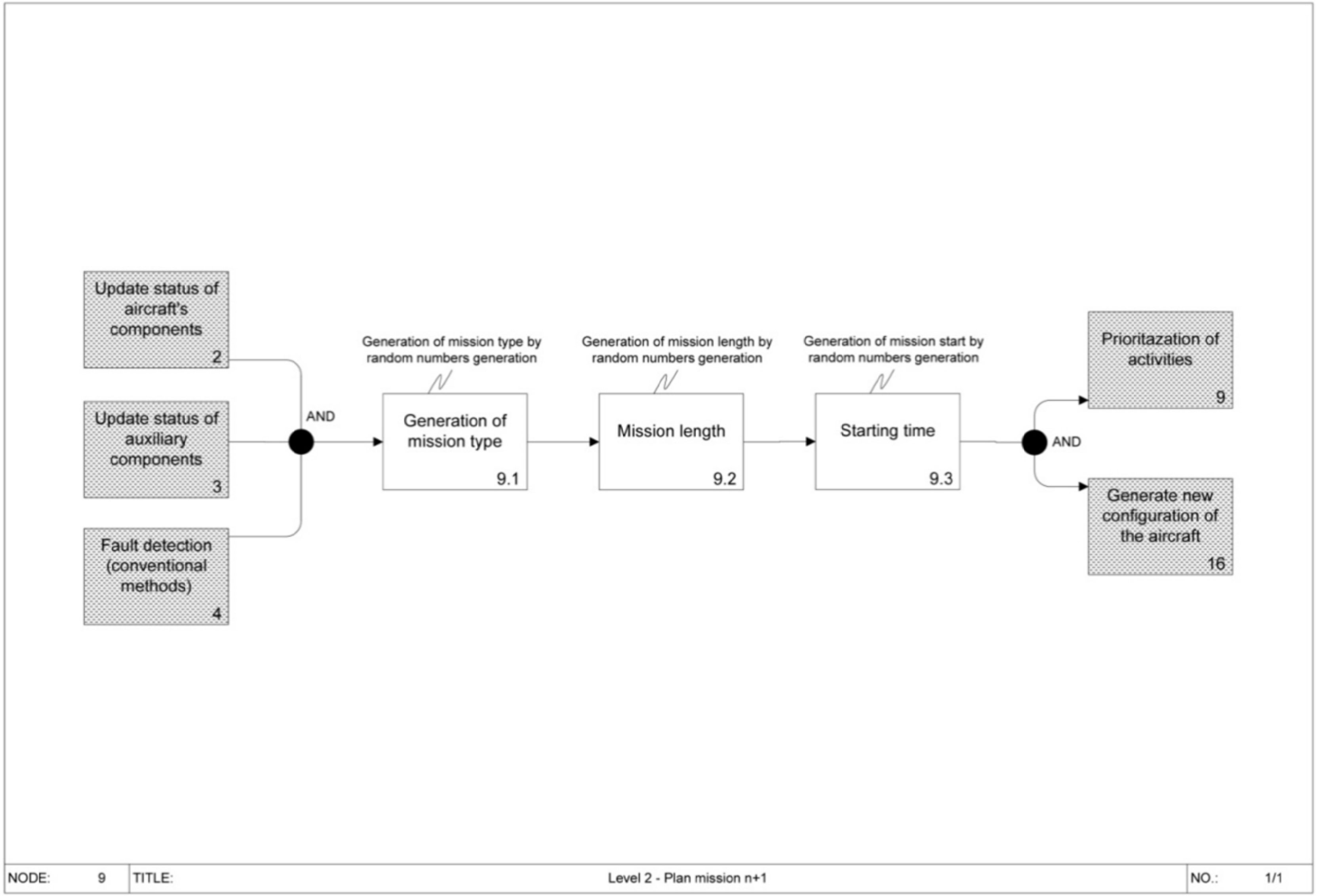


NODE:	4	TITLE:	Level 2 - Fault detection (conventional methods)	NO.:	1/1

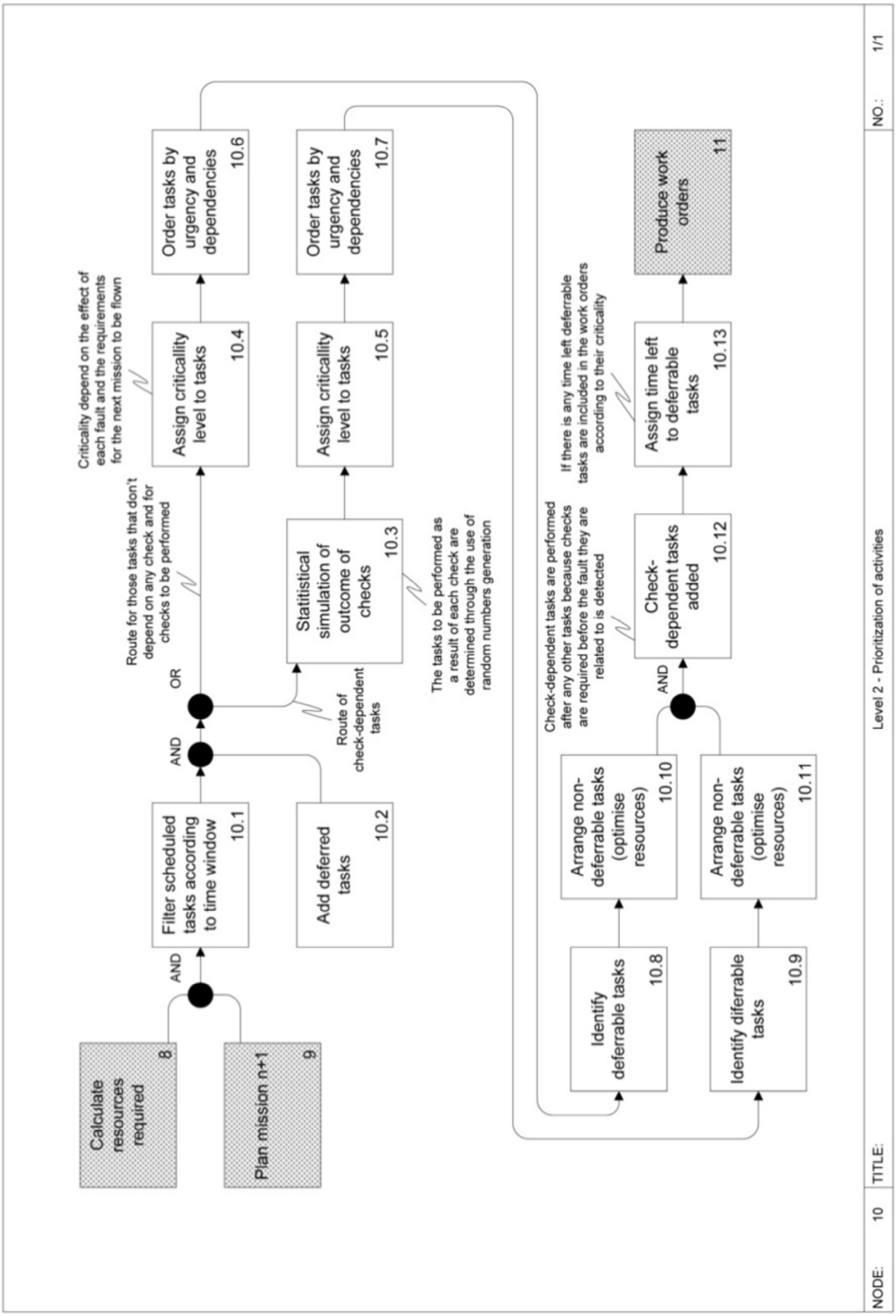

Update status of aircraft's components 2
Update status of auxiliary components 3
AND
Simulation of data corruption 5.1
On-board data corruption checker 5.2
Data Storage 5.3
AND
Airborne wireless data transfer 5.4
Ground data transfer 5.5
AND
Simulation of data corruption by transmission 5.6
Off-board data corruption checker 5.7
Delete useless data 5.8
AND
IVHM Prognosis 6
IVHM Diagnosis 7
NODE: 5
TITLE: Level 2 - Transfer data to IVHM module
NO.: 1/1

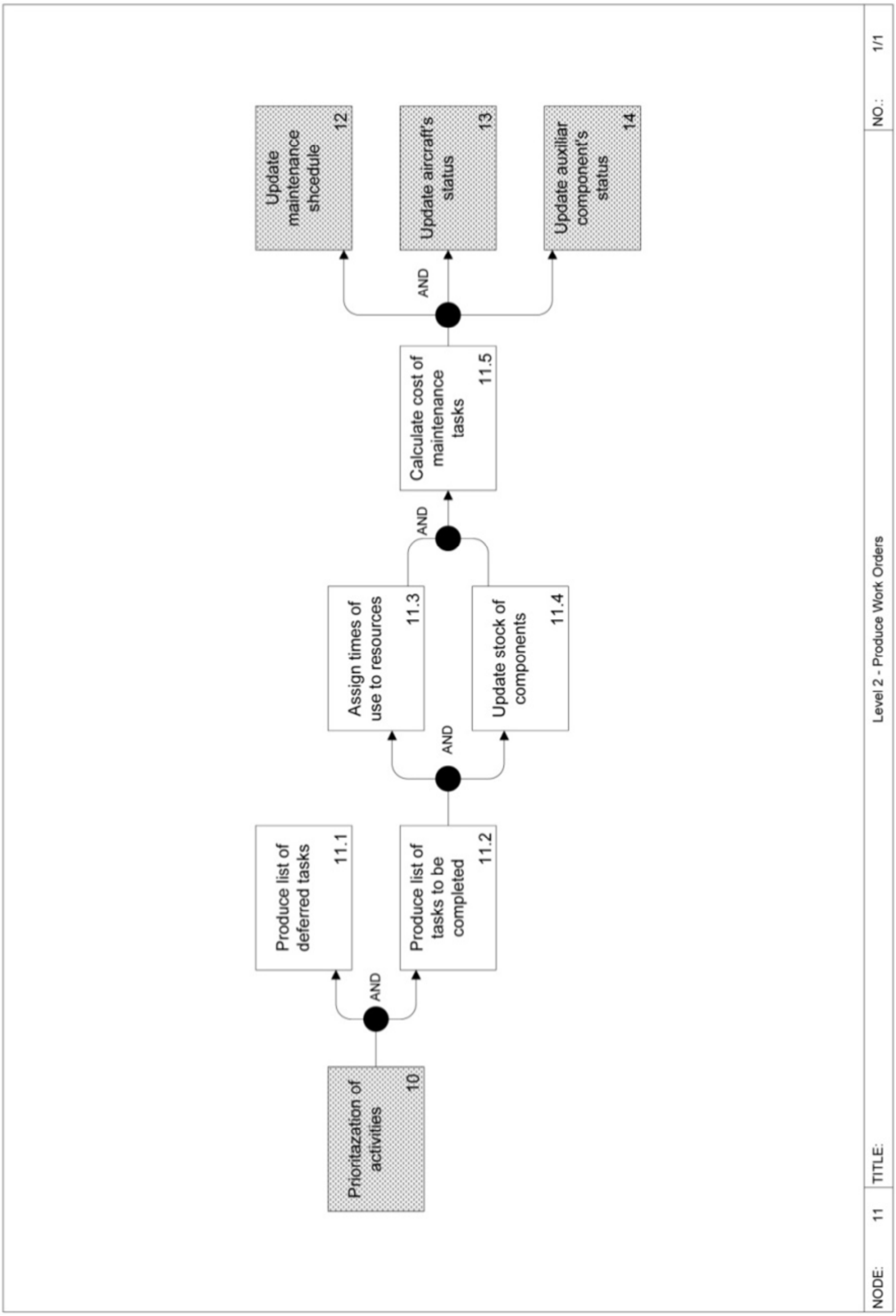

Transfer IVHM data to IVHM module
5
Cross refference components and prognostic tools available
6.1
AND
Experience-based prognostic tools
6.2
Data-driven prognostic tools
6.3
Model-based prognostic tools
6.4
AND
Produce list of components and their RUL
6.5
Extract non-critical predicted RUL
6.6
AND
List of RULS of components to be checked
6.7
List of RUL of components to be replaced
6.8
Based on the component and the accuracy of the prediction some components are checked instead of replaced
AND
Calculate resources required
8
NODE: 6
TITLE: Level 2 - IVHM Prognosis
NO.: 1/1

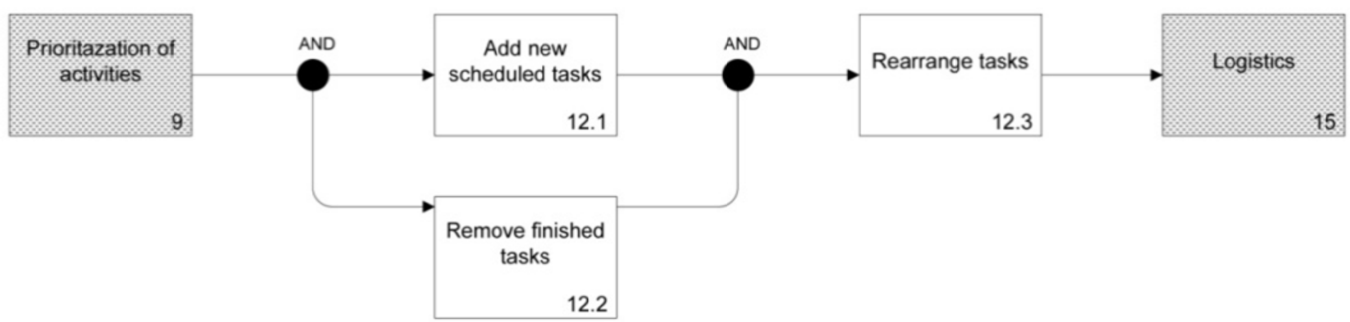

Transfer IVHM data to IVHM module
5
Cross refference faults and diagnostic tools available
7.1
AND
Identification of modules to be checked
7.2
Identification of components to be replaced
7.3
Identifiaction of components to be adjusted
7.4
Identification of faults in diagnostic module
7.5
OR
AND
Only for onboard IVHM with Active Fault Tolerant Control Systems
Automatic readjustment of control systems
7.6
AND
Components flagged by diagnostic system
7.7
Calculate resources required
8
NODE: 7
TITLE: Level 2 - IVHM Diagnosis
NO.: 1/1



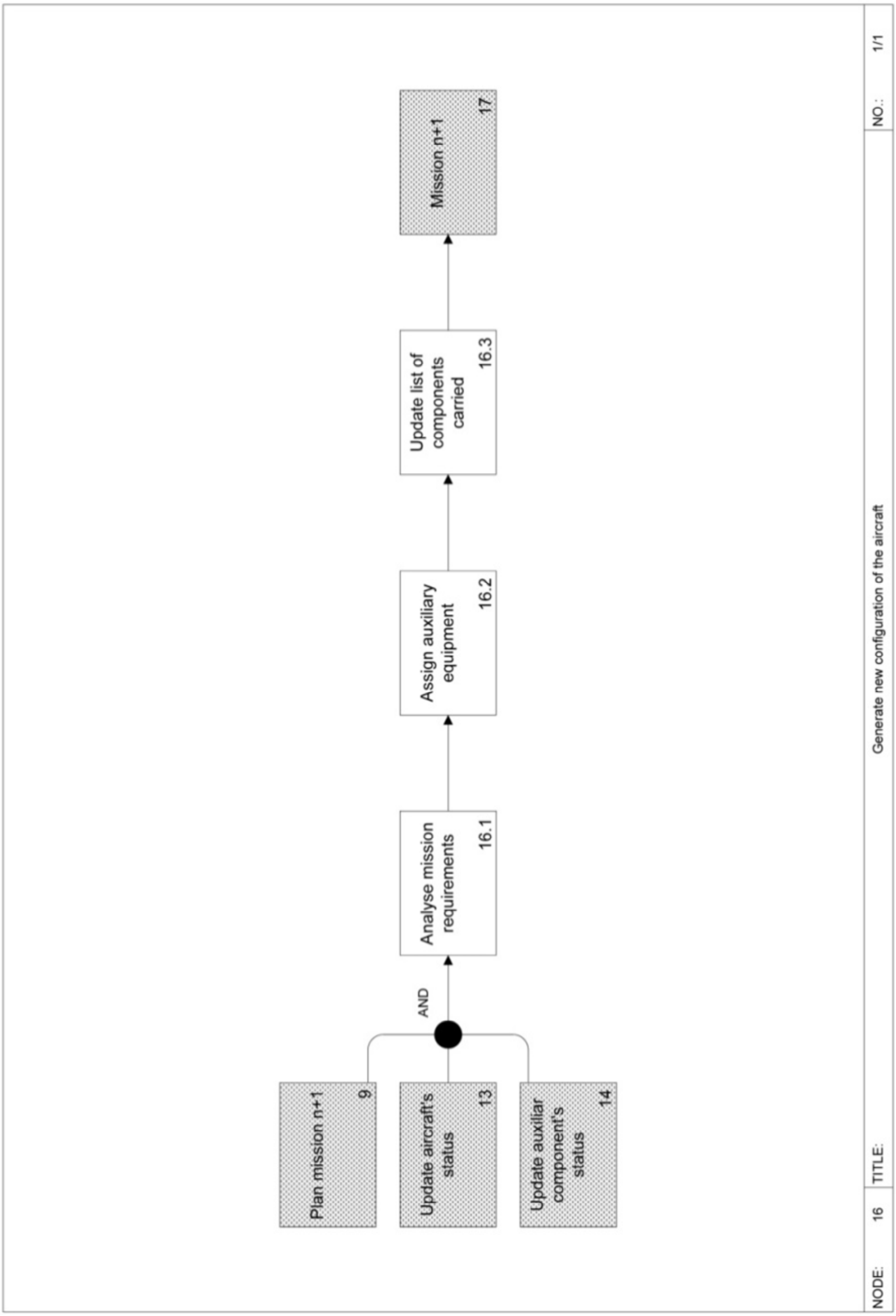
Update status of aircraft's components
2
Update status of auxiliary components
3
Fault detection (conventional methods)
4
AND
Generation of mission type by random numbers generation
Generation of mission type
9.1
Generation of mission length by random numbers generation
Mission length
9.2
Generation of mission start by random numbers generation
Starting time
9.3
AND
Prioritazation of activities
9
Generate new configuration of the aircraft
16
NODE: 9
TITLE: Level 2 - Plan mission n+1
NO.: 1/1


Calculate resources required
8
Plan mission n+1
9
AND
Filter scheduled tasks according to time window
10.1
Add deferred tasks
10.2
AND
OR
Route of check-dependent tasks
Route for those tasks that don't depend on any check and for checks to be performed
Statitistical simulation of outcome of checks
10.3
The tasks to be performed as a result of each check are determined through the use of random numbers generation
Criticality depend on the effect of each fault and the requirements for the next mission to be flown
Assign criticallity level to tasks
10.4
Assign criticallity level to tasks
10.5
Order tasks by urgency and dependencies
10.6
Order tasks by urgency and dependencies
10.7
Identify deferrable tasks
10.8
Identify diferrable tasks
10.9
Arrange non-deferrable tasks (optimise resources)
10.10
Arrange non-deferrable tasks (optimise resources)
10.11
AND
Check-dependent tasks are performed after any other tasks because checks are required before the fault they are related to is detected
Check-dependent tasks added
10.12
If there is any time left deferrable tasks are included in the work orders according to their criticality
Assign time left to deferrable tasks
10.13
Produce work orders
11
NODE: 10
TITLE: Level 2 - Prioritization of activities
NO.: 1/1


Prioritazation of activities 10
AND
Produce list of deferred tasks 11.1
Produce list of tasks to be completed 11.2
AND
Assign times of use to resources 11.3
Update stock of components 11.4
AND
Calculate cost of maintenance tasks 11.5
AND
Update maintenance shcedule 12
Update aircraft's status 13
Update auxiliar component's status 14
NODE: 11
TITLE: Level 2 - Produce Work Orders
NO.: 1/1



NODE:	12	TITLE:	Level 2 - Update maintenance shedule	NO.:	1/1


Plan mission n+1
9
Update aircraft's status
13
Update auxiliar component's status
14
AND
Analyse mission requirements
16.1
Assign auxiliary equipment
16.2
Update list of components carried
16.3
Mission n+1
17
NODE:
16
TITLE:
Generate new configuration of the aircraft
NO.:
1/1

Appendix C Publications

LIST OF PUBLICATIONS

Journal Papers

Esperon-Miguez, M., John, P., Jennions, I.K., 2012, A review of Integrated Vehicle Health Management tools for legacy platforms: challenges and opportunities, January 2013, Progress in Aerospace Sciences, Vol.56, Pages 19–34

Conference Papers

Esperon-Miguez, M., John, P., Jennions, I. K., 2012, Uncertainty of Performance Metrics for IVHM Tools According to Business Targets. PHM Conference Europe, July 2012, Dresden.

Esperon-Miguez, M., John, P., Jennions, I. K., 2012, The Effect of Current Military Maintenance Practices and Regulations on the Implementation of IVHM Technology. IFAC Workshop A-MEST, 2012, Seville

Esperon-Miguez, M., John, P., Jennions, I. K., 2012, Downtime uncertainty reduction through correct implementation of health monitoring tools. IET Asset Management Conference, November 2012, London

Esperon-Miguez, M., John, P., Jennions, I. K., 2013, Implementing IVHM on Legacy Aircraft: Progress towards identifying an Optimal Combination of Technologies. 8th World Congress on Engineering Asset Management, October 2013, Hong Kong

Journal Papers Under Review

Esperon-Miguez, M., John, P., Jennions, I.K., 2013, Selection of Health Monitoring Tools Based on Sensitivity Analysis of Maintenance Parameters. Submitted to the Aerospace Science and Technology Journal on March 2013.

Esperon-Miguez, M., John, P., Jennions, I.K., 2013, Configuring IVHM Toolsets for legacy platforms according to economic risk analysis at the preliminary design stage. Submitted to the Journal of Mechanical Design (ASME) on May 2013

Progress in Aerospace Sciences 56 (2013) 19–34

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Progress in Aerospace Sciences

journal homepage: www.elsevier.com/locate/paerosci

A review of Integrated Vehicle Health Management tools for legacy platforms: Challenges and opportunities

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Legacy
Availability contracts

ABSTRACT

Integrated Vehicle Health Management (IVHM) comprises a set of tools, technologies and techniques for automated detection, diagnosis and prognosis of faults in order to support platforms more efficiently. Specific challenges are faced when IVHM tools are to be retrofitted into legacy vehicles since major modifications are much more challenging than with platforms whose design can still be modified. The topics covered in this Review Paper include the state of the art of IVHM tools and how their characteristics match the requirements of legacy aircraft, a summary of problems faced in the past trying to retrofit IVHM tools both from a technical and organisational perspective and the current level of implementation of IVHM in industry. Although the technology has not reached the level necessary to implement IVHM to its full potential on every kind of component, significant progress has been achieved on rotating equipment, structures or electronics. Attempts to retrofit some of these tools in the past faced both technical difficulties and opposition by some stakeholders, the later being responsible for the failure of technically sound projects in more than one occasion. Nevertheless, despite these difficulties, products and services based on IVHM technology have started to be offered by the manufacturers and, what is more important, demanded by the operators, providing guidance on what the industry would demand from IVHM on legacy aircraft.

Contents

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1. Introduction

In order to reduce costs and increase the availability of aircraft, diagnostic and prognostic tools can be used to generate valuable information to inform decisions regarding maintenance and logistics. Advances in automated decision making can also be applied to reduce the need for human intervention and increase the benefits of using these technologies. This set of tools broadly envelops Integrated Vehicle Health Management (IVHM) technology.

The introduction of this technology can produce additional benefits besides those for which they were originally intended for. It has been proposed to use IVHM not only for the operation of the vehicle, but also for manufacturing, testing and certification phases [1]. Another way of using health monitoring tools is adapting the aircraft's controls according to its health status to raise safety margins and improve mission effectiveness [2]. Benedettini et al. [3] even suggest that IVHM can be helpful for continuous improvement by using it as a quality management tool for new and legacy platforms.

Regarding the technical difficulties that are faced when a new IVHM system is installed on a pre-existing vehicle, they can arise for several reasons: they may be caused by the limitations imposed by the vehicle, or by issues that are intrinsic to the system itself, or by problems that arise when the new tool interacts with the aircraft's systems. As important as the technical challenges, organisational ones can also undermine the success of the project from the development phase up to the implementation of the new tool, and these issues can be either structural or cultural, the later being much more difficult to address.

An analysis of the state of the art of the IVHM toolset has been carried out to understand the potential of different monitoring technologies and how they can be applied on legacy platforms. Several technical challenges hinder the implementation of these tools on this type of aircraft. Diagnostic tools such as Built in Tests (BIT) have been used in the aerospace industry since the 1980s, but prognostic tools and diagnostic tools for more complex systems require in depth knowledge of the behaviour of the components and their degradation modes. To increment the number of components monitored on an aircraft it is necessary to understand the limitations of the technology and how the characteristics of the aircraft affect their performance.

As with many others new technologies, organisations play a major role in how successfully they are implemented. Putting IVHM into practice means shifting from support systems based on input parameters such as components, personnel or tools to a new paradigm in which performance is focused on output parameters such as availability. This introduces additional challenges regarding developing the technology and putting it into action. Retrofitting health monitoring tools on an aircraft presents additional challenges because of the constraints it imposes. On the other hand, legacy platforms provide more information to understand how components fail and validate monitoring tools. All these problems are often mentioned in the literature.

The effort put on this technology has started to produce benefits and many Original Equipment Manufacturers (OEM) have started to shift from their traditional role as product suppliers to a more service oriented business model. From logistics and maintenance outsourcing to fully availability oriented contracts, the main services based on technology related to IVHM have been identified to determine the growth potential as described in Section 4.

2. Review of IVHM toolsets

In order for an IVHM system to reach its full potential it must comprise tools that enable the whole process of managing the maintenance of a fleet using the available information in an optimum way. To achieve this goal it is necessary to acquire data that can then be used by a set of diagnostic and prognostic tools which transform them into valuable information to manage the maintenance of the vehicles and, in some cases, reconfigure certain systems to keep the vehicle safe after a failure.

Diagnostic and prognostic tools are usually classified according to how the data available are analysed and conclusions reached. Vachtsevanos et al. [4] have proposed a classification of health monitoring tools (now widespread in literature) by which they are divided into two main groups:

- Data-driven methods
- Model-based methods

Additionally, using the information generated by health monitoring tools dynamic control systems allow the vehicle to adapt automatically to a fault to ensure the safety of the crew, passengers and cargo. These systems rely on the accuracy of the conclusions reached by the health monitoring system for a correct reconfiguration and therefore, can only be implemented once the diagnostic and prognostic tools have been thoroughly tested. These control systems can help to increase the number of missions completed successfully and increase safety.

To enable the benefit of using diagnostic and prognostic tools, maintenance management and logistics must evolve to use the new information provided by these systems. The prediction of future faults makes it possible to foresee the optimal use of components, tools and personnel.

2.1. *Diagnostic and prognostic tools*

2.1.1. *Data-driven methods*

Data-driven methods consist of techniques to find out hidden patterns in data which can then be used either to determine which component or module is causing a system to fail (diagnostic data-driven methods), or to estimate the Remaining Useful Life (RUL) of a component (prognostic data-driven methods). Medjaher et al. [5] and Muller et al. [6] believe that these techniques lack precision, especially compared with mathematical models based on the physical properties of the system. However, most diagnostic and prognostic tools found in the literature focus on data-driven methods, probably because of their capability to be applied to complex systems for which physical models would be nearly impossible to develop.

Sometimes experience-based methods are included as a subgroup of data-based methods. Experience-based tools comprise the more "traditional" statistical methods used for the development of preventive maintenance procedures and estimate the RUL of a component. Obviously, this presumes the existence of historical maintenance data with statistically significant failures, and that they can be correlated to time or other measurable parameter. By adjusting a statistical distribution to the recorded information available it is possible to obtain a function to relate its RUL to a monitoring parameter. The failure distribution of most components can be approximated to at least one commonly used probability distribution, such as Weibull, Poisson, exponential, and normal

Acronyms

ADVISE	Analysis & Design for Vertical Integration and Systems Engineering
AFTCS	Active Fault Tolerant Control Systems
AL	Autonomic Logistics
ALIS	Automatic Logistics Information System
ANN	Artificial Neural Networks
APU	Auxiliary Power Units
BIT	Built in Tests
BN	Bayesian Networks
CAS	Crew Alerting System
CBS	Case-Based Reasoning
CCS	Common Core System
CI	Condition Indicators
CLOE	Common Logistic Operating Environment
CMMS	Computerised Maintenance Management Systems
COTS	Commercial off The Shelf
DBN	Dynamic Bayesian Networks
DLO	Defence Logistic Organisation
EA	Evolutionary Algorithms
EHUMS	Enhanced Heath and Usage Monitoring System
ETA	Event Tree Analysis
ETA	Event Tree Analysis
EUCAMS	Engine Usage, Condition Monitoring and Management Systems
FDD	Fault Detection and Diagnosis
FIPS	Federal Information Processing Standard
FMECA	Failure Mode Effects and Criticality Analysis
FTA	Fault Tree Analysis
FTCS	Fault Tolerant Control Systems
FUMS	Fleet Usage Management Software
GBR	Ground Base Reasoner
GME	Generic Modelling Environment
GS	Global Sustainment
HAZOP	HAZard and OPerability study
HIC	Health Index Code
HMM	Hidden Markov Models
HUMS	Health and Usage Monitoring Systems
IDVTB	Integrated Diagnostics Virtual Test Bench
IOS	Integrated Operational Support
JSF	Joint Strike Fighter
KDD	Knowledge Discovery from Data
KF	Kalman Filters
LFT	Linear Fraction Transformation
MAOS	Maintenance Approved Organisation Scheme
MIMOSA	Machinery Information Management Open Systems Alliance
MoD	Ministry of Defence
NEL	Network Enabled Logistics
OEM	Original Equipment Manufacturer
OFCDS	Online Flight Control Diagnostic System
OMS	Orbital Manoeuvring Subsystem
OSA CBM	Open System Architecture for Condition Based Maintenance
PBL	Performance Based Logistics
PFTCS	Passive Fault Tolerant Control Systems
PGG	Power Generation Group
PHARM	Predictive Health And Reliability Management
PICAM	Probabilistic IVHM Cost–benefit Analysis Model
PLOC	Probability of Loss of Control
RMS	Root Mean Square
RUL	Remaining Useful Life
SHM	Structural Health Monitoring
SHOAM	System Health Operational Analysis Model
SPHM	Structural Prognostic Health Management
SPN	Stochastic Petri Nets
TFPG	Time Failure Propagation Graph
UCAV	USAF/DARPA Uninhabited Combat Air Vehicle
UFCM	Uncommanded Flying Control Movements
UI	Usage Indices

distributions. Weibull distribution has been applied successfully for decades to mechanical components since it is specially suited for elements that get worn, besides, it can be adjusted for those parts that present infant mortality and follow a bathtub curve.

According to Atlas et al. [7], since the health curve of a component is created using statistical data, the model to which every component is compared is just an average and is a function of time or the number of cycles. Due to the variability during the manufacturing process (across and within manufacturers), age disparity across the fleet, differences in parts replaced on each aircraft and repairs carried out, the behaviour of each aircraft under certain conditions may vary, making components degrade at a different pace across the fleet.

Experience based prognosis has been widely used by industry for decades, especially by those manufacturers which produce components in high volume and have an immense data-base containing the time-to-failure of their parts. This limits its application to components that have been operated for a long period or, at least, have been thoroughly tested.

For many mechanical and electrical components it is possible to determine a probability density function to relate their failures to the time they have been operated. However, once they are installed on a vehicle it becomes very difficult to record the exact duration of the periods they have been working, and the failure distribution might not be related to the hours of use of the aircraft. Other types of components are not so easy to study using these methods, especially if their faults are more likely to be caused by environmental effects than by prolonged periods of operation, such as the failure of electronic components due to cosmic radiation mentioned by Dyer et al. [8].

Data mining techniques have been used for many years for different applications that require finding out hidden patterns in large datasets which could not be obtained using traditional statistical methods. Fayyad et al. [9] and Skormin et al. [10] refer to these methods as Knowledge Discovery from Data (KDD) technology and divide the process into [9]: the domain in which the problem is framed and identifying the goal of the analysis; selecting the dataset to be analysed; cleaning and pre-processing the data; reducing and transforming the data; selecting the appropriate data mining method; perform the data mining; checking the results; and finally applying the newly acquired knowledge for the purpose it was intended for.

The engineer is responsible for describing the problem to solve and, subsequently, choosing which data must be collected. Both decisions depend on the knowledge and experience about the system to be analysed and are considerably subjective, which can limit the effectiveness of these methods. Nevertheless, it is necessary to find the right balance between analysing excessive data, which increases cost and time, and reducing it to a point at which it is too limited to extract any valuable information.

Once the data to be used for data mining has been selected, it has to be pre-processed to transform it into the appropriate format from which patterns will be extracted. Imperfections in the dataset have to be addressed before any further steps are taken. Noise, gaps and data corruption are the most common problems encountered. Several techniques have been developed to tackle these problems [11–13], as well as reducing the dimensions to facilitate processing large amounts of information [14,15]. However, in some cases, the transformation of data is not carried out to reduce the calculation cost, but because the data are stored using variables that do not represent the information in a useful manner. For example, this is the case of structural analysis in which modal analysis requires data to be studied in the frequency domain. After all the pre-processes have been finished the developer must have a set of training data to be used by the data mining algorithm and a test set to check the results [9,10].

KDD processes have been used to verify the user's hypotheses or to let the system discover patterns autonomously. The use of data mining to develop IVHM tools tends to focus on the latter, which may try to predict the evolution of the system or to describe how it behaves in normal circumstances. Both diagnostic and prognostic tools can be developed using data mining, but the goal of the analysis influences which method is to be chosen. Fayyad et al. [9] propose dividing data mining methods into six groups:

- Classification: once the engineer has defined a set of classes, the dataset is partitioned according to the patterns found.
- Regression: a function is obtained by analysing the correlation between the variables of the dataset.
- Clustering: different categories or clusters are identified within the data set. Clusters can be mutually exclusive, overlapping or use hierarchical categories. Unlike classification methods, clusters do not use previous knowledge to define the groups data are sorted in.
- Summarization: data are divided into groups which are analysed to find a simple description of the information contained in them in ways such as statistical properties, relationship between variables, etc.
- Dependency modelling or association rule learning: relationships between different subcategories are found and association rules are obtained from the use of these methods. These methods are limited to large databases to obtain statistically sound associations [16].
- Change and deviation detection: changes in data gathered in different moments are detected using these techniques.

Finally, the findings from data mining must be validated using the test set of data previously defined. The developer focuses on the accuracy of the results obtained from running the model on the test set as well as on the consistency of its performance when different test sets are used. The model must also provide relevant information, since the patterns detected by data mining might not be useful for health monitoring.

Artificial Intelligence (AI) techniques have been used for the development of both diagnostic and prognostic techniques in aerospace industry and have been successful in several applications thanks to their learning capability. Artificial Neural Networks (ANN), Bayesian Networks (BN), Evolutionary Algorithms (EA) and Stochastic Petri Nets (SPN) are some of the most common techniques used [5]. One of the main limitations of these methods is the need of large datasets to train the system and these are seldom available [17].

ANN mimic the structure of a biological neural network by interconnecting individual nodes or neurons and allowing them to transfer information to each other. Each neuron has several input signals, each of which is multiplied by its synaptic weight before they are all summated and fed to the activation function. Since the activation functions can be non-linear (e.g., tangent hyperbolic) ANN are well suited for non-linear applications [18]. Multilayer feed-forward ANN (which are the most commonly used in IVHM) organise neurons in layers in which neurons belonging to a layer only receive information from neurons of the previous layer and their output is only fed to the next layer. The network has to undergo a learning process in which the weights of the inputs are adjusted. Supervised learning algorithms use data which have been analysed previously and include known faults, while unsupervised learning is carried using new information. The latter still has to be proven successful in health monitoring. ANN have been tested on identifying simultaneous faults [19] and even detecting faults in the sensors used to obtain the data [20]. Using a gas turbine performance model to generate the required data, Joly et al. [21] proposed a diagnostic tool using ANN for a Rolls Royce engine with which the components were analysed in pairs obtaining mixed performances for different components. Besides diagnoses, ANN have been used successfully to obtain prognoses in Auxiliary Power Units (APU) and hydraulics systems [22]; jet engines [23]; and actuators [24].

BN are probabilistic graphical models in which the variables that are analysed are represented as nodes and their causal relations as arrows connecting them. These variables can be of different nature (numerical, logic, etc.) according to the way the component degrades. Predefined causal relations can be obtained from a Failure Mode Effects and Criticality Analysis (FMECA), a HAZard and OPerability study (HAZOP) or from consulting an expert on the system. However, best results are obtained when the structure and parameters are learnt. Dynamic Bayesian Networks (DBN) are a development of conventional BN in which time evolution of variables is taken into account. DBN are basically conventional BN in which the graphic representation includes two static BN, one at time t and another $t+1$. This requires the definition of dynamic relations linking variables that belong to different time slices and which represent the degradation that takes place in the system. DBN have become very popular for the development of prognostic tools with diverse applications such as chemical processes, ball bearings or manufacturing, to cite a few [5,6,25,26]. Kalman Filters (KF) and Hidden Markov Models (HMM) are the two of the simplest forms of DBN [27] and are widely used in the development of health monitoring tools.

Although AI involves a diverse range of techniques besides ANN and BN, these two approaches seem to dominate the literature. However, there are some examples in which other AI techniques have been proven successful. For example, Dutuit et al. [28] used SPN and Montecarlo simulation to study the reliability of electronic equipment obtaining better results than following a Markovian approach. EA have also been applied successfully, having performed better for the diagnosis of faults in power transformers than ANN, fuzzy systems and even IEC/IEEE standards [29]. However, none of the approaches mentioned has been proved to be the best as a generic tool for the development of diagnostic or prognostic tools.

Finding 1: Data-driven methods have numerous examples of successful applications when there is little understanding of the failure modes and degradation mechanisms involved. However, no specific data-driven method has been proven to perform better than the others for all possible applications, which means that a case by case analysis is still required.

2.1.2. Model-based methods

Model-based methods, also known as physics-based methods, have been the traditional choice to develop health monitoring tools when rich data gathered by sensors was available and there was a good understanding of the behaviour of the system under healthy and faulty conditions. Diagnostic and prognostic systems based on using models can be produced using two different approaches: failure propagation models, which focus on how each failure affects the system and propagates producing symptoms and affecting each component or function; and performance models, which use mathematical functions to reproduce the behaviour of the component under both normal and failed operation. The latter are much more precise, but also much more expensive to develop (more man-hours and experimental equipment). Although Medjaher et al. [5] claim that one of the disadvantages of model-based health monitoring is its case by case approach, Ofsthun and Wilmering [30] showed how blocks developed to model components and subsystems can be reused to build up models of larger systems.

Time Failure Propagation Graphs (TFPG) are used to diagnose failures based on which components or functions have been working out of range (or failing), in which order and at what time. Analysing this information it is possible to generate a set of possible explanations and, in some cases, even predict which components or functions will experience problems in the near future and in which time interval [31]. The fault propagation model is based on a simplified model of the system dynamics in which nodes represent failure modes. Some of these nodes can be grouped attending to which function or component they belong (e.g., pump or electric generation). Failure modes are linked according to how they can propagate. Each link is defined by its probability of occurring and a time interval in which the predecessor failure mode can affect its successor. Monitors represent sensors or alarms which are present in the real system and help to distinguish between the real state of the system and what the health monitoring system can actually detect. Some failure modes are connected to the failed state of a specific component, making it possible to determine the source of the problem [31,32]. When one or more monitors detect that some failure modes are active a diagnosis process is followed to determine to more plausible explanation. First, a set of hypotheses are generated; then, they are evaluated according to which alarms have been triggered and the plausibility, robustness and frequency of each hypothesis; after comparing the results a diagnosis is obtained, although it can consist of a probability ranking of the hypotheses rather than simply pinpointing a single explanation [32]. Examples of the algorithms used for hypothesis generation, hypothesis evaluation and diagnostic reasoning can found in [33–35]. TFPGs are easy to develop as long as the interrelations among functions in the system and how faults affect them are well understood, that is why this method is specially suited for systems in which mass and/or energy are being exchanged, such as power generation [31] or aircraft fuel systems [32].

Performance models generate a set of residuals or fault indicators which represent the difference between the signals from the sensors and the expected values obtained from the model. Under normal operation the residuals are nearly zero, but once the components starts degrading or a fault appears their value changes, providing information to the health monitoring system. Therefore, the reliability of the diagnoses and prognoses generated with these methods are very sensitive to the accuracy of the model.

To develop the model some authors have suggested the use bond graphs modelling techniques since they have already been proven successful in several engineering disciplines [36–40]. A bond graph of a system is a graphic model in which dynamic properties are represented using basic elements which exchange energy in different forms and, since the models are energy-oriented, it is possible to use them to analyse the dynamics across different energy domains (i.e., mechanical, electrical, hydraulic, thermal, etc). The graphic representation can be used to obtain a set of state equations which describe the model and, once solved, permit obtaining the time response. Furthermore, Beez et al. [36] have developed a program capable of generating the diagrams automatically using object-oriented computer aided engineering tools, although their work focuses on process plants. An example of this kind of models would be the work done by Wong and Rad [37] to simulate electrical systems or by Mosterman [38] to take into account discontinuities in physical systems. To consider the uncertainties of some parameters in the model it has been proposed to use bond graph elements [39]. To study the accuracy of a model developed using bond graphs Djeziri et al. [40] tested and validated the option of characterizing the uncertainties using Linear Fraction Transformation (LFT).

In many aerospace applications data-based methods have not been able to produce diagnoses that are accurate enough to be useful for maintenance teams, therefore it has been proposed to combine them with model-based models. This has lead to the use of expert systems in which the knowledge base of the system is combined with an inference engine which analyses data gathered by sensors. The knowledge base is often programmed as a set of rules that define the possible states of the system under both healthy and faulty conditions [41]. To define this set of rules systematic methods to study the effect and causes of faults like Fault Tree Analysis (FTA) or Event Tree Analysis (ETA) are common practice. Expert systems have been used for diagnostic systems such as structural damage [42], power electronics [43], fuel systems [41] or embedded electronics [44].

Finding 2: Model-based methods require a good knowledge of the degradation and failure mechanisms that affect the component being monitored and, since many models are often generated during the development phase of components, the implementation of monitoring techniques based on this approach can be much easier to develop than other methods. However, in the case of components installed on legacy aircraft, these methods can be too expensive to implement if there is not comprehensive documentation to base the models on.

2.2. Dynamic control systems

The evolution of Fault Detection and Diagnosis (FDD) tools has made it possible to develop control systems capable of dealing with the abnormal behaviour of a system. Fault Tolerant Control Systems (FTCS) can be passive (PFTCS), which are designed to remain effective after a fault appears without any modification; and active (AFTCS), if their internal logic is reconfigured according to the state of certain components [45].

Since PFTCS (also known as robust systems) are not informed of the existence of a fault, they need to be designed to work under some faulty conditions. Robust systems have been used successfully in many engineering applications over the decades, and they perform very efficiently when dealing with a small number of faults; although their performance drops significantly as the number of scenarios increases. Unlike AFTCS, PFTCS do not benefit from the use of continuous health monitoring and, therefore, are not affected by the implementation of IVHM technology. AFTCS can use techniques to react to the detection of an unexpected fault (fault accommodation techniques) [46], use dynamic models of the system (model predictive control techniques) [47], or monitor the state of a system and readjust the controller continuously (adaptive control techniques) [48]. The latter can be developed for systems with no diagnostic capability, but only perform well as long as the variations of the parameters of the system are small and slow. Similarly, model predictive controls perform poorly when the fault of the system too severe [42].

Model predictive control approaches are capable of dealing with complex and non-linear systems, but they require considerable computing power [47].

Most AFTCS are developed under the assumption that an ideal FDD tool is available while most FDD systems are designed without taking into account the close-loop effect of its interaction with a dynamic control system. Although some papers have been published regarding the integration of both systems [49–51], the effect of the uncertainty of diagnosis is an issue that is widely disregarded. Additionally, neither the detection of a fault nor the reconfiguration of the control system is immediate, an important factor in time-critical control systems. To improve the overall performance the reconfiguration is carried out by a combination of adaptive, switching or following mechanisms with optimization or matching techniques. Although changes in AFTCS can be limited to their parameters (reconfigurable control systems) it is also possible to change aspects of their structure such as the order, type and number of controllers they use (restructurable control systems) [46]. The first approach, although simpler to apply, reduces the capability of the control system to deal with severe faults.

In many applications, as long as a fault produces small variations of those parameters of the systems relevant for its control, it is possible to apply linear systems control theory for the design of the AFTCS. Sometimes, in order to provide a solution to deal with a fault, even if it is not optimal, linearity is considered an acceptable simplification if no better alternative is found. To deal with non-linear systems the use of artificial intelligence tools to adjust the control parameters has been considered for several years, including neural networks, fuzzy logic, Bayesian probability, machine learning and many others [52]. Since software redundancy has become critical by the introduction of fly-by-wire, AFTCS must be designed to deal with information that might become contradictive. For complex applications the use of expert systems has been proposed [53].

Dynamic control systems have been tested successfully on several experimental platforms such as NASA's F-15S TOL/MTD (a modified version of the fighter jet with additional control surfaces) as well as Boeing UAVs X-36 X-40A, X-45, and T-33 [54,55]. Tailless airplane control was tested successfully on a VISTA F-16, a modified version by General Dynamics, which used an indirect adaptive scheme [56]. These projects have focused on keeping the aircraft under control once the damage of a component affects its dynamic behaviour. A step further has been proposed using the Structural Health Monitoring (SHM) system developed for Eurofighter Typhoon, which has been tested and validated [57,58], by using the flight control system to prevent the pilot from pushing the aircraft beyond its structural limits—these limits would change in case a damage in the structure is detected. Similarly, Stewart Hughes Limited (now part of GE Aviation) has worked on a carefree handling system for helicopters. This system would help the pilot to control operational parameters to avoid exceeding the limits defined the structure, the aerodynamic conditions and control capabilities reducing the pilot's workload. The system used neural network to predict the value of parameters (e.g., torque) and use them to predict future envelope exceedances and produce cues for the pilot [59].

Finding 3: Since dynamic control systems are underpinned by reliable health monitoring tools, they still have limited capabilities, although they have a high potential to reduce the number of flights cut short due to failures that can be dealt with on-board, increasing the effectiveness of the fleet.

2.3. Maintenance and logistics management

The use of diagnostic and prognostic tools generates new information regarding the use of components, aircraft and the whole fleet. This new data, already in digital format, can be used to make better informed decisions regarding maintenance management and, up to a certain point, reduce the need of human intervention to produce maintenance orders. Davies et al. [60] carried out a survey to investigate the effectiveness of using maintenance information systems already available. They concluded that users are very satisfied with the performance of Computerised Maintenance Management Systems (CMMS), but less enthusiastic about information support systems. Although the majority agreed that the downtime was reduced thanks to the use of these tools, they also believed that they still need to be improved.

E-maintenance is a web-based system through which expertise on every step of the maintenance and logistics processes can be shared and many activities automated [61]. These tools help to improve the efficiency of maintenance orders processing, tool logistics, human resources planning, spare parts logistics and inventory management. However, it is necessary to ensure that the information generated on every stage of the process is formatted to be easily shared and understood. Using Case-Based Reasoning (CBS) it is possible to translate the structure of the maintenance process into a decision model [62]. A framework for developing e-maintenance systems with enabled proactive maintenance including prognosis, remote diagnosis and fault-recovery can be found in [63]. Rasoyska et al. [62] tested the use of decision support systems working with incomplete information and Muller et al. [6] demonstrated, by experimenting on an industrial system, the feasibility of implementing a DBN-based prognostic tool on an e-maintenance architecture. Saint-Voirin et al. [64] established a set of modelling principles to develop e-maintenance models using multi-agent systems and Petri nets.

For the development of different tools that can be applied to the maintenance system of the Joint Strike Fighter (JSF) the Integrated Diagnostics Virtual Test Bench (IDVTB) was developed. It uses models and simulations to foresee how upgrades and updates will interact with the platform. However, this still presents some difficulties, especially concerning the compliance with the Model and Simulation Office High-Level Architecture [65].

Logistics have a high potential for improvement since this discipline has been highly automated in manufacturing and transport industries for decades, making it easy to adopt these techniques once the information they require is available. For those parts that are replaced according to a predictive maintenance approach, the use of prognostic tools enables a logistic system focused on supplying components based on the immediate need instead of following a fixed schedule.

Taking into account the worldwide distribution of the aerospace industry Hess et al. [66] propose implementing a Global Sustainment (GS) solution to provide support through a common platform. This requires a long term business case analysis taking into account the uncertainty of the performance of new health monitoring tools combined with the changes in contract conditions as the project evolves, especially if a price improvement policy based on performance is applied.

Since IVHM capability was among the design requirements for JSF from early in its development. The Autonomic Logistics (AL) system has been proposed to automate the logistics environment and, reduce human intervention. The health monitoring system transmits the information wirelessly so the maintenance actions can be decided on the ground and personnel and materiel can be ready by the time the aircraft has landed [65]. The information is exchanged between the stakeholders using the Automatic Logistics Information System (ALIS) which collects and analyses data and is used for decision support and action tracking [67]. Provided the system is proved successful it is planned to retrofit the on-board data capture capability to the F-22, F-18/F and the V-22 [65].

Finding 4: From the information available in the literature, it can be said that IVHM can benefit from the maintenance and logistics technology already developed for other industries with very little modifications required to reach full capability, provided the information from diagnostic and prognostic tools is reliable enough.

3. Challenges of implementing IVHM on legacy platforms

Given the current state of the art of most monitoring techniques, their application on legacy platforms faces some of the same challenges as in newly design aircraft. Although legacy aircraft present the advantage of having historical maintenance data generated after years of service, the cost of making modifications on pre-existing vehicles is too high in most cases. This means that diagnoses and prognoses have to be carried out using information obtained through hardware that was chosen for purposes different from health monitoring. Technical challenges can be divided into those related to the characteristics of the health monitoring tool, those related to the platform, and the problems that arise during implementation. In the literature, organizational problems are considered to have been the cause of the failure of some projects. Most organizational problems are common for new and existing aircraft, but those regarding changes in a predefined support system are exclusive of the latter.

3.1. Technical challenges

A classification of most common technical challenges face when retrofitting IVHM can be seen in Fig. 1.

3.1.1. Limitations of health monitoring tools

Uncertainty. Any diagnostic and prognostic tool has a limited accuracy and, therefore, to determine to what extent the information it provides is useful, it is necessary to find out the uncertainty of the results. This subject is often found in the literature, either related to a specific tool, or as research topic itself [42,68–70]. While the uncertainty of a diagnosis means that it is not possible to pinpoint a single component or module as the cause of a fault, in a prognosis it means that the exact RUL of a part cannot be determined because of the variance of the prediction. Due to the presence of a nearly constant segment in the degradation curve of many parameters, determining the exact position on the curve becomes extremely difficult when factors such as sensors' resolution and precision are taken into account (Fig. 2). The variance of the prediction must be small enough to be able to make an accurate forecast. If the variance is excessively high, only short term predictions will be accurate enough to be useful for maintenance tasks. A possible solution to this problem proposed by Atlas et al. [7] is to contrast the information from the prognostics system to the life usage model of the component, but that requires that a proven model has to be available.

Lopez and Sarigul-Klijn [42] have divided the sources of uncertainty into environmental and operational uncertainties (e.g., weather, loading conditions); scenario abstractions (e.g., subjective decisions, lack of knowledge); system uncertainties (e.g., nonlinearity, boundary conditions, complexity); signal processing uncertainties (e.g., sensors, data fusion, decision making); and model uncertainties (e.g., form, parameters). Walley [70] proposes a classification splits uncertainties into two groups: random uncertainties, which are those that can be described using a probability density function or some deterministic approach; and epistemic uncertainty for those that cannot, mainly because of lack of information or knowledge. Sometimes random uncertainty is also called variability, irreducible uncertainty, stochastic uncertainty or random uncertainty; and to epistemic uncertainty can sometimes be found as subjective uncertainty, state-of-knowledge uncertainty or irreducible uncertainty.

Several techniques have been developed to quantify and describe different types of uncertainties, of which the most important are [30]:

- Probability-based methods
- Possibility-based methods
- Set-theoretical methods
- Evaluation and measures
- Epistemological concepts (verification, validation and usability)

Assumptions. Developing models involves assuming certain simplifications either because they improve their performance, or because it is not possible to obtain information about a parameter that otherwise would help to assess the state of

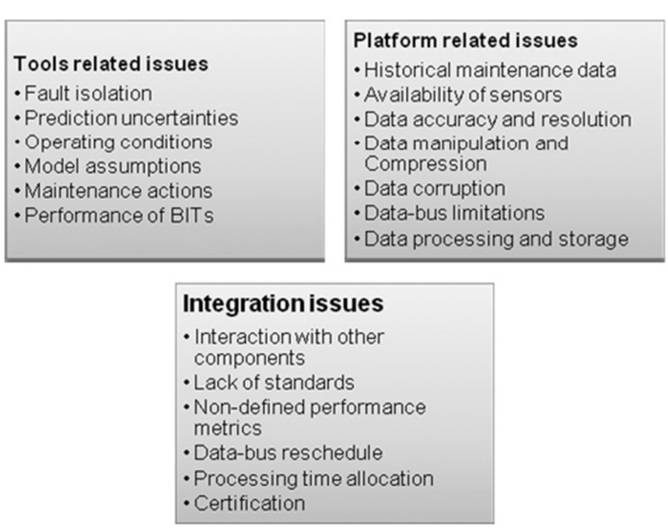

Fig. 1. Classification of most common technical issues regarding retrofitting IVHM.

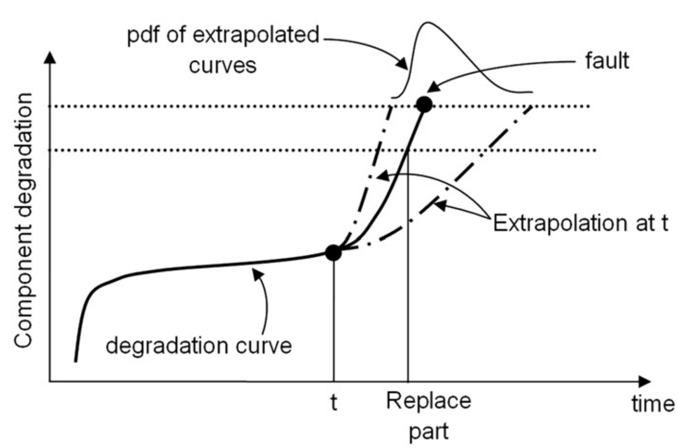

Fig. 2. Prediction variance by extrapolating at time *t*.

the component. This introduces additional uncertainties that are difficult to evaluate and, during the development phase, can only be assessed in a qualitative manner by the engineer since they vary significantly from one application to another. In a good example of this problem Li et al. [71] demonstrated through numerical simulation and testing how a model-based prognostic tool for bearings required to have very precisely adjusted parameters to be able to produce satisfactory results.

Effect of operating conditions. Several diagnostic and prognostic techniques monitor parameters that can be directly affected by variations of the operating conditions of the vehicle such as accelerations, temperatures, current and many more. Stander et al. [72] attempted to transform the variables which are used in diagnostic tools when working on gear faults by averaging the accelerations to the speed of the shaft, this is synchronously averaging the signals with the parameter they are related to and which varies with the operating conditions. McFadden [73], on the other hand, transforms the variables to work on the frequency domain. For prognosis Lee et al. [74] proposed the use of clustering methods and a feature normalization technique. However, it is still necessary to validate any of these methods under real operational conditions and this has not been done for any of the health monitoring systems found in the literature.

Effect of maintenance actions. The fact that a component has been replaced or repaired does not guaranty a return to the starting point for the estimation of its RUL. Carrying out a maintenance action involves a certain amount of risk of introducing a new fault in the system, which is difficult to evaluate, especially since it is difficult to identify some of the faults that can be caused by the inappropriate execution of a maintenance task. Obviously, this kind of faults cannot be predicted and, usually, are not frequent enough to justify the development of a specific diagnostic tool. However, their interaction with other diagnostic and prognostic systems should be addressed. Even more critical is the evaluation of how the deterioration rate changes on repaired components. Monga and Zuo [75] have proposed the use of deterioration factors while Bloch-Mercier [76] believes the best approach is to use Markov models in which the component would evolve from one state to another with every repair.

False alarms. Several years ago suppliers started to install in the systems they BIT or some other form of diagnostic tool. These tools have been very successful reducing the time required to detect faults and identify the source of the problem. However, these systems have faced problems like false alarms, ‘Can Not Duplicate’ and ‘No Fault Found’ that have fed the scepticism regarding the use of automatic health monitoring tools [77]. Although there has been significant improvement in the reliability of these tools, reducing the false alarm rate remains a basically a case-by-case activity [78].

Finding 5: The information used to develop health monitoring tools and that is used by their algorithms plays a key role in the reliability of the diagnoses and prognoses they produce. It is necessary to understand how its limitations affect the accuracy of the results in order to avoid encountering problems too late into their development.

3.1.2. Problems caused by the platform

Data acquisition. Data-based methods rely on the analysis of recorded maintenance data obtained from components run to failure, which in the aerospace industry tends to be problematic to obtain for both technical and organizational reasons. On one hand, parts tend to be replaced when they are believed to show the first signs of an imminent fault, although it is common to remove components whose RUL is longer than the time they have been used [79]. Therefore, the data available only provides information regarding how long parts have been running successfully in what is known as suspended or censored data. Although some prognostic models use it to produce an estimation of the RUL, the resulting algorithm is too conservative. Heng et al. [80] have started to investigate how the omission of censored data produces even worse results and finding the optimum way of using these data has started to be investigated.

On the other hand, given the sensitivity of some of the data required to develop predictive models it can be extremely difficult (if not impossible) to convince the operator to release it. Additionally, this problem worsens when the health of a component has to be inferred through indirect methods that require extracting signals from modules manufactured by subcontractors, who might not want to share information concerning the internal logic of their products.

Condition monitoring data is usually automatically collected requiring minimal or no human intervention while event data normally has to be input manually and tend to be incomplete and more error-prone. Therefore, it is very common to find much more information available regarding the parameters measured in a system than events to correlate all that data against. This problem is even acuter when the monitoring system is already in operation and the Condition Indicators seem to be well adjusted since it becomes more difficult to persuade personnel of the importance of this information. Jardine et al. [17] propose using automated even data collection, but identifying the nature of the event, especially in components with multiple failure modes, can be a complex task that introduces additional uncertainty.

Sensors availability and resolution. The quality of the data used to assess the state of a system depends on the characteristics of the sensors used to measure the different parameters used by the algorithm. In many cases, engineers are forced to measure certain variables indirectly through different parameters measured by other sensors [81]. This is because when a monitoring tool is being developed for an aircraft that is already operative or whose design is in an advanced state, designers have to rely on the sensors already installed. In those situations most sensors have been installed for other purposes (e.g., control). Even if a sensor measures a parameter useful to monitor the system, its characteristics might be different for those required to infer the state of component.

Data manipulation and compression. Given the architecture of monitoring systems, it is relatively common to capture unnecessary or even redundant information. By compressing data and reducing their dimensions data analysis can be carried out more effectively and accurately while computational effort and memory requirements remain within practicable limits. Obviously, truncating and compressing data increases the uncertainty of the results and this must be addressed carefully. On the other hand, it is important to remember that when data classifiers are used, although increasing the dimensions of the data available reduces the error at the beginning, the error can soar if dimensions are increased carelessly: this is known as the “peaking phenomenon” or “curse of dimensionality” [14,15,82,83]. Therefore, developers must find the correct balance by understanding the interrelationships between datasets.

In many cases, time-related data is transformed to extract information such as modal properties (which is frequency-related) in Structural Health Monitoring [42]. However, transferring data to a frequency domain usually requires removing data from the extremes which are affected by error propagation. In other cases, signals are transformed into a simple parameter that indicates the state of the components like Condition Indicators (CI) [57,58].

Data corruption. Due to problems during the capture, transmission or storage of data it is possible that part of the information is either lost or contaminated with values different from those really measured. If this problems are not detected these data can be used by a health monitoring algorithm producing wrong diagnoses or prognoses. Data corruption can be either continuous or sporadic, the latter being the most difficult to detect.

Since many sensors operate at a very low voltage, small changes in their electrical properties or noise can affect the measures significantly. Failure in compensation mechanisms for pressure, temperature and other environmental factors are behind many of the problems related to sensors' accuracy. Fuzzy logic has been proven successful to detect data corruption as shown by Wakefield et al. [11] with an application for off-board post-analysis of the data which was included as a part of a larger tool for structural health analysis.

Data buses limitations. Modern airplanes use several sensors which are connected to different computers through data buses, and they have a limited capacity. Monitoring systems normally require data with very high resolution and, usually, in a nearly constant flow. These requirements can exceed the maximum capacity of the buses which is rarely available due to the normal flow of data between systems required to fly the aircraft. Retrofitting modern buses would offer higher performance, but they might not be compatible with all the subsystems already in place. Increasing the wiring also increases weight and the risk of a faulty wire or connector. Besides, both options are nearly impossible to be applied on legacy platforms unless they are carried out during a major upgrade. Even when the internal communication system is not upgraded, the use of new health monitoring tools requires bus scheduling reprogramming.

Nowadays, the standard bus used in commercial aviation is the ARINC 429 or Mark 33. ARINC 659 is an evolution of the original ARINC 429 already installed successfully on the Boeing 777 [84]. Many US military airplanes have used the 1553 data bus since it was introduced in 1973 and has since been upgraded by the use of optic fibre in what is known as the 1773 data bus [85]. Computer buses like VME have been used on numerous military applications. Most common commercial data buses and their characteristics can be found in Table 1.

In order to increase the capacity of the buses and, at the same time, reduce the wiring, it has been proposed to use wireless communication. Dunsdon and Harrington [86] describe a Remote Interface Unit (RIU) that can be installed next to the sensors and collates and digitises up to 200 signals which are then sent wirelessly to the health monitoring system.

Table 1
Commercial data buses.

Name	Data path (bit)	Max. Speed	Standard
ARINC 429	25–32	100 kb/s (12.5 kb/s @ 32 bit)	ARNIC 429
ARINC 659	32	2 Mb/s	ARNIC 469
1553 Data Bus	16	1 Mb/s	Mil Std 1553B
1773 Data Bus	32	1 Mb/s	Mil Std 1773
VME	32	40 Mb/s	IEEE P1014-1987
VME 64	64	80 Mb/s	ANSI/VITA 1–1994
PCI	32	132 Mb/s (peak)	PCI-SIG 2.1
ISA	16	3 Mb/s	IEEE P-1882.1
SIB	32	5 Mb/s	LeCroy P1123

On-board/off-board applications. It is impractical to process all data on a ground stations since it would require a huge amount of on-board memory (increasing weight and cost) and a long time to download all the information. Once the data have been compressed they can be transferred to the ground station using either a wireless connection or a smaller and lighter memory cartridge [77,87,88]. Therefore, when an IVHM system is developed for an aircraft it is necessary to define to what extent the analysis is going to be carried out on-board and what will be left to be finished in a ground station.

On the other hand, carrying out all the analyses on-board is nearly impossible since it would require significant computer power on-board and some of the data required for prognosis is only available on the ground. Increasing processing capacity means increasing weight and cost. Furthermore, the certification of additional on-board software packages can be very expensive [88].

To find an optimum solution it is necessary to find and equilibrium between both extremes. Swearingen and Keller [77,88] propose to carry out the data acquisition, data manipulation, state detection and health assessment on-board and leave ground based modules take care of prognosis and decision support. Health assessment can be implemented on both platforms and even divided between them. The final decision will depend on the compromise between the weight of the on-board systems and the compression of the data.

Data processing and storage. As explained by Keller et al. [89], most health monitoring algorithms are too demanding for current on-board master computers and upgrading on-board computers can be extremely complex and expensive, specially taking into account the certification process.

Off-board analysis, on the other hand, avoids the need of modifying key hardware components, but it means that the information must be stored during the flight to be then downloaded. It is possible to use the data stored on the crash survivable memory for further analysis, but the information recorded might not comply with the requirements of some health analysis tools. Most modern aircraft use additional storage systems for maintenance purposes, but as demand for data increases with new diagnostic and prognostic tools their capacity will have to be increased [89].

> *Finding 6: Working with legacy platforms implies having to work with hardware originally installed for purposes different from health monitoring. Upgrading the hardware is very expensive and, therefore, the data fed to the health monitoring algorithms might not suit the requirements of the tool to generate reliable results.*

3.1.3. Implementation issues

Standardization. The lack of a common architecture for developing IVHM tools has limited the development of the technology by forcing engineers to design health monitoring systems compatible with specific vehicles, increasing the cost of industry-wide compatible tools. Driver et al. [90] insist on the need to establish a set of standards which allow subsystem suppliers to increase the potential market for diagnostic and prognostic systems and ensure those who integrate those subsystems that the ensemble will operate correctly.

The industry is starting to follow the Open System Architecture for Condition Based Maintenance (OSA CBM). The OSA architecture was originated by Boeing under the Navy Dual Use Science and Technology program [87]. Later, the standard was supported by the Machinery Information Management Open Systems Alliance (MIMOSA) [74,87]. The will to establish standards for IVHM technology boosted the development of a communications standard for transducers specific for health monitoring (IEEE 1451) and even standards for condition monitoring and diagnosis of machines (ISO 13,374) [74,86,88].

OSA CBM is a layered architecture formed by seven different levels and each of these layers represents a group of similar functions and tasks. The architecture works in such way that any module of any layer can communicate with any other module belonging to any other layer. These layers are [30,77,87]:

1. Data acquisition
2. Data manipulation
3. State detection
4. Health assessment
5. Prognosis assessment
6. Decision support
7. Presentation

OSA CBM uses the Unified Modelling Language (UML) in order to be able to used different programming languages. Dunsdon and Harrinton [86,88] have mapped UML for C++ and Swearingen et al. [86,88] have developed it to use XML [86,88]. The latter is especially useful for those developers who work on portable maintenance solutions since it is quite easy to apply to web services. Additionally, since the experts who can develop diagnosis and prognosis tools generally are not software experts, a library of Simulink blocks has been developed. They chose this platform because many developers are familiar with it and it is capable of generating embedded C code.

OSA CBM has been used for the development of tools for the NAVAIR DUS&T Reconfigurable Control and Fault Identification System (RCFIS) and for the US Air Force DUS&T Advanced Electrical Power Health Management (AEPHM) program [87]. However, it has not been implemented yet and is not applicable to legacy platforms without major modifications.

Performance metrics. One to the main difficulties of finding a suitable diagnostic or prognostic tool is the lack of information regarding the performance of the different solutions available in the literature. Although sometimes values for some widespread metrics such as fault detection percentages, fault identification percentages, failure ambiguity groups, and false alarm rates can be found, these variables are not comprehensive enough to fully describe the performance of a monitoring tool. Furthermore, there is not a standard defining these parameters which leads to ambiguous and inconsistent interpretations [66]. Saxena et al. [91] propose classifying the metrics based on either the end user requirements (operating, engineering and regulatory) or the function they represent (algorithm performance, computational performance, cost–benefit-risk).

Datta and Squires [92] used an Event Tree Analysis (ETA) to parameterise the performance of different IVHM tools based on the probabilities of different outcomes of several steps in the support process. Saxena et al. [93] have also proposed a comprehensive set of metrics for prognostics concerning accuracy, precision, robustness and cost/benefit, but their definition is still far from being standardized across the aerospace industry.

Systems integration and IVHM. Traditionally, aircraft's systems have been installed following a federated approach, with health monitoring systems being developed for specific subsystems. Many of them have a similar structure and even use some common data. Monitoring systems developed for different systems usually have different providers, each of them with its own architecture and ground equipment, which means that personnel have to be trained to operate all these modules. Furthermore, they could generate contradictory results very easily, making it necessary to check the components using traditional methods, eliminating any advantage of installing the monitoring systems in the first place [86]. To reduce cost and contradictory results, companies are developing unified systems in which data from all the sensors can be analysed by a vehicle-wide single monitoring system [86,94].

Certification. Airworthiness regulations represent one of the main challenges that IVHM faces since modifications of hardware and software whose failure can affect the safe flight and landing of the aircraft or reduce the ability of the aircraft or the crew to fly under adverse conditions [95,96]. These regulations cover design, manufacturing, integration and installation of any system installed on an aircraft.

In many cases it is necessary to modify the component being monitored to accommodate new sensors and this represents additional certification problems [97]. If this could be avoided, as long as the hardware used on a new health monitoring system uses components similar to existing certified products available in the market, certification can be relatively straightforward.

The cost of software certification depends on the functions implemented since different functions require different certification levels. Taking into account that audio, visual and physical clues can be very distracting, a malfunctioning diagnostic or prognostic program can affect operations significantly. It is possible to take advantage of this progressive certification levels to introduce IVHM capabilities gradually reducing costs significantly. Azzam et al. [97] proposed the use of a certified architecture (including the timing scheduler to organize the execution of all processes) which would make the implementation of each new program a standalone task.

Finding 7: The lack of a standard platform for the development and implementation of IVHM increases development costs significantly, since putting into service the technology is limited to a case-by-case activity with high certification costs. This has the additional disadvantage of increasing the probability of integration problems appearing.

3.2. Organisational challenges

Since IVHM requires a commitment of the whole organisation to be put into service successfully, organisational issues play a key role from the development to the implementation of the tools. The problems that have to be faced by those involved in the design of IVHM technology are both structural and cultural, the latter being more difficult to tackle. The classification of most common organisational challenges face when retrofitting IVHM can be seen in Fig. 3.

3.2.1. Development

Program planning. Aircraft manufacturers often lack the expertise necessary to understand the potential of certain technologies and, therefore, tend to avoid health monitoring techniques that are not fully matured, limiting the development of IVHM technology [66]. Additionally, the scepticism based on previous failures to meet expectations has made it difficult to justify the development of some diagnostic of prognostic tools.

Developing a fully operational prognostic tool is a very long process. In most cases a successful diagnostic tool is necessary before attempting the development of a prognostic tool. However, presupposing a set of BITs and Fault Detection Isolation and Recovery (FDIR) techniques based on previous designs often leads to removing and adding features several times, increasing the development cost [1]. Additionally, according to Hess et al. [81],

	Development	Implementation
Cultural	• Lack of compromise • Unwillingness to share information • Focus only on technical criteria • Low attention on keeping exhaustive records • Scepticism leads to little resources allocated to IVHM	• Resistance to shift from traditional maintenance procedures • Little benefit perceived despite significant improvement reached • Unwillingness to share information
Structural	• Lack of specific development tools • Use previous designs (with pre-existing problems) • Ambiguity of goals • Several organizations per project • Lack of accountability	• Uncertainties at the start of projects are not updated • Cost of case-by-case implementation • Lack of design reviews to check if integration requirements are met

Fig. 3. Classification of most common organisational challenges regarding retrofitting IVHM.

maturation time can become very long and this must be taken into account when the development program is planned, especially for those cases where the roots of the fault are random or the physics of the degradation are not well understood.

Deviations from the original development plan are very common, especially among incoming managers who did not take part in the original planning and who also refuse to abide by agreements made by their predecessors [1], producing as a result a lack of accountability which increases the chances of repeating the same mistakes.

Ambiguity when the goals are defined during the initial stages of the design of a new tool often result in unsatisfactory results. Tsang [98] mentions how in the past it was very common to have objectives such as “minimize the costs” or “maximize the availability”.

The development cost of IVHM tools is usually too high for a single platform program and should be divided among different programs [81], but this introduces new organisational problems when different teams, with different priorities and dynamics, have to work on the same product. When different companies are involved in the same project this problem aggravates [94].

It is easy to find in the literature different strategies for the design process, although they remain relatively vague. Tsang [98], being one of the few with specific solutions, proposed a decision tree for classifying failure modes and determine the best applicable solution. Wilmering and Ramesh [99] followed a systems engineering approach which consisted of five stages: requirements development, system/functional analysis, design synthesis and integration, system test and evaluation and system maturation. Beshears and Butler [100] have developed a closed loop design methodology to implement health monitoring in some of Raytheon’s products which also consists of five stages: requirements analysis, analysis/design influence, resting, reasoned development and fielding.

Resources. Since there are no standards established for IVHM technology, engineers often start from scratch or use pre-existing tools as a base for further development. This means that there are very few design tools specifically developed for designing monitoring systems and in many occasions teams have to develop their own [94]. Although Boeing has developed some programs such as the Diagnostic Tool Suit (DTS) or AutoTEST they are specific for their fleet and do not take into account all the aspects involved in IVHM [30].

According to Hess et al. [81], given the little popularity of health monitoring techniques when compared to other programs in the aerospace industry, funding cuts tend to be more severe for them and this should be foreseen by preparing specific benefit justifications.

Aircraft manufacturers act many times as system integrators, therefore subsystems suppliers are required to design their products with health monitoring capability or even retrofit it. This can eventually cascade down to component suppliers who normally do not have the technical expertise, tools or capacity to deliver these capabilities, meaning that knowledge, resources and costs need to be shared [66].

Information. Information regarding failure modes, maintenance procedures and cost is indispensible to develop new diagnostic and prognostic tools. However, given the large number of different players in the overall support process, obtaining the necessary data can be extremely difficult. Economic parameters, essential for a cost–benefit analysis are the most difficult to obtain. According to Hess et al. [81], lead-time interval, or the time between an accurate prediction is generated and the moment the component has to be replaced, is key for the designer. To determine the optimum value of this parameter it is necessary to analyse the effect on the overall maintenance process of different lead-times. This information is rarely available and the designer tends to focus on optimising the accuracy of the tool if no economic criterion is available.

The lack of information is not always related to the unwillingness to share it, but to the fact that sometimes, records of some parameters are not kept. In order to automate part of maintenance and logistics it is necessary to carry out an analysis of these processes. Since many times processes emerge from history, they are not well documented, making it difficult to be understood by people not involved in them. Additionally, if a process is unstable and is executed differently each time, it becomes impossible to model. A lack of stability means that the structure of the process changes depending on the situation while flexible process can still be modelled as long as their structure remains unchanged. Therefore, and as stated by Hausladen and Bechheim [61], only processes with a certain level of complexity and a significant volume of activities generate value by being automated.

Finding 8: Previous problems with the development of IVHM tools have created certain scepticism within organizations which eventually diminishes the interest of some of the people involved in their design. This lack of commitment can make it difficult to obtain the resources and information necessary to reach the objectives.

3.2.2. Implementation

The introduction of IVHM faces important cultural challenges within the organisations involved that include breaking with tradition and shifting mission operations and ground operations paradigm. It is very common that, even in those cases in which a new tool has worked successfully throughout its first development phases, it fails to perform as expected when it is integrated with other systems.

Traditionally, monitoring systems where installed on a case-by-cases basis, with different modules for different systems. The installation of these modules required a lot of time, reducing the availability of the aircraft increasing the costs even further [86]. Inadequate program management has created situations in which many subsystems worked according to the specifications, but the whole system did not meet the costumer’s expectations [1].

The uncertainties at the beginning of any project can lead to erroneous conclusions regarding the economic and organisational benefits of implementing a monitoring system. To tackle this problem Hess et al. [66] propose using a spiral development strategy to carry out the business case analysis to incorporate more detailed qualitative information as different elements are re-evaluated.

Surprisingly, Scandura [1] report that one of the reasons so many problems are encountered during the implementation phase is the lack or misuse of design reviews. This creates situations in which the design of the monitoring systems does not comply with the specifications originally defined.

Finding 9: For a long time, IVHM has been relegated to projects focused on implementing isolated applications undermining the development of a strategy for implementing a comprehensive IVHM program. The complexity of retrofitting several tools remains an unexplored area, undermining the chances of success of future projects.

4. Current products and services related to IVHM

IVHM tools have been tested on several platforms and at different levels over the last decades. Many companies have already started to provide products with health monitoring systems capable of interacting with other tools of the support chain. Some have even started to provide services enabled by the use of IVHM technology. Here the most prominent examples of different categories are included to illustrate the stat of the art.

4.1. Health monitoring tools

One of the oldest and most successful monitoring tools used in aerospace industry is the Health Usage and Monitoring System (HUMS). HUMS was first introduced on helicopters to gather data from different sensors to be then stored on a removable memory unit from which they can be downloaded after landing for further analysis. It has been used to measure vibration at different points of the rotating components of the helicopter and diagnose and predict failures. HUMS has been used on both rotary and fixed wing aircraft such as Chinook, Merlin, Hawk and Apache, to name a few. However, this system is basically a recording system which requires the intervention of a specialist or the development of an application to produce useful information.

Aircraft manufacturers have been very active developing health monitoring tools for their products as well as procedures to verify the correct integration of subcontracted subsystems and their own health monitoring tools. Boeing has developed a set of software tools specifically for health management called the Diagnostic Tool Suite (DTS) to conceptualize, analyse and test new systems installed on an airplane. One of these tools is AutoTEST, which uses an expert system to automatically check analogue and digital electronic systems [30]. It evaluates various scenarios to check how the system will behave on both normal and faulty conditions. Using the Generic Modelling Environment (GME) they developed ADVISE (Analysis & Design for Vertical Integration and Systems Engineering), which is used to model functions, hardware and diagnostics of a new system and can be used at any stage of the development process (from conceptual design up to field tests) and to any level of complexity (from subcomponents up to the full system). With this tool it is possible to carry out: Hierarchical System Modelling, Trade study support, System redundancy and reconfiguration analysis, Mission reliability and Probability of Loss of Control (PLOC) analysis, automatically generated Failure Mode and Effects Analysis (FMEA) and Diagnosis development and evaluation. Similarly, since 2000 BAE Systems has been collaborating with Smiths Industries to develop a Structural Prognostic Health Management (SPHM), which is key for aircraft with structural monitoring systems such as Typhoon [101]. However, most tools provided by OEMs for either new aircraft or as a retrofit are only capable of generating relatively simple diagnoses (i.e.: BIT level). Furthermore, at this point prognostic tools are not capable of calculating a RUL accurately enough to be of any use for the maintainer.

Operators have also been involved in the development of IVHM tools taking advantage of their experience and the first-hand availability of flight data. This is the case of the UK MoD which, through the Power Generation Group (PGG), is responsible for the development of the Engine Usage, Condition Monitoring and Management Systems (EUCAMS). The system will be applied to the JSF and the FOAS combat UAV, and the possibility of installing it on Typhoon, Storm Shadow, A400M and helicopters is being studied. EUCAMS has a whole life approach and therefore has been developed according to the requirements of the Defence Logistic Organisation (DLO) [90]. In a similar case the US Navy, in collaboration with Boeing, has developed the Online Flight Control Diagnostic System (OFCDS) and the USAF/DARPA Uninhabited Combat Air Vehicle (UCAV) [78]. These systems report information on the monitors only when there are changes in the condition of a certain subsystem (event driven basis). Onboard analysis only uses information concerning the current flight. For more thorough analyses data has to be downloaded to a Ground Base Reasoner (GBR). For each failure mode that is downloaded to the GBR there is a Health Index Code (HIC) is associated with it. Using Bayesian network models the GBR calculates the probability associated with each different explanation for the failure mode and associates them with its HIC.

Some companies have focused on developing multipurpose software that can be used for post-flight analysis rather than tools that have to be tailored to the system they monitor. This is the case of Smiths Industries (now part of GE Aviation) which during the 1990s started to develop neural networks, dynamic models, error detection models, Usage Indices (UI) and fatigue evaluation algorithms all of which would be later part of the company's Fleet Usage Management Software (FUMS). Many of the features included in this software were inspired by the collaboration with the MoD in the development of Health and Usage Monitoring Systems (HUMS) for helicopters which started in the 1980s. FUMS is a software tool intended to be capable of unifying the applications that different users require for an end-to-end support of any platform. Some of the applications currently available in FUMS are [90]: signal processing and vibration analysis, intelligent management of HUMS data, study of Uncommanded Flying Control Movements (UFCM), Verification of fleet management approaches, fleet management. Additionally, the use of fuzzy logic algorithms to detect gauges failures has been tested. Wakefield et al. [11] determined that the fidelity of the prediction generated by the software using regression analysis and Root Mean Square (RMS) and the also developed an alternative method using Bayesian Networks. FUMS has been used to aid the qualification process of the Merlin HUMS airborne system and will be deployed for Typhoon and integrated within the JSF. Additionally it has been used for the life-management of the Harrier engine fleet [90].

However, IVHM is not only being developed for aircraft and has been applied to ground and space vehicles. Health monitoring systems with diagnostic capabilities have been retrofitted successfully on gas turbines of M1 Abrams tanks using a combination of factory-installed and retrofitted sensors [102]. The automotive industry has been using automatic diagnostic systems for a long time and has even established CAN as the standard which allows an easy reading of the failure codes of any car, although this requires an inspection with the vehicle stopped. GM's OnStar system has been a successful product which includes diagnostic capabilities for different components of the car and a communication system that reports the state of the vehicle to a centralised system where the information is analysed and informs the owner of the condition of several subsystems. OnStar also has some prognostics capabilities like the remaining life of the oil

[103]. Another example of a military application could be the development by the US Army of an embedded health monitoring and diagnostics system to be installed in its ground vehicles fleet called Smart Wireless ICE (SWICE) mentioned by Zachos and Schohl [104]. This is an evolution of the existing ICE which has wireless capability using Commercial Off The Shelf (COTS) equipment and that is going to be first tested on the Army's TWVs fleet. This system is supposed to help to implement the Common Logistic Operating Environment (CLOE). The data managed by the systems has to be encrypted according to the Federal Information Processing Standard (FIPS) 140-2 Level 2 which means that the probability of success of a random attempt to access the system is less than one in one million.

In space applications IVHM not only helps to reduce operational costs cutting the amount of personnel required to monitor a space mission and maintain the spaceship, but also reduces the probability of human error. Using IVHM on a spacecraft it is possible to program responses to different critical events giving immediate solution to problems that might appear during the mission [105].For deep exploration missions IVHM provides autonomous decision making capability once the distance to the spaceship slows communications to a point at which troubleshooting becomes extremely difficult. The Space Shuttle (considered a 1st generation reusable launch vehicle) has been maintained mainly following planned activities, replacing components and running tests in fixed intervals. To tackle some of the problems of this approach NASA developed an informed maintenance systems for the space shuttle called Predictive Health And Reliability Management (PHARM). The system, which started to be developed in 1997, assesses the health of the Orbital Manoeuvring Subsystem (OMS). An early version of this system was used on Deep Space 1, an unmanned spacecraft launched on October 1998 which flew by asteroid 9969 Braille and comet Borrelly and was used as a test bed for 12 new technologies applied to space exploration, among them, a remote decision-making agent [106]. This system was basically an IVHM module especially designed for space exploration. It used model based methods for decision-making which were considerably faster than expert systems.

4.2. Maintenance, logistics and availability contracts

Outsourcing logistic and maintenance services has been very successful with military organisations, with many air forces contracting these kinds of services in the last decade. The US Department of Defence is shifting towards Performance Based Logistics (PBL) contracts which make the contractors responsible of any increase of maintenance costs or reduction of availability [2]. Following this trend, in 2006 BAE Systems signed an availability contract with the UK MoD to maintain the Tornado fleet [107].

AgustaWestland provides the MoD with maintenance support for the Sea Kings and Merlins. The company has named these services Integrated Operational Support (IOS) [108]. In March 2006 AgustaWestland and the MoD signed the Integrated Merlin Operational Support (IMOS) and Sea King Integrated Operational Support (SKIOS) contracts for the Merlin fleet of both the Royal Navy (Merlin Mk1) and RAF (Merlin Mk3) and the Sea King fleet [109]. With this contract AgustaWestland became responsible for the availability of the helicopters and the cost reduction of their maintenance [109]. From April 2010 they also provide similar services for the Apache helicopters fleet in collaboration with Boeing, Lockhead Martin and Longbow [110,111]. Merlin helicopters use the Enhanced Heath and Usage Monitoring System (EHUMS) for failure diagnosis and prognosis. According to public statements AgustaWestland has managed to increase the availability of Merlin helicopters by 60% [112].

Probably one of the best known availability-based services in aerospace industry is TotalCare, offered by Rolls-Royce. This service provides customers with full operational support for the engines and only charges an agreed fee per flying hour in what is commonly known as "power-by-the-hour" [113]. GE Aviation provides tailor-made service packages to costumers which can include maintenance, material and asset management. These are based on remote integrated vehicle health monitoring services and Integrated Logistics Management (ILM) solutions [114]. GE also provides a support services that links the Costumer Services Centre (CSC) with the airplane via satellite and is capable of warning the costumer about a fault in 15 min and identify dangerous trends in 2 h. This is possible thanks to the continuous monitoring of 300 engine parameters via the Full Authority Digital Electronic Control (FADEC) [103].

In the recent years airplanes manufacturers have started to offer full-care services to the airlines. With the introduction of the 787 Dreamliner, Boeing has offered a package called GoldCare which consists of maintenance, engineering and material management services. The system uses data downloaded from the airplanes which is obtained using tools like Boeing's Electronic Log Book [115]. Airbus has enhanced the capabilities of its AIRTAC support centre by using satellite and ground communication systems to monitor the state of the A380, enabling proactive recommendations to their customers [116]. Embraer and Bombardier offer similar services for their commercial jets and have started to expand them to their executive jets [117,118].

BAE Systems, through its subsidiary Aerosystems International Ltd. (AeI) offers different support tools that enhance the maintenance management of military assets [119]. Sapphire is used to track and record the components installed in different airplanes helping the maintenance management of the fleet. Trilogy is a program that can be used to manage the technical documentation in electronic format and ensure it is adequately updated according to S1000D standard. By combining these and other tools BAE Systems offers its customers to develop a semi-automated logistic solution called Network Enabled Logistics (NEL)

Although companies are heading towards providing services to manage the whole support system, governments prefer to follow a gradual implementation and most contracts are limited to a specific step process. For example, in December 2010 the signing of a contract between the UK MoD and Boeing Defence UK to outsource operationally essential logistics information was made public. Boeing became a single delivery partner and managers of a number of subcontractors [120].

Given the progress in maintenance and logistics outsourcing of the last decades, organisations are starting to develop their own compliance standards to ensure the services they receive match their requirements. The UK Ministry of Defence publishes the Maintenance Approved Organisation Scheme (MAOS) which, in Part 145 [121], defines the requirements for the approval of those companies who supply maintenance services. Similarly, there are standards defined for those organisations that are involved in training personnel [122]. Engineering policies and regulations [123] as well as engineering documentation and procedures [124] are also made public to help subcontractors offer services that comply with the MoD's standards. This shows a trend towards the outsourcing of maintenance activities within military organisations whose main objective is to have aircraft available for their missions rather than have to take care of their repairs.

These examples show an evolution from a product based business model to a new one in which health monitoring enables selling services to operators. However, these services are not yet based on the use of automated diagnostic and prognostic tools, but on the use of experts to interpret parameters being stored or transmitted during each flight.

Finding 10: Advanced diagnostic and prognostic are not yet reliable enough to provide useful information to the maintainer. Therefore, companies are still far from being capable of providing support services based on using a fully functional IVHM platform. However, from the evolution in the services available for operators, it can be inferred that there is a will to outsource support activities within the clients and to take that responsibility within the OEM. Investing on IVHM technology is the only way service providers can achieve the increasing availability demanded by both civilian and military operators.

5. Conclusions

The current state of diagnostic and prognostic technologies presents significantly different results depending on the characteristics of the systems being monitored. While diagnostic for simple systems has been successful, tools for more complex systems are still far from reaching implementation level. On the prognostics side, the research projects published show promising results, but it is still necessary to transform these successes into prognostic tools capable of operating under real conditions. Estimating the RUL for components whose failure mechanisms are not as well known and which are used under variable conditions has been prove to be extremely difficult. The combination of model-based and data-driven methods have shown promising results in this area, but in most cases they are not ready for being used in industry.

Since health monitoring technology is a discipline which is still evolving in many areas, the implementation of IVHM on any platform must take into account the possibility of new tools appearing over time. This means that it is necessary to use an architecture that allows the addition of new capabilities while disturbing as little as possible of the normal operation of the aircraft.

Logistics management has been implementing autonomous decision making in other industries for many years. Since this technology is underpinned by the automatic generation of data, it will not be until diagnostic and prognostic tools are fully developed and integrated that human intervention in maintenance and logistics management in aerospace can be reduced. Even with fully functional health monitoring tools it is necessary to have a good understanding of their accuracy, since the uncertainties play a key role in the decision making process. To evaluate the impact of any new tool used to monitor the health of an aircraft it is necessary to assess how the limitations of the hardware, software and integration process affect the final performance of each tool.

Despite the numerous organisational issues mentioned in the literature, an analysis of the evolution of the services offered by OEMs shows a tendency towards the implementation of IVHM throughout the whole aerospace industry. These problematic issues must still be taken into account when planning the implementation of IVHM since their effects can be difficult to notice until the late stages of the projects, when a lot of money and effort have already been invested.

As a result of this review, it has been discovered that there is a lack of a comprehensive study on how the process of retrofitting IVHM technology should be carried out. Although some work has been done on procedures to implement IVHM, it focuses on new aircraft, and the few papers that address this issue ignore the challenges faced when working with legacy aircraft. A system to guide the development and implementation of IVHM into pre-existing aircraft is needed, and it must take into account technical, organisational, and economic aspects of the process to ensure the objectives are met.

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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).

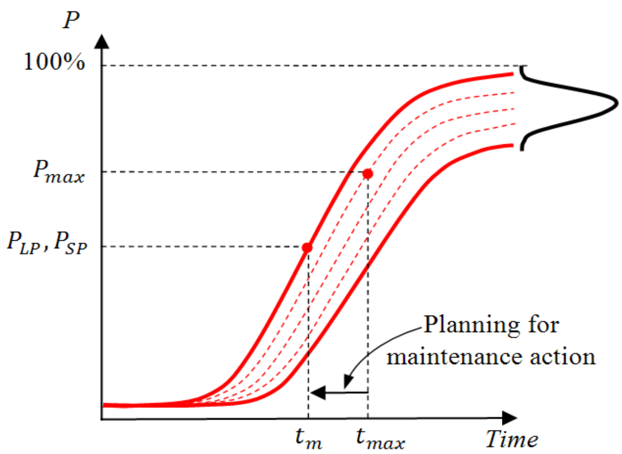


Figure 1. Degradation curves generated by a prognostic tool used to estimate the probability of failure of a component before it has been replaced.

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.

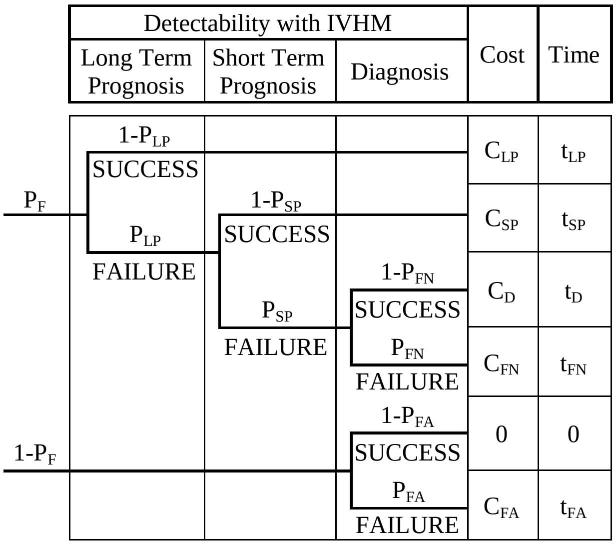


Figure 2. ETA for the use of health monitoring tools on a single component.

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.

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

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

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

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

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

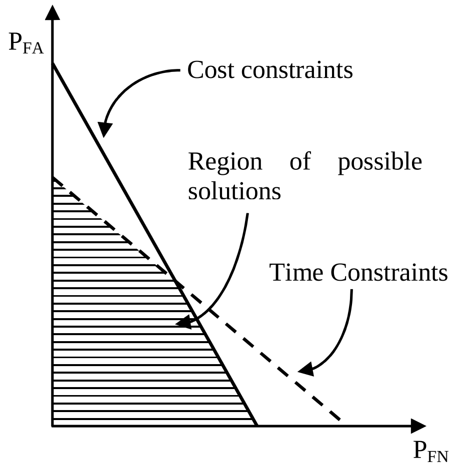


Figure 3. Region of acceptable performance of a diagnostic tool

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:

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

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

$$P_{FA} \geq 0 \;\&\; P_{FN} \geq 0 \tag{18}$$

Where

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

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

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

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

From equation (16)

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

Additionally

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

where

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

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

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

As a result

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

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

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

where

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

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

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

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:

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

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

The difference being

$$P_{LP} \geq 0 \tag{35}$$

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

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

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

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

From equation (33)

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

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

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

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

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

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

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.

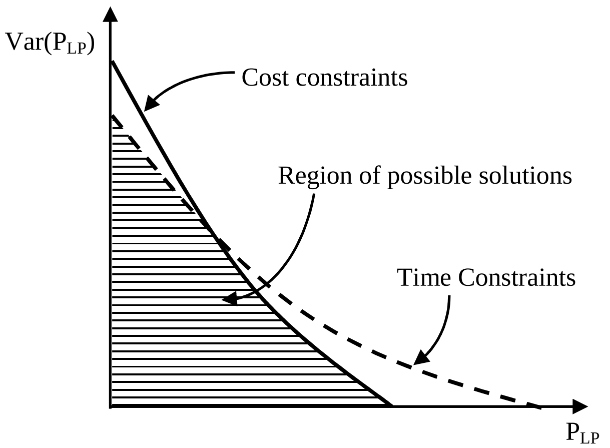


Figure 4. Region of acceptable performance and variance of performance of a long-term prognostic tool

6. Case Study

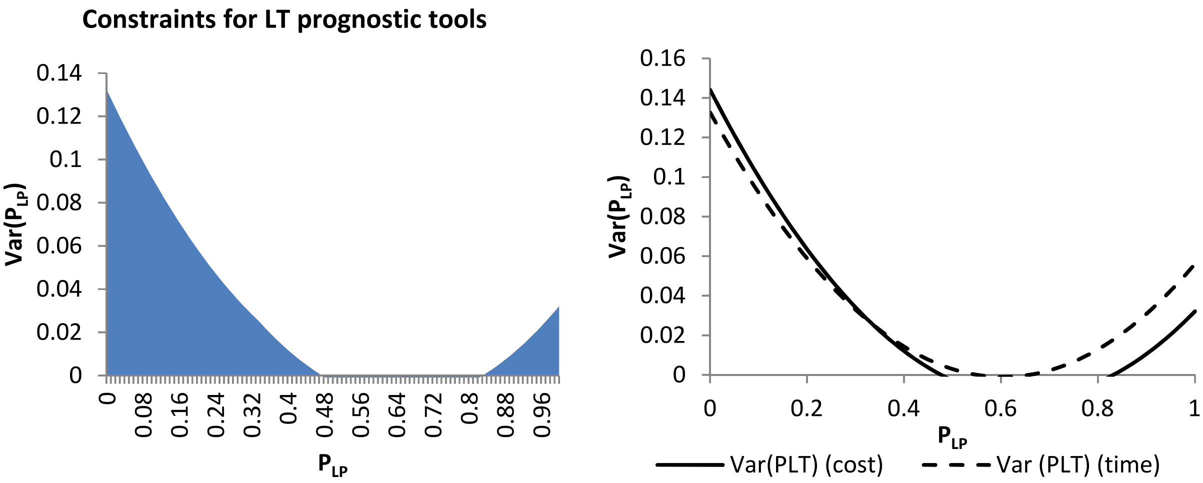
The following example is based on synthetic data for a generic component that fails every 250 flying hours. Although the values chosen for the parameters used in this case do not belong to a specific real component, they are representative of the costs and maintenance times of many parts currently run 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.

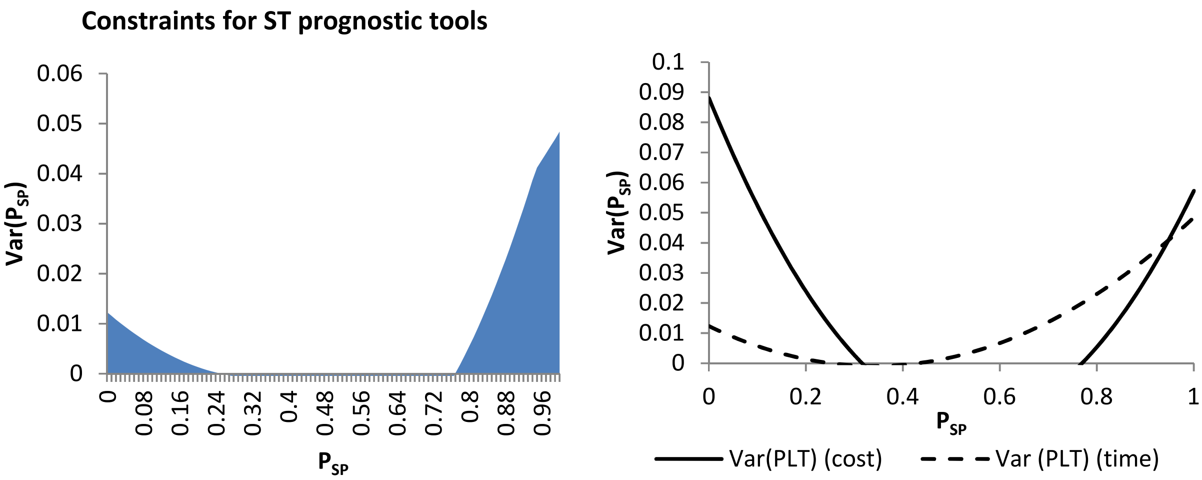
Since the performance of diagnostic tools is described by four variables it is not possible to represent the limits of the requirements. To provide some guidance, the graphs for diagnostic tools shown in Figure 6c represent the relation between the probability of false alarm and the probability of false 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: L-T Prognosis	S-T Prognosis	Diagnosis	Cost (£)	Time (h)
P_F	$1-P_{LP}$ S			773.5 [2.95E+02]	1.35 [9.00E-04]
	P_{LP} F	$1-P_{SP}$ S		906.1 [1.88E+02]	1.35 [9.00E-04]
		P_{SP} F	$1-P_{FN}$ S	1021.7 [1.86E+02]	1.35 [3.16E-03]
			P_{FN} F	1319.825 [3.10E+02]	3.375 [6.46E-03]
$1-P_F$			$1-P_{FA}$ S	0	0
			P_{FA} F	330 [3.03E+01]	2 [2.27E-03]
			Total	5.279 [6.82E-02]	0.0135 [5.17E-07]

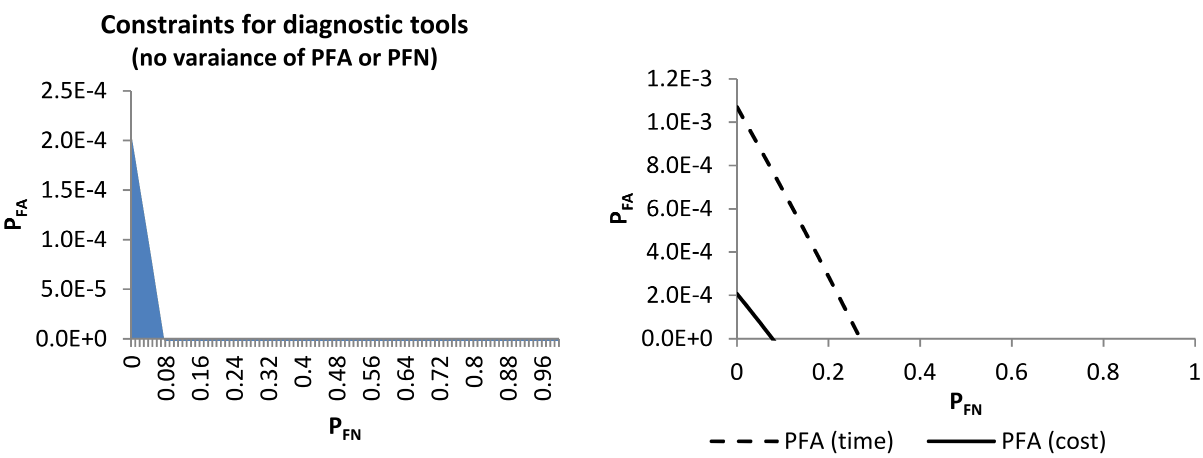
Figure 5. Costs, times and their variances (in brackets) for each maintenance scenario.



a)

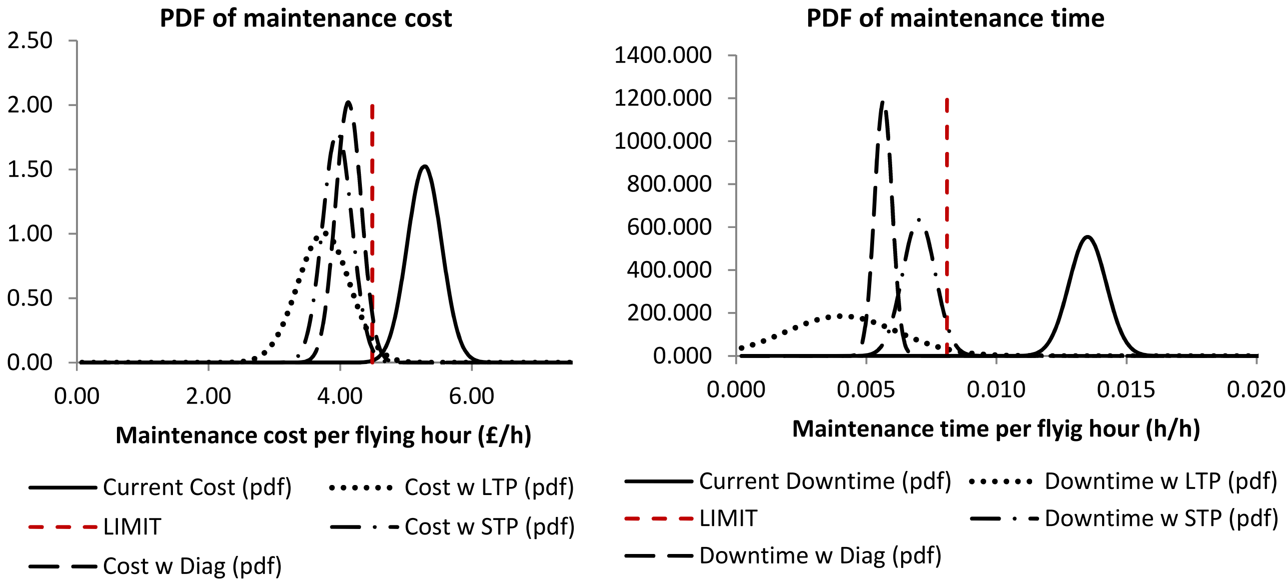


b)



c)

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.

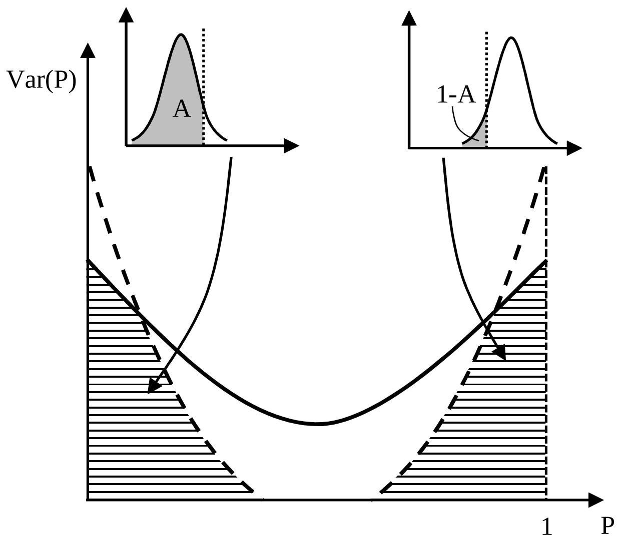


Figure 8. Region of acceptable performance and variance of performance of a long-term prognostic tool

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.

ACKNOWLEDGEMENT

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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.

The effect of current military maintenance practices and regulations on the implementation of Integrated Vehicle Health Management technology

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Abstract: Health monitoring tools can be used to diagnose failures and estimate the remaining useful life of certain components, generating information that can be used to improve the management of logistics and maintenance activities in what is known as Integrated Vehicle Health Management (IVHM). The work presented here analyzes the effect of military practices and regulations on the benefits that can be expected from installing health monitoring tools on military aircraft. The findings on the impact of the military environment on short-term and medium-term goals of maintainers and operators are key to produce an accurate and reliable Cost-Benefit Analysis (CBA) for IVHM technology. The results of this work are based on information obtained through the use of a questionnaire to gather the knowledge of experts in the field and by studying military standards. Secondary benefits of implementing IVHM have been studied in detail to provide a guide of which are really relevant when working on a CBA and which can be ignored. The transition from current Condition Based Maintenance (CBM) practices included in military standards to the use of continuous health monitoring tools is also discussed. The effect of current outsourcing practices, such as availability contracts, is taken into account in the analysis of these issues.

Keywords: From PHM and CBM+ considerations to Maintenance, Maintenance Related Services, Service Improvement, Asset and maintenance management, Cost-Benefit Analysis, Maintenance Costs, Maintenance Policies, Standards, Program Costs.

1. INTRODUCTION

In order to reduce maintenance costs and increase the availability of a vehicle, diagnostic and prognostics can be used to generate information to be used to make decisions regarding maintenance and logistics. Advances in automated decision making can also be applied to reduce the need for human intervention. When these tools are implemented in conjunction to improve the performance of the support infrastructure we talk of Integrated Vehicle Health Management (IVHM).

The capabilities of health monitoring tools have improved significantly in recent years, making industrial applications possible. As a consequence, several Cost Benefit Analysis (CBA) procedures for IVHM have been proposed to determine the improvements in support cost and vehicle availability (Leao et al., 2008; Banks and Merenich, 2007; Hoyle et al., 2007). Some have even gone further by proposing methodologies to optimize the design of certain tools from a CBA perspective (Kacprzynski et al., 2002).

Calculating the decrease in maintenance cost and time is crucial to justify the investment on a certain tool. Quantitative methods focus on three main areas:

- Reducing maintenance time using diagnostic tools.
- Deferring jobs until they can be carried out along other scheduled activities using prognostics.
- Reduce the stock of components and delays by improving logistics (Khalak and Tierno, 2006).

As a result, CBAs for IVHM technology are carried out considering the following areas (Banks et al., 2009):

- Coverage of the health monitoring system
- Cost of development and implementation
- Cost of operation of the new IVHM system
- The expected range of missions to be flown
- The expected scheduled maintenance operations

However, the knowledge that can be inferred from the exponential increment of data generates all sorts of additional benefits. These tools can be used to, among other things, enforce quality policies (Benedettini et al., 2009), to reduce costs in manufacturing, testing and certification phases (Scandura, 2005; Trichy et al., 2001), to react automatically to a fault (Kurien and R-Moreno, 2008); and to generate all sort of benefits for stakeholders that are not directly involved in manufacturing, supporting or operating the vehicle (Wheeler et al., 2009). It is important to realise that some of these secondary benefits can be used to develop new business practices with the potential to reshape the way cash flows through the aerospace sector (Hess et al., 2006).

At the same time, regulations already in place impose numerous limitations to the benefits these systems can bring. Many scheduled checks and replacement of components must be followed regardless of the indications of a health monitoring tool. As a consequence, in many cases it is necessary to wait until they are proven reliable to modify the standards being followed. Only once this point is reached it is possible to start to perceive a return on the investment.

Although it is possible to enumerate the multiple advantages and disadvantages of installing health monitoring tools on an aircraft, it is necessary to determine which are really relevant for each platform. Evidently there are major differences in the way stakeholders perceive these issues for different vehicles, specially taking into account how the goals change from civilian to military platforms (Williams, 2006). We focus on military aircraft and the effect of the support system put in place by military organizations on the use of IVHM technology.

1.1 Outsourcing

The maintenance of military aircraft has been increasingly outsourced, mostly to companies or divisions that are part of aircraft or engine manufacturers and act as maintenance service providers. Originally, these maintainers carried out scheduled activities of high technical complexity and workload, also known as depth maintenance activities. Air forces remained in charge of daily operations to ensure the airworthiness of aircraft between flights in what is normally known as forward maintenance. In recent years forward maintenance has started to be outsourced to a higher or lesser degree for some platforms, even with contractors deployed overseas.

The complexity of the contracts between air forces and maintainers means that there are nearly as many outsourcing formats as contracts. One of the extremes corresponds to those agreements where the maintainer charges the operator for every single job (meaning there is no incentive to reduce maintenance costs). On the other hand, availability contracts ensure the operator is charged based on the availability of the vehicle, regardless of the cost to the maintainer.

Stakeholders' objectives depend on the characteristics of these contracts since they define the way maintenance costs are allocated and availability objectives achieved. The observations made here are intended to include those issues IVHM will face in the near future; the relevance of some of them to specific platforms will depend on the details of the agreement between the maintainer and the operator.

1.2 Regulations

The benefits of predicting the failure of a component or reducing the time necessary to diagnose a problem are obvious, however current military regulations my undermine some of them. Barriers to install onboard IVHM tools or the continuance with standardise maintenance practices made redundant with new health monitoring tools are some of the regulatory obstacles that reduce the chances of technically sound tools being implemented.

Both NATO and British Ministry Of Defence (MoD) standards were studied to identify the most problematic areas. Given the similarity of the practices between major western air forces and the uniformity of some procedures imposed by NATO, the findings mentioned are relevant to several nations.

1.3 Questionnaire

In order to obtain information on the frequency of certain maintenance activities and the amount of resources and time dedicated to them a questionnaire was prepared. The questionnaire was used to collect the opinions of experts on maintenance of military aircraft. The objective was to get information that could be used to infer the relative importance of the numerous benefits and challenges often mentioned in the literature and to identify those that could be missing.

The results from the questionnaire are not exact figures extracted from the analysis of maintenance logs of a specific type of aircraft. Experts provided approximate average values for the range of vehicles operated by a modern air force that comprises aircraft with a wide range of ages, sizes and roles.

2. FOCUSING ON THE RIGHT MAINTENANCE PHASE

The ultimate goal of IVHM is to defer as many maintenance activities as possible so they can be carried out when the impact on the availability of the aircraft is the lowest. In essence corrective maintenance jobs would be transformed into predictive maintenance tasks. Additionally, flight servicing between missions could be accelerated by reducing the time necessary to determine the condition of the aircraft. However, the use of health monitoring tools has proven to be counterproductive on some cases (Swearingen and Keller, 2007; Keller et al., 2001), making the flight servicing longer and more unpredictable, with the latter possibly being the most disruptive side-effect.

There are two main flight servicing regimes followed by most air forces in the world. The first consists of Before Flight (BF) servicing, After Flight (AF) servicing and Turn Round servicing for those cases when the AF is still valid and the aircraft can be deployed after a set of preventive maintenance tasks. The second regime consists of Technical Flight Servicing (TFS), which is valid for a defined period; and Daily Flight Servicing (DFS), which comprises those tasks necessary to ensure the aircraft can be deployed at any time during the following 24 hours.

For the last two decades there has been a continuous increase in the coverage of Built In Test Equipment (BITE) used on board aircraft. At the same time, the introduction of digital avionics and data buses enabled the storage and continuous monitoring of an increasing number of parameters. Consequently, the number of components and subsystems with some degree of diagnostic capability has grown.

However, as increasingly complex subsystems started to be monitored and the interactions between them became more numerous and intricate, the reliability of the BITE was affected. Consequently, false positives or false alarms have become a major source of problems in modern aircraft.

As for the parameters being monitored, many of them were given thresholds that produce a fault code if reached or crossed. Since military aircraft are often operated at the limit of their capability, it is not uncommon to have to go through numerous fault codes after each flight. These arisings need to be checked by experienced personnel and sometimes require further checks to discard certain faults as the cause for the code being flagged.

As a consequence, the duration of post flight servicing has not only increased but also become more unpredictable. This represents a major problem for mission planning, especially for those squadrons that fly the same airplanes several times per day. Thus, in the short term IVHM technology is more likely to produce benefits if it is aimed at increasing the reliability of diagnostic systems already in place and to speed up the analysis of the numerous occasions thresholds are crossed.

3. ANALYSIS OF SECONDARY BENEFITS OF IVHM

3.1 Flight Tests

Most CBAs focus on the how computer aided diagnoses improve the efficiency of maintenance jobs by reducing the time necessary to identify and isolate a fault. If a prognostic tool is being considered, the deferral of the job until it can be carried out at more convenient time is regarded as the main benefit. In some cases the increase in the number of missions completed successfully is also taken into account in the analysis. However, the effect of flight tests is rarely mentioned in the literature and is missing from most comprehensive quantitative CBAs.

Flight tests are common practice for diagnosing problems or for checking that a job on some critical system (e.g.: helicopter rotor) was completed correctly. The decision to use a health monitoring tool on a certain component is normally based on the frequency of failure of the component, the time necessary to repair it and its cost. However, flight tests can be necessary on cheap reliable components which are not normally regarded as candidates for the use of IVHM. Perkins (2011) showed how the cost of replacing a rotor bearing on a Chinook is largely driven by the cost of the test flight, which is several orders of magnitude higher than the cost of replacing the part. If the maintenance of the vehicle is outsourced, the cost or loss of availability due to a test flight might not be considered critical by the maintainer, but it still affects the operator.

While the cost of a flight test can be easily calculated, the allocation of the cost and the analysis of the effect of the test on the availability of the vehicle might not be that simple. Depending on the requirements the test can be carried as part of a routine flight (known as Partial Test Flights, PTFs) or it might need a specific maintenance flight (known as Maintenance Test Flights, MTFs). It is not uncommon for test flights to be repeated because additional work or adjustments need to be made (e.g.: helicopter rotor balancing). Diagnostic and prognostic tools have the potential to reduce the duration of certain test flights or even eliminate them, but computer models which simulate both maintenance operations and fleet management are necessary to quantify the improvement on availability.

According to the answers to the questionnaire, approximately only 10% of test flights are MTFs, which can lead experts to believe that analysing the potential of IVHM to improve costs and downtimes in this area is not worth the effort. However, the answers also showed that about 70% of PTFs are not carried out in combination with a routine flight, effectively having the same impact as an MTF. This shows that operational demands play a major role in the way flight tests are planned.

The benefits of IVHM rely on the correct and efficient use of the information health monitoring tools produce by maintenance and mission planners. This issue illustrates how important it is to determine whether the data generated by a diagnostic or prognostic tool will be put to use in order to make sure the estimated return on investment is accurate enough.

3.2 Training

It is often claimed that the use of computer based diagnosis and electronic documentation can help to reduce the amount of time personnel dedicate to training. While this claim is evidently true, it was not clear to what extent this would produce a significant improvement in personnel availability and productivity.

According to the answers to the questionnaire, it is estimated that, over a year, nearly 10% of the total man-hours are spent on training, 50% of which are dedicated to learning on check, damage evaluation and failure diagnosis. Therefore, the gain of man-hours due to a reduction in training by the use of diagnostic tools would be, at best, 5%. Nevertheless, there is potential to make important savings if less experienced personnel (with lower salaries) can be dedicated to more complex tasks thanks to the use of IVHM.

3.3 Administrative tasks

Regarding the personnel working in the technical offices, it is estimated that 30% of their total man-hours are spent on administrative and logistic affairs, meaning that the use of automated decision making tools could help to reduce not only the delays, but also the fixed costs of personnel. Currently, less than 25% of the time left is dedicated to activities aimed at improving the efficiency of the maintenance process, part of which is spent analysing historical maintenance data, something that could be significantly reduced if IVHM data-based tools are implemented.

The questionnaire helped to shed some light on the effect administrative task have on the availability of personnel with hands on the aircraft. Of all the delays affecting maintenance tasks between 10% and 15% are delayed because the necessary personnel are not available. Most of the delays come as result of the maintenance tasks requiring more time than that available between missions. Therefore, little improvement can be expected from focusing on micromanaging workers, given the complexity of such task, compared to what can be achieved by using IVHM to improve the performance on logistics and administrative tasks. Especially taking into account that approximately between 10% and 15% of maintenance personnel's time is dedicated to administrative tasks, a proportion that can be reduced as the different IVHM tools become more integrated with logistics.

3.4 Auditing

Maintenance practices of legacy aircraft must be reviewed to take into account any unforeseen changes in the way they are operated, their components degrade or the way they impact the support systems of other platforms. Structural, systems and propulsion audits are carried out to verify the airworthiness of the aircraft and that the operational and maintenance costs are under control. Normally, the first set of audits starts 15 years after the aircraft was declared in service or at 50% of its expected operational life. In most air forces these audits are to be repeated every 10 years.

These audits are exhaustive and can take years to complete resulting in a significant expense. The analysis of historical maintenance data is the core activity of these audits and requires going through numerous documents to put the information together before any kind of analysis can be performed. Health monitoring tools can store the same information in digital format making it accessible at any time much faster than it used to be. Additionally, they allow for much more component-specific information to be stored, improving the detail of the analyses that can be carried out. Furthermore, data mining techniques can be used to detect trend hidden in the data that would be missed in a conventional audit.

3.5 Quality policies

Most maintenance organizations that work on the support of military aircraft, either subcontractors or ministries of defence, meet the basic requirements of ISO 9001. This quality policy is to be applied to both fixed and rotary wing aircraft.

In case an issue regarding the quality of any of the activities or systems involved is detected it must be reported immediately through the generation of an occurrence report. The quality of an activity is considered to be compromised when normal fault reporting cannot be applied, problems with the technical information have been detected, problems regarding the information contained in reports are found or when there is suspicion of a deficiency in the management of the quality policy (UK Ministry of Defence - Military Aviation Authority, 2010a; UK Ministry of Defence - Military Aviation Authority, 2010b).

Time is normally an important factor when these occurrences are investigated since most organizations expect that the report must have been received, the matter must be studied, and subsequent action recommended, within 7 working days.

Health monitoring tools can help on two main areas regarding this matter. First, they provide additional data that can help to better understand the issue in a format that allows for all sort of computer-based analyses to be carried out. Second, they are time-saving tools that accelerate the generation of occurrence reports and investigation of the problem. And third, a comprehensive health monitoring system implemented on the whole fleet can be used as the basis to partially automate the detection of deviations from the quality policy by detecting abnormal fault rates.

3.6 Logistic Information Systems

A Logistics Information System (LIS) comprises electronic information tools used for the management of the logistics operations capable of performing any combination of the following functions (UK Ministry of Defence, 2010):

- Administrative
- Financial
- Asset management
- Maintenance management

Although there are LISs already in place to a higher or lesser degree in most modern air forces in NATO, currently they are normally limited to electronic tracking of orders and stock, with no automation based on the information from IVHM systems.

The integration of logistics with the use of health monitoring tools is key to ensure the success of an IVHM system, but it is important to keep in mind that, according to the answers received to the questionnaire, about 10% of the times an aircraft is not available for a mission the cause is a logistics or administrative delay. Although this shows that an improvement in the management of logistics can have a noteworthy impact on the availability of the aircraft, it is necessary to keep in mind that the cost of developing and implementing these technologies is high and might not justify an increase in availability that might not reach 10%.

3.7 Data transfer and management

Most health monitoring systems currently in use, such as HUMS (standard in all modern helicopters) or Typhoon's Integrated Monitoring and Recording System (IMRS), rely on some sort of Portable Maintenance Data Stores (PMDS) to download the data. PMDSs are memory cards that are removed after each flight and then taken to a ground station. Although sometimes it is possible to read the arisings onboard through some kind of Maintenance Data Panel (MDP) installed on board of some aircraft, it is still necessary to download the information from the PMDS to carry out an analysis with enough depth.

All the steps involved in this part of the process can take several minutes, especially in those cases in which the data are first sent to a centralised system and then they have to be requested from the ground station again, increasing the amount of time wasted. This must be acknowledge in the CBA to make sure the time gained through installing an IVHM tools does not end up wasted transferring the data.

4. CURRENT CBM STANDARDS AND IVHM

Most air forces have been using Condition Based Monitoring (CBM) for some systems for long enough to become part of their regulations. As a result, these practices will not be abandoned automatically if a continuous health monitoring tool is installed on a vehicle since that would be in violation of the regulations. Consequently, there is not saving associated with the use of a new tool that performs the same function as one of these CBM procedures. Furthermore, the cost of development and implementation of such tool cannot be justified unless the accuracy of the new tool exceeds that of the current procedure considerably.

It is possible to develop an IVHM tool to replace a CBM technique that is currently part of the military standards if the objective is to advocate for the derogation of the standard once the tool is proven reliable. However, this introduces a significant delay in the profitability of the project and is a significant risk that must be taken into account in the CBA.

The following CBM procedures are the most common and widespread among nations that are part of NATO.

4.1 Vibration Control

Vibration monitoring is a widespread method to assess the health of all sorts of rotating equipment and it is used on aircraft engines, transmissions and even structures. Forward maintenance organizations must measure the vibrations after maintenance activities such as rectification, fitting major assemblies, events that may have affected the natural frequency of some systems (e.g., heavy landing, bird strike) or if the crew reports an abnormal vibration in the aircraft.

Special groups are in charge of analysing data gathered by systems such as HUMS and provide technical assistance to the operating units. Any diagnostic tool that uses vibrations as an indicator of a fault will probably be affected by these regulations and should try to make the most of the means available to reduce development and operational costs.

4.2 Wear Debris Monitoring (WDM)

Those systems that use some sort of lubricant can be subjected to debris monitoring to detect excessive friction or abnormal loading that, eventually, can lead to the failure of the system. WDM is specially suited for rotating machinery and hydraulic systems in which the content of metallic particles in the oil can very useful for the detection or prediction of faults.

Spectrometric Oil Analysis Programme (SOAP), Magnetic Detector Plug (MDP) and filter debris assessment, and The Wear Debris Management System (WDMS) are the techniques normally used. Normally, the samples are analysed using a centralised system which will remain operative if a new IVHM tool performs the same function.

4.2 Hydraulic Fluid Monitoring

The cleanliness of hydraulic fluid is defined by NATO standards (NATO, 2006) and must be monitored regularly. Particles, water and other contaminants must be monitored to ensure the integrity of the hydraulic system is not compromised by the use of inadequate fluid. Some of the different techniques that can be used for this purpose are: CM20 particle counter, Patch testing, Filter Examination, Compar testing, HIAC particle counter, etc.

As with WDM, a set of laboratories specialised on making these analyses is already in place, reducing the profitability of an IVHM that tries to replace their function.

5. CONCLUSIONS

This work sets the basis for a deeper analysis of the secondary benefits of using IVHM on military aircraft. Although the main target of CBAs regarding IVHM technology is to quantify the direct impact of using a set health monitoring on the time and cost of maintenance tasks, there are all kinds of additional aspects that must be taken into account to make an informed decision and strike the right balance between current CBM practices and the implementation of new health monitoring technology.

Some of the secondary benefits often mentioned in the literature have been proven to have little impact on maintenance costs or the availability of the aircraft. On the other hand, the study of current military practices and regulations has helped to discover some additional benefits that are worth analysing in more detail.

During the life of an aircraft, audits are to be carried out periodically. They can be carried out quite deeply and an important amount of resources may be allocated to perform them. If they were to be combined with a viability analysis this would reduce its cost and, what is more important, would take advantage of a "time window of good faith" during which operators and OEMs are more willing to share information than under normal circumstances.

Any tool developed to bridge the gap between the diagnoses and predictions generated with IVHM tools and the logistics systems will have to take into consideration the characteristics of the current LIS and how regulations impose certain constrains on the automation of the management of the logistics. Nevertheless, this presents an important advantage for the developer, since regulations provides a framework on which some requirements are already defined.

Since there some data gathering systems already being used by air forces such as HUMS there is a record of different parameters during several flights. Therefore diagnostic and prognostic algorithms should be based on the data already provided by these systems. In case the objective is to retrofit this technology on legacy aircraft, it seems logical to take into account the limitations imposed by the existing recording systems on the quantity, resolution and accuracy of the parameters fed to any IVHM tool.

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Downtime Uncertainty Reduction Through the Correct Implementation of Health Monitoring Tools

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Keywords: Technology selection, Cost-benefit analysis, Product-service system

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].

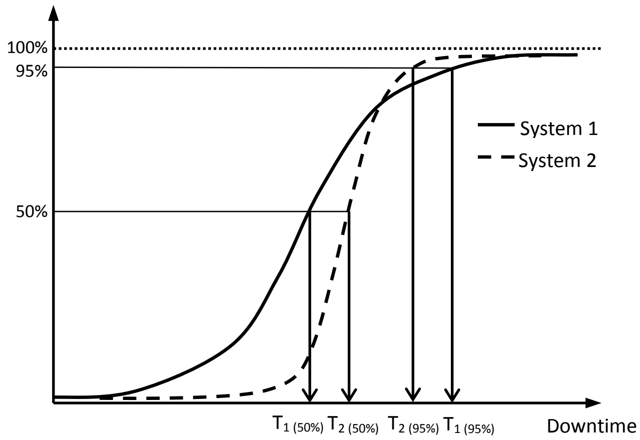

Figure 1: CPF of the expected downtime with two different IVHM systems. System 2, which has a lower average downtime, is more reliable for a confidence level of 95%.

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.

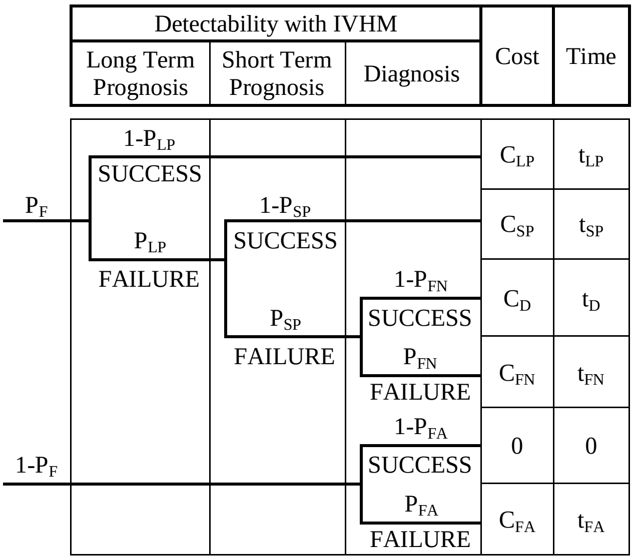

Figure 2: Event tree for the health monitoring of a single component and the possible outcomes of using different IVHM tools.

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.

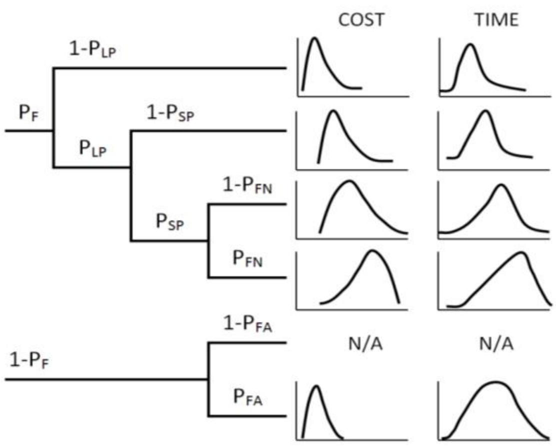

Figure 3: The result of implementing IVHM technology can be seen as combining the PDF of maintenance cost and time of different scenarios.

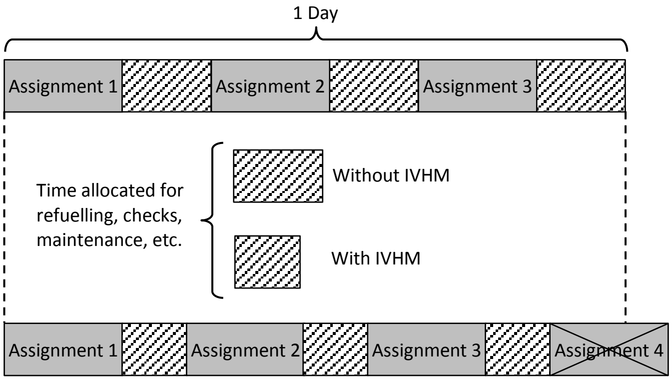

Figure 4: Example of how reducing the time allocated for maintenance can result in no operational gains if additional assignments cannot be scheduled.

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

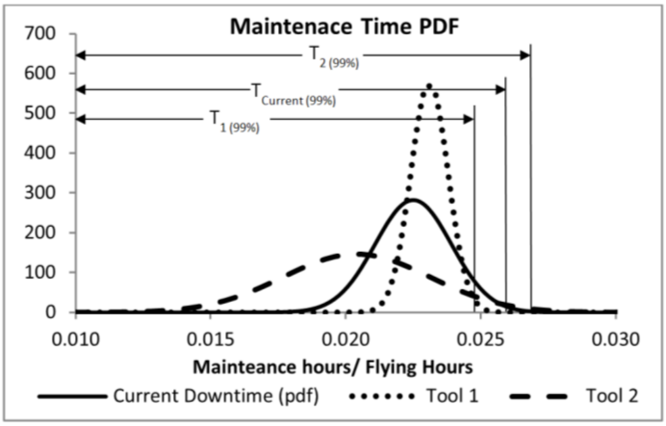

Figure 5: Comparison of maintenance time PDFs and their 99% confidence intervals.

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.

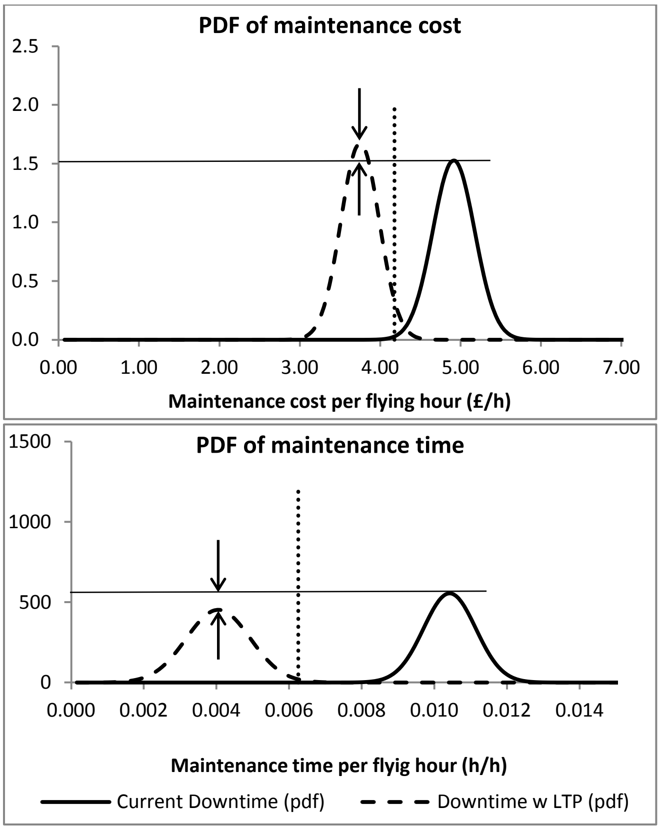

Figure 6: Improvement on a vehicle with BITE by installing a prognostic tool. Vertical lines indicate the required reduction in cost and downtime by 15% and 40% respectively.

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.

Acknowledgements

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Implementing IVHM on Legacy Aircraft: Progress towards identifying an Optimal Combination of Technologies

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Abstract The aim of Integrated Vehicle Health Management (IVHM) is to improve the management of maintenance operations through the implementation of health monitoring tools on key components either by diagnosing deterioration or by estimating Remaining Useful Life (RUL) so as to effect timely, and cost effective, maintenance. Regarding the use of IVHM technology in legacy aircraft, one has to keep in mind that hardware modifications to improve the reliability of components is not normally considered a viable alternative to diagnostic and prognostic tools due to high certification costs. At the same time, the data and expertise gathered over years of operating the aircraft help to estimate much more accurately how different health monitoring tools could impact maintenance activities. Consequently, selecting the optimal combination of health monitoring tools for legacy aircraft is significantly easier than for a new design. While computer simulations of the maintenance process are essential to determine how different IVHM tools generate value for the stakeholders, it is not practicable to simulate all possible combinations in order to select which tools are to be installed. This paper describes a process to reduce their number of toolsets to be simulated starting with the identification of those components that present a higher potential to reduce maintenance costs and times in case their faults could be detected and/or predicted. This is followed by the definition of the minimum required accuracy of diagnostic and prognostic tools for each component. This enables designers to determine which tools –available or still being developed– can be implemented to achieve the expected improvement in maintenance operations. Different combinations of IVHM tools are then subjected to a preliminary risk and cost-benefit analysis. A significantly reduced number of combinations are then simulated to select the optimal blend of technologies.

Keywords Cost-Benefit Analysis, Legacy Systems, Technology Selection, Maintenance Models, Risk Analysis

1 Introduction

Integrated Vehicle Health Management (IVHM) aims to maximise the use of an asset and reduce its through life maintenance cost through the implementation of health monitoring tools that generate information regarding the condition of multiple components. This information is generated by either diagnostic or prognostic tools. Diagnostic tools reduce the time necessary to detect and isolate a fault, and can be used to avoid human error in the identification of faulty components. Prognostic tools estimate the Remaining Useful Life (RUL) of the component which, at least, helps to avoid a failure during a flight, allowing for the mission to be completed

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successfully and avoiding any secondary damage. If an accurate prognosis can be generated with enough time in advance (a.k.a. prognostic window or lead time), the replacement of the component can be scheduled at a time and location that minimises -or avoids- any disruption in the operation of the vehicle.

The implementation of IVHM technology has traditionally followed a reactive approach according to which a health monitoring tool is developed individually and, once its performance has been tested, it is put into service. There are two explanations for this approach: on one hand diagnostic and prognostic algorithms and the hardware necessary to implement them are normally developed independently by teams with expertise in the component/system being monitored; on the other hand, organizations lack a high level IVHM policy or program that requires a comprehensive analysis of the optimal combinations of tools to be developed and implemented. Consequently, aircraft end up with an eclectic set of IVHM tools that improve the maintainability of each part, but may have a negligible effect on the availability of the fleet.

However, it must be noted that the lack of a systems approach to IVHM implementation is not caused by lack of competence or vision. The use of several tools on a given aircraft results in interactions that must be carefully studied to ensure objectives are reached and their performance not undermined by overseeing critical interdependencies. From a maintenance perspective it is essential that the selection of components to be monitored takes into account their failure/replacement frequency, replacement time, delays and how IVHM can affect them. Given the complexity of maintenance operations this problem must be studied using computer-based simulations. From an implementation perspective, the interactions between tools can result in unforseen problems with the hardware and/or the software. Thus, implementing and IVHM system that comprises diagnostic and prognostic tools that monitor several component becomes an engineering project that requires a significant investment and involves a great uncertainty.

Some methodologies to approach this problem do exist, but they normally focus on individual parts or a limited number of components or subsystems. It has been proposed to use Failure Modes, Effects and Criticality Analysis (FMECA) as the main basis for the design of full IVHM systems [1-3]. However, these methodologies, while applicable to a limited number of components, are not suitable for the analysis of a complete aircraft since it would be impractical to carry out a FMECA for each individual part, not to mention the analysis of all possible interactions between components and between their potential monitoring tools. As it is explained in the following sections, in the case of legacy aircraft, their unique combination of abundant historical maintenance data and constraints that rule out significant modifications of their systems, allow for a series of quantitative analyses leading to an optimal combination of diagnostic and prognostic tools.

Although IVHM can include the use of tools to improve the management of logistics, maintenance and operations, this paper discusses a methodology to select the optimal combination of diagnostic and prognostic tools by performing different quantitative analyses before defining the final set of tools based on the results obtained from a computer-based simulation of maintenance activities. Consequently, in this text the use of the terms “health monitoring tools” or simply “tools” makes reference to diagnostic or prognostic tools.

2 IVHM and legacy systems

Retrofitting IVHM into legacy platforms presents a very specific set of challenges that must be acknowledged from the beginning. While some of these issues affect all kinds of aircraft, they are more acute for aircraft that have been operated for years but are no longer being manufactured. A short list and discussion are presented bellow to show the breadth and depth of these issues.

Technical constraints: Geometric and weight constraints can result in the need to make changes to the structure or other components to accommodate new sensors, wires, electronics, etc. However, the cost of certifying the new tools and any changes required can exceed that of the design, manufacturing and installation of the necessary hardware. The need to ground the aircraft to install and test any new IVHM tool can disrupt normal operations and result in a loss of revenue, making these modifications even more difficult to justify. Software faces similar challenges given the critical role it plays nowadays both on-board and off-board [4]. The cost of certifying major hardware modifications and the uncertainty of potential benefits undermine the implementation of IVHM technology on legacy aircraft [5]. Consequently, for health monitoring tools to be implemented they must require very small or no modifications of existing systems.

Role of organizations: The implementation of IVHM has a significant impact on each stakeholder’s organization and vice versa. Aircraft will have to remain grounded for a significant amount of time resulting in significant disruptions in normal operations [4]. Moreover, in order to maximise the benefit of this technology maintenance practices have to change to be able to act based on the information provided by the new health monitoring system. Cultural barriers such as lack of understanding of the real benefits of IVHM and insufficient management support can jeopardize its development and put in service [6, 7].

Regulations and standards: Maintenance organizations normally have some Condition-Based Maintenance (CBM) policies already in place. Depending on the aircraft, the organization it belongs to and its area of operation some of these procedures can be regulated and made compulsory. As a consequence, a prognostic tool that monitors a component for which CBM is compulsory is not likely to be justifiable from an economic stand point since the investment will not be translated into a significant saving [8]. Therefore, special attention must be paid to maintenance regulations and standards.

Historical Maintenance Data: What sets legacy aircraft apart is the amount of information regarding the reliability of their components, operational environment, maintenance processes and failure modes. While new aircraft rely on estimates based on their design characteristics or a few tests, legacy aircraft present much more comprehensive datasets with information gathered in real operational conditions. As a result, not only is there more information available, but also it is much more accurate.

Although there is a lot of information recorded in maintenance and mission logs it can be difficult to transform it into useful data for the development of an IVHM system. Analysing records kept in handwritten documents or early databases can become an arduous task. Nevertheless, this still represents a significant advantage over new aircraft and, as will be discussed in the following sections, proves crucial in the selection of the optimal combination of health monitoring tools to be retrofitted on a given aircraft.

2.1 Identifying the role of stakeholders

Given the complexity of the aviation industry nowadays, the role of different stakeholders must be identified from a very early stage. Whereas in the past the owner, operator and maintainer of a fleet were the same entity, outsourcing and leasing have generated all sort of different sources of revenue, but also makes it difficult to pinpoint who should pay for the development of IVHM technology. Furthermore, health monitoring technology can underpin the transformation of manufacturers to service providers, meaning any CBA for IVHM must take into account the effect it can have on current and future contracts as well as the company's mid and long-term strategy [9]. Wheeler *et al.* [10] identified the goals for different stakeholders according to their responsibilities: logistics, mission operation, maintenance and fleet management. These goals are then divided into those which can be achieved using diagnostic tools and those which need the use of prognostic tools.

2.2 Framing the problem

The fact that major modifications of a legacy aircraft's systems are too expensive represents an advantage compared to new aircraft for which this is a viable option. For legacy aircraft, the business case for an IVHM system to monitor a certain group of components is very easy to justify when faced with the option of modifying such components to improve their reliability and maintainability to a level that results in the same improvement in cost and availability. Consequently, these limitations can be seen as the constraints for a mathematical problem in which major changes in an aircraft's systems are no longer an option. As a result, it can be assumed that the performance of the aircraft is not going to be affected, nor will its interdependencies between systems.

Computer simulation of aircraft maintenance systems can be used to study how health monitoring technology affect maintenance activities and, consequently, maintenance cost and availability at aircraft and fleet level. Unlike aircraft that are being designed or have only been operated for a short period, legacy aircraft can rely on historical maintenance data to provide all the information necessary for the development of these models.

In summary, the use of historical maintenance data in combinations with the constraints just mentioned helps to formulate accurate CBAs for IVHM systems for legacy aircraft.

3 Quantifying the benefits of IVHM

IVHM affects both maintenance costs and times. Consequently, the availability of an aircraft -and the squadron and fleet to which it belongs- will depend on the tools that form such an IVHM system. Not only does health monitoring reduce the time necessary to replace a component by performing faster diagnoses or avoiding secondary failures, but it can also affect the timing of, and location for, maintenance actions. Taking into account that several tasks are performed simultaneously during both scheduled and unscheduled maintenance stops, it is not possible to calculate analytically the duration of each stop. Furthermore, delays play a major role in maintenance and can be due to different logistic, administrative or technical causes. The fact that maintainers organise maintenance tasks depending on operational demands and the minimum equipment lists for future missions only increases the complexity of the problem. It is only through the use of computer-based simulations of maintenance activities that these complexities can be captured and the effect of IVHM technology estimated quantitatively.

The development and validation of these models requires significant amounts of data. To ensure the benefits of implementing IVHM are estimated correctly these datasets must include, not only the average of variables such as Mean Time Between Failures (MTBF) or Mean Time To Replace (MTTR), but also their variances.

Evidently, the model must take into account the effect any potential diagnostic or prognostic tool can have on maintenance costs and times as well as availability. In order to do so it is essential to acknowledge that health monitoring tools are not 100% accurate. Diagnostic tools can produce false positives (a.k.a. false alarms) by indicating a healthy component has failed, or false negatives if a faulty component is not detected. Similarly, prognostic tools estimate the RUL of a component at certain point in time and its replacement is scheduled according to that estimate, but if the estimation is too optimistic it might have to be replaced at a less convenient time and location or even fail during a flight. Being able to simulate the performance of health monitoring tools is essential to compare tools with lower cost and performance with more reliable and expensive ones.

3.1 Reducing the number of runs

Ideally, once the maintenance model has been developed and validated, different combinations of diagnostic and prognostic tools can be tested on it. However, while the computer model is the only way to carry out a solid CBA, it is not practical –or even possible– to simulate the effect of all potential combinations. Taking into account that aircraft comprise thousands of components, a comprehensive analysis of all options should consider, at least, a few dozen components to be monitored, even if the final number of tools to be implemented may be lower. For example, if 10 tools are to be chosen out of 50 possible options, this represents more than 10 billion possible combinations. Even taking into account incompatibilities between tools due to conflicts caused by their hardware or software, it is unlikely that the total number of toolsets is reduced significantly enough so all combinations can be studied and compared thoroughly.

Consequently, there is a need for a methodology to reduce the number of combinations of diagnostic and prognostic tools whose impact on maintenance cost and availability is to be studied using a computer simulation of aircraft maintenance activities. Such methodology must be based on a set of quantitative analyses to avoid any bias. Several combinations must be generated with this methodology to allow for sanity checks and to compare how they affect other factors apart from cost and availability. This methodology has been developed taking into account the constraints imposed on legacy aircraft, the availability and accuracy of historical maintenance data and the information that can be gathered at the conceptual design stage on the characteristics and performance of health monitoring tools. The main steps, which will be discussed in detail in the following sections, are:

1. Identify components more likely to have their maintenance time and cost reduced if monitored.
2. Select a preliminary list of health monitoring tools capable of detecting or predicting the failure of the components previously selected.
3. Identify incompatible combinations of tools due to software or hardware conflicts.
4. Preselect toolsets according to their expected Return On Investment (ROI) and financial risk.

3.2 Identifying critical components

The first step to reduce the number of simulations necessary for a comprehensive comparison of all the alternatives for an IVHM system involves identifying which components should be monitored. At this phase the number of components preselected is larger than the number of parts that will finally be monitored to allow for modifications in later stages. The objective is to identify which components are more likely to reduce maintenance time and cost if they are monitored by a diagnostic or a prognostic tool.

It is easy to evaluate what is the cost of replacing each component per flying hour as well as its corrective or preventive maintenance time per flying hour. Diagnostic tools essentially reduce the time dedicate to fault identification and isolation which will only affect labour costs. A prognostic tool affect the probability of a component having to be replaced at different locations (affecting logistic delays and shipping costs) and whether it will be an unscheduled task or part of a scheduled maintenance stop (with different costs and delays).

A method proposed in the past consists of analysing the possible outcomes of failure using Event Tree Analysis (ETA) [11] (Figure 1). Using the probability of a certain component failing as starting point, the tree forks based on the outcome of using a certain type of IVHM tool. A long-term prognostic tool can provide a RUL with a prognostic window long enough to schedule the replacement of the part so it will not affect the inherent availability of the aircraft. However, the estimated RUL can be incorrect. In that case there is the possibility to use a short-term prognostic algorithm and replace the part during an unscheduled stop, avoiding a possible mission loss or even secondary damages. Nevertheless, this recalculated RUL can also be overly optimistic, meaning the failure will take place and will need to be detected and isolated. If a diagnostic tool is fitted this can be performed automatically, but there is always the possibility of a false negative resulting in a longer time to diagnose the fault. The tree also includes the possibility of a healthy component being flagged as faulty by a diagnostic tool.

The order in which these tools appear in the tree does not reflect how health monitoring algorithms operate, it simply indicates in which order they will define the final outcome. Additionally, the fact that three kinds of tools are included in the tree does not imply that each component counts with all of them.

One of the advantages of this setup is that it accounts for the fact that some components can utilise some diagnostic capability in the form of Built-In Test Equipment (BITE) or be replaced according a preventive maintenance scheme, which, for the purpose of the ETA, has the same effect as a prognostic tool. Since it is possible to upgrade a health monitoring tool, there is no reason to exclude them from this analysis.

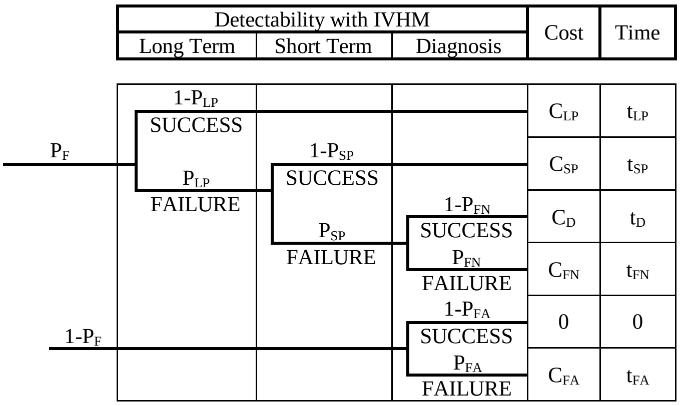


Figure 1: ETA for the use of health monitoring tools on a single component.

Analytical equations for the maintenance time, *T*, and costs, *C*, incurred per flying hour for each component are easy obtained based on this ETA [11]. Since they are polynomial expressions the derivatives can also be calculated analytically quite easily.

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

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

where the performance of long and short term prognostic tools is defined by P_{LP} and P_{SP}, respectively; and the probability of false alarms and false negatives by P_{FA} and P_{FN} respectively. If a long term prognostic tool works correctly the cost and time of replacing the components are C_{LP} and t_{LP} respectively, and C_{SP} and t_{SP} in case a short term prognostic tool is used. If the fault is detected by a diagnostic tool the cost and downtime will be C_D and t_D. For false alarms costs and downtimes are denoted by C_{FA} and t_{FA}, and by C_{FN} and t_{FN} for false negatives.

This ranking takes into account the maintenance time spent on individual components. As it has been discussed previously, there is not a direct correlation between the reduction of maintenance time of certain individual parts and the availability of the aircraft. However, components with longer maintenance times and higher sensitivities to the use of IVHM are more likely to have an important role in the improvement of the availability of the fleet. Once the components have been ranked the computer model can be used to verify which of those at the top of the list are responsible for most of the unscheduled maintenance stops and delays.

Identifying which components are the best candidates to be monitored by diagnostic and prognostic tools is useful, but it is not the kind of information that can be used to run computer simulations. The model uses the performance of health monitoring tools, meaning tools capable of assessing the condition of these top components have to found, as explained in the following section.

3.3 Performance requirements for a preliminary selection of health monitoring tools

Once key components have been identified it is necessary to find which tools can be used to monitor them. Original Equipment Manufacturers (OEMs), companies specialised in health monitoring technology and universities can be contacted to determine which tools are available or can be developed.

Even at such an early stage in the design of an IVHM system it is necessary to define basic technical and economic requirements to be able to compare different toolsets. Once again, the computer model is essential to define the minimum expected reductions in maintenance times and costs for each component to achieve the desired availability and total maintenance cost.

As shown in Eq. 1 and 2, it is possible to define the maintenance cost, and time of a component as a function of the performance of different health monitoring tools. If cost and time become a design requirement (C^* and T^* respectively) these equations can be used to define the required performance for a diagnostic (Eq. 3 to 6) or prognostic tools (Eq. 7 to 9).

Diagnostic Tools

$$P_{FA} \geq 0\ ;\ P_{FN} \geq 0 \quad (3;4)$$

$$P_{FA} \leq \frac{C^* - P_F\left[\left(1-P_{FN}\right)C_D + P_{FN}\,C_{FN}\right]}{(1-P_F)C_{FA}} \quad (5)$$

$$P_{FA} \leq \frac{T^* - P_F\left[\left(1-P_{FN}\right)t_D + P_{FN}\,t_{FN}\right]}{(1-P_F)t_{FA}} \quad (6)$$

Prognostic Tools

$$P_{LP} \geq 0 \quad (7)$$

$$P_{LP} \leq \frac{\dfrac{C^* - (1-P_F)P_{FA}C_{FA}}{P_F} - C_{LP}}{\left(1-P_{FN}\right)C_D + P_{FN}\,C_{FN} - C_{LP}} \quad (8)$$

$$P_{LP} \leq \frac{\dfrac{T^* - (1-P_F)P_{FA}t_{FA}}{P_F} - t_{LP}}{\left(1-P_{FN}\right)t_D + P_{FN}\,t_{FN} - t_{LP}} \quad (9)$$

The progress in health monitoring technology has not been homogeneous for all kind of systems and it is possible that for certain components diagnostic or prognostic tools that satisfy the performance requirements are not available yet. The possibility of developing a new tool, or improving on an existing one, should be studied at this stage. Conversely, it is also possible that for other components several candidates can be identified. Rather than select a single tool for each component by a process of elimination, all possible options should be considered. The following sections illustrates how the interactions between tools can be studied to identify which components should finally be monitored and by which tool.

3.4 Uncertainties and their effect on CBAs for IVHM

Most parameters in maintenance activities are normally random variables due to the fact that even repetitive tasks seldom take the same amount of time or require the same amount of attention and resources. It is possible to work with average values for some basic analyses, but if the objective is to ensure availability stays above a certain value and maintenance costs do not exceed a given limit working with average values results in a 50% chance of failing to reach the objectives.

The sources of uncertainty can be divided into two main categories. Epistemic, or systemic, uncertainties 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.

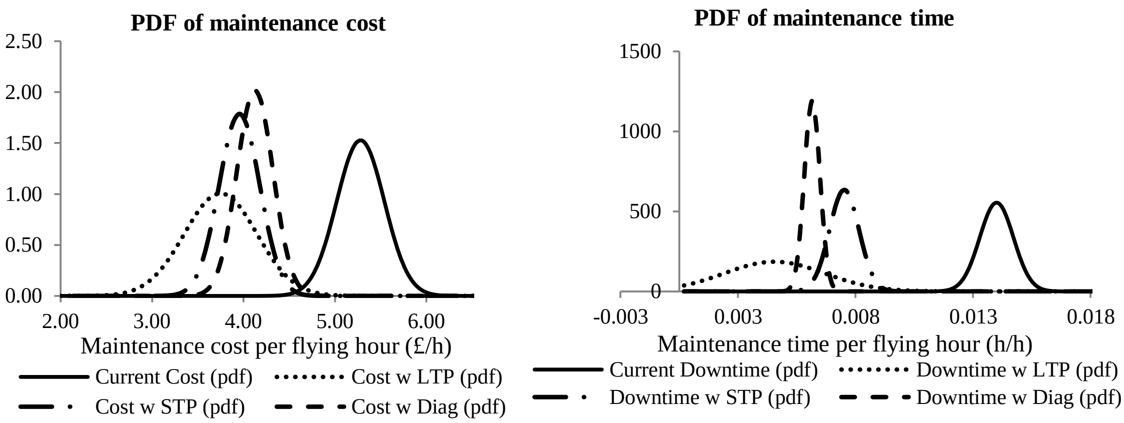
The second group comprises the sources of aleatoric, or statistical, uncertainties which are those caused by the random variation of parameters over time. Recurring costs, time spent on different activities, delays and the performance of health monitoring tools are the most prominent. While the amount 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 [12], 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. [13] 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.

As a result, engineers who define the performance requirements not only must acknowledge that expected maintenance costs and times follow probability distributions but also take into account that the variance of the performance of each tool must be below a certain threshold. This threshold can be defined using Eq. 1 and 2 as a basis to determine the variances of performance parameters:

$$Var(C) = Var(P_{FN}P_F\,(C_{FN} - C_D)) + Var(P_F\,C_D) + Var(P_{FA}(1 - P_F)C_{FA}) \quad (10)$$

$$Var(T) = Var(P_{FN}P_F\,(t_{FN} - t_D)) + Var(P_F\,t_D) + Var(P_{FA}(1 - P_F)t_{FA}) \quad (11)$$



a) b)

Figure 2: Examples of the effect of IVHM tools on the PDF of maintenance a) cost and b) time of a component.

Figure 2 shows the effect diagnostic tools, short term prognostic tools and long-term prognostic tools can have in the probability distributions of the maintenance cost and time per flying hour of a component.

It would seem as if these uncertainties add complexity to our problem increasing the difficulty of finding an optimal combination of diagnostic and prognostic tools. However, as explained in the following section, these uncertainties can be used to carry out a risk analysis of the different sets of tools and to reduce the number of combinations that should finally be studied using computer simulation.

3.5 Balancing ROI and risk

Comparing toolsets must take into account the possibility of sharing resources between tools in their design, testing, manufacturing, implementation and operation. In other words, tools can share -among others- sensors, memory, flight test expenses, recurring costs, etc. This translates to a reduction in the investment necessary to put a certain group of tools in service. Consequently, the ROI of each toolset is not the weighted average of the ROIs of those tools it comprises, but the ratio between the sum of their expected profits and the total cost of developing, implementing and operating the complete IVHM system. This profit is essentially based on the costs avoided thanks to the use of a certain health monitoring tool, but other benefits can be included. In mathematical terms, for a toolset with n tools in which the project budget for each tool has been divided into m phases or parts this can expressed as:

$$ROI = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} C_i} = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} \sum_{j}^{m} c_{ij} \quad \alpha_{ij}} \tag{12}$$

where P_i is the expected profit from tool *i*; C_i the total cost of tool *i*; c_{ij} the cost of tool *i* for part *j* of its budget; and α_{ij} the number of tools with which c_{ij} is shared.

However, sharing resources means that a deviation in their cost can effectively raise the cost of several tools. For example, if algorithms are processed in a centralised unit whose costs exceeds the original budget this will also impact the cost of each individual health monitoring tool. A federated IVHM system with algorithms run in individual processing units may be more expensive, but its total cost is less vulnerable to this kind of problems.

Comparing toolsets becomes even more complicated when options include tools that are under development and not fully proven. Mature diagnostic and prognostic tools are less likely to present problems and have significant cost variations, but their performance can be lower than tools that are still being developed and employ the latest technology. The cost of the latter, however, is more likely to deviate from the budget.

This resembles a classic financial investment problem in which investors must select the optimal combination of assets to maximise the return of their portfolio while keeping risk within reasonable limits. As in the problem described in this article, financial assets have some degree of correlation and this must be carefully studied to avoid situations in which an investor can be severely affected by fluctuations in the market (e.g.: stock prices of logistic companies are affected by the fluctuation of oil prices in commodity markets, gold prices and the U$D are normally inversely correlated, etc.).

There are all sorts of financial analysis tools that can be applied to solve this problem, but there is an important part of this financial analysis tools ignore: the variation of the ROI of each health monitoring tool depending on how it is combined with others. This is due to the fact that the return on a financial product is not affected by how much one invests in other assets.

Figure 3.a shows the result of using a tool known as the efficient portfolio frontier to analyse combinations of IVHM tools. As toolsets include larger numbers of diagnostic and prognostic tools the risk decreases because deviations in the cost of individual tools have a smaller impact on the total investment. However, the ROI tends to the average ROI of all possible options because the savings are not taken into account. Figure 3.b shows how the ROI can increase significantly if IVHM tools are combined appropriately taking into account Eq. 13.

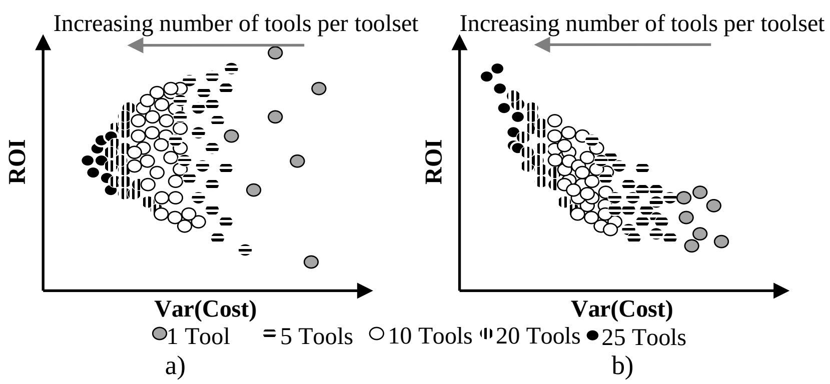


Figure 3: ROI vs. variance of cost for IVHM toolsets using financial analysis (a) and including shared costs (b)

Those toolsets that present a higher ROI and a lower variance of costs can be tested on the computer simulation. This will determine which combination of tools should be retrofitted on the aircraft and provide a much more accurate estimation of the final outcome.

4 Conclusions

The methodology presented in this paper illustrates how it is possible to carry out exhaustive quantitative analyses of the effect of retrofitting different IVHM toolsets on legacy aircraft without being overwhelmed by the number of options to compare. While computer simulations are essential to ensure CBAs for IVHM are accurate, they cannot be the only tool available to define the optimal combination of health monitoring tools.

Uncertainty plays a major role in the analysis and comparison of different toolsets. Design teams must be aware of the main sources or uncertainty and to what degree it affects the information generated at each stage of the process. Second order uncertainties or "uncertainty of uncertainties" is a major area of research IVHM developers cannot ignore. The trustworthiness of any CBA is directly affected by the variance of the variables it uses and to be able to define them a deep knowledge of aircraft design, maintenance and operations is required.

While financial analysis tools can be used to determine how risk changes depending on how diagnostic and prognostic tools are combined, they must be modified to take into account the effect potential savings have on the resulting ROI.

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Selection of Health Monitoring Tools Based on Sensitivity Analysis of Maintenance Parameters

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Abstract

The increasing demand for higher availability of both civil and military aircraft is driving the development of health monitoring tools capable of assessing their condition to help support teams to manage their activities more efficiently as part of Integrated Vehicle Health Management (IVHM) technology. The implementation of diagnostic and prognostic tools on an aircraft must be justified by estimating their impact on safety, maintenance costs and availability. For obvious technical and economic reasons, it is not possible to monitor all the components of a given aircraft. Therefore, it is necessary to identify which of them have a higher potential to improve the aspects just mentioned. This article presents a methodology to identify which components present a higher potential to reduce maintenance costs and times through the implementation of health monitoring tools. Equations for the maintenance cost and the estimated downtime related to each component or subsystem are obtained using an Event Tree Analysis (ETA). These are

used to derive analytical expressions to calculate the sensitivities of cost and downtime to the performance of the monitoring tools. These parameters can then be used to identify on which components or subsystems diagnostic or prognostic tools should be installed. A quantitative case study is included to illustrate the application of this method to identify the best candidates to be monitored by an IVHM system among 2300 components.

Keywords

Integrated Vehicle Health Management, Condition-Based Maintenance, health monitoring, cost-benefit analysis, maintenance costs, availability, sensitivity analysis

Nomenclature

ΔT	Total increase over scheduled downtime
$\Delta t_{,i}$	Increase over scheduled downtime for scenario i
Δt_{D}	Increase over scheduled downtime caused by successful operation of diagnostic tool
Δt_{FA}	Increase over scheduled downtime caused by false alarms tool
Δt_{FN}	Increase over scheduled downtime caused by false negatives of diagnostic tool
Δt_{SP}	Increase over scheduled downtime caused by successful operation of short-term prognostic tool
μ	Mean of a normal distribution
C	Total maintenance cost
$C_{C,i}$	Economic compensation for loss of availability for scenario i
C_{D}	Maintenance cost associated with successful operation of diagnostic tool
C_{FA}	Maintenance cost associated with false alarm of diagnostic tool
C_{FN}	Maintenance cost associated with false negative of diagnostic tool

$C_{L,i}$ Cost of labour for scenario i

$C_{LA,i}$ Loss of income due to loss of availability for scenario i

C_{LP} Maintenance Cost associated with successful operation of long-term prognostic tool

$C_{P,i}$ Cost of part for scenario i

$C_{R,i}$ Cost associated to RUL for scenario i

$C_{SF,i}$ Cost of secondary failure for scenario i

C_{SP} Maintenance cost associated with successful operation of short-term prognostic tool

$C_{T,i}$ Cost of test for scenario i

$f_{AV}(t)$ Probability density function of time available for maintenance between missions

k Shape parameter of a Weibull distribution

LRU Line Replaceable Unit

P_{AV} Probability of the maintenance activity exceeding the time available between missions

P_{CA} Probability of reducing availability because of a check of a false alarm

P_{DA} Probability of reducing availability because of a diagnosis

P_{max} Maximum probability of failure allowed on component removed before failure

P_F Probability of failure per flying hour

P_{FA} Probability of false alarm

P_{FN} Probability of false negative

P_i Probability of scenario i regardless of the performance of the health monitoring tools

P_{LP} Probability of failure of long-term prognostic tool

P_{MA} Probability of aborting the missions due to erroneous indication of failure

P_{MF}	Probability of losing the mission due to failure of the component
P_{RA}	Probability of reducing availability because of a repair
P_{RC}	Probability the capability of the aircraft being reduced
P_{RDA}	Probability of reducing availability because of diagnosis and repair
P_{SP}	Probability of failure of short-term prognostic tool
P_{VL}	Probability of vehicle loss due to failure of the component
RUL	Remaining Useful Life
t_{bm}	Average time available between missions
$t_{D,i}$	Time wasted on delays for scenario i
t_{exp}	Expected value of time available between missions for scenarios with expected loss of availability
t_f	Mean Time Between Failures of the component
t_m	Maintenance time
t_{max}	Life of the component corresponding to the maximum allowed probability of failure
t_r	Mean Time Between Replacements of the component
$t_{R,i}$	Time necessary to detect and repair a fault for scenario i
t_{sm}	Average time between scheduled maintenance activities in which the component can be replaced
$W_{L,i}$	Warranty on labour for scenario i
$W_{P,i}$	Warranty on part for scenario i
λ	Scale parameter of a Weibull distribution

σ standard deviation

1 INTRODUCTION

The development of health monitoring tools seen in the last decades has fuelled the imagination of many engineers who see the information these tools provide as the answer to their prayers on how to reduce maintenance costs and increase the availability of the aircraft. Services like Condition Based Maintenance (CBM) are underpinned by Integrated Vehicle Health Management (IVHM) which employs diagnostic and prognostic tools to determine the condition of some components and help to manage the workload and logistics more efficiently.

Diagnostic tools can detect and isolate faults faster than trained personnel, resulting in a reduction of the active maintenance time dedicated to the replacement of the components they monitor. Prognostic tools measure different parameters to assess the current condition of a component and then use algorithms to infer its Remaining Useful Life (RUL). Based on the prognostic window (a.k.a. lead time) provided by the algorithm and its accuracy maintainers can schedule the replacement of the part at the moment and location which have the lowest possible impact on normal operations.

Numerous factors affect the maintenance cost and time associated with each replaceable element of a vehicle and the values of many of the parameters that intervene in this calculation depend on the probabilities of different situations or events (e.g.: need to ship component to different locations, variations of the availability of personnel or auxiliary equipment over time, etc.) In this article a new methodology to estimate the maintenance costs and the increase of downtime caused by each component or subsystem is presented. The method uses Event Tree Analysis (ETA) to determine the different effects of a failure and the final values are obtained taking into account the likelihood of each outcome. By including diagnostic and prognostic tools in the analysis it is possible to estimate how the cost and the downtime would be affected by the implementation of a health monitoring tool and even their sensitivity to the performance of the monitoring system.

ETA has been used to quantify the requirements for IVHM tools applied to aerospace platforms [1] and to analyse the operational consequences of a failure [2]. The method described here represents a step further, obtaining mathematical expressions to calculate the cost of maintenance and increase of downtime per part and their sensitivity to the implementation of diagnostic and prognostic tools. Saxena et al. [3] presented a comprehensive list of parameters to analyse the cost-benefit of prognostic tools, but did not specify how some of them should be calculated or include parameters for diagnostic tools. Banks et al. [4] described the key drivers to determine on which assets prognostic tools should be installed, but did not develop a complete methodology to calculate costs or the effect on downtimes. Kurien et al. [5] described how to estimate the net value of implementing model-based diagnosis considering the costs of operational outcomes. Leão et al. [6] proposed a set of equation to calculate the costs and benefits of implementing Prognostics and Health Management (PHM). The method presented in this article goes further and takes into account the possibility of using different health monitoring tools simultaneously and provides analytical expressions to calculate the sensitivity of the results to the performance of these tools. This information can be used to help to select which components will be monitored

The versatility of this method means that it can be applied with fixed values to all parameters or Monte Carlo analyses can be run if there is enough data available to define probability distributions for some parameters. Another aspect the reader must keep in mind is that the same equations can be applied to components, modules, Line Replaceable Units (LRUs) or subsystems, depending on the level of detail desired. In the rest of the document the terms “component” or “part” will be used to refer to all the previous for simplicity. Similarly, while IVHM can include the use of tools to make decision regarding the management of maintenance activities or logistics based on the condition of the aircraft, in this text terms such as “health monitoring tools”, or simply “tools”, make reference to diagnostic and prognostic tools.

2 DESCRIPTION OF THE METHOD

2.1 EVENT TREE

The diagram shown in Figure 1 illustrates how the use of different health monitoring tools can lead to outcomes with different maintenance costs and times. The ETA starts with two initial events which correspond to the two possible states of the component: faulty or healthy. The first case is given a probability per flying hour, P_F, and the second, evidently, $1-P_F$. It is important to take into account that this analysis can be carried out for components that have failed completely or which have degraded to their replacement point. The only requisite is that, as a consequence of the change in the state of the part, a maintenance action has to be undertaken and/or the availability of the vehicle is affected.

Health monitoring tools have been divided into three different categories according to the information they can produce: long term prognosis, short term prognosis and diagnosis. The first group is capable of predicting the failure of the components with enough anticipation to have it replaced or repaired during the next scheduled maintenance operation. The second group can only make predictions that avoid running the part until it fails, but still require an unscheduled maintenance operation. The third group includes those tools that help maintenance personnel either to identify the component responsible for a malfunction whose origin is not obvious, or to flag a failure that would otherwise be unnoticed.

In the ETA a prognostic tool is considered to perform unsuccessfully if the component it monitors fails before the predicted period. The probability of this scenario depends on the accuracy of the predicted reliability curve and the instant chosen to repair, or replace, the part. In the case of diagnostic tools, they can fail to perform as expected in two different ways: producing false negatives or false positives. The probabilities of these outcomes depend on the accuracy of the tool.

The order in which these tools produce a new pair of outcomes does not reflect the way prognosis and diagnosis algorithms work, but how the performance of each tool affects maintenance costs and downtime. If a long term prognostic tool works properly and generates a correct prognosis, there is no need to use another health monitoring tool. However, if the prediction is erroneous, or no long term prognostic tool is being used, the information provided by a short term prognostic tool becomes relevant. In a similar way, diagnostic tools are only used when either the prognoses have been mistaken and the component has failed anyway, or prognostic tools are not being used. The lack of a prognostic tool can be reflected in the ETA by giving it a 100% probability of failure. In case no diagnostic tool is being used, its probability of triggering a false alarm (indication of a non-existing failure) would be 0% and the probability of giving a false negative (failure to detect a fault) would be 100%.

The branches of the different outcomes of using health monitoring tools are then divided according to operational aspects. If the component fails during a flight it can make the vehicle uncontrollable and impossible to land on a safe location. If the failure is not critical, it still can be serious enough to force the pilot to abort the mission. In case none of the two previous outcomes occur, the performance of the vehicle can still be affected while still allowing it to complete its mission (e.g., a clogged fuel pipe could reduce the power of an engine limiting the speed of the airplane and still allow the flight to reach its destination).

These options are also given probabilities on the ETA which in many cases will be either 0% or 100% (e.g., the failure of the engines will always be critical). However, the component might not be used on every flight (e.g., external fuel tanks) or its criticality might depend on the mission (e.g., weapons systems are only relevant for combat and some training exercises). Additionally, the probability of aborting a mission or having the performance of the aircraft affected depends on the information provided by the health monitoring system to the pilot and to what extent it is possible to perceive the malfunction during the flight without the help of electronic aids. This problem is analysed in the following scenarios:

- If the failure of the component is key for the success of the mission, the pilot should notice the problem whether the diagnostic tool informs of the failure or not. Therefore, the probability of losing the mission would be the same with a correct diagnosis or a false negative. However, if a false alarm is reported to the pilot the mission would be aborted while if it the diagnostic tool does not communicate with the instruments the mission would continue.
- If the failure of the components means a limitation in the capability of the aircraft, again the probability would be the same after a correct diagnosis or a false negative since the pilot would notice the problem. This changes when a false alarm is triggered, because this information could be used by an Active Fault Tolerant Control System (AFTCS) which would modify the response of the vehicle, or it could misinform the pilot who could start flying the aircraft bellow its capability. If the false alarm is not reported then the aircraft will be flown as normal.

The failure of a component that has no consequence on the completion of a mission or the performance of the aircraft is assumed to be deferred until the component can be replaced with no disruption to normal operations. In that case, the effect on the availability depends on the time required to detect the fault (in case the diagnostic tool gives a false negative) or the time necessary to confirm the part is healthy (in case of a false positive).

Twenty two different outcomes are possible as a result of including all this aspects into the ETA, each of them with an overall operational impact. This impact can be one, or a combination, of the following:

- Catastrophic
- Mission loss
- Capability reduced
- Availability reduced
- No operational impact

2.2 COSTS AND INCREASE OF DOWNTIME

For each case it is possible to calculate the maintenance cost and the downtime. In order to do so, they are divided into parameters that are easy to calculate and that simply have to be added up to determine the economic and managerial impact of each scenario.

To calculate the cost associated with each case it is necessary to calculate both the expenditure and the income (from warranties) of each scenario. The example shown in Figure 2 includes all possible factors to be taken into account, although in some of them might not be relevant for some components. Maintenance cost can be calculated as the sum of the cost of the part, C_P including acquisition, shipping and storage; cost of labour, C_L, which is affected by the time necessary to diagnose and repair each fault; cost of test, C_T:, which accounts mainly for expensive tests such as flight tests; cost of RUL, C_R, or the remaining value of components replaced before they have failed; cost of secondary failure, C_{SF}, in case other components are damaged as a consequence of the original fault; loss of income, C_{LI}, due to the aircraft being grounded; and finally the compensations, C_C, in case the maintainer is expected to pay penalties if availability expectations are not met.

Additionally, the failure of the part can be covered by a warranty which might include the cost of the component, W_P, and the labour, W_L. These warranties would be executed in case the component failed before the period specified according to a preventive maintenance plan.

One of the aims of IVHM technology is to increase the availability of the vehicle; therefore for aircraft that are normally flown several times per day and with very short turn round times, the main factor to focus on is the difference between the time necessary to replace the component and the average time available for maintenance between flights. However, for those aircraft which remain on the ground for hours between flights availability cannot be determined analytically since some maintenance tasks could be carried out simultaneously. In this case it is best to focus on the corrective maintenance time of each part.

In the calculations regarding maintenance times one must include not only the time necessary to remove the faulty component and install a new one, but also the administrative and logistic delays. The CBA can involve diagnostic tools capable of detecting faults while the aircraft is still flying and report them the maintainer which would reduce the effect of any delays. Assuming failures can happen at any moment, the average reduction of these delays would be half of the average duration of a flight. It is important to take this possibility into account since this feature, already available in some commercial airplanes, has such an impact on the availability of the platform that retrofitting it to legacy aircraft is being considered despite the challenges it presents [8].

The time available for maintenance between missions can change significantly and can be approximated by a probability density function, $f_{AV}(t)$, with an average time available between missions, t_{bm} (Figure 3). This curve is defined by the operator since it is directly related to mission planning. The odds of affecting the availability can be obtained using this function. It should be noted that the time available for maintenance is shorter than the total time between flights due to factors such as taxing, loading/unloading cargo and passengers, pre-flight checking, etc.

The effect on availability is represented in the ETA as two different cases:

- The availability of the platform <u>is</u> affected. The probability of this case, P_{AV}, is calculated using Eq. (1).
- The availability of the platform <u>is not</u> affected. The probability of this case is complementary to the previous.

Since P_{AV} has different values in different scenarios it is indicated in the ETA as P_{RA}, P_{RDA}, P_{DA} and P_{CA}, all of which can be calculated using Eq. (1).

$$P_{AV} = P(t \geq t_m) = 1 - \int_0^{t_m} f_{AV}(t)dt \qquad (1)$$

where t_m is the total time necessary to complete the maintenance task.

If the inherent availability is affected, it is necessary to calculate the average increase of downtime, Δt. This is given by the difference between the maintenance time and the average time available. However, in these scenarios, the time available for maintenance must be between 0 and t_m (a higher value would mean the availability is not compromised), which means that the new expected value will be lower than the average time available between missions calculated for the previous time range, t_{bm}. Therefore, the increase of downtime can be calculated as the difference between the repair time and the expected value of the probability distribution of the available time for maintenance for the new time range, t_{exp}.

$$\Delta t = t_m - t_{exp} = t_m - E(f_{AV}(t)) = t_m - \int_0^{t_m} t f_{AV}(t)dt \quad (2)$$

3 SIMPLIFIED EVENT TREE, EQUATIONS AND SENSITIVITIES

While the effect a failure has on a flight and the performance of the aircraft must be taken into account, the objective is to analyse the effect of IVHM tools on maintenance costs and times. Focusing only on the performance of the health monitoring tools, the ETA can be compressed and the 22 original scenarios can be grouped into 6 branches, each of which is associated to a cost and an increase of downtime (Figure 4). The values of the cost and increase of downtime corresponding to each branch of the simplified ETA are calculated using the following expressions:

$$C_{k,m} = \sum_{i=k}^{m} P_i \left(C_{P,i} + C_{L,i} + C_{T,i} + C_{R,i} + C_{SF,i} + C_{LI,i} + C_{C,i} - W_{P,i} - W_{L,i}\right) \qquad (3)$$

$$\Delta t_{k,m} = \sum_{i=k}^{m} P_i \, \Delta t_i \qquad (4)$$

Where

for Long Term Prognostic Tools: $C_{LP} \rightarrow k = m = 1$

for Short Term Prognostic Tools: $C_{SP} \rightarrow k = 2,\ m = 2$

for Diagnostic Tools: $C_D \rightarrow k = 4, m = 9$

for False Negatives: $C_{FN} \rightarrow k = 10, m = 16$

for False Alarms: $C_{FA} \rightarrow k = 18, m = 22$

In this way it is possible to express the cost and the increase of downtime using polynomial expressions whose variables are the performance of the health monitoring tools (Eqs. (5) and (6)).

$$C = P_F\left((1-P_{LP})C_{LP} + P_{LP}\left((1-P_{SP})C_{SP} + P_{SP}\left((1-P_{FN})C_D + P_{FN}C_{FN}\right)\right)\right) + (1-P_F)P_{FA}C_{FA} \quad (5)$$

$$\Delta T = P_F P_{LP}\left((1-P_{SP})\Delta t_{SP} + P_{SP}\left((1-P_{FN})\Delta t_D + P_{FN}\Delta t_{FN}\right)\right) + (1-P_F)P_{FA}\Delta t_{FA} \quad (6)$$

These expressions can be derived to obtain their sensitivity to the performance of the tools, as shown in equations Eqs. (7) to (14):

$$\frac{dC}{dP_{LP}} = P_F\left((1-P_{LP})\frac{dC_{LP}}{dP_{LP}} - C_{LP} + \left((1-P_{SP})C_{SP} + P_{SP}\left((1-P_{FN})C_D + P_{FN}C_{FN}\right)\right)\right) \quad (7)$$

$$\frac{d\Delta T}{dP_{LP}} = P_F\left((1-P_{SP})\Delta t_{SP} + P_{SP}\left((1-P_{FN})\Delta t_D + P_{FN}\Delta t_{FN}\right)\right) \quad (8)$$

$$\frac{dC}{dP_{SP}} = P_F P_{LP}\left((1-P_{SP})\frac{dC_{SP}}{dP_{LP}} - C_{SP} + \left((1-P_{FN})C_D + P_{FN}C_{FN}\right)\right) \quad (9)$$

$$\frac{d\Delta T}{dP_{SP}} = P_F P_{LP}\left(\left((1-P_{FN})\Delta t_D + P_{FN}\Delta t_{FN}\right) - \Delta t_{SP}\right) \quad (10)$$

$$\frac{dC}{dP_{FN}} = P_F P_{LP} P_{SP}(C_{FN} - C_D) \quad (11)$$

$$\frac{d\Delta T}{dP_{FN}} = P_F P_{LP} P_{SP}(\Delta t_{FN} - \Delta t_D) \quad (12)$$

$$\frac{dC}{dP_{FA}} = (1-P_F)C_{FA} \quad (13)$$

$$\frac{dT}{dP_{FA}} = (1-P_F)\Delta t_{FA} \quad (14)$$

For prognostic tools there is a cost associated to the residual value of every component that is replaced before it reaches its point of failure. Essentially, components monitored with prognostic tools will be replaced more frequently than if they were run until they fail and a larger number of them will have to be purchased during the remaining life of the aircraft. This residual cost of the RUL of a component is related to the moment chosen to remove it from the vehicle, which also determines the probability of that part failing before that instant or, for the purpose of this analysis, the probability of failure of the prognostic tool. Therefore, in order to calculate the sensitivities it is necessary to calculate the derivative of the cost of the RUL to the probability of failure of the prognostic tool.

The cost of the RUL of the components is directly proportional to the difference between the average life of the parts when they fail, t_f, and their average life when they are removed, t_r (Figure 5). Since prognostic tools determine the moment the probability of failure of a part will reach the maximum level allowed, P_{max}, it must be replaced before this limit is reached. Therefore, the average RUL of the removed components must be shorter than the life corresponding to the limit of the probability of failure, t_{max}. Maintenance stops are scheduled with a determined periodicity, t_{sm}, thus the soonest a part can be replaced is $t_{max} – t_{sm}$ and the latest is t_{max}. Consequently, the average RUL can be calculated (Eq. (16) and the cost associated with it obtained (Eq. (17)).

$$t_r = t_{max} - \frac{t_{sm}}{2} \tag{15}$$

$$RUL = t_f - t_r = t_f - t_{max} + \frac{t_{sm}}{2} \tag{16}$$

$$C_R = C_P \frac{RUL}{t_f} = C_P \frac{t_f - t_{max} + \frac{t_{sm}}{2}}{t_f} = C_P \left(1 - \frac{t_{max} - \frac{t_{sm}}{2}}{t_f}\right) \tag{17}$$

$$\frac{dC_R}{dP} = \frac{d}{dP}\left(C_P \frac{RUL}{t_f}\right) = \frac{d}{dP}\left(C_P \frac{t_f - t}{t_f}\right) = C_P \frac{-\frac{dt}{dP}}{t_f} = -\frac{C_P}{t_f} \frac{1}{\frac{dP(t)}{dt}} \tag{18}$$

Degradation models employed by prognostic tools are not completely accurate and they provide a range of probability functions for the failure of the component. In this analysis the function represented in Figure 5 is assumed to have the same confidence level as the curve used by the maintenance team to choose the moment to remove the component.

The degradation of a component can be approximated to an explicit expression defined by the probability distribution which best matches the empirical data gathered. Mechanical components tend to fit a Weibull distribution and the failure of many electronic devices can be modelled using normal distributions. Therefore, the derivative of the cost of RUL can be calculated analytically since it is a function of time (Eq. (18)).

In case of a Weibull distribution:

$$P(x) = 1 - e^{-\left(\frac{x}{\lambda}\right)^k} \tag{19}$$

$$\frac{dP(t)}{dt} = \frac{d}{dt}\left(1 - e^{-\left(\frac{t}{\lambda}\right)^k}\right) = -e^{-\left(\frac{t}{\lambda}\right)^k}\left(-k\left(\frac{t}{\lambda}\right)^{k-1}\right)\frac{1}{\lambda} = \frac{kt^{k-1}}{\lambda^k}\frac{1}{e^{\left(\frac{t}{\lambda}\right)^k}} \tag{20}$$

$$\frac{dC_R}{dP} = -\frac{C_P}{t_f}\frac{\lambda^k e^{\left(\frac{t}{\lambda}\right)^k}}{kt^{k-1}} \tag{21}$$

By combining Eq. (21) with Eqs. (7) and (9) the final analytical expressions of the sensitivity of the cost using a Weibull distribution for the degradation of the component are:

$$\frac{dC}{dP_{LP}} = P_F\left((P_{LP} - 1)\frac{C_P}{t_f}\frac{\lambda^k e^{\left(\frac{t}{\lambda}\right)^k}}{kt^{k-1}} - C_{LP} + \left((1 - P_{SP})C_{SP} + P_{SP}\left((1-P_{FN})C_D + P_{FN}\,C_{FN}\right)\right)\right) \tag{22}$$

$$\frac{dC}{dP_{SP}} = P_F\,P_{LP}\left((P_{SP} - 1)\frac{C_P}{t_f}\frac{\lambda^k e^{\left(\frac{t}{\lambda}\right)^k}}{kt^{k-1}} - C_{SP} + \left((1-P_{FN})C_D + P_{FN}\,C_{FN}\right)\right) \tag{23}$$

In case the degradation of the component fit a normal distribution:

$$P(x) = \int_{-\infty}^{x}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}\,dt = \frac{1}{2}\left(1 + erf\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right) \tag{24}$$

$$\frac{dP(t)}{dt} = \frac{d}{dt}\left(\frac{1}{2}\left(1 + erf\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)\right)\right) = \frac{1}{\sqrt{2\sigma^2}}\frac{d}{dt}\left(erf\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)\right) \tag{25}$$

$$erf(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\,dt \rightarrow \frac{derf(x)}{dx} = \frac{2}{\sqrt{\pi}}e^{-x^2} \tag{26}$$

$$\frac{dP(t)}{dt} = \frac{1}{\sqrt{2\sigma^2}}\frac{2}{\sqrt{\pi}}e^{-\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} = \sqrt{\frac{2}{\pi\sigma^2}}e^{-\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} \quad (27)$$

$$\frac{dC_R}{dP} = -\frac{C_P}{t_f}\sqrt{\frac{\pi\sigma^2}{2}}e^{\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} \quad (28)$$

By combining Eq. (28) with Eqs. (7) and (9) the final analytical expressions of the sensitivity of the cost using a normal distribution for the degradation of the component are:

$$\frac{dC}{dP_{LP}} = P_F\left((P_{LP}-1)\frac{C_P}{t_f}\sqrt{\frac{\pi\sigma^2}{2}}e^{\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} - C_{LP} + \left((1-P_{SP})C_{SP} + P_{SP}\left((1-P_{FN})C_D + P_{FN}C_{FN}\right)\right)\right) \quad (29)$$

$$\frac{dC}{dP_{SP}} = P_F\,P_{LP}\left((P_{SP}-1)\frac{C_P}{t_f}\sqrt{\frac{\pi\sigma^2}{2}}e^{\left(\frac{t-t_f}{\sqrt{2\sigma^2}}\right)^2} - C_{SP} + \left((1-P_{FN})C_D + P_{FN}\,C_{FN}\right)\right) \quad (30)$$

These analytical expressions relate the sensitivity of the cost and downtime to the performance of health monitoring tools. If they are combined with Eqs. (7) and (9) it is possible to identify which components would benefit the most from installing IVHM tools and which kind of tools should implemented.

The inverse problem can be solved to determine the requirements for these tools during the early stages of the design phase. Furthermore, given that the performance of these tools is likely to suffer some degree of variability, calculating the sensitivity of costs and downtimes to

4 CASE STUDY

The following analysis focuses on 2300 components, 1335 of which degraded following a Weibull distribution and the failure of the remaining 965 was modelled using Gaussian probability distributions. The aim was to define two sets of approximately 100 components (according costs and availability criteria) to start the basic design of an IVHM system for the aircraft. The analysis does not account for effects of any Built In Test Equipment (BITE) or false positives and negatives that may occur during routine checks.

The cost of each component included shipping and storage costs and the cost associated with the value of the RUL of components removed before they fail ranged between 2% and 20% of the total cost of the part. This cost was only taken into account in scenarios 1 to 3, where prognostic tools are involved. Labour costs per hour were also different for unscheduled maintenance tasks because sometimes they are carried out during night shifts or require overtime, resulting in a higher average labour costs. To account for this phenomenon, labour cost per hour of unscheduled maintenance tasks were assumed to be 15% higher than the labour cost for prognostic tools. Finally, the costs of secondary failures, which affect 18 components, ranged from £580 to £24,579 and included parts and labour.

To estimate the effect of IVHM tools on the inherent availability of the vehicle we need to calculate the increase of downtime as shown in Eq. (2). To solve this equation the time available for maintenance between missions was modelled using an exponential distribution with an average of 3 hours. Each component was assigned an active maintenance time, a diagnostic time and an average delay. The latter was not taken into account with prognostic tools and the average diagnostic time only affected false negatives and false alarms (remember that components without any diagnostic capability are equivalent to using a diagnostic tool with 100% probability of false negative).

The analysis of the sensitivities of increases of downtimes showed how long term prognostic tools are more likely to produce a sharper decrease on a larger number of components (Figure 6). Not surprisingly, diagnostic tools, while still capable of improving aircraft availability, cannot produce the same results.

Shifting attention to the sensitivities of costs we find that prognostic tools can have two opposite effects (Figure 7). In most cases, replacing components before they fail instead of following a reactive maintenance approach results in a higher number of components being replaced over a given time period. Lower labour costs and not spending time diagnosing faults do not compensate for the additional cost associated with the RUL at replacement. Consequently, the sensitivity of maintenance costs to the implementation of prognostic tools is negative in most cases. Figure 7 shows how in some extreme cases in which the cost of the part is high and the prognostic window long, installing a prognostic tool could result in a steep rise in costs. This shows how this method, besides helping to identify the best candidates among all the components of the vehicle, can also help to avoid focusing on certain parts which would have seem good options given their high value.

However, preventive maintenance can result in significant savings when the failure of a part causes further damage. Avoiding secondary failures, lower average cost of labour and not spending time diagnosing faults mean that the sensitivity of the maintenance cost of some components to the implementation of prognostic tools can be positive. Thanks to this effect 49.52% of components would see their maintenance costs reduced if their degradation was monitored.

Components were ranked according to the sensitivity of downtimes to the performance of long term prognostic tools, short term prognostic tools and diagnostic tools. Another way of identifying critical parts to be monitored is by ranking them based on the sensitivity of their maintenance costs to the use of prognostic and diagnostic tools. The top 100 components with the highest sensitivities were included in independent lists which were later compared to remove those parts that appeared more than one time (Table 2). The sensitivities of maintenance costs with long and short term prognostic tools, are exactly the same due to the choice of parameters to calculate them (Figure 8). These results show that, while the majority of components selected for prognostic and diagnostic tools are the same, focusing on just one group of IVHM tools can leave 37% of critical components out of the analysis without any justification.

Table 1 - Number of tools unique to each ranking list corresponding to the different performance parameters of IVHM tools.

Sensitivity to	Ranking criteria	
	$d\Delta T$	dC
Long Term Prognostic tools (P_{LP})	100	100
Short Term Prognostic Tools (P_{SP})	24	0
Diagnostic Tools (P_{FN})	19	37
Total	143	137
False Alarms (P_{FA})	33	34
Total (final)	110	103

False alarms normally result in shorter downtimes and lower costs than any other possible scenario because it was assumed that false positives were detected and therefore healthy parts were not replaced. Provided the data is available, it is possible to define a component cost specific for false alarms which would be the average expense on new components and repairs undertaken. However, regardless of the values of costs and downtimes, the impact of false alarms in comparison to other scenarios is magnified by the fact that the initial condition, a healthy component, has a much higher probability (Figure 4). Consequently, the sensitivity to a variation of the probability of false alarms is much higher than for any other parameter, as shown in Figure 9.

The disproportionate sensitivity to false alarms provides little information for the selection of components. However, being able to identify which components are more sensitive to false positives is very useful from a risk management perspective. Since at this point the performance of the health monitoring tools that will be used is unknown designer must consider the possibility that the false alarm rate of a diagnostic tool can be increased by multiple factors (e.g.: low sensor accuracy, signal noise, etc.), which could result in higher maintenance costs and longer downtimes.

To avoid developing IVHM system to monitor components too sensitive to false alarms these components can be removed from the list of those preselected attending to the rankings of sensitivities to prognostics or diagnostic tools [see Table 2]. In doing so, we generate a list with components that present a higher potential to reach the desired reduction in maintenance costs and increase in availability, while avoiding those which could have the opposite effect if the performance of the diagnostic tool that monitored them was worse than originally planned. Additionally, with this risk-avoidance step we ended up with two lists which were close enough to our original objective of 100 components.

5 CONCLUSIONS

The use of a quantitative comparative approach to the selection of components to be monitored by either diagnostic or prognostic tools is essential to ensure the decision is based on objective information avoiding any personal bias. By focusing on maintenance costs and times and their sensitivities to the performance of health monitoring tools, the results of this methodology are useful to any stakeholder regardless of the maintenance scheme under which the aircraft operates. Depending on who (and how) is going to pay for this technology, focus will be placed on costs, times or both.

This method can be applied assuming there is no health monitoring capability, that the state of some components is already being monitored or even to compare the benefits of different tools would have on the maintenance cost and time of a certain component or LRU. The sensitivity analyses that can be performed with the analytical expressions proposed here not only help to determine on which components or subsystems it would be beneficial to install health monitoring capabilities, but also help to decide whether improving the performance of some of the tools already in place could be useful too.

Selecting components for the development of an IVHM system must take into account the current state of the technology. Designers are advised to revise the lists produced with this method to avoid wasting time on components whose degradation and failure mechanisms are likely to make any health monitoring tool useless.

Some of the variables of the formulas presented here do not have a fixed value in the real world and can be approximated using probability distributions (e.g., maintenance times or delays). Although it is possible to use their average value if there is not enough information for a more detailed analysis, it is important to acknowledge the consequences of these simplifications, especially with those parameters that have high standard deviations. Even if a Monte Carlo analysis is performed, taking into account the variability of these parameters, the distribution of the cost and increase of downtime of some parts are likely to overlap. Nevertheless, this still provides enough information to rank the components in order of potential impact on costs and availability and give a confidence level of the results.

Another important feature of these equations is that they can be used to determine the design specifications of new diagnostic and prognostic tools. If the cost reduction and the improvement of availability are used as design constraints it is possible to calculate the performance that these tools must achieve to comply with the requirements. Furthermore, the expressions shown in this article can be used to determine if the uncertainties regarding the performance of a given tool can result in significant variations in maintenance costs or times, in which case such tool should not be installed.

ACKNOWLEDGEMENTS

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6 VITAE

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List of captions

Table 2 - Number of tools unique to each ranking list corresponding to the different performance parameters of IVHM tools.

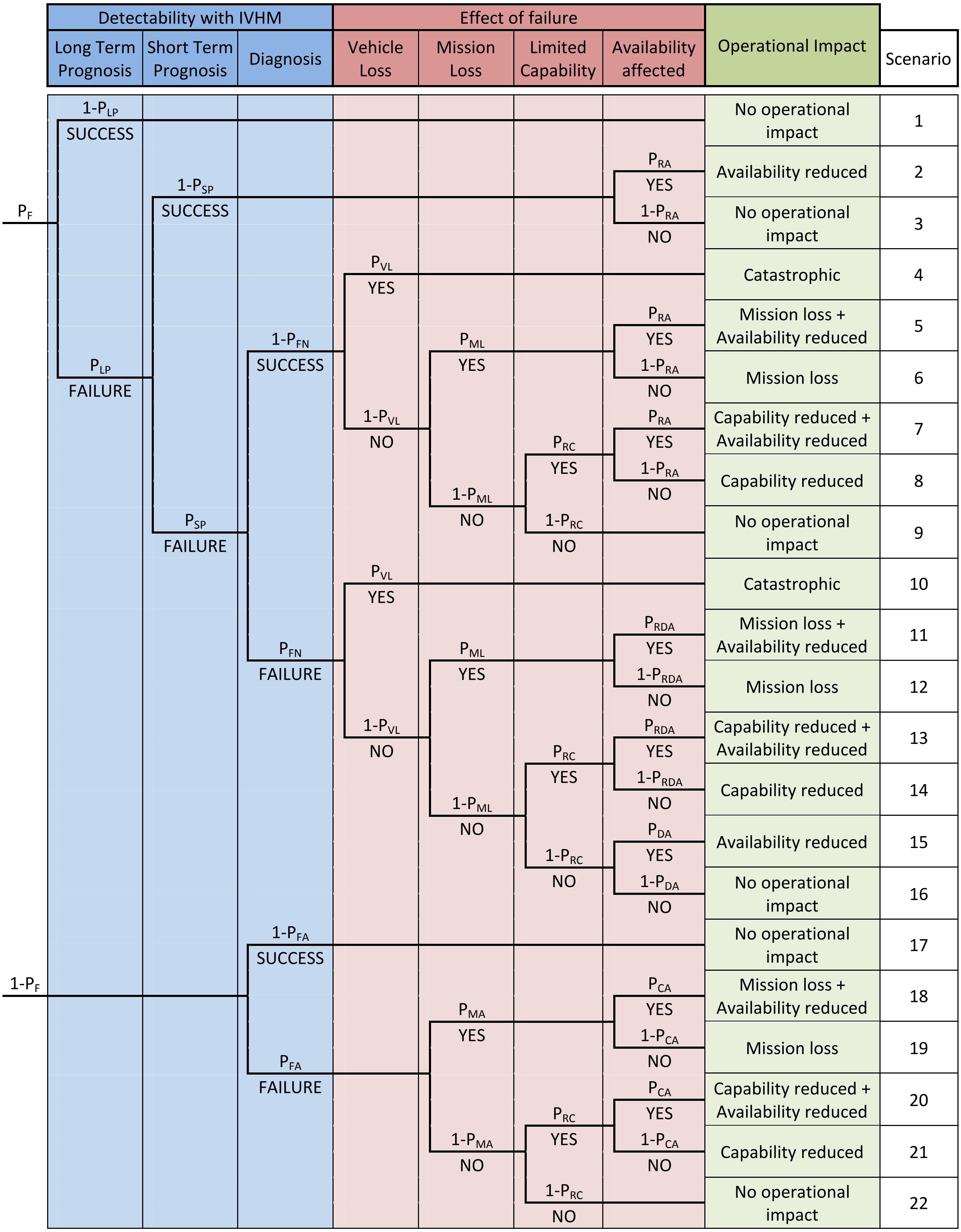

Figure 1.- Event Tree Analysis of Aircraft with Health Monitoring Capabilities.

	Cost							Warranty		Time		
Scenario	Parts, C_P	Labour, C_L	Test, C_T	RUL, C_R	Secondary failure, C_{SF}	Loss of income, C_{LI}	Compensation, C_C	Parts, W_P	Labour, W_L	Check and Repair time, t_R	Delays, t_D	Increase of Downtime, Δt
1	$C_{P,1}$	$C_{L,1}$	$C_{T,1}$	$C_{R,1}$	0	0	0	0	0	0	0	0
2	$C_{P,2}$	$C_{L,2}$	$C_{T,2}$	$C_{R,2}$	0	$C_{LI,2}$	0	0	0	$t_{R,2}$	$t_{D,2}$	Δt_2
3	$C_{P,3}$	$C_{L,3}$	$C_{T,3}$	$C_{R,3}$	0	0	0	0	0	0	0	0
4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
5	$C_{P,5}$	$C_{L,5}$	$C_{T,5}$	0	$C_{SF,5}$	$C_{LI,5}$	$C_{C,5}$	$W_{P,5}$	$W_{L,5}$	$t_{R,5}$	$t_{D,5}$	Δt_5
6	$C_{P,6}$	$C_{L,6}$	$C_{T,6}$	0	$C_{SF,6}$	0	$C_{C,6}$	$W_{P,6}$	$W_{L,6}$	0	0	0
7	$C_{P,7}$	$C_{L,7}$	$C_{T,7}$	0	$C_{SF,7}$	$C_{LI,7}$	$C_{C,7}$	$W_{P,7}$	$W_{L,7}$	$t_{R,7}$	$t_{D,7}$	Δt_7
8	$C_{P,8}$	$C_{L,8}$	$C_{T,8}$	0	$C_{SF,8}$	0	$C_{C,8}$	$W_{P,8}$	$W_{L,8}$	0	0	0
9	$C_{P,9}$	$C_{L,9}$	$C_{T,9}$	0	$C_{SF,9}$	0	0	$W_{P,9}$	$- W_{L,9}$	0	0	0
10	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
11	$C_{P,11}$	$C_{L,11}$	$C_{T,11}$	0	$C_{SF,11}$	$C_{LI,11}$	$C_{C,11}$	$W_{P,11}$	$W_{L,11}$	$t_{R,11}$	$t_{D,11}$	Δt_{11}
12	$C_{P,12}$	$C_{L,12}$	$C_{T,12}$	0	$C_{SF,12}$	0	$C_{C,12}$	$W_{P,12}$	$W_{L,12}$	0	0	0
13	$C_{P,13}$	$C_{L,13}$	$C_{T,13}$	0	$C_{SF,13}$	$C_{LI,13}$	$C_{C,13}$	$W_{P,13}$	$W_{L,13}$	$t_{R,13}$	$t_{D,13}$	Δt_{13}
14	$C_{P,14}$	$C_{L,14}$	$C_{T,14}$	0	$C_{SF,14}$	0	$C_{C,14}$	$W_{P,14}$	$W_{L,14}$	0	0	0
15	$C_{P,15}$	$C_{L,15}$	$C_{T,15}$	0	$C_{SF,15}$	$C_{LI,15}$	0	$W_{P,15}$	$W_{L,15}$	$t_{R,15}$	$t_{D,15}$	Δt
16	$C_{P,16}$	$C_{L,16}$	$C_{T,16}$	0	$C_{SF,16}$	0	0	$W_{P,16}$	$W_{L,16}$	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0
18	$C_{P,18}$	$C_{L,18}$	$C_{T,18}$	0	0	$C_{LI,18}$	$C_{C,18}$	$W_{P,18}$	$W_{L,18}$	$t_{R,18}$	$t_{D,18}$	Δt_{18}
19	$C_{P,19}$	$C_{L,19}$	$C_{T,19}$	0	0	0	$C_{C,19}$	$W_{P,19}$	$W_{L,19}$	0	0	0
20	$C_{P,20}$	$C_{L,20}$	$C_{T,20}$	0	0	$C_{LI,20}$	$C_{C,20}$	$W_{P,20}$	$W_{L,20}$	$t_{R,20}$	$t_{D,20}$	Δt_{20}
21	$C_{P,21}$	$C_{L,21}$	$C_{T,21}$	0	0	0	$C_{C,21}$	$W_{P,21}$	$W_{L,21}$	0	0	0
22	$C_{P,22}$	$C_{L,22}$	$C_{T,22}$	0	0	0	0	$W_{P,22}$	$W_{L,22}$	0	0	0

Figure 2.- Costs and increases of downtime for the scenarios obtained from the ETA.

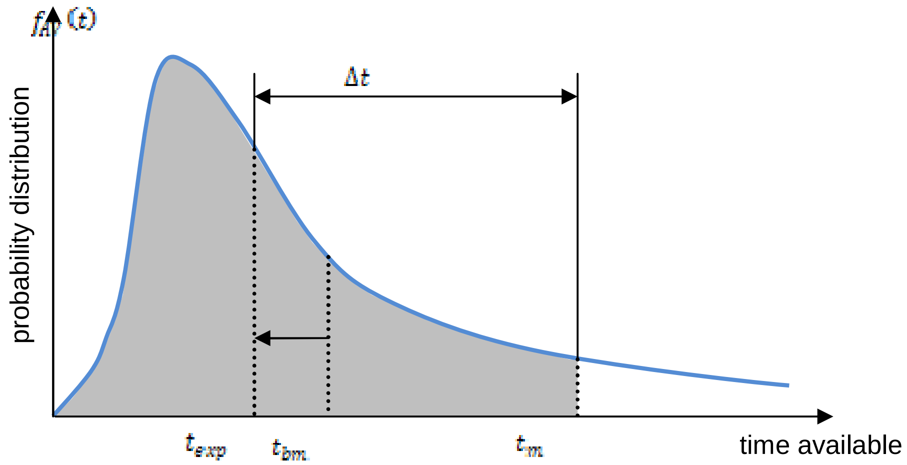

Figure 3.- Probability distribution of time available between missions for maintenance tasks.

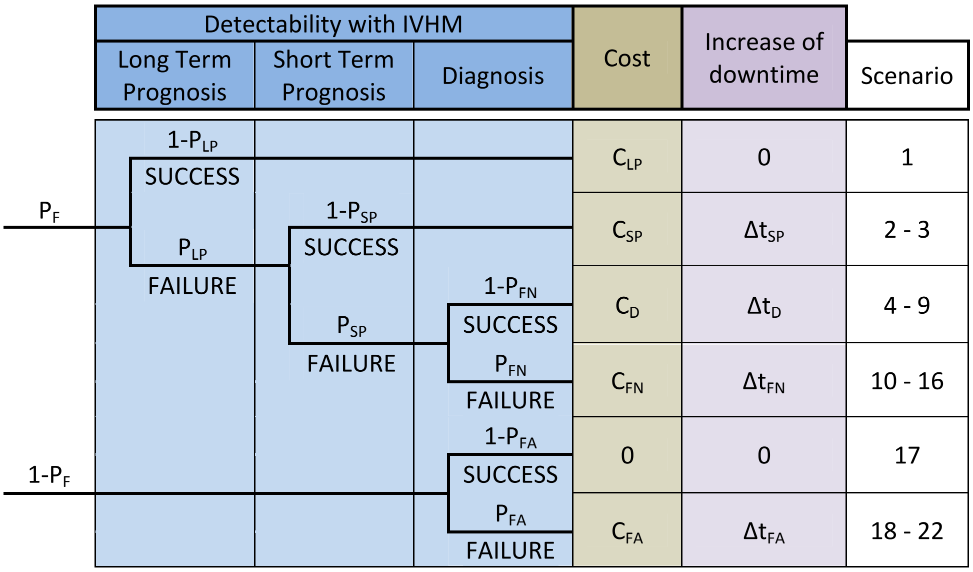

Figure 4.- Simplified ETA with branches for diagnostic and prognostic tools only.

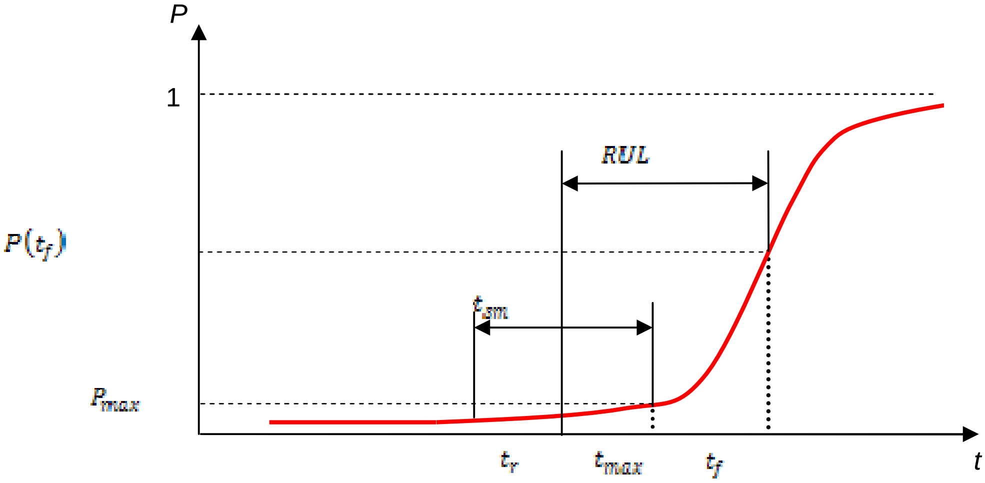

Figure 5.- Probability function of the failure of a component as a function of the time it has been operated.

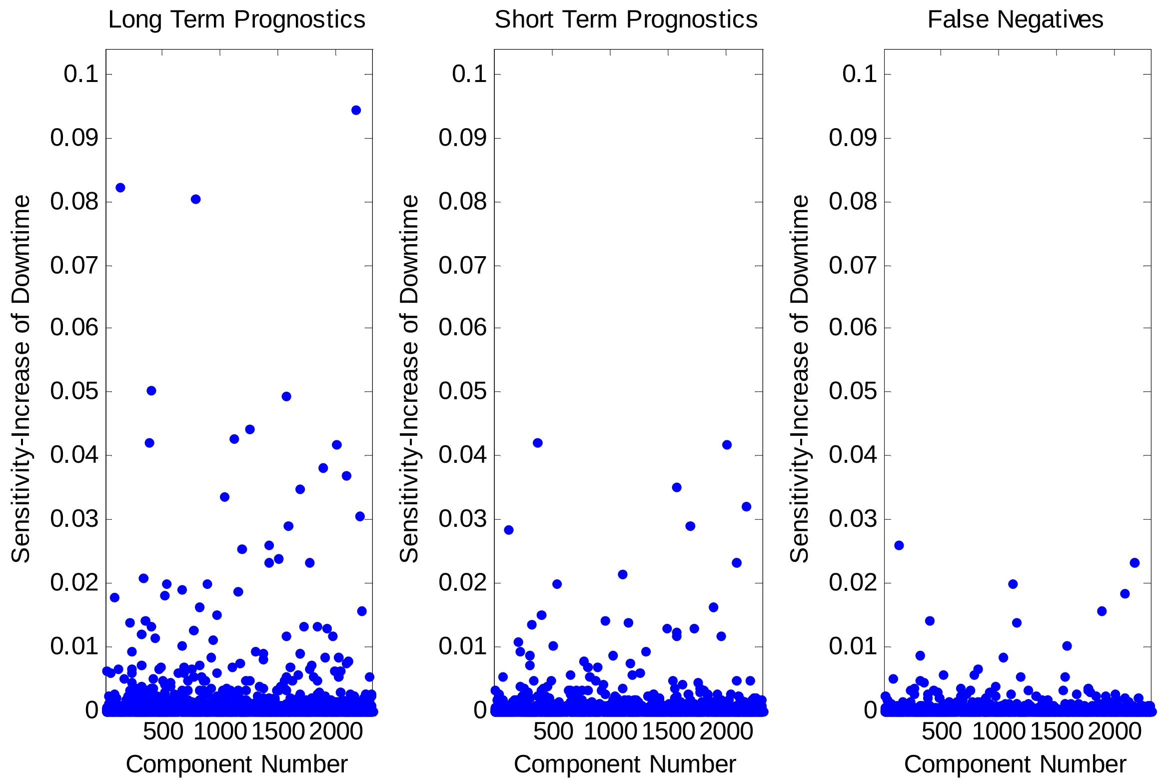

Figure 6.- Sensitivities of increases of downtime to the performance of long term prognostic tools (left), short term prognostic tools (centre) and diagnostic tools (right).

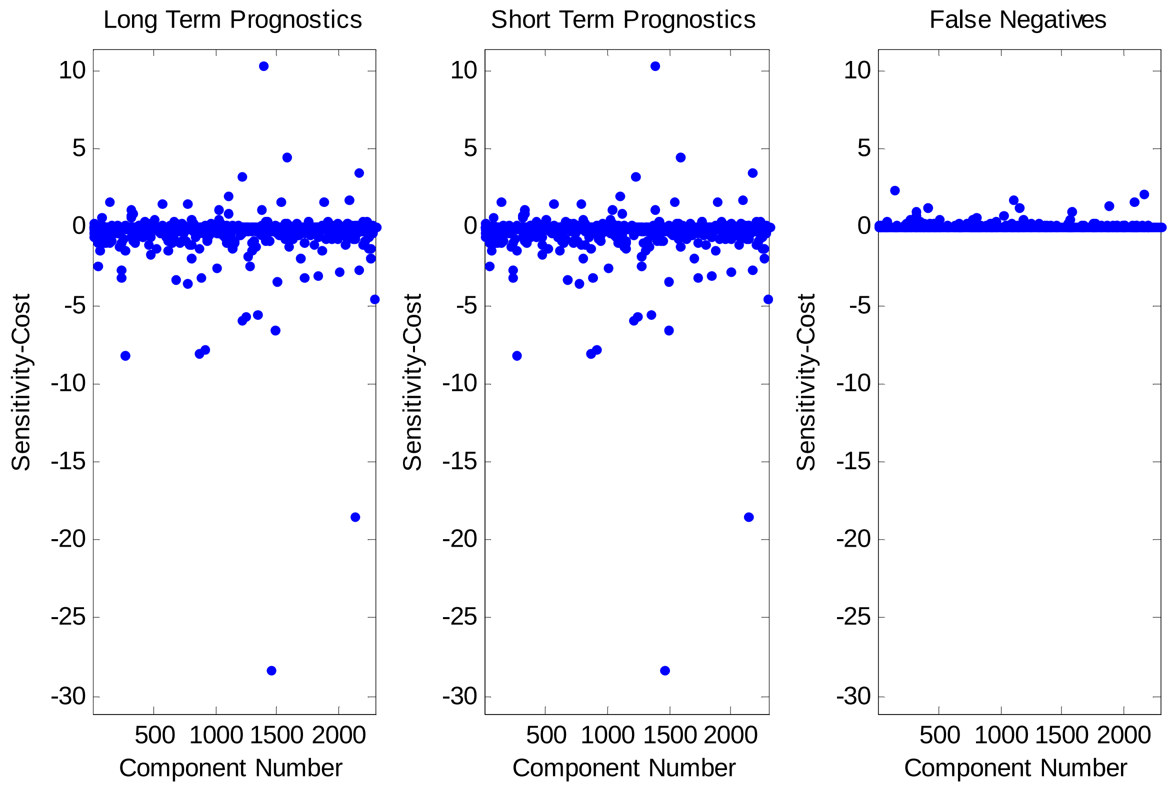

Figure 7.- Sensitivities of maintenance costs to the performance of long term prognostic tools (left), short term prognostic tools (centre) and diagnostic tools (right).

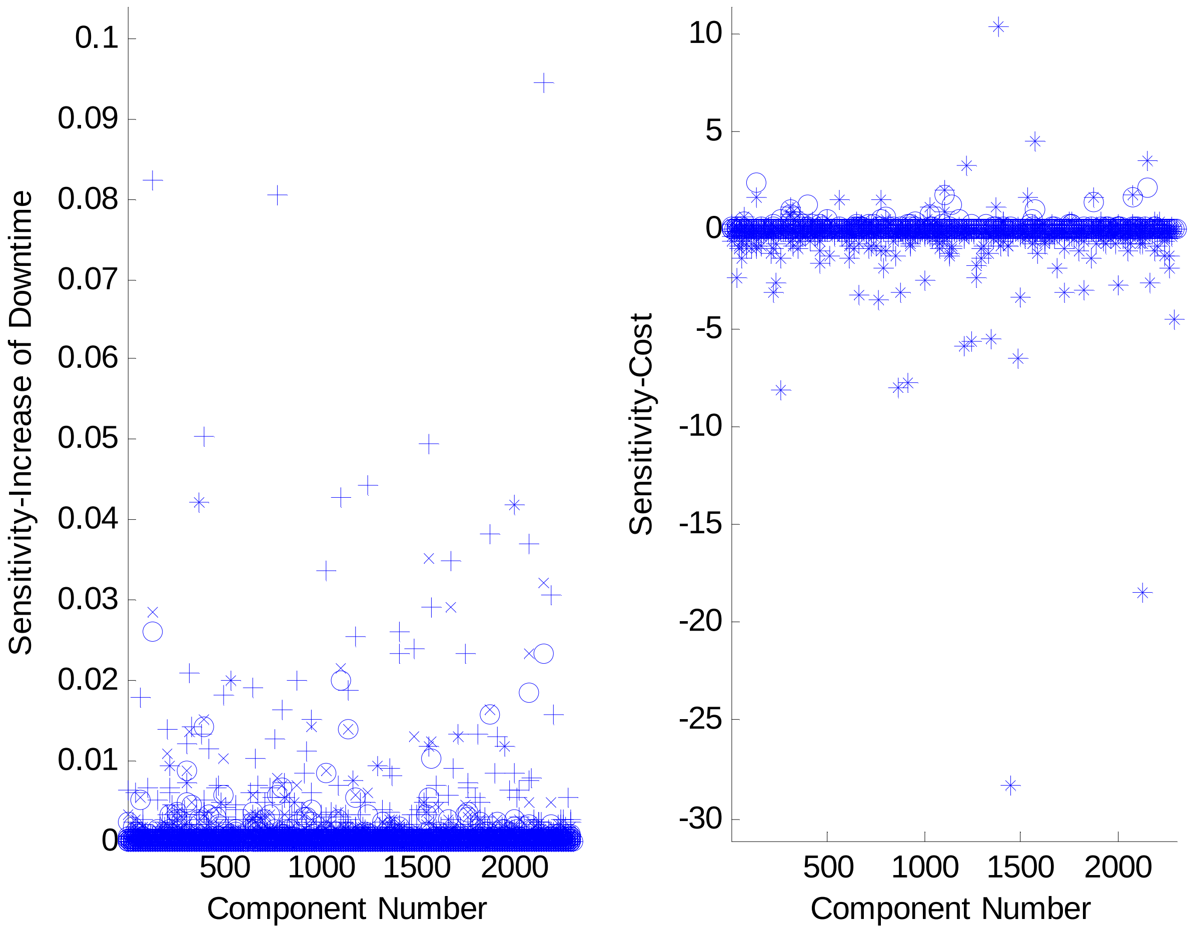

Figure 8.- Comparison of the sensitivities of increases of downtime (left) and maintenance costs (right) to the use of long term prognostic tools (+), short term prognostic tools (x) and diagnostic tools (o).

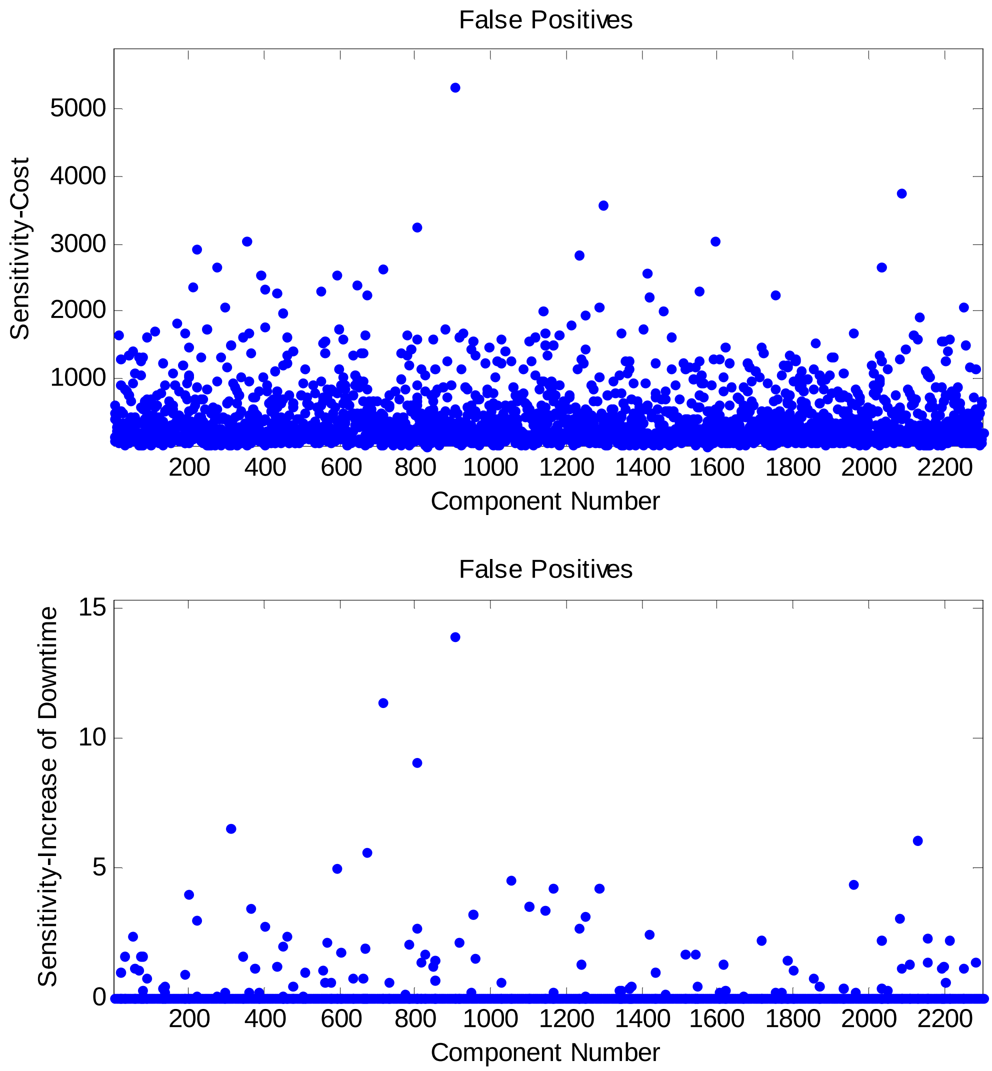

Figure 9.- Sensitivities of maintenance costs (top) and increases of downtime (bottom) to the probability of false alarms.

Table 1 - Number of tools unique to each ranking list corresponding to the different performance parameters of IVHM tools.

Sensitivity to	Ranking criteria	
	$d\Delta T$	dC
Long Term Prognostic tools (P_{LP})	100	100
Short Term Prognostic Tools (P_{SP})	24	0
Diagnostic Tools (P_{FN})	19	37
Total	143	137
False Alarms (P_{FA})	33	34
Total (final)	110	103

Configuring IVHM Toolsets for legacy platforms according to economic risk analysis at the preliminary design stage

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The availability and maintenance cost of legacy aircraft can be improved by using diagnostic and prognostic tools to monitor key components in order to inform the management of maintenance operations. To ensure this improvement justifies the investment necessary to put this technology into service designers must make sure they select the optimal combination of health monitoring tools. Given the complexity of aircraft systems, the number of possible combinations of tools is too large to have them studied one by one by the design team. Additionally the uncertainty of multiple factors that are taken into account in this analysis increases the complexity of the problem. However, this uncertainty can be used to make an even more comprehensive analysis of the possible configuration of the final health monitoring system. To this end, the method described in this article helps to analyse the risk of investing on each possible combination of diagnostic and prognostic tools as well as their the expected Return on Investment (ROI), providing a strong case for the implementation of a health monitoring system. The result is a system that has been configured to ensure maintainers and operators extract all the value from health monitoring technology. This method also takes into account the effect of sharing resources to develop and implement these tools. A description on how to exclude combinations of tools that are incompatible between themselves is also included.

Keywords: Design Integration, Life-Cycle Analysis and Design, Risk-based design, Systems design, Systems Engineering, Uncertainty Analysis

1 Introduction

The implementation of Integrated Vehicle Health Management (IVHM) technology has traditionally followed a reactive approach according to which a health monitoring tool is developed individually and, once its performance has been tested, it is put into service. There are two explanations for this approach: on one hand diagnostic and prognostic algorithms and the hardware necessary to implement them are normally developed by independent teams with expertise in the component/system being monitored; on the other hand, organizations lack a high level IVHM policy or program that would require a comprehensive analysis of the optimal combinations of tools to be developed and implemented. Consequently, aircraft end up with an eclectic set of IVHM tools that improve the maintainability of each part, but may have a negligible effect on the fleet.

Nevertheless, it must be noted that the lack of a systems approach to IVHM implementation may not be caused by lack of competence or vision. The use of several tools on a given aircraft results in interactions that must be carefully studied to ensure objectives are reached and their performance not undermined by overseeing critical interdependencies. From a maintenance perspective it is essential that the selection of components to be monitored takes into account their failure/replacement frequency, replacement time, delays and how IVHM can affect them. Given the complexity of maintenance operations this problem must be studied using computer-based simulations of maintenance activities. From an implementation perspective, the interactions between tools can result in unforseen problems with the hardware and/or the software. Therefore, implementing and IVHM system that comprises diagnostic and prognostic tools to monitor several components becomes an engineering project that requires a significant investment and involves great uncertainty.

Some methodologies to approach this problem do exist, but they normally focus on individual parts or a limited number of components or subsystems. It has been proposed to use Failure Modes, Effects and Criticality Analysis (FMECA) as the main basis for the design of full IVHM systems [1-3]. However, these methodologies, while applicable to a limited number of components, are not suitable for the analysis of a complete aircraft since it would be impractical to carry out an FMECA for each individual part, not to mention to analyse all possible interactions between components and between their potential monitoring tools. In their Cost Benefit Analysis (CBA) to study the use of Prognostics Health Management (PHM) on legacy commercial aircraft Leao et al. [4] presented a comprehensive set of equations that can be used both by aircraft manufacturers and operators, but did not acknowledge the interactions between tools and how this affects the resulting platform availability.

However, in the case of legacy aircraft, their unique combinations of abundant historical maintenance data and constraints that rule out significant modifications of their systems, allow for a series of quantitative analyses that can lead to an optimal combination of diagnostic and prognostic tools. Computer simulations of maintenance activities which take into account the use of diagnostic and prognostic tools are essential to quantify the effect of implementing this technology.

Ideally, once the maintenance model has been developed and validated, different combinations of diagnostic and prognostic tools can be tested. However, while a computer essential to carry out a solid CBA, it is not practical, or even possible, to simulate the effect of all potential combinations of health monitoring tools. Taking into account that aircraft are comprised of thousands of components, a comprehensive analysis of all options should consider, at least, the possibility of monitoring a few dozen components, even if the final number of tools implemented may be lower. For example, if designers have to choose 10 tools out of 50 possible options, this represents more than 10 billion combinations. Even taking into account incompatibilities between tools due to conflicts caused by their hardware or software, it is unlikely that the total number of toolsets is reduced significantly enough so all combinations can be studied and compared thoroughly.

The method described in this article analyses the financial risk incurred by investing on different combinations of IVHM tools. The financial risk is determined by calculating the variance of the expected Return On Investment (ROI) for each toolset. This allows ranking toolsets according to the probability of their ROI falling below a given threshold (normally the cost of money). Those toolsets that present a lower financial risk can then be analyse thoroughly using computer models.

2 IVHM tools as financial assets

Each diagnostic and prognostic tool is essentially an investment from which a return is expected. This return is the result of avoiding certain maintenance costs and, if contemplated in the agreement between operator and maintainer, increasing the availability of the asset. From this point of view diagnostic tools are equivalent to financial assets.

Comparing toolsets must take into account the possibility of sharing resources between tools in their design, testing, manufacturing, implementation and operation. In other words, tools can share -among others- sensors, memory, flight test expenses, recurring costs, etc. This translates to a reduction in the investment necessary to put a certain group of tools in service. Consequently, the ROI of each toolset is not the weighted average of the ROIs of those tools it comprises, but the ratio between the sum of their expected profits and the total cost of developing, implementing and operating the complete IVHM system.

In mathematical terms, for a toolset with n tools in which the project budget for each tool has been divided into m phases or parts this can expressed as:

$$ROI = \frac{\sum_{i=1}^{n} P_i + \sum_{i=1}^{n} C_i}{\sum_{i=1}^{n} C_i} = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} \sum_{j}^{m} c_{ij}/\alpha_{ij}} + 1 \qquad (1)$$

where

P_i = Expected profit from tool i

C_i = Total cost of tool i

c_{ij} = Cost of tool i for part j of its budget

α_{ij} = Number of tools with which c_{ij} is shared

However, sharing resources means that a deviation in their cost can effectively raise the cost of several tools. For example, if algorithms are processed in a centralised unit whose costs exceeds the original budget this will also impact the cost of each individual health monitoring tool. A federated IVHM system with algorithms run in individual processing units may be more expensive, but its total cost is less vulnerable to this kind of problems.

Comparing toolsets becomes even more complicated when options include tools that are under development and not fully proven. Mature diagnostic and prognostic tools are less likely to present problems and have significant variations in their cost, but their performance can be lower than tools that are still being developed and employ the latest hardware and software. The cost of the latter however is more likely to deviate from the original budget.

This resembles a classic financial investment problem in which investors must select the optimal combination of assets to maximise the return of their portfolio while keeping risk within reasonable limits. As in the problem described in this article, financial assets have some degree of correlation and this must be carefully studied to avoid situations in which an investor can be severely affected by fluctuations in the market (e.g.: stock prices of logistic companies are affected by the fluctuation of oil prices in commodity markets, gold prices and the USD are normally inversely correlated, etc.).

There are all sorts of financial analysis tools that can be applied to solve this problem, but there is an important part of this financial analysis tools ignore: the variation of the ROI of each health monitoring tool depending on how it is combined with others. This is due to the fact that the return on a financial product is not affected by how much one invests in other assets. Figure 1.a shows an example of using conventional financial risk analysis to compare combinations of a generic set of IVHM tools. As toolsets include larger numbers of diagnostic and prognostic tools the risk decreases because deviations in the cost of individual tools have a smaller impact on the total investment. However, the ROI tends to the average ROI of all possible options because the savings are not taken into account. Figure 1.b shows how the ROI can increase significantly if IVHM tools are combined appropriately taking into account Eq. (1).

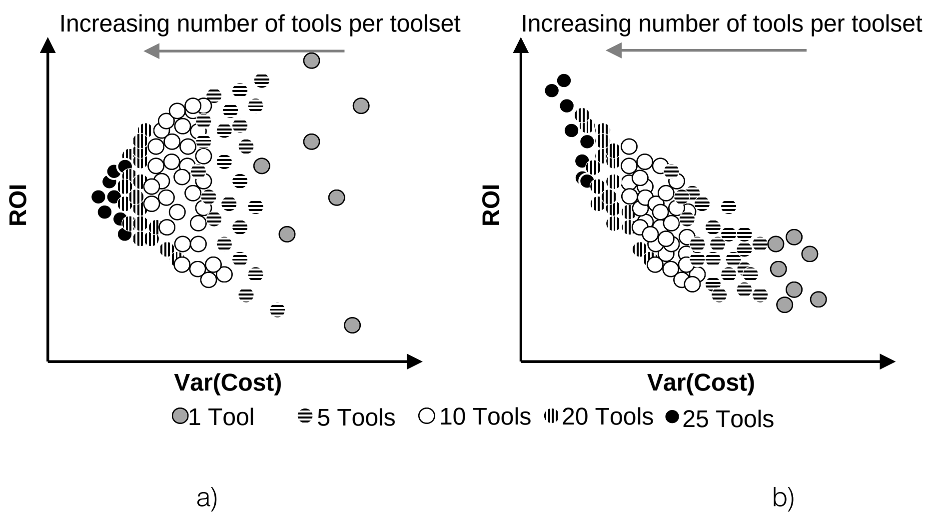

Figure 1 Comparison of the plots of ROI and variance of the cost of IVHM toolsets based using financial analysis (a) and including cost sharing (b).

3 Removing incompatible combinations

The starting point for the comparison of different combinations of health monitoring tools is a list of diagnostic and prognostic tools. However, designers would be interested in analysing more than one possible tool for each component which means that some of the them cannot be combined in the same toolset (i.e.: there is no reason to monitor the condition of a component with more than one tool). Furthermore, incompatibilities between tools can also be caused by technical factors such as geometric constraints or incompatible communication protocols. Therefore, it is essential to identify and remove any toolset that includes tools that are incompatible. This also helps to run the risk analysis algorithm faster thanks to the reduction in the number of combinations that need to be analysed.

For an original list with a total of t health monitoring tools, incompatibilities between each pair of tools are included in the symmetrical matrix $\boldsymbol{I}$ in which the values of the diagonal are all zeros:

$$\boldsymbol{I} = \begin{bmatrix} 0 & i_{12} & \cdots & i_{1t} \\ i_{21} & 0 & \cdots & i_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ i_{t1} & i_{t2} & \cdots & 0 \end{bmatrix}_{t\times t}$$

$$i_{ij} = i_{ij} \quad \& \quad i_{ij} \in \mathbb{N}, [0,1]$$

where:

if tools i and j are compatible $i_{ij} = 0$

if tools i and j are incompatible $i_{ij} = 1$

For a given combination of tools defined by vector $\boldsymbol{t}$ (where t_n is the position of each tool on the list), the viability of each combination will be determined by the value of k:

$$k = \boldsymbol{l}_n \cdot \boldsymbol{I}(\boldsymbol{t}, \boldsymbol{t}) \cdot \boldsymbol{l}_n^T \qquad (2)$$

where $\boldsymbol{l}_n=[1,\ldots,1]_n$ and:

if all tools included in $\boldsymbol{t}$ are compatible $k = 0$

if any pair of tools included in $\boldsymbol{t}$ are incompatible $k \neq 0$

There is no difficulty in identifying which tools cannot be part of the same toolset because they would monitor the same component. However, to be able to include all other technical incompatibilities at this stage, experts on each tool and in systems engineering should be consulted.

4 Comparison of Toolsets

As mentioned in the introduction, toolsets are to be compared based on the risk they represent from a financial point of view. Knowing the ROI and its variance for each viable combination of health monitoring tools is not enough to identify which toolset represents a sounder investment. Both parameters need to be transformed into a single metric that can gives a clear indication of which is the best option available.

There are numerous ways of doing this in financial analysis, such as the Value at Risk or the Expected Shortfall, but those are more suitable for portfolio analysis. Another way of parameterising the risk of an investment is to determine the likelihood of their ROIs falling below the cost of money used by the organization, C_m. The less likely a toolset is to produce a lower profit than a generic investment within the organization the higher it appears in the ranking. The formula to calculate this probability is:

$$\Pr(ROI \leq C_m) = \int_0^{C_m} f(x)dx \qquad (3)$$

All these methods rely on knowing the shape of the probability distribution of the ROI, *f(x)*. In this section we will demonstrate how to calculate the function of this distribution applying statistics to information obtained using conventional risk analysis methods.

4.1 Using moments to characterise probability distributions

Moments can be used to characterise the shape of any probability distribution. Moments are a quantitative measure of the shape of a set of points. The nth moment of a probability distribution *f(x)* about a value *a* is:

$$\mu'_n = \int_{-\infty}^{\infty} (x-a)^n f(x)dx \qquad (4)$$

The first order moment taken about 0 is known as the expected value of the probability distribution, *E[X]*, and is equal to the mean of the distribution.

$$\bar{x} = E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

When moments are taken about the mean of the distribution they are known as central moments

$$\mu_n = E\left[(X - E[X])^n\right] = \int_{-\infty}^{\infty} (x - \bar{x})^n f(x) dx \qquad (5)$$

The second central moment of a probability distribution is equal to its variance, $\sigma\sigma^2$, the third is its skewness, γ_1, and the fourth its kourtosis, β_2. The skewness provides a measurement of the asymmetry of the distribution (Figure 2), while the kurtosis is a measurement of the "peakedness" of the distribution (Figure 3). The kurtosis can also be interpreted as an indication of the heaviness of the tails of the distribution.

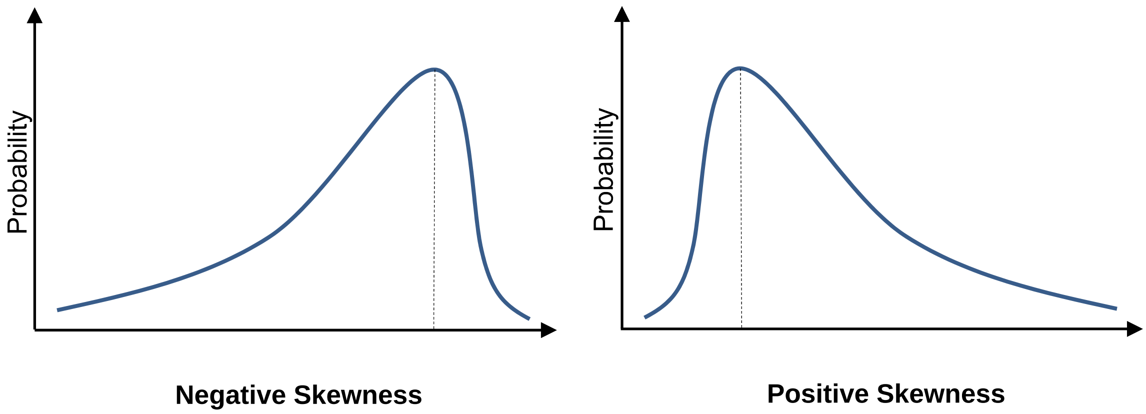

Figure 2 Examples of negative (left and positive (right) skewness.

When working with probabilities it is much more common to use the excess of kurtosis, γ_2, rather than the "classic" kurtosis, β_2 (eq. (6)). In essence, the excess of kurtosis defines "peakedness" of a distribution in comparison to a normal distribution, whose kurtosis is always 0 (Figure 3). Distributions with positive excess of kurtosis have "heavier tails" than the normal distribution and are called leptokurtic distributions ("lepto-"="slender"), conversely, those that have a negative of kurtosis are called platykurtic ("platy-"="broad"). The reader might be interested to know that the coin toss is the most platykurtic distribution, with γ_2=-2.

$$\gamma_2 = \beta_2 - 3 \qquad (6)$$

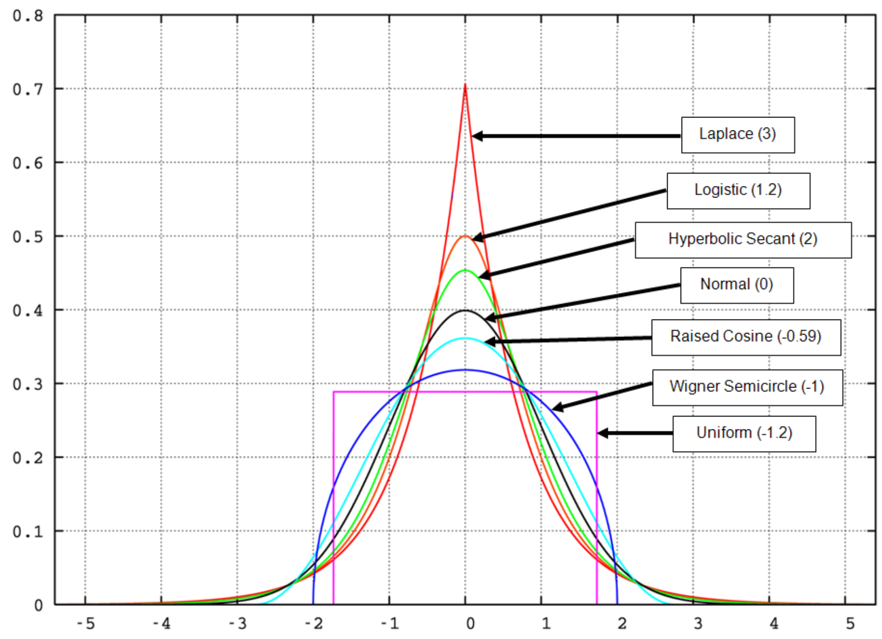

Figure 3 Excess kurtosis of various common statistical distributions

The more moments used, the more precise the estimation of the probability distribution. However, in this case it is not possible to calculate them using eq. (5) because the objective is to calculate *f(x)* which is unknown at this point. The next sections describe how to calculate the first four moments of the ROI based on the information available regarding the cost and expected profit of each combination of tools.

4.2 Probability distributions of cost and profit

The ROI is the ratio of two random variables: the cost and expected profit of each toolset. The cost of each toolset is equal to the summation of multiple expenses. Similarly, the profit is the difference between the summation of future savings and incomes produced by the use of the IVHM system minus its cost.

In risk analysis costs are normally estimated by providing an estimated average cost and a lower and upper boundary [5; 6], which means using triangular probability distributions. Detailed methods for elicitation in cost analysis can be found in [5; 7; 8]. The same process can be followed to estimate the savings and incomes the IVHM system will generate since they will be based on information gathered using experts' opinion. The variance of the profit can be estimated taking into account the variance of: maintenance costs, maintenance times and the performance of health monitoring tools [9; 10].

The Central Limit Theorem (CLT) states that the sum of independent and identically distributed random variables can be approximated to a normally distributed function (see [11; 12]). However, the probability distributions of the different estimated costs and profits are not identically distributed (they all have different means and variances). Nevertheless, these random variables do not need to be identical as long as they comply with Lindeberg's condition [11], which, for every ε>0, requires:

$$\lim_{n\to\infty}\frac{\sum_{i=1}^{n}\int_{\{|X_i-E[X_i]|>\varepsilon s_n\}}E[|X_i-E[X_i]|^2]}{s_n^2}=0 \qquad (7)$$

where $s_n^2 = \sum_{i=1}^{n}\sigma_i^2$.

Since the triangular probability distribution complies with Lindeberg's condition, the CLT can be applied and the total cost and profit produced by each toolset can be considered normally distributed.

Characterizing the ROI becomes much simpler because the central moments of random Gaussian variables are:

$$\begin{cases}\mu_{2n} = \frac{(2n)!}{n!2^n}\sigma^{2n} \\ \mu_{2n+1} = 0\end{cases} \qquad (8)$$

This means that the only parameters necessary to carry out this risk analysis are the mean and the variance of the cost and expected profit of each combination of tools. The next section explains how the first four moments of the ROI can be calculated using just these four inputs.

4.3 <u>Calculating the moments of the ROI</u>

4.4 <u>Mean</u>

Since the ROI is a ratio between two random variables its mean does not necessarily correspond to the ratio between their averages. The new mean can be estimated using Taylor expansions for the first moment of random variables:

$$E\left[\frac{x}{y}\right] \approx f(E[\boldsymbol{x}]) + \frac{1}{2}f''(E[\boldsymbol{x}])var\big(f(E[\boldsymbol{x}])\big) \qquad (9)$$

For the ratio of two random variables:

$$E\left[\frac{x}{y}\right] \approx \frac{\bar{x}}{\bar{y}} + \frac{\bar{x}}{\bar{y}^3}\sigma_y - \frac{\sigma_{x,y}}{\bar{y}^2} \quad (10)$$

where σ_y=*var(y)* and $\sigma_{x,y}$=*cov(x,y).*

Intuitively, it might seem as if the cost of an IVHM system and the savings it will eventually produce should be connected: investing on a system that is more expensive because it is capable of detecting and predicting faults more accurately should result in bigger savings. However, this particular point of the analysis is not about comparing different configurations of an IVHM system. Instead, it focuses on evaluating how unforeseeable events that could deviate costs from the original budget affect the risk of the investment. In other words: is any deviation from the original budget correlated with the accuracy of the IVHM system and, therefore, correlated with its effect on maintenance costs and the availability of the fleet? It is not difficult to see that problems encountered during the design, installation and testing of an IVHM system can result in modifications that improve, worsen or leave unaffected its performance. Therefore, it is safe to say that the cost of the system and the savings it produces are independent and *cov(C, P)=0*.

Consequently, applying eq. (1) to eq. (10) we obtain the mean (a.k.a. expected value) of the ROI:

$$E[ROI] \approx \frac{\bar{P}}{\bar{C}} + \frac{\bar{P}}{\bar{C}^3}\sigma_C + 1 \quad (11)$$

4.5 Variance

The delta method can be used to estimate confidence intervals of a random variables. It uses Taylor expansions to approximate the variance of random variables (a.k.a.: second central moment). The formula for a multivariate function is:

$$var\big(f(\boldsymbol{x})\big) \approx \nabla f(E[\boldsymbol{x}])^T var(\bar{x}) \nabla f(E[\boldsymbol{x}]) \quad (12)$$

Since the ROI is a fraction we are interested in the following expression:

$$var\left(\frac{x}{y}\right) \approx \frac{\sigma_x}{\bar{y}^2} + \bar{x}^2\frac{\sigma_y}{\bar{y}^4} - \frac{2\bar{x}}{\bar{y}^3}\sigma_{x,y} \qquad (13)$$

Since profits and costs can be considered independent the variance of the ROI is:

$$var(ROI) = var\left(\frac{P}{C}\right) \approx \frac{\bar{C}^2\sigma_P + \bar{P}^2\sigma_C}{\bar{C}^4} \quad (14)$$

4.6 Skewness and kurtosis

Anderson and Mattson [13] have obtained the formulas for the propagating skewness and kurtosis for monovariate functions using Taylor expansions.

Assuming *y=f(x),*the skewness as a function of the central moments of *x* is:

$$\gamma_1 = E\left[\left(\frac{y-\bar{y}}{\sigma}\right)^3\right] = \frac{E\left[(y-\bar{y})^3\right]}{\left(E\left[(y-\bar{y})^2\right]\right)^{1.5}} \approx \frac{\begin{bmatrix} \mu_3 \\ \frac{3}{2}\left(\mu_4-\mu_2^2\right) \\ \left(\frac{3}{4}\mu_5-\frac{3}{2}\mu_2\mu_3\right) \\ \left(\frac{1}{4}\mu_2^3-\frac{3}{8}\mu_2\mu_4+\frac{1}{8}\mu_6\right) \end{bmatrix}\begin{bmatrix} \partial_1^3 \\ \partial_1^2\partial_2 \\ \partial_1\partial_2^2 \\ \partial_2^3 \end{bmatrix}}{\left[\mu_2\partial_1^2+\mu_3\partial_1\partial_2+\frac{1}{4}\left(\mu_4-\mu_2^2\right)\partial_2^2\right]^{1.5}} \quad (15)$$

where $\partial_1 = \frac{\partial f}{\partial x}$, $\partial_2 = \frac{\partial^2 f}{\partial x^2}$ and μ_i is the *ith* central moment of *x*.

For the kurtosis the formula for monovariate functions is [13]:

$$\beta_2 = E\left[\left(\frac{y-\bar{y}}{\sigma}\right)^4\right] = \frac{E\left[(y-\bar{y})^4\right]}{\left(E\left[(y-\bar{y})^2\right]\right)^2} \approx \frac{\begin{bmatrix} \mu_4 \\ 2\left(\mu_5-\mu_2\mu_3\right) \\ \frac{3}{2}\left(\mu_2^3-2\mu_2\mu_4+\mu_6\right) \\ \frac{3}{2}\left(\mu_2^2\mu_3-\mu_2\mu_5+\frac{1}{3}\mu_7\right) \\ \frac{1}{16}\left(6\mu_2^2\mu_4-3\mu_2^4-4\mu_2\mu_6+\mu_8\right) \end{bmatrix}\begin{bmatrix} \partial_1^4 \\ \partial_1^3\partial_2 \\ \partial_1^2\partial_2^2 \\ \partial_1\partial_2^3 \\ \partial_2^4 \end{bmatrix}}{\left[\mu_2\partial_1^2+\mu_3\partial_1\partial_2+\frac{1}{4}\left(\mu_4-\mu_2^2\right)\partial_2^2\right]^2} \quad (16)$$

The reader is reminded that *E([y-E[y]]²)* is the second moment or variance of the ROI which has already been calculated for each toolset using eq. (14). Therefore, we only need to find the numerators of eq. (15) and (16).

Since *f(x)=f(C,P)*, the next step is to find a way to calculate the central moments of the cost and profit for each toolset. From eq. (8) we know that $\mu_3=\mu_5=\mu_7=0$, $\mu_4=3\sigma^4$, $\mu_6=15\sigma^6$, $\mu_8=105\sigma^8$, resulting in:

$$\gamma_1 \approx \frac{3\sigma_x\partial_1^2\partial_2+\sigma_x^3\partial_2^3}{\left(\partial_1^2+\frac{1}{2}\partial_2^2\sigma_x^2\right)^{1.5}} = \frac{3\sigma_x\partial_1^2\partial_2+\sigma_x^3\partial_2^3}{\sigma_y^3} \quad (17)$$

$$\beta_2 \approx \frac{3\sigma_x^4\partial_1^4+15\sigma_x^6\partial_1^2\partial_2^2+\frac{15}{4}\sigma_x^8\partial_2^4}{\sigma_y^4} \quad (18)$$

The problem at hand involves working with multivariate functions, transforming eq. (17) and (18) into:

$$\gamma_1 \approx \frac{1}{\sigma_y^3}\left(\sum_{j=1}^{n}\sum_{i=1}^{n} 3\sigma_{i,j}\left(\frac{\partial f}{\partial x_i}\right)^2\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right) + \sigma_{i,j}^3\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^3\right) \qquad (19)$$

$$\beta_2 \approx \frac{1}{\sigma_y^4}\sum_{i=1}^{n}\left[3\sigma_i^4\left(\frac{\partial f}{\partial x_i}\right)^4 + \sum_{j=1}^{n} 15\sigma_{i,j}^6\left(\frac{\partial f}{\partial x_i}\right)^2\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^2 + \frac{15}{4}\sigma_{i,j}^8\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^4\right] \qquad (20)$$

Since for every toolset its cost and profit and considered independent $\sigma_{C,P}=0$. As for the derivatives of *f(C,P)*:

$$\begin{cases} \frac{\partial f}{\partial P} = \frac{1}{C} \\ \frac{\partial f}{\partial C} = -\frac{P}{C^2} \\ \frac{\partial^2 f}{\partial P^2} = 0 \\ \frac{\partial^2 f}{\partial C^2} = 2\frac{P}{C^3} \\ \frac{\partial^2 f}{\partial P \partial C} = -\frac{1}{C^2} \end{cases} \qquad (21)$$

Applying eq. (21) to eq. (19) and (20) results in the final equations to calculate the skewness and kurtosis of the probability distribution of the ROI:

$$\gamma_1(ROI) \approx \frac{8\sigma_C^3\frac{\overline{P}^3}{\overline{C}^9}+6\sigma_C\frac{\overline{P}^4}{\overline{C}^7}}{\left(\frac{\overline{C}^2\sigma_P^2+\overline{P}^2\sigma_C^2}{\overline{C}^4}\right)^{1.5}} \qquad (22)$$

$$\beta_2(ROI) \approx \frac{3\sigma_P^4\frac{1}{\overline{C}^4}+3\sigma_C^4\frac{\overline{P}^4}{\overline{C}^8}+60\sigma_C^6\frac{\overline{P}^4}{\overline{C}^{10}}+\frac{15}{4}\sigma_C^8\frac{\overline{P}^4}{\overline{C}^{12}}}{\left(\frac{\overline{C}^2\sigma_P^2+\overline{P}^2\sigma_C^2}{\overline{C}^4}\right)^2} \qquad (23)$$

Now, armed with the mean, variance, skewness and kurtosis of the ROI designers can compare the risk of investing on different IVHM toolsets. However, before eq. (10), (11), (22) and (23) can be solved, the mean and standard deviations of the cost and expected profit of each combination of tools have to be calculated.

Since the mean and variance of the ROI are always positive, looking at eq. (22) is easy to see that the probability distribution of the ROI will always present positive skewness.

As explained before, profits are essentially a summation of different incomes. Since the different costs avoided and other sources of revenue can be considered independent $\sigma_P = \sum_{k=1}^{n} var(P_i)$. However, this is not so straight forward for costs due to the sharing of expenses. The next section describes how the mean and variance can be calculated based on which costs are shared.

4.7 Correlation of costs and its effect on the risk

Sharing costs results in correlations that affect the way errors propagate, increasing the difficulty of calculating the standard deviation of the cost of each combination of health monitoring tools. The budget for each tool includes all the expenses necessary to develop, test, manufacture and install each tool. This budget can be divided in as many parts or steps as desired, but keeping in mind that as these divisions become more detailed, it will be more difficult to estimate the expenses incurred in each of them. These costs can include (but are not limited to) the cost of components, cost of hardware modifications, cost of tests, etc. For a total number of tools *t*, with project budgets divided into *p* elements, each of these costs, denoted by b_{ij}, are included in the Budget Matrix $\boldsymbol{B}_{txp}$.

$$\boldsymbol{B} = \begin{bmatrix} b_{11} & \cdots & b_{1p} \\ \vdots & \ddots & \vdots \\ b_{t1} & \cdots & b_{tp} \end{bmatrix}$$

Once the different costs can be quantified experts on each tool and systems engineers have to be consulted to determine which of them can be shared by which tools. Each shared cost is to be included in the Share Tensor, ***S***.

$$\boldsymbol{S} = \begin{bmatrix} 1 & s_{12x} & \cdots & s_{1tx} \\ s_{21x} & 1 & \cdots & s_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ s_{t1x} & s_{t2x} & \cdots & 1 \end{bmatrix}_{t \times t \times p}$$

$$s_{ijx} = s_{ijx} \ \forall \ x \in \mathbb{N} \quad \& \quad s_{ij} \in \mathbb{N}\,, [0{,}1]$$

where:

if tools *i* and *j* share cost *k* then $s_{ijk} = 1$

if tools *i* and *j* do not share cost *k* then $s_{ijk} = 0$

For a toolset with *n* tools matrix ***A*** defines which fraction of each cost is allocated to each tool. This matrix is a function of the Share Tensor and the Budget Matrix. The newly calculated costs incurred in implementing the toolset are defined by the elements of the Toolset Budget Matrix, ***B****. This matrix is essential to calculate vector of the final cost of each tool, ***c***, and eventually the total cost of the toolset, *C* as shown in eq. (25) and (26)

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1p} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{np} \end{bmatrix}_{n\times p}$$

$$\boldsymbol{A} = f(\boldsymbol{B}_{n\times p}\ ,\ \ \boldsymbol{S}_{n\times n\times p}) \quad (24)$$

$$\boldsymbol{B}^{*} = \begin{bmatrix} a_{11}b_{11} & \cdots & a_{1p}b_{1p} \\ \vdots & \ddots & \vdots \\ a_{n1}b_{n1} & \cdots & a_{np}b_{np} \end{bmatrix}_{n\times p}$$

$$\boldsymbol{c} = \boldsymbol{B}^{*} \cdot \boldsymbol{l}_p^T \qquad (25)$$

$$C = \boldsymbol{l}_n \cdot \boldsymbol{c} = \boldsymbol{l}_n \cdot \boldsymbol{B}^{*}\boldsymbol{l}_p^T \qquad (26)$$

where $\boldsymbol{l}_p=[1,\ldots,1]_p$ and $\boldsymbol{l}_n=[1,\ldots,1]_n$

The simplest way to allocate each cost is to divide it evenly amongst those tools that share it as shown in Eq.(27), but other formulas can be applied.

$$a_{ij} = \frac{1}{\sum_{k=1}^{n} s_{ikj}} \qquad (27)$$

The variance of the cost of a given combination of diagnostic and prognostic tools can be calculated with the following expression:

$$\sigma_C = \boldsymbol{w} \cdot \boldsymbol{Cov}(\boldsymbol{c}) \cdot \boldsymbol{w}^T \qquad (28)$$

where ***w*** is the vector with the weighed cost of each tools included in the toolset in which

$$w_i = \frac{q_i}{\sum_{j=1}^{n} q_j} \qquad (29)$$

and ***Cov(c)*** is the covariance matrix of ***c***

$$\boldsymbol{Cov}(\boldsymbol{c}) = \begin{bmatrix} var(c_1) & Cov(c_1, c_2) & \cdots & Cov(c_1, c_n) \\ Cov(c_2, c_1) & var(c_2) & \cdots & Cov(c_2, c_n) \\ \vdots & \vdots & \ddots & \vdots \\ Cov(c_n, c_1) & Cov(c_n, c_2) & \cdots & var(c_n) \end{bmatrix}_{n\times n}$$

The elements of ***Cov***(***c***) are the covariances of the sum of the costs of each tool, whose covariances are easy to calculate since they are first grade polynomial expressions.

$$Cov(c_i, c_j) = Cov\left(\sum_{k=1}^{p} b_{ik}^*, \sum_{k=1}^{p} b_{jk}^*\right) = \sum_{k=1}^{p}\sum_{m=1}^{p} Cov(b_{ik}^*, b_{jm}^*) = \sum_{k=1}^{p}\sum_{m=1}^{p} Cov(a_{ik}b_{ik}, a_{jm}b_{jm}) \qquad (30)$$

Only those costs or budget elements that are in the same category can be correlated and consequently:

$$\textstyle\sum_{k=1}^{p} Cov(a_{ik}b_{ik}, a_{jk}b_{jk}) = \sum_{k=1}^{p} a_{ik}a_{jk}Cov(b_{ik}, b_{jk}) \qquad (31)$$

$$Cov(c_i, c_j) = \textstyle\sum_{k=1}^{p} a_{ik}a_{jk}var(b_{ik}) \; (32)$$

It must be noted that as ***A*** and ***B***, ***Cov***(***c***) has to be recalculated for each combination of health monitoring tools.

Using Eq. (32) to solve eq. (28) provides the last part necessary to carry out the risk analysis. In essence, we have transformed the variances of individual items of the budget into the variance of the cost of each toolset. This is the used in eq. (11), (22) and (23), along with eq. (10) for the mean, to determine the shape of the probability distribution of the ROI of each combination of tools.

4.8 Characterising the ROI using moments

Having shown how the moments of the ROI can be calculated the final step is to use them to obtain a mathematical expression of its probability distribution. There are multiple probability distributions that are defined by four parameters that can be used to estimate the ROI. While there are differences between their shapes, given the accuracy achieved by using four moments to adjust the curve of the probability and the lack of further information to infer which would be closer to real values, one should work with the distribution with simpler analytical expressions and/or requires less computational power.

Among all probabilities distributions that use four parameters the most commonly used are the Pearson, Johnson and Generalised Lambda distributions. These distributions have been widely used to fit probability curves to statistical data. However, while all of them are defined by four different shape parameters, in the case of Johnson and Generalised Lambda distribution, said parameters cannot be calculated analytically using the moments of the distribution. They could be calculated using numerical methods, but that would result in too long a computational time to estimate the distribution of the ROI for all possible combinations of health monitoring tools.

In contrast, the shape parameters of Pearson distributions can be calculated using moments Pearson distributions with an average μ satisfy the following differential equation:

$$\frac{f'(x)}{f(x)} = \frac{(x-\mu)-b_1}{b_2(x-\mu)^2+b_1(x-\mu)+b_0} \quad (33)$$

where

$$b_0 = \frac{4\beta_2-3\gamma_1^2}{10\beta_2-12\gamma_1^2-18}\mu_2 \quad (34)$$

$$b_1 = \gamma_1\sqrt{\mu_2}\frac{\beta_2+3\gamma_1^2}{10\beta_2-12\gamma_1^2-18} \quad (35)$$

$$b_2 = \frac{2\beta_2-3\gamma_1^2-6}{10\beta_2-12\gamma_1^2-18} \quad (36)$$

There are different solutions for eq (33) depending on the value of $K = b_1^2/(4b_0b_2)$. For $K<0$ the roots of the denominator of eq (33) are real and the distribution is known as a Pearson type-I or beta distribution. If $0<K<1$ roots are complex and the solution of the differential equation is a Pearson type-IV distribution. Finally, if $K>1$ the distribution is known as type-VII.

Another approach is to fit a ratio distribution using the parameters of the probability distributions of the expected profit and cost of each toolset. However, that means not taking into account the values of the skewness and kurtosis which reduces the accuracy of the risk analysis.

5 Case study

The following example illustrates what kind of results can be obtained from the use of this method. Figure 4 shows the expected ROI and the risk (or variance of the ROI) over 7 years of each possible combination of 20 health monitoring tools with a maximum of 11 tools per toolset. As an average, each health monitoring tool was incompatible with 20% of the remaining 19 tools. As a result of these incompatibilities the total number of viable toolsets decreases as their size increases (see Figure 5).

The results show how increasing the size of the toolset increases the ROI thanks to the savings generated by sharing costs among more tools. However, this effect is counteracted by the increase of uncertainty as errors propagate. Therefore, toolsets were compared according to the risk of their return falling below the cost of the money of the organization, which for this particular case was 8.5% per year. Based on this condition, the best toolset presented an average ROI of 378% (over 7 years) with a probability distribution as shown in Figure 6.

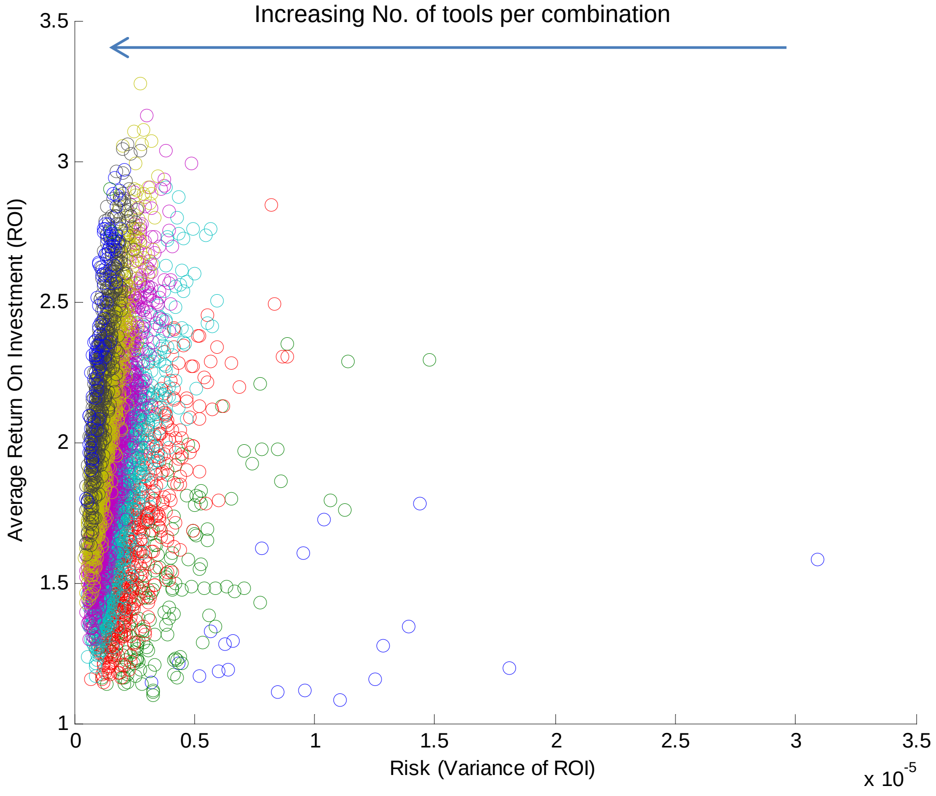

Figure 4 Return on Investment VS Risk for combinations with different numbers of diagnostic and prognostic tools. Dots with the same colour represent toolsets with the same number of tools.

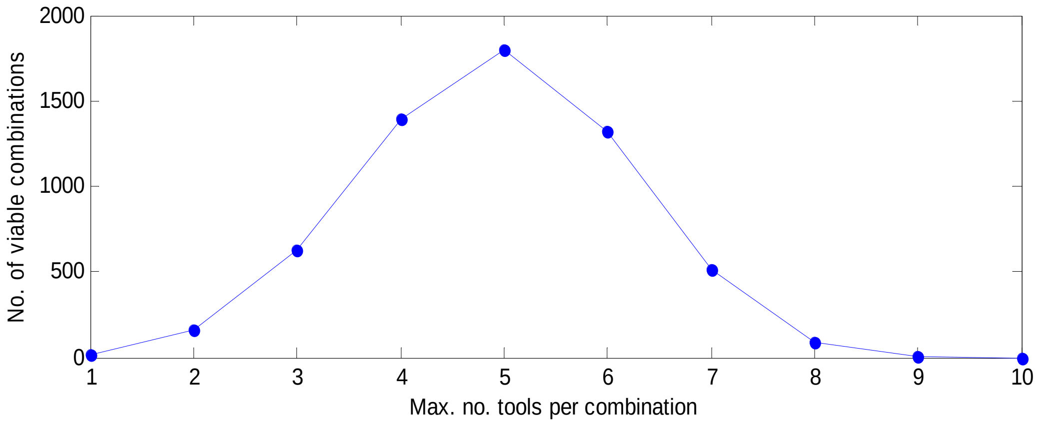

Figure 5 Maximum number of combinations of health monitoring tools taking into account the incompatibilities between them.

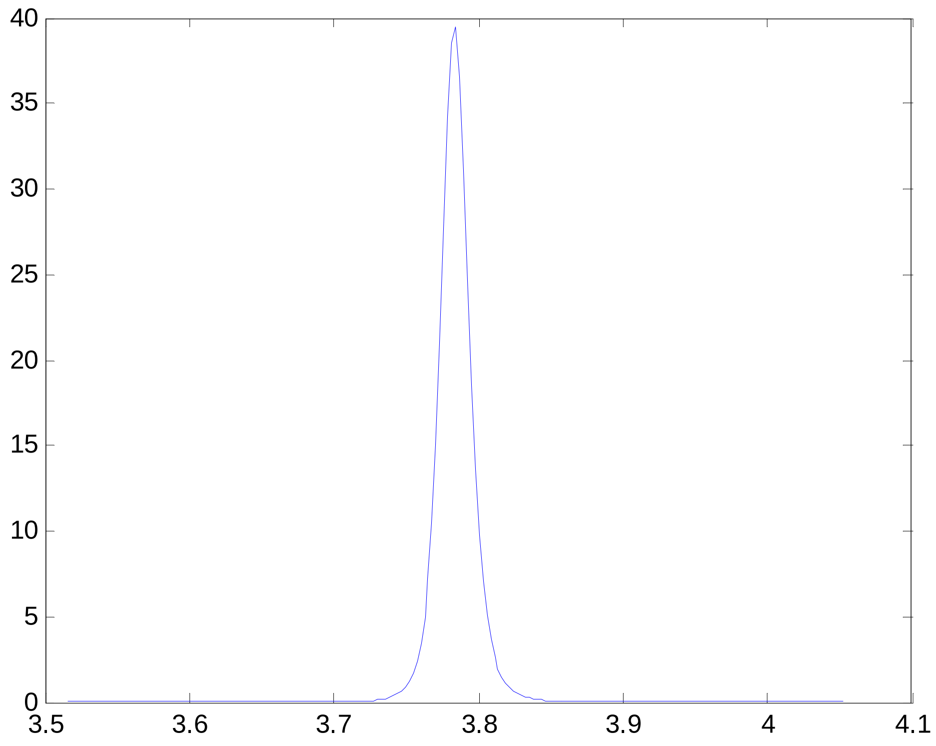

Figure 6 Probability distribution of the best possible combination of IVHM tools according to economic objectives and risk analysis.

As shown in Figure 7, increasing the number of tool does not necessarily translate into a higher ROI, but it narrows the margin between the riskier and safer combination of tools. In other words, in case of not having enough information to populate the matrices described in the previous section we can at least know that as we increase the size of toolsets they probability of making a poor choice diminishes. However, as show at the bottom of Figure 7, this can result in a significant penalty in future revenues. Furthermore, it also shows that increasing the number of tools can result a reduction of the ROI. Consequently, given the wide variation of possible ROIs it is recommendable to make every effort necessary to obtain all the data necessary to apply the method described in this article.

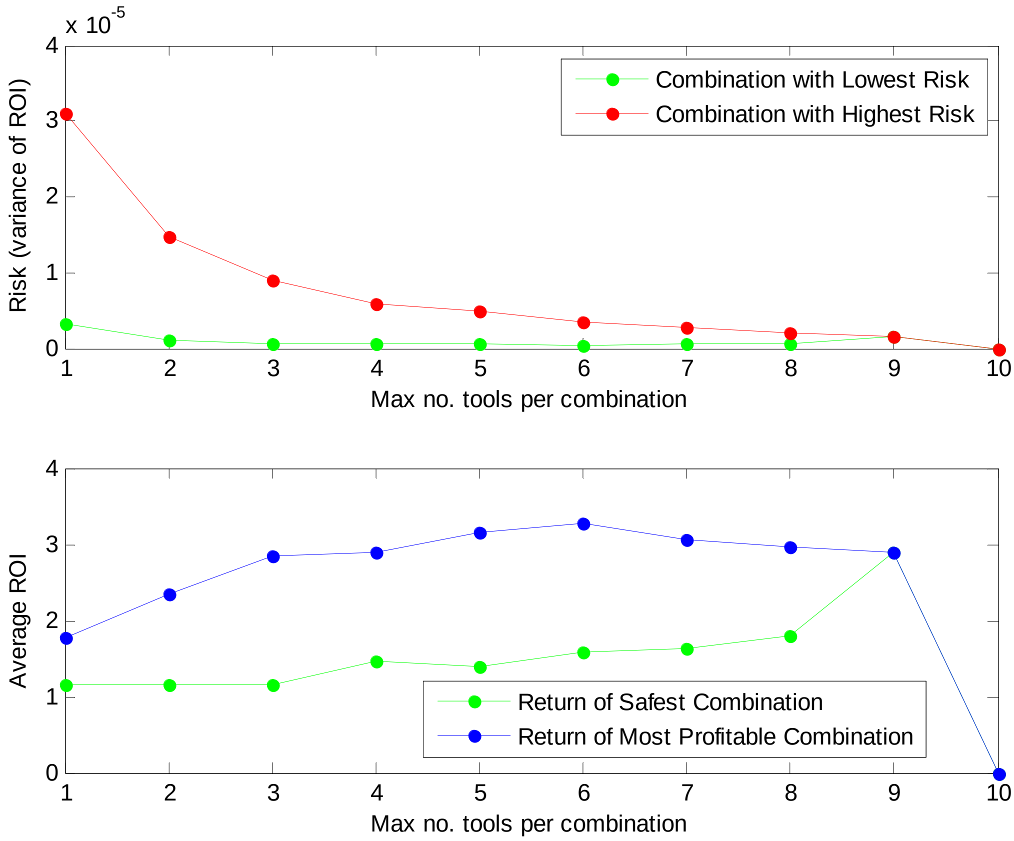

Figure 7 Evolution of the risk (top) and ROI (bottom) of the combinations of health monitoring tools with the lowest and highest variance of ROI for a given number of health monitoring tools.

6 Conclusions

Mathematical proof on how to calculate the probability distribution of the ROI of a combination of diagnostic and prognostic tools has been provided. Not only does this method provide a way to compare large numbers of combinations of IVHM tools, but also it presents a way of doing it objectively.

Being able to characterise the probability distribution of the ROI since the very early stages of the design strengthens the case for investing in this technology and helps to produce more accurate CBAs and business cases for IVHM technology.

The method described in this article can be used to analyse how different combinations of IVHM tools result in different ROIs and present different risks to investors. This leads to a direct comparison of all possible combinations from which the optimal configuration for the IVHM system according to business targets is identified.

Being able to determine from an early stage the optimal number of health monitoring tools means that the IVHM system that is eventually implemented is more likely to remain unmodified for a long period.

It is possible to add constraints that can help to reduce the time necessary to run the algorithm. Since the calculation of variances requires considerably more power than the estimation of the ROI of each combination, the algorithm could be run much faster by setting thresholds for the maximum and minimum number of tools per toolset, minimum expected ROI and the maximum investment.

Further work is necessary to adapt this method to those cases in which the combination of certain tools produces an increase in the total cost instead of savings. This can be due to tools interfering with each other and resulting in further modifications.

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