Optimised Sensor Placement Strategies to Reduce False Alarms in Avionic Units

***Abstract*—The paper investigates the effects of system design on its maintenance requirements. This becomes significantly important when investigating fault alarms that cannot be verified, diagnosed or even duplicated under standard manual inspection regimes. Modern complex mechanical systems, such as a UAV fuel system, often face a high number of NFF events due to design limitations associated with testability. This research identifies a strategy to optimise system diagnostics by using extra sensors and tests that can recognise and reduce failure ambiguity groups that lead NFF events. It helps indicate how the most appropriate system design can be selected to represent the cumulative replacement costs due to false avionic unit removals, and hence, the overall system life-cycle costs during the design stage.**

***Index Terms*—Health management, testability, false alarms, ambiguity groups, system diagnostics.**

I. Introduction

In order for systems to be effective, they have to be coherent [1] - this means viewing the system as a "whole", including its environment, behavioural patterns and interrelations. The adoption of availability based contracting has seen significant changes in how industrial sectors look at the "whole" system. For example, with military aircrafts, governments are driving changes in the defence sector given the increase in the total cost of ownership of these platforms, reducing defence budgets and the need for a flexible force projection capability [2]. This represents a significant proportion of the external expenditure. Consequently the Ministry of Defence (MoD) issued the Defence Industrial Strategy in December 2005 - outlining their requirements to industry for close partnering and increased availability based, product-service package offerings [3]. Such contractual agreements transfer risk in the total cost of ownership of assets from the operator to the supplier [4], [5]. Such practices continue to drive requirements to support a move towards availability based contracting. With such changing needs, a system that was originally designed to be coherent, may cease to maintain this characteristic. Therefore, any such transformation requires changes within both the operator and supplier organisations - including changes in the ownership and management of the supply chain. Although significant progress has been made to this end, further transformation continues and hence delivering a service (maintaining system effectiveness) is more important than the quality of service (system optimisation/efficiency).

The aerospace industry needs to drive optimisation/efficiency improvements on to support and maintenance regimes in order to maximize a return on such contracts [6]. Some organisations have taken advantage of this emerging market by investing heavily in establishing a global support network for their civil aerospace gas turbine market [7]. Their "whole" understanding of their systems has allowed them to drive changes from operator training up to placement of sensors on their products to collect health data; all to increase the reliability of the subsystem while enabling a move towards condition based maintenance rather than a corrective based support regime. As a result, investment and research in health management technologies has increased across various industrial sectors - to collect data from platforms that are a combination of on-board and off-board systems. Traditionally, health management was not considered during the design stages of electrical and mechanical systems [8]. Systems were first developed and then the health monitoring strategies were considered by adding new sensors and/or tests as required. As both phases were done separately, addition of new sensors proved to be difficult due to design limitations - in case of a UAV, there are weight and space constraints [9]. As the industry became aware of this gap, techniques that integrate the two design phases started to become more prominent [10], [11]. Here, the key enabler for reducing support costs is the collection and timely analysis of the correct data for diagnostics (detection and isolation) and even prognostics (predicting failures). Given the obvious danger of incorrect sensor placement, collecting incorrect data (and even large quantities of data) which are never analysed due to lack of resource, there is a challenge in specifying and designing a health management system for safety critical applications [12].

The aim of this paper is to demonstrate that an enhanced design process can reduce through-life costs by reducing the NFF event of false removals. It investigates a methodology to define the impact of adding new sensors to an existing design on failures identification and demonstrates that their consideration during the design stage could be beneficial to reduce the NFF phenomenon by the reduction of ambiguity groups and false removals[1]. The rest of the paper is structured as follows: Section 2 describes maintenance requirements and describes how the NFF phenomena can impact them throughout the life of the system. Section 3 discusses the methodology used to carry out this research work. This is followed by sections describing the case study (of a representative fuel system) that is used to demonstrate the strategy to reduce false alarms, and developing alternative models for comparison. The limitations of the approach is discussed in Section 7. Finally, some conclusions are reached in Section 8 from the preceding analysis.

[1]The ambiguity group is a collection of failure mechanisms for which diagnostics can detect a fault and can isolate the fault to that collection, yet cannot further isolate the fault to any subset of the collection.

II. Maintenance Requirements

Given the increase in the product-service oriented market across many sectors, the market for software tools and standards to assist in the design and specification of Health Management Systems (HMS) is expanding [13]. Khella et al. (2009) identified a core gap whereby the underlying HMS sensors (and their derived data) are not necessarily related directly to maintenance requirements that will utilise the health information [14], [15]. In order to address the issue, this paper is scoped to utilise a representative fuel system of a typical UAV. While the case study only considered the fuel system, a range of stakeholders (such as the pilot/operator, maintenance engineer and fleet manager) provided a number of complex interacting requirements. For simplicity, the authors only consider the maintenance engineer requirement - to reduce the unnecessary replacement of Line Replaceable Units (LRU)[2] on the UAV, referred to as NFF occurrences. This paper describes NFF as the output of a diagnostic process, where the root case of the reported fault was not verified. This is not a complete requirement as it does not quantify the required level of availability, or the number by which to reduce the NFF occurrences. It is however defined to a sufficient level of detail to support evaluation of the concept. It also considers the context of the in scope fuel system only, excluding the wider UAV vehicle systems.

The above requirement was chosen for its conflicting nature - to show the value of the Systems Engineering approach embedded within the concept for resolving them. The conflict in these requirements manifests itself (with the maintenance engineer removing several potentially faulty components from the fuel system) without further fault finding and isolation, in an attempt to reduce the downtime and increase the UAVs operational availability. This can result in several of the components returning from the manufacturers' repair facility with NFF, unnecessarily expending support budget and reducing the number of LRU available to hand at the maintenance facility. Alternatively, to correctly detected and isolate the failure down to the actual component, the maintenance engineer may require a longer maintenance period, reducing the availability of the UAV. Considering only the fuel system, the following requirement was provided by the participating organisation - Spherea Test and Services - to limit the scope of the case study: isolate engine fuel system failures to "x" number of LRUs. The "x" in the refers to a specific number of LRUs.

A. No Fault Found phenomenon - False alarms

The NFF phenomenon is one of the main problems in maintenance for the stakeholders. Within the aerospace sector, research on NFF events has gained renewed interest in the past decade [16]. One significant example is the avionics components where this phenomenon reaches 85% of their failures and 90% of the total cost of maintenance [17]. Its effects are non-negligible because it impacts the system safety and dependability, so it is necessary to limit the NFF consequences to satisfy stakeholders. This also demonstrates how an inconsequential event can build up into a strategic concern for organisations within their competitive environment. Currently, there is a drive towards a more electric aircraft [18], which indicates a rise in the number of reported NFF events.

When faults occur in a typical maintenance activity, maintenance personnel are called to find them. Procedurally, they rely on fault isolation manuals or manufacturer documents. If a component is not removed, then it is tagged serviceable. On the other hand, if the maintainer removes a component, it is sent to depth maintenance for further testing. At depth, if no fault is discovered, concerns are raised on why a serviceable component was removed from service. It is tagged as an NFF. There are three different scenarios which can explain unsuccessful fault diagnostics during the repair process:

- The fault cannot be reproduced with the real conditions. The fault is hence considered as "one off" and the system is declared serviceable. However, the fault reappears later because the origin hasn't been identified.
- The maintainer decides to replace a unit because he considers that it is the main fault's root. After few tests on the new unit, the system is declared serviceable. Nevertheless, the fault reappears so the root was not clearly identified.
- The same fault reoccurs, but the only difference is that the fault's root was not in the unit replaced.

Academic literature also recognises NFF tagged components as false removals [17], [19], [20]. False alarms can be classified as a subset of NFF, and indicate, at the system level, of failures when no fault exists, or a call for a maintenance action when none was needed. System level false alarms can send serviceable components for repair; or if the result is questioned, the predefined system level tests are repeated in order to gain confidence in the initial conclusions.

III. Methodology

A key component within the research was the application of a robust data collection phase that can effectively capture failure data from the targeted maintenance chain. Emphasis was primarily place on gathering information from maintenance engineers and related managers, but other personnel in technical support services were also included. A detailed account of the all the collaboration channels explored during this research work have been described in Khan (2015) [21].

1) Literature review: The state of the art on the NFF phenomena has been published in [16], [22]. These reviews identified that currently there are no widely accepted methods for guiding or training staff on NFF occurrences, indicating the growing gap between the 'anticipated failures' captured during system design, and the 'actual failures' that appear in service. One key gap identified was the imitations in achieving diagnostic success during troubleshooting: "The current key areas for NFF mitigation are focused around understanding test coverage represented by Built in Test (BIT)/Automatic Test Equipment (ATE) deficiencies, development of new maintenance troubleshooting tools, techniques and concepts as well

[2]An LRU is a modular component designed to be replaced quickly from on-site inventory. Thus, restoring system availability, while the removed/failed/unserviceable LRU is undergoing maintenance.

as changes to management processes. Accurate fault models, fault/event trees and system understanding, are paramount to recognizing false alarms (caused by such things as a sensor system synchronization). Also, new systematic tests should be identified in the product design."
Therefore, a test methodology is explored in this paper.

2) Model development - Design software: For Fault Identification and Isolation (FDI) during operations and maintenance, there are several software tools available for system design. Each tool is different in terms of techniques and methods for system representation and diagnostic development (see [14] for a review). In order to achieve diagnostic success, the design analysis tool should enable studying the diagnostic ambiguity and help optimise test regimes for accuracy/sensitivity [14]. eXpress^{TM} is a fully-featured, off-the-shelf software application providing an environment for the design, capture, integration, evaluation and optimization of System Diagnostics, Prognostics Health Management, and holistic Systems Testability engineering. Such testability software can also offer the possibility to provide a diagnostic analysis and a Failure Modes Effects and Criticality Analysis (FMECA).
For the purpose of this work, eXpress^{TM} has been used for:

- Dependency model development: Modelling the system is the first step; the different components are represented with their causal relationship to each other and their attributes.
- Test definition: It is possible to create several types of tests which run as it is in the real system and measure the ability of the system to test at each maintenance level. The detection and isolation of faults do not necessarily require all types of test because the only difference between tests is its coverage.
- Diagnostic analysis: This option represents the capability for the tool to do fault detection and fault isolation. A diagnostic flow diagram representing the test sequence and many reports on fault detection and fault isolation are provided by the tool. It allows studying the diagnostics and finding actions to implement on the system.
- Failure Mode Effects and Criticality Analysis: This tool builds FMECAs using the diagnostic analysis capability to identify the effects of failure modes and the criticality of the effects.

IV. UAV Fuel System - Model Overview

The fuel system is one of the most important and complex systems in an aircraft [23]. A top level diagram of the fuel rig is shown in Figure 1. In addition to its main functions of storing fuel, feeding the engines with the required flow and pressure; it is used for other external applications like management of the centre of gravity of the plane and the wing loading relief. That is why the fuel flow into various different tanks (especially in the wing tanks) has to be managed efficiently and effectively. Any failure of the system has to be avoided to fulfil the safety requirements which result from a continuous feeding of the engines throughout the flight.

eXpress^{TM} is used to model a variety of subsystems composed by several components. There are several sub-systems in the aircraft fuel system that can be seen on Figure 2:

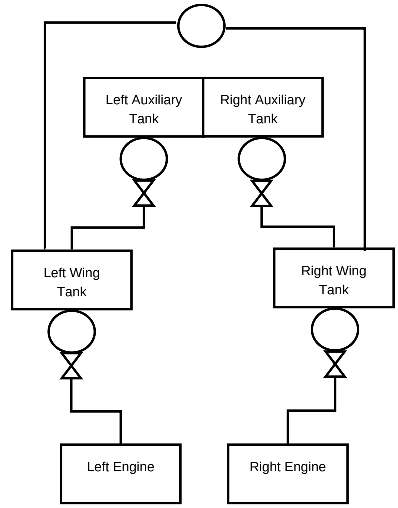


Fig. 1. Top level diagram [24].

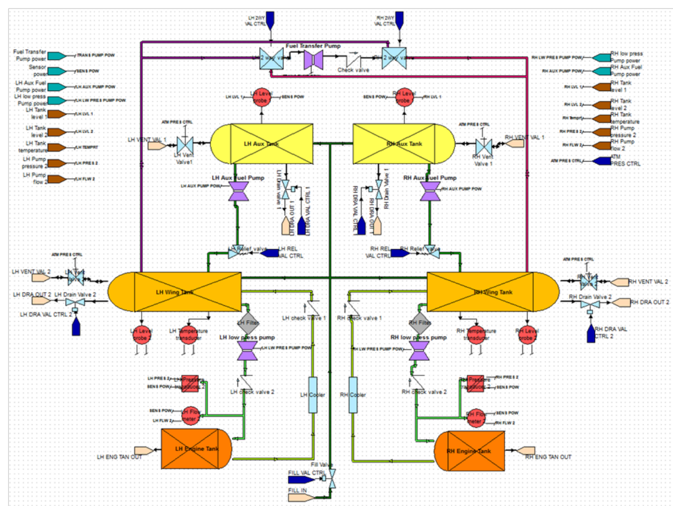
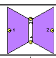
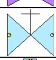
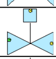
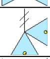
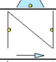
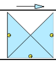
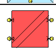
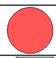
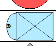
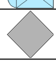
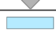
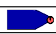
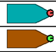


Fig. 2. Design of the fuel system model in eXpress^{TM}.

- Filling sub-system: Normally there are several fillers but in the model one filler is used to fill the wing and auxiliary tanks.
- Feeding sub-system: This sub-system is made with valves, pump, filter and also sensors and transfers the fuel from one tank to another when it is necessary (e.g. auxiliary tank ' wing tank).
- Transfer sub-system: It is used to transfer fuel from between both wing tanks to control the centre of gravity and keep the stability. The flow and pressure is controlled by a transfer pump and two two-ways valves.
- Refuel sub-system: For example, when too much fluid flow arrives in the left hand side engine this sub-system transfers surplus to the left wing tank. It is made with a cooler and a check valve. An assumption to simply the model has been made by removing the cross feed sub-system. Each sub-system is composed from a single to several components that are all linked with pipes.

Some components have an interface between the model and the outside world represented by Input/Output flags. To make clearer, some of them are on the side of the model. Table I summarises these different Input/Output flags:

TABLE I
DIFFERENT ICONS REPRESENTING COMPONENTS IN THE MODEL

Icon	Component
	Transfer pump, Auxliary pump or Low pressure pump
	Vent valve
	Fill Valve or Drain valve
	Relief valve
	Check valve
	2 Way valve
	Pressure sensor
	Flow sensor, Temperature sensor or level sensor
	Auxiliary tank, Wing tank or Engine tank
	Filter
	Cooler
	Control monitoring
	Source of power
	Output values for the sensors
	Input/output for the flow

The developed model is composed of four mains types of components: the fuel tanks, pumps, sensors and valves.

3) Fuel tanks: In each aircraft there are dedicated spaces for storing fuel. Generally, the main fuel tank is located into the wing structures due to some benefits saw in the overview part. This eXpress^{TM} model has got three different types of fuel tank located in different places of the UAV. There is symmetry for each type of tank: one for the left hand side and one for the right hand side.

- First, the auxiliary tank is used to balance the plane and to gain more stability but also to store the fuel to feed the wing tanks throughout the flight. It holds vent and drain valves to prevent against the accumulation of vapours but also sensor to measure its fuel level.
- The second type of tank is the wing tank. The weight of the fuel tanked in the wings is used to balance the lift effect so the bending moment is reduced. However, the drawback is that the wings have to create more lift effects to support the extra load applied on the fuselage.
- Finally, the engine tank that is fed by the wing tank is located just before the transformation of fuel into propulsion [17,20].

4) Pumps: In the fuel system model, several types of pumps are used. Each pump is specific for a sub-system and play a role in the non-gravity feed designs because the fuel has to move from one of the different fuel tanks to both engines. The different pumps are:

- The transfer pump is to move the fuel between the two wing tanks in order to manage the center of gravity.
- The auxiliary pump is used to feed the wing tank because it hasn't to be dry for the reason of stability and management of center of gravity.
- The low pressure pump is integrating in the engine feed sub-system. It provides the fuel at the required pressure and flow to the engine.

5) Sensors: To detect and identify critical failures, the sensors are the key components. The model integrates four types of sensors which have to be placed at the right place:

- The level sensors are located in the two wing tanks and two auxiliary tanks. It continuously controls the level of fuel in the different tank to inform on an eventually fuel transfer from one tank to another.
- The temperature sensor measures the fuel temperature in the wing tank because the fuel may be hotter than normal if the cooler does not work well.
- The flow and pressure sensors are integrated in the engine feed sub-system to control the flow and the pressure of the fuel after the low pressure pump.

6) Valves: Along the pipe system there are valves controlled by monitoring to stop the fuel flow. In this model there are four main types of valves:

- The shutoff valve is used to fill the tanks but also to drain the tanks. It is a simple valve which is controlled to be open or closed.
- The vent valve is fixed to the two wing tanks and two auxiliary tanks and balances the pressure in the different tanks. An assumption has been made because the model design is composed with only one vent valve for each tank whereas in reality there are always two vent valves to cope with of the obstruction issue.
- The relief valve is also a valve for the pressure but it allows protecting and limiting tanks against pressure that could exceed their design limits.
- The check valve controls the direction of the fuel flow at the exit of pumps or coolers. It works automatically without being controlled by any external control.

A. Attributes

In order to develop and simulate the system component attribute data is required. In this case, three main attributes have been considered that have greater impact on maintenance decisions:

- Reliability: representing the failure rate of the component expressed in Mean Time Between Failure (MTBF)
- Time-to-change: represents the time to replace a unit and has an impact upon the time to repair
- Cost: changing a unit has an impact on the cost to repair

Reliability data was provided by component suppliers, or taken from existing models made by Spherea T&S. The time-to-repair and costs estimates were mostly taken from existing models and research publications [24], [25]. A summary is presented in Table II.

B. Failure modes

Failure modes describe the observable behaviours in which an item can fail. These are essential to build a diagnostic as it helps to provide much more detailed visibility of component activity. For the fuel system model, failure modes have been

TABLE II
ATTRIBUTES OF THE DIFFERENT COMPONENTS

Component	Reliability (MTBF)	Time-to-change (Minutes)	Cost ($)
Auxiliary tank	1.01 decades	600	2000
Wing tank	1.01 decades	600	2000
Engine tank	2.8 decades	600	2000
Transfer pump	2.11 decades	120	202
Auxiliary pump	1.14 decades	120	202
Low pressure pump	2.11 decades	120	202
Fill valve	4.21 decades	30	137
Drain valve	4.21 decades	90	137
Vent valve	2.85 decades	30	137
Relief valve	1.56 decades	30	137
2-way valve	1.56 decades	30	137
Check valve	4.09 decades	30	57
Filter	2.74 years	10	21
Cooler	11.4 centuries	60	300
Pressure sensor	3.54 decades	30	250
Flow sensor	6.47 years	30	250
Temperature sensor	1.75 decades	30	40
Level sensor	1.75 decades	30	40

TABLE III
FAILURE MODES OF THE FUEL SYSTEM MODEL

Component	Failure mode	Occurrence
Auxiliary tank	Tank failed	1%
Wing tank	Tank failed	1%
Engine tank	Tank level low	99%
Transfer pump	Pump failed	50%
Auxiliary pump	Pump failed	50%
Low pressure pump	Pump flow incorrect	50%
Fill valve	Leakage, stuck open	50%
Drain valve	Leakage	35%
Vent valve	Vent in/out failed	50%
Relief valve	Stuck open	20%
2-way valve	Clogged	10%
Check valve	Stuck open	35%
Filter	Clogged filter (partly/fully)	80% (partly) 20% (fully)
Cooler	Cooler blocked, leakage	50%
Pressure sensor	Out of calibration	95%
Flow sensor	Out of calibration	95%
Temperature sensor	Sensor failure	5%
Level sensor	Out of calibration	95%

defined for each component with a value representing that failure mode's percentage of the object's total failures. When the percentages of occurrence for object failure modes add up to 100%, that means that all the ways in which an object can fail have been taken into account. A summary of failure modes is presented in Table III.

C. Failure effects

The attributes and the failure modes are not the only data added to complete the model. It is also necessary to add failure effects. These represent the consequences of the failures modes and can be defined in two ways with eXpress^{TM} - object failure effects and design failure effects. Object failure effects represent how failure modes on an object manifest themselves, whereas design failure effects are the representation of how the object failure effects manifest themselves at the design level. The failure modes defined before and the failure effects are essential to build a diagnostic analysis and a FMECA. For the fuel system model, the design failures effects are listed and explained below:

- False alarms: There are two types of false alarm: false positive is when the system detects a failure, however, this is none. The other, a false negative, is when the system does not detect a failure where in fact there was one.
- Fuel flow incorrect: This failure effect appears when the fuel flow is incorrect in the system due to a component (e.g. a pump).
- Fuel level low: This means that the level of fuel is low inside the fuel system.
- Fuel not flowing: This design failure design is when the fuel is not slowing due to a component or several components (e.g. filter clogged).
- Hydraulic leak: This is related to leakage of the components.
- Sensor failure warning: Indicates sensor failure.
- Tank not equally filled: This is indicates incorrect balance between the right and left side tanks.
- Tank pressure incorrect: This indicates that the pressure inside the tank is incorrect.

V. DIAGNOSTIC STUDY

After model development, a reference diagnostic study will be used to allow comparisons. eXpress^{TM} generates a diagnostic study that represents the test sequence composed by tests and fault groups. It indicates the ambiguity group size of the analysis. This allows the designer to concentrate efforts on particular fault group that have the highest ambiguity (15 in the fuel system case study) and understand which modification works, or fails to isolate failures. After identifying the fault group new sensors placement or tests can be identified to help the detection of failures.

Table IV summarises the main statistics provided by the diagnostic study for the "reference" model; summarising the probability of detection, the probability of isolation and the average fault group size number (average ambiguity). This helps to investigate improvements in any new sensors (or tests) can detect and isolate faults. The table also lists the different ambiguities with the associated number of fault groups. For this reference model, the highest ambiguity is 15, with 4 fault groups. The aim of adding any new sensors (or tests) will be to to remove these 4 fault groups. The diagnostic study can provide a lot of information to develop a strategy on the implementation of new sensors.

The number of NFF events can be reduced by focusing on the fault groups with higher ambiguity. A diagnostic study is generated, followed by the trade-off between the ambiguity

TABLE IV
DETECTION AND ISOLATION STATISTICS FOR THE "REFERENCE" MODEL OF FUEL SYSTEM WITHOUT ADDING NEW SENSORS

Prob of detection	**99.1%**		
Prob of isolation	**57.09%**		
Average fault group size	**3.97**		
Fault group size	**Fault count**	**Fault percentage (%)**	**Cumulative (%)**
1	44	57.09	57.09
2	5	1.56	58.65
3	15	5.94	64.59
4	6	3.51	68.09
5	15	5.27	73.37
6	14	4.68	78.05
7	6	3.28	81.33
8	4	2.02	83.35
9	5	7.22	90.58
11	1	1.97	92.55
15	4	7.45	100

and the criticality of the large fault groups sizes[3]. After identifying the essential components, new sensors are selected and added accordingly. After this step, a new diagnostic study is generated that can provide revised diagnostic statistics. Finally, these results are compared with the reference model results. Figure 3 summarises the strategy to reach the aim (e.g. ambiguity=1) by reducing the average size group.

It should be noted that there are various diagnostic algorithms that can influence the order of testing for fault detection or fault isolation [26], and eXpress^{TM} provides a number of them. Each algorithm (available in the software) is comprised of a set of test candidate groupings, test weighting and test cut-offs. These groupings and weighting defined for each algorithm are the result of a sophisticated understanding of the test selection criteria that, as a rule of thumb, tend to produce "good" diagnostics in a variety of diagnostic situations (production testing, regular maintenance, trouble-shooting, damage assessment, etc.). Such algorithms are not meant to be definitive diagnostic methodologies that can handle any contingency, but to rather act as baseline approaches that can be modified to customize diagnostics to the task at hand. In fact, none of the predefined detection or isolation algorithms initially take into consideration attributes such as cost or time. These are added by the authors to prove the concept. Therefore, it is assumed that a designer will add additional weighting as necessary to accommodate the specific needs of a particular diagnostic requirements/study.

VI. ALTERNATE MODELS

Following the strategy established in the previous section, a new model can now been created to compare potential improvements between the initial model and the new alternative models.

[3]Instead of reducing the fault groups with the highest ambiguity, the criticality of the fault groups must also influence decision-making.

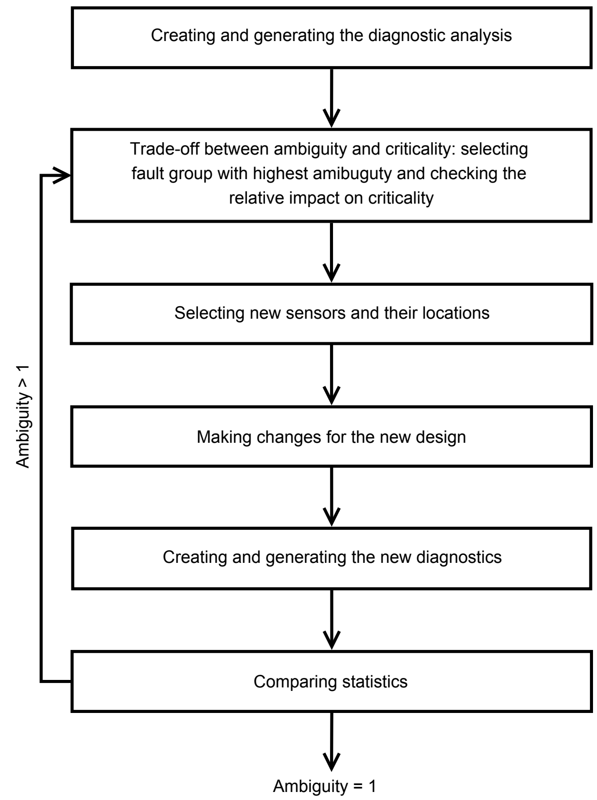


Fig. 3. Strategy to decide on new sensor locations.

This section details the three different fuel system models redesigned with the diagnostic analysis and STAGE simulations. For each model, there is an alternative way of sensors placement.

A. Design 1

The first alternative model has been done according to the results generated from the diagnostic analysis of the reference model. After analysing those results and following the strategy explained in the previous section, efforts are focussed on the four fault groups with 15 items (because this is the highest ambiguity). The new design of the fuel system is displayed in Figure 4. The additional sensors are circled in red.

The diagnostic study generated four faults groups highlighted in the upper part of the fuel system. This is presented in Table V. Moreover, the FMECA revealed two failures of the left and right hand side of the relief valves that are not being detected.

In conclusion, the extra sensors have an impact on some features for the model in terms of faults isolation. However, it does not solve the problem of ambiguity.

To complete this analysis, STAGE^{TM} is used. STAGE^{TM} is an add-on simulation package that can provide a range of statistical charts representing total costs and reliability of the developed eXpress model over a period of time. These charts include the:

- Average removals over time
- Extra cost due to false removals over time
- Fault isolation over time

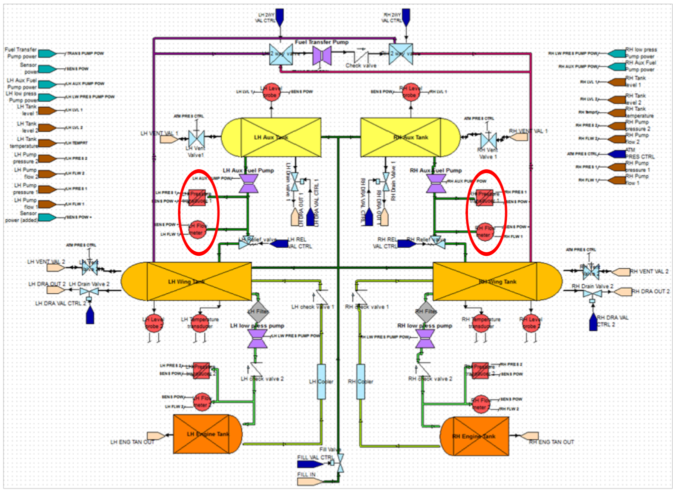


Fig. 4. Alternative Design 1.

TABLE V
DIAGNOSTIC STUDY FOR THE ALTERNATIVE DESIGN 1 MODEL

Prob of detection	**99.21%**
Prob of isolation	**62.04%**
Average fault group size	**3.64**

Fault group size	**Fault count**	**Fault percentage (%)**	**Cumulative (%)**
1	56	62.04	62.04
2	11	4.1	66.14
3	16	4.81	70.95
4	6	2.76	73.71
5	14	4.19	77.9
6	16	4.98	82.88
7	6	2.81	85.69
8	4	1.74	87.43
9	5	5.34	92.77
11	1	1.58	94.35
15	4	5.65	100

The metrics produced in the STAGE simulation allow for any common metric to be viewed in an assortment of graphs, and many described using stochastic values. The metrics that can be generated from the pulling of the functional or failure attributes contained within the diagnostic design do not need to be limited.

The model time period has been set at 20000 hours (account to approximately 22.8 years)

1) Average component removal charts: The comparison between the reference model and the first alternative model begins with a chart that is relevant for the NFF phenomenon - the "Average removal over time". This is illustrated in Figure 14, representing all removed units for maintenance against time (22.8 years). The grey area accounts for total removals, whereas the yellow area accounts for false removals due to large ambiguity groups.

Figure 5 is the original model and shows that the components removed without being faulty represent approximately 70% of all removals. Without new sensors, the No Fault Found

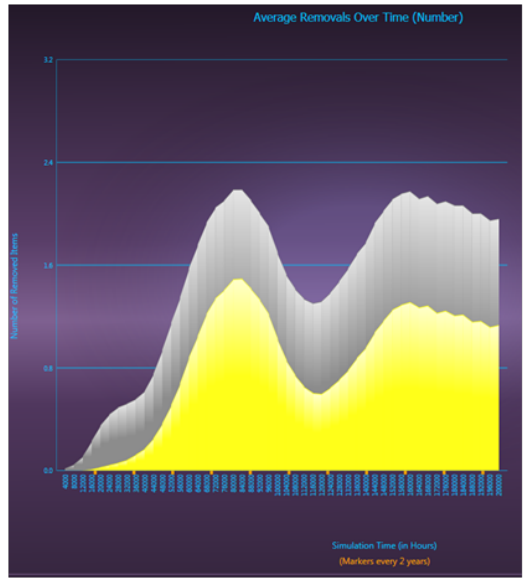


Fig. 5. Average removals over time for the "reference" model.

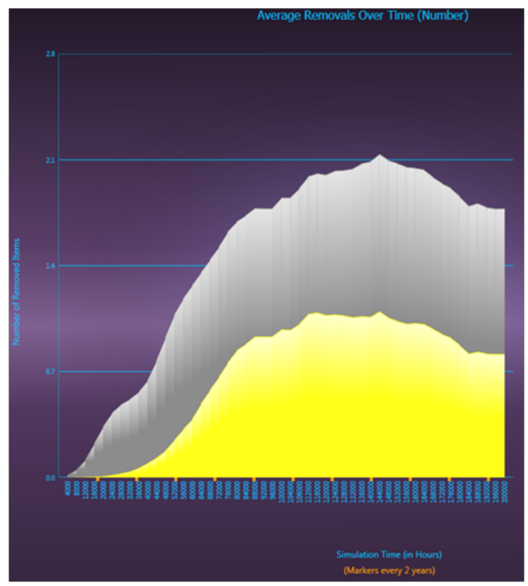


Fig. 6. Average removals over time for the Alternative Design 1 model.

phenomenon is prevalent over the specified time period. Figure 6 shows the average removals for the alternative model. It can be seen, analytically, that by adding new sensors to the original design (after the auxiliary pump) has changed the proportion of the false removals from that section of the fuel rig design.

These charts maintain the conclusions made in the previous section that placing new sensors in the design improve fault isolation.

2) Cost analysis charts: eXpress^{TM} allows the designer to put a price tag on each component, time taken for maintenance and labour costs. This can be useful in predicting a cost

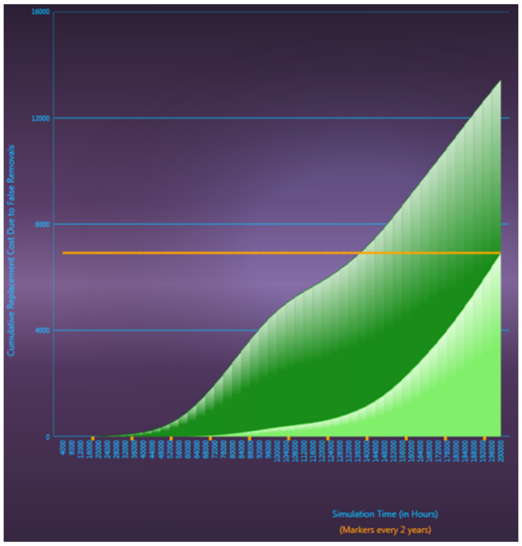


Fig. 7. Extra costs due false removals over time for the “reference” model.

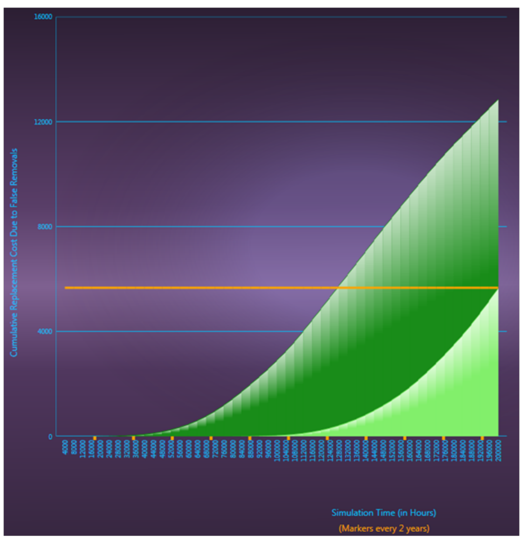


Fig. 8. Extra costs due false removals over time for the Alternative Design 1 model.

estimate for overall cost on false removals. As an example to demonstrate the concept, the authors have used fictitious cost values in the model. The following chart accounts the cumulative cost of false removals over the 20000 hours. The comparison between both models is done with the chart calls “extra cost due to false removals over time”.

The y-axis in Figure 7 and 8 represents the cumulative replacement cost for the reference and Design 1 models. The dark green palette is used to represent total wastage - labour, maintenance, etc, whereas, the light green palette represents the cost of additional component replacements - due to false removals. Comparing the total costs between the two developed models shows a slight difference; with a reduction of the cost by 18%. In fact, the cost of extra replacements for the initial model is approximately $6917 whereas for the first alternative model it is around $5663. These costs only represent the cost of the repair, not the cost of consequently

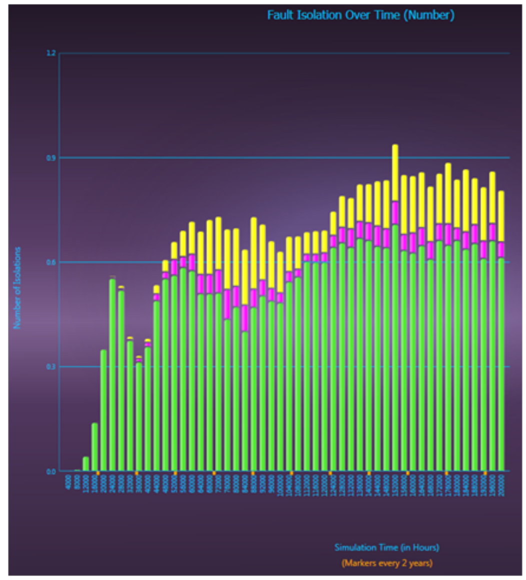


Fig. 9. Fault isolation over time for the “reference” model.

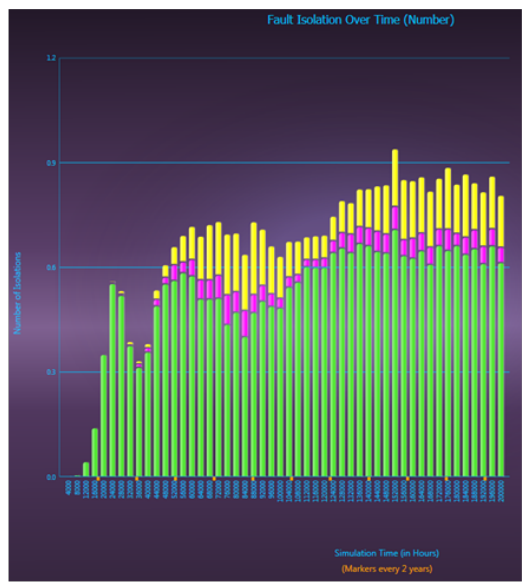


Fig. 10. Fault isolation over time for the Alternative Design 1 model.

diagnosing a good unit (which would be extra time and effort). Therefore, the addition of sensors has an impact on overall false removal costs.

3) Fault isolation charts: The last type of charts, (Figure 9 and 10), represent the fault isolation over the model life-cycle and aims to study the progression of different fault group size.

The y-axis represents the number of isolations (in other words, the number of the different size of fault groups). These charts use four different colours:

- Green for fault groups = 1 item
- Blue for fault groups = 2 items
- Pink for fault groups = 3 items
- Yellow for fault groups $\geq$ 4 items

Examining the two model chart results, there can be seen an increasing proportion of green and pink lines in the alternative model. This is because; with new sensors the model reduces the number of fault groups with 4 or more items. The fault isolation is better because the number of fault groups with 1 and 3 items increases. Also, the addition of new sensors between auxiliary tanks and wing tanks has a significant influence on the fault group size. However the 4 fault groups with an ambiguity of 15 are not removed.

Overall, the addition of new sensors between the auxiliary tanks and the wing tanks improves the model by reducing the cost and getting a better isolation. However, the highest ambiguity is still 15 so the results might be better by changing the sensors placement. Therefore, the next design develops another strategy using a second alternative model of fuel system.

B. Design 2

After the first exercise, a new design for the fuel system will now be simulated using the same strategy. According to the diagnostic analysis of the original model, the highest ambiguity is fifteen (in four faults groups), including components on the transfer way. The transfer way is a critical path within the fuel rig as it helps an aircraft to keep its stability by transferring fuel from a wing tank to another. Therefore, the additional sensors will be placed on the transfer way between the check valve and the right hand side two way valves to control the flow and the pressure after the transfer pump. By adding these new sensors in this area, improvements in terms of isolation of failures are expected. The choice for the type of additional sensors is the same as the choice made in the first alternative model. The two additional sensors are a pressure transducer and flow metre with the same features than the others pressure and flow sensors.

Figure 11 presents the second alternative design of the fuel system.

The diagnostic study for the Alternative Design 2 model is presented in Table VI. Comparing these results to the previous alternative model, the results have worsened because:

- The probability of isolation has decreased
- The average fault group size is higher
- The highest ambiguity is still 15 with 4 fault groups

So, the changes brought by this design, in terms of fault detection and isolation, are not an improvement.

1) Average fault removal charts: As compared to Design 1 in Figure 5, Figure 12 of Design 2 shows almost no difference. Although there is some improvement in the number of false removals over time.

2) Cost analysis charts: Figure 13 illustrates the cost resulting for the model. There is a higher cumulative cost of extra sensor placements - \$7167. Adding extra sensors can be expensive at the end of the system system life cycle even

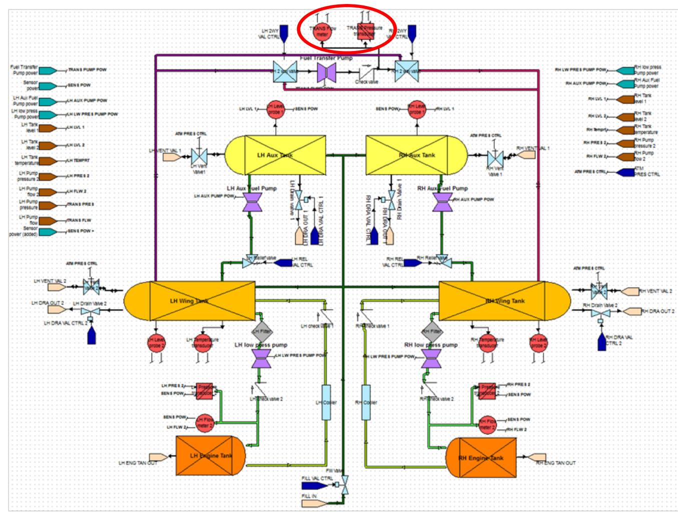


Fig. 11. Alternative Design 2 model.

TABLE VI
DIAGNOSTIC STUDY FOR THE SECOND ALTERNATIVE MODEL

Prob of detection	**99.16%**
Prob of isolation	**59.25%**
Average fault group size	**3.77**

Fault group size	Fault count	Fault percentage (%)	Cumulative (%)
1	48	59.25	59.25
2	13	2.03	61.28
3	25	6.67	67.96
4	5	3.14	71.09
5	21	5.71	76.8
6	8	2.29	79.1
7	6	2.64	81.74
8	4	1.68	83.42
9	5	6.83	90.25
11	1	1.76	92.01
12	2	1.33	93.34
15	4	5.65	100

though they might help to increase isolation, as can be seen in the following analysis.

3) Fault isolation charts: The last exercise for Design 2 is for fault isolation over the life-cycle. The results in Figure 14 remains similar to Design 1. The only difference noticeable difference is the number of fault groups with one item is higher for Design 2.

The three charts confirm that Design 2, with extra sensors on the transfer way, is not necessarily an effective one. However, there is slight improvement within the diagnostic study which indicates that a combination of Design 1 and Design 2 models can help reduce false removals. The next section goes through this idea to build the final model.

C. Design 3

The two prior alternative models show some improvements in the diagnostic analysis. The third model combines both

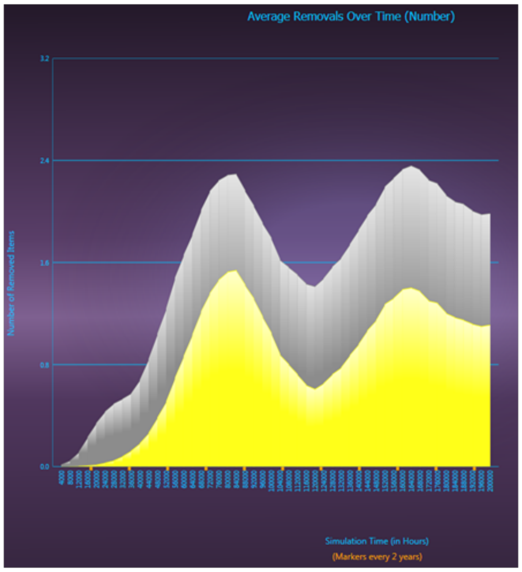


Fig. 12. Average removals over time for the Alternative Design 2 model.

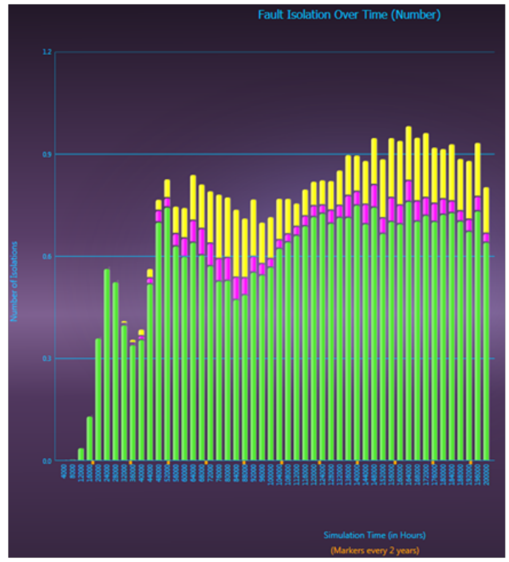


Fig. 14. Fault isolation over time for the Alternative Design 2 model.

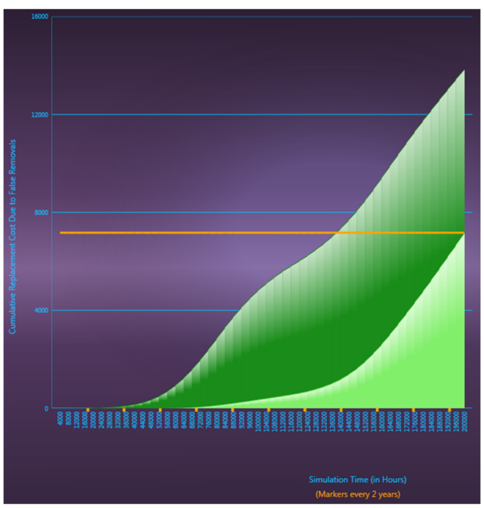


Fig. 13. Extra cost due false removals over time for the Alternative Design 2 model.

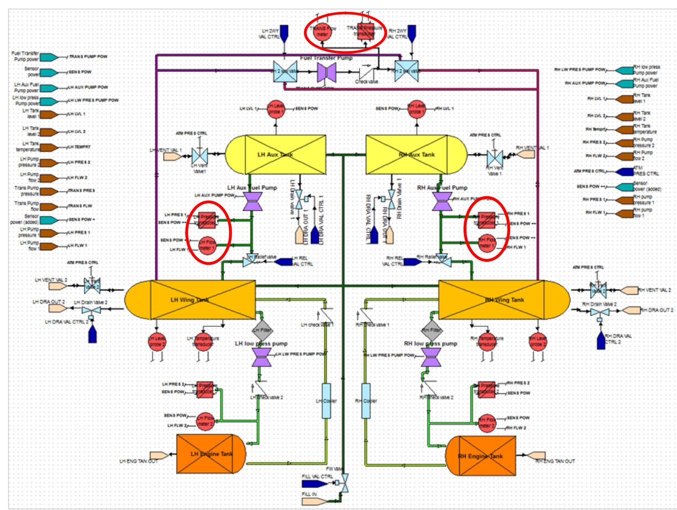


Fig. 15. Alternative Design 3 model.

previous models by adding extra sensors after the auxiliary pumps and the transfer pump. As before, the new sensors in Figure 15, are circled in red.
The diagnostic study in Table VII shows improvements compared to the two alternative models:

- The probabilities for the fault detection and isolation increases as well as the number of the average fault group size.
- The probability of isolation increases by 11%
- The average fault group size decreases by 34%
- The removal of the 4 fault groups of 15 items. The highest ambiguity is 11 for only one fault group Reduction in the number of fault groups with an ambiguity greater than 1

It is evident that adding extra sensors has improved the fault detection and isolation aspect of the model. Furthermore, the simulations confirm the results obtained of the diagnostic analysis.

1) Average fault removal charts: Figure 24 shows the charts of the average removals of the original model and the final model. By comparison, it is visible that the extra sensors placements have made differences. The percentage of false removals is around 70% of the total removal for the initial model whereas with the new design, this percentage is approximately less than 50%.

2) Cost analysis charts: Figure 17 presents the extra costs due to false removals for the model. More sensors results in more improvements and hence the reduction in the "whole" system cost. The original model is \$6917, whereas for the final one it is \$3260. Concerning the wasted item cost, there is also a reduction of approximately 30% between both models.

TABLE VII
DIAGNOSTIC STUDY FOR THE ALTERNATIVE DESIGN 3 MODEL

Prob of detection		**99.25%**	
Prob of isolation		**63.76%**	
Average fault group size		**2.61**	
Fault group size	**Fault count**	**Fault percentage (%)**	**Cumulative (%)**
1	42	63.76	63.76
2	5	2.58	66.33
3	9	6.27	72.6
4	2	6.66	79.26
5	2	3.7	82.97
6	8	5.42	88.39
7	4	3.51	91.89
9	1	3.81	95.7
11	1	4.3	100

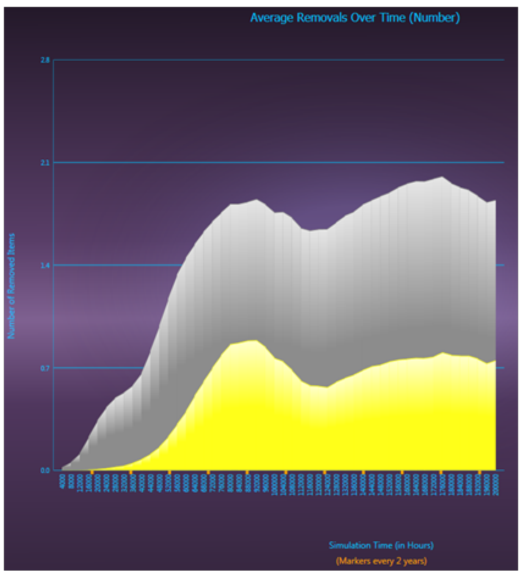


Fig. 16. Average removals over time for the Alternative Design 3 model.

3) Fault isolation charts: The final chart in Figure 18is for fault isolation over the 20000 hours:

- The proportion of fault groups size of 2 items (represented by the colour blue) increases.
- The fault groups size of 3 items increases
- It is possible to notice a reduction of the number of fault group size of 4 or more items (due to the removal of the 4 fault groups of 15 items)

These simulations confirm the results of the diagnostic study, and highlight the improvements due to additional sensors.

VII. DISCUSSION ON LIMITATIONS

After presenting the strategy for designs improvements, the diagnostic analysis and simulations; it is important to put things into perspective. There are some limitations that has consequences on the study:

- The system model: The primary step of this paper was to model a fuel system. It is a complex system therefore a simplification of the design was necessary to obtain simpler analysis for study. The main simplification is the removal of the cross feed sub-system because it simplifies the number of functions and tests. Then the two other design changes have also been made to reduce the test number because each tank do not hold a second vent valve to avoid the problem of valve obstruction. Moreover, it was challenging to find realistic attributes to model the system. Therefore, instead of getting these data from one source, several have been used.
- Software limitations: The comparison of the diagnostic analyses generated in eXpress^{TM} between the various models shows that adding sensors improves the fault isolation. This also enables cost analysis from false removals. However, design changes were done with little

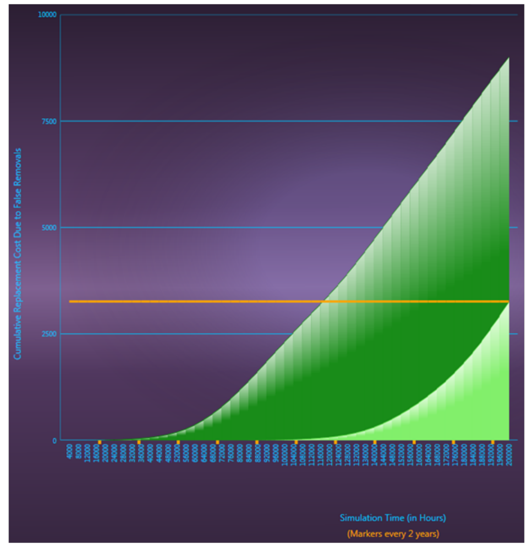


Fig. 17. Extra cost due false removals over time for the Alternative Design 3 model.

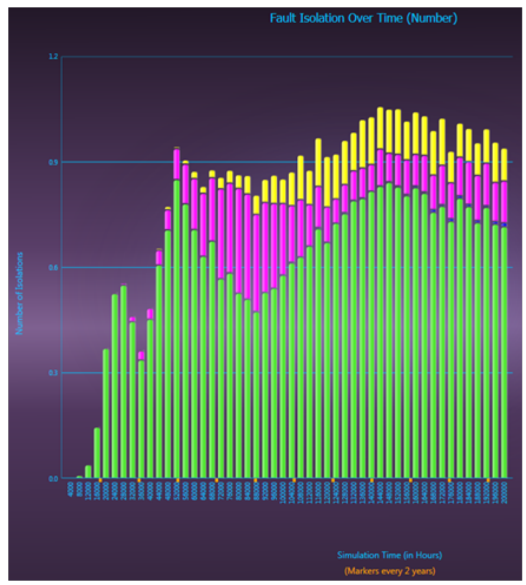


Fig. 18. Fault isolation over time for the Alternative Design 3 model.

information about the type of sensors and the additional effort required for sensor placement. The improvement between the original and final models has been done by adding six new sensors. Therefore, before reaching to any conclusions, it is important to take into account such costs. The obsolescence of the component and their cost inflation were not considered, but will heavily influence the design decisions.

- The STAGE simulation can describe many metrics. Some are based upon typical design assessment requirements while others are advanced design requirements for assessing future HM requirements. The STAGE graphs can describe the increase in risk of any failure (or the combination of failures), since the last time it was diagnosed - considering the impact of maintenance. Surprisingly, this consideration is not included in any of the algorithms in academic literature on the embodiment of the topic. Instead, one must effectively bury the likelihood of uncertainty in the use of distributions. Yet, if that is a preference, one can even use any distribution curve of choice as an attribute assigned to any failure effect "test" used in their model. If design engineers can glance at the characteristics or trends presented in quick (gestalt) graphs to "visualize" the impact of design-decision modifications, then it is possible to understand their impact - originating from the same identical knowledge base where all of the component interrelationships are captured, and in a form enabling optimization "whole design model swapping".

VIII. Conclusions

Throughout this paper, the impact of the NFF phenomena on the system life cycle has been discussed. A methodology to reduce its effects was investigated by optimising the placement of new sensors on an existing design and investigating the ratio between weight/cost. The selected case study, of an UAV fuel system, has shown improvement in terms of reducing the number of false removals. This process can be performed before the final components are selected in the design. These (and many other assessments) can be charted at any time, but all will be based upon known "iterations/versions" of "in-process" data artifacts and traceable to that specific point in the design development process.

A fuel rig system model used in the case study was developed in eXpress^{TM}; with STAGE^{TM} running simulations to determine the impact of design changes. The results from the simulations indicate how significant improvements can be achieved in terms of fault detection and isolation, and hence the overall system life-cycle cost for improvements in ambiguity reduction during the design stage. By comparing various sensor placements on an reference design, the results provide a source of guidance for the decision-making process in organisations on resources requirements.

Although the methodology developed shows that it is possible to simulate the impact on the NFF phenomenon using software tools. However, further work is required to improve the quality of the simulation results:

- It would be applicable to use genuine component weight and cost values to estimate the whole model cost. This realistic model would allow better diagnostic analysis and the simulation results.
- Obsolescence: Adding the obsolescence of components and the cost inflation on certain high value components will improve the NFF event cost analysis.
- Degradation of parameters: Depending on the operating environment certain components are exposed to, their degradation profile will vary. This information can be added to the analysis to study the cost impact on the system life cycle.
- Trade-offs: The strategy implemented in this paper has been built on the requirement of removing the fault group with the highest ambiguity. But fault groups with highest ambiguity do not always have the highest criticality. There is still work to be completed on the strategy of the fault group selection according to the ambiguity or the criticality. For example, selecting between a fault group with an ambiguity of fifteen and a criticality smaller than the one of a fault group with an ambiguity of fourteen and thirteen is quite complex. Studying this trade-off could improve the sensors placement and decrease the average ambiguity of the model.

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