Progress towards a Framework for Aerospace Vehicle Reasoning (FAVER)

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ABSTRACT

This paper proposes a reasoning framework to diagnose faults at the vehicle level in a complex machine like an aircraft. The current focus of Integrated Vehicle Health Management (IVHM) is on diagnosing and prognosing faults at the component and subsystem levels; only a few IVHM systems consider the interaction between the systems. To diagnose faults at the vehicle level, an IVHM System needs a framework that recognizes the causal relationships between systems and the likelihood of fault propagation between them. The framework should also possess an element of reasoning to assess data from all systems, to assign priorities, and to resolve ambiguities. The Framework for Aerospace VEhicle Reasoning (FAVER) that is proposed in this paper uses a Digital Twin (DT) of the aircraft systems to emulate functioning of the aircraft and to simulate the effect of fault propagation due to systems interactions. FAVER applies reasoning that can handle fault signatures from multiple systems in the form of symptom vectors, to detect and isolate cascading faults and their root causes. The blending of a DT and reasoning in this framework will enable FAVER to: i) isolate faults that have both local and cascading effects on the concerned systems, ii) identify faults that were previously unknown, and iii) resolve ambiguous faults. This paper explains the different steps involved in developing FAVER and how this framework can be demonstrated in the aforementioned scenarios with the help of different use cases. This paper also talks about the challenges to be faced while developing this framework and ways to overcome them.

1. INTRODUCTION

Any aerospace vehicle, like an aircraft, is a complex machine comprising various multi-physical systems, each having functions and objectives of their own. These systems interact with each other at different levels to attain full functionality of the aircraft (Ezhilarasu, 2018). In general, the aircraft systems are built in such a way that they remain stand-alone to a greater degree, to avoid unnecessary complexities. Still, due to the interactions between systems, it is not uncommon for a fault arising from one system to propagate and affect another system that the former is interacting with. Such cascading faults, whose paths are already known, are isolated in maintenance and troubleshooting activities. This is sometimes performed with aircraft maintenance systems like Honeywell's Prime Epic Aircraft Diagnostic Maintenance Systems (ADMS) (Scandura, Christensen, Lutz, & Bird, 2011). However, when a fault propagation takes a new/ unexpected path and affects multiple systems, it cannot be isolated easily during maintenance. One such real-world incident is the engine rollback of a Boeing 777 at Heathrow airport in 2008 (Sleight & Carter, 2014). During the investigation, the reason behind the engine rollback was found to be a drop in its power due to restricted fuel flow to both the engines. Further root cause analysis found that the fuel remained in the 'sticky' temperature range (less than -10ºC) for a prolonged period of time; this resulted in ice formation, which in turn was released in the fuel feed pipe and blocked the fuel oil heat exchanger and the rest of the fuel lines. Another such example is the emergency evacuation of a Fokker F28 in 2002, due to smoke in the cabin (Conradi, 2015). The investigation found that it was due to a crack in the Auxiliary Power Unit's compressor blade, the debris eventually causing a crack in an oil seal and resulting in oil spray in the bleed valve, leading to smoke in the cabin (Conradi, 2015).

In cases like the abovementioned incidents, which are met with unexpected failure propagation involving multiple aircraft systems, troubleshooting is not a straight forward activity, and it results in extended downtime. Any Integrated Vehicle Health Management (IVHM) System that attempts diagnosing such cascading faults requires a holistic view of the aircraft, and the micro effects (confined to a system) and macro effects (affecting the system in addition to the system of origin) of the interactions between the various systems (A.N.Srivatsava, R.W.Mah, R.Bharadwaj, & D.Mylaraswamy, 2013). The current focus of IVHM systems involve automated procedures focused at Line Replacement Units (LRUs) and subsystems level, but there are very few research publications that consider 'vehicle level' as their primary driver (Ezhilarasu, Skaf, & Jennions, 2019). This paper proposes a framework that aims to isolate the cascading faults affecting multiple systems of the aircraft. The Framework for Aerospace VEhicle Reasoning, also known as FAVER, incorporates the concept of a Digital Twin (DT) to produce simulations of what-if scenarios between the aircraft systems, along with an element of reasoning, to investigate data from the concerned systems and to isolate the root cause of cascaded faults.

2. FAVER FUNDAMENTALS

FAVER is a proposed framework for isolating faults in aircraft systems, particularly a fault or degradation in one system that affects another. FAVER comprises of two components: i) Digital Twin (DT) and ii) Reasoning. The following subsections present the background of both elements and explain how they will fit together to enable FAVER to isolate cascading faults in different scenarios.

2.1. Digital Twin (DT)

A DT is a virtual representation of any physical or functional asset that helps in monitoring the performance of the asset for a variety of outcomes like efficiency, health, or lifecycle cost. The term 'Digital Twin' was first coined by Dr. Michael Grieves from the University of Michigan in 2002, to mean a virtual/digital representation of any physical asset (Grieves, 2016). NASA brought the concept of DT into the aerospace field in 2012, to integrate the simulation with on-board IVHM systems, along with historical maintenance and fleet data to represent its exact physical twin for further analysis (Glaessgen & Stargel, 2012). Over the last decade, the application of the DT has expanded, due to the abundance of data produced by the physical systems and the digitization of data collection and processing. In the field of IVHM, the DT has been applied for anomaly detection, predictive and prescriptive analysis and operation optimization (Auweraer, 2018; General Electric, 2016; The Aerospace Technology Institute, 2017).

By the definition of the DT, it is evident that it is, at its core, a simulation model of any physical asset, and that it functions as a living model and provides results based on its application. For a given instance, in the case of predictive analysis in IVHM, the DT can provide simulation results of the system's remaining life and, in the case of manufacturing, it can give the results required for operation optimization. When extended to the field of health monitoring, the DT is capable of producing what-if scenarios to understand the hidden relationship between the systems; it is this capability of the DT which will be useful to the proposed framework for isolating cascading faults. FAVER uses the DT, as it can establish the interaction between the systems and enable simulations of a healthy state as well as possible fault propagations between the systems.

2.2. Reasoning

Reasoning is a systematic methodology for problem-solving by using the application of logic and cognition. There are a variety of reasoning strategies such as deduction, induction, abduction, analogical and temporal reasoning, which are applied depending upon the data available to solve problems (Ezhilarasu et al., 2019). A reasoning system is a software system that employs reasoning strategies in a systematic 'input-process-output' manner. In the field of aerospace IVHM, several reasoning systems have been developed to monitor the systems health (Bunus, Isaksson, Frey, & Münker, 2009; Gaudette & Alwardt, 2006; Park et al., 2004; Sebastian, Peripinayagam, Jennions, & Alghassi, 2016). Reasoning is required in IVHM systems for many roles such as analyzing data from multiple sources, isolating the root cause of any faults, helping in decision-making processes, resolving ambiguities, detecting anomalies and upgrading diagnostic accuracies. Reasoning is an invaluable component for developing IVHM systems for vehicle level health monitoring (Ezhilarasu et al., 2019).

In order to diagnose faults at the vehicle level, FAVER requires the reasoning element to meet with the following objectives: i) to process data from multiple aircraft systems, ii) to assess information, iii) set priorities, iv) resolve conflicts, v) pass judgement on the possible root causes of any fault, and vi) to update FAVER's knowledge of any new fault that affects a system.

2.3. The synergy between the Digital Twin and Reasoning

The proposed framework, FAVER combines the versatility of a Digital Twin (DT) with the power of reasoning, in such a way that both these components compensate for each other's lacking. A DT could emulate the functioning of an aircraft through simulations of its systems at healthy and faulty (or degraded) states; yet, the output from such simulations require further intense analysis and intelligence to isolate the root cause of the fault from the data produced. On the contrary, reasoning in a health monitoring system is only as effective as its domain knowledge either in the form of expert systems, models or datasets. Hence, FAVER aims to make use of the synergy between the ability of a DT to emulate the effects of fault propagation between the aircraft systems and reasoning's ability to investigate the data produced to isolate the root cause of the fault propagation. This blending of DT and reasoning will enable FAVER to:

i) isolate faults that have both local and cascading effects on the concerned aircraft systems,

ii) identify faults that were previously unknown, and

iii) resolve ambiguous faults.

3. FAVER METHODOLOGY

Figure 1 shows the schematic of the proposed framework. The schematic is represented with two main layers, viz, i) The Digital Twin layer (bottom of figure 1), and ii) the Reasoning layer (top of figure 1). The two intermediate layers in figure 1 represent the system level diagnostics and fault detection layers. Each vertical in figure 1 represents the modules required from each system, contributing to reasoning at the top level.

Consider the Fuel System, the Engine, the Environmental Control System (ECS) and the Electrical Power System (EPS) of an aircraft (as shown in the bottom-most layer of figure 1). These systems have functions of their own and part of their functions that involve interacting with the other systems. For illustration, the fuel system provides fuel to the engine, the engine provides bleed air to the ECS and shaft power required for the EPS, and the EPS provides electric power to the components in the fuel system, the engine and the ECS. These systems interactions are considered for emulating the interactions in an aircraft via DT within FAVER. Besides, the EPS is also chosen to add a multi-physical dimension to the problem chosen. The DT can be a physics-based or a function-based model, or it can be a Hardware-in-the-loop or a data-driven representation as well.

The second horizontal layer from the bottom in figure 1 represents the number of fault modes being considered at the system level. These fault modes degrade the systems from its 100% healthy state to degraded or faulty states. Only a limited number of fault modes are taken into account for the initial setup of the framework, as FAVER aims to demonstrate its capability of isolating a certain number of fault modes with a broader range of systems rather than focusing on a large number of fault modes only from a few systems. The third horizontal layer from the bottom in figure 1 shows that each system has its own diagnostics for the determined fault modes. These systems diagnostics are fed by sensor data from the DT for isolation of local fault with micro effects. They are incorporated in FAVER's schematic so as to contribute to overall reasoning at the vehicle level.

The reasoning is built on the diagnostic capability of the systems and their interactions. The reasoning module has access to both sensor data and diagnostic information from the systems. The knowledge is stored in the form of a symptom vector (sensor readings from each system), and any fault injected that affects one or more systems is isolated as a 'known fault', with the help of built-in knowledge about the interacting functions of the systems.

In figure 1, it is to be noted that the right-most vertical for the electrical power system does not possess any diagnostic module. This is to test FAVER for its ability to isolate faults that are previously unknown, as it is impractical to assume that reasoning in any health monitoring system is aware of all possible faults that might affect the systems. Consider a scenario where a fault signature is introduced in the EPS and it affects another system like the fuel system. Since the top-level reasoning module depends upon the sensor data and system diagnostic information for isolating faults, this fault injected in the EPS will not be detected as a 'known fault'

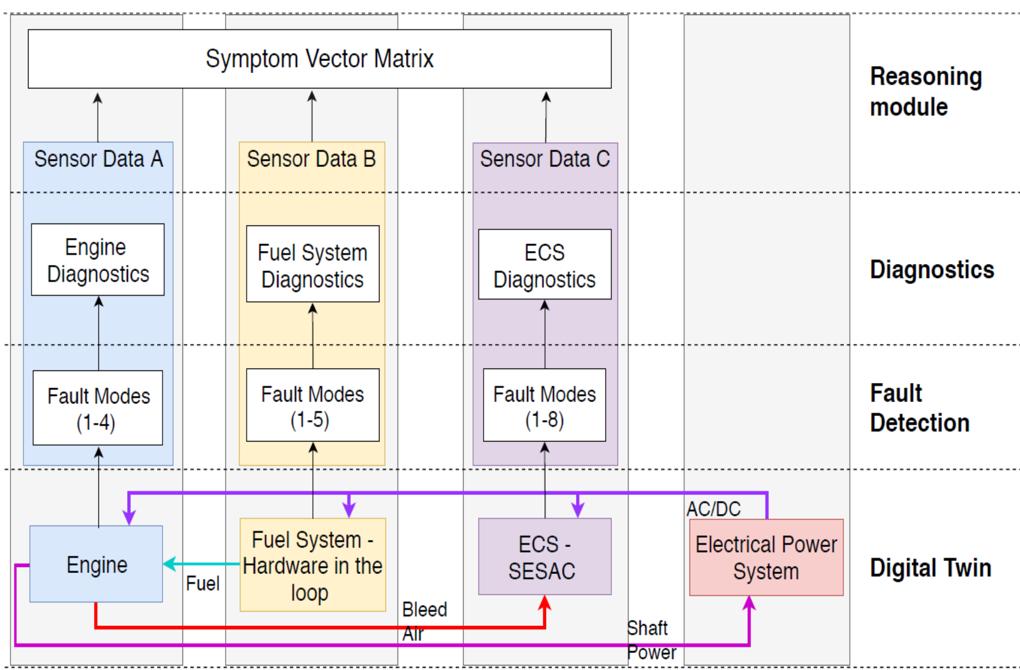

Figure 1: The schematic of FAVER

right away by reasoning. In general, the maintenance engineers will have to troubleshoot and isolate such a fault manually, since it will go unnoticed or misclassified by any diagnostic system. However, in this case, instead of misidentifying the electrical fault as 'no fault' or misclassifying it as a fault in the fuel system, FAVER would use the EPS DT with suitable virtual sensors to identify the combination of parameters that would lead to the injected fault signature. This fault signature can then be added to reasoning's knowledge module with the electrical fault as its new label.

The EPS DT is also used by FAVER to flag ambiguity. This is especially useful for the interacting systems, as many mechanical faults have similar symptoms as the electrical faults. As the EPS supplies power to many components in multiple systems, it is possible that fault symptoms occurring due to degradation in the EPS are ambiguous with mechanical degradations. In such cases, there is a risk of misclassifying a fault mode as a mechanical fault when it was originally an electrical fault. Using the EPS DT, FAVER will be able to reverse engineer the fault symptoms that match with the mechanical fault modes, to check if they can also be produced by the electrical parameters. When a suitable combination of parameters which could lead to the symptom (that matches with the mechanical fault), ambiguity will be flagged for that fault, and the reasoning's knowledge module will be updated.

4. DEVELOPMENT OF FAVER

FAVER is being developed through four stages, as shown in Figure 2: i) Use-case Conceptualization, ii) Development of the building blocks, iii) Implementation and Testing, and iv) Evaluation. This section talks about the different steps involved in each stage of development.

Stage 1: Use case Conceptualization

This initial stage involves conceptualization of use cases that will be demonstrated through FAVER. The use cases are defined in such a way that the overall objectives of FAVER are satisfied through the demonstration. The cases of isolating single (system-level) and cascading faults (vehicle-level) that are previously known and unknown are framed into a number of distinct scenarios (as shown in table 1) for which the use cases are defined. These scenarios will enable demonstration of FAVER to isolate faults that affect a system locally, at a

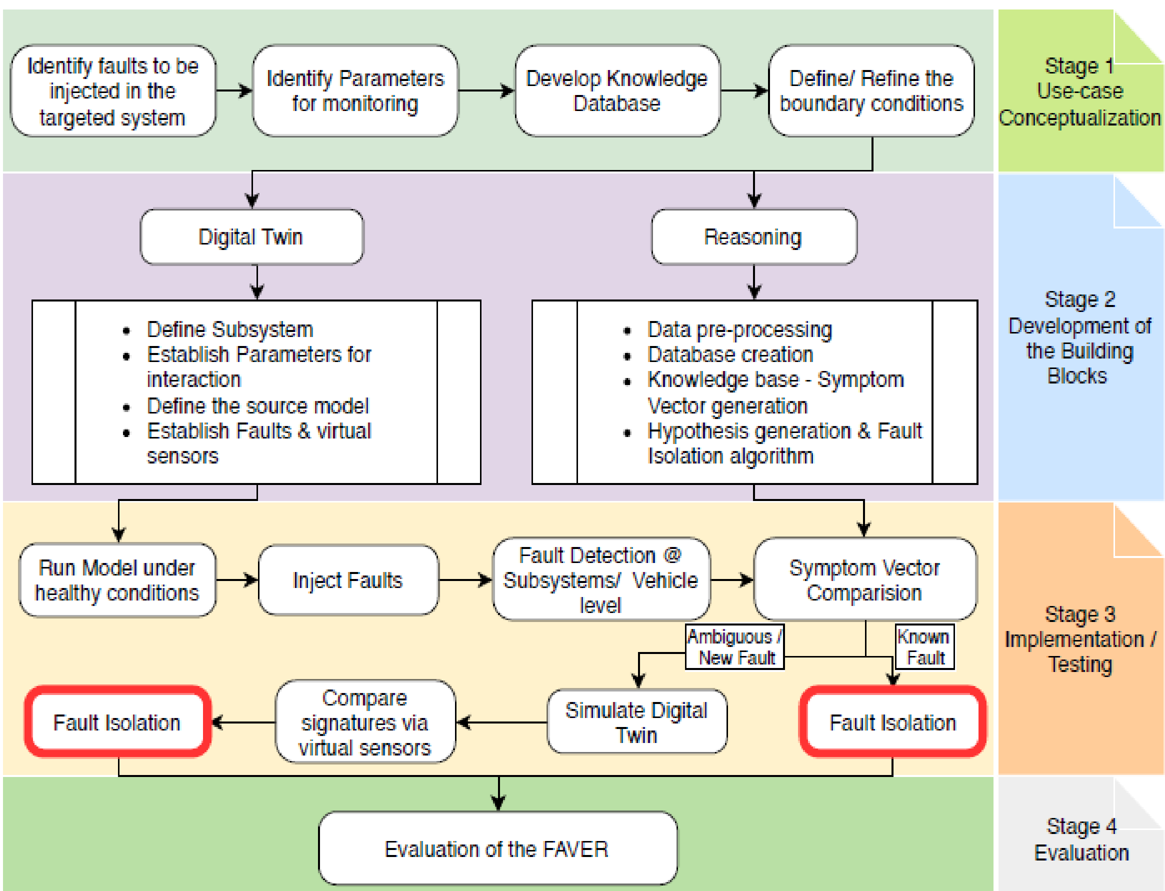

Figure 2: Stages in developing FAVER

micro scale as well as those that have a macro effect on other systems. It is to be noted that, for a fault mode that is previously unknown, its interaction effect cannot possibly be known and thus, the sixth case in table 1 is also not possible.

Table 1: Use Case Scenarios

Fault Mode	Interaction Effect	Use Case Scenario	Effect -scale
Known	-	Known Single Fault	Micro
Known	Known	Known fault, known Interaction Effect	Macro
Known	Unknown	Known fault, new interaction effect	Macro
Unknown	-	New Single Fault	Micro
Unknown	Unknown	New fault, new interaction effect	Macro
Unknown	Known	*Not Possible*	

The use cases will be formed for the remaining scenarios in table 1 and ambiguity can be checked for the known faults. The use cases (faults to be injected) are chosen from the scenarios from table 1, with reference to the four systems considered in the FAVER schematic (figure 1) that emulate the interaction between the systems of an aircraft. The faults chosen for demonstration can either be a single fault affecting a local system or a cascading fault that has a macro effect on another system.

For example, consider figure 3. A reduced AC supply to a motor pump in the fuel system has its origin in EPS. However, this fault in the EPS has a cascading effect, which is to reduce the power to the motor pump, which in turn affects the fuel delivery to the engine and results in reduced power from the engine (redundancy is not considered in the use cases for demonstration purposes). This 'domino effect' has its root cause, the reduced AC supply from the EPS, and this fault can be flagged as one with a macro effect. This example can be used to check multiple use case scenarios like i) known fault with known interaction effect, ii) known fault with new interaction effect, and iii) new fault with a new interaction effect. Similar examples are being formulated to test the capability of fault isolation by FAVER.

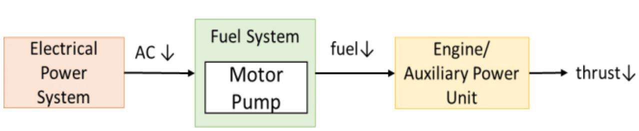

Figure 3: An example of a system fault with macro effect

For the use case scenarios of a known single fault and a new single fault, faults injected at the system level can be chosen and tested. Ambiguity can be introduced in the system by injecting faults in components like valves. For example, a sticking valve in the fuel system can be a mechanical fault, and also a result of a stuck relay that reduces the voltage supplied to power the valve. The symptom vector for a sticking valve will be the same, despite the cause. Introducing such ambiguity could showcase the ability of FAVER to resolve such faults. When the use cases are defined, health parameters to be monitored will be decided, and the domain knowledge required for that use case are collected.

Stage 2: Development of the building blocks

This stage involves the development of the Digital Twin (DT) of the systems and the corresponding diagnostic reasoning at both system and vehicle level. For example, when the fuel system DT is built with respect to its source model, faults to be injected are defined, sensors to isolate faults are established and the parameters required for interaction with the EPS and the engine to demonstrate one of the use case scenarios are defined. In parallel, the fuel system diagnostics with isolation algorithms is built at the systems level and the knowledge base in the form of symptom vector is populated for reasoning at the vehicle level.

Stage 3: Implementation and Testing

The third stage of developing FAVER involves implementation and testing. In this stage, the DT of a system is run in a healthy condition, followed by fault injection and data collection. The symptom vector generated is compared with the knowledge base of reasoning to identify whether the fault is previously known. If no matches are found, the DT is used to check if any other system is the root cause of the injected fault, resulting in a previously unknown or ambiguous fault. Stage 2 and Stage 3 are repeated for building the DT and diagnostics for all four systems shown in figure 1. The reasoning module at the vehicle level is expanded to accommodate the different domain knowledge and suitable isolation algorithms.

Stage 4: Evaluation

Once all the systems are accounted for, in terms of the DT, their interactions, system level diagnostics, and top-level reasoning, FAVER will be evaluated for the performance metrics like classification accuracy, misclassification rate, number of false positives and false negatives and the time taken for classification. It will also be tested for its scalability and its sustainability to add or remove an aircraft system module to the framework.

5. A THOUGHT EXPERIMENT

A thought experiment was conducted with an experimental fuel rig to understand the interdependencies between various systems. The idea is to develop a conceptual model of how the reasoning is going to be demonstrated, while keeping the logic tractable. Too complex and the logic won't be traceable or obvious, too simple and it won't be effective as a framework. With the help of this thought experiment, a number of assumptions are seen to be necessary for the initial demonstration of FAVER.

The fuel rig on which the thought experiment was conducted was developed in the IVHM lab in Cranfield University (Yufei Lin, 2017) and is representative of a commercial aircraft fuel system. Consider figure 4, where a small mechanical layout from the rig is presented for this thought experiment. Figure 4 can be seen to involve seven different layers. The mechanical system (hardware layer) consists of a reservoir from which the fuel is pumped by a gear pump GP, powered by a motor M, and it passes through a shutoff valve and filter F, followed by a flow control valve V, and back to the reservoir. There are four pressure sensors (S1, S2, S3 & S4), a laser sensor L, and a flow meter FM that provide sensor readings from the mechanical layer to the health monitoring layer (topmost layer of figure 4). The electrical system is shown via DC and AC layers; the sensors, the flow meter, the flow control, and the shutoff valves are all powered by 12-24 VDC; the motor M that drives the gear pump is supplied by 230VAC power. The electrical layer is required for the functioning of the mechanical components. Similarly, the control system is shown in two layers, viz, control and the feedback layers: they consist of the control functions pump speed N, the valve positions and the flow Q through the flowmeter, and their feedbacks respectively. The fault modes are injected into the fuel rig via the control system. For the effective functioning and diagnosing of the fuel rig, it is essential that all the dependent systems, i.e., the mechanical system, the electrical power system, and the control system should work together, along with the sensors and flowmeters which connect them to the health monitoring for diagnosis.

Table 2: List of fault modes for the thought experiment

Mode	Fault	Type
FM1	Filter Clogging	Mechanical
FM2	Pipe Leaking	Mechanical
FM3	Gear tooth broken in the pump	Mechanical
FM4	Low power to the electric pump	Electrical
FM5	Clogged flow control valve	Mechanical
FM6	Low power to the flow control valve	Electrical

In the beginning, faults are considered only within the mechanical and electrical systems. Six fault modes that are planned to be injected are listed in table 2. Among these fault modes, the clogged filter (FM1) and the pipe leak (FM2) are mechanical faults, whereas the reduced pump speed can either be due to reduced electric power to the pump (FM4) or due to a broken gear tooth in the pump (FM3). Similarly, a

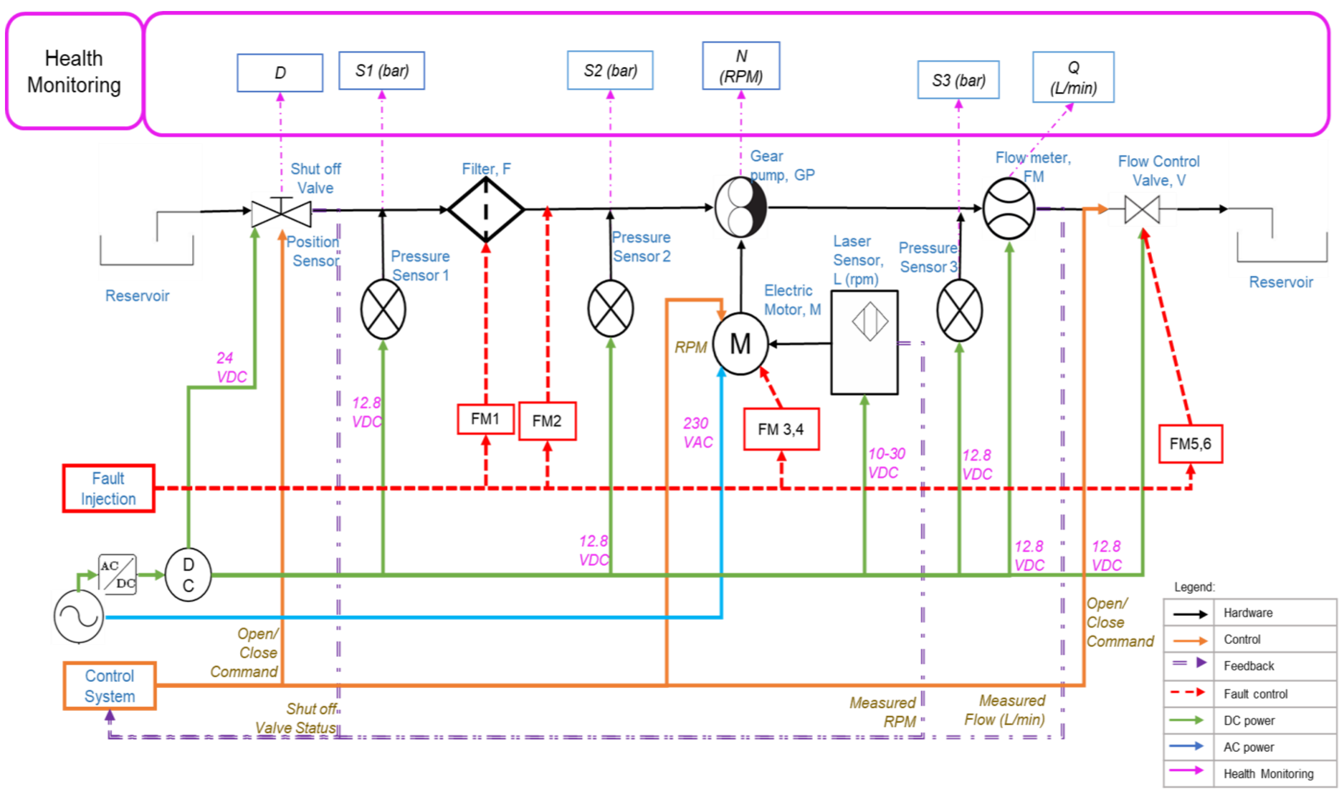

Figure 4: Multiple systems in a fuel rig - A thought experiment

clogged nozzle may occur due to either mechanical blockage (FM5) or lack of electrical power (FM6).

Since the electromechanical components used in the test rig are susceptible to both mechanical and electrical faults, the symptom vectors for such fault modes resembled each other, thus introducing ambiguity to the problem. The symptom vector matrix was developed to represent the fault signatures at the system level, using which the diagnostic rules were developed to isolate both mechanical and electrical faults. In the case of the control system, with respect to the fuel rig, its role does not stop only at controlling the valves and motor speed and receiving the feedback. Rather, the control system is essential for injecting faults into the rig for diagnosis. Thus, introducing faults in the control system will render the diagnosis of fuel rig invalid. In practice the control system may well mask potential faults. Hence, for demonstrating FAVER with the fuel rig, only mechanical and electrical systems are assumed to be at fault, the control system is considered to be healthy. The same is the case for considering faulty sensors. Since the health monitoring layer, the output of which is used for diagnosing the faults in the fuel rig, is dependent upon the sensor readings, for the purpose of initial testing, the sensor data are assumed to be reliable. In a similar fashion, a few more assumptions are made to define the scope of the research, within which FAVER will be demonstrated. A complete list of the assumptions made is as follows:

1. The EPS is not instrumented for diagnostics
2. The control system is assumed to be 100% healthy
3. Only single faults are considered
4. Sensors are always healthy
5. Fault modes signatures are to be studied at steady state
6. No False Alarms are considered

As previously mentioned, these assumptions can be relaxed at the later stage, to expand the framework and prove FAVER's ability to isolate faults under complex conditions.

6. CHALLENGES

The development of FAVER poses a number of challenges. In order to enable FAVER to isolate cascading faults that are previously known and unknown and to flag ambiguity, a certain number of assumptions will be made, as mentioned in the previous section. These, however, will not affect the overall ability of FAVER to isolate the faults; instead, these assumptions will be treated as special conditions. Future research will relax these assumptions.

FAVER requires validated simulations with which to build the Digital Twin (DT) for emulating the systems interactions. Developing every system from scratch is time-consuming and will not fit into the timescale for completing FAVER. Hence the DT sources are taken from previously developed and validated simulation models from research work within the IVHM Centre. Similarly, existing diagnostic methods are chosen for system level diagnosis, and reasoning is developed only at the vehicle level to isolate the faults that have a macro effect on multiple systems.

One more challenge for developing FAVER is the complexity involved in establishing interaction between the systems. As FAVER is designed to accommodate multiple systems, the framework must possess the required features to enable systems interactions at the vehicle level. If a new system is introduced, it must be checked for all possible connections with the other systems and every system interacting with the new one must be updated for enabling the interactions via DT. All the concerned systems must go through rigorous verification and validation to account for the change. For this purpose, modularity is being introduced to the framework's architecture. Every system will be encapsulated and will be treated as an independent module. The interaction between the modules will be established only through the modules meant for communication. In this case, when a new system is added, the necessary parameters will only be updated in the communication modules and the sources of other systems DT will not be disturbed. It is to be noted that, along with the challenge of complexity and sustainability, the modularity feature takes care of the issues of scalability for the framework. Even if the systems are of different scales, the scaling factor can be introduced in the communication modules, through which the DT interactions can be enabled.

7. CONCLUSION & FUTURE WORK

A Framework for Aerospace Vehicle Reasoning (FAVER), conceptualized with its main components of Digital Twin (DT) and reasoning, is discussed in this paper, along with the different stages of development and the use case scenarios. Developing and demonstrating FAVER will provide a pathway to isolate cascading faults and resolve ambiguities under multiple scenarios in the aircraft systems.

Currently, the architecture of FAVER is being designed systematically, to include all of the essential components. As most sources of aircraft systems are available for the DT from the IVHM Centre, they will be brought into the framework via the modularity feature and tested for interaction with the other systems. Once the interactions are established, the reasoning strategies will be built to isolate cascading faults that are previously known or unknown to the system, as well as to identify ambiguity, i.e., figure 1 will be executed.

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BIOGRAPHIES

Cordelia Mattuvarkuzhali Ezhilarasu is a PhD researcher in Cranfield University, working with the IVHM Centre since 2017. She received her Bachelors degree in Aeronautical Engineering in 2011 and a Masters in Industrial Engineering in 2013 from Anna University, Chennai, India. Cordelia has worked as a Data Analysis engineer with Bloom Energy and as a Senior Industrial engineer with Lam Research for a period of 4 years. In her role as an Industrial engineer, she has worked on various process improvement projects and developed several semi-automated tools, that contributed to time and cost savings for the organization. Cordelia is a recognized ASQ Certified Six Sigma Black Belt. Her current research interest involves IVHM technologies, Digital Twin, and machine learning related to aerospace applications.

Dr Zakwan Skaf is currently a Lecturer in Diagnostics and Prognostics in the Integrated Vehicle Health Management (IVHM) at Cranfield University. Before joining Cranfield University, he held several positions with Loughborough University, Sheffield University, Warwick University and the University of Manchester. Zakwan received his B.S. degree from the faculty of Mechanical Engineering in 2001, and his

MSc and PhD degrees from the University of Manchester, Control Systems Centre, Manchester. He is an active researcher with over 35 publications in many world classes peer-reviewed journals and conferences. His research interest involves control engineering, data analytics, machine learning, condition monitoring, diagnostics, and prognostics related to aerospace, railway, marine, energy, and automotive applications.

Ian K. Jennions. Ian's career spans over 40 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. Ian moved to Cranfield in July 2008 as Professor and Director of the newly formed IVHM Centre. He is on the editorial Board for the International Journal of Condition Monitoring, a Director of the PHM Society, Chairman of SAE's IVHM Steering Group, contributing member of the SAE HM-1 IVHM committee, a Chartered Engineer and a Fellow of IMechE, RAeS and ASME. He is the editor of five SAE books and co-author of another one.