

A Hierarchical Reasoning Structure to Support Aerospace IVHM

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ABSTRACT

One of the inherent functions of an integrated vehicle health management (IVHM) system is the reasoning capability that is built on the knowledge of how the individual line replaceable units (LRU) and subsystems are functionally interconnected across the vehicle. Once known and mathematically represented, the IVHM system has the ability to utilize knowledge obtained from the individual LRU/subsystems to determine the overall health state and functional capabilities of the vehicle. This process must go beyond the basic diagnoses of the observed health condition of the isolated subsystems and their remaining functionality. The IVHM reasoning process described herein employs a hierarchical structure that accounts for the failure modes at the LRU level and can also determine the functional impact of those LRUs in terms of remaining functional/operational availability at the subsystem and vehicle levels. This type of architecture is also consistent with an enhanced fault isolation process in cases when fault indications result in ambiguous outcomes, providing additional information to help isolate the root cause and reduce the ambiguity group size. In addition, the IVHM reasoner must also attempt to provide estimates of the severity of the underlying fault/failure modes and the remaining useful life of the integrated systems when prognostic information is available. Thus, providing real-time vehicle health and remaining functionality information will be useful to operations and maintenance personnel for decision support.

The following paper will present a framework and an associated aircraft system use case for performing hierarchical reasoning at the vehicle level based on individual subsystem health indicators. Within the presented architecture, a low level diagnostic reasoning engine seeks to classify fault/failure mode indications from raw sensor data

or feature data processed by the subsystem specific modules within the monitoring system. Mid-level reasoning is employed to determine the overall functional capability of the constituent subsystems, specifically what are the implications of the detected failure modes on the functional availability of the subsystem. The vehicle-level reasoning will then “roll up” and quantify the true capability of the vehicle based on the health assessments from all underlying subsystems, taking into account their interconnections (failure mode propagation), criticality and redundancies.

INTRODUCTION

Integrated Vehicle Health Management (IVHM) is the next evolutionary step in technology in support of condition based management, building on the safety and readiness benefits currently obtained from legacy systems. Over the years, the evolution of data acquisition, processing, and storage capabilities has enabled continuous advancements in the practice of Prognostics and Health Management (PHM) and condition-based asset management approaches. For air vehicles, this can result in more autonomous and reliable flight operations as well as improved ground support through optimized maintenance and repair processes. Through the integration and coordination of the embedded aspects of health and usage monitoring, advanced on-board reasoning and a ground-based supporting infrastructure, the IVHM system can help mitigate the impact of component/system faults/failures on mission readiness.

As the name implies, the foundation of IVHM in its true sense is highly integrated into the vehicle, its constituent subsystems, and the supporting ground based infrastructure. In broad terms an IVHM system can be thought of as an enabling, decision support service which provides autonomous, timely, and accurate assessments of a vehicle's health and functional availability to operations personnel. The

greater vision of the system seeks to include utilizing this information on the ground to facilitate decreasing operational costs and increasing operational readiness in order to provide significant life cycle benefits to aerospace programs. As such, a pragmatic view of an IVHM approach would be realized through two distinct areas of functionality: The first, an embedded aspect, facilitating the goal of on-board vehicle health monitoring as summarized by Ofsthun; “to have the vehicle dynamically identify any degradation in functional performance that may affect safety or successful field operations as well as to identify the specific subsystems that require maintenance to restore full operational capability.” The knowledge gained from the embedded IVHM functionality must then be forwarded to a ground-based support system to be used by operations and maintenance personnel. The ground based system provides the interface between the onboard monitoring and reasoning functionality and operations, maintenance, and logistics personnel and infrastructure, facilitating informed, condition based asset management and support. The scope of this paper is focused on the on-board implementation of the IVHM architecture in aerospace applications.

The development of an IVHM system to monitor advanced aerospace platforms is predicated upon expert knowledge of the vehicle and the subsystems called upon for its operation. Engineers tasked with development of an IVHM system require a detailed understanding of the critical subsystems, their dominant failure mechanisms, and the characteristics of failure interaction and propagation. Pareto analysis of these subsystems, in conjunction with relevant Failure Modes and Effects Analysis (FMECA), provides a solid starting point. Overall, system safety and operationally critical subsystems are given a high priority when considering which subsystems to target. FMECAs of these subsystems provide insight into the physical effects of dominant failure modes and how to isolate these manifestations as evidence of a particular fault. The developer weighs this information along with the ‘real-world’ constraints of available data acquisition and processing capabilities to formulate the cost/benefit design choices and model the embedded aspect of the IVHM system.

Developing an integrated model of the IVHM system prior to installation provides two distinct benefits: First, the model provides the functional blueprint to aid in the development of the specific monitoring approach, including required sensors and PHM software. This model can be exercised to ensure a satisfactory level of health monitoring coverage (diagnosability) is provided by the system prior to its development in software and implementation in hardware. Second, the model provides the functional architecture which can be exploited by the IVHM system reasoner to isolate root cause failure modes and remaining functionality available in the presence of a detected fault/failure.

LOW-LEVEL REASONING

Typically, PHM approaches implemented within health and usage monitoring modules are designed to target specific failure modes within an LRC, assembly, or subsystem, often utilizing a common set of diagnostic features. Low-level reasoning seeks to sort out the evidence provided by these diagnostic features and identify the failure mode or modes most likely present. Several different technical approaches have been used by PHM/CBM practitioners over the years; we will provide a brief description of two leading approaches in order to give context to the overall IVHM reasoner system described herein. First, data-driven based reasoning approaches can be used where qualitative and quantitative knowledge of the manner in which failure modes manifest themselves in the diagnostic data/features is applied to correlate the observed features to the most likely diagnosis. This knowledge can be obtained either during the design process, from similar systems already fielded or from collected data during test programs, etc. Another common method is referred to as model-based reasoning, which builds upon an “integrated model” and directly links or maps collected evidence with specific failure modes or LRUs. The model-based approach applies knowledge of the actual system functionality to accurately indict a given failure mode and rank the likelihood of a given failure given the current observations.

Data-Driven Based Reasoning Methods

Data-driven based reasoning techniques typically map a set of observations to a hypothesis which best explains or accounts for the observations. Numerous approaches can be employed to accomplish data-driven based reasoning. Artificial intelligence techniques are well suited to this type reasoning task, with approaches such as neural networks or fuzzy inference systems being implemented to determine a diagnosis based on the set of input feature data presented to the classification system. Neural networks generally require a training step to map input data to failure modes, severity, and confidence. Fuzzy Inference Systems (FIS) require development of an expert system rule base to interpret the soft input membership values. The concept of soft membership values, employed in FIS, allows for shades of gray to interpret the feature values relative to black and white absolute of a threshold-based classification technique.

Model-Based Reasoning Methods

Model-based reasoning derives its name from its dependence upon a model of the system. The premise of the approach is to assign each plausible failure mode a score, or rank, by considering the historical efficacy of a piece of evidence in indicting the particular failure. Evidence may originate from sources monitoring the particular failure, such as Built-In-Tests (BITs), diagnostic algorithms, prognostic algorithms, usage information, etc.

The process of fault isolation using model-based approaches is to assign each failure mode a score, or rank, by considering all positive and negative evidence sources. The accuracy of the evidence sources and their relationship to the true failure mode is quantified in two parameters, Real Fault Probability and False Alarm Probability. The probability of a fault existing given that an evidence source has detected it corresponds to the Real Fault Probability (RFP); the ideal monitor (a.k.a diagnostic feature, diagnostic indicator, health indicator, evidence source) has an RFP of one. The False Alarm Probability (FAP) is related to the likelihood of an evidence source indicating the fault, when there is in fact no fault. The ideal monitor has an FAP of zero. As an example, in [Figure 1](#), we know that a diagnostic alarm, an inspection, and a sensor value reaching a threshold are all indicators of failure mode one. In this case, the diagnostic and inspection yield a positive result and are thus referred to as Positive Evidence, but the sensor value hasn't reached the threshold value and is therefore termed Negative Evidence. Each of these evidence sources has an associated RFP and FAP which get applied, see [Figure 2](#), to determine the failure mode's score relative to indictment.

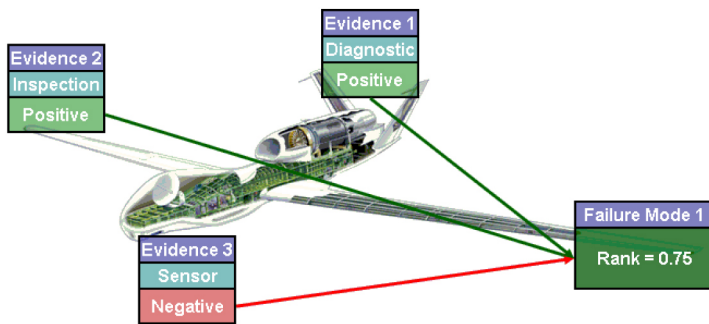


Figure 1. Model-based Reasoning Example

In such an approach, we can capitalize on the notion that the absence of anticipated information in the presence of a fault (negative evidence) can also lend insight into the true health state. The core ranking equation, shown in [Equation \(1\)](#), mitigates the indictment of a failure mode by the potential of the monitor going active without the presence of a fault and the inactive (negative) evidence weighted by how likely the monitor is to detect a true fault (Real Fault Probability). These values of False Alarm Probability and Real Fault Probability between each evidence and failure mode are updated based on historical information and can be updated as more data are collected.

$$RANK_{FM(i)} = \frac{\sum_{j=1}^{PosE} (1 - FAP_j) - \sum_{k=1}^{NegE} RFP_k}{\text{No. of Evidence Sources}} \quad (1)$$

MID-LEVEL REASONING

Building on the health state information provided by the low-level reasoning, the mid-level reasoning function determines the capability or health of the subsystems based on the health of the components/LRUs indicted by the low-level reasoning. The mid and high-level reasoning can also employ data-driven or model-based approaches, but we will only discuss the model-based approach herein. Similar to the model-based approach discussed previously, we will use model to obtain functional dependency information necessary to calculate the capability roll-up of the subsystems based on the underlying component health. The approach for assessing remaining functionality of the parent component is based upon the remaining capabilities of the child/children in concert with the criticality of the anomalous components (child/children) in enabling the subsystem (parent) to perform its role as needed.

Operational criticality alludes to the functional dependence of the parent subsystem employing the failing component to function as required or expected. As an example, we can consider a car's engine: the operational criticality of a timing belt breaking is great, whereas the operational criticality of the thermostat sticking open is much lower. The criticality assessments are parameters obtained from expert knowledge and contained in the model representing the vehicle's PHM system. The operational capabilities of degraded or failed components are recursively combined into a single overall assessment of the subsystem's capacity to perform its designated role as designed as the functional topography of the vehicle is ascended.

The efficacy of the mid-level reasoner to assess subsystem capability is predicated on two tasks. First, we must have the ability to initiate and execute queries of the dependency model based on results obtained from the low-level reasoning. This process traverses the functional layers of the subsystem under investigation to ensure the failure modes reported by the lower levels do not have a root cause which can be attributed to an upstream functional dependence. The effect is to effectively perform a "reachability" analysis on all evidence activated in the model and assess the most likely fault/failure modes based on several attributes within the model. Second, we must be able to combine results, obtained from the queries, to assess the subsystem's functional capabilities, as well as isolate a possible root cause initiated from a component upstream in the functional dependence hierarchy. This final step combines the results obtained from querying the dependency model to verify the likely failure modes and their respective severities from the subsystem perspective and modify the indicted failure modes if necessary. These results, in concert with the operational criticality rolled up from the indicted LRC through each subsequent level in its implementation path, are used to determine the overall capability of the subsystem. The overall