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Optimal Design of Integrated Systems Health Management (ISHM) for Improving the Safety of NASA's Exploration Missions: A Multidisciplinary Design Approach

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1. Abstract
Integrated Systems Health Management (ISHM) systems are used to detect, assess, and isolate functional and physical faults in order to improve the safety of complex aerospace systems. An ISHM system, as a whole, consists of several subsystems that monitor different components of a space mission. In this research, we propose a new methodology to design and optimize ISHM as a distributed system with multiple interacting modeling teams (i.e. disciplines) as well as multiple conflicting design objectives (i.e. Figures Of Merit or FOMs). A paramount amount of interest has been given in the literature to the multidisciplinary design optimization of problems with similar architecture over the past decade. As such, an ongoing effort at NASA Ames Research Center focuses on crafting a specialized multidisciplinary design approach that can be used to optimize the effectiveness of ISHMs for future NASA missions. At the top level, the overall performance of the mission consists of system-level variables, parameters, objectives, and constraints that are shared throughout the system and by all subsystems. Each subsystem will then comprise of these shared values in addition to subsystem-specific variables, parameters, objectives and constraints. The proposed approach, referred to as ISHM Multidisciplinary Multiobjective System Analysis & Optimization (or ISHM MMSA&O), has a hierarchical structure to pass up or down shared values between the two levels with system-level and subsystem-level optimization routines.
2. Keywords: Integrated Systems Health Management (ISHM); Multidisciplinary Optimization, Space Exploration Missions

3. Introduction
NASA's future space exploration systems will include a highly integrated subsystem, referred to as Integrated Systems Health Management (ISHM), which can detect, predict, isolate and respond to system and component failures in order to improve safety and maintainability [1][2][3][4][5]. An ISHM system consists of instrumentation components (e.g. sensors, recorders etc.), Fault Detection-Isolation and Recovery (FDIR) module, diagnostic and prognostic software, as well as other reasoning and processing algorithms that are responsible for collecting information about the overall vehicle and mission health and making decisions accordingly. ISHM is currently the subject of intense research for application in various industries, including: automotive, aeronautics and aerospace, and railroad [4]. Figure 1 shows a high-level breakdown of a generic vehicle. ISHM collects data from all subsystems to detect and isolate faults, and make appropriate decisions to ensure the overall safety of the system.

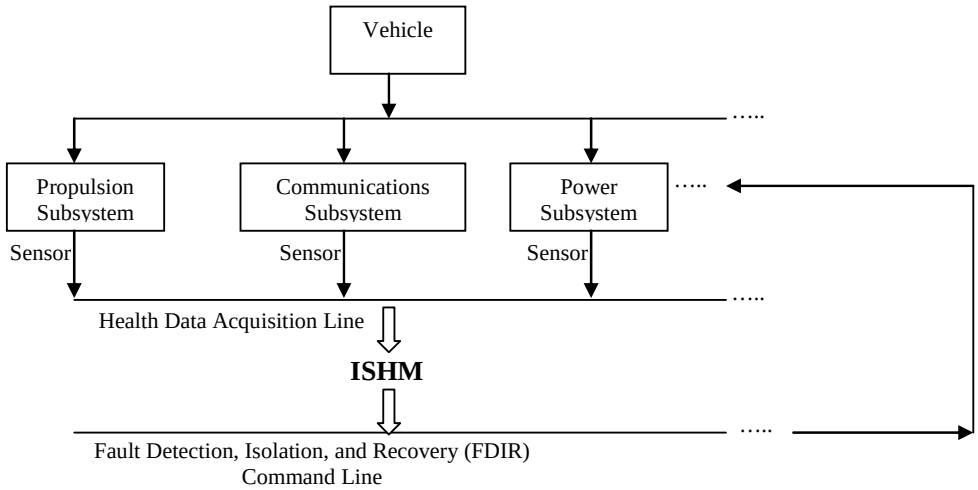

Figure 1. High-level breakdown of a generic vehicle and integration with ISHM

ISHM systems are envisioned to serve two main goals in future space missions: 1) to improve the safety of the mission by monitoring the "functional health" of the system and making real-time decisions to mitigate potential faults; and 2) to facilitate the maintenance and availability of the vehicle by diagnosing the physical break-downs in the system that can be replaced off-line. These two goals are explained below.

1. Real-time monitoring of the functional health of the system: ISHM must constantly monitor the functional health of the system, detect and isolate functional faults, and make 'real-time' decisions to reroute flow of information, energy, or material via alternative paths to ensure the operability of the system. From this standpoint, the system is regarded as a 'collection of functional units' (rather than physical units) that must perform flawlessly to constitute the overall functions of the mission. Once a functional unit fails to perform its intended purpose, ISHM must rapidly detect the faulty functional unit and make a real-time decision to compensate for it (for example, by switching to an alternative functional unit). In Figure 1, for example, if the communications module fails to perform its intended function, i.e. "send/receive data to and from ground station", ISHM must quickly detect this functional failure and take appropriate action to compensate for it (e.g. switch to an alternative communication module). Such detection and recovery actions must be done in real-time and are extremely crucial to the safety of the mission.
2. Determining the physical health of the system: To help maintain the physical health of the system, ISHM must also be able to determine which physical Line Replaceable Unit (LRU[1]) has failed and needs to be replaced. In the above example, the functional failure in the communications module can be due to a physical failure in the UHF communication antenna that needs to be replaced after landing.

While these two goals intersect in many cases, they impose different and sometimes conflicting design requirements on the architecture of the ISHM, placement of the sensors and development of the reasoning algorithms. Furthermore, the existence of multiple incommensurable design goals and constraints in both system and subsystem levels makes the design of an efficient ISHM a non-trivial task that should be conducted carefully and based on quantifiable metrics. As such, an ongoing effort at NASA Ames Research Center is aiming to develop a robust methodology that can evaluate different ISHM architectures in an automated fashion to optimize a set of pre-determined Figures Of Merit[2] (FOMs) [3]. This process, known as ISHM Systems Analysis and Optimization (or ISHM SA&O, see [3][4]), consist of a modular network of simulations and models that can be easily customized for every specific space system. Using SA&O process offers two immediate advantages:

- The effect of ISHM on the overall safety, maintainability, performance, and cost of the mission can be accurately calculated.
- During the design phase, engineers can find the 'optimal ISHM architecture' based on quantitative FOMs.

The latter is particularly important in the early phases of designing a space exploration system where design decisions are still evolving and easy to change. Choosing the optimal ISHM architecture at this stage has the highest impact and offers significant cost reduction downstream as the system design matures. The SA&O process developed at NASA ARC has been reported to significantly improve the efficiency of the ISHM architecture (For instance, in one case study, the percentage of the total faults that could be detected using the optimized ISHM increased to 75%, up from 12% in the original design [3]). Nevertheless, the previous SA&O process had several shortcomings that hindered its application and generalization to larger and more complex spacecraft systems, as explained below.

- Design of an ISHM is <u>multidisciplinary</u> by nature: Designing an ISHM that encompasses all subsystems of a space mission is the result of interaction among engineers and managers from different disciplines with their own domain expertise. As shown later in this paper, the general process of analyzing an ISHM system involves complex numerical simulations, each addressing a different aspect of the overall system. These distinct disciplines often share certain design parameters, but also contain local parameters that are not necessarily relayed to other disciplines or the system-level managers. Therefore, unlike previous versions of SA&O process, the newly proposed optimization process of this paper is structured in a two-level hierarchical architecture[3] with shared (global) as well as local design parameters that mimics the autonomy of subsystem engineering groups as well as their interactions with each other and with the system-level design requirements (for a review of multidisciplinary design techniques in the aerospace industry, see [6][7]).
- Design of an optimal ISHM is <u>multiobjective</u> by requirement: NASA considers multiple Figures Of Merit (FOM's) in both subsystem and system levels. These design objectives are conflicting and incommensurable (they address different aspects of performance in a space mission). Because of the tradeoff among these various objectives, the proposed approach of this paper employs a multi-objective optimization strategy that aims to capture the entire Pareto frontier (or as much of the Pareto frontier as possible) in an attempt to generate a set of design alternatives to represent the tradeoff among various objectives(for a thorough review of multiobjective optimization techniques, see [8]). The previous SA&O tool was only capable of generating a 'point-design' and was not able to find a suite of design alternatives [3].
- The flow of information among various numerical models should be automated: In this paper, we used a commercial integration tool to automate the flow of information among various numerical models (more on this later in this paper). Previous SA&O practice at NASA involved passing information back and forth as part of a partly-manual partly-automated process that prohibited a comprehensive and time-efficient analysis of possible ISHM architectures.

As such in this paper, we present a new approach, hereafter referred to as ISHM Multidisciplinary Multiobjective Systems Analysis & Optimization (or MMSA&O), that can be used to find a set of Pareto-optimal ISHM design alternatives for complex aerospace systems in a multidisciplinary fashion. As part of this paper, we will discuss the case of a generic two-stage-to-orbit launch vehicle.

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[1] LRU is the lowest level object (as defined by the maintenance plan) that would be replaced as part of Ground Operations in order to restore a failed system function [4].
[2] Examples of FOM: Probability of Loss of Mission, Probability of Loss of Crew, Turnaround Time (see Section 4).
[3] While the proposed approach is described only for a two-level decomposition, it can be further generalized and extended for decomposition to any number of levels.

Using this relatively simple case study, we will explain the proposed approach of this paper to obtain an optimal ISHM architecture in a multiobjective multidisciplinary fashion. The organization of the rest of this paper is as follows: In Section 4, we will explain the case study of this paper, its various numerical simulations, design parameters, and FOMs. Section 5 describes the proposed ISHM Multidisciplinary Multiobjective Systems Analysis and Optimization (MMSA&O) process. Section 6 includes the implementation and integration details. Finally, Section 7 includes the concluding remarks and an outlook for future work.

4. Case Study: Designing an ISHM for X-34 System-of-Systems

In order to demonstrate the MMSA&O process in this paper, we use the example of an X-34 Main Propulsion Subsystem (MPS) which was designed to be part of the boosters for a Re-usable Launch Vehicle [9]. Figure 2 shows the re-usable boosters as the first stage of a Two-Stage-To-Orbit (TSTO) vehicle which docks to the International Space Station (ISS) and returns to Earth.

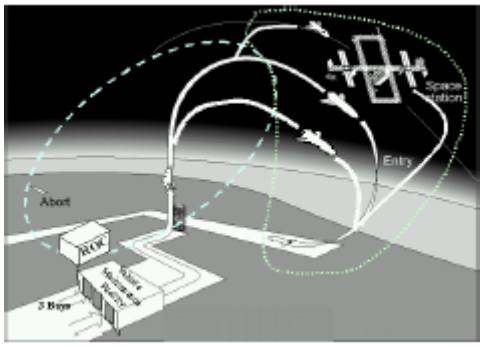

Figure 2. A general Reusable Launch Vehicle

Several models have been developed at NASA to analyze different aspects of performance in this spacecraft design. Datta et al. [3] have published an initial study of the SA&O process for this system using an ad-hoc optimization technique and several Figures of Merits (FOMs). These FOMs are listed below.

- Probability of Loss Of Mission (LOM)
- Probability of Loss Of Vehicle (LOV)
- Probability of Loss Of Crew (LOC)
- Launch Availability
- Development Cost
- Production Cost
- Annual Operational Cost
- $/lb (Mission Price/lb)
- Inherent IVHM Reliability
- Subsystem Reliability
- Subsystem Failure Probability
- RLV/Subsystem Mean Time To Repair (MTTR)
- RLV/Subsystem Mean Time Between Failure (MTBF)
- Subsystem Availability
- RLV Turnaround Time
- Cost of Spares
- ISHM Weight
- Subsystem Weight
- Fault Detection Coverage
- Fault Isolation Coverage
- ISHM False Alarm Rate
- Net Present Value and IRR of RLV Program
- Probability of unscheduled maintenance

Later in this paper, we will re-arrange these FOMs in a hierarchical fashion. The MMSA&O process then provides a platform on which such complex systems can be optimized as a multidisciplinary system-of-systems, based on a hierarchical decomposition of these FOMs (and other local sub-problem objectives). Section 6 briefly describes some of the models that are used to calculate FOMs and the ongoing effort at NASA to integrate and automate this process.

5. ISHM Multidisciplinary Multiobjective Systems Analysis & Optimization (MMSA&O)

A general 'single-disciplinary' multi-objective optimization problem can be formulated as follows:

$$\begin{aligned} &\text{minimize} \quad \boldsymbol{f}(\boldsymbol{x}) = \{f_1,\ldots,f_M\}^{\mathrm{t}} \quad (M \geq 2) \\ &\text{subject to:} \quad g_k(\boldsymbol{x}) \leq 0; \quad k = 1,\ldots,K \end{aligned} \tag{1}$$

In this formulation, $\boldsymbol{x} = \{x_1,\ldots,x_N\}^{\mathrm{t}}$, is the design variable vector, $\boldsymbol{f}$ is the design objective vector (there exist more than one objective), and g_k is the kth constraint. Although solving the above problem in its single-disciplinary (one-level optimization) seems to be easier than solving it in a multidisciplinary manner, a single-level formulation of the problem is not practical in large-scale design problem where multiple engineering teams and various numerical models interact in a distributed and asynchronous manner. A Multi-Disciplinary Optimization (MDO) is often used for such problems where a single-level solution strategy is either intractable or very difficult to organize due to the size of the problem and the issue of communicating data among all various engineering teams on a single level. The main advantage of MDO lies in its ability to decompose a large problem into several sub-problems of manageable size that can be solved, almost independently, using single-disciplinary optimization techniques (For a comprehensive review of multidisciplinary optimization techniques, see, among others, [6][10][11]) ISHM design is an example of a problem that cannot be managed and solved effectively in a one-level form due to the complexity of the communication among multiple disciplines. The goal of MMSA&O, therefore, is to introduce a methodology to decompose such design problems into a hierarchy of several sub-

problems (each of which may contain multiple objectives). The proposed approach is a modification from an original version developed by Farhang Mehr and Azarm [12] and later by Gunawan et. al [13], tailored specifically in this paper to address the problem of designing an optimal ISHM in a hierarchical multi-subsystem fashion.

In its multi-disciplinary form, the optimization problem of Equation 1 can be re-written in a hierarchical two-level fashion, as shown in Figure 3. The problem consists of J+1 sub-problems organized into two levels: one sub-problem at the system level (i.e., system sub-problem), and J sub-problems at the sub-system level (i.e., sub-system sub-problems). Note that in this paper, we present our method only for a two-level problem, but the method can be readily extended to more than two levels. Each sub-system sub-problem has a design variable vector, objective vector, and constraint vector that are exclusive to that sub-problem. The system sub-problem has a design variable vector that is shared by the sub-system sub-problems, i.e., a shared variable vector.

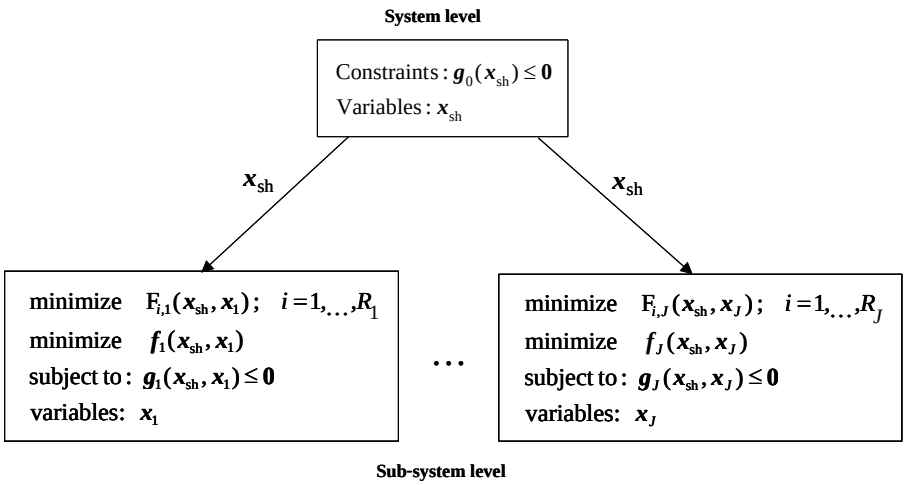

Figure 3. Multi-disciplinary form of a multi-objective optimization problem

In this formulation, $\boldsymbol{x}_{\text{sh}}$ denotes the shared variable vector while $\boldsymbol{x}_j$ (j = 1,…,J) denotes the variable vector that is exclusive to the jth sub-problem. For the constraints, $\boldsymbol{g}_0$ denotes the system constraint vector while $\boldsymbol{g}_j$ (j = 1,…,J) denotes the constraint vector that is exclusive to the jth sub-problem. The constraint vector $\boldsymbol{g}_0$ is a function of $\boldsymbol{x}_{\text{sh}}$ only, while the constraint vector $\boldsymbol{g}_j$ is a function of both $\boldsymbol{x}_{\text{sh}}$ and $\boldsymbol{x}_j$.

In the sub-system sub-problem, there are two types of objectives: the *functionally-separable objectives* and *exclusive objectives* (denoted by $\mathrm{F}_{i,j}$ and $\boldsymbol{f}_j$, respectively, j = 1,…,J). A functionally-separable objective $\mathrm{F}_{i,j}$ (i = 1,…,R_j) is an objective function which is formed by combining the corresponding functionally-separable objectives from some or all sub-problems to obtain the objective of the overall problem [13]. Weight is an example of a functionally (i.e., additively) separable objective function since the weight of a product is equal to the sum of the weights of its components. The exclusive objective, on the other hand, is an objective (or vector of objectives) that is unique to a particular sub-system sub-problem. False alarm rate is an example of an exclusive objective that is computed exclusively in the ISHM sub-problem. The goal of the optimization approach is then to obtain a set of solutions ($\boldsymbol{x}_{\text{sh}}$,$\boldsymbol{x}_1$,…,$\boldsymbol{x}_J$) that minimizes all objectives (i.e., functionally separable objectives as well as exclusive objectives) while satisfying the constraints in all sub-problems. The equivalent single-level form of the multi-disciplinary problem is given below.

$$
\begin{aligned}
&\text{minimize} \quad \mathbf{F} = \{\mathrm{F}_1(\boldsymbol{x}),\ldots,\mathrm{F}_i(\boldsymbol{x}),\ldots,\mathrm{F}_R(\boldsymbol{x})\}^{\mathrm{t}} \\
&\qquad \mathrm{F}_i(\boldsymbol{x}) = \text{function}\left(\mathrm{F}_{i,1}(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_1),\ldots,\mathrm{F}_{i,J}(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_J)\right);\ i = 1,\ldots,R_j;\ j = 1,\ldots,J \\
&\text{minimize} \quad \boldsymbol{f} = \{\boldsymbol{f}_1(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_1),\ldots,\boldsymbol{f}_J(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_J)\}^{\mathrm{t}} \\
&\text{subject to:} \quad \boldsymbol{g}(\boldsymbol{x}) = \{\boldsymbol{g}_0(\boldsymbol{x}_{\text{sh}}), \boldsymbol{g}_1(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_1),\ldots,\boldsymbol{g}_J(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_J)\}^{\mathrm{t}} \le \boldsymbol{0}
\end{aligned}
\tag{2}
$$

In this section, we will first setup the generalized ISHM design problem of X-34 in a hierarchical multidisciplinary fashion. In its multidisciplinary form we will account for all FOMs as well as subsystem level design parameters. In order to improve convergence and diversity of design solutions we will artificially impose two new performance metrics (details later in this paper): 1. An S metric that measures the convergence of solutions to optimum; and 2- An S metric that measures diversity of solutions. Later in this section, we will propose an optimization algorithm to solve the problem as a hierarchical collection of sub-problems in order to obtain a set of ISHM design alternatives that are optimal with respect to FOMs.

5.1. Architecture of a Generalized ISHM MMSA&O

Figure 4 shows a hierarchical decomposition of the generalized X-34 launch system, described in Section 4. Note that certain FOMs that relate to the high-level system are retained at the top-level. These are all high-level functionally-separable objectives that should be computed once each sub-problem yields its design solutions. These main objectives are categorized in 3 categorizes: 1- Performance, 2-Costs, and 3- Risks (Note that this categorization is for demonstration purpose only, and these high-level FOMs are

all treated equally in the proposed MMSA&O). At the lower-level, we consider 3 distinct disciplines (sub-problems): 1- ISHM itself; 2- RLV system; and 3- Everything else is lumped into one sub-problem.

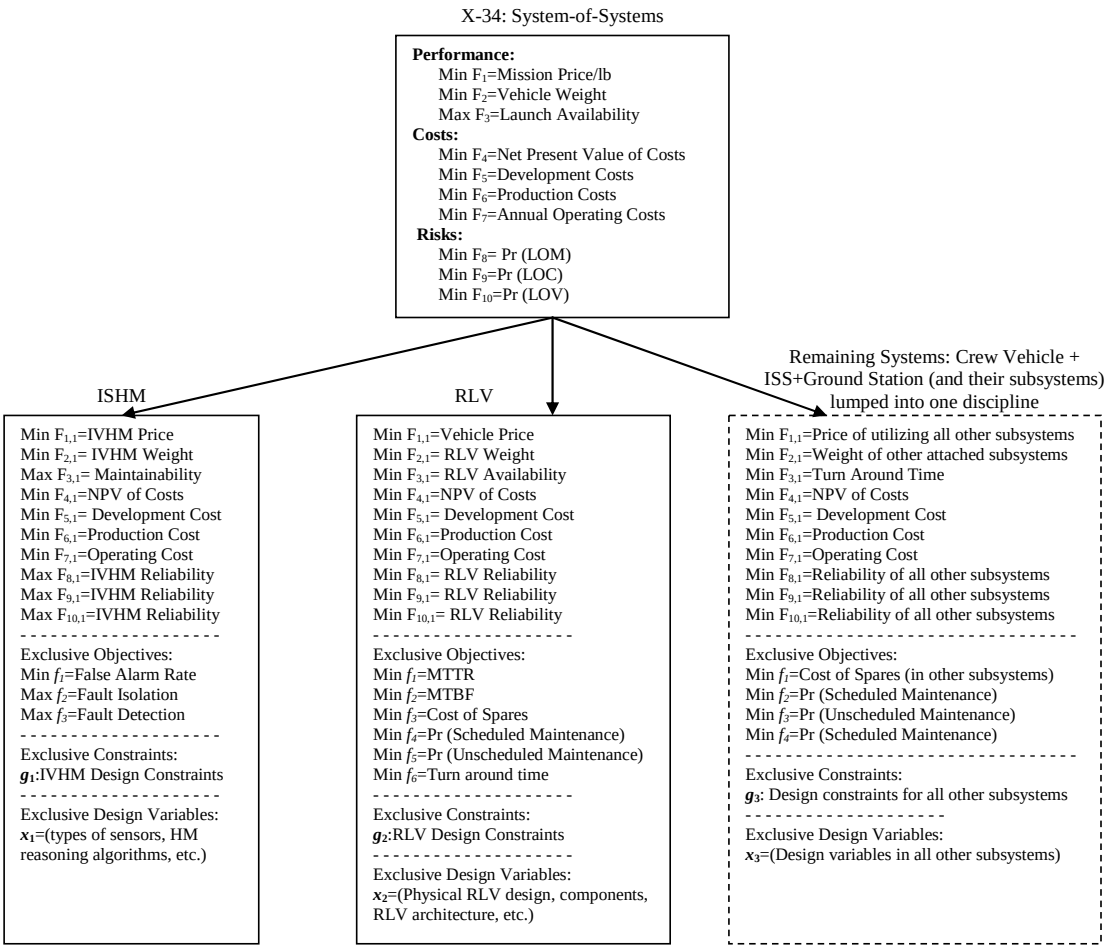

Figure 4. A multidisciplinary formulation of ISHM design problem

In the following subsection, MMSA&O will be introduced to solve the above problem in its multidisciplinary form. Later in Section 6, we will discuss the implementation and integration details. Note that the proposed MMSA&O approach is not specific to the above architecture and can be easily generalized to solve similar problems with different discipline breakdowns or with more than 2 levels of decomposition.

5.2. Solving ISHM MMSA&O

Based the hierarchical problem decomposition of Figure 4, the sub-problems can be solved independently given the shared design variables and constraints. The shared variables and constraints ($\boldsymbol{x}_{\text{sh}}$ and $\boldsymbol{g}_0$) are integrated into the sub-system sub-problems from the top-level. Following this integration, the optimization at each sub-system sub-problem is performed with respect to $\{\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_j\}$ and subject to $\{\boldsymbol{g}_0, \boldsymbol{g}_j\}$, $j = 1,...,J$. The objectives of the sub-problem remain the same. The mathematical formulation of the sub-problem j in MMSA&O is therefore:

$$\begin{aligned} &\text{minimize} \quad \mathrm{F}_{i,j}(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_j); \quad i = 1,\ldots,R_j \\ &\text{minimize} \quad \boldsymbol{f}_j(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_j) \\ &\text{subject to}: \begin{Bmatrix} \boldsymbol{g}_0(\boldsymbol{x}_{\text{sh}}) \\ \boldsymbol{g}_j(\boldsymbol{x}_{\text{sh}}, \boldsymbol{x}_j) \end{Bmatrix} \leq \boldsymbol{0} \end{aligned} \tag{3}$$

The solutions from sub-problems are rolled up to the top-level for integration. However, since each sub-problem is solved independently in every grand iteration, the design solutions from various sub-problems are biased in distinct directions in the design space. MMSA&O, therefore, employs two additional artificial metrics at the top-level to guide the optimization process and manipulate a better convergence and diversity among sub-problem solutions, as explained below:

<u>Convergence Metric (S Metric): Size of Dominated Space</u>: This metric (developed originally by Fonseca et al. [8]) provides a

measure of convergence (or optimality) for a given set of design solutions, i.e. the closer the solution set gets to the Pareto frontier, the lower the value of S metric becomes ([8][14]). Consider a minimization solution set: $A=\{p_1,\ldots,p_i,\ldots\}$ in a normalized design objective space (with the minimum of each objective shifted to the origin). The size of the dominated space by set A, denoted by $S(A)$, is defined as the volume of the union of hypercubes $\{C_1,\ldots,C_i,\ldots\}$, where C_i is a hypercube whose two opposite vertices are p_i and the origin of the objective space. Figure 5, for instance, shows the two hypercubes generated by the solution set $A=\{p_1, p_2\}$. The volume of the union of these two hypercubes measures $S(A)$[4]. In MMSA&O, the S metric is explicitly minimized at the top-level in order to guide the design processes to converge.

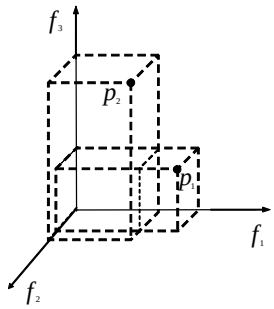

Figure 5. Size of dominated space, S metric, for the set $\{p_1, p_2\}$

Entropy Metric (H Metric): Just as it is important to converge to the Pareto-optimal frontier, it is equally important to maintain diversity in the solution set to ensure that we have a good coverage of all potentially-interesting solutions. When solving a multi-objective optimization problem in its multi-disciplinary form, it is generally very difficult to maintain the diversity of solutions. This is because the overall solutions are biased towards the solutions of sub-problems. This difficulty in obtaining a diverse set of solutions is compounded further in complex systems with many objectives where the design space is quite large and has many dimensions. Farhang-Mehr and Azarm [12] have developed an entropy-based quality metric that can be used to assess the 'diversity' of a solution set. This provides a measure for the spread of a solution set in the design space. In MMSA&O, H metric (along with S metric) is explicitly maximized to maintain a well-distributed set of solutions throughout the design process.

Figure 6 shows the overall schematic of MMSA&O. Each sub-problem operates on its own set of design solutions of $\{\boldsymbol{x}_{sh}, \boldsymbol{x}_j\}$. In addition, MMSA&O maintains a top-level *main design set* external to the sub-problems, which is a set of complete design variable vector: $\{\boldsymbol{x}_{sh},\boldsymbol{x}_1,\ldots,\boldsymbol{x}_J\}$. After convergence, the main design set provides a set of Pareto-optimal solutions for the overall optimization problem in Equation 2 (It is MMSA&O's equivalent of a multi-objective optimization solution set obtained from solving the problem in its single-level form in Equation 1). The main design set archives the solutions generated by the sub-problems and uses both H and S metrics operate for down-selection (selecting a subset of total solutions rolled-up to the top-level) to ensure convergence and diversity of the whole design process. Initially, the main design set is generated using a baseline design (perhaps from a previous design experience with a similar system).

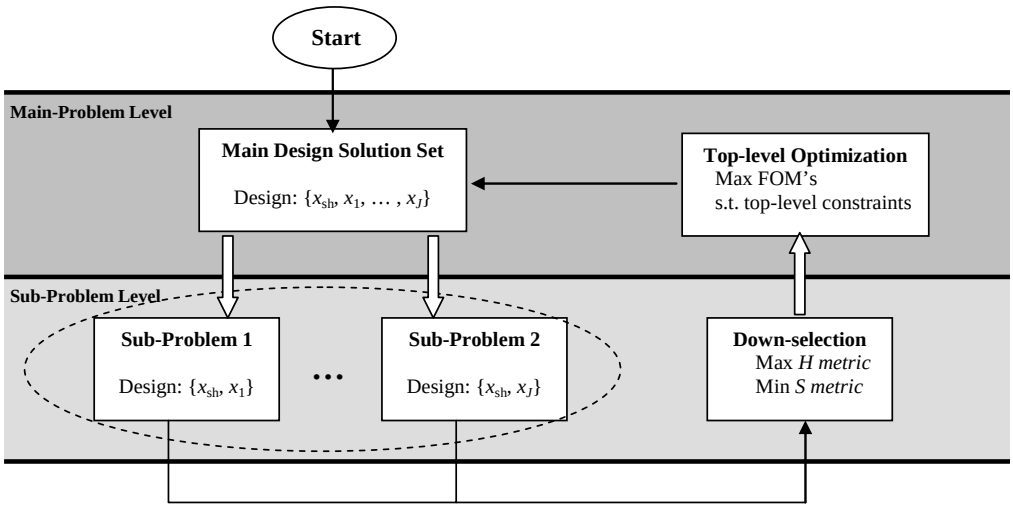

Figure 6. Overall schematic of MMSA&O

[4] Note that this definition of S metric assumes a minimization problem with normalized objectives. In MMSA&O, in order to compute both S and H metrics, the objectives are first normalized and converted into minimization problem (by applying a negative sign to those objectives that need to be maximized).

The sub-problems are individual multi-objective optimization problems that can be solved using any appropriate optimization technique. In this case study, we used a Multi-Objective Genetic Algorithm (MOGA) to solve the sub-problems (see [15][16] for a comprehensive review of MOGAs). MOGAs are particularly appropriate for this case study mainly because of the mixed continuous-binary nature of design variables. For instance, the placement of ISHM sensors in certain positions in the MPS feed system is a binary design variable, i.e. 1's or 0's represent the existence or nonexistence of a sensor at those certain location. These variables would be represented as a binary string in GA (referred to as 'chromosomes'). Also, MOGAs are population-based approaches that can produce many optimal design points in a single run. Given the multi-objective nature of each sub-problem and the fact that H metric is used explicitly to improve the distribution of solutions, a successful MOGA can produce a set of design solutions that represents the entire Pareto-optimal frontier (the entire tradeoff space among conflicting objectives). The chromosomes (design solutions) in the main design set are used as the initial population (or seed) to start the MOGA for each sub-problem. Since each sub-problem MOGA operates on its own variables $\{\boldsymbol{x}_{sh}, \boldsymbol{x}_j\}$, only the chromosomes corresponding to $\boldsymbol{x}_{sh}$ and $\boldsymbol{x}_j$ are used as the seed for the jth sub-problem. Each sub-problem takes these initial chromosomes and evolves them to optimize its own objectives subject to its own constraints. After each sub-problem MOGA is run for a certain number of iterations, they are all terminated. Since there are J independent MOGAs, after termination, there will be J populations having P chromosomes each. Each of the J populations contains the chromosomes of only $\{\boldsymbol{x}_{sh},\boldsymbol{x}_j\}$, $j=1,...,J$. To obtain chromosomes of complete design variable vector $\{\boldsymbol{x}_{sh},\boldsymbol{x}_1,\ldots,\boldsymbol{x}_J\}$, the chromosomes obtained from the jth sub-problem are completed using the rest of the chromosome sequence $\{\boldsymbol{x}_1,\ldots,\boldsymbol{x}_{j-1}, \boldsymbol{x}_{j+1}, \ldots,\boldsymbol{x}_J\}$ from the main design set.

After the design solutions in all J populations are re-sequenced to form complete design variable vectors, they are stored for additional analysis at the top-level. This marks the end of sub-problem optimization routines. Before the next grand MMSA&O iteration, the main design set must be updated based on these design solutions. However, immediately after the end of the process, there are a total of $J \times P$ chromosomes of complete design variable vectors, among which only P chromosomes must be selected for the next grand iteration. Each of the design solutions in the main design set maps to a point in the objective space of the problem ($\mathbf{F}$ and $\boldsymbol{f}$). As mentioned previously, the goal of MMSA&O is to obtain solutions that facilitate convergence and are as diverse as possible in this space. To do so, from the $J \times P$ chromosomes in the main design set, MMSA&O picks only P chromosomes that maximize the H and S metrics and discards the rest. The problem of choosing P chromosomes that maximize the H and S metrics can be posed as a separate optimization problem (as suggested in Figure 6). However, since the size of the search space for this optimization problem can become very large, we use a rather simplistic heuristic instead: MMSA&O generates 20 random samples of size P among all design solutions that come from lower sub-problems and choose the one set that maximizes the desired metrics. This set is then replaced in the main design set and used in the next grand iteration to serve as the initial starting point for individual sub-problems. This would gradually guide the optimization process to converge to the Pareto-optimal frontier while maintaining diversity of represented design solutions.

6. MMSA&O Implementation Details for X-34 Main Propulsion System (MPS)

This section provides a brief description of some of the models that are used to calculate FOMs (for a more detailed description of these models, see [3]). An integration process is currently under development at NASA Ames Research Center to enable a fully-automated analysis of such complex systems.

6.1. Design for Testability (DFT) Model

Design For Testability (DFT) modeling is the primary technique used in determining fault detection coverage, ambiguity groups, fault isolation and reliability. DFT modeling generates a testing strategy in the form of a diagnostic decision tree. To do testability analysis, a functional model is created to keep track of the inputs and outputs from each component and the relations between components[5]. The model also captures the association between components and failure modes with respect to the state of the components (Figure 7).

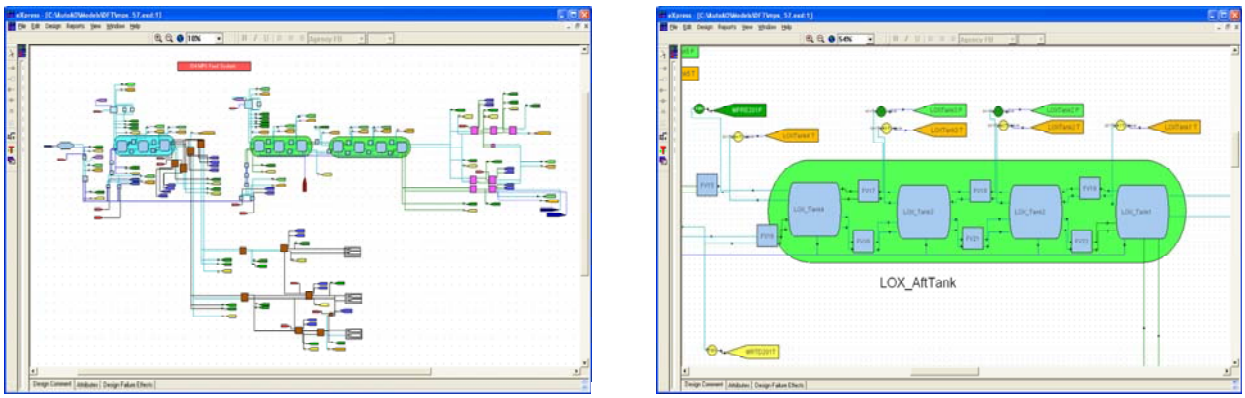

Figure 7. Design For Testability (DFT) for an MPS feed system

[5] DSI International's eXpress 2001 v5.8.0 is the DFT software package used in this study.

6.2. False Alarm Model

The False Alarm Rate (FAR) model accounts for possible false alarms introduced by the ISHM system. False Alarm Rate is defined as the ratio of false alarms to the total number of alarms. The False Alarm Rate for a general system is determined by decomposing the system into independent subsystems. The Expected Values for false alarms (FA's) for the subsystems are then combined into an overall Expected False Alarm Value. This is a recursive process as the subsystems, in turn, are decomposed into simpler, independent subsystems whose Expected FA Values are directly determined.

6.3. Maintenance Models

Three maintenance models are used to provide maintenance related input on a subsystem-by-subsystem basis, as described below.

- Scheduled Maintenance Model: The Scheduled Maintenance Model generates an expected turn around time based on predictable maintenance and work schedules.
- Probability of Unscheduled Maintenance Model: The Probability of Unscheduled Maintenance Model computes a probability that corrective maintenance is required. Corrective maintenance is all actions performed (a) as a result of a failure to an item in prior mission, (b) to restore an item to a specified condition (condition based maintenance), or (c) because of a false alarm.
- Unscheduled Maintenance Duration Model: The Unscheduled Maintenance Duration is made up of 'fault detection time' and 'Fault correction time'. Any additional time to verify the faulty item(s) is also a portion of this maintenance model. Unscheduled maintenance includes any or all of the following steps: Localization, Isolation, Disassembly, Interchange, Reassembly, Alignment, and Checkout.

6.4. Discrete Event Simulation Model

The DES Model performs a discrete event simulation to predict the time required to prepare the RLV for the next mission. The model includes all those activities that transpire after vehicle elements have been recovered, undergone safety inspections and returned to the maintenance facilities[6]. Turnaround activities conclude when all subsystems contained within each of the vehicle elements have successfully passed integrated system tests (Figure 8).

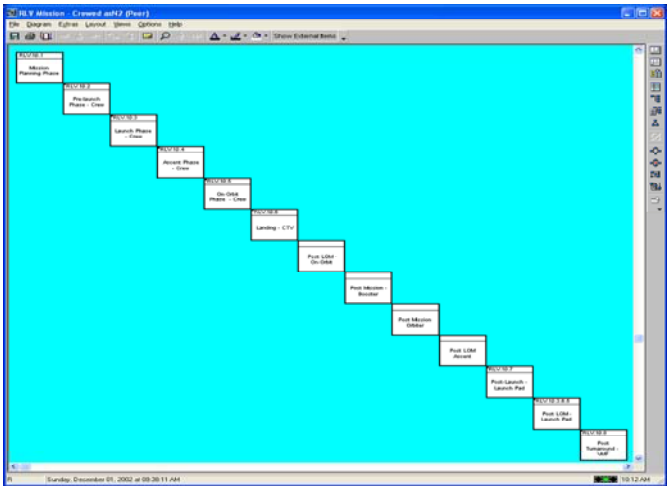

Figure 8. Discrete Event Simulation Model

6.5. Probabilistic Risk Assessment Model

Probabilistic Risk Assessment (PRA) identifies and assesses risks in complex technological systems. The Loss of Mission model assesses the likelihood that a failure will result in the inability to complete a mission. A fault tree is developed to evaluate the reliability of the vehicle subsystems including ISHM, during a Flight Mission[7]. ISHM typically increases the fault detection coverage and fault remediation options. However, an ISHM system may increase the number of false alarms and be a source of new faults.

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[6] This study uses Vitech Corp.'s CORE 4.0 as the discrete event simulation modeling tool.

[7] In this study, Idaho National Engineering and Environmental Laboratory's Saphire 7 is used as the PRA tool. It is called twice in each process pass-through. The first call determines the risk assessment for the component being changed. The second call computes the overall loss of mission probability. In between the two PRA calls, the effect of the faulty component on the performance of the ISHM subsystem is computed in a spreadsheet.

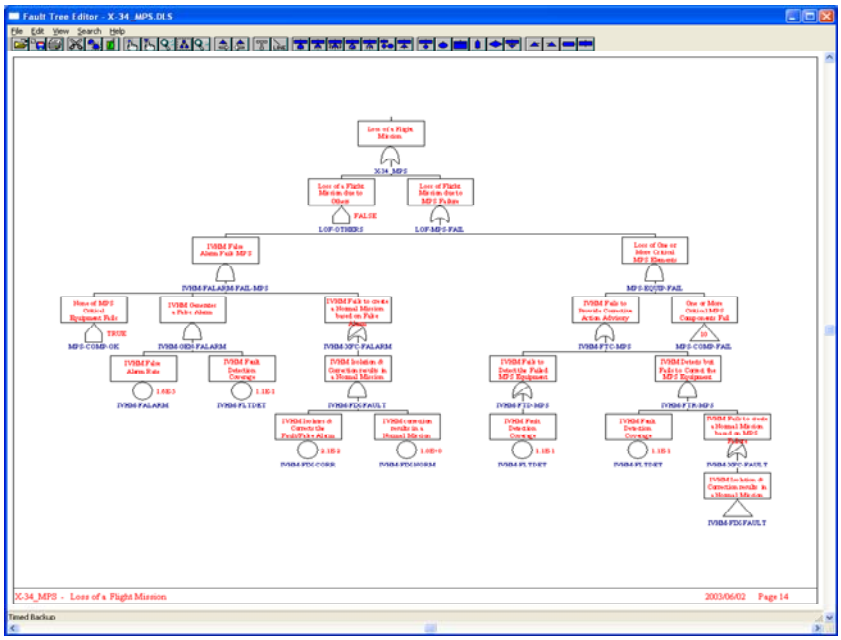

Figure 9. Probabilistic Risk Assessment Model

6.6. Integration and Automation

Phoenix Integration's Model Center v6.0.3 is used to automate the passing of parameters between models and to initiate execution of the models when input parameters change. The current integrated process at NASA Ames Research Center is fully automated except for two modules that have to be initialized manually by the user (the integrated process notifies users during each pass-through that these two models need to executed by hand). Once output reports have been generated from each model, they are parsed for the desired parameters and then passed onto the next models (Figure 10).

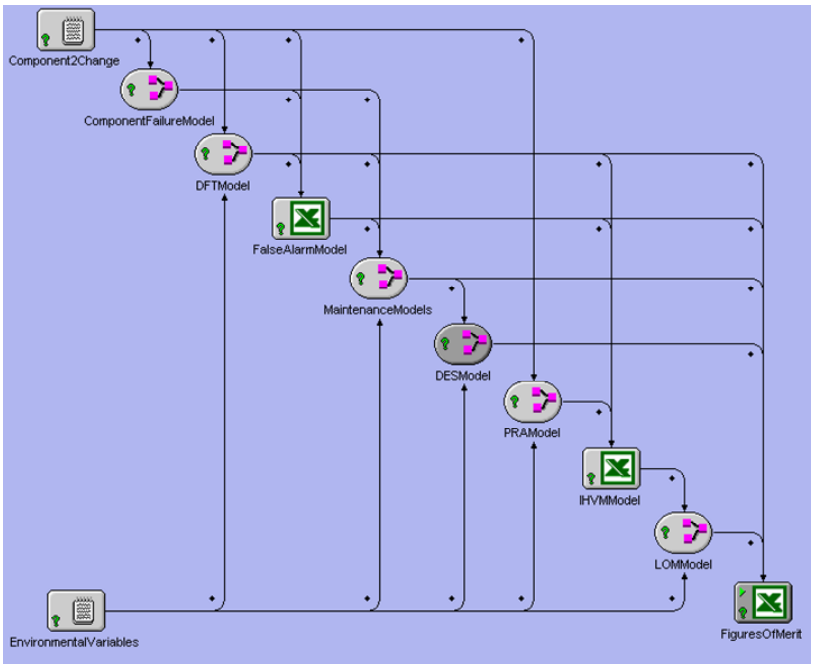

Figure 10. Integrated Process: The general flow of information is top-down and left-to-right. Arcs below the diagonal represent the environmental parameters. The arcs above the diagonal represent the inter-model dependencies, with the top left representing the input variables from the ISHM design.

7. Concluding Remarks

In this paper, we investigated the multidisciplinary and multiobjective nature of designing ISHMs for complex space exploration systems. In particular, we argued that in order to maximize the merits of using ISHM, one should integrate the ISHM design process

with that of the space exploration system itself. In other words, the ISHM sub-system should be designed *concurrently* along with other sub-systems of the exploration system. The proposed MMSA&O process of this paper, therefore, decomposes the entire system-design problem into several subsystems (one of which is ISHM). While these disciplines are regarded as independent domains with a certain degree of autonomy and exclusive (local) design parameters, they all share a subset of design variables and contribute to high-level system objectives. MMSA&O then provides a platform to pass information up and down between subsystems and system-level design in a hierarchical fashion, and integrates various design processes conducted in sub-systems. Finally, the generic ISHM design problem of this paper is decomposed as a two-level optimization process; however, it can be easily generalized to more levels of decomposition.

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