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ROCKET ENGINE HEALTH MANAGEMENT - EARLY DEFINITION OF CRITICAL FLIGHT MEASUREMENTS

R.L. Christenson
Michael A. Nelson
John P. Butas
NASA Marshall Space Flight Center
Huntsville, AL 35812

ABSTRACT

The NASA led Space Launch Initiative (SLI) program has established key requirements related to safety, reliability, launch availability and operations cost to be met by the next generation of reusable launch vehicles. Key to meeting these requirements will be an integrated vehicle health management (IVHM) system that includes sensors, harnesses, software, memory, and processors. Such a system must be integrated across all the vehicle subsystems and meet component, subsystem, and system requirements relative to fault detection, fault isolation, and false alarm rate. The purpose of this activity is to evolve techniques for defining critical flight engine system measurements early within the definition of an engine health management system (EHMS). Two approaches, performance-based and failure mode-based, are integrated to provide a proposed set of measurements to be collected. This integrated approach is applied to MSFC's MC-1 engine. Early identification of measurements supports early identification of candidate sensor systems whose design and impacts to the engine components must be considered in engine design.

INTRODUCTION

NASA's Space Launch Initiative (SLI) program has focused on the need for a safe, reliable, and low recurring cost reusable launch vehicle (RLV). It has as its goal at least an order of magnitude improvement in launch system safety, reliability and operations cost. Top-level program requirements enforce the critical nature of these goals and go far in stressing the need for a non-traditional design to reliability (and cost) approach. One of the key technologies at the system level is an engine health management system (EHMS) that is part of an overall integrated vehicle health management (IVHM) system. While IVHM is often seen as a panacea for any unreliability in the system, true design requirements for an IVHM system have been difficult to establish. The assumption here is that credible and quantifiable improvements in reliability are possible through the effective use of sensors, processors and algorithms. The challenge at hand is to balance the need for EHMS with the need for high performance, low weight, higher reliability, and lower cost – all critical issues to rocket engines. Careful definition of critical measurements; prudent selection of highly reliable sensors, harnesses, and processors; and inclusion of appropriate fusion logic are all necessary to build an effective rocket engine health monitoring system.

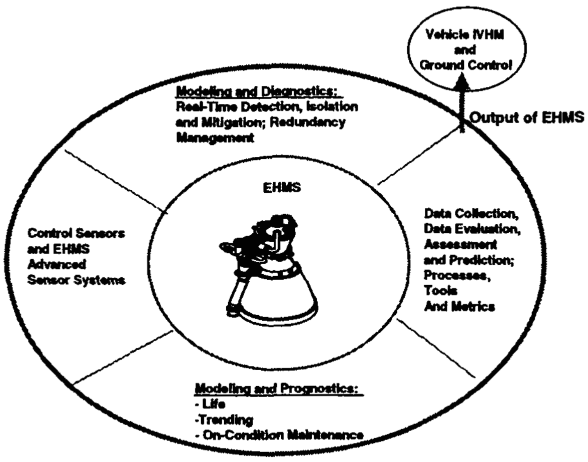

Figure 1: EHMS Vision

Figure 1 presents the EHMS vision. Included in this are prognostic and diagnostic capabilities, advanced sensor systems and processes to ensure data collection, evaluation, prediction that use appropriate tools and metrics.

The paper presents a two-pronged approach for identifying these measurements. The first approach is a performance-based modeling approach that defines the minimal set of measurements critical for engine data reduction and control. This approach identifies required pressure, temperature, speed and flow measurements. The second approach is a more traditional failure mode-based analysis of the engine that defines an extensive set of measurements necessary for monitoring a large number of critical failure modes. This approach identifies the need to monitor measurements critical to engine control while also picking up the need to monitor other characteristics such as vibration and acoustics. This approach will yield a large number of sensors required to evaluate engine component health. The integration of these two approaches is a goal that will allow a convergence on an optimal set of measurements that can be used for engine control and engine failure mode monitoring.

Both approaches identify parameters (and thus sensor systems) that are critical to the engine operation. Supporting these approaches must be a quantitative reliability evaluation process that is necessary to evaluate and rank the criticality of the measurements. This supports the decision to include or not.[1] A major part of the reliability evaluation is determining whether the sensor system would actually degrade the overall reliability of the engine system. This is possible through unreliable sensor, harness or processing software and through implementing a system that has a high incidence of generating false alarms (indicates a failure when none is present). The details of this reliability evaluation process are beyond the scope of this paper. Effective candidates for this are in place and also evolving. Such techniques include probabilistic design analysis (PDA) and probabilistic risk assessment (PRA). The former is oriented more to the physics of failure – less dependent upon condition reports and inspections but more dependent upon structural analysis data. PRA is more oriented to traditional roll-up of component and part estimates using fault trees or event trees and Boolean logic to calculate an overall system reliability. Good references for both techniques are shown in the reference section.[2-5]

BACKGROUND

EHMS (and IVHM) are defined herein as the diagnostic, prognostic and maintenance management system consisting of sensors, harnesses, processors and algorithms. Included in the management system are capabilities to detect, isolate, and mitigate failures and maintenance issues. Independent algorithms can support detection and isolation for each sensor or can be used to fuse information to supplement detection and isolation information across the sensors. Algorithms may also refer to real-time models that are developed to assist in predicting the health of the system given the sensor readings are missing or suspect. The EHMS and IVHM are viewed as critical to fulfilling the need for improved safety, reliability and maintainability for engines and launch systems.

Commercial EHMS systems such as those for aircraft provide the basis for belief in health management as highly effective in helping mitigate both critical and non-critical (maintenance) events. Other commercial systems are also successful in this regard (automobiles, commercial plant operations, etc.). The case is often made that rocket EHMS should show the same kind of benefit as aircraft EHMS. While this may be true in theory, commercial aircraft operations have large amounts of data, excellent understanding of the failure modes and life of the system components, and an ability to test to drive out failure modes, effects, and life limits. Also, aircraft systems are not as weight critical since they have much higher performance margins than spacecraft. Other commercial systems, being ground-based, can build more robust components and provide even higher margins than aircraft. Technology for these systems may be at a greater readiness level. Rocket and aircraft propulsion systems vary considerably in several areas. These areas include operating environment; operating temperatures, pressures and thrust; ability to idle, taxi, and loiter aircraft engines and vehicles; use of cryogenic fuels on rockets; large performance margins on aircraft; relatively open access to support aircraft engine inspections; and, perhaps the major difference, a philosophy of use with aircraft that tolerates test and operational failures (and even loss of life).

A rigorous and credible process must be in place to support the definition of the rocket EHMS since there is a perception, among many rocket engine designers that any EHMS, particularly the sensors and harnesses, are less reliable than the actual hardware. Thus, adding sensors is generally viewed as a bad thing. Such perceptions exist with good basis - this basis is the historical data collected during test and flight of launch vehicles. Early data (prior to '95) from the space shuttle main engine (SSME) flights supports this perception – 2 of first 5 engine related aborts (4 on pad, 1 abort-to-orbit) were sensor related. The only shuttle abort-to-orbit vehicle flight occurred due to a sensor failure. Also, 2 of first 7 engine related scrubs and delays were sensor related. Also, 24 of the first 29 engine anomaly reports since STS-26R were due to sensors. Sensor-related anomalies still occur and, given the data, one can see where the negative perspective regarding sensors came from. Unsatisfactory Condition Reports (UCR's) collected after test and flight consistently reflect sensor and harness problems. The perception is that extra software, sensors, fusion algorithms might only add to these totals relative to scrubs, delays, anomalies and UCR's.

In the reliability analysis of the EHMS candidates several factors have to be considered. These include the feasibility of detecting the failure mode, the ability to isolate it, whether the failure can be mitigated, and how fast the failure occurs. Other factors include the availability of appropriate sensors and the technology readiness levels of candidate sensor systems. False alarms in systems where mitigation capability is limited makes it a major concern. A logic to stop false alarms (data fusion, modeling, redundant sensors) also must be in place.

OBJECTIVE

The objective of this activity is to put a rigorous process in place for more accurate definition of required EHMS measurements, first for test but also for flight. An example to illustrate this process will be provided. As much as possible, the goal is to seek a quantifiable "closed form" solution. This is a goal, since, while the use of models to generate control and flow health measurements is fairly well established, the ability to model failure modes and effects and to quantify reliability and maintainability benefits is a developing technology.

Reliability and maintainability design models need to be of high fidelity and in place for the design to effectively consider adding new sensors to the health management function. Reliability models have improved dramatically with the acceptance of probabilistic risk assessment (PRA) types of models. Models such as PRA will support the generation of quantitative metrics, which is important to decision support. Thus, any additional sensor (or removal of a sensor) would be based on an analysis that indicates convincingly that such a sensor should be added/removed. This analysis includes looking at all possible failures, times to failure, mitigation probabilities, and other information. There may be instances of failures that can be detected and isolated but not mitigated. If critical, EHMS will not be able to fully address this. If not critical, then sensors may be useful for maintenance purposes. Also, the probability of lowering reliability and increasing false alarms must be explored. False readings could be of two types: indicating failure when there is none, or indicating no failure when, in fact, such failure did occur.

The following philosophy of design applies:

- the goal is a minimal yet necessary suite of sensors and effective, sufficient coverage
- due primarily to the concerns with sensor unreliability, measurements must "buy their way in" by showing their reliability and maintainability benefit; any sensors selected will need extensive testing in an applicable environment to be considered for inclusion.
- the approach defined should be applicable to a complete vehicle and integrated MPS system
- the approach must focus on measurements needed for control and flow monitoring with add-in high value measurements needed for failure mode/life/maintenance monitoring.

Thus, to get started, the following information is needed and for the purpose of this paper it is assumed it to be in place: a good performance model to support control and health measurement definition; preliminary failure modes and effects definition; and good reliability (and maintainability) models generating credible quantitative metrics.

The approach described in this paper has been applied to the proposed engine health management system of the MC-1 rocket engine, as defined in the following section.

MC-1 APPLICATION

The MC-1 Engine (Figures 2 & 3) is a pump-fed, liquid rocket engine with fixed thrust. The engine was designed for the Low Cost Technology Project, and for the X-34 vehicle. The engine burns a mixture of RP-1 hydrocarbon fuel and liquid oxygen propellants, in a gas generator power cycle. Propellants are tapped from the engine propellant lines, and are burned as a fuel-rich mixture in a gas generator, to power a turbine, which rotates an in-line turbopump assembly. Turbine exhaust gas is routed overboard via a turbine exhaust duct routed along side the engine nozzle. The chamber/nozzle is built as one piece with ablative liner and composite overwrap. The engine operates at one rated power level, nominally 60,000 lbf at vacuum conditions for the 15:1 area ratio nozzle configuration, and slightly higher for the 30:1 nozzle.

Figure 2: MC-1 Engine

Thrust and mixture ratio are open-loop controlled by setting fixed orifices in the engine propellant lines during engine calibration testing. Therefore, variations in engine propellant inlet conditions cause engine performance variations. An electronic controller, external to the engine, issues electrical commands for engine start and shutdown. Engine start includes helium spin-up of the turbopump assembly, hypergolic ignition of the main injector, and pyrotechnic device ignition of the gas generator. The engine is capable of reuse, and is designed with line replaceable units (LRU).

The engine is configurable for vertical operation, typical of booster application, or for horizontal application as used on the air launched X-34 vehicle. The engine actuator attach ring includes mounting locations for thrust vector control actuators as required for X-34.

PERFORMANCE-BASED MODELING APPROACH

The first method for selecting measurements is a performance-based modeling approach. This approach focuses on defining the minimum set of conventional measurements necessary for identifying shifts within component hardware used in an engine system diagnostic model. The output of this approach identifies both an optimal and redundant set of pressures, temperatures, speeds and flow measurements for evaluating engine component health and identifying failures. The two primary tools needed to support this sensor selection study are the ROCETS MC-1 mainstage engine design model and the Generalized Data Reduction (GDR) model.[6] The engine design model is a system level model that uses physical relationships to predict the various operating states of the engine. This physics-based system model solves for mass, momentum and energy throughout the engine. This model is used to generate the functional relationships between both selected hardware characteristics and physical measurements.

The GDR model is a robust data integration model that is used for numerically computing selected engine hardware characteristics from a specified set of engine measurements. The GDR model uses the functional relationships as a basis for determining performance shift causality at the component level. The model employs a scheme for determining the optimal set of sensors, as well as determining if the selected sensors can numerically solve for the desired set of hardware parameters. This GDR model was developed and utilized along with the design model to support test data reduction. Experienced engineers selected the initial sensors for the MC-1 engine, based upon acquiring the data necessary to evaluate the individual components. The GDR model was developed to provide a systematic approach for identifying the value of each of these conventional measurements on the health of the engine hardware. This procedure provides system-modeling engineers a tool for selecting engine measurements to support diagnostic modeling.

The following section will outline the process and the results from a detailed sensor selection study performed on the MC-1 engine.[7] The study was based on a premise of starting with a clean sheet wish list of desired hardware characteristics and a set of potential test measurements. The results of this sensor selection process is a list of sensors that can accurately solve for the final set of hardware parameters.

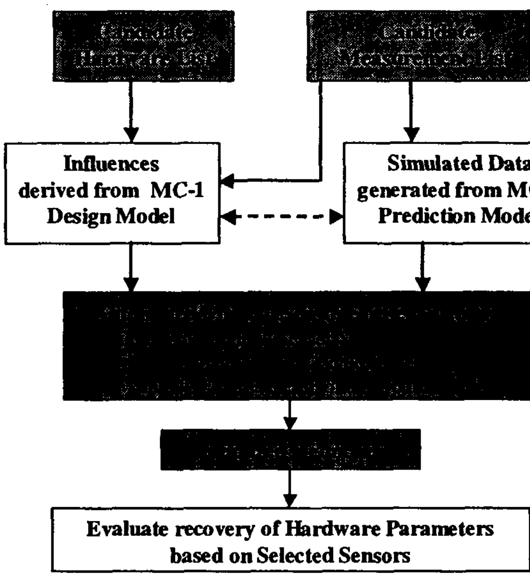

Figure 3: Process for Diagnostic Sensor Selection

A procedure was developed in the GDR model that selects hardware parameters and test measurements to be used within the reduction process based upon examining the condition number of a performance model influence matrix. Predicted hardware characteristics are recovered from the solution of a quadratic programming problem. Computational tests indicate that the GDR modeling procedure generates a consistent set of hardware adjustments, thus providing an accurate tool for supporting test data reduction. The subset selection process employed within GDR provides a method of identifying appropriate combinations of hardware parameters and internal measurement variables that limit the solution error bound. The L_2 condition number of the hardware Jacobian, provides a measure of the computational limits of solution accuracy separate from model and measurement uncertainty effects. The automated parameter subset selection is applied primarily to eliminate measurements and stabilize ill-conditioned underdetermined systems. This method appears to effectively isolate and eliminate measurement redundancy and scaling problems. The criteria for evaluating and eliminating the hardware parameters is based primarily on the ability to successfully recover predetermined numerical adjustments.

The process for identifying the minimum and best set of diagnostic measurements is shown in figure 3. The process begins with identifying both a candidate set of hardware parameters and physical sensors. For the MC-1 engine, there are 32 potential candidate measurements that were selected, and 22 desired candidate hardware parameters to be solved.

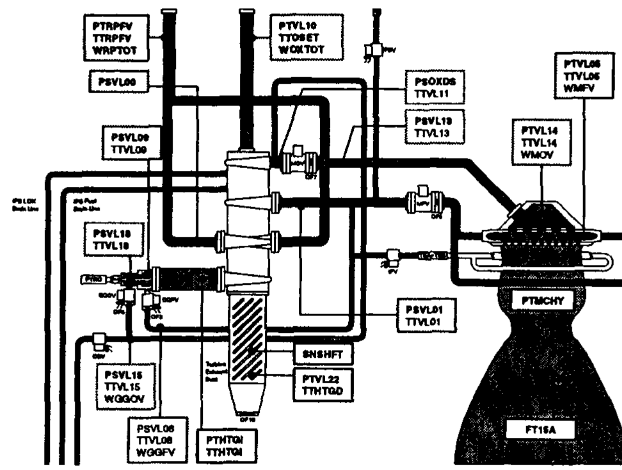

Figure 4: MC-1 Engine Candidate Sensor List

Note: Figure 4 above reflects a measurement labeling format common to rocket engine development. For example, PTRPFV is the total pressure in the RP line upstream of the turbopump. This is a measurement that also could be an actual sensor.

Figure 4 above shows a schematic of the MC-1 engine with the 32 candidate measurements and the 4 engine inlet measurements. The initial selections of these sensors are based on identifying pressures, temperatures, and flows at both the inlet and discharge of each main engine component. The selection of the candidate hardware parameters was based upon component failure modes, and hardware characteristics within the design model that are calibrated using test data. Each of these 22 hardware parameters was individual perturbed +/-10% within the design model. The corresponding responses in each of the 32 potential sensors were recorded. A total of 704 influence coefficients were generated and organized into a matrix. In addition, these influence coefficients were used in a predictive model that was constructed for generating simulated test data. Data was generated for all 32 measurements by individually adjusting each of the 22-hardware parameters +10%. This simulated data was generated assuming the measurements readings are pristine or without any precision error. The GDR model requires the base states of these 54 parameters, the matrix, and the simulated test data.

The first step in evaluating these hardware and physical parameters within the GDR model is to calibrate the numerical process to the design model. The same sets of parameters are numerically solved in both models to ensure the results are identical. Within this first step, the GDR model yields the same set of test measurements as derived by engineers, with identical numerical results.

The second step is to determine whether all of the hardware parameters can be numerically recovered based on the optimized selected set of sensors from the 32 candidate measurements. The purpose of this step is to ensure that all the desired hardware parameters can be accurately computed.

	Hardware Parameters	Descriptions	% Recovery of Hdwr. Parm.
		Discharge Coefficients	
1	CDGGKI	GG Fuel Injector Cd	10.02%
2	CDGGOI	GG Oxid Injector Cd	10.04%
3	CDKINJ	MCC Fuel Injector Cd	10.00%
4	CDOINJ	MCC Oxid Injector Cd	10.00%
5	CDGGNZ	GG Exhaust Duct Orifice Cd	10.00%
6	XMGGKO	GG Fuel Orifice Cd Mult	9.99%
7	XMGGOO	GG Oxid Orifice Cd Mult	9.99%
8	~~XMMCKO~~	~~Main Fuel Orifice Cd Mult~~	~~0.00%~~
9	~~XMMCOO~~	~~Main Oxid Orifice Cd Mult~~	~~0.00%~~
		Chamber/Nozzle Parameters	
10	CDNOZL	Nozzle Cd	10.00%
11	ECSMMCHB	MCC C* Efficiency Mult	10.00%
		Turbomachinery Parameters	
12	PSIMKPMP	Fuel Pump Head Coefficient Mult	10.00%
13	PSIMOPMP	Oxid Pump Head Coefficient Mult	10.00%
14	~~TRQMKPMP~~	~~Fuel Pump Torque Mult~~	~~0.00%~~
15	~~TRQMOPMP~~	~~Oxid Pump Torque Mult~~	~~0.00%~~
16	ETAMHTGT	Turbine Efficiency Mult	9.99%
17	~~FRICFACT~~	~~Turbopump Shaft Friction~~	~~0.00%~~
		Resistances/Others	
18	RKFL1	Fuel Pump Inlet Line Resis	10.01%
19	RCALMF	Main Fuel Line Resis	10.00%
20	RCALMO	Main Oxid Line Resis	10.00%
21	ROLN1	Main Oxid Inlet Dome Resis	10.00%
22	QDOTVL18	Heat Xfer (GG Lox Flow)	9.98%

Table 1: Evaluation of the 22 Candidate Hardware Parameters

Note: Table 1 reflects a hardware characteristics labeling convention common to rocket engine development. For example, CDGGKI is the derived discharge coefficient for the gas generator fuel injector.

Table 1 shows the GDR numerical solution using the simulated test data for each individual hardware parameter. Of the desired 22 hardware parameters, 17 successfully recovered the perturbed 10%, and 5 were unable to be numerically recovered regardless of the selection of sensors. The slight difference in numerical values is attributed to the solution error. Each of these 5 hardware parameters is confounded with other hardware characteristics that were successfully solved. These 5 hardware parameters were eliminated from further sensor selection studies. In addition, a set of 17 sensors with the highest ranking was identified from the GDR automated sensor subset selection process. Table 2 below provides a summary of these 17 sensors. The 4 flow measurements highlighted represent new measurements selected that were not available during MC-1 testing.

	Fuel System		***Oxidizer System***
Rank	Descriptions	Rank	Descriptions
15	Fuel_Pump_inlet_P	1	LOX_Pump_ds_P
13	Fuel_Pump_ds_P	11	**GGOV_inlet_Flow**
3	**GGFV_inlet_Flow**	14	GG_LOX_inlet_P
8	GG_Fuel_inlet_P	17	GG_LOX_inlet_T
9	Fuel_Manifold_P	16	LOX_Orifice_ds_P
2	**Fuel_Manifold_Flow**	10	LOX_Dome_P
		5	**Fuel_Manifold_Flow**
	Turbine		***Engine System***
Rank	Descriptions	Rank	Descriptions
4	Turbine_ds_P	7	MCC_Pc
12	Speed	6	Eng_SL_Thrust

Table 2: Optimized Subset Sensor Selection Results

The third step involves manually forcing each of the 32-candidate measurement, one at a time, to be included into the subset selection process. The purpose of this step is to determine whether or not, each of the individual candidate sensors could be added to 16 other sensors to accurately solve for the 17 hardware characteristics. This approach is used to assess the usefulness of all the candidate measurements. The process identified that 8 of the 32 candidate sensors produced unacceptably high condition numbers. These 8 sensors were individually confounded with the other sensors that would result with inaccuracies in solving for the hardware characteristics.

Table 3 provides a list of the 8 sensors along with the ratio of the absolute condition number to a reference value of a desirable condition number. The 2 sensors highlighted were measurements available during MC-1 testing. This process also identified several sensors that were redundant to other candidate sensors.

The fourth step involved manually forcing each of the 17 optimally selected sensors, one at a time, to be eliminated from the subset selection process. The purpose of this step is to determine whether alternate sensors could be used in place of these 17 sensors. This step is used to determine the relative value and importance of each of these 17 optimal sensors. As before, this step will use both the condition number and accuracy for assessing these sensors. The results from step 3 and 4 have identified 24 of the 32 candidate sensors as recommended measurements for the MC-1 engine test program.

	Descriptions	Condition # Ratio
	Fuel System	
1	Fuel_Pump_ds_T	2.22
2	GGFV_inlet_T	2.22
3	GG_Fuel_inlet_T	2.22
4	**Fuel_Manifold_T**	2.22
	Oxidizer System	
5	LOX_Pump_ds_T	1.54
6	GGOV_inlet_T	1.54
7	LOX_Orifice_ds_T	1.54
8	**LOX_Dome_T**	1.54

Table 3: Candidate Sensors that were Eliminated

	Sensors	Descriptions	Assessment of each Sensor
		Fuel System	
1	**PSVL00**	**Fuel_Pump_Inlet_P**	**Critical (no redundancy)**
2	**PSVL01**	**Fuel_Pump_ds_P**	**Critical (no redundancy)**
3	PSVL08	GGFV_inlet_P	Redundant to PSVL09
4	**WGGFV**	GGFV_inlet_Flow	Redundant to TTHTGI, TTHTGD
5	**PSVL09**	**GG_Fuel_Inlet_P**	Redundant to PSVL08
6	**PTVL05**	**Fuel_Manifold_P**	**Critical (no redundancy)**
7	WMFV	Fuel_Manifold_Flow	Redundant to WRPTOT
		Oxidizer System	
8	**PSOXDS**	**LOX_Pump_ds_P**	Redundant to PSVL15
9	**PSVL15**	**GGOV_Inlet_P**	Redundant to PSOXDS
10	WGGOV	GGOV_inlet_Flow	Redundant to TTHTGI, TTHTGD
11	**PSVL18**	**GG_LOX_Inlet_P**	**Critical (no redundancy)**
12	**TTVL18**	**GG_LOX_Inlet_T**	**Critical (no redundancy)**
13	**PSVL13**	**LOX_Orifice_ds_P**	**Critical (no redundancy)**
14	**PTVL14**	**LOX_Dome_P**	**Critical (no redundancy)**
15	WMOV	Fuel_Manifold_Flow	Redundant to WOXTOT
		Turbine	
16	**TTHTGI**	**Turbine_Inlet_T**	Redundant to WGGFV, TTHTGD, SNSHFT
17	**PTVL22**	**Turbine_ds_P**	**Critical (no redundancy)**
18	**TTHTGD**	**Turbine_ds_T**	Redundant to WGGOV, TTHTGI, SNSHFT
19	**SNSHFT**	**Speed**	Redundant to TTHTGI, TTHTGD
		Chamber	
20	**PTHTGI**	**GG_Pc**	Redundant to WGGOV
21	**PTMCHY**	**MCC_Pc**	**Critical (no redundancy)**
		Engine System	
22	**WRPTOT**	**Eng_RP-1_Inlet_Flow**	Redundant to WMFV
23	**WOXTOT**	**Eng_LOX_Inlet_Flow**	Redundant to WMOV
24	**FT15A**	**Eng_SL_Thrust**	**Critical (no redundancy)**

Table 4: Recommended MC-1 Engine Sensor List

Table 4 provides a list and assessment of these 24 sensors. The 19 sensors highlighted on the left side of the table were sensors available during MC-1 testing. This study confirmed that the test program had a very good set of measurements to support modeling engine hardware. The process identified 10 sensors that are critical to the numerical process that if not available would impact the solution of the 17 hardware parameters. The process also identified 14 sensors that are redundant to each other. Having these redundant sensors is extremely important for sensor validation and for providing alternate paths for numerical solving for the hardware characteristics.

All of the results for this performance-based modeling approach were generated from 51 GDR model runs. This process systematically identified key sensors to be measured within the MC-1 engine for identifying shifts in the hardware performance. A future step beyond the sensor selection process is to account for precision error estimates associated with these final 24 sensors. This can be accomplished by generating the simulated test data with various levels of random sensor noise. The results from this process were not included within this paper. This process will provide the necessary information to evaluate the impact of the measurement accuracy to the accuracy in generating engine hardware characteristics. The results will provide a basis for determining sensor accuracy requirements or to differentiate the value of redundant sensors. This information is necessary for down selecting to a final set of engine diagnostic sensors.

Limitations to this approach should be noted. These include:

- Coverage of non-power balance information such as vibration and plume composition are not included.
- Real-time control is the focus – maintenance concerns not generally reflected.
- There is a lack of characterization of certain failure modes and effects.

FAILURE MODE-BASED ANALYSIS APPROACH EXAMPLE (TRADITIONAL)

The failure mode approach is augmented early in design through the application of lessons learned, previous studies, and best practices. References exist looking at historical data on engines and launch vehicles that list the top failure mode concerns and their criticality.[8] For example, an historical list of tradition failure mode concerns may include external leakage from joints on the engine, excessive turbopump torque, internal leakage of valves, bolt torque failure, coolant passage leakage, turbine blade failure, loose electrical connectors, bearing damage, seal leakage, valve failure, and contaminated systems including hydraulics. External leakage is always ranked as an overriding concern for the historical engines studied.

This type of analysis serves to pre-identify technologies for application to engines such as optical temperature and flow sensors, data fusion and model algorithms, optical particle detection for wear-out indication, infrared and area leak detection, and others. A list must also be generated as more detail is collected on the actual design failure modes of concern relative to the hardware of interest. Characteristics of the engine such as engine cycle, type of fuel and oxidizer, materials selected, mission requirements, turnaround requirements, and turbopump characteristics will of course be critical in identifying failure modes and their criticality. From a merger of the historical list and the current design analysis comes the candidate set of measurements for the engine under design. Of course, a quantitative evaluation of the impact to the reliability of the engine system is critical for ranking the items on this list.

The following example is a selected failure mode analysis associated with MSFC's MC-1 engine. Focus is on special sensor requirements associated with high risk criticality-1 (catastrophic failure) failure modes associated with non-control type measurements.

By analyzing failure modes of the engine components while taking into account the probability of those failure modes as given from historical data, three different types of sensors would be selected to improve the reliability and safety of the MC-1 engine.

A Failure Mode analysis would begin by establishing functional dependencies of all major components across the engine. Functionality may be further decomposed by engine operating modes such as "Chill Down", "Prestart", "Start", "Mainstage", and "Shutdown". Instrumentation including sensors, harnesses, and processing units as well as mechanical components such as the turbopump, valves, ducts, the combustion chamber, and nozzle would be included in the analysis. Failure modes effects and their causes would be defined at each of the component levels with a resulting effect at the engine system level. Diagnostic tests are then defined that are used to determine the occurrence of the failure modes. An example of a commercial off the shelf (COTS) tool to aid in performing this analysis would be eXpress by DSI[9], which employs a diagnostic dependency model approach.

From this analysis, a table may be developed that lists each failure mode, whether or not the failure can be detected, instrumentation used to detect it, and what kind of mitigation action if any can be taken. Many of the decisions about failure mode detection and mitigation are heavily dependent on engineering experience and professional judgment both at the component level and at the system level.

From the above analysis it was determined that a sensor or array of sensors that will detect concentrations of oxidizer and hydrocarbon fuel across various components of the engine including valves and ducts would be necessary to detect fluid leaks during mainstage operation of the engine. The technical specifics of the sensors are yet to be defined but the end result would allow detection of leaks of oxidizer and fuel that could potentially lead to fire and or explosion especially where the engine is mounted in the closed compartment of a vehicle. Mitigation strategies might include shutting down the engine or purging the compartment with a non-combustible gas.

A second sensor or array of sensors that will detect vibrations on the turbopump would be necessary to detect degradation or failure of internal rotating machinery components such as the bearings, turbine blisk, and the turbo shaft. Again the technical specifics of the sensor and associated algorithms and the actual location for these sensors are to be defined but the result would allow detection of off-balance turbine blisk due to blade breakage or loss, turbo shaft whorl, and possibly ball bearing wear or degradation. The effect of these types of failures would contribute to loss of turbine efficiency or possible catastrophic failure of the engine system due to foreign object debris (FOD) down stream of the turbopump. Mitigation strategy for the MC-1 would require engine shutdown.

Finally, a third sensor that will monitor temperature of turbine blades to a high resolution with a small uncertainty would be necessary to monitor peak temperatures of either the hot gases moving across the turbine blade surfaces or the metal of the turbine blades themselves. Technical specifics of the sensor implementation are to be defined, but this type of monitoring would be able to detect when the strength modulus of the blade has been affected due to high temperatures. During flight, when a certain threshold temperature has been exceeded for a specific period of time blade failure can be predicted. Mitigation strategy in real-time would involve shutting the engine down. Since exposure to thermal stresses contribute to blade failures, another use for this type of sensor would be for the prediction of blade life from post mission analysis of blade by blade exposure to peak temperatures during start up, mainstage, and shutdown phases of engine operation. Post flight analysis of this type might indicate the need for manual inspection and replacement of the component as a ground based mitigation strategy.

The above example has identified three special sensor systems for use on the MC-1 engine consistent with a limited crit-1 failure mode analysis. There are limitations to this approach and these include:

- failure modes/life concerns not generally well understood, especially early in program
- behavior of the system operating in the environment not well characterized, especially in the presence of failure
- limited test time to validate models
- high failure rates on new technology, especially sensor systems
- unreliability of sensors, harnesses, software; added probability of false alarms with more sensors; negative impact to component performance having additional sensors (espec. intrusive sensors); are all difficult to analyze

INTEGRATED MODEL APPROACH

The limitations listed for the two approaches described in the sections above hint at the advantages for combining them. The philosophy of minimizing sensors is countered by the need to mitigate, as much

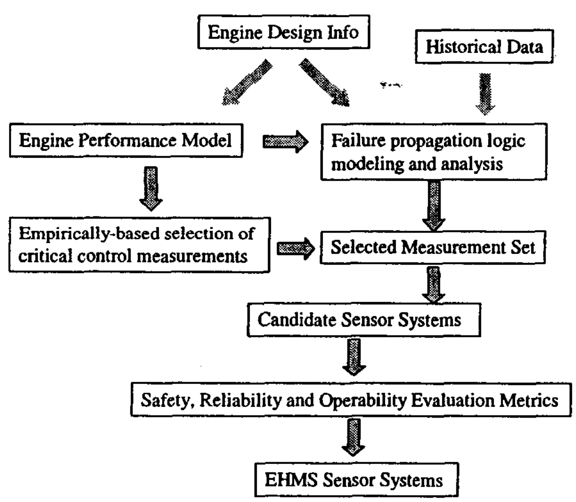

Figure 5: Overview of EHMS Definition Process

as possible, critical failure modes. Likewise, the logic of identifying all possible sensors is countered by the need to minimize sensors (focus on building robust hardware and avoid using unreliable and false alarm-prone sensor systems).

In order to do this, an integrated modeling approach (see figure 5) is necessary. As much as possible, validated flow models that can provide attributes of the system in the presence of failure are necessary to couple the two. Physics of flow information that is augmented by failure mode information, required control measurements and the overall effect on the system best supports the integration of EHMS on the engine hardware and software. Thus, in such a model environment, performance concerns would be effectively coupled with reliability concerns. This model integration is a goal for future programs.

CONCLUSIONS

The paper presents an evolving analytical approach for defining the sensor suite for an EHMS system. This approach couples failure mode analysis with a control measurement definition approach to generate a set of critical control measurements and high-value health monitoring measurements. These are forced to "buy their way in" through the use of quantifiable reliability metrics. From this set of measurements, a set of sensor systems can be proposed for inclusion on the engine and included in engine design.

Current limitations on models and reliability analysis must be rectified to take the next step – the integration of performance and failure mode modeling. Only when this occurs, can full characterization of the failures in the engine system be modeled.

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