

Optimal Sensor Selection for Health Monitoring Systems

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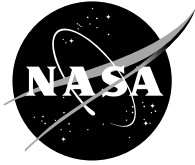
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Abstract

Sensor data are the basis for performance and health assessment of most complex systems. Careful selection and implementation of sensors is critical to enable high fidelity system health assessment. A model-based procedure that systematically selects an optimal sensor suite for overall health assessment of a designated host system is described. This procedure, termed the Systematic Sensor Selection Strategy (S4), was developed at NASA John H. Glenn Research Center in order to enhance design phase planning and preparations for in-space propulsion health management systems (HMS). Information and capabilities required to utilize the S4 approach in support of design phase development of robust health diagnostics are outlined. A merit metric that quantifies diagnostic performance and overall risk reduction potential of individual sensor suites is introduced. The conceptual foundation for this merit metric is presented and the algorithmic organization of the S4 optimization process is described. Representative results from S4 analyses of a boost stage rocket engine previously under development as part of NASA's Next Generation Launch Technology (NGLT) program are presented.

Nomenclature

DM	Diagnostic Model
DT	Detection Threshold
FMEA	Failure Modes and Effects Analysis
FT	Appropriate Fault Response Family
FM	Diagnostic Model Indicated Fault Response Family
GA	Genetic Algorithm
HMS	Health Management System(s)
LOX	Liquid Oxygen
LT	Failure Threshold
MMSE	Minimum Mean Square Error
NGLT	Next Generation Launch Technology
NP	Nonlinear Polynomial Time
RTM	Real Time Model
RP1	Type of hydrocarbon fuel
SLI	Space Launch Initiative
S4	Systematic Sensor Selection Strategy
A	State space model state matrix
B	State space model input matrix
C	State space model output matrix
D	State space model influence or direct transmission matrix
F	Matrix of hardware influence functions
O	Observability matrix
Q	Observability Gramian matrix

\mathbf{h}	Vector of health parameters
\mathbf{s}_h	Hardware parameter summation vector
\mathbf{x}	Vector of state parameters
\mathbf{y}	Vector of sensor derived measurements
\mathbf{u}	Vector of independent inputs
δ_c	Diagnostic model solution convergence criterion
δ_{det}	Measurement shift from normal indicating anomaly conditions
δ_p	Distance to equal likelihood boundary
n_h	Number of hardware parameters
N_m	Number of fault modes
N_T	Number of characteristic fault trajectories
P	Minimum probability most likely diagnosis is correct over all pairwise fault mode comparisons
Prb	Probability most likely diagnosis is correct for pairwise fault mode comparison
R	Risk reduction potential for timely diagnosis
T	Time to reach diagnostic threshold
T_{min}	Minimum time to reach diagnostic threshold

I. Introduction

Health management systems (HMS) monitor and control the function of critical systems and components in order to ensure safe and efficient operation. The need for autonomous health management capability depends on the risk associated with system failure and the potential benefit of timely response to faulted or degraded operations. The criticality of the system and the intensity and/or hostility of the operating environment are important factors in assessing the need for HMS. Space systems in general, and especially man-rated systems, present an ideal application for realizing the benefits of health management technologies.

Sensor data provide the foundation for performance and health assessment of most complex systems. Although opportunities for remote sensing of system function exist, the primary input for health diagnostics is generally provided by a network of sensors integrated within or in close proximity to the system of interest. Robust HMS require effective specification and placement of these sensors in order to support reliable and timely diagnoses over the range of potentially critical failure modes. Therefore effective sensor selection is an HMS enabling technology that supports agile control and planning for safe, productive, and cost effective system function.

There is a substantial body of literature that treats the many, often competing, criteria that impact selection of sensors for system monitoring. This paper focuses on sensor selection for effective health diagnostics. It is organized in five parts. Background information on current selection strategies is presented in this section. While not an exhaustive review, the survey provides perspective of representative methods for diagnostic sensor selection. Subsequent sections present a conceptual foundation for sensor selection that facilitates health diagnostics and the logic structure of a new sensor selection process termed the Systematic Sensor Selection Strategy (S4). Representative results from an application of the S4 process to select diagnostic sensors for a large boost stage rocket engine system are then reported. The final section contains recommendations based on early experience with the S4 process.

A. Traditional Approach

There are many considerations that impact sensor selection for space propulsion health management applications (see ref. 1 for a list of typical criteria). Traditional approaches to measurement and sensor selection for space propulsion applications are generally heuristic and support performance measures, but may not produce an optimal suite for health diagnostics/prognostics. A typical first step in the selection process is to have the various engine component teams submit lists of desired measurements. These measurements are used to support engine development, model verification, and/or detection of physical limit (redline) violations. As the system design matures, the component teams supply more detailed specifications such as measurement ranges, response requirements, etc. This information along with reliability requirements is used to determine the type and number of sensors needed at each engine location. The compiled list is then separated into categories associated with measurement use, e.g. ground test, flight, etc. Measurements are assigned a priority, with the highest priority given to measurements required for engine control. The list is often condensed as the design matures due to factors such as accessibility, cable routing, or reduced need. A maximum number of sensors is then determined based on storage/transmission capability, cost, and other considerations, which may include arbitrary limits. The component teams and chief engineer then negotiate until the final suite is selected.

Traditional approaches to sensor selection draw heavily upon domain expertise. They do not generally utilize a consistent quantitative method to assess the implications of choices on the diagnostic capability that enables effective health management. The absence of an accepted quantitative assessment methodology is a technology gap that must be closed to achieve the ambitious objectives of future space missions. Methods for assessing diagnostic capability are available, and specific procedures are discussed in the sections that follow.

B. Linear System Measures

A well-developed theory and an extensive array of computational tools are available for solution of linear system problems and estimation of solution error bounds (see ref. 2). If health diagnostics for the system of interest can be effectively modeled in terms of a linear algebraic system, mature error estimation tools are available to guide sensor selection. A number of linear algebraic influence models (see refs. 3 to 8) have been developed for estimation of propulsion system health parameters. These models generally take the matrix form

$$\mathbf{y} = [\mathbf{D}_h \quad \mathbf{D}_c] \begin{bmatrix} \mathbf{u}_h \\ \mathbf{u}_c \end{bmatrix} \quad (1)$$

where \mathbf{D}_h is the hardware parameter influence matrix, \mathbf{D}_c is the matrix of control input influences, \mathbf{u}_h is the vector of hardware parameter deviations from a nominal baseline, \mathbf{u}_c is the vector of control input changes from a baseline command state, and \mathbf{y} is the vector of measurement deviations from normal operating conditions. Knowledge of the control state \mathbf{u}_c and full column rank of the influence matrix \mathbf{D}_h are the criteria for detectability of any fault state that can be represented as a linear combination of hardware parameter deviations. Fault discrimination can be characterized by the condition number of the influence matrix \mathbf{D}_h . The condition number provides an indication of potential hardware state estimation error and its relation to measurement uncertainty. Large values increase state estimation uncertainty and impede clear and timely response to faults. Systematic selection of sensors to improve the condition estimate is a natural row partitioning process that provides quantitative metrics of diagnostic capability in terms of solution error bounds. Mathioudakis and Kamboukos (ref. 9) describe a sensor selection process based on minimization of the influence Jacobian condition number. Butas et al. (ref. 8) use a heuristic procedure for row partitioning of equation (1) to achieve influence matrix condition estimates consistent with accurate diagnostics.

Although useful in many applications, sensor selection based on influence model condition estimates has several limitations. A linear influence model is inherently range limited for systems with appreciable nonlinear response characteristics. It does not explicitly consider sensor/system response dynamics nor does it discriminate hardware parameter solutions based on probability of occurrence over the range of combinations representing potential fault states. Good discrimination of hardware state solutions in regions with low probability of occurrence obviously contributes little to diagnostic effectiveness.

State space models are a natural extension of influence methods commonly used to represent the behavior of physical systems. State space models can be represented by the general matrix relation

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{f}(\mathbf{x}, \mathbf{u}) \\ \mathbf{g}(\mathbf{x}, \mathbf{u}) \end{bmatrix} \quad (2)$$

where $\mathbf{x}(t)$ is the state vector composed of variables needed to describe system behavior, $\dot{\mathbf{x}}$ is the time derivative of \mathbf{x} , and \mathbf{f} and \mathbf{g} are vector functions of the state and input variables (see ref. 10). Linear state space models are a simplified first order approximation of the general relations in equation (2) often used to approximate the behavior of systems (see refs. 11 and 12). Linear state space models can be expressed in the matrix form

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{u} \end{bmatrix} \quad (3)$$

where \mathbf{A} , \mathbf{B} , \mathbf{C} , and \mathbf{D} are the state, input, output, and direct transmission matrices respectively. A system described by equation (3) is said to be state observable if, for any time $t_1 > 0$, the initial state $\mathbf{x}_0 = \mathbf{x}(t = 0)$ can be determined from the time history of the input $\mathbf{u}(t)$, and the output $\mathbf{y}(t)$ in the interval $[0, t_1]$. A linear time invariant system is said to be state detectable if all unstable modes are state observable (ref. 10). For such a system, state detectability is assured if and only if the observability matrix \mathbf{O} given by the relation

$$\mathbf{O} = \begin{bmatrix} \mathbf{C} & \mathbf{CA} & \dots & \mathbf{CA}^{n-1} \end{bmatrix}^T \quad (4)$$

has full column rank.

Fault detectability is of course necessary for effective health diagnostics; however, it does not characterize the timeliness of detection or the quality of fault discrimination. A number of scalar functions of the observability Gramian have been proposed to characterize the degree or quality of observability (refs. 13 to 15). The Gramian matrix \mathbf{Q} is defined by the relation

$$\mathbf{Q} \equiv \int_0^{\infty} e^{\mathbf{A}^T t} \mathbf{C}^T \mathbf{C} e^{\mathbf{A} t} dt \quad (5)$$

A clear description of the Gramian matrix and its role in state vector determination is provided by van den Berg (ref. 15). Dochain et al. (ref. 14) use the condition number of the Gramian to determine the most observable system model, and van den Berg describes several related Gramian metrics. Selection of the measurement variables \mathbf{y} , together with the associated output matrix \mathbf{C} , to optimize a Gramian fault discrimination metric provides a quantitative basis for systematic sensor selection.

Although state space models are an effective means of characterizing system dynamics, they retain the range restrictions inherent with linear approximation of nonlinear system response. In addition, sensor selection strategies based on Gramian metrics do not explicitly consider the distribution of fault occurrences or severity over the range of potential state solutions \mathbf{x} . For example, preferred fault directionality is an implicit fault distribution constraint that is not considered in Gramian metrics. As previously noted, good fault discrimination in state space regions with low probability of occurrence contributes little to diagnostic value.

In practical applications, measurements are corrupted by random noise, and the system itself may be subjected to random disturbances. Therefore, individual state variables of a dynamic system can seldom be determined exactly from direct measurements. They must be estimated from noisy observations. The basic Kalman filter is a linear system estimator used when processes and measurements contain significant random components. Kalman filtering has been the subject of extensive research and application. If all random components are Gaussian, the Kalman filter estimator can be shown to be optimal in the minimum-mean-square-error (MMSE) sense (refs. 19 to 21). Extended Kalman filter strategies that approximate nonlinear system dynamics, albeit with additional complexity, are also available (refs. 19 to 21). Kalman filtering is especially useful for off-line diagnostics and error analysis studies. With continuing improvement in computational speed, Kalman filtering has increased potential for real-time diagnostics depending on response time requirements.

Sensor selection based on minimizing the variance of health parameter estimation error from a state estimation Kalman filter has been considered in a number of studies (see refs. 16 to 20). However use of error variance measures alone to guide sensor selection has certain shortcomings. Selection of measurement type and location can affect system dynamic response, potentially impacting timeliness of diagnosis as well as health parameter estimation error. In addition, models that describe fault propagation dynamics are generally immature in the early phases of system design. As a consequence, measurement distributions during fault sequences may be difficult to characterize with sufficient confidence for effective Kalman filtering.

C. Targeted Fault Strategies

System health diagnostics based on physical models associate fault conditions with the deviation of model health parameters from normal values. Sensor suites admitting reliable determination of fault states over the full continuum of potential health parameter values are most desirable. However realistic fault scenarios will in general occupy only a fraction of the full parameter space range. This observation suggests the use of strategies that target regions of highest fault probability and severity. Targeted fault selection strategies often utilize specialized criteria to identify the optimal sensor suite for health diagnostics. In a series of papers, Bhushan and Rengaswamy (refs. 22 to 24) investigate the problem of sensor location based on various fault observability and resolution criteria. Narasimhan et al. (ref. 25) present four measurement selection algorithms using a qualitative reasoning framework to assess fault detection and isolation for dynamic systems. A method for designing a cost optimal sensor system for a designated diagnosability level is presented by Spanache et al. (ref. 26). In this latter study, a system is said to be fully diagnosable with a given set of sensors if and only if (i) for any relevant combination of sensor readings, there is only one minimal diagnosis candidate, and (ii) all faults of the system belong to a candidate diagnosis for some sensor readings. For most physical systems, only partial diagnosability can be realistically achieved because

multiple faults may share the same approximate signature and/or some faults are not detectable before failure occurs. In a recent study, Yan (ref. 27) considers sensor placement based on discriminability analysis where two faults may be discriminated if they generate different measurement output signatures over some subset of the available sensors.

D. Complexity Analysis

The complexity of various sensor selection problems has been investigated. Problems associated with determination of sensor sets of minimum cardinality guaranteeing diagnosability, normality, or observability for discrete event systems are considered by Yoo and Lafortune (ref. 28). Each is shown to be a member of the class of problems termed NP-complete (ref. 29). Problems in this class are notoriously difficult to solve, suggesting that optimal diagnostic sensor selection for complex systems can be a formidable task. This result motivates consideration of special problem structures and heuristic strategies leading to efficient selection algorithms. To be useful, however, the specified sensor suite must optimize diagnostic performance regardless of selection process complexity. The absence of a universally accepted diagnostic performance measure presents a significant impediment to robust sensor selection.

II. Conceptual Basis

There are a variety of pertinent criteria for selection of sensors supporting system health diagnostics. The focused objective of this effort was to develop a sensor selection strategy supporting high fidelity, real-time, targeted fault diagnostics that maximizes operational risk reduction. More specifically, we wish to select sensors to minimize fault detection time and maximize fault source discrimination in order to maximize targeted fault risk reduction for the system of interest.

To facilitate overall system design assuring safety and reliability, and to minimize potentially expensive system retrofits, selection of sensors for effective health diagnostics is properly a design phase function. This limits the availability of test data as a selection guide, especially for prototype systems, and suggests that selection of sensors must be supported by fault simulations and diagnostic models. Limited system experience does not support fault diagnostics based on changes in measurement data variances, spectral properties, and/or complex pattern characteristics. Because of design evolution and limited test data availability, use of mean shifted performance data for fault detection and discrimination is indicated.

To establish foundation and motivation for the S4 process, it is useful to have a conceptual understanding of propagating fault manifestations, and to characterize the impact of sensor selection on fault detection and isolation. The following subsections provide a pertinent conceptual framework.

A. Trajectories

For fault conditions to be diagnosable, they must induce sufficiently large measurement deviations from normal. A representation of the states traversed during a specific fault development history will be referred to as a fault signature or trajectory. The fault trajectory refers to both the measurement space sequence and the causal hardware parameter sequence associated with fault development. The function of the diagnostic model (DM) is to predict the hardware parameter sequence consistent with the observed measurement space trajectory. An approximation to the observed measurement sequence may be recovered by inserting the hardware parameter trajectory predicted by the DM into the system performance model and generating a measurement trajectory consistent with the DM solution. Differences between the observed measurement trajectory and the measurement trajectory recovered using the DM solution are a measure of the fidelity of the diagnostic model. Regenerated measurement trajectories based on DM results for faults designated A and B together with the actual fault B trajectory are identified in the notional two-dimensional measurement space depicted in figure 1.

An accurate DM is essential for reliable fault isolation. Inaccuracies can also delay fault detection or lead to false alarms. Trajectory implications for fault diagnostics are treated more fully in the subsections that follow.

B. Fault Detection

Fault detection requires sufficient measurement deviation to discriminate an anomaly condition from normal state variation. A plant hardware fault cannot be reliably discriminated from a sensor fault if measurements from only a single sensor source exhibit an anomaly excursion. Therefore, measurements from multiple sensor sources must exceed a prescribed threshold limit for reliable plant hardware fault detection. The minimum measurement deviation level for reliable fault detection within defined false alarm limits is designated δ_{det} . This is termed the detection threshold limit. In figure 1, the detectable fault zone is simply the measurement space region in which the output from both displayed measurement space sensors has exceeded the detection threshold limit. The boundary of

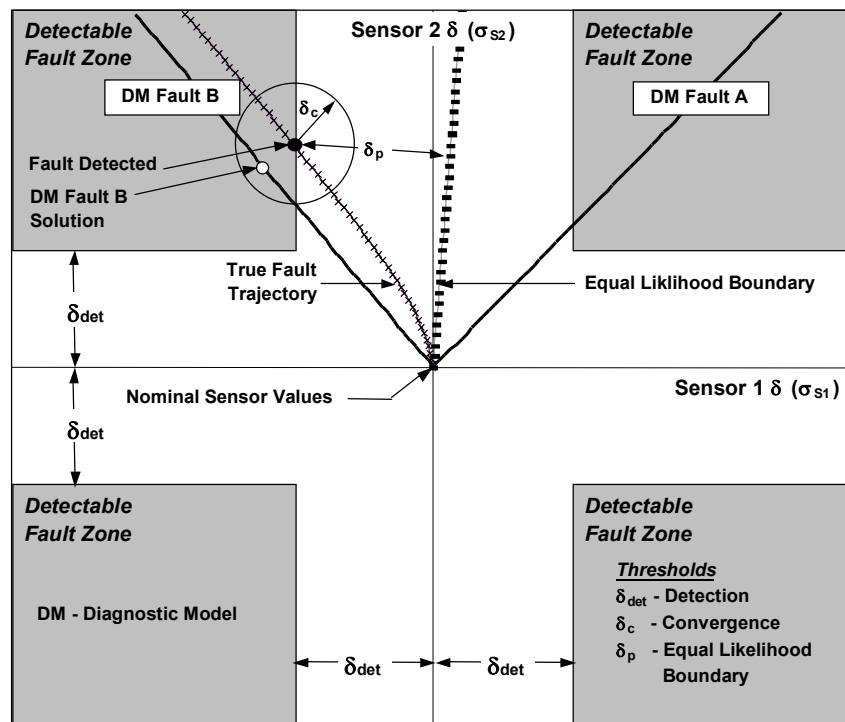


Figure 1.—Notional measurement space with well-defined fault trajectories.

the detectable fault zone is termed the fault detection threshold. A fault is initially detectable when its level is sufficient to reach a measurement trajectory location that intersects the detection threshold.

C. Fault Isolation

Once a fault condition has been detected, the DM attempts to isolate the fault source and provide a measure of fault severity. A fault is deemed to be isolated when the recovered DM solution trajectory point closest to the observed measurement data point is within a defined convergence threshold limit δ_c for one and only one fault. A fault is correctly diagnosed if the isolated DM solution corresponds to the true input fault type.

The selection of sensors affects the proximity of the individual fault trajectories and hence the fidelity of fault discrimination. Closer measurement space trajectories are associated with less effective fault discrimination. For faults that may induce measurement shifts in opposed directions from the normal operating state (faults with linear bi-directional measurement trajectories), orthogonal trajectories are ideal for reliable fault discrimination. For a fast response system well represented by an influence model of the form given in equation (1), orthogonal trajectories correspond to minimal hardware influence matrix condition number and lower hardware parameter solution error bounds in the traditional sense (ref. 2). However, component degradation and fault induced measurement trajectories are generally nonlinear and/or unidirectional (induce measurement shifts in only one direction). In such cases, orthogonal trajectories may not be optimal and a more general measure of fault discrimination is needed.

During a realistic fault progression, measurement data exhibit random scatter due to system/sensor noise and uncharacterized fault dynamics as depicted conceptually in figure 2. This scatter obscures the fault induced measurement trajectory and complicates the detection process. If the selected sensor suite admits closely aligned measurement trajectories for distinct faults, reliable fault discrimination may be delayed well beyond the detection point. This is clearly seen in figure 2 by examining the fault A data for sensor suite 1 and the fault B measurement data. An effective sensor suite separates fault induced measurement trajectories and provides good fault discrimination capability. This is clearly depicted in figure 2 by the large separation of the fault A data using sensor suite 2 and the fault B data near their respective detection points.

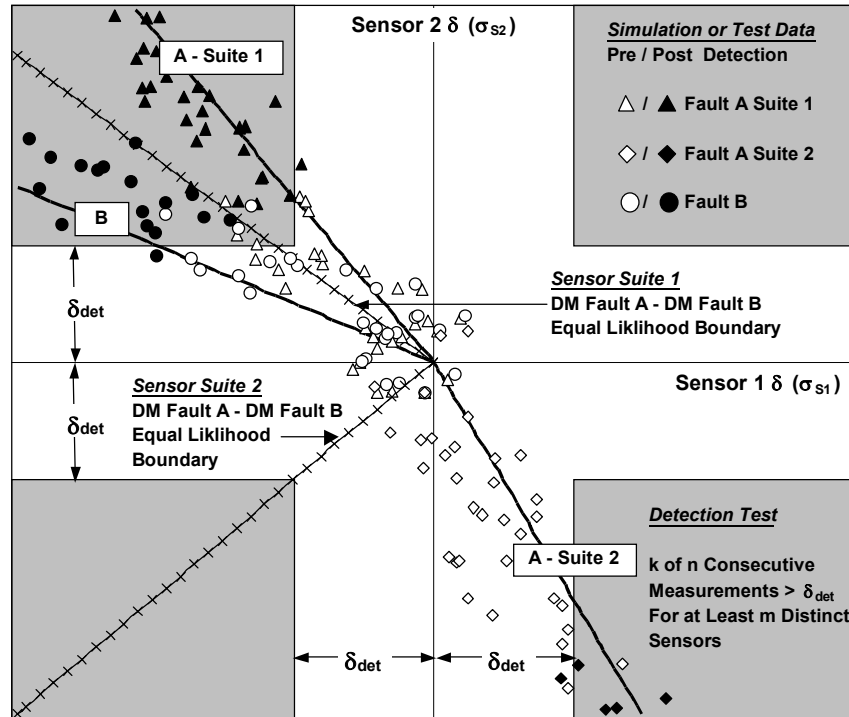


Figure 2.—Notional measurement space with fault trajectories from diagnostic model solutions, and actual data from propagating faults for two distinct sensor suites.

DM predicted fault trajectories are also displayed figure 2. For diagnostic systems utilizing measurement data with significant random fluctuation, a natural measure of fault discrimination is the probability that the most likely solution fault mode is the true fault mode. Since the objective is to select sensors that support reliable real-time fault diagnosis, it is important to achieve good fault discrimination immediately upon fault detection. Therefore the probability that the most likely DM solution fault mode corresponds to the true fault mode at the detection threshold is an appropriate measure of real-time fault discrimination potential. One method of estimating this probability is to determine the equal likelihood threshold limit δ_p depicted in figure 1. This threshold parameter is defined as a measure of the proximity of the initial fault detection state to the equal likelihood boundary between the DM fault signature of the true fault and the most proximate DM signature of another targeted fault mode.

D. Fault Families

Sensor selection that is narrowly focused to optimize health diagnostics for a small group of well defined faults is unlikely to support robust health management for systems with a wide range of potential fault manifestations. Fault families defined by combinations of hardware parameters describe large arrays of potential fault trajectories. Conceptual measurement space representations of a pair of two parameter fault family ranges are depicted in figure 3. A specific fault occurrence generates an individual trajectory within the appropriate fault family measurement space range. The distribution of realistic fault trajectories within a given family is generally unknown. However, a conservative estimate of DM fault family discrimination can be determined by examining the most proximate family trajectories. In figure 3, the single parameter fault A1 trajectory is the most proximate family A member to fault family B. Data scatter about the mean fault A1 detection point defines the probability that a family A fault will be determined as most likely. The previously described equal likelihood threshold distance δ_p can be used to generate an estimate of this probability.

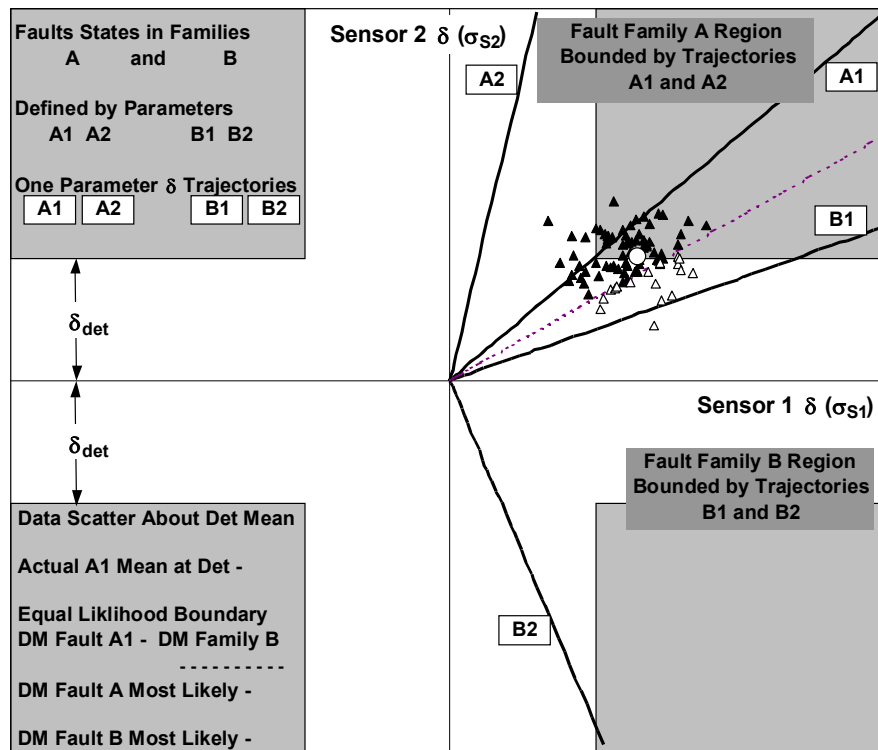


Figure 3.—Notional measurement space with distinct fault families defined in terms of hardware parameter combinations.

III. Selection Process

The Systematic Sensor Selection Strategy, referred to as S4, is described in this section. S4 is intended primarily for system design phase utilization. It is a model-based, targeted-fault process for selection of sensors supporting health diagnostics. S4 can be logically partitioned into the three major subdivisions displayed in figure 4: the knowledge base, the down-select iteration, and the final selection analysis. Each of these subdivisions is described below.

A. Knowledge Base

The inputs required for productive use of S4 consist of evolving system design information together with a condensed form of related systems experience focused on components with health implications. This information provides a foundation for construction of effective system models, and together with these models constitutes the knowledge base needed to support use of S4. Pertinent knowledge base components are listed below.

1. Failure modes and effects analysis (FMEA) identifying system critical faults and providing initial indications of sensible fault signatures
2. Risk assessments associated with critical fault modes targeted for health diagnosis
3. Candidate sensors listed by location and type, including associated response characteristics
4. Estimates of measurement output variances due to sensor noise and system effects for candidate sensors
5. Remediation response families correlated to targeted fault modes and severity levels
6. False alarm constraints
7. Model(s) of normal system operation based on the experience base of related systems and the appropriate physics governing as designed system function
8. Fault simulation model(s) correlating targeted fault modes to the system model hardware parameters whose deviations can be used to describe these modes and their severity

It is important to note that knowledge base components evolve during the system design phase and hence diagnostic sensor selection should be considered an integral component of the overall system design iteration sequence.

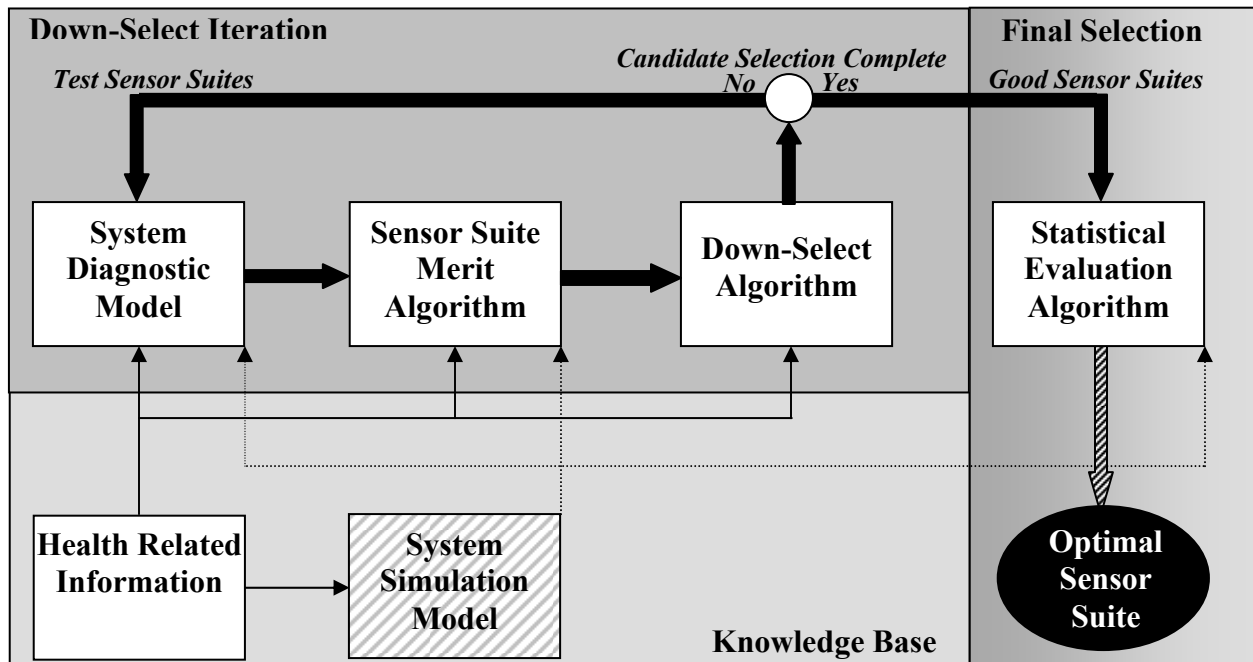


Figure 4.—Systematic Sensor Selection Process Diagram.

B. Down-Select Iteration

The sensor suite down-selection is an iterative process for identifying a group of sensor suites that provide good fault detection and isolation for targeted fault trajectories. It is composed of three basic components: a system health diagnostic model, a sensor suite merit algorithm, and a sensor suite down-select algorithm. The function and interactions of each component are described below.

1. Sensor Suite Merit Algorithm

The merit algorithm assigns a diagnostic merit value to each candidate sensor suite based on detection speed, probability of correct fault remediation family identification at the fault detection threshold, and risk reduction measures. The hardware parameter groups that describe each fault mode and the remediation response family associated with each fault mode are knowledge base inputs. An individual measurement trajectory for a given fault mode is an output sequence that may be approximated by the system simulation model. It is generated by causal hardware parameter time evolution input to the system simulation model. The number of discrete fault trajectories considered in characterizing diagnostic capability for a targeted fault mode is dictated by the range and distribution of mode faults. System domain expertise and knowledge base information guide definition of mode characteristic hardware fault trajectories. At a minimum, a single parameter trajectory for each hardware parameter pertinent to the fault mode as well as the highest likelihood multiple hardware parameter trajectories associated with the fault mode should be considered. Using characteristic fault mode trajectories, the merit value associated with a specific sensor suite is constructed using the component definitions below.

DT_{ij}	detection threshold state for true fault mode i trajectory j
LT_{ij}	failure threshold state for true fault mode i trajectory j
DM_{ij}	diagnostic model mode i solution state for DT_{ij} using measurements available with current sensor suite
DM_{kij}	diagnostic model mode k solution state for DT_{ij} using measurements available with current sensor suite
FT_{ij}	appropriate fault response family for DT_{ij}
FM_{ij}	fault response family associated with best mode i DM solution state for DT_{ij} using measurements available with current sensor suite
FM_{kij}	fault response family associated with best mode k DM solution state for DT_{ij} using measurements available with current sensor suite
N_m	number of fault modes considered
N_{Ti}	number of characteristic trajectories considered for fault mode i

R_{ij}	risk reduction potential allocated to timely diagnosis of fault mode i trajectory j
R_T	total risk reduction potential $= \sum_{i=1}^{N_m} \sum_{j=1}^{N_{T_i}} R_{ij}$
T_{ij}	time to reach DT_{ij} using a given sensor suite
$T_{min_{ij}}$	minimum time to reach DT_{ij} using any sensor suite
Prb_{kij}	$\begin{cases} 0 & \text{if } LT_{ij} \text{ reached before } DT_{ij} \text{ using the given sensor suite or } FM_{ij} \neq FT_{ij} \\ 1 & \text{if } DT_{ij} \text{ reached before } LT_{ij} \text{ using the given sensor suite, } FM_{ij} = FT_{ij}, \text{ and } FM_{kij} = FT_{ij} \\ B < 1 & \text{if } DT_{ij} \text{ reached before } LT_{ij}, B = \text{probability } FM_{ij} = FT_{ij} \text{ more likely than } FM_{kij} \neq FT_{ij} \end{cases}$
P_{ij}	$\min_{\text{modes } k \neq i} (Prb_{kij})$

The overall merit value of a specific sensor suite is defined in terms of the parameters above.

$$\text{Merit} = \frac{1}{R_T} \sum_{i=1}^{N_m} \sum_{j=1}^{N_{T_i}} \left(R_{ij} P_{ij} \frac{T_{ij}}{T_{min_{ij}}} \right) \quad (6)$$

The merit function identifies, i) the overall timeliness of fault condition detection as a fraction of the fastest possible detection time using any set of candidate sensors (terms $T_{ij}/T_{min_{ij}}$), and ii) the quality of fault discrimination in terms of the minimum probability of correct remediation response family identification near the detection threshold (terms P_{ij}). The discrimination quality metric is based on pairwise fault mode likelihood comparisons. The product of these two terms is used to estimate the fraction of risk reduction potential that can be ideally realized at the fault detection threshold with a specific sensor suite. This is a useful metric for assessing real-time health monitoring potential of candidate sensor suites. The ideal merit value is 1.0, indicating greatest potential real-time risk reduction for targeted fault modes using available sensors.

The merit evaluation algorithm accepts a variety of one-time inputs from the knowledge base including true trajectory characteristics for all targeted fault modes. It also receives diagnostic model solutions for targeted fault trajectories and proximate mode trajectories for each sensor suite under consideration. The merit algorithm supplies diagnostic merit values for each current sensor suite to the down-select algorithm described below.

2. Down-Select Algorithm

The combinatorial nature of the down-select iteration lends itself to the use of a genetic algorithm (GA), hence a GA was developed to perform down-selection of candidate sensor suites. At each GA iteration stage or generation, candidate sensor suites in the current (input) population compete to evolve suites with improved diagnostic capability, and to pass desirable properties to subsequent stages of iteration or generations. A detailed description of typical GA operations is given in Goldberg (ref. 30).

Encoding the sensor selection problem in a GA format is a simple process. Each individual member of a population is referred to as a chromosome and represents a single candidate sensor suite. Each chromosome is composed of bits called genes associated with individual candidate sensors. Binary encoding of the gene indicates if the particular sensor associated with the gene is in the sensor suite represented by the chromosome. A chromosome mask may be employed to force either selection or omission of particular sensors as desired.

Each chromosome in the input population has an assigned merit value received as input from the merit algorithm. To choose output sensor suites passed to the next generation, roulette-wheel selection was employed (ref. 30). With roulette-wheel selection, sensor suites with higher relative merit values have an increased probability of being selected as parents. Once parent suites are selected, single point crossover is employed to construct offspring suites for the next generation. The crossover point is selected randomly and genes are copied from the parents as depicted in figure 5. Elitism is used to advance the best sensor suites to the next generation without modification.

Mutation or random bit-flipping, is employed during parent-to-child gene copying for its diversifying effects. As the generations progress, the population will increasingly converge to a group of similar sensor suites providing

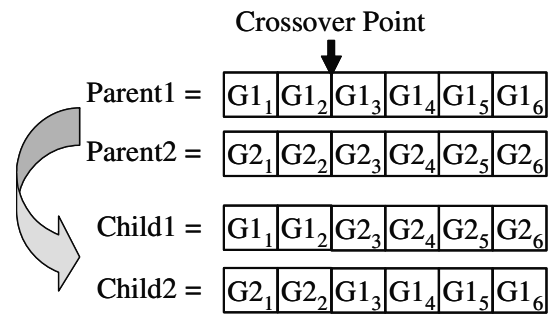


Figure 5.—Single point crossover example.

good diagnostic capability. Increasing the probability of mutation with each generation aids in increasing the diversity of the population. Preserving diversity assists the population in evolving away from local optima in the solution space.

The basic steps of the GA employed in this study are given below.

- Step 1 Initialize**—Input the initial population of sensors from the knowledge base and make it the current generation. The initial population is randomly generated.
- Step 2 Merit Function**—Input the merit algorithm assigned value for each sensor suite in the current generation.
- Step 3 Elitism**—Automatically advance 2 sensor suites with the highest merit value to the next generation.
- Step 4 Selection**—Select two sensor suites using roulette-wheel selection.
- Step 5 Crossover**—Determine if crossover occurs.
 - Step 5a No Crossover**—Both parents advance to the next generation without modification.
 - Step 5b Crossover**—Apply single point crossover with the possibility of mutation as each gene is copied.
- Step 6 Repeat**—Return to Step 4 until next generation is populated.
- Step 7 Repeat**—Set the current generation equal to the newly formed next generation.
- Step 8 Output**—Send current generation of sensor suites to the DM to reinitiate the merit assignment process. Return to Step 2 until target number of generations is reached.

3. System Diagnostic Model

Any procedure that is capable of assigning time indexed hardware health parameter values based on current and past measurement states is a candidate system diagnostic model. Since diagnostic speed is a critical issue for real-time applications, an inverse model was employed to estimate hardware state conditions at each time increment. The most straightforward type of inverse model determines hardware parameter deviations \mathbf{u}_h from normal by solving a set of system approximating relations of the form

$$\mathbf{y} = \mathbf{g}(\mathbf{u}_h, \mathbf{u}_c) \quad (7)$$

where \mathbf{y} is the vector of diagnostic system measurements available for a given sensor suite. The control state vector \mathbf{u}_c and diagnostic measurement state vector \mathbf{y} are treated as inputs and some type of general nonlinear equation solver is used to determine hardware state conditions \mathbf{u}_h at each sampled time slice. For S4 purposes, a modified Levinberg-Marquardt procedure (ref. 31) was used as the DM solver

If the output measurement variation from normal is assumed to be a summation of control effects and independent single parameter fault effects, a considerable simplification of equation (7) may be achieved.

$$\mathbf{y} = \mathbf{F}(\mathbf{u}_h) \mathbf{s}_h + \mathbf{g}(\mathbf{u}_c) \quad (8)$$

In this expression, the function matrix $\mathbf{F}(\mathbf{u}_h)$ is composed of elements $f_{ij}(\mathbf{u}_{hj})$ that provide the contribution of each hardware parameter \mathbf{u}_{hj} to each individual measurement y_i . The $n_h \times 1$ summation vector $\mathbf{s}_h = [1 \ 1 \ \dots \ 1]^T$ effects superposition of the individual hardware parameter contributions. A planned sequence of system fault simulations is required to support development of the functional relations in either of equations (7) or (8). Of course the support sequence is much simplified if the summation form of equation (8) provides an adequate representation of targeted fault manifestations. This would be the case if for instance targeted fault modes are primarily single parameter modes.

The standard inverse model approach trades increased fidelity available from more detailed dynamic response models for improved diagnostic speed afforded by assuming instantaneous or matched propagation characteristics. For systems with well-matched measurement time constants or slow fault propagation rates, this trade is most favorable for effective real-time diagnostics.

C. Statistical Evaluation Algorithm

Because effective real-time diagnostic models must address the trade between diagnostic fidelity and speed, it is important to challenge both criteria in selecting an optimal sensor suite. The down-select iteration provides a set of “good” sensor suites based on approximate risk coverage, and speed. However, diagnostic model simplifications, sensor/system noise characteristics, and variations in fault manifestation dynamics from the assumed form for targeted fault trajectories provide sources of diagnostic performance uncertainty. The statistical evaluation algorithm is intended to provide a final robustness test for each down-selected sensor suite. The fault test case protocol may

include best estimates of measurement fluctuation due to i) sensor/system noise, ii) systematic variation in fault mode manifestation dynamics, and/or iii) random variations in fault manifestation. Once the test protocol is established, fault simulations are run to provide near detection point data for each test case. The ability of the diagnostic model to identify the correct response family using this data is assessed using the evaluation metric described in equation (6). The sensor suite that maximizes the merit metric is identified as the optimal sensor suite for health diagnostics.

IV. Representative Results

The S4 process described above was applied to identify optimal suites of flow path sensors for health diagnostics of rocket engine systems. Two systems developed through conceptual design by Boeing Rocketdyne as part of NASA's Space Launch Initiative (SLI) and Next Generation Launch Technology (NGLT) programs served as test platforms for the S4 process. S4 analysis information and representative results for the RS-84 engine system are presented below. The RS-84 engine system was a large liquid fueled LOX-RP1 staged combustion engine originally intended for boost stage use in support of payload/vehicle orbital insertion. Its design vacuum thrust was in excess of one million pounds.

The knowledge base for this application was obtained primarily from Space Shuttle Main Engine (SSME) data archives and Rocketdyne engine system component teams. A Real Time Model (RTM) of the RS-84 engine provided the basis of engine performance predictions and fault simulation cases used to support the S4 process, including construction of the RS-84 inverse model that served as the DM basis. General characteristics of Real Time Models for related system applications can be found in references 32 and 33. Only single parameter hardware faults and single source leaks were considered, hence equation (8) was used as the basic DM relation. System faults and risks defined by component teams were allocated to single parameter fault modes using a heuristic but logical procedure. The population of each generation considered in the GA was composed of 100 sensor suites.

Information defining the scope of the S4 analysis for the RS-84 engine system is presented in table 1 below. The 30 hardware faults included i) turbomachinery parameter faults, ii) duct, valve, and injector resistance or blockage faults, and iii) combustion chamber and nozzle performance faults. The 42 single source leak faults were specified by device and location. A total of 58 sensors was defined as the pool of candidates for health diagnostics.

Summary results of the S4 analysis are presented in table 2. Leak faults were generally undetected prior to reaching a system failure point using the inverse model with candidate flow path sensors, typical system/sensor noise levels, and detection thresholds consistent with a low allowable false alarm rate. One way to address this problem is to invoke data filters that reduce noise levels and hence the detection threshold value. This is a viable option only if leak rate propagation is long relative to the filter interval. Data filtering experimentation was performed with considerable success relative to reduction in detection thresholds to facilitate leak detectability. However, no knowledge base information was available to characterize leak rate propagation rates and timeframes relative to failure onset or filtering intervals. Therefore sensor selection was performed targeting only the 30 single parameter hardware faults in the list of targeted faults. A complete inverse model diagnostic cycle, including inversions for all 30 hardware parameter faults, could be performed at a frequency greater than 20 Hz using a standard 800 megahertz Pentium processor.

Control responses for various fault modes had not been formalized as of initial S4 analyses. Therefore control and maintenance response families had not been finalized and the DM discrimination requirement was not well defined. For initial S4 testing, individual hardware parameter response families were assumed and single parameter faults initiated only during steady-state operation were considered. Use of individual parameter specific response families is an extremely ambitious fault discrimination requirement, certainly more stringent than is likely to be required for effective health diagnostics. Using individual hardware parameter response families, an optimal merit index value of 0.62 was achieved as displayed in table 2. Most of the merit losses from the ideal value of 1.0 were, not surprisingly, due to fault discrimination issues rather than fault detection. The merit index value of 0.62 for the optimal sensor suite was considered reasonable considering the level of design definition as of the initial S4 analysis sequence.

The general configuration of the optimal sensor suite is also identified in table 2. It is composed of 31 sensors used for health diagnostics, 6 of which are used to establish control and boundary conditions defining the normal engine operating state.

TABLE 1.—RS-84 S4 ANALYSIS BASIS.

Targeted Faults			
Hardware Faults (single param)	30		
Leak Faults (single source)	42		
Total Faults		72	
Candidate Sensors (type+location)			
Flow Rate	17		
Pressure	22		
Shaft Speed	4		
Temperature	11		
Valve Position	3		
Composite	1		
Total Sensors		58	

TABLE 2.—S4 OPTIMAL SENSOR SUITE FOR RS-84.

Optimal Diagnostic Sensor Suite Merit Evaluation (Hdwe Faults Only)	
Merit Index	0.62
Optimal Diagnostic Sensor Suite (Hardware Faults Only)	
Flow Rate	3
Pressure	12
Shaft Speed	4
Temperature	10
Valve Position	2
Total Sensors	31
<i>(Total includes 6 boundary and control state input defining sensors)</i>	

V. Summary and Recommendations

The Systematic Sensor Selection Strategy described herein provides a logical procedure for quantifying the value of candidate sensor suites for targeted fault diagnostics based on criteria pertinent to real-time health management. These criteria include speed of detection, probability of correct fault source isolation, and overall risk reduction potential. The S4 process also provides a framework for organizing and utilizing an evolving system knowledge base, including system performance and simulation models, in the selection process. The sensor suite identified by the S4 process as optimal for health diagnostics is closely associated with the diagnostic model employed for fault identification. The diagnostic model must reflect the desired compromise of diagnostic fidelity and speed consistent with false alarm limits and potential remediation responses that maximize overall operational risk reduction.

Based on experience with S4 development and general consideration of the role of sensor selection in effective system health management, the following recommendations are offered.

1. Effective health management is enabled by the availability of sensor data that facilitates health diagnosis. Therefore systematic sensor selection for improved diagnostics should be an integral component of health management system development.
2. To maximize potential risk reduction benefit, sensor selection for health diagnostics should be an integral system design phase activity that both evolves with and impacts host system design.
3. The linkage between physical fault modes, the parameter based simulation of these modes, and the model based use of hardware parameter shifts for fault isolation should be strengthened to support more robust health diagnostics.
4. Sensor faults are not explicitly considered by the current S4 process. Methods of expanding the process to support sensor selection for health management system data qualification/validation should be explored.
5. Extensions of the standard inverse model to better consider system nonlinearity and fault dynamics are accessible. These extensions and other diagnostic models should be examined within the S4 framework to determine the best compromise of diagnostic fidelity and speed for specific applications.
6. The S4 process may be used to quantitatively assess the impact of specific sensor losses during operation and potential sensor additions on diagnostic capability. This capability should be refined and systematically applied for long-term health management system development and maintenance.

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