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Application of the Systematic Sensor Selection Strategy for Turbofan Engine Diagnostics

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Abstract

The data acquired from available system sensors forms the foundation upon which any health management system is based, and the available sensor suite directly impacts the overall diagnostic performance that can be achieved. While additional sensors may provide improved fault diagnostic performance there are other factors that also need to be considered such as instrumentation cost, weight, and reliability. A systematic sensor selection approach is desired to perform sensor selection from a holistic system-level perspective as opposed to performing decisions in an ad hoc or heuristic fashion. The Systematic Sensor Selection Strategy is a methodology that optimally selects a sensor suite from a pool of sensors based on the system fault diagnostic approach, with the ability of taking cost, weight and reliability into consideration. This procedure was applied to a large commercial turbofan engine simulation. In this initial study, sensor suites tailored for improved diagnostic performance are constructed from a prescribed collection of candidate sensors. The diagnostic performance of the best performing sensor suites in terms of fault detection and identification are demonstrated, with a discussion of the results and implications for future research.

Introduction

Aircraft turbine engine gas path diagnostics are typically performed utilizing the available control sensor measurements. This set of instrumentation is primarily chosen to permit control of the engine to satisfy performance and safety requirements. Consequently, additional sensors, optimally selected and placed, should improve diagnostic performance.

Any instrumentation added to an engine must be rugged enough to endure the harsh operating environment. Modern commercial off-the-shelf (COTS) sensor technologies expand the possible measurement locations throughout the engine, but restrictions remain. COTS sensors can function in such areas as the fan or compressor, but would normally fail in higher temperature sections. Sensor technology development is necessary for instrumentation to survive in these harsher engine locations. Technology research is costly and justification is required to augment the existing sensor suite. A demonstration of improvements in system health monitoring could help justify and direct research efforts for advanced sensors.

Reference 1 provides a historical overview of sensor selection methodologies and justifies the selection of the Systematic Sensor Selection Strategy (S4) (refs. 2 and 3) for aerospace health assessment needs. S4 is a model-based procedure that methodically determines measurement type and location to optimize the host system sensor suite toward a particular goal. For this paper, S4 (refs. 1 to 3) was used to demonstrate the utility of optimally placing sensors in an aircraft engine in order to enhance diagnostic performance. In this preliminary investigation, the S4 methodology was used to evaluate and arrive at optimal sensor suites that show marked improvement in the detection and identification of a prescribed set of fault scenarios. To create the pool of candidate sensor solutions, two classifications of sensors were considered beyond the existing (baseline) Full Authority Digital Electronic Control (FADEC) sensor suite: optional sensors that are available with current COTS technology; and advanced sensors that are not currently available in a flight qualified form. Figure 1 shows a notional engine sensor diagram partitioning candidate sensors into the three categories: typical control, optional, and advanced sensors. A description of the sensor parameters is given in table 1.

This preliminary study had two central objectives. First, the applicability of S4 to aircraft engine diagnostics is to be verified since S4 has traditionally been applied to rocket engine health monitoring (ref. 2). Secondly, a functional S4 framework is to be established that will explore and quantify the benefits of including additional sensors to diagnose a specific list of fault conditions.

To support these goals, the following initial assumptions were made:

- Only a single steady-state engine operating point with no variation in ambient conditions is to be used.
- Each fault case is composed as a single system fault modeled as a deviation in a single engine health parameter.
- Diagnostic timing considerations are to be ignored.

- Fault accommodation, in terms of designing and simulating a control strategy to accommodate or remove the fault from the system is not considered.
- Only diagnostic performance metrics are incorporated. Metrics associated with sensor cost, reliability or precision are not included.

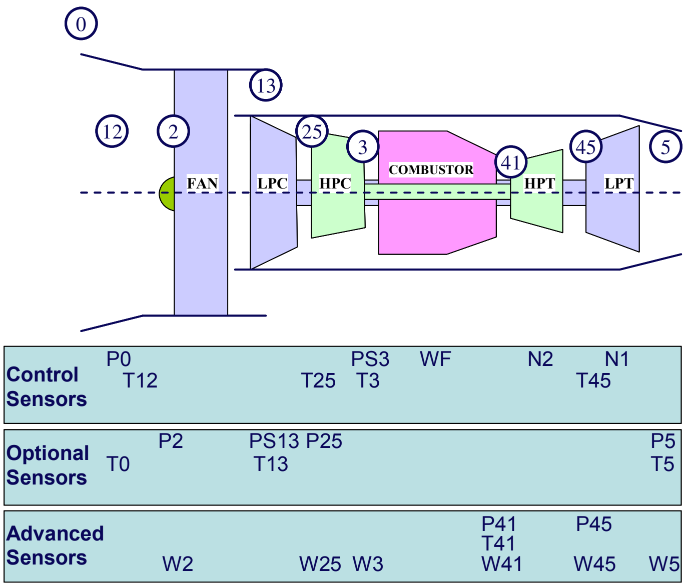

Figure 1.—Engine representation with generic sensor type, location and classification.

TABLE 1.—DESCRIPTION PF SENSOR PARAMETERS

Parameter	Description
N1	Low Pressure Shaft Speed
N2	High Pressure Shaft Speed
P0	Ambient Pressure
PS13	Bypass Discharge Static Pressure
P2	Fan Inlet Pressure
P25	High Pressure Compressor Inlet Pressure
PS3	High Pressure Compressor Exit Static Pressure
P41	High Pressure Turbine Inlet Pressure
P45	Low Pressure Turbine Inlet Pressure
P5	Low Pressure Turbine Exit Pressure
T0	Ambient Temperature
T12	Fan Inlet Temperature
T13	Bypass Discharge Temperature
T25	High Pressure Compressor Inlet Temperature
T3	High Pressure Compressor Exit Temperature
T41	High Pressure Turbine Inlet Temperature
T45	Low Pressure Turbine Inlet Temperature
T5	Low Pressure Turbine Exit Temperature
WF	Fuel Flow Rate
W25	High Pressure Compressor Inlet Flow Rate
W3	High Pressure Compressor Exit Flow Rate
W41	High Pressure Turbine Inlet Flow Rate
W45	Low Pressure Turbine Inlet Flow Rate
W2	Fan Inlet Flow Rate
W5	Low Pressure Turbine Exit Flow Rate

This paper is organized as follows. First, an overview of the S4 process is given. The S4 turbofan engine diagnostic application is then described and details are provided on how this investigation was conducted. Next, results from the sensor selection process are presented with relevant discussion. Finally, future work is proposed that highlights areas of interest for follow-on research.

Systematic Sensor Selection Strategy Overview

S4 is best described as a general architecture structured to accommodate application-specific components and requirements to perform sensor selection. A knowledge base, an iterative down-select process, and a final selection process comprise the main functions of the S4 framework. Each function is intended to be customized for the host system application. Their general relationships are depicted in figure 2 and a brief description of each S4 component is given in the following sub-sections.

Knowledge Base

The knowledge base contains health-related information about the system under evaluation and a system simulation. If historical information or test data on the host system is not available, experience from similar systems provide a basis from which to define and collect pertinent health-assessment information.

Health-related information is extracted from domain experts, manufacturer reports, and failure modes and effects analysis and hazard analysis studies. The type of information gathered includes fault signatures, fault progressions, component/sensor reliabilities, and sensor characteristics (e.g. noise). These data are used as inputs to establish the system diagnostic model, and define key optimization parameters for the sensor suite merit algorithm and down-select algorithm. In addition, this health-related information is used to define the required system simulation.

The system simulation provides input in the form of data sets for the iterative down-select process and statistical evaluation algorithm. This module may be a collection of simulations of varying fidelities that are applicable at various stages of the system operation. The system simulation for S4 can be developed using a process model, which may be as simple as algebraic relations between the monitoring variables and fault conditions, or contain more complicated dynamic system models that incorporate health parameters. When available and appropriate, test or flight data could be provided from this module.

Iterative Down-Select Process

The down-select process is an iterative procedure to select a group of near-optimal sensor suites for health assessment. The

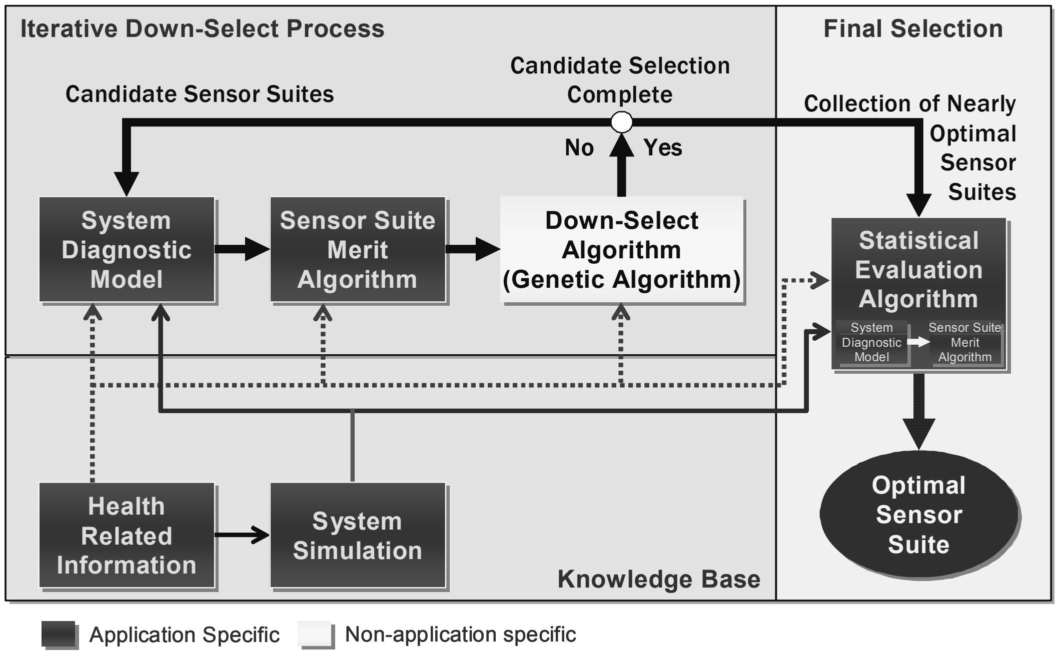

Figure 2.—Systematic Sensor Selection Strategy Architecture

process involves sequentially generating and evaluating a collection of candidate sensor suites, eventually converging towards a more optimal sensor suite. The process can be repeated with systematic permutations to the initialization of the search process, until the results stabilize to a small set of near-optimal suites. The procedure includes a system diagnostic model, a sensor suite merit algorithm and a down-select algorithm.

The system diagnostic model represents the diagnostic analysis to be applied to the host system. The performance of the diagnostic model is measured for each candidate sensor suite at each relevant operational mode. The measures of performance are provided to the sensor suite merit algorithm. A key feature for this model is that it must be complete and capable of providing diagnostic analysis for all or any subset of the possible sensors. Developments of applied system diagnostic models to date have used system simulations and health-related information for fault characterization. During the down-selection process, the system diagnostic model receives sensor suite configuration information from the down-select algorithm and outputs diagnostic performance information for these sensor suites to the sensor suite merit algorithm.

The sensor suite merit algorithm assigns an evaluation score or merit value for each candidate sensor suite. It generates quantified metrics utilizing performance information from the system diagnostic model along with other pertinent characteristics such as life cycle cost of the measurement suite being evaluated. It receives sensor suite diagnostic performance information from the system diagnostic model and it outputs sensor suite merit values to the down-select algorithm. The merit algorithm is normally in the form of an algorithmic unction, where performance criteria of interest to the particular system can be combined.

The down-select algorithm is a search algorithm that utilizes an optimization technique to select sensor suites that will allow progression toward an optimal or near-optimal solution. Because the search space grows factorially with the number of sensors to be evaluated, a search algorithm must be utilized capable of conducting an effective global search within an acceptable amount of time. Optimization techniques such as Genetic Algorithms (ref. 4) are generally well-suited for this function. While a Genetic Algorithm has typically been utilized, this particular module in the methodology can be replaced with any search algorithm suitable to the user. The down-select algorithm receives system and sensor information from the knowledge base to establish any specific guidelines or constraints used in the sensor suite search. During the iterative process, merit values from the sensor suite merit algorithm are used by the down-select algorithm to generate a collection of new candidate sensor suites that should converge toward the optimum solution.

Final Selection

In the final selection process, a collection of the best candidate sensor suites generated from the iterative down-select process is challenged further. The user inspects the output and determines how well the optimal sensor suite satisfies the performance criteria and whether some of the performance objectives, within the merit algorithm, need to be modified. Often times these results yield trends that encourage further trade studies to enhance the selection process and the overall final sensor suite selection.

The statistical evaluation algorithm is intended as a final test of each candidate sensor suite. When constructing the iterative loop of the down-select process, often there is a tradeoff between fidelity and speed with importance placed on speed. During the final selection process, fidelity is desired. Therefore additional uncertainty effects such as sensor and system noise characteristics and variations in fault dynamics are incorporated. The system diagnostic model and sensor suite merit algorithm utilized in the down-select process can be used to evaluate each sensor suite. The statistical evaluation algorithm uses input from the health-related information and the system simulation data to establish the high fidelity fault scenario data sets. Results from the statistical evaluation enable a ranking or stratification of the near-optimal sensor suite for final selection.

Application

A large commercial turbofan engine computer simulation was selected as the host platform for the initial S4 aircraft engine demonstration. A cruise operating point was selected to investigate single fault scenarios at a steady state condition.

The assortment of candidate sensors and failure scenarios were prescribed by the engine simulation. The notional sensors in figure 1 were mapped to the appropriate variables within the model. The sensors which measure ambient and inlet conditions (i.e., P0, P2, T0, and T12) were not included as they were assumed to remain constant during the fault scenarios. For the purpose of this study, 10 single health parameter fault cases were considered as shown in Table 2. Each fault case was modeled as a single system fault which was induced in the simulation by changing the value of one of the health parameters within the model. The 10 single health parameter fault cases were composed of an efficiency and flow capacity modifier for each major module of the engine. While these simulated fault conditions are not necessarily identical to more complex fault conditions that may be experienced in an actual aircraft engine application, they are representative and serve as an example to illustrate the functionality of the S4 methodology. Additional and/or different fault cases can be readily incorporated into the S4 methodology. Appropriate fault influence coefficients relating changes in sensed engine outputs to the various fault conditions were extracted from the model over a range of fault magnitudes.

TABLE 2.—LIST OF SIMULATION FAILURE DESCRIPTIONS

Failure	Description
FANeff	Fan efficiency loss
FANflow	Fan flow restriction
BSTeff	Booster efficiency loss
BSTflow	Booster flow restriction
HPCeff	High pressure compressor efficiency loss
HPCflow	High pressure compressor flow restriction
HPTeff	High pressure turbine efficiency loss
HPTflow	High pressure turbine flow restriction
LPTeff	Low pressure turbine efficiency loss
LPTflow	Low pressure turbine flow restriction

Specific host system information is necessary for proper construction, execution, and analysis of results of the S4 framework. The diagnostic philosophy of the host system is to be understood in order to select sensors that will be effective based on the system fault detection and identification strategy, and the missed detection and false alarm requirements. A catalog of failure conditions of interest is required, and furthermore can be prioritized to direct the sensor selection procedure toward those faults that are critical or have a higher probability of occurrence. Critical failures can include a fault condition that would trigger a maintenance event, or one that would require immediate action in order to prevent a serious situation. The latter fault type would require diagnostic latency considerations in the sensor selection study, which is not considered in this initial demonstration. Through all of this, relevant engine operating environments are to be characterized including closed-loop control effects.

With the information available, the S4 process for the turbofan application was designed and implemented based on the framework described in the Systematic Sensor Selection Strategy (S4) User's Guide (ref. 3). The system simulation was utilized to run fault simulations of various types and magnitudes. Data from these simulations were processed to develop a system diagnostic model in the form of an inverse model. A sensor suite merit value algorithm was formulated to evaluate the candidate sensor suites. For the down-select algorithm, a genetic algorithm was implemented. Finally, a statistical evaluation algorithm was applied to more thoroughly evaluate the diagnostic performance of the resulting measurement sets.

The inverse model uses a piece-wise linear approximation to compute a vector of estimated sensor values. The estimated value for each sensor, $\hat{y}_i$, is given by,

$$\begin{aligned}\hat{y}_i &= f_i\left(\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n\right)\\ &= \sum_{j=1}^{n}\left[A_{ij}^{p}\left(\hat{x}_j - x_j^{p}\right) + y_{ij}^{p}\right]\end{aligned} \tag{1}$$

where A_{ij}^{p} is the influence matrix at interpolation point p, that relates the magnitude of the j^{th} fault condition, x_j, to the corresponding i^{th} sensor value, y_i. y_{ij}^{p} is the value for sensor i for fault condition j at interpolation point p and x_{ij}^{p} is the fault condition magnitude for interpolation point p and fault condition j. From the vector of predicted sensor values, a residual summation term, $\tilde{y}_{sum}$, is calculated by,

$$\tilde{y}_{sum} = \sum_{i=1}^{m}\left|y_i - \hat{y}_i\right| \tag{2}$$

where m is the number of sensors.

A Levenberg-Marquardt optimization technique (ref. 5) is used to isolate the most plausible single fault case given a set of sensor measurements. For each of the possible fault hypothesis cases, the Levenberg-Marquardt optimization technique is applied in an attempt to minimize the actual vs. estimated sensor error by adjusting the estimated magnitude of the fault condition, $\hat{x}_j$, so that the estimated sensor value $\hat{y}_i$ closely matches the actual sensor measurement y_i. A residual summation term at or near zero indicates good agreement between the estimated and actual fault condition—an indication that the hypothesized fault is indeed the true fault condition. A large residual summation term indicates poor agreement—an indication that the hypothesized fault condition is incorrect. Through this process fault discrimination takes place and a diagnosis of the most plausible fault cause is produced.

The elementary merit value calculation for a sensor suite is given by,

$$Merit = U \times P \times \sum_{j=1}^{n} D_j \tag{3}$$

where n is the number of fault conditions.

In Eq. (3), U is the utility weighting term; and is a measure of the benefit of a particular sensor suite. This utility term may incorporate factors such as cost, weight, power requirements, etc. As shown in Eq. (4), U is an average of the utility of a given sensor, U_i, in a suite with m sensors. In this preliminary study, each sensor was assigned a utility value of 1.0 since detailed sensor information was not available.

$$U = \frac{\sum_{i=1}^{m} U_i}{m} \tag{4}$$

Also, in Eq. (3), the penalty term, P, quantitatively defines the importance of a particular characteristic which in this application is the number of measurements in the optimal sensor suite. As shown in Eq. (5), the penalty term is calculated by comparing the desired number of sensors, $N_{desired}$, to the actual number of sensors, N_{actual} with a penalty weighting value, $W_{penalty}$, and a normalization term, K. The normalization term, K, was assigned a value of 1.0. The penalty weighting value, $W_{penalty}$, was set to the lowest value (between 0.001 and 0.1) that would give a solution with the desired number of sensors

$$P = \frac{K}{K + \left(W_{penalty} \left| N_{desired} - N_{actual} \right| \right)} \tag{5}$$

The diagnostic term, D_j, is the final term used in Eq. (3). D_j is a measure of the fault detection and identification capability of the sensor suite for fault condition j. The method for calculating D_j is given in Eq. (6) and is described as follows. A fault detection level $F_{DL,j}$, is used to rate the fault detection sensitivity of the sensor suite. The magnitude at which a sensor suite can sense a fault condition is its fault detection level. Because fault sensitivity is desired, a large fault detection level will decrease the diagnostic term. The fault identification value, $F_{ID,j}$, is a fault discrimination measure from the inverse model diagnostic algorithm (ref. 3), which is a measure of the ability of the sensor suite to distinguish between known failure conditions. This measure is based on the residual calculations discussed above. The fault criticality value, $F_{CRIT,j}$, is a user defined measure of the criticality of detecting and identifying fault condition j. In this exercise, each of the fault conditions was assigned an arbitrary fault criticality value of 0.333.

$$D_j = \frac{F_{ID,j} \times F_{CRIT,j}}{F_{DL,j}} \tag{6}$$

The diagnostic term calculation applied in this study is a modification to the merit algorithm described in the S4 User's Guide (ref. 3). A detectability study is normally performed before the sensor selection procedure is employed to determine the fault magnitudes for each fault test scenario. Once the fault magnitude is set, it does not change to account for the different sensor measurements available. By determining the magnitude at which a particular candidate sensor suite can detect a fault condition, a more realistic methodology is employed. In the fault detection check, a measurement observation vector is constructed using data only available from the sensors in the candidate suite. At first, the data for the minimum fault perturbation is used. If the fault is not detectable at this level, then the observation vector is reassembled and reevaluated with the observable data for the next larger increment of the fault. The process is repeated until the fault becomes observable using the system's fault detection criteria.

The embedded fault detection check has two components that both rely on a change in the measurement value from the nominal baseline. Violation of either check component will cause a fault detection declaration. In the first, a change in value for each sensor measurement from the baseline is computed and compared to a threshold limit. If the limit is exceeded, then fault detection is declared. In the second, the root mean squared, RMS, value of the shift of the entire measurement set is calculated for the fault condition and compared to another threshold limit. If the value exceeds the limit, then fault detection is stated. The calculation is shown in Eq. (7) where m is the number of sensors in the suite, and $y_{baseline,i}$ is the nominal baseline value of sensor i.

$$RMS = \sqrt{\frac{1}{m} \sum_{i=1}^{m} \left(y_i - y_{baseline,i} \right)^2} \tag{7}$$

The procedure to detect faults in a particular system primarily depends on the system fault detection requirements or the health monitoring philosophy of the system. Differences in the applied fault detection procedure will influence sensor selection results. In previous studies, fault detection is declared when two sensors exceeded a prescribed value of 3σ where σ is the standard deviation of sensor uncertainty. The shift in value of two sensors is intended to safeguard against sensor failures being declared as system faults. However, when this detection criterion is used during a preliminary sensor selection evaluation, three of the fault scenarios were not detectable within the prescribed fault magnitude limits as shown in table 3. Enhancements were made to the fault detection methodology which included the addition of the root mean squared method as presented in Eq. (7). With the modifications, all of the fault conditions become detectable, though these three fault conditions remain difficult from a diagnostics perspective.

TABLE 3.—INITIAL DETECTABILITY STUDY RESULTS FOR OPTIONAL AND ADVANCED SENSOR SETS

Failure	Fault Magnitude at Detection
FANeff	2.2 %
FANflow	1.2 %
BSTeff	Not detectable within limits
BSTflow	Not detectable within limits
HPCeff	2.6 %
HPCflow	Not detectable within limits
HPTeff	1.9 %
HPTflow	1.4 %
LPTeff	1.6 %
LPTflow	2.1 %

With the establishment of the S4 framework for the turbofan engine system, the preliminary study procedure was structured as follows. The merit value of the current control sensor suite is measured and established as the baseline. Next, the sensor selection procedure is performed using optional sensors only. Without any requirements for the size of the ideal sensor suite, the full range of possible sensor suite sizes are to be examined. The procedure incrementally adds a sensor to the desired sensor suite size until all of the candidate sensors are included. Stated in another way, the S4 process can be used to find the optimal sensor suite for a given desired number of sensors. The desired number of sensors ranges from one additional sensor to all of the candidate sensors. The merit value of each of the resulting optimum measurement sets is measured and compared to the baseline. The process is to be repeated until all the candidate sensors that encompass the optional and advanced sensor sets are included. In this way, the quantitative benefits of adding more sensors can be evaluated and the selection of advanced sensors can be compared to COTS only sensor suites for this application example.

Results

The sensor selection studies were executed and the results were documented and analyzed. A plot of the merit value in Eq. (3), for the optimum sensor suite for each desired number of sensors is given in Figure 3. While Tables 4a and 4b show the corresponding sensors lists with their merit values. Tables 4a and 4b respectively correspond to the *Optional Sensors* data and the *Optional and Advanced Sensors* data shown in Figure 3. The first data point in both sets represents the baseline control sensor set of seven sensors. Table 4a shows that, for the second point, P25 is selected, for the third point, P25 and P5 are selected, and so on. The best merit value, for the study that includes the optional sensors, is found at two additional sensors. When advanced sensors are included in the potential sensor pool, also see Table 4b, the first sensor selected is still P25. However with two additional sensors, P5 from the optional sensors and P45 from the advanced sensors are selected, while P25 is not selected. The merit value indicated in Figure 3 and Table 4b increases as more sensors are added, until a maximum performance is reached at point 5 with four additional sensors.

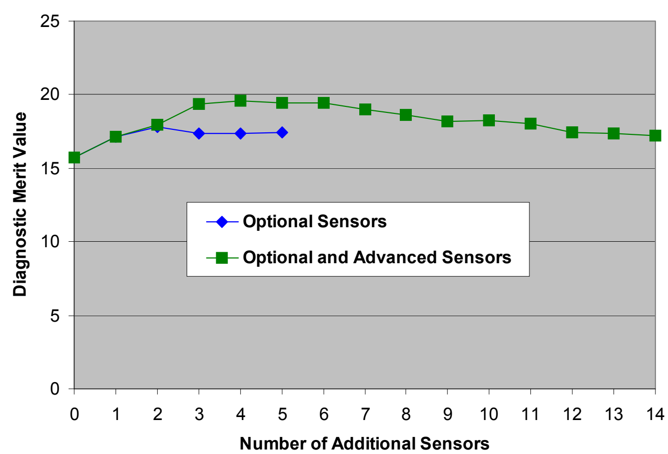

Figure 3.—Diagnostic merit value for each optimum sensor suite.

TABLE 4A.—SENSOR LIST FOR THE BEST OPTIONAL SENSOR SUITES

Additional Sensors	Optional Sensors PS13	T13	P25	P5	T5	Merit
0						15.75
1			X			17.10
2			X	X		17.84
3	X		X		X	17.33
4	X		X	X	X	17.35
5	X	X	X	X	X	17.42

TABLE 4B.—SENSOR LISTING FOR THE BEST OPTIONAL AND ADVANCED SENSOR SUITES

	Optional Sensors					Advanced Sensors									
Additional Sensors	PS13	T13	P25	P5	T5	W2	W25	W3	P41	T41	W41	P45	W45	W5	Merit
0															15.75
1			X												17.10
2				X								X			17.94
3			X	X								X			19.40
4			X	X					X			X			19.56
5			X	X	X				X			X			19.44
6			X	X	X		X		X			X			19.40
7	X		X	X					X	X		X		X	18.98
8	X	X	X	X	X		X		X			X			18.61
9	X		X	X		X		X	X	X		X	X		18.21
10	X	X	X		X	X			X		X	X	X	X	18.25
11	X		X		X	X		X	X	X	X	X	X	X	18.05
12	X	X	X	X	X		X	X	X	X	X		X	X	17.43
13	X	X	X	X	X	X	X	X	X	X	X	X		X	17.35
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X	17.18

Past the maximum diagnostic merit value, performance generally tends to decrease with the inclusion of more sensors in the selected sensor suite. Conventional wisdom would expect performance to increase, or at a minimum, to plateau with each additional sensor. These merit value reductions could stem from the fact that the sensors being added do not provide significant diagnostic information relative to other measurements within the set. This seems to effect the merit value calculation in two ways. First, even though both fault detection criteria are being used, faults are normally detected with the root-mean square test. Since this calculation is essentially an average of the measurement perturbation from the nominal condition, Eq. (7), adding a sensor with a relatively lower observable measurement shift lowers the overall root mean square value thereby, making the fault more difficult to sense with this detection check. To a lesser degree in fault discrimination, the inverse model diagnostic system performance can be degraded when the sensors are not measuring independent variables. Sensors that measure parameters with inter-dependence will cause a shifting of the solution during the optimization process.

Another interesting observation seen in Tables 4a and 4b is that some sensors are consistently selected as the size of the sensor suite is increased, while some other sensors are not selected as often or they are only selected when the size of the sensor pool is substantially increased. This gives an indication of the importance of these sensors in the particular diagnostic system. An effective sensor selection scheme should be able to distinguish those measurement sets with sensors which are useful from those which are nonessential.

A statistical evaluation algorithm was developed to determine how the resulting sensor suites would function in an increasingly realistic evaluation environment. The sensor suites were assessed against ten fault test conditions with fault magnitude perturbations that progressed from 3.0 to 5.0% in 0.5% increments. At each fault magnitude, the evaluations were repeated 100 times with random noise added; therefore each fault test condition was evaluated 500 times. Sensor signal statistics were used to apply a Gaussian distribution for determination of the random noise values. In addition to the fault test cases, 100 nominal (no fault) test cases were evaluated to examine the potential of false alarms. Data for each of the fault and no-fault test cases were regenerated for each sensor suite evaluation. This statistical evaluation was conducted for three different sensor suites, which includes the baseline control sensor suite, a suboptimal sensor suite and an optimal sensor suite. The suboptimal suite with a merit value of 19.40, see Table 4b, includes two optional sensors and one advanced sensor. The optimal sensor suite with a merit value of 19.56 includes two optional and two advanced sensors. Results were tabulated in a confusion matrix and are shown in Tables 5a, 5b and 5c, with a summary of their fault discrimination accuracy presented in Table 6.

TABLE 5A.—CONFUSION MATRIX FOR BASELINE CONTROL ONLY SENSOR SUITE

		Inferred Fault Condition											
		FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
True Fault Condition	FANeff	126	261	0	0	0	0	0	0	113	0	0	25%
	FANflow	66	377	0	0	0	0	0	0	57	0	0	75%
	BSTeff	0	0	13	0	0	0	0	0	0	0	487	3%
	BSTflow	0	0	0	0	0	0	0	0	0	0	500	0%
	HPCeff	0	0	0	0	499	0	1	0	0	0	0	100%
	HPCflow	0	0	0	0	0	145	0	0	0	0	355	29%
	HPTeff	0	0	0	0	0	0	500	0	0	0	0	100%
	HPTflow	0	0	0	0	0	0	0	500	0	0	0	100%
	LPTeff	128	137	0	0	0	0	0	0	235	0	0	47%
	LPTflow	0	0	0	0	0	0	0	4	0	496	0	99%
	Nominal	0	0	0	0	0	0	0	0	0	0	100	100%

TABLE 5B.—CONFUSION MATRIX FOR SUB-OPTIMAL SENSOR SUITE WITH THREE ADDITIONAL SENSORS (OPTIONAL AND ADVANCED)

		Inferred Fault Condition											
		FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
True Fault Condition	FANeff	400	72	0	0	0	0	0	0	28	0	0	80%
	FANflow	27	462	0	0	0	0	0	0	11	0	0	92%
	BSTeff	0	0	0	0	0	0	0	0	0	0	500	0%
	BSTflow	0	0	0	248	0	0	0	0	0	0	252	50%
	HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
	HPCflow	0	0	0	0	0	7	0	0	0	0	493	1%
	HPTeff	0	0	0	0	0	0	500	0	0	0	0	100%
	HPTflow	0	0	0	0	0	0	0	500	0	0	0	100%
	LPTeff	31	58	0	0	0	0	0	0	411	0	0	82%
	LPTflow	0	0	0	0	0	0	0	0	0	500	0	100%
	Nominal	0	0	0	0	0	0	0	0	0	0	100	100%

TABLE 5C.—CONFUSION MATRIX FOR THE BEST SENSOR SUITE WITH FOUR ADDITIONAL SENSORS (OPTIONAL AND ADVANCED)

		Inferred Fault Condition											
		FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
True Fault Condition	FANeff	426	55	0	0	0	0	0	0	19	0	0	85%
	FANflow	26	468	0	0	0	0	0	0	6	0	0	94%
	BSTeff	0	0	0	0	0	0	0	0	0	0	500	0%
	BSTflow	0	0	0	225	0	0	0	0	0	0	275	45%
	HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
	HPCflow	0	0	0	0	0	5	0	0	0	0	495	1%
	HPTeff	0	0	0	0	0	0	500	0	0	0	0	100%
	HPTflow	0	0	0	0	0	0	0	500	0	0	0	100%
	LPTeff	16	39	0	0	0	0	0	0	445	0	0	89%
	LPTflow	0	0	0	0	0	0	0	0	0	500	0	100%
	Nominal	0	0	0	0	0	0	0	0	0	0	100	100%

TABLE 6.—SUMMARY OF SENSOR SUITE ACCURACY FROM CONFUSION MATRIX RESULTS

	Baseline	3 Additional Sensors (Sub-Optimal)	4 Additional Sensors (Optimal)
FANeff	25%	80%	85%
FANflow	75%	92%	94%
BSTeff	3%	0%	0%
BSTflow	0%	50%	45%
HPCeff	100%	100%	100%
HPCflow	29%	1%	1%
HPTeff	100%	100%	100%
HPTflow	100%	100%	100%
LPTeff	47%	82%	89%
LPTflow	99%	100%	100%
Nominal	100%	100%	100%
Overall	**62%**	**73%**	**74%**

A confusion matrix is a visualization tool showing the results of the diagnostic algorithm. In the matrix, the rows list the true fault condition while the columns have the inferred fault condition. The matrix displays any "confusion" between the inferred and true fault conditions through non-zero values in the off-diagonal elements. The baseline control sensor suite, Table 5a, displays difficulty in discriminating between the fan efficiency, fan flow and low pressure turbine efficiency faults as the inferred and true fault conditions do not match as well. With the optimum and sub-optimal sensor suites, Tables 5b and 5c, these faults are better discriminated as indicated by the improved matching of the inferred and true fault conditions. All of the sensor suites had difficulty in sensing the failure conditions which were not detectable in the original detectability study shown in Table 3, which were booster fan efficiency and flow, and high pressure compressor flow.

The optimal sensor suite from Figure 3 and Table 4b shows improved accuracy as seen in Table 5c. But the overall or the averaged fault discrimination accuracy, Table 6, is not significantly different between the suboptimal and optimal sensor suites. However, the optimal sensor suite shows improved fault diagnostic accuracy for those cases which are closer to 100%. This is more important because it implies that this sensor suite could discriminate all these faults with near 100% accuracy if the health parameter shift limits (from nominal) for declaring a fault are relaxed a bit. And the main difference between the suboptimal and optimal sensor suites is how much more the health parameter shift limits would need to be relaxed in order to isolate these faults within the desired accuracy for a given system. On the other hand, for faults with low diagnostic accuracy, like the high pressure compressor flow for which the diagnostic accuracy has not improved from baseline to the suboptimal to the optimal sensor suite, this would suggest that the pool of candidate sensors is insufficient to properly detect and identify these types of faults. This could also mean that a different diagnostic method could provide somewhat different results. If it turns out that the given pool of sensors is inadequate to accurately diagnose all the faults, then one or more sensors sensitive to those faults would need to be added to the available pool of sensors. The reason that adding more sensors starting from the baseline sensor suite Table 5a, causes the fault detection accuracy for the high pressure compressor flow to deteriorate is due to the RMS measure of Eq. (7) that is being utilized for fault detection. When additional sensors are included in the sensor suite which do not improve fault detection for that particular fault, the RMS value can effect decrease because it is averaged by the number of sensors.

Generally, as expected, the optimal and sub-optimal sensor suites exhibit improved performance for fault discrimination. All three sensor suites exhibited perfect performance in generating no false alarms for the nominal (no fault) cases evaluated in this study.

These types of studies can help to identify trends such as the importance of each candidate sensor measurement based on the given diagnostic approach. It also helps to identify whether the available pool of sensors is sufficient to identify the desired set of fault conditions, within the desired fault detection accuracy and health parameter shift limits. Finally, it establishes a vehicle to quantify the benefits of adding certain sensor measurements and provides a basis to support further sensor research.

Future Work

With the objectives of the preliminary S4 investigation being achieved, the goals of this effort are being expanded. An ambition of this study was to determine the applicability of the S4 methodology to aero-vehicle propulsion systems. With the framework established, the research can continue with more specific details of the host system being incorporated. This particular study essentially provides the proof of concept, but it also opens more questions and provides some guidance for further research.

Opportunities to expand on this preliminary effort include the investigation of fault conditions at additional engine operating points. Data can be obtained for the nominal and fault conditions over a range of operating conditions and power settings. The merit algorithm would be modified to account for the expanded operating envelope.

Future investigations could also focus on the merit algorithm to improve upon the general assumptions. Importance can be given to false alarm and missed detection rates for each of the fault scenarios. Sensor statistics such as reliability, desirability, availability and possibly cost could be incorporated if available. Furthermore, results from this study could be used to refine the general fault detection and identification procedures employed in any future work.

Conclusion

This preliminary investigation serves as a proof of concept for the applicability of the optimal sensor selection methodology Systematic Sensor Selection Strategy (S4), for aircraft turbofan engine health monitoring applications. When applied to a turbofan engine simulation, results show that there is a diagnostic benefit when the current baseline control sensor suite is augmented by additional sensors and that the diagnostic benefit varies with the number of additional sensors. The flexibility of the Systematic Sensor Selection Strategy is evident in these studies and the methodology is closely tied to the system fault diagnostic philosophy, which is highly desirable. The methodology could ultimately be used to justify new sensor research by quantifying its benefits in terms of additional diagnostic capability, and cost in terms of sensor cost or preventive maintenance. Additionally, the methodology can expose fault conditions that are difficult to diagnose suggesting improvements to either the diagnostic philosophy or expansion of the pool of candidate sensors.

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14. ABSTRACT
The data acquired from available system sensors forms the foundation upon which any health management system is based, and the available sensor suite directly impacts the overall diagnostic performance that can be achieved. While additional sensors may provide improved fault diagnostic performance, there are other factors that also need to be considered such as instrumentation cost, weight, and reliability. A systematic sensor selection approach is desired to perform sensor selection from a holistic system-level perspective as opposed to performing decisions in an ad hoc or heuristic fashion. The Systematic Sensor Selection Strategy is a methodology that optimally selects a sensor suite from a pool of sensors based on the system fault diagnostic approach, with the ability of taking cost, weight, and reliability into consideration. This procedure was applied to a large commercial turbofan engine simulation. In this initial study, sensor suites tailored for improved diagnostic performance are constructed from a prescribed collection of candidate sensors. The diagnostic performance of the best performing sensor suites in terms of fault detection and identification are demonstrated, with a discussion of the results and implications for future research.

15. SUBJECT TERMS
Sensor optimization; Optimal sensor selection; Sensor selection; Sensor diagnostic; Health management; Integrated vehicle health management

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