



Sensor Selection for Aircraft Engine Performance Estimation and Gas Path Fault Diagnostics

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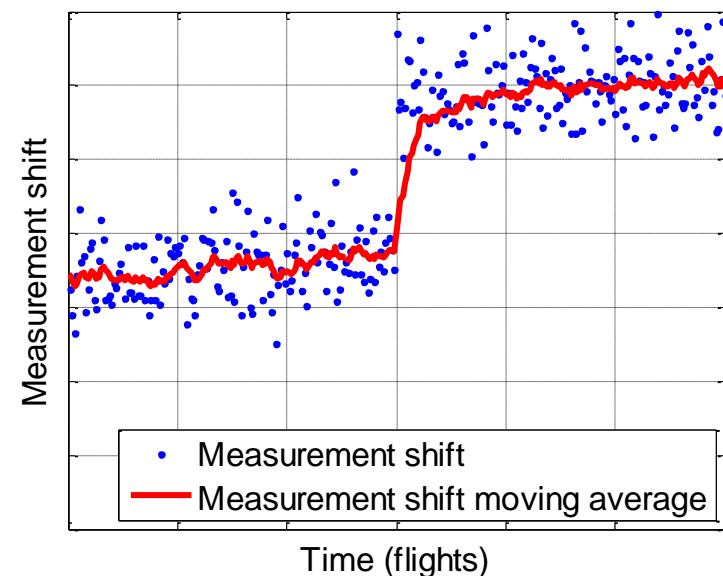
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Outline

- Background – aircraft engine performance estimation and gas path fault diagnostics
- Application-Specific Sensor Selection Metrics
 - Kalman filter-based health parameter estimation
 - Maximum a posteriori health parameter estimation
 - Weighted least squares single fault diagnostic approach
- Linear Turbofan Engine Model Example
- Conclusions

Background – aircraft engine performance estimation and gas path fault diagnostics

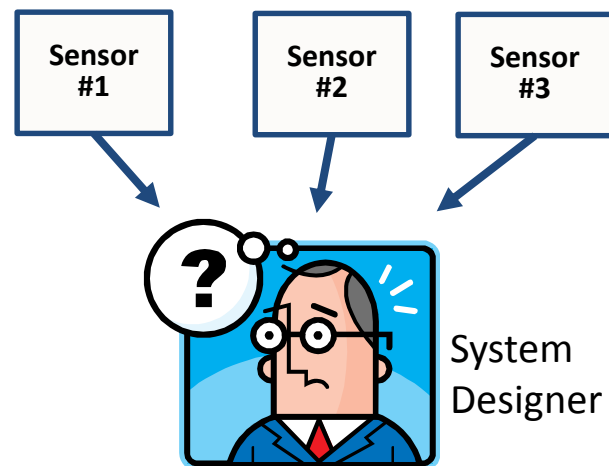
- Performance Estimation:
 - Estimation and trending of gradual performance deterioration due to fouling and erosion of turbomachinery
 - Entails the estimation of health parameters such as efficiency and flow capacity scalars, which reflect deterioration in major engine components
 - Poses an underdetermined estimation problem—more unknowns than available sensor measurements
- Gas Path Fault Diagnostics:
 - Detection and isolation of gas path system faults affecting engine performance such as sensor faults, actuator faults, turbomachinery damage
 - Faults are relatively abrupt or rapid in nature
 - Single-fault assumption makes the diagnostic problem overdetermined



Gradual versus rapid performance shifts

Sensor Selection

- Problem: In general, additional sensed measurements will improve estimation and diagnostic results, but which sensors are best and how much improvement will they provide?
- Objective: Develop techniques to aid in engine health management sensor selection decisions, tailored to the specific estimation or diagnostic method applied.
- Approach: Develop analytical metrics based on linear estimation and probability theory to quantify theoretical accuracy enabled by different candidate sensor suites.



Kalman filter-based performance estimation

Linear dynamic measurement process:

$$\Delta x_{k+1} = A\Delta x_k + B\Delta u_k + L\Delta h_k + w_k$$

$$\Delta y_k = C\Delta x_k + D\Delta u_k + M\Delta h_k + v_k$$

k = discrete time index

y = sensed output vector

h = health parameter vector

x = state vector

u = actuator command vector

v = measurement noise ($N(0, \sigma)$ with covariance R)

w = process noise ($N(0, \sigma)$ with covariance Q)

Optimal tuner selection methodology* applied to produce reduced-order system and enable Kalman filter estimation when facing underdetermined estimation problem:

- Define $q = V^*h$
where V^* is a transformation matrix
- V^* is selected through an optimal iterative search to minimize Kalman filter mean squared estimation error in the parameters of interest
- Health parameter estimation: $\hat{h} = V^{*+} \hat{q}$

Sensor selection methodology designed to determine sensor suite that minimizes the mean SSEE

Kalman filter mean sum of squared estimation errors (SSEE) is the sum of the following components:

- Mean squared bias
- Variance

Kalman filter mean squared bias and variance are functions of:

- Linear state-space model
- Choice of V^*
- Process noise, Q
- Health parameter covariance, P_h
- Available sensor suite and corresponding measurement covariance, R

*Reference: Simon, D.L., Garg, S., (2010), "Optimal Tuner Selection for Kalman Filter-Based Aircraft Engine Performance Estimation," *Journal of Engineering for Gas Turbines and Power*, Vol. 132 / 0231601-1.

Maximum *a posteriori* (MAP) performance estimation

Linear steady-state measurement process:

$$\Delta y = H\Delta h + v$$

Δy = residuals in the sensed measurement vector

H = influence coefficient matrix

Δh = health parameter vector

v = measurement noise ($N(0, \sigma)$ with covariance R)

Maximum a posteriori estimator:

$$\Delta \hat{h} = \underbrace{(P_h^{-1} + H^T R^{-1} H)^{-1} H^T R^{-1}}_{G_h} \Delta y$$

$$\Delta \hat{h} = G_h \Delta y$$

P_h is the health parameter covariance matrix.

Note: Incorporating *a priori* knowledge through P_h allows estimates to be produced when facing underdetermined estimation problems

Sensor selection methodology designed to determine sensor suite that minimizes the mean SSEE

MAP estimation mean sum of squared estimation errors (SSEE) is the sum of the following components:

- Mean squared bias:

$$\bar{\tilde{h}}^2 = tr\{(G_h H - I)P_h(G_h H - I)^T\}$$

- Variance :

$$var = tr\{G_h R G_h^T\}$$

MAP mean squared bias and variance are functions of:

- Linear state-space model
- Health parameter covariance, P_h
- Available sensor suite and corresponding measurement covariance, R

Weighted Least Squares

Single Fault Diagnostic Approach

Linear steady-state measurement process:

$$\Delta\Delta y = H_f f + v$$

$\Delta\Delta y$ = vector of measurement residuals reflecting recent abrupt shifts in sensor measurements

H_f = fault influence coefficient matrix

f = vector of gas path fault magnitudes

v = measurement noise ($N(0, \sigma)$ with covariance R)

Fault diagnostics performed via a two-step process:

- 1) Fault detection performed by monitoring a weighted sum of squared measurements ($WSSM$):

$$WSSM = \Delta\Delta y^T R^{-1} \Delta\Delta y$$

If $WSSM > \text{Threshold}, T$, fault declared

- 2) Single fault isolation performed by comparing known system fault signatures to observed vector of measurement residuals, $\Delta\Delta y$. Fault type that most closely matches observed signature in a weighted least squares sense is isolated as fault.

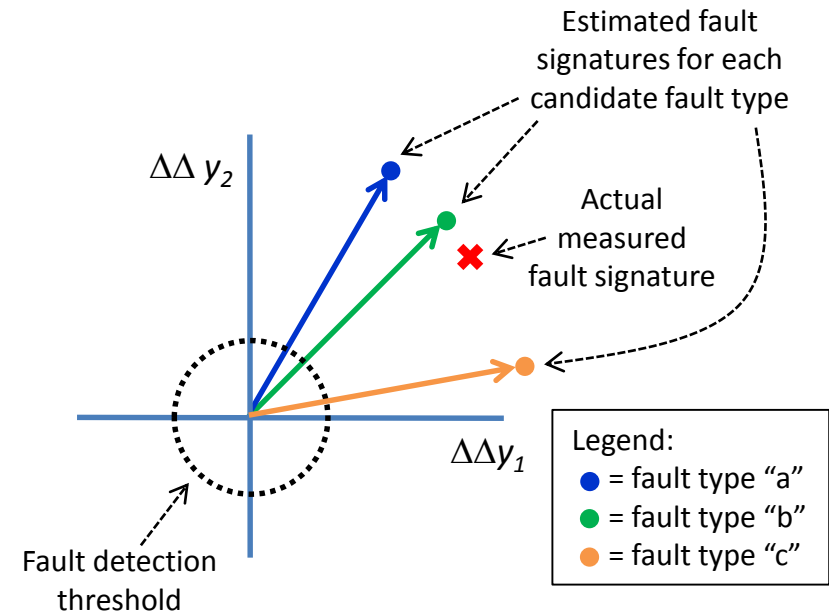


Illustration of Single-Fault Diagnostic Approach in Two-Dimensional Measurement Space

- Fault signature, exceeding defined failure threshold, is detected (indicated by red "x")
- Fault signatures of three system fault types (a, b, and c) are individually compared to measured fault signature
- In this example, fault type "b" will be classified as the fault as it most closely approximates the observed fault signature

Weighted Least Squares

Single Fault Diagnostic Approach (continued)

Sensor selection methodology determines sensor suite that maximizes the correct classification rate (CCR)

- 1) *WSSM* signal fault detection threshold, T , is set to yield a common target false positive rate (FPR):

$$FPR(T, k) = 1 - \frac{\gamma\left(\frac{k}{2}, \frac{T}{2}\right)}{\Gamma\left(\frac{k}{2}\right)}$$

Where:

- T = *WSSM* detection threshold
- k = Number of sensors
- λ = Mean value of the *WSSM* signal
- Γ = Gamma function

- 2) In the presence of a fault, the *WSSM* signal is distributed as a non-central chi-square distribution, and the true positive rate (TPR) is calculated as:

$$TPR(T, k, \lambda) = 1 - \left(\sum_{j=0}^{\infty} e^{-\lambda/2} \frac{(\lambda/2)^j}{j!} \frac{\gamma(j + k/2, T/2)}{\Gamma(j + k/2)} \right)$$

Where:

- λ = Mean value of *WSSM* signal in the presence of a fault

- 3) Applying a two-fault class assumption, the probability of misclassifying fault type “a” as fault type “b” is approximated as:

$$PMC_{b|a} = 1 - \Phi\left(\frac{1}{2} \cdot D_M\right)$$

Where:

- Φ = Standard normal distribution
- D_M = Mahalanobis distance

The probability of misclassifying fault type “a” as any other single fault type is:

$$PMC_a = \sum_{\substack{b=1 \\ b \neq a}}^N PMC_{b|a}$$

Where:

- N = number of fault types

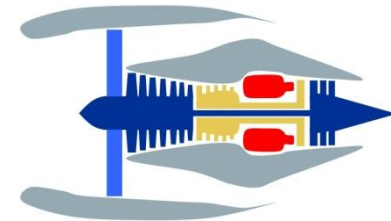
- 4) Correct classification rate (CCR) for fault type “a” and all fault types is:

$$CCR_a = TPR_a \times (1 - PMC_a)$$

$$CCR = \sum_{a=1}^N \frac{CCR_a}{N}$$

Linear Turbofan Engine Model Example

The sensor selection approaches were applied to a linear point model extracted from the NASA Commercial Modular Aero-Propulsion System Simulation 40k (C-MAPSS40k) high-bypass turbofan engine model.



7 State variables, x	3 Actuators, u	10 Health Parameters, h	6 baseline + 4 Optional Sensed outputs, y	
Nf – fan speed	Wf – fuel flow	FAN efficiency	Nf – fan speed	Baseline Sensors
Nc – core speed	VSV – variable stator vane	FAN flow capacity	Nc – core speed	
Hs_LPC – LPC metal temp	VBV – variable bleed valve	LPC efficiency	Ps30 – HPC exit static press	
Hs_HPC – HPC metal temp		LPC flow capacity	T30 – HPC exit total temp	
Hs_burner – burner metal temp		HPC efficiency	P50 – LPT exit total pressure	
Hs_HPT – HPT metal temp		HPC flow capacity	T50 – LPT exit total temp	Additional (Optional) Sensors
Hs_LPT – LPT metal temp		HPT efficiency	P14 – Bypass duct total pressure	
		HPT flow capacity	T14 – Bypass duct total temp	
		LPT efficiency	P25 – HPC inlet total pressure	
		LPT flow capacity	T25 – HPC inlet total temp.	

Objective: assess the estimation and diagnostic improvements that can be gained by adding sensors individually or in combination to the baseline sensor suite

Sensor Selection for Health Parameter Estimation

Health Parameter Estimation:

- Objective is to minimize sum of squared estimation errors (SSEE) across all 10 health parameters
- Health parameters are assumed to exhibit simultaneous, uncorrelated, normally distributed random variations with a standard deviation of $\pm 2\%$
- Health parameter covariance matrix, P_h , is a 10×10 diagonal matrix with elements of 4.0 along the diagonal.

C-MAPSS40k Health Parameters

Health parameters		
1	η_{FAN}	Fan efficiency
2	Y_{FAN}	Fan flow capacity
3	η_{LPC}	Low pressure compressor (LPC) efficiency
4	Y_{LPC}	Low pressure compressor (LPC) flow capacity
5	η_{HPC}	High pressure compressor (HPC) efficiency
6	Y_{HPC}	High pressure compressor (HPC) flow capacity
7	η_{HPT}	High pressure turbine (HPT) efficiency
8	Y_{HPT}	High pressure turbine (HPT) flow capacity
9	η_{LPT}	Low pressure turbine (LPT) efficiency
10	Y_{LPT}	Low pressure turbine (LPT) flow capacity

Analytical techniques applied to predict theoretical SSEE for each candidate sensor suite

Monte Carlo simulations conducted to validate theoretical predictions

- Uses C-MAPSS40k linear point model
- Health parameters randomly assigned according to health parameter covariance matrix, P_h
- Random sensor measurement noise added in accordance with sensor measurement covariance matrix, R
- Kalman Filter Estimator – 200 trials, each 30 seconds in duration
- MAP Estimator – 400,000 trials, each a single sample in time

Sensor Selection Results for Health Parameter Estimation

Kalman Filter Estimator Results

# Sensors	sensors added to baseline				Sum of Squared Estimation Errors	
	P14	T14	P25	T25	Theoretical	Monte Carlo Simulation
6					17.21	17.35
7	x				13.66	13.94
7		x			13.81	14.44
7			x		12.83	13.19
7				x	12.58	12.90
8	x	x			22.45	23.74
8	x		x		9.14	9.94
8	x			x	8.78	9.60
8		x	x		10.44	11.47
8		x		x	9.27	9.84
8			x	x	8.60	8.90
9	x	x	x		10.07	11.66
9	x	x		x	6.13	7.29
9	x		x	x	4.79	5.45
9		x	x	x	4.95	5.75
10	x	x	x	x	4.47	4.98

MAP Estimator Results

# Sensors	sensors added to baseline				Sum of Squared Estimation Errors	
	P14	T14	P25	T25	Theoretical	Monte Carlo Simulation
6					16.35	16.36
7	x				12.86	12.86
7		x			14.54	14.55
7			x		12.36	12.37
7				x	12.36	12.36
8	x	x			12.38	12.38
8	x		x		8.87	8.86
8	x			x	8.87	8.86
8		x	x		10.55	10.55
8		x		x	10.55	10.54
8			x	x	8.40	8.41
9	x	x	x		8.39	8.38
9	x	x		x	8.39	8.38
9	x		x	x	4.91	4.91
9		x	x	x	6.59	6.60
10	x	x	x	x	4.43	4.43

Sensor Selection Results (Kalman filter and MAP estimator select the same sensors):

- **Baseline + 1 sensor, choose: T25**
- **Baseline + 2 sensors, choose: T25 and P25**
- **Baseline + 3 sensors, choose: T25, P25, and P14**

Sensor Selection for Gas Path Fault Diagnostics

Gas Path Fault Diagnostics:

- Objective is to maximize the correct classification rate (CCR) across all 8 gas path faults
- Each fault considered to occur in isolation, and to be of equal criticality and probability of occurrence

Gas Path Fault Types

Fault ID	Fault type	Health parameters and actuator biases
1	Fan fault	$\eta_{FAN} = -1\%$, $\gamma_{FAN} = -2\%$
2	LPC fault	$\eta_{LPC} = -1\%$, $\gamma_{LPC} = -2\%$
3	HPC fault	$\eta_{HPC} = -1\%$, $\gamma_{HPC} = -2\%$
4	HPT fault	$\eta_{HPT} = -2\%$, $\gamma_{HPT} = +1\%$
5	LPT fault	$\eta_{LPT} = -2\%$, $\gamma_{LPT} = +1\%$
6	Wf bias	Wf bias = -2%
7	VSV bias	VSV bias = -1 degree stroke
8	VBV bias	VBV bias = +20%

Analytical techniques applied to predict theoretical CCR for each candidate sensor suite

Monte Carlo simulations conducted to validate theoretical predictions

- Uses C-MAPSS40k linear fault influence coefficient matrix
- Random sensor measurement noise added in accordance with sensor measurement covariance matrix, R
- Monte Carlo simulation study consisted of 80,000 no fault cases and 10,000 cases for each of the 8 gas path fault types
- Detection threshold set to achieve theoretical false positive rate of 0.01 (1%)

Sensor Selection Results for Gas Path Diagnostics

Gas Path Diagnostic Results

# Sensors	sensors added to baseline				False Positive Rate (%)		Correct Classification Rate (%)	
	P14	T14	P25	T25	Theoretical	Monte Carlo Simulation	Theoretical	Monte Carlo Simulation
6					1.00	1.04	84.60	88.40
7	x				1.00	1.02	85.51	89.06
7		x			1.00	0.99	85.84	89.18
7			x		1.00	1.00	88.98	90.39
7				x	1.00	1.07	91.58	92.59
8	x	x			1.00	1.03	86.29	89.47
8	x		x		1.00	1.03	89.73	91.11
8	x			x	1.00	1.05	92.28	93.23
8		x	x		1.00	1.02	89.97	91.19
8		x		x	1.00	1.02	92.42	93.30
8			x	x	1.00	1.01	92.04	92.57
9	x	x	x		1.00	1.02	90.28	91.48
9	x	x		x	1.00	1.02	92.69	93.55
9	x		x	x	1.00	1.01	92.70	93.29
9		x	x	x	1.00	1.02	92.83	93.32
10	x	x	x	x	1.00	1.00	93.07	93.57

Monte Carlo results

- Confirmed theoretical target false positive rate of 1%
- Theoretical correct classification rate (CCR) found to under-predict Monte Carlo CCR. This is attributed to the 2 fault class simplifying assumption made in calculating the theoretical CCR.

Sensor Selection Choices:

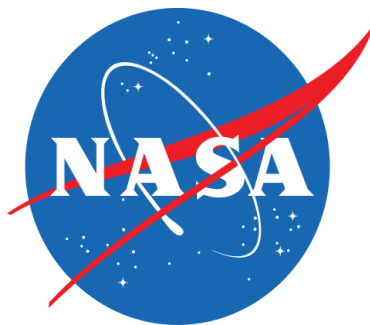
- Baseline + 1 sensor, choose: T25
- Baseline + 2 sensors, choose: T25 and T14
- Baseline + 3 sensors:
 - Theoretical choose: T25, T14, and P25
 - Monte Carlo choose: T25, T14 and P14

Conclusions

- Sensor selection methods introduced in this paper were found to perform well in identifying optimal sensor suites
- Results are application-specific to engine model considered and measurement noise, health parameter variations, and fault types assumed
- Kalman filter and MAP estimator based sensor-selection methods found to yield good agreement between theoretical predictions and simulation results. Also found to yield same sensor selection choices.
- Weighted Least Squares Single Fault Diagnostic sensor selection methods found to slightly under-predict correct classification rate
- Follow-on recommendations
 - Incorporate other factors of merit such as sensor life cycle cost (cost, weight, reliability, etc.) and criticality of different fault types
 - Extend to additional operating points beyond single linear point analysis

Acknowledgments

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Backup Slides

Linear Turbofan Engine Model Example

Sensor Selection Approach:

- Optional sensors are evaluated for estimation accuracy or diagnostic improvement they provide if added individually or in combination to baseline sensor suite.
- Given n sensors to choose from, and a target number, k , of additional sensors, the total number of sensor suite combinations will be:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

- Thus, the number of sensor combinations when adding 1, 2, 3, or 4 sensors to the baseline 6 sensors are:
 - Baseline sensors 1 combination
 - Baseline + 1 sensor 4 combinations
 - Baseline + 2 sensors 6 combinations
 - Baseline + 3 sensors 4 combinations
 - Baseline + 4 sensors 1 combination
- Analytical metrics are applied to calculate theoretical performance for each sensor suite
- Monte Carlo simulation analysis is then conducted to verify theoretical predictions

Performance estimation and gas path fault diagnostic methods considered in this study

- Performance Estimation Methods:
 - Kalman filter estimation
 - Applied in dynamic, streaming (continuous) engine measurement process
 - Underdetermined estimation addressed by combining health parameters into a reduced set of optimal tuners
 - Maximum a posteriori estimation
 - Applied in steady-state measurement process as available through “snapshot” measurements
 - Underdetermined estimation addressed by leveraging *a priori* knowledge regarding health parameter covariance
- Gas Path Fault Diagnostic Method:
 - Weighted-least squares single fault diagnostic approach
 - Fault detection performed by monitoring for abrupt shifts in measurements
 - Fault isolation performed by identifying the known fault signature that most closely matches observed measurement signature in multi-parameter measurement space in a weighted-least squares approach

Sensor selection methods tailored to given estimation/diagnostic method