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

**Donald L. Simon**
**NASA GRC**

**Aidan W. Rinehart**
**Vantage Partners LLC**

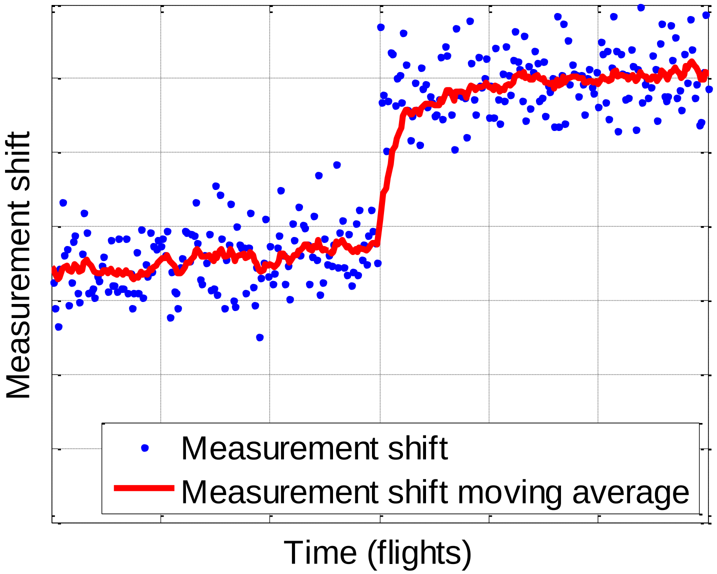
5th NASA GRC Propulsion Control and Diagnostics (PCD) Workshop
September 16 - 17, 2015
Cleveland, Ohio

# 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

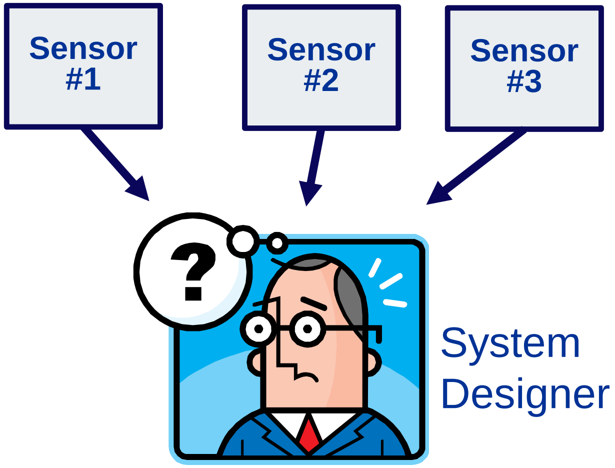
- Performance Estimation:
  - Estimation and trending of gradual performance deterioration due to fouling and erosion of turbomachinery
  - Entails the estimation of health parameters such as efficiency and flow capacity scalars, which reflect deterioration in major engine components
  - Poses an underdetermined 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:
  $$\hat{h} = V^{*+}\hat{q}$$

*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.

# Kalman filter-based performance estimation

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, $R$

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

# Maximum *a posteriori* (MAP) performance estimation

Linear steady-state measurement process:

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

$\Delta y$ = residuals in the sensed measurement vector
$H$ = influence coefficient matrix
$\Delta h$ = health parameter vector
$v$ = measurement noise ($N(0,\sigma)$ with covariance $R$)

Maximum a posteriori estimator:

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

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

$P_h$ is the health parameter covariance matrix.

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

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

- Mean squared bias:

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

- Variance :

$$\mathrm{var} = tr\left\{G_h R G_h^T\right\}$$

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, $R$

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

# 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 $WSSM$ > 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.

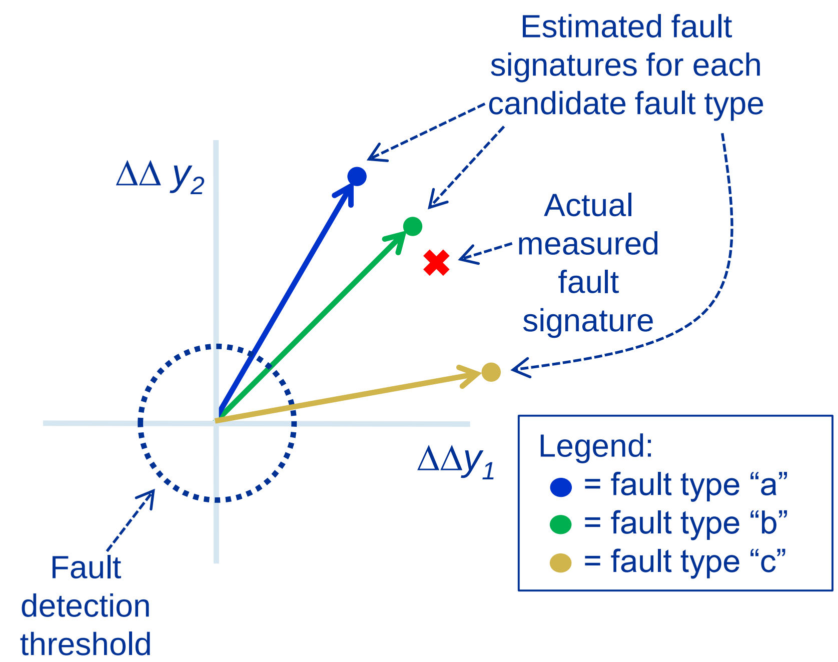



Illustration of Single-Fault Diagnostic Approach in Two-Dimensional Measurement Space

- 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)

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
- $\lambda$ = Mean value of the WSSM signal
- $\Gamma$ = 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:

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

Where:
$\lambda$ = 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:
- $\Phi$ = 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:

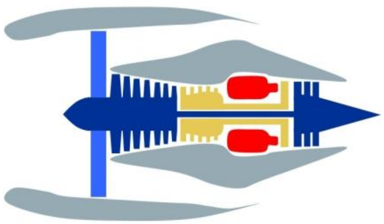
$$CCR_a=TPR_a\times(1-PMC_a)$$

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

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

# 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 | |
| Hs_LPT – LPT metal temp | | HPT efficiency | P14 – Bypass duct total pressure | Additional (Optional) Sensors |
| | | 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 ±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 | $\eta_{FAN}$ | Fan efficiency |
| 2 | $\gamma_{FAN}$ | Fan flow capacity |
| 3 | $\eta_{LPC}$ | Low pressure compressor (LPC) efficiency |
| 4 | $\gamma_{LPC}$ | Low pressure compressor (LPC) flow capacity |
| 5 | $\eta_{HPC}$ | High pressure compressor (HPC) efficiency |
| 6 | $\gamma_{HPC}$ | High pressure compressor (HPC) flow capacity |
| 7 | $\eta_{HPT}$ | High pressure turbine (HPT) efficiency |
| 8 | $\gamma_{HPT}$ | High pressure turbine (HPT) flow capacity |
| 9 | $\eta_{LPT}$ | Low pressure turbine (LPT) efficiency |
| 10 | $\gamma_{LPT}$ | 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 | P14 | T14 | P25 | T25 | Theoretical | Monte Carlo Simulation |
|---|---|---|---|---|---|---|
| | sensors added to baseline | | | | Sum of Squared Estimation Errors | |
| 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 | P14 | T14 | P25 | T25 | Theoretical | Monte Carlo Simulation |
|---|---|---|---|---|---|---|
| | sensors added to baseline | | | | Sum of Squared Estimation Errors | |
| 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 | P14 | T14 | P25 | T25 | False Positive Rate (%) Theoretical | False Positive Rate (%) Monte Carlo Simulation | Correct Classification Rate (%) Theoretical | Correct Classification Rate (%) 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


- This work was conducted under the NASA Aviation Safety Program, Vehicle Systems Safety Technologies Project and the NASA Transformative Aeronautics Concept Program, Convergent Aeronautics Solutions Project

# References


- Simon, D.L. (2015), “Sensor Selection for Aircraft Engine Performance Estimation and Gas Path Fault Diagnostics,” ASME Turbo Expo Conference, paper ASME GT2015-43744, Montreal, Canada, June 2015
- 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.
- Simon, D.L., Garg, S., (2009), “A Systematic Approach to Sensor Selection for Aircraft Engine Health Estimation,”*19th ISABE Conference (ISABE 2009) sponsored by the International Society for Air Breathing Engines*, ISABE-2009-1125, Montreal, Canada, September 7-11.
- Sowers, T.S., Kopasakis, G., and Simon. D.L., (2008), “Application of the Systematic Sensor Selection Strategy for Turbofan Engine Diagnostics,” *ASME Turbo Expo Conference*, paper ASME GT2008-50525, Berlin, Germany, June 9-13.

# 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*