IVHM Propulsion Health Management

Gas Path Health Management

Propulsion Control and Diagnostics Research Under NASA Aeronautics Research Mission Programs

Workshop at Ohio Aerospace Institute, Cleveland OH
Nov. 6-7, 2007

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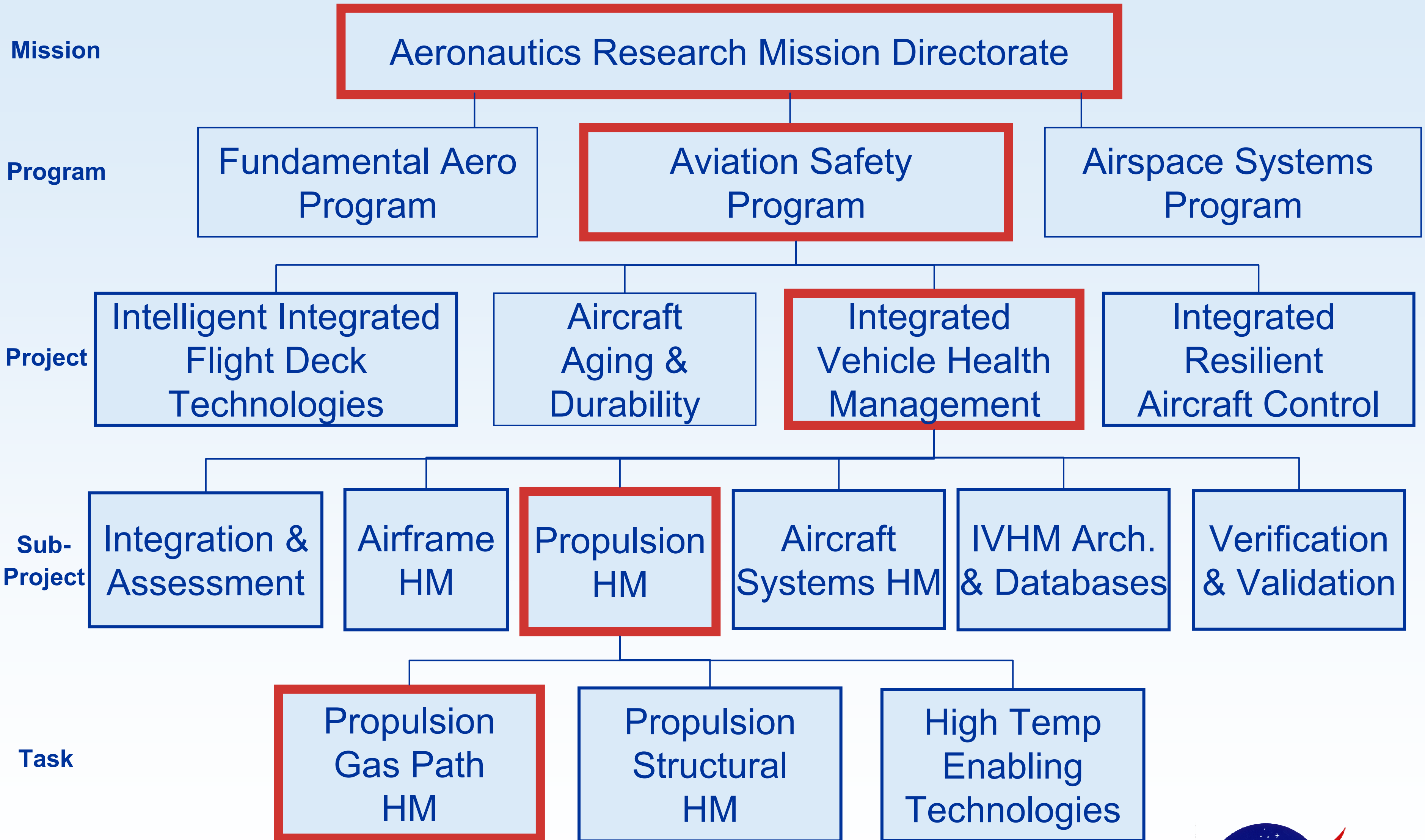
Propulsion Gas Path Health Management GRC Team Members

• Don Simon	US Army Research Laboratory
• George Kopasakis	NASA Glenn
• Tak Kobayashi	ASRC Aerospace Corporation
• Shane Sowers	Analex Corporation

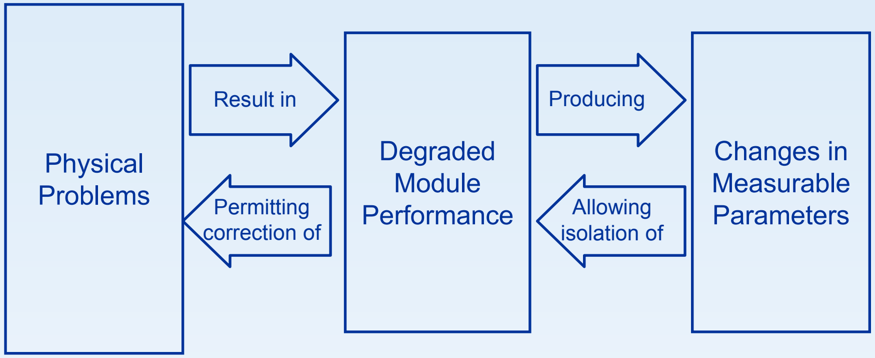
IVHM Propulsion HM Gas Path Health Management

Program/Project Structure

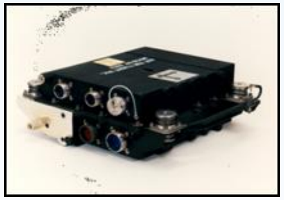


Propulsion Gas Path Health Management

- Aircraft engine gas path diagnostics
  - System-level engine health assessment
  - Based upon parameter interrelationships within the gas turbine cycle
  - Enabled by digital engine controls



Gas Turbine Cycle Parameter Inter-relationships



A key enabling technology for IVHM

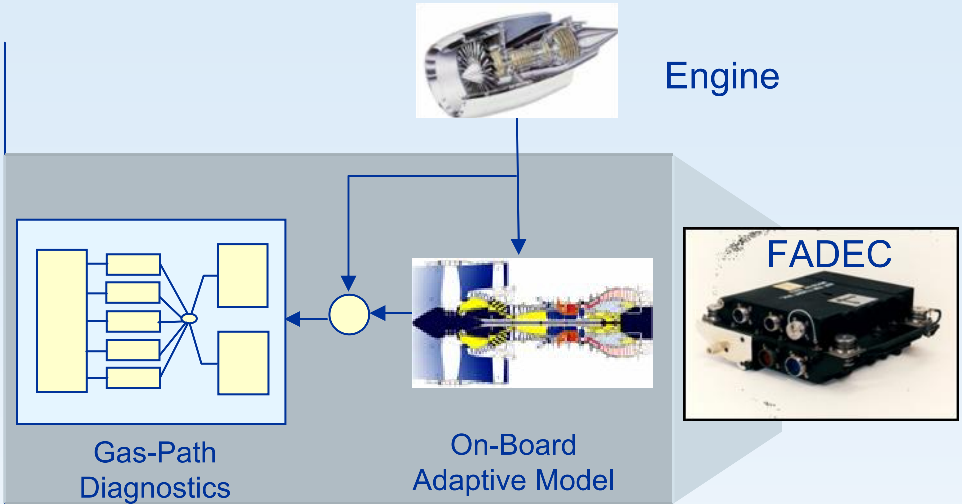
Propulsion Gas Path Health Management

Objectives

- Develop advanced gas path health management technologies to improve the safety, affordability and reliability of aircraft propulsion systems

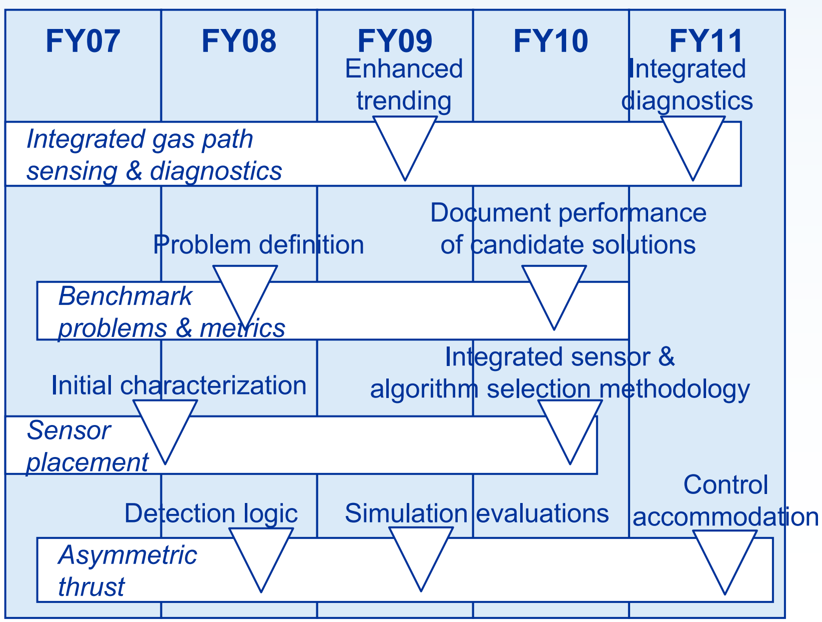
Approach

- Establish gas path diagnostic benchmark problems and metrics
- Advanced on-board model-based diagnostics
- Optimal sensor placement methodology for gas-path diagnostics
- Develop and demonstrate an integrated approach for asymmetric thrust detection



Model-Based Gas Path Diagnostics Architecture

Gas Path HM Milestone Chart



Propulsion Gas Path Health Management

- Collaborative Opportunities
  - NRA's
    - IVHM Project has had two rounds of NRA solicitations yielding several awards including one in Propulsion Gas Path Health Management:
      - Penn State University: "Health State Assessment and Failure Prognosis of Integrated Aircraft Propulsion Systems." Applying Symbolic Dynamic Filtering (SDF) for real-time fault detection and isolation.
    - Future IVHM Project NRA solicitation topics and schedule has not yet been announced
  - SBIR sub-topic A1.07 - Advanced Health Management for Aircraft Subsystems
  - Space Act Agreements no direct NASA funding
    - Enables collaboration on mutual areas of interest

Propulsion Gas Path Health Management
Review of Progress to Date

- Gas Path Diagnostic Benchmark Problem & Metrics *(Don Simon)*
- Integration of On-line and Off-line Diagnostic Algorithms for Aircraft Engine Health Management *(Tak Kobayashi)*
- Optimal Sensor Placement for Propulsion Gas Path Diagnostics *(George Kopasakis)*
- Asymmetric Thrust Detection *(Don Simon)*

Gas Path Diagnostic Benchmark Problem and Metrics

Propulsion Control and Diagnostics Research Under NASA Aeronautics Research Mission Programs

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Outline

- Background/Motivation
- Conventional Gas Path Diagnostic Process
- Benchmark Problem
  - Engine Fleet Simulator (EFS)
  - Solution Process
  - Evaluation Metrics
- Summary

Benchmark Problem – Background/Motivation

- Motivation: Establish a benchmark problem to facilitate the development and comparison of aircraft engine gas-path diagnostic approaches
  - Allow side-by-side comparison of candidate solutions
- Problem requirements:
  - Maintain realism to ensure solutions are relevant
  - Publicly available to all of government, industry & academia
  - Solution evaluation metrics defined to enable a uniform comparison of diagnostic solutions
- Conducted in conjunction with the The Technical Cooperation Program (TTCP) Propulsion & Power Systems Technical Panel Engine Health Management Industry Review

Conventional Gas Path Diagnostics Process

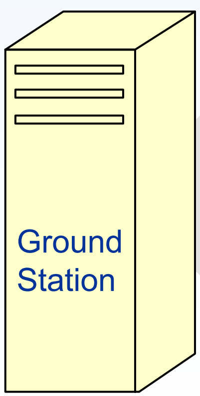
Consists of on-board and ground-based functionality …

Data Transmission
("snap shot"
measurements)

On-board Diagnostics

- Embedded in FADEC
- Typically consists of …
  - Exceedance checks
  - Rate of change checks
  - Channel cross checks
- Mitigation steps …
  - Fault codes generated
  - Revert to redundant (backup) hardware
  - Revert to secondary control mode

Benchmark Diagnostic problem will specifically focus on a ground-based application



Ground-Based Diagnostics

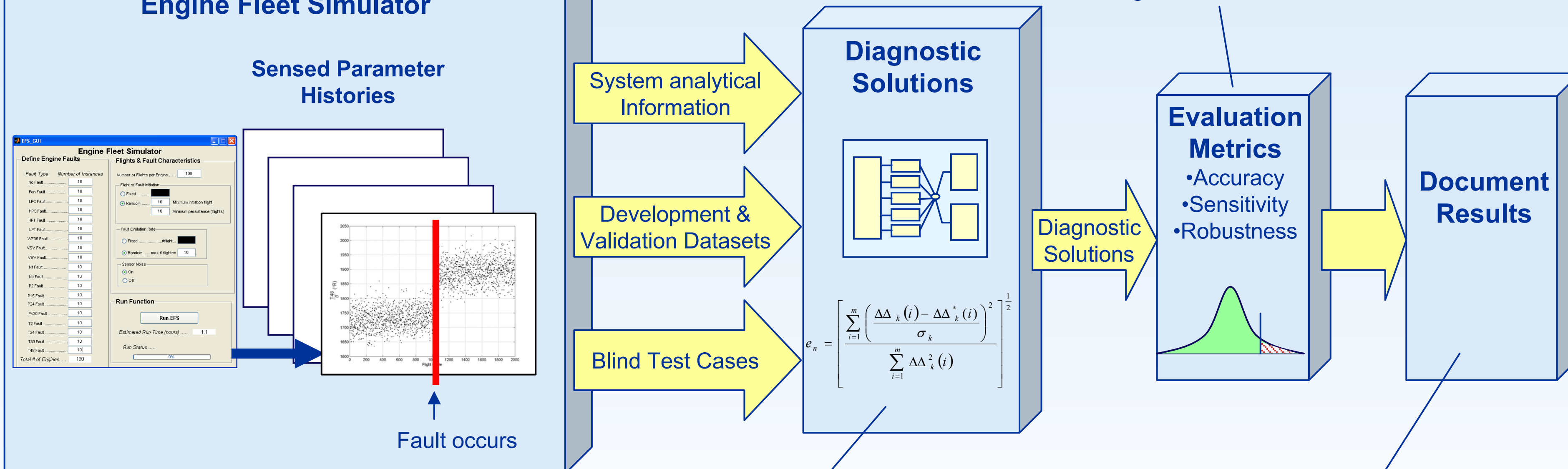
- "Snap Shot" engine measurements recorded each flight
  - Consists of engine control sensors (~4-10 measurements)
  - Typically collected at takeoff & cruise
- Transmitted to ground station for fleet-wide engine trend & condition monitoring
- <u>Trended</u> over time to monitor engine deterioration and schedule overhaul & maintenance actions
- Monitored to <u>detect</u> abrupt/rapid shifts events indicative of a fault
- <u>Isolation</u> techniques invoked to identify root-cause of event
- Generates inspection actions

Benchmark Diagnostic Problem

Overview

1. Benchmark problem:
Relevant problem constructed from publicly available models and datasets

3. Evaluation Metrics:
Defined and applied to provide a uniform assessment of diagnostic solutions

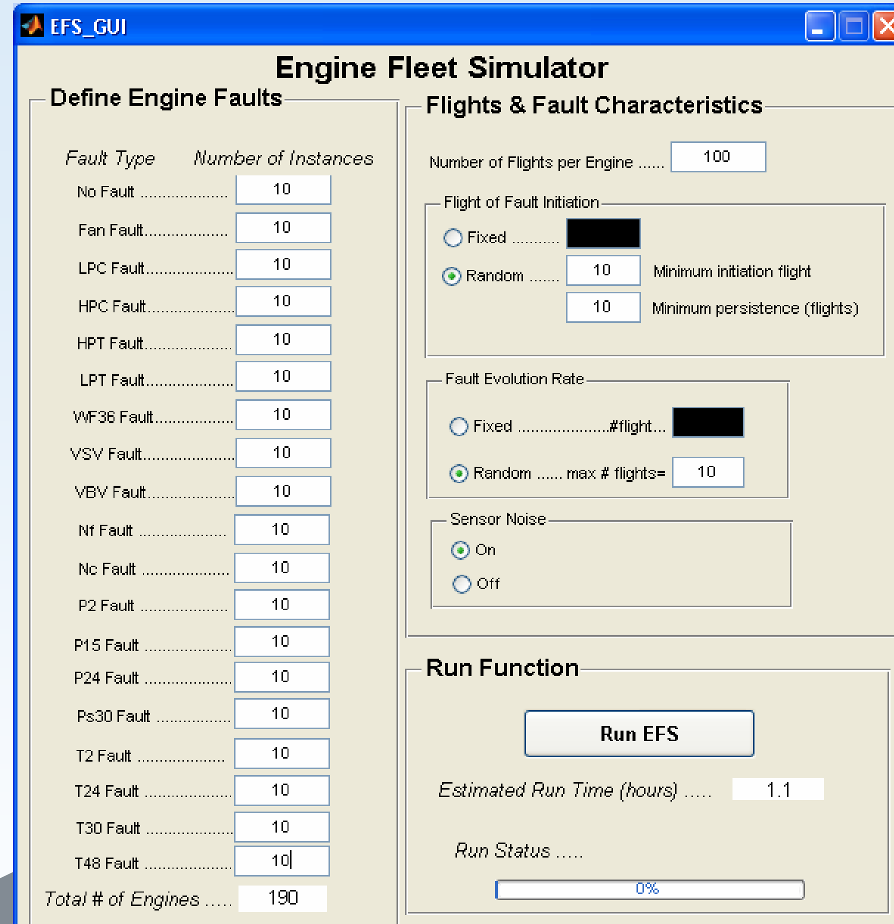


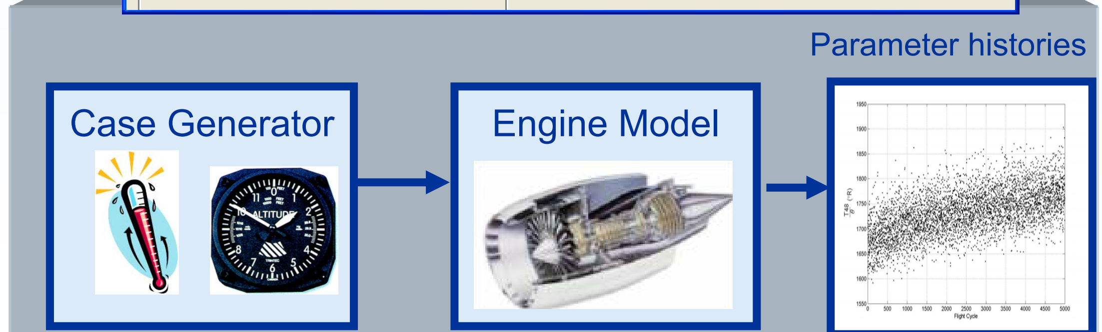
2. Solution providers invited to apply diagnostic approaches given:
- Diagnostic requirements
- System analytical information
- Development & validation datasets
- Blind-test cases
- Example solutions

4. Documentation:
- Document and publish results

Benchmark Diagnostic Problem
Engine Fleet Simulator (EFS)

- Coded as a GUI in Matlab
- EFS generates “snap shot” sensed parameter histories collected from a fleet of engines over their lifetime
- Enables end user to specify …
  - Number of engines in fleet
  - Number of flights per engine
  - Fault / No fault scenarios
    - # of occurrences
    - Flight of fault initiation – fixed or random
    - Fault evolution rate – abrupt or rapid
  - Sensor noise on/off
- Components include …
  - **Case generator** includes random variation effects to produce unique outputs each run
  - **Engine model** receives case generator inputs and produces sensed parameter histories

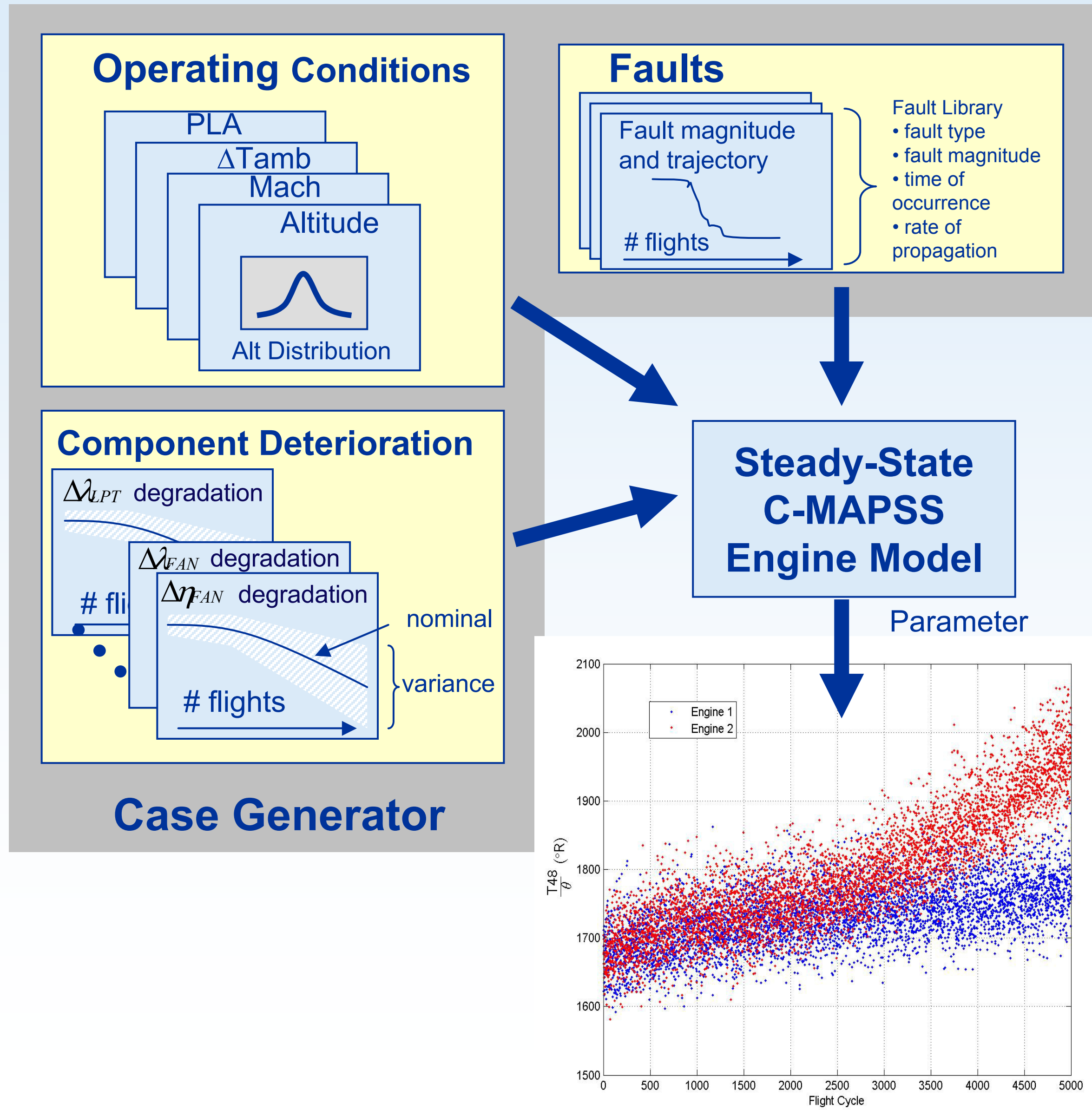




Benchmark Diagnostic Problem
EFS – Case Generator

Case generator includes random variation effects to produce unique outputs each run
- Flight-to-flight variation in altitude, temperature, Mach # and power setting
- Engine-to-engine manufacturing variation
- Unique engine deterioration profile (based on NASA Contractor Reports)
- Sensor noise
- Fault magnitude, rate, time of initiation, and manifestation characteristics

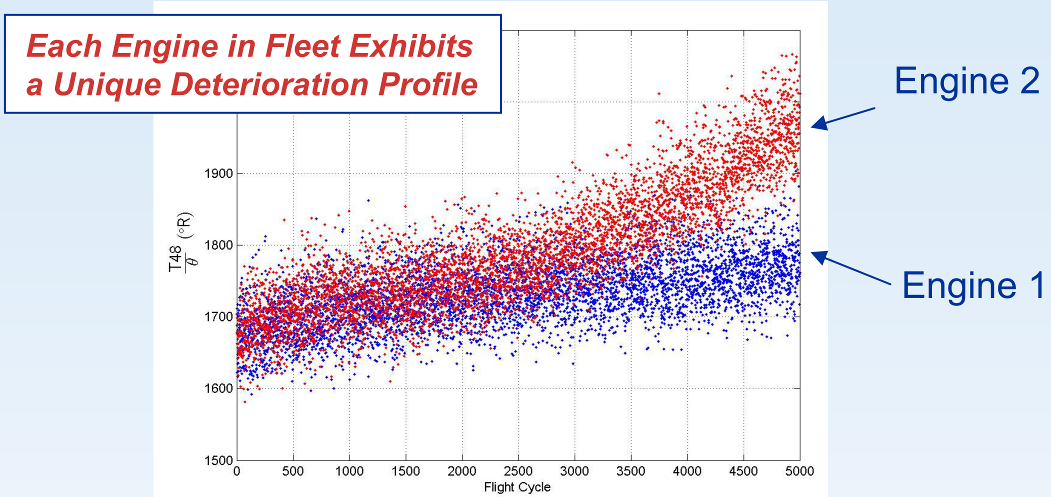
- Case generator inputs provided to steady-state version of NASA C-MAPSS engine model to produce sensed parameter histories



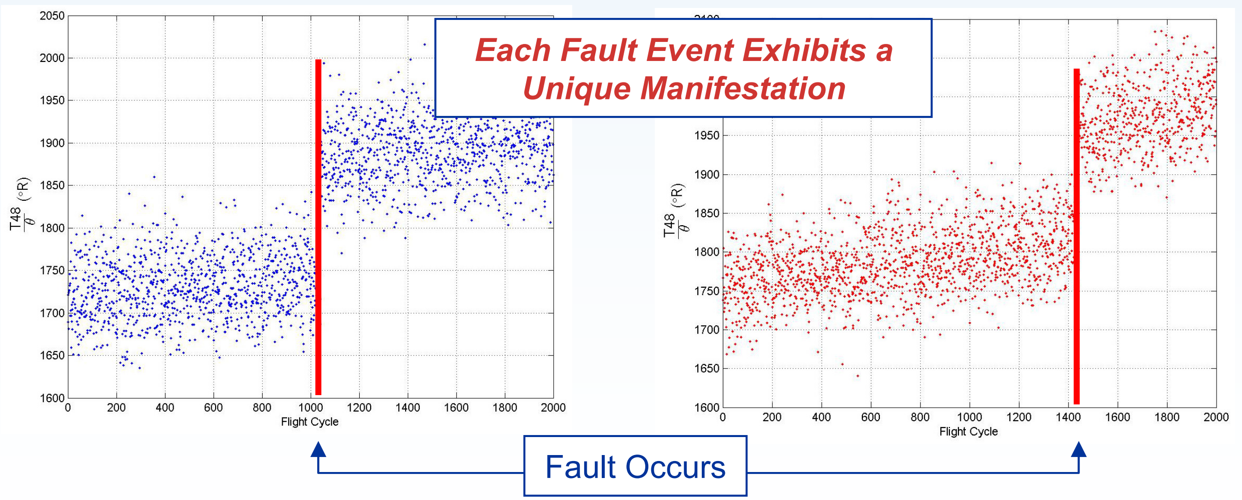
Benchmark Diagnostic Problem
EFS – Parameter Histories

Parameter Histories

- For each engine in fleet consists of:
  - 9 engine sensed outputs, plus T2 and P2
  - Collected at takeoff and cruise
  - Fault information also archived (type, magnitude, flight of initiation, evolution rate)
- Each engine in fleet exhibits unique parameter history due to variation in deterioration and operating conditions
- Each fault event will be unique in terms magnitude and, if specified, flight of occurrence, and propagation rate



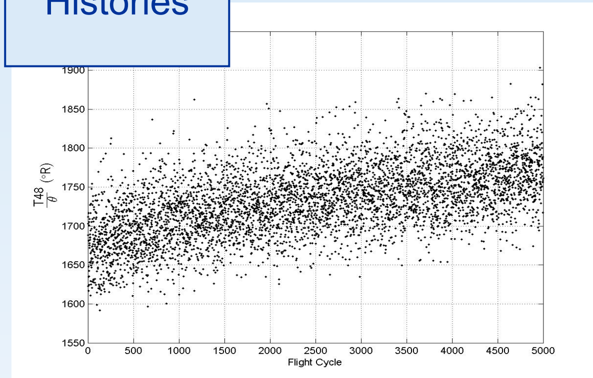
Example of Exhaust Gas Temperature (T48) Histories
(2 engines / No Faults)



Example of T48 Sensor Histories w/ HPT Fault
(Engine 1 (left) and Engine 2 (right))

Benchmark Diagnostic Problem
Solution Process

Parameter Histories

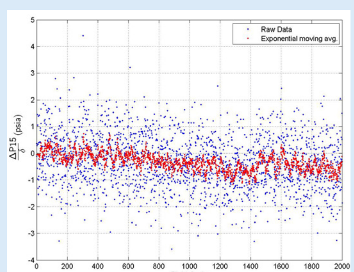


Parameter Correction:
Accounts for variation in ambient conditions at the engine inlet

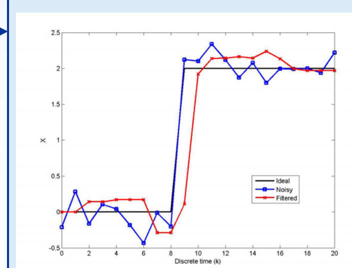
$$N1_C = \frac{N1}{\sqrt{\theta}}$$

$$Wf_c = \frac{Wf}{\sqrt{\theta\delta}}$$

Trend Monitoring:
Monitors trends in engine performance "deltas" relative to established baseline



Event Detection:
Rapid/abrupt trend shift detection logic



Fault/Event Isolation:
Identifies & ranks most plausible root causes for fault/event & estimates fault magnitude

$$e_n = \left[\frac{\sum_{i=1}^{m} \left(\frac{\Delta\Delta_k(i) - \Delta\Delta_k^*(i)}{\sigma_k} \right)^2}{\sum_{i=1}^{m} \Delta\Delta_k^2(i)} \right]^{\frac{1}{2}}$$

Benchmark Diagnostic Problem

Evaluation Metrics

Fault Classification Confusion Matrix

Diagnostic Performance Metrics

Additional Evaluation Metric Considerations:

- Diagnostic latency – for abrupt and rapid faults
- Robustness (to noise / model uncertainty)
- Cost
- Algorithm complexity
- Fault family classification performance

Truth (rows) / Classification (columns)

Fault magnitude	Fault type	Fault 1	Fault 2	…	Fault N	No Fault
Level 1	Fault 1	100%	0%	0%	0%	0%
	Fault 2	0%	100%	0%	0%	0%
	⋮	0%	0%	100%	0%	0%
	Fault N	0%	0%	0%	100%	0%
Level 2	Fault 1	100%	0%	0%	0%	0%
	Fault 2	0%	100%	0%	0%	0%
	⋮	0%	0%	100%	0%	0%
	Fault N	0%	0%	0%	100%	0%
Level 3	Fault 1	100%	0%	0%	0%	0%
	Fault 2	0%	100%	0%	0%	0%
	⋮	0%	0%	100%	0%	0%
	Fault N	0%	0%	0%	100%	0%
	No Fault	0%	0%	0%	0%	100%

Color code > Correct assessment | Miss-classification | Missed-detection | False alarm

Summary

- Beta version of ground-based gas path diagnostic benchmark problem completed
- Will enable side-by-side comparison of candidate diagnostic approaches
- Future steps
  - Define and apply evaluation metrics
  - Advertise and disseminate problem to IVHM community and invite diagnostic solutions (Version 1 release June 2008)
  - Hold workshop to brief/share results
  - Publish workshop proceedings

Integration of On-Line and Off-Line Diagnostic Algorithms for Aircraft Engine Health Management

Tak Kobayashi
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Propulsion Control and Diagnostics Research Under NASA Aeronautics Research Mission Programs

Workshop at Ohio Aerospace Institute, Cleveland OH
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Overview

1. Objective

2. Integration of On-Line and Off-Line Algorithms

3. Application to Aircraft Engine Simulation

4. Performance Evaluation

5. Summary

Objective

Objective

- Develop health management technology for aircraft engines
- Detect faults as early as possible
- Track engine's health condition

Benefits

- Improved safety, performance, efficiency
- Improved maintenance

Challenges

Challenges

- Various fault types

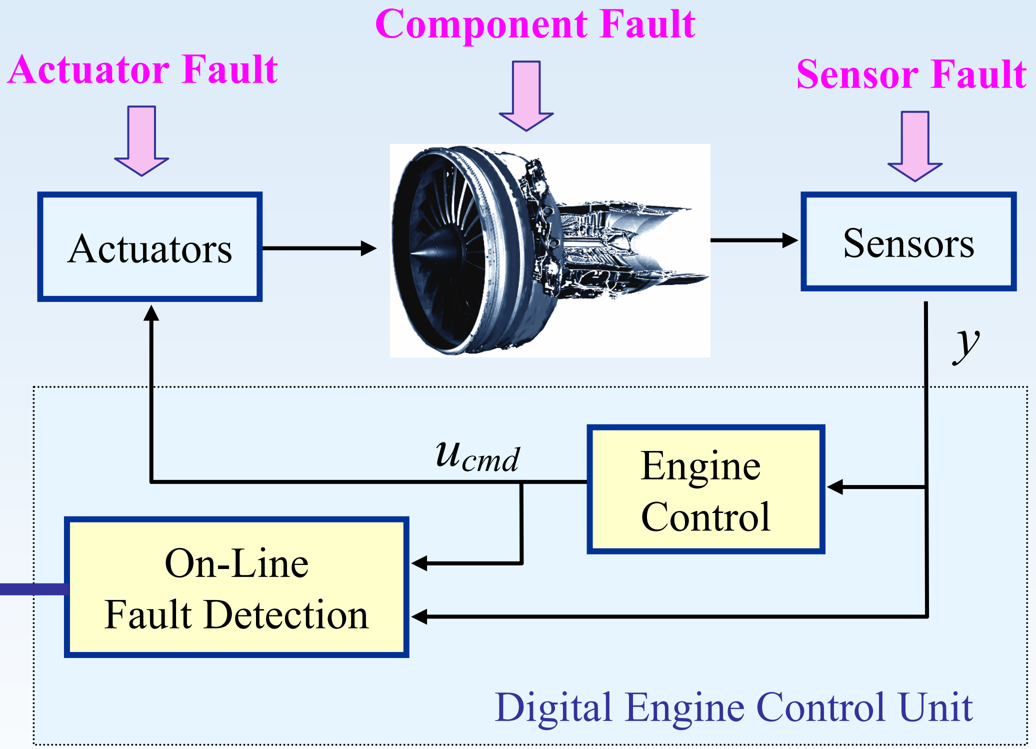
  → Faults in sensors, actuators, components

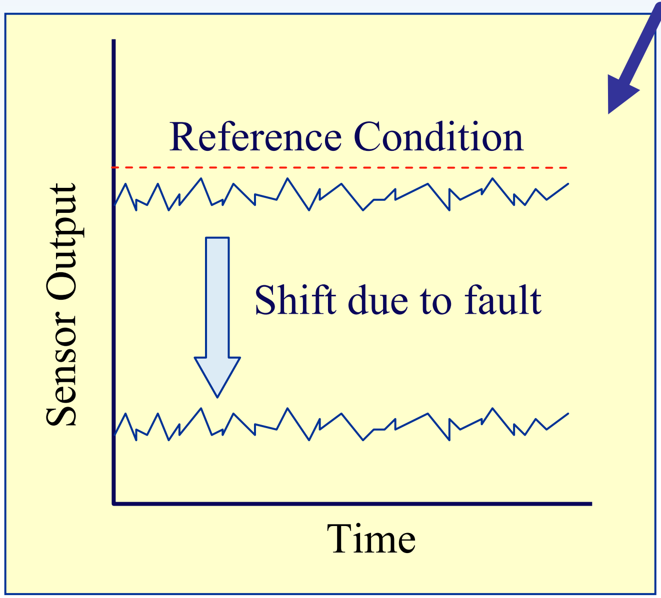
- Component health degradation

Fault → Abnormal, Unexpected Event

Degradation → Normal, Expected Process

Background: On-Line Fault Detection





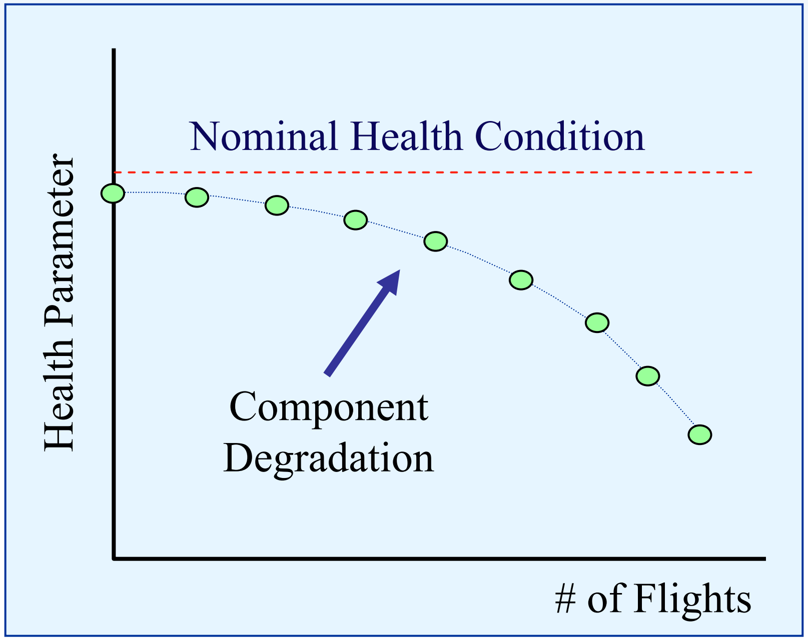
On-Line Fault Detection

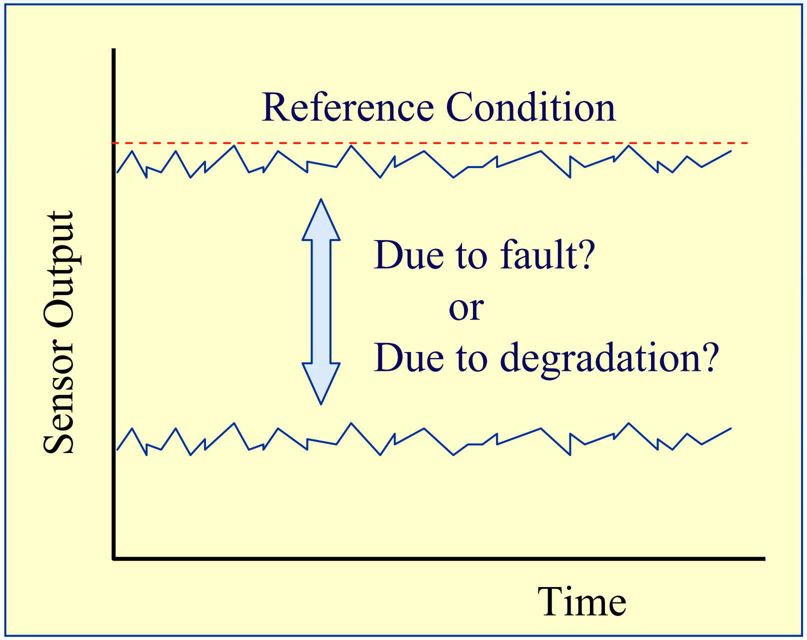
- Diagnostics is based on sensor outputs
- Diagnostic algorithm is designed at a specific health condition (Health Baseline)

Challenge: On-Line Fault Detection

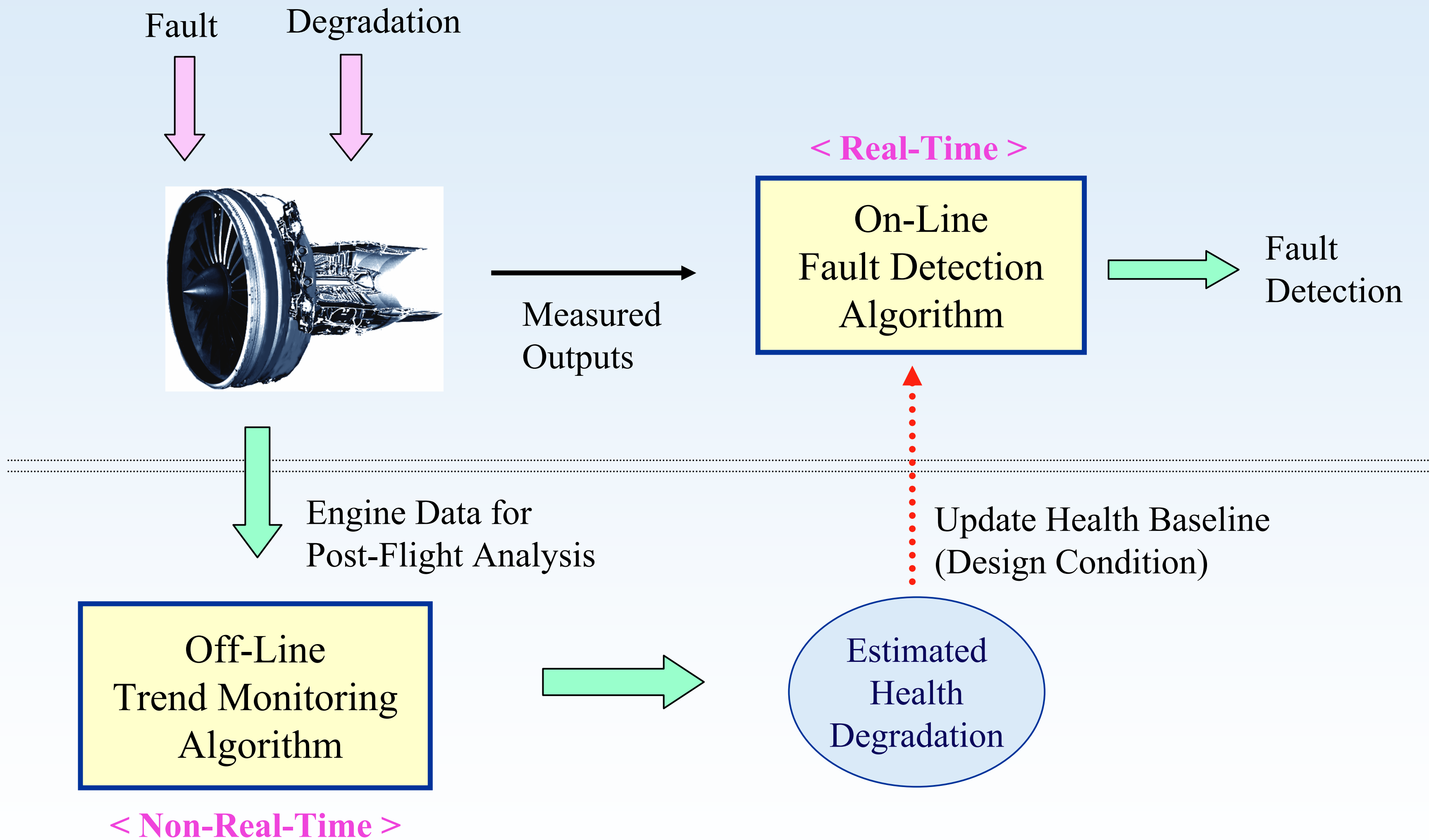
Component Health Degradation:

- Aging process due to usage
- Not a fault
- Results in engine output shifts
- False alarm?
- Missed detection?





Integration: On-Line and Off-Line



Off-Line Trend Monitoring Algorithm

Objective: Estimate health parameters from steady-state sensor outputs

Aircraft Engine

$$Y_k = \bar{g}_{ss}\left(h_k, U_k\right) + V_k$$

$\longrightarrow$ Y_k, U_k $\longrightarrow$ $\hat{h}_k$?

Engine Model

$$\hat{Y}_k = g_{ss}\left(\hat{h}_k, U_k\right)$$

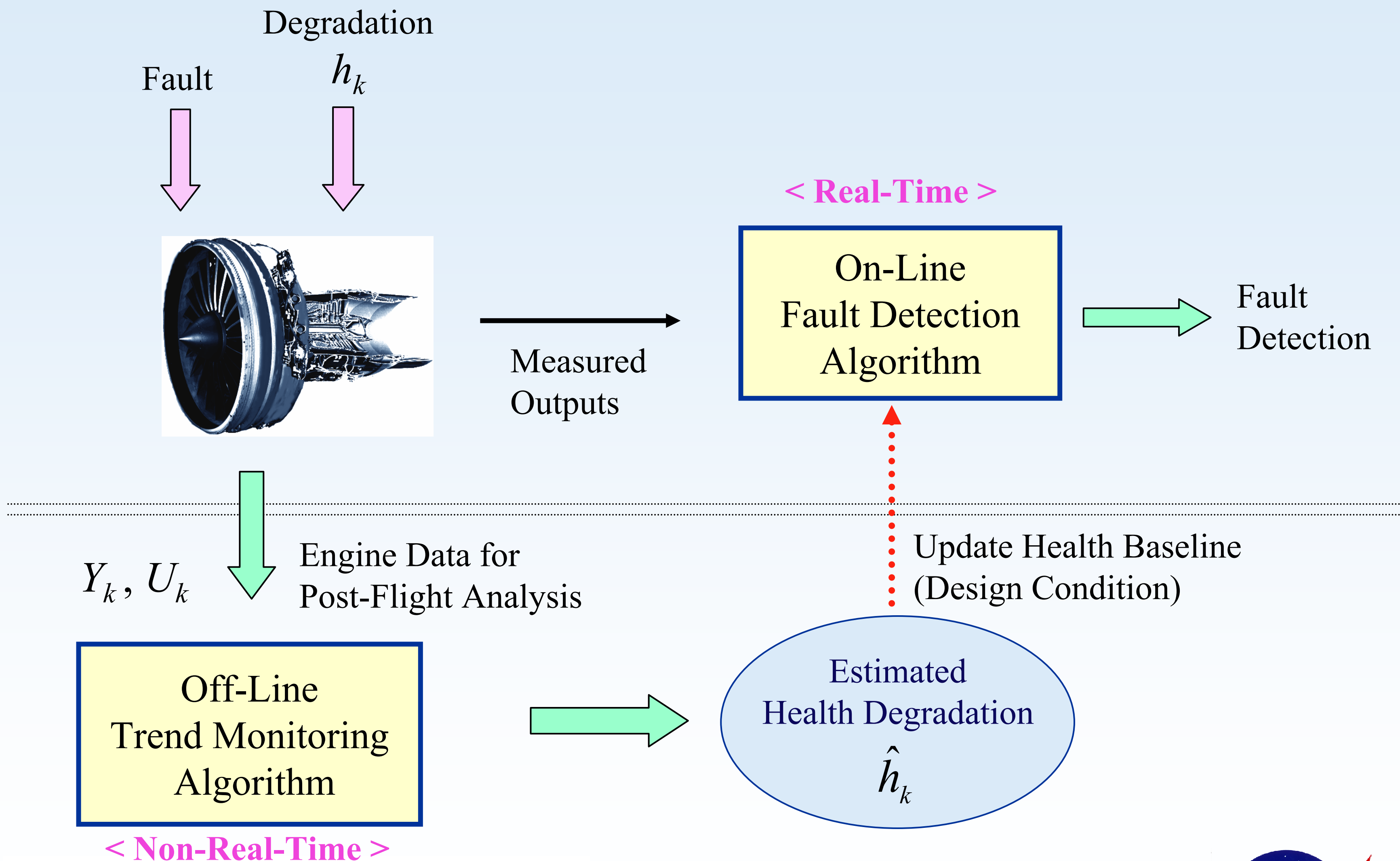
$$\hat{h}_k = \hat{h}_{k-1} + L\left(Y_k - \hat{Y}_{k|k-1}\right)$$

$$\hat{Y}_{k|k-1} = g_{ss}\left(\hat{h}_{k-1}, U_k\right)$$

$$G_{k|k-1} = \frac{\partial}{\partial \hat{h}} g_{ss}\left(\hat{h}_{k-1}, U_k\right)$$

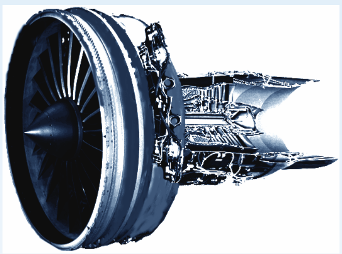
$$L = P_0 G_{k|k-1}^T \left(G_{k|k-1} P_0 G_{k|k-1}^T + R\right)^{-1}$$

Integration of On-Line and Off-Line Algorithms



On-Line Fault Detection Algorithm: Kalman Filter Based Approach

Engine at Nominal Condition



Control System

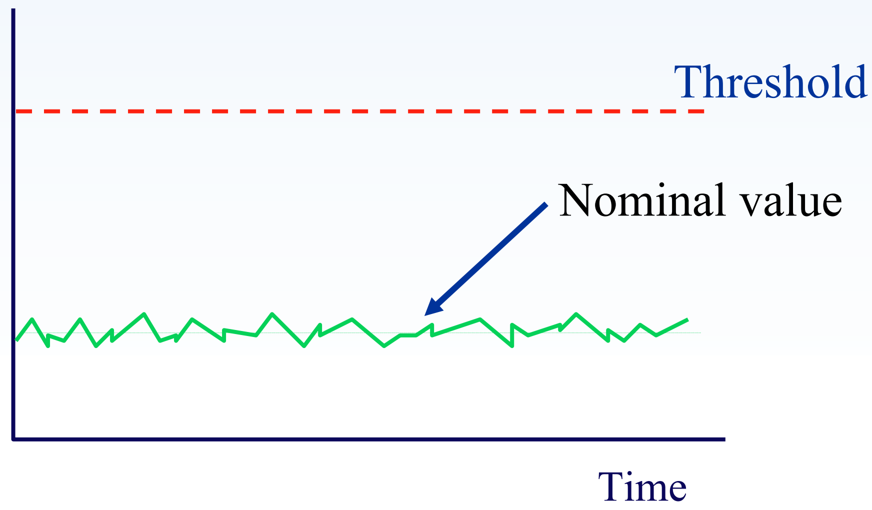
y

u_{cmd}

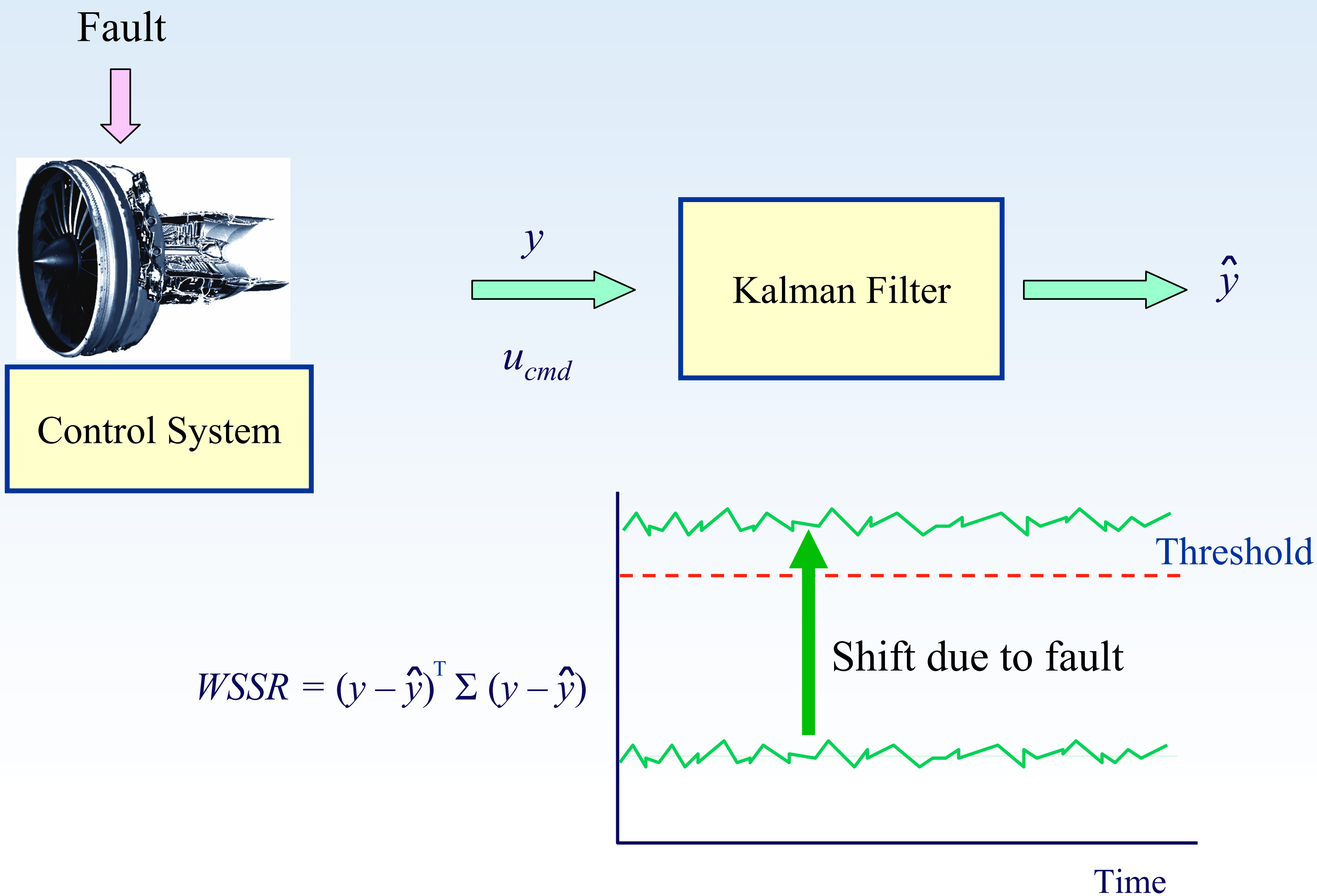
Kalman Filter

$\hat{y}$

$$WSSR = (y - \hat{y})^T \, \Sigma \, (y - \hat{y})$$

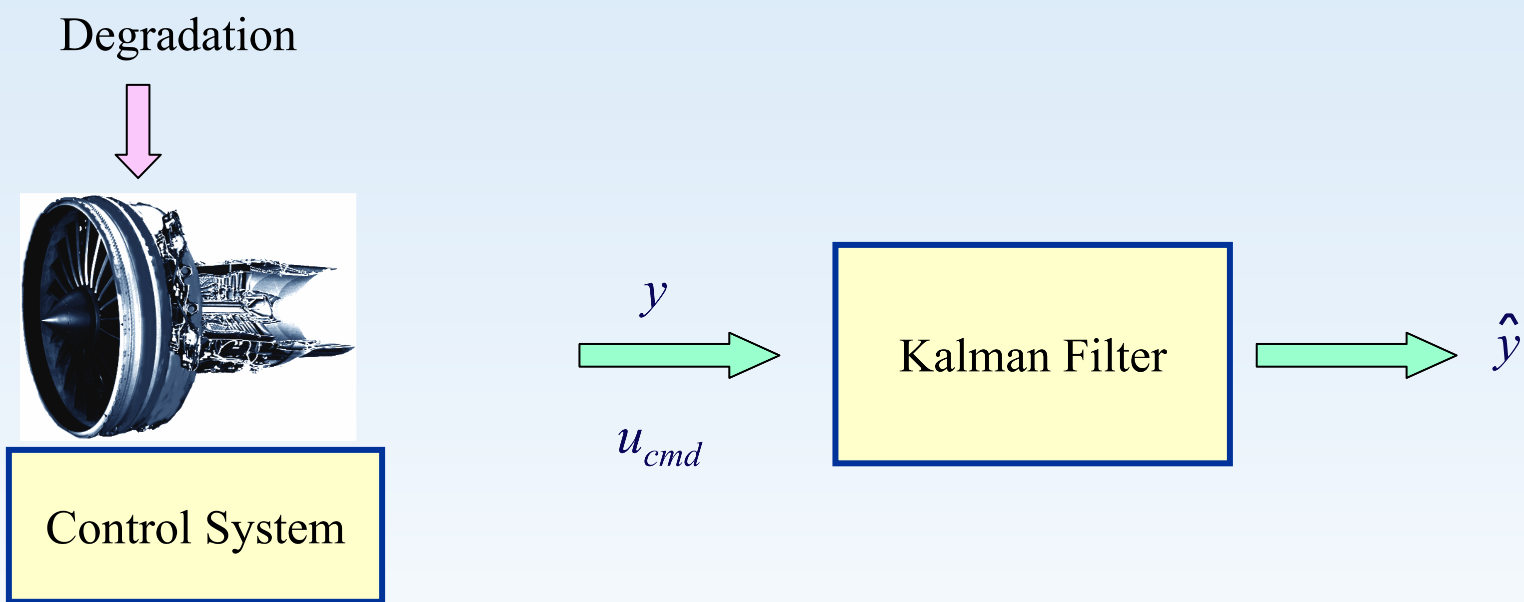


On-Line Fault Detection Algorithm: Kalman Filter Based Approach

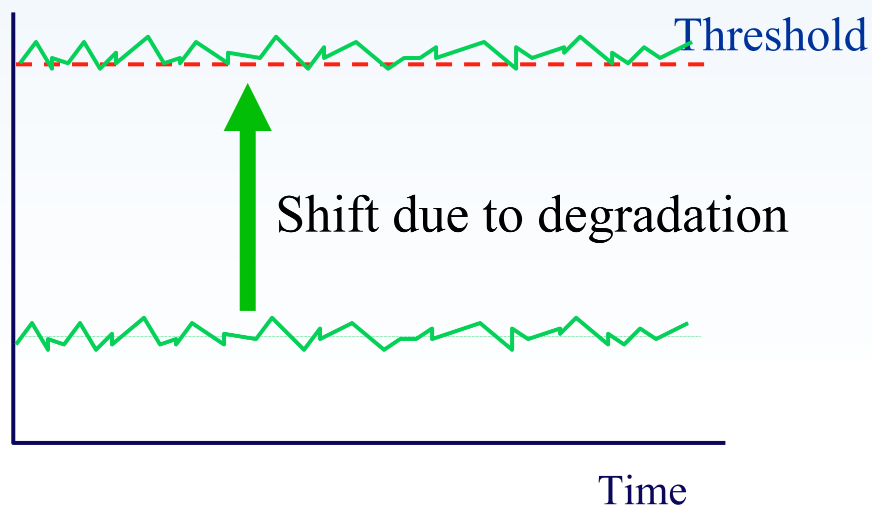


$$WSSR = (y - \hat{y})^{T} \, \Sigma \, (y - \hat{y})$$

On-Line Fault Detection Algorithm: Kalman Filter Based Approach
Challenge due to Health Degradation

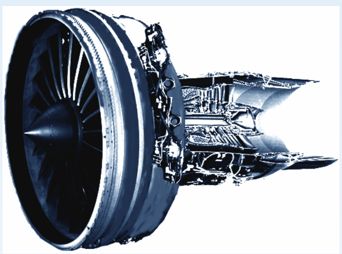


$$WSSR = (y - \hat{y})^{T} \Sigma (y - \hat{y})$$



On-Line Fault Detection Algorithm: Kalman Filter Based Approach
Health Baseline Update

Degradation



Control System

y

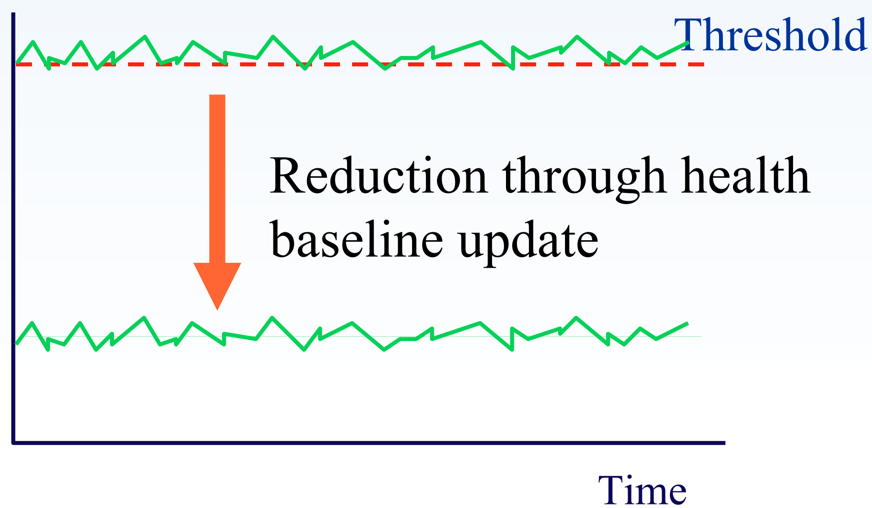
u_{cmd}

Update Using $\hat{h}_k$

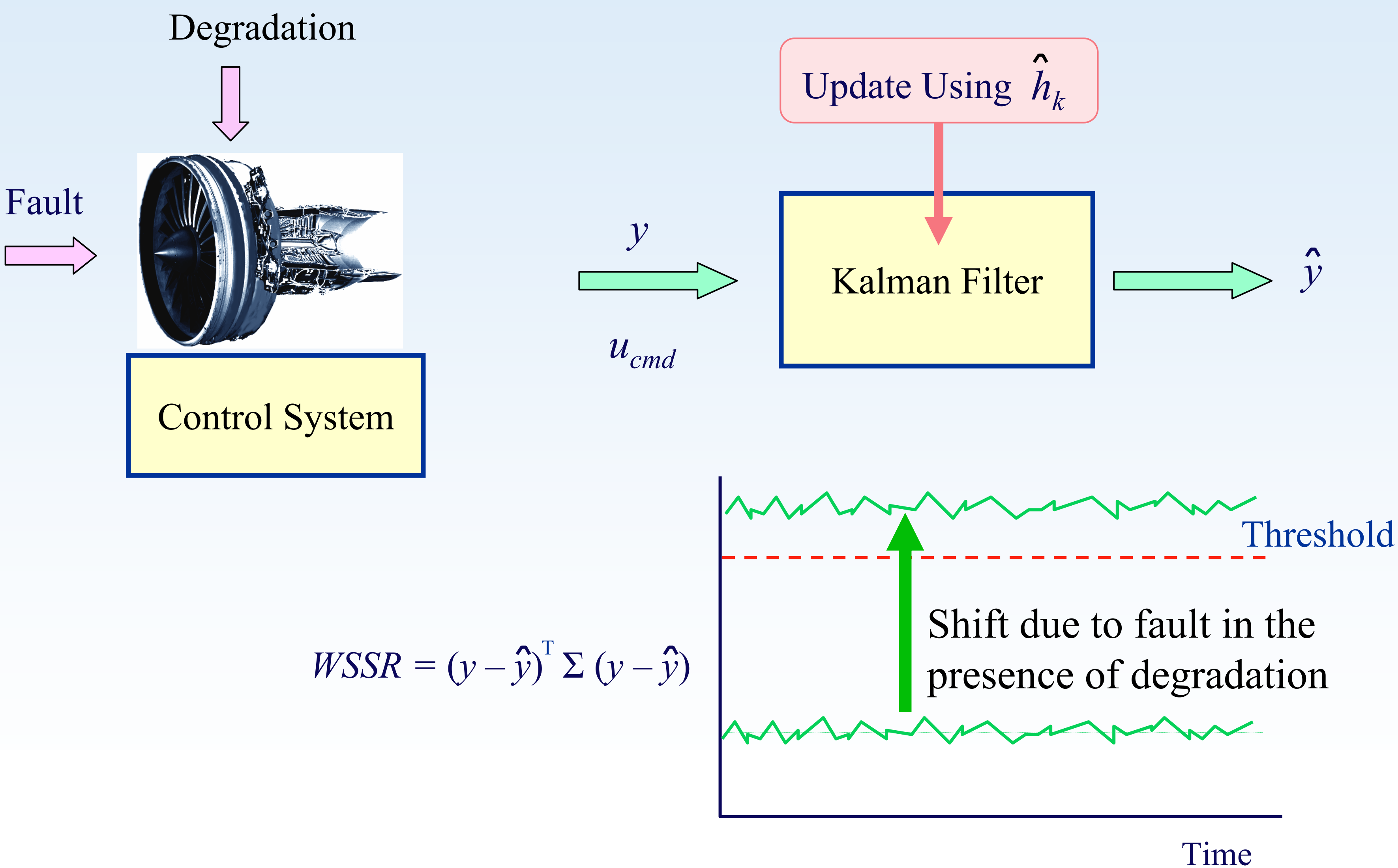
Kalman Filter

$\hat{y}$

$$WSSR = (y - \hat{y})^T \Sigma (y - \hat{y})$$



On-Line Fault Detection Algorithm: Kalman Filter Based Approach
Fault Detection in the Presence of Health Degradation



On-Line Fault Detection Algorithm: Hybrid Kalman Filter Technique

Aircraft Engine

$$\dot{x} = \bar{f}\left(x, h_k, u_{cmd}\right)$$
$$y = \bar{g}\left(x, h_k, u_{cmd}\right) + v$$

y, u_{cmd}

Hybrid Kalman Filter

$$\dot{x}_{OBEM} = f\left(x_{OBEM}, h_{OBEM}, u_{cmd}\right)$$
$$y_{OBEM} = g\left(x_{OBEM}, h_{OBEM}, u_{cmd}\right)$$

$$h_{OBEM} = \hat{h}_k$$

$$\dot{\hat{x}} = A\left(\hat{x} - x_{OBEM}\right) + K\left(y - \hat{y}\right)$$
$$\hat{y} = C\left(\hat{x} - x_{OBEM}\right) + y_{OBEM}$$

Off-Line Trend Monitoring Algorithm

$$WSSR = (y - \hat{y})^{\mathrm{T}}\, \Sigma\, (y - \hat{y})$$

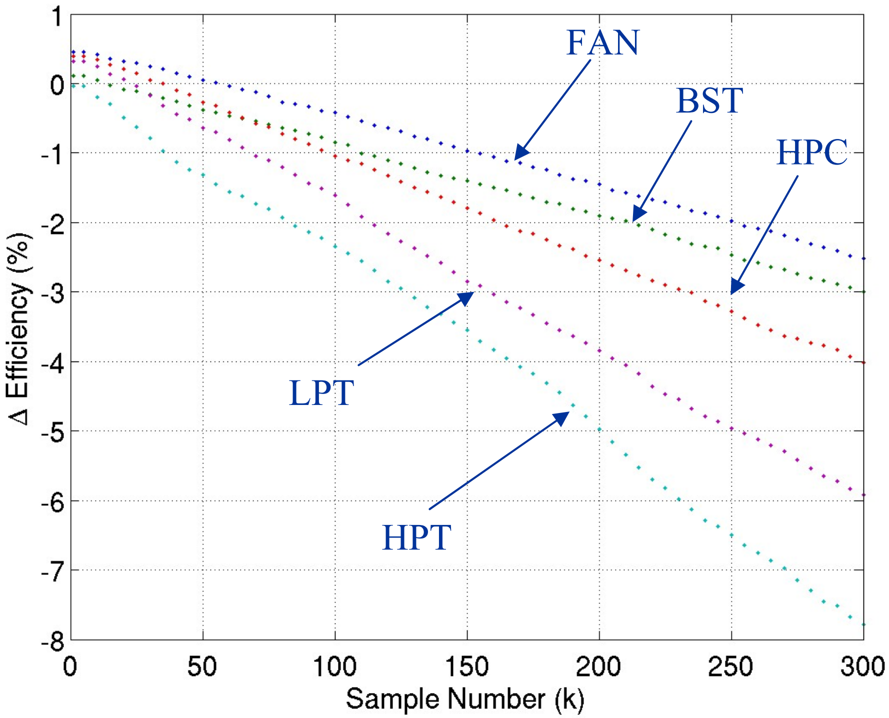
Application to Aircraft Engine Simulation

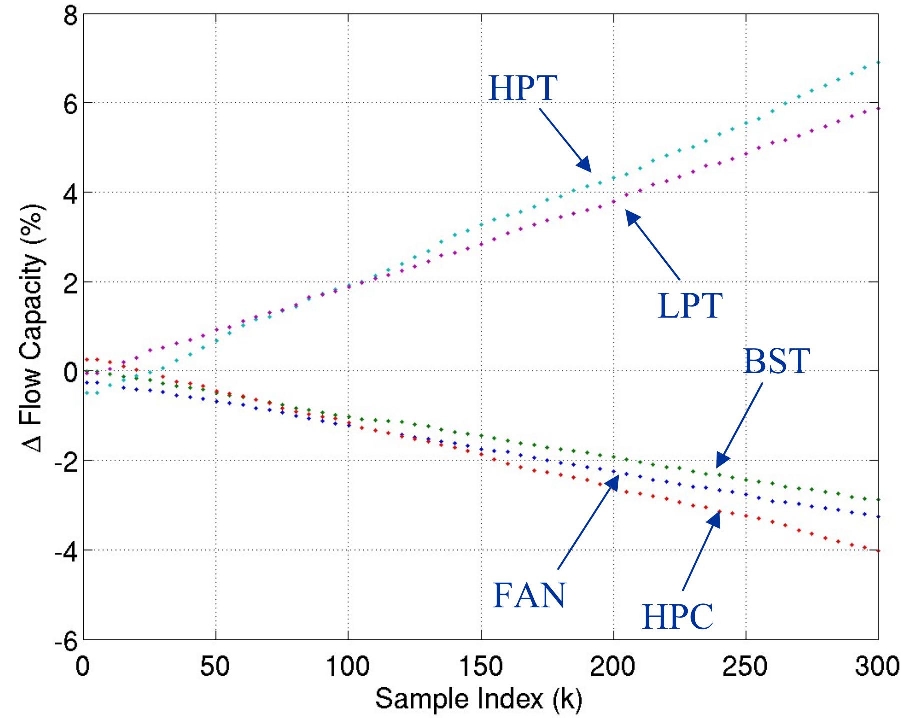
Advanced High-Bypass Commercial Aircraft Engine Simulation

- Non-linear engine model with real-time execution capability
- 5 Rotating Components (FAN, BST, HPC, HPT, LPT)

State Variables (x)	**Health Parameters** (h)	**Actuators** (u_{cmd})	**Sensors** (y)
XNL	FAN efficiency	WF36	XN12
XNH	FAN flow capacity	VBV	XN25
TMH23	BST efficiency	VSV	P25
TMH3	BST flow capacity		T25
TMHBL	HPC efficiency		PS3
TMHBC	HPC flow capacity		T3
TMH41	HPT efficiency		T49
TMH42	HPT flow capacity		
TMH5	LPT efficiency		
	LPT flow capacity		

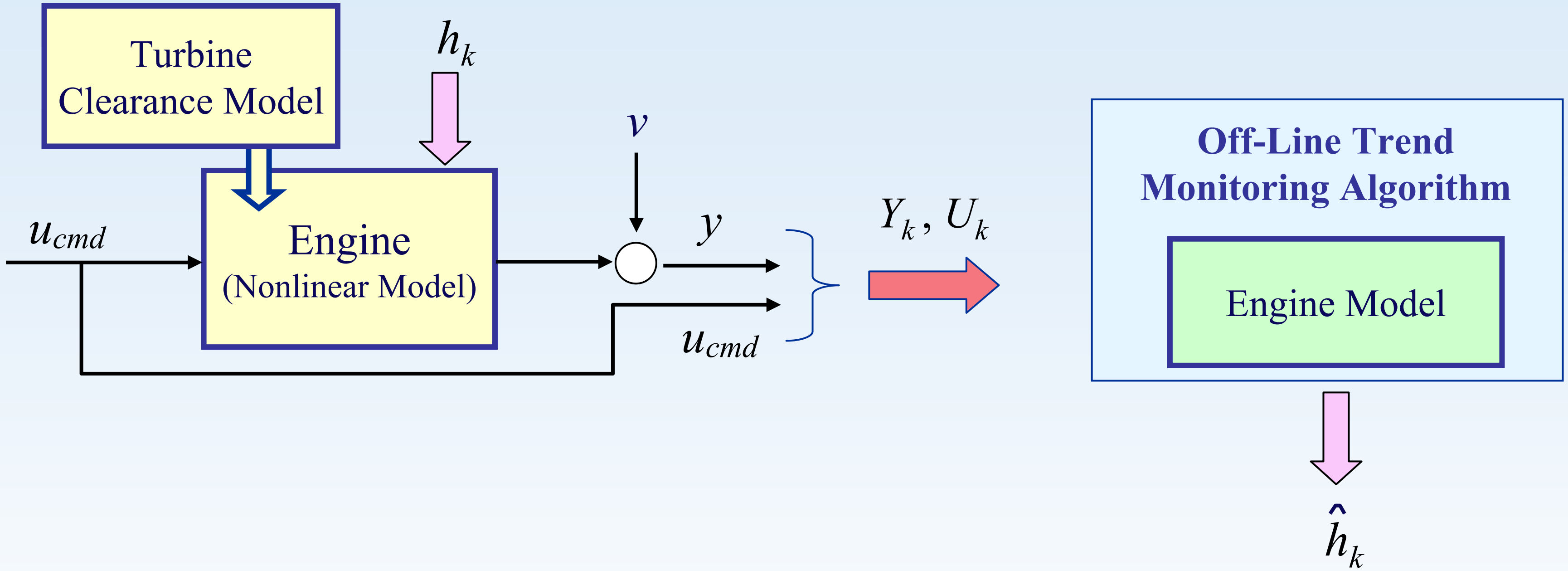
Health Degradation Profile





Engine's life span

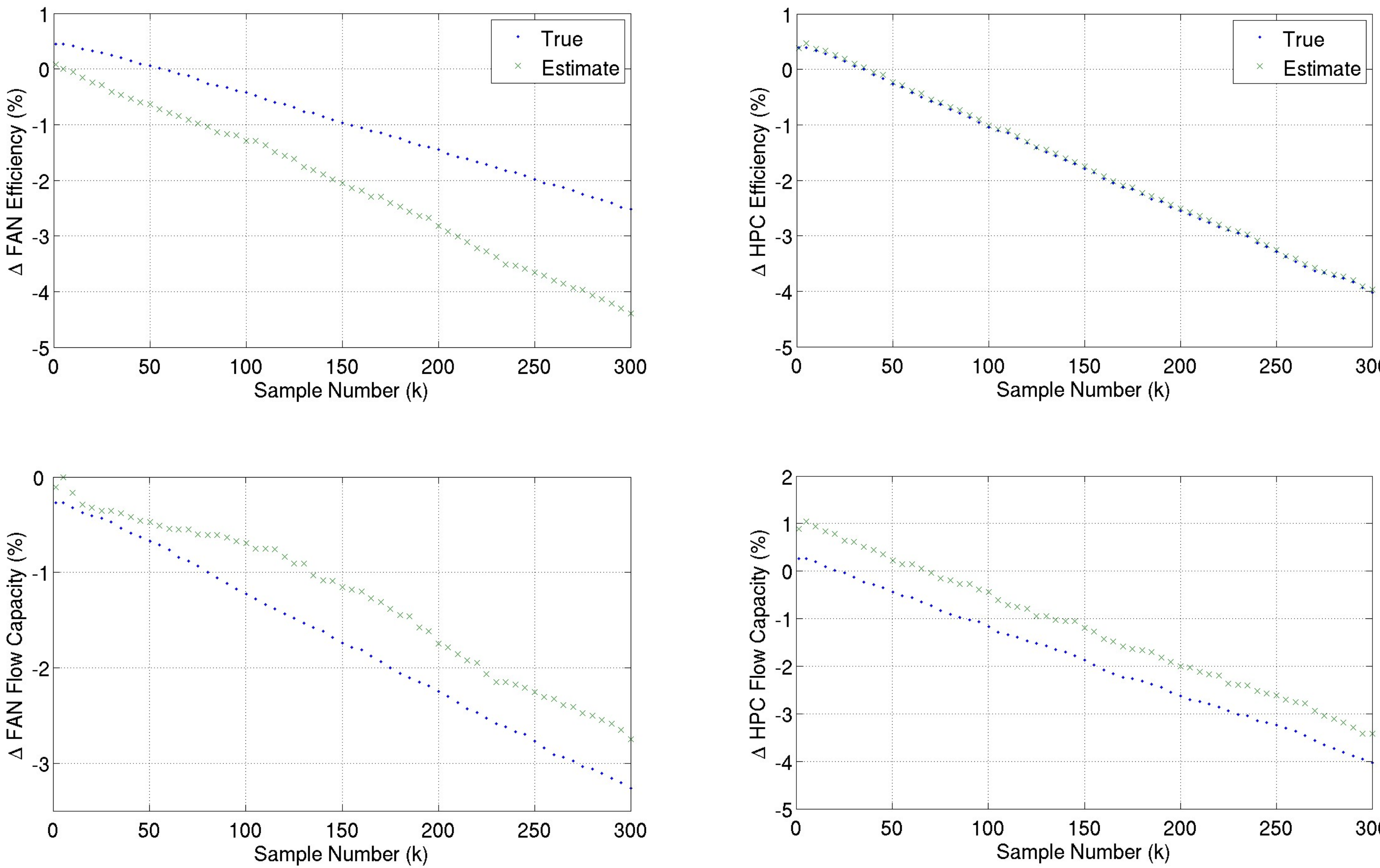
Performance Evaluation: Off-Line Algorithm



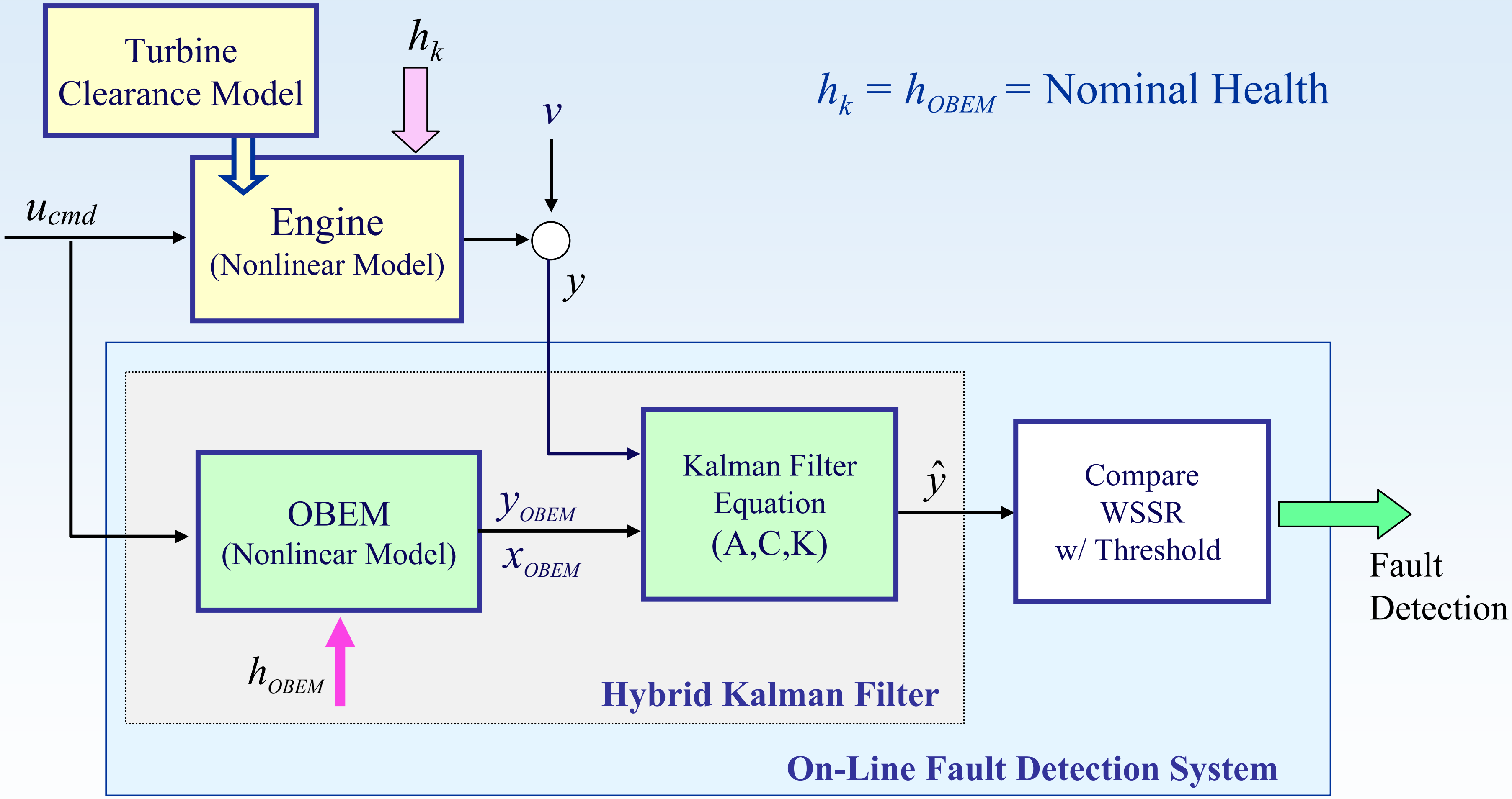
Snapshot data (Y_k, U_k) generated for post-flight analysis:

- Ran the engine at steady-state cruise condition
- Recorded engine output data for one second
- Averaged "one-second" data

Performance Evaluation: Off-Line Algorithm



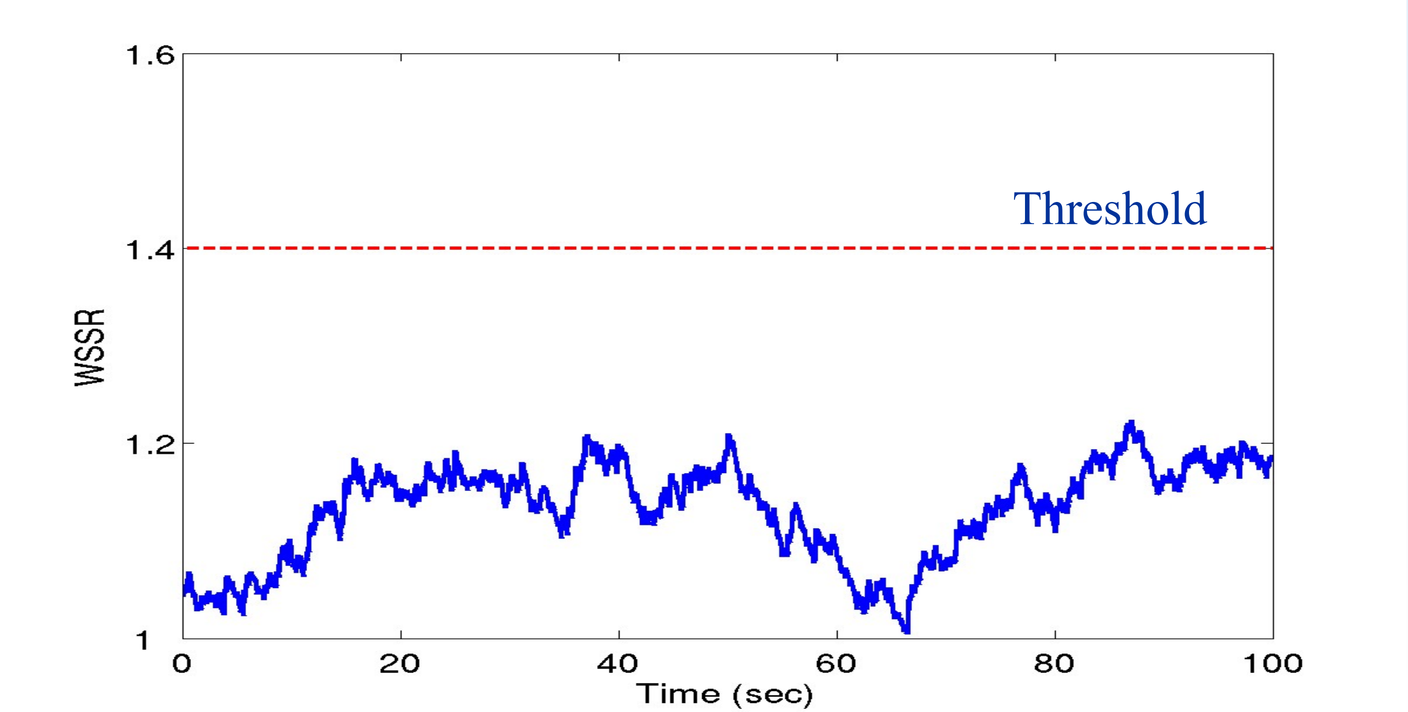
Performance Evaluation: On-Line Algorithm



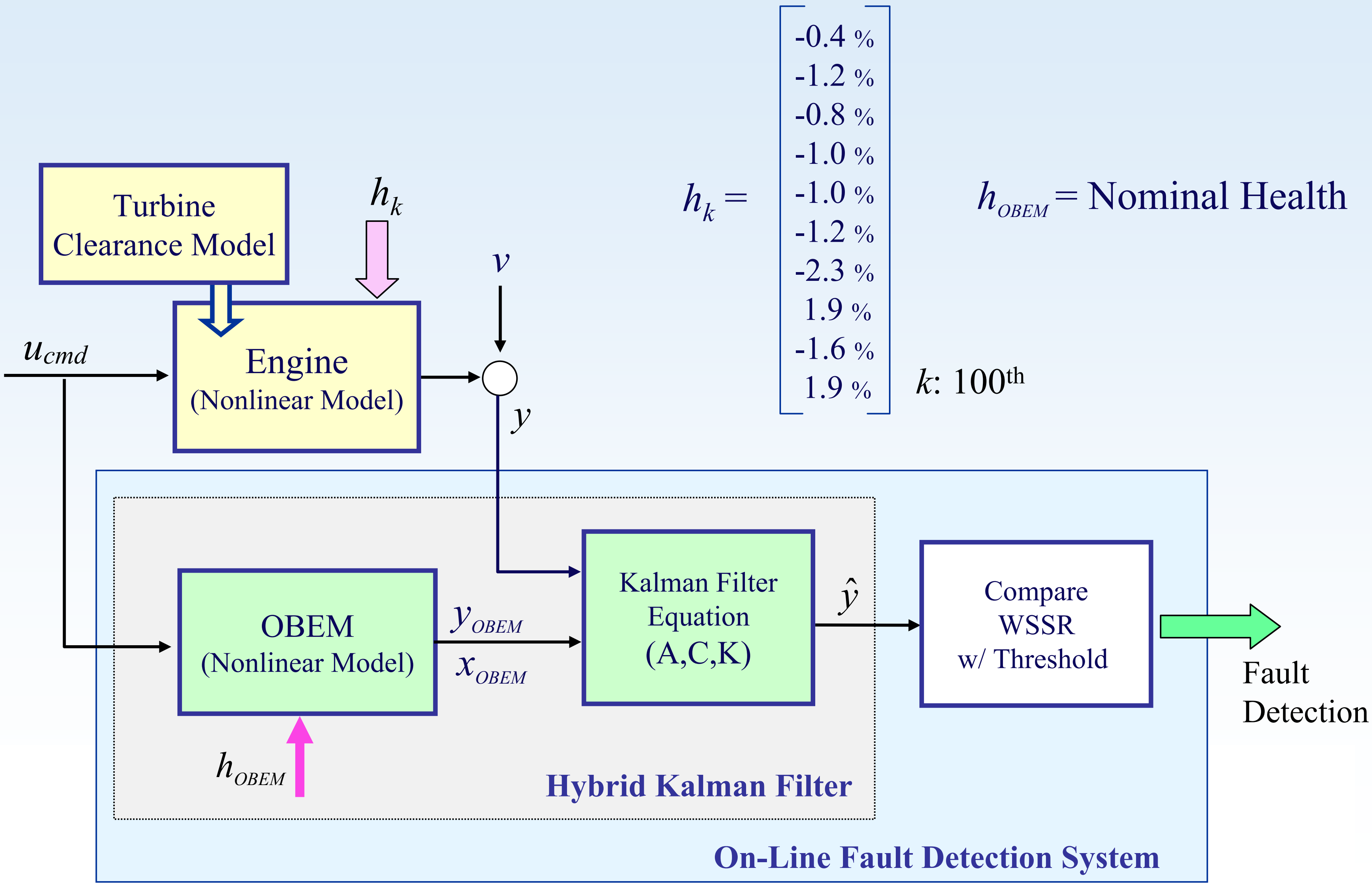
Performance Evaluation: On-Line Algorithm

Engine: Nominal Health Condition

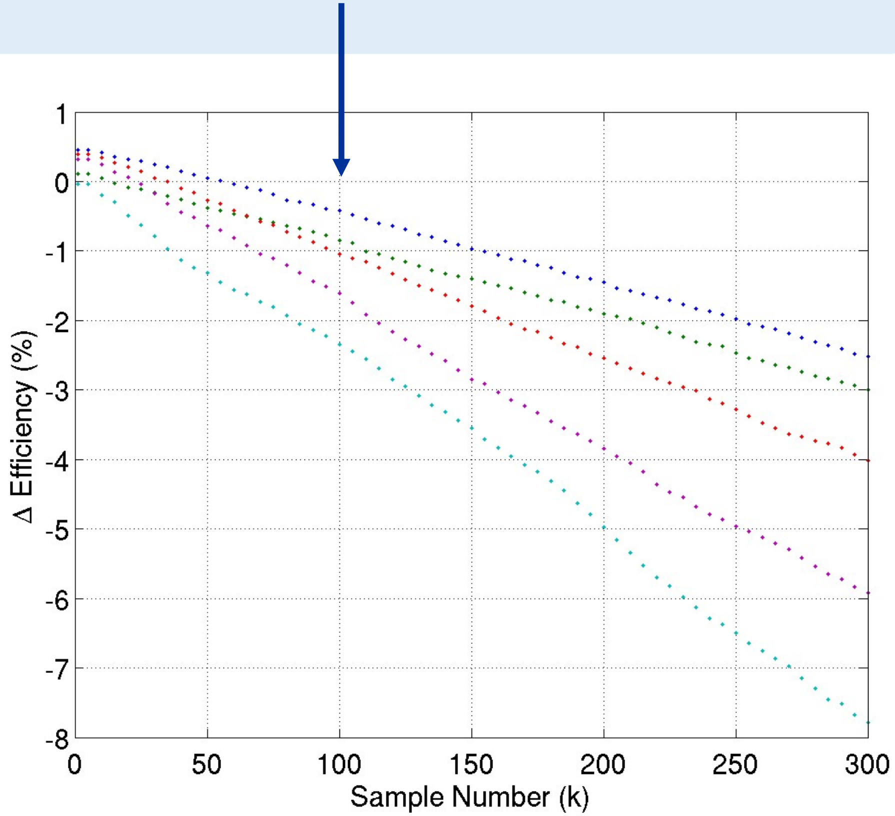
OBEM: Nominal Health Baseline

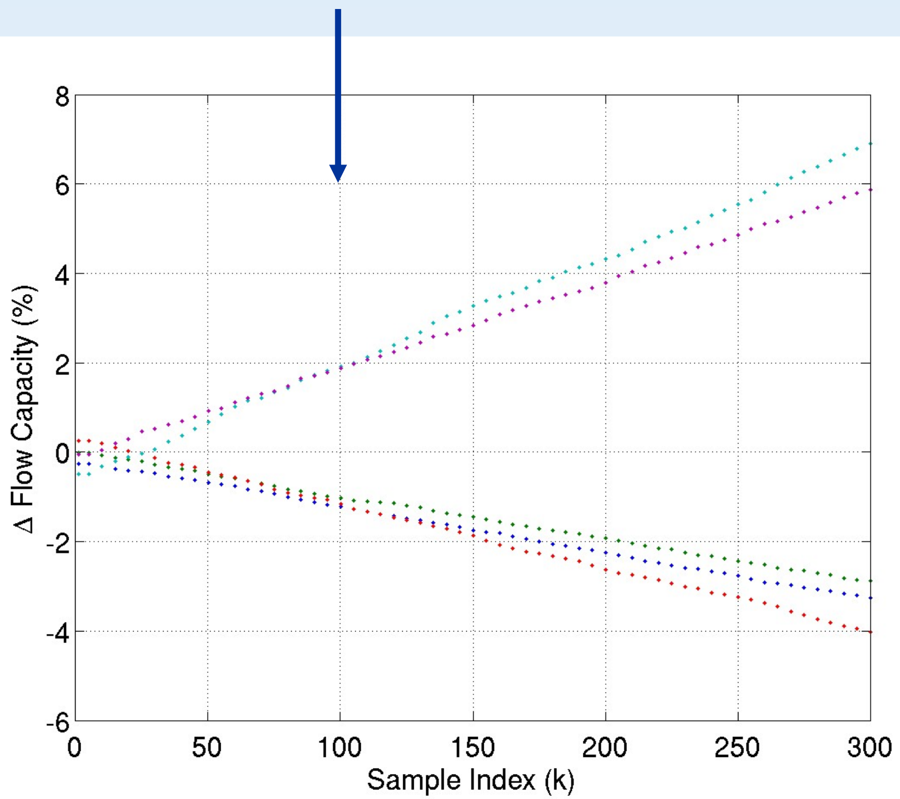


Performance Evaluation: On-Line Algorithm



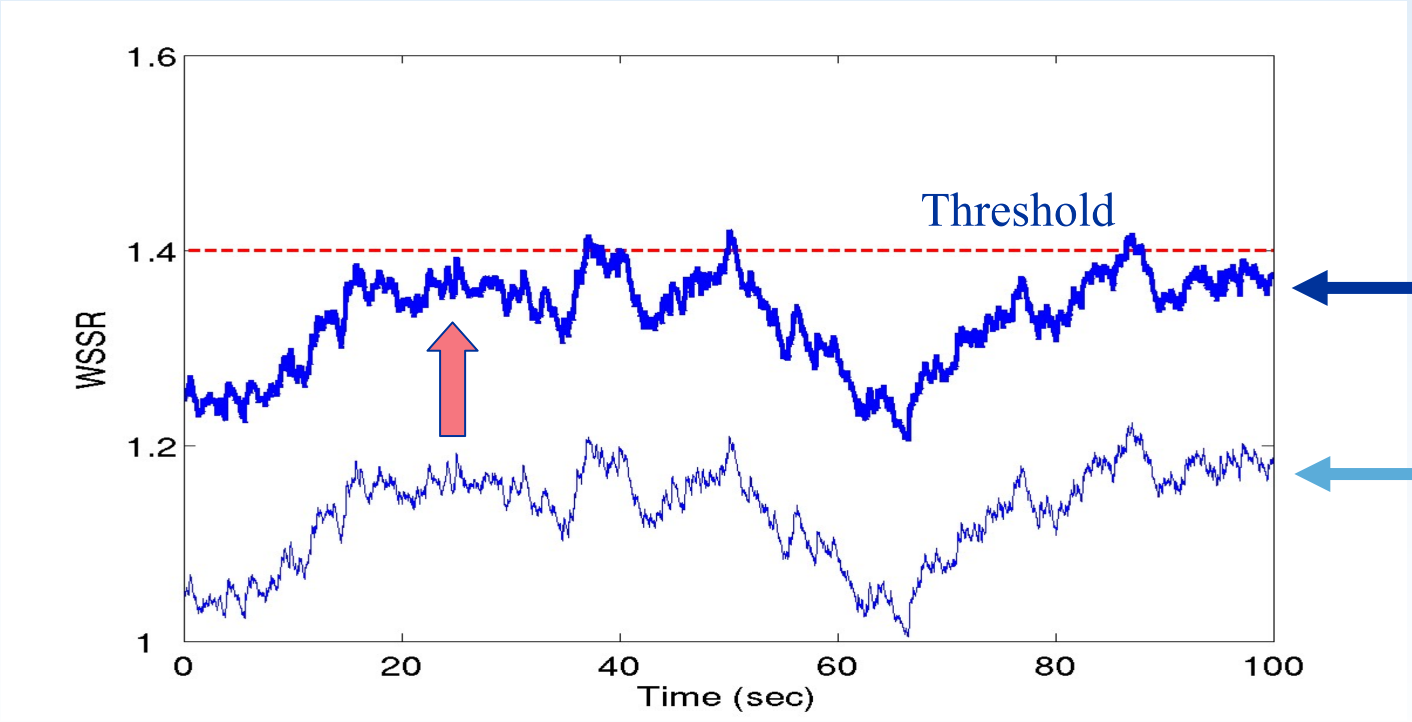
Performance Evaluation: On-Line Algorithm





Performance Evaluation: On-Line Algorithm

OBEM: Nominal Health Baseline

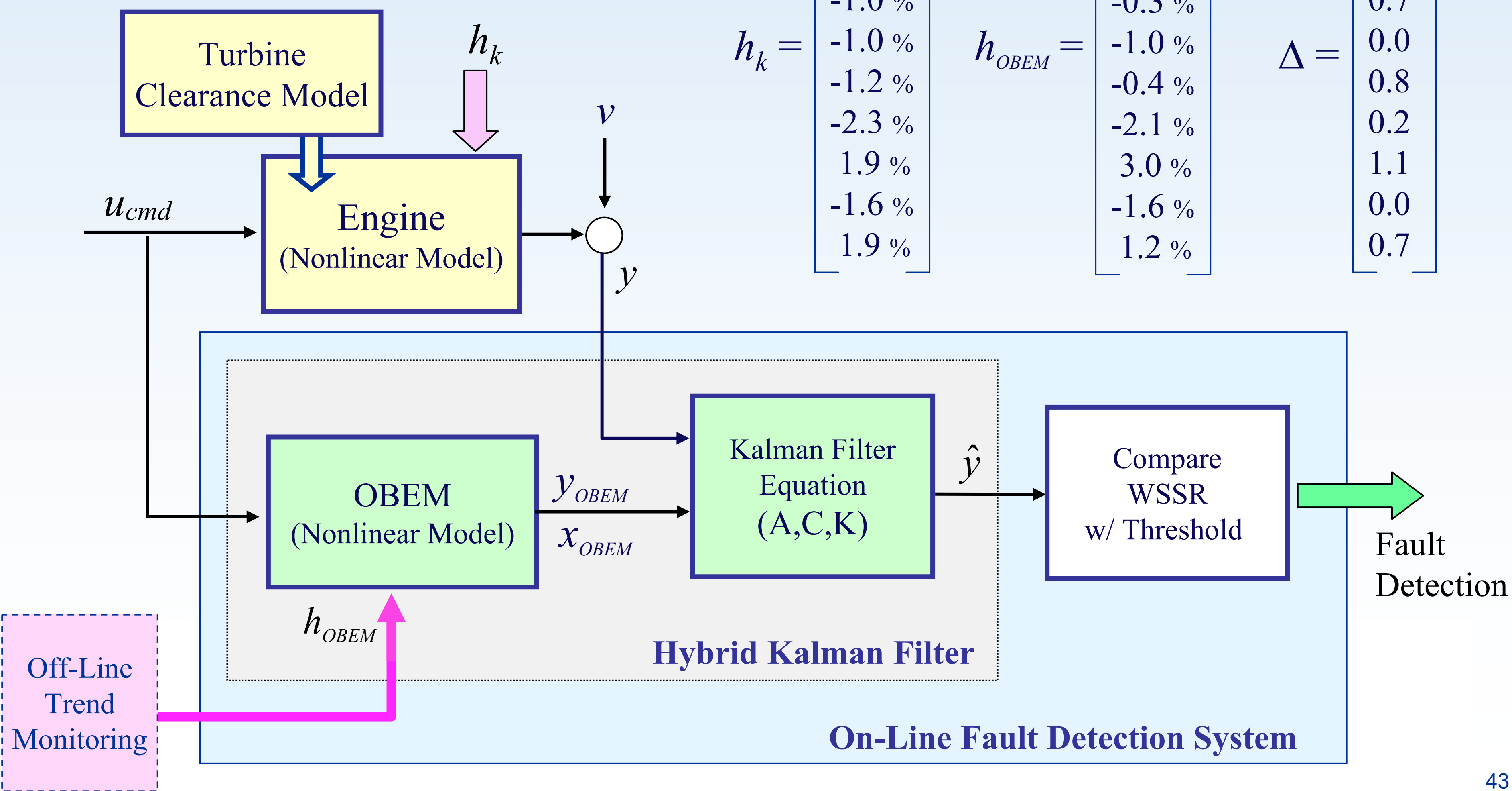


Degraded Engine

Nominal Engine

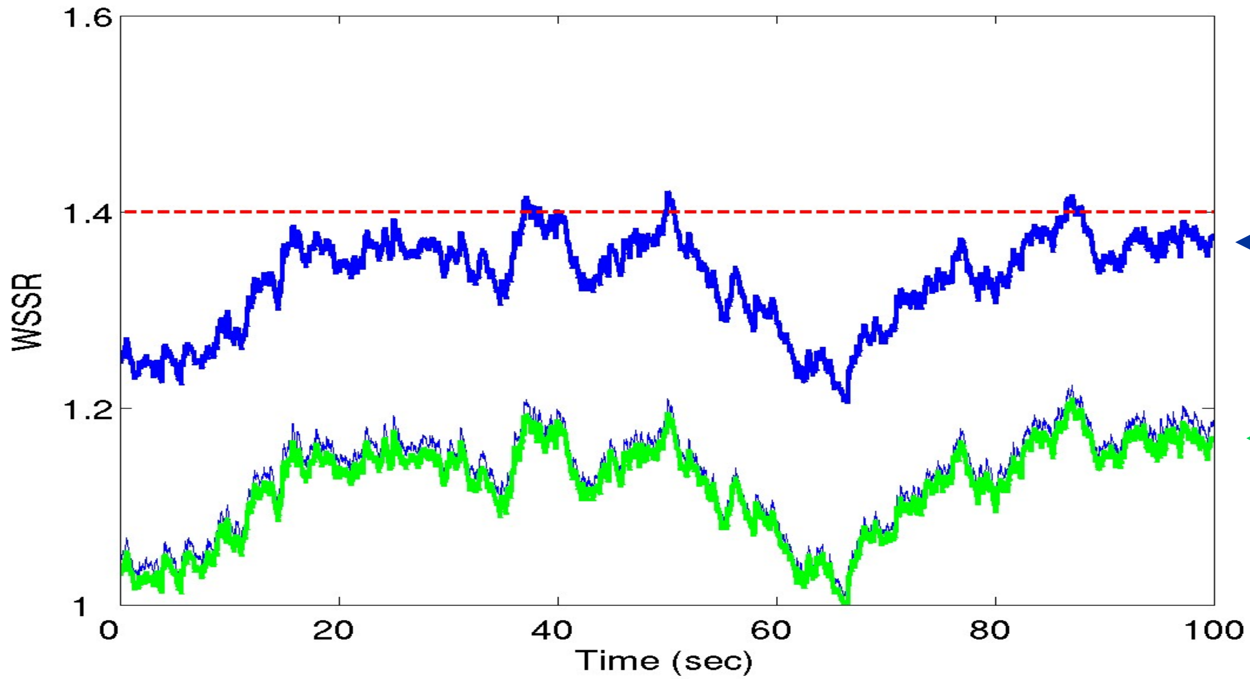
Performance Evaluation: On-Line Algorithm

$$h_k = \begin{bmatrix} -0.4\ \% \\ -1.2\ \% \\ -0.8\ \% \\ -1.0\ \% \\ -1.0\ \% \\ -1.2\ \% \\ -2.3\ \% \\ 1.9\ \% \\ -1.6\ \% \\ 1.9\ \% \end{bmatrix} \qquad h_{OBEM} = \begin{bmatrix} -1.3\ \% \\ -0.7\ \% \\ -0.3\ \% \\ -0.3\ \% \\ -1.0\ \% \\ -0.4\ \% \\ -2.1\ \% \\ 3.0\ \% \\ -1.6\ \% \\ 1.2\ \% \end{bmatrix} \qquad \Delta = \begin{bmatrix} 0.9 \\ 0.5 \\ 0.5 \\ 0.7 \\ 0.0 \\ 0.8 \\ 0.2 \\ 1.1 \\ 0.0 \\ 0.7 \end{bmatrix}$$



Performance Evaluation: On-Line Algorithm

Engine: Degraded Health Condition



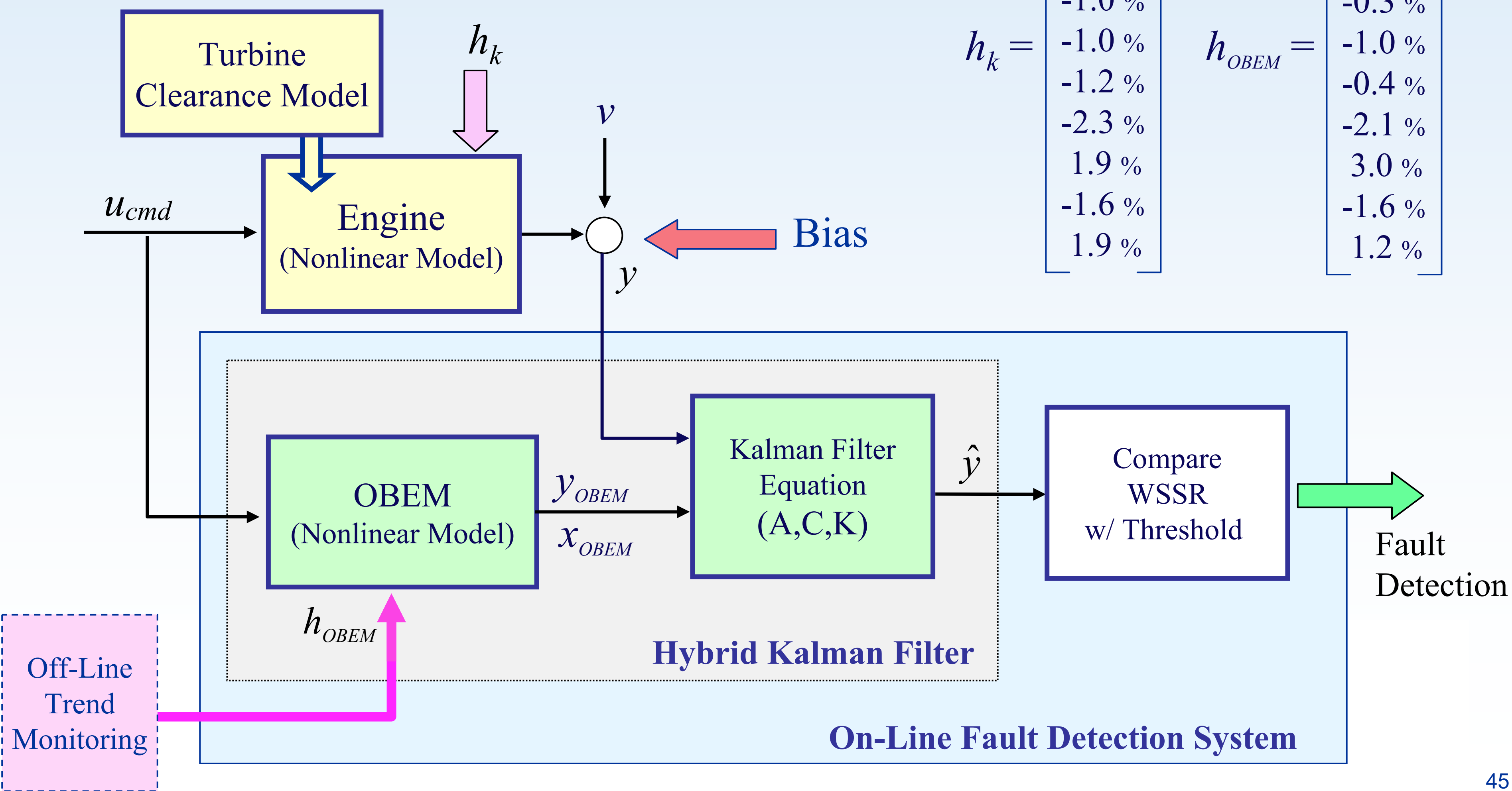
Before Update

After Update

$$h_{OBEM} = \hat{h}_k$$

Performance Evaluation: On-Line Algorithm

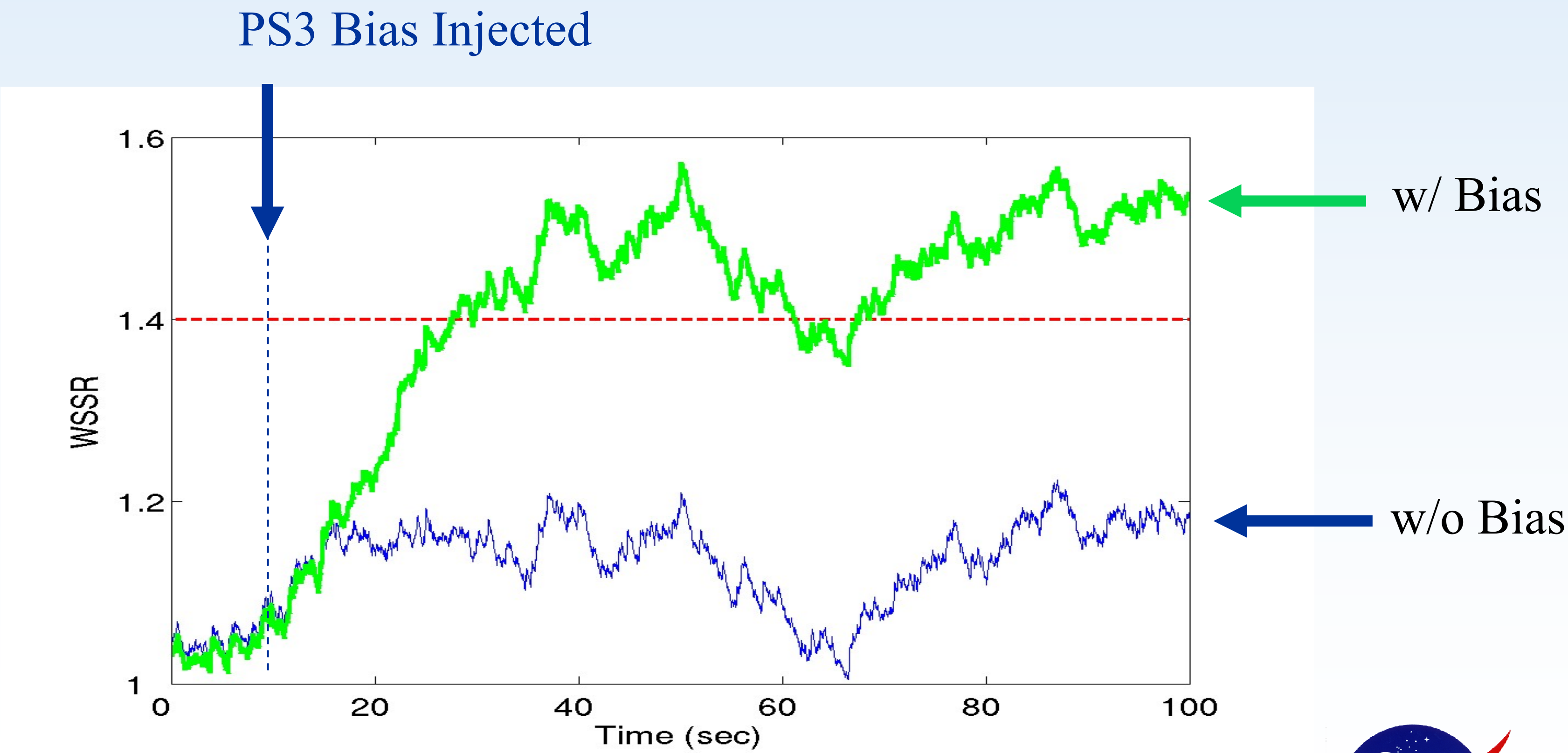
$$h_k = \begin{bmatrix} -0.4\ \% \\ -1.2\ \% \\ -0.8\ \% \\ -1.0\ \% \\ -1.0\ \% \\ -1.2\ \% \\ -2.3\ \% \\ 1.9\ \% \\ -1.6\ \% \\ 1.9\ \% \end{bmatrix} \qquad h_{OBEM} = \begin{bmatrix} -1.3\ \% \\ -0.7\ \% \\ -0.3\ \% \\ -0.3\ \% \\ -1.0\ \% \\ -0.4\ \% \\ -2.1\ \% \\ 3.0\ \% \\ -1.6\ \% \\ 1.2\ \% \end{bmatrix}$$



Performance Evaluation: On-Line Algorithm

Engine: Degraded Health Condition

OBEM: Updated Health Baseline



Summary

Integration of On-Line and Off-Line Algorithms:

- On-line algorithm: in-flight, real-time fault detection
- Off-line algorithm: non-real-time trend monitoring

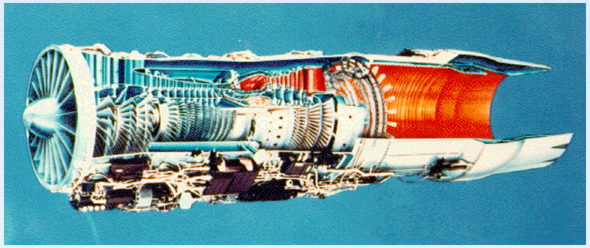
Reference:

[1] Integration of On-Line and Off-Line Diagnostic Algorithms for Aircraft Engine Health Management, http://gltrs.grc.nasa.gov/reports/2007/TM-2007-214980.pdf
[2] Hybrid Kalman Filter Approach for Aircraft Engine In-Flight Diagnostics: Sensor Fault Detection Case, http://gltrs.grc.nasa.gov/reports/2006/TM-2006-214418.pdf
[3] Hybrid Kalman Filter: A New Approach for Aircraft Engine In-Flight Diagnostics, http://gltrs.grc.nasa.gov/reports/2006/TM-2006-214491.pdf

Next Step:

- On-line fault detection and isolation

Optimal Sensor Placement for Propulsion Gas Path Diagnostics



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Propulsion Control and Diagnostics Research Under NASA Aeronautics Research Mission Programs

Workshop at Ohio Aerospace Institute, Cleveland OH
Nov. 6-7, 2007

Outline

- Sensor Placement Background / Motivation
- Systematic Sensor Selection Strategy (S4) Methodology Overview
- Turbofan Engine Application Example
- Discussion and Summary

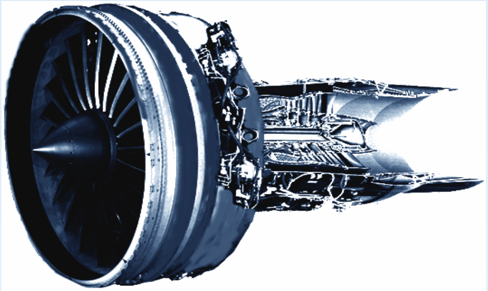
Optimal Sensor Placement Motivation

- Aircraft engine gas path diagnostics consists of engine performance trend monitoring, event detection, and fault isolation.
- The industry trend is moving towards performing more comprehensive gas path diagnostics, but fault types exceed number of available sensor measurements.
- Historically, gas path diagnostics has relied on available engine control sensors.
- With the increased scope of health monitoring, the need would be to perform sensor selection in an optimal way to minimize the number of sensors while satisfying fault diagnostic requirements.

Systematic Sensor Selection Strategy (S4) Methodology Overview

Background:

- Developed under NASA Space IVHM efforts, generally applicable
- Provides a systematic way to perform sensor selection relative to the system diagnostics philosophy/fault detection requirements
- Selects sensors (type/location) to optimize the fidelity and response of engine health diagnostics



Architecture Functionality:

Knowledge Base:

System simulation

Health information

Down-select process:

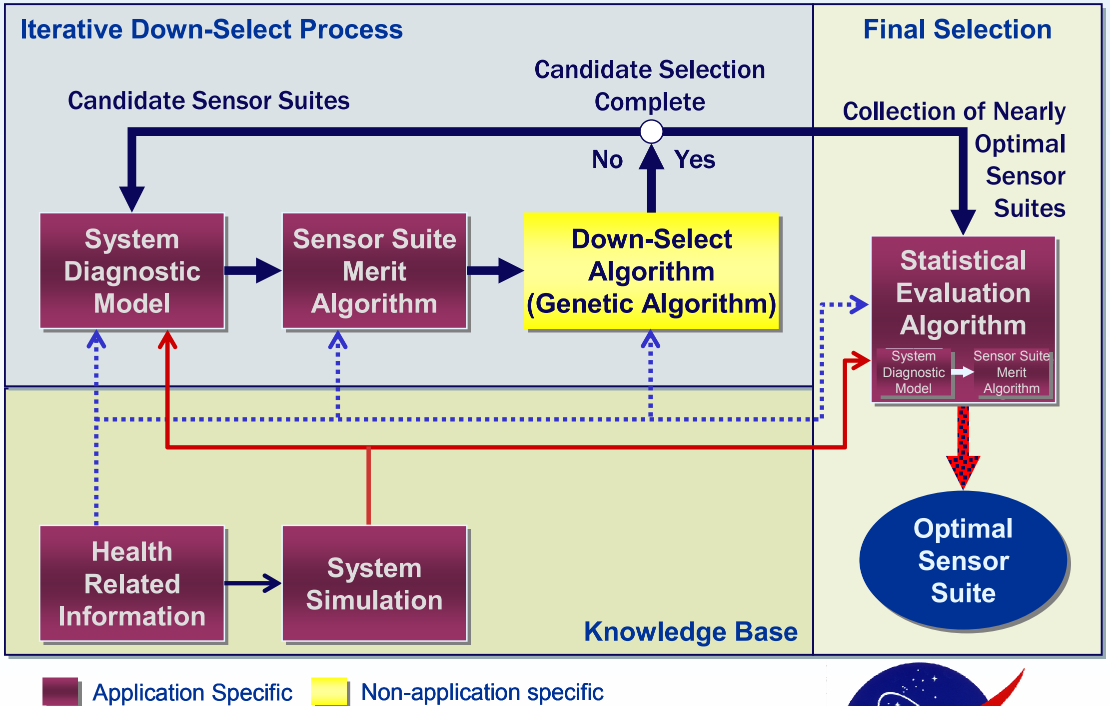
Diagnostic model

Merit function

Down-select algorithm

Statistical evaluation:

Considers sensor response and system/signal noise characteristics



S4 Methodology Algorithm Overview

- Form vector of predicted sensor values

$$\hat{y}_i = f_i(\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n) = \sum_{j=1}^{n} \left[A_{ij}^{p_{jq}} \left(\hat{x}_j - \hat{x}_j^{p_{jq}} \right) + \hat{y}_{ij}^{p_{jq}} \right]$$

- Compute the residual sum $d = \sum \tilde{y}_i = \sum_{i=1}^{m} \left| y_i - \hat{y}_i \right|$

- Minimize d by adjusting health parameters x_i for sensor measurements y_i to closely match estimated $\hat{y}_i$ sensor values

- The residual measurement agreement

$$D_{residual,j} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} \left(\tilde{y}_{i,adj} \right)^2} \quad \text{RMS}$$

$$\tilde{y}_{i,adj} = \begin{cases} |\tilde{y}_i| - T_i & \text{if } |\tilde{y}_i| > T_i \\ 0 & \text{if } |\tilde{y}_i| \le T_i \end{cases}$$

is computed for every fault scenario

- The residual agreement value is used by the fault discrimination metric

$$Z_k = \sum_{j=1}^{n} aD_{j,k}$$

to compute the merit value or performance metric for the sensor suite under evaluation

$$Merit = U\,P \sum_{k=1}^{q} C_k W_k Z_k$$

q = number of fault test cases (3 for this example)

U = utility weighting term of the sensor suite

P = penalty weighting term of the sensor suite

C_k = criticality weighting factor of fault test case k (0.33 for each fault case in this example)

W_k = addition weighting factor for fault test case k (1.0 for each fault case in this example)

Z_k = detection distance metric for fault test case k

Statistical Evaluation Algorithm

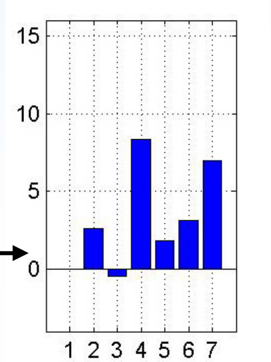
- System diagnostic model used and noise is added to further evaluate the performance of the best sensor suites

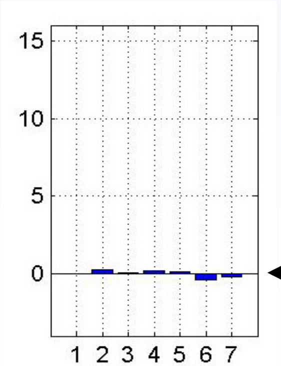
- The ability of the selected sensor suite to discriminate against simulated faults is evaluated by using the RMS of the residuals

- One fault condition is simulated at a time. When the residual value pertaining to the simulated fault condition is small compared to the residuals of the other fault conditions, then the fault can be discriminated

- This done for all fault conditions, for many fault cases, and the percentage of correct fault identification is computed for each fault case

Good Fault Discrimination

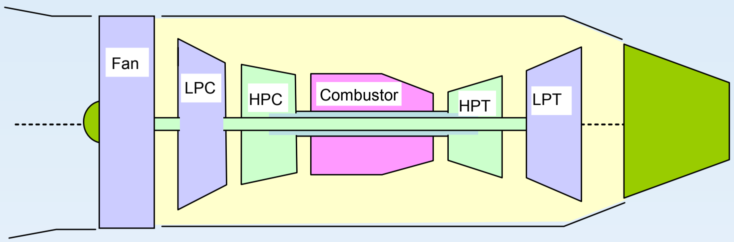




Poor Fault Discrimination

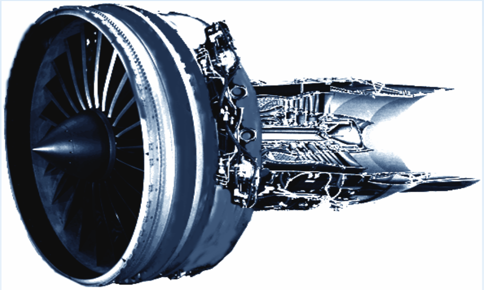
Residual Values for two Different Fault Simulations

S4: Turbofan Engine Application Example
High-Bypass Commercial Turbofan Engine Simulation



FADEC Control Sensors	T2A P2A	N1	T25 N2	T3 PS3	WF		T45	
Optional Sensors	P0 T0	PS13 T13	P25					T5 P5
Advanced Sensors	W2		W25	W3		T41 P41 W41	P45 W45	W5

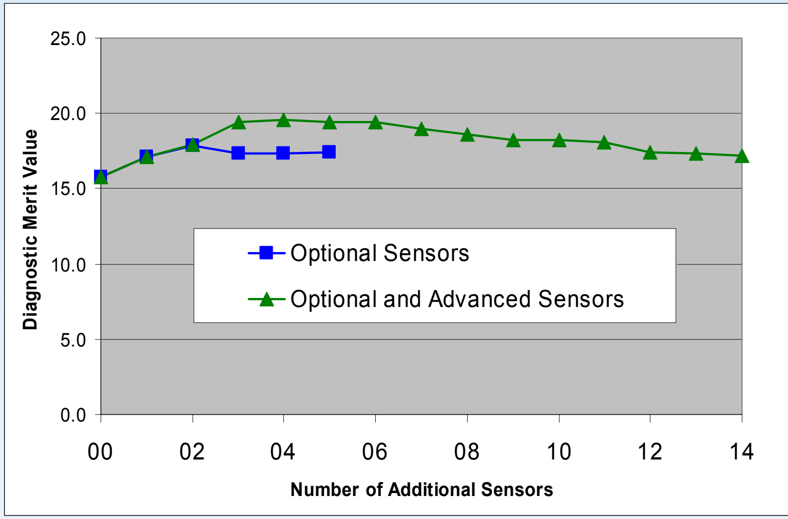
Blue = typical sensors
Green = optional sensors
Red = advanced sensors



Non-linear aero-thermodynamic component level model

- Gas Path Faults Considered
  - 10 single parameter engine faults (ηFan , γFan , ηLPC , γLPC , ηHPC , γHPC , ηHPT , γHPT , ηLPT , γLPT)
- Engine simulation accuracy up to 5% health parameter shift from nominal value

S4: Turbofan Engine Application Example



NOS	Opt.	Opt+Adv
0	15.755	15.755
1	17.103	17.103
2	**17.837**	17.945
3	17.334	19.397
4	17.348	**19.563**
5	17.420	19.445
6		19.399
7		18.980
8		18.610
9		18.209
10		18.250
11		18.051
12		17.430
13		17.349
14		17.181

- There is a point that increasing the number of sensors in the suite further doesn’t increase performance
- When the number of sensors increase the same sensors are not always selected
- Some sensors are selected most of the time, which shows the importance of these sensors in fault diagnostics

	Optional Sensors					Advanced Sensors									
Num Sensors	PS13	T13	P25	P5	T5	W2	W25	W3	P41	T41	W41	P45	W45	W5	Merit
7	0	0	0	0	0										15.754728
8	0	0	1	0	0										17.103078
9	**0**	**0**	**1**	**1**	**0**										17.836713
10	1	0	1	0	1										17.334462
11	1	0	1	1	1										17.348126
12	1	1	1	1	1										17.419933

Baseline (7 Sensors)

Optional Sensors

	Optional Sensors					Advanced Sensors									
Num Sensors	PS13	T13	P25	P5	T5	W2	W25	W3	P41	T41	W41	P45	W45	W5	Merit
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15.754728
8	0	0	1	0	0	0	0	0	0	0	0	0	0	0	17.103078
9	0	0	0	1	0	0	0	0	0	0	0	1	0	0	17.944952
10	0	0	1	1	0	0	0	0	0	0	0	1	0	0	19.396679
11	**0**	**0**	**1**	**1**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**1**	**0**	**0**	19.563002
12	0	0	1	1	1	0	0	0	1	0	0	1	0	0	19.444500
13	0	0	1	1	1	0	1	0	1	0	0	1	0	0	19.399235
14	1	0	1	1	0	0	0	0	1	1	0	1	0	1	18.980293
15	1	1	1	1	1	0	1	0	1	0	0	1	0	0	18.609817
16	1	0	1	1	0	1	0	1	1	1	0	1	1	0	18.208658
17	1	1	1	0	1	1	0	0	1	0	1	1	1	1	18.249840
18	1	0	1	0	1	1	0	1	1	1	1	1	1	1	18.050955
19	1	1	1	1	1	0	1	1	1	1	1	0	1	1	17.430000
20	1	1	1	1	1	1	1	1	1	1	1	1	0	1	17.349441
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17.180743

Baseline (7 Sensors)

Optional and Advanced Sensors

Fault Diagnostic Performance of Selected Sensor Suites (2.5 to 5 % health parameter shift from nominal, w/ system noise)

Baseline: xn2, xn25, t25, ps3, t3, t49, wf36

baseline — Inferred Fault Condition (rows: True Fault Condition)

	FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
FANeff	142	274	0	0	0	0	0	0	84	0	0	28%
FANflow	61	389	0	0	0	0	0	0	50	0	0	78%
BSTeff	0	0	12	0	0	0	0	0	0	0	488	2%
BSTflow	0	0	0	0	0	0	0	0	0	0	500	0%
HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
HPCflow	0	0	0	0	0	129	0	0	0	0	371	26%
HPTeff	0	0	0	0	0	0	500	0	0	0	0	100%
HPTflow	0	0	0	0	0	0	0	499	0	1	0	100%
LPTeff	135	139	0	0	0	0	0	0	226	0	0	45%
LPTflow	0	0	0	0	0	0	0	1	0	499	0	100%
Nominal	0	0	0	0	0	0	0	0	0	0	100	100%

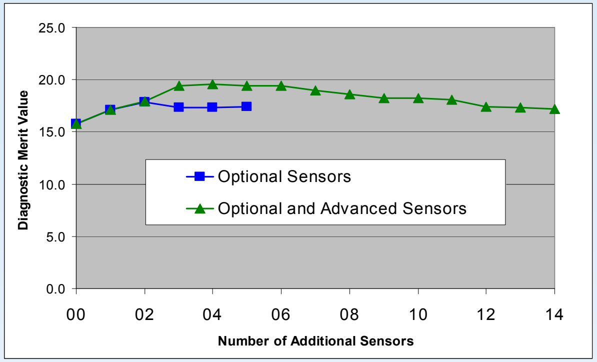
Baseline + Optional: p17, p25

	FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
FANeff	424	49	0	0	0	0	0	0	27	0	0	85%
FANflow	25	463	0	0	0	0	0	0	12	0	0	93%
BSTeff	0	0	2	0	0	0	0	0	0	0	498	0%
BSTflow	0	0	0	231	0	0	0	0	0	0	269	46%
HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
HPCflow	0	0	0	0	0	3	0	0	0	0	497	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	26	20	0	0	0	0	0	0	454	0	0	91%
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%

Baseline + Optional p17, P25 **+ Advance** p4, p48

	FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
FANeff	490	3	0	0	0	0	0	0	7	0	0	98%
FANflow	0	500	0	0	0	0	0	0	0	0	0	100%
BSTeff	0	0	0	0	0	0	0	0	0	0	500	0%
BSTflow	0	0	0	186	0	0	0	0	0	0	314	37%
HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
HPCflow	0	0	0	0	0	9	0	0	0	0	491	2%
HPTeff	0	0	0	0	0	0	500	0	0	0	0	100%
HPTflow	0	0	0	0	0	0	0	499	0	1	0	100%
LPTeff	3	0	0	0	0	0	0	0	497	0	0	99%
LPTflow	0	0	0	0	0	0	0	1	0	499	0	100%
Nominal	0	0	0	0	0	0	0	0	0	0	100	100%

Fault Diagnostic Performance of Optimal –vs. a Suboptimal Sensor Suite w/ More Sensors



Best Performing Sensor Suite (Baseline +2 optional+2 advance)

	FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
FANeff	490	3	0	0	0	0	0	0	7	0	0	98%
FANflow	0	500	0	0	0	0	0	0	0	0	0	100%
BSTeff	0	0	0	0	0	0	0	0	0	0	500	0%
BSTflow	0	0	0	186	0	0	0	0	0	0	314	37%
HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
HPCflow	0	0	0	0	0	9	0	0	0	0	491	2%
HPTeff	0	0	0	0	0	0	500	0	0	0	0	100%
HPTflow	0	0	0	0	0	0	0	499	0	1	0	100%
LPTeff	3	0	0	0	0	0	0	0	497	0	0	99%
LPTflow	0	0	0	0	0	0	0	1	0	499	0	100%
Nominal	0	0	0	0	0	0	0	0	0	0	100	100%

Performing of Sensor Suite of (Baseline +2 optional+3 advance)

True Fault Condition	FANeff	FANflow	BSTeff	BSTflow	HPCeff	HPCflow	HPTeff	HPTflow	LPTeff	LPTflow	None Detected	Accuracy
FANeff	429	54	0	0	0	0	0	0	17	0	0	86%
FANflow	33	459	0	0	0	0	0	0	8	0	0	92%
BSTeff	0	0	1	0	0	0	0	0	0	0	499	0%
BSTflow	0	0	0	171	0	0	0	0	0	0	329	34%
HPCeff	0	0	0	0	500	0	0	0	0	0	0	100%
HPCflow	0	0	0	0	0	1	0	0	0	0	499	0%
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	17	0	0	0	0	0	0	467	0	0	93%
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%

Discussion and Summary

- Sensor selection (S4) methodology has been demonstrated for propulsion gas path diagnostics
  -- Optimality depends applied diagnostic approach, fault types and magnitudes, system simulation accuracy, sensor characteristics, and merit function

- Demonstrated improved diagnostic performance with selected optimal sensor suite

- Provides a systematic approach towards the evaluation and selection of candidate sensors and diagnostic algorithms

- Future Development Steps
  -- Evaluate multi-parameter fault types
  -- Expand engine operation envelope
  -- Include engine deterioration effects
  -- Evaluate advanced sensors
  -- Modify metric function to emphasize fault discrimination

Asymmetric Thrust Detection

Propulsion Control and Diagnostics Research Under NASA Aeronautics Research Mission Programs

Workshop at Ohio Aerospace Institute, Cleveland OH
Nov. 6-7, 2007

Don Simon
Ph: (216) 433-3740
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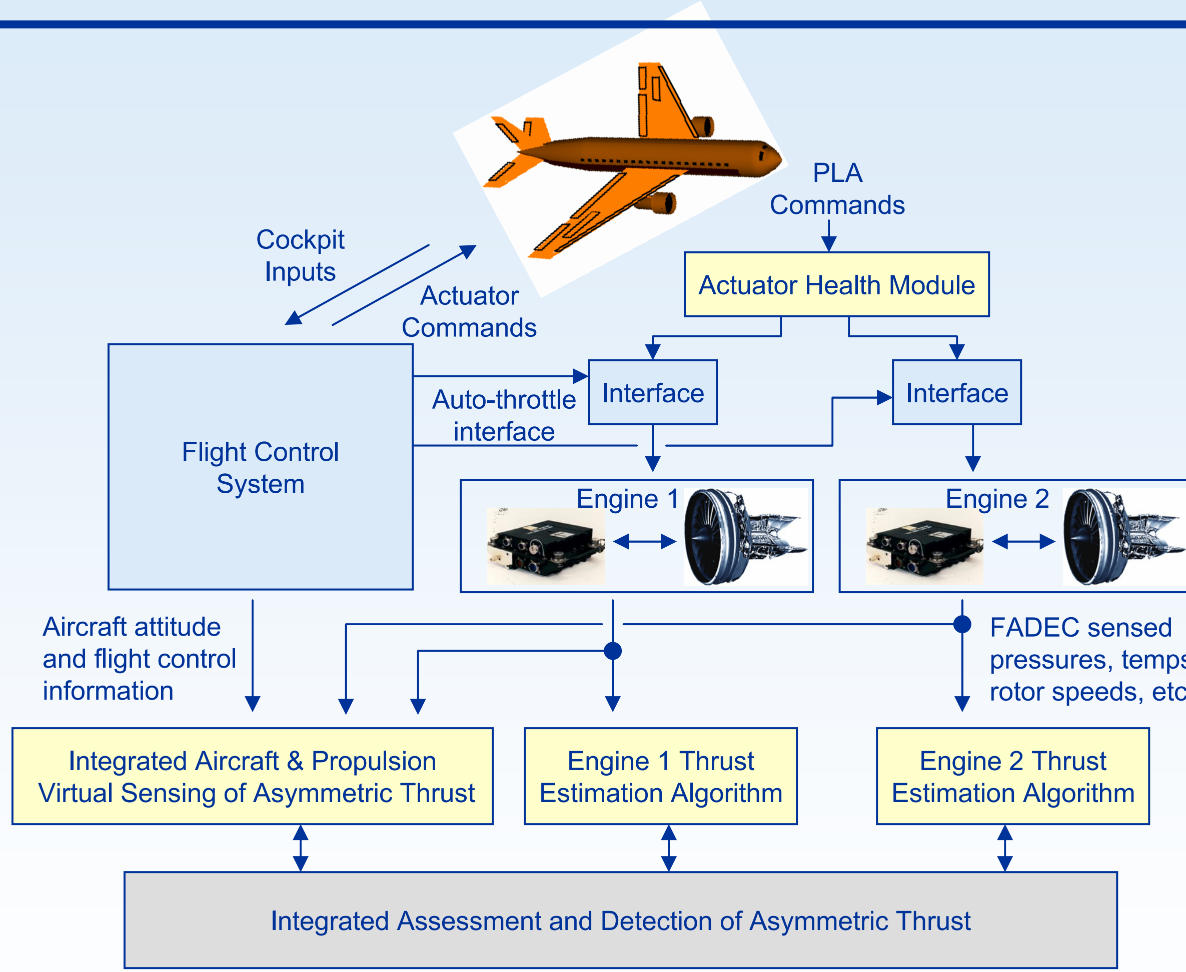
Asymmetric Thrust Detection

Background: Asymmetric thrust conditions, if large enough and undetected, can compromise vehicle safety

Objective: Develop a reliable “integrated” approach for the detection of asymmetric thrust

Approach:

- Apply thrust estimation techniques at the individual engine level
  - Regression techniques & model based approaches
- Apply vehicle wide “virtual” asymmetric thrust estimation
- Apply actuator health monitoring to assess the condition of throttle interface servo-actuator
- Perform high-level fusion of engine thrust & thrust asymmetry assessments



Notional Asymmetric Thrust Detection Architecture

Detection of Mismatch in Commanded vs. Actual Thrust

- Focus on detecting a mismatch between commanded vs. actual thrust
  - Avoid nuisance alarms which can occur if focus is exclusively on asymmetric thrust detection
- Assess accuracy of
  - Thrust estimation based upon statistical regression of sensed engine parameters
  - Thrust estimation based upon on-board adaptive model output
- Planned Demonstrations
  - C-17 flight simulator demonstration at NASA DFRC
  - C-17 flight demonstration at NASA DFRC

IVHM Propulsion HM

Gas Path Health Management

Summary

- Current Activities
  - Gas Path Diagnostic Benchmark Problems and Metrics
  - Advanced On-board Model-based Diagnostics
  - Optimal Sensor Placement Methodology
  - Asymmetric Thrust Detection

- Requested Feedback
  - Are we taking the correct approach?
  - Are there related efforts that we can leverage?
  - Potential future research areas & approaches