INTEGRATED VEHICLE HEALTH MANAGEMENT

Onboard Model-Based Aircraft Engine Performance Estimation for IVHM Applications

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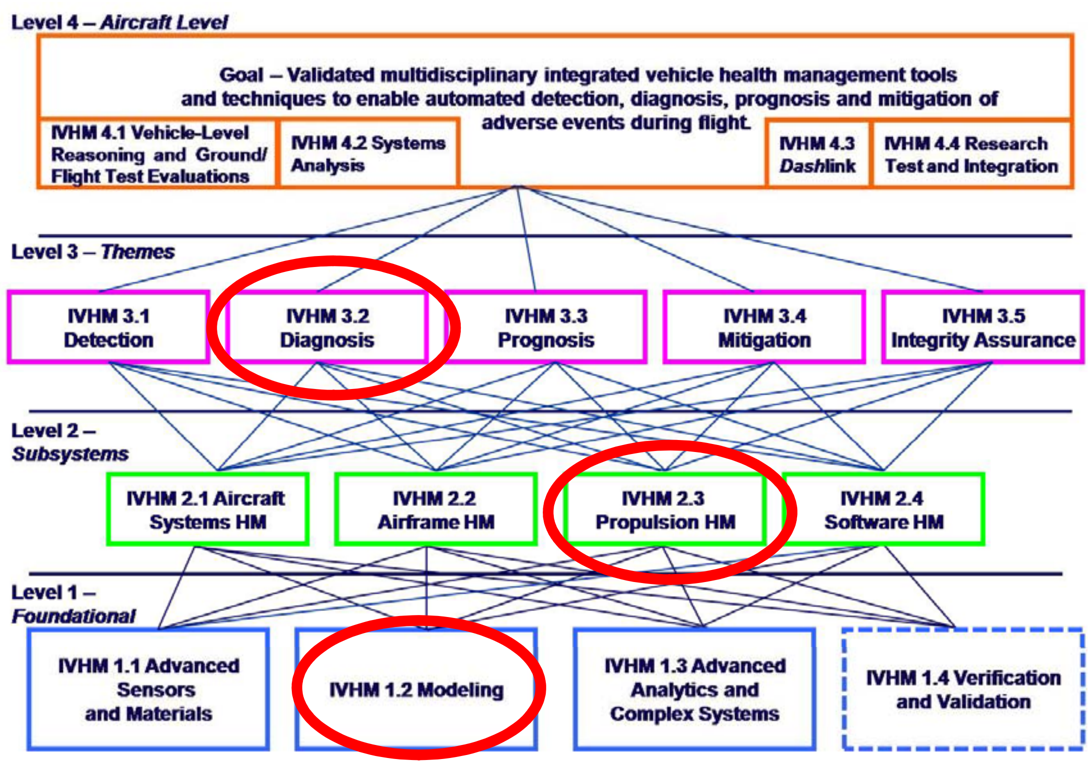
Outline

- Problem Statement – aircraft engine performance estimation accuracy
- Background – onboard model-based performance estimation
- IVHM Project milestones being addressed
- Approach – systematic approach to model tuning parameter selection
- Results
- Conclusions
- Future Plans



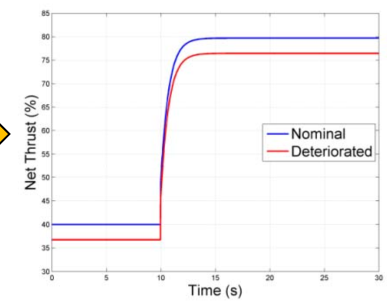
Problem Statement

- The accurate estimation of unmeasured aircraft gas turbine engine performance parameters is an enabling technology area for:
  - Detection
  - Diagnostics
  - Prognostics
  - Controls

Aircraft gas turbine engine

- Challenges:
  - Each engine will exhibit a unique level of performance due to deterioration and manufacturing tolerances
  - Poses an underdetermined estimation problem (i.e., more unknowns than available sensor measurements).

Deteriorated turbomachinery

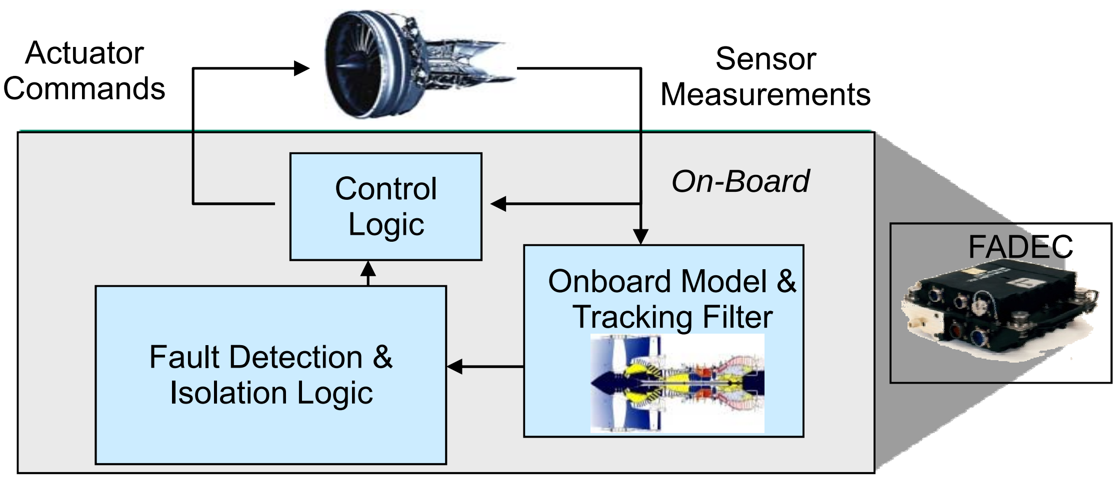


Deteriorated engine performance

- Current state of the art:
  - Estimates are based upon fleet-average engine models
  - Emerging approach: onboard adaptive model-based estimation
- Goal: Develop a methodology for minimizing the onboard model-based estimation error when facing the underdetermined estimation problem.

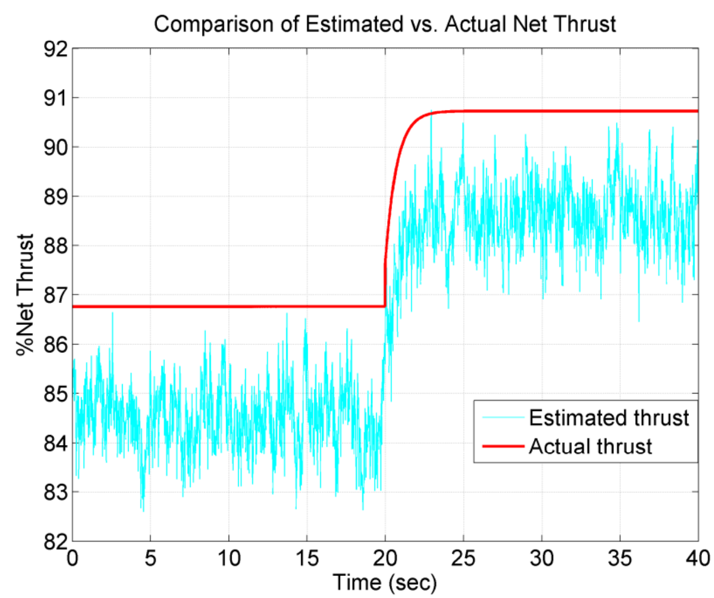
Adaptive Onboard Model-Based Performance Estimation

Background:
- Adaptive on-board engine model embedded within engine control computer
- A tracking filter automatically tunes the onboard model to match the physical engine performance
- The tracking filter is typically based upon Kalman filter estimation concepts



Model-based Diagnostics Architecture

Challenges:
- Performance deterioration and underdetermined estimation problem can cause errors between estimated and actual engine performance.



Related IVHM Project milestones

The accurate on-board estimation of aircraft gas turbine engine performance parameters enables:

- On-board engine performance trend monitoring and event detection.
- Analytical redundancy for diagnostic applications.
- Synthesis of unmeasured engine parameters for life usage calculations (prognostics) and/or controls applications.

IVHM Project Milestones

2.3.2.1 (iii) Demonstrate a 10% improvement in estimation accuracy of integrated gas path sensing and diagnostics for aircraft engine health (FY09Q4).

In simulation, quantify the improved estimation accuracy provide by advanced propulsion HM algorithms and sensors under NASA development.

2.3.2.1 (iv) Demonstrate integrated propulsion gas path sensing and diagnostics (FY10Q4).

In simulation, quantify the improved estimation and diagnostic performance provided by the advanced propulsion HM algorithms and sensors under NASA development. (85% ROC diagnostic accuracy).

1.2.2.6: Develop and demonstrate propulsion gas-path performance deterioration trending (FY10Q4).

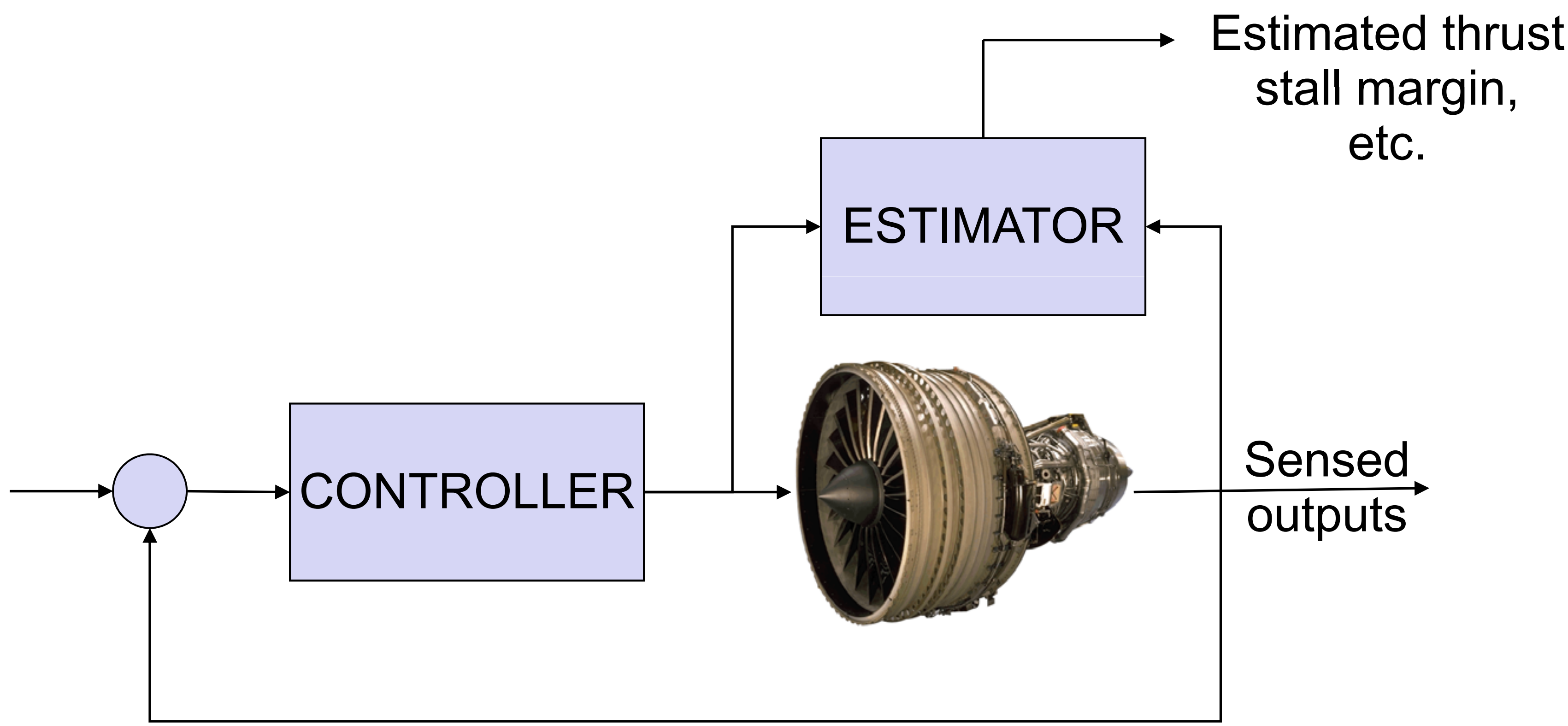
In simulation, demonstrate on-board propulsion performance deterioration trending with < 2% average estimation error.

1.2.2.7: Develop and demonstrate propulsion thrust estimation techniques (FY10Q4).

Demonstrate thrust estimation techniques to detect thrust asymmetry conditions > 10% absolute thrust, within 20% relative accuracy.

Objective

Objective: develop a systematic methodology for combined sensor and model tuning parameter selection that minimizes the linear Kalman filter estimation error.



Linearized Engine Model

State equations: $x_{k+1} = Ax_k + Bu_k + Lh_k + w_k$

Output equations: $y_k = Cx_k + Du_k + Mh_k + v_k$

Auxiliary equations: $z_k = Fx_k + Gu_k + Nh_k$

x_k: state variables (spool speeds)
y_k: measured variables (spool speeds, temperatures, pressures)
z_k: auxiliary outputs (thrust, stall margins)
u_k: control inputs (fuel flow, variable stator vanes, variable bleed)
h_k: engine health parameters (component efficiency, flow capacity)
w_k: process noise (zero mean, normally distributed)
v_k: sensor noise (zero mean, normally distributed)

z can be computed if *x*, *u*, and *h* are known

Problem Formulation

Linearized Engine Model

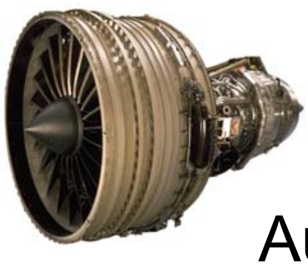
State equations: $x_{k+1} = Ax_k + Bu_k + Lh_k + w_k$

Output equations: $y_k = Cx_k + Du_k + Mh_k + v_k$

Auxiliary equations: $z_k = Fx_k + Gu_k + Nh_k$

Engine performance deterioration evolves slowly, thus health parameters are typically modeled without dynamics → $h_{k+1} = h_k$

Linearized Engine Model



State equations:

$$\begin{bmatrix} x_{k+1} \\ h_{k+1} \end{bmatrix} = \underbrace{\begin{bmatrix} A & L \\ 0 & I \end{bmatrix}}_{A_{xh}} \underbrace{\begin{bmatrix} x_k \\ h_k \end{bmatrix}}_{x_{xh,k}} + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{B_{xh}} u_k + \underbrace{\begin{bmatrix} w_k \\ w_{h,k} \end{bmatrix}}_{w_{xh,k}}$$

$$= A_{xh} x_{xh,k} + B_{xh} u_k + w_{xh,k}$$

Output equations:

$$y_k = \underbrace{\begin{bmatrix} C & M \end{bmatrix}}_{C_{xh}} \underbrace{\begin{bmatrix} x_k \\ h_k \end{bmatrix}}_{x_{xh,k}} + D u_k + v_k$$

$$= C_{xh} x_{xh,k} + D u_k + v_k$$

Auxiliary equations:

$$z_k = \underbrace{\begin{bmatrix} F & N \end{bmatrix}}_{F_{xh}} \underbrace{\begin{bmatrix} x_k \\ h_k \end{bmatrix}}_{x_{xh,k}} + G u_k$$

$$= F_{xh} x_{xh,k} + G u_k$$

Once *h* is part of the augmented state vector, it can be estimated using a Kalman filter as long as the system is observable

It is a necessary condition for observability that there be at least as many sensors as health parameters to be estimated

Conventional approach is to only estimate a subset of health parameters and assume others remain constant

Formulation of Reduced-Order State Space Equations

Reduced-order state space equations

Reduced-order state space equations are constructed by defining a reduced-order tuner vector, q, that is a linear combination of all health parameters, and of appropriate dimension to enable Kalman estimation:

$$q = V^* h$$

q : reduced order model tuner vector
h: engine health parameters
V^*: transformation matrix

Formulation of the reduced-order state space equations:

- h is replaced with q
- L, M, and N matrices are post-multiplied by $V^{*\dagger}$

$$\begin{bmatrix} x_{k+1} \\ q_{k+1} \end{bmatrix} = \underbrace{\begin{bmatrix} A & LV^{*\dagger} \\ 0 & I \end{bmatrix}}_{A_{xq}} \underbrace{\begin{bmatrix} x_k \\ q_k \end{bmatrix}}_{x_{xq,k}} + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{B_{xq}} u_k + \underbrace{\begin{bmatrix} w_k \\ w_{q,k} \end{bmatrix}}_{w_{xq,k}}$$

$$= A_{xq} x_{xq,k} + B_{xq} u_k + w_{xq,k}$$

$$y_k = \underbrace{\begin{bmatrix} C & MV^{*\dagger} \end{bmatrix}}_{C_{xq}} \underbrace{\begin{bmatrix} x_k \\ q_k \end{bmatrix}}_{x_{xq,k}} + D u_k + v_k$$

$$= C_{xq} x_{xq,k} + D u_k + v_k$$

$$z_k = \underbrace{\begin{bmatrix} F & NV^{*\dagger} \end{bmatrix}}_{F_{xq}} \underbrace{\begin{bmatrix} x_k \\ q_k \end{bmatrix}}_{x_{xq,k}} + G u_k$$

$$= F_{xq} x_{xq,k} + G u_k$$

Kalman Filter Formulation

In this study steady-state Kalman filtering is applied

At steady-state open loop operating conditions (u = 0), the Kalman filter estimator is given as

$$\hat{x}_{xq,k} = \begin{bmatrix} \hat{x}_k \\ \hat{q}_k \end{bmatrix} = A_{xq}\hat{x}_{xq,k-1} + K_\infty\left(y_k - C_{xq}A_{xq}\hat{x}_{xq,k-1}\right)$$

The estimate of $x_{xh,k}$ can be converted into estimates of h_k and z_k

$$\hat{x}_{xh,k} = \begin{bmatrix} \hat{x}_k \\ \hat{h}_k \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & V^{*\dagger} \end{bmatrix}\hat{x}_{xq,k}$$

$$\hat{z}_k = \begin{bmatrix} F & NV^{*\dagger} \end{bmatrix}\hat{x}_{xq,k}$$

Analytical Derivation of Kalman Estimation Error

Squared estimation error bias

$$SSEE(\hat{z}_{bias}) = trace\left\{\left(E\left[\hat{z}_k - z_k\right]\right)\left(E\left[\hat{z}_k - z_k\right]\right)^T\right\}$$

$$= trace\left\{G_z P_h G_z^T\right\}$$

where

$$G_z = \begin{bmatrix} \begin{bmatrix} F & NV^{*\dagger} \end{bmatrix} \left(I - A_{xq} + K_\infty C_{xq} A_{xq}\right)^{-1} \ldots \\ \times K_\infty \left[C\left[I - A\right]^{-1} L + M\right] \ldots \\ -\left[F\left(I - A\right)^{-1} L + N\right] \end{bmatrix}$$

and P_h reflects a priori knowledge of the covariance in health parameters

Estimation variance

$$SSEE(\hat{z}_{var}) = trace\left\{E\left[\left(\hat{z}_k - E\left[\hat{z}_k\right]\right)\left(\hat{z}_k - E\left[\hat{z}_k\right]\right)^T\right]\right\}$$

$$= trace\left\{\begin{bmatrix} F & NV^{*\dagger} \end{bmatrix} P_{\hat{x}\hat{q},k} \begin{bmatrix} F & NV^{*\dagger} \end{bmatrix}^T\right\}$$

where $P_{\hat{x}\hat{q},k}$ is obtained by solving the following Ricatti equation

$$P_{\hat{x}\hat{q},k} = \left[A_{xq} - K_\infty C_{xq} A_{xq}\right] P_{\hat{x}\hat{q},k} \left[A_{xq} - K_\infty C_{xq} A_{xq}\right]^T \ldots$$
$$+ K_\infty R K_\infty^T$$

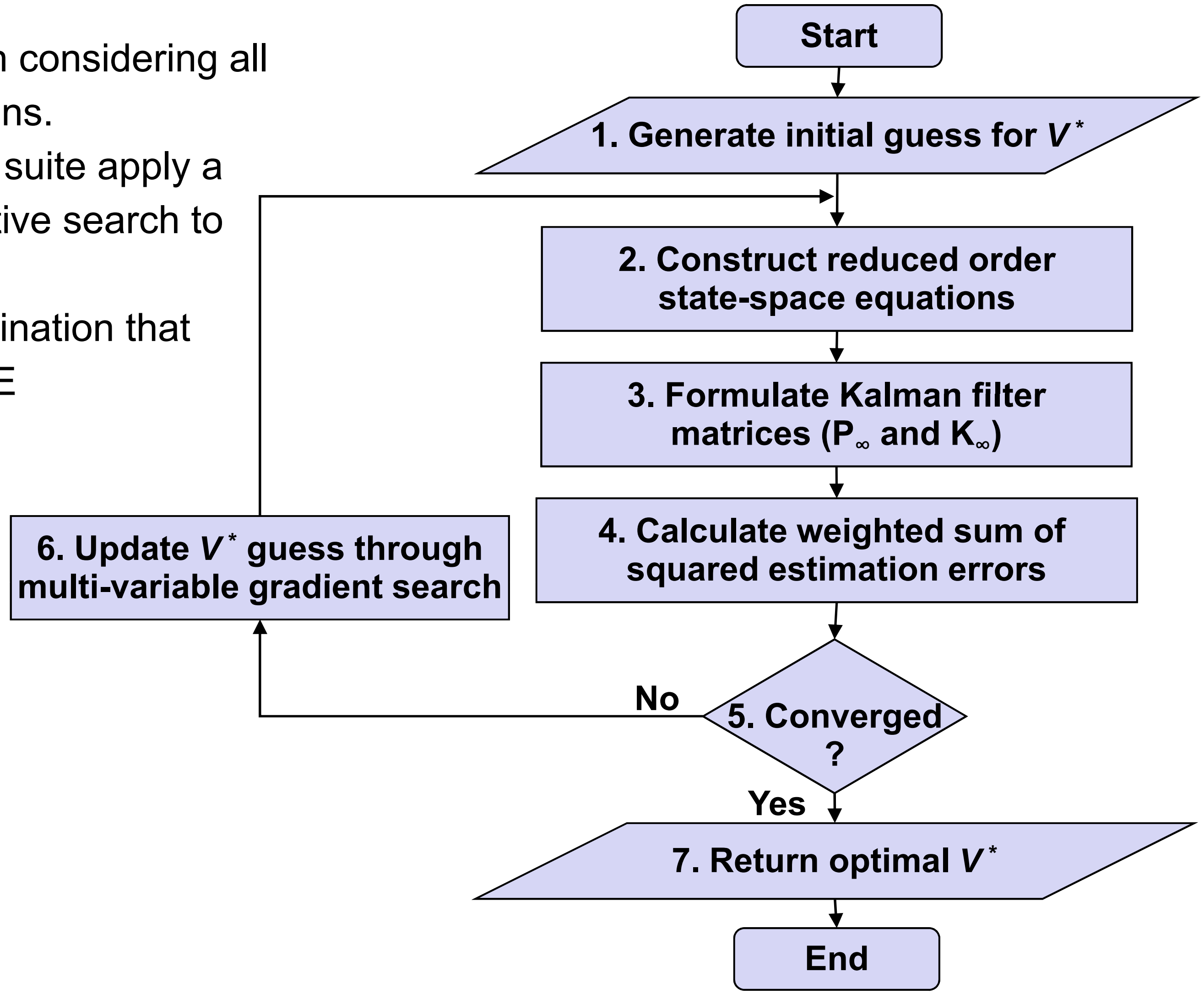
$$SSEE(\hat{z}_{fleet}) = trace\left\{G_z P_h G_z^T + \begin{bmatrix} F & NV^{*\dagger} \end{bmatrix} P_{\hat{x}\hat{q},k} \begin{bmatrix} F & NV^{*\dagger} \end{bmatrix}^T\right\}$$

Squared bias and variance are combined to form sum of squared estimation errors (SSEE)

Optimization: Choose V^* and sensors to minimize SSEE in the parameters of interest

Optimal Search for Sensor Suite and V^*

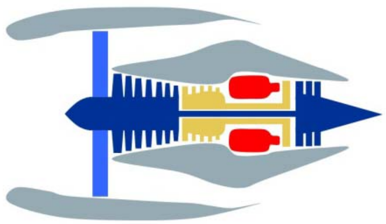
1. Apply an exhaustive search considering all possible sensor combinations.
2. For each candidate sensor suite apply a Matlab-based optimal iterative search to determine optimal V^*
3. Choose sensor/tuner combination that minimizes SSEE or WSSEE



V^* optimal iterative search flow chart

Turbofan Engine Example

Applied to NASA Commercial Modular Aero-Propulsion System Simulation (C-MAPSS)



State equations: $x_{k+1} = Ax_k + Bu_k + Lh_k + w_k$

Output equations: $y_k = Cx_k + Du_k + Mh_k + v_k$

Auxiliary equations: $z_k = Fx_k + Gu_k + Nh_k$

	State Variables *x*	Health Parameters *h*	Actuators *u*	Sensors *y*	Auxiliary Outputs *z*
1	Nf	FAN efficiency	WF36	Nf	T40
2	Nc	FAN flow capacity	VBV	Nc	T50
3		LPC efficiency	VSV	P24	Fn
4		LPC flow capacity		T24	SmLPC
5		HPC efficiency		Ps30	
6		HPC flow capacity		T30	
7		HPT efficiency		T48	
8		HPT flow capacity			
9		LPT efficiency			
10		LPT flow capacity			

Turbofan Engine Example (cont.)

- Designed different Kalman filters applying the following two approaches:
  - Tuners selected as a subset of health parameters (conventional approach) – exhaustive search applied to find the best "subset"
  - Systematic tuner selection (approach developed under IVHM project)

- Theoretically derived the Kalman filter mean squared estimation error for each Kalman filter

- Conducted Monte Carlo simulation studies to experimentally validate estimation errors
  - Health parameter vectors are normally distributed in accordance with covariance matrix, P_h
  - Sensor noise included
  - Ran 375 test cases, each 30 seconds in duration, $\Delta t = 15$ ms

Monte Carlo Simulation (*z* estimation results)

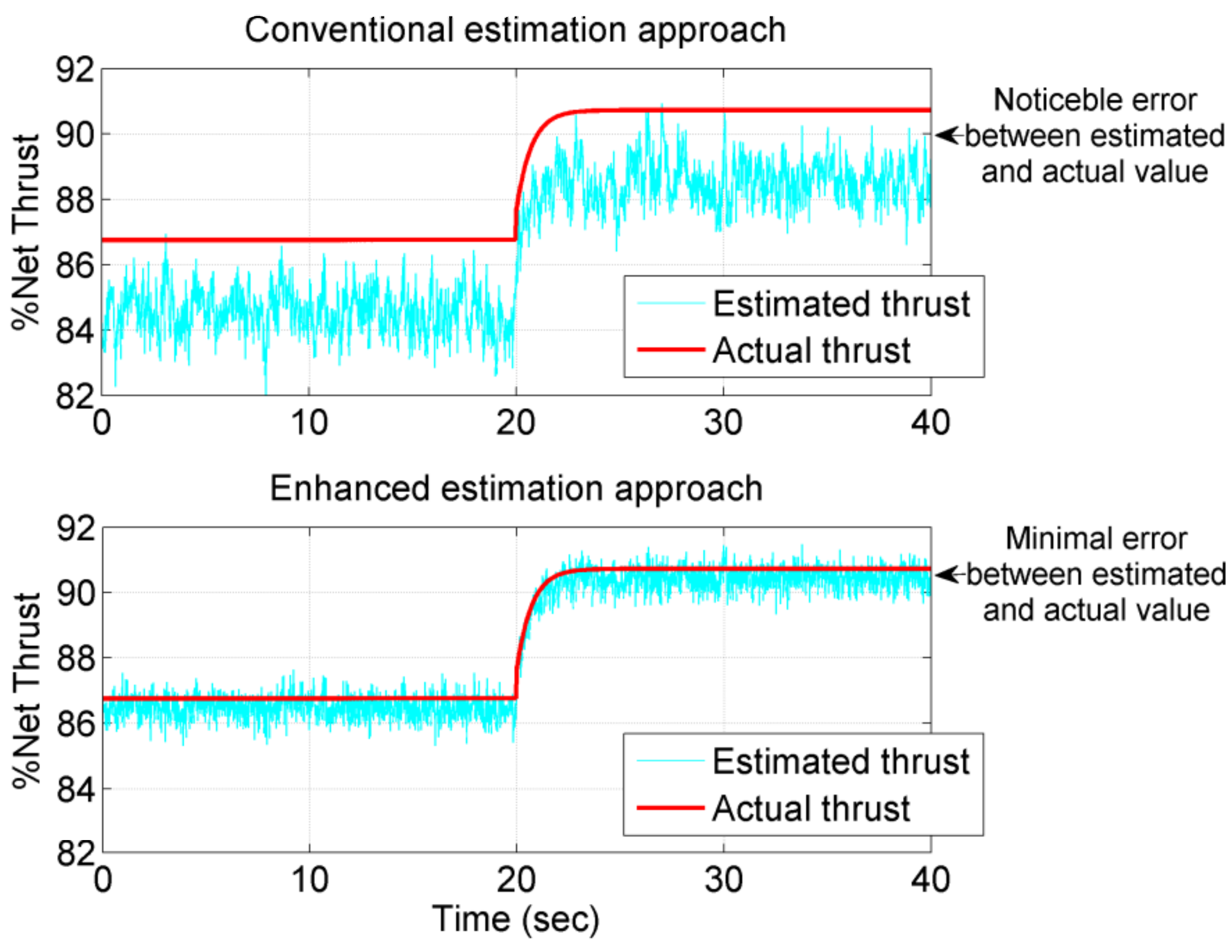
Auxiliary parameter mean squared estimation errors

Tuners	Error	T40 (°R)	T50 (°R)	Fn (%)	SmLPC (%)	WSSEE *z*
Subset of health parameters (conventional approach)	Theor. sqr. bias	0.00	191.35	1.33	2.47	
	Theor. variance	73.56	26.37	0.29	0.32	
	Theor. sqr. error	73.56	217.72	1.62	2.79	0.53
	Exper. sqr. error	73.97	215.41	1.65	2.85	0.53
Systematic tuner selection (new approach)	Theor. sqr. bias	0.00	84.95	0.66	0.95	
	Theor. variance	24.19	20.58	0.14	0.52	
	Theor. sqr. error	24.19	105.53	0.80	1.47	0.26
	Exper. sqr. error	24.34	101.44	0.78	1.41	0.25

Average mean squared estimation error reduction (experimental) = 53%
Average mean estimation error reduction (experimental) = 32%

Auxiliary Parameter Estimation Example

Thrust estimation accuracy comparison of conventional vs. enhanced estimation approaches



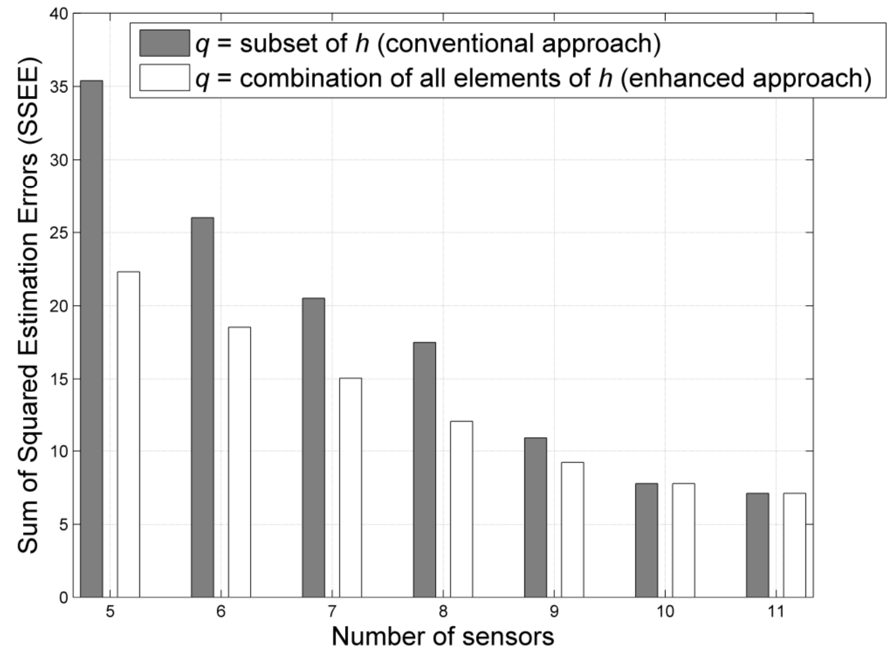
Integrated Tuner and Sensor Selection

Integrated tuner and sensor selection was also performed

- Also applied to C-MAPSS Turbofan Engine Model
- Objective: Minimize health parameter (*h*) estimation error
- Assumed a baseline sensor suite of five sensors
  - Nf, Nc, T24, Ps30, T48
- Considered six optional sensors
  - P24, T30, P45, P50, T50, P15
- Selected optimal tuner and sensor suite for suites of 5 to 11 sensors in size
- Selection was performed applying an exhaustive search (considered all tuner and sensor combinations for a given target number of sensors)

Integrated Tuner and Sensor Selection

# Sensors	sensors added to baseline						Health Parameter Mean Sum of Squared Estimation Errors (SSEE)	
	P24	T30	P45	P50	T50	P15	Conventional Approach (q = subset of h)	Enhanced Tuner Approach (q = linear combination of all elements of h)
5							**35.40**	**22.30**
6			○		x		**26.01**	**18.53**
7		⊗	○		x		**20.51**	**15.06**
8		⊗	⊗		⊗		**15.28**	**11.95**
9		⊗	⊗		⊗	⊗	**10.90**	**9.22**
10	⊗	⊗	⊗		⊗	⊗	**7.77**	**7.77**
11	⊗	⊗	⊗	⊗	⊗	⊗	**7.11**	**7.11**



Sensor Selection Legend:
× = Conventional tuner selection approach
○ = Enhanced tuner selection approach

Findings:
- Estimation accuracy improves as additional sensors are added
- The enhanced tuner selection approach provides superior estimation accuracy relative to the conventional approach
- Optimal sensor suite is dependent on the tuner selection approach applied

Conclusions

- Sensor and model tuning parameter selection decisions have a significant impact on onboard Kalman filter estimation accuracy
- The optimal sensor and model tuner vector combination will vary dependent upon the estimation objective
- The presented methodology provides designers a systematic approach for performing combined sensor <u>and</u> tuner selection for their individual applications
- Methodology shown to yield a significant improvement in Kalman filter estimation accuracy

Next Steps

The systematic tuner/sensor selection methodology will be used to support future adaptive model-based aircraft engine performance diagnostics research under the IVHM Project. Areas for future work include:

- Extending the technique to select tuning parameters optimal over a range of operating conditions
- Applying piecewise linear (full envelope) Kalman filter estimation
- Apply technique to support the following IVHM Project milestones
  - 2.3.2.1 (iv): Integrated propulsion gas path sensing and diagnostics (FY10Q4).
  - 1.2.2.6: Gas-path performance deterioration trending (FY10Q4).
  - 1.2.2.7: Thrust estimation techniques (FY10Q4).

Peer Feedback

- One of five papers (of 26 total papers) in 2009 ASME Turbo Expo Controls, Diagnostics, and Instrumentation track selected for ASME journal publication.
- Reviewer comments:
  - It is a monumental work … I hope this all encapsulates at least a year or two worth of work (the theoretical + simulation). I can not imagine banging through something of this magnitude in a few months.
  - The paper represents an advancement of engineering practice in a currently vital topic.
  - This is an excellent paper, very well written and thoroughly developed. I recommend it for publication in a journal, as it will serve as an essential foundation to develop practical applications of this new approach to a problem of continuing interest.
  - Recommended for journal publication, honors, and best paper by session organizer.
- Pratt & Whitney and GE have expressed interest in this technology. Technical interchanges and collaborative research discussions with engine OEMs are ongoing.

Publications

Conference papers/presentations:

- Donald L. Simon, Sanjay Garg (2009), "A Systematic Approach for Model-Based Aircraft Engine Performance Estimation," AIAA Infotech@Aerospace Conference, Apr. 6-9, 2009 Seattle, WA.
- Donald L. Simon, Sanjay Garg (2009), "Optimal Tuner Selection for Kalman Filter-Based Aircraft Engine Performance Estimation," GT2009-59684, ASME Turbo Expo Conference, Jun. 8-12, 2009 Orlando, FL.
- Donald L. Simon, Sanjay Garg (2009), "A Systematic Approach to Sensor Selection for Aircraft Engine Health Estimation," ISABE-209-1125, International Society of Air Breathing Engines Conference, Sep. 7-11, 2009 Montreal, QC, Canada.

Journal article:

- Simon, D.L., Garg, S., (2009), "Optimal Tuner Selection for Kalman-Filter Based Aircraft Engine Performance Estimation," ASME GTP-09-1052, *Journal of Engineering for Gas Turbines and Power*, (to appear in early 2010).