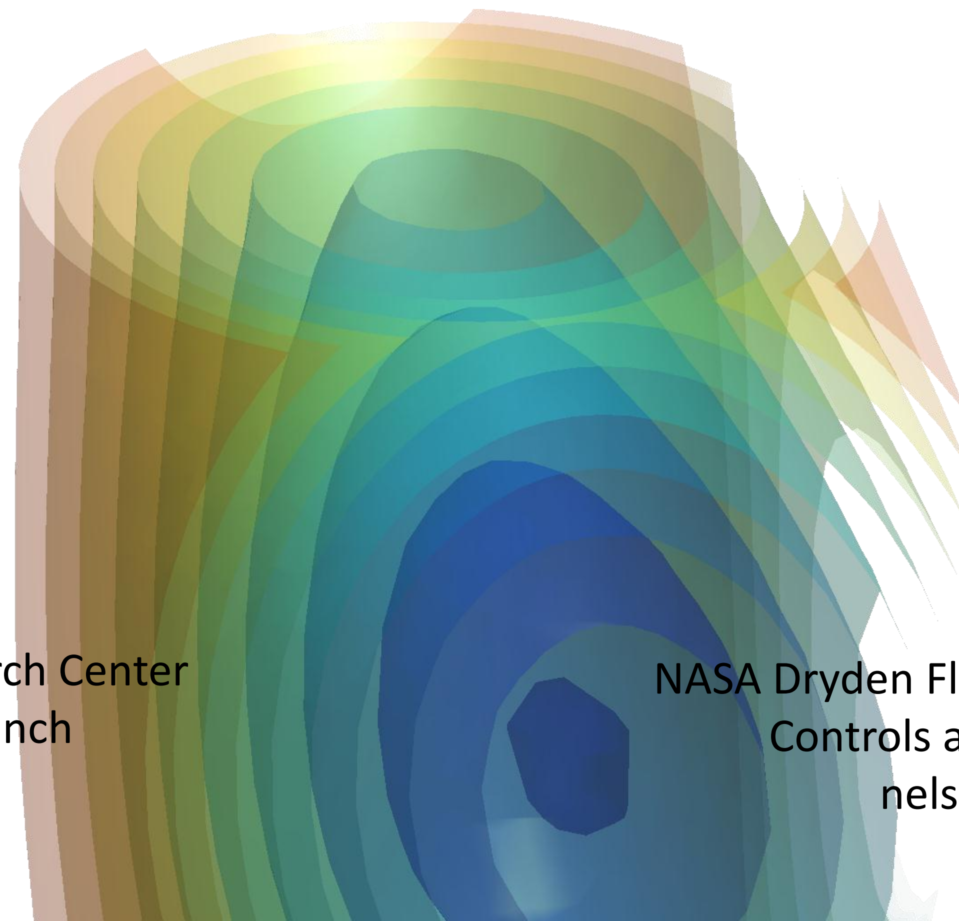
AIAA Guidance, Navigation and Control
Boston, MA
August 20th, 2013

Peak-Seeking Optimization of Trim for Reduced Fuel Consumption: Architecture and Performance Predictions



Jacob Schaefer
NASA Dryden Flight Research Center
Controls and Dynamics Branch
jacob.schaefer@nasa.gov

Nelson Brown
NASA Dryden Flight Research Center
Controls and Dynamics Branch
nelson.brown@nasa.gov

Agenda

- Motivation and background
- Description of peak-seeking algorithm
- Implementation on F/A-18
- Performance data flight
- Simulation results

Introduction

- US domestic flights in 2011:
  - 12.1 billion gallons of fuel
  - 114.6 million metric tons of CO_2 equivalent

- NASA's Environmentally Responsible Aviation project
  - Mitigate the impact of aviation on environment
  - Reduce fuel consumption, emissions, and noise

- Concept presented here:
  - Reduce drag in cruise by altering the trim configuration, applicable to many types of aircraft

Background

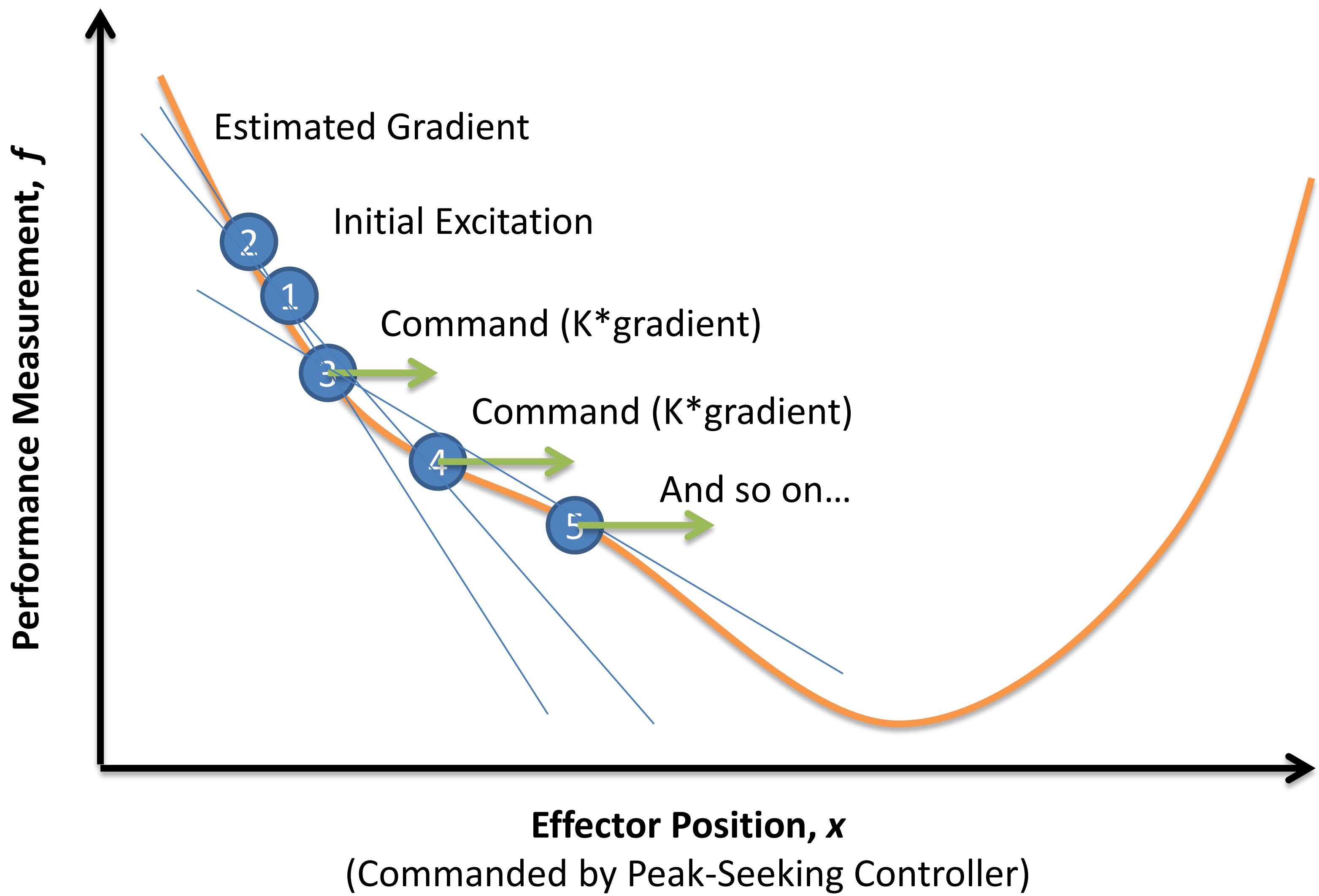
- Existing Trim Methods
  - Often scheduled with flight condition
  - Based on a priori information (analytic, wind tunnel, flight data)
  - Differences between models and reality may degrade performance
    - Off nominal flight conditions, lifetime variations, manufacturing differences, external modifications or stores, etc…

- Real-time optimization methods
  - Adaptive Performance Optimization
    - Drag reduction on L-1011 by use of symmetric aileron, (Gilyard et al.)
  - Formation flight
    - Position optimization (Ryan and Speyer)
    - Spanwise lift distribution optimization (Hanson and Ryan)
  - Trim optimization
    - Drag reduction by use of single trailing edge surface group on X-48, in simulation (Griffin et al)

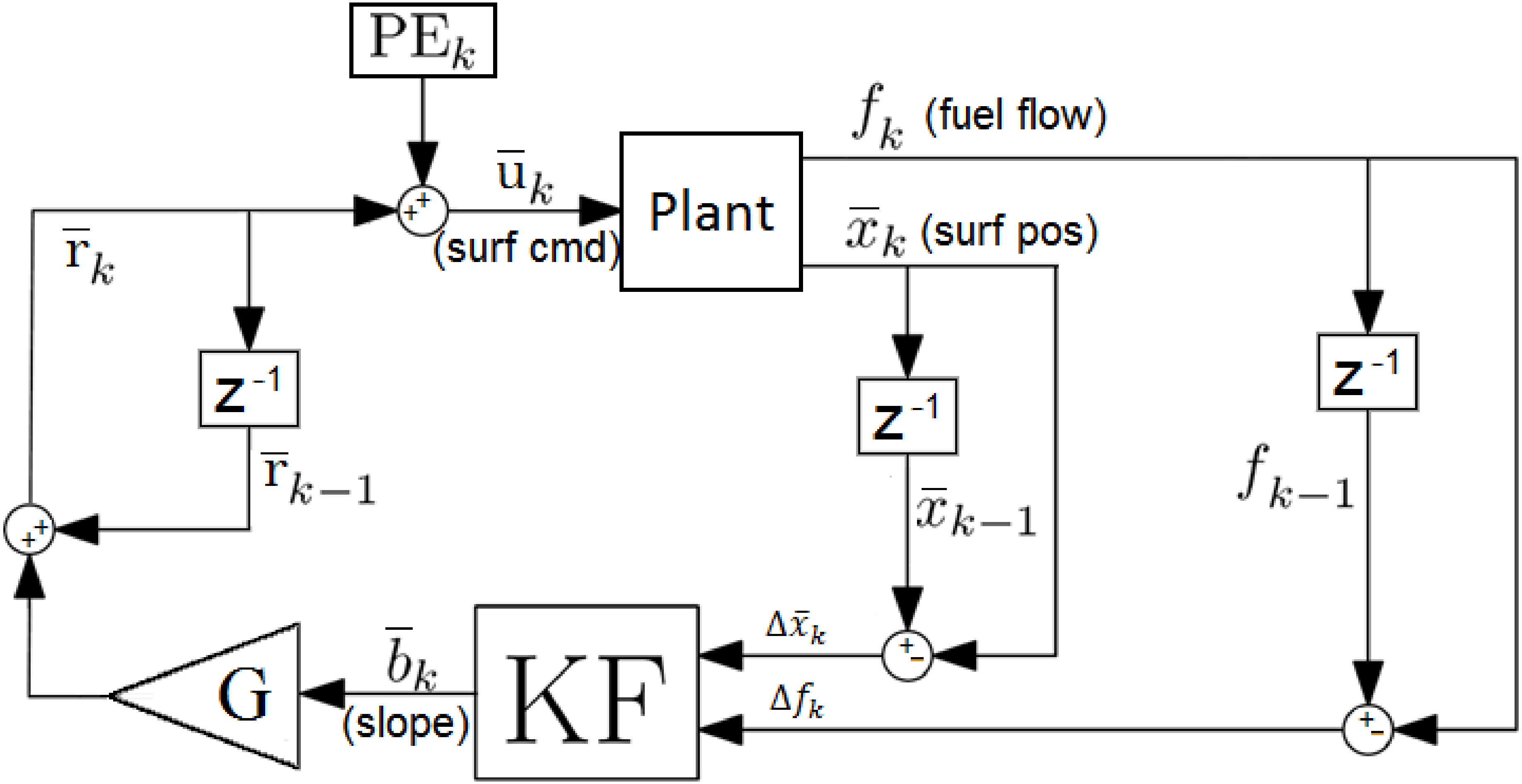
Approach

- Real-time optimization of trim configuration to reduce drag
- Use any number of control effectors
- Utilize onboard measurements of performance, which may be noisy

Peak-seeking Scheme (simplified for 1 effector)



Peak-seeking algorithm



Technical Formulation: Performance Function

Performance Function (Taylor series):

$$f(\bar{x}_k) \approx f(\bar{x}_{k-1}) + b_k^T(\bar{x}_k - \bar{x}_{k-1}) + O(\bar{x}_k - \bar{x}_{k-1})$$

Assuming the performance function can be treated as linear at any control surface position and expanding to include any number of control effectors, n, gives:

$$f(\bar{x}_{k-1}) - f(\bar{x}_k) = \begin{bmatrix} b_{1_k} \\ b_{2_k} \\ \vdots \\ b_{n_k} \end{bmatrix}^T \begin{bmatrix} x_{1_{k-1}} - x_{1_k} \\ x_{2_{k-1}} - x_{2_k} \\ \vdots \\ x_{n_{k-1}} - x_{n_k} \end{bmatrix}$$

F and x are measureable, b_k is unknown and to be estimated, and since F and x are noisy and F varies with x, a time-varying Kalman Filter is an appropriate choice for an estimator. The states of the Kalman filter are define as the gradient vector:

$$\zeta_k = \begin{bmatrix} b_{1_k} \\ b_{2_k} \\ \vdots \\ b_{n_k} \end{bmatrix}$$

Technical Formulation: Kalman Filter

Measurement equations are expanded to include multiple previous measurements, M:

$$\Delta \mathrm{F}_k = \begin{bmatrix} f(\bar{x}_{k-1}) - f(\bar{x}_k) \\ f(\bar{x}_{k-2}) - f(\bar{x}_k) \\ \vdots \\ f(\bar{x}_{k-M}) - f(\bar{x}_k) \end{bmatrix}^T \qquad H_k = \begin{bmatrix} x_{1_{k-1}} - x_{1_k} & x_{2_{k-1}} - x_{2_k} & \cdots & x_{n_{k-1}} - x_{n_k} \\ x_{1_{k-2}} - x_{1_k} & x_{2_{k-2}} - x_{2_k} & \cdots & x_{n_{k-2}} - x_{n_k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1_{k-M}} - x_{1_k} & x_{2_{k-M}} - x_{2_k} & \cdots & x_{n_{k-M}} - x_{n_k} \end{bmatrix}$$

Kalman filter measurement equation:

$$\Delta \mathrm{F}_k = {\zeta_k}^T {H_k}^T + v_k$$

Kalman filter process equation:

$$\zeta_k = \zeta_{k-1} + w_k$$

where v_k, w_k are Gaussian white-noise with covariance matrices R_k and Q_k respectively

A standard linear time varying Kalman filter is then implemented as follows:

$$K = \hat{P}_k H_k^T \left(H_k \hat{P}_k H_k^T + R_k \right)^{-1}$$

$$\zeta_k = \hat{\zeta}_k + K\left(\Delta \mathrm{F}_k - H_k \hat{\zeta}_k \right)$$

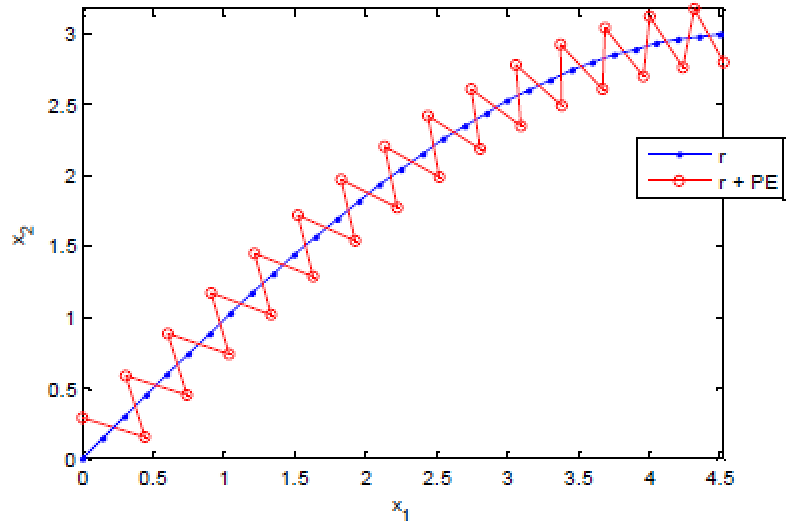
$$P_k = (I - K H_k) \hat{P}_k$$

$$\hat{\zeta}_{k+1} = \zeta_k$$

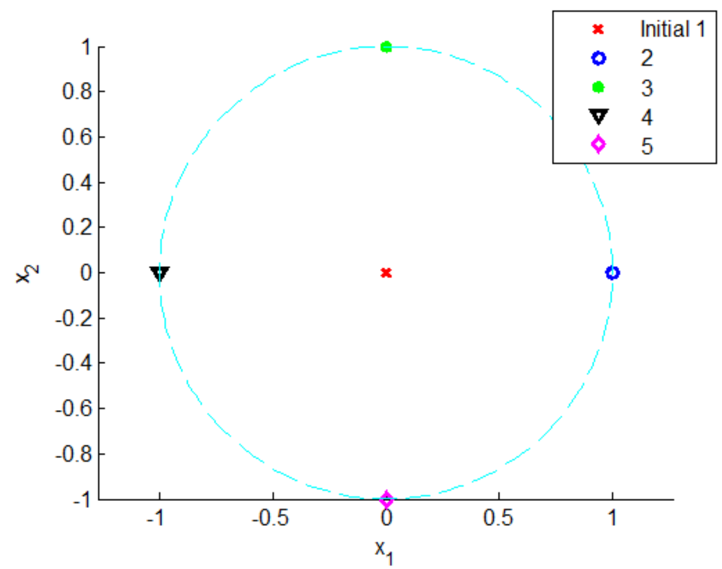
$$\hat{P}_{k+1} = P_k + Q_k$$

Persistent Excitation and Initial Excitation

- Persistent Excitation
  - Addition to commanded surface positions that is helical about the trajectory

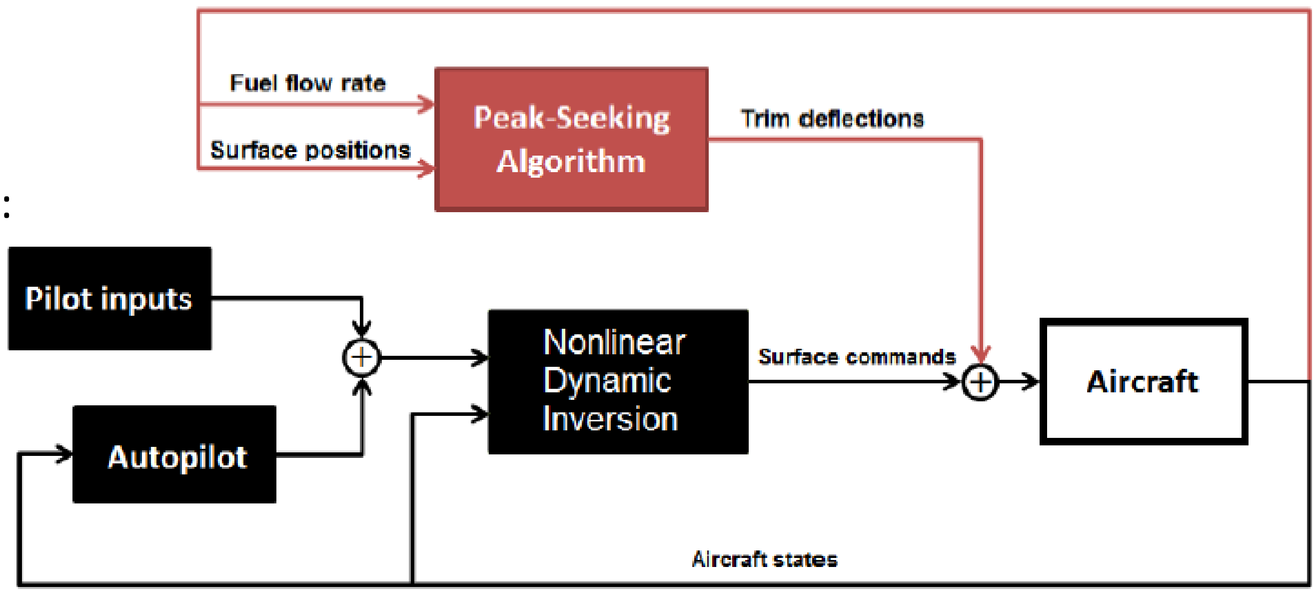


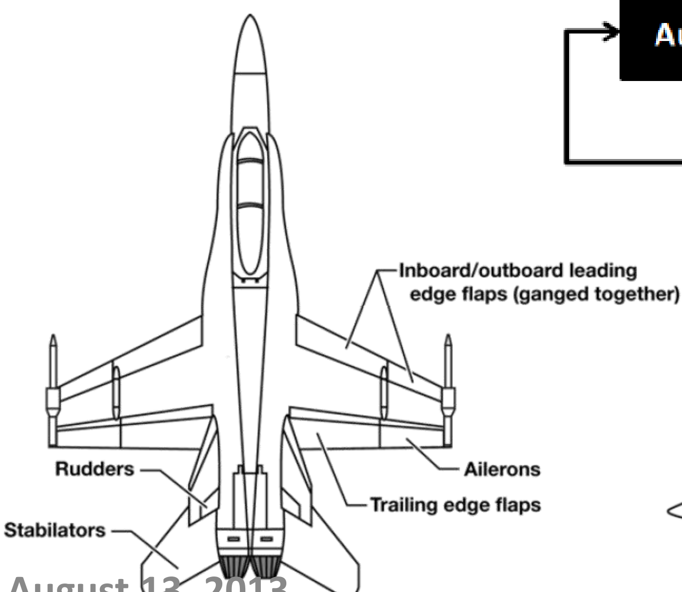
- Initial Excitation
  - M points around a circle/sphere centered at the initial condition

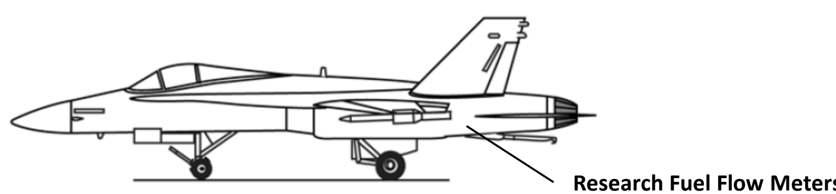


F/A-18 : NASA 853

- Modified F/A-18 Aircraft - Research flight control computers
- Nonlinear Dynamic Inversion inner loop control laws
- Autopilots:
  - Altitude Hold
  - Airspeed Hold
  - Wing Leveler
- Algorithm adds biases to:
  - Symmetric aileron
  - Trailing-edge flaps
  - Leading-edge flaps







Performance Data Flight

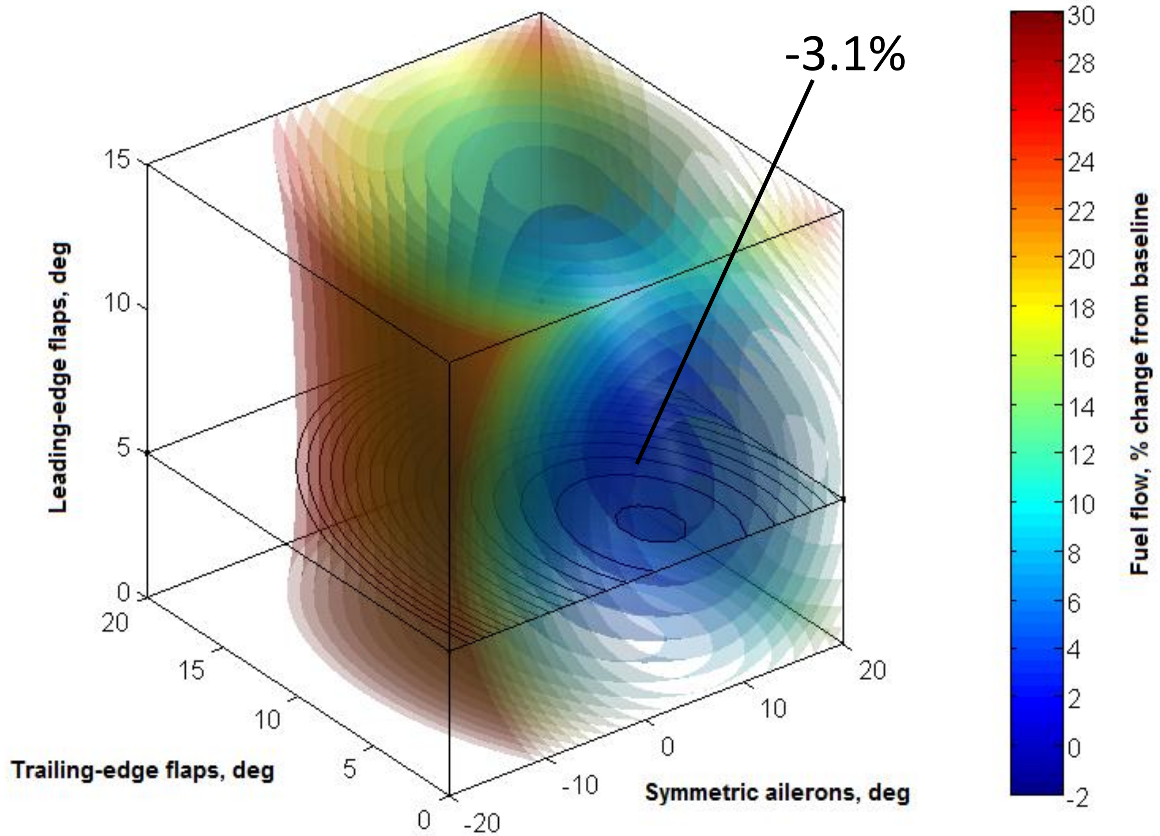
- Early in development an opportunity was presented to collect performance data during another research activity’s flight.

- Commanded 80 test points with combinations of leading edge flaps, trailing edge flaps, and symmetric ailerons and recorded resulting fuel flow over >30sec per pt.

- Evaluated at a single flight condition of 25,000ft, 240 KCAS

Performance Model

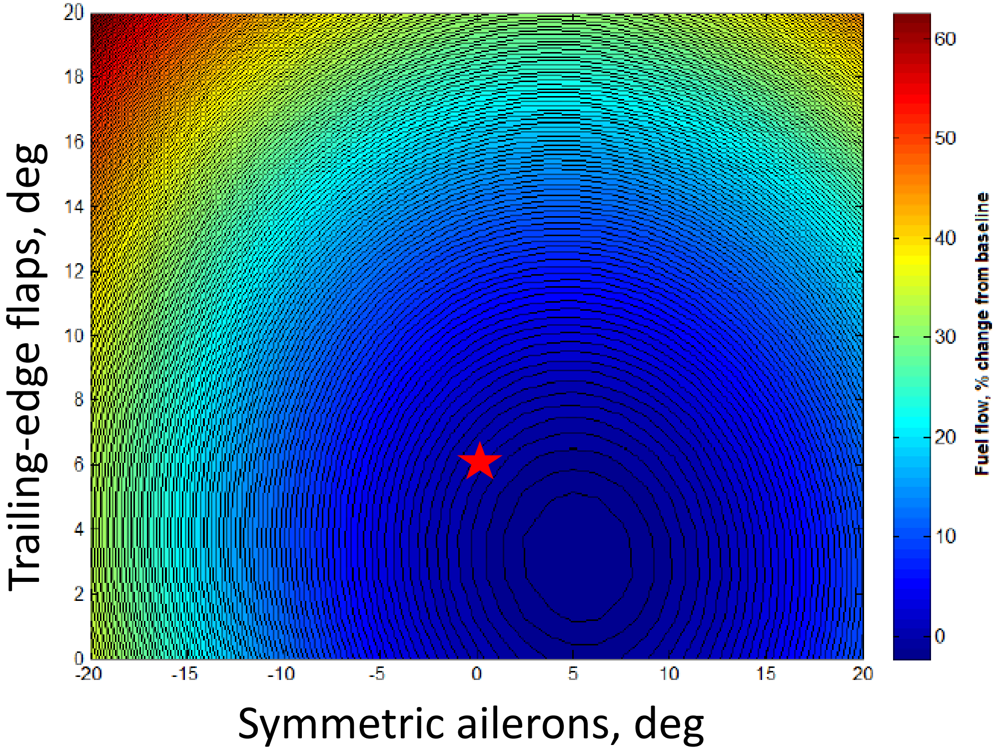
- Developed a new plant model for simulation testing.
- Polynomial fit to flight data across 3 axes



Performance Model

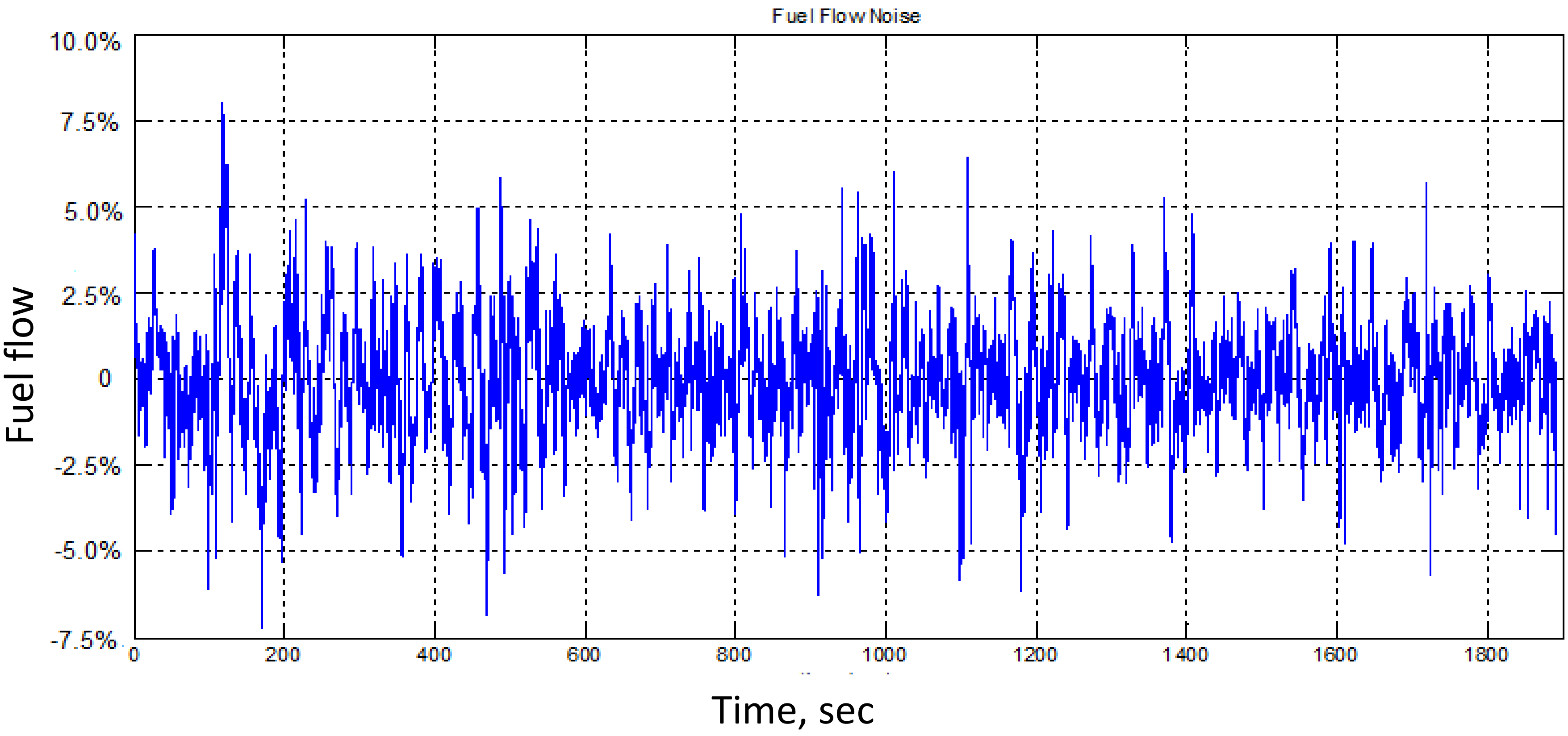
- More detailed data set collected for trailing edge flaps vs symmetric ailerons, leading edge at 5 deg
  - Spanwise lift distribution control

- Baseline
  - Trailing edge flaps, 5 to 6 deg
  - Symmetric ailerons, 0 deg
- Minimum, -2.3%
  - Trailing edge flaps, 3 deg
  - Symmetric ailerons, 5 deg



Noise Model

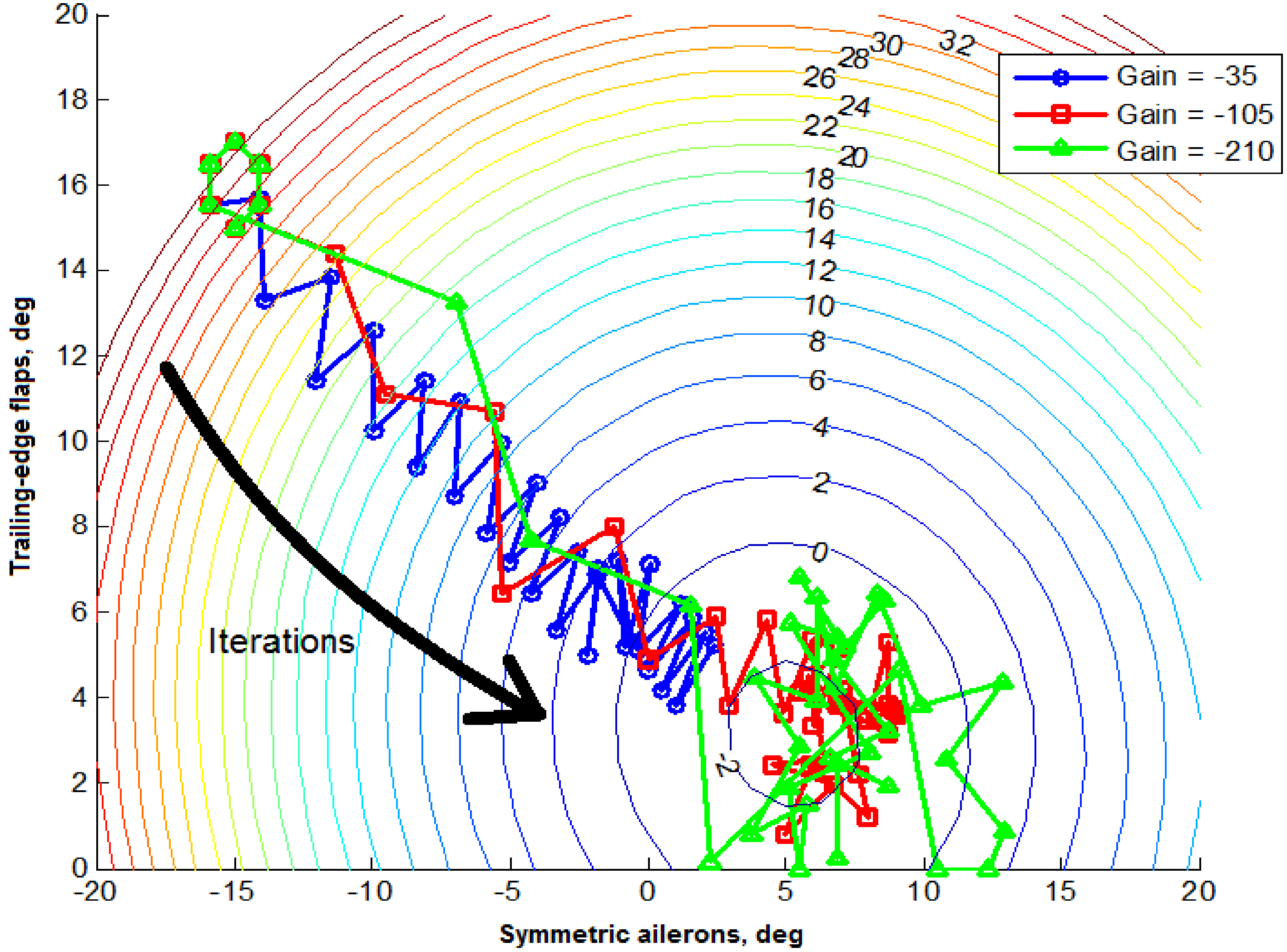
- Generated a noise model for simulation, added onto output from new performance plant model



New plant model for simulation

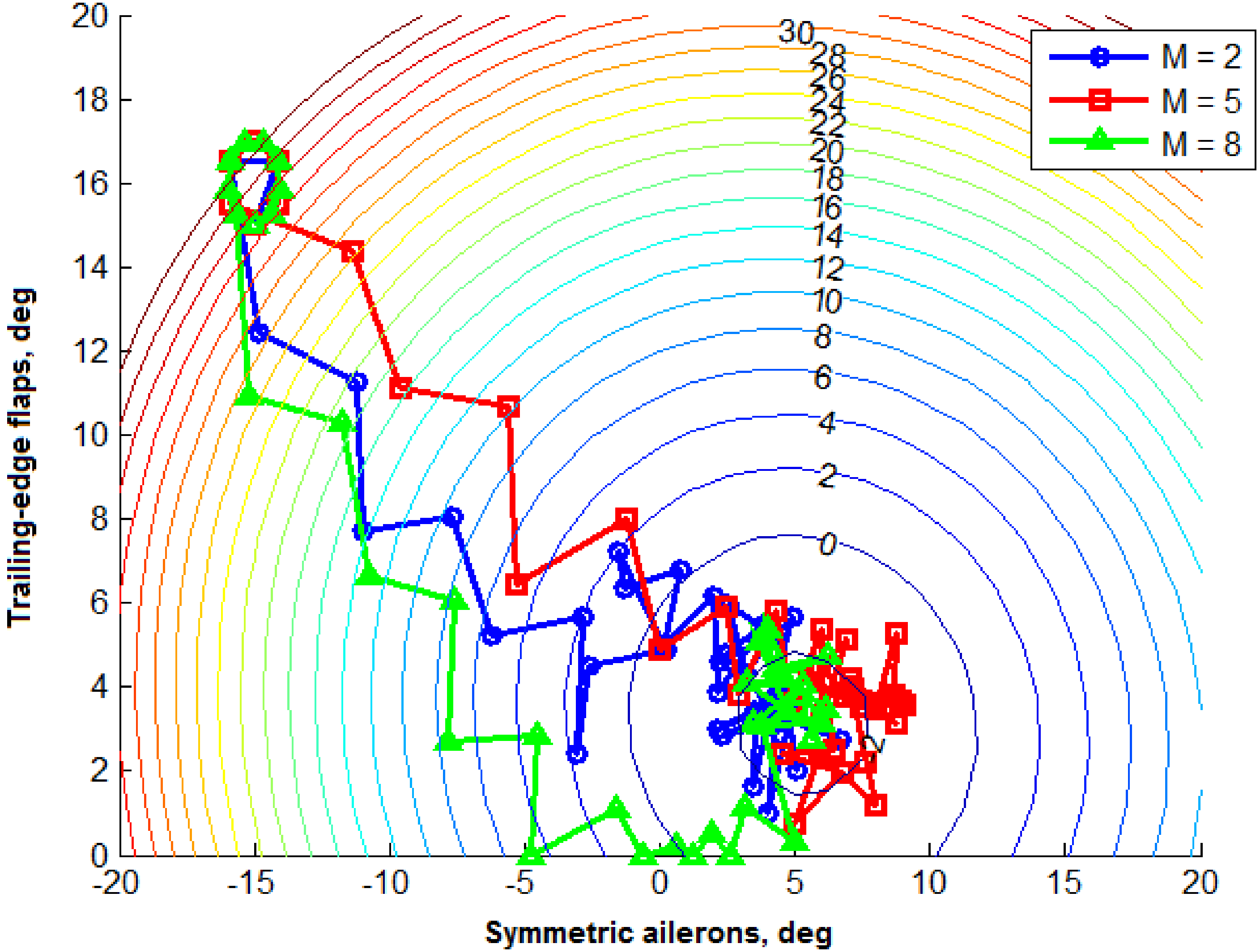
- Using new plant model in simulation, peak seeking controller was evaluated and tuned
- Tuning variables:
  - Gain applied to gradient, “controller gain”
  - M, number of previous measurements used by Kalman Filter
  - R and fuel flow filter time constant, tuned for signal noise
  - Q, Kalman filter process covariance

Gain Tuning



Gain = -35
Gain = -105
Gain = -210
Iterations
Trailing-edge flaps, deg
Symmetric ailerons, deg
-20
-15
-10
-5
0
5
10
15
20
0
2
4
6
8
10
12
14
16
18
20
32
30
28
26
24
22
20
18
16
14
12
10
8
6
4
2
0
-2

M, previous measurements



Q, R, Fuel flow filter

- Filter on fuel flow time constant and R matrix
  - filter to reduce noise on signal going into Kalman filter, adjust R accordingly

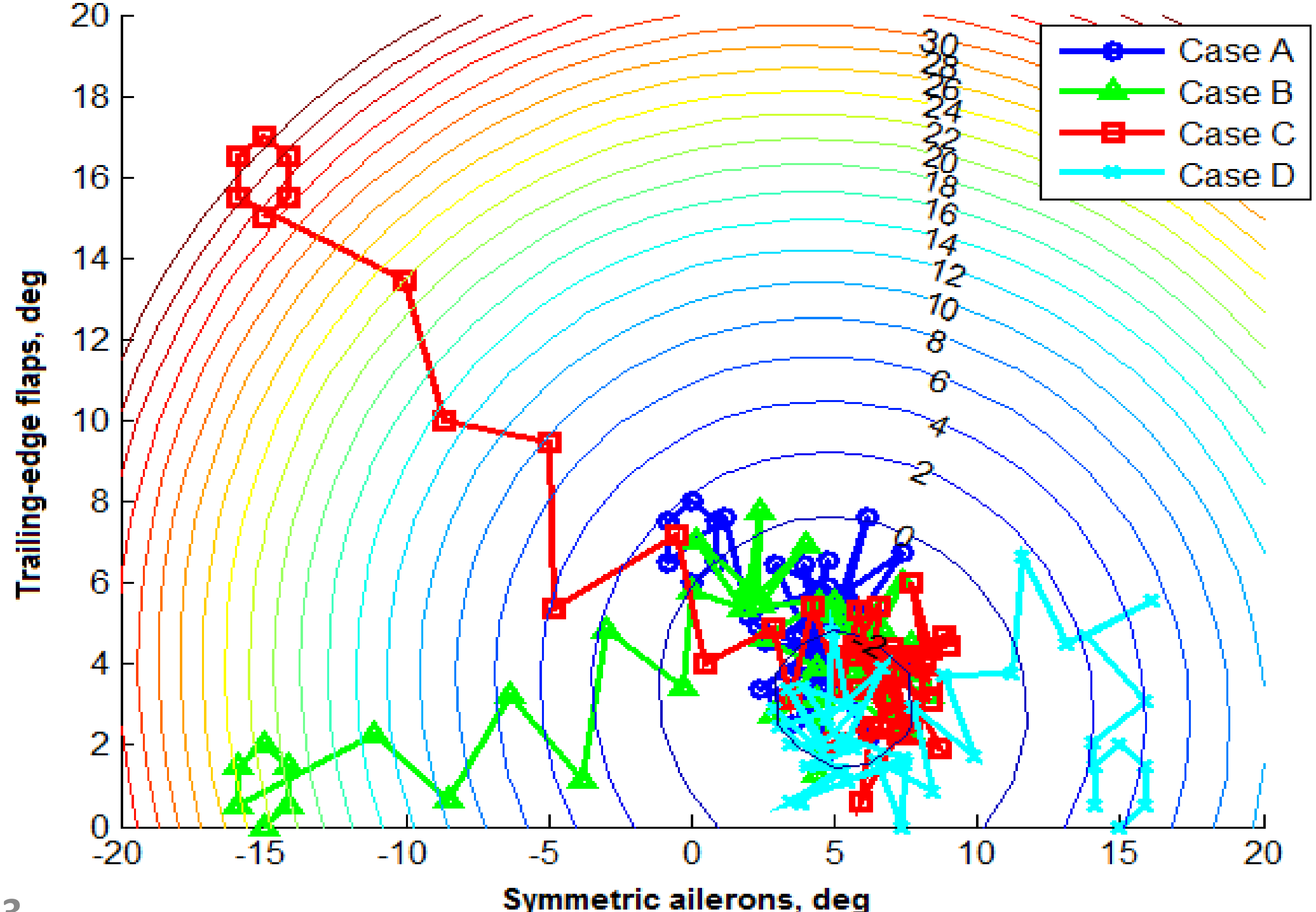
- Q matrix, process covariance, tuned through Monte Carlo type simulation

Final Tuned Parameters

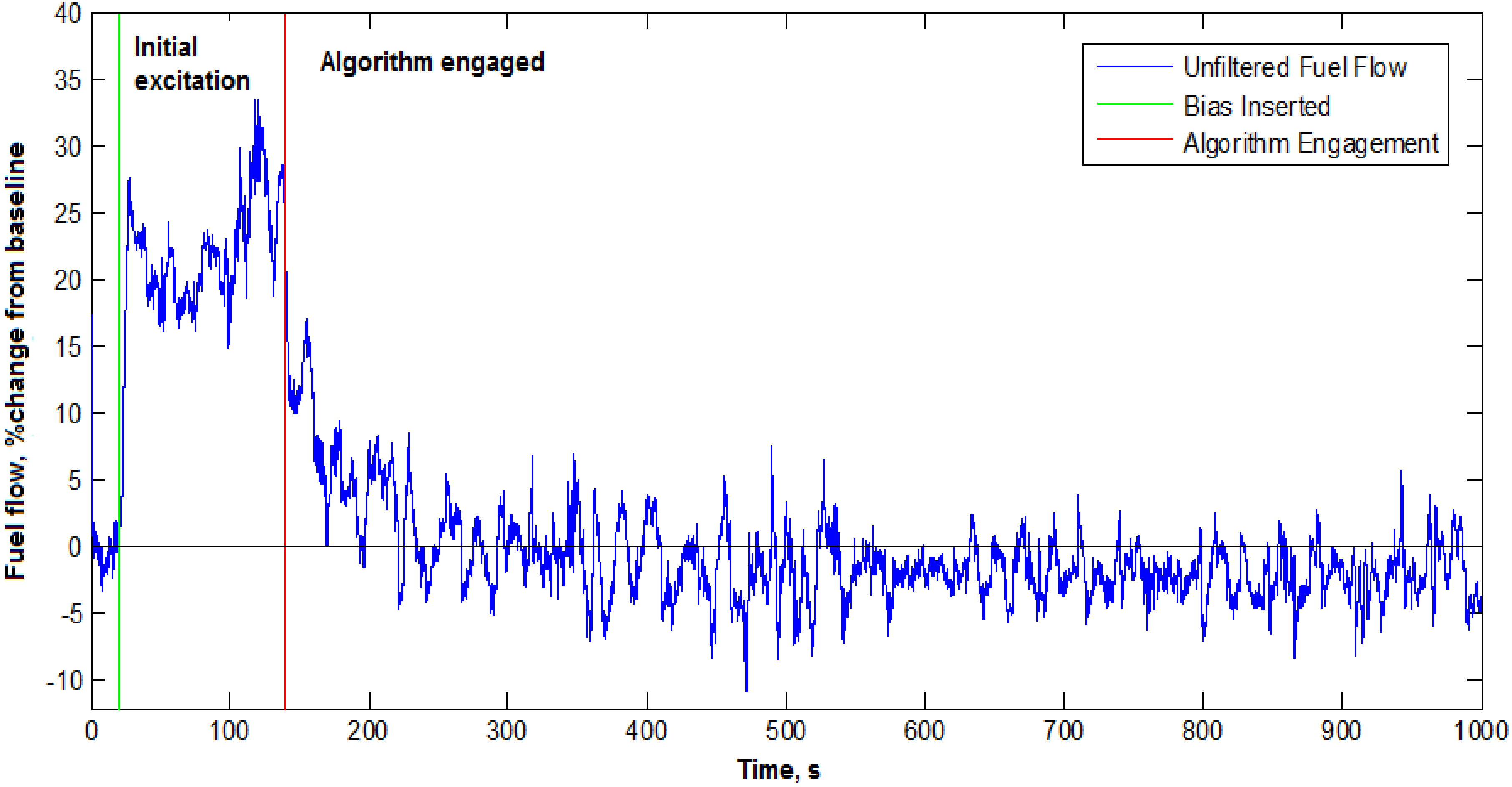
Parameter	Value
Gain	-105
M	5 for 2 effectors 7 for 3 effectors
Fuel flow filter time average	20 s
R	1.85^2 I
Q	1.98^2 I

Simulation Results – 2 effector

- Starting from 4 different positions, algorithm converges around -2%

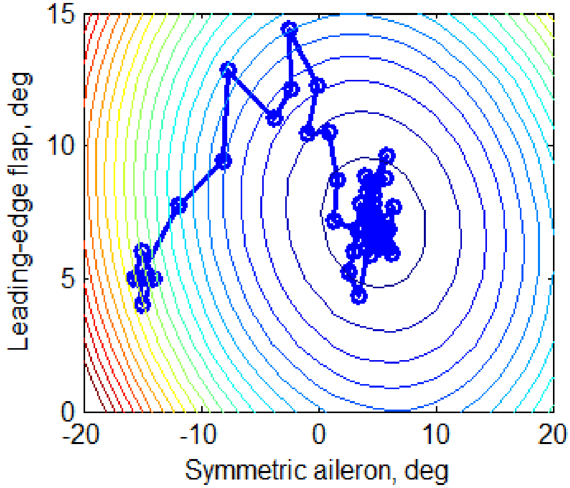


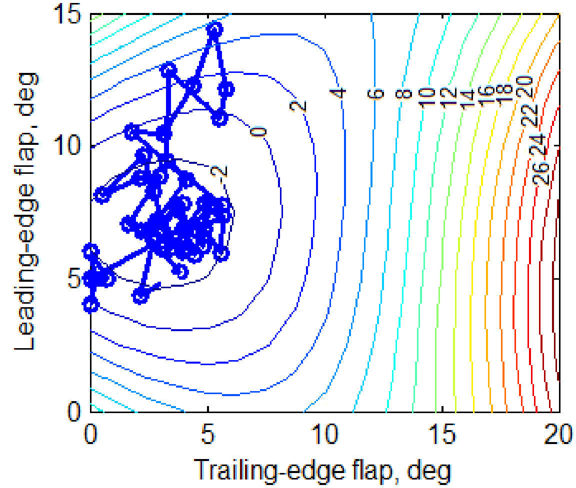
Simulation Results – 2 effector, case B

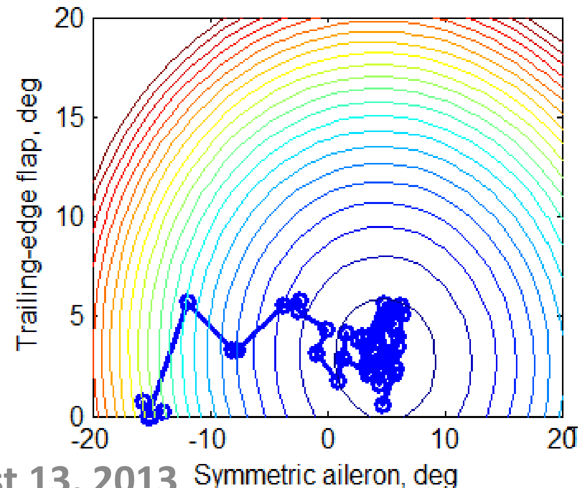


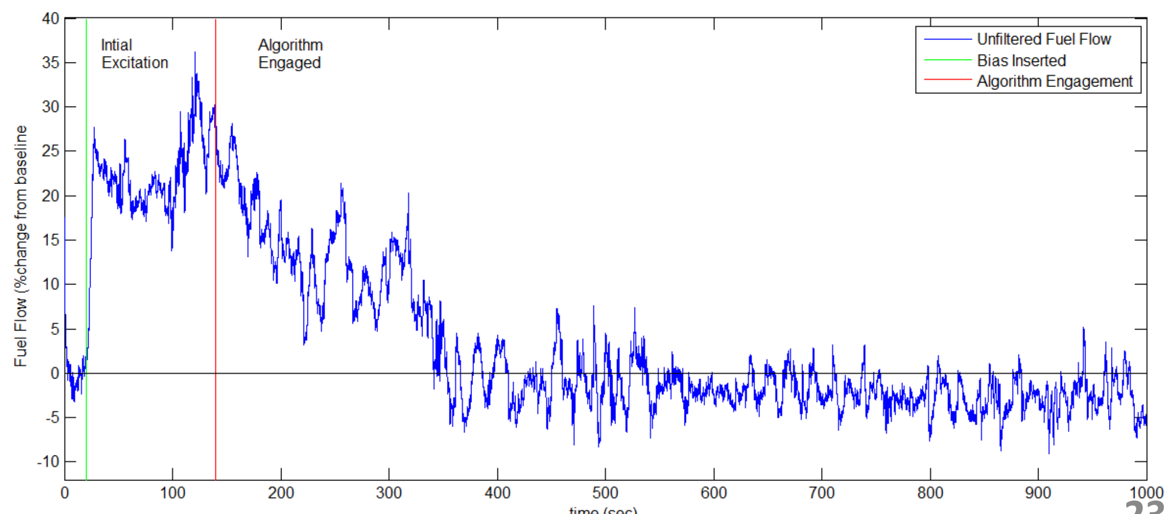
Simulation Results – 3 effector

- 3 effector test, converges to -2.5%









Conclusions

- Peak-seeking algorithm has potential to reduce fuel consumption on wide variety of aircraft types
- Can easily be implemented into existing control structure (assuming ability to actuate multiple effectors, and digital control)
- Algorithm was subsequently flown on 5 flights accumulating about 5 hours worth of test data
  - Results will be presented tomorrow at 5:30pm (Salon J)