

Simulation and Flight Evaluation of a Parameter Estimation Input Design Method for Hybrid-Wing-Body Aircraft

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As part of an effort to improve emissions, noise, and performance of next generation aircraft, it is expected that future aircraft will make use of distributed, multi-objective control effectors in a closed-loop flight control system. Correlation challenges associated with parameter estimation will arise with this expected aircraft configuration. Research presented in this paper focuses on addressing the correlation problem with an appropriate input design technique and validating this technique through simulation and flight test of the X-48B aircraft. The X-48B aircraft is an 8.5 percent-scale hybrid wing body aircraft demonstrator designed by The Boeing Company (Chicago, Illinois, USA), built by Cranfield Aerospace Limited (Cranfield, Bedford, United Kingdom) and flight tested at the National Aeronautics and Space Administration Dryden Flight Research Center (Edwards, California, USA). Based on data from flight test maneuvers performed at Dryden Flight Research Center, aerodynamic parameter estimation was performed using linear regression and output error techniques. An input design technique that uses temporal separation for de-correlation of control surfaces is proposed, and simulation and flight test results are compared with the aerodynamic database. This paper will present a method to determine individual control surface aerodynamic derivatives.

Nomenclature

AFRL = Air Force Research Laboratory
ERA = Environmentally Responsible Aviation
GPS = global positioning system
HWB = hybrid wing body
IMU = inertial measurement unit
NASA = National Aeronautics and Space Administration
OBES = on board excitation system

I. Introduction

Estimation of single surface control effectiveness for aircraft with many multi-objective, redundant control surfaces is possible with appropriate input design methods. Longitudinal parameter estimation results are disseminated in this paper for one input design method that involves the use of temporal separation to de-correlate control surfaces. Validation was performed in simulation with idealized and degraded measurements, and flight test data was used to estimate control surface effectiveness for a range of angle of attack.

Environmentally Responsible Aviation (ERA) is a National Aeronautics and Space Administration (NASA) project designed to improve emissions, noise, and performance of next generation aircraft.¹ It is expected that many of these aircraft will make use of redundant, multi-objective control effectors in a closed-loop flight control system. A distributed control system has the ability to tailor the wing to optimize performance at multiple operating points and provides redundancy for control surface failure. Isolating the aircraft response due to each control surface becomes difficult with large numbers of nearly coplanar control surfaces operating in a closed-loop flight control

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system.² Due to correlation problems, analysis of these aircraft will require advances in parameter estimation tools and methods to enable validation of aerodynamic models, simulations, and control laws.

II. Aircraft Description

The X-48B aircraft, shown in Fig. 1, is a joint partnership between NASA, the Air Force Research Laboratory (AFRL), and The Boeing Company (Chicago, Illinois, USA). Built by Cranfield Aerospace Limited (Cranfield, Bedford, United Kingdom), the aircraft is an 8.5-percent dynamically scaled hybrid wing body (HWB) with twenty aerodynamic control surfaces and three JetCat (Paso Robles, California, USA) turbojet engines. Eighteen of the twenty control surfaces are redundant and multi-objective. Due to the inherent longitudinal instability of the aircraft in parts of the flight envelope, it is augmented with a closed-loop flight control system. At the flight conditions used for parameter estimation in this paper, the aircraft was statically stable so no changes were made to the parameter estimation algorithms used.



Figure 1. The X-48B aircraft in flight.

Instruments relevant to parameter estimation include dual airdata probes to measure airspeed, angle of attack, and angle of sideslip. Additionally, the aircraft is equipped with an inertial measurement unit (IMU)/global positioning system (GPS) that provides linear acceleration, angular rotation rates, and Euler angles. Control surface positions are inferred from the measured actuator position and are not measured directly. The control surface actuation on the X-48B aircraft consists of an electro-mechanical servo that moves the control surface through a linkage. Position measurement is taken at the output shaft of the servo, so differences between the surface position and actuator position may be due to linkage bending or slop. No corrections were made to the control surface data because data or models necessary for corrections were not available. Fig. 2 is a depiction of the X-48B aircraft systems and sensors.³

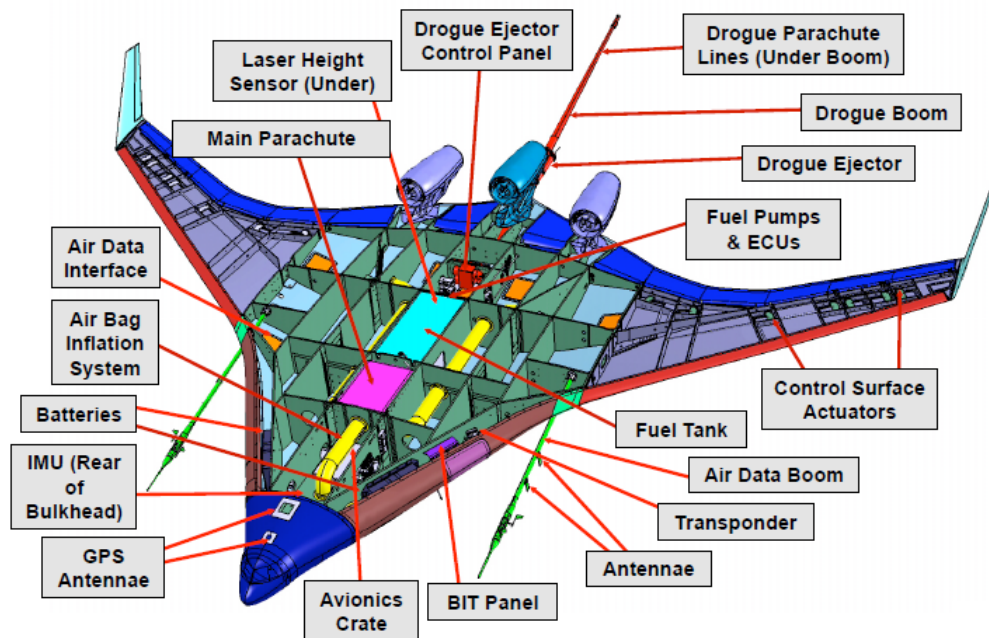


Figure 2. X-48B aircraft systems description.

The aircraft can be configured with leading edge slats extended or retracted, although, they cannot be adjusted in flight. Center of gravity can be adjusted on the ground between forward and aft configurations. The analysis in this paper is the aircraft in a slats-retracted, forward center-of-gravity configuration. Allocation of the control surfaces is depicted in Fig. 3 with surface pairs numbered for reference. Additionally, surface 6 and surface 7 are split ailerons; the top and bottom surface can be moved together to produce roll moments or they can be split to produce a yaw moment. Rudders are incorporated into the winglets to provide yaw control.

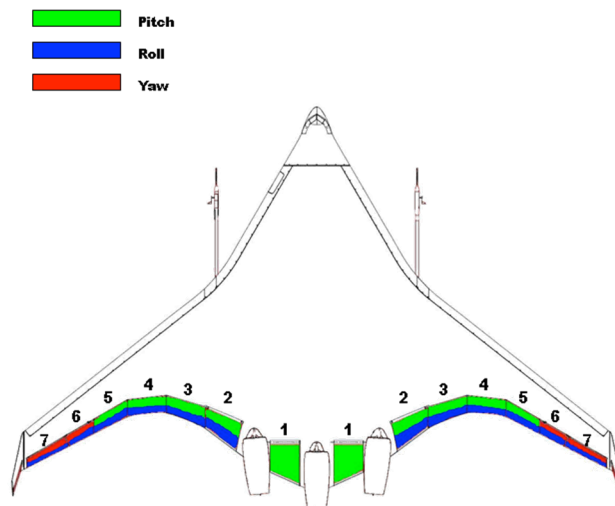


Figure 3. Control surface allocation.

For additional information on the X-48B aircraft see Ref. 4.

III. Parameter Estimation Background

Parameter estimation involves the creation of mathematical models for physical systems from knowledge of the input and response of the system (Fig. 4).

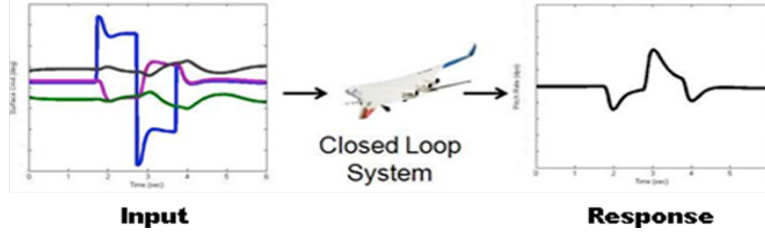


Figure 4. Dynamic response of a system.

As it relates to aircraft, inputs are generally control effectors, and responses are sensor measurements. Standard time-domain linear regression and output error techniques were employed for parameter estimation. Linear regression is a technique in which the coefficients of an assumed linear relationship between known inputs and observed outputs are estimated using least-squared fits. More information on linear regression parameter estimation techniques can be found in Ref. 5. Output error minimizes the difference between computed measurements and actual measurements to estimate parameters. More information on output error and maximum likelihood techniques can be found in Refs. 6-10. Prior work to de-correlate control surfaces can be found in Refs. 5, 11-17. Multi-sines have been used in the past to de-correlate control surfaces, although, this approach was not an option due to limitations in the X-48B on board excitation system (OBES).

During input design and parameter estimation, it is important to consider the effect on Cramér-Rao bounds. The Cramér-Rao lower bound represents the lowest magnitude limit for the variance of an estimator with a given bias. The derivation of the Cramér-Rao inequality is given by Maine and Iliff¹⁸ and provided in Eq. (1).

$$E \left\{ \left(\hat{\xi} - \xi_t \right) \left(\hat{\xi} - \xi_t \right)^* \mid \xi_t \right\} \geq \left[I + \nabla_{\xi_t} b(\xi_t) \right] M(\xi_t)^{-1} \left[I + \nabla_{\xi_t} b(\xi_t) \right]^* \quad (1)$$

Un-modeled dynamics can make the true value of the variance of the estimator much higher. In the simplest case where the variance is assumed to be unbiased and have a normal distribution, then the Cramér-Rao bound becomes simply the inverse of the Fisher information matrix, which is a metric for measuring the amount of usable information content in a set of data.

In the broader sense, the Cramér-Rao bounds represent approximations of the true, unconditional standard deviation of a data set, which in turn are the square-roots of the estimated variances calculated for each data point, and with biases and assumptions about the system are taken into account.¹⁸ This approach is different from the sample standard deviation and sample variance, which are associated with merely the scatter in the data set as a whole.

Even with a biased estimator, the Cramér-Rao bound remains inversely proportional to the Fisher information matrix. Thus, choosing input design methods and flight test techniques that lower the Cramér-Rao bounds is an effective approach to choosing inputs that maximize usable information content of the flight data.

In reality, un-modeled aircraft dynamics cause the variance in parameter estimates to look like colored noise instead of white noise generated by a normal distribution. Using a method described in Section 6.3.3 of Klein and Morelli,⁵ colored Cramér-Rao bounds assuming colored residuals were computed and are depicted in the results as error bars on both the output error results and the ordinary least-squares linear regression.

IV. Input Design Methods

In order to determine a mathematical model for the system, the inputs to a system that cause a response must be uniquely identified. Challenges arise with parameter estimation of HWB aircraft due to their use of redundant, multi-objective control surfaces with highly augmented closed-loop flight control systems. The majority of these challenges involve identifying the response attributable to each input. Redundant, multi-objective, nearly co-planar control surfaces will evoke similar aircraft responses and excite the aircraft in multiple axes. Compounding the

problem, a closed-loop control system will treat all input excitations as a disturbance and attempt to damp them out with the use of the remaining control surfaces. In order to overcome these challenges, inputs must be designed in a manner that allows identification of control-surface response within the constraints of the closed-loop controller.

In the case of a single input system, the solution is trivial. Control effectors are moved individually and the corresponding aircraft response is measured. For multiple input systems, input correlation becomes an important factor. Fig. 5 is a good example of input correlation for a longitudinal maneuver. Notice that as surface pair one is excited, the other surface pairs that can contribute to the aircraft response move to counteract the excitation. Estimation of control effectiveness is challenging because it becomes difficult to determine the portion of the response attributable to excited surfaces.

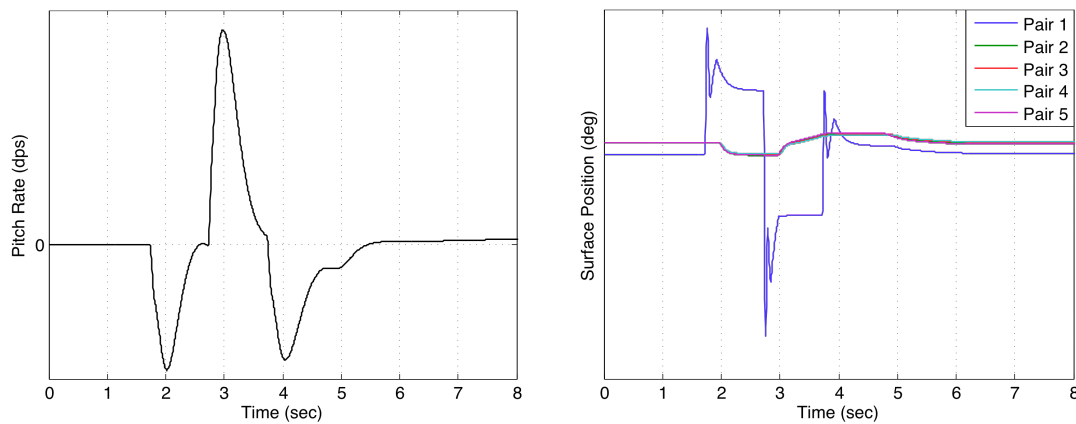


Figure 5. Input correlation.

A. Temporal Separation for De-Correlation

One solution is to individually excite each surface capable of contributing to the aircraft response and de-correlate with temporal separation. Due to limitations in the X-48B OBES, each surface excitation had to be performed individually and then pieced together prior to analysis. This approach to input design was termed a “super maneuver” since it involved piecing together flight test information from several individual maneuvers. A potential for errors in the parameter estimates existed if the initial conditions for each of the individual excitations that make up a super maneuver were not the same. On the other hand, because the super maneuver consisted of many short duration excitations, the aircraft remained near its trim condition.

In order to simplify the problem, control surfaces on the left and right wings were grouped to constrain their effect on aircraft dynamics to either longitudinal or lateral-directional. Fig. 6 is an example of a doublet sequence used for a longitudinal super maneuver.

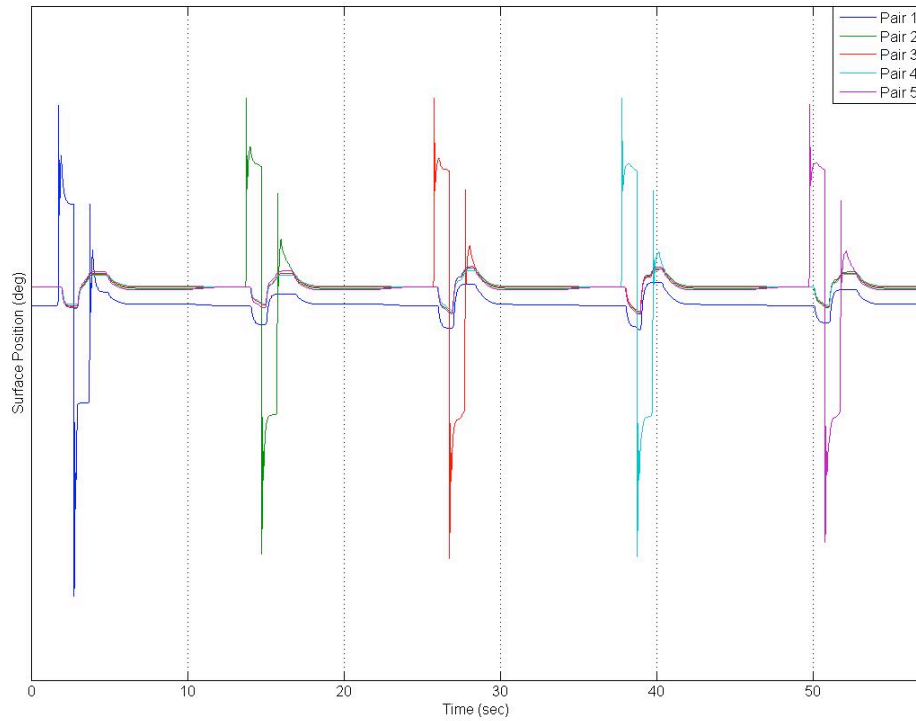


Figure 6. Super maneuver to de-correlate inputs.

B. Validation of Techniques using Simulation

The Boeing Company developed a non-linear simulation of the X-48B aircraft. This simulation uses an aerodynamic model of the aircraft that was derived from wind tunnel data and updated with flight data. Parameter estimation methods and input design techniques were validated in simulation by comparing the estimated parameters with the aerodynamic model parameters for various flight conditions and aircraft configurations (Fig. 7).

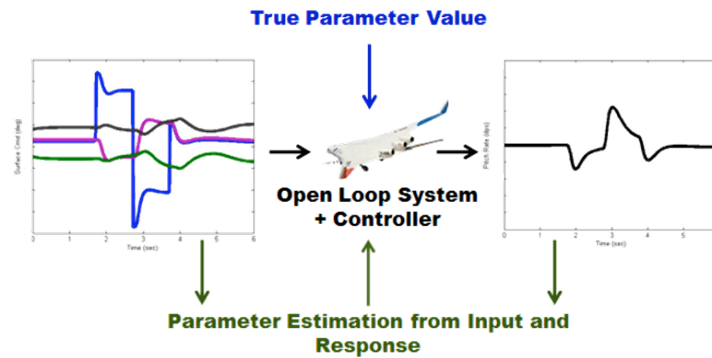


Figure 7. Using simulation to validate parameter estimation methods and input design techniques.

Airdata, linear acceleration, and rotational rate measurement signals were degraded with the use of time delays, transfer functions, and noise to simulate real-world sensor dynamics and inaccuracies as shown in Fig. 8. Parameter estimation was performed with the degraded signals to gauge the potential accuracy and challenges associated with imperfect measurements. Appendix A contains additional plots of the measurement degradation.

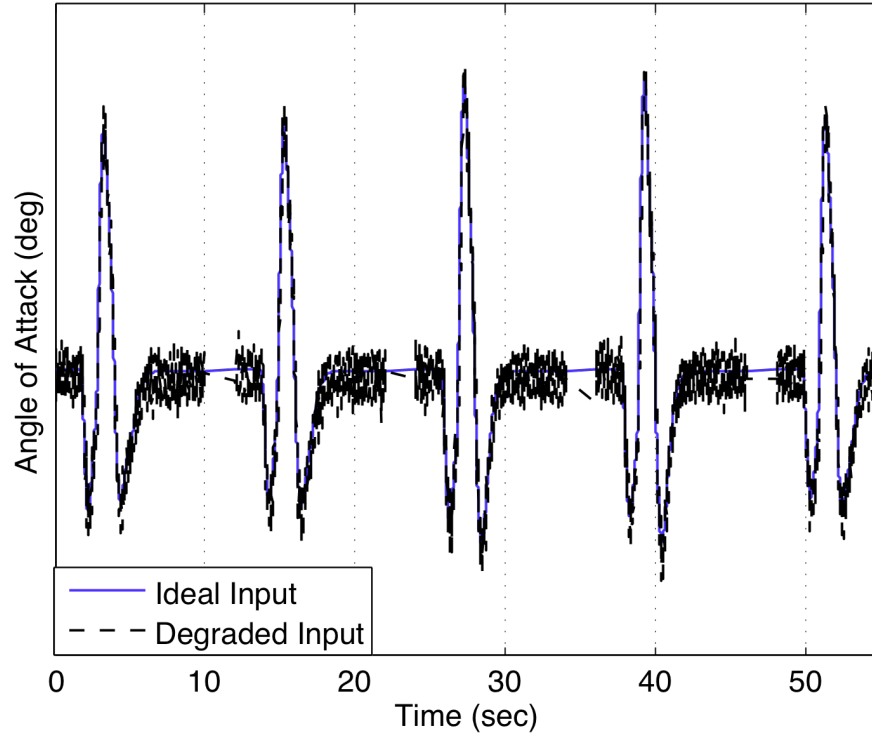


Figure 8. Degraded measurement example.

V. Results and Discussion

Flight data for this paper was collected during two flights on September 17 and September 22, 2009 within an altitude block of 5,000 to 9,000 feet. Individual doublets were performed using the on-board excitation system (OBES), and the pilot returned the aircraft to the target flight conditions between excitations. The aircraft was tested in a slats-retracted, forward center-of-gravity configuration. Nonlinear simulation data was collected for similar conditions and aircraft configuration as the flight data.

A. Simulation

Validation of the input design and parameter-estimation techniques was the primary purpose of performing parameter estimation with simulation data. Parameter estimation quality can be evaluated by the fit of reconstructed time history data with measured time history data. Fig. 9 gives an example of the fit for a simulated longitudinal super maneuver. Additional plots of time history fits are in Appendix B.

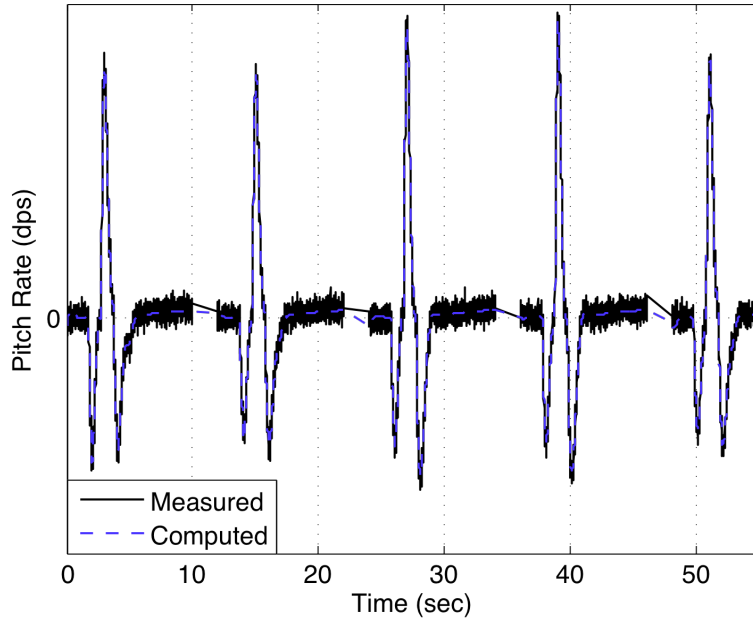


Figure 9. Simulation pitch rate time history fit.

Fig. 10. shows the control effectiveness for the inboard elevon pair as a function of angle of attack. For additional parameter estimation plots with simulation data see Appendix C. The error bars on the aerodynamic model indicate the uncertainty from the aerodynamic model that was used for control law analysis. Degraded signals led to an estimate of lower control effectiveness, although, the basic trends were still captured.

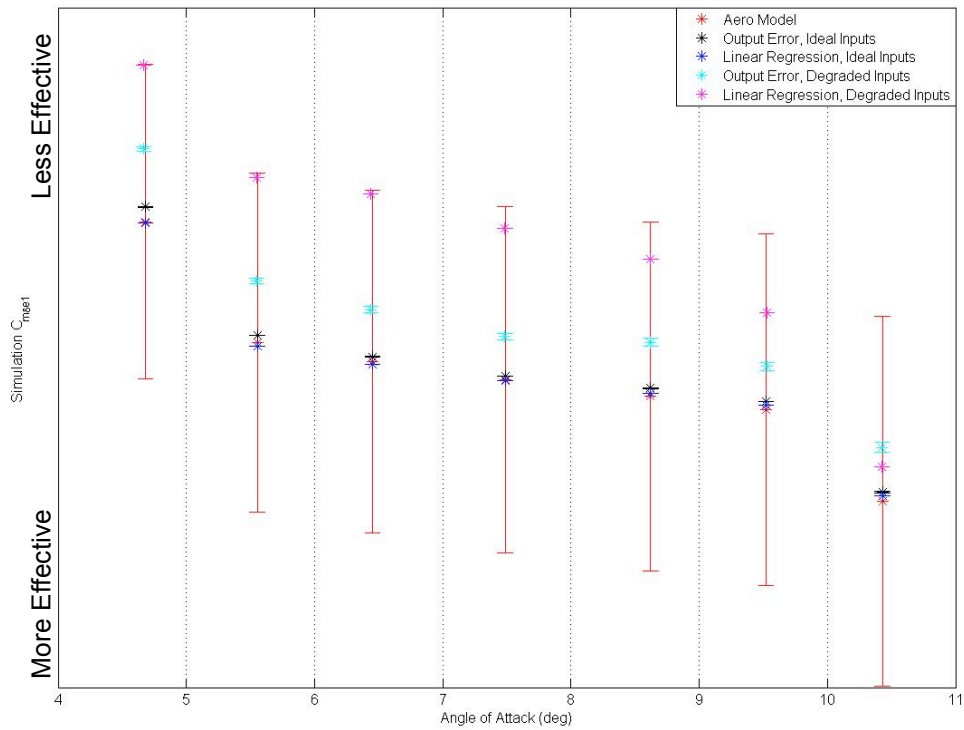


Figure 10. Simulation inboard elevon pair control effectiveness.

B. Flight

Figs. 11 and 12 are examples of the time history fits for flight data. Appendix D contains additional plots of time history fits.

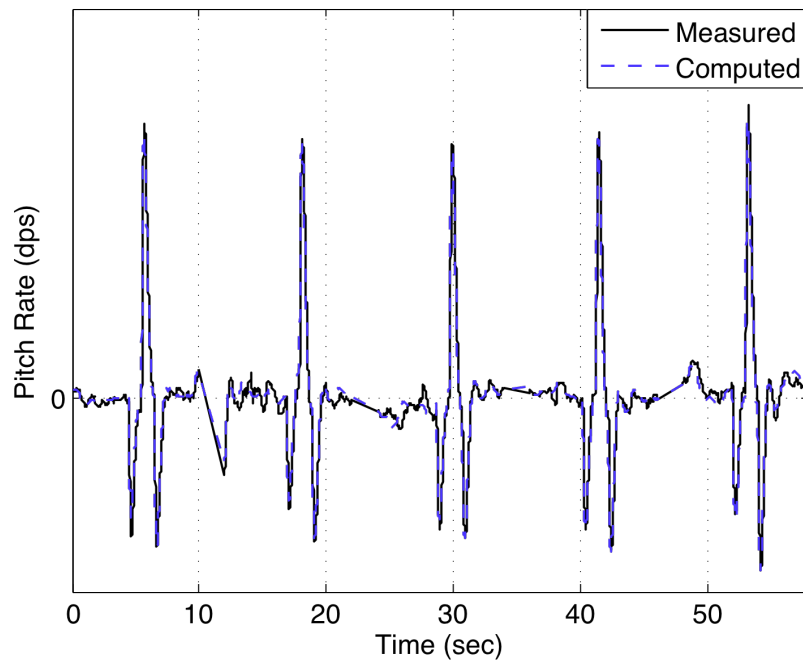


Figure 11. Flight pitch rate time history fit.

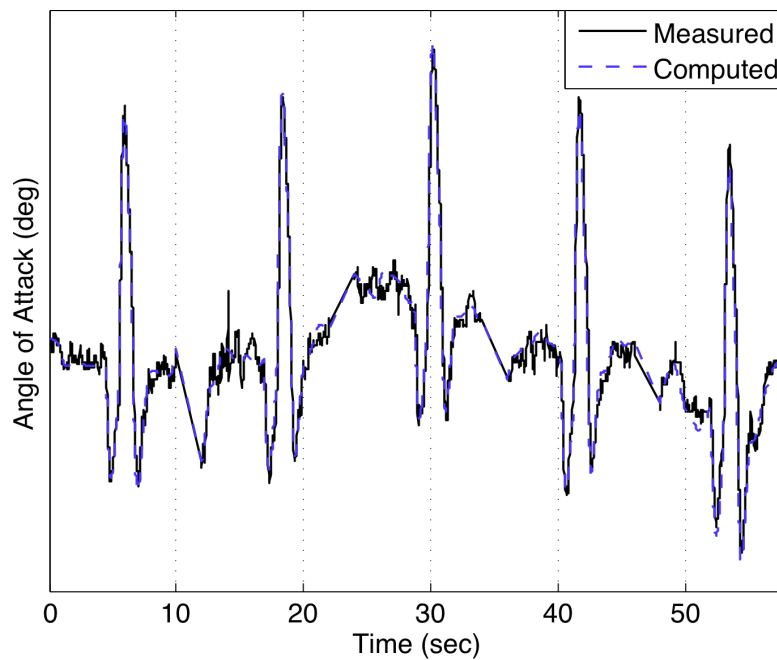


Figure 12. Flight angle of attack time history fit.

Inboard elevon control effectiveness estimated using super maneuver inputs with flight data is shown in Fig. 13, while additional parameter estimates are in Appendix E.

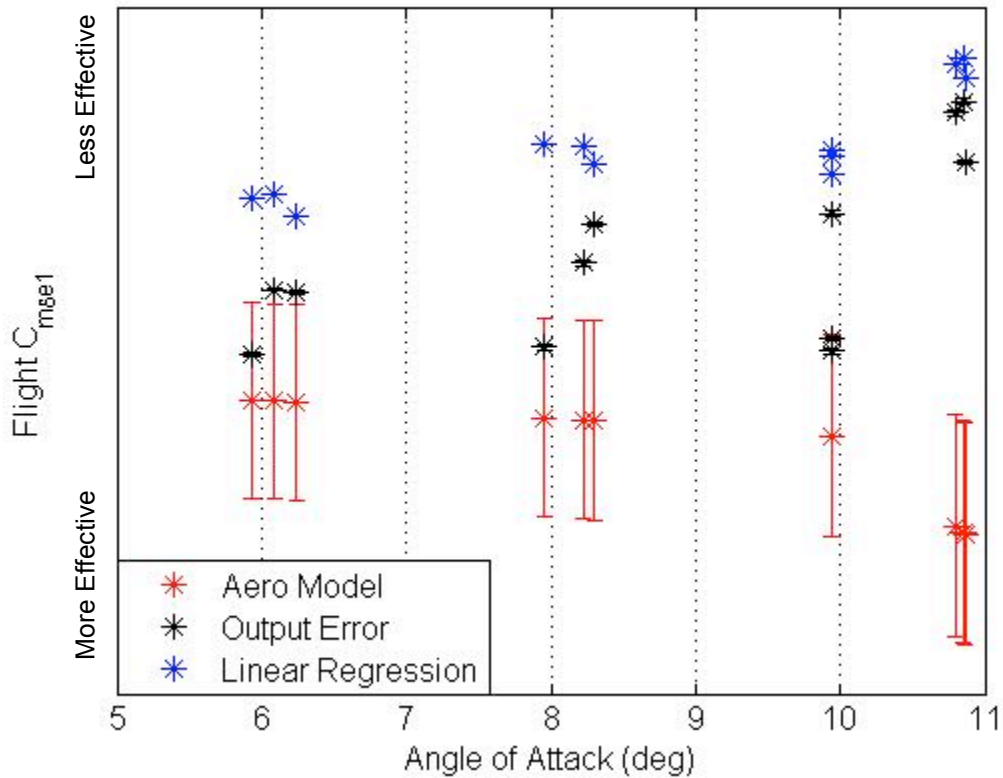


Figure 13. Flight inboard elevon pair control effectiveness.

It is interesting to note that the flight derived control effectiveness is relatively constant at low angle of attack, decreasing slightly as angle of attack is increased. This trend is present for the flight-derived estimates of all of the control surfaces. Differences from the aerodynamic database could be due to a variety of factors including inadequate moment of inertia testing, inaccurate control surface position measurements, differences in doublet initial conditions, or errors in the aerodynamic database. Moment of inertia and control position errors would tend to bias control effectiveness estimates while still retaining the general trends. Errors in the parameter estimation method, input design technique, or sensor measurements are less likely due to their accuracy with simulation data even with imperfect data sets. Errors in the aerodynamic database are likely the cause of differences from flight derived parameter estimates.

To quantify uncertainty in moment of inertia testing and control surface position measurement, NASA researchers are planning to conduct testing in both areas during aircraft downtime in September 2010. Several conventional and novel moment of inertia testing techniques will be conducted with a representative structure of known mass properties in order to evaluate and validate estimation uncertainty. The X-48B aircraft will then be tested using the best techniques in order to obtain the most accurate inertia information as possible. In addition, frequency sweeps of the control surfaces will be conducted on the ground with independent surface position measurement equipment installed to gauge the accuracy of the positions reported in flight data.

In general, output error techniques tended to estimate parameters with corrupted data better than linear regression techniques, although, large scatter in the data were occasionally observed with output error estimation on flight data.

VI. Conclusions and Future Research

Temporal separation was used to de-correlate control surface excitations of an aircraft with a large number of multi-objective, redundant control surfaces with a closed-loop flight control system. Longitudinal parameter estimation was performed with simulation and flight data. Simulation validated the input design technique and its robustness to sensor errors. Parameter estimation of flight data yielded results that suggest errors may be present in the current X-48B aerodynamic model.

Upcoming flight tests will explore two additional input design techniques. The first technique will excite each control surface independently and perform parameter estimation to produce both longitudinal and lateral-directional results simultaneously. The second technique involves exciting the control surfaces in pairs with optimized mutually orthogonal square waves. Both of these planned inputs may reduce the amount of flight time necessary to perform parameter estimation on HWB aircraft. Planned research, flight testing, and analysis will evaluate the feasibility of these input designs.

Appendix A: Degraded Input Figures

Simulated measurement of pitch rate, vertical acceleration, and axial acceleration were degraded with time delays, transfer functions, and noise. Examples of these degradations for a longitudinal super maneuver are shown in Figs. 14-16.

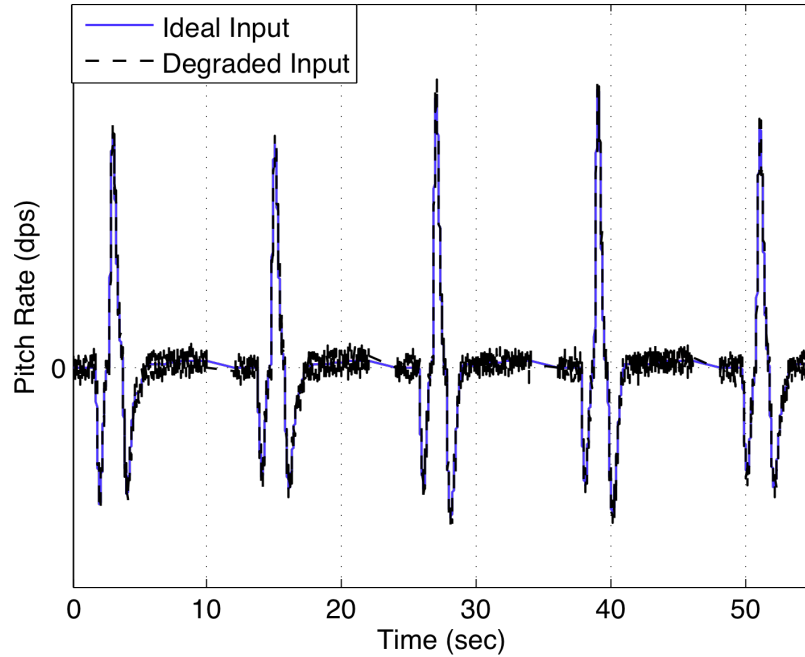


Figure 14. Pitch rate degradation.

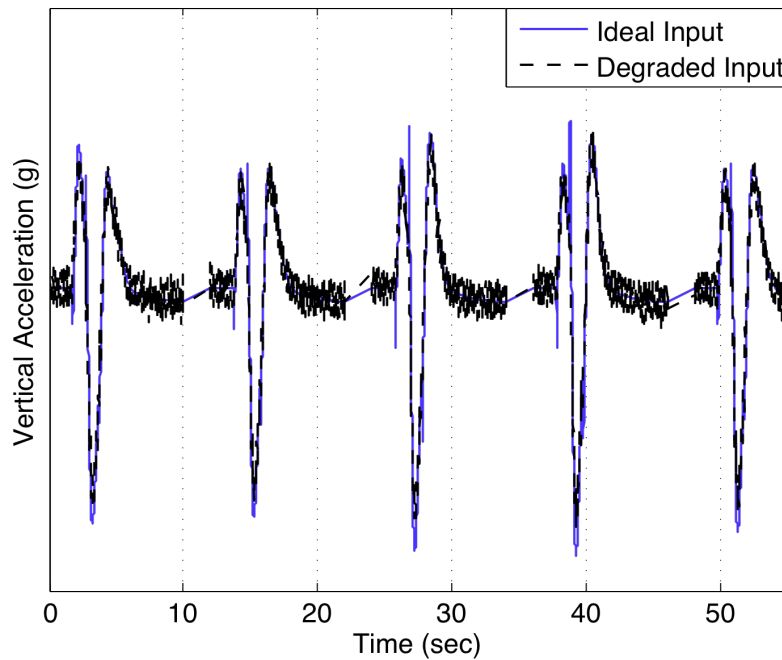


Figure 15. Vertical acceleration degradation.

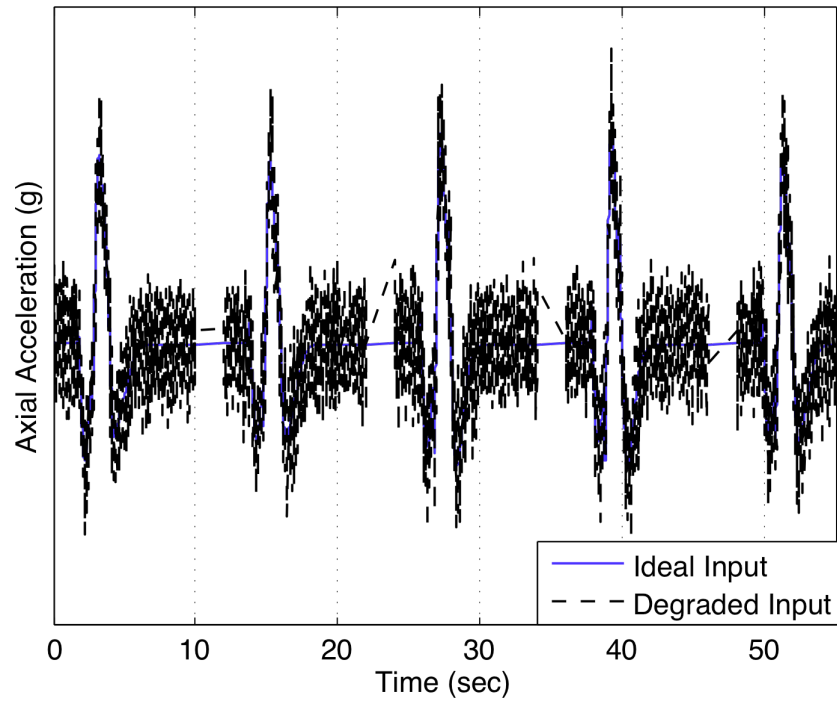


Figure 16. Axial acceleration degradation.

Appendix B: Time History Fits from Simulation Data

Simulation was used to validate the super maneuver input design technique and its robustness to sensor errors. A qualitative measure of the parameter estimation accuracy is given by qualitatively evaluating the fit between the simulated and reconstructed sensor measurements, shown in Figs. 17-19.

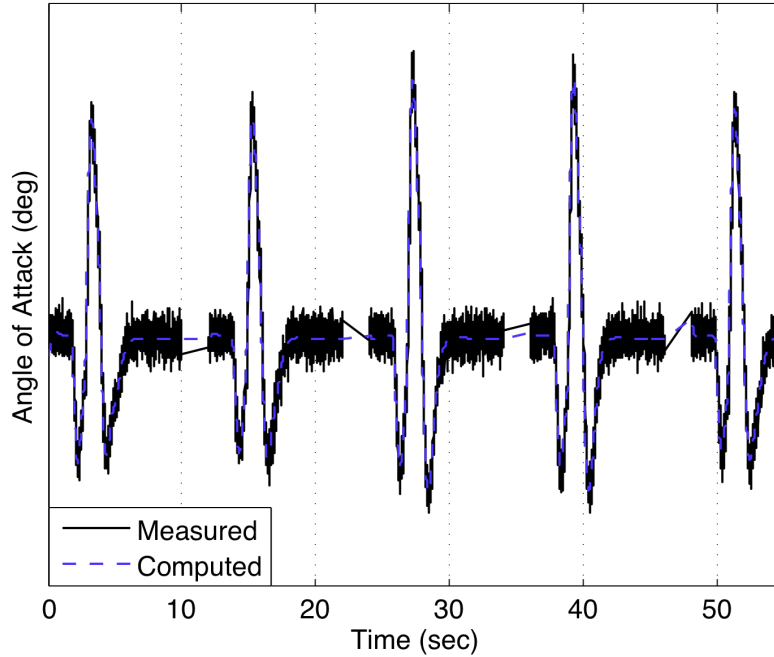


Figure 17. Angle-of-attack simulation time history fit.

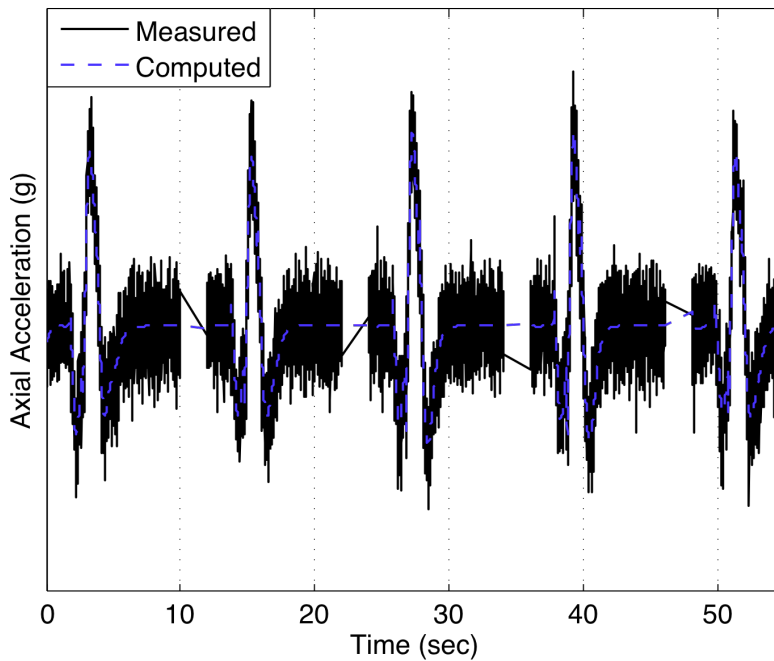


Figure 18. Axial acceleration simulation time history fit.

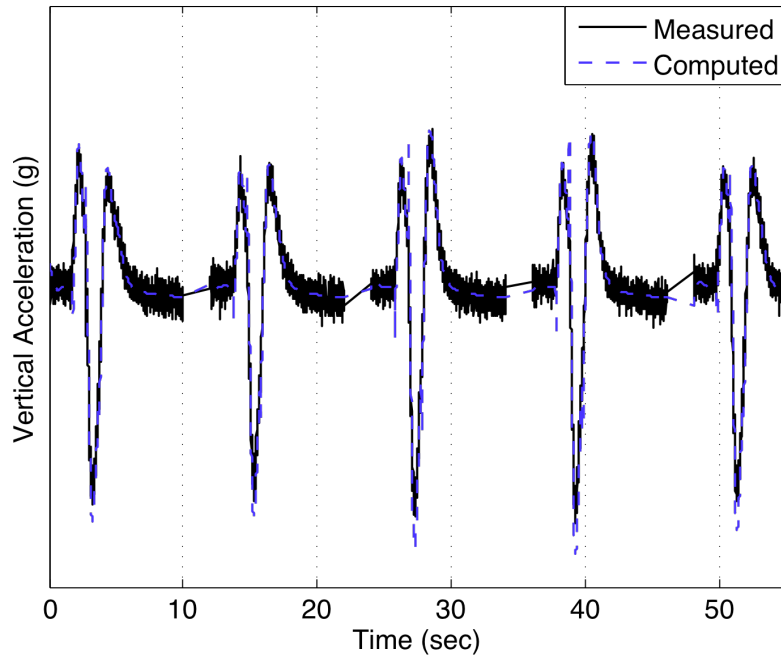


Figure 19. Vertical acceleration simulation time history fit.

Appendix C: Figures of Parameter Estimates from Simulation Data

Simulation was used to validate the super maneuver input design technique and its robustness to sensor errors. Longitudinal parameter estimation was used with both output error and linear regression techniques as shown in Figs. 20-26. Ideal sensor measurements (the same data used in equations of motion of the simulation) were used to validate the super maneuver input design technique. For these measurements, estimation of control effectiveness was within 1.7 percent of the aerodynamic model values. Sensor models were degraded with the use of delays, transfer functions, and noise to evaluate the robustness of the input design technique. Generally, this led to an estimate of lower control effectiveness, however, the general trend as a function of angle of attack was still captured.

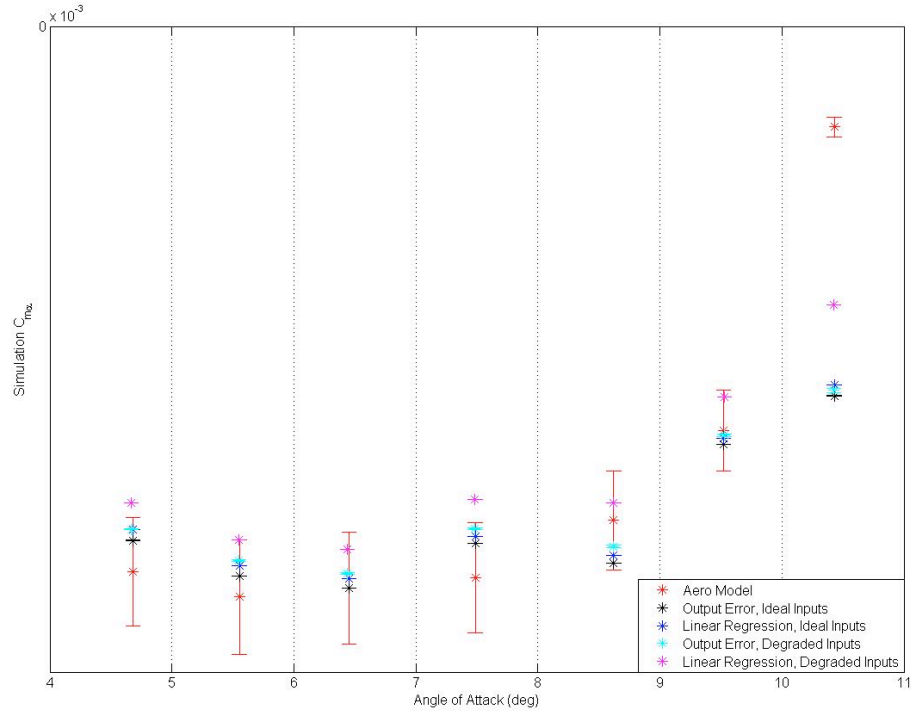


Figure 20. Simulation estimate of change in pitching moment with a change in angle of attack.

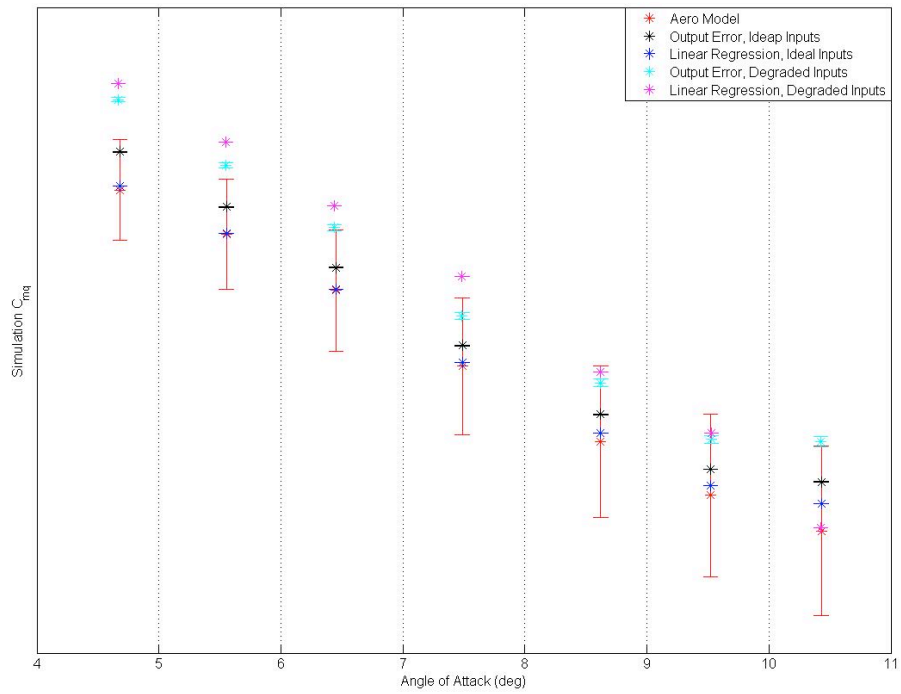


Figure 21. Simulation estimate of change in pitching moment with a change in pitch rate.

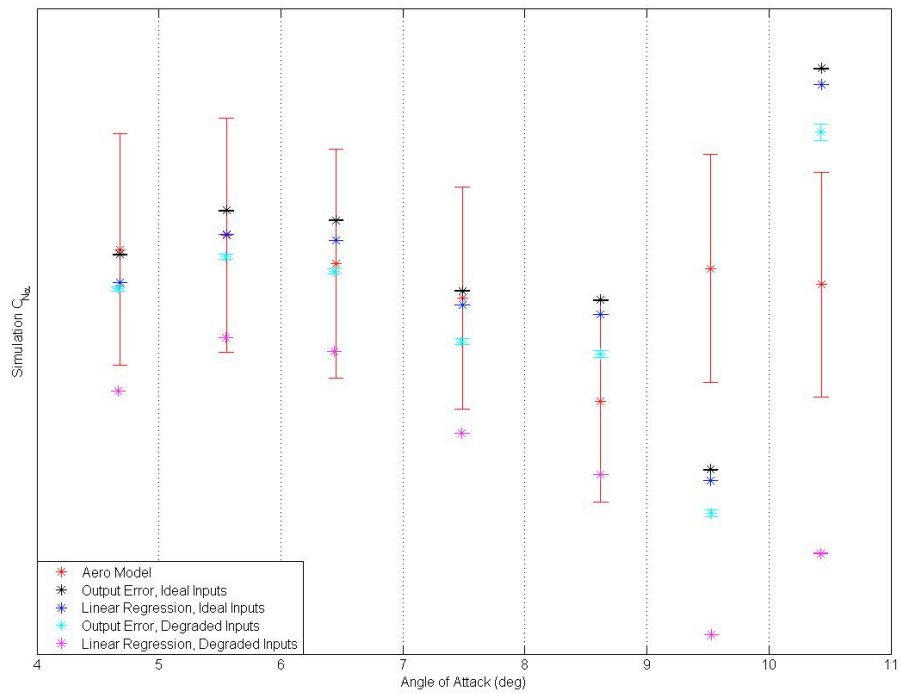


Figure 22. Simulation estimate of change in normal force with a change in angle of attack.

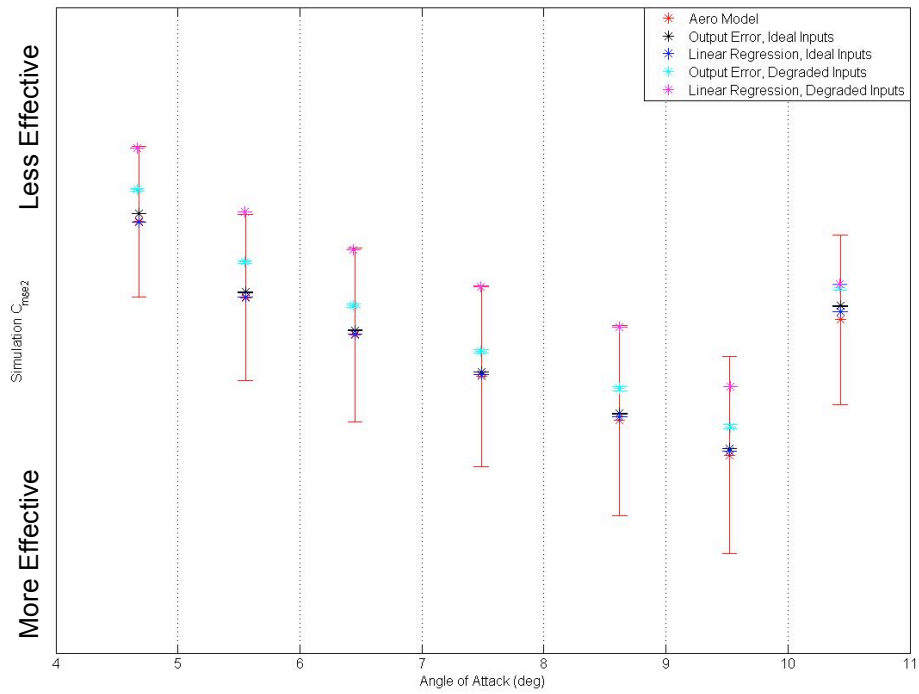


Figure 23. Simulation estimate of longitudinal control effectiveness, surface pair 2.

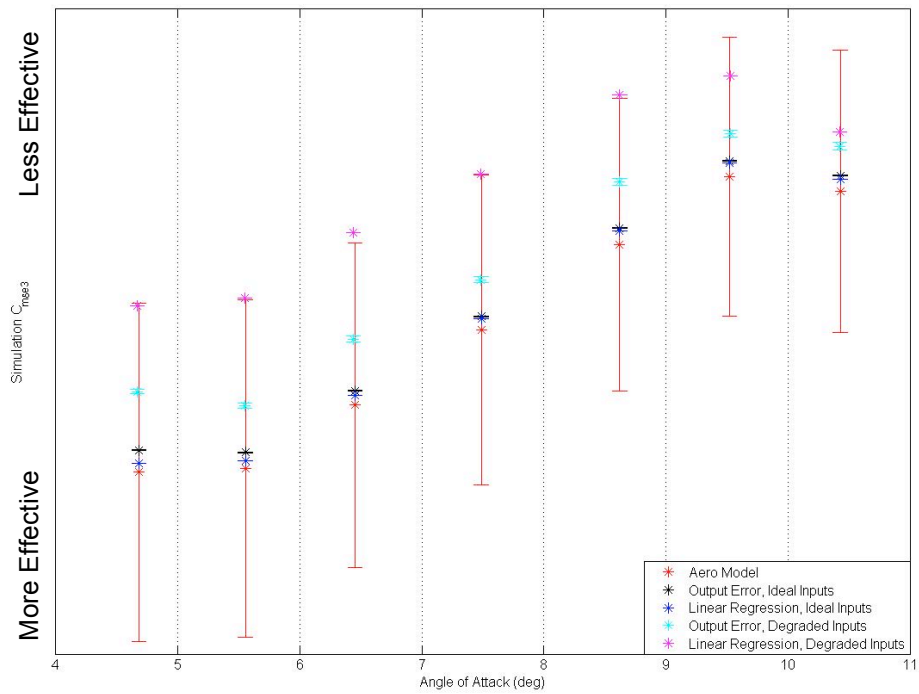


Figure 24. Simulation estimate of longitudinal control effectiveness, surface pair 3.

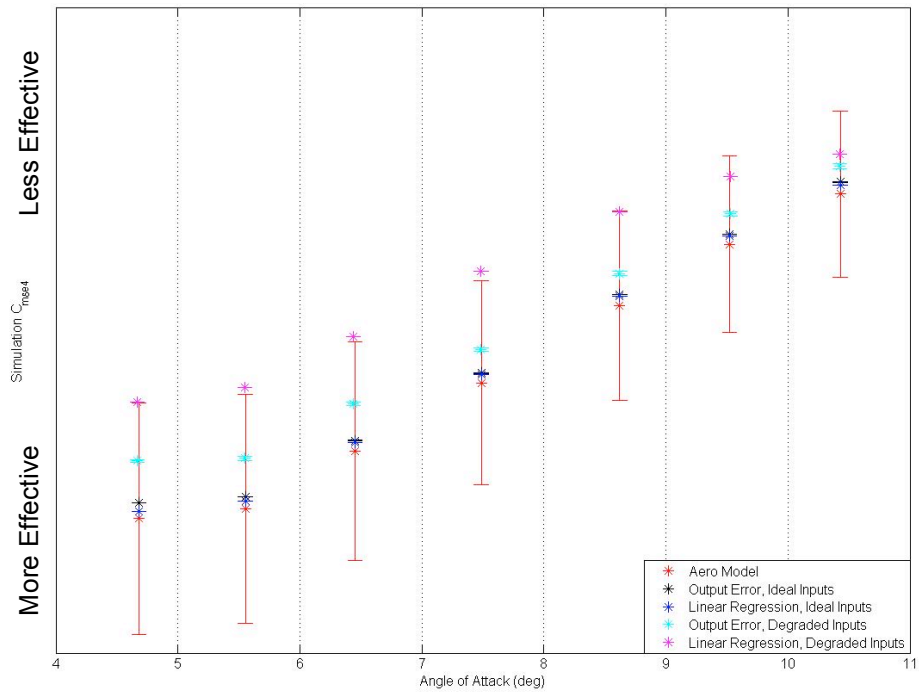


Figure 25. Simulation estimate of longitudinal control effectiveness, surface pair 4.

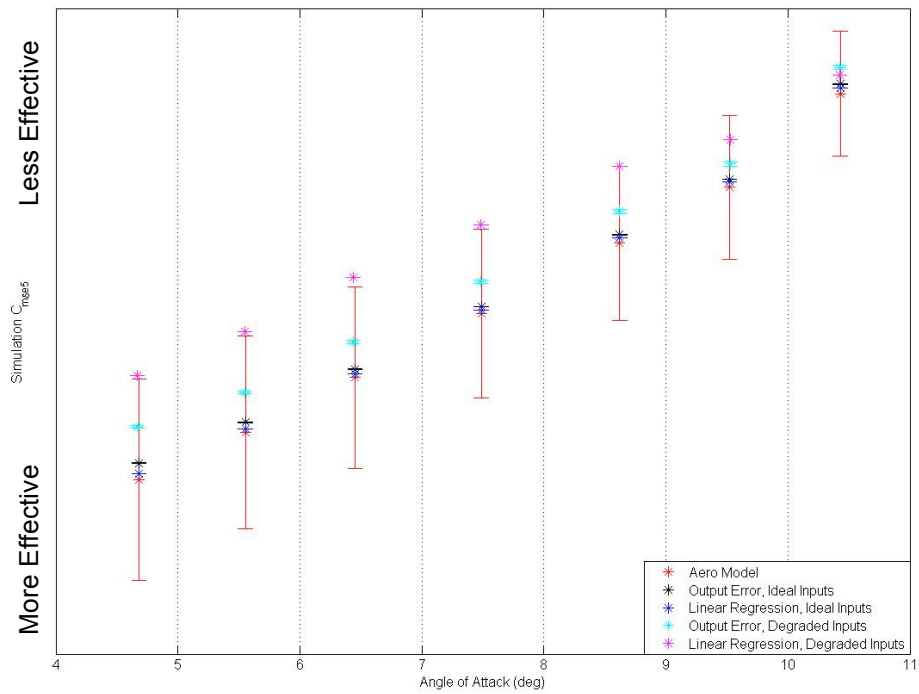


Figure 26. Simulation estimate of longitudinal control effectiveness, surface pair 5.

Appendix D: Time History Fits from Flight Data

A qualitative measure of the parameter estimation accuracy is given by qualitatively evaluating the fit between the actual and reconstructed sensor measurements. Time history fits for an example longitudinal super maneuver are shown in Figs. 27-28.

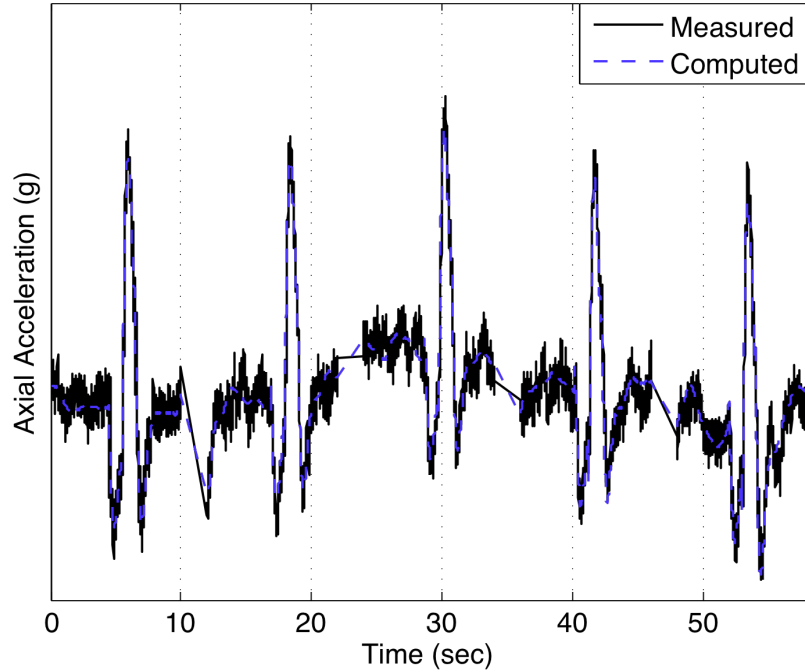


Figure 27. Axial acceleration flight time history fit.

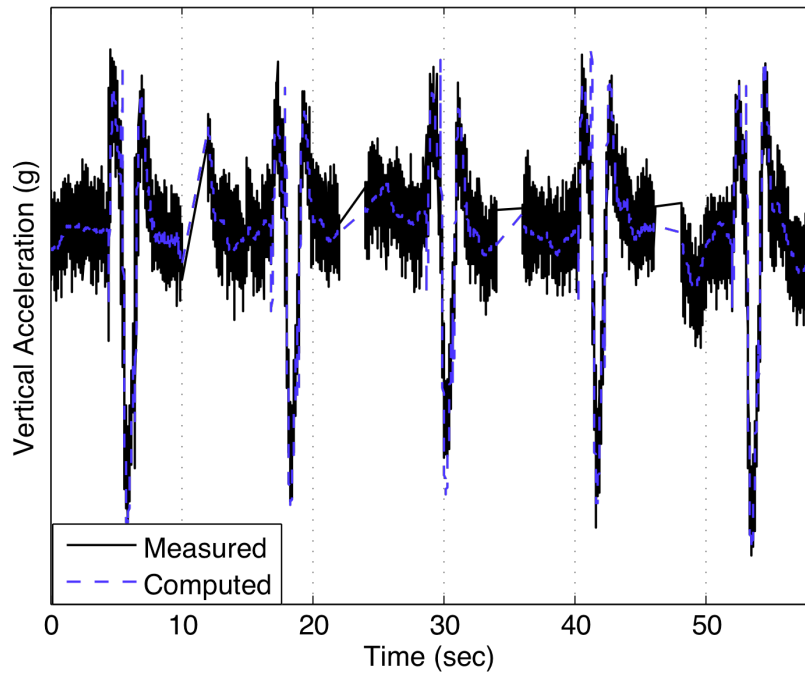


Figure 28. Vertical acceleration flight time history fit.

Appendix E: Figures of Parameter Estimates from Flight Data

Parameter estimates from flight data for a range of angle of attacks is shown in Figs. 29-35. Control effectiveness is relatively constant at low angle of attack, decreasing slightly as angle of attack is increased. This trend is present for the flight-derived estimates of all of the control surfaces.

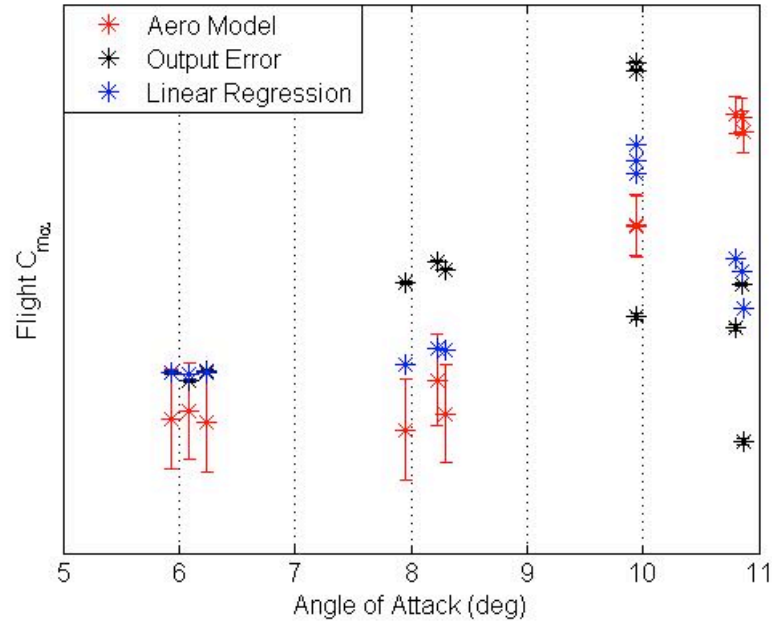


Figure 29. Flight estimate of change in pitching moment with a change in angle of attack.

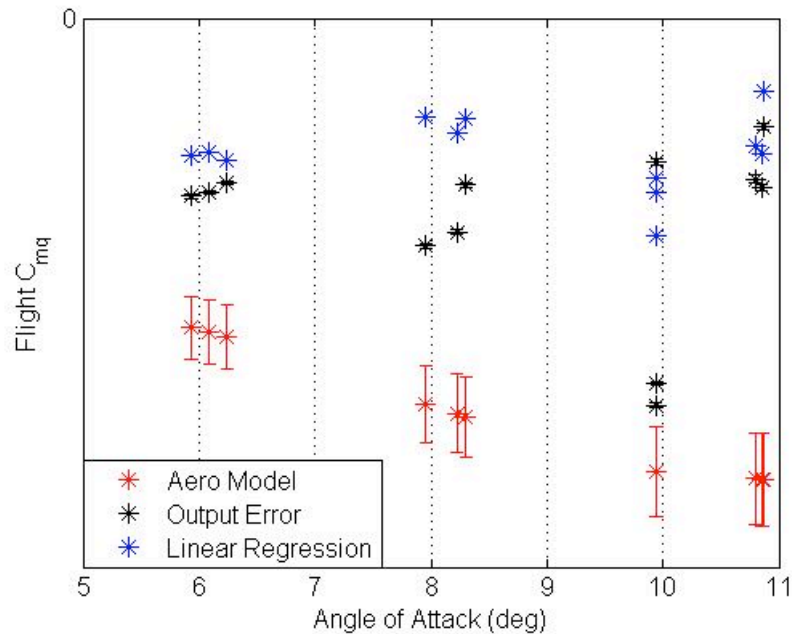


Figure 30. Flight estimate of change in pitching moment with a change in pitch rate.

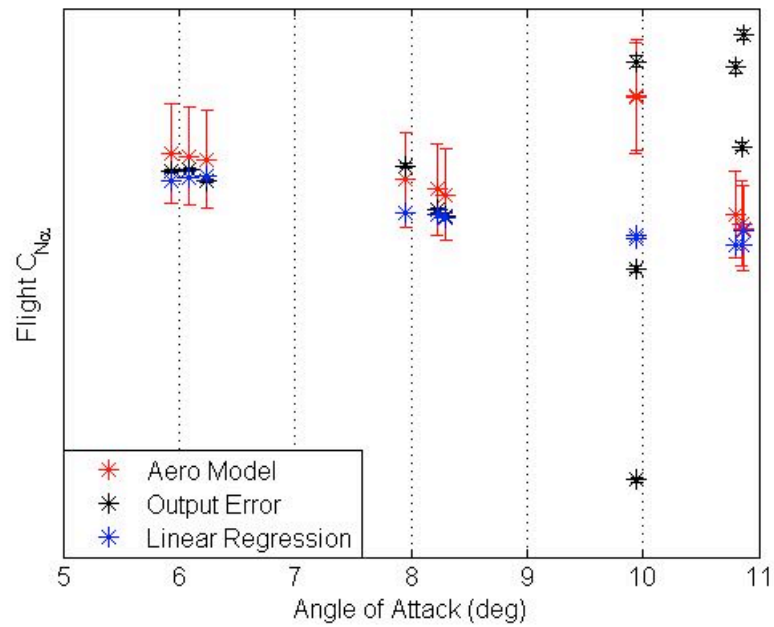


Figure 31. Flight estimate of change in normal force with a change in angle of attack.

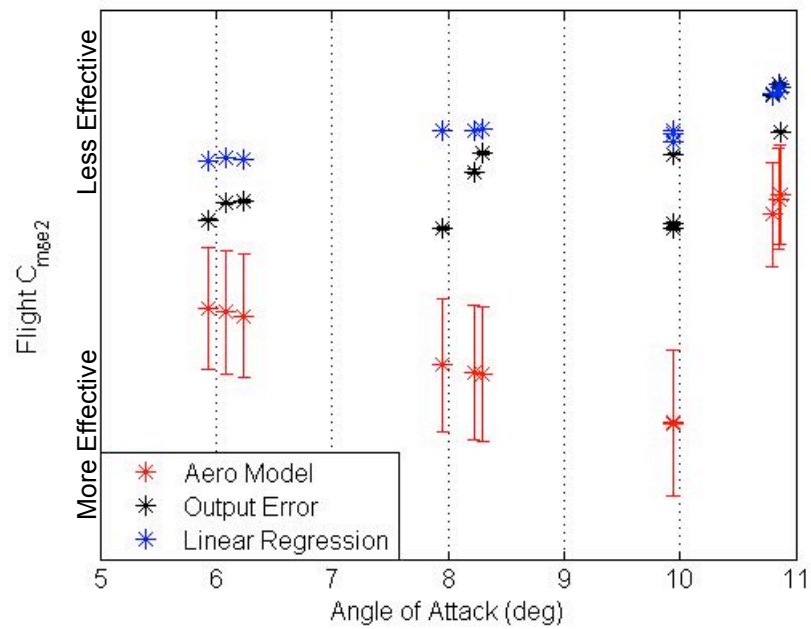


Figure 32. Flight estimate of longitudinal control effectiveness, surface pair 2.

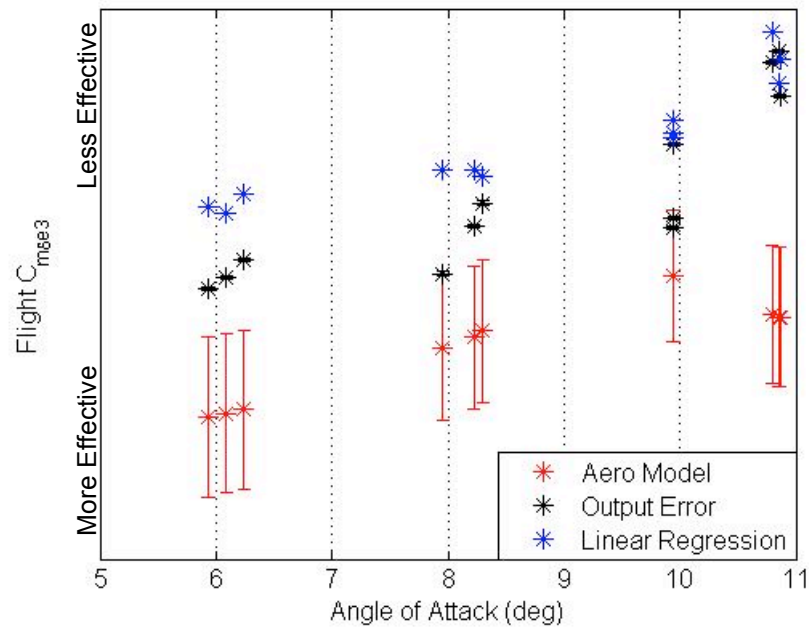


Figure 33. Flight estimate of longitudinal control effectiveness, surface pair 3.

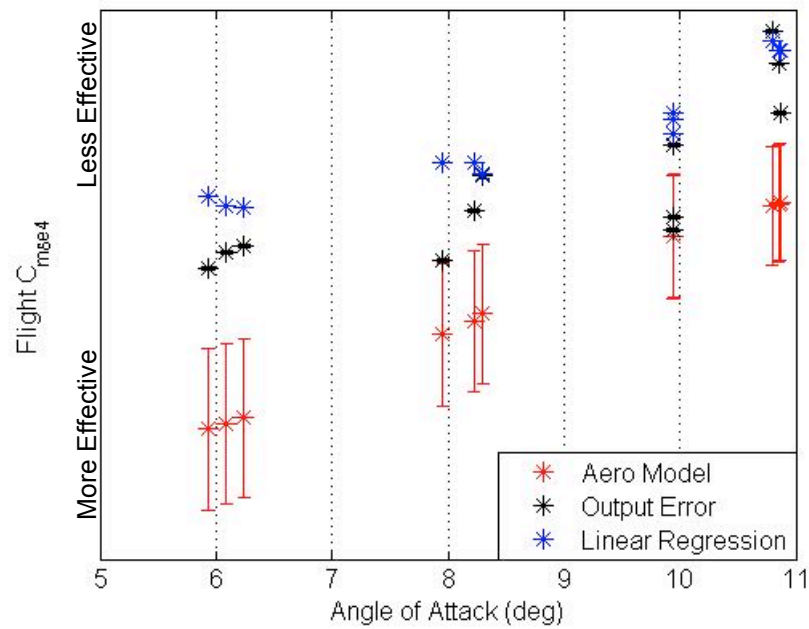


Figure 34. Flight estimate of longitudinal control effectiveness, surface pair 4.

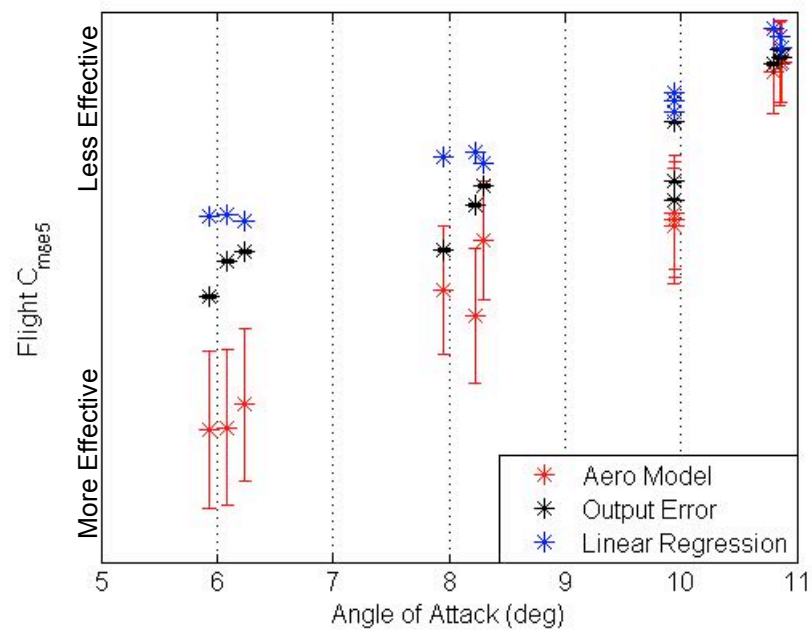


Figure 35. Flight estimate of longitudinal control effectiveness, surface pair 5.

References

- ¹Collier, F., "Overview of NASA's Environmentally Responsible Aviation Project," *48th AIAA Aerospace Sciences Meeting*, Orlando, Florida, January 4, 2010.
- ²Smith, M. S., Moes, T. R., and Morelli, A. E., "Real-Time Stability and Control Derivative Extraction From F-15 Flight Data," NASA TM-2003-212027, September 2003.
- ³Risch, T., Cosentino, G., Regan, C., Kisska, M., and Princen, N., "X-48B Flight Research – Test Progress and Instrumentation Needs for the Future," *ITEA 13th Annual Test Instrumentation Workshop*, Ridecrest, California, May 12-14, 2009.
- ⁴Risch, T. K., *Blended Wing-Body (BWB) Low Speed Vehicle X-48B Blocks 1 and 2 Flight Data Report*, NASA TM-2010-214653/VOL1, April 2010, (available from the X-48B project manager, Dryden Flight Research Center, Edwards, California).
- ⁵Klein, V., and Morelli, E. A., *Aircraft System Identification, Theory and Practice*, AIAA, Reston, Virginia, 2006.
- ⁶Steers, S. T., and Iliff, K. W., "Effects of Time-Shifted Data on Flight-Determined Stability and Control Derivatives," NASA TN D-7830, March 1975.
- ⁷Iliff, K. W., Maine, R. E., and Montgomery, T. D., "Important Factors in the Maximum Likelihood Analysis of Flight Test Maneuvers," NASA TP-1459, April 1979.
- ⁸Maine, R. E., and Iliff, K. W., "Application of Parameter Estimation to Aircraft Stability and Control, The Output-Error Approach," NASA RP-1168, June 1986.
- ⁹Maine, R. E., and Iliff, K. W., "Identification of Dynamic Systems-Theory and Formulation," NASA RP-1138, February 1985.
- ¹⁰Trujillo, B. M., "Determination of Lift and Drag Characteristics of Space Shuttle Orbiter Using Maximum Likelihood Estimation Technique," AIAA 1986-2225, 1986.
- ¹¹Brasil Neto, N. S., Hemerly, E. M., and Sandoval Goes, L. C., "Aircraft Parameter Estimation Experiment Design Considering Measurement Colored Residuals," *Journal of Aircraft*, Vol. 46, No. 6, 2009, pp. 1857-1865.
- ¹²Morelli, E. A., "F-18 High Alpha Research Vehicle (HARV) Parameter Identification Flight Test Maneuvers for Optimal Input Design Validation and Lateral Control Effectiveness," NASA CR-198248, December 1995.
- ¹³Morelli, E. A., "Flight Test Validation of Optimal Input Design and Comparison to Conventional Inputs," AIAA 97-3711, 1997.
- ¹⁴Morelli, E. A., "Flight-Test Experiment Design for Characterizing Stability and Control of Hypersonic Vehicles," *Journal of Guidance, Control, and Dynamics*, Vol. 32, No. 3, May-June 2009.
- ¹⁵Morelli, E. A., "Multiple Input Design for Real-Time Parameter Estimation in the Frequency Domain," *13th IFAC Symposium on System Identification*, 2003.
- ¹⁶Morelli, E. A., "Practical Input Optimization for Aircraft Parameter Estimation Experiments," NASA CR-191462, May 1993.
- ¹⁷Morelli, E. A., and Klein, V., "Optimal Input Design for Aircraft Parameter Estimation using Dynamic Programming Principles," AIAA 90-2801, August 1990.
- ¹⁸Maine, R. E., and Iliff, K. W., "The Theory and Practice of Estimating the Accuracy of Dynamic Flight-Determined Coefficients," NASA RP-1077, July 1981.



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Agenda

- Research Objectives
- Aircraft Background
- Parameter Estimation Background
- Correlation Challenges
- Temporal Separation for De-Correlation
- Results
 - Simulation
 - Flight
- Discussion
- Future Work
- Conclusion



Research Objectives

- Determine individual control surface aerodynamic derivatives on hybrid-wing-body aircraft
 - Highly actuated, closed loop flight control system
 - De-correlation challenge
- Output error and linear regression parameter estimation techniques
- Simulation and flight test data for longitudinal maneuvers
- X-48B used as a testbed for this research
 - Two flights, September 17 and 22, 2009
 - 5,000 to 9,000 ft altitude block
 - Slats retracted, forward center of gravity
 - 6 to 11 degrees angle of attack



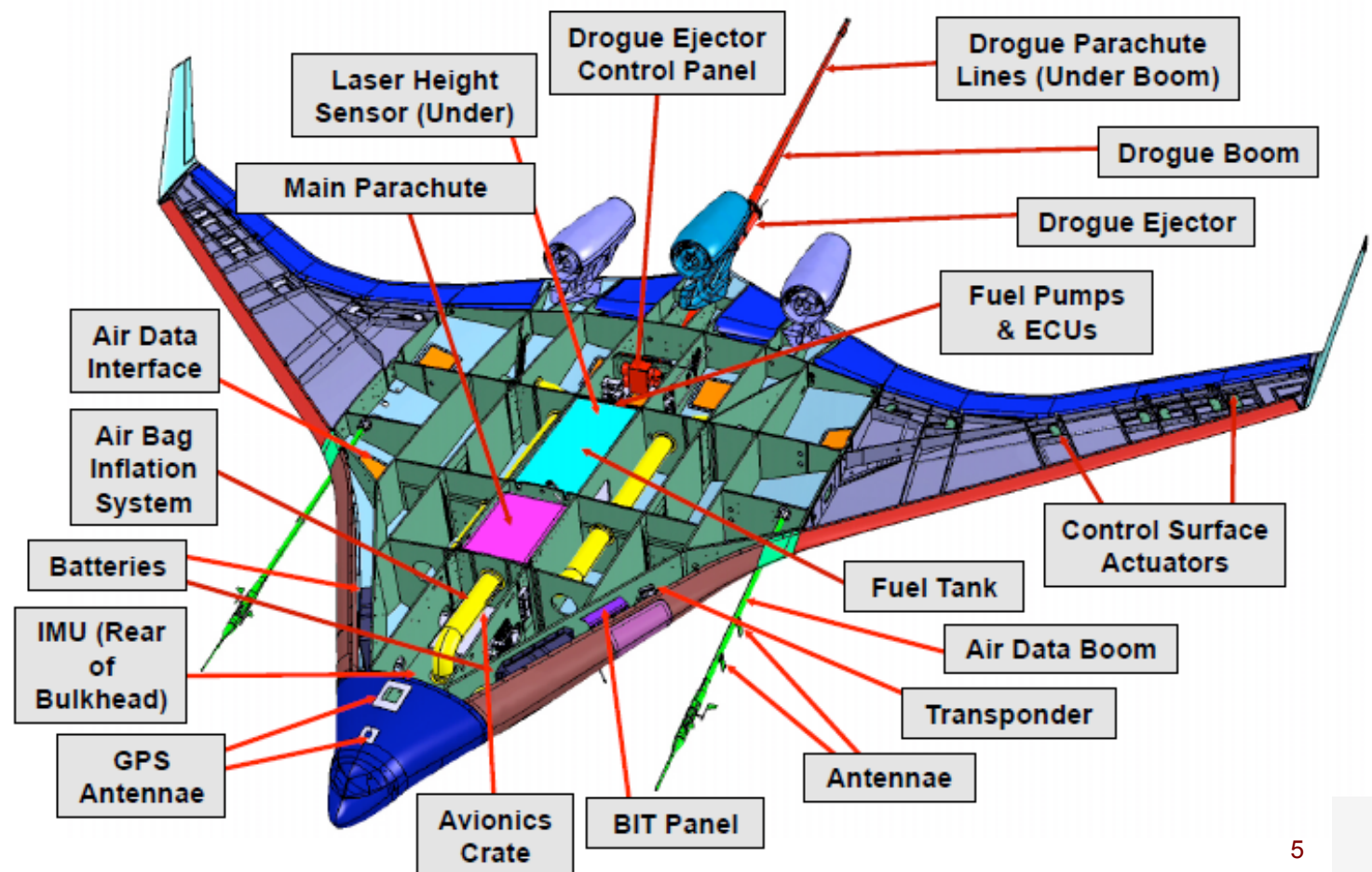
X-48B Background

- Research partnership of Boeing, NASA, and AFRL
 - Design and fabrication contracted to Cranfield Aerospace
- Purpose
 - Evaluate low speed stability and control of hybrid wing body configuration in free-flight
 - Evaluate flight control algorithms
 - Evaluate prediction and test methods for hybrid wing body class vehicles
- Airframe
 - Remotely piloted from ground control station
 - 8.5% dynamically scaled (rigid body)
 - Wingspan: 20.4 ft
 - Weight: 525 lbf
 - Thrust: 54 lbf each (3 JetCat turbojets)
 - 20 control surfaces
 - 10 elevons
 - 8 split ailerons (4 clamshell pairs)
 - 2 winglet rudders
 - 2 ground adjustable slat positions
 - Forward and aft center of gravity locations

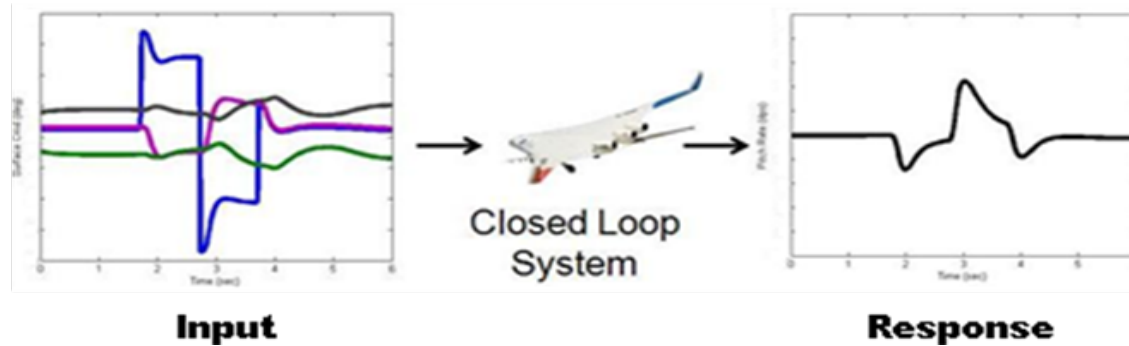


X-48B Instrumentation

- Dual air data probes
- IMU/GPS
- Surface position inferred from measured actuator position

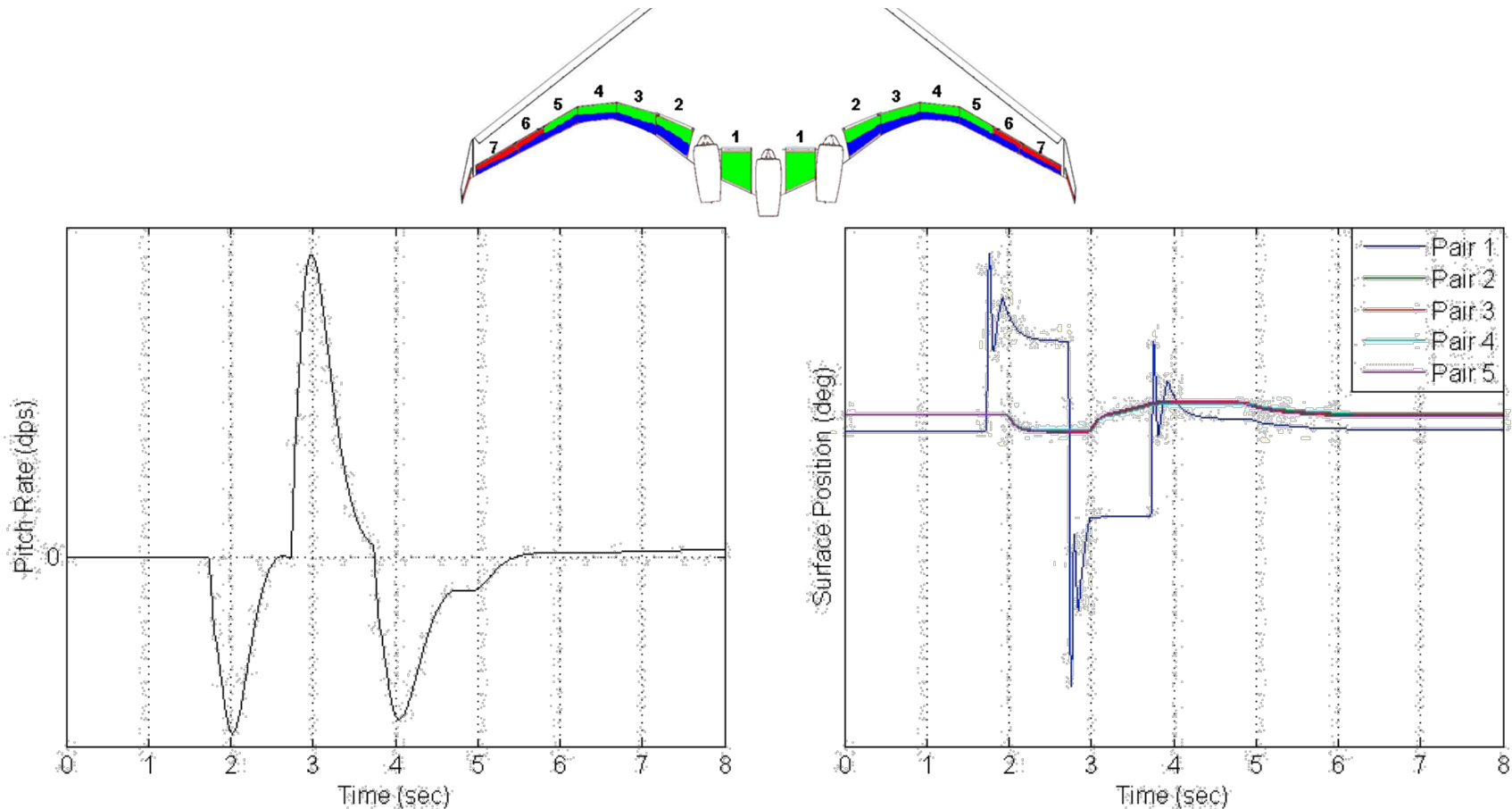


Parameter Estimation Background



- Develop mathematical model of the system with knowledge of the input and response
 - Input: control surface excitations
 - Response: sensor measurements (angle of attack, pitch rate, acceleration, ...)
- Requires accurate measurement of inputs and responses as well as accurate knowledge of the aircraft mass properties
- Time domain linear regression and output-error parameter estimation techniques used for this research

Control Effector Correlation



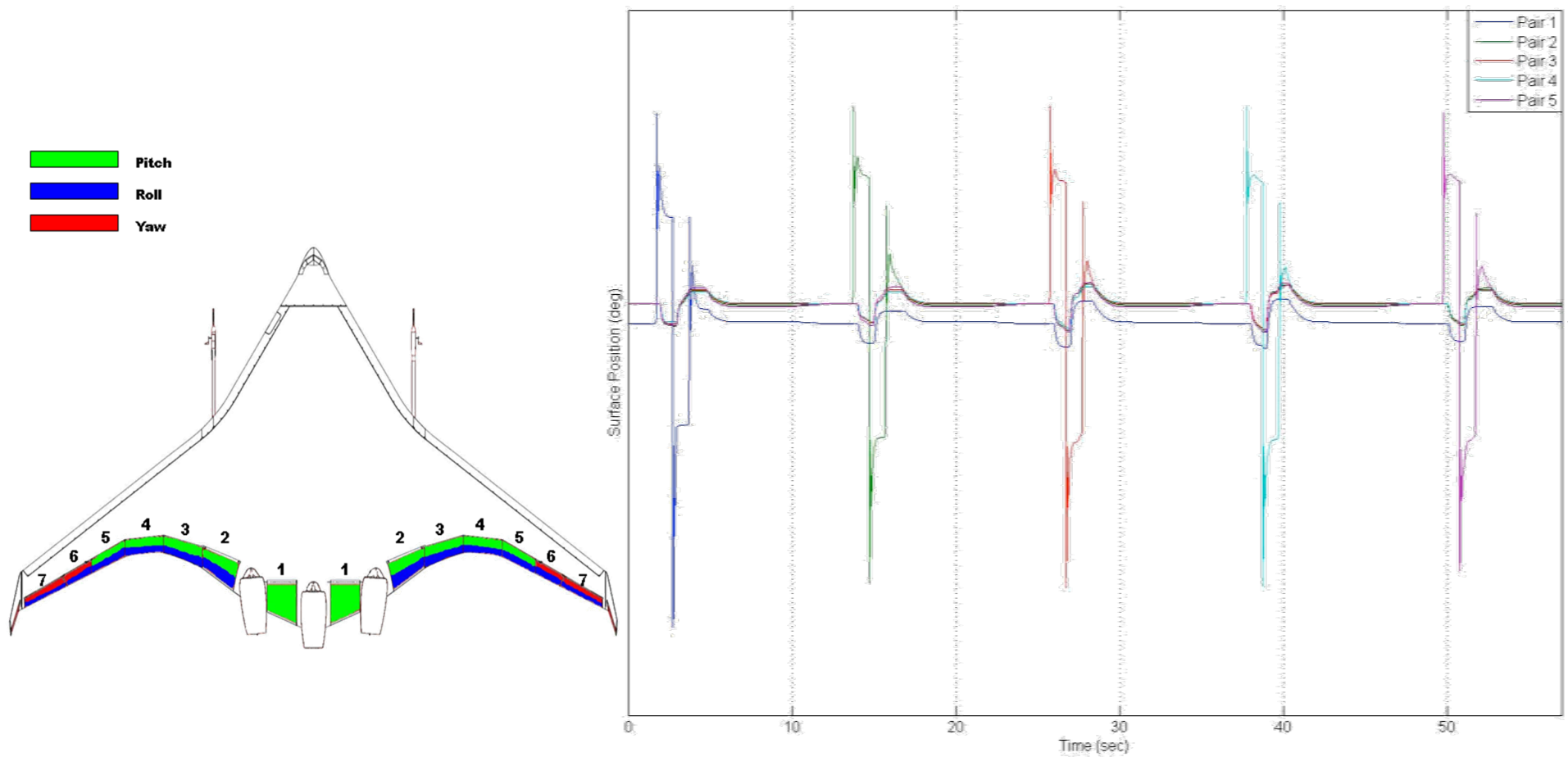
Redundant, multi-objective, nearly co-planar control surfaces coupled with a closed-loop controller challenge ability to uniquely identify response attributable to each input



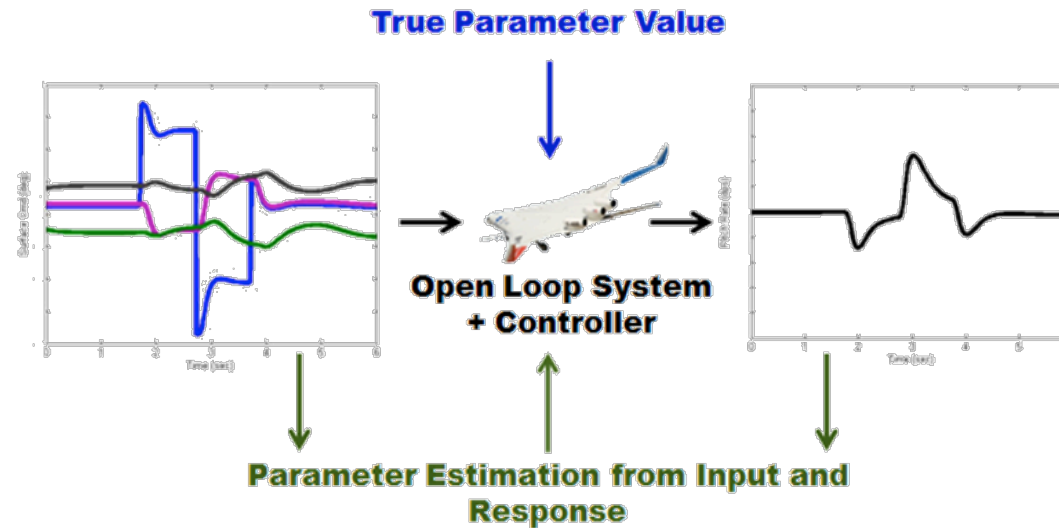
Temporal Separation for De-Correlation

- Excite each surface capable of contributing to the aircraft response
- De-correlate with temporal separation
- Each surface excitation performed individually and then pieced together prior to analysis
 - Limitations in X-48B On Board Excitation System (OBES)
 - Aircraft remains near trim conditions
 - Differences in initial conditions for individual maneuvers potential source of error
- Group surfaces in left/right wing pairs to constrain response
 - Only longitudinal excitations presented

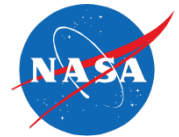
Temporal Separation Example



Method Validation with Simulation

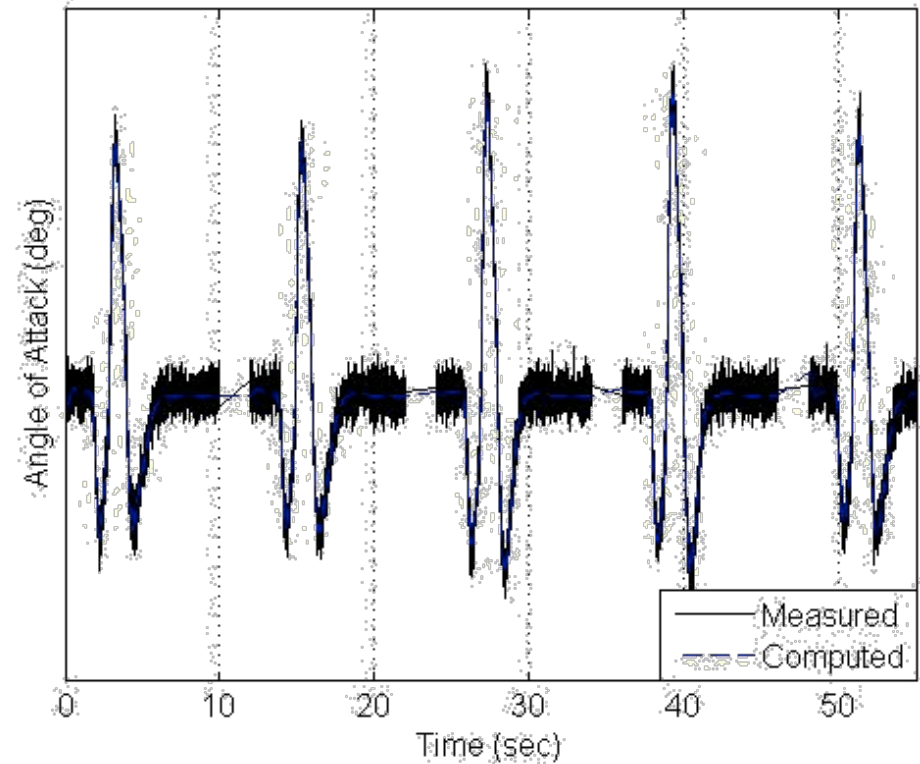
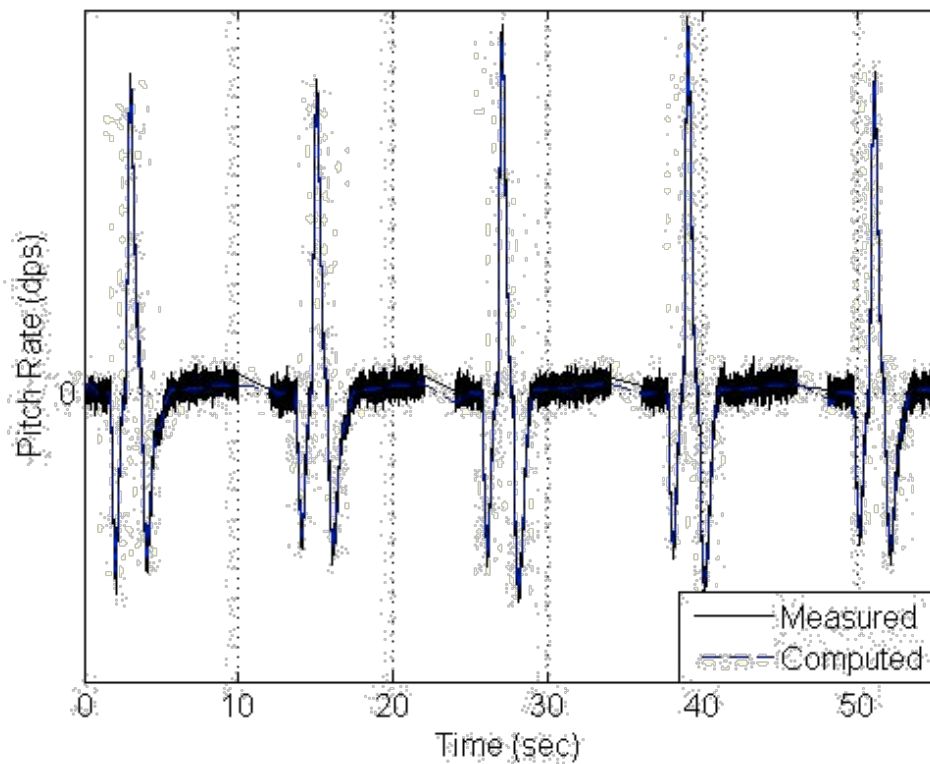


- Estimated parameters should match aerodynamic model parameters in simulation
- Time delays, transfer functions, and noise used to degrade air data, linear acceleration, and rotational rate measurements



Simulation Results – Time History

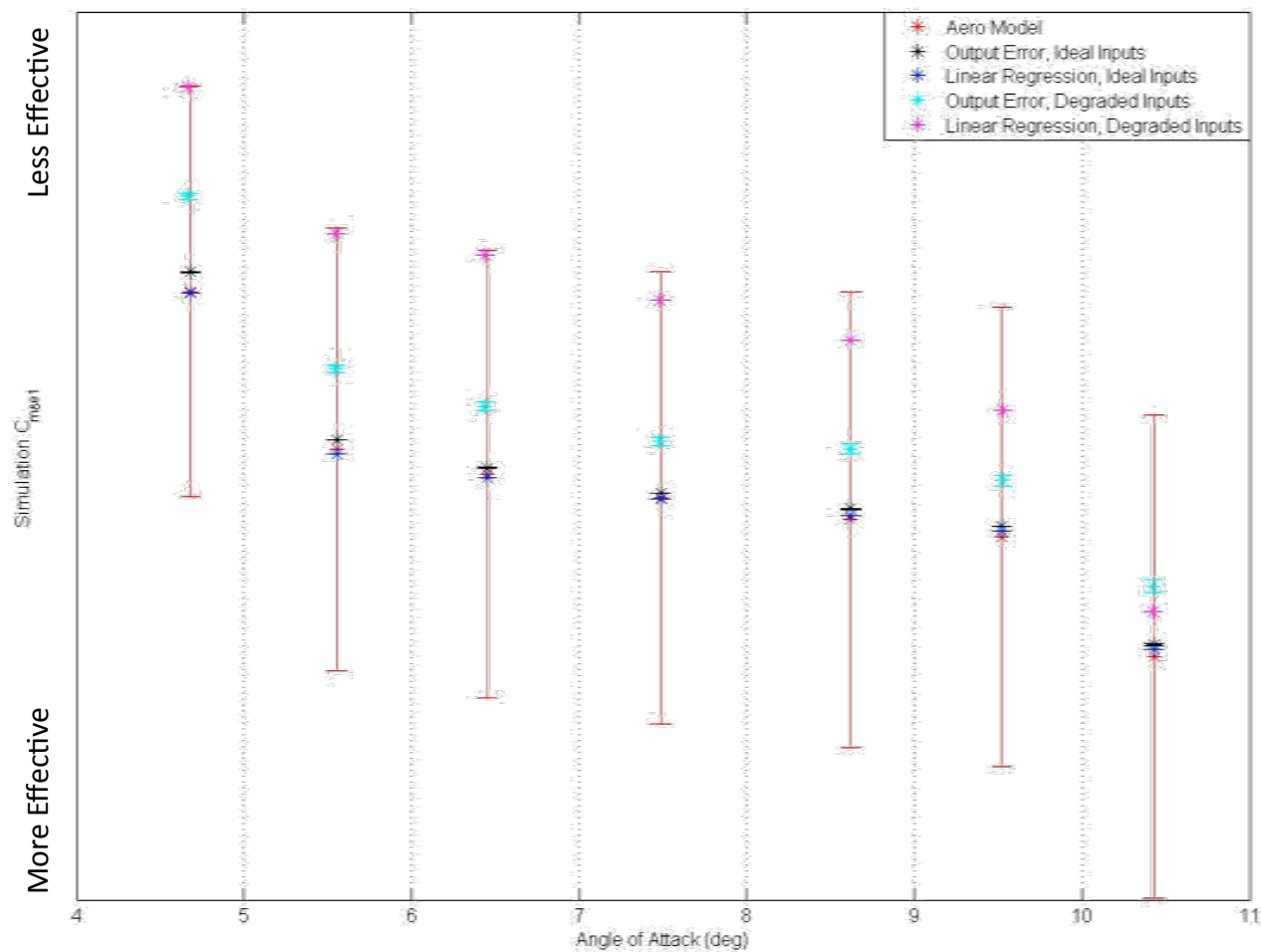
- Parameter estimation quality
- Simulation pitch rate time history



Simulation Results – Parameter Estimates



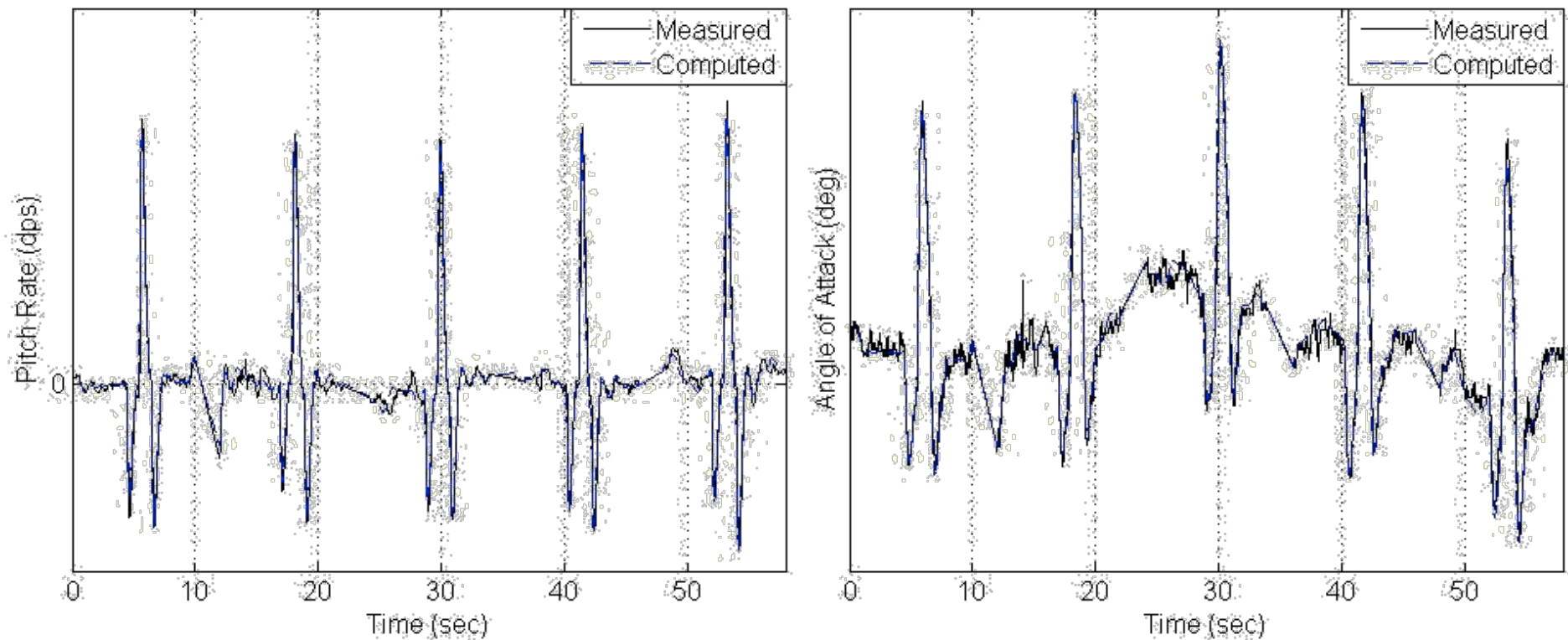
- Estimation of control effectiveness within 1.7% of aerodynamic model
- Degraded measurements led to estimation of lower effectiveness





Flight Results – Time History

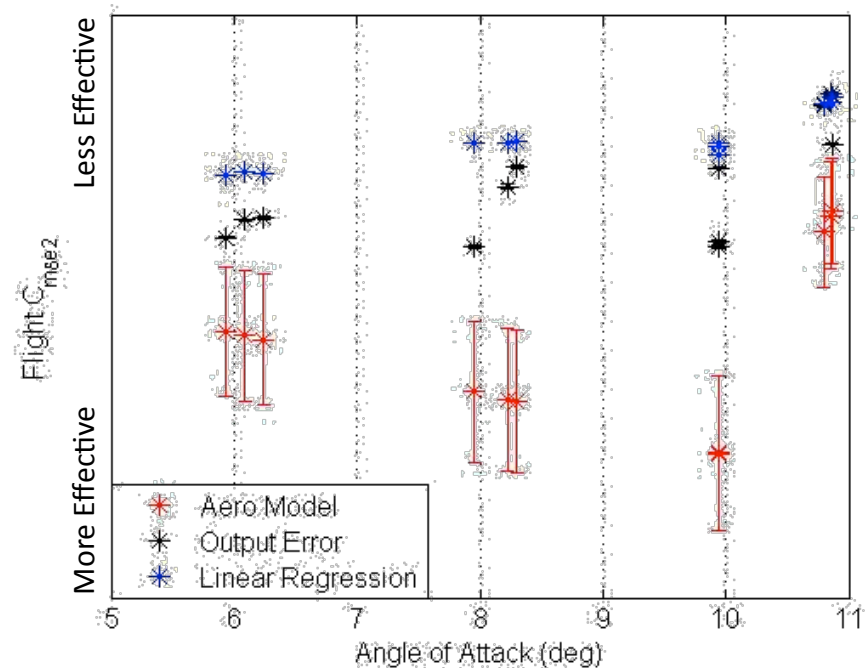
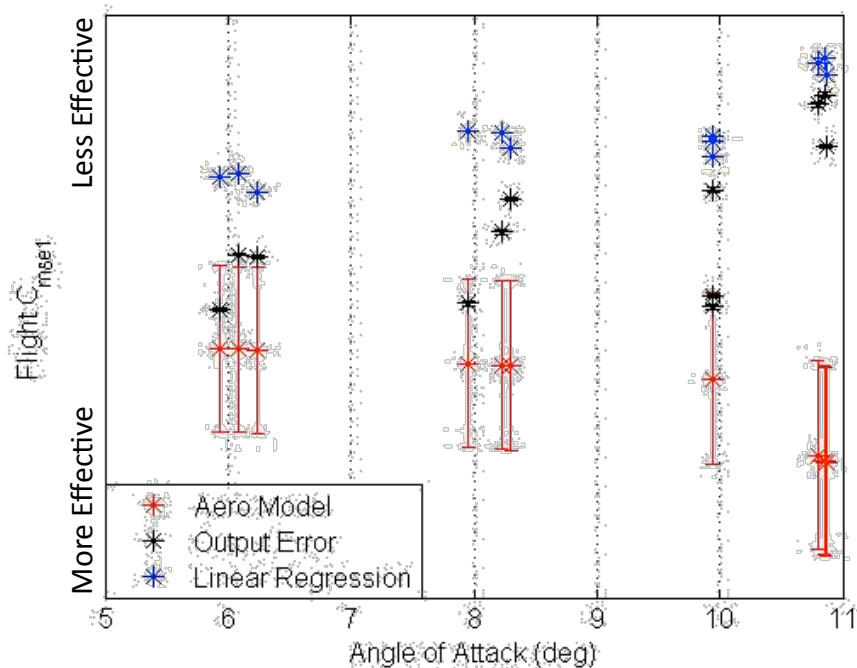
- Time history fits for flight data seem very good
- Differences in initial conditions observed



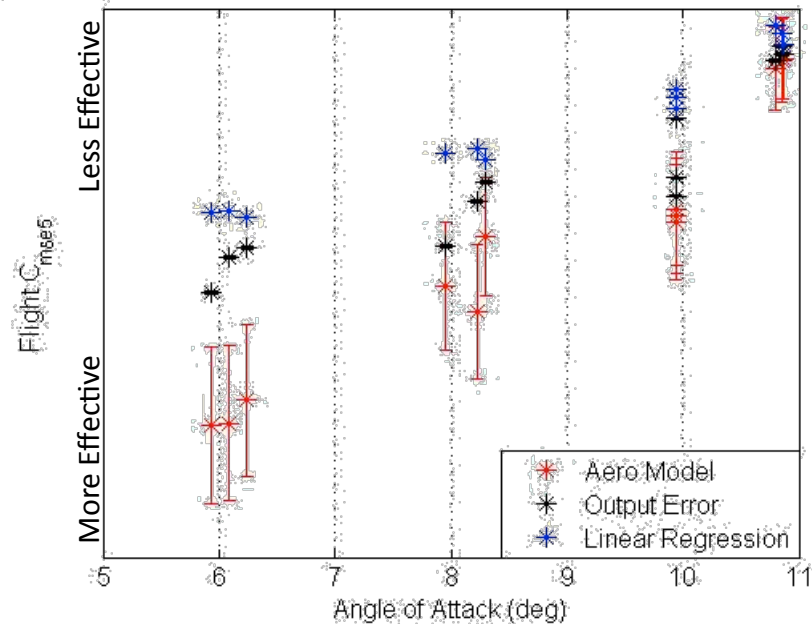
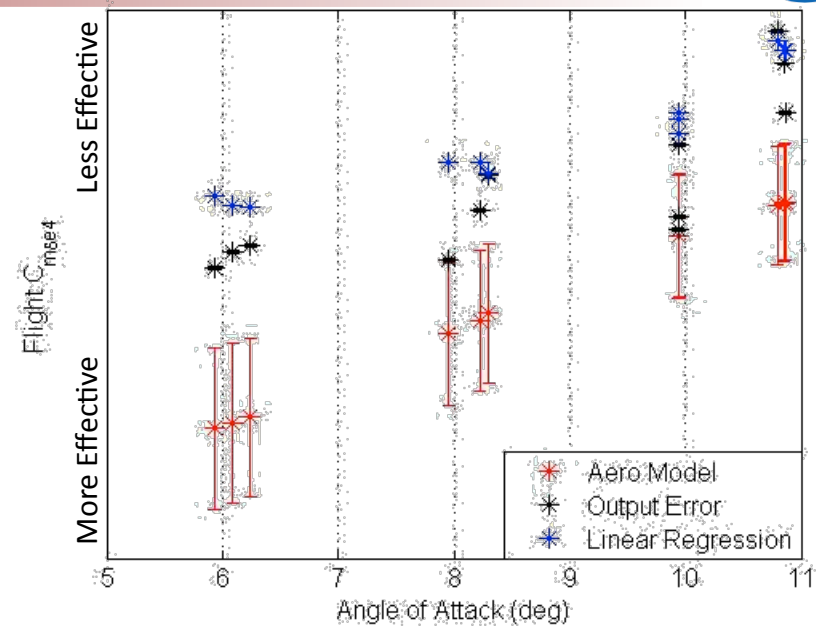
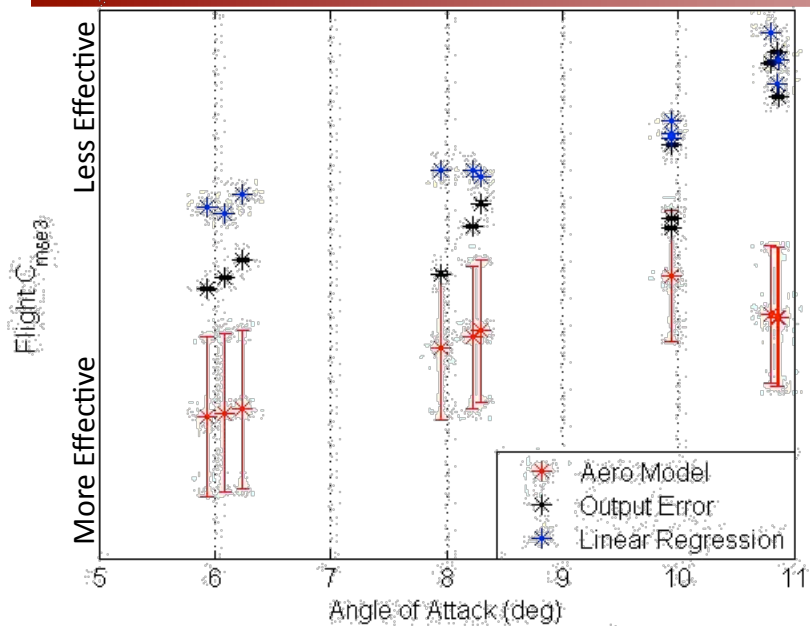
Flight Results – Parameter Estimates



- Estimates consistently show a slight reduction in control effectiveness with an increase in angle of attack
 - Trend does not match aerodynamic model



Flight Results – Parameter Estimates



Flight Results – Discussion



- Differences could be due to a variety of factors:
 - Inadequate moment of inertia testing
 - Inaccurate control surface position measurements
 - Differences in doublet initial conditions
 - Errors in the aerodynamic database
- Moment of inertia and control position errors bias control effectiveness estimates while still retaining general trends
- Errors in parameter estimation method, input design technique, or sensor measurements less likely due to accuracy with simulation data even with imperfect data sets
- Errors in the aerodynamic database are likely the cause of differences from flight derived parameter estimates

Future Work



- Quantify uncertainty in moment of inertia testing and control surface position measurement
 - Conduct several conventional and novel moment of inertia testing techniques with representative structure of known mass properties
 - Evaluate and validate estimation uncertainty
 - X-48B will then be tested with the best available techniques
 - Frequency sweep control surfaces with independent surface measurement equipment installed to gauge accuracy of positions reported in flight data
- Flight test input design techniques for more time efficient parameter estimation
 - Optimal square wave inputs to excite surface pairs simultaneously
 - De-correlate with mutually orthogonal waveform inputs
 - Single surface parameter estimation
 - Excite each surface independently with temporal separation and perform longitudinal and lateral-direction parameter estimation simultaneously

Conclusions



- Simulation validated temporal separation technique and robustness to sensor errors
 - Output error seems to produce better estimates with measurement errors than linear regression techniques, but produced larger scatter with flight data
- Current X-48B aerodynamic database may be in error
- Future testing will increase confidence in parameter estimates

