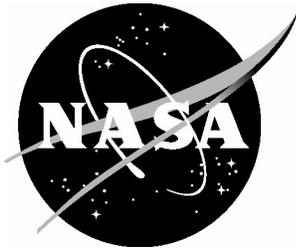


NASA/TM-2012-217778



Nonlinear Aerodynamic Modeling From Flight Data Using Advanced Piloted Maneuvers and Fuzzy Logic

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October 2012

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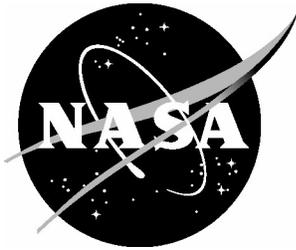
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Acknowledgements

This project was made possible by the close work, cooperation, and resources provided by the National Test Pilot School, Mojave, CA. Thanks to the engineering, piloting, and technical staff who facilitated obtaining the flight data.

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Abstract

Results of the Aeronautics Research Mission Directorate Seedling Project Phase I research project entitled “Nonlinear Aerodynamics Modeling using Fuzzy Logic” are presented. Efficient and rapid flight test capabilities were developed for estimating highly nonlinear models of airplane aerodynamics over a large flight envelope. Results showed that the flight maneuvers developed, used in conjunction with the fuzzy-logic system identification algorithms, produced very good model fits of the data, with no model structure inputs required, for flight conditions ranging from cruise to departure and spin conditions.

Introduction

This report summarizes the results from a NASA Aeronautics Research Mission (ARMD) Seedling Phase I project entitled, “Nonlinear Aerodynamics Modeling using Fuzzy Logic”.

Mathematical models are required for analysis and understanding of any physical system. One challenge with designing and testing aircraft that operate over large flight envelopes or are unconventional in design is the identification of proper aerodynamic models and model structures. The aerodynamic characteristics may be functions of many variables and can vary in nonlinear and time-dependent ways.

The current state-of-the-art for nonlinear aerodynamic model structure determination involves selection of terms from a pool of postulated modeling terms, sometimes in an iterative fashion, based on data transformations and statistical modeling metrics computed from the data. In this research, advanced modeling techniques using fuzzy logic are used to advance the state-of-the-art in nonlinear aerodynamic modeling in a way that does not require specification of candidate modeling terms other than selection of a set of explanatory variables to use in the model development. The ability to model the nonlinear behaviors that exist due to separated aerodynamic flow, structural / propulsive / aerodynamic / flight control interactions, mass properties changes, etc., is absolutely critical to the successful and efficient

development of future novel airplanes that will be needed to fulfill the goals of increased performance for future aircraft. This is a key component in the NASA “Learn-to-Fly” concept, where the intent is to autonomously develop vehicle characterization and control strategies, up through the ability to fly a vehicle, with minimum human interaction and time. The ability to rapidly update simulation tools (either aerodynamic models, or flight response models) based on flight test can be improved with the results of this work, and the results are applicable to both piloted and autonomous vehicles.

The focus of the research was to enable the identification of nonlinear aerodynamic models over a large flight envelope with very little flight test time required. Novel, continuously-varying manual control inputs were applied as flight conditions changed, resulting in rich data content from the flight test for model development across large flight envelopes – including post-stall conditions. The use of fuzzy logic system identification allowed for aerodynamics modeling without need for formal model structure determination by the analyst. This work builds on previous studies using fuzzy logic for system identification¹, and on maneuver design concepts using uncorrelated multi-axis flight test inputs^{2,3}.

Symbols

a_x, a_y, a_z body-axis translational accelerations, g

A(x)	membership function value for variable x
b	reference wing span, ft
\bar{c}	reference mean aerodynamic chord, ft
C_l, C_m, C_n	nondimensional aerodynamic rolling, pitching, and yawing moment
C_x, C_y, C_z	nondimensional body-axis aerodynamic force coefficients
g	gravitational acceleration, 32.174 ft/sec ²
M	Mach number
Ns	model search stage number
p	coefficient of membership function
P	value of membership function
p, q, r	body-axis roll, pitch, and yaw rates, deg/s
\hat{p} or phat	nondimensional pitch rate, $\hat{p} = \frac{pb}{2V}$
\bar{q}	dynamic pressure, psf
\hat{q} or qhat	nondimensional pitch rate, $\hat{q} = \frac{q\bar{c}}{2V}$
\hat{r} or rhat	nondimensional pitch rate, $\hat{r} = \frac{rb}{2V}$
R ²	multiple correlation coefficient, $R^2 = 1 - \frac{\sum_{j=1}^m (\hat{y}_j - y_j)^2}{\sum_{j=1}^m (\bar{y}_j - y_j)^2}$
y	output to be modeled
\bar{y}	mean of the output to be modeled
\hat{y}	output estimate
α	angle of attack, deg
β	angle of sideslip, deg
δ	control deflection, deg
ω	angular rate

Subscripts:

a	aileron
e	elevator
r	rudder
dot	time rate of change

Abbreviations:

CG	Center of gravity
Hp	Pressure altitude, ft
KCAS	Calibrated airspeed, kt
NTPS	National Test Pilot School
SSE	Sum of squared errors, $SSE = \sum_{j=1}^m (\hat{y}_j - y_j)^2$

Approach

Flight maneuver development was an important aspect of the project. The data from the flight tests must have enough information content to be suitable for identifying the aerodynamic effects. Therefore, several input types were used in flight during this research, ranging from traditional doublet, single-axis inputs, multi-step inputs, and a range of small and larger amplitude “fuzzy” (semi-random, variable frequency and amplitude) maneuvers – both single axis and simultaneous multi-axis control inputs. Additionally, inputs were superimposed on gradually changing flight conditions (decelerations or accelerations to change nominal angle of attack), and also through stall and post-stall flight conditions.

After obtaining flight data, preprocessing of the data was done to reduce sensor systematic errors, reduce noise effects, generate necessary computed parameters from flight data such as dynamic pressure, and compute overall nondimensional forces and moments. This preprocessing was required before modeling work began. After the data preprocessing steps were completed, fuzzy logic system identification algorithms were used to develop nonlinear mathematical models of the aerodynamics of the airplane over a wide range of flight conditions.

Fuzzy Logic Model Development

An objective of the Phase I project was to develop a system identification approach without a requirement for prior specification of model structure for nonlinear and multivariable aerodynamic responses of an aircraft in flight. Several tasks had to be accomplished to successfully complete this research.

First, the development of the fuzzy logic algorithm was completed based on work done previously¹ with improvements in the underlying membership functions and in several other aspects. A schematic of the fuzzy logic algorithm and procedures used to analyze flight data are

shown in Figure 1. The process steps are outlined below:

1. Pre-processing: Obtain flight data and make the required corrections to be able to compute overall forces and moments acting on the aircraft and the aircraft states. This includes such things as airspeed and altitude corrections, conversion to pressures, computation of ambient air temperature from measured total temperature, correction of angle of attack and sideslip vane data for sensor location, etc.
2. Selection of Explanatory Variables: Flight variables are selected that the algorithm will use to develop mathematical models for the nondimensional aerodynamic coefficients. Although no functional form of the models is needed to be specified (such as interactions between variables, etc. – those come from the fuzzy logic algorithm), the variables that will be used in a resulting model need to be defined. The data is partitioned into training and testing databases.
3. Calculation of Membership Functions: Membership functions are used to divide explanatory variables into various ranges. The interpretation of membership function values is as follows: the membership function value is 1 over the range of values of the associated explanatory variable where that explanatory variable is very important. For a membership function value of 0, the explanatory variable is not important over that range of values. When only one membership function is selected, it has a constant value of one over the entire range of the explanatory variable. With only one membership function for a selected explanatory variable, the fuzzy model is identical to a standard linear model. An example of selection of 1, 2, or 3 membership functions for a particular explanatory variable, x , is shown in Figure 2. A set of membership functions is graphically depicted in Figure 1 for a case with 6 membership functions for a given explanatory variable, x . All explanatory variable inputs into the fuzzy algorithm are scaled to be between 0-1.
4. Calculation of Internal Function Coefficients for all Fuzzy Cells: The fuzzification of the data is accomplished by the use of many fuzzy cells, each comprised of a linear equation in the explanatory variables through the use of their associated membership functions. Each fuzzy cell internal function includes a combination of one membership function for each explanatory variable. A coefficient for each of the membership function variables in each fuzzy cell is determined by gradient optimization or least squares procedures to minimize the summation of squared errors using the set of data partitioned for training. Currently an exhaustive set of all combinations of membership functions for each explanatory variable is used to populate the fuzzy cells. Therefore, the models can become large.
5. Calculate Model Output: With the fuzzy cells defined, the estimates of the model are computed using a weighted output of the fuzzy cells obtained by multiplication of the membership functions to determine the subset of fuzzy cells that will be important in the model estimate.
6. Check for Adequacy of Model: The multiple correlation coefficient (R^2) of the fit of the model to the training data is evaluated. If it is above a chosen threshold (indicating a good model fit to the data), then that fuzzy model is applied to the set of data for testing. If the fit of the training data is not good enough, or if the testing data results are continuing to show a better fit of the data as more membership functions are added, more membership functions are added to the model, and the training and testing processes are re-done.
7. Compute Final Fuzzy Model: After reaching an acceptable fit of the flight data with the training data, and when the testing data R^2 value starts to decrease, the fit is considered complete and all of the data (training and testing) is used in a final estimation procedure to compute the final coefficients of all the internal functions in the fuzzy cells.

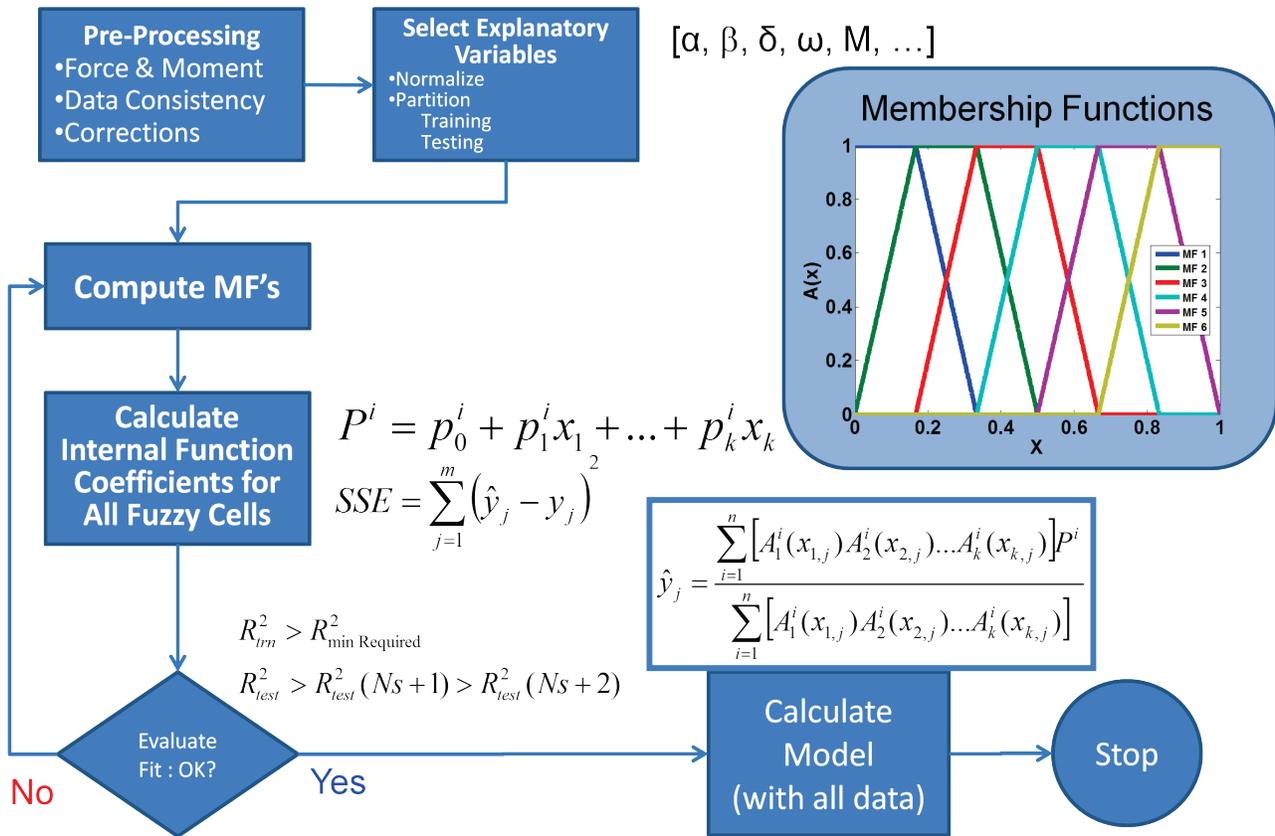


Figure 1 Fuzzy logic system identification flow diagram

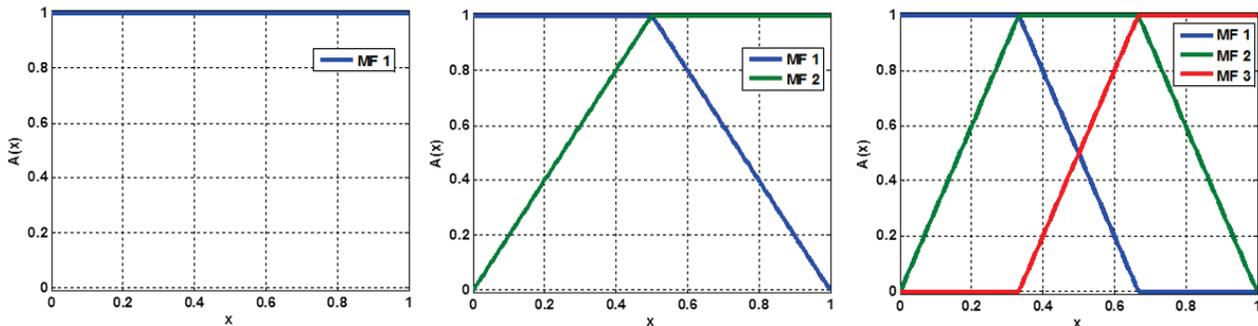


Figure 2 Example of membership function orders.

Flight Test Maneuvers

A piloted flight test technique was developed, called “fuzzy inputs”, that resulted in rich dynamic content from the flight test over a large range of flight conditions with a small number of maneuvers. These maneuvers were hand-flown approximations to optimized inputs already tested on other aircraft using programmed maneuvers^{2,3}, applied over a very large flight envelope range

including conditions representing cruise, maneuvering, stall, departure, and post-stall departure dynamics. The intent of the maneuvers was to apply uncorrelated, multi-axis inputs to produce uncorrelated multi-axis aircraft responses with signal-to-noise ratios high enough for accurate aerodynamics modeling. The pilot’s task was to input commands without the maneuvers prescribed in detail before-hand, to attempt as large of a variation combinations of

airplane states with as little correlation as possible between the piloted inputs across axes.

Test Aircraft Description

The test airplane was an Aermacchi Impala MB-326M operated at the National Test Pilot School in Mojave CA, shown in Figure 3. The Impala is a 2-seat, tandem single-engine turbojet, and is used as a trainer or light attack aircraft. This particular airplane is fitted with a flight test noseboom with angle-of-attack and sideslip angle measurement vanes. Airdata is provided through the production system. The primary flight control system is completely reversible, with control pushrods connecting the stick and pedals with the ailerons, elevator, and rudder. All control surfaces are statically and dynamically balanced. The aileron aerodynamic balancing is obtained by Irving diaphragms and balance tabs on the trailing edge. The elevator is aerodynamically balanced by two tabs on the trailing edge. Trim for roll and pitch forces is obtained through a coolie-hat switch on the control sticks. Trim tabs are actuated by electromechanical servos. Trim indications are available in both cockpits. No springs or bobweights are included in the control system. Secondary flight controls are powered by the hydraulic system. The speedbrake is on the bottom surface of the fuselage, and the deflection is automatically limited to approximately half travel when the gear is extended to preclude the speed brake from striking the ground. Flaps are selectable in 3 positions: up, take-off, and landing. Steering is accomplished on the ground by differential braking and a castoring nosewheel.

The airplane is powered by a single Rolls Royce Viper turbojet engine. The engine produces approximately 2500 lb of thrust at sea level static conditions. The maximum gross weight is 9600 lb (basic airplane with tiptanks). For this test, the weight of the fueled airplane with crew was approximately 8185 lb.

Each cockpit is equipped with a Martin-Baker MK-AS.06A/M ejection seat that allows ejection from the airplane at all speeds and flight altitudes

down to zero speed and altitude. Flight controls and flight instruments are repeated in both cockpits. A cabin pressurization system maintains cabin pressure and provides heat and air conditioning. A single canopy covers both cockpits.



Figure 3 Test Aircraft.

Reference geometric characteristics of the airplane are listed in Table 1.

Table 1 Airplane Geometry

Wing Area (includes projected area to centerline)	204.5 ft ²
Wing Span	34.659 ft
\bar{c}	6.233 ft
FS leading-edge of \bar{c}	327.72 in
Height	12.20 ft
Distance between main wheels	7.78 ft
Distance from main gear to nose gear	13.64 ft

A 3-view sketch of the airplane is shown in Figure 4, although the sketch does not include the nose boom which is fitted onto the test airplane. The FS, WL, and BL stations are all in inches. Positive numbers are: FS aft, WL up, BL out the right wing.

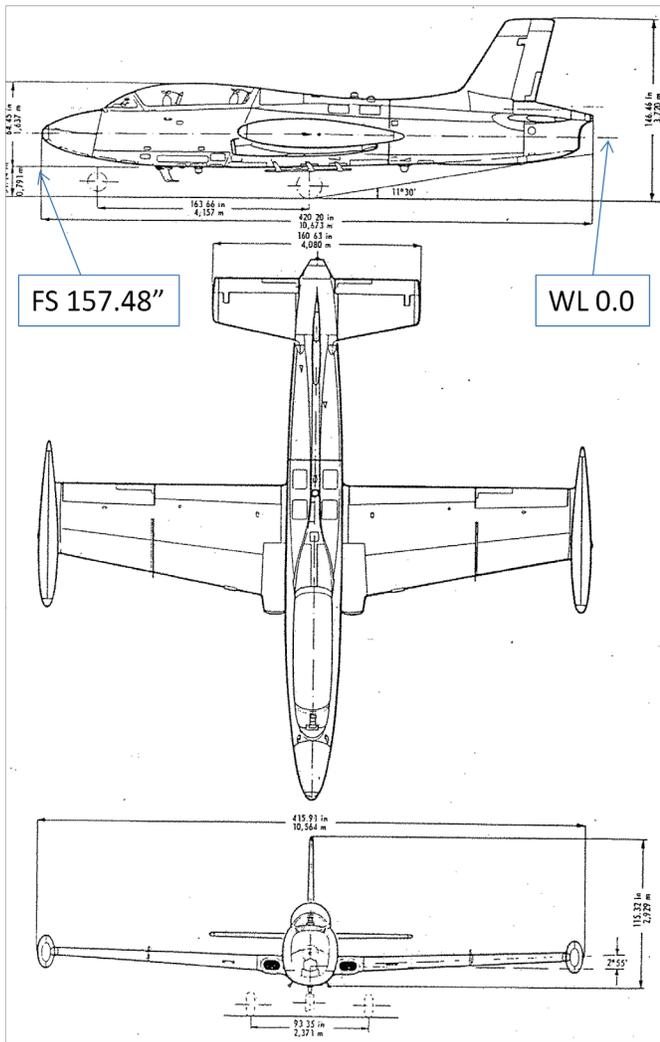


Figure 4 Three-view sketch of airplane.

The maximum gross weight of the airplane is 9,600 lb. The allowable CG range is 22% - 30% \bar{c} . The weight and balance limitations can not be exceeded by normal operating or loading conditions. Table 2 shows the typical CG burn diagram for the airplane as tested, and Table 3 lists the inertia estimates available for the test airplane.

Measurements recorded with the onboard data system and telemetered to the ground included: α , β , a_x , a_y , a_z , p , q , r , δ_a , δ_e , δ_r , KCAS, and Hp. Table 4 shows the location of the inertial sensors and α/β vanes. Additionally, total temperature, fuel used, and engine RPM were recorded by hand for each flight maneuver. A second set of inertial data was recorded with a tablet computer mounted in the aft cockpit (Figure 5) including

additional measurements of a_x , a_y , a_z , p , q , r , and GPS position and velocities.

Table 2 Weight and Balance

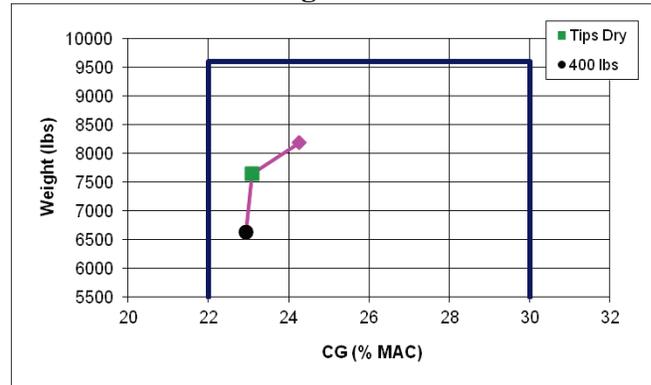


Table 3 Inertia Estimates

Configuration	Moments of Inertia, slug-ft ²		
	I _{xx}	I _{yy}	I _{zz}
Full Fuselage Fuel, Tip Tanks Full, 2 Crew	14515	7880	21900
300 lb Fuselage Fuel, Tip Tanks Empty, 2 Crew	4785	7830	12075

Table 4 Sensor Locations

Sensor	Location, in		
	FS	WL	BL
AHRS (rate gyros and accelerometers)	334.98	28	1.25
α vane	124.04	10	6.25
β vane	120.42	16.25	0



Figure 5 Tablet computer installation in rear cockpit.

Results from Phase I

All milestones and plans proposed for Phase I ARMD Seedling Fund research, which funded this work, have been completed. The 12 planned data flights were conducted to test the development of nonlinear aerodynamic models from flight test using fuzzy logic and more conventional analysis tools.

The aerodynamic forces and moments were nondimensionalized to the standard coefficients of body-axis forces (C_x , C_y , C_z) and moments (C_l , C_m , C_n). One of the most significant aspects of the project was the development and demonstration of test and analysis techniques that allowed for development of models

encompassing a large range of flight conditions using very little flight test time. The flight testing used “fuzzy maneuvers”, which ideally were airplane excitations implemented by the pilot in which quantities used for the aerodynamic modeling (control surface positions and airplane responses) were varied in an uncorrelated manner over a large range. An example comparison of a traditional multi-axis doublet maneuver and a multi-axis fuzzy input maneuver is shown in Figure 6. Note that fuzzy maneuvering decorrelated the explanatory variables by having the pilot fly the aircraft to enforce that condition, whereas conventional doublet maneuvers rely on moving controls one at a time to bring about decorrelation through time sequencing.

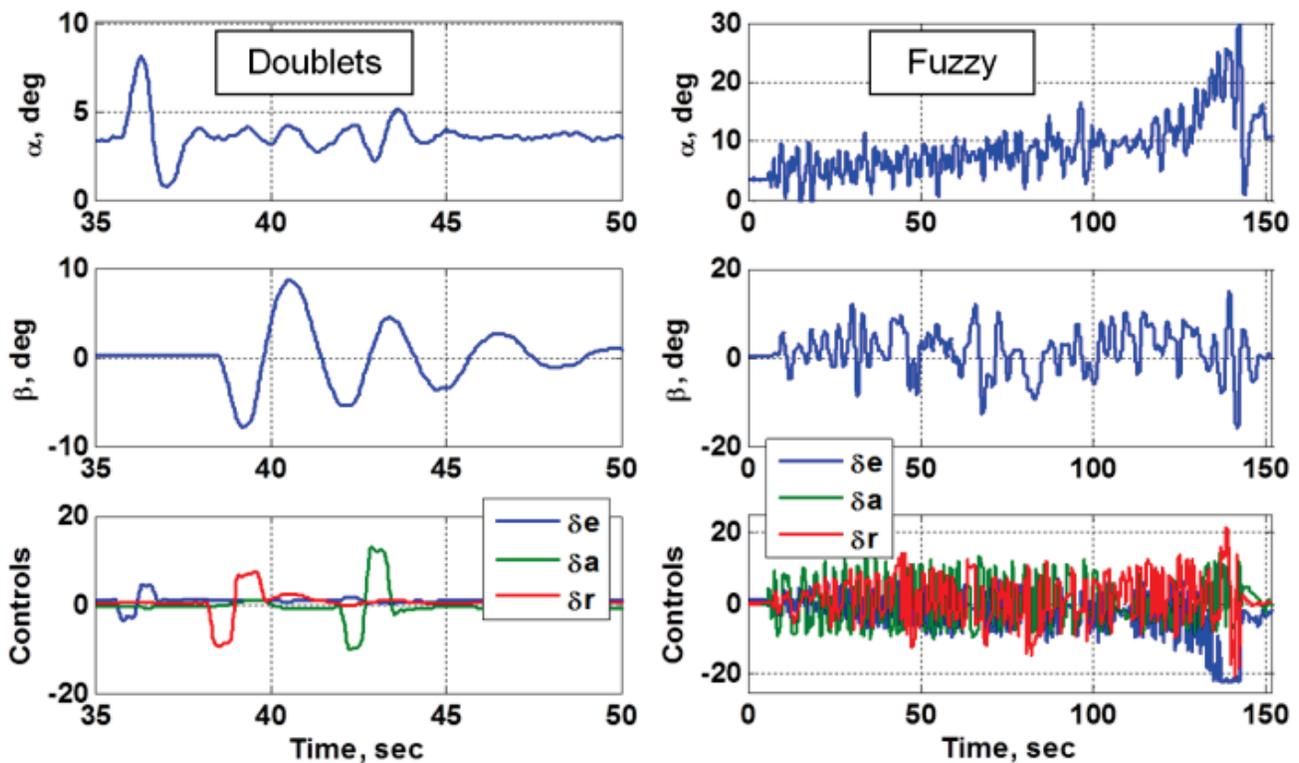


Figure 6 Comparison of traditional doublet inputs and fuzzy inputs.

With practice, the multi-axis combined inputs were achieved by the pilot with a cross-correlation coefficient of about 0.3 – indicating a good level of independence between the inputs in

each of the axes. Using maneuver designs such as orthogonal sum-of-sines control inputs that are programmed and executed directly by a

computer, even better independence of inputs can be achieved².

Using one fuzzy maneuver, a nonlinear aerodynamic model can be developed that covers a large range of flight conditions from low angle of attack cruise up through stall angles of attack. Figure 6 shows that the fuzzy maneuver evokes more dynamic response from the airplane than a conventional doublet maneuver, which is important for accurate and efficient modeling. Furthermore, the fuzzy maneuver covered a range of flight conditions with a single maneuver.

Twelve data flights were conducted during this research project, see Table 5. After analysis of the first 6 flights, data inconsistencies were observed that led to an extensive effort to correct and recalibrate the flight test instrumentation. It was found that several of the instrumentation channels were affected very significantly by changes in temperature, and there were indications of some data channels interacting with other data channels. Because of the data system problems, models developed with data from one maneuver and flight would not produce consistent results with models developed from similar maneuvers later in the flight or from other flights. As a result, improvements in the data system were made, and the first 6 flights were largely ignored for detailed model work. Due to time and funding constraints, the instrumentation system was not fully corrected and calibrated; however, the second set of 6 flights were conducted with a much more consistent system with better data quality.

Table 5 Data Flight Summary

Flight	Primary Maneuvers / Objectives
1	Systems checks and model verification
2	Systems checks and model verification
3	Multi-step and fuzzy step inputs
4	Decels and larger amplitude fuzzy inputs
5	Air data cal and small amplitude high-speed flight inputs
6	Stall and post-stall inputs
7	Conventional doublet maneuvers and low amplitude inputs across α range
8	Fuzzy inputs at discrete flight conditions
9	Large amplitude fuzzy maneuvers and thrust modeling maneuvers
10	Departures - spins
11	Small amplitude maneuvers across envelope
12	Thrust modeling maneuvers, steady sideslips, small and moderate fuzzy maneuvers

Using the fuzzy inputs and the resultant flight data, the model fit to nondimensional pitching moment coefficient using the fuzzy algorithm described above is shown in Figure 7, for a maneuver from Flight 9. Explanatory variables selected for use by the fuzzy logic algorithm were: α , β , δ_e , δ_a , δ_r , \hat{p} , \hat{q} , r . The selection of explanatory variables was made to include possible effects of coupling of lateral-directional and longitudinal effects. The correlation coefficient for the fit is high (0.96), indicating a good fit, as can be seen in the plot of the identified model output and flight data. This example is one model for flight conditions corresponding to cruise flight all the way to stall.

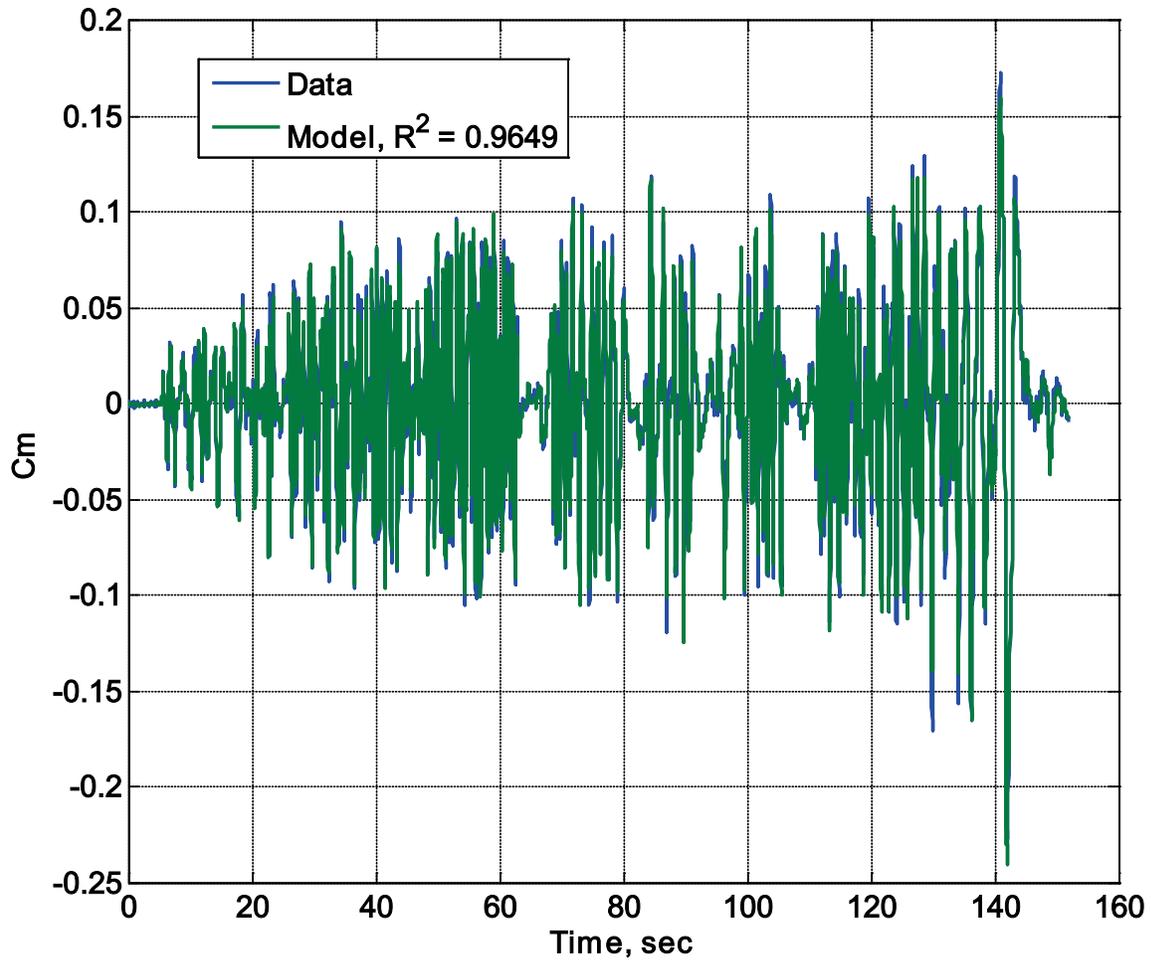


Figure 7 Example fuzzy model fit to pitching moment data.

Another example of the fuzzy logic model fit to the flight data, using the same explanatory variables from Flight 9, is shown in Figure 8. This demonstrates the hysteresis and overshoots in the vertical force coefficient (similar to the lift

coefficient) seen in dynamic maneuvers through the stall angle of attack using different angle of attack rates. The fuzzy logic modeling accurately characterizes these nonlinear effects in the flight data.

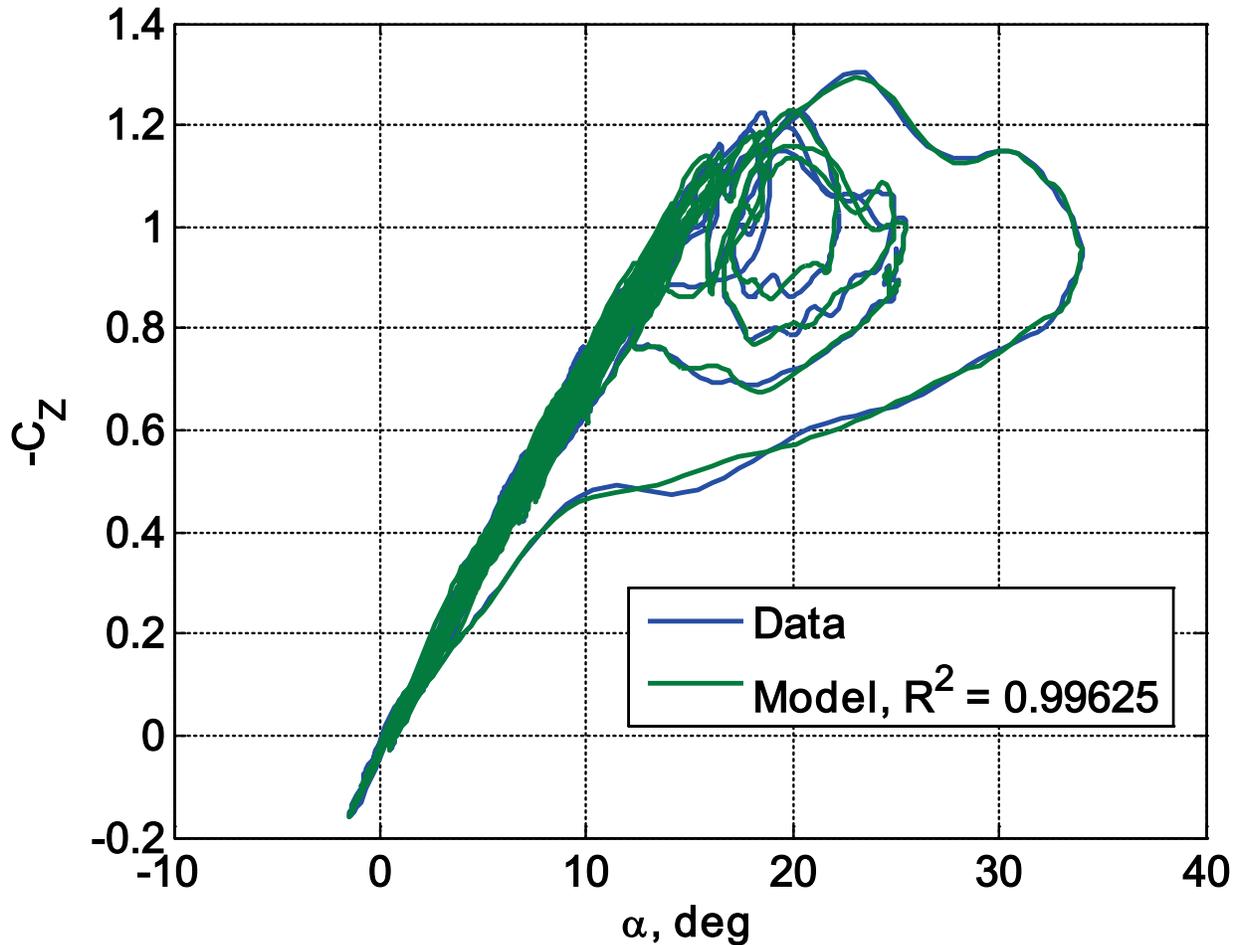


Figure 8 Model fit to Normal force coefficient.

An example of a model from the fuzzy maneuver, showing values of some standard stability derivatives linearized along the normal trim conditions, is shown in Figure 9. Also shown in Figure 9 is a comparison of results from flight test data obtained with doublet inputs and a least-squares equation error modeling method. The doublet data were obtained from 20 maneuvers over 6 different data flights. The fuzzy model was obtained with one maneuver during one flight and used the explanatory variables listed in Table 6. The explanatory variable, $\dot{\alpha}$, was added because of results including departure and spin data, it was seen to provide better predictions of flight data not used in the model development – some examples of the predictive capability of the models will be presented later. The comparisons with standard doublet techniques illustrate that the flight test technique employing fuzzy inputs

provided high information content in a highly efficient manner, compared to conventional trim-based approaches. Of even more significance, the conventional results yield no modeling results for angle of attack above stall (about $\alpha = 12^\circ$) due to constraints of the employed method to be perturbations about a trim condition, whereas the fuzzy modeling results go through the stall and departed regions of flight.

Comparison of the results shown in Figure 9 shows excellent correlation of the static terms from the two different methods. The conventional method shows more scatter for the dynamic derivatives and less damping predicted. The reduced pitch rate damping compared to the fuzzy model is likely due to the lack of the explanatory variable of angle-of-attack rate in the conventional results that were part of the fuzzy

logic model. Although the fuzzy logic modeling developed the complex nonlinear aerodynamic model without an analyst specifying a model structure beyond providing a set of candidate

explanatory variables, other modeling approaches could use the same fuzzy input data and provide the improvement in test efficiency demonstrated by this test approach.

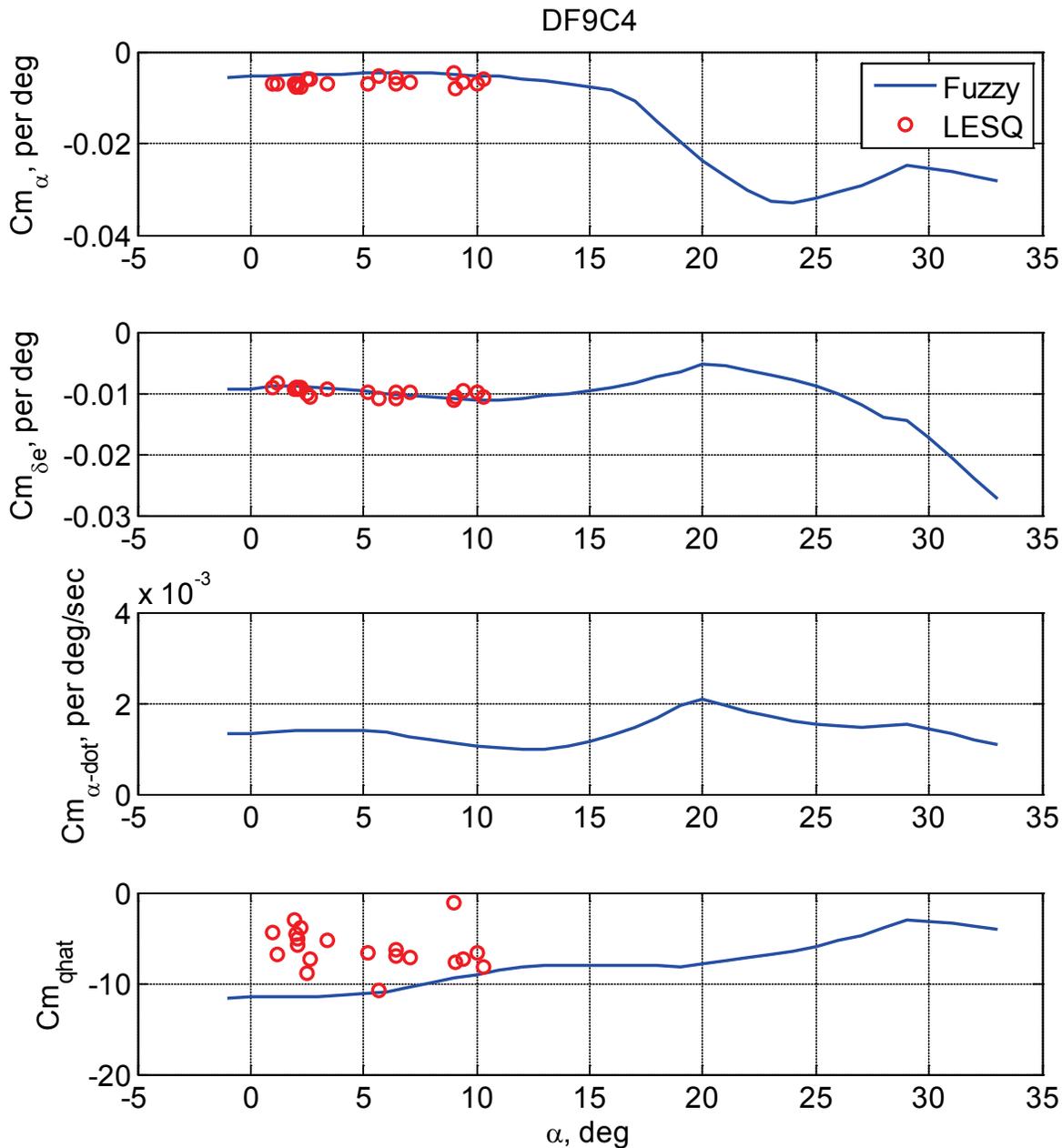


Figure 9 Linearized fuzzy model results from one maneuver and comparison with traditional results.

Combining several maneuvers from Flight 10 so that characteristics at extreme flight conditions could be included in the model was done by including a deceleration maneuver such as shown

on the right side of Figure 6 with maneuvers including departures that resulted in right and left upright spins, and a left inverted spin. Fuzzy logic models were then developed from this

combined set of maneuvers (all obtained during one flight) resulting in data with large angular rates and large attitude angles of approximately $-40 \leq \alpha \leq 40$ and $-20 \leq \beta \leq 20$. Due to limitations of time and instrumentation, an engine thrust model was not developed, so the axial coefficient includes some thrust effects, although to minimize that effect, all combined runs had the power set to idle.

Model fit quality for the 6 components of the aerodynamics with the set of combined maneuvers covering the extended flight envelope are shown in Table 6. One set of explanatory variables was used in all the fits (across the flight envelope), so engineering judgement was made in selecting the state variables most likely to contribute to the aerodynamics. The chosen variables are also listed in Table 6 for each axis.

Table 6 Fuzzy Model Fit Quality with Combined Maneuvers

Coefficient	Correlation Coefficient, R^2	Explanatory Variables
Cx	0.983	$\alpha, \beta, \delta_e, \delta_a, \delta_r, \dot{\alpha}, \dot{\beta}, \dot{q}, \dot{r}$
Cy	0.967	$\alpha, \beta, \delta_e, \delta_a, \delta_r, \dot{\beta}, \dot{p}, \dot{q}, \dot{r}$
Cz	0.997	$\alpha, \beta, \delta_e, \delta_a, \delta_r, \dot{\alpha}, \dot{\beta}, \dot{q}, \dot{r}$
Cl	0.950	$\alpha, \beta, \delta_e, \delta_a, \delta_r, \dot{\beta}, \dot{p}, \dot{q}, \dot{r}$
Cm	0.971	$\alpha, \beta, \delta_e, \delta_a, \delta_r, \dot{\alpha}, \dot{\beta}, \dot{q}, \dot{r}$
Cn	0.964	$\alpha, \beta, \delta_e, \delta_a, \delta_r, \dot{\beta}, \dot{p}, \dot{q}, \dot{r}$

A test of model adequacy is whether or not the model can predict data that were not used in the development of the model. There were many instrumentation issues that made flight-to-flight data comparisons difficult in the present study; however, some examples of the model predictive capability are presented below. A maneuver from Flight 8 (deceleration from cruise to stall conditions with fuzzy inputs) was used for an example case. The data from the Flight 8 maneuver (explanatory variables) were input into the fuzzy logic models developed from the combined maneuvers from Flight 10, and the model outputs were compared to the calculations of force and moment coefficients directly from Flight 8 data. Figures 10 through 15 show the comparisons of the model and flight data, and the correlation coefficient for predictions on all 6 components of aerodynamic forces and moments.

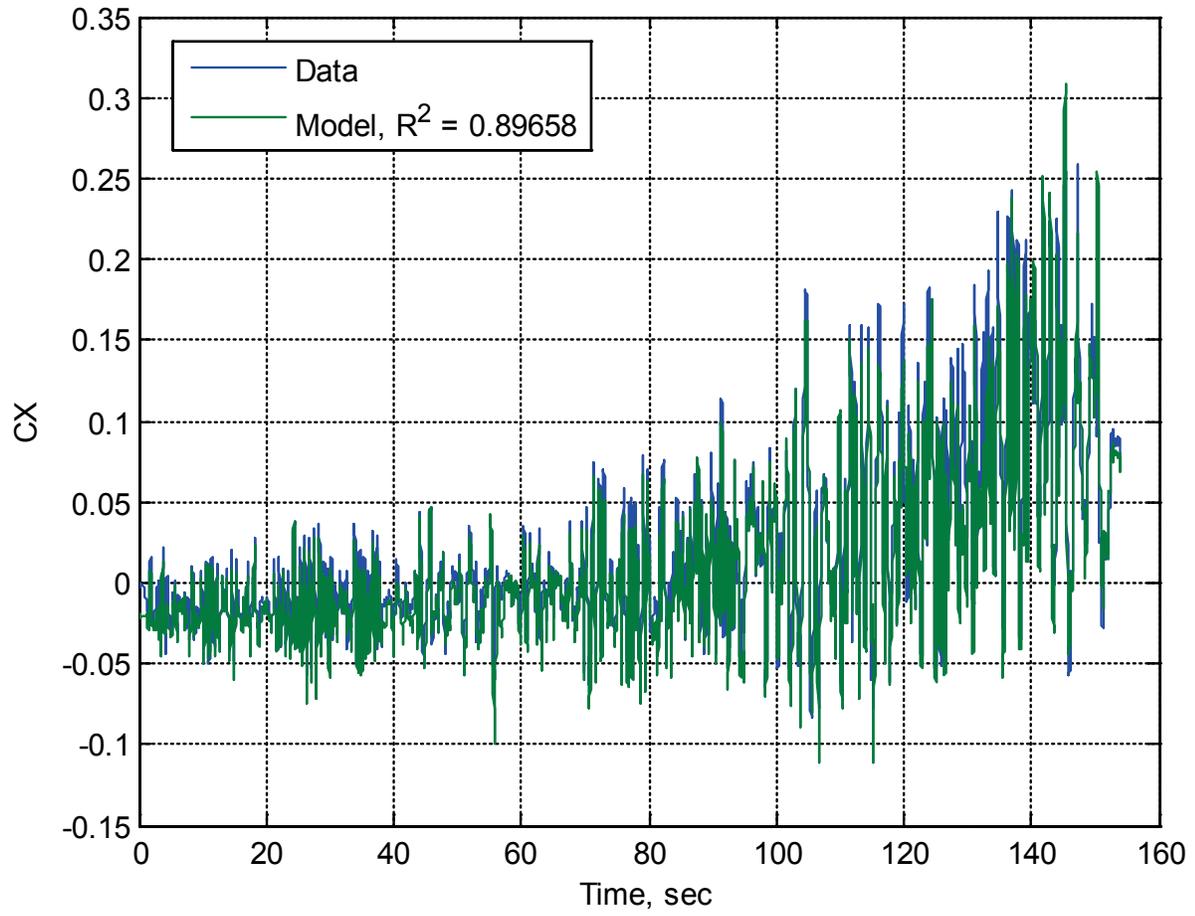


Figure 10 Model prediction of axial force.

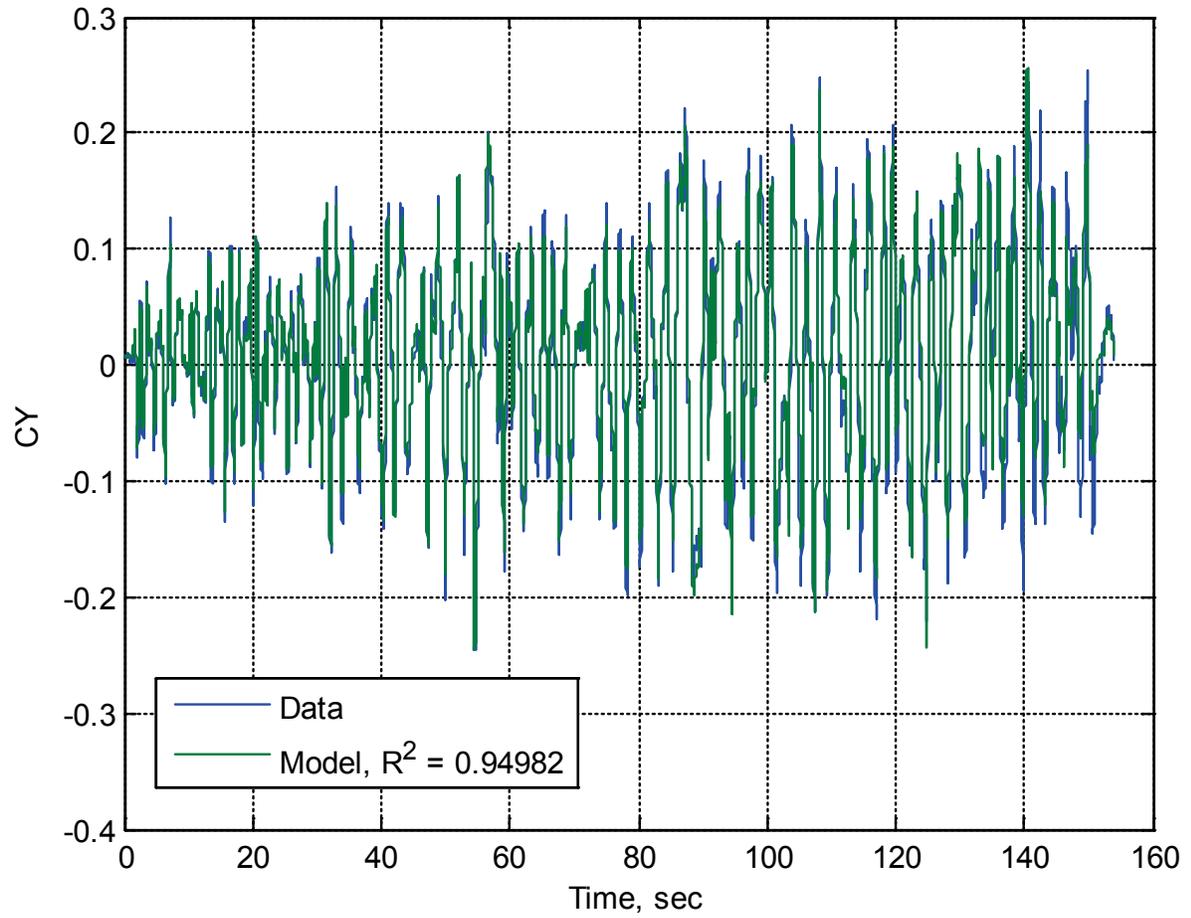


Figure 11 Model prediction of side force.

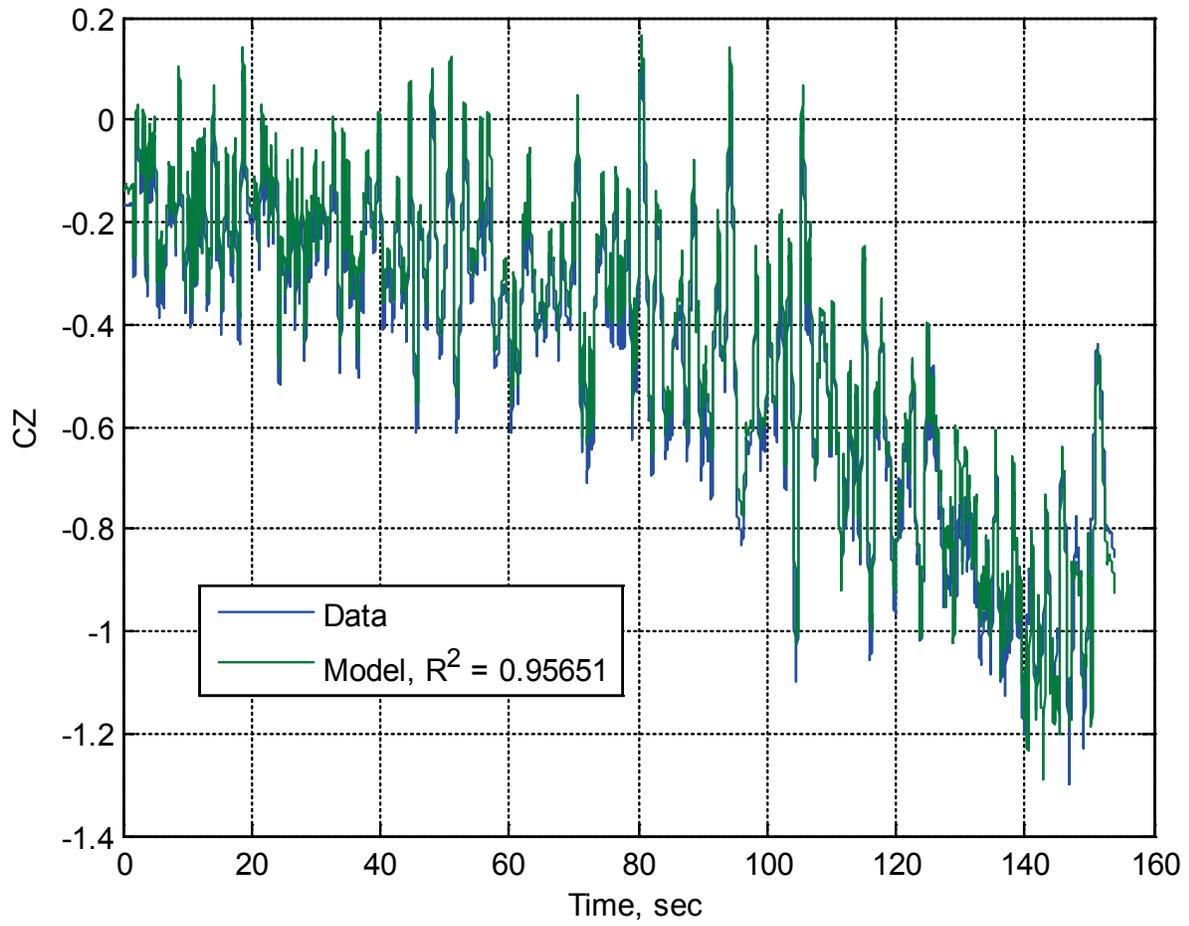


Figure 12 Model prediction of normal force.

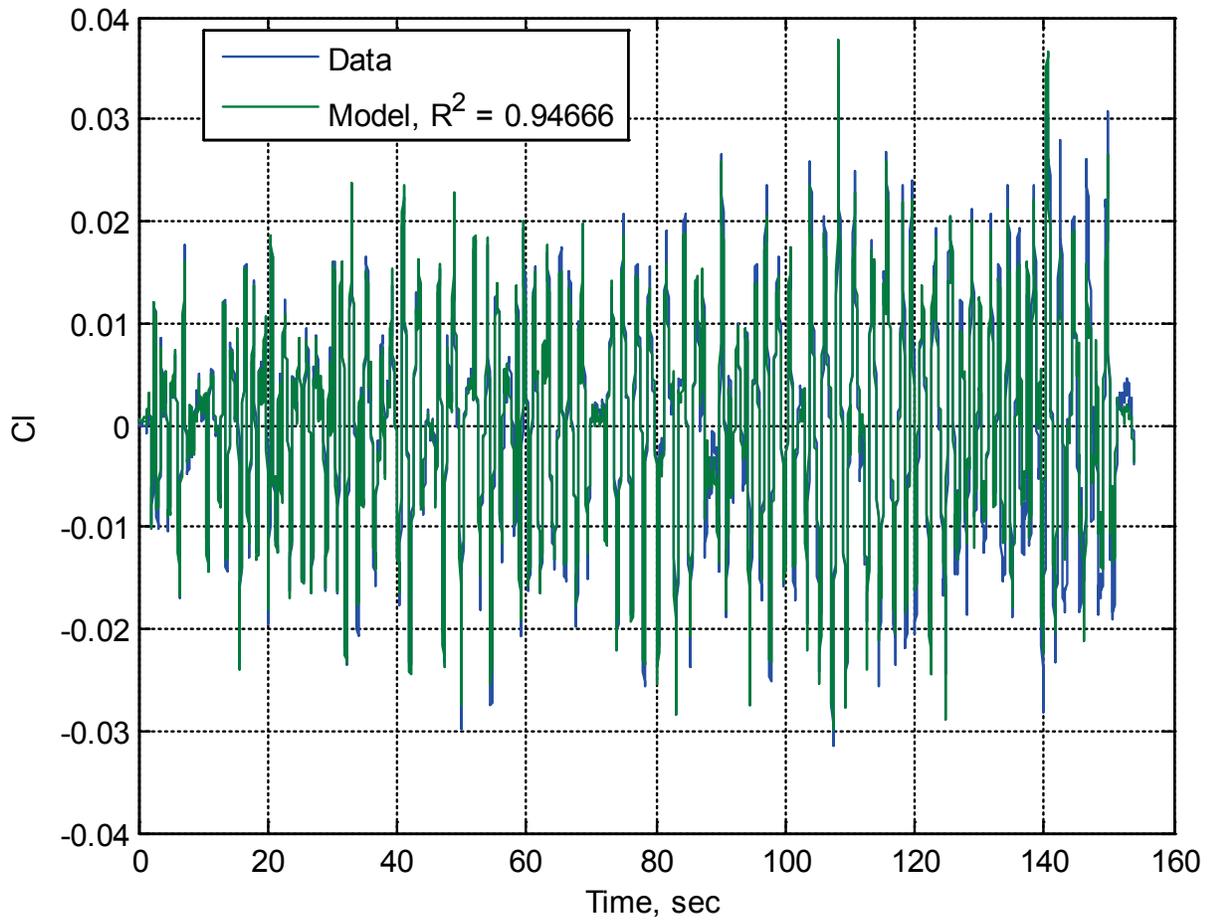


Figure 13 Model prediction of rolling moment.

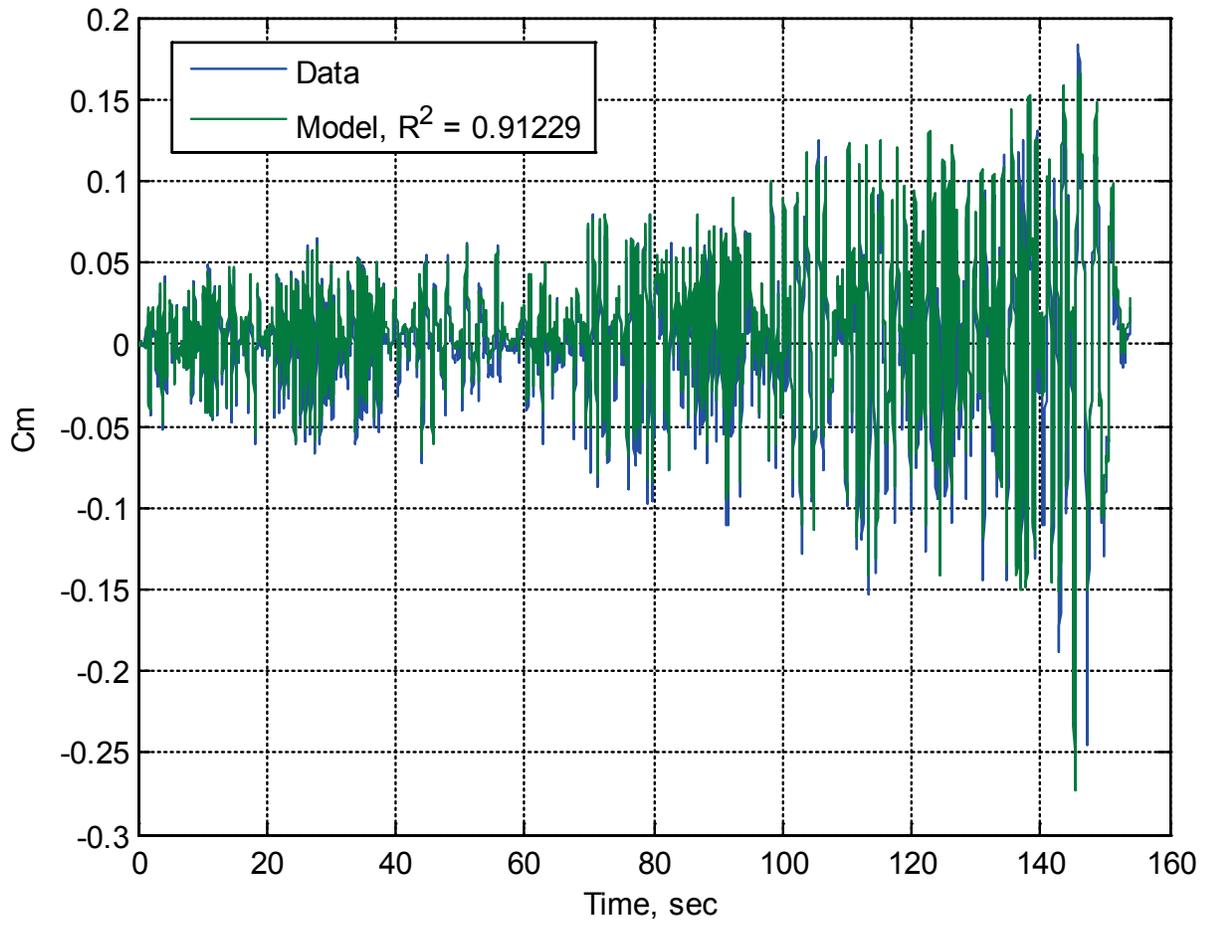


Figure 14 Model prediction of pitching moment.

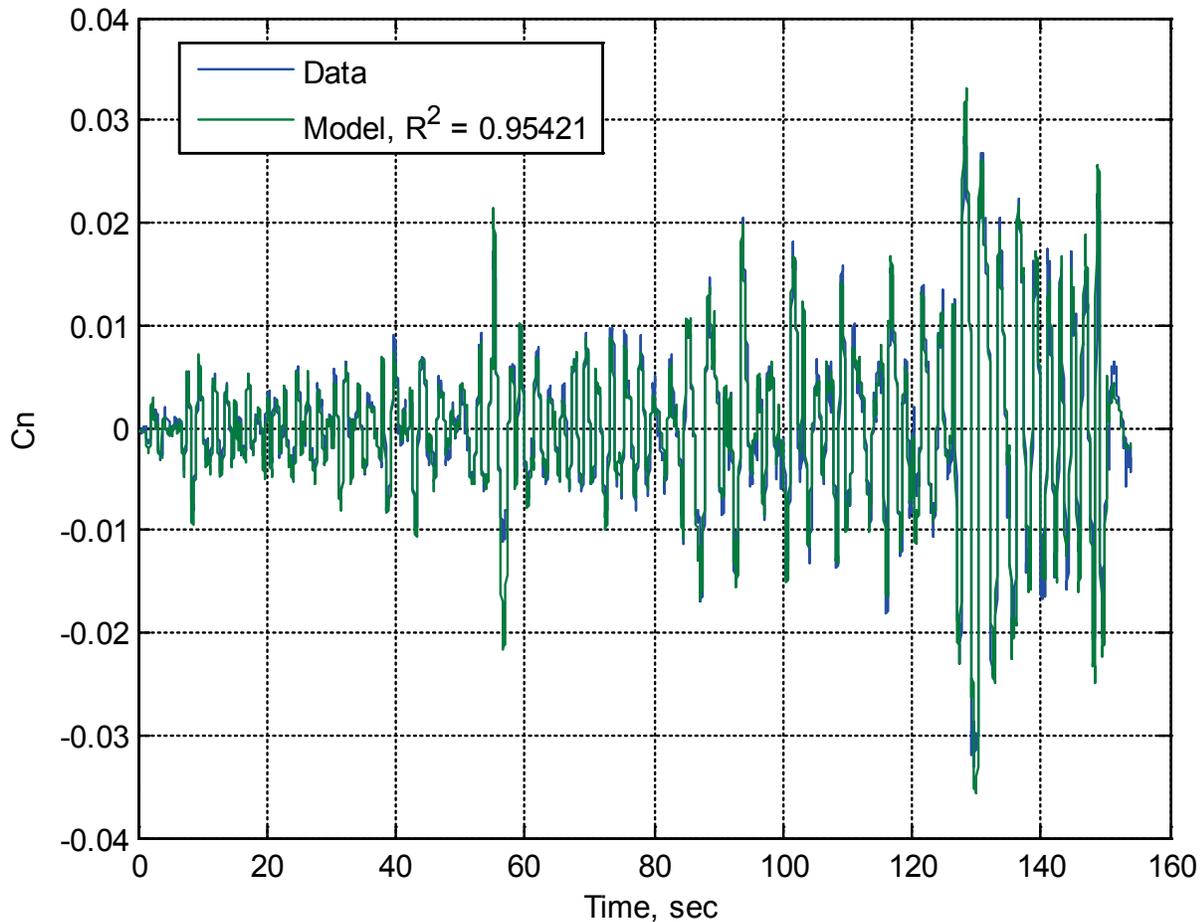


Figure 15 Model prediction of yawing moment.

These results show good model comparisons with the flight data for this prediction case. The axial force coefficient shows the least accurate fit, with the correlation coefficient just under $R^2 = 0.9$, which is likely due to the unmodeled thrust effects mentioned previously. All aerodynamic coefficient models exhibited a very high correlation coefficient for prediction over a large portion of the aircraft flight envelope.

In summary, the Phase I ARMD Seedling Fund project experienced many of the typical issues and problems found in flight testing projects. Instrumentation issues including faulty electronic components and unknown sensitivities to changes in temperature resulted in inconsistent data over the first six flights. Project funding and time constraints did not allow for comprehensive data system development and checkout, but the data

system was substantially improved for the second set of 6 data flights. An alternate inertial instrumentation system was installed (tablet computer) and was used with the ship data system to improve the accuracy of the flight test measurements. Results show promise of substantial improvements in the capability for developing models of airplane aerodynamics in flight regimes that traditional methods can not even obtain, and in the development of very nonlinear models rapidly with significantly reduced flight test time. Maturation of this technology could result in substantial cost and time savings in flight test programs, and can be an enabler for self-learning airplanes, resulting in reduced development cost of new vehicles and more robust and safe flight operations.

Lessons Learned

The Phase I research project was an initial step to investigate methods to develop models of highly nonlinear aerodynamics from flight without needing to define model structure. Multi-axis input techniques for piloted maneuver execution were developed to provide rich data with small amounts of flight time. During the testing, several issues were encountered that will need to be addressed in future research of this type.

Data Parameters. Several parameters were recorded by hand due to the cost of adding additional data parameters to the existing data stream. This resulted in difficulties in reducing the flight data. Future tests should include engine (RPM, fuel used) and air temperature measurements in the automated data system.

Instrumentation system checkout and calibration. Calibration and resolution of the data were problematic for many of the parameters. It was found after the sixth flight that several parameters had very large variations due to temperature changes, and cross-talk between channels was discovered. Pre-flight comprehensive data checks need to be conducted to develop confidence in the data system – including calibration checks with multiple-inputs-at-a-time, and checks for temperature sensitivities. Calibration for temperature effects can be made if appropriate temperature measurements are added.

Pre and post flight checks. All flights should use procedures to identify if data values have drifted during flight. Starting and stopping the data system recording at the same location on the ramp, conducting control deflection checks on the ground, and including repeatable flight conditions on each flight can help identify problems. Implementing real-time modeling could also help to diagnose these conditions.

Fuzzy logic model results can be sensitive to explanatory variable selection and can also generate very nonlinear results. Care must be taken to not over-parameterize the model, and future work is needed to develop criteria for optimizing the models and to assess the magnitude of uncertainties of the model.

Extrapolation of the models outside of data used to develop the model can result in unexpected results due to nonlinearities, so care needs to be taken in the development of the input ranges and use of the models.

Next Steps

The technology readiness level (TRL) of this technology is currently estimated at level 4. The concepts have been applied to flight data and preliminary results have been obtained; however, many refinements need to be completed to make the fuzzy logic algorithm ready for wide application, and real-time analysis needs to be included to support the “Learn-To-Fly” objectives. Next steps should include:

1. Advancement of fuzzy logic algorithms
 - a. Improvements in speed of model determination
 - b. Optimization of model size
 - c. Quantification of uncertainties
2. Development of real-time inflight maneuver assessment and pilot guidance
3. Demonstration of inflight maneuver assessment and pilot guidance
4. Demonstration of inflight aerodynamic model development
5. Demonstration of inflight model verification using flight maneuvers from current flight
6. Demonstration of development of aerodynamic models suitable for analysis and simulation post flight.

Concluding Remarks

A research study was conducted to develop efficient flight test and analysis methods for estimation of highly nonlinear aerodynamic models of a jet trainer aircraft. Flight data were obtained using simultaneous multi-axis perturbation inputs throughout large flight envelope excursions, resulting in flight data with rich information content for aerodynamic modeling over large portions of the flight envelope. A fuzzy logic algorithm was used to identify a model of the aerodynamics without any

specification of the model structure beyond selection of explanatory variables. Excellent matching of flight data – even through stall and post-stall gyrations - was achieved with the flight test methods and fuzzy logic algorithms, showing promise for practical, rapid simulation model development directly from flight test data.

References

1. Wang, Zhongjun; Lan, C. Edward; and Brandon, Jay M.: “Fuzzy Logic Modeling of Nonlinear Unsteady Aerodynamics”, AIAA 98-4351.
2. Morelli, E.A. “Flight Test Maneuvers for Efficient Aerodynamic Modeling,” AIAA-2011-6672, *AIAA Atmospheric Flight Mechanics Conference*, Portland, OR, August 2011.
3. Morelli, E.A. “Efficient Global Aerodynamic Modeling from Flight Data,” AIAA-2012-1050, *50th AIAA Aerospace Sciences Meeting*, Nashville, TN, January 2012.

REPORT DOCUMENTATION PAGE

*Form Approved
OMB No. 0704-0188*

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1. REPORT DATE (DD-MM-YYYY) 01-10-2012		2. REPORT TYPE Technical Memorandum		3. DATES COVERED (From - To)	
4. TITLE AND SUBTITLE Nonlinear Aerodynamic Modeling From Flight Data Using Advanced Piloted Maneuvers and Fuzzy Logic				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Brandon, Jay M.; Morelli, Eugene A.				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER 561581.02.08.07.46.04	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) NASA Langley Research Center Hampton, VA 23681-2199				8. PERFORMING ORGANIZATION REPORT NUMBER L-20181	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) National Aeronautics and Space Administration Washington, DC 20546-0001				10. SPONSOR/MONITOR'S ACRONYM(S) NASA	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S) NASA/TM-2012-217778	
12. DISTRIBUTION/AVAILABILITY STATEMENT Unclassified - Unlimited Subject Category 05 Availability: NASA CASI (443) 757-5802					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT Results of the Aeronautics Research Mission Directorate Seedling Project Phase I research project entitled "Nonlinear Aerodynamics Modeling using Fuzzy Logic" are presented. Efficient and rapid flight test capabilities were developed for estimating highly nonlinear models of airplane aerodynamics over a large flight envelope. Results showed that the flight maneuvers developed, used in conjunction with the fuzzy-logic system identification algorithms, produced very good model fits of the data, with no model structure inputs required, for flight conditions ranging from cruise to departure and spin conditions.					
15. SUBJECT TERMS Aerodynamics; Flight tests; Fuzzy logic; System identification					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			STI Help Desk (email: help@sti.nasa.gov)
U	U	U	UU	25	19b. TELEPHONE NUMBER (Include area code) (443) 757-5802