

Aeroservoelastic Control Law Development for the Integrated Adaptive Wing Technology Maturation Wind-Tunnel Test

Josiah M. Waite*, Jared Grauer†, Robert E. Bartels‡ and Bret K. Stanford§
NASA Langley Research Center, Hampton, VA, 23681

In this paper, a linear quadratic Gaussian (LQG) regulator was applied to a computational aeroservoelastic (ASE) model of the Integrated Adaptive Wing Technology Maturation (IAWTM) wind-tunnel model to demonstrate its effectiveness for active flutter suppression. The aerodynamics within this computational ASE model were solved using unsteady Reynolds-averaged Navier-Stokes (RANS) equations; the structural dynamics of the model were solved using modal analysis. This RANS-based ASE model was used as the plant for the LQG regulator, which utilized a Kalman filter and controller that were derived from a reduced-order model (ROM) of the RANS-based ASE model. This ROM-based ASE model was generated using system identification techniques. It was shown that the Kalman filter adequately predicted important states of the plant, and that the LQG regulator successfully stabilized an aeroelastically unstable plant without exceeding reasonable control surface limitations. All of this was demonstrated using simulation data, and the methods presented here appear feasible for use in the upcoming IAWTM wind-tunnel tests.

Nomenclature

A, B, C, D	=	State space matrices
dt	=	Time step
J	=	Performance index
K, L	=	Feedback & Kalman gain matrices
Q, R	=	Weighting matrices
u	=	Input control surface amplitude vector
v	=	Measurement noise vector
w	=	Process noise vector
x	=	State vector
$\hat{x}$	=	Estimated state vector
$\ddot{\delta}$	=	Physical accelerations
$\hat{\ddot{\delta}}$	=	Estimated physical accelerations
$\ddot{\eta}$	=	Modal accelerations

I. Background

THE NASA Advanced Air Transport Technology (AATT) Project seeks to “explore and develop technologies and concepts for improved energy efficiency and environmental compatibility for fixed wing subsonic transports” [1]. The Integrated Adaptive Wing Technology Maturation (IAWTM) project is a subproject within AATT and is a joint Boeing/NASA effort to, in part, demonstrate the active control systems necessary to employ high-aspect ratio wings for improved aerodynamic efficiency. The aircraft configuration under study for the IAWTM project is a generic jet transport based on the NASA Common Research Model (CRM) whose wing aspect ratio has been increased to 13.5 (as opposed to nominal CRM aspect ratio of 9) and whose development is given in Ref. [2].

*Research Aerospace Engineer, Aeroelasticity Branch, MS 340, AIAA Member, josiah.m.waite@nasa.gov.

†Research Engineer, Dynamic Systems and Control Branch, MS 308, AIAA Associate Fellow.

‡Research Aerospace Engineer, Aeroelasticity Branch, MS 340, AIAA Senior Member.

§Research Aerospace Engineer, Aeroelasticity Branch, MS 340, AIAA Associate Fellow.

A semispan model of the high-aspect-ratio CRM with 10 trailing edge control surfaces is currently being fabricated and will be delivered to the NASA Langley Transonic Dynamics Tunnel (TDT). There, several tests will be conducted to demonstrate maneuver load alleviation (MLA), gust load alleviation (GLA), active flutter suppression (AFS), and drag reduction, all at transonic conditions. A layout of the wind-tunnel model is shown in Fig. 1.

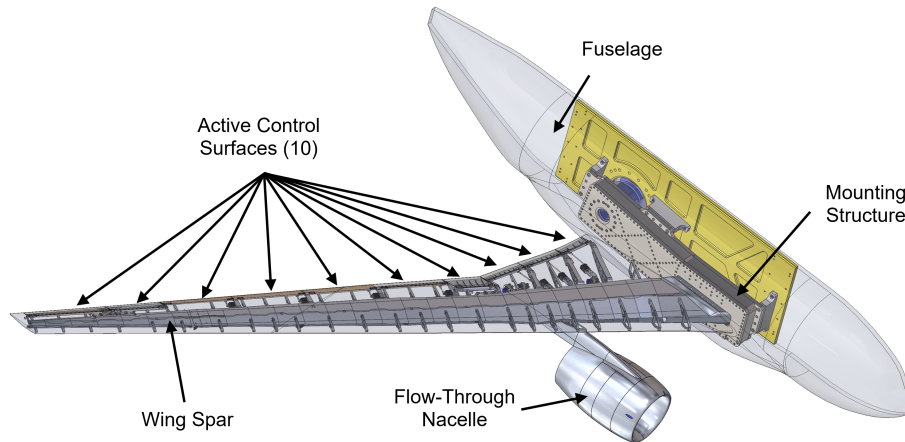


Fig. 1 Layout of the IAWTM wind-tunnel model showing the placement of all ten active control surfaces.

The wind-tunnel model is a spar/pod wing design with a relatively rigid fuselage attached to a mounting structure (seen in Fig. 1), which in turn is attached to a load balance behind the tunnel wall. Shims exist that can be attached to force the load to go through the fuselage, rather than through the balance, to avoid damage to the balance in the event of flutter. The spar/pod design is similar to that used in the Boeing truss-braced wing aeroelastic model tested in the TDT in 2013 [3]. There is a central spar running the span of the wing to which the pods are attached that form the aerodynamic shape of the wing. The pods are constructed of ribs for attachment to the spar and skins to create the outer mold line. There are ten active control surfaces that will be used for the test objectives discussed above. Three of these (two outboard ailerons and one inboard aileron) are driven by high-speed electrohydraulic actuators. The remaining seven are driven by slower servo motors and will be used primarily for drag and maneuver load reductions.

Control laws must be developed for each test (MLA, GLA, AFS, and drag reduction) and must be able to work in tandem when two or more control strategies are being tested simultaneously (e.g., when control laws to mitigate maneuver loads and gust loads operate simultaneously). The development of these control laws requires accurate mathematical representations of the aerodynamics, structural dynamics, and control surface dynamics of the system. Taken together, this mathematical representation is the aeroservoelastic (ASE) model.

In this work, a reduced-order, state-space ASE model was derived from an ASE model based on the unsteady Reynolds-averaged Navier-Stokes (RANS) equations. A linear quadratic Gaussian (LQG) regulator, meant for AFS, was then designed from this reduced-order ASE model. The purpose of this work was to demonstrate active flutter suppression using the RANS-based ASE model as the plant, and by designing a controller based on the reduced-order ASE model. Demonstrating AFS on this computational model will provide insight that will be useful when designing controllers for the actual wind-tunnel model.

II. Aeroservoelastic Modeling

Two ASE models are discussed in this paper. Each has three inputs, which are commanded control surface deflections, and 22 outputs, which are acceleration measurements from sensors placed along the wing. For simplicity, results from only three of the 22 sensors will be shown here. The three inputs (AILRN1, AILRN2, AILRN3) and three outputs (vertical accelerations from sensors 3, 9, and 21) discussed in this paper are shown in Fig. 2.

In this section, the structural model used for both ASE models will be presented. Next, a brief explanation of control surface modeling will be given. Then, a description of aerodynamic modeling for each ASE model will be presented.

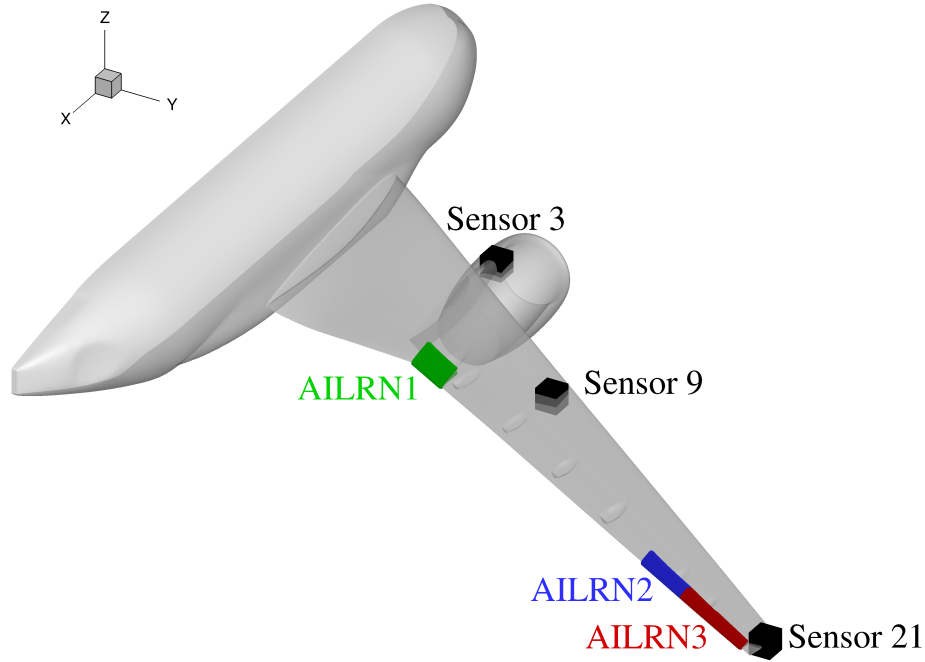


Fig. 2 Visualization of the three control surfaces (AILRN1, AILRN2, and AILRN3), and locations of the three sensors for which results will be presented in this paper.

A. Structural Dynamics Modeling

The structural model has a detailed fuselage and wind-tunnel mount modeled by solid plate elements. The finite-element model (FEM) treats the spar as an equivalent beam with rigid elements to place concentrated masses and to attach control surfaces. The active control surfaces are modeled as flat plates.

Table 1 presents the frequencies and descriptions of the first ten structural modes. Because the wing structure is modeled with a sparse distribution of flexible and rigid beam elements, the method of modal displacement is based on zonal mathematical descriptions of the structural model displacements. A similar method was used for the SUGAR wind-tunnel model [4]. Because the computational fluid dynamics (CFD) model has a symmetry plane at the fuselage centerline, y-displacements of the fuselage that cross the $y=0$ plane have been made zero in the structural model.

Table 1 Frequencies and descriptions of the first ten (FEM) structural modes.

mode number	frequency (Hz)	description
1	3.61	1 st wing vertical bending
2	7.65	1 st fuselage pitch / wing 1 st vertical bending
3	8.35	1 st wing/balance fore/aft bending
4	11.08	2 nd wing vertical bending
5	14.98	2 nd wing / balance fore/aft bending
6	15.15	2 nd wing vertical bending / fuselage pitch
7	17.11	1 st nacelle pitch / inboard wing 1 st torsion
8	24.04	nacelle lateral
9	26.78	3 rd wing vertical bending
10	29.34	nacelle lateral / balance axial

For coupling to the aerodynamic models, a linear modal representation of the structural dynamics was formed using 24 structural modes. Inputs to the structural model included generalized masses, modal frequencies, and modal damping ratios. For the cases presented in this paper, these parameters for the 24 structural modes came from MSC.NASTRAN [5].

B. Control Surface Dynamics Modeling

The IAWTM wind-tunnel model has ten control surfaces. Since active flutter suppression requires relatively high-frequency motion from the control surfaces, only the three hydraulically-actuated control surfaces (AILRN1, AILRN2, and AILRN3; see Fig. 2) were modeled here. This was done by including mode shapes representing unit deflections for each of the three control surfaces and treating them similar to the 24 structural modes. Unlike the structural modes, however, the control surface modes had no inertial or structural properties associated with them, and actuator dynamics were not included, which meant that only the aerodynamic influence for each control surface's motion was accounted for in the analyses. The impact of excluding the control surface inertias was not expected to significantly impact the results. Previous comparisons of ASE models employing panel-based aerodynamics showed that including the inertias of the control surfaces had little effect on the overall response of the IAWTM model.

C. ASE Modeling

Two ASE models were developed using different aerodynamic representations. The first, which will be referred to as the FUN3D-based ASE model, modeled the aerodynamics by solving the RANS equations. The second, referred to as "SysID ROM", used system identification techniques to create a reduced-order model of the aerodynamics from the FUN3D-based ASE model. A description of both is given here.

1. FUN3D-based ASE Model

The NASA Langley Research Center FUN3D (Fully Unstructured 3-Dimensional Navier-Stokes) code is primarily a node-centered, finite-volume, unstructured CFD solver for compressible flows [6, 7]. It was used to solve the steady and unsteady RANS equations and couple them to modal structural dynamics equations. In this work, FUN3D solved the RANS equations using a second-order upwind scheme with the Spalart-Allmaras turbulence model [8]. The structural dynamics were solved using a second-order accurate predictor-corrector scheme that was marched in time along with the CFD solver. The CFD mesh was moved at each time step to represent (1) structural deflections in response to aerodynamic forces and (2) control surfaces deflections, and the aerodynamics were solved based on the new shape. This coupled, time-marching simulation constituted the FUN3D-based ASE model.

The volume grid used in the FUN3D analyses was a semi-infinite flow-field grid with a symmetry plane at the wind-tunnel mounting wall. It had 14,618,916 nodes, 3,598,892 tetrahedral cells, 184,622 pyramid cells and 27,598,875 prism cells. The overall surface mesh distribution is shown in Fig. 3a. Note that there is clustering of nodes in the area of the control surfaces. Figure 3b shows the mesh layout over several of the inboard control surfaces.

A typical FUN3D aeroelastic analysis consists of sequentially obtaining three solutions: (1) the converged steady solution about a rigid wing, (2) the converged unsteady solution of an aeroelastically-deforming body with critical structural damping—this is the static aeroelastic solution, and (3) the converged unsteady solution of an aeroelastically-deforming body with zero, or low, structural damping. Typically, the static aeroelastic simulation is restarted from the converged steady solution about a rigid wing, and this static aeroelastic solution serves as the starting point for the unsteady simulation with low (or zero) structural damping. When performing flutter analyses, a modal disturbance of some type—generally a modal velocity in one of the modes—is introduced in the unsteady aeroelastic simulation with low structural damping to excite the dynamics of the system.

2. Reduced-Order Model based on System Identification (SysID ROM)

ASE state-space models can be generated from experimental data using system identification (SysID) techniques such as the eigensystem realization algorithm (ERA) [9]. To use this technique, prescribed inputs are applied to the system (which, as in the current case, may be control surface rotations applied to the physical wind-tunnel model) and outputs of the system are measured. The system identification technique then operates on the set of input-output data to generate a state-space model of the dynamics of the system, whose inputs and outputs are of the same types as the applied inputs and measured outputs of the physical model during the system identification process. Since, for the

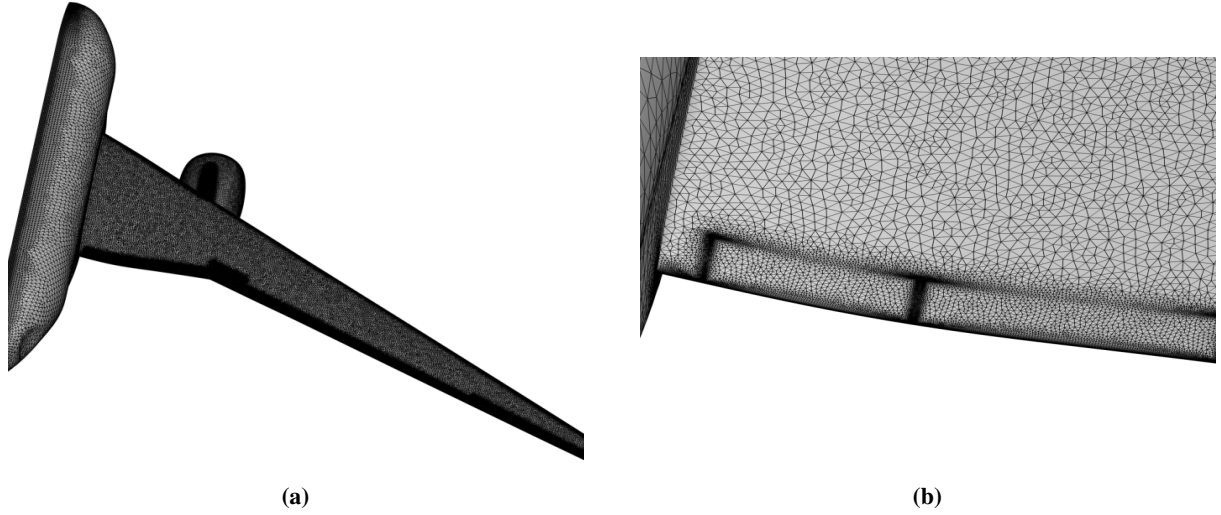


Fig. 3 Visualization of the CFD surface mesh for (a) the entire wind-tunnel model and (b) the inboard control surfaces.

IAWTM tests, the physical model will be outfitted with accelerometers along the wing, the outputs of the ASE model derived from the system identification process will also be accelerations.

ASE state-space models can also be generated from computational simulation data using the same system identification techniques. One advantage to using simulation data is the ability to monitor any variable within the simulation as output. Access to such a wide variety of variables is often infeasible, and sometimes impossible, when using experimental data. For example, in a computational environment, it is relatively easy to apply a control surface rotation to the aerodynamic grid and monitor forces over the surface of the wing. Exercising a system identification algorithm on that input-output data set leads to a reduced-order aerodynamic state-space model without the interaction of the structural dynamics. This is useful since this purely aerodynamic model could then be coupled to a structural dynamics state-space model through a gain representing dynamic pressure, and the result would be an aeroservoelastic state-space model that is valid over a wide range of dynamic pressures, at a single Mach number. To derive an ASE model that is valid over a similar range of dynamic pressures experimentally, one would either have to instrument the wind tunnel model with additional sensors to measure the purely aerodynamic response, or apply inputs at several dynamic pressures and interpolate the results. This is a major advantage of deriving ASE models, and their associated control laws, from simulation data.

The process of generating ASE state-space models from computational simulation data using ERA has been previously demonstrated [10, 11]. A similar process was followed in this work. A converged static aeroelastic solution was obtained at a dynamic pressure of 275 psf, Mach 0.8, and at zero degrees angle of attack. Then, several input-output data sets were generated from a series of aerodynamic training simulations, conducted using FUN3D. As previously mentioned, mode shapes representing control surface rotations were generated and included in these training simulations in a manner similar to the structural mode representations. In these training simulations, the displacements and velocities of each structural and control mode were prescribed using Walsh functions [12], and the resulting aerodynamic forces induced on every structural mode were calculated.

Once the aerodynamic training simulations were completed, the input-output data, which in this case were modal displacement and modal aerodynamic force data, were passed to the AEROM software [13]. AEROM is a suite of tools developed at the NASA Langley Research Center particularly for generating aeroelastic reduced-order models. AEROM is largely based on the System/Observer/Controller Identification Toolbox [14], or SOCIT, another code developed at the NASA Langley Research Center. Two tools in particular from SOCIT were used in this work: its “pulse” algorithm and its eigensystem realization algorithm (ERA). The “pulse” algorithm [14] was used to generate individual impulse responses of all inputs on all outputs from the input-output data produced by the training simulations. A brief overview of how this algorithm works in aeroelastic applications is given in Ref. [13]. A discrete-time state-space model of the system was then generated via ERA [9, 14]. For the present case, SOCIT’s “pulse” and ERA were used to generate aerodynamic state-space models whose inputs were modal displacements (of structural and control

modes) and whose outputs were generalized aerodynamic forces (GAFs) on the 24 structural modes. Note that this aerodynamic model was “trained” about the nonlinear static aeroelastic CFD solution. The pulse/ERA algorithms approximated the influence of the nonlinearities in the mean flow by adding extra states to the aerodynamic state-space model. This approximation of aerodynamic nonlinearities may lead to better accuracy, especially in transonic flow, where shocks on the vehicle can significantly influence the GAFs.

Lastly, these aerodynamic state-space models were combined with a linear representation of the structural dynamics, which was described in Section II.A, resulting in a reduced-order ASE model where the aerodynamic models pass GAFs to the structural model, and the structural model returns generalized displacements back to the aerodynamic model. This ASE ROM had two sets of inputs: (1) the dynamic pressure, which simply acts as a gain on the GAFs from the aerodynamic models, and (2) the control surface displacements. Note that no actuator or controller dynamics were included here. Only the aerodynamic influence of control surface motion was captured, which implies that the control surfaces themselves were assumed to be perfectly rigid with infinite stiffness. The outputs of this combined ASE ROM were acceleration measurements that represented the accelerometers used on the IAWTM wind-tunnel model.

III. Linear Quadratic Gaussian (LQG) Regulator

A linear quadratic Gaussian (LQG) regulator was developed to mitigate flutter in the IAWTM model. LQG regulators use a Kalman filter to approximate the states of the plant (which, in this case, was the FUN3D ASE model). The Kalman filter assumed the plant dynamics to be of the form:

$$\begin{aligned}\dot{x} &= Ax + Bu + w \\ y &= Cx + Du + v\end{aligned}\tag{1}$$

where w and v represent process and measurement noise, respectively, which were both zero-mean, white, random processes. The Kalman filter itself was integrated in time alongside FUN3D and was assumed to be of the form:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(\ddot{\delta} - \hat{\ddot{\delta}})\tag{2}$$

where A and B come from the SysID ROM, u is a 3×1 vector of control surface deflections, and $\hat{x}$ is a vector of the estimated linear states; $\ddot{\delta}$ is the 22×1 vector of accelerations along the wing (which comes from the plant, the FUN3D ASE model) and $\hat{\ddot{\delta}}$ is its estimate generated from the SysID ROM; L is an observer gain matrix whose derivation will be described below. When L is properly designed, the error between the plant’s accelerations and the Kalman filter’s estimates of the accelerations ($\ddot{\delta} - \hat{\ddot{\delta}}$) will quickly decay to zero.

A full-state feedback controller was then developed using the estimated state vector, $\hat{x}$. Full-state feedback implies knowing the states of the plant. Since the plant being used in this work was a computational simulation with an extremely large number of states, using its states was not tractable. Instead, a small amount of data was taken from FUN3D at each time step (24 modal accelerations, $\ddot{\eta}$, converted to a number of acceleration measurements along the wing, $\ddot{\delta}$), and passed to the Kalman filter, which estimated the full state vector of a stand-alone ASE model (Eqn. 2). This estimate of the linear ASE states was then used to produce the commanded control surface rotations, u , of the form:

$$u = -K\hat{x}$$

The feedback gain matrix (i.e., the controller), K , was found such that a performance index, J , was minimized:

$$J = \frac{1}{2} \int_0^\infty \left(\hat{x}^T Q \hat{x} + u^T R u \right) dt\tag{3}$$

where $\frac{1}{2} \int_0^\infty \hat{x}^T Q \hat{x} dt$ represents the energy of some combination of the states, and $\frac{1}{2} \int_0^\infty u^T R u dt$ represents the energy necessary for control; Q is a state weighting matrix; R is a control weighting matrix. Larger values of R relative to Q penalize the controls more. The goal was to minimize the energy in the states without using too much energy in the control effort.

The L matrix from Equation 2 can be generated using a similar equation to the J performance index with Q and R prescribing white process and measurement noise inputs [15]. Calculating L in this manner minimizes the steady state error covariance [16], making the Kalman filter effective as an estimation tool.

When minimizing Eq. 3 to find a controller, K , the choices for the Q and R matrices have a significant influence on the positions of the closed-loop plant poles. Similarly, when minimizing Eq. 3 to find an observer gain matrix, L ,

the choices for the Q and R matrices influence the closed-loop observer poles. Thus, there were two sets of Q and R matrices associated with K and L , respectively. The method used here to find Q and R follows that found in Ref. [15], which was to assume some performance output — which was to be kept small — of the form $z = H\hat{x}$. To find the Q and R matrices associated with the controller, K , z was chosen to be the modal velocities of the structural modes; therefore, H was simply a matrix that isolated the modal velocity terms from the estimated state vector $\hat{x}$ and zeroed out all other terms. Then, the performance index was redefined as:

$$J = \frac{1}{2} \int_0^\infty \left(z^T \bar{Q} z + u^T R u \right) dt$$

where $\bar{Q}$ was a diagonal matrix containing $q_i = \frac{1}{z_{max_i}^2}$ and z_{max_i} was some maximum allowable deviation in each element of z for i equal to 1 to the number of elements in z . In Ref. [15], R is defined in a similar fashion as $\bar{Q}$, but for control inputs. For this work, R was defined such that the maximum allowable deviation in the control inputs was 0.1 degrees.

IV. Results

A. ASE Model Verification

Verification of the *aeroelastic* portion of the ASE model (i.e., only including the structural modes, not the control surface modes) was documented in Ref. [17], where it was shown that the SysID ROM predicted flutter around 440 psf. The verification that will be described here expands previous work to include control surface modeling.

In order to verify that the ASE correctly predicted responses to control surface motions, sinusoidal inputs of varying frequencies, with amplitudes of 2 degrees, and at a dynamic pressure of 225 psf, Mach 0.8, were applied to the modal displacements of AILRN3. The open loop response computed by the SysID ROM were compared to the response predicted by FUN3D. The real and imaginary parts of the oscillatory responses of the first 4 structural modes predicted by both codes are shown in Fig. 4. The SysID ROM response matches the FUN3D response well up to about 6 Hz. Between 6 and 8 Hz, there are discrepancies, but overall, the SysID ROM seems to capture the correct trend.

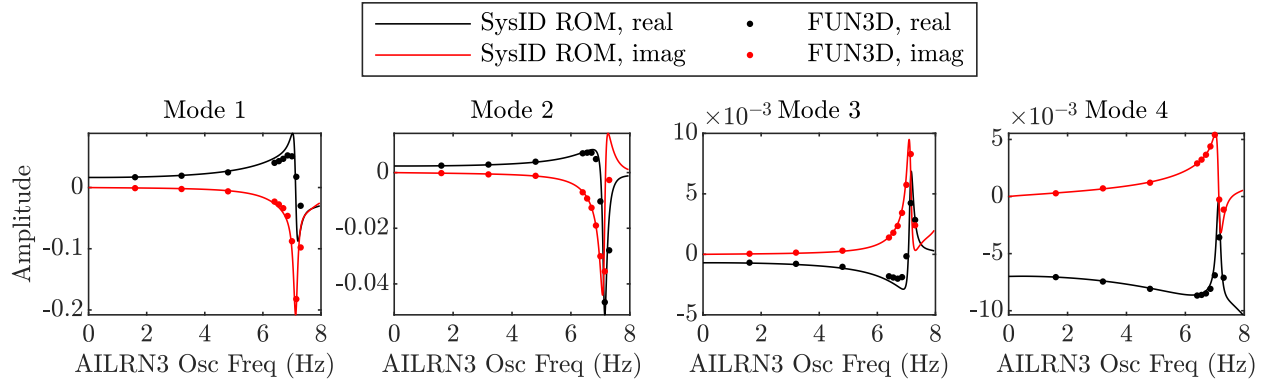


Fig. 4 Real and imaginary components of responses in modal displacement due to a sinusoidal input to AILRN3 as a function of oscillation frequency.

The FUN3D data for Fig. 4 were generated in the time domain. A single sinusoid was fit to the time domain response, from which the real and imaginary parts were extracted. For many of the structural modes, the steady-state response between 6 and 8 Hz was not a sinusoid with a single amplitude. Instead, the response was similar to wave trains, or wave packets, where the amplitude of the response would increase and decrease periodically. Thus, it was difficult to fit a single sinusoid to the response, which may explain the slight discrepancies seen between the two codes between 6 and 8 Hz.

An additional comparison was made where all three control surfaces were oscillated simultaneously at different frequencies. Those results are shown in Fig. 5. This comparison was also made at a dynamic pressure of 225 psf and Mach 0.8. Figure 5a shows the input signals of the three control surfaces. Figure 5b shows the responses for the first

four structural modes as predicted by FUN3D and SysID ROM. At these conditions, and for the given control surface inputs, the SysID ROM prediction matches the FUN3D prediction well.

The results shown in Figs. 4 and 5 lend confidence that, while not perfect, the SysID ROM predicted the responses to control surface oscillations with amplitudes up to 2 deg and frequencies up to 8 Hz with sufficient accuracy to use for control law development.

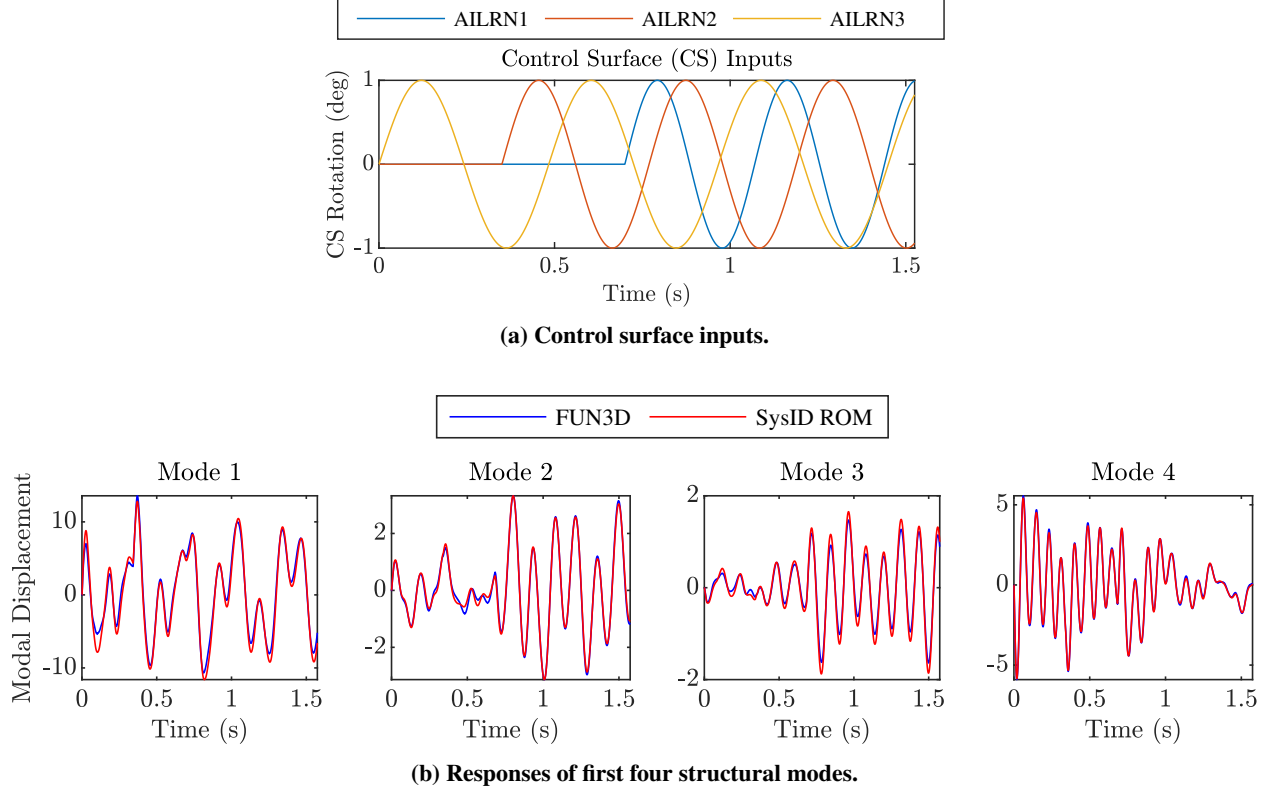
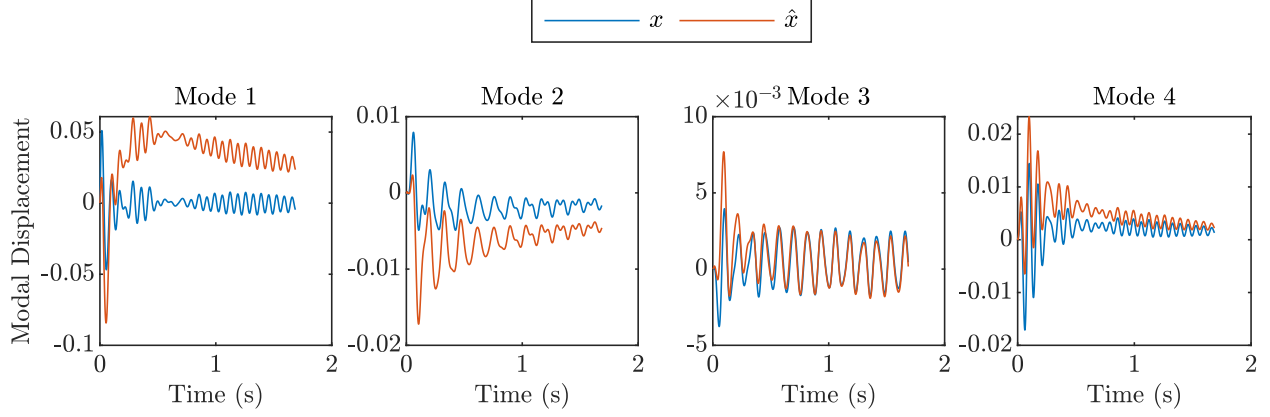


Fig. 5 Control surface inputs are shown in (a) above, followed by (b) the responses of the first four structural modes due to prescribed control surface inputs as computed by FUN3D and SysID ROM.

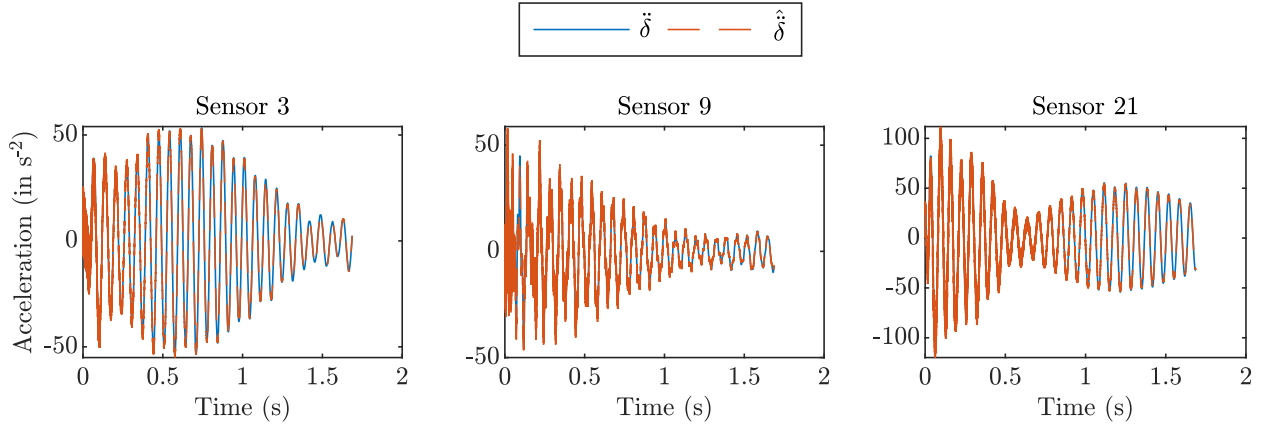
B. Kalman Filter Estimations

The purpose of the Kalman filter was to provide estimates for the states of a linear representation of the plant. It is instructive, therefore, to compare the Kalman filter's estimations with known values. To do this, and to demonstrate the effectiveness of the controller at the same time, an LQG regulator was designed and implemented at an unstable dynamic pressure of 470 psf at Mach 0.8. The plant was the FUN3D ASE simulation, and the SysID ROM was used to create a Kalman filter and controller. The plant was given an initial condition in the first structural mode's velocity, then was marched through time along with the Kalman filter. The modal displacements of each of the structural modes were included in the Kalman filter's state estimations ($\hat{x}$), and these were compared directly to the modal displacement information available from the plant (x). Figure 6a shows that comparison for the first four structural modes. The Kalman filter's estimates are a fair prediction of the actual states in the time frame shown. Since the Kalman filter was designed to make the size of the error between the actual states and the estimated states small over time, it may be that the offsets seen in modes 1 and 2, and to some degree in mode 4, will disappear, or at least become less severe, given a long enough time horizon. It is also possible that these offsets occur due to modeling errors in the Kalman filter, since it is a reduced-order model of the RANS-based plant. While both of these are possibilities, the exact causes for these offsets have not been thoroughly explored.

Another measure of how well the Kalman filter is performing is to compare its predicted sensor measurements ($\hat{\delta}$) to the plant's actual sensor measurements (δ). Figure 6b shows that these quantities are very similar, which is an indication that the Kalman filter is performing well.



(a) Kalman filter estimate ($\hat{x}$) versus the actual value (x).



(b) Kalman filter estimate ($\hat{\delta}$) versus the actual value (δ).

Fig. 6 Comparison of the Kalman filter estimate versus the actual values for (a) the modal displacement of the first four structural modes and (b) the acceleration measurements from three sensors.

C. Controller Performance

An initial measure of the controller's effectiveness was obtained by increasing the dynamic pressure to an unstable condition of 470 psf at Mach 0.8 and assuming the plant to be the SysID ROM (instead of the FUN3D ASE model), then comparing open- and closed-loop poles. While this doesn't necessarily reflect the exact behavior of the actual plant because of modeling errors between the SysID ROM and FUN3D, it does give a good initial indication of how effective the controller may be. This comparison of open- and closed-loop poles is seen in Fig. 7 and shows that the controller does indeed stabilize the unstable open-loop system—there are no closed-loop poles with positive real parts. This increased confidence that the controller would be effective when implemented with the real plant.

Next, the FUN3D ASE model was again assumed to be the plant at an unstable dynamic pressure of 470 psf and Mach 0.8. Just as before when examining the effectiveness of the Kalman filter, the plant was given an initial condition in the first structural mode's velocity, and the entire system (plant and LQG regulator, which included the Kalman filter and controller) was then marched through time. Figure 8a shows the open- and closed-loop response in modal displacement for the first 4 structural modes as a function of time. The open-loop response becomes unstable early in the simulation, which is expected. The controller appears to successfully arrest the instability, as shown in the closed-loop response. Figure 8b shows the control surface inputs commanded by the controller. The amplitudes of these commands are well within reasonable limits, but the frequencies of the commands, which are each approximately 16 Hz, do not fall within the range of frequencies that were tested in Sec. IV.A. This is something that will be explored in the future, but given the fact that the controller appears to stabilize the plant successfully, this was not a major concern.

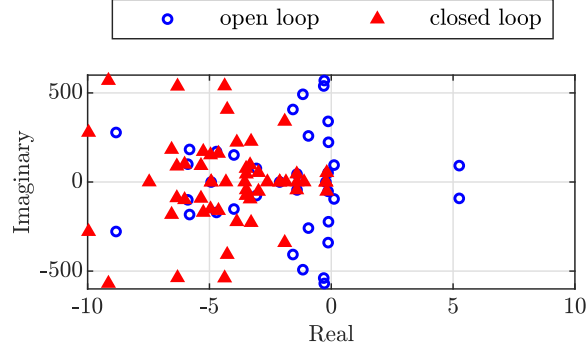


Fig. 7 Visualization of the SysID ROM open- and closed-loop poles.

V. Conclusions

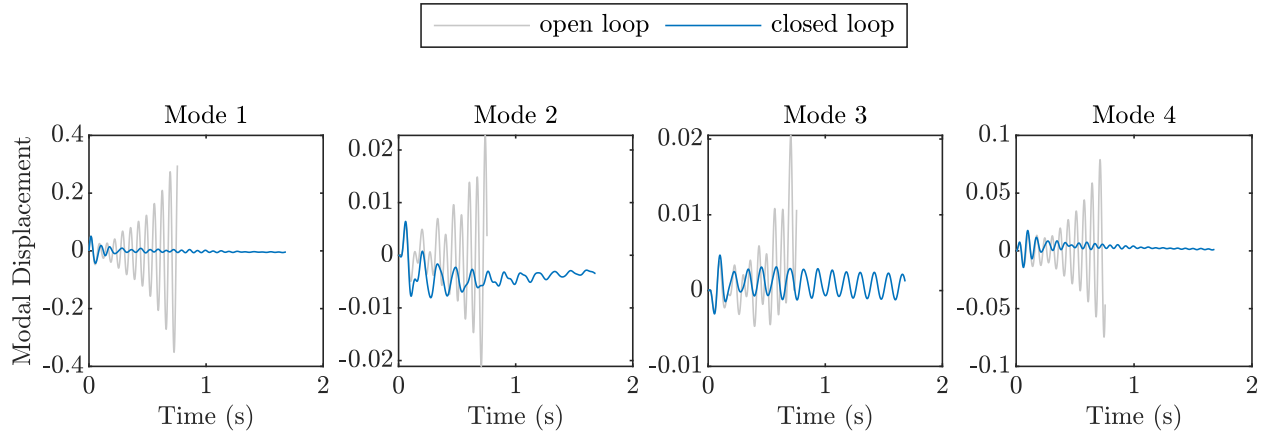
Two ASE models were presented in this paper that represent the IAWTM wind-tunnel model. The first model solved the aerodynamics using the unsteady RANS equations; the second model was a reduced-order model of the first, generated using system identification techniques. Both models employed a modal representation of the structural dynamics. The reduced-order model was shown to accurately predict the structural responses due to control surface inputs. It was then used as the basis for generating a Kalman filter, which adequately estimated structural states of the higher-order ASE model.

A controller was then designed based on the reduced-order ASE model, and both the controller and Kalman filter were implemented within an LQG regulator. This LQG regulator was then used to demonstrate active flutter suppression, using the higher-order ASE model as the plant. An instability in the plant was successfully arrested without exceeding reasonable control surface limits.

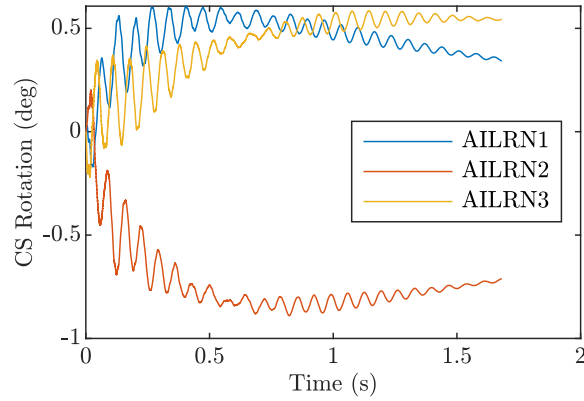
The insights gained in this work will be used in the control law development of the actual IAWTM wind-tunnel test. Future work will include using the reduced-order ASE model discussed in the paper (SysID ROM) to design controllers for maneuver load alleviation and gust load alleviation. Generating a Kalman filter and controller based on linearized frequency domain techniques (as opposed to system identification techniques) will also be conducted in the future.

Acknowledgments

This work was supported by the NASA Advanced Air Transport Technologies (AATT) project. The authors thank NASA LaRC GEOLAB for their support in creating the CFD grids, Walt Silva of the NASA Langley Aeroelasticity Branch for providing essential codes for this work, and Dan Ortega and Greg Seber of Boeing Research and Technology for developing and providing the FEM.



(a) Unstable, open-loop response compared to the stabilized, closed-loop response.



(b) Control surface deflections during closed-loop simulation.

Fig. 8 Results showing (a) a comparison between open- and closed-loop responses to a nonzero initial condition in the first structural modal velocity, and (b) the control surfaces commanded by the controller during the closed-loop simulation. These data sets were computed at a dynamic pressure of 470 psf and Mach 0.8.

References

- [1] “Advanced Air Transport Technology (AATT) Project Technical Challenges,” <https://www.nasa.gov/aeroresearch/programs/aavp/aatt/technical-challenges>, 2017. Accessed: 2019-10-20.
- [2] Brooks, T. R., Kenway, G. K., and Martins, J. R., “Benchmark Aerostructural Models for the Study of Transonic Aircraft Wings,” *AIAA Journal*, Vol. 56, No. 7, 2018, pp. 2840–2855.
- [3] Allen, T. J., Sexton, B. W., and Scott, M. J., “SUGAR Truss Braced Wing Full Scale Aeroelastic Analysis and Dynamically Scaled Wind Tunnel Model Development,” *AIAA SciTech Forum*, 2015.
- [4] Bartels, R. E., Scott, R. C., Allen, T. J., and Sexton, B. W., “Aeroelastic Analysis of SUGAR Truss-Braced Wing Wind-Tunnel Model Using FUN3D and a Nonlinear Structural Model,” *AIAA SciTech Conference*, 2015.
- [5] Rodden, W. P., and Johnson, E. H., *MSC/NASTRAN Aeroelastic Analysis: User’s Guide; Version 68*, MacNeal-Schwendler Corporation, 1994.
- [6] Biedron, R., Carlson, J.-R., Derlaga, J., Gnoffo, P., Hammond, D., Jones, W., Kleb, B., Lee-Rausch, E., Nielsen, E., Park, M., Rumsey, C., Thomas, J., and Wood, W., “FUN3D Manual: 13.4,” Tech. Rep. TM-2018-220096, NASA, 2018.
- [7] Anderson, W. K., and Bonhaus, D. L., “An Implicit Upwind Algorithm for Computing Turbulent Flows on Unstructured Grids,” *Computers and Fluids*, Vol. 23, No. 1, 1994, pp. 1–22. URL <https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20040112057.pdf>.
- [8] Spalart, P. R., and Allmaras, S. R., “One-Equation Turbulence Model for Aerodynamic Flows,” *30th AIAA Aerospace Sciences Meeting and Exhibit*, Reno, NV, 1992. <https://doi.org/https://arc.aiaa.org/doi/pdf/10.2514/6.1992-439>, URL <https://arc.aiaa.org/doi/pdf/10.2514/6.1992-439>.
- [9] Juang, J.-N., and Pappa, R. S., “An Eigensystem Realization Algorithm for Modal Parameter Identification and Model Reduction,” *Journal of Guidance, Control, and Dynamics*, Vol. 8, No. 5, 1985, pp. 620–627.
- [10] Waite, J., Stanford, B., Bartels, R. E., and Silva, W. A., “Reduced Order Modeling for Transonic Aeroservoelastic Control Law Development,” *AIAA Scitech 2019 Forum*, 2019, p. 1022.
- [11] Waite, J., Stanford, B., Bartels, R. E., and Silva, W. A., “Active Flutter Suppression Using Reduced Order Modeling for Transonic Aeroservoelastic Control Law Development,” *AIAA Aviation 2019 Forum*, 2019, p. 3025.
- [12] Waite, J., Stanford, B., Bartels, R. E., Silva, W. A., and Massey, S. J., “Active Flutter Suppression Controllers Derived from Linear and Nonlinear Aerodynamics: Application to a Transport Aircraft Model,” *2018 Applied Aerodynamics Conference*, Atlanta, GA, 25-29 Jun 2018.
- [13] Silva, W. A., “AEROM: NASA’s Unsteady Aerodynamic and Aeroelastic Reduced-Order Modeling Software,” *Aerospace*, Vol. 5, No. 2, 2018.
- [14] Juang, J.-N., Horta, L. G., and Phan, M., “System/Observer/Controller Identification Toolbox,” Tech. Rep. TM-107566, NASA, 1992.
- [15] Stevens, B. L., Lewis, F. L., and Johnson, E. N., *Aircraft Control and Simulation: Dynamics, Controls Design, and Autonomous Systems, 3rd Edition*, John Wiley and Sons, 2015.
- [16] Glad, T., and Ljung, L., *Control Theory*, CRC press, 2018.
- [17] Waite, J., Bartels, R. E., and Stanford, B., “Aeroelastic Model Development for the Integrated Adaptive Wing Technology Maturation Project Wind-Tunnel Test,” *AIAA Aviation 2020 Forum*, Virtual Event, 15-19 Jun 2020.