

Design and Experimental Validation of Real-Time Drag Optimization and Maneuver Load Alleviation Controls for a High Aspect Ratio Flexible Transport Wing

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This paper presents control strategies for cruise drag minimization and maneuver load alleviation on a high-aspect-ratio flexible transport wing. The approach combines online parameter estimation with real-time control to optimize aerodynamic performance and reduce wing-root loads in a wind tunnel environment. Experiments were conducted on an aeroelastically scaled, half-span Common Research Model in the NASA Langley Transonic Dynamics Tunnel at Mach 0.55. Results demonstrate a 12.2% reduction in drag from an initial high-drag condition while maintaining the target lift, and wing-root strain reductions of approximately 7.0% and 13.2% for $\pm 5^\circ$ and $\pm 10^\circ$ actuator saturation limits during lift maneuvers. These findings validate the effectiveness of the proposed strategies in achieving drag reduction and load alleviation under realistic actuation and measurement constraints.

I. Introduction

THE aircraft industry has been striving for improved energy efficiency by redesigning airframes to be aerodynamically and structurally more efficient. Manufacturers are employing energy-efficient engines and lightweight advanced composites to achieve this goal, as reducing aircraft operational weight is a primary consideration in improving aircraft efficiency. These lightweight materials may provide less structural rigidity while still maintaining load carrying capacity. This reduced rigidity leads to increased structural flexibility, which can make aircraft more susceptible to aeroelastic interactions such as gust excitation and maneuver-induced loading. An increase in wing aspect ratio can also exacerbate this problem. Wing twist under load may also be substantial, causing the optimal lift distribution for minimum drag to vary significantly across the flight envelope. As a result, cruise drag-minimization control becomes necessary to compensate for these adverse aeroelastic effects. Current cruise drag optimization practices in modern transport aircraft are typically implemented using lookup tables, which rely on validated analytical models for a specific aircraft geometry. These models must be validated using wind-tunnel and flight-test data to ensure accuracy and performance. Variability in aircraft production can lead to performance differences among individual aircraft. In addition, a wide range of operating conditions, such as gross weight, airspeed, and altitude, results in significant variation in aircraft performance characteristics. A real-time optimization strategy could provide more flexibility than the current practice. Similarly, a maneuver load alleviation control (MLA) can reduce the loading on the wing during a maneuver.

This paper details the design and implementation of real-time drag optimization and MLA control strategies for the 13.5 aspect ratio Common Research Model (CRM)[1] wind tunnel model. This model is developed by Boeing under a NASA cooperative arrangement under the Integrated Adaptive Wing Technology Maturation (IAWTM) program. The wind tunnel model is a 10.8%, aeroelastically scaled, half-span and wall-mounted version of the 13.5 aspect ratio CRM, as shown in Fig. 1. The model is highly flexible relative to current transport designs. The model is equipped with a distributed mini-plain flap system that consists of 7 electric mini-plain flaps and 3 hydraulically actuated ailerons seen in Fig. 4. These actuators are an extension of the VCCTEF[2, 3] concept which utilizes distributed flaps for control applications. The purpose of the IAWTM program is to mature technologies associated with highly flexible transport wing design. Towards that end, a test was conducted in July of 2024 to collect steady-state and dynamic aerodynamic and structural characterization data. This test was conducted at the NASA Langley Research Center in the Transonic

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Dynamics Tunnel (TDT). A second entry is planned in June 2026, to test control laws developed for the wind tunnel model[4–7].

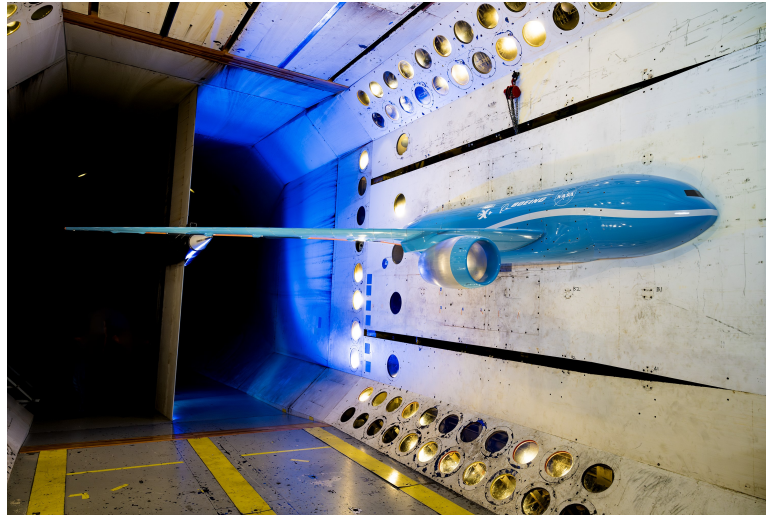


Fig. 1 IAWTM Test Article in TDT Test Section

The real-time drag-optimization and MLA controller designs are detailed in this paper and build on previous designs for the CRM wind-tunnel model [4, 5]. The framework for the controllers can be seen in Fig. 3. The model is first excited to generate aerodynamic data, which are provided to a recursive least-squares algorithm for identification of an onboard surrogate model. This surrogate model is utilized to perform an optimization with respect to drag minimization for the real time drag optimization controller and alternatively for bending moment minimization for the MLA controller. This process yields optimal control-surface deflections and angle-of-attack commands for drag or bending-moment minimization while maintaining a target lift. Similar control strategies have achieved up to a 9.4% reduction in drag for off-design conditions [8, 9]. This work builds on previous designs using an aerodynamic database derived from the aerodynamic characterization data from the first wind tunnel test entry as opposed to analytically derived models[10].

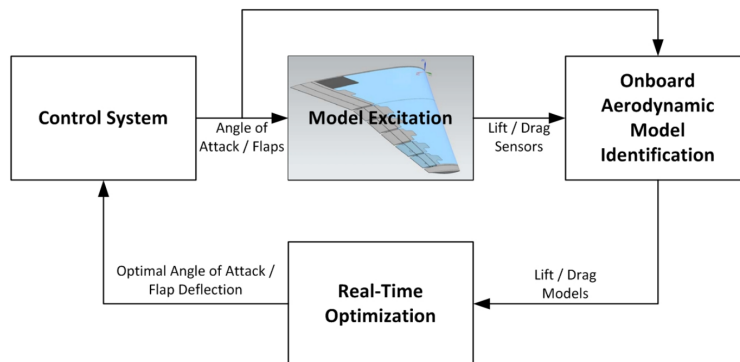


Fig. 2 Real-Time Drag Optimization Framework

II. Wind Tunnel Experiment Overview

A. Test Article Description

The IAWTM model, illustrated in detail in Fig. 3, represents a 10.8%-scale, aeroelastically scaled, half-span version of the 13.5-aspect-ratio CRM, mounted on a wall. The wing is dynamically scaled, while the fuselage length has been reduced to accommodate the dimensions of the TDT test section. A flow-through nacelle is included to account for the influence of nacelle mass and inertia on the wing structural dynamics. Overall, the configuration preserves the high-aspect-ratio characteristics of the full-scale aircraft and exhibits significantly greater flexibility than a conventional transport wing.

The IAWTM model in Fig. 3 has 10 control surfaces. Three control surfaces are high speed hydraulically actuated ailerons designated AILA-AILC and are intended for gust load alleviation and active flutter suppression controls. The 7 remaining control surfaces are slower acting electric actuators, called mini plain flaps (MPFs), and are designated MPFA-MPFG. The MPFs and hydraulic ailerons are used in conjunction for the drag minimization and maneuver load alleviation controls. Under standard operating conditions, surface deflections are limited to $\pm 10^\circ$, reducing to $\pm 5^\circ$ at elevated dynamic pressures. The MPFC control surface was not available for closed-loop testing due to hardware issues.

Structural response measurements are obtained using ten full-bridge strain gages and sixteen accelerometers, with their locations indicated in Fig. 4. The model is attached to the TDT electric turntable (ETT) via a mounting-box adapter and instrumented with a five-component balance (NASA balance 1637S), providing direct lift and drag measurements. Further details on the test article are provided in Ref. [11, 12].

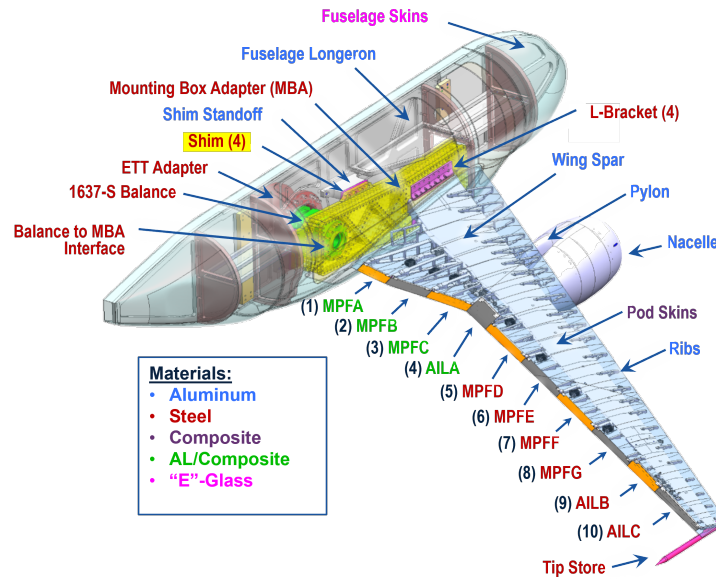


Fig. 3 IAWTM test article.

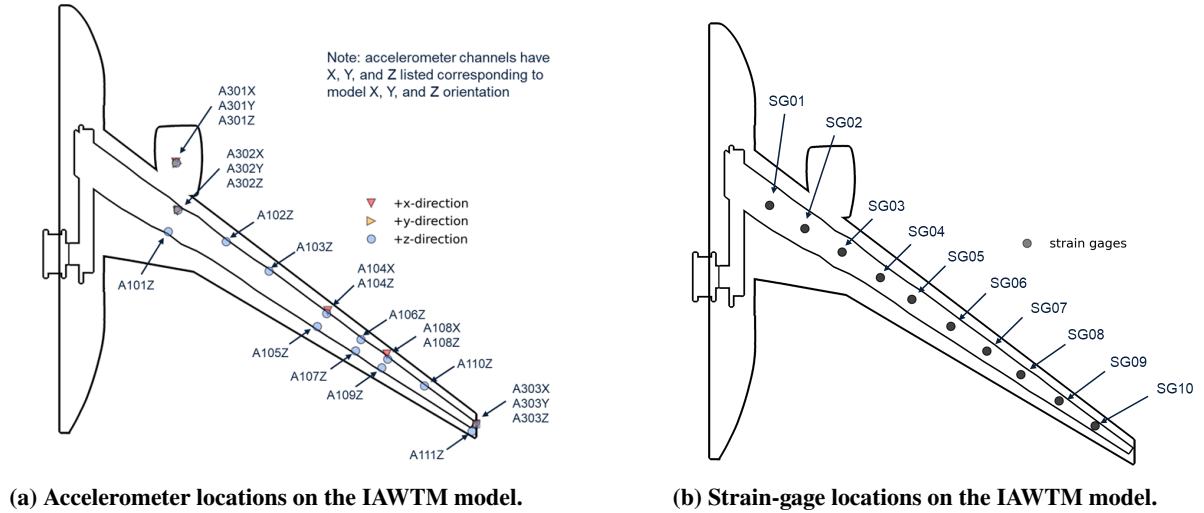


Fig. 4 Sensor locations on the IAWTM model.

B. Transonic Dynamics Tunnel (TDT)

The experiments were conducted in the TDT facility, depicted in Fig. 5. The tunnel can operate with air or heavy gas (R134a) to match the full-scale aeroelastic response accurately. Hydraulic power is supplied for the high-speed ailerons, and an airstream oscillation system (AOS) enables controlled gust excitation for maneuver-load-alleviation testing. Bypass valves are included to rapidly reduce dynamic pressure as a safety measure in the event of flow instability.

For both drag-minimization and MLA control experiments, lift and drag are determined from five-component balance measurements, while the ETT is used to set and maintain the model pitch. The strain gauge SG01 located nearest the wing root serves as a surrogate for wing-root bending moment.

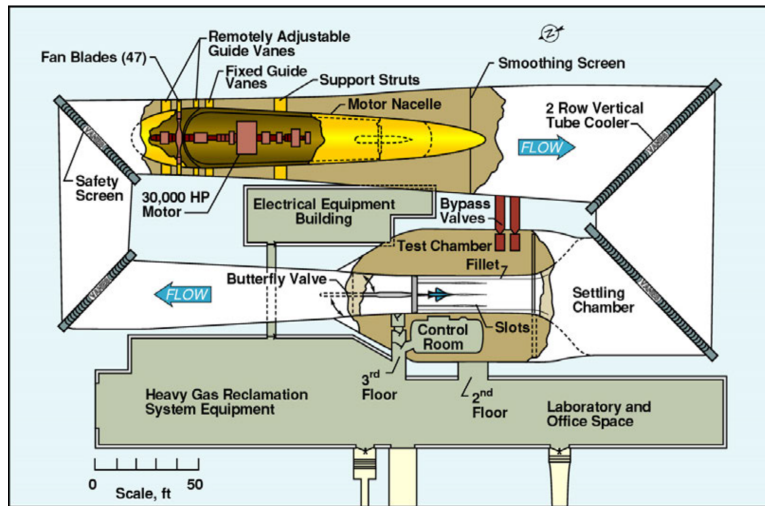


Fig. 5 Overview of the Transonic Dynamics Tunnel.

C. Aerodynamic Model Database

An aerodynamic database was developed to characterize variations in lift, drag, and wing-root strain as functions of control-surface deflection and angle of attack. This database is used to support real-time drag-optimization and maneuver-load-alleviation (MLA) controllers, providing pre-test predictions and enabling algorithm verification.

The database contains the sensitivities of lift, drag, and wing-root strain to both angle of attack and control surface

deflection. It was constructed from data obtained during the first IAWTM wind-tunnel entry in 2024, which included steady-state aerodynamic characterization tests. In these tests, each control surface was individually perturbed while all other surfaces and the angle of attack were held constant. An example of such a characterization run for aileron A (AILA) is shown in Fig. 8. Similar tests were performed for all control surfaces at angles of attack $\alpha = [-2^\circ, 0^\circ, 2^\circ]$.

The aerodynamic model was then identified using the full set of steady-state characterization data. It is important to note that the sensitivities with respect to flap deflections are not constant—they vary with angle of attack. Therefore, these parameters are evaluated separately at each breakpoint in $\alpha = [-2^\circ, 0^\circ, 2^\circ]$.

$$C_L = C_{L_0} + C_{L_\alpha} \alpha + C_{L_\alpha^2} \alpha^2 + C_{L_\delta}(\alpha) \delta + \delta^T C_{L_\delta^2}(\alpha) \delta \quad (1)$$

$$C_D = C_{D_0} + C_{D_\alpha} \alpha + C_{D_\alpha^2} \alpha^2 + C_{D_\delta}(\alpha) \delta + \delta^T C_{D_\delta^2}(\alpha) \delta \quad (2)$$

$$M_y = M_{y_0} + M_{y_\alpha} \alpha + M_{y_\alpha^2} \alpha^2 + M_{y_\delta}(\alpha) \delta + \delta^T M_{y_\delta^2}(\alpha) \delta \quad (3)$$

III. Recursive Least-Square Parameter Estimation

In order to perform an optimization with the goal of drag minimization or the minimization of wing root strain, an onboard surrogate model is used. This model contains the unknown sensitivities of lift, drag, and wing root strain with respect to angle of attack and control surface deflection. The unknown sensitivities are identified via a recursive least-squares parameter estimation algorithm. These unknown sensitivities can be synthesized from force balance data and the onboard root strain gauge. The parameter estimation is divided into two identification stages. The first stage excites angle of attack to perturb its value from the trim position while also maintaining trim control surface deflections. The sensitivities of angle of attack are then estimated via RLS algorithm using the first stage perturbation data. During the second stage, the control surfaces are individually excited while angle of attack is maintained at the current trim position. This allows for the sensitivities of lift, drag, and wing root strain gauge to be estimated via the RLS algorithm.

The aerodynamic sensitivities with respect to control surface deflections in Eq. 1-3 are dependent on angle of attack.

For the first stage, angle of attack is perturbed by $\pm \Delta \alpha$. During this stage the control surfaces δ are held at constant values. A linear regression is performed by minimizing error squared

$$\min J = \sum_{i=1}^{3n} \left(\begin{bmatrix} \Delta C_L \\ \Delta C_D \\ \Delta M_y \end{bmatrix}_i - \begin{bmatrix} C_{L_0} \\ C_{D_0} \\ M_{y_0} \end{bmatrix} - \begin{bmatrix} C_{L_\alpha} \\ C_{D_\alpha} \\ M_{y_\alpha} \end{bmatrix} \alpha_i - \begin{bmatrix} C_{L_{\alpha^2}} \\ C_{D_{\alpha^2}} \\ M_{y_{\alpha^2}} \end{bmatrix} \alpha_i^2 \right)^2 \quad (4)$$

where n is the number of iterations and

$$\begin{bmatrix} \Delta C_L \\ \Delta C_D \\ \Delta M_y \end{bmatrix} = \begin{bmatrix} C_L \\ C_D \\ M_y \end{bmatrix} - \begin{bmatrix} C_{L_\delta} \\ C_{D_\delta} \\ M_{y_\delta} \end{bmatrix} \bar{\delta} - \begin{bmatrix} \bar{\delta}^T C_{L_{\delta^2}} \bar{\delta} \\ \bar{\delta}^T C_{D_{\delta^2}} \bar{\delta} \\ \bar{\delta}^T M_{y_{\delta^2}} \bar{\delta} \end{bmatrix} \quad (5)$$

ΔC_L , ΔC_D and ΔM_y are evaluated using current estimates of the control surface sensitivities.

For brevity, we denote $y_i = \begin{bmatrix} \Delta C_L \\ \Delta C_D \\ \Delta M_y \end{bmatrix}_i$, $\Theta_\alpha = \begin{bmatrix} C_{L_{\alpha^2}} & C_{D_{\alpha^2}} & M_{y_{\alpha^2}} \\ C_{L_\alpha} & C_{D_\alpha} & M_{y_\alpha} \\ C_{L_0} & C_{D_0} & M_{y_0} \end{bmatrix}$, $\Phi(\alpha_i) = \begin{bmatrix} \alpha_i^2 \\ \alpha_i \\ 1 \end{bmatrix}$. Then, the cost function can be written as

$$\min J = \sum_{i=1}^{3n} [y_i - \Theta_\alpha^T \Phi(\alpha_i)]^2 \quad (6)$$

The partial derivative of the cost function with respect to the parameter matrix Θ_α is given by

$$\frac{\partial J}{\partial \Theta_\alpha} = - \sum_{i=1}^{3n} \Phi(\alpha_i) [y_i^T - \Phi^T(\alpha_i) \Theta_\alpha] \quad (7)$$

The minimum squared error is then obtained by setting $\frac{\partial J}{\partial \Theta_\alpha} = 0$, resulting in

$$\sum_{i=1}^{3n} \Phi(\alpha_i) \Phi^T(\alpha_i) \Theta_\alpha = \sum_{i=1}^{3n} \Phi(\alpha_i) y_i \quad (8)$$

Let $H_{n-1} = \sum_{i=1}^{3n} \Phi(\alpha_i) \Phi^\top(\alpha_i)$ and $V_{n-1} = \sum_{i=1}^{3n} \Phi(\alpha_i) y_i^\top$ where $n = 1, 2, \dots, N$. Then,

$$\Theta_\alpha^{(n-1)} = H_{n-1}^{-1} V_{n-1} \quad (9)$$

where

$$H_{n-1} = \begin{bmatrix} \sum_{i=1}^{3n} \alpha_i^4 & \sum_{i=1}^{3n} \alpha_i^3 & \sum_{i=1}^{3n} \alpha_i^2 \\ \sum_{i=1}^{3n} \alpha_i^3 & \sum_{i=1}^{3n} \alpha_i^2 & \sum_{i=1}^{3n} \alpha_i \\ \sum_{i=1}^{3n} \alpha_i^2 & \sum_{i=1}^{3n} \alpha_i & \sum_{i=1}^{3n} 1 \end{bmatrix} \quad (10)$$

$$V_{n-1} = \begin{bmatrix} \sum_{i=1}^{3n} \alpha_i^2 \Delta C_{L_i} & \sum_{i=1}^{3n} \alpha_i^2 \Delta C_{D_i} & \sum_{i=1}^{3n} \alpha_i^2 \Delta M_{y_i} \\ \sum_{i=1}^{3n} \alpha_i \Delta C_{L_i} & \sum_{i=1}^{3n} \alpha_i \Delta C_{D_i} & \sum_{i=1}^{3n} \alpha_i \Delta M_{y_i} \\ \sum_{i=1}^{3n} \Delta C_{L_i} & \sum_{i=1}^{3n} \Delta C_{D_i} & \sum_{i=1}^{3n} \Delta M_{y_i} \end{bmatrix} \quad (11)$$

During the first excitation iteration, there are $n = 3$ data points. Additional excitations are performed adding 3 more data points for each iteration. A recursive algorithm is implemented to take advantage of previous parameter estimates. The regression equation for the estimated parameters is formed as

$$\Theta_\alpha^{(n)} = H_n^{-1} V_n \quad (12)$$

H_n and V_n can be written as

$$H_n = \sum_{i=1}^{3n} \Phi(\alpha_i) \Phi^\top(\alpha_i) + \sum_{i=1}^3 \Phi(\alpha_i) \Phi^\top(\alpha_i) = H_{n-1} + H_0 \quad (13)$$

$$V_n = \sum_{i=1}^{3n} \Phi(\alpha_i) y_i + \sum_{i=1}^3 \Phi(\alpha_i) y_i = H_{n-1} \Theta_\alpha^{(n-1)} + V_0 \quad (14)$$

where $H_0 = \sum_{i=1}^3 \Phi(\alpha_i) \Phi^\top(\alpha_i)$ and $V_0 = \sum_{i=1}^3 \Phi(\alpha_i) y_i^\top$ are evaluated using the past data. Therefore, the RLS algorithm can be written as

$$\Theta_\alpha^{(n)} = (H_{n-1} + H_0)^{-1} (H_{n-1} \Theta_\alpha^{(n-1)} + V_0) \quad (15)$$

For the second stage, angle of attack is held constant and the control surfaces δ are individually perturbed by $\pm \Delta \delta$. The difference between the perturbed lift, drag, and bending moment, C_L , C_D , and M_y , and the respective trim values $\bar{C}_L$, $\bar{C}_D$, and $\bar{M}_y$ during a single control surface perturbation is examined.

$$\begin{bmatrix} \delta C_L \\ \delta C_D \\ \delta M_y \end{bmatrix} = \begin{bmatrix} C_L \\ C_D \\ M_y \end{bmatrix} - \begin{bmatrix} \bar{C}_L \\ \bar{C}_D \\ \bar{M}_y \end{bmatrix} \quad (16)$$

where

$$\begin{bmatrix} C_L \\ C_D \\ M_y \end{bmatrix} = \begin{bmatrix} C_{L_0} \\ C_{D_0} \\ M_{y_0} \end{bmatrix} + \begin{bmatrix} C_{L_\alpha} \\ C_{D_\alpha} \\ M_{y_\alpha} \end{bmatrix} \bar{\alpha} + \begin{bmatrix} C_{L_{\alpha^2}} \\ C_{D_{\alpha^2}} \\ M_{y_{\alpha^2}} \end{bmatrix} \bar{\alpha}^2 + \begin{bmatrix} C_{L_\delta} \\ C_{D_\delta} \\ M_{y_\delta} \end{bmatrix} \delta + \begin{bmatrix} \delta^\top C_{L_{\delta^2}} \delta \\ \delta^\top C_{D_{\delta^2}} \delta \\ \delta^\top M_{y_{\delta^2}} \delta \end{bmatrix} \quad (17)$$

and

$$\begin{bmatrix} \bar{C}_L \\ \bar{C}_D \\ \bar{M}_y \end{bmatrix} = \begin{bmatrix} C_{L_0} \\ C_{D_0} \\ M_{y_0} \end{bmatrix} + \begin{bmatrix} C_{L_\alpha} \\ C_{D_\alpha} \\ M_{y_\alpha} \end{bmatrix} \bar{\alpha} + \begin{bmatrix} C_{L_{\alpha^2}} \\ C_{D_{\alpha^2}} \\ M_{y_{\alpha^2}} \end{bmatrix} \bar{\alpha}^2 + \begin{bmatrix} C_{L_\delta} \\ C_{D_\delta} \\ M_{y_\delta} \end{bmatrix} \bar{\delta} + \begin{bmatrix} \bar{\delta}^\top C_{L_{\delta^2}} \bar{\delta} \\ \bar{\delta}^\top C_{D_{\delta^2}} \bar{\delta} \\ \bar{\delta}^\top M_{y_{\delta^2}} \bar{\delta} \end{bmatrix} \quad (18)$$

The flap deflection vector δ for perturbed flap k is defined by

$$\delta_j = \begin{cases} \bar{\delta}_j & j \neq k \\ \bar{\delta}_j + \Delta \delta_k & j = k \end{cases} \quad (19)$$

Eq. 16 simplifies to

$$\begin{bmatrix} \delta C_L \\ \delta C_D \\ \delta M_y \end{bmatrix} = \begin{bmatrix} C_{L\delta_k} \\ C_{D\delta_k} \\ M_{y\delta_k} \end{bmatrix} \Delta\delta_k + \begin{bmatrix} C_{L\delta_k^2} \\ C_{D\delta_k^2} \\ M_{y\delta_k^2} \end{bmatrix} (2\delta_k\Delta\delta_k + \Delta\delta_k^2) \quad (20)$$

A linear regression can then be performed by minimizing the error squared using a similar cost function to the one used for the first stage. This is written as

$$\min J = \sum_{i=1}^{2n} [z_i - \Theta_{\delta_k}^\top \Phi(\Delta\delta_k)]^2 \quad (21)$$

where

$$z_i = \begin{bmatrix} \delta C_L \\ \delta C_D \\ \delta M_y \end{bmatrix}_i \quad (22)$$

$$\Theta_{\delta_k} = \begin{bmatrix} C_{L\delta_k^2} & C_{D\delta_k^2} & M_{y\delta_k^2} \\ C_{L\delta_k} & C_{D\delta_k} & M_{y\delta_k} \end{bmatrix} \quad (23)$$

$$\Phi(\Delta\delta_i) = \begin{bmatrix} 2\bar{\delta}_{k,i}\Delta\delta_{k,i} + \Delta\delta_{k,i}^2 \\ \Delta\delta_{k,i} \end{bmatrix} \quad (24)$$

The estimates of the sensitivities of lift, drag, and bending moment with respect to the flap deflections are computed similarly as

$$\Theta_{\delta_k}^{(n-1)} = G_{n-1}^{-1} U_{n-1} \quad (25)$$

where

$$G_{n-1} = \sum_{i=1}^{2n} \Phi(\Delta\delta_i) \Phi(\Delta\delta_i)^\top \quad (26)$$

$$U_{n-1} = \sum_{i=1}^{2n} \Phi(\Delta\delta_i) z_i \quad (27)$$

The RLS algorithm is also established as follows

$$\Theta_{\delta_k}^{(n)} = (G_{n-1} G_0)^{-1} (G_{n-1} \Theta_{\delta_k}^{(n-1)} + U_0) \quad (28)$$

where $G_0 = \sum_{i=1}^2 \Phi(\Delta\delta_i) \Phi(\Delta\delta_i)^\top$ and $U_0 = \sum_{i=1}^2 \Phi(\Delta\delta_i) z_i$ are evaluated using past data.

IV. Controller Designs

A. Real-Time Drag Optimization

After the system excitation and RLS parameter identification, the optimal control surface deflections and angle of attack are computed. The optimization is performed on the onboard surrogate model. For drag minimization, the optimal control surface deflection and angle of attack are computed via the evaluation of the following cost function.

$$\min J = C_D + \lambda_L (\bar{C}_L - C_L) \quad (29)$$

where λ_L is the adjoint variable for lift.

Evaluating the partial derivatives of the cost function gives

$$\frac{\partial J}{\partial \alpha} = \frac{\partial C_D}{\partial \alpha} + \lambda_L \frac{\partial C_L}{\partial \alpha} \quad (30)$$

$$\frac{\partial J}{\partial \delta^\top} = \frac{\partial C_D}{\partial \delta^\top} + \lambda_L \frac{\partial C_L}{\partial \delta^\top} \quad (31)$$

$$\frac{\partial J}{\partial \lambda_L} = C_L - \bar{C}_L \quad (32)$$

Setting $\frac{\partial J}{\partial \alpha}$ yields

$$\lambda_L = - \left(\frac{\partial C_L}{\partial \alpha} \right)^{-1} \left(\frac{\partial C_D}{\partial \alpha} \right) \quad (33)$$

At each iteration, λ_L is evaluated using previous values for α and δ . By setting $\frac{\partial J}{\partial \delta^\top} = 0$ and using the updated value for λ_L , the optimal control surface deflections are obtained. First, Eq. 31 is expanded:

$$\frac{\partial J}{\partial \delta^\top} = C_{D_\delta} + \lambda_L C_{L_\delta} + 2C_{D_{\delta^2}}\delta + 2\lambda_L C_{L_{\delta^2}}\delta \quad (34)$$

Then, the optimal control surface deflections are obtained by solving for δ . This is written as

$$\delta = - \left(2C_{D_{\delta^2}} + 2\lambda_L C_{L_{\delta^2}} \right)^{-1} (C_{D_\delta} + \lambda_L C_{L_\delta}) \quad (35)$$

By setting $\frac{\partial J}{\partial \lambda_L} = 0$ the lift constraint equation is obtained

$$\bar{C}_L = C_{L_0} + C_{L_\alpha}\alpha + C_{L_{\alpha^2}}\alpha^2 + C_{L_\delta}\delta + \delta^\top C_{L_{\delta^2}}\delta \quad (36)$$

from which the angle of attack α is computed using the current values for δ .

B. MLA Control Using Online Surrogate Model

For MLA the objective of the optimization is to minimize bending moment as opposed drag, while still maintaining lift. Thus, the following cost function is evaluated to compute optimal control surface deflections and angle of attack for MLA.

$$\min J = M_y^2 + \lambda_L (\bar{C}_L - C_L) \quad (37)$$

Evaluating partial derivatives of this cost function yields

$$\frac{\partial J}{\partial \alpha} = 2 \frac{\partial M_y}{\partial \alpha} M_y + \lambda_L \frac{\partial C_L}{\partial \alpha} \quad (38)$$

$$\frac{\partial J}{\partial \delta^\top} = 2 \frac{\partial M_y}{\partial \delta^\top} M_y + \lambda_L \frac{\partial C_L}{\partial \delta^\top} \quad (39)$$

$$\frac{\partial J}{\partial \lambda_L} = C_L - \bar{C}_L \quad (40)$$

The MLA algorithm leverages the already identified surrogate model to schedule optimal flap profiles and corresponding angles of attack as a function of the target lift, $\bar{C}_L$. The optimal flap deflections, angle of attack, and adjoint variable λ_L are obtained by setting $\frac{\partial J}{\partial \alpha} = 0$, $\frac{\partial J}{\partial \delta^\top} = 0$, and $\frac{\partial J}{\partial \lambda_L} = 0$. The resulting system in δ , α , and λ_L is then solved using the Newton-Raphson method. The controller subsequently applies the computed control inputs to minimize the wing-root bending moment for a given commanded lift coefficient, $C_{L_{cmd}}$.

C. Multi-Objective MLA

A separate MLA controller is designed using a more active control approach within a multi-objective optimal control framework. The aerodynamic forces and moments, originally nonlinear in angle-of-attack α and actuator deflection δ , are linearized about the initial angle-of-attack $\alpha_0 = -2^\circ$ and small δ , neglecting quadratic terms in δ .

The linearized lift and pitching moment become:

$$\Delta C_L = \bar{C}_{L_\alpha} \Delta \alpha + \bar{C}_{L_\delta} \delta \quad (41)$$

$$\Delta M_y = \bar{M}_{y_\alpha} \Delta \alpha + \bar{M}_{y_\delta} \delta \quad (42)$$

where

$$\Delta\alpha = \alpha - \alpha_0 \quad (43)$$

$$\bar{C}_{L\alpha} = C_{L\alpha} + 2C_{L\alpha^2}\alpha_0 \quad (44)$$

$$\bar{C}_{L\delta} = C_{L\delta}(\alpha_0) \quad (45)$$

$$\bar{M}_{y\alpha} = M_{y\alpha} + 2M_{y\alpha^2}\alpha_0 \quad (46)$$

$$\bar{M}_{y\delta} = M_{y\delta}(\alpha_0) \quad (47)$$

The actuator dynamics are given by:

$$\dot{x}_a = A_a x_a + B_a u_\delta \quad (48)$$

$$\delta = C_a x_a \quad (49)$$

The angle-of-attack dynamics are represented by:

$$\Delta\dot{\alpha} = -a(\Delta\alpha - \alpha_c) \quad (50)$$

Combining actuator and AOA dynamics, the overall state-space system is:

$$\dot{x} = Ax + Bu \quad (51)$$

$$x = \begin{bmatrix} x_a \\ \Delta\alpha \end{bmatrix} \quad (52)$$

$$u = \begin{bmatrix} u_\delta \\ \alpha_c \end{bmatrix} \quad (53)$$

$$A = \begin{bmatrix} A_a & 0 \\ 0 & -a \end{bmatrix} \quad (54)$$

$$B = \begin{bmatrix} B_a & 0 \\ 0 & a \end{bmatrix} \quad (55)$$

The outputs are:

$$\begin{bmatrix} \Delta C_L \\ \Delta M_y \end{bmatrix} = \begin{bmatrix} C_y \\ C_{M_y} \end{bmatrix} x \quad (56)$$

$$C_y = \begin{bmatrix} \bar{C}_{L\delta} C_a & \bar{C}_{L\alpha} \end{bmatrix} \quad (57)$$

$$C_{M_y} = \begin{bmatrix} \bar{M}_{y\delta} C_a & \bar{M}_{y\alpha} \end{bmatrix} \quad (58)$$

The infinite-horizon quadratic cost function is:

$$J = \lim_{t_f \rightarrow \infty} \frac{1}{2} \int_0^{t_f} [(\Delta C_L - \Delta C_{L_c})^\top Q (\Delta C_L - \Delta C_{L_c}) + u^\top R u + \Delta M_y^\top Q_M \Delta M_y] dt \quad (59)$$

The Hamiltonian is:

$$H = \frac{1}{2} (\Delta C_L - \Delta C_{L_c})^\top Q (\Delta C_L - \Delta C_{L_c}) + \frac{1}{2} u^\top R u + \frac{1}{2} \Delta M_y^\top Q_M \Delta M_y + \lambda^\top (Ax + Bu) \quad (60)$$

The costate dynamics are:

$$\dot{\lambda} = -\frac{\partial H^\top}{\partial x} = -C_y^\top Q C_y x + C_y^\top Q \Delta C_{L_c} - C_{M_y}^\top Q_M C_{M_y} x - A^\top \lambda \quad (61)$$

The stationarity condition gives:

$$\frac{\partial H^\top}{\partial u} = Ru + B^\top \lambda = 0 \quad (62)$$

Assuming $\lambda = Wx + V$ for an infinite-horizon problem, the optimal state-feedback control is:

$$u = -K_x x + K_{y_c} \Delta C_{L_c} \quad (63)$$

$$K_x = R^{-1} B^T W \quad (64)$$

$$K_{y_c} = R^{-1} B^T (A^T - W B R^{-1} B^T)^{-1} C_y^T Q \quad (65)$$

where W satisfies the continuous-time algebraic Riccati equation:

$$W A + A^T W - W B R^{-1} B^T W + \bar{Q} = 0 \quad (66)$$

where

$$\bar{Q} = C_y^T Q C_y + C_{M_y}^T Q_M C_{M_y} \quad (67)$$

The full state x is not directly measurable. To implement the optimal controller, a Kalman filter is used with measurements from the actuator position sensors and the angle-of-attack sensor. The available measurements consist of the actuator positions and the angle-of-attack, which form the output vector

$$y = \begin{bmatrix} \delta \\ \Delta \alpha \end{bmatrix} = \begin{bmatrix} C_a & 0 \\ 0 & 1 \end{bmatrix} x \quad (68)$$

These measurements are used in the state estimator. The observer dynamics are:

$$\dot{\hat{x}} = A \hat{x} + B u + L(y - C \hat{x}) \quad (69)$$

where $\hat{x}$ is the estimated state and L is the Kalman gain. The optimal control is then applied using $\hat{x}$:

$$u = -K_x \hat{x} + K_{y_c} \Delta C_{L_c} \quad (70)$$

It should be noted that this controller was not evaluated during the wind tunnel experiments, as it did not perform as expected in the hardware-in-the-loop environment, and the issues could not be resolved within the available testing time frame.

V. Control and Measurement Considerations

The model's high flexibility and sensitivity to tunnel turbulence result in particularly noisy drag measurements, whereas lift data remain relatively robust. Figure 7 shows the open-loop input history for aileron A during preliminary aerodynamic characterization, and Figure 8 presents the corresponding lift and drag coefficients derived from the balance measurements. While the lift exhibits a clear trend, the drag data are heavily affected by high-frequency noise.

To mitigate measurement noise, a second-order Butterworth low-pass filter (Figure 6) is applied with a cutoff frequency of 0.5 Hz. This cutoff is chosen well below the first structural frequency of approximately 5 Hz to suppress structural response contributions while attenuating sensor noise. Each control surface is held at a set-point for 15 seconds, with an initial 8 second delay to allow settling. The remaining 7 seconds of data are time-averaged, with an additional check to ensure the control surface reaches the commanded position.

Model pitch is controlled manually by the tunnel operator rather than through the flight-control system. Therefore, any controller that relies on angle-of-attack (AOA) commands must accommodate this limitation. For AOA-dependent measurements, a 40 second period is used for each control set-point, with a 20 second settling delay before data acquisition. The remaining data are time-averaged, and the commanded AOA is verified prior to analysis.

Additional sources of uncertainty include flap freeplay and potential inaccuracies in flap-position sensing. As noted previously, the MPFC system was unavailable for all control experiments.

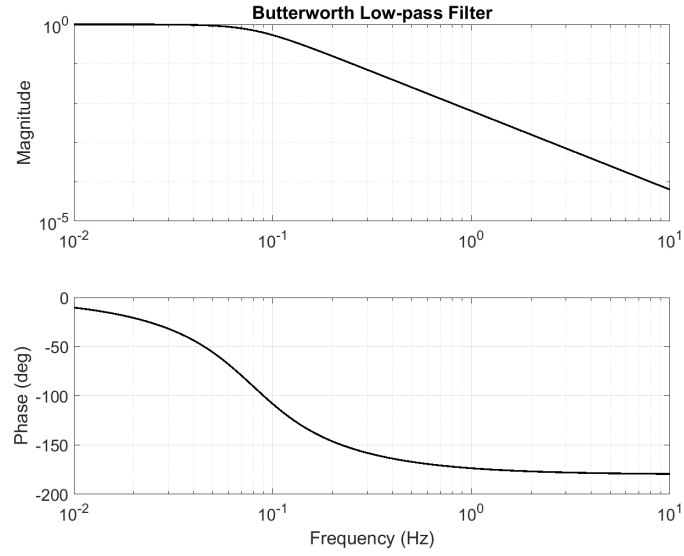


Fig. 6 Butterworth Filter Utilized for Noise Filtering: Frequency Response

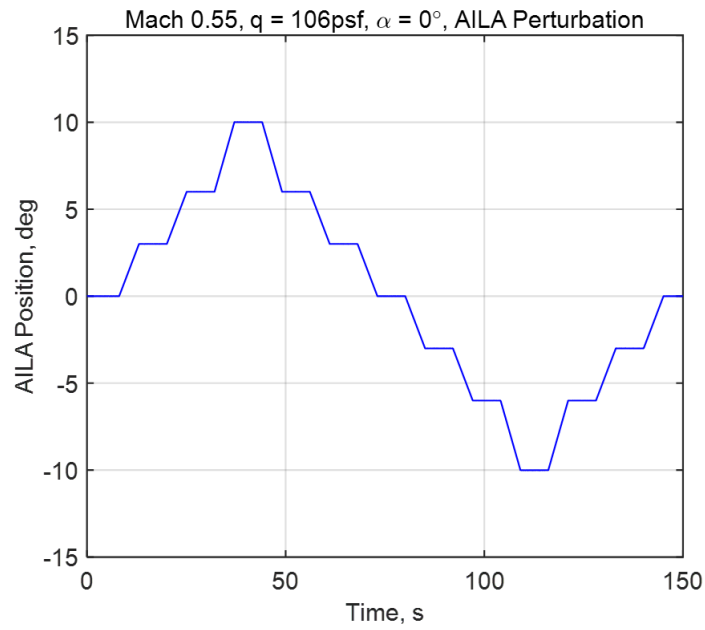


Fig. 7 Open-loop pitch command for aileron A.

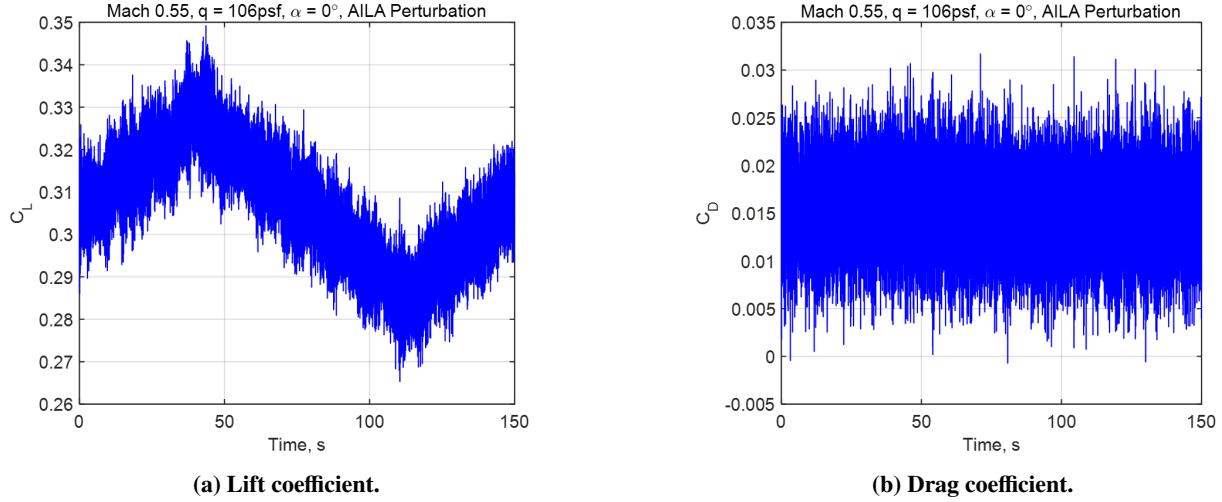


Fig. 8 Lift and drag coefficients derived from balance measurements.

VI. Wind Tunnel Test Results

A. Real-Time Drag Optimization Results

The Real-Time Drag Optimization (RTD) controller is evaluated at the primary test condition of Mach 0.55 and $\bar{q}_\infty = 110 \text{ psf}$. During system-identification perturbation sequences, the angle of attack is varied by $\pm 0.5^\circ$, and each control surface is individually perturbed by $\pm 4^\circ$. Saturation limits are imposed at $\pm 5^\circ$ for the electrically actuated mini-plain flaps and $\pm 10^\circ$ for the hydraulic ailerons. If a control surface reaches its saturation limit and cannot achieve the full $\pm 4^\circ$ command, successive perturbations in the same direction are applied to remain within allowable deflections. The lift target for the optimization is $C_L = 0.388$.

The test is initialized from a maximum-drag configuration, in which all control surfaces are commanded to their maximum-drag deflections within the prescribed saturation limits. This improves the signal-to-noise ratio of drag measurements, enhancing the reliability of the optimization. A low-pass filter with a conservative cutoff frequency is applied to suppress high-frequency fluctuations arising from structural dynamics and tunnel turbulence. Long set-point durations and time-averaging of the filtered measurements further improve accuracy, while settling times ensure the system reaches steady state after each set-point change.

The RTD controller computes control-surface commands, while physical actuation is executed by the hardware-in-the-loop control system computer. Angle of attack is manually adjusted by the tunnel operator, with additional timing delays incorporated to allow accurate tracking of the commanded pitch.

Figure 9 presents drag time histories during controller operation. The raw drag signal is smoothed using a moving-average filter for clarity, alongside the low-pass-filtered drag measurement. The dashed black line indicates the drag at the initial condition, while the dashed blue line shows the final drag at the optimized angle of attack and flap configuration. This corresponds to a 12.2% reduction relative to the initial high-drag state, which is slightly lower than the predicted drag reduction of 14.4%.

Fig. 10 depicts the lift measurement for the full test duration. The optimized lift reaches $C_L = 0.390$, which is 0.52% above the target. Early iterations exhibit larger deviations from the target lift, which gradually diminish as the parameter identification improves. From approximately 0 to 400 s, the initial set of perturbations is applied, consisting primarily of angle-of-attack perturbations followed by individual control-surface perturbations. Because lift and drag sensitivities are initialized to zero, the onboard model initially has low fidelity, leading to the observed drop in lift between 500 and 1500 s. As additional data are incorporated into the recursive least-squares identification, the model accuracy improves and the lift converges closely to the target value.

Figure 11 shows the angle of attack measurement with an initial value of 0.16° and a final optimized value of 1.47° . The perturbations applied for system identification are also clearly visible. Figure 12 presents the control surface history, showing perturbations and reasonable convergence. Given the significant noise in the lift and drag measurements,

perfect convergence is not expected.

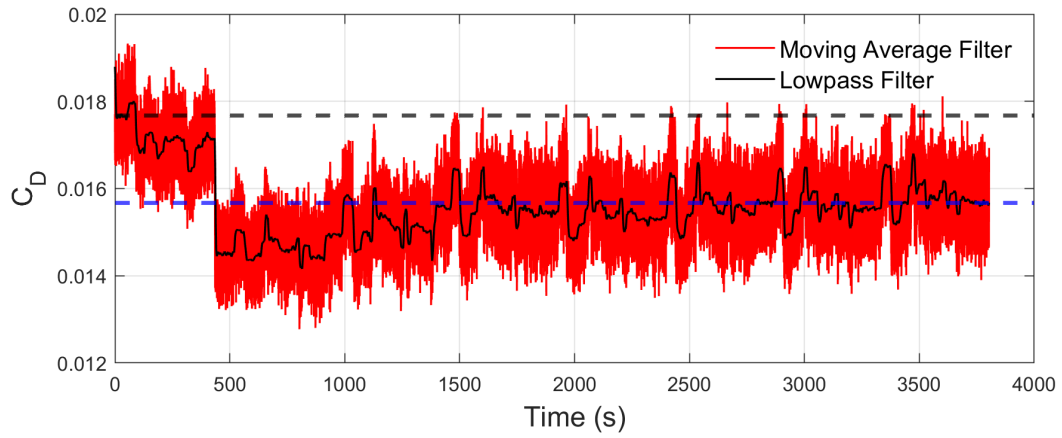


Fig. 9 Drag Time History during RTD testing.

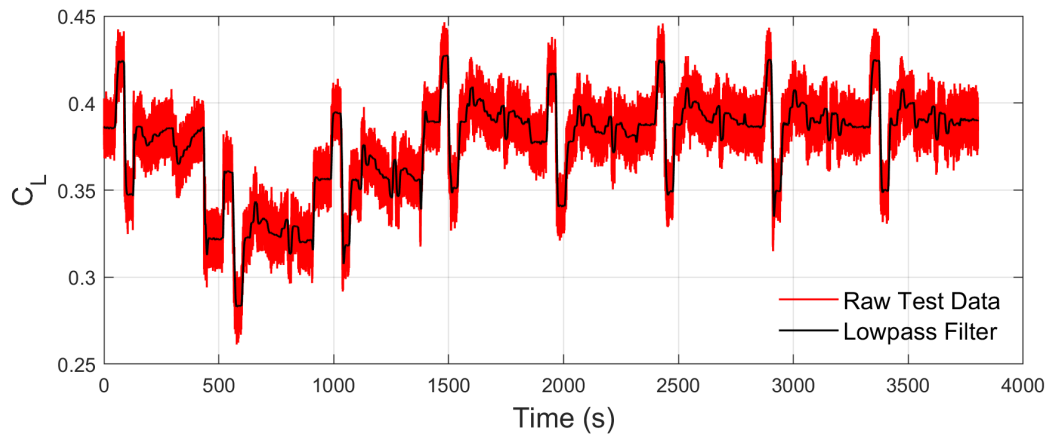


Fig. 10 Lift Time History during RTD testing.

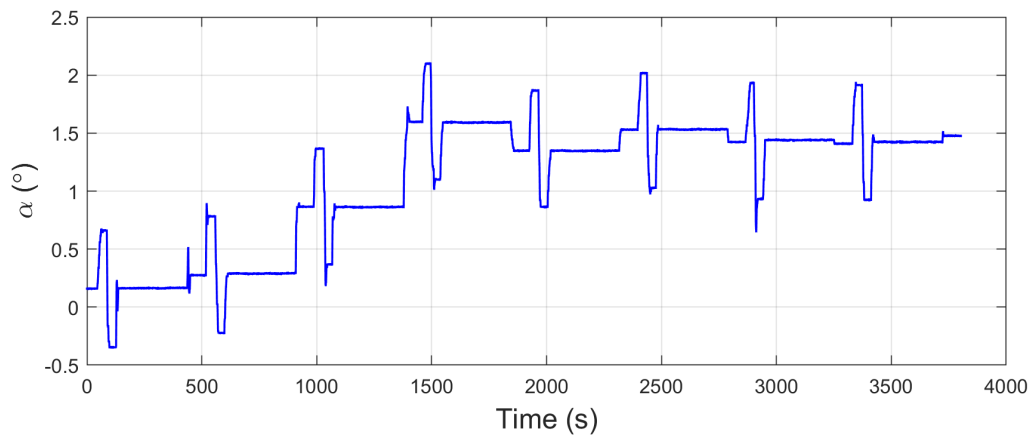


Fig. 11 Angle-of-Attack Time History during RTD testing.

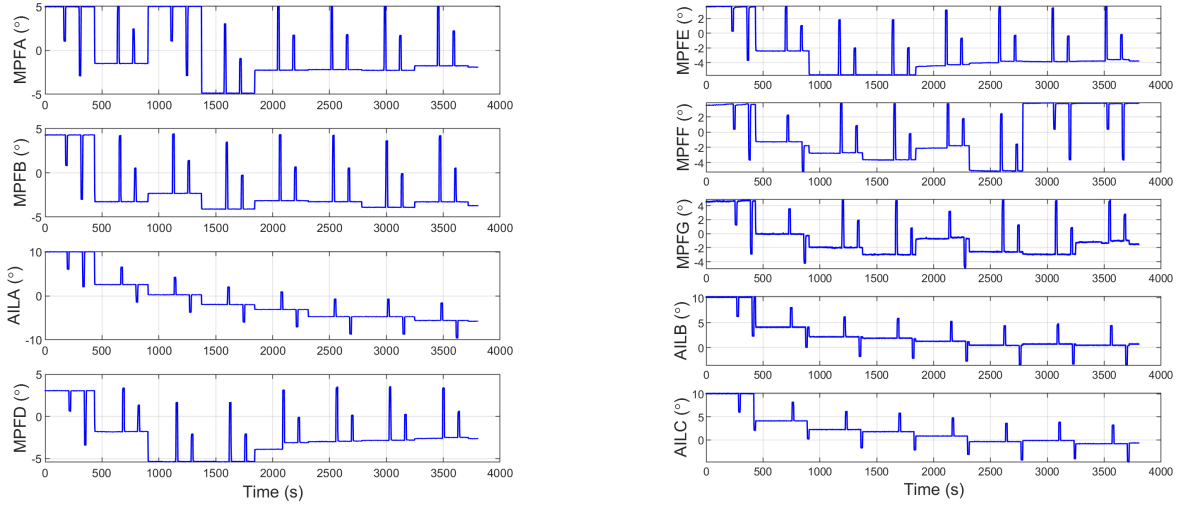


Fig. 12 Control Surface Position Histories during RTD testing.

B. Maneuver Load Alleviation Results

The Maneuver Load Alleviation (MLA) controller operates at the same primary test condition of Mach 0.55 and $\bar{q}_\infty = 110$ psf. The controller receives a commanded lift increment of $\Delta C_L = 0.4$, starting from $C_L = 0.15$, corresponding to an approximate maneuver from -2° to 3° under angle-of-attack-only control. Two saturation scenarios are tested: $\pm 5^\circ$ for the first run and $\pm 10^\circ$ for the second.

Figure 13 shows lift versus wing-root strain magnitude. Blue markers indicate the baseline maneuver using angle of attack only, with no MLA control. Red and green markers correspond to MLA-active cases with $\pm 5^\circ$ and $\pm 10^\circ$ saturation limits, respectively. Both MLA-active cases reduce wing-root strain for a given lift, with larger reductions achieved under the higher saturation limit.

Figure 14 presents the optimal control-surface deflection patterns at $C_L = 0.5$. Inboard surfaces deflect positively while outboard surfaces deflect negatively, shifting aerodynamic load inboard and reducing wing-root bending moments. At $C_L = 0.5$, wing-root strain decreases by roughly 7.0% for the $\pm 5^\circ$ case and 13.2% for the $\pm 10^\circ$ case compared to the nominal maneuver. The predicted reductions are 7.5% and 14.1%, respectively.

Figure 15a shows the angle-of-attack time history, where the black trace denotes the AOA command and the red trace shows the measured AOA, which is manually commanded by a tunnel operator. The results correspond to the 10° actuator saturation limit tests. Notably, the achieved AOA is slightly lower than that of the nominal AOA-only maneuver.

Figure 15b presents the commanded lift time history. Figure 16 shows the control-surface position time histories, which apply previously computed optimal profiles corresponding to the commanded lift. Notably, the optimal control-surface commands remain relatively constant at lower lift levels, while at higher commanded lift the optimal commands for the AILA and MPFD surfaces begin to vary more significantly.

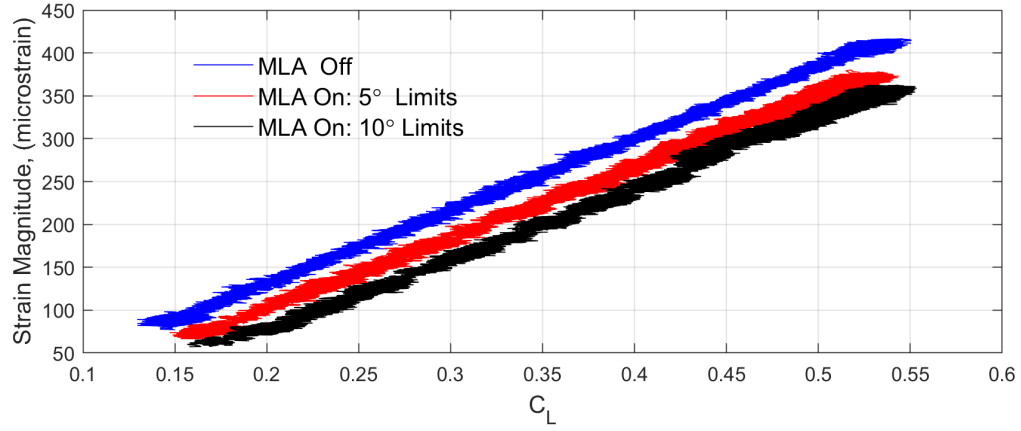


Fig. 13 Lift versus wing-root strain magnitude for MLA tests.

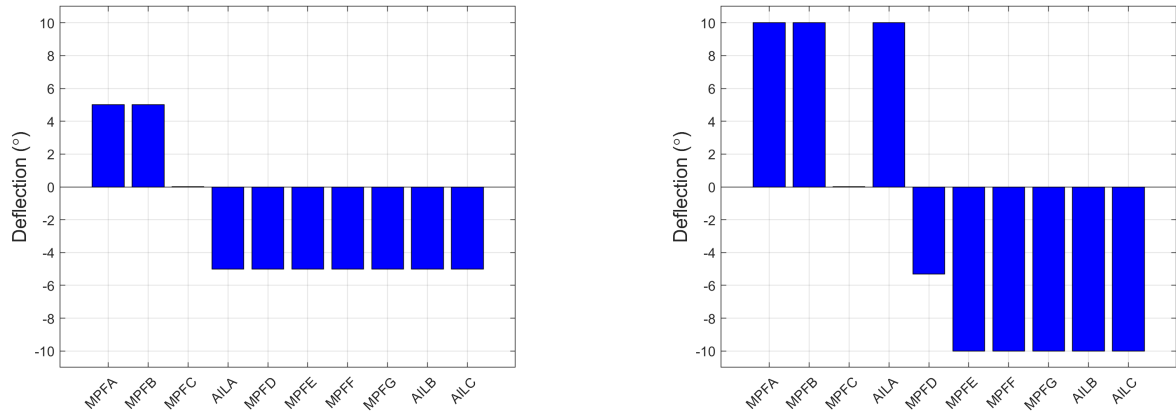
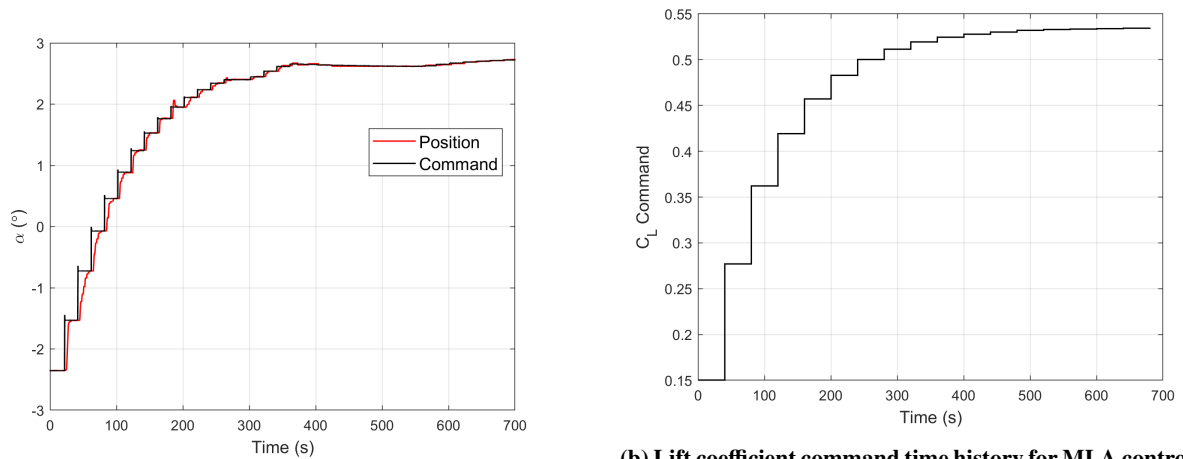


Fig. 14 Optimal control-surface deflections at $C_L = 0.5$ for MLA tests: left $\pm 5^\circ$, right $\pm 10^\circ$.



(a) Angle-of-attack time history for MLA controller test.

(b) Lift coefficient command time history for MLA controller test.

Fig. 15 MLA controller time histories.

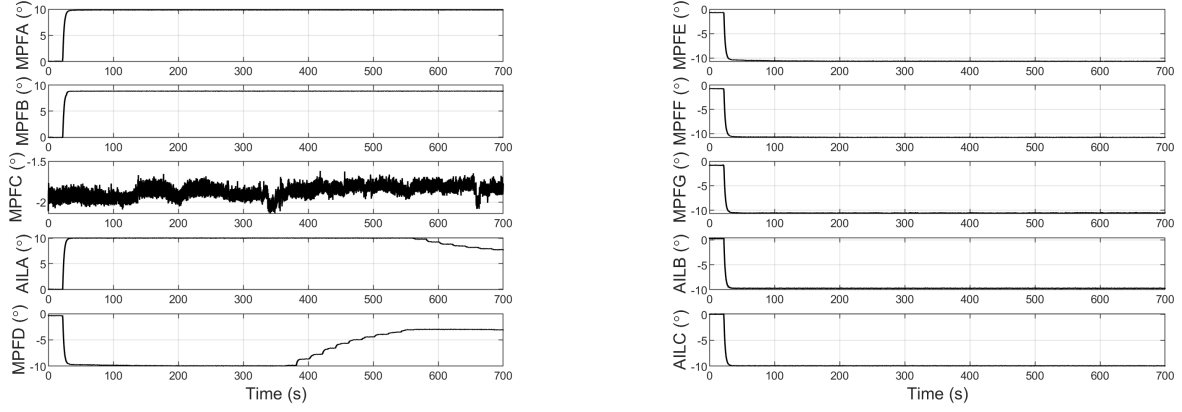


Fig. 16 Control surface time history for MLA controller test.

C. Online Parameter Estimation Performance

This section presents the performance of the online parameter identification process for lift and drag, including convergence behavior and comparison with independently measured aerodynamic data.

Figure 17 shows the final lift model estimated by the online parameter identification process compared to the aerodynamic data, while Figure 18 shows the corresponding drag model. At the initial angle of attack (AOA), estimation performance is poor because the flap sensitivities are initialized to zero while the initial flap deflections are nonzero. As the system progresses to the final AOA, the identified model closely matches the aerodynamic data near the convergence point for both lift and drag. The drag measurements exhibit more scatter, likely due to higher measurement noise.

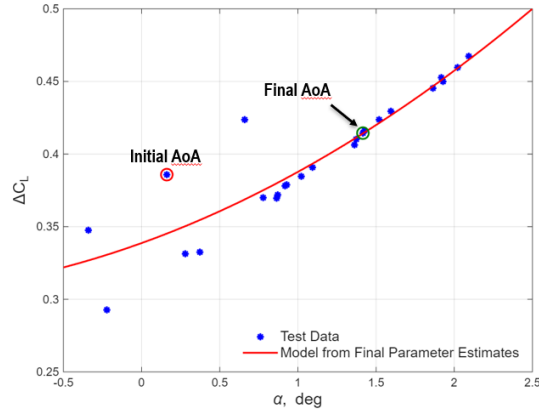


Fig. 17 Lift curve estimation performance compared to aerodynamic data.

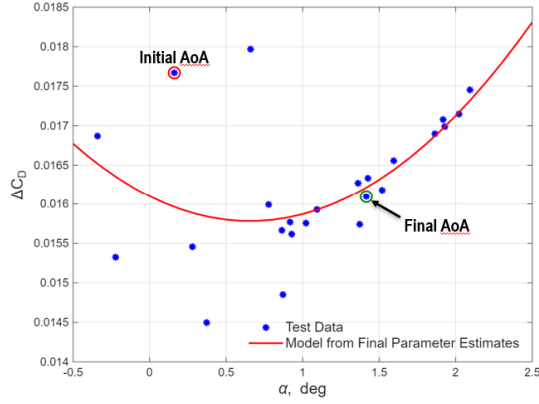


Fig. 18 Drag curve estimation performance compared to aerodynamic data.

Figures 19–21 show the estimated control surface sensitivities compared to predicted values from steady-state aerodynamic characterization performed prior to the closed-loop control runs. For legibility, the control surfaces are labeled 1–10 from inboard to outboard, with surface 3 (MPFC) not used in the estimation.

Figure 19 presents the lift sensitivities, $C_{L_{\delta}}$, which converge closely to predicted values for most surfaces. Figure 20 presents the drag sensitivities, $C_{D_{\delta}}$, which take slightly longer to converge than the lift sensitivities. Figure 21 shows the quadratic drag sensitivities, $C_{D_{\delta}^2}$, which exhibit the largest differences from the predicted values, reflecting their higher sensitivity to noise.

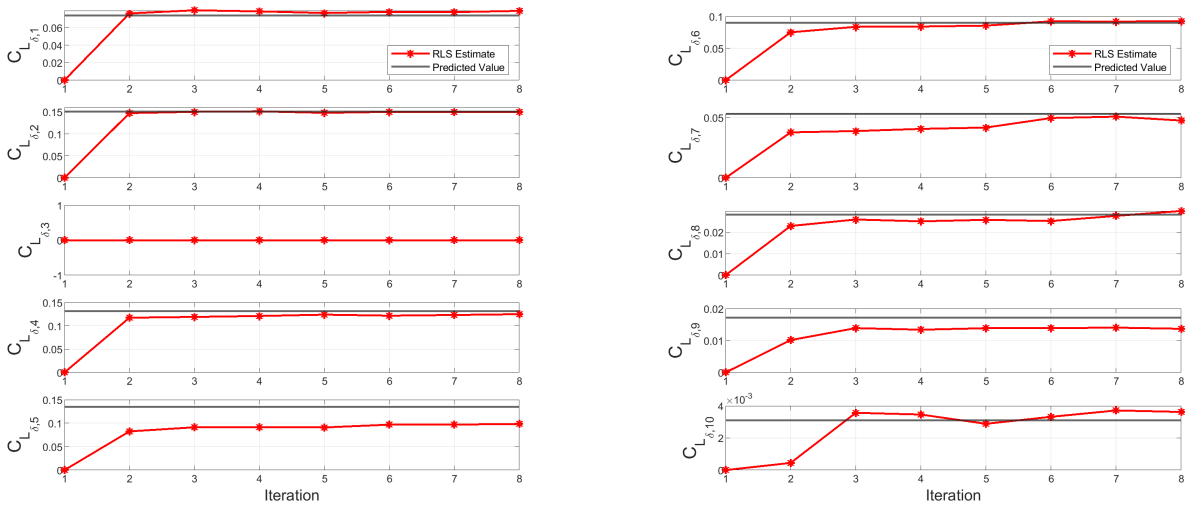


Fig. 19 $C_{L_{\delta}}$ estimated sensitivities compared to predicted values.

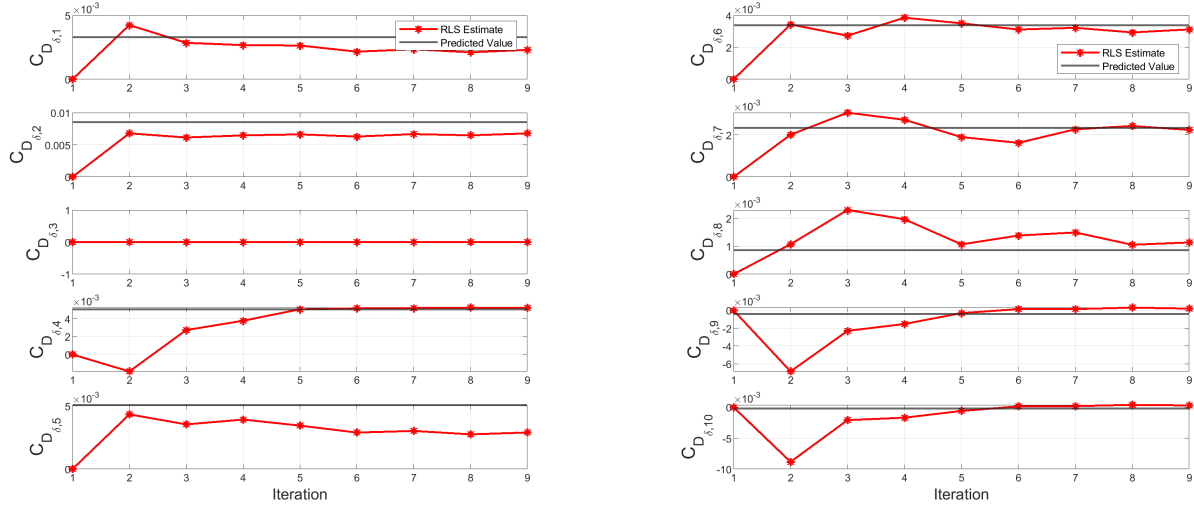


Fig. 20 $C_{D\delta}$ estimated sensitivities compared to predicted values.

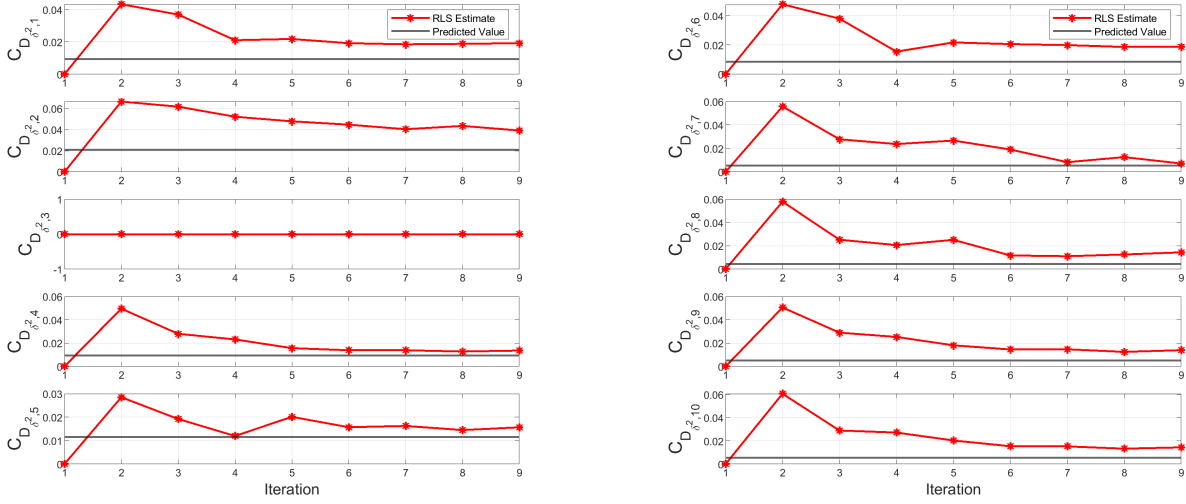


Fig. 21 $C_{D\delta^2}$ estimated sensitivities compared to predicted values

VII. Conclusions

This paper presented the design and experimental validation of a multi-objective optimal control framework for a high aspect ratio flexible transport wing, incorporating real-time drag optimization, maneuver load alleviation, and online parameter estimation. The approach was implemented and evaluated in the NASA Langley Transonic Dynamics Tunnel using an aeroelastically scaled wind tunnel model.

The real-time drag optimization controller achieved a 12.2% reduction in drag from an initial high-drag condition while maintaining the target lift, closely matching predicted performance despite significant measurement noise and actuator constraints. The maneuver load alleviation controller successfully reduced wing-root bending loads during lift maneuvers, achieving strain reductions of approximately 7.0% and 13.2% for $\pm 5^\circ$ and $\pm 10^\circ$ control surface saturation limits, respectively. These reductions were consistent with pre-test predictions and were achieved through physically intuitive load redistribution enabled by distributed control surfaces.

Online parameter estimation results demonstrated convergence of lift and drag models toward independently measured aerodynamic data near the final operating condition, validating the feasibility of closed-loop identification in a noisy experimental environment. Overall, the experimental results confirm that real-time optimization and load-alleviation control can be simultaneously and reliably implemented on a highly flexible transport-wing model to improve aerodynamic efficiency and reduce maneuver-induced structural loading.

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References

- [1] Vassberg, J., Dehaan, M., Rivers, M., and Wahls, R., "Development of a Common Research Model for Applied CFD Validation Studies," *26th AIAA Applied Aerodynamics Conference*, Honolulu, HI, 2008. <https://doi.org/https://doi.org/10.2514/6.2008-6919>.
- [2] Nguyen, N. T., "Elastically Shaped Future Air Vehicle Concept," *NASA Innovation Fund Award 2010 Report*, 2010.
- [3] Nguyen, N. T., and Urnes, J., "Aeroelastic Modeling of Elastically Shaped Aircraft Concept via Wing Shaping Control for Drag Reduction," *AIAA Atmospheric Flight Mechanics Conference*, 2012.
- [4] Nguyen, N., and Xiong, J., "Real-Time Drag Optimization of Aspect Ratio 13.5 Common Research Model with Distributed Flap System," *AIAA SciTech Forum*, 2021. <https://doi.org/https://doi.org/10.2514/6.2021-0069>.
- [5] Forte, C., Nguyen, N., Xiong, J., and Sager, J., "Real-Time Drag Optimization and Maneuver Load Alleviation Control for a High Aspect Ratio Wing Wind Tunnel Model," *AIAA SciTech Forum*, San Diego, CA, 2022. <https://doi.org/https://doi.org/10.2514/6.2022-0715>.
- [6] Grauer, J. A., and Waite, J., "Design of a Collocation-Based Active Flutter Suppression Control Law for the IAWTM Wind Tunnel Model," *AIAA SciTech*, 2024.
- [7] Forte, C., and Nguyen, N., "Multi-Objective Optimal Control of High Aspect Ratio Wing Wind Tunnel Model," *AIAA SciTech Forum*, Orlando, FL, 2024. <https://doi.org/https://doi.org/10.2514/6.2024-1782>.
- [8] Nguyen, N. T., Cramer, N. B., Hashemi, K. E., Ting, E., Drew, M., Wise, R., Boskovic, J., Precup, N., Mundt, T., and Livne, E., "Real-Time Adaptive Drag Minimization Wind Tunnel Investigation of a Flexible Wing with Variable Camber Continuous Trailing Edge Flap System," *AIAA Applied Aerodynamic Conference*, 2019.
- [9] Ferrier, Y., Nguyen, N., and Ting, E., "Real-Time Adaptive Least-Squares Drag Minimization for Performance Adaptive Aeroelastic Wing," *AIAA Applied Aerodynamics Conference*, 2016.
- [10] Xiong, J., Nguyen, N., Standford, B., and Bartels, R., "Aeroelastic Modeling and CFD Simulation of Wind-Tunnel Scale Aspect Ratio 13.5 Common Research Model," *AIAA Aviation 2021 Forum*, 2021.
- [11] Heaney, P. S., and Quindlen, J. F., "Overview of the Integrated Adaptive Wing Technology Maturation Wind-Tunnel Test Objectives," *AIAA SciTech Forum*, Orlando, FL, 2024. <https://doi.org/https://doi.org/10.2514/6.2024-2509>.
- [12] Quindlen, J. F., Ortega, D. M., Clark, G. J., Hussain, H. S., Forte, C. J., Nguyen, N. T., Xiong, J., Heaney, P. S., Bentley, P. J., Coulson, D. A., Giles, I. M., McHugh, G. R., Pinkerton, J. L., Ramey, J. M., and Stevens, W. L., "Summary of the Integrated Adaptive Wing Technology Maturation Wind Tunnel Tests of a High Aspect Ratio Commercial Transport Aircraft," *AIAA SciTech Forum*, Orlando, FL, 2026.