

Reduced-Order Aerodynamic Modeling Based on CFD Frequency Responses from Multisine Inputs

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A system identification analysis was performed to determine reduced-order models of a computational fluid dynamics (CFD) solver for linear aeroelastic analysis and control design. The application was to the FUN3D code and the flexible half-span wind tunnel test article, in transonic flow conditions, used in the NASA-Boeing collaboration called the Integrated Adaptive Wing Technology Maturation (IAWTM) project. Multiple inputs (structural mode displacements and control surface deflections) were simultaneously excited with orthogonal phase-optimized multisines and multiple outputs (generalized aerodynamic forces) were recorded, from which the matrix of frequency responses were computed using a single CFD run. A state-space model was then fit to the frequency response data using a maximum-likelihood estimator.

I. Nomenclature

$\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}$	=	state-space matrices
$\text{cov}(\cdot)$	=	covariance operator
f	=	frequency, Hz
$\mathbf{H}(s)$	=	transfer function matrix
j	=	imaginary number, $= \sqrt{-1}$
$\ln$	=	natural logarithm
n	=	number of elements
$\Re$	=	real part of number
s	=	Laplace variable
t	=	time, s
$\mathbf{Q}_{\cdot\cdot}(s)$	=	aerodynamic transfer functions
$\mathbf{q}_{\delta}, \mathbf{q}_{\eta}$	=	generalized aerodynamic force vectors
$\mathbf{u}$	=	input vector
$\mathbf{x}$	=	state vector
$\mathbf{y}$	=	output vector
Δ	=	perturbation
δ	=	control surface deflection, rad
η	=	structural mode displacement
ω	=	radian frequency, rad/s
0	=	steady value
$\cdot$	=	time derivative
$\dagger$	=	complex conjugate transpose
-1	=	matrix inverse
$\wedge$	=	estimate

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II. Introduction

COMPUTATIONAL fluid dynamics (CFD) flow solvers coupled to structural models offer higher-fidelity aeroelastic modeling capability than first-principles approaches or linear panel code solutions, particularly in the transonic flow regime. However, it is not generally feasible to use CFD solutions directly for aeroelastic analysis and control design due to the high computational costs, nonlinearities present, and incompatibility with standard modeling tools. As a result, lower-fidelity aerodynamic solutions that are rapidly constructed and easily incorporated into aeroelastic analysis tools are often preferred.

When linear aerodynamic solutions cannot meet modeling accuracy requirements, a different approach is to perform a system identification analysis on the CFD code, using measured input and output data. The result is a reduced-order model that approximates the CFD outputs to specific inputs under certain conditions to a reasonable level of accuracy, and which can be coupled to existing tools for efficient aeroelastic analysis. The excitation inputs for identification could be sinusoidal functions, impulses, squares waves (steps, doublets, or multisteps), frequency sweeps, random excitations, and other waveforms [1–4]. However, single-input designs require longer durations of computation time to achieve solutions of multiple-input systems. Alternatively, orthogonal excitations on multiple simultaneously-moved inputs have included Gaussian functions [2] and Walsh functions (orthogonal square waves) [4–6], and can generate data for identifying the entire model from a single CFD run. From the obtained input and output data, impulse response functions and frequency response functions can be computed [6, 7]. The eigenvalue realization algorithm (ERA) [7] is often employed to directly realize state-space approximations directly from time history data. Many of these techniques are compiled into the software package called AEROM [6].

A similar approach is pursued in this paper for identifying reduced-order state-space models of CFD codes. Multiple inputs are simultaneously excited using orthogonal phase-optimized sinusoids. From the recorded input and output data from a single CFD run, the frequency responses are computed. A model structure is then determined and a maximum-likelihood estimator is applied to fit a state-space model to the frequency response data. The approach is applied to the FUN3D solver [8, 9] and a flexible half-span wind tunnel test article, set up in transonic flow conditions, used in the Integrated Adaptive Wing Technology Maturation (IAWTM) project. In the past, the approach has been used in flight testing of aircraft, including the X-56A aeroelastic demonstrator [10].

The paper is hereafter organized as follows. The IAWTM project, wind tunnel test article, and structural and aerodynamic models are discussed in Section III. The aerodynamic reduced-order model of interest is described in Section IV. The method for identifying reduced-order models of the CFD code is explained in Section V. Results are shown in Section VI, with further discussion and comparisons in Section VII. Lastly, conclusions are given in Section VIII.

III. Description of IAWTM

A. Overview of Project

The NASA N+3 High Aspect Ratio Wing (HARW) subproject, under the NASA Advanced Air Transport Technology (AATT) Project, seeks to develop advanced next-generation subsonic commercial transports with higher fuel economy and lower emissions and noise signatures [11]. The resulting high aspect ratio, low-weight aircraft designs have increased the need for aeroelastic modeling and flight control design. Under this heading, the IAWTM project is a collaboration between NASA and Boeing to identify, develop, and demonstrate new technologies towards these goals.

To test and demonstrate these new technologies, a wind-tunnel test in the NASA Langley Research Center (LaRC) Transonic Dynamics Tunnel (TDT) is scheduled for late 2020. A half-span test article will be installed in the tunnel and tests will be conducted. Hardware tests are currently being conducted and aeroelastic models are being developed for active flutter suppression (AFS), maneuver load alleviation (MLA), gust load alleviation (GLA), and drag reduction.

B. Wind Tunnel Test Article

A computer rendering of the wind tunnel test article showing the component subassemblies is given in Fig. 1. The model is based on the Common Research Model (CRM-13), but is a half-span and aeroelastically-scaled version. It has a 12.9 ft half-span, 13.3 ft fuselage length, and 13.5 wing aspect ratio. The wing is composed of a wing spar, ribs, actuators, instrumentation, wing skin, and a flow-through engine nacelle. The wing attaches to a mounting structure inside the fuselage skin, which can be attached to the tunnel load balance.

The test article includes 10 independently-actuated trailing-edge control surfaces, as shown by the computer

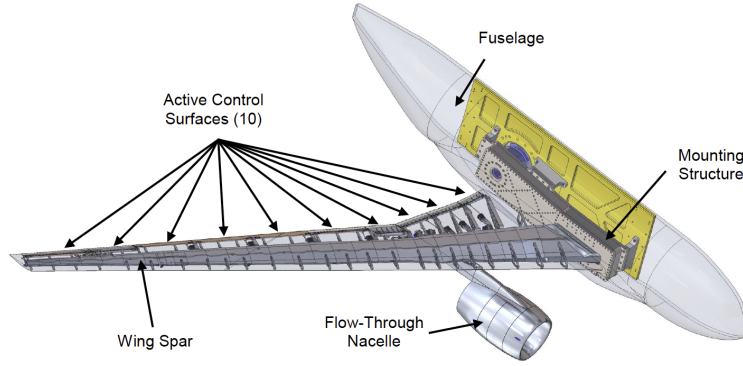


Fig. 1 Cutaway rendering of component subassemblies (credit: Boeing Research and Technology).

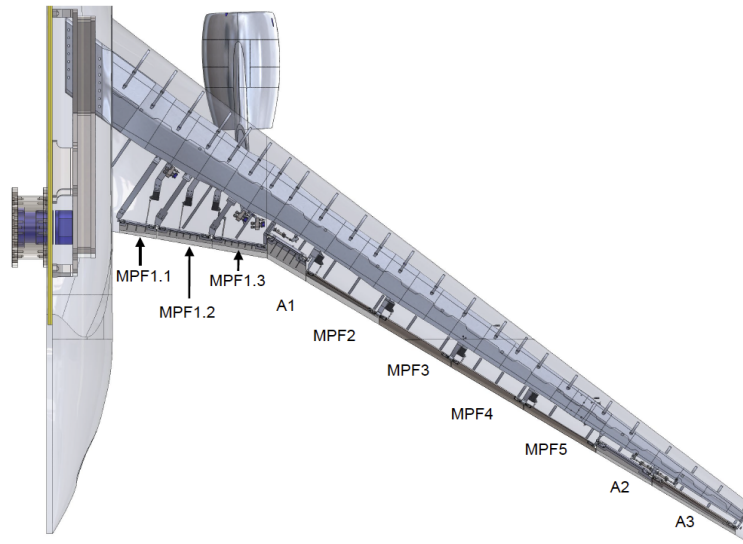


Fig. 2 Control surfaces (credit: Boeing Research and Technology).

rendering in Fig. 2. The labels MPF stand for mini plain flap. These surfaces are controlled by electric servo motors and are primarily intended for lower-frequency drag optimization and maneuver load alleviation. Flaps 1.1, 1.2, and 1.3 were designed as one continuous flap, but were segmented for implementation considerations. The surfaces labeled A1, A2, and A3 are independent ailerons that are hydraulically actuated and intended for higher-frequency aeroelastic control.

The test article will be mounted to the wall of the test section in the TDT. Conditions are expected to cover subsonic and transonic flow. Oscillating vanes are present on the upstream walls for simulating turbulence. More information on TDT capabilities and operations can be found in Ref. [12].

C. Structural Dynamics Model

The finite element model describing the structural dynamics of the IAWTM wind tunnel test article was performed using MSC NASTRAN (MSC Software, Newport Beach, CA). The model had 38,667 grid points that consisted of rigid beam, flexible beam, shell, and solid hexahedral elements. A total of 24 elastic modes were used, ranging in frequency from 3.6 to 100 Hz. A free-vibration analysis was used to compute the modes and mode shapes, which were normalized so to have unit generalized mass.

It was determined that only 11 structural modes were needed to accurately model the flutter instability. These modes are listed in Table 1 with resonant frequencies and descriptions. For this work, only these modes were considered in the modeling.

Table 1 Structural modes considered.

Mode	Frequency, rad/s	Frequency, Hz	Description
1	22.7	3.6	1st wing vertical bending
2	48.0	7.6	1st fuselage pitch, wing 1st vertical bending
4	69.6	11.1	2nd wing vertical bending
5	94.1	15.0	2nd wing/balance fore/aft bending
6	95.2	15.1	2nd wing vertical bending, fuselage pitch
7	107.5	17.1	1st nacelle pitch, inboard wing 1st torsion
8	151.1	24.0	nacelle lateral
10	184.3	29.3	nacelle lateral, balance axial
13	275.4	43.8	—
14	287.1	45.7	—
18	466.2	74.2	—

D. Aerodynamics Models

The aerodynamics acting on the IAWTM wind tunnel test article were modeled using two numerical codes. The first was ZAEROTM (ZONA Technology Incorporated, Scottsdale, Arizona), which uses a panel method [13]. Flat plate elements were used for the wing and pylon, and body elements were used for the fuselage and engine nacelle. The ZAERO results are included in this paper as a comparison for the CFD solution, which is described next.

The second code used was the CFD code named FUN3D, which was developed at NASA Langley Research Center [8, 9]. FUN3D is a node-centered finite-volume unstructured code used to solve the steady and unsteady Reynolds-averaged Navier-Stokes equations. The solutions for this work used 14,618,916 nodes, 3,598,892 tetrahedral cells, 184,622 pyramid cells and 27,598,875 prism cells.

IV. Aerodynamic Reduced-Order Model

The purpose of this work is to identify a reduced-order model of the CFD solver. This reduced-order model can then be simulated more quickly and coupled with other physics for aeroelastic analysis and control design, albeit at a reduction in accuracy.

Typically for an aeroelastic simulation, FUN3D or another aerodynamic code is coupled to a structural dynamics solver and the solution steps through time [14–16]. For this work, the flow solver was decoupled from the structural dynamics solver for system identification, as described in Refs. [2, 5, 6]. The inputs to the system were arranged as the $(n_u \times 1)$ vector

$$\mathbf{u}(t) = \begin{bmatrix} \boldsymbol{\eta}(t) \\ \boldsymbol{\delta}(t) \end{bmatrix} \quad (1)$$

where $\boldsymbol{\eta}$ is an $(n_\eta \times 1)$ vector containing displacements of the structural modes in generalized coordinates, and where $\boldsymbol{\delta}$ is an $(n_\delta \times 1)$ vector of control surface deflections. Only the 11 structural modes listed in Table 1 and the three aileron surfaces in Fig. 2 were retained in this model. To consider moving control surfaces in the CFD, the control surfaces were analyzed as a type of structural mode as well. The outputs of the CFD, arranged in the $(n_y \times 1)$ vector $\mathbf{y}$, were the frequency-dependent generalized aerodynamic forces (GAFs). When coupled to a structural dynamics solver, these GAFs are scaled by dynamic pressure and force the structural mode degrees of freedom.

A block diagram of the aerodynamics solver system used for system identification is shown in Fig. 3. As discussed more in Section VI, steady values of the input, $\mathbf{u}_0$ are found by converging the flow solution. After this occurs, an excitation signal $\Delta\mathbf{u}(t)$ (described more in Sections V.A and VI) is added to the steady input to generate informative dynamic responses from the system.

The aerodynamic input and output perturbations are assumed to be related by a linear system, so that the resulting model can later be coupled with other linear models for aeroelastic analysis. This relationship can be written using transfer functions as

$$\Delta\mathbf{y}(s) = \mathbf{H}(s) \Delta\mathbf{u}(s) \quad (2)$$

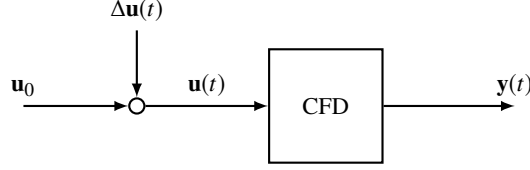


Fig. 3 Input-output block diagram of the aerodynamic CFD flow solver.

or further decomposed as

$$\begin{bmatrix} \mathbf{q}_\eta(s) \\ \mathbf{q}_\delta(s) \end{bmatrix} = \begin{bmatrix} \mathbf{Q}_{\eta\eta}(s) & \mathbf{Q}_{\eta\delta}(s) \\ \mathbf{Q}_{\delta\eta}(s) & \mathbf{Q}_{\delta\delta}(s) \end{bmatrix} \begin{bmatrix} \boldsymbol{\eta}(s) \\ \boldsymbol{\delta}(s) \end{bmatrix} \quad (3)$$

The outputs $\mathbf{q}_\eta$ and $\mathbf{q}_\delta$ are the GAFs for the elastic modes and the control modes, respectively, in the structural dynamics equations of motion. The submatrices $\mathbf{Q}$ are the transfer function matrices to be identified. For example, $\mathbf{Q}_{\eta\delta}(s)$ is the transfer function relating a control surface deflection to the GAF forcing the structural modes. The transfer function matrix $\mathbf{H}(s)$ is square because there is one GAF output for each structural mode or control surface input. For proper transfer functions, Eq. (3) can be realized in the state-space format

$$\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) \quad (4a)$$

$$\mathbf{y}(t) = \mathbf{C} \mathbf{x}(t) + \mathbf{D} \mathbf{u}(t) \quad (4b)$$

where $\mathbf{x}$ an $(n_x \times 1)$ vector of the system states.

V. System Identification Method

This section presents the method used to identify a reduced-order model, as Eq. (3) or (4), of the aerodynamic CFD flow solver. The process includes exciting the system, computing frequency responses from recorded input and output data, identifying a model structure, and estimating model parameters to fit the model to the empirical frequency response data. This discussion is adapted from Ref. [10] and references therein, and adapted for aeroelastic applications. A software package developed at NASA Langley Research Center called System IDentification Programs for AirCRAFT (SIDPAC) [17, 18] was used for the input design, Fourier transforms, and parameter estimation.

A. Input Design

The first step is to design the input excitations to generate responses used for computing frequency responses. The excitations for this work were orthogonal phase-optimized multisines [17, 18], hereafter referred to as multisines, of the form

$$\Delta u_j(t) = \sum_{k \in K_j} a_k \sin\left(\frac{2\pi k}{T} t + \phi_k\right) \quad (5)$$

for $j = 1, 2, \dots, n_u$. Equation (5) represents summations of sinusoids that are each the k th harmonic of the fundamental frequency $1/T$ Hz for the fundamental period T seconds.

The harmonics are chosen to span the bandwidth of interest for the data and model. Theoretically, the harmonics can be between the frequencies $1/T$ and $1/2\Delta t$, where Δt is the sampling period. For practical reasons, however, the lower limit is usually restricted to about $4/T$, to allow for a few complete cycles of the input at the lowest frequencies. The upper limit is usually desired to be at least 25 times below the Nyquist frequency, to allow for sufficient samples per cycle. Each harmonic is assigned to a single input u_j using the set K_j . Therefore, it is important to design T to be long enough that each K_j provides the inputs with sufficient frequency resolution over the bandwidth of interest. The union of all the sets K_j — all the harmonics used for excitation — is the set K .

Each of the n_u multisines designed using Eq. (5) is orthogonal to the other multisines because harmonic sinusoids are orthogonal, and because each harmonic was assigned to a unique input. This orthogonality property enables the system to be excited using all the inputs at once, simultaneously, without correlating the output data. The use of orthogonal functions can significantly improve the efficiency and decrease the amount of time needed to run the CFD solutions. If

the system is excited within its linear range, the outputs will only contain power at the harmonics used in the multisine inputs.

After the harmonics are assigned to the inputs, the phase angles ϕ_k are optimized using a Simplex algorithm for each input to minimize the relative peak factor (RPF). This process compresses the amplitude of the multisines and reduces large peaks in the waveform. For frequency response applications, this helps keep the system in its linear region.

Lastly, the amplitude spectrum a_k is designed for each input. Although this can be an arbitrary function of frequency, perhaps to emphasize or de-emphasize certain bandwidths, uniform spectra were used for the inputs here, reducing the design to a single value of a_k for each input.

B. Frequency Response Computation

The second step is to compute frequency responses from the measured input and response time history data. This process starts by detrending the measured time histories to minimize spectral leakage. Then the detrended data are transformed into the frequency domain using the finite-time Fourier transform, implemented using the chirp-z transform [17, 18]. Since the system is assumed to be linear, the steady-state outputs only contain power at the frequencies in the inputs. As a result, the transforms are only performed at frequencies ω_k which correspond to harmonics in K . This reduces the computational load to a relatively small number of frequencies.

The frequency response matrix $\mathbf{H}(j\omega_k)$ can then be computed as the ratios of the output Fourier transforms to the input Fourier transforms. Elements of the frequency response matrix are computed as

$$H_{ij}(j\omega_k) = \frac{y_i(j\omega_k)}{u_j(j\omega_k)} \quad (6)$$

for $i = 1, 2, \dots, n_y$ and $j = 1, 2, \dots, n_u$.

The only errors in the frequency response for identifying reduced-order models of a CFD solver involve nonlinearity and transient dynamics. Frequency responses assume linearity, and any nonlinearity in the system will degrade the input-output modeling capability of the frequency response. However, the frequency response is the best linear approximation to the nonlinear system. The inputs should be chosen to remain within the linear range of the system. Some error in Eq. (6) may also arise from the presence of transient responses in the data. However, aerodynamic systems are typically well damped, and the input excitation was designed to include many cycles of the harmonics, so this was not an issue. Measurement noise and external disturbances were not an issue for computing frequency responses for this application, because the inputs and outputs to the CFD code are known exactly, unlike in flight test applications.

C. Model Structure Determination

This section will discuss the determination of the model structure of Eqs. (3) and (4) for estimating the model parameters with techniques explained in the following section.

D. Parameter Estimation

Parameter estimation was performed by obtaining the elements of the state-space model from Section V.C which has a frequency response that best matches the frequency response data computed in Section V.B. This approach can be called Frequency Response-Error (FRE) parameter estimation, and is described in Refs. [10, 17, 19].

The cost function to estimate the model parameters is the negative-log likelihood function

$$J(\boldsymbol{\theta}, \mathbf{S}_{vv}) = n_f \sum_{k \in K} \mathbf{v}^\dagger(j\omega_k) \mathbf{S}_{vv}^{-1} \mathbf{v}(j\omega_k) + n_f \ln |\mathbf{S}_{vv}| \quad (7)$$

where a constant term having no impact on the optimization has been removed. All the unknown model parameters from Eq. (3) or (4) have been arranged in the $(n_\theta \times 1)$ vector $\boldsymbol{\theta}$. In Eq. (7), n_f is the number of harmonics or frequencies, and the residuals

$$\mathbf{v}(j\omega_k) = \text{vec} [\mathbf{H}(j\omega_k) - \hat{\mathbf{H}}(j\omega_k)] \quad (8)$$

are the complex-valued differences between the frequency response data and the model for that data, $\hat{\mathbf{H}}(j\omega_k)$, where the vectorization operator $\text{vec}[\cdot]$ stacks the columns of the matrix argument. The matrix $\mathbf{S}_{vv}$ is the spectral density of $\mathbf{v}(t)$.

Optimization of Eq. (7) is in general ill-posed and leads to convergence issues. Instead, a relaxation technique is typically employed where $\boldsymbol{\theta}$ is held constant while $\mathbf{S}_{vv}$ is estimated, and vice-versa, until convergence is attained. For a

constant θ , optimization of Eq. (7) with respect to $\mathbf{S}_{vv}$ is

$$\hat{\mathbf{S}}_{vv} = \frac{1}{2(f_{n_f} - f_1)} \sum_{k \in K} \mathbf{v}(j\omega_k) \mathbf{v}^\dagger(j\omega_k) \quad (9)$$

Given this estimate of the residual spectral density, the cost function in Eq. (7) reduces to

$$J(\theta) = n_f \sum_{k \in K} \mathbf{v}^\dagger(j\omega_k) \hat{\mathbf{S}}_{vv}^{-1} \mathbf{v}(j\omega_k) \quad (10)$$

which is a nonlinear optimization problem. The Gauss-Newton method was used, which has iterative parameter updates

$$\hat{\theta} = \hat{\theta}_0 - \left[\mathbf{M}^{-1} \frac{\partial J(\theta)}{\partial \theta} \right]_{\hat{\theta}_0} \quad (11)$$

from the previous estimate $\hat{\theta}_0$. In Eq. (11),

$$\mathbf{M} = 2n_f \Re \left[\sum_{k \in K} \mathbf{S}^\dagger(j\omega_k) \hat{\mathbf{S}}_{vv}^{-1} \mathbf{S}(j\omega_k) \right] \quad (12)$$

is the information matrix,

$$\frac{\partial J(\theta)}{\partial \theta} = -2n_f \Re \left[\sum_{k \in K} \mathbf{S}^\dagger(j\omega_k) \hat{\mathbf{S}}_{vv}^{-1} \mathbf{v}(j\omega_k) \right] \quad (13)$$

is the local cost gradient, and

$$\mathbf{S}(j\omega_k) = \frac{\partial}{\partial \theta} \text{vec} [\hat{\mathbf{H}}(j\omega_k)] \quad (14)$$

is the frequency response sensitivity matrix, obtained from analytical partial derivatives or numerical finite differences.

The optimization is considered converged when the parameter estimates, cost function, cost gradient, and residual spectral density matrix converge within specified threshold values. At that point, the uncertainties in the parameter estimates are computed as the Cramér-Rao bounds

$$\text{cov}(\hat{\theta}) = \mathbf{M}^{-1} \quad (15)$$

where the standard errors of the model parameters are the square-root of the diagonal terms of this matrix.

E. Comparison with Other Methods

This section will compare and contrast the proposed approach for system identification of the CFD solver with other standard techniques.

VI. Results

A. Input Design

Multisine inputs were designed, as described in Section V.A, for 14 inputs: 11 structural modes of interest and 3 control surface deflections. The time duration was selected as $T = 20$ s to provide a relatively short excitation but with sufficient frequency resolution. The sampling time was selected as $\Delta t = 0.0025$ s (corresponding to 17 samples along the mean aerodynamic chord length) which was relatively coarse but used to decrease computation time for the CFD solution. The harmonics were selected between $k = 5$ and $k = 1600$, which corresponded to frequencies between 0.25 and 80 Hz, which spanned the frequency band of the structural modes of interest, as shown in Table 1. In total, there were 1596 harmonics excited, or 114 harmonics per input. Some parameters for the multisine input design are listed in Table 2. Due to the large number of inputs and harmonic frequencies, a complete description of the multisines used is not feasible here.

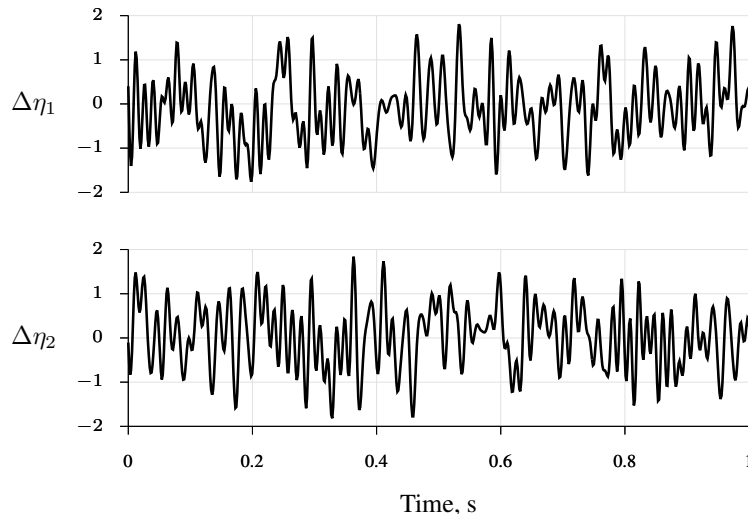
The harmonics were assigned to the different inputs in an alternating manner, but were staggered so that adjacent inputs did not have adjacent frequencies. The amplitudes for the structural mode displacements were selected such that

Table 2 Multisine input design, $T = 20$ s.

Input	Harmonics	Frequencies	Amplitude	RPF
u_j	k	k/T , Hz	a_k	
η_1	6, 20, ..., 1588	0.3, 1.0, ..., 79.4	0.0222	1.88
η_2	11, 25, ..., 1593	0.55, 1.25, ..., 79.65	0.0098	1.88
η_4	16, 30, ..., 1598	0.8, 1.5, ..., 79.9	0.0136	1.89
η_5	7, 21, ..., 1589	0.35, 1.05, ..., 79.45	0.0142	1.72
η_6	12, 26, ..., 1594	0.6, 1.3, ..., 79.7	0.0133	1.90
η_7	17, 31, ..., 1599	0.85, 1.55, ..., 79.95	0.0014	1.85
η_8	8, 22, ..., 1590	0.4, 1.1, ..., 79.5	0.0091	1.90
η_{10}	13, 27, ..., 1595	0.65, 1.35, ..., 79.75	0.0001	1.88
η_{13}	18, 32, ..., 1600	0.9, 1.6, ..., 80.0	0.0001	1.90
η_{14}	9, 23, ..., 1591	0.45, 1.15, ..., 79.55	0.0067	1.90
η_{18}	14, 28, ..., 1596	0.7, 1.4, ..., 79.8	0.0047	1.70
δ_{a_1}	5, 19, ..., 1587	0.25, 0.95, ..., 79.35	0.0937	1.82
δ_{a_2}	10, 24, ..., 1592	0.5, 1.2, ..., 79.6	0.0937	1.90
δ_{a_3}	15, 29, ..., 1597	0.75, 1.45, ..., 79.85	0.0937	1.90

the maximum displacement of each structural mode corresponded to 2% of the tip chord of the wing. The amplitudes for the control surface deflections were selected as 1 deg based on experience obtained from flight testing airplanes.

Figure 4 shows a segment of the first two perturbation inputs. Amplitudes are normalized in these plots, and only 1 s of the 20 s excitation is shown, for clarity. Although the time histories may appear random, they are summations of 114 sinusoids, per Eq. (5). The structural mode η_1 inputs contain harmonics $k = 6, 20, \dots, 1588$, while the aileron δ_{a_1} contains harmonics $k = 11, 25, \dots, 1593$. To within machine precision, the inner product between these two inputs (or any combination of the multisines) is zero, meaning they are orthogonal.

**Fig. 4 Sample of two structural mode displacement inputs.**

B. Time Histories and Frequency Responses

Before the input excitations could be applied to the CFD code, a trimming procedure was performed. This is depicted in Fig. 5 for the first two structural mode displacements and first 5 s of the simulation. First, FUN3D was coupled to the structural dynamics solver, and the damping ratio of the structural modes was increased. When the simulation initiated at $t = 0$ s, the solution quickly converged on the static-elastic deformations by about $t = 0.25$ s. The simulation was allowed to run for another 3.5 s to allow the flow to settle. With this trim condition obtained, FUN3D was decoupled from the structural dynamics solver, and the structural mode displacements and control surface deflections were prescribed. These inputs were the steady-state solutions with the multisines superimposed, as in Fig. 3. In total, the simulation was for about 25.75 s, which required about 3 days of processing time. Also evident in Fig. 5 are the relative amplitudes of the static structural displacements, as well as the amplitudes of the perturbations.

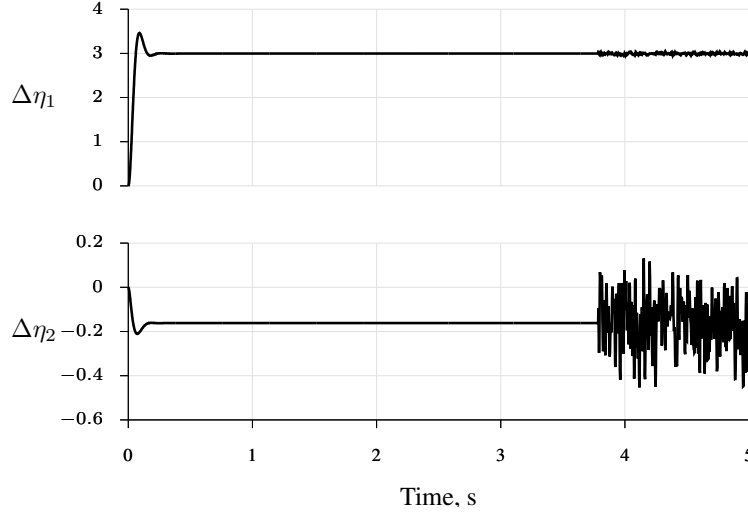


Fig. 5 Flow solver trimming and excitation.

Time histories for the GAFs corresponding to the first structural modes are shown in Fig. 6. These are shown for 1 s of excitation, starting at the excitation onset, for clarity.

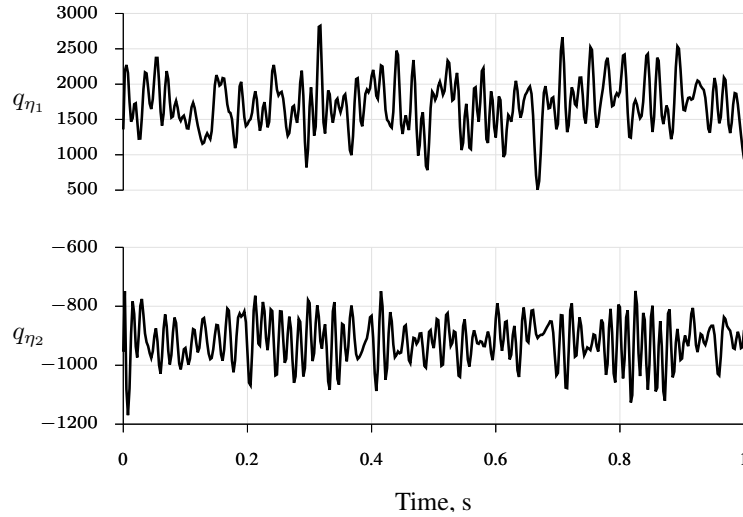
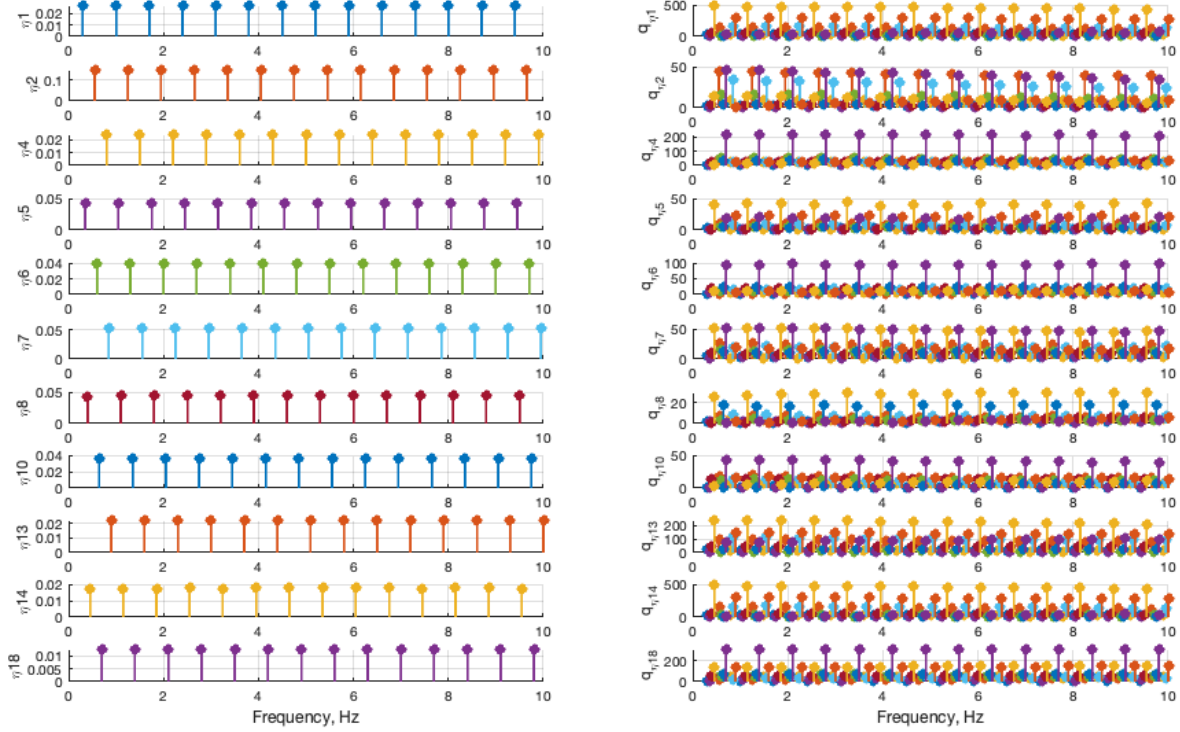


Fig. 6 Sample of two generalized aerodynamic force outputs.

Figure 7 shows Fourier transform magnitude data for the structural mode inputs and the corresponding GAF outputs. Content is only shown up to 10 Hz, instead of the full 80 Hz bandwidth, for clarity. The input data in Fig. 7(a) are

color-coded, and have power only at a set of unique, discrete frequencies in the multisines and used for the Fourier transforms. The output data show that all of the inputs participate in all the outputs because there is content at all frequencies.



(a) Input data.

(b) Output data.

Fig. 7 Fourier transform magnitudes of structural mode input data and corresponding GAF output data.

Figure 8 shows the frequency responses between the input structural mode displacements and the output GAFs. Only the first two structural mode displacements and GAFs are shown, for clarity. The frequency responses shown are empirical representations of the transfer functions $\mathbf{Q}(s)$ in Eq. (3). The marker color indicates the input and frequencies for which the frequency response was computed. Frequency responses, for the first three structural mode displacements and corresponding GAFs, are shown in Fig. 9 in terms of real and imaginary parts.

C. Model Structure Determination

This section will describe the results of model structure determination and the form of the transfer function and state-space models in Eqs. (3) and (4).

D. Parameter Estimation

This section will describe the results of parameter estimation for fitting the model frequency responses to the frequency response data.

E. Predictive Capability

This section will describe predictive capability of the identified reduced-order model, and compare predicted outputs to outputs of the CFD solver using different inputs than used for the identification.

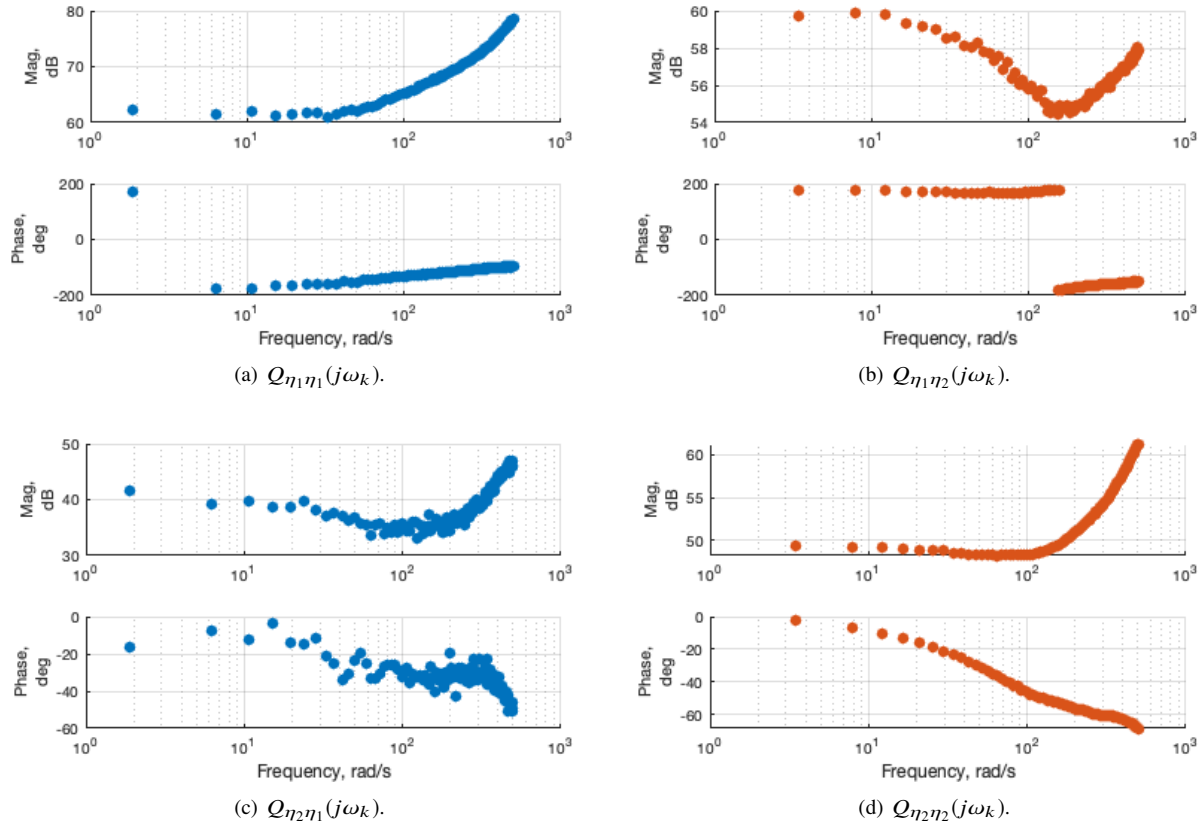


Fig. 8 Frequency responses as Bode plots.

VII. Discussion

This section will further discuss the results and make comparisons with the linear aerodynamic model and another reduced-order model determined using other techniques.

VIII. Conclusions

This section will discuss the conclusions of the paper.

Acknowledgments

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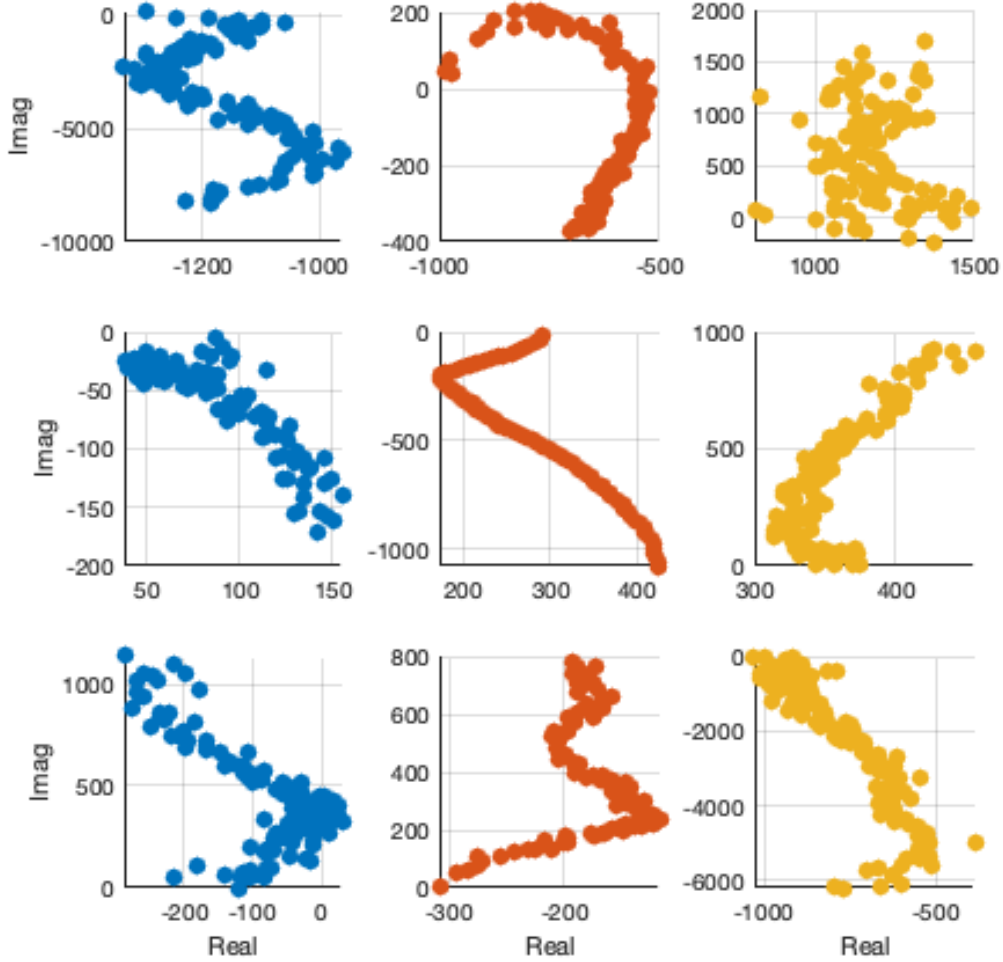


Fig. 9 Frequency responses as real and imaginary parts.

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