Advances in Aircraft System Identification at NASA Langley Research Center

Jared Grauer

Department of Mechanical & Aerospace Engineering
Princeton University
16 April 2024

Special Issue in the Journal of Aircraft

JOURNAL OF AIRCRAFT
Vol. 60, No. 5, September–October 2023

Check for updates

Introduction to the Advances in Aircraft System Identification from Flight Test Data Virtual Collection

https://doi.org/10.2514/1.C037583

Advances in Aircraft System Identification from Flight Test Data Virtual Collection:
https://arc.aiaa.org/toc/ja/Virtual+Collection/1

AIRCRAFT system identification is the process of determining mathematical models for aircraft from flight test data. As aircraft designs have become more complex and the capabilities of computers and experimental hardware have improved, system identification has become increasingly important for the efficient development of new aircraft. Applications for aircraft system identification include comparisons to theoretical predictions, simulation development and updating, stability and control assessment, control law development, flying qualities assessments, and stability margin extraction, among others.

During 2004–2005, Dr. Ravindra Jategaonkar from the Deutsches Zentrum für Luft- und Raumfahrt (DLR) organized an excellent two-part special section in the *Journal of Aircraft* on aircraft system identification. The primary motivations for that special section included reflecting on the recent expansion of techniques and applications of aircraft system identification, and addressing the perception that the practical utility of aircraft system identification was not well known. A total of 18 papers were published from different institutions, countries, and sectors of the aerospace community.

In the almost 20 years that have elapsed since that special section, aircraft system identification has continued to advance and expand in importance, as evidenced by its widespread presence. For example, the AIAA Atmospheric Flight Mechanics (AFM) conference typically hosts several sessions related to aircraft system identification at the yearly SciTech Forum. Likewise, papers on the subject routinely appear in the *Journal of Aircraft* and the *Journal of Guidance, Control, and Dynamics*. Short courses are periodically given by subject experts, and the number of graduate courses offered by universities has grown. Several software packages, which use a variety of methods, can now be accessed to perform system identification analyses. Perhaps most noteworthy is that in the year following the 2004–2005 special section, three textbooks on aircraft system identification from flight test data [1–3] were published. All three of these books are currently in their second editions [4–6] and have expanded content.

In talking with colleagues, it was apparent that the methods and applications have advanced significantly, and that another special section, now called a Virtual Collection (VC), in the *Journal of Aircraft* was warranted for sharing the current state of the art in aircraft system identification. A total of 58 people spanning 34 institutions from 8 countries (USA, Canada, Brazil, United Kingdom, France, Germany, the Netherlands, and Australia) and 3 sectors (government, industry, and academia) were invited to contribute a paper summarizing experiences and methods used at their institution related to aircraft system identification. For many reasons, including lack of time and the sometimes restrictive nature of information related to aerospace vehicles, about two-thirds of the organizations did not participate. Therefore, several groups of experts are absent from this VC. In the end, 10 organizations participated. The quality of the papers from the participating authors is high, and the contributions represent a balanced view of current and active practitioners.

The goal of this VC was to summarize experiences with aircraft system identification at leading institutions and to present methods that have been proven for specific problems, in particular those developed over the last 20 years. The primary focus was on system identification from flight test data rather than from simulation data or wind tunnel tests, although those subjects are also important.

The papers assembled for this VC exhibited several common themes, despite the fact that the papers describe work at different organizations. The vehicles studied were mostly small and low-cost aircraft or manned fixed-wing and rotary-wing aircraft, but there were also hypersonic vehicles and launch/re-entry vehicles. The dynamics of interest extended beyond the traditional rigid-body fixed-wing dynamics at low angles of attack and included more comprehensive models with aeroelasticity, high-order aerodynamics and rotor dynamics, icing, turbulence, high angles of attack and sideslip angles, and global nonlinear aerodynamics. In addition, the methods used to perform the system identification analysis are being advanced in similar areas of interest. Techniques are presented for creating or updating global model databases, designing efficient experiments, exploring time-varying dynamics, identifying models in the presence of high-gain feedback control systems, contending with the effects of both noise and disturbances, quantifying uncertainty, and identifying models in real time during a flight test.

Based on the practical utility and active development in aircraft system identification demonstrated in the papers of this VC, it is clear that aircraft system identification will remain an important and extensible skill that will aid the vehicle development process in the future. A continued effort to do this with more complex and descriptive global nonlinear models can be expected, with results available faster and/or in real time, and with more efficient and effective flight tests through advances in experiment design. Cheaper high-quality sensors, such as miniature inertial measurement units and fiber-optic strain sensors, are enabling system identification of flexible structures using distributed sensing and modeling. Although there are areas related to aircraft where machine learning and artificial intelligence may be usefully applied, these approaches have yet to exhibit significant benefits for aircraft system identification, perhaps due to the continued success and practical utility of physics-based and statistical modeling techniques.

In closing, we would like to acknowledge the work of the contributors to this VC. The authors have spent significant time and effort writing and revising their work for the benefit of this VC. In addition, each paper was anonymously peer-reviewed by several other contributing authors, and the comments in general were extremely thorough and constructive. These reviews by expert colleagues were arranged to ensure the accuracy and practical applicability of the material presented in the papers. We would also like to warmly thank the former Editor-in-Chief, Dr. Eli Livne, for approving this VC and enthusiastically supporting this effort. The current Editor-in-Chief, Dr. Mark Drela, has matched this support, which is similarly appreciated. In addition, we would like to thank Karina Bustillo from the AIAA and Liz Gibson from Technica Editorial Services for their work in publishing this VC.

References

[1] Klein, V., and Morelli, E., "Aircraft System Identification: Theory and Practice," Education Series, AIAA, Reston VA, 2006.

Downloaded by NASA LANGLEY RESEARCH CENTER on November 10, 2023 | http://arc.aiaa.org | DOI: 10.2514/1.C037583

- US Army: Berger, Tobias, Tischler, Juhasz
- NASA LaRC: Morelli, Grauer
- DLR: Deiler, Mönnich, Sehere-Weiß, Wartmann
- IPEV: Dias, Silva
- TUM: Hosseini, Steinert, Hofmann, Fang, Steffensen, Holzapfel, Göttlicher
- TAMU: Leshikar, Valasek, McQuinn
- Barron: Cooper, DeVore, Reed, Morelli
- TUDelft: de Visser, Pool
- VT: Simmons, Gresham, Woolsey
- STI: Lampton, Klyde, Schulze

Self Introduction

University of Maryland

credit: Grauer, 2011

NASA Langley Research Center

credit: NASA / Sandie Gibbs

Research Engineer Duties

Technical Analysis

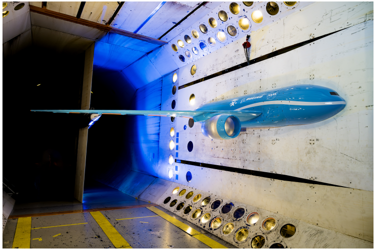
- IAWTM wind tunnel test
- X-59 low-boom flight demonstrator

Publications

- Conference papers, journal articles, and technical reports (`www.ntrs.nasa.gov`)
- Internal presentations and reviews

Professional Service

- Technical committees
- Journal reviewer
- Advise industry and academia
- Teaching



credit: NASA / Mark Knopp

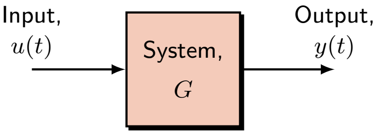
credit: Lockheed Martin Skunk Works

Introduction to Aircraft System Identification

What is System Identification?

"System identification is the determination, on the basis of observation of input and output, of a system within a specified class of systems to which the system under test is equivalent"

— Lofti Zadeh, 1962



Given $u(t)$ and $y(t)$, identify G

Uses of Aircraft System Identification

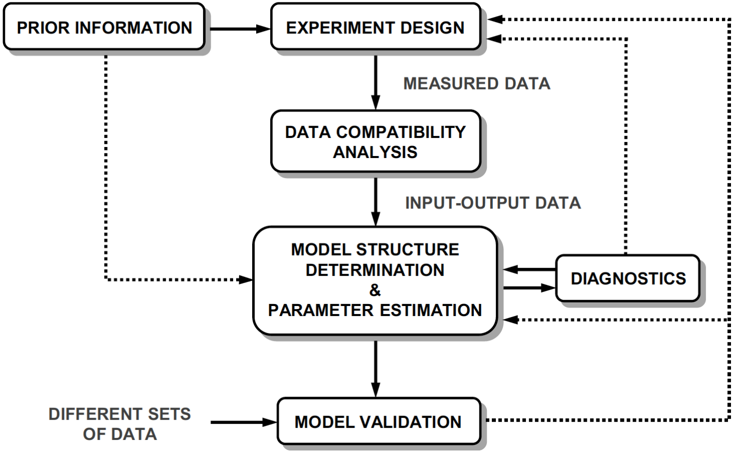
Aerodynamic Modeling

- Linear stability and control derivatives, e.g., C_{m_α} or M_α
- Nonlinear models, e.g., post-stall, unsteady aerodynamics, control interaction effects
- Validate prediction tools, e.g., wind tunnel tests, CFD, DatCom
- Update models for pilot simulation, mission rehearsal, control system tuning

System Modeling

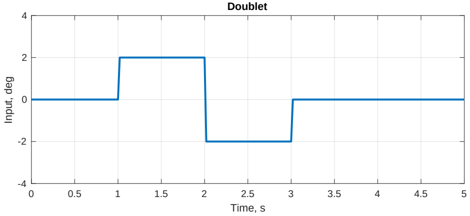
- Extract gain and phase margins for robustness analysis
- Verify controller performance
- Low-order equivalent systems (LOES) for flying qualities analysis, e.g., CAP
- Reduced-order models (ROMs)
- Characterize subsystems, e.g., actuators, sensor calibration errors, fault detection

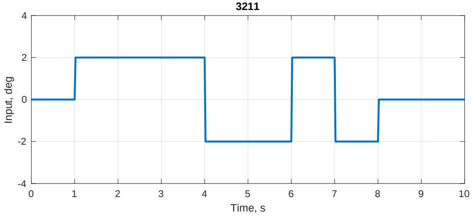
Flowchart for Aircraft System Identification

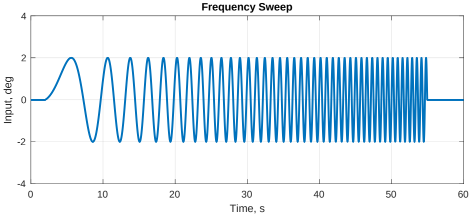


credit: Morelli & Klein, 2016

Traditional Inputs for Identification







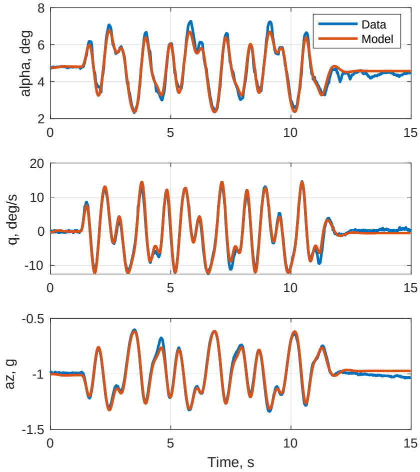
Output Error Parameter Estimation

Drive a simulation model with measured inputs, and adjust parameters until the modeled outputs "best" match the measured outputs in a *maximum likelihood* sense

$$\begin{bmatrix} \dot{\alpha} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} Z_\alpha & 1 \\ M_\alpha & M_q \end{bmatrix} \begin{bmatrix} \Delta\alpha \\ q \end{bmatrix} + \begin{bmatrix} 0 & b_{\dot{\alpha}} \\ M_{\delta_e} & b_{\dot{q}} \end{bmatrix} \begin{bmatrix} \delta_e \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} \alpha \\ q \\ a_z \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ \frac{V}{g} Z_\alpha & 0 \end{bmatrix} \begin{bmatrix} \Delta\alpha \\ q \end{bmatrix} + \begin{bmatrix} 0 & b_\alpha \\ 0 & b_q \\ 0 & b_{a_z} \end{bmatrix} \begin{bmatrix} \delta_e \\ 1 \end{bmatrix}$$

Parameter	Estimate	Std Error	% Error	95 % Confidence Interval
CZa	-4.210e+00	9.765e-02	2.3	[-4.406 , -4.015]
Cma	-1.581e+00	2.136e-02	1.4	[-1.624 , -1.538]
Cmq	-4.795e+01	2.023e+00	4.2	[-52.001 , -43.907]
Cmde	-1.820e+00	4.581e-02	2.5	[-1.912 , -1.729]
bad	-6.082e-03	1.866e-02	306.9	[-0.043 , 0.031]
bqd	-4.922e-02	8.447e-02	171.6	[-0.218 , 0.120]
ba	8.319e-02	2.052e-03	2.5	[0.079 , 0.087]
bq	-8.251e-03	1.683e-02	204.0	[-0.042 , 0.025]
baz	-1.004e+00	2.023e-02	2.0	[-1.045 , -0.964]

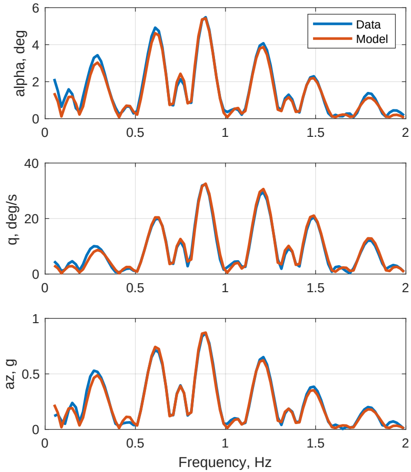


Output Error with Fourier Transform Data

Same idea, but match Fourier transform data over a bandwidth of interest instead of time history data with the analogous estimator

$$\begin{bmatrix} \alpha(j\omega) \\ q(j\omega) \\ a_z(j\omega) \end{bmatrix} = \frac{\begin{bmatrix} M_{\delta_e} \\ (j\omega - Z_\alpha)\, M_{\delta_e} \\ \frac{V}{g} Z_\alpha M_{\delta_e} \end{bmatrix} \delta_e(j\omega)}{-\omega^2 - (Z_\alpha + M_q)\, j\omega + (Z_\alpha M_q - M_\alpha)}$$

Parameter	Estimate	Std Error	% Error	95 % Confidence Interval
CZa	-4.198e+00	8.147e-02	1.9	[-4.361 , -4.035]
Cma	-1.574e+00	1.715e-02	1.1	[-1.608 , -1.540]
Cmq	-4.775e+01	1.691e+00	3.5	[-51.132 , -44.370]
Cmde	-1.818e+00	3.490e-02	1.9	[-1.888 , -1.748]

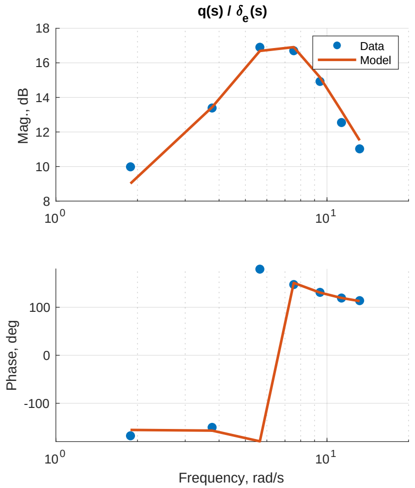


Frequency Responses and Parameter Estimation

Can also match the complex-valued MIMO frequency responses in a maximum likelihood sense

$$\begin{bmatrix} \dfrac{\alpha(j\omega)}{\delta_e(j\omega)} \\ \dfrac{q(j\omega)}{\delta_e(j\omega)} \\ \dfrac{a_z(j\omega)}{\delta_e(j\omega)} \end{bmatrix} = \dfrac{\begin{bmatrix} M_{\delta_e} \\ (j\omega - Z_\alpha)\, M_{\delta_e} \\ \frac{V}{g} Z_\alpha M_{\delta_e} \end{bmatrix}}{-\omega^2 - (Z_\alpha + M_q)\, j\omega + (Z_\alpha M_q - M_\alpha)}$$

Parameter	Estimate	Std Error	% Error	95 % Confidence Interval
CZa	-4.354e+00	4.981e-02	1.1	[-4.453 , -4.254]
Cma	-1.629e+00	1.445e-02	0.9	[-1.658 , -1.600]
Cmq	-5.002e+01	1.242e+00	2.5	[-52.508 , -47.542]
Cmde	-1.842e+00	2.559e-02	1.4	[-1.893 , -1.791]



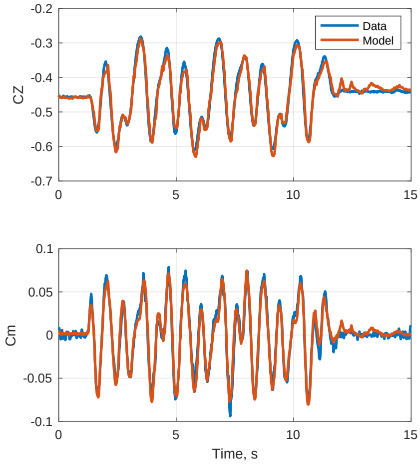
Equation Error Parameter Estimation

The aerodynamic modeling problem can usually be reworked into a least squares problem

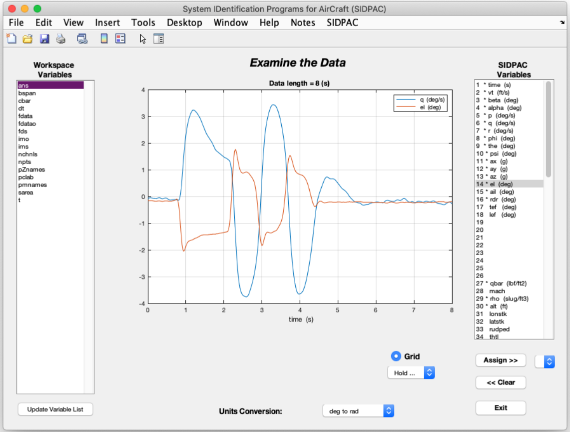
$$C_Z = C_{Z_0} + C_{Z_\alpha}\Delta\alpha$$

$$C_m = C_{m_0} + C_{m_\alpha}\Delta\alpha + C_{m_q}\frac{q\bar{c}}{2V} + C_{m_{\delta_e}}\Delta\delta_e$$

Parameter	Estimate	Std Error	% Error	95 % Confidence Interval
CZ0	-4.506e-01	1.596e-03	0.4	[-0.454 , -0.447]
CZa	-3.962e+00	9.234e-02	2.3	[-4.147 , -3.778]
Cm0	-2.440e-04	4.758e-04	195.0	[-0.001 , 0.001]
Cma	-1.402e+00	3.985e-02	2.8	[-1.482 , -1.323]
Cmq	-4.992e+01	2.812e+00	5.6	[-55.547 , -44.299]
Cmde	-1.695e+00	4.814e-02	2.8	[-1.791 , -1.599]



System IDentification Programs for AirCraft (SIDPAC)



https://software.nasa.gov/software/LAR-16100-1

Recent Applications at NASA LaRC

Some Recent Applications

T-2

Credit: NASA LaRC

X-56A

Credit: NASA AFRC

Modified F-15B

Credit: NASA AFRC

Ares I-X

Credit: NASA LaRC

X-43A Hyper-X

Credit: NASA LaRC

Bat-4

Credit: NASA LaRC

E1

Credit: NASA LaRC

S-2

Credit: NASA LaRC

credit: Morelli & Grauer, 2023

T-2 Generic Transport Model

credit: NASA Langley Research Center

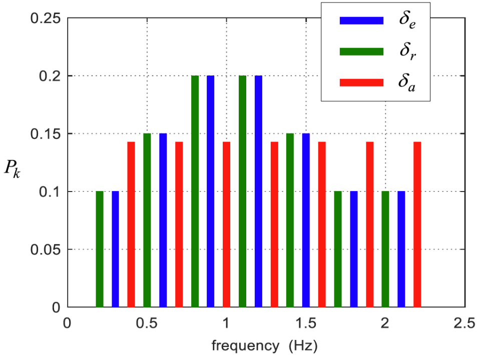
AirSTAR Mobile Operations Station

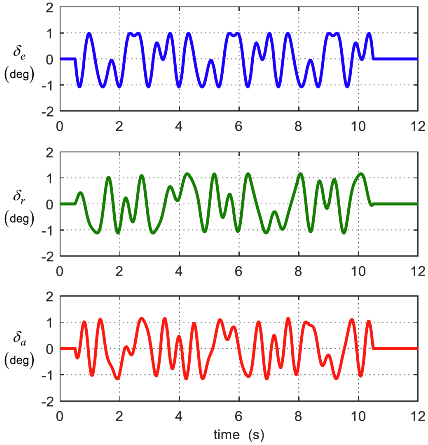
credit: NASA / Sean Smith

Recent Advancements at NASA LaRC

Orthogonal Phase-Optimized Multisine Inputs

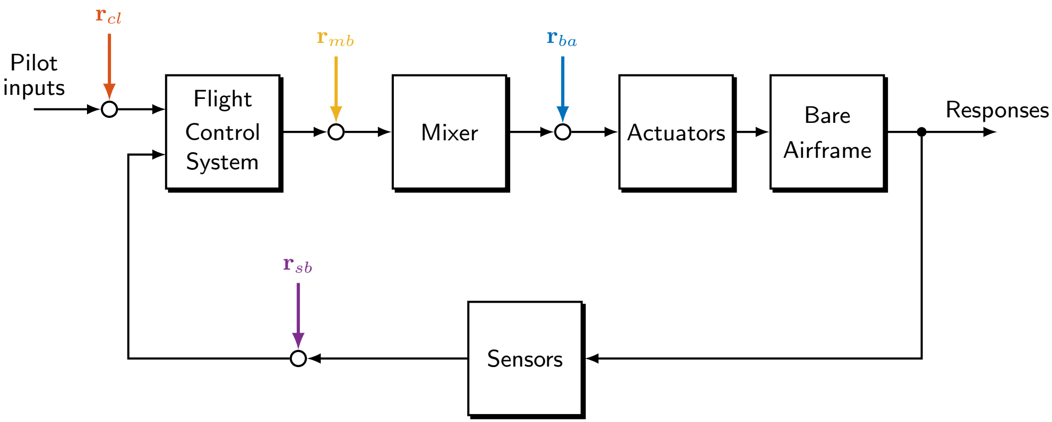
$$r_j(t) = \sum_{k \in K_j} a_k \sin\left(\frac{2\pi k}{T} t + \phi_k\right)$$





credit: Morelli & Grauer, 2023

Locations to Inject Multisine Inputs



credit: Grauer, 2022

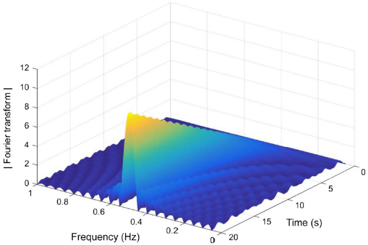
Real-Time Parameter Estimation with Equation Error

Recursive Fourier transform (25 Hz), e.g.,

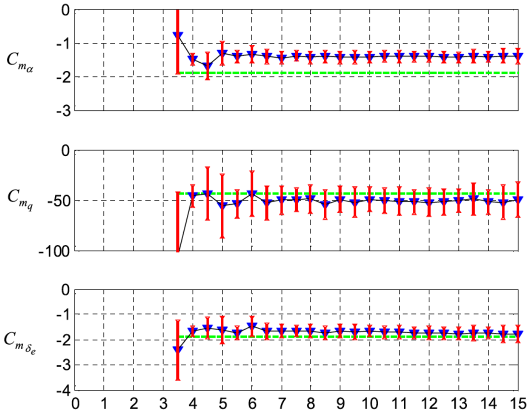
$$y(j\omega_k, t_i) = y(j\omega_k, t_{i-1}) + y(t_i)e^{-j\omega_k t_i}$$

Periodic updating of estimates ($\sim$ 1 Hz)

$$\hat{\boldsymbol{\theta}} = \left[\Re\left(\mathbf{X}^\dagger \mathbf{X}\right)\right]^{-1} \Re\left(\mathbf{X}^\dagger \mathbf{z}\right)$$



credit: Morelli & Grauer, 2020



credit: Morelli, 2012

Real-Time Estimation of MIMO Frequency Responses

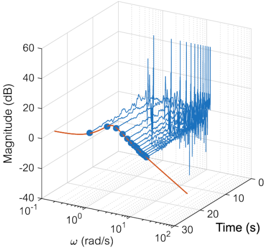
Apply multisine excitations before the actuators

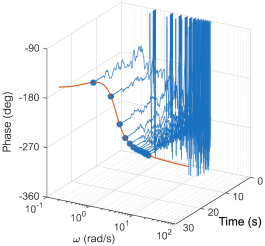
Recursive Fourier transform of the input and output data at the multisine frequencies, e.g.,

$$y(j\omega_k, t_i) = y(j\omega_k, t_{i-1}) + y(t_i)e^{-j\omega_k t_i}$$

Periodic updating (e.g., 1 Hz) of frequency response estimates from Fourier transforms

$$\hat{G}(j\omega_k, t_i) = \frac{y(j\omega_k, t_i)}{u(j\omega_k, t_i)}$$





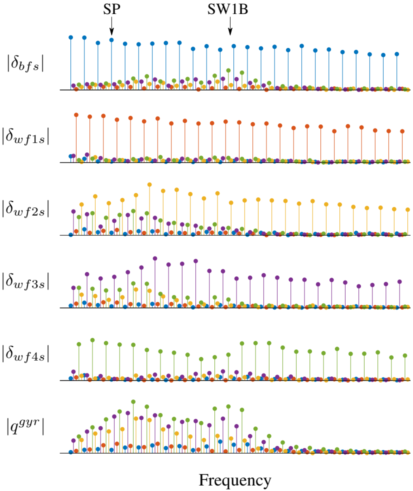
credit: Morelli & Grauer, 2020

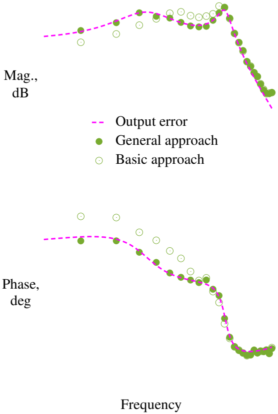
MIMO Frequency Responses from Closed-Loop Data

Feedback control correlates the plant input data and biases frequency response estimates

Joint input-output approach to correctly estimate plant dynamics from closed-loop data

$$\hat{G}(j\omega_k) = \frac{y(j\omega_k)}{r(j\omega_k)} \frac{r(j\omega_k)}{u(j\omega_k)}$$





credit: Grauer & Boucher, 2020

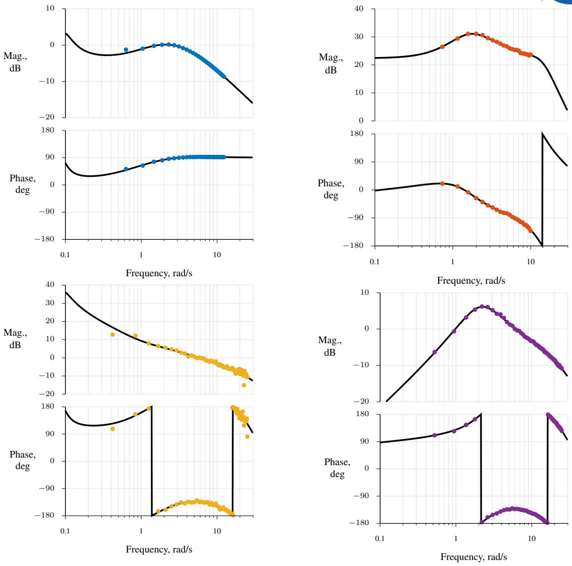
Multiple-Loop MIMO Frequency Response Estimation

Can add multisines to multiple points within the system for simultaneous frequency response estimation of different MIMO loops

- Bare airframe
- Closed loop
- Broken loop at mixer
- Broken loop at sensors

credit: NASA / Jim Ross

credit: Lockheed Martin Skunk Works



credit: Grauer, 2022

Turbulence Reconstruction as a Measured Input

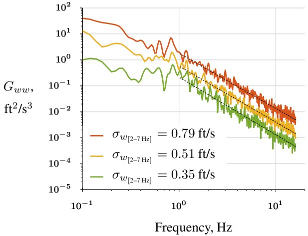
Atmospheric turbulence can be thought of as an unmeasured input acting on the system

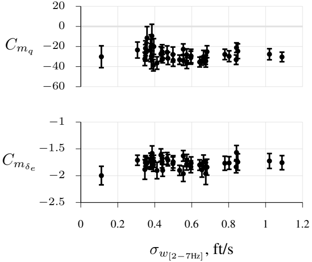
One approach is to reconstruct the turbulence from other data and use it in the modeling

The original concept is from the 1950's, e.g.,

$$\alpha_m = \alpha - \frac{x_a}{V} q + \frac{y_a}{V} p + \alpha_g$$

credit: NASA Langley Research Center

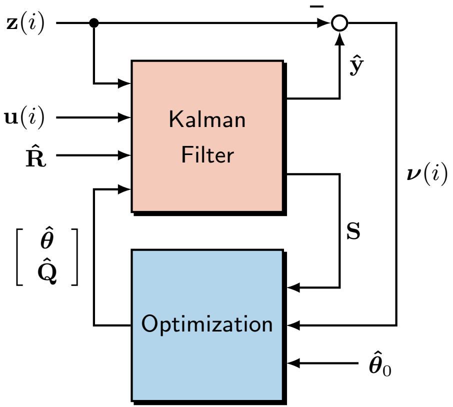


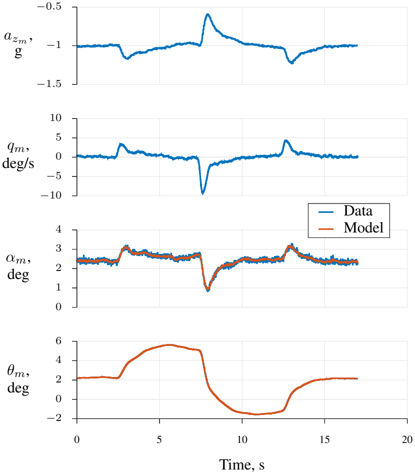


credit: Grauer, 2021

Filter Error Parameter Estimation

Another approach is to use maximum likelihood estimators that explicitly account for process noise and disturbances



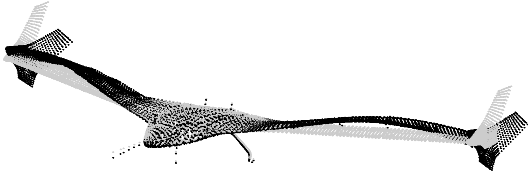


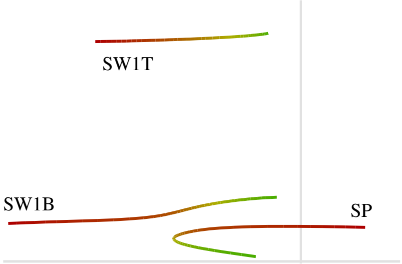
credit: Grauer & Morelli, 2015

X-56A Aeroelastic System Identification

Aeroservoelasticity in the X-56A

- Created a flutter instability
- Coupled with rigid-body dynamics
- Interacted with the control system
- Observed in sensor data





credit: Grauer, 2020

Linear quasi-steady models for identification:

$$\begin{bmatrix} \dot{\mathbf{x}}_r \\ \dot{\mathbf{x}}_e \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{rr} & \mathbf{A}_{re} \\ \mathbf{A}_{er} & \mathbf{A}_{ee} \end{bmatrix} \begin{bmatrix} \mathbf{x}_r \\ \mathbf{x}_e \end{bmatrix} + \begin{bmatrix} \mathbf{B}_r \\ \mathbf{B}_e \end{bmatrix} \mathbf{u}$$

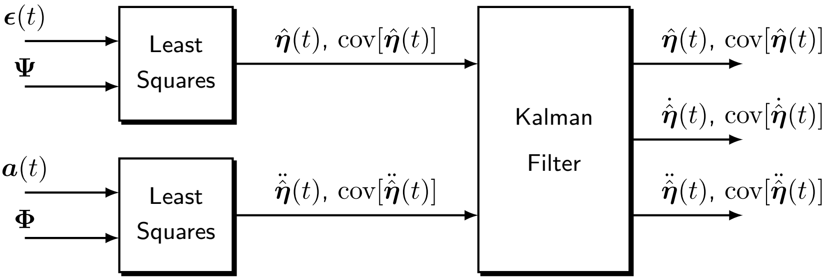
$$\mathbf{y} = \begin{bmatrix} \mathbf{C}_r & \mathbf{C}_e \end{bmatrix} \begin{bmatrix} \mathbf{x}_r \\ \mathbf{x}_e \end{bmatrix} + \mathbf{D}\mathbf{u}$$

Modal State Estimation from Multiple Sensors

Vibration states are measured in linear combination and not directly by sensors

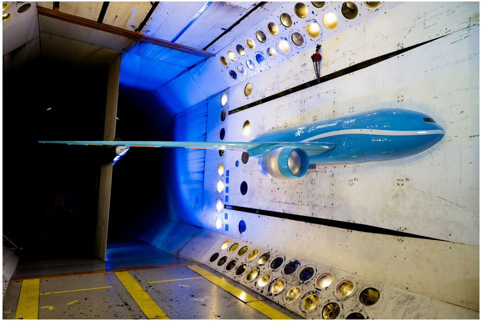
An abundance of strain and accelerometer measurements with an accurate finite element model facilitates estimation of modal displacements, rates, and accelerations

This can be used for aeroelastic system identification and feedback control



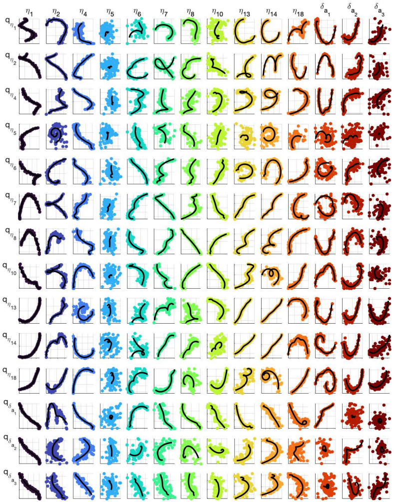
credit: Grauer & Boucher, 2018 and Grauer & Waite, 2021

Unsteady Aerodynamics ROM from CFD



credit: NASA / Mark Knopp

Computed the full 14x14-element frequency response matrix and modeled it with rational function approximations from a single CFD run



credit: Grauer, Waite, & Stanford, 2021

Summary and Future Outlook

Active research field with several open problems

Helpful to have a variety of modeling tools, e.g., SIDPAC

Expect continued emphasis on

- Real-time identification
- Efficient testing and rapid model update
- Aeroelastic systems and spatially-distributed sensors
- Large-amplitude maneuvers and unusual conditions
- High-order and nonlinear modeling
- Non-conventional vehicle configurations