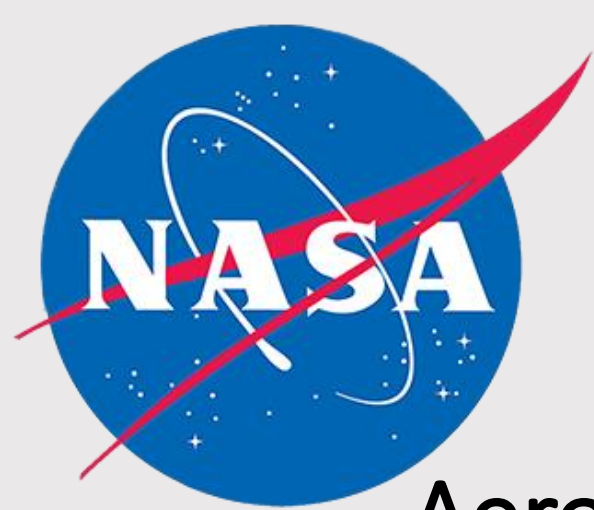




AeroFusion: Data Fusion and Uncertainty Quantification for Entry Vehicles

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NASA Langley Research Center

NASA AeroFusion-MLUQ Early Career Initiative

AIAA SciTech Forum

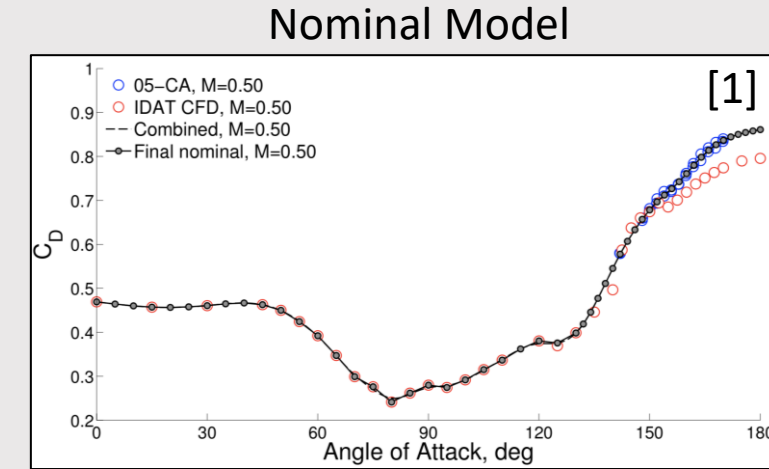
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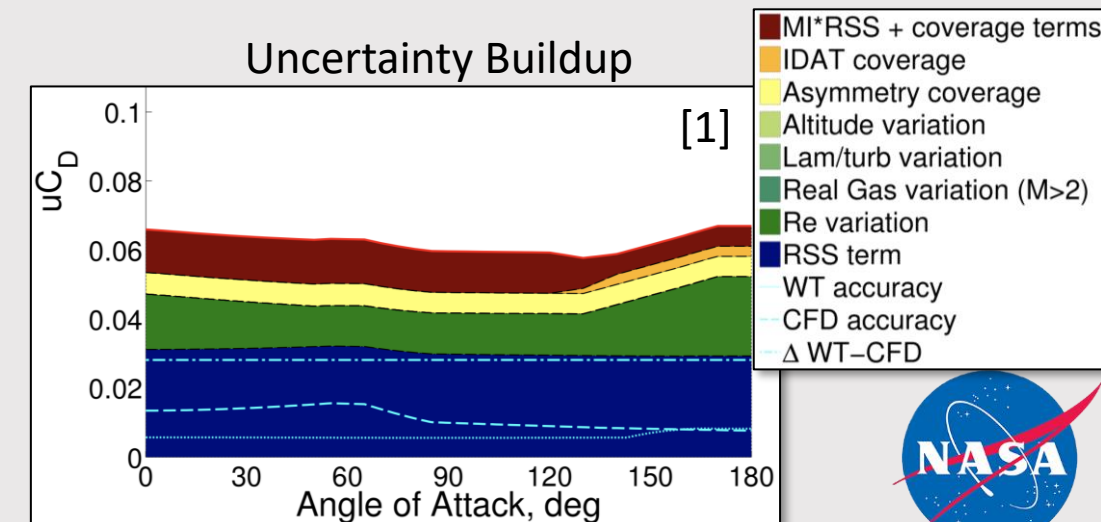
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Can We Improve the Aerodynamic Modeling Process?

- Current process:
 - is often ad hoc
 - has high dependence on engineering judgment
 - does not use data efficiently
- We would like to:
 - make process more consistent
 - reduce dependence on engineering judgment
 - extract the most information out of our data



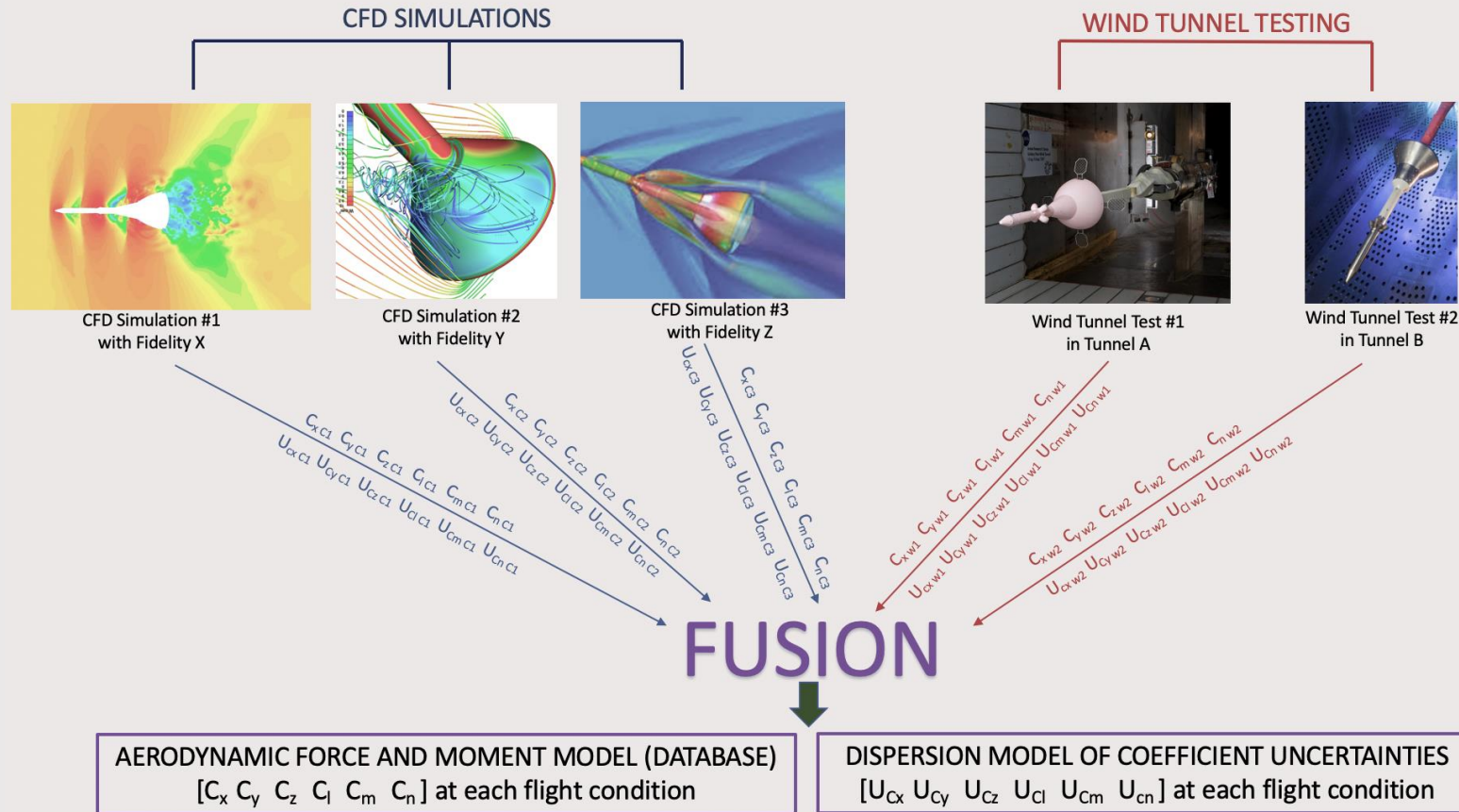
$$uC_D = \delta_{Re} + MI_{hs}MI_{idat}MI \cdot k \sqrt{(\sigma_{wt2cfd})^2 + (\max\{\sigma_{wt}, \sigma_{cfd}\})^2}$$



[1] Bibb et al., "Development of the Orion Crew Module Static Aerodynamic Database, Part I: Hypersonic & Part II: Subsonic/supersonic"



What is AeroFusion?



Fidelity based on:

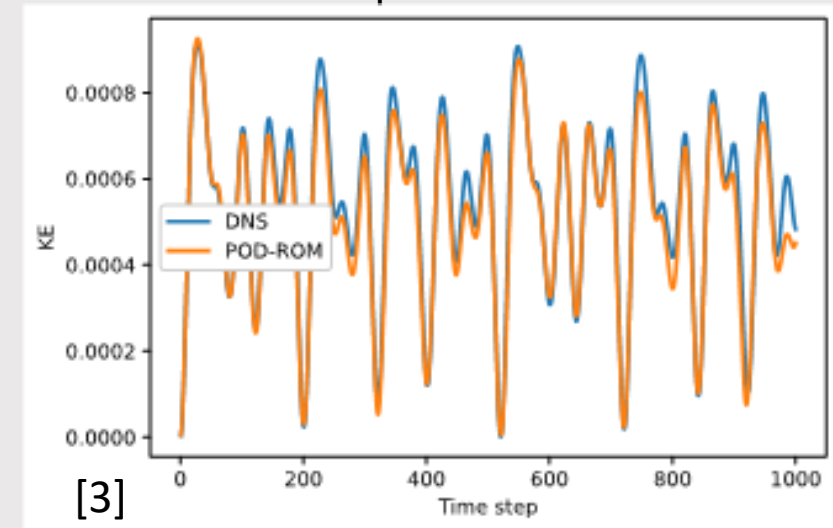
- Outer Mold Line (OML)
- Modeling Assumptions
- Resolution
- Noise Levels
- Etc.

Creating and Using Low-Fidelity Data

- Reduced-order models (ROMs) provide computationally efficient means of producing large amounts of additional data [1]
- Sensitivity analysis can therefore be performed at reduced cost [2]
- Trends can be extracted by interpolating between ROMs [3]
- Simplified physics models (such as RANS) can be used to study aerodynamic trends under different simplifying assumptions [4]

Training Data at Re=16k, 17.5k

Results Interpolated at Re=17k



[1] Ramezani et al., “Application of an Affine Nonlinear Galerkin Reduced-order Model to Compressible Fluid Flows”

[2] Hanes et al., “Low-cost Quantification of Fluid Flow Parameter Sensitivity using Reduced-order Modeling”

[3] Edwards et al., “Quantifying Emergent Fluid Dynamics Using Reynolds-Interpolated Reduced-Order Models”

[4] Buchmeier et al., “Parametric Studies of Subsonic and Supersonic Reentry Phases of the Orion Crew Module



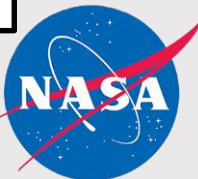
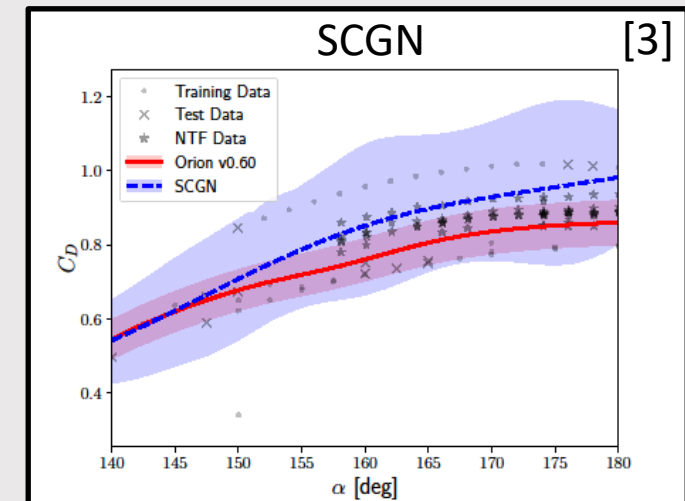
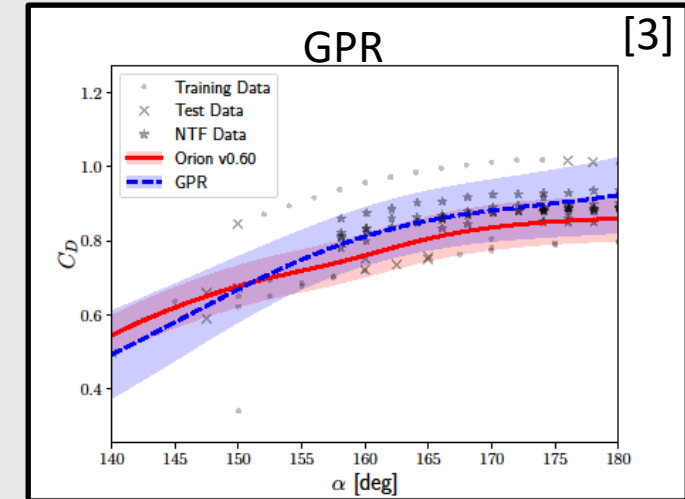
Surrogate Modeling

- Structured covariance Gaussian networks (SCGN) can be created to efficiently produce a distribution of models that fit the given data [1]
- Gaussian process regression (GPR) can be modified to allow for hierarchical data of different levels of fidelity [2]
- Comparing models and distributions of models is challenging; many different metrics possible [3]

[1] Nakamura-Zimmerer et al., “Structured Covariance Gaussian Networks for Orion Crew Module Aerodynamic Uncertainty Quantification”

[2] Scoggins et al., “Multihierarchy Gaussian Process Models for Probabilistic Aerodynamic Databases using Uncertain Nominal and Off-Nominal Configuration Data”

[3] Wignall et al., “Comparisons of Performance Metrics and Machine Learning Methods on an Entry, Descent, and Landing Database”

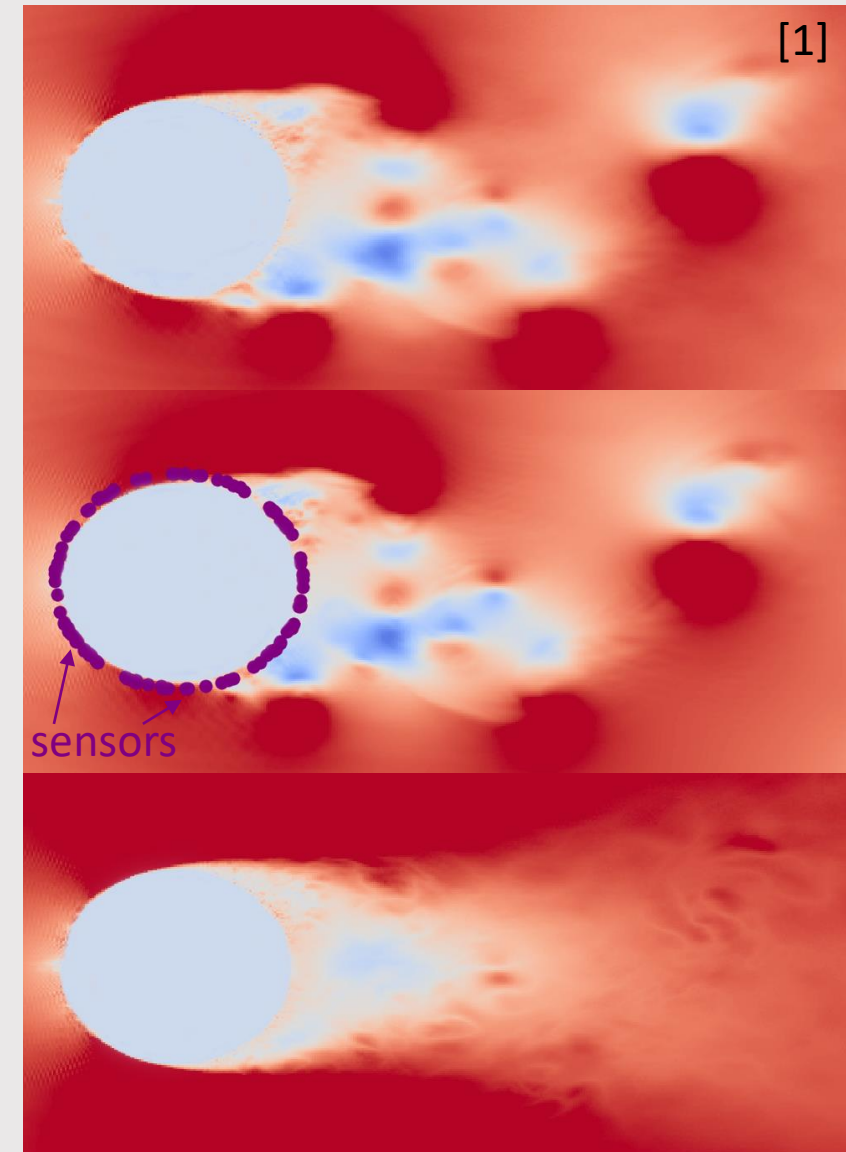


Data Fusion

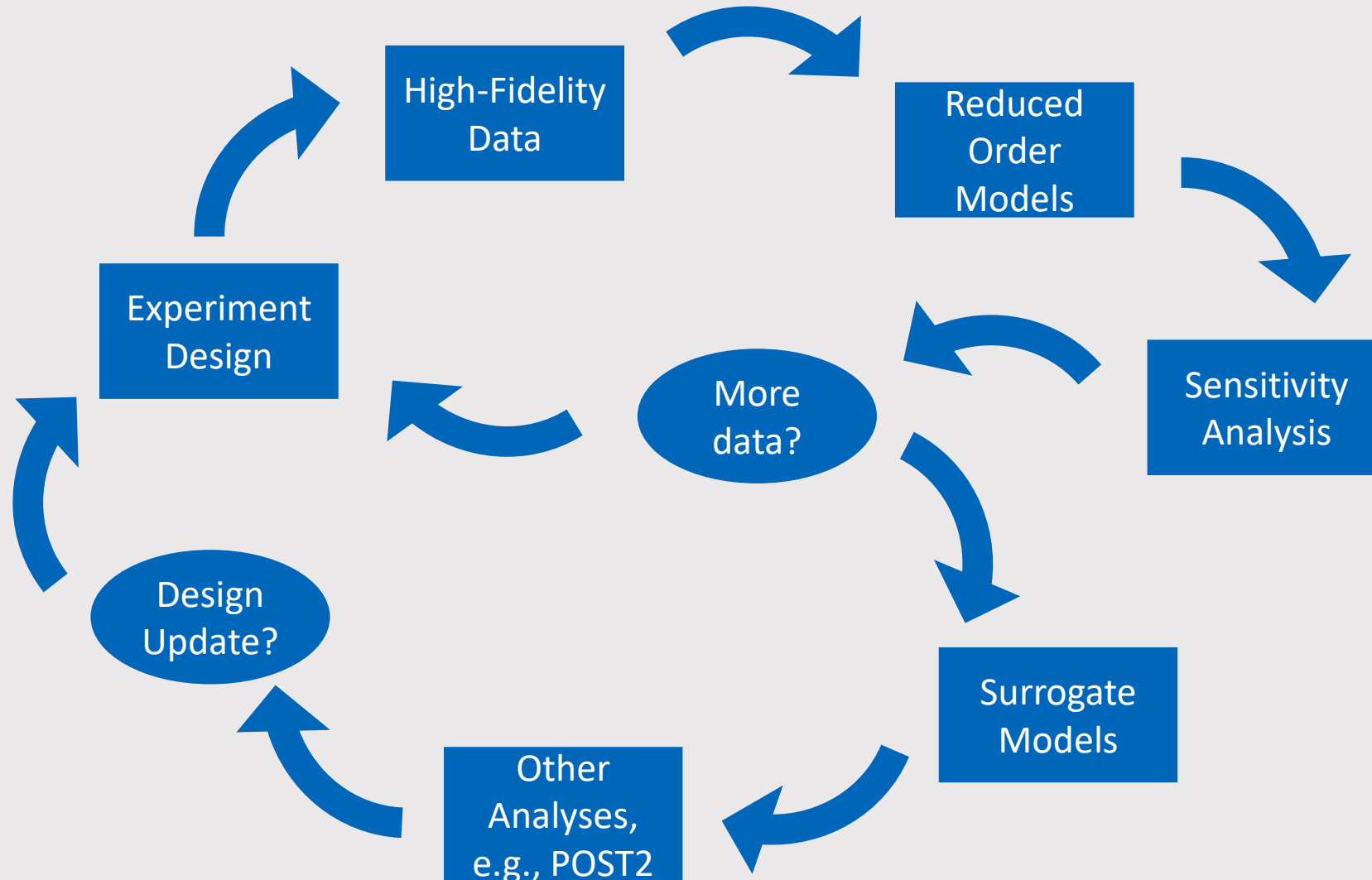
- Full flowfields can be reconstructed from discrete measurements [1]
- Applying sensitivity analysis to that provides UQ and can help with optimal sensor placement [2]
- Flowfield reconstruction can be useful for comparing spatially sparse WTT data and spatially dense CFD results

[1] Lebedev et al., “Construction of a Fluid Flowfield from Discrete Point Data using Machine Learning”

[2] Hanes et al., “Convergent Uncertainty Quantification in Fluid Dynamics using Reduced-order Models and Machine Learning”



Combining the Technologies



Contact with Questions

- steven.m.snyder@nasa.gov
- How can AeroFusion help you?
- How can you help AeroFusion?

