AEROFUSION-MLUQ

Mars Lander Aerodynamic Model Data Fusion

Using Machine Learning with Embedded Uncertainty Quantification

NASA Space Technology Mission Directorate

EARLY CAREER INITIATIVE FY 2021/2022

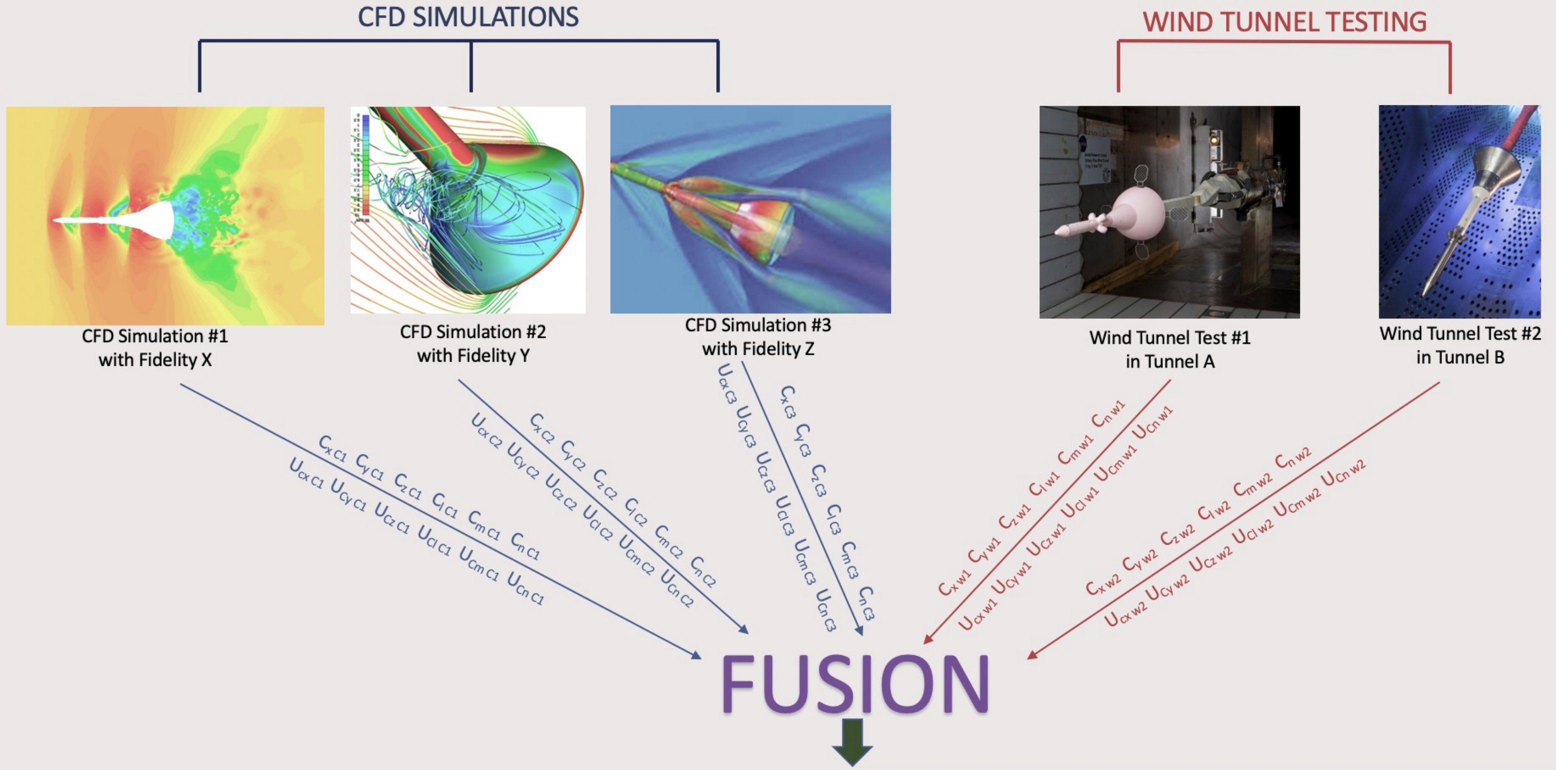
Project Leads: Steve Snyder and TJ Wignall

EDL Seminar Series

4 August 2022

Project Overview

The AEROFUSION team was selected to look at leveraging and extending data science advances to modernize the aerodynamic model data fusion process for the Mars EDL application- specifically large payload and manned missions that require novel aero shells.



AERODYNAMIC FORCE AND MOMENT MODEL (DATABASE)
$[C_x\ C_y\ C_z\ C_l\ C_m\ C_n]$ at each flight condition

DISPERSION MODEL OF COEFFICIENT UNCERTAINTIES
$[U_{Cx}\ U_{Cy}\ U_{Cz}\ U_{Cl}\ U_{Cm}\ U_{cn}]$ at each flight condition

The team will utilize the extensive collection of Orion aerodynamic test data to leverage and workshop modern methods and extend their capabilities to meet the needs of the aerospace application.

NASA Alignment:

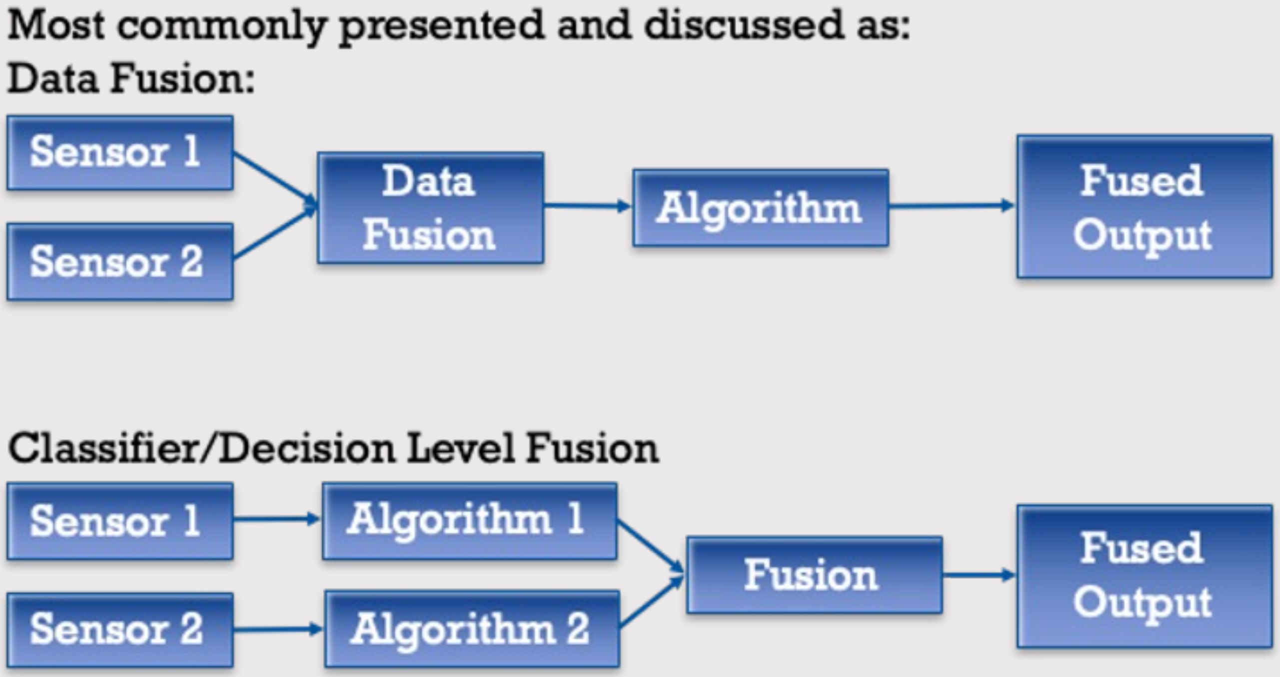
- Innovative Concepts for Landing 20 mt on Mars (LARC STIP)
- Land: Expanded Access to Diverse Surface Destinations (STMD CAPABILITY)
  - Human & Robotic Entry, Descent and Landing (EDL)
  - Precision Landing

Crewed Mars Mission EDL Challenges:

- Novel vehicle designs cannot leverage risk-reducing aeroshell or deceleration tech reuse
- Computationally expensive aerodynamic model development process for data fusion and UQ conducted by inspection results in labor intensive SME event with conservative coverage factors on dispersion models
- Robust control law development for EDL precision landing and terrain relative navigation are highly dependent on aerodynamic force and moment coefficients and uncertainty dispersions

Approaches to Data Fusion

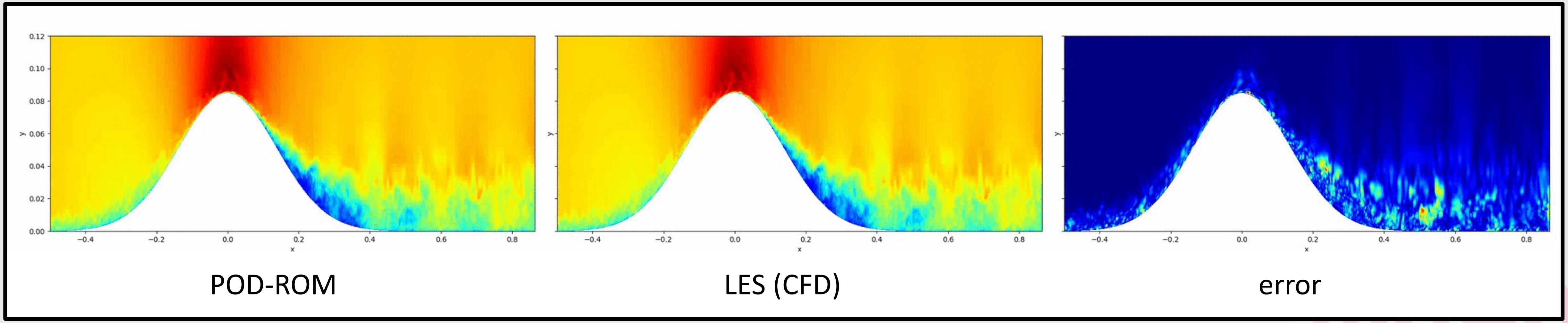
- Data can be fused at different levels
  - WT and CFD forces/moments to output forces/moments
  - Fluid temperatures and pressures to output fluid velocity
  - Flow fields determined via different procedures to output flow fields



Modeling Fluid Volume Data

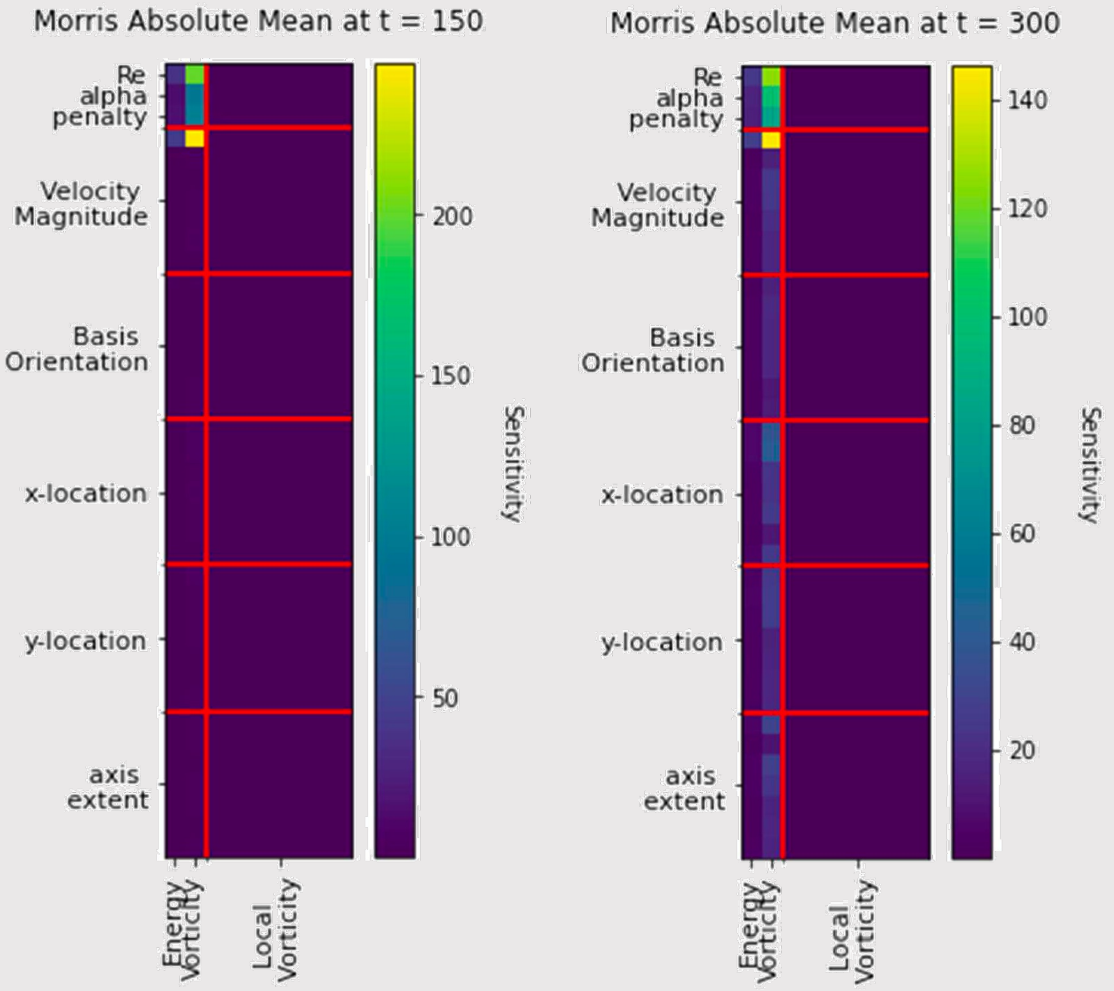
Fluid Reduced-order Model (ROM)

- Pattern recognition from CFD snapshots
  - Linear algorithm like from Proper Orthogonal Decomposition (currently used)
  - Nonlinear algorithm like Shallow Neural Network (not currently used)
- Use patterns to run low-cost physics-based fluid simulations
  - Can make 100 CFD iterations produce 1000s of iterations worth of data
  - Can make 100 CFD simulations (sparse α, Ma, etc.) produce data at other conditions
  - Can make rigorous CFD uncertainty quantification computationally tractable



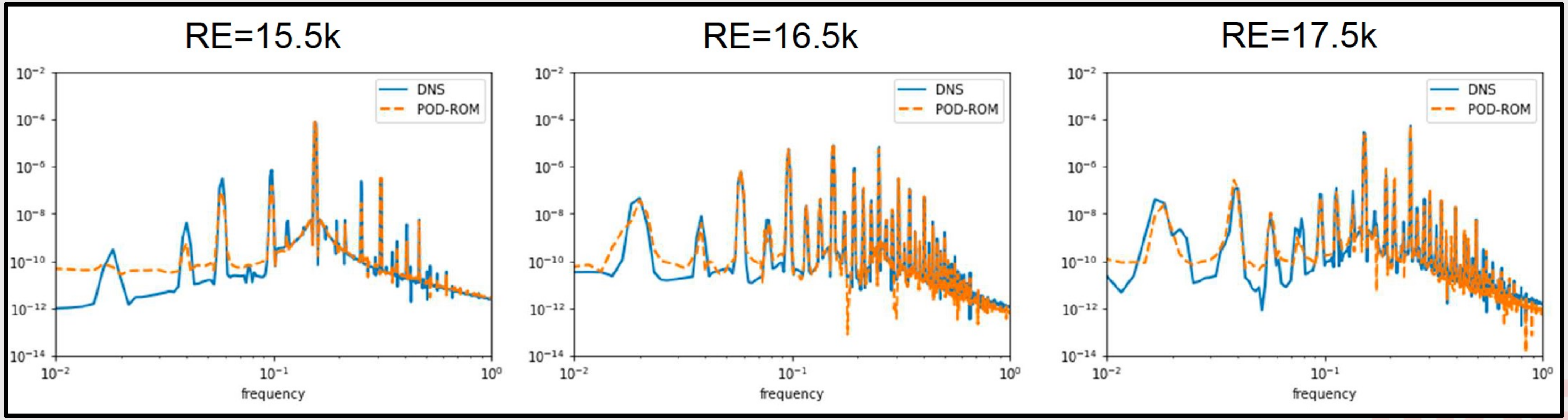
ROMs for Parameter Sensitivity

- Quantify simulation sensitivity to all known parameters at low cost
  - Surface roughness
  - Upstream turbulence
  - Incidence fluctuations
- Morris Screening (right) is a global estimator of this sensitivity
- Parameter Subset Selection (under development) is a local estimator of this sensitivity



ROMs for Parametric Interpolation

- Buffet and flutter prediction requires fluid frequency information that is often too complex for QoI models to anticipate
- A patched-basis ROM correctly interpolates frequency shifts (below ROMs were only given data at Re = [15k, 16k, 17k, 18k])

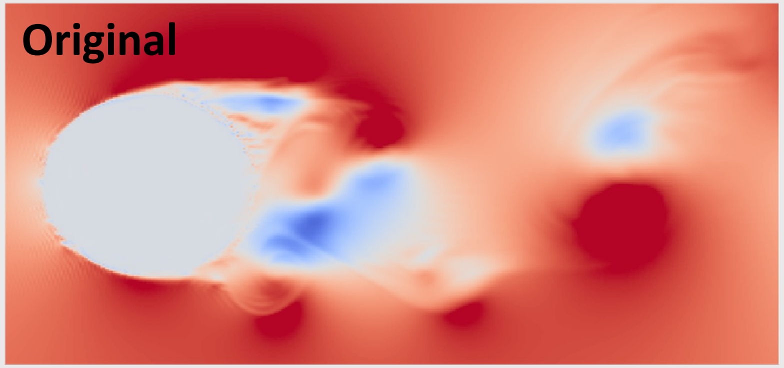


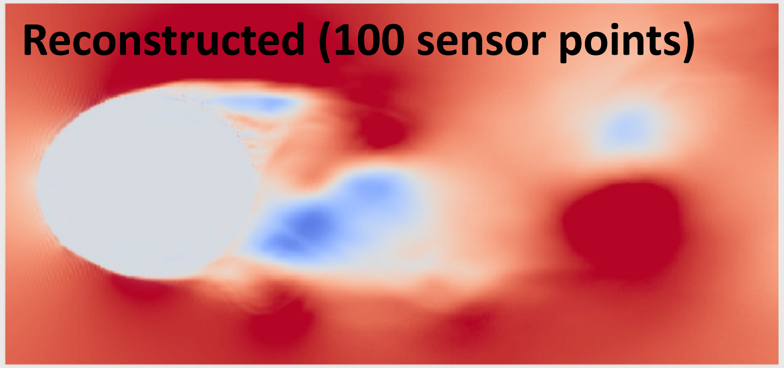
Sensor Upscaling Neural Network

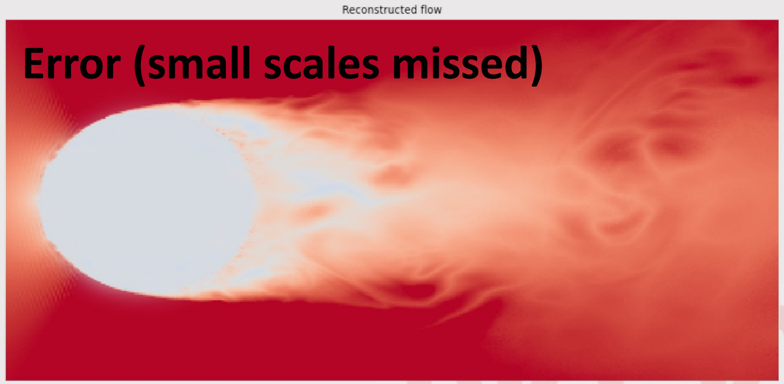
- Model trained (on CFD data) to draw volume-filling fluid snapshots given only the tap data that would be available in a wind tunnel test

- Ongoing work to anticipate the necessary number of points for a given flow type

- Even with high quantitative error, the qualitative pattern agreement can be invaluable for WT-CFD comparisons and elucidating confusing results that may come from a tunnel test







Modeling Quantities of Interest

Existing Method of UQ for Orion

- Lots of engineering judgment required
- Unclear what the uncertainty bounds that are tested represent → conservatism

$$UC_x = \delta_{Re} + MI_{hs} MI_{idat} MI k \sqrt{\sigma^2_{wt2cfd} + \max(\sigma^2_{wt}, \sigma^2_{cfd})}, \quad (M < 1)$$

$$UC_x = \delta_{ltp} + \delta_{chem} + \delta_{hs} + MI_{idat} MI k \sqrt{\sigma^2_{wt2cfd} + \max(\sigma^2_{wt}, \sigma^2_{cfd}}, \quad (M > 1)$$

$$k = \sqrt{3}$$

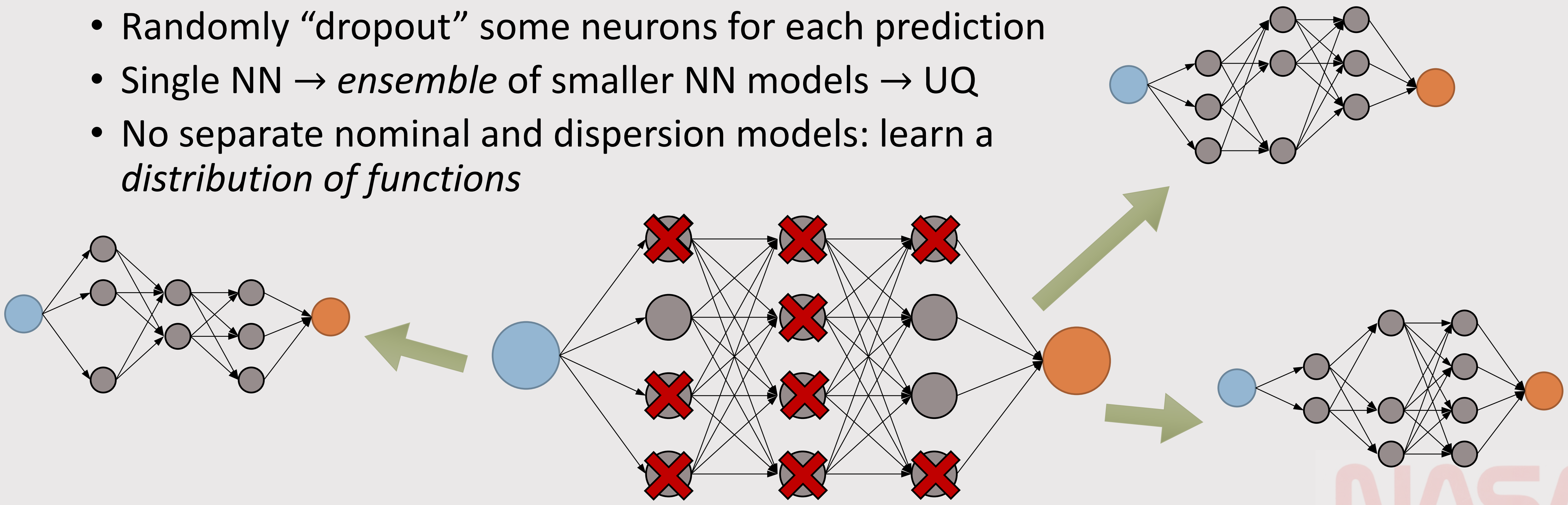
$$MI_{idat} = \begin{cases} 1.0 & \text{if } \alpha \leq 120^\circ \\ \text{linear} & \text{if } 120^\circ \leq \alpha \leq 140^\circ \\ 1.1 & \text{if } \alpha \geq 140^\circ, \ M \leq 1.4 \\ 1.0 & \text{if } M > 1.4 \end{cases}$$

$$MI_{hs} = 1.2$$

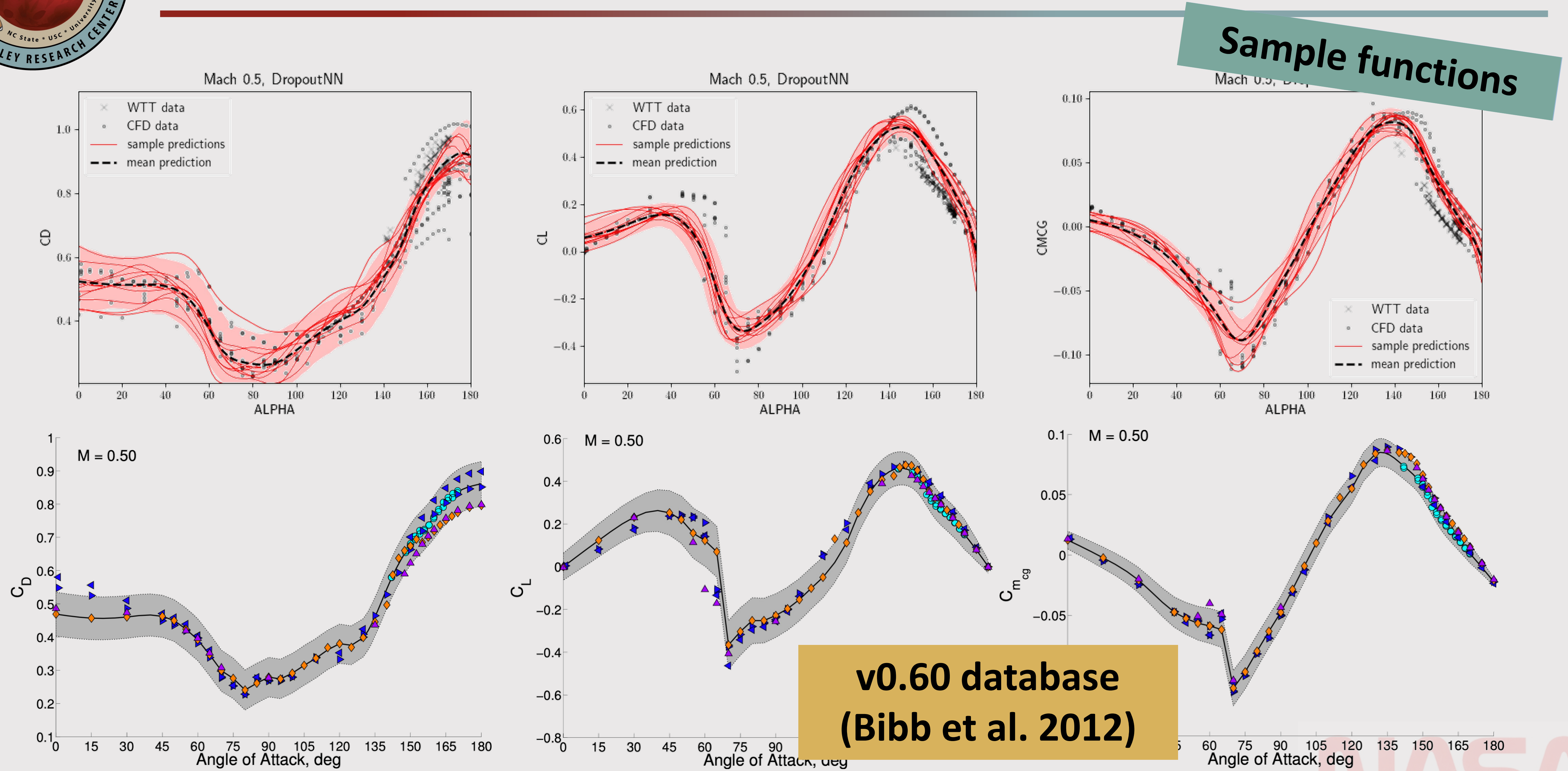
$$MI = \begin{cases} 1.4 & \text{if } \alpha \leq 120^\circ \\ \text{linear} & \text{if } 120^\circ \leq \alpha \leq 140^\circ \\ 1.2 & \text{if } \alpha \geq 140^\circ \end{cases}$$

Aero Models for Orion: Dropout NN

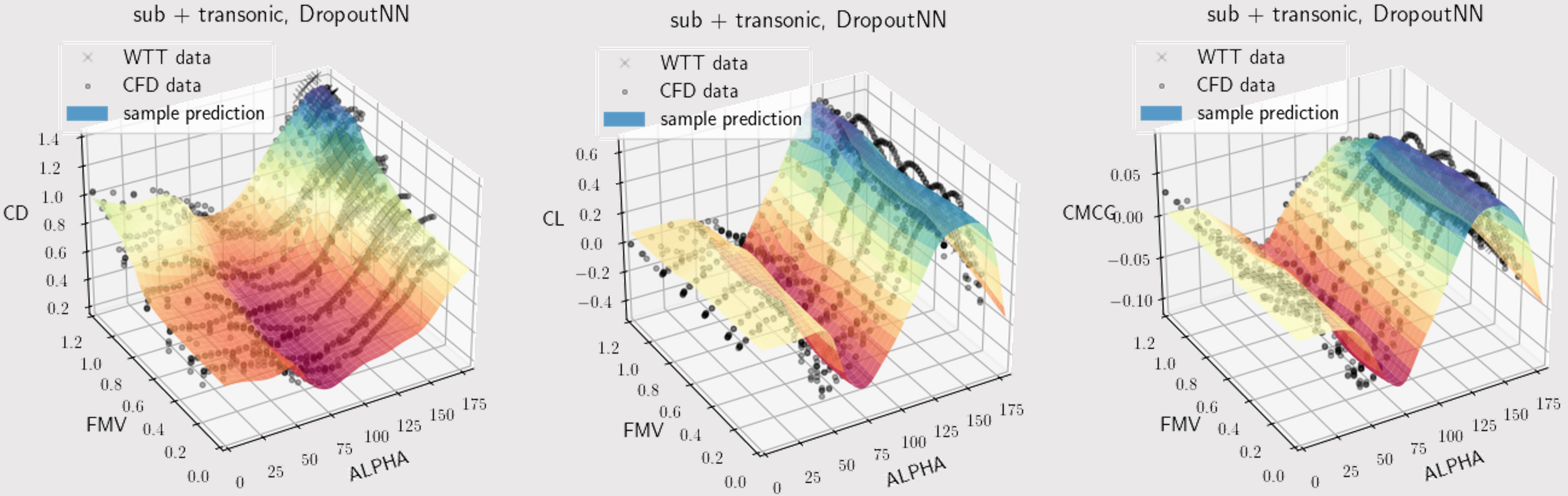
- CFD + WTT data used in v0.60 database
- Dropout neural network:
  - Same structure as standard NN
  - Randomly “dropout” some neurons for each prediction
  - Single NN → *ensemble* of smaller NN models → UQ
  - No separate nominal and dispersion models: learn a *distribution of functions*



Aero Models for Orion – Results: Dropout NN



Aero Models for Orion – Results: Dropout NN

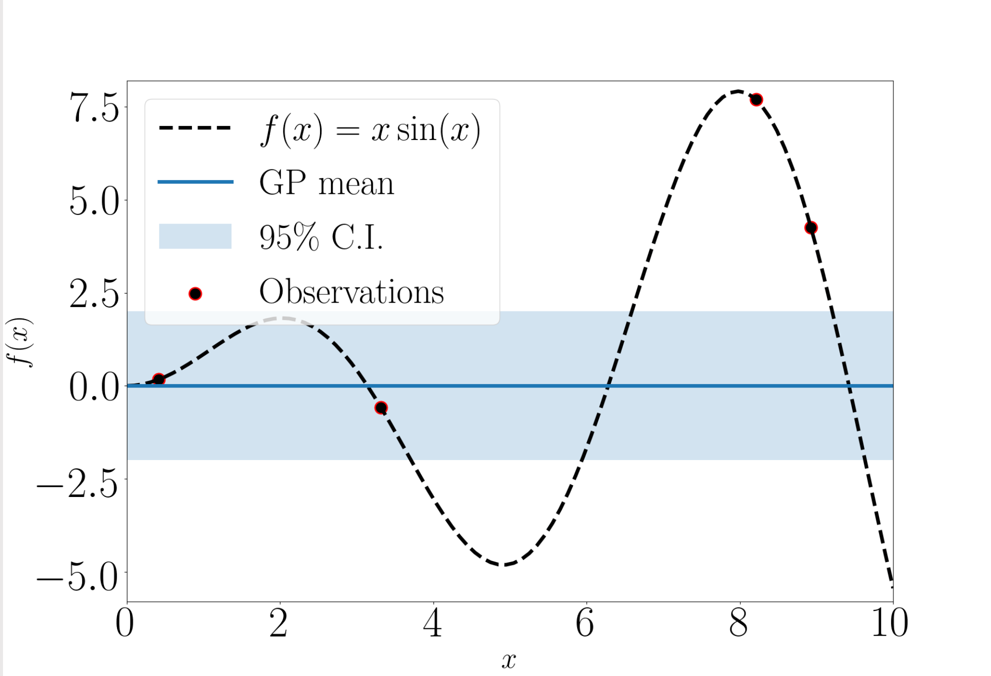


- 2d "slices" at $\beta = 0°$
- Sample *functions*: vary according to learned function distribution

Aero Models for Orion: NARGP

- Gaussian Process Regression (GPR):
  - "Non-parametric" model representing a gaussian distribution over functions
  - Interpretable hyper-parameters learned by maximizing likelihood that the model distribution would produce the dataset when sampled
- Multi-fidelity GPs:
  - Leverage low fidelity data ($) to learn high fidelity data ($$$)
  - Reduce amount of high fidelity required for same accuracy
  - Correlation between fidelity levels is learned along with the data
  - Many different approaches: (non)linear, (non)hierarchical
- Nonlinear Autoregressive GP (NARGP):
  - Learns a nonlinear correlation between fidelity levels

    f2(x) = GP(x, f1(x))

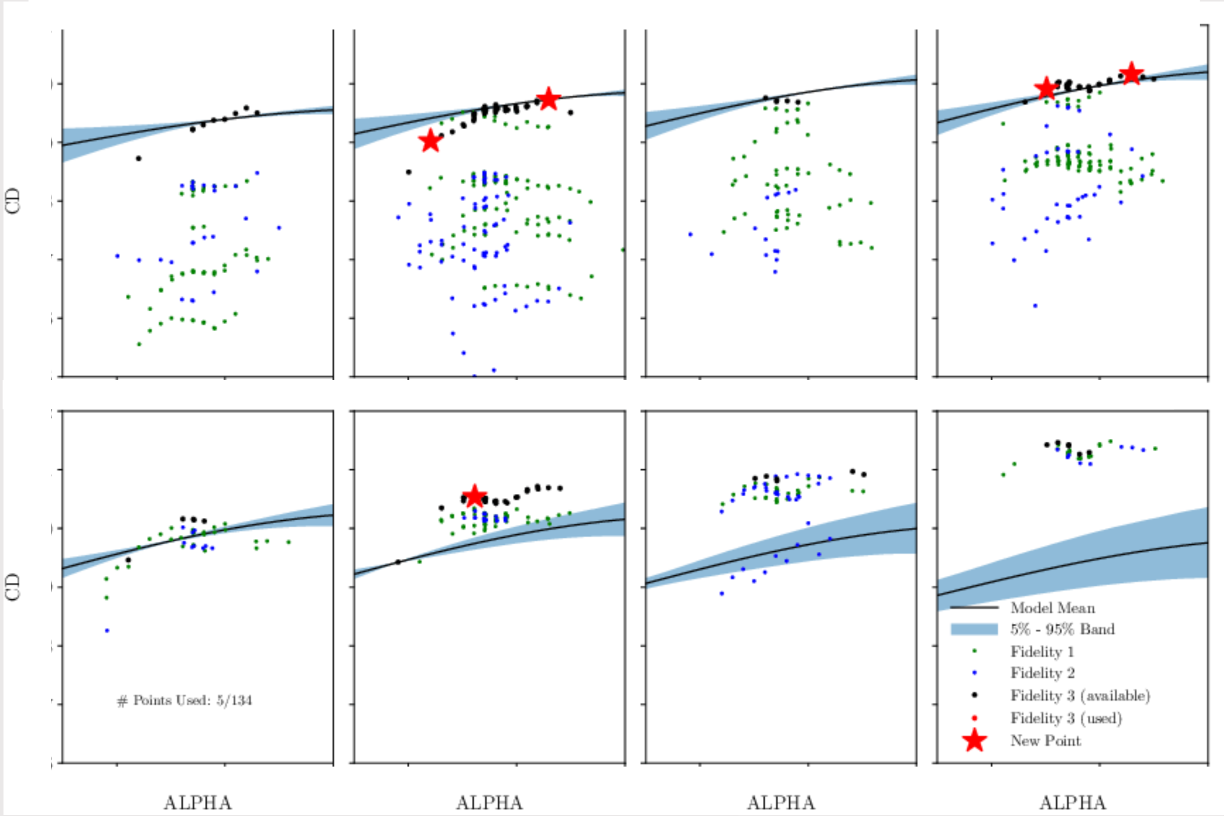


Credit: A. del Val, Ph.D. Thesis, Institute Polytechnique Paris (2021).

Multi-fidelity Design of Experiment

- Design of Experiment (DoE):
  - Iterative online training of model with data acquisition
  - Use model to propose new data points to acquire at each iteration
- <u>Example</u>: Select WT conditions for aero DB generation
  - Maximize information gain / reduce required tests
  - Multi-fidelity model to incorporate previous tests / CFD
- AeroFusion toolbox provides adaptable DoE framework
  - Selection of different "utility" functions to maximize
  - Continuous or discrete parameter spaces
  - Works with all models in the toolbox

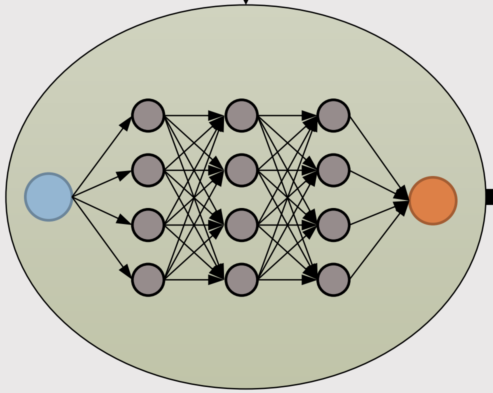
Simulated DoE: Select point with largest model variance from unused pool of data.



C/Python Interface with POST2

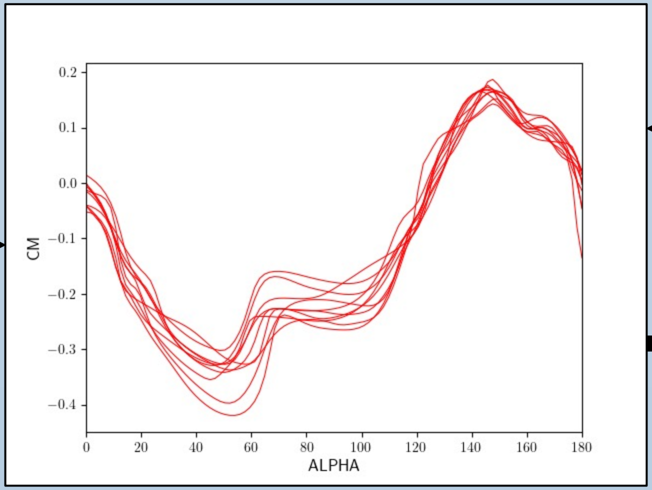
AeroFusion

- Leverages ML+UQ packages written in python
- Handles data processing, model fitting, testing, selection



Model server

- Keeps model ready to query
- Random function samples for **repeatable** Monte Carlo
- Easy, fast cross-language communication, without writing data to disk



POST2 Interface

- Written in C
- Interacts with model server – model-agnostic*
- Each Monte Carlo sim gets its own random function

Case number, $FMV, \alpha, \beta, \ldots$

$C_A, C_N, C_Y, C_m, C_\ell, C_n$

Credits

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