Georgia Tech ESI Grant: Seminar

A Reduced Order Modeling Approach to the Dynamic Stability Analysis of Blunt-Body Entry Vehicles

Aerospace Systems Design Laboratory

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Introduction

Early Stage Innovation Research Topic

- Project began in January 2023
- This research is part of the 2022 ESI topic: Improved Methods for Characterization of Blunt-Body Dynamic Stability
  - Goal is to develop novel approaches to aerodynamic modeling, data collection, and reduction
  - Improve the state of the art for understanding and predicting the dynamic behavior of entry vehicles in flight regimes of interest spanning from Mach 0.3 to Mach 2.5
- General proposed approach:
  - Create reduced order models (ROMs) of the fore- and afterbody pressure and shear force distributions
  - Recover physically consistent flow fields from proper orthogonal decomposition (POD) modes
  - Reduced high dimensional flow fields into lower dimensions using POD
  - Replace linearized aerodynamic databases with ROMs, preserving more aerodynamic information and eliminating linearization assumptions

Aerodynamic Databases and Dynamic Stability

- Entry vehicles rely on physical experiments and CFD simulations to quantify dynamic behavior [1]
- From these tests, an aerodynamic database is generated:
  - At a specified flight condition (M, h, α, β), linear aerodynamic coefficients are generated
  - Databases span multi flight regimes including hypersonic, supersonic, transonic, and subsonic, often involving multiple models to generate the data
- Physical tests produce few data points, with large amounts of uncertainty associated with data reduction techniques [2]
  - Most testing methods do not directly measure forces and moments on vehicle, relying on trajectory reconstructions to determine dynamic stability coefficients

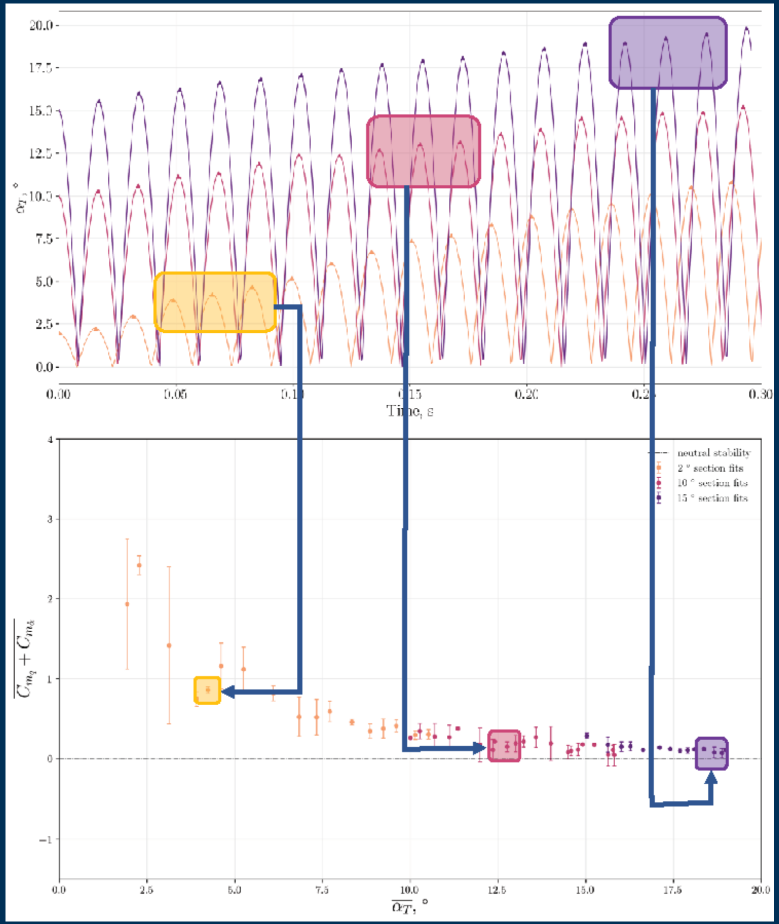


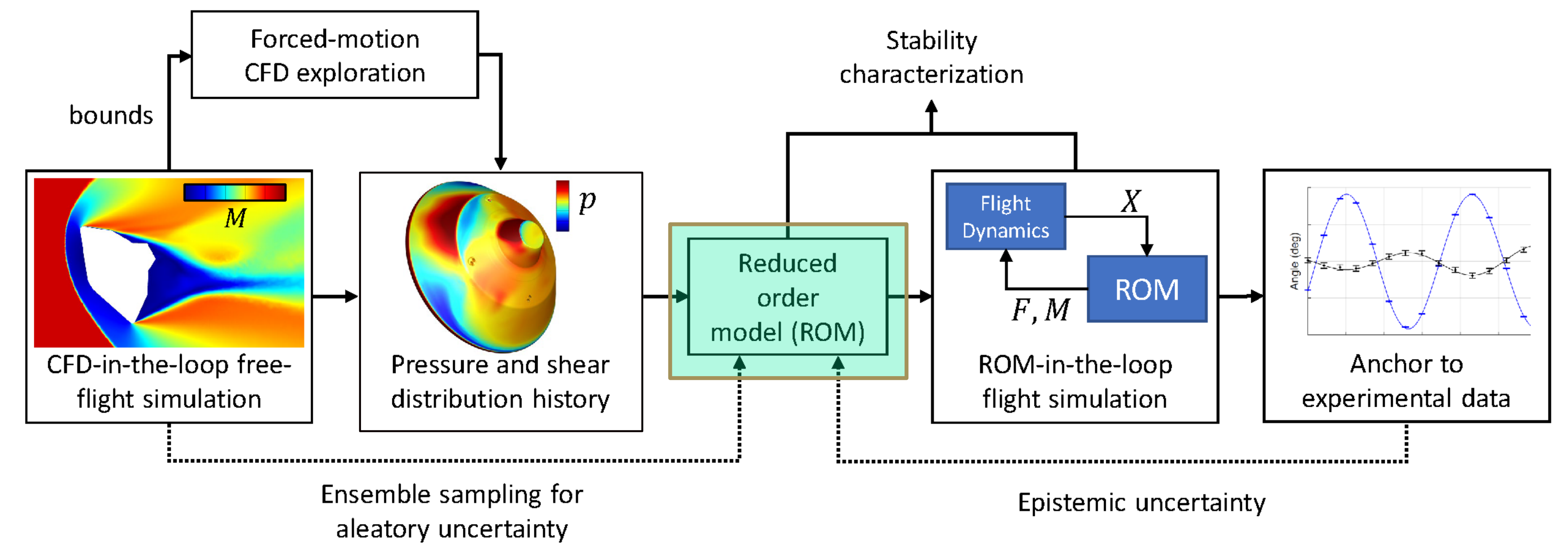
Fig 1. Dynamic stability coefficients from free-flight CFD [3]

1. Ernst, Z. *A Controller Development Methodology Incorporating Unsteady, Coupled Aerodynamics and Flight Control Modeling for Atmospheric Entry Vehicles*. Georgia Institute of Technology, 2022.
2. C. D. Kazemba, R. D. Braun, I. G. Clark, and M. Schoenenberger, "Survey of blunt-body supersonic dynamic stability," Journal of Spacecraft and Rockets, vol. 54, no. 1, pp. 109–127, 2017
3. Brock, J. M., and Kazemba, C. D. "Dynamic Stability Methodologies and Capabilities". AIAA, 2023. https://doi.org/10.2514/6.2023-1335

Integrating CFD Data for Dynamic Stability Characterization

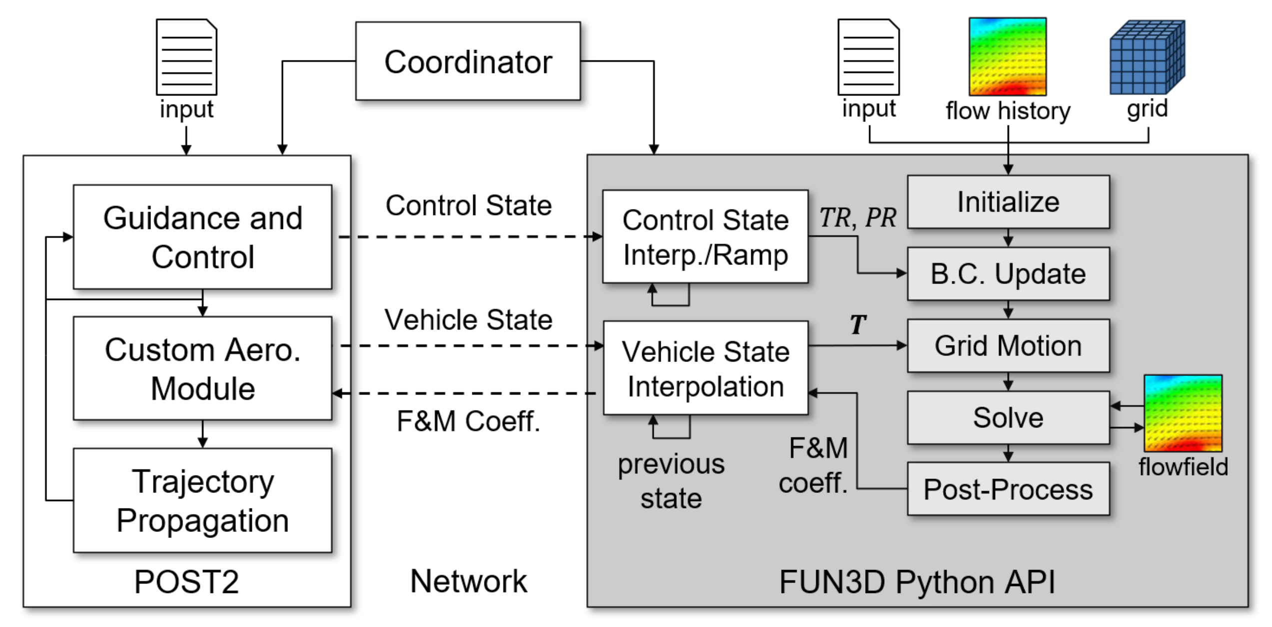
- When coupled with a trajectory optimizer, it can provide time accurate results of vehicle behavior
  - This is critical in dynamic stability quantification because there is a temporal dependency
  - Free-to-heave, free-to-decelerate characteristics can be captured
- CFD-in-the-loop flight simulations generate a large amount of data:
  - Pressure distribution vs time
  - Shear distribution vs time
  - 6DOF trajectories
- **Main Challenge** – we want to leverage the data produced by CFD-in-the-loop flight simulations to quantify dynamic stability without the need for trajectory-based regressions

Methodology Overview



Instead of linearized aerodynamic coefficients, reduced order models of shear and pressure force distributions of the entry vehicle can be used to directly compute aerodynamic forces and moments as a function of freestream and vehicle state parameters

Generating the Aerodynamic Data Set



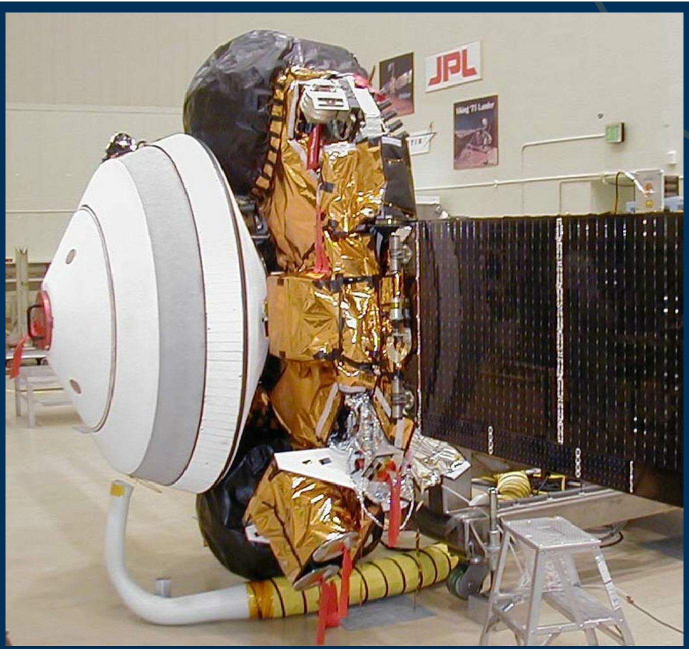
- The POST2/FUN3D framework is a CFD-RBD framework developed by the Aerospace Systems Design Laboratory at the Georgia Institute of Technology
  - Framework interfaces between POST2 (trajectory solver) and FUN3D (CFD solver) to generate time-accurate vehicle behavior which will be used for training data
  - Framework will be used to generate vehicle dataset
- Forced motion CFD runs will be used to supplement free-flight runs in order to fully capture vehicle flight space and quantify aleatory uncertainty of the aerodynamics

1. Zachary Ernst, Madilyn Drosendahl, Bradford Robertson, and Dimitri Mavris, “Development of a Trajectory-Centric CFD-RBD Framework for Advanced Multidisciplinary/Multiphysics Simulation.” AIAA SCITECH 2022 Forum. 2022. AIAA 2022-1793.
2. Zachary Ernst, Alexandra Hickey, Bradford Robertson, and Dimitri Mavris, “The Effect of Roll Rate on Simulated Entry Vehicle Ballistic Range Tests.” Journal of Spacecraft and Rockets 60 (2023), No. 1: 261-272.
3. Alexandra Hickey, Victor Petitgenet, Bradford E. Robertson, and Dimitri N. Mavris, “A Methodology for Actuating RCS Jets in a Continuous, Time-Accurate CFD Simulation.” AIAA SCITECH 2022 Forum. 2022. AIAA 2022-1673.
4. Zachary Ernst, Bradford E. Robertson and Dimitri N. Mavris, “Construction of Entry Vehicle Aerodynamic Surrogates from CFD-in-the-loop Flight Simulations” AIAA SCITECH 2023 Forum. 2023. AIAA 2023-1166.
5. Alexandra M. Hickey, Zach Ernst, Bradford E. Robertson and Dimitri N. Mavris, “Demonstration of a coupled CFD-RBD-FCS framework on Mars Science Laboratory Vehicle” AIAA SCITECH 2023 Forum. 2023. AIAA 2023-1167.

CFD Data Generation

Entry Vehicle Test Geometry

- Motivated to study blunt-body effects, such as:
  - Dynamic stability at lower supersonic and subsonic regime
  - Increasing instability at lower Mach numbers [1]
  - Complex and stochastic aerodynamic behavior of unsteady recirculating wake
  - Deceleration and oscillation adverse stability implications [2]
- Genesis Sample Return Capsule was chosen as the geometry of interest
- Vehicle choice was motivated by:
  - Previously observed instability
  - Applicability to Dragonfly using scaled Genesis aeroshell [3]
  - Availability of ballistic range test data



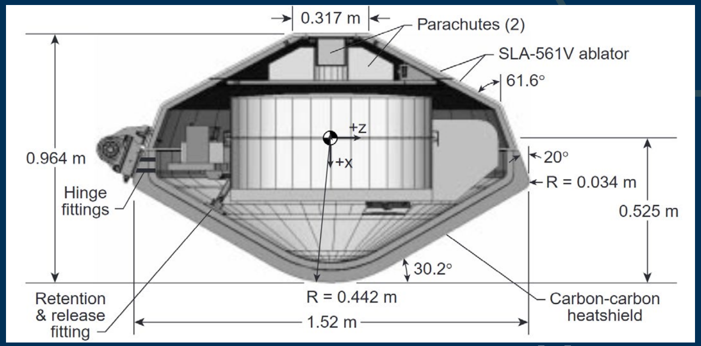
Genesis capsule during assembly [4]

Impacted Genesis capsule at Utah Test and Training Range [4]

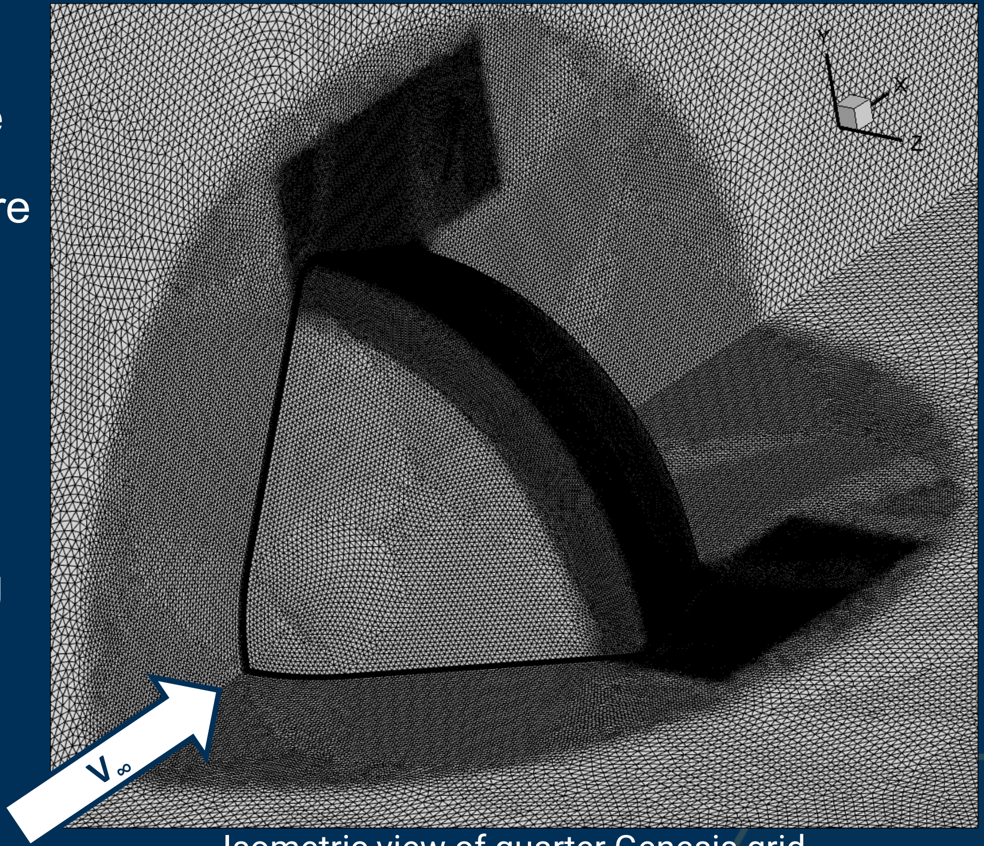
1. Schoenenberger, M., Dyakonov, A., Buning, P., Scallion, W., and Van Norman, J., "Aerodynamic challenges for the Mars Science Laboratory entry, decent and landing," 41st AIAA Thermophysics Conference, 2009. https://doi.org/10.2514/6.2009-3914
2. Kazemba, C. D., Braun, R. D., Clark, I. G., and Schoenenberger, M., "Survey of blunt-body supersonic dynamic stability," Journal of Spacecraft and Rockets, Vol. 54, American Institute of Aeronautics and Astronautics Inc., 2017, pp. 109–127. https://doi.org/10.2514/1.A33552
3. Wright, M. et al.,"The Dragonfly Entry and Descent System," IPPW Oxford, UK., 2019.
4. Curation | Genesis, *Capsule Recovery and Operations,* NASA, 2023. https://curator.jsc.nasa.gov/genesis/reentry.cfm

Genesis Grid Generation

- Grid overview:
  - Generated in Capstone
  - Hemispherical fluid volume
  - 6 vehicle lengths in front of the vehicle
  - 15 vehicle lengths in the aft direction
  - 53.8 million node, semi-structured, tetrahedral
- Additional refinement regions:
  - Toroidal source placed around the shoulder of the vehicle to provide further refinement of key flow transitions
  - Spherical source placed around the entire vehicle to allow for capture of the bow shock at supersonic speeds and of the forward propagation of the flow at subsonic speeds
  - Cylindrical sources placed in the wake to ensure sufficient definition for turbulence modeling
- Grid refinement driven by:
  - Required resolution to accurately capture pressure and shear to create reduced order models
  - Performance from Mach 0.3 to 2.5, through angles of attack ranging from -20 to 20 degrees
- Not a candidate for more complex meshing techniques like adaptive mesh refinement.



Full Scale Genesis Vehicle [1]



Isometric view of quarter Genesis grid

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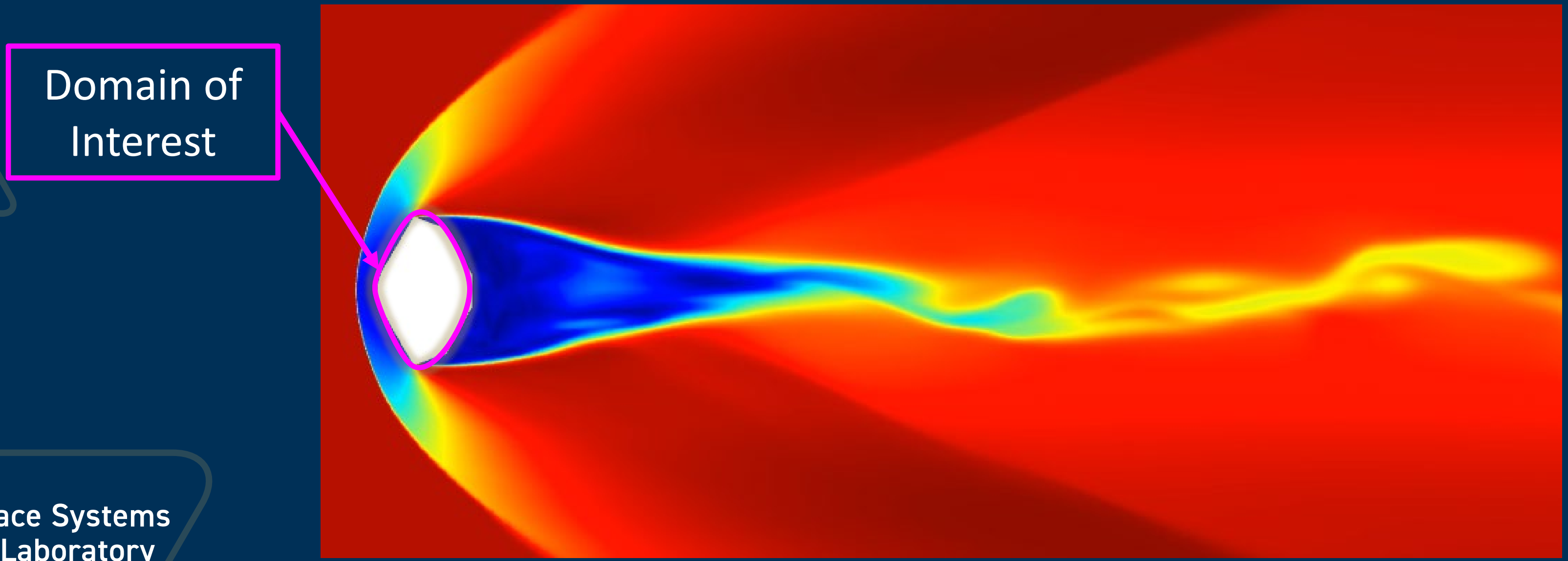
1. Desai, P. N., Mcneil Cheatwood, F., and Girdwood, A., "Entry Dispersion Analysis for the Genesis Sample Return Capsule AAS/AIAA Astrodynamics Specialist Conference ENTRY DISPERSION ANALYSIS FOR THE GENESIS SAMPLE RETURN CAPSULE," Tech. rep., 1999.

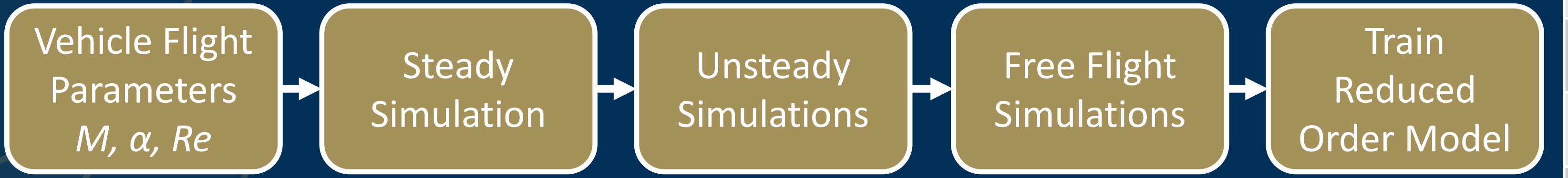
Metrics of Interest for Reduced Order Modeling

- Flow field around the vehicle is generating pressure and shear forces and moments on the vehicle's surface
- Important to properly model wake structures in CFD, but vehicle motion is determined by pressure and shear interactions on the surface of the vehicle
  - Wake has multiple components that are impacting the vehicle behavior
  - Aggregate behavior can be summed into a force/moment interaction occurring on the surface of the vehicle
- The goal of the CFD simulations are to properly resolve pressure and shear forces and moments on the vehicle's surface
- ROM only needs surface pressure and shear data in order to resolve dynamic behavior of the vehicle



CFD Simulation Process

- Initial simulations were run using atmospheric settings from Cheatwood et al. flight test data
- Data generation process should minimize the changes in CFD parameters over the course of the flight regime



- Experimenting with low subsonic and transonic solutions while evaluating grid performance
- A screening was performed for sample conditions:
  - Mach 0.3, 0.5, 0.8, 1.5, and 2.5
  - Angles of attack 0.0 degrees and 20.0 degrees

Namelist Variable	Setting
Temperature [K]	292.94
Angle of Attack [deg]	0.0 and 20.0
Governing Equations	compressible
Viscous Term	turbulent
Turbulence Model	DES
Reynolds Stress Model	qcr2000
SA Rotation Correction	True
Delayed DES	False
Large Angle Fix	on
Smooth Limiter Coefficient	1
Temporal Scheme	2ndorderOPT
Schedule CFL	0.95
Schedule CFL_{turb}	0.90

1. McNeil Cheatwood, F., Winchenbach, G. L., Hathaway, W., and Chapman, G., "Dynamic stability testing of the Genesis Sample Return Capsule," 38th Aerospace Sciences Meeting and Exhibit, 2000. https://doi.org/10.2514/6.2000-1009.

Genesis: Mach 0.3 at 0.0 deg AoA

- Solver settings:
  - Reynolds number = 6977645.94
  - Flux Construction = Roe
  - Flux Limiter = hvanleer
  - Timestep = 1.121E-07
  - Non-dim timestep = 0.0003846
  - Subiterations = 7

Genesis: Mach 0.5 at 0.0 deg AoA

- Solver settings:
  - Reynolds number = 11629409.90
  - Flux Construction = LDRoe
  - Flux Limiter = hvanleer
  - Timestep = 9.715E-07
  - Non-dim timestep = 0.0003333
  - Subiterations = 7

Genesis: Mach 0.8 at 0.0 deg AoA

- Solver settings:
  - Reynolds number = 18607055.84
  - Flux Construction = LDRoe
  - Flux Limiter = hvanalbada
  - Timestep = 8.096E-07
  - Non-dim timestep = 0.0002778
  - Subiterations = 7

Genesis: Mach 1.5 at 0.0 deg AoA

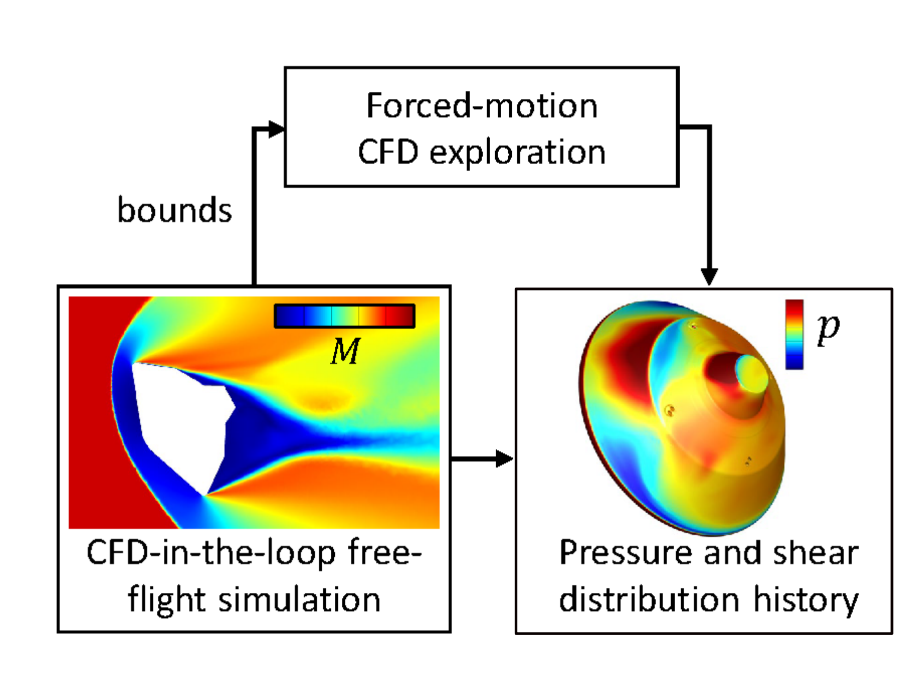
- Solver settings:
  - Reynolds number = 34888229.7
  - Flux Construction = DLDFSS
  - Flux Limiter = hvanalbada
  - Timestep = 5.829E-07
  - Non-dim timestep = 0.0002000
  - Subiterations = 7

Genesis: Mach 2.5 at 0.0 deg AoA

- Solver settings:
  - Reynolds number = 58147049.51
  - Flux Construction = DLDFSS
  - Flux Limiter = hvanalbada
  - Timestep = 5.22E-07
  - Non-dim timestep = 0.0001791
  - Subiterations = 7

CFD Progress

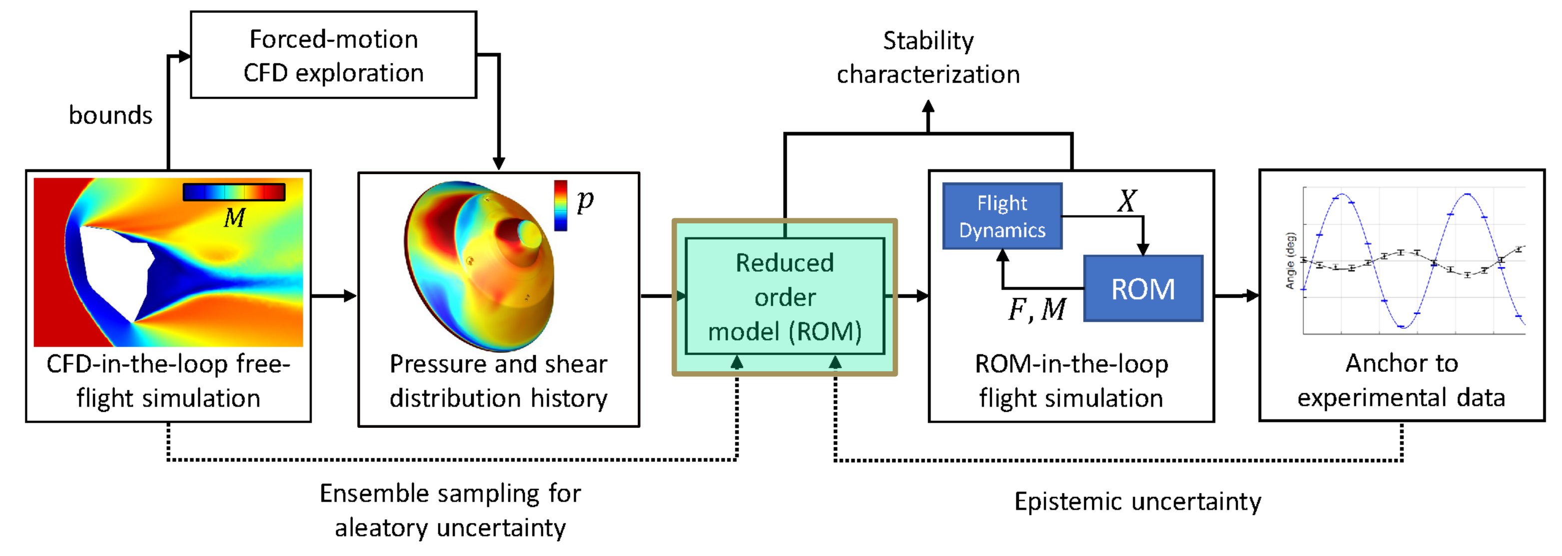
- Current CFD efforts
  - Continue screening of transonic solver settings
  - Further grid refinement based on boundary shear distribution performance
  - Extend forced motion run time
- Future CFD plans
  - Perform CFD-in-the-loop free flight simulations with POST2/FUN3D framework



Refining CFD solver settings across the entire Mach regime is critical to provide the pressure and shear distributions on the Genesis vehicle to train Reduced Order Models.

Reduced Order Modeling

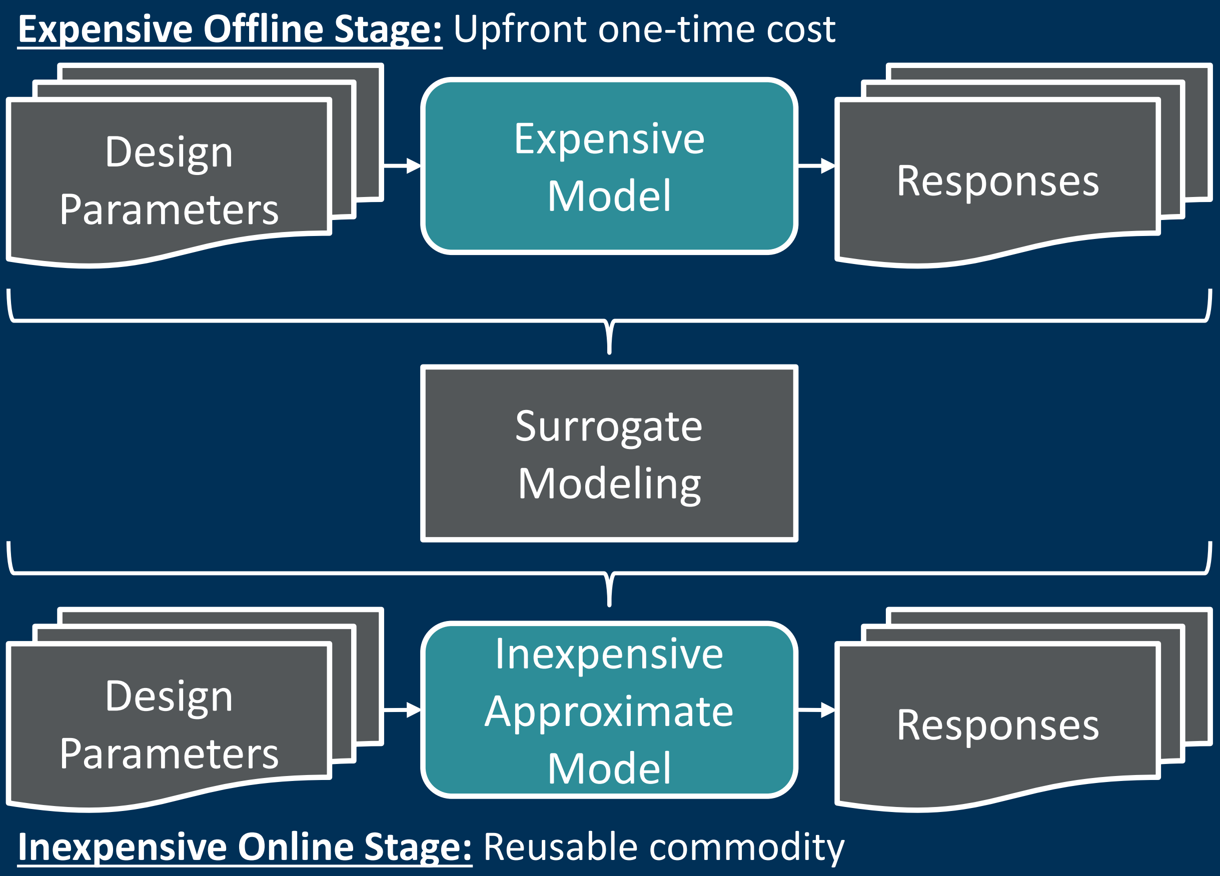
Leveraging CFD for Reduced Order Modeling



- CFD simulations provide the data needed to quantify vehicle behavior
- Traditionally CFD data is compressed into aerodynamic databases
    - Databases are leveraged in entry, descent, and landing (EDL) modeling and simulation
    - Databases are queried during simulation to determine vehicle aerodynamic behavior
    - Interpolation is used when sampling an unseen data point
- This program aims to leverage the pressure and shear surface fields, instead of compressing data into coefficients
- Enables ROM-in-the-loop flight simulation
    - Provides the high-fidelity data of CFD-in-the-loop flight simulation, without the large computational expense
    - Allows for Monte Carlo analysis with a higher fidelity aerodynamic input

Surrogate Modeling

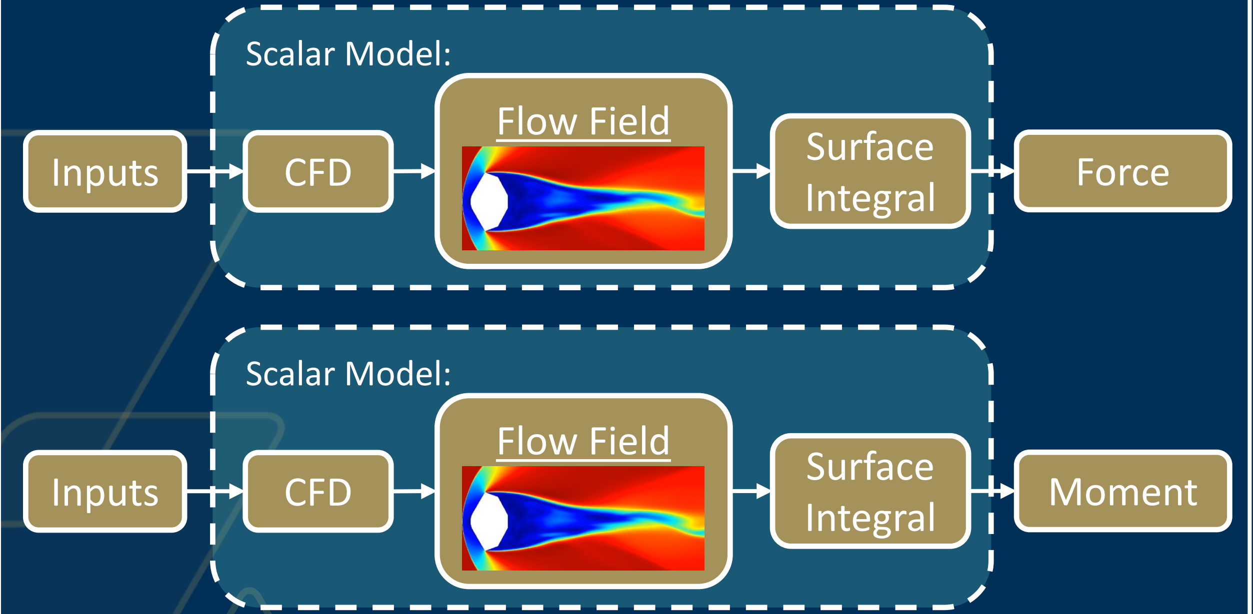
- Surrogates are inexpensive models that approximate an underlying true function/process/model
- Literature classifies them into categories in the engineering community:
  - **Data-fit** – surface fit to a scalar response
    - E.g. scalar aerodynamic databases
  - **Hierarchical models** – Exploits varying fidelity between models
  - **Reduced Order Models (ROMs)** – Approximates the governing-equations; enables faster computation of fields
- Employed as an enabler for many-query contexts involving expensive analyses
  - E.g. Flight simulation and uncertainty quantification



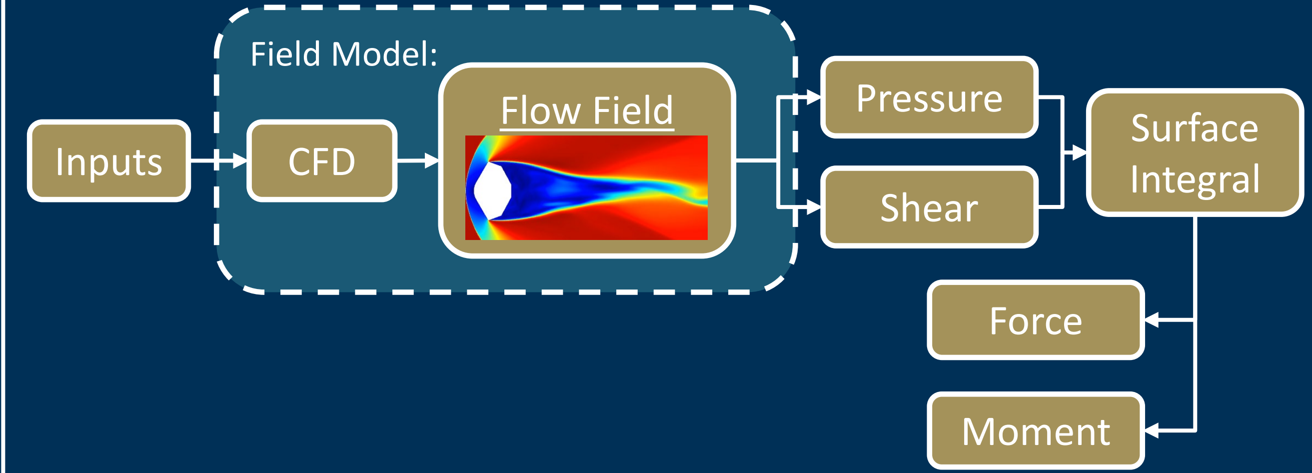
Reduced Order Models enable field data to be stored and modeled in a compact manner that makes field data accessible within many-query analyses

Scalar Surrogate Models vs. Reduced Order Models

Scalar Models:



ROMs/Field Surrogate Models:

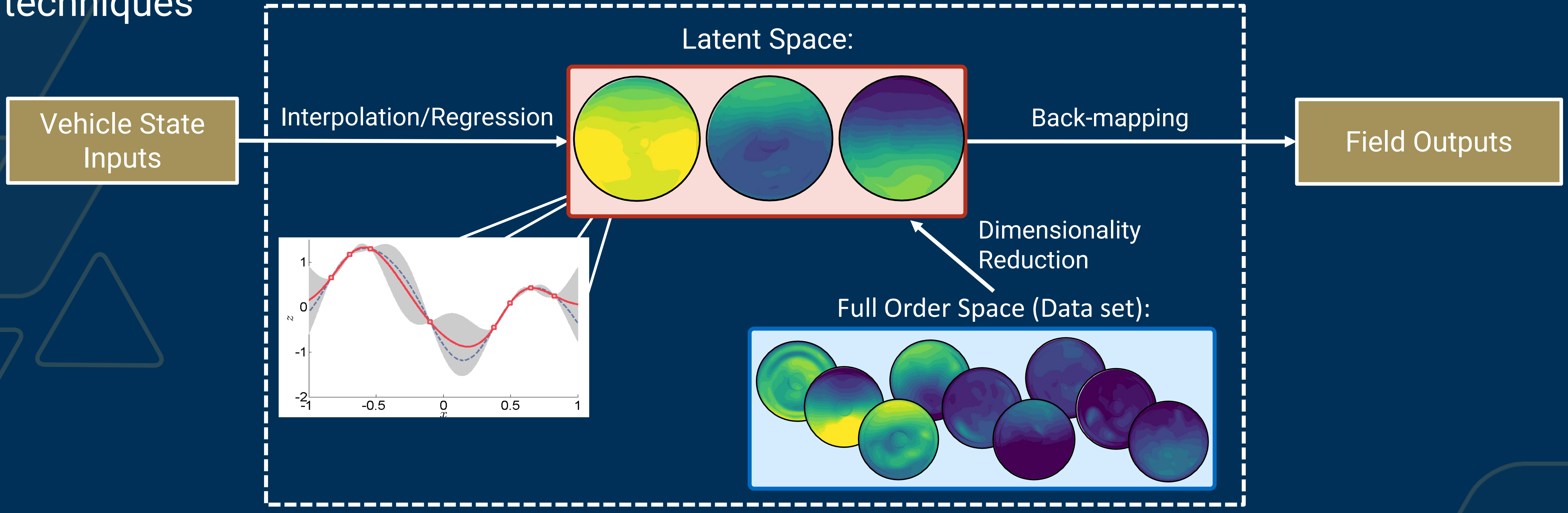


ROMs contain more physical information, predicting many quantities of interest simultaneously from a single ROM

Previous studies have identified ROMs as key enablers for leveraging high-dimensional and high-fidelity data within coupled analysis

Reduced Order Modeling

- ROMs take high-fidelity data and reduce it down into a low dimension called a *latent space* through reduction of basis techniques
- Vehicle state inputs can be mapped to the *latent space*, allowing for the parametric prediction of the full order space given a series of inputs
- The latent space can be converted into the Full Order Model (FOM) using back-mapping techniques



Data Set Generation ⇒ Dimension Reduction ⇒ Regression/ Interpolation ⇒ Back-mapping

Data Set Generation

Data Set Generation ⇒ Dimension Reduction ⇒ Regression/ Interpolation ⇒ Back-mapping

- Need data that spans multiple vehicle states (Mach, Angle of Attack, Sideslip, flow properties, etc.)
- Free-flight captures free-to-pitch, free-to-heave, free-to-oscillate behavior needed for dynamic stability quantification
- Simulating the vehicle in free-flight using the POST2/FUN3D Framework will allow for the vehicle state space to be captured and identify the bounds of the state space
- Stern et al. identified there is an observed correlation between the vehicle states [1]
  - A single flight test tends to oscillate with a set frequency within a small range of amplitudes
  - Only a small portion of the state space can be captured with a single flight test

Free-flight simulations will provide the starting point to generating the necessary data set for predicting dynamic stability with a ROM

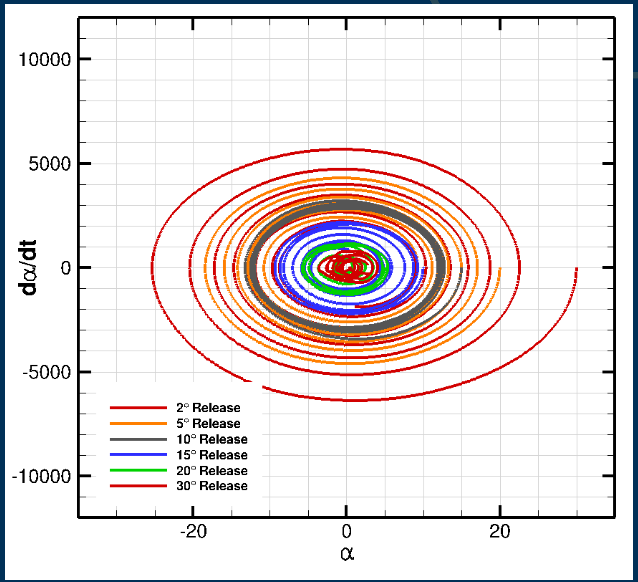


Fig 2. α vs $\dot{\alpha}$ phase space trajectories for MSL at Mach 2.5 [1]

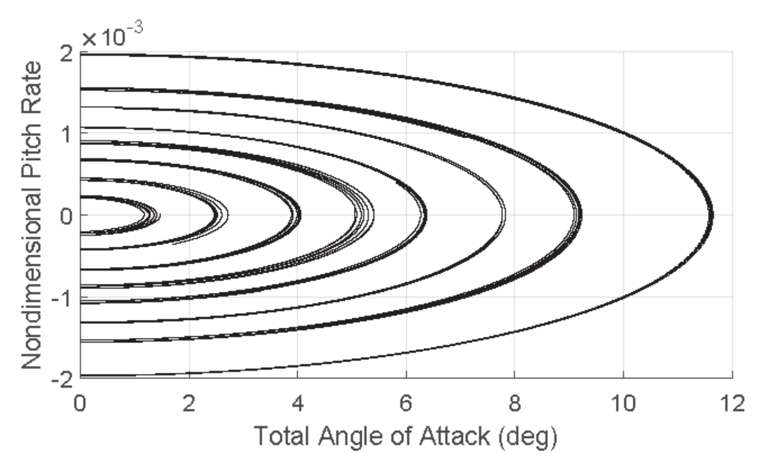


Fig 2. α vs $\dot{\alpha}$ phase space trajectories for SIAD [2]

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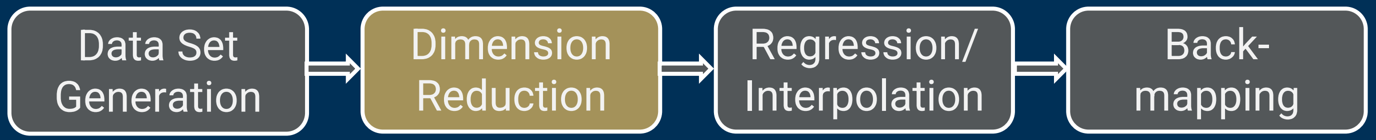
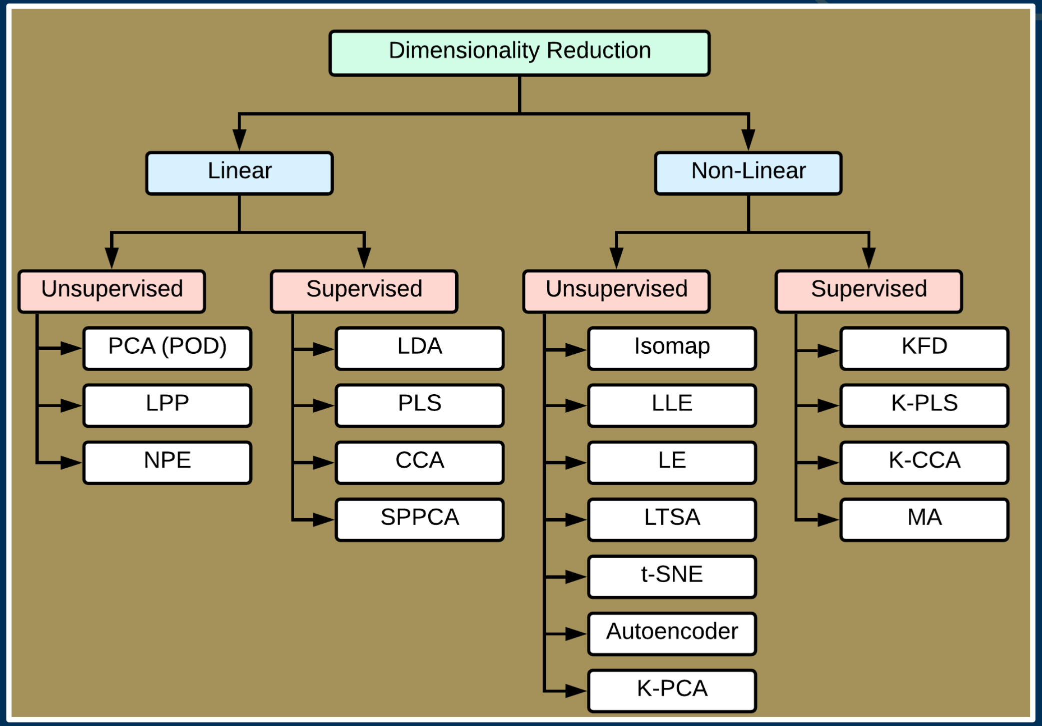
1. Stern, E. C., Gidzak, V. M., and Candler, G. V., "Estimation of dynamic stability coefficients for aerodynamic decelerators using CFD," 30th AIAA Applied Aerodynamics Conference 2012, , No. June, 2012, pp. 2217–2230. https://doi.org/10.2514/6.2012-3225
2. Ernst, Z. J., Drosendahl, M. K., Robertson, B. E., and Mavris, D. N., "Development of a Trajectory-Centric CFD-RBD Framework for Advanced Multidisciplinary/Multiphysics Simulation," AIAA Science and Technology Forum and Exposition, AIAA SciTech Forum 2022, 2022, pp. 1–19. https://doi.org/10.2514/6.2022-1793.

Dimensionality Reduction Techniques



- Many DR techniques have been developed and tend to share common features
  - Assume the "intrinsic" dimension of a data set is lower than it appears
  - Find the "best" low-dimensional representation through optimization
  - Must be "told" what dimension the latent space must be
- DR techniques primarily differ between the specific methods for each step
- Different metrics and objectives have different strengths and weakness for the types of features that can be extracted
- Typically, we start with linear ROMs since they are simple, inexpensive, and require the least data and tuning
  - Usually only pursue more complex nonlinear models when we know linear models are insufficient



Linear Method:

Mapping is a linear projection

✓ Simple and quick

✓ Easy data transformation *(explicit mapping)*

✗ Struggles with more complex latent space

Non-Linear Method:

Mapping is a non-linear function

✓ Better on complex problems

✗ Difficult to reconstruct data *(implicit mapping)*

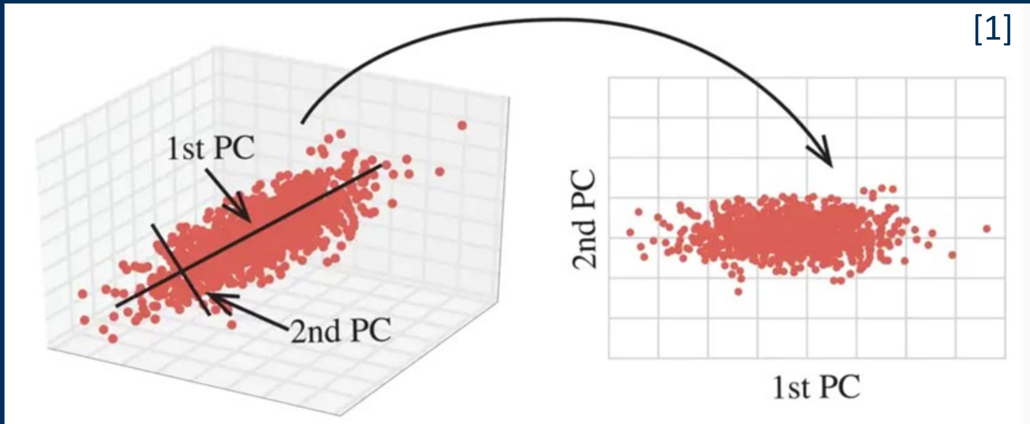
✗ Requires more data

Dimensionality Reduction with POD/PCA

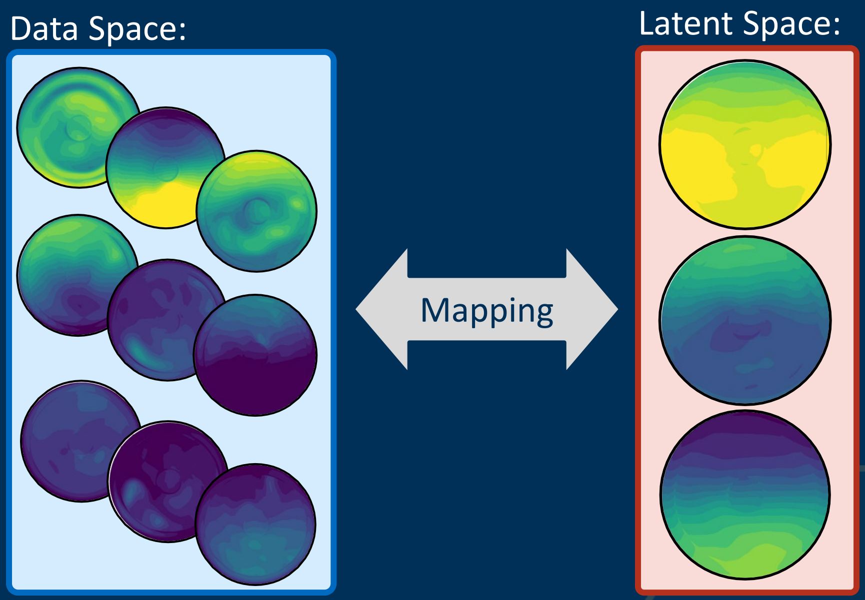
Data Set Generation → **Dimension Reduction** → Regression/ Interpolation → Back-mapping

- For this program, we will start with POD ROMs since
  - Want to start with the simplest DR techniques
  - Have many favorable properties
- The core element of any ROM is the extraction of the dominant features (referred to as "modes" when using POD)
- Assumptions
  - In a high-dimensional field, the dimensions are unlikely to be independent
  - Within the data, there is likely to exist an intrinsic coherence
  - The "best" latent space representation is the one that preserves the most observed covariance
  - Modes should be orthogonal to maximize information per mode

Simple DR using PCA [1]



POD Applied to Backshell of Genesis:

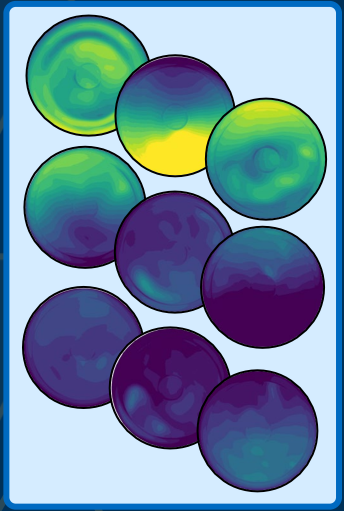


1. https://medium.com/@TheDataGyan/dimensionality-reduction-with-pca-and-t-sne-in-r-2715683819

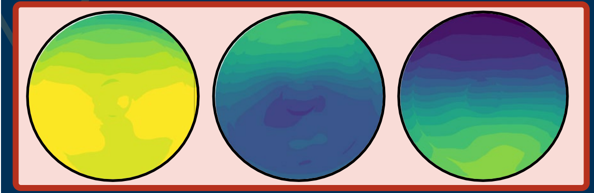
Dimensionality Reduction with POD/PCA

Data Set Generation → Dimension Reduction → Regression/ Interpolation → Back-mapping

Snapshots:



POD Modes:



Step-1: Initial Sampling (LHS Design)

$$p = [p_1, \dots, p_m]$$

Step-2: Snapshot Matrix

$$x_i = f(p_i)$$
$$X = [x_1, \dots, x_m]$$

Step-3: Perform Singular Value Decomposition (SVD)

$$X = U\Sigma V^{\mathrm{T}}$$
$$U = [\mathbf{u}_1, \dots, \mathbf{u}_n]$$
$$\Sigma = diag(\sigma_1, \dots \sigma_n)$$

Step-4: Determine Latent Space Dimension (d)

$$RIC(d) = \frac{\sum_{i=1}^{d} \sigma_i^2}{\sum_{j=1}^{n} \sigma_j^2} > \delta$$

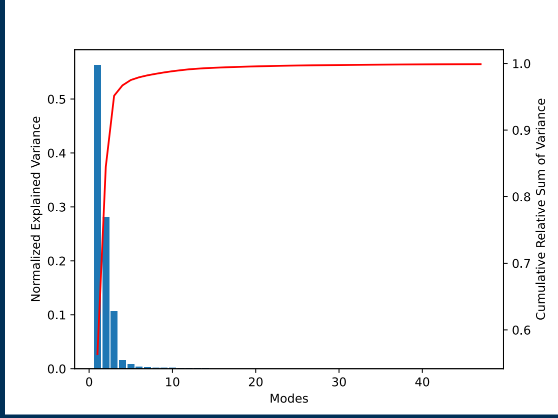
Step-5: Determine Latent Space Coordinates of Training Set

$$Z = [z_1, \dots, z_m] = \mathbf{\Phi}^{\mathrm{T}}\mathrm{X}$$
$$\mathbf{\Phi} = U_d$$

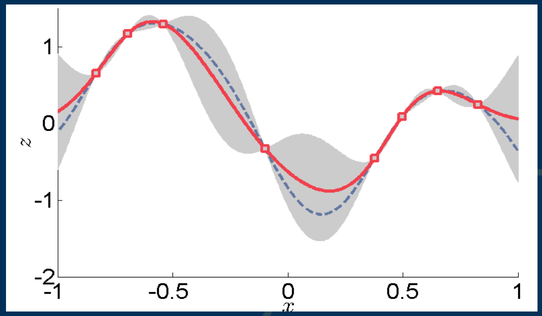
Step-6: Fit mapping from input space to latent space

$$\tilde{z}_i = g_i(p_i)$$

Relative Information Content Plot:



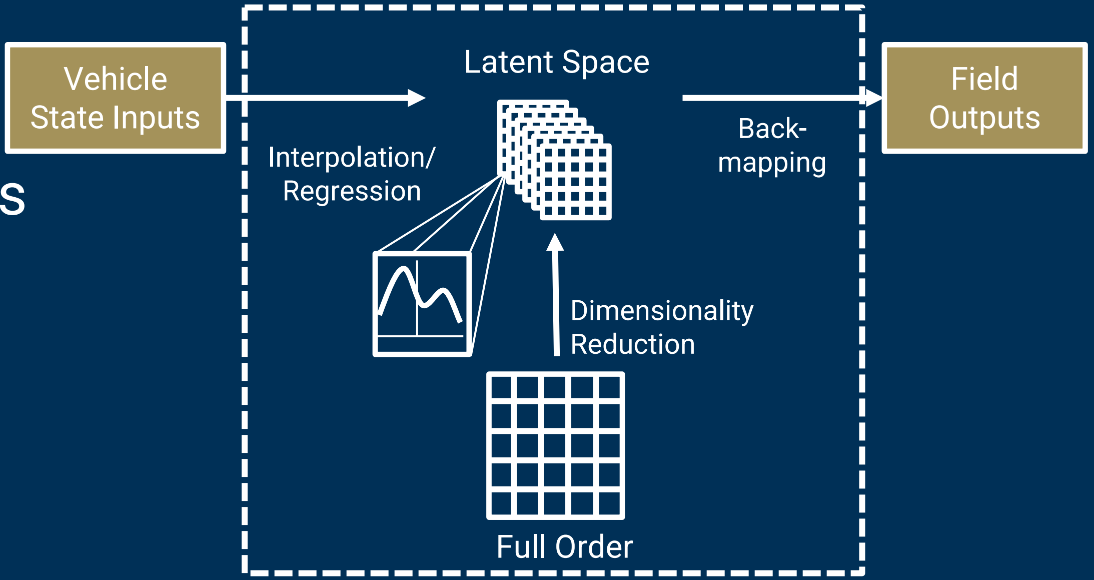
Regressor:

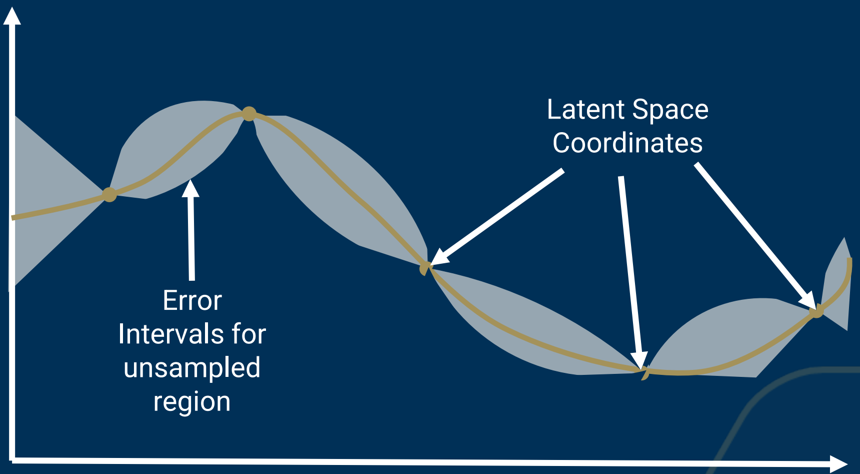


Interpolation/Regression

Data Set Generation ⇒ Dimension Reduction ⇒ Regression/ Interpolation ⇒ Back-mapping

- Once generated, the input parameters (i.e. Mach number, dynamic pressure, vehicle state variables, etc.) must be mapped to the latent space
- This process is achieved using regression techniques
- Requirements for selecting a regression model:
    - Account for uncertainty/error
    - Must be able to handle large data set
    - Provide accurate (within some tolerance) latent space coordinate predictions
- Need an interpolation/regression model that can provide the mapping and mean squared prediction error
- A Kriging-variant is proposed for the initial regressor
    - Will enable the quantification of interpolation error
    - Allow for aleatory uncertainty quantification
- Neural networks will be explored as a potential option





Sample Kriging Regression

Back-mapping

Data Set Generation ⇒ Dimension Reduction ⇒ Regression/ Interpolation ⇒ Back-mapping

- The final step in ROM generation is back-mapping, in which high-dimensional field is reconstructed for a given latent space prediction
  - For POD, it will be a linear subspace spanned by the training data, thus allowing the use of linear transformations for back-mapping
  - Otherwise, nonlinear methods such as manifold back-mapping or neural networks have been used [1]

Input parameters (vehicle motion state, from POST2)

Mean of sample data

POD mode

Matrix form

Surrogate model of high-dimensional field

$$\hat{\boldsymbol{f}}(\boldsymbol{x};\boldsymbol{p}) = \boldsymbol{\mu}(\boldsymbol{x}) + \sum_{i=1}^{d} z_i(\boldsymbol{p})\boldsymbol{\phi}_i(\boldsymbol{x}) = \overbrace{\boldsymbol{\mu} + \boldsymbol{\Phi}\boldsymbol{z}}^{\text{Matrix form}}$$

Spatial coordinate in field (from grid)

Latent coordinate (from regressor)

- $\hat{\boldsymbol{f}}(\boldsymbol{x};\boldsymbol{p};)$: $\mathbb{R}^{\boldsymbol{p}} \mapsto \mathbb{R}^{\boldsymbol{n}}$: Approximation of high-dimensional function
- $\boldsymbol{\mu}(\boldsymbol{x}) \in \mathbb{R}^{\boldsymbol{n}}$: Sample mean across the field
- $\boldsymbol{\Phi} = [\boldsymbol{\phi}_1, \dots, \boldsymbol{\phi}_d] \in \mathbb{R}^{\boldsymbol{n}\times\boldsymbol{d}}$: Matrix whose column vectors are POD modes
- $\boldsymbol{z} \in \mathbb{R}^{\boldsymbol{d}}$: Vector of latent space coordinates
- $\boldsymbol{p} \in \mathbb{R}^{\boldsymbol{p}}$: Vector of input parameters

1. Decker et. Al. “Manifold Alignment-based Nonintrusive and Nonlinear Multifidelity Reduced Order Modeling.” AIAA Journal, 2023.

POD Error Metrics

- Due to the significant number of data points being input into the ROM, a L2 norm error metric is insufficient
- Mean Absolute Error (MAE) will be used to quantify the ability for the components of the ROM to capture specific data
- Due to the modular nature of the ROM, the error can be split into two metrics: reconstruction error, and regression error

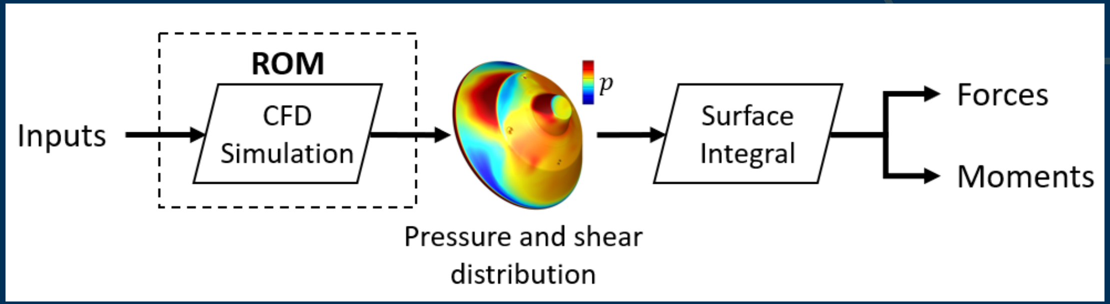
$$\underbrace{MAE_{recon} = \frac{\sum_{j=1}^{v} |\boldsymbol{\Phi}\boldsymbol{\Phi}^{T}\boldsymbol{x}_j^{*} - \boldsymbol{x}_j|}{v}}_{\text{Unacceptably large error means POD can't recover the features of interest}}$$

$$\underbrace{MAE_{reg} = \frac{\sum_{j=1}^{v} |\boldsymbol{z}_j(\boldsymbol{p}^{*}) - \boldsymbol{z}_j|}{v}}_{\text{Unacceptably large error means the regression model can't make good predictions in the latent space}}$$

- The total MAE of the ROM can be calculated by:

$$MAE_{total} = \frac{\sum_{j=1}^{v} |\boldsymbol{x}_j(\boldsymbol{p}^{*}) - \boldsymbol{x}_j|}{v}$$

ROM Implementation

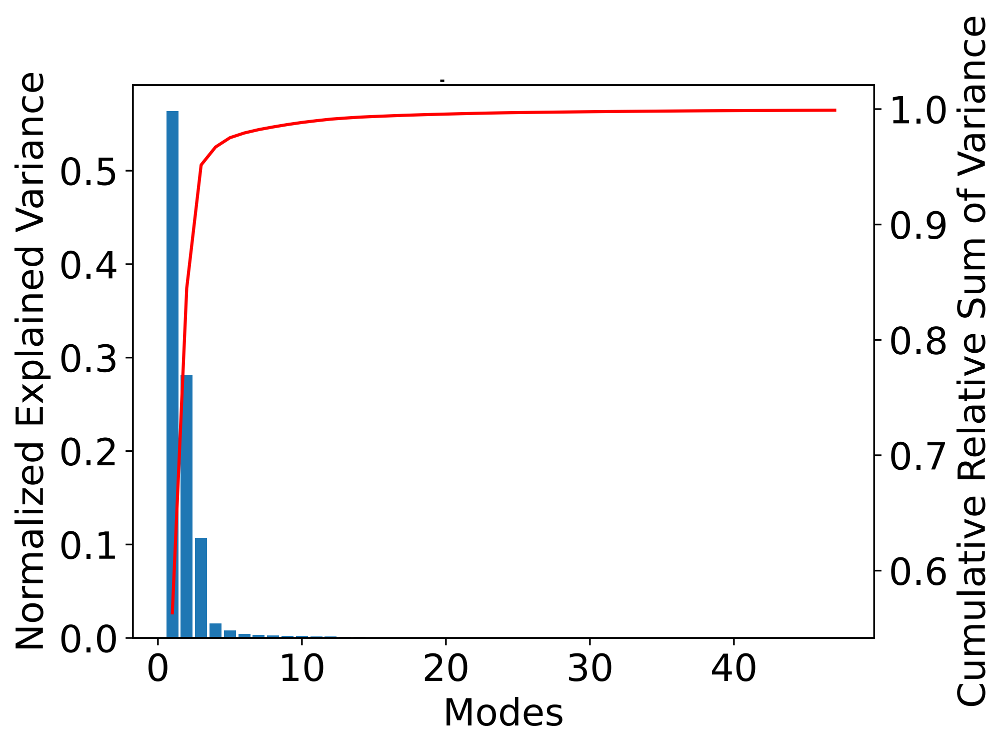


- A POD ROM can be constructed using the CFD data produced during free-flight simulations
- Based on the vehicle state, the pressure and shear fields on the heatshield and backshell can be generated
  - Force distributions can be visualized
  - Aerodynamic coefficients can be generated by integrating the fields
  - Dynamic stability coefficients can be generated by using derivative methods for discrete fields
- ROM can be directly coupled with trajectory simulations
  - Bypassing the aerodynamic database
  - Directly provide ROM generated forces and moments to the trajectory solver

Initial ROM Results

- 3-forced motion runs of C_p distributions were generated for initial testing of the ROM methodology
  - Runs display pure translation motion resulting in more interesting features for the ROM to generate
  - Each run simulated for 1 full period (5000 time steps)
  - First 100 time steps eliminated to remove any instances of non-developed flow
  - Data from runs 1 and 3 were used in the ROM snapshot matrix
  - Run 2 was used as a validation case to test ROM accuracy
- POD Reconstruction Analysis:
  - ROM needs 47 modes to capture 99.9% of the data variance in the snapshot matrix
  - MAE = 0.00142

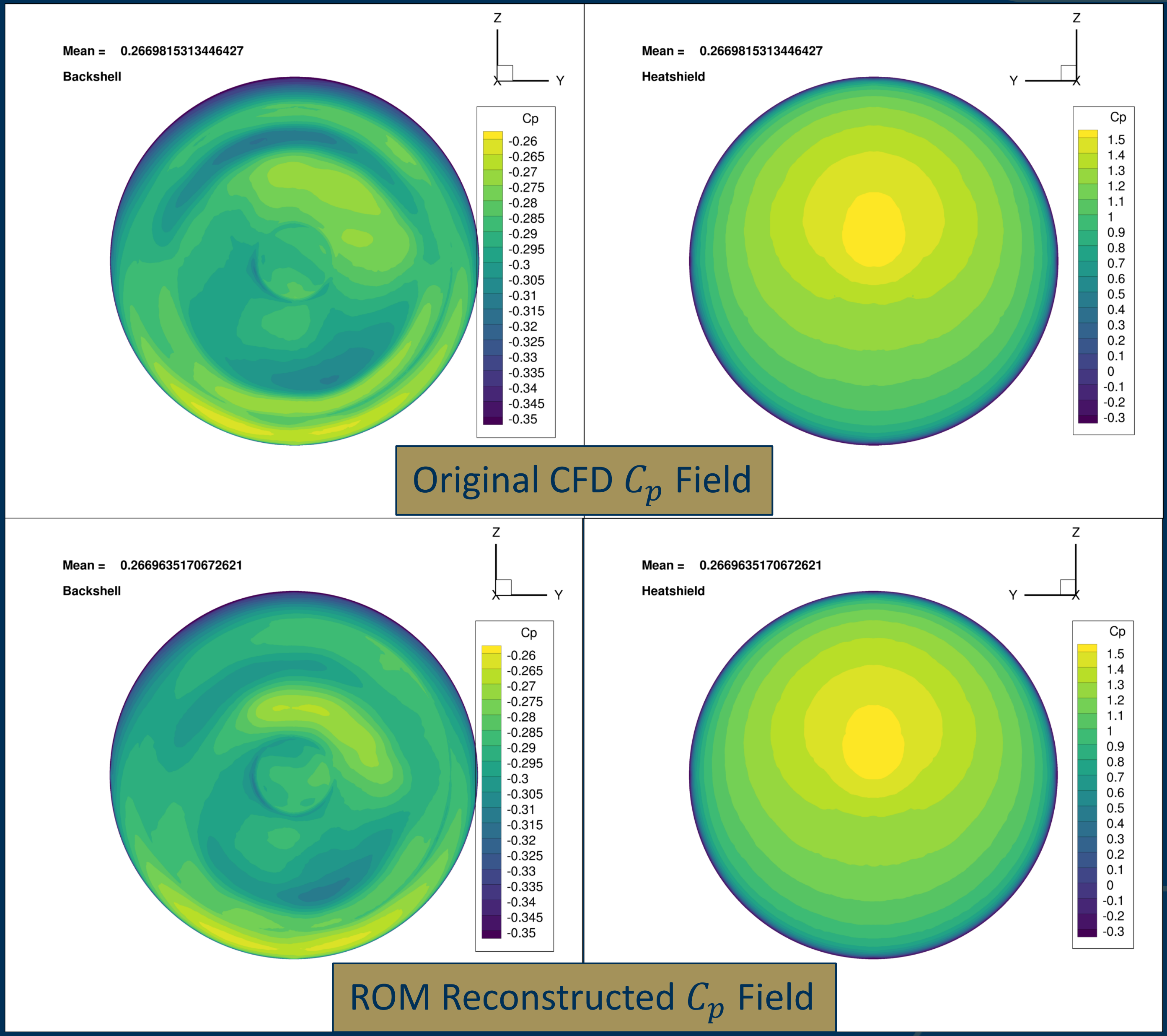
Run	Mach	Amplitude (m)	Phase (deg)	Frequency (Hz)
1	1.5	0.01	0	343.11
2	1.5	0.03	0	343.11
3	1.5	0.05	0	343.11



Initial ROM Results

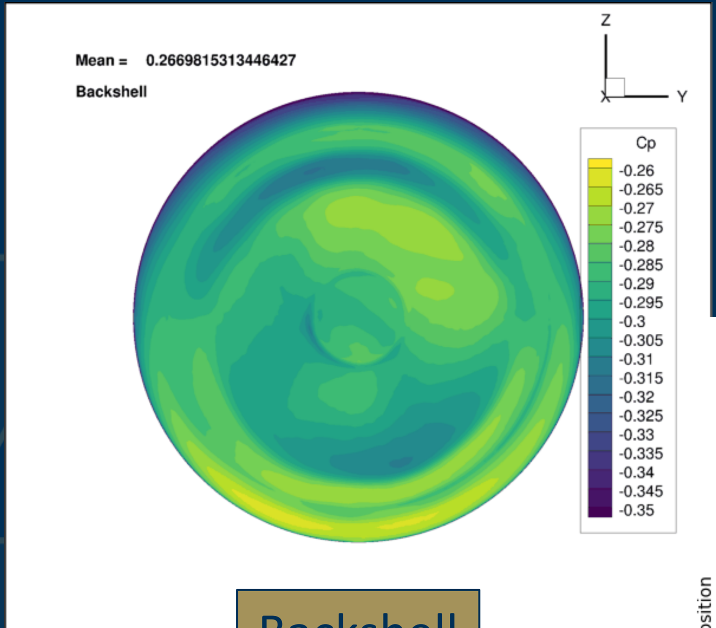
- A linear interpolator was used to predict the latent coordinates of the unseen data point
  - Amplitude = 0.03
- Linear transform used on predicted latent coordinates to reconstruct the C_p field for the given amplitude
- Figures show C_p field for single snapshot of the simulated forced motion
- Verification steps:
  - CFD data from run 2 is compressed into the latent space and compared to the predicted latent coordinates of the ROM
  - Resulting MAE for all the snapshots = 7.78

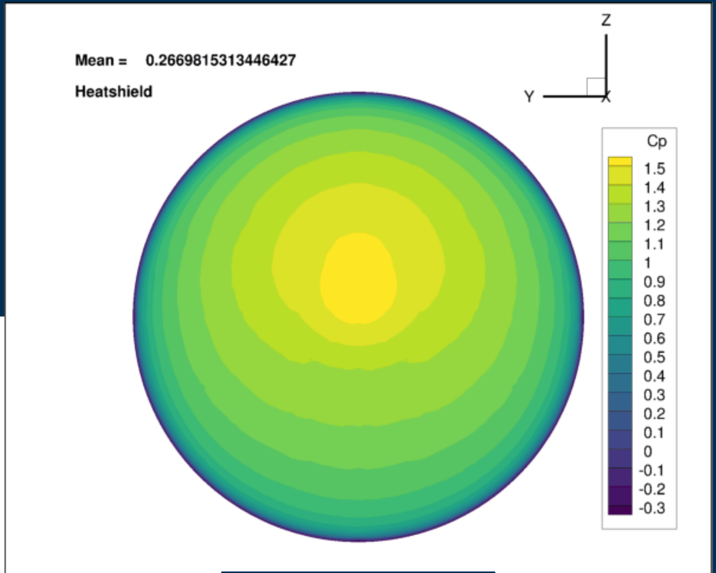
Backshell | Heatshield



C_p Field vs Time for CFD Field and ROM Field

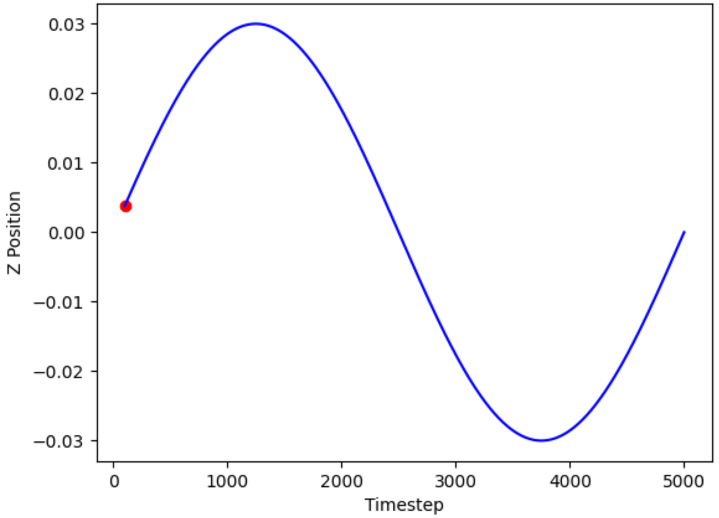
CFD C_p Field

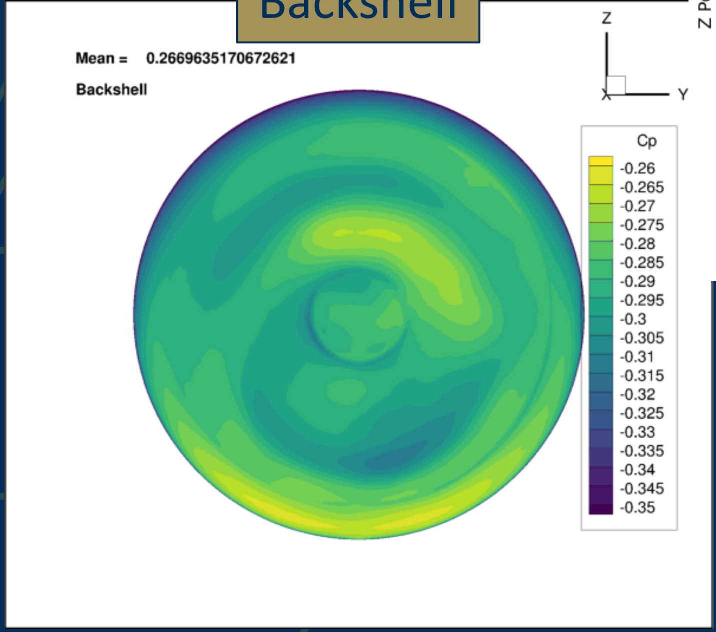


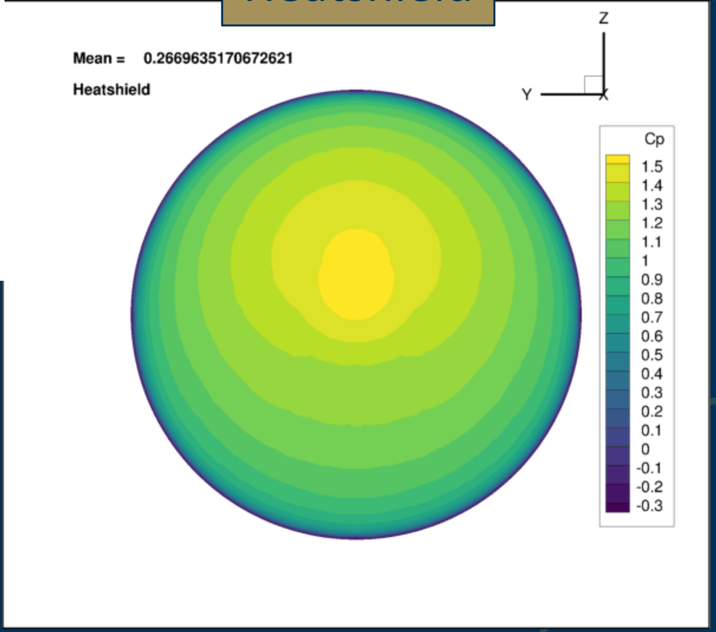


Backshell

Heatshield



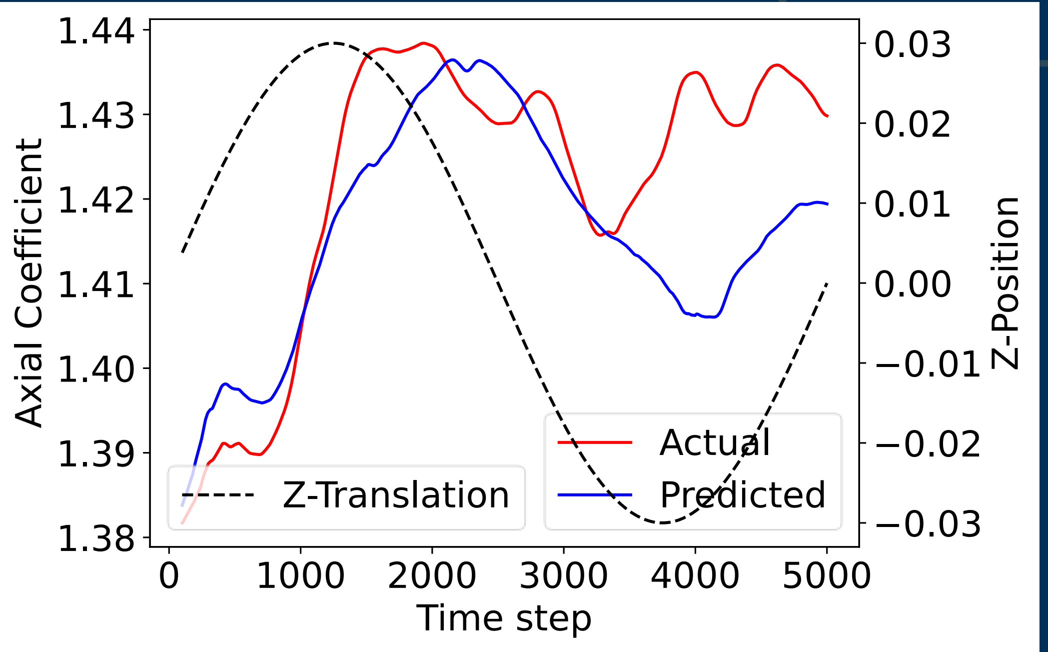


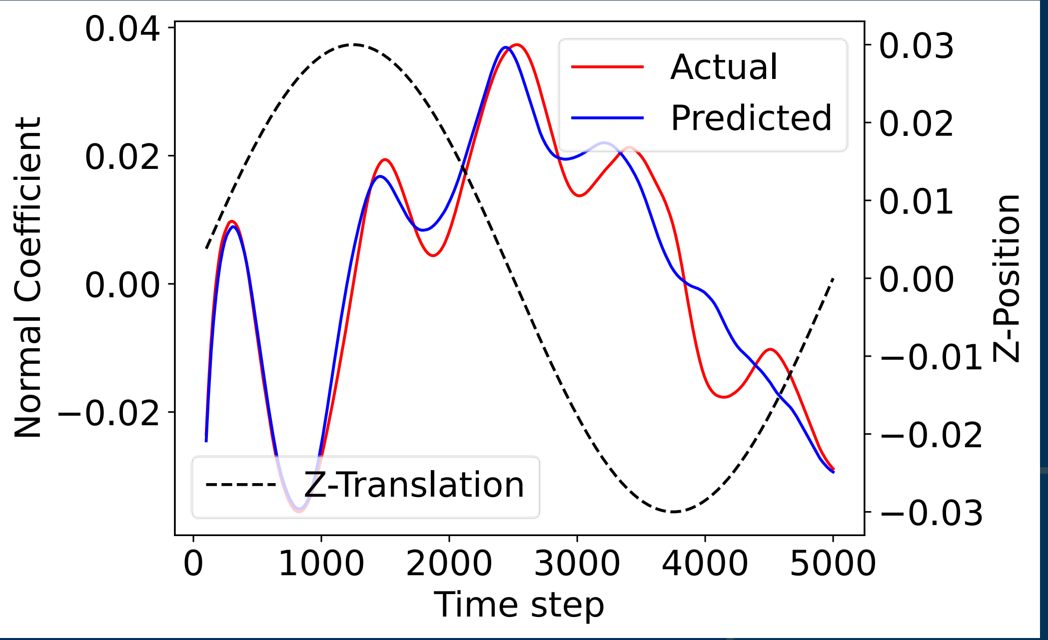


ROM C_p Field

Aerodynamic Coefficients vs Time

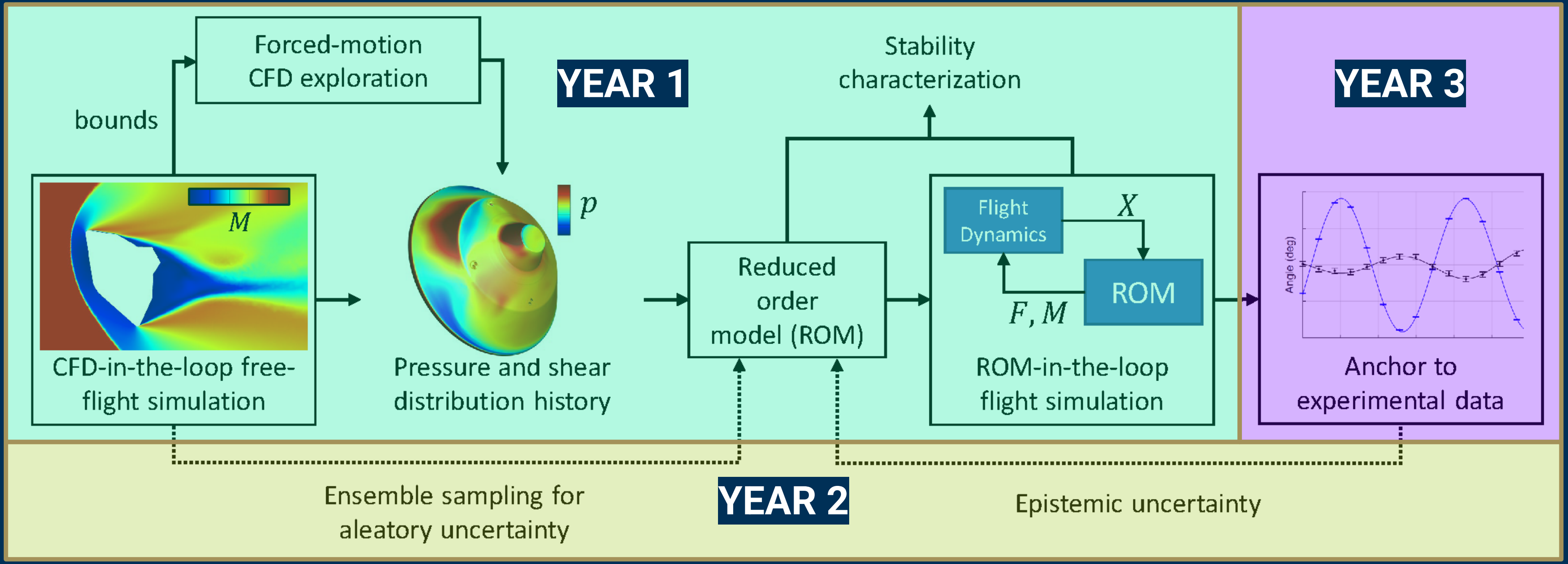
- By integrating over the C_p field, the aerodynamic coefficients can be generated
- ROM can capture the trends in the aerodynamic coefficients
- Discrepancies in aerodynamic coefficients indicate that potentially a low order mode is not accurately captured with a single period forcing function simulation
- Ongoing ROM work:
  - Simulate more periods of flight for the ROM snapshot matrix
  - Evaluate moment coefficients from the ROM
  - Explore the use of a split ROM (i.e. heatshield and backshell fields are produced from their own ROMs)





Timeline/Next Steps

Project Summary



- Accomplishments over the first six months:
  - Genesis grid generation and testing
  - Initial POD experiments with sinusoidal forced motion show promising results
  - Basic interpolation and backmapping has shown the ability to predict un-sampled flight states

Next Steps

- Immediate:
  - CFD focuses on performing free-flight runs and sampling the space
  - Update ROMs to utilize free-flight data
  - Focus of ROM work will be to encode awareness of the previous flow state
    - Needs the ROM to predict a reasonable “next” flow state in the presence of unsteady aerodynamics
    - Fundamental advance in the field of ROMs

- Long term:
  - Implement ROM module in POST2
  - ROM-in-the-loop flight simulation
  - Understand aleatory and epistemic uncertainty