

Progress Towards Improving the Models in Model Based Systems Engineering with High Fidelity Physics

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Definition: Digital Engineering vs. MBSE

- **Model-based systems engineering (MBSE)** – a formalized methodology used to support the requirements, design, analysis, verification, and validation associated with the development of complex systems (*Nataliya Shevchenko, “An Introduction to Model-Based Systems Engineering (MBSE),” Software Engineering Institute (SEI), 21 Dec 2020*)
- **Digital engineering (DE)** – an **integrated digital approach** that uses authoritative sources of systems' **data** and **models** as a **continuum across disciplines** to support life cycle activities **from concept through disposal**. (*Defense Acquisition University*)
 - Integrated digital approach → a monolithic solution that suggests there can be no R&E / A&S divide
 - Data → must be regularly managed/updated/curated at each stage of the process
 - Models → both compute and data-intensive; range from basic analysis to high-end computing (HEC)
 - Availability → accessible to anyone in the design, test, evaluation, sustainment, mission planning pipeline
 - Duration → from concept through disposal (and possibly beyond); decades to centuries
 - Extensity → continuum across disciplines; simultaneous accounting of all assets at all lifecycle stages to facilitate projection of current and future forces in a full range of scenarios, to determine gaps, to advise the characteristics of future platforms, and to build preventive maintenance plans for individual assets



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HPC Impacting Digital Engineering



Physics Based Simulation

High Fidelity Physics Simulations Primarily Used for Issue Diagnosis and Resolution or Design

Downselect

- Many Single Point Calcs
- Close match with Reality
- Typically Occurs after wind tunnel tests or after flight tests (days!/M's CPU Hrs)
- Fixes can be costly since vehicle is farther in the design process
- Data computed not in a form easily reused for other needed points

Models

System Level Models Useful for Systems Engineering

- Calculations are faster than real time
- Broad applicability of model to vehicle envelope
- Can be available any time in the design cycle
- Only useful if decision level data is accurate enough
- Easily moved through the design cycle
- Continuously updated as system design changes

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Physics Based Surrogates

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- Based on pre-computed high fidelity simulations
- Broad applicability to vehicle flight envelope
- Faster than real time calc times

- Single or multi-physics applicability depending on pre-computed physics sims
- Can be combined with other surrogates

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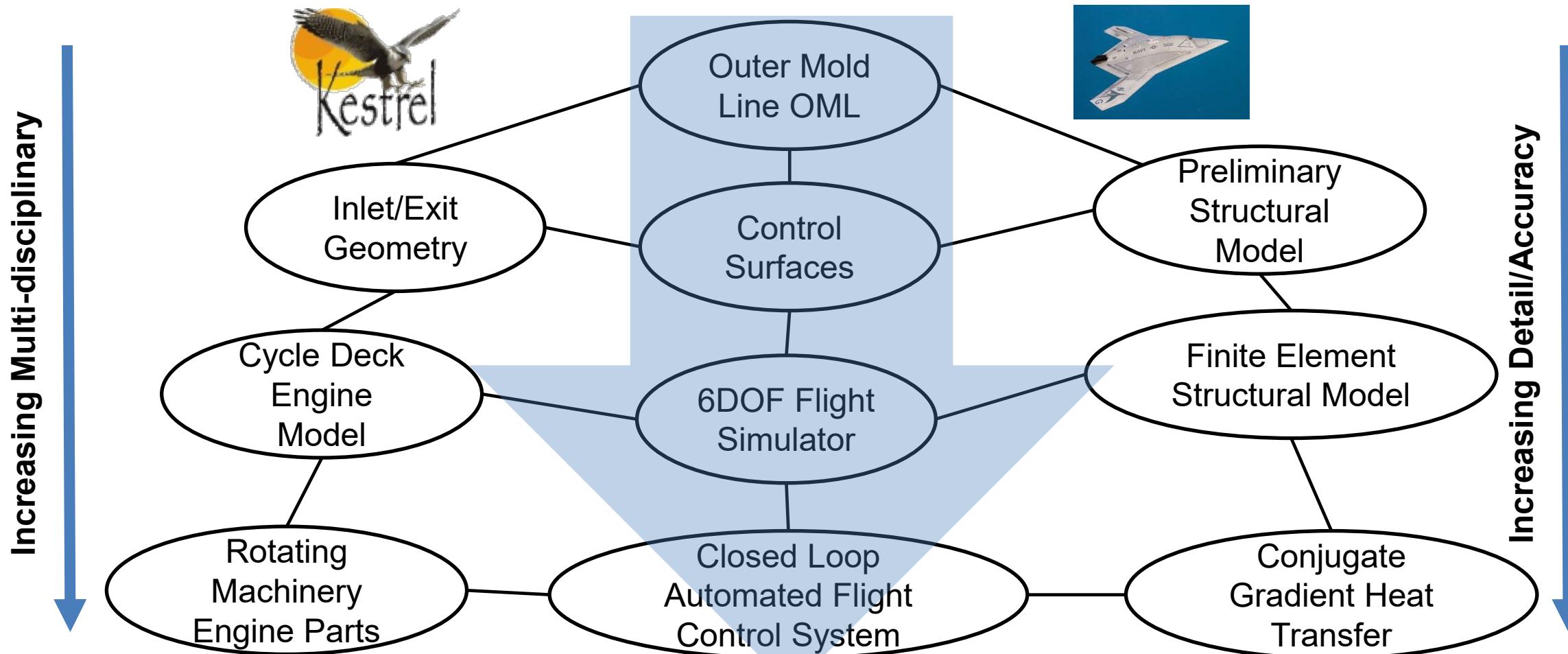
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Model Based Systems Engineering



Physics Based Simulations

- During the design process we can eliminate poor design choices by increasing the fidelity of the PBAs as more information is known (objects and connection notional)





Physics-Based Simulations



Integrated Rotating Machinery



Integrated Structural Elasticity



Integrated Moving Control Surfaces



Single Point Physics-Based Surrogates

- Many methods of building Surrogates/ROMS
- Aircraft C.G. Loads using System Identification
- Distributed Loads using Proper Orthogonal Decomposition
- Machine Learning using Neural Networks

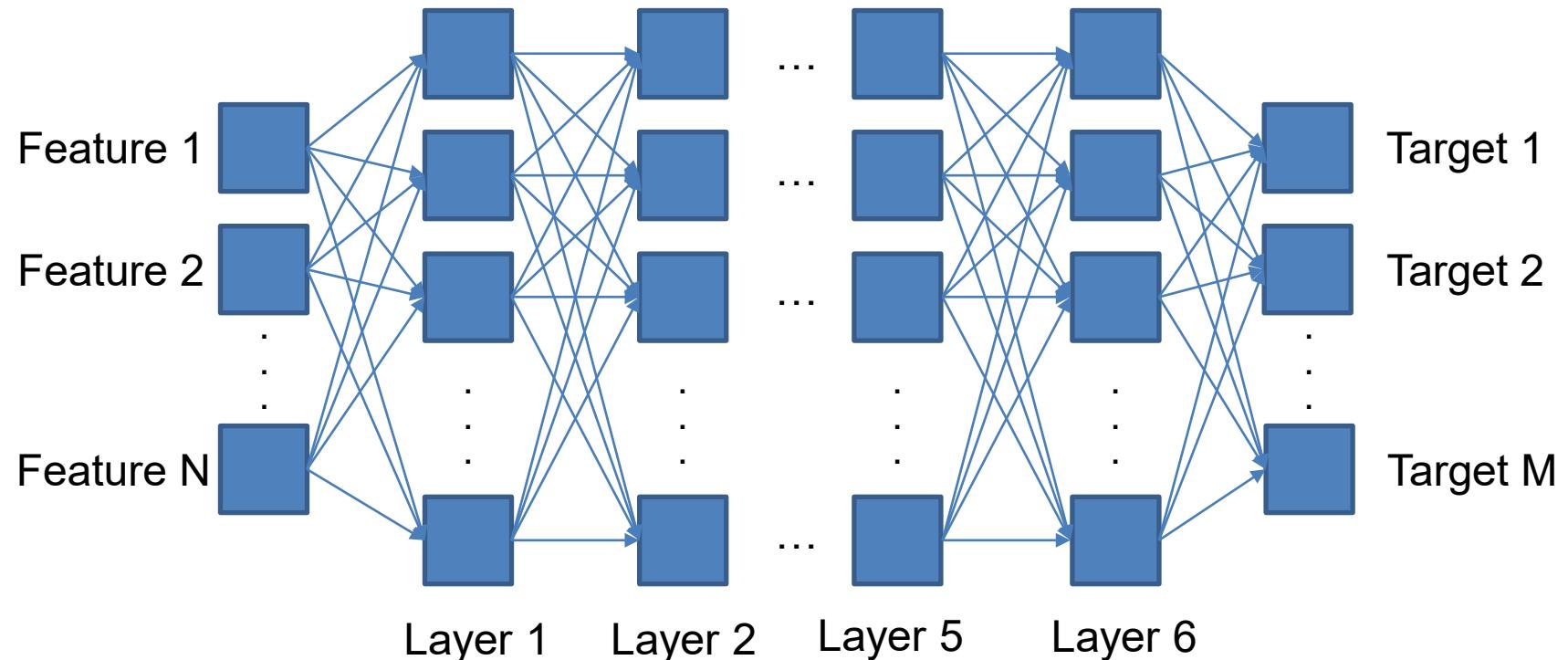
Vehicle Envelope Level Surrogates-AI/ML

Machine Learning Methods

- A wide variety of machine learning methods exist
- For the current effort the Deep Neural Network (DNN) and the Convolutional Neural Network (CNN) are the primary focus
- The DNN is a simpler method that learns based on point based information
 - This is the main ML driver for the effort
- The CNN is a more complex method that learns based on patterns in distributed information
 - This is included as an optional feature that allows for the inclusion of more complex physics into the analysis when needed

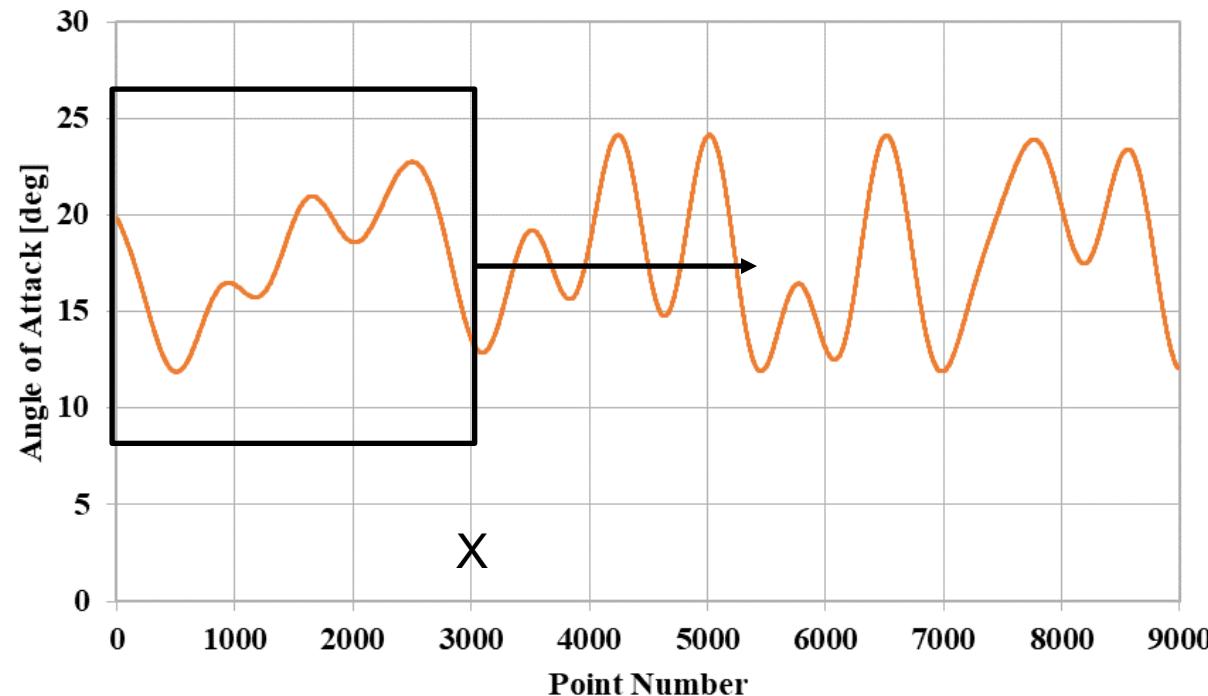
Deep Neural Network (DNN)

- The DNN is the core ML method employed for this effort
- The DNN implemented is a multi-layer perceptron regressor
- The current setup uses 6 hidden layers of 100 neurons



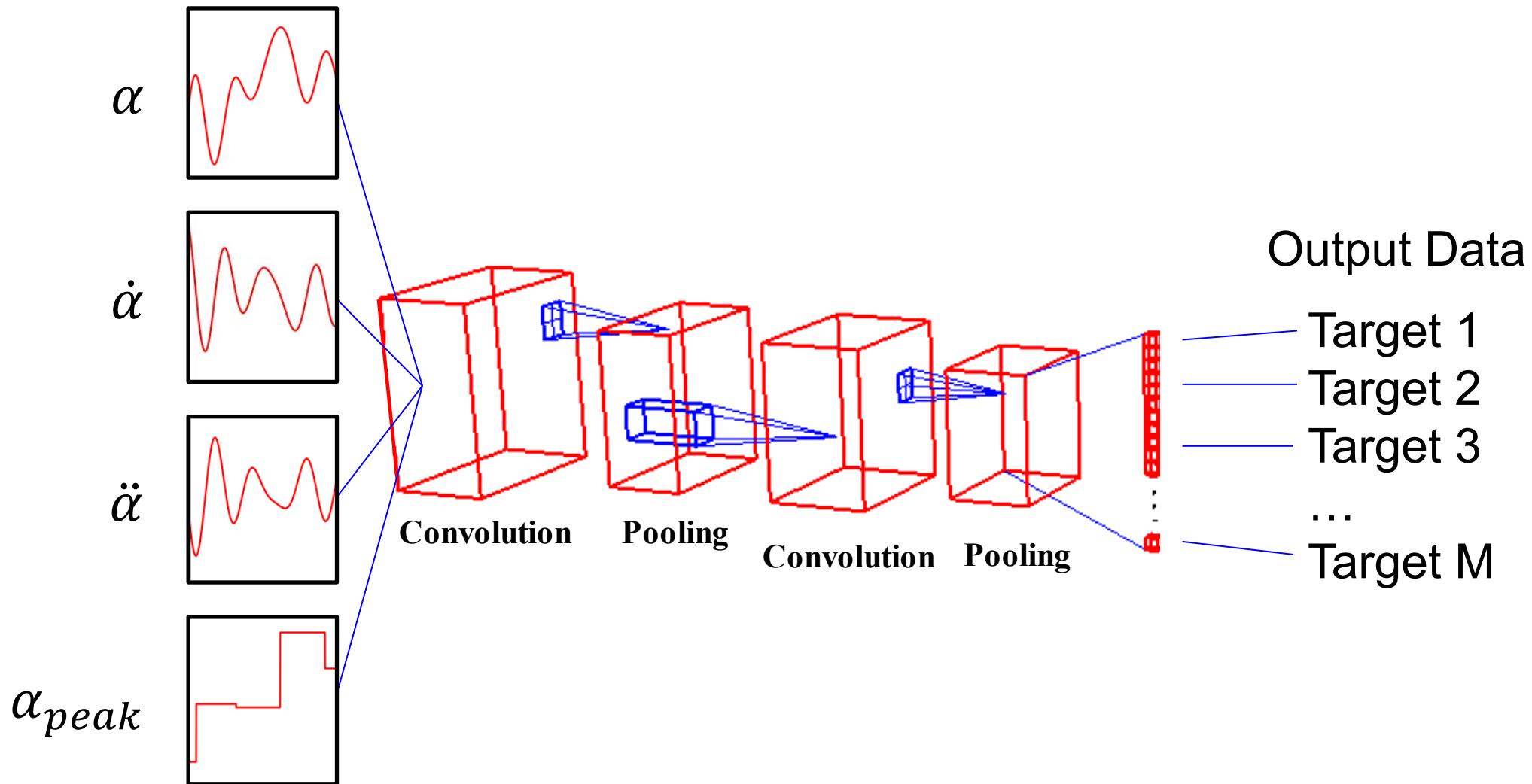
Convolutional Neural Network (CNN)

- A one-dimensional form of the CNN is employed in this effort
- The input time-history data are divided into sequences to train the model
- The target data are extracted at the next point in the sequence



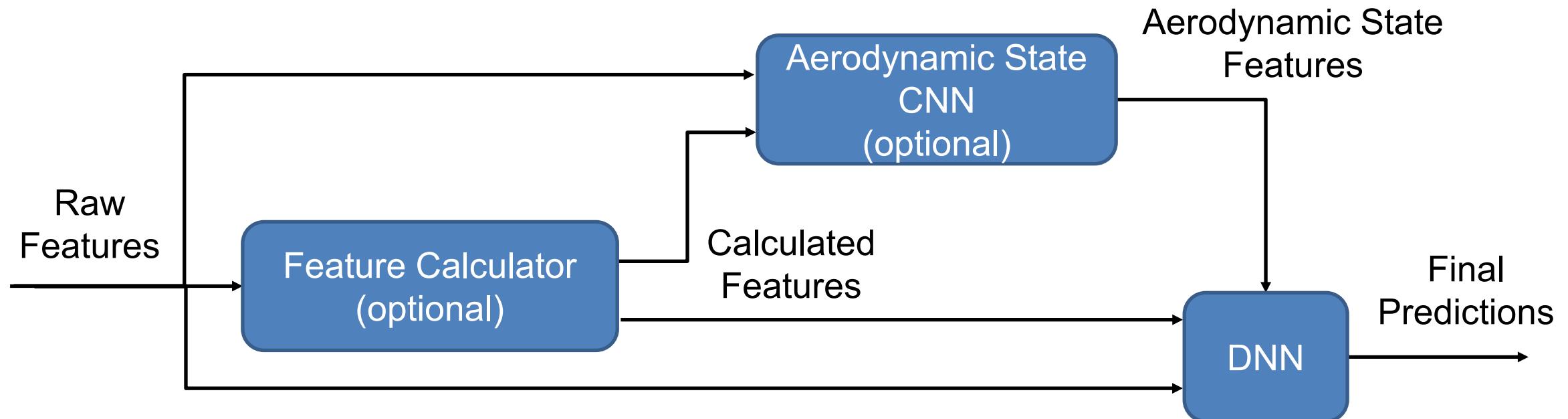
CNN Architecture Illustration

Input Sequences



Dual Machine Learning Framework

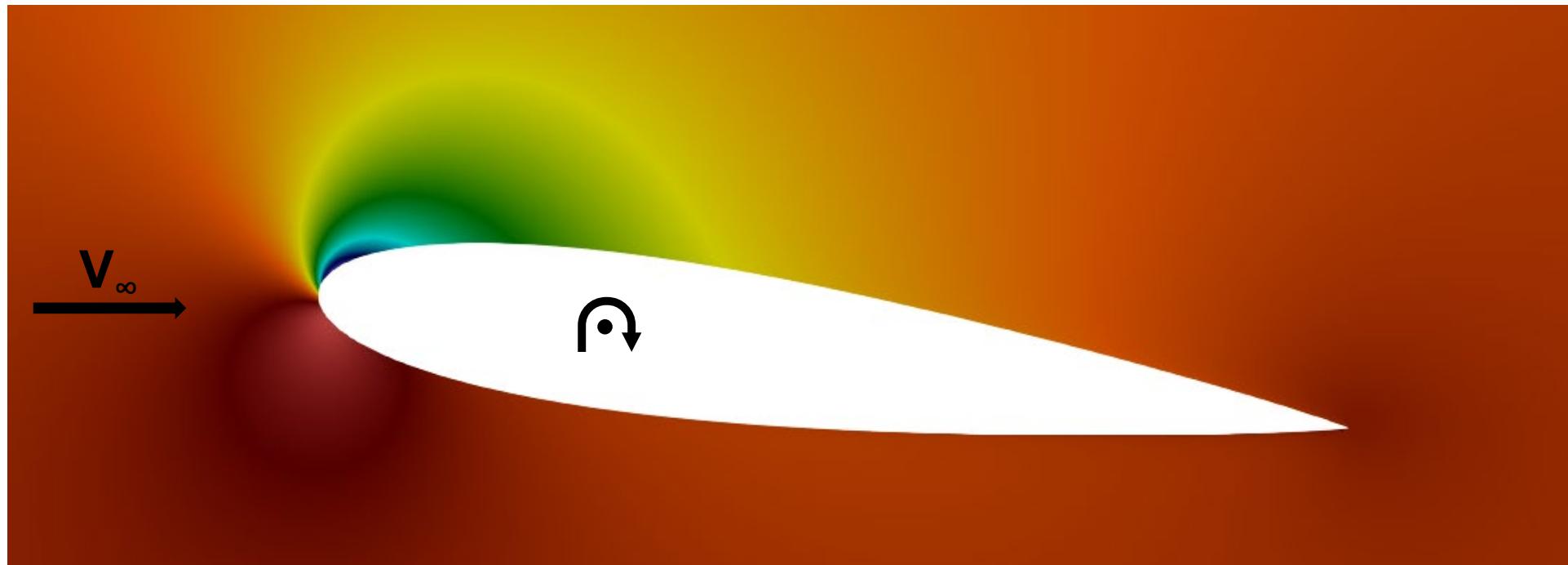
- The DNN and CNN are combined into a dual ML framework
- Inclusion of the aerodynamic state is beneficial for the prediction of loads where the contribution of more complex physics is a non-trivial factor
 - The CNN is used to include the more complex physics behavior where needed
 - Use of the CNN is optional because for a majority of the use cases targeted the contribution of complex physics isn't a major factor in predicting sufficiently accurate integrated loads





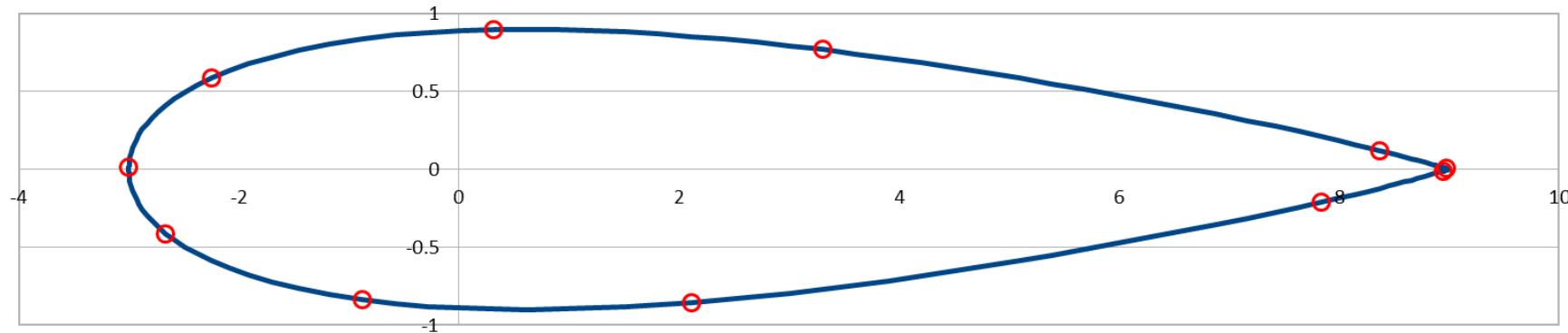
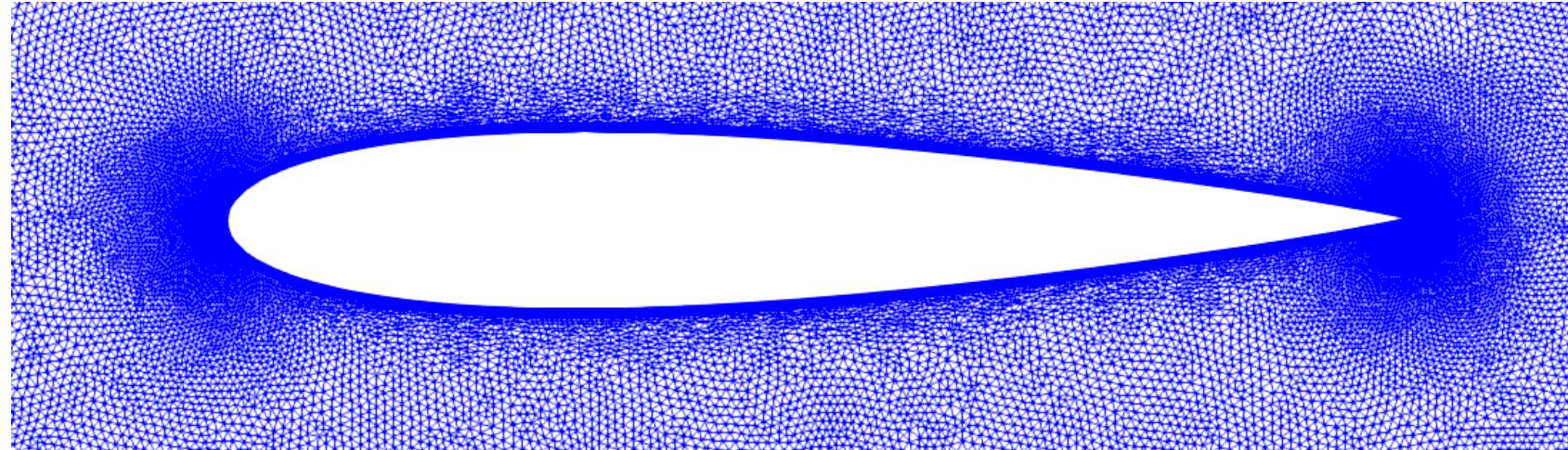
NACA0015: Problem Description

- NACA0015 pitching airfoil about the quarter chord
 - R. A. Piziali, "2D and 3D Oscillating Wing Aerodynamics for a Range of Angles of Attack Including Stall," NASA-TM-4632, 1994
- Case setup to match this report as well as to define parameter bounds for angle and frequency
 - No comparisons to experimental data are intended



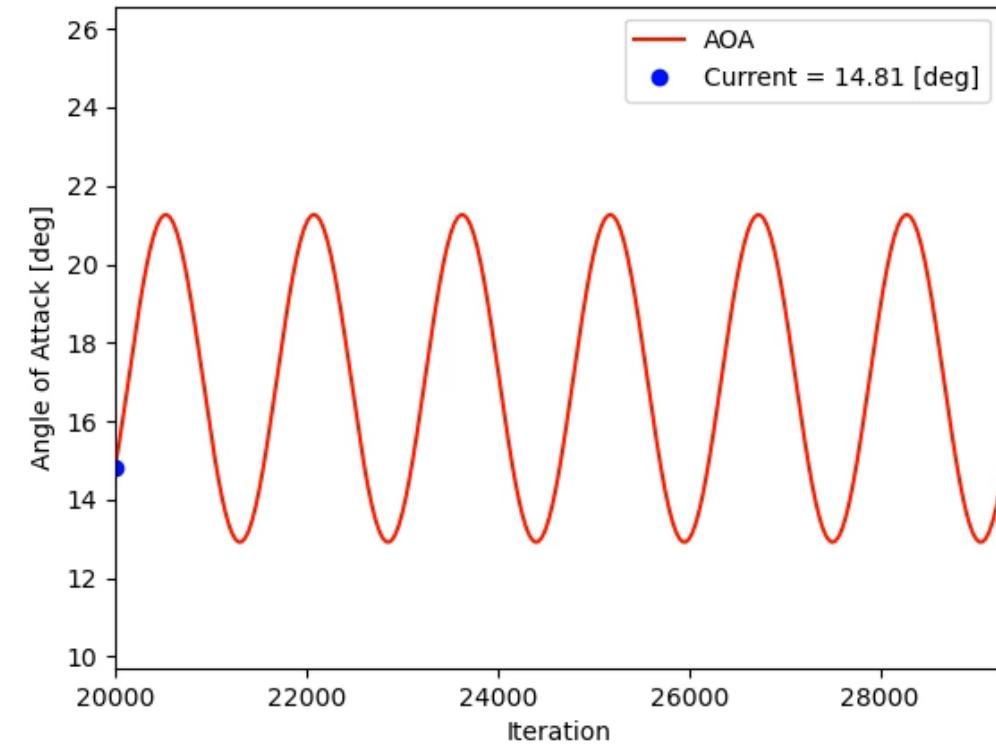
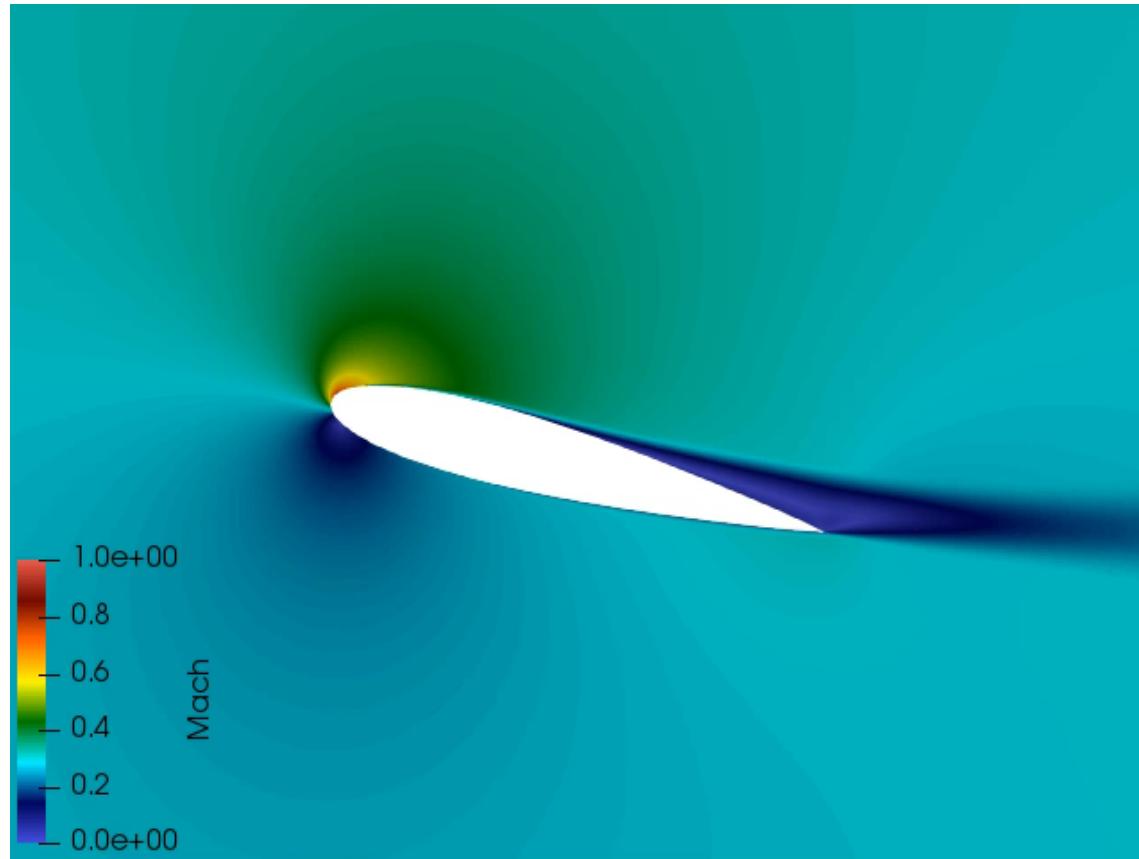
NACA0015: CFD Setup Description

- Kestrel v12.1, 44 Procs (Onyx)
- 2D Airfoil, 200 surface taps, 11 taps used for the ML study



NACA0015: Simulation Illustration

- Illustrates the degrees of freedom for the setup
- Also provides an example of why predicting the aerodynamic state is sometimes needed

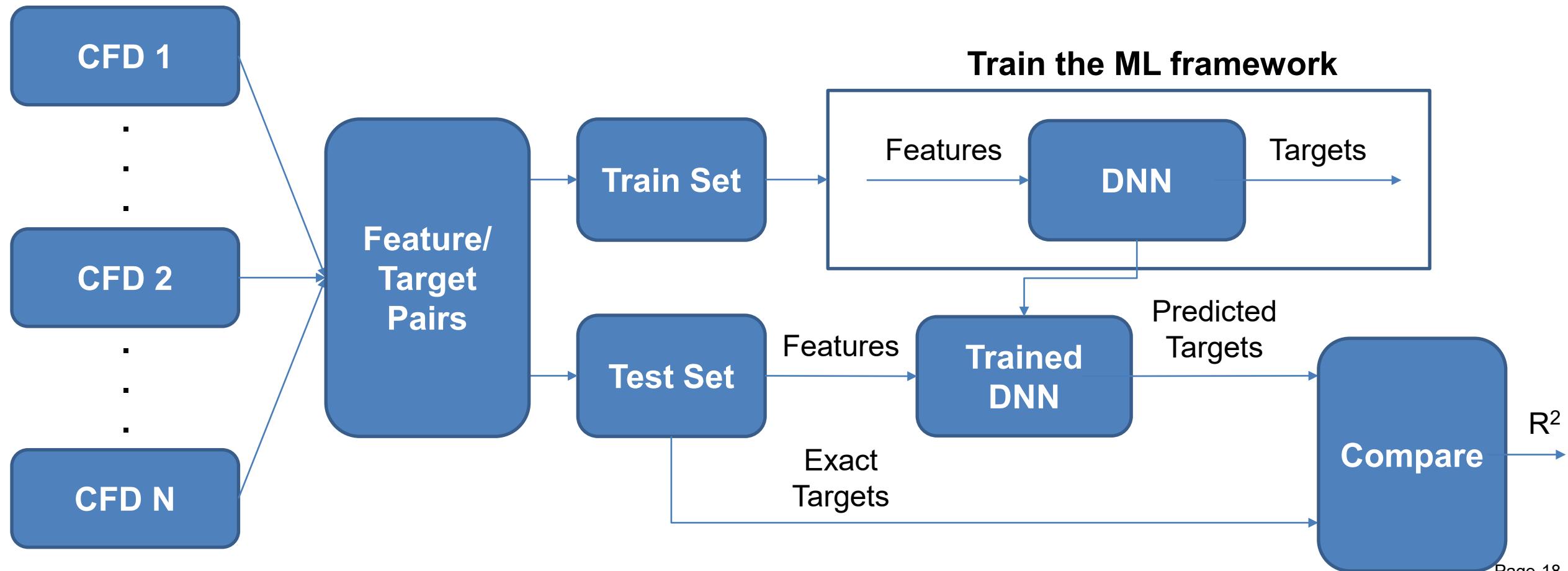


NACA0015: ML Model Setup

- **Input Features**
 - Case 0: α
 - Case 5: $\alpha, \dot{\alpha}, \ddot{\alpha}, \alpha_{Peak}$
- **Output Targets**
 - CNORMAL, CAXIAL, CPITCH
- **Case 0 is trained using steady CFD data**
- **Case 5 is trained using unsteady CFD data**

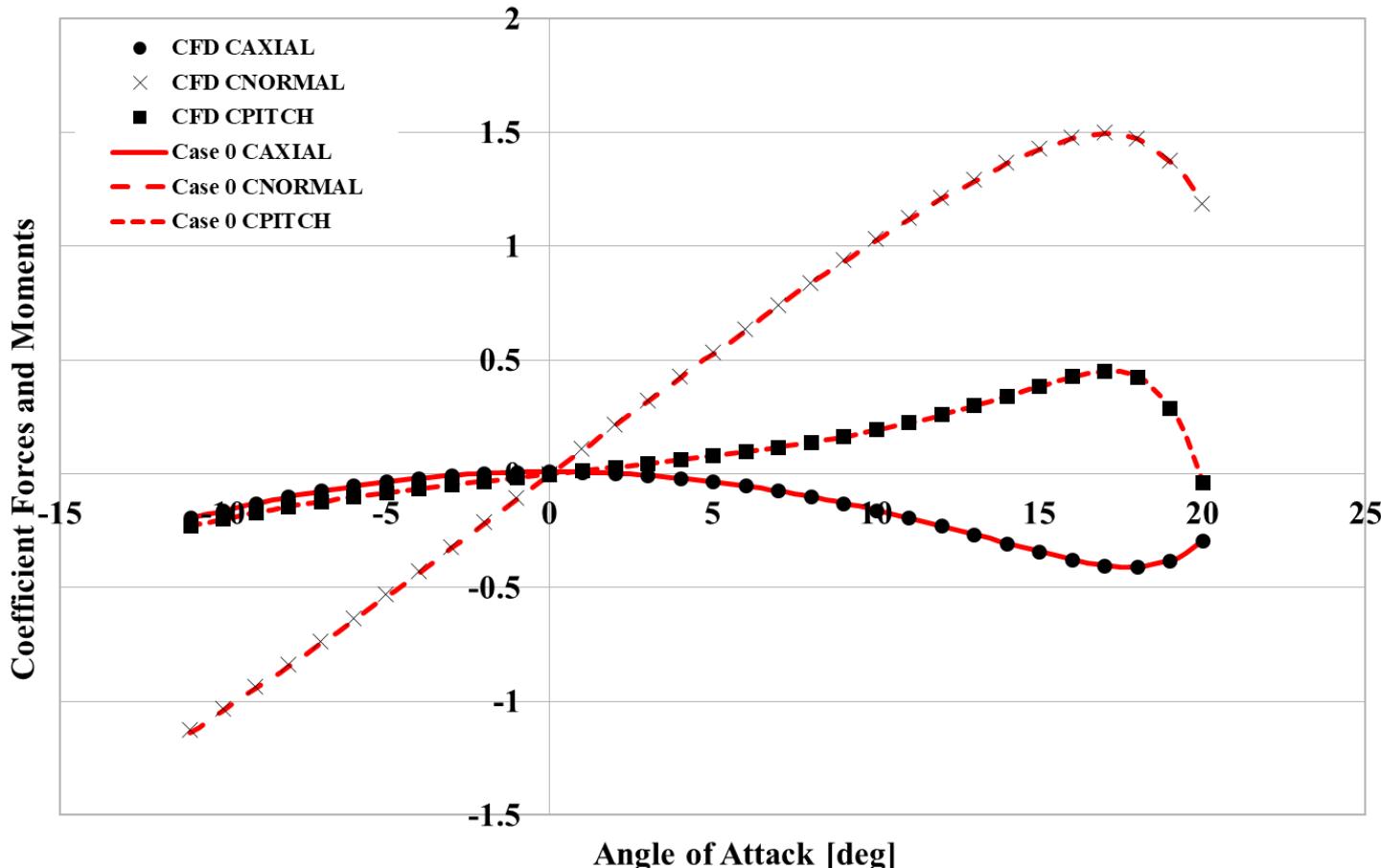
NACA0015: Training Workflow

- Time-history data sourced from multiple CFD simulations
- Each iteration of each simulation is treated as an individual example



NACA0015: Steady Train and Prediction Results

- For the airfoil case the results are a good fit for Case 0 where only steady-state data are used to train the model
- In this database lookup type use case having only angle of attack as input is acceptable/preferable

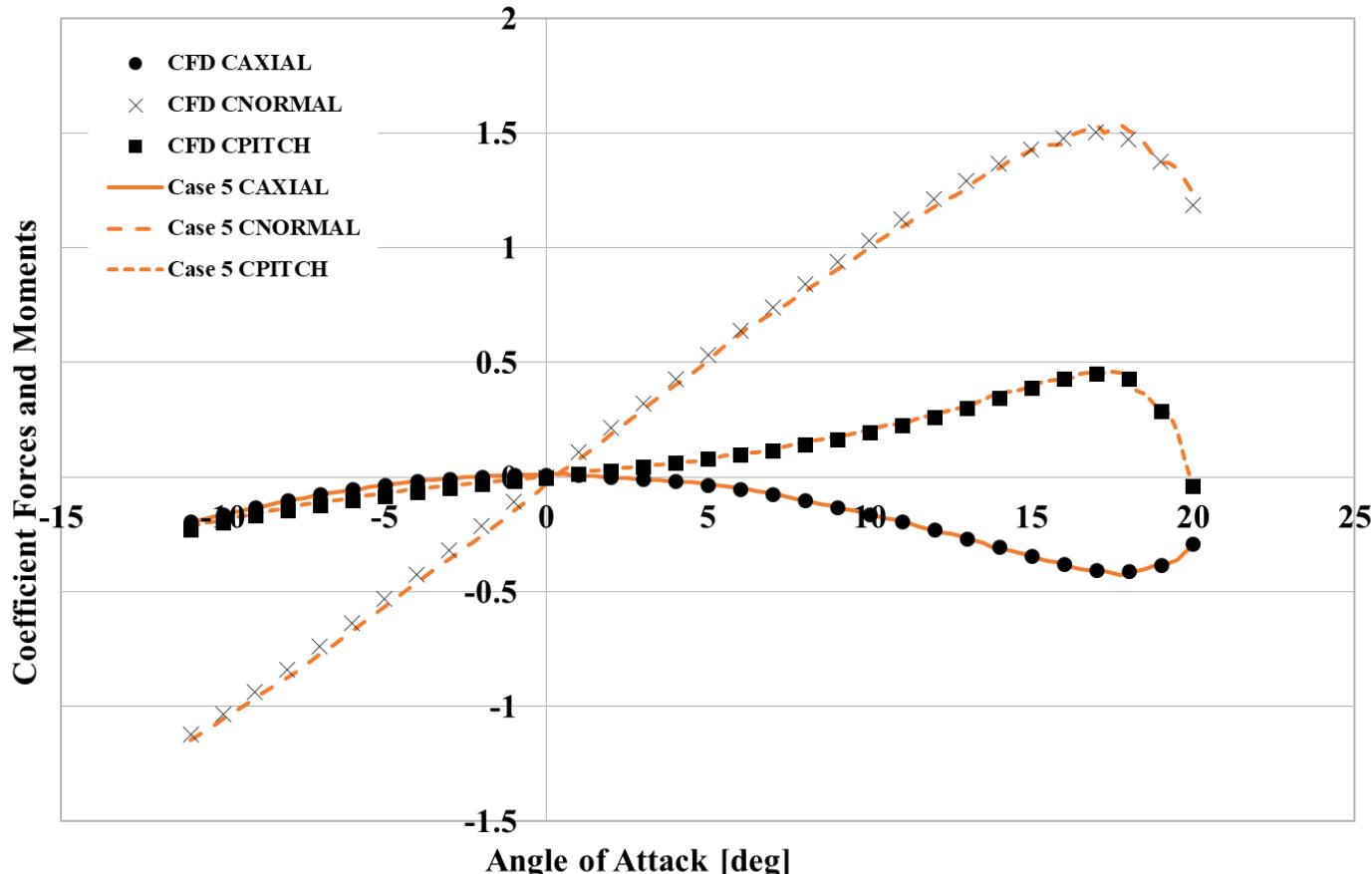


NACA0015	Case 0 (α)
Test Data Score	0.9998

NACA0015: Results using Unsteady Train Data



- Steady predictions are still possible using the unsteady dataset
- Increasing the feature space to include rate and prior peak data is able to capture the steady angle of attack sweep



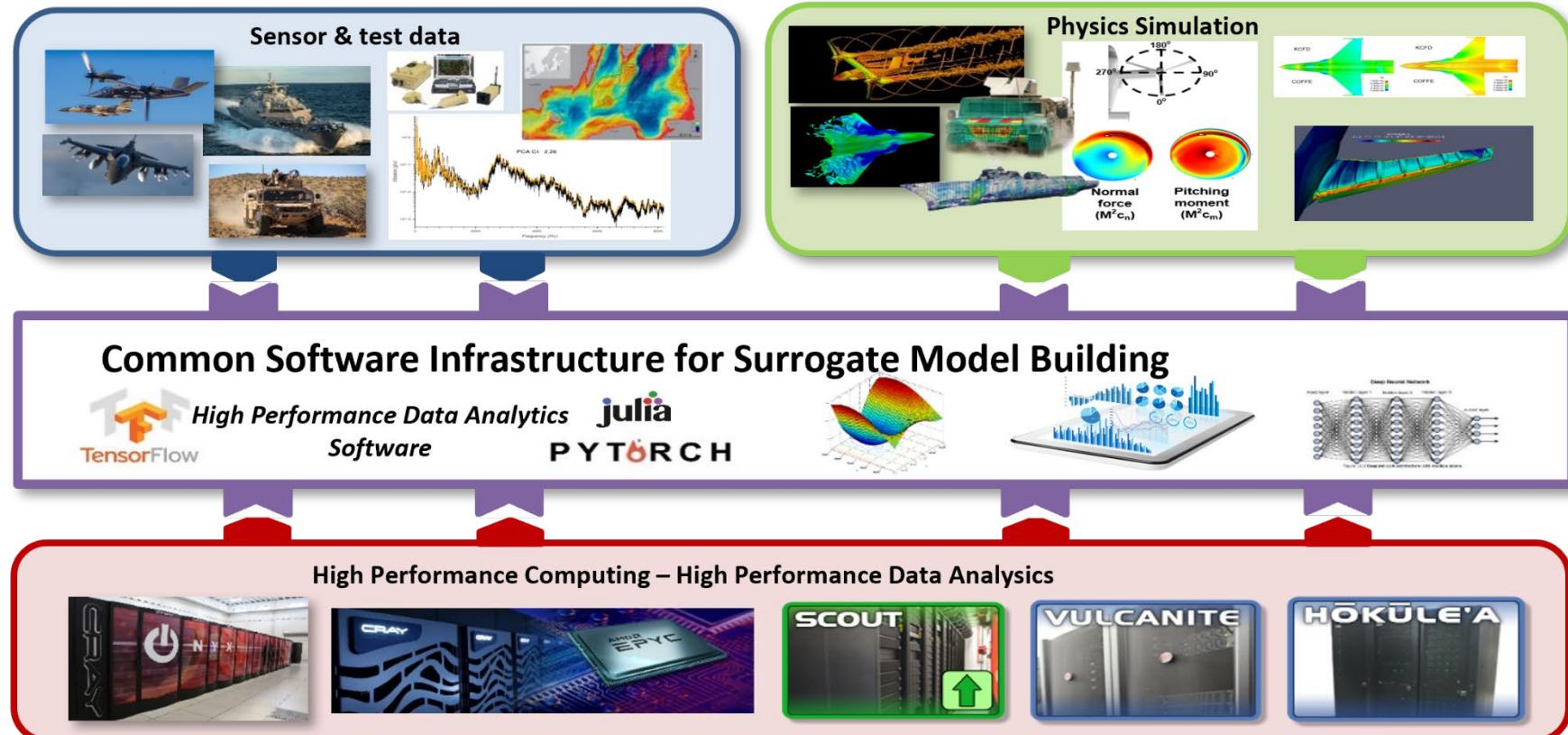
NACA001 5	Case 5 ($\alpha, \dot{\alpha}, \ddot{\alpha}, \alpha_{Peak}$)
Test Data Score	0.9452



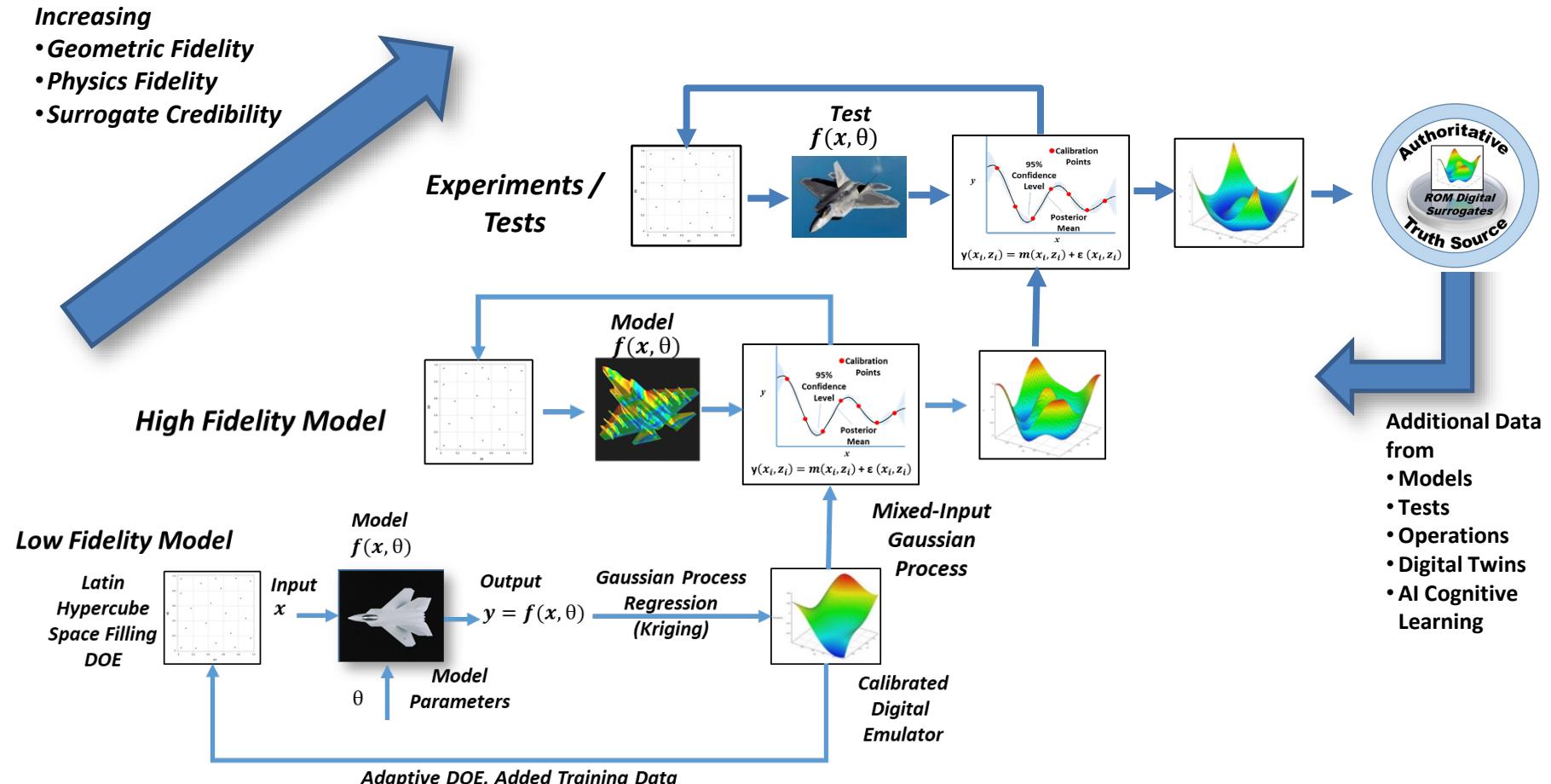
Surrogate Building Infrastructure

Software infrastructure to enable *surrogate model generation from data-driven analytics and physics-based analytics for DoD Air, Land, and Sea Vehicles

*Surrogate = approximate model used when a full-physics computational model is intractable



Developing an Authoritative Digital Surrogate Reduced Order Model for Aerodynamics



Edward M. Kraft, "Development and Application of a Digital Thread / Digital Twin Aerodynamic Performance Authoritative Truth Source," AIAA-2018-4003. Aviation Systems Conference, Atlanta, GA, June 25-29, 2018

Concluding Remarks and Discussion

- The Connection between Physics Based Simulation and Useful Models for Model Based Systems Engineering have been described
- The union of Machine Learning and Digital Surrogate Training via Physics-Based virtual test is what will deliver decision support data at the speed of relevance
- A ML based surrogate model has been developed using a combination of Deep Neural Network based Machine Learning techniques
- A generalized framework that incorporates the novel ideas of aerodynamic state prediction can capture complex temporal variations
- The model has been validated for a number of 2D and 3D steady-state and unsteady cases
- Broader applicability to the aircraft system are underway to include more than just aerodynamics and across the vehicle envelope

Acknowledgements



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Questions?