Development of Machine Learning Models for Predicting Wind Fields Around a Military Ground Vehicle

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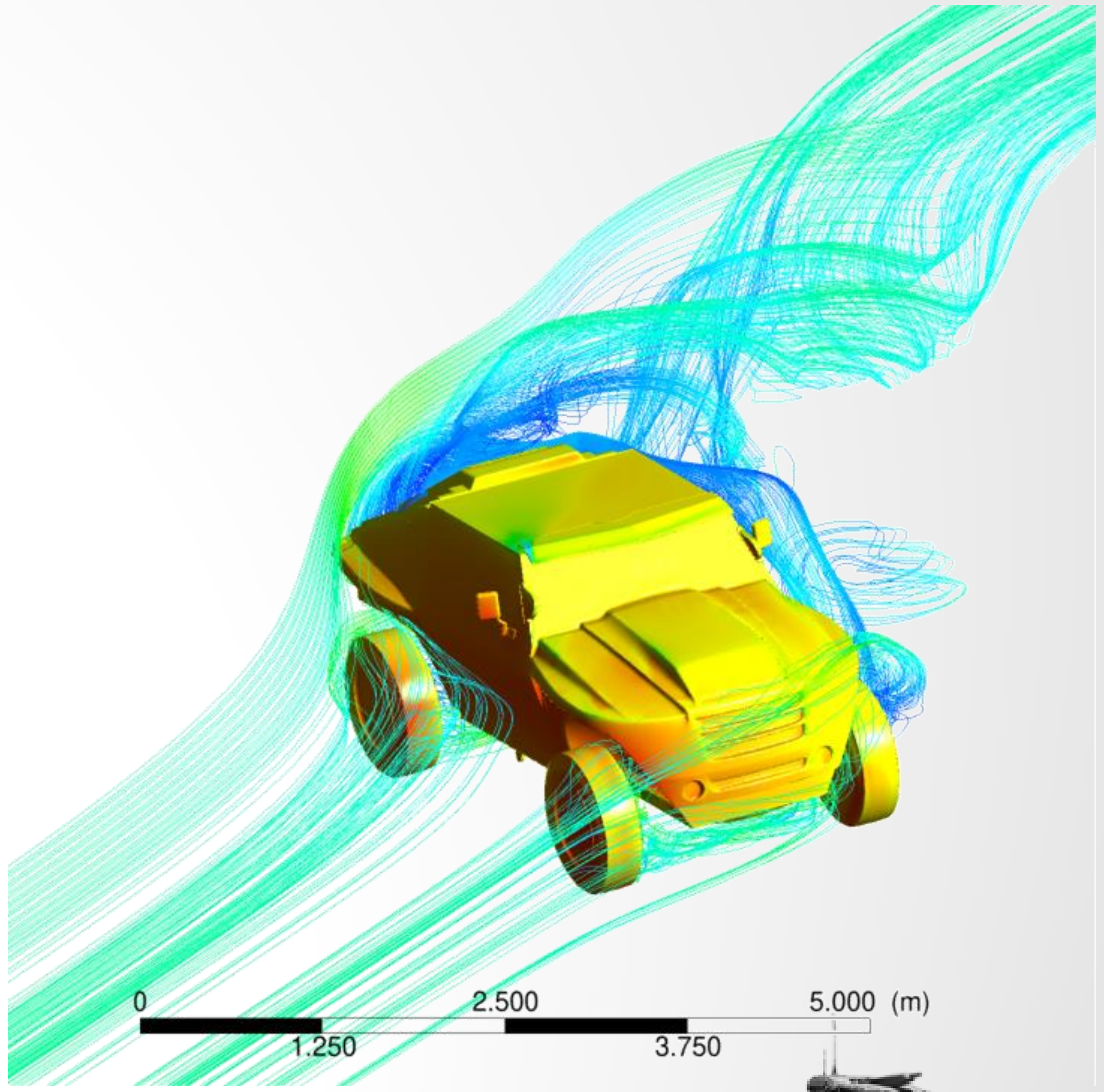
Outline

- Problem definition
- Study approach
- High fidelity data preparation
- Dimensionality reduction
- Machine learning models
- Results and discussions
- Conclusions
- Future work

Problem Definition

- Military vehicles during extended missions face varying environmental conditions
- Predicting wind and temperature fields around these vehicles is crucial to avoid detectability by infrared (IR) devices
- Computational fluid dynamics (CFD) can be used for this purpose
    - CFD is time-consuming
- Research questions
    - How to calculate flow fields in real-time?
    - Which machine learning model is most accurate for prediction of fluid flow data?
    - What is the error between the prediction and CFD solution?



Study Approach

High Fidelity Data Generation

- Computational Fluid Dynamics

Dimensionality Reduction

- Proper Orthogonal Decomposition (POD)

Machine Learning (ML) Model Development

- Neural Network Development

Low Dimensional Data Prediction

- Prediction using Trained ML Model

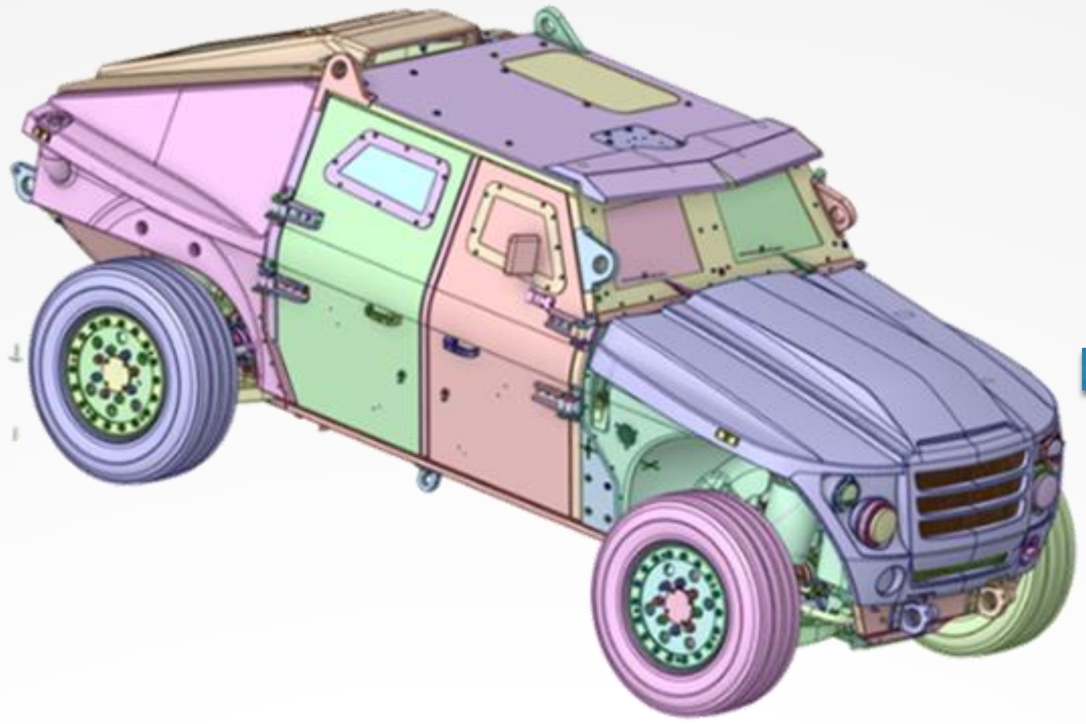
Projection of Low Dimensional Data to Higher Dimension

- Flow Field Reconstruction

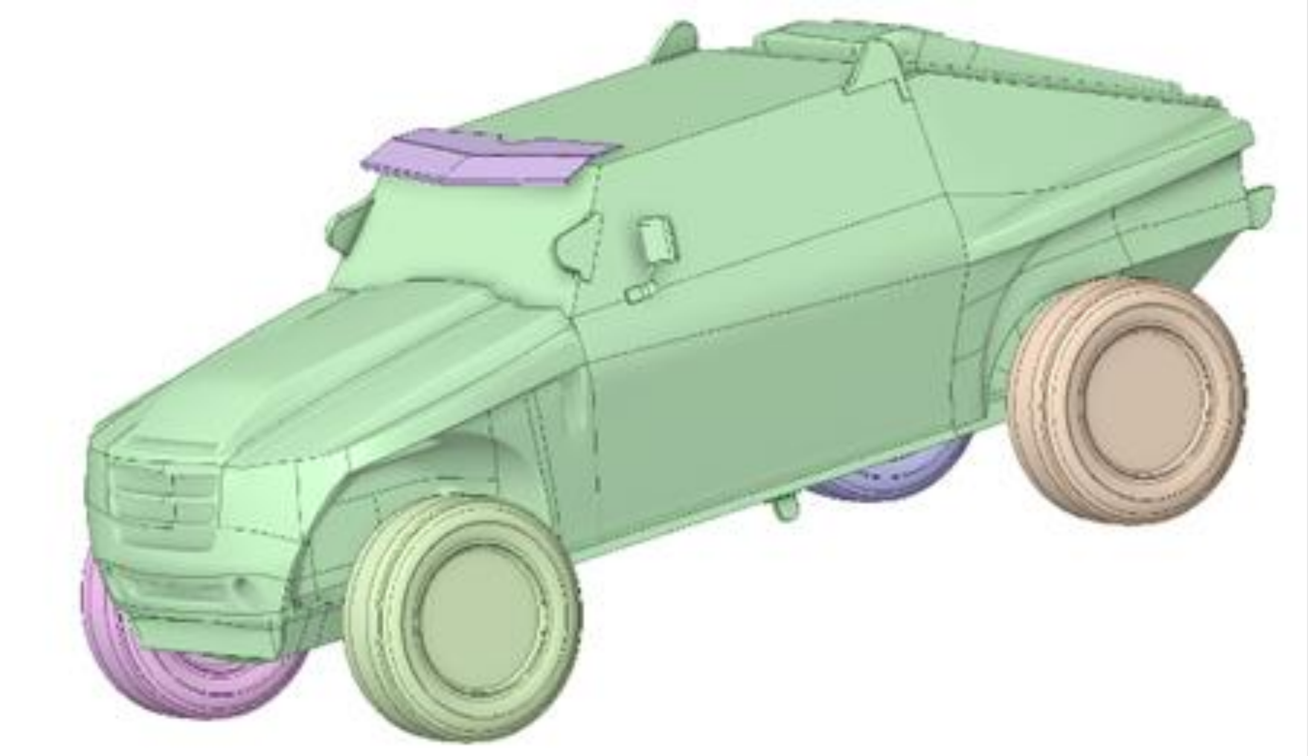
High Fidelity Data Generation

Geometry Preparation and Mesh Generation

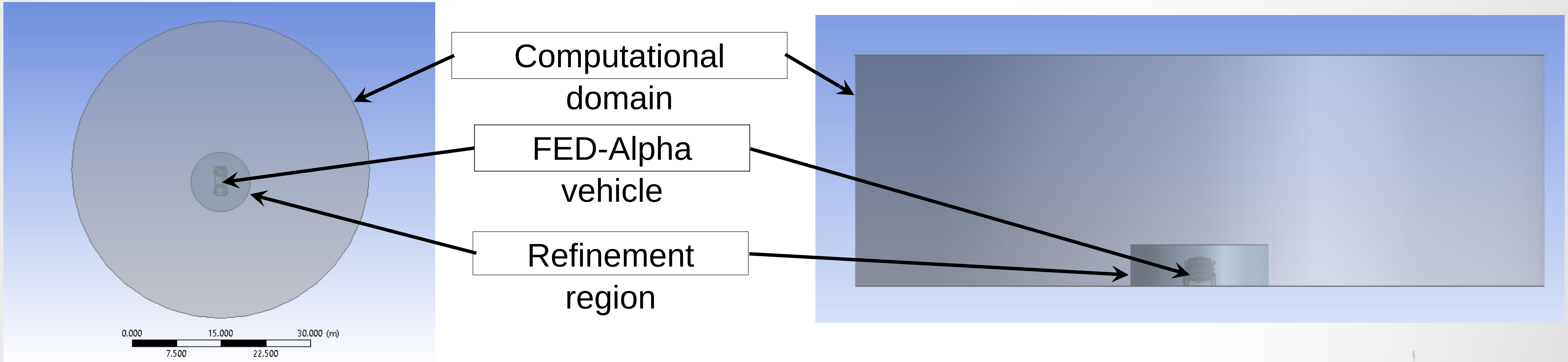
FED-Alpha Vehicle



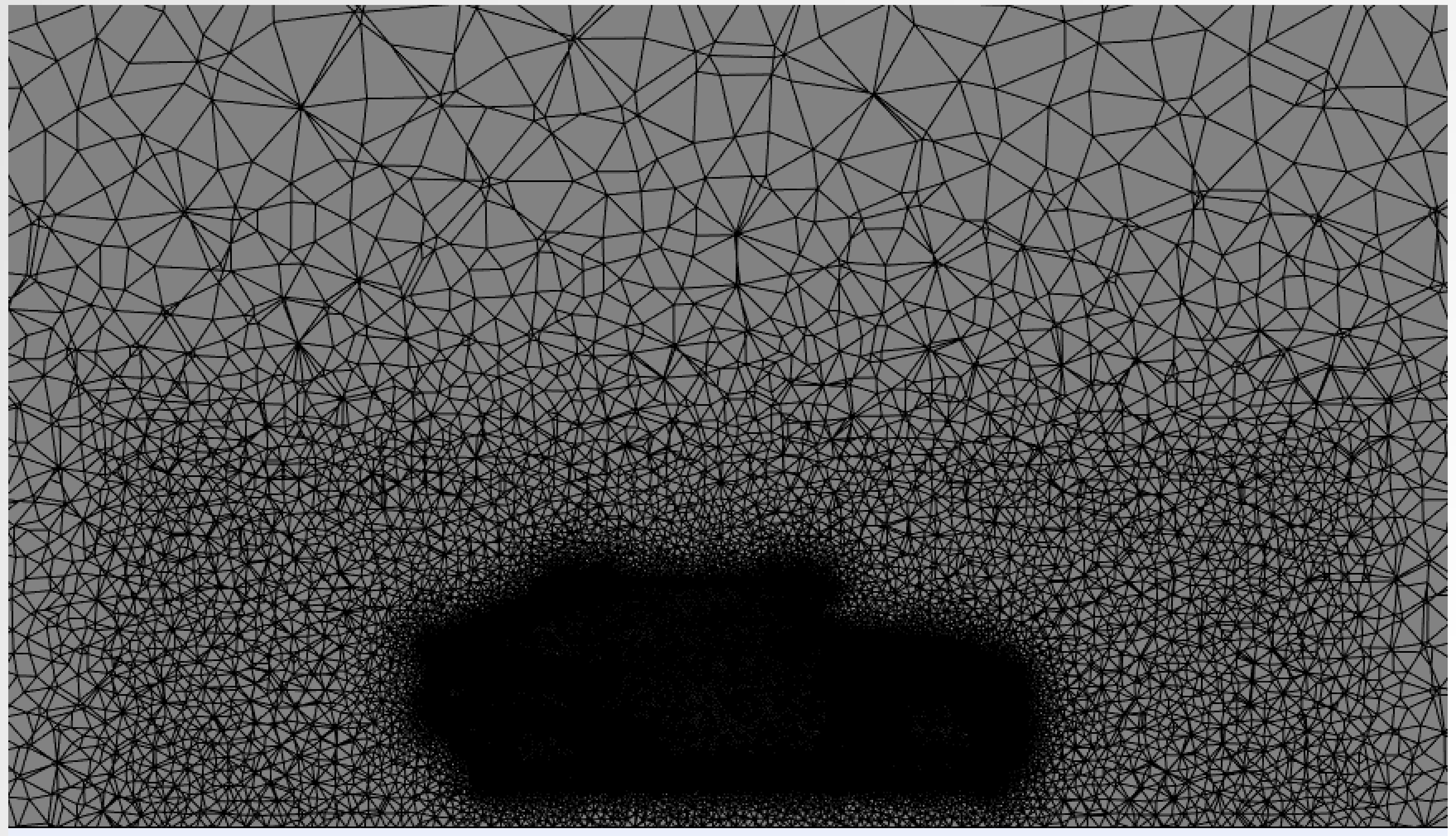
Detailed Geometry

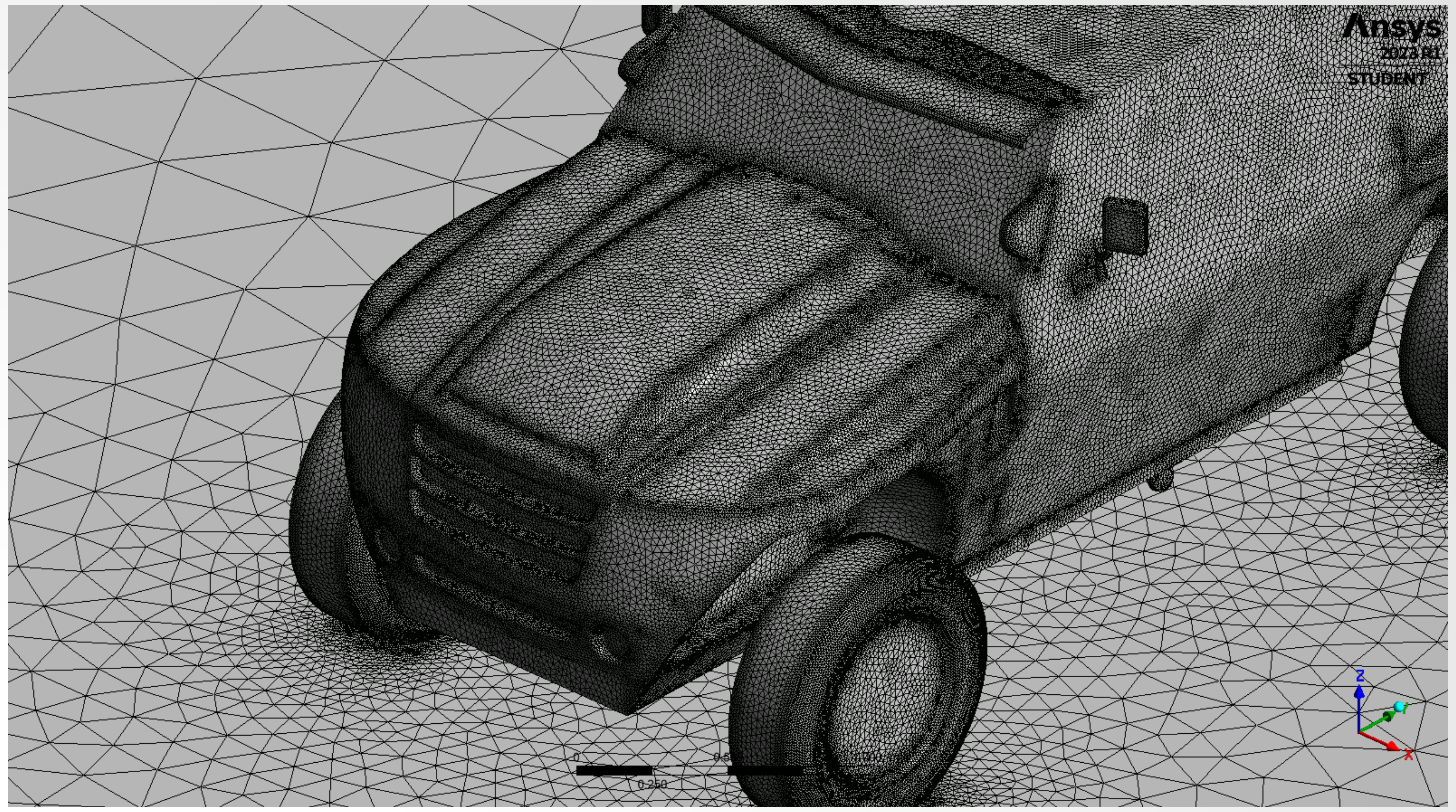


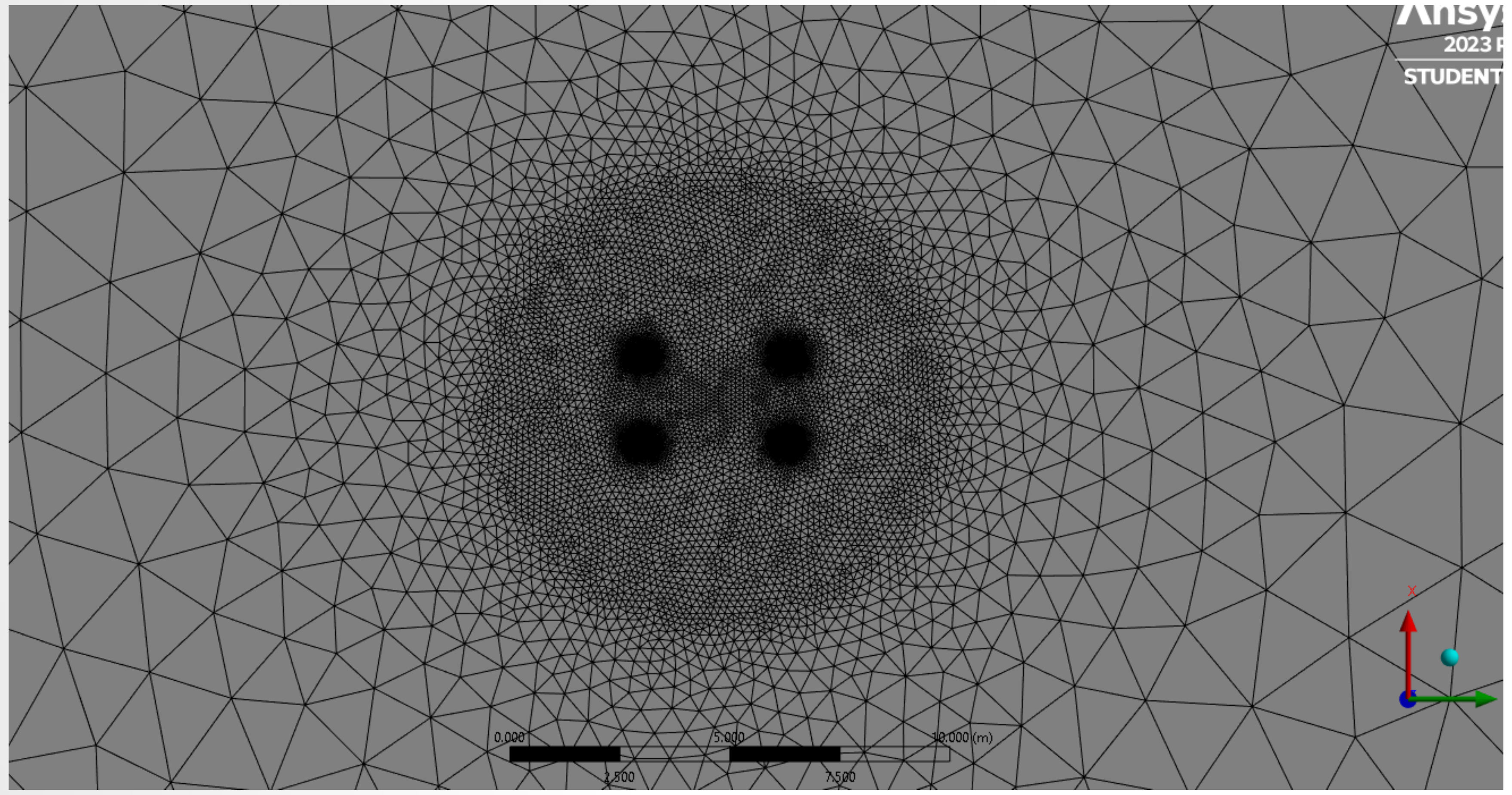
Simplified Geometry



Geometry Preparation and Mesh Generation (contd.)







Specified refinements on the vehicle and in the refinement region

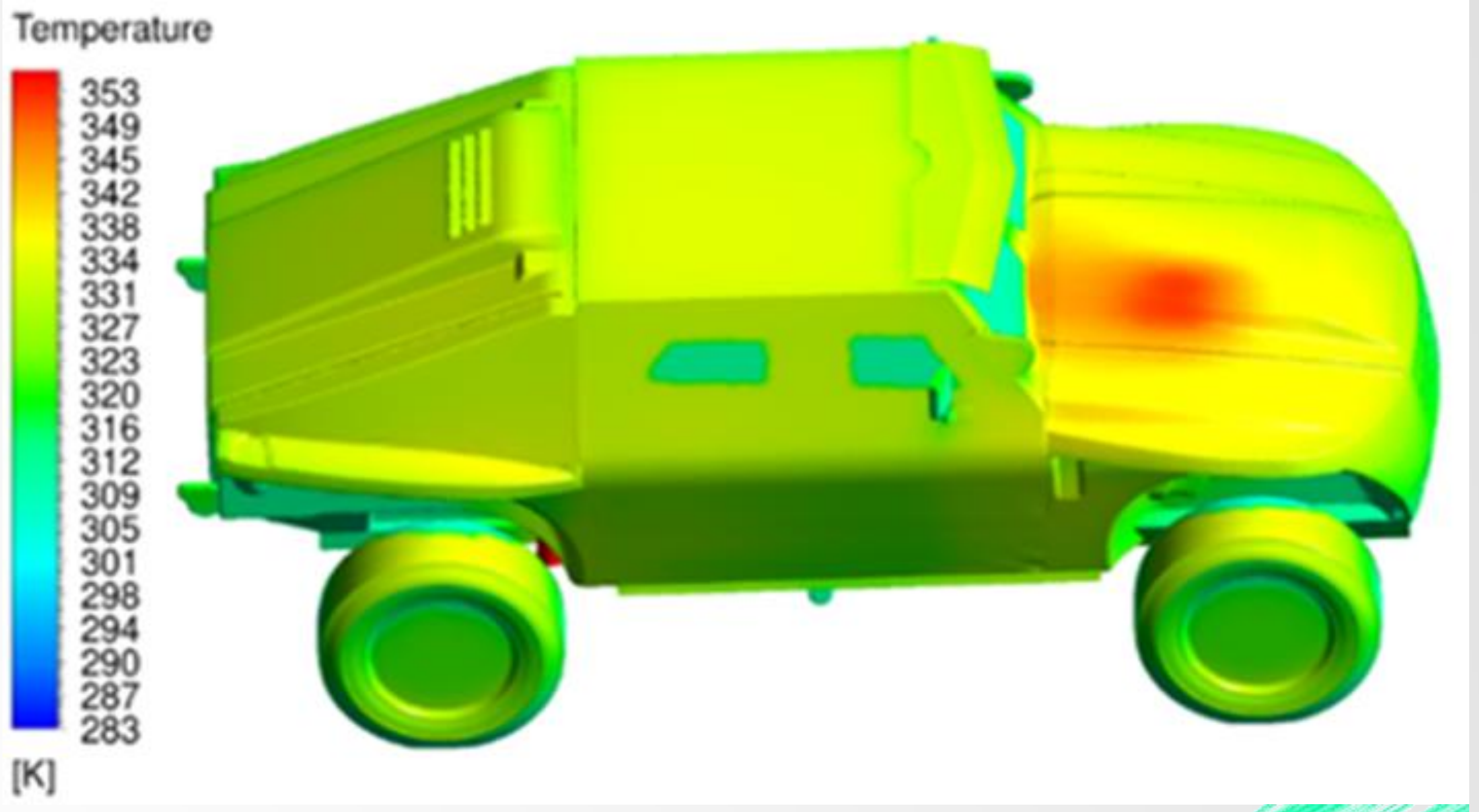
Used boundary layer mesh on the vehicle

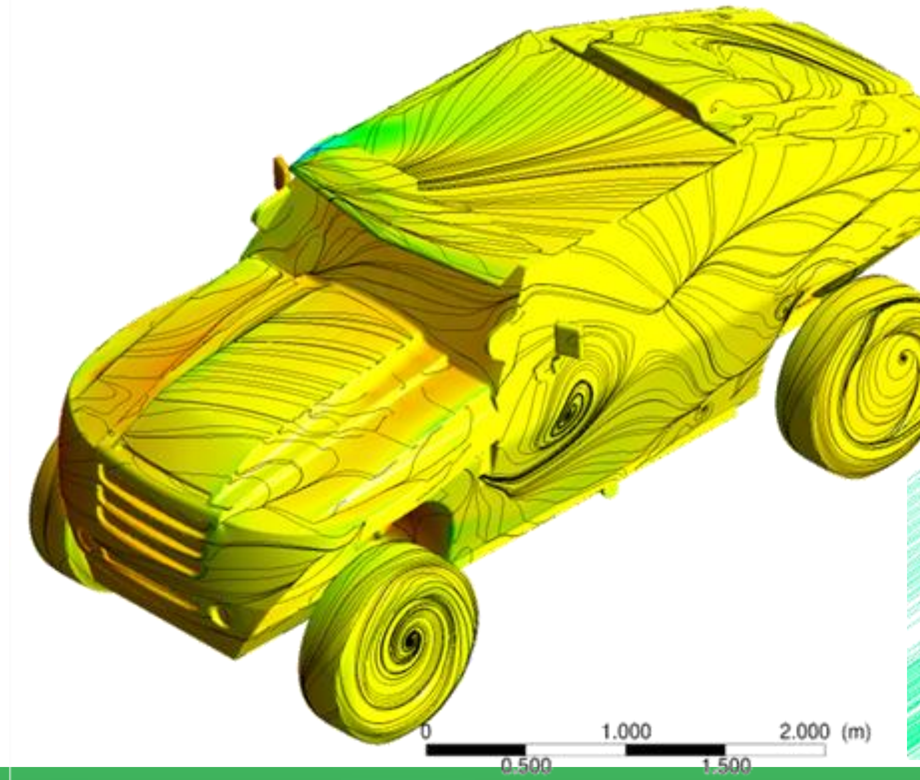
Number of nodes: 4,463,607

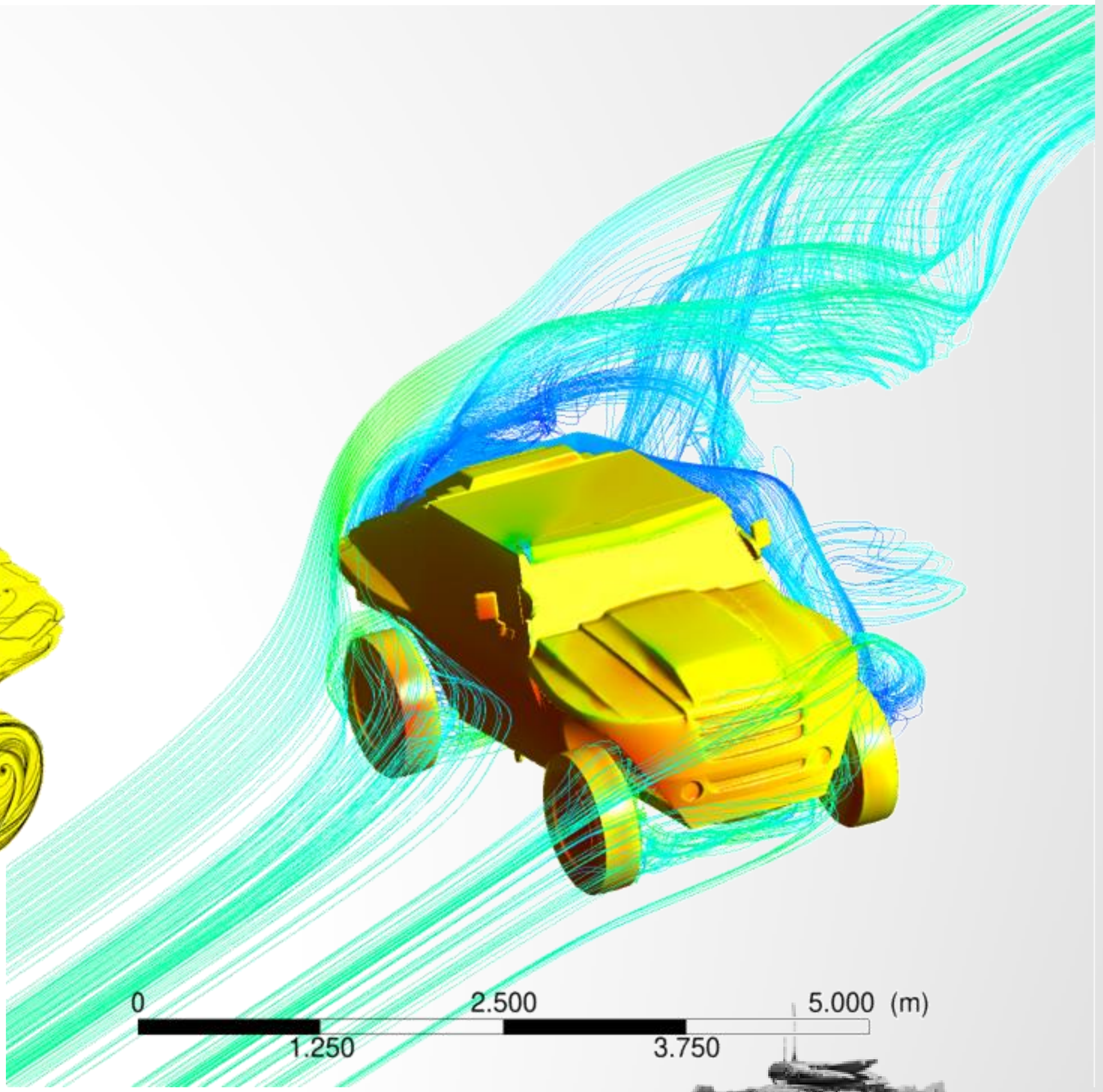
Number of elements: 11,790,809

Boundary Conditions and Physics Models

- Incoming velocity is set as 20 m/s (~45 mph)
- Incoming air temperature as 300K
- Surface temperature is set based on system level modeling using TAITherm
  - Based on the environmental and operating condition of the vehicle
- Eddy viscosity is calculated using k-omega SST Model
- Rotational speed is specified for tires
- Wind direction is varied from 0 to 180 degrees, in steps of 2 degrees
  - Total of 91 simulations

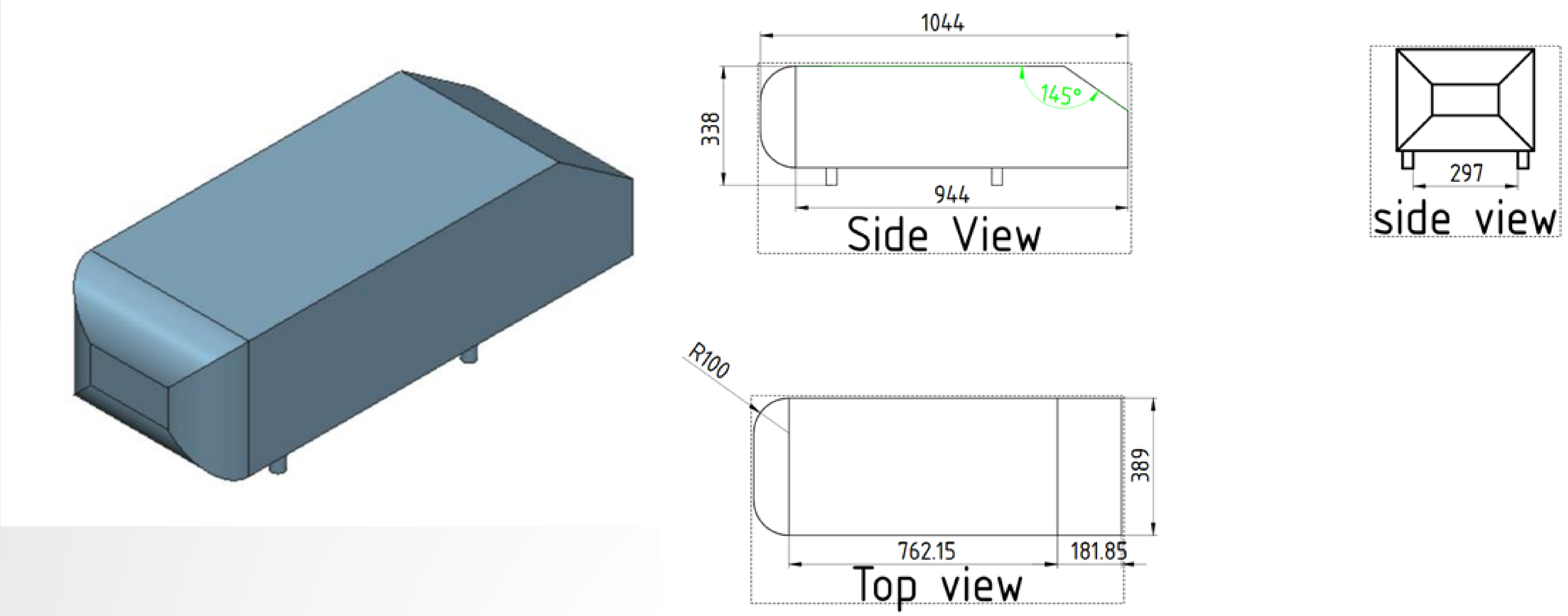


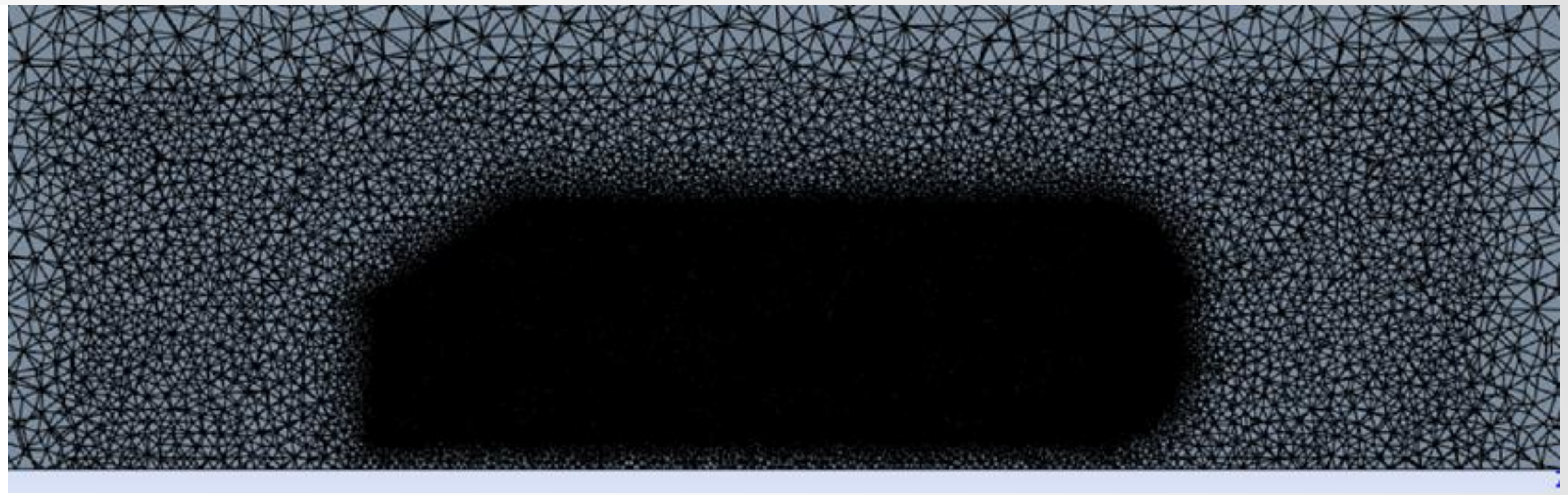


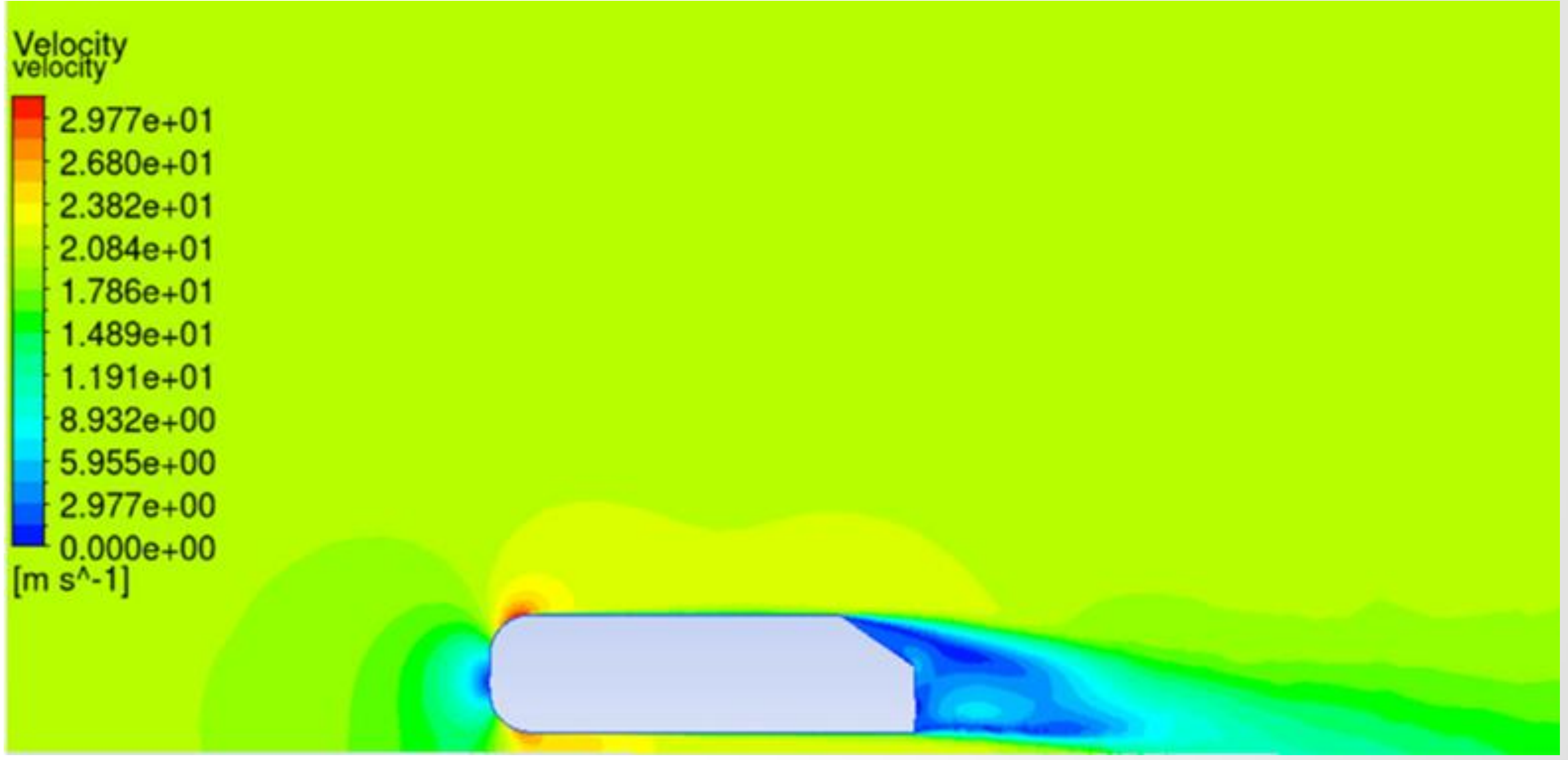


CFD Model Validation

- Testcase: Ahmed body with 35 degrees slant angle







	Drag Coefficient (With Stilts)
Experimental data	0.260
Current simulation	0.258

Dimensionality Reduction

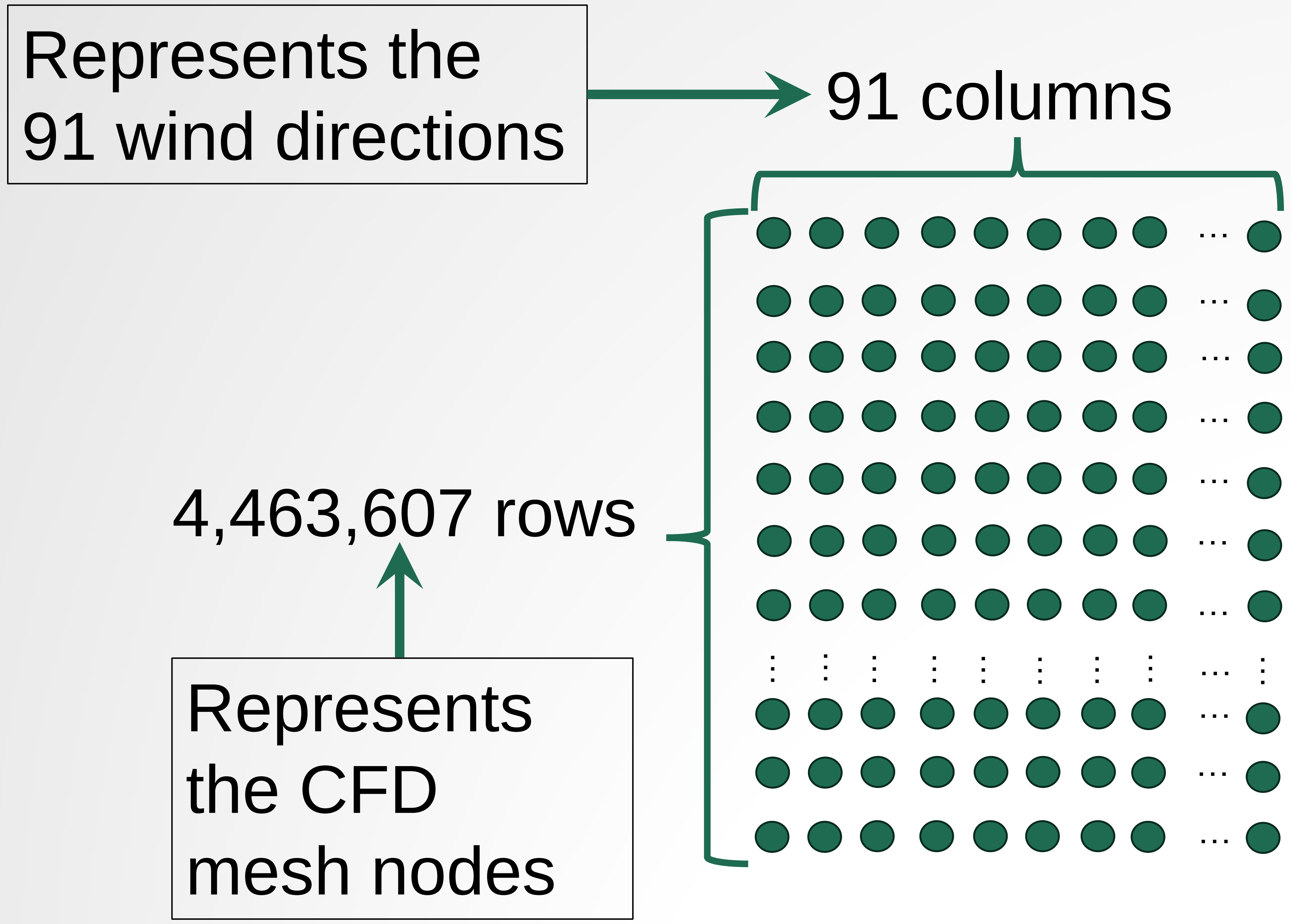
Proper Orthogonal Decomposition

- Proper Orthogonal Decomposition (POD) is used to reduce the data dimensionality of the CFD data
  - Singular value decomposition (SVD) is used to find the modes and the corresponding mode coefficients
- Singular value decomposition (SVD)

$$A = U\Sigma V^T$$

  - Where A is the snapshot matrix with each column representing any given flow variable at all nodes
  - U is the matrix with each column as Eigenvectors of the matrix AA^T
  - V^T is the matrix with each row as Eigenvector of the matrix A^TA
  - Σ is a diagonal matrix with diagonal elements as the square of the Eigenvalues in the descending order
- Physical interpretation of SVD
  - Each column in U represents mode shapes
  - ΣV^T represents mode coefficients

Proper Orthogonal Decomposition (contd.)



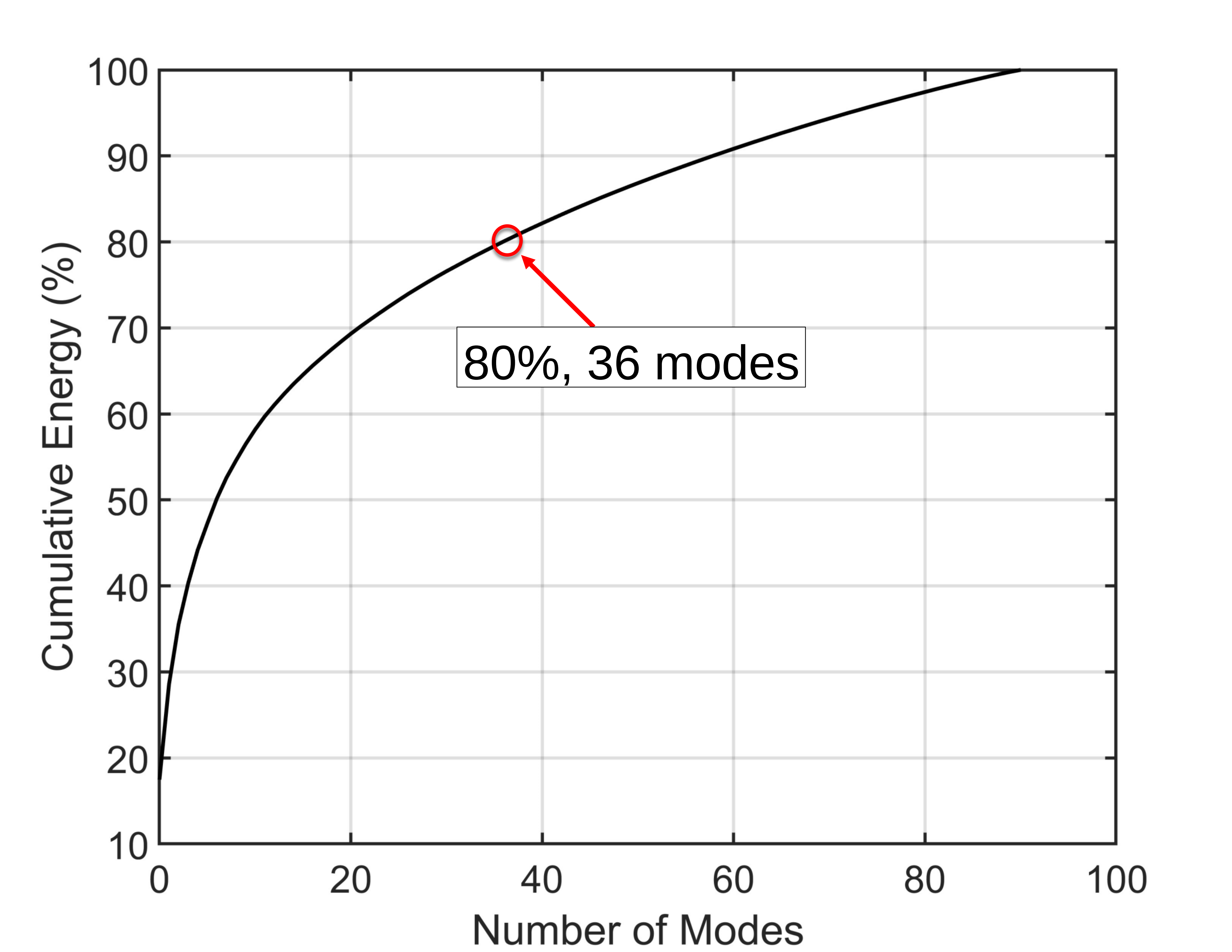
Snapshot Matrix

The flow variable at the nodes used for the analysis are x, y, and z velocity components and temperature.

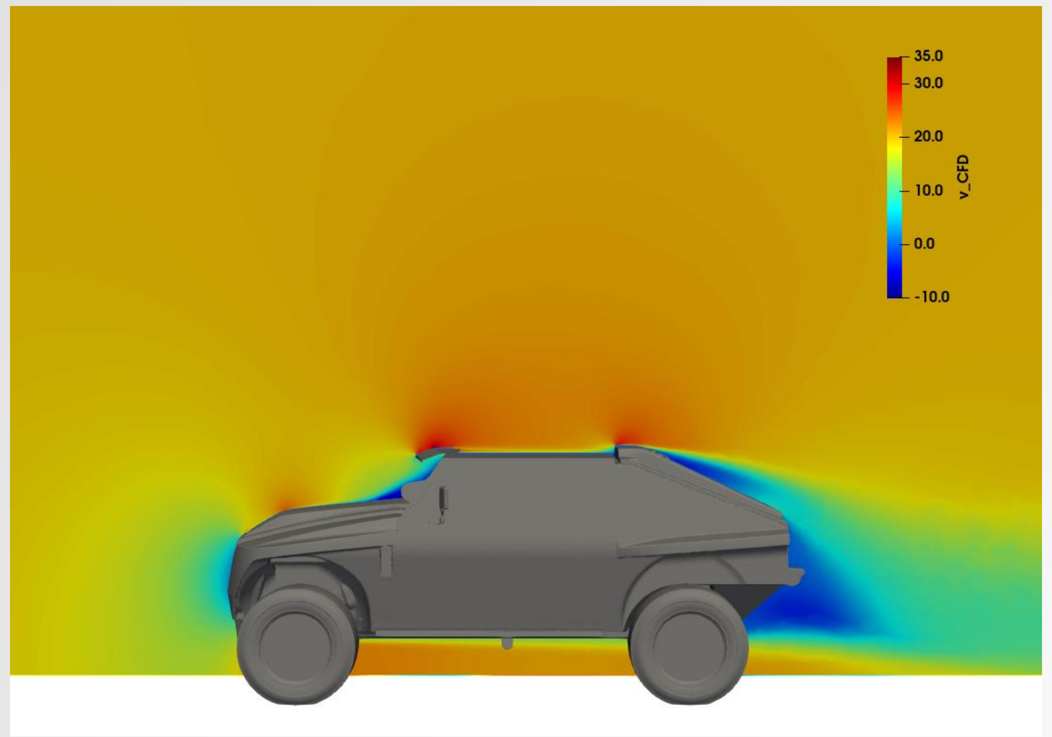
Four snapshot matrices with the same dimensions

Proper Orthogonal Decomposition (contd.)

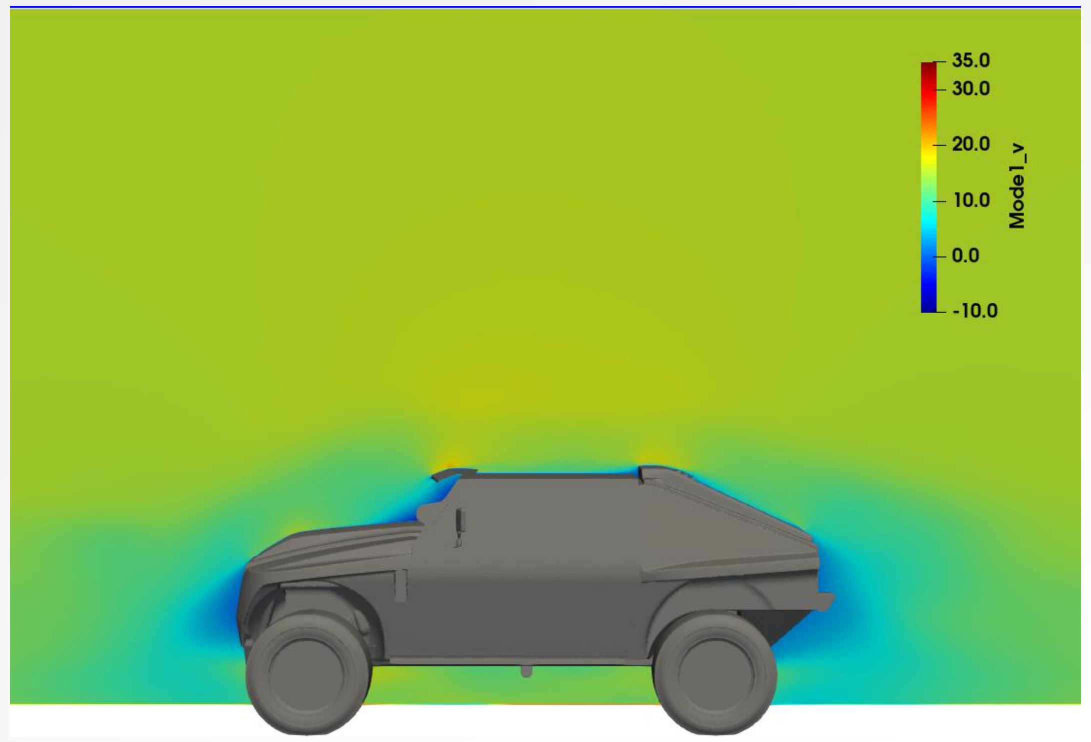
Cumulative energy (%)	Number of modes for field data			
	x velocity component	y velocity component	z velocity component	Temperature
10			1	
20	2	1	2	
30	3	3	3	
40	4	4	5	
50	7	7	9	
60	13	12	15	
70	22	21	26	
80	**37**	**36**	**41**	
90	59	58	63	1
95	73	73	76	12



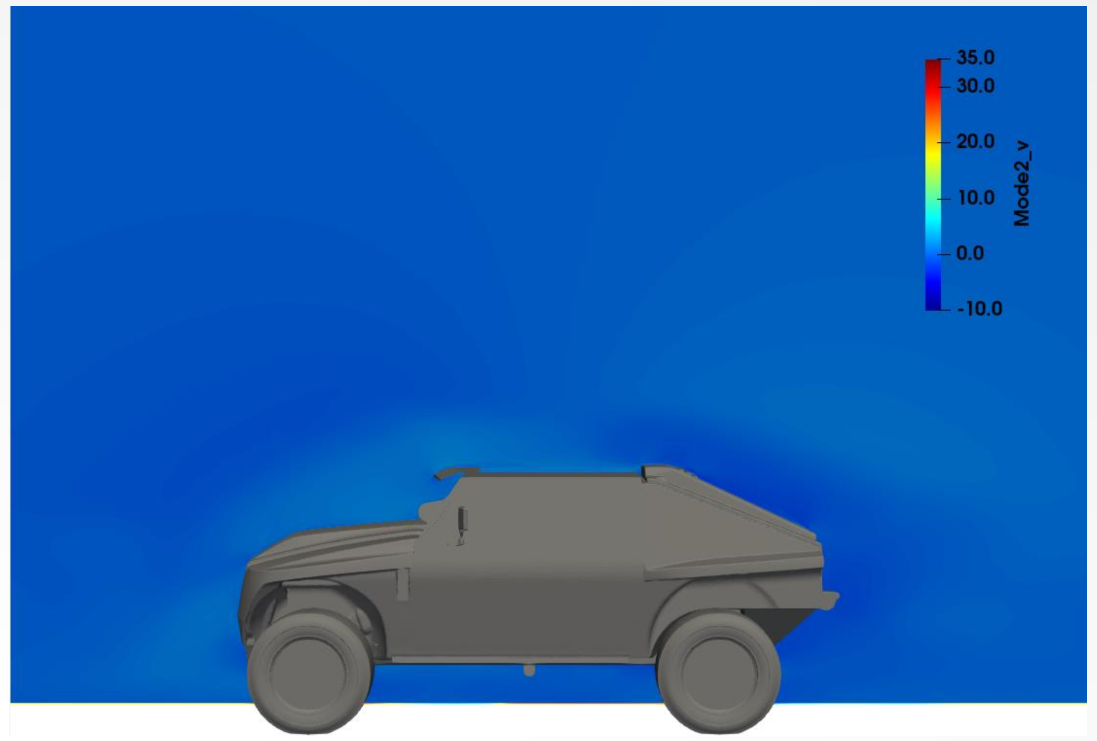
POD: Contributions from Different Modes



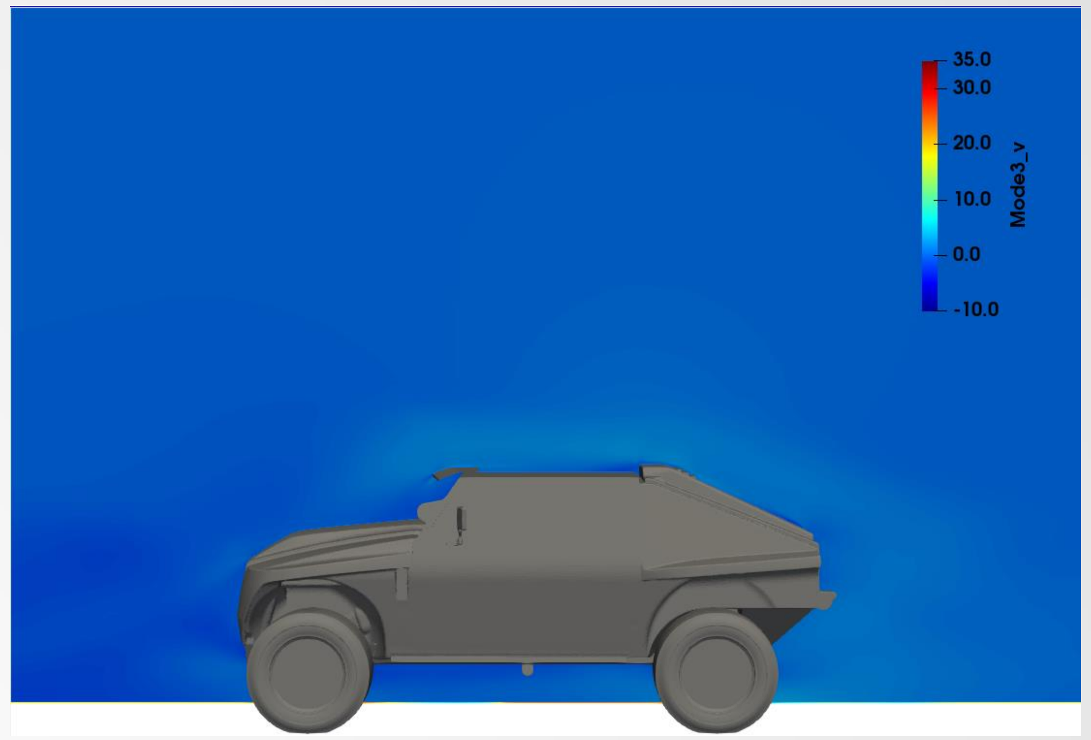
CFD Results



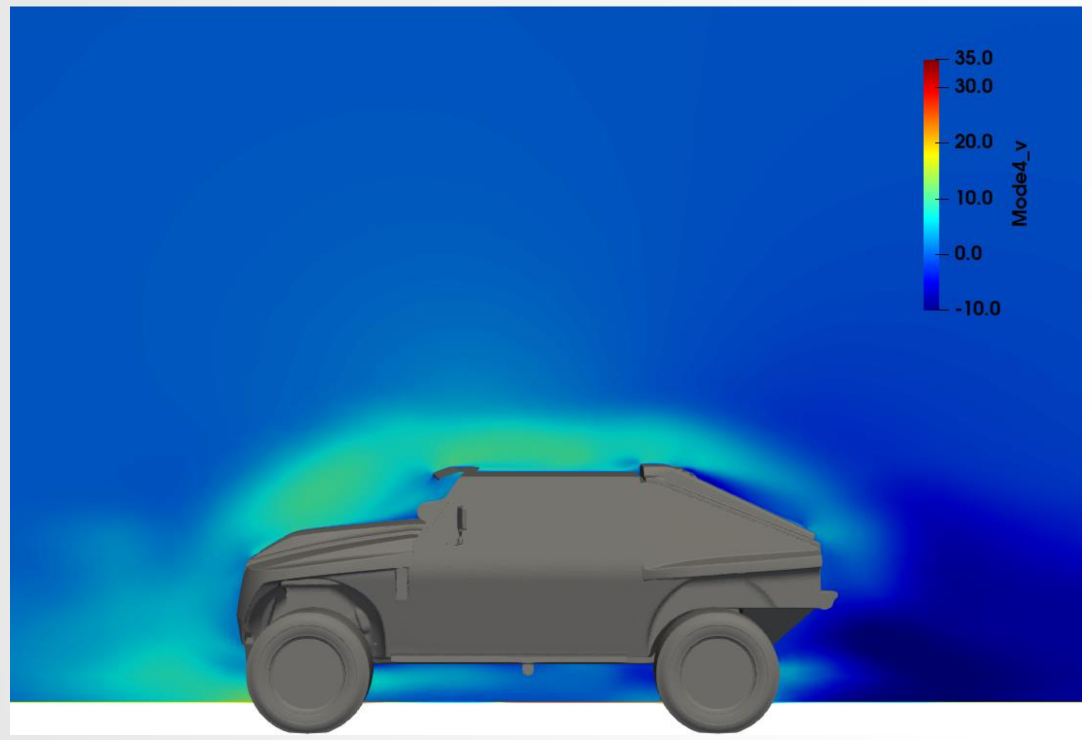
First Mode



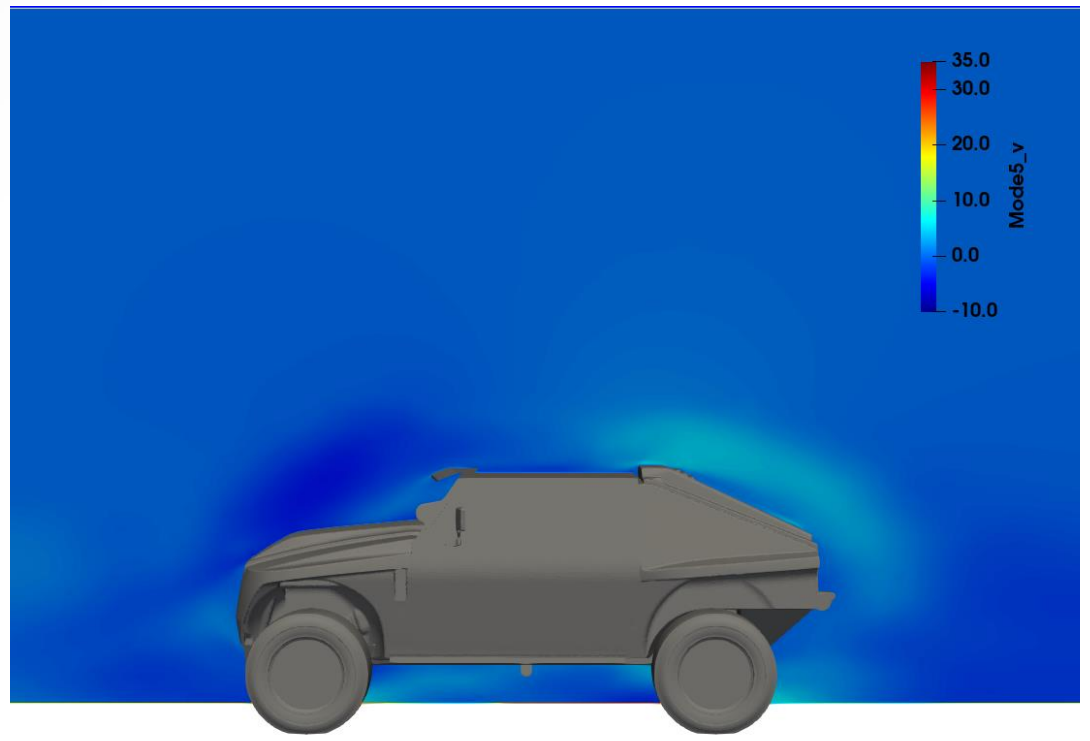
Second Mode



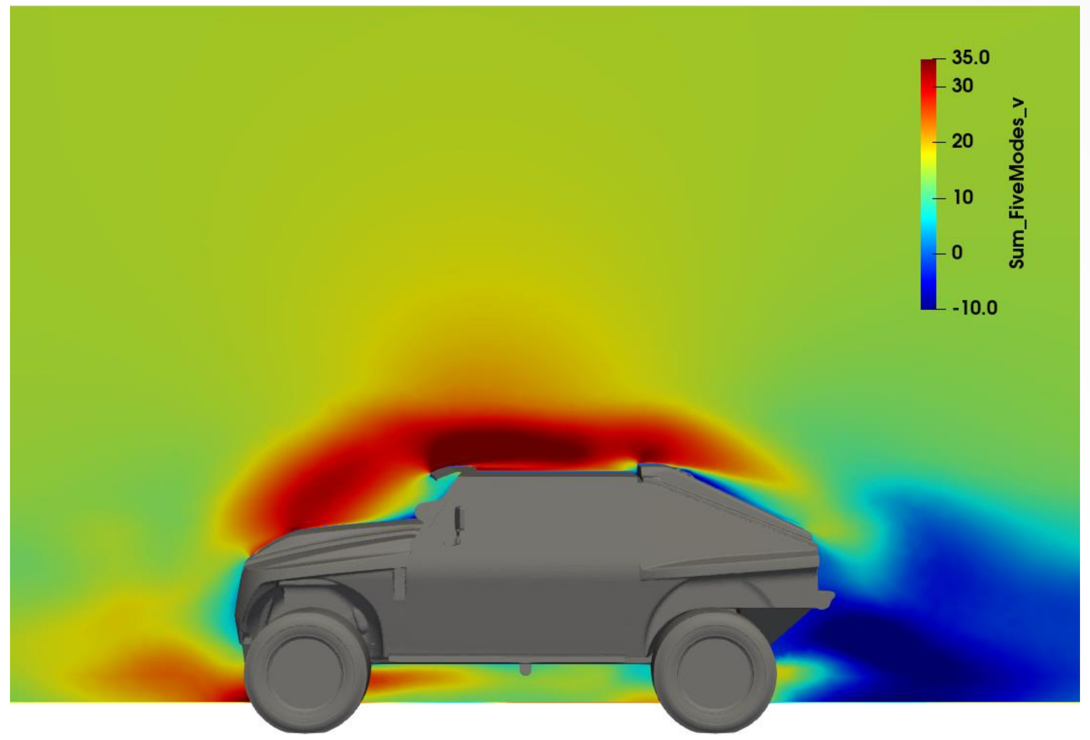
Third Mode



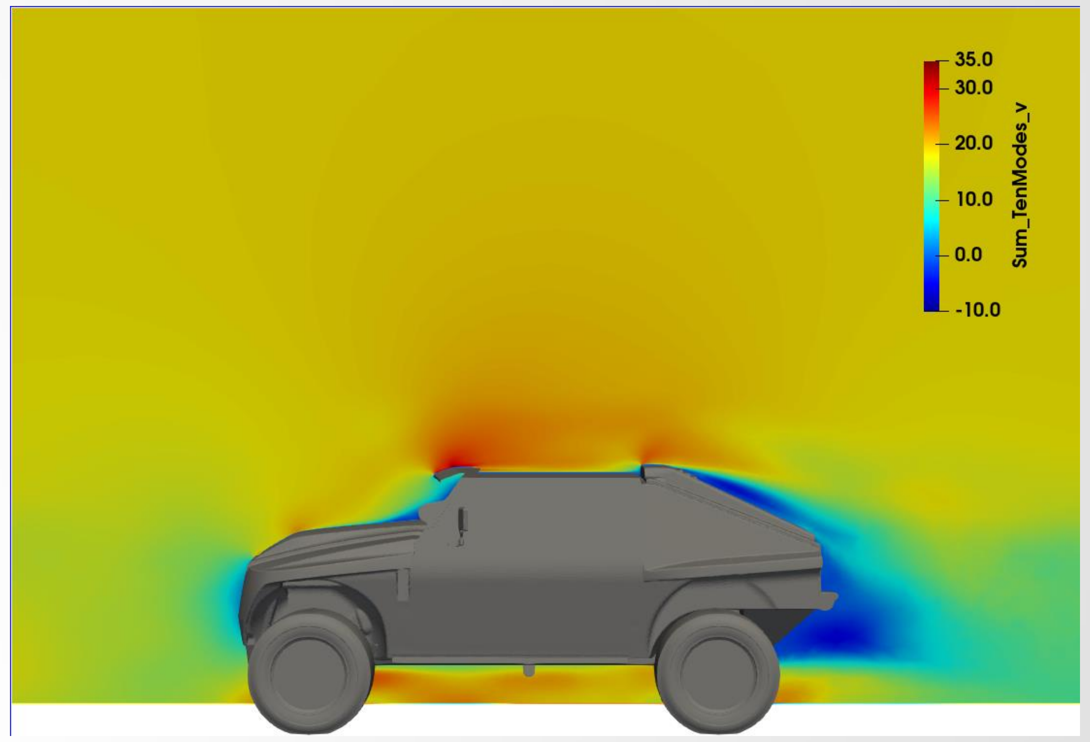
Fourth Mode



Fifth Mode



Sum of Contributions from the First Five Modes



Sum of Contributions from the First Ten Modes

Machine Learning (ML) Models

ML Model Details

- Machine learning (ML) model architecture
  - Dense Neural Network
  - 6 hidden layers with 32 neurons each
  - Activation functions used: Leaky-RELU
  - Loss function: Mean square error (MSE)
  - Optimizer: Adam
- Input to the ML model is taken as the wind direction
  - Only one neuron in the input layer
- The output from the ML model is taken as the mode coefficient
  - Number of neurons in the output layer varies based on the number of modes used and the model architecture

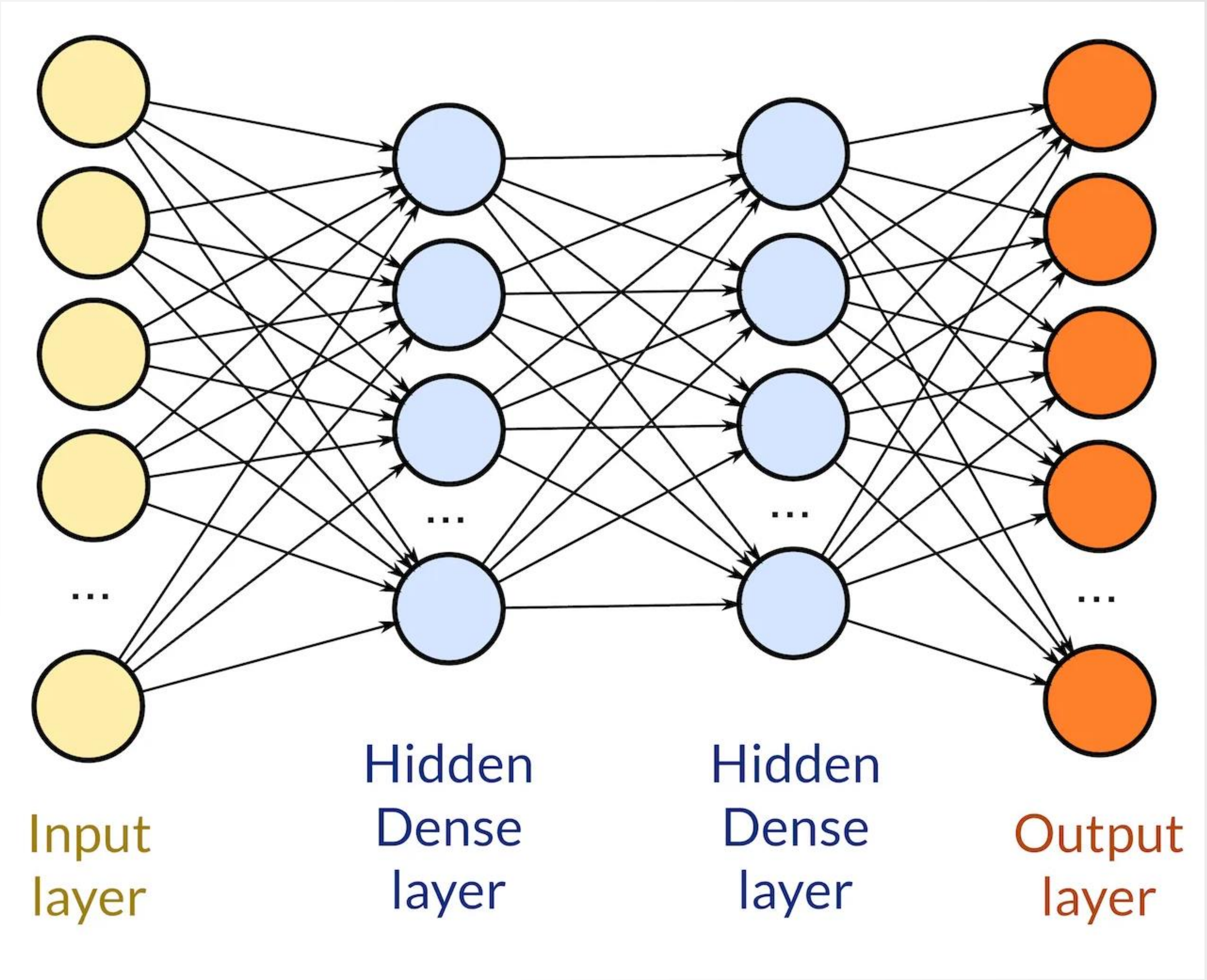
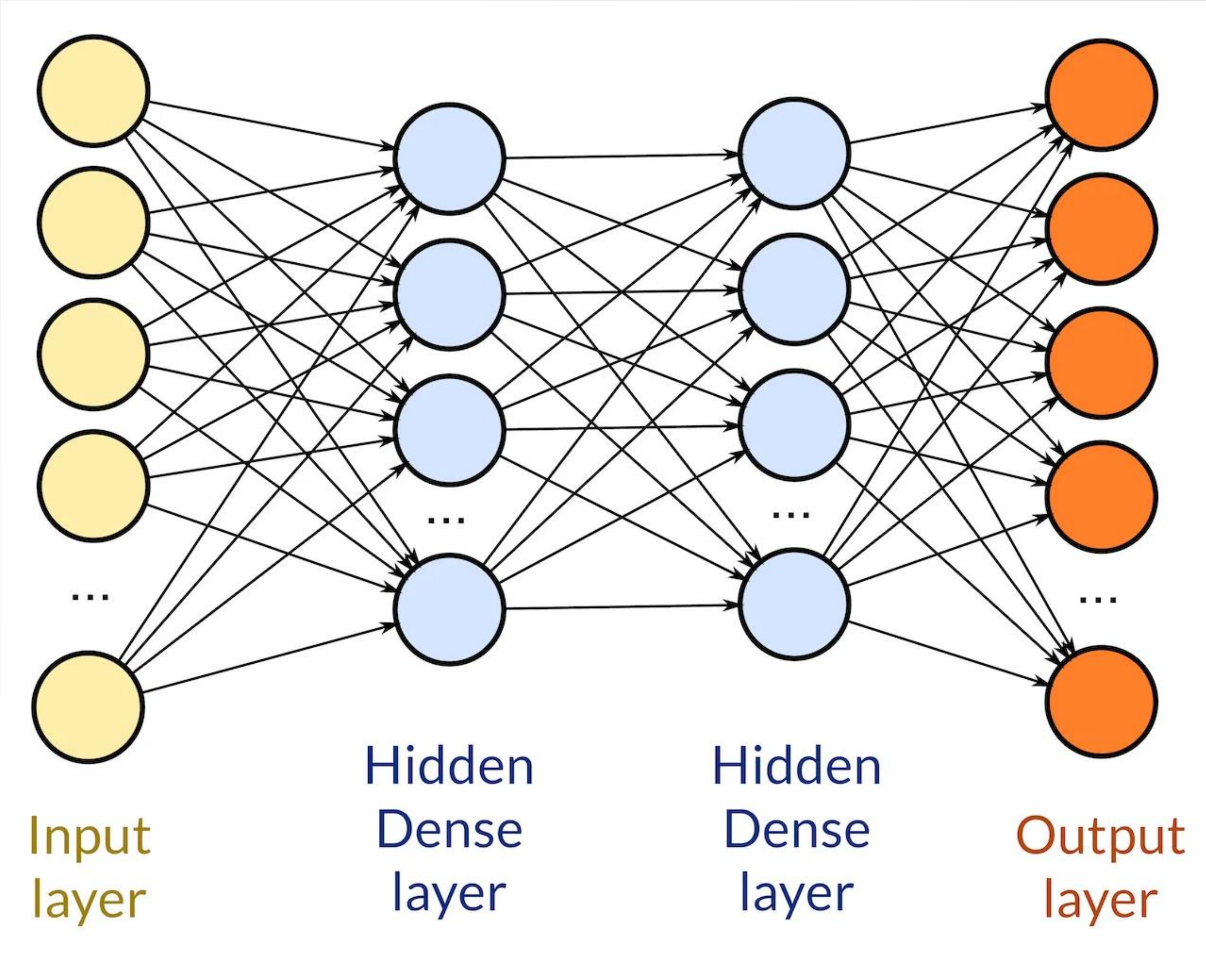


Image Source:
https://medium.datadriveninvestor.com/custom-layers-in-keras-de5f793217aa

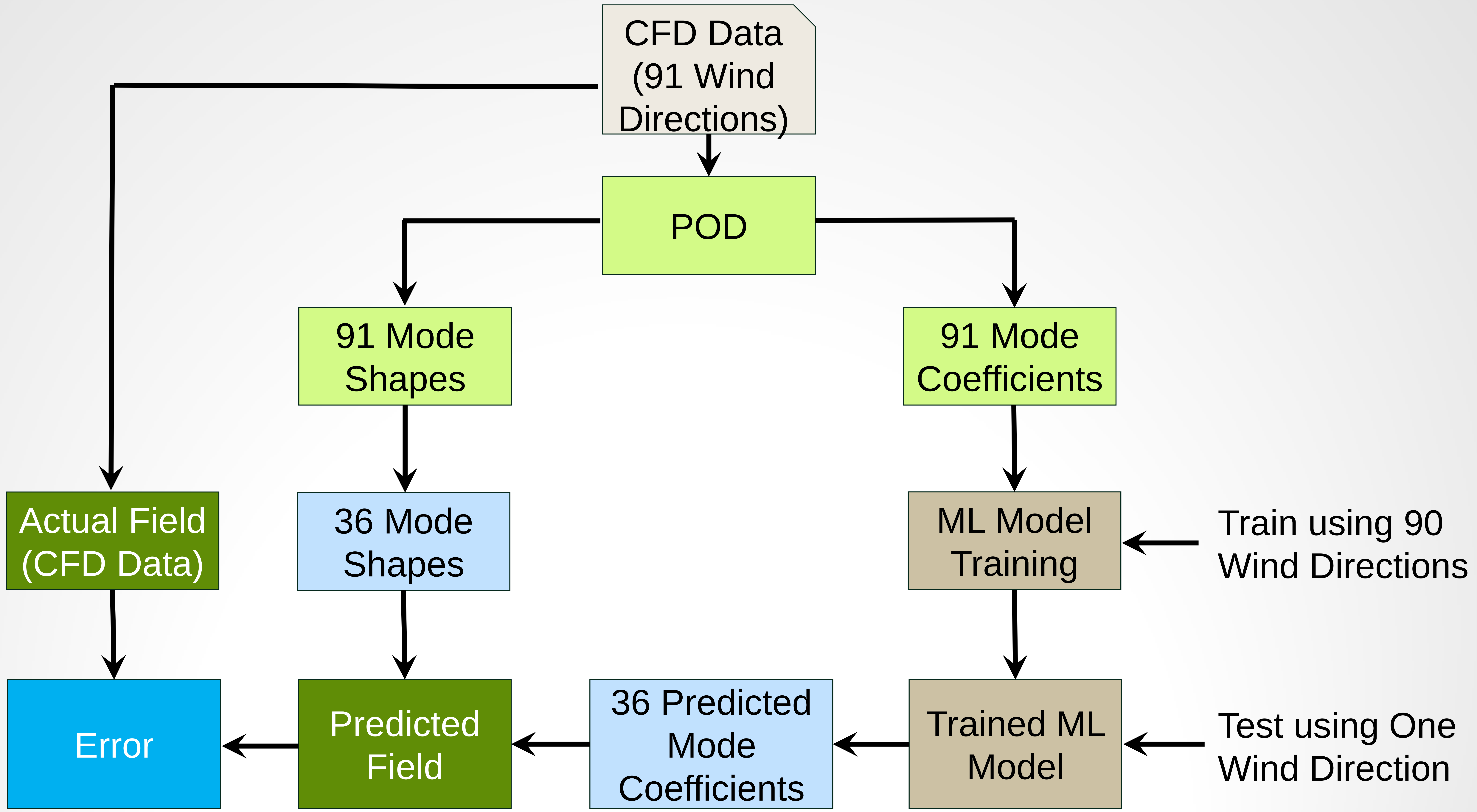
ML Models Tested

- **Approach 1**: No. of ML models used for the prediction of the flow field is the same as the total number of mode coefficients present in POD
- **Approach 2**: Only one ML model is used for the prediction of the flow field
  - No. of neurons in the output layer for this ML model is the same as the total number of modes present in POD
- **Approach 3**: Only one ML model is used for the prediction of the flow field
  - No. of neurons in the output layer is the same as the number of modes that are used for the reconstruction of the flow field using the ML model

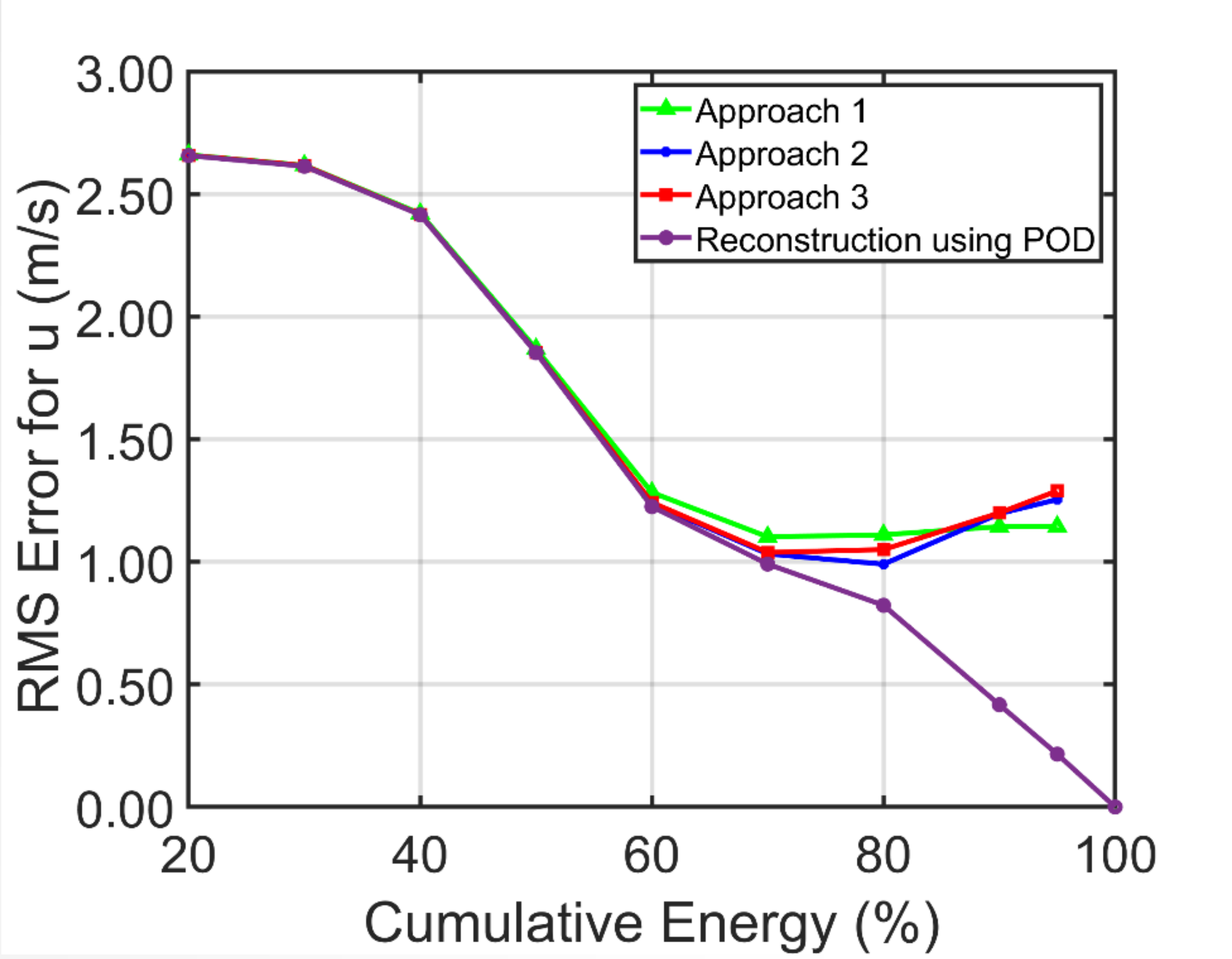


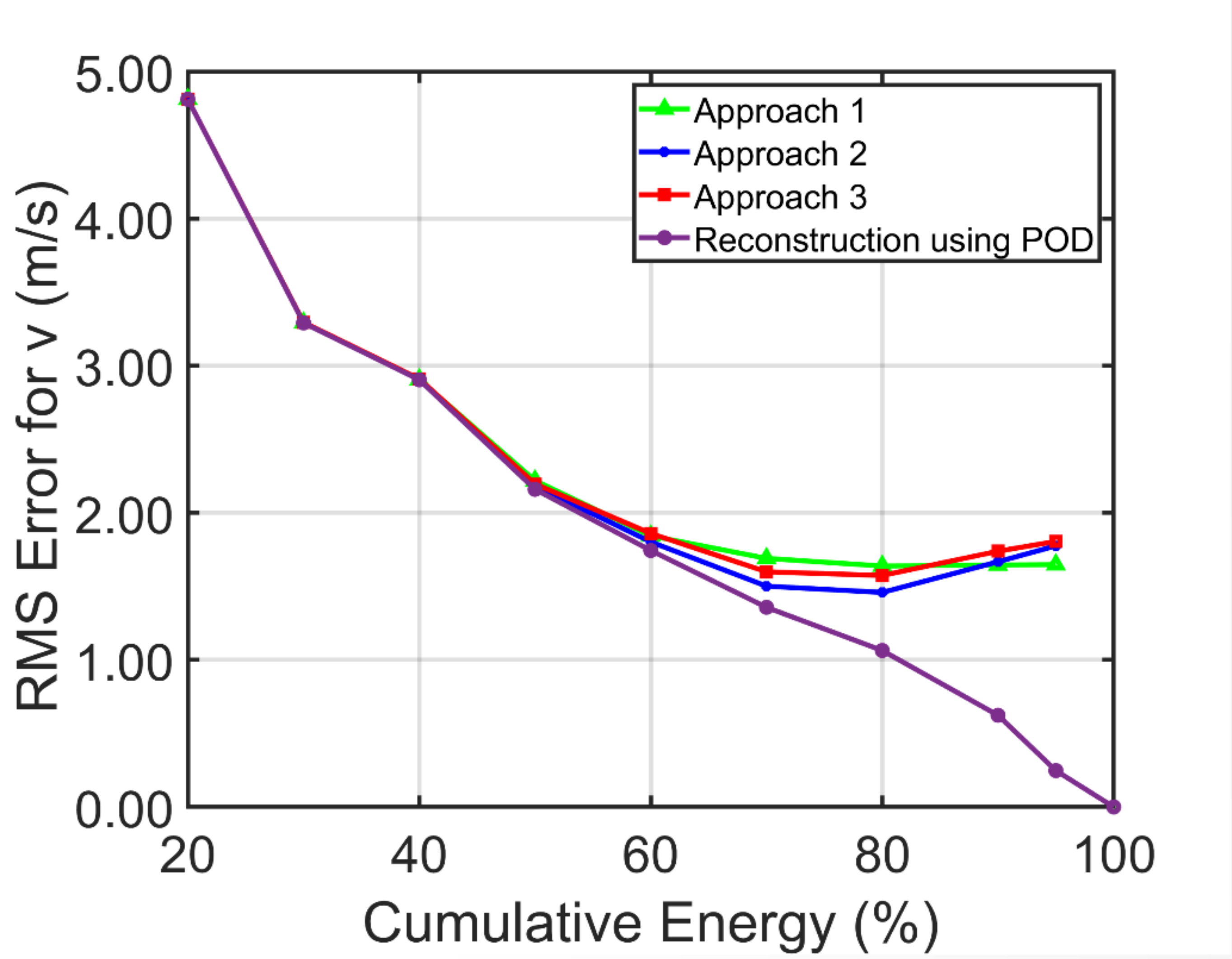
Results and Discussion

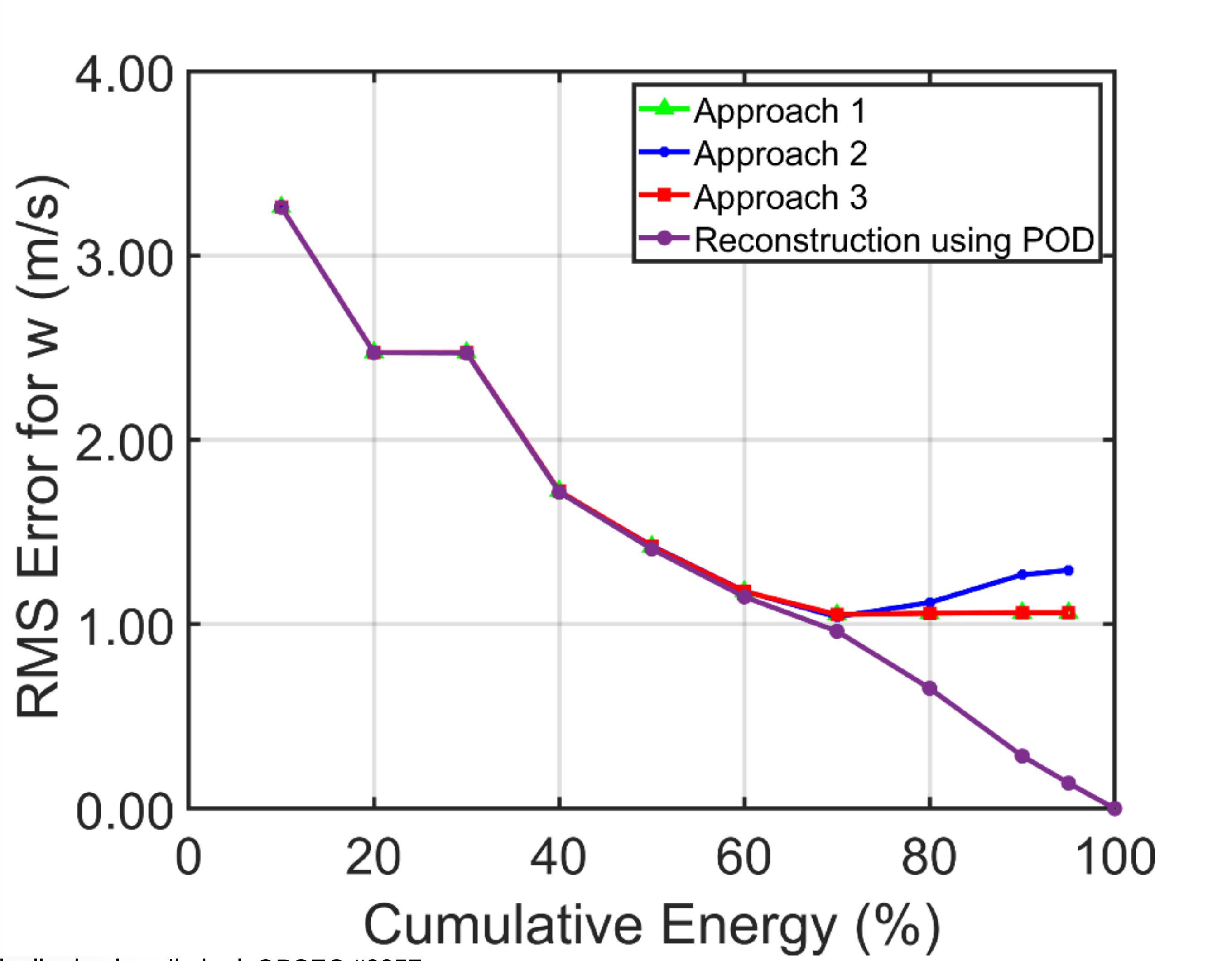
Accuracy Estimation

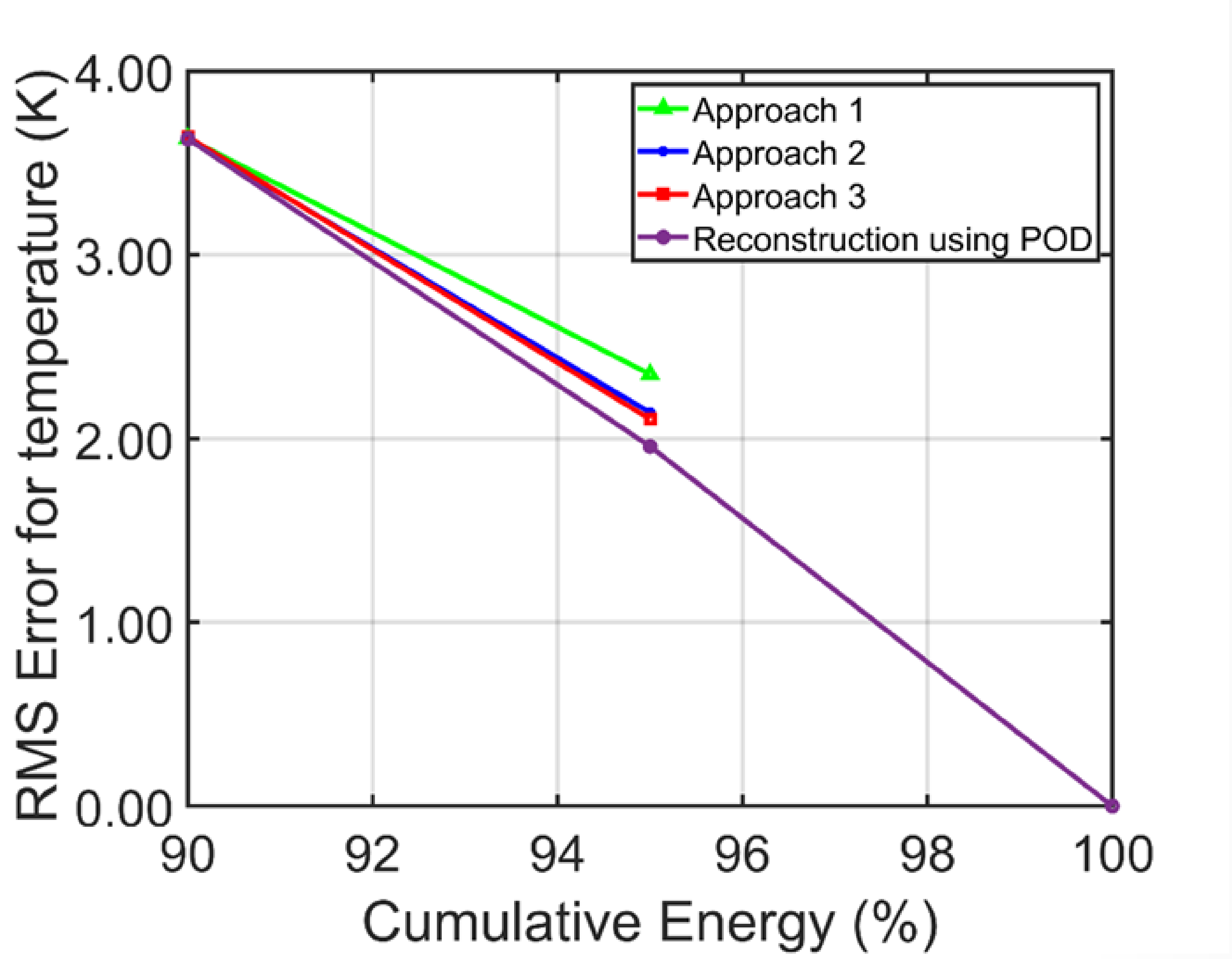


ML Models Comparisons

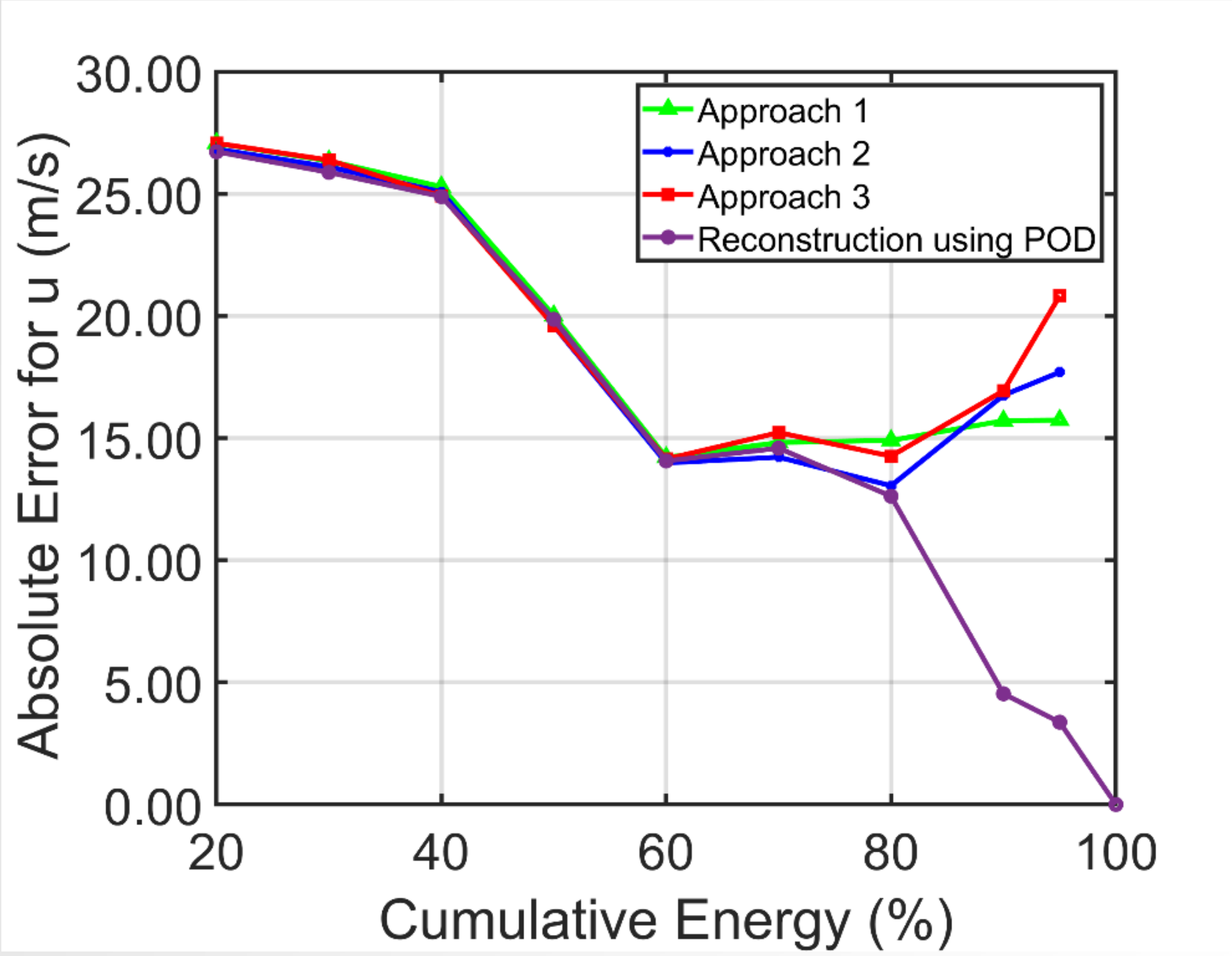


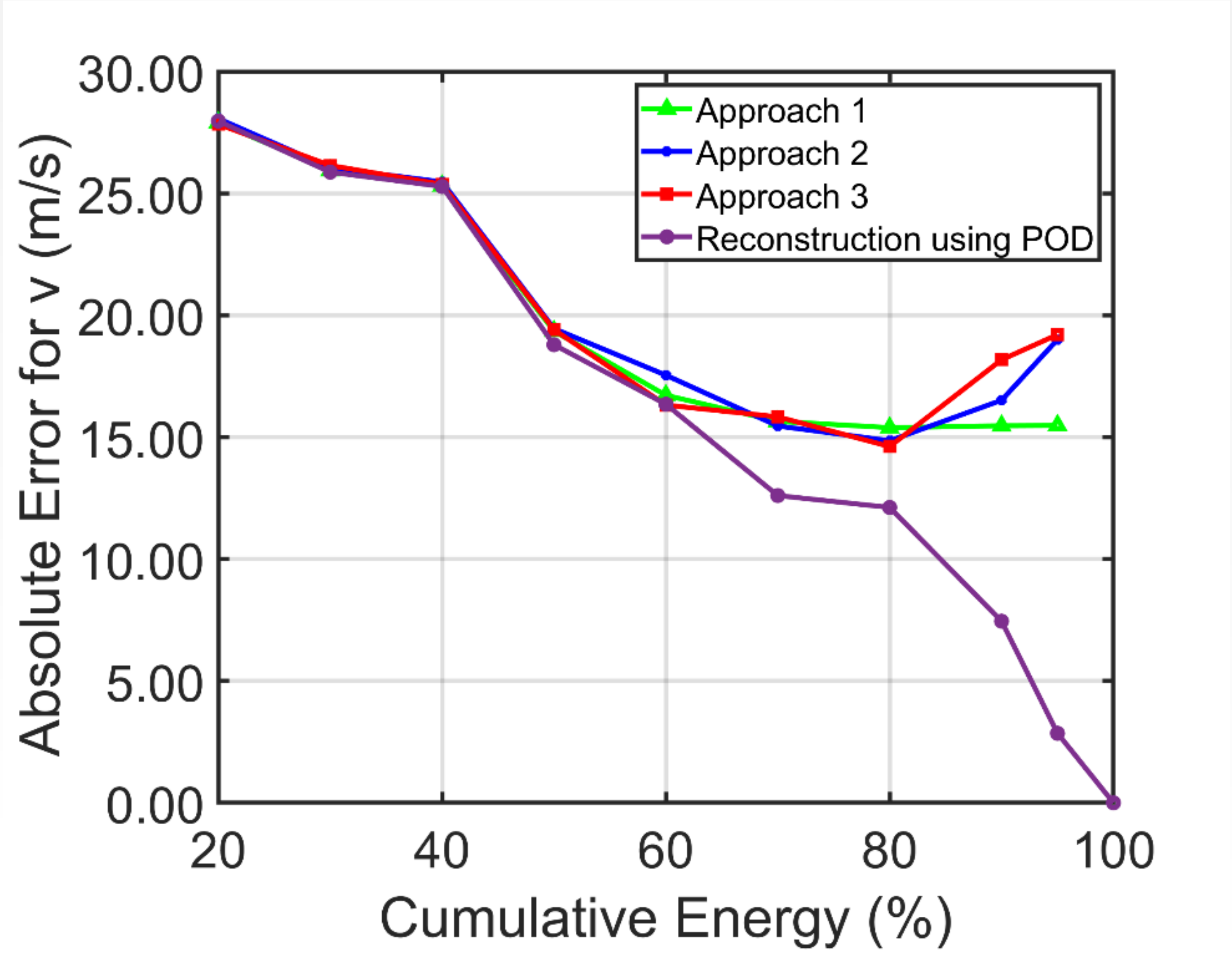


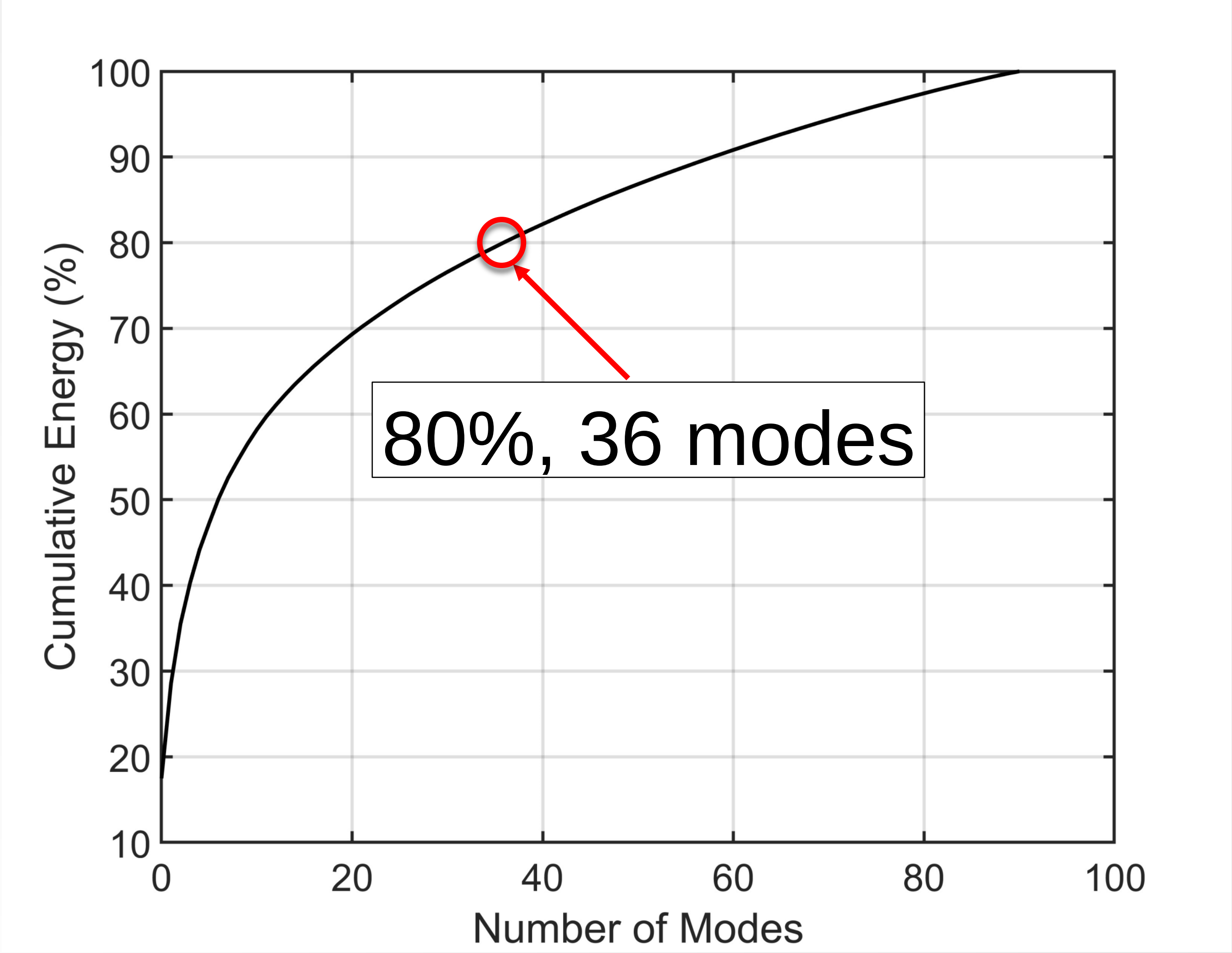


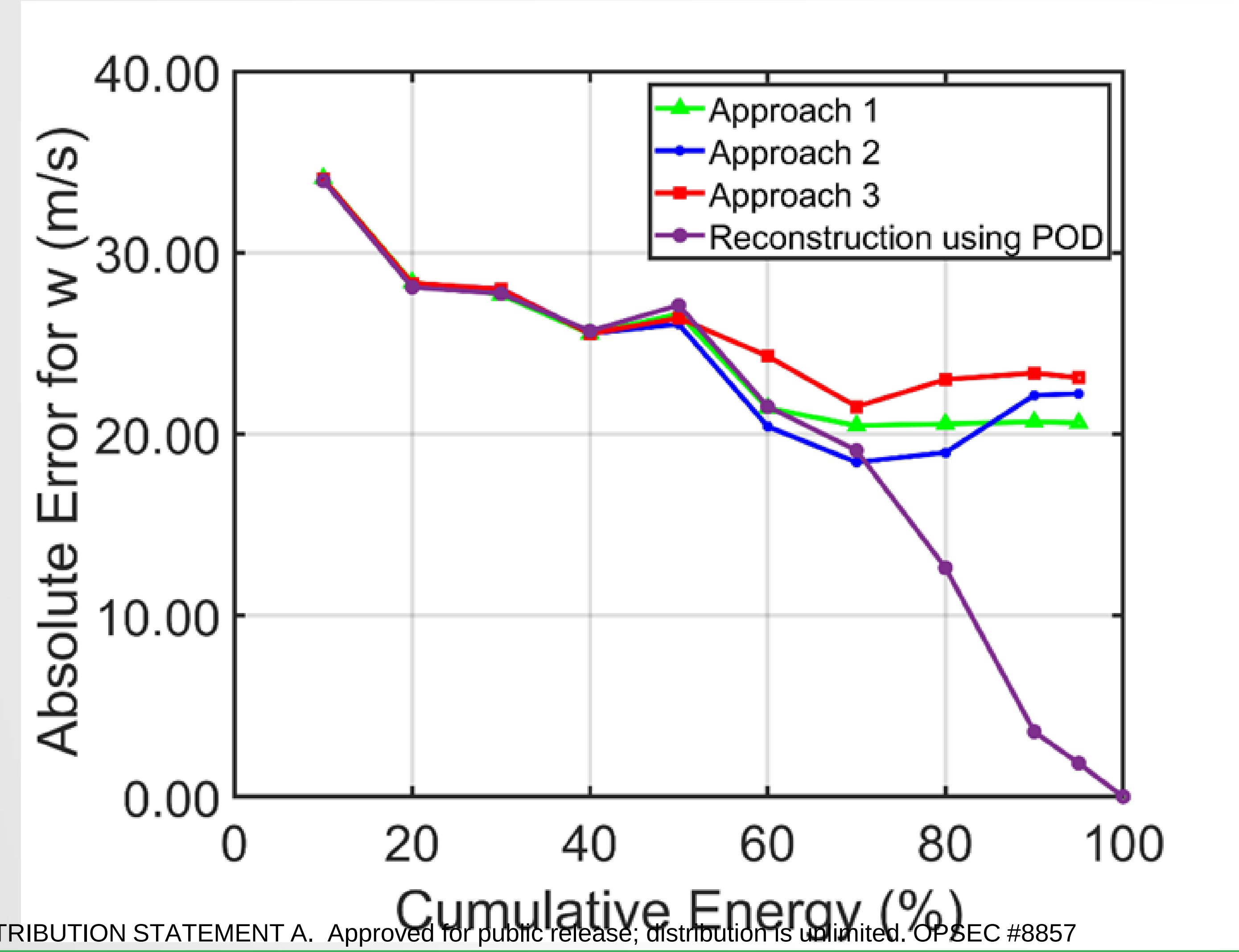


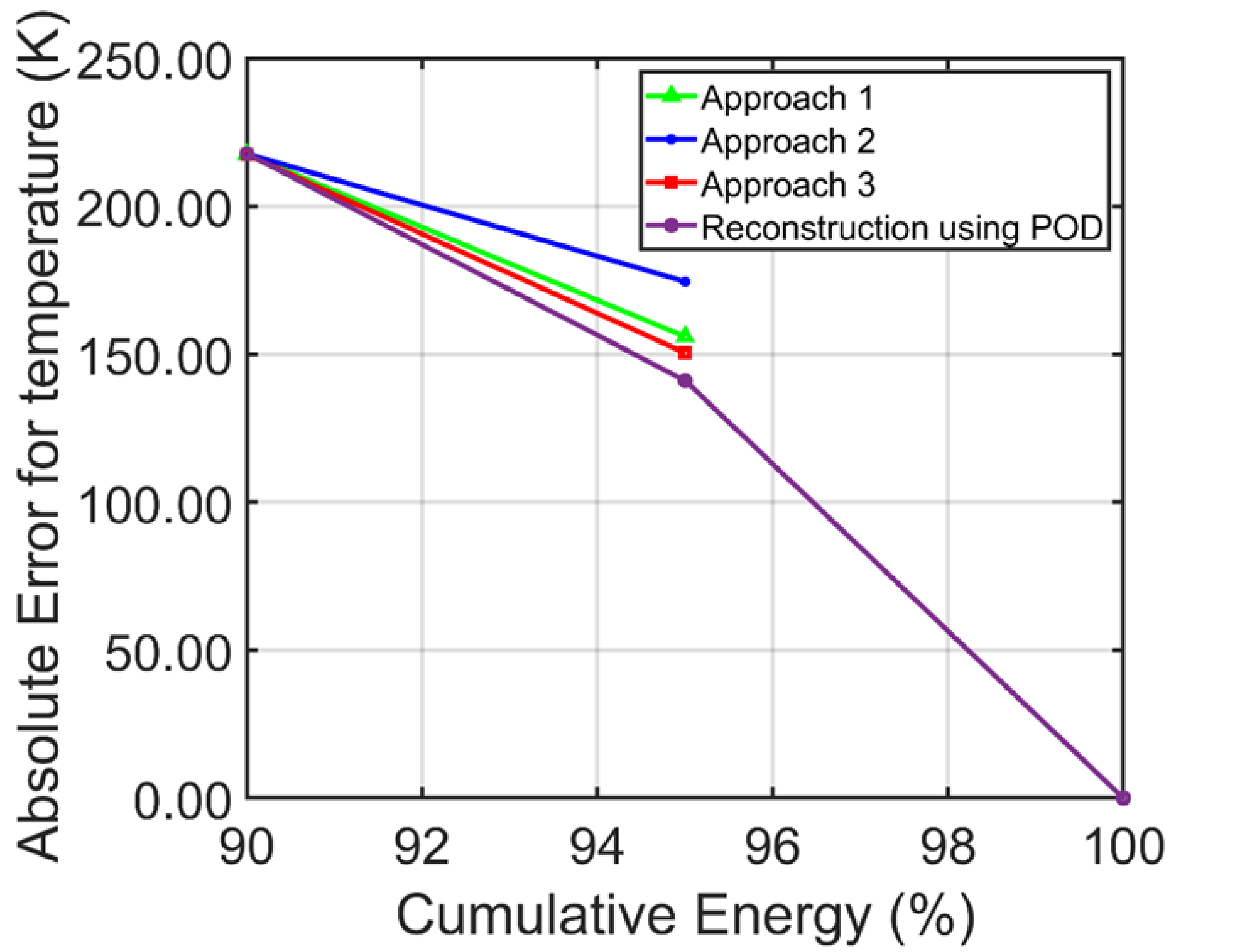
ML Models Comparisons (Contd..)

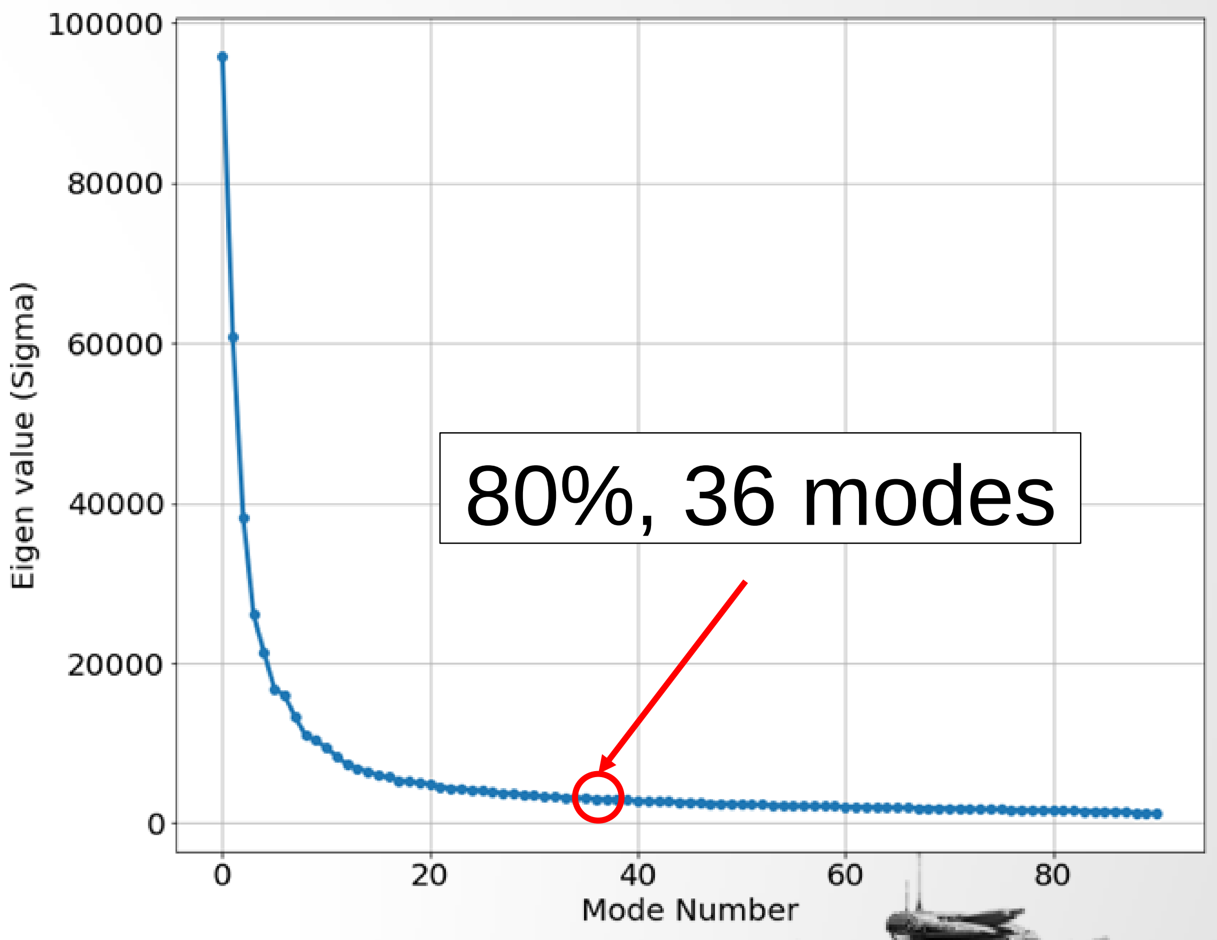




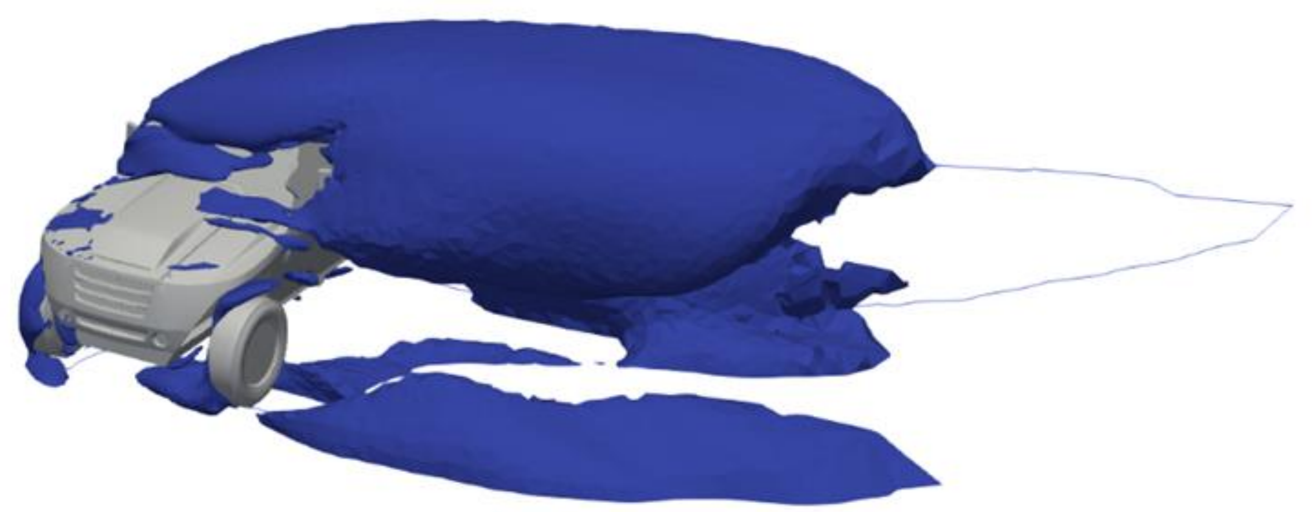




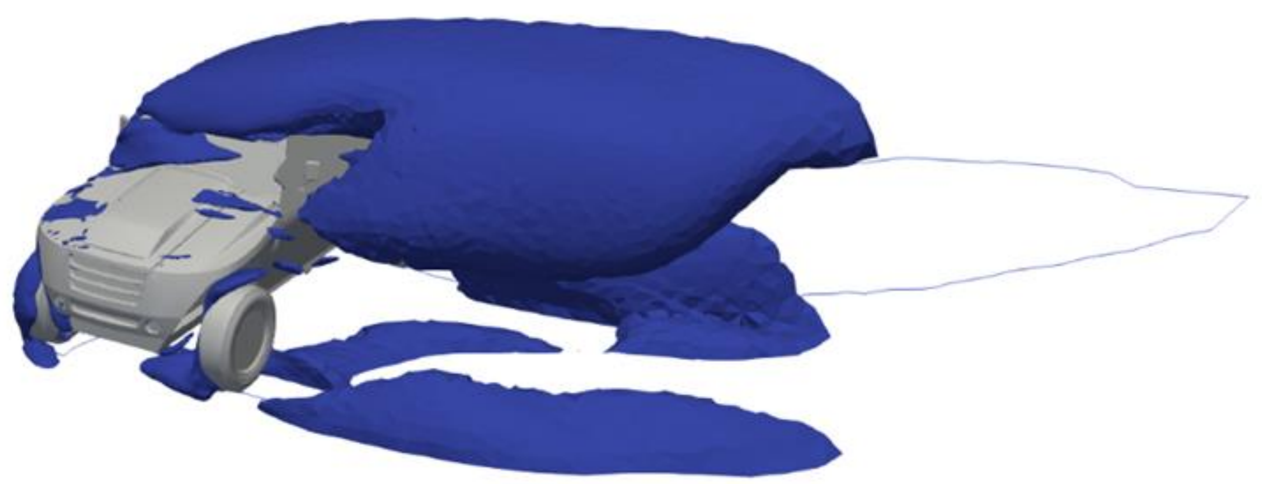




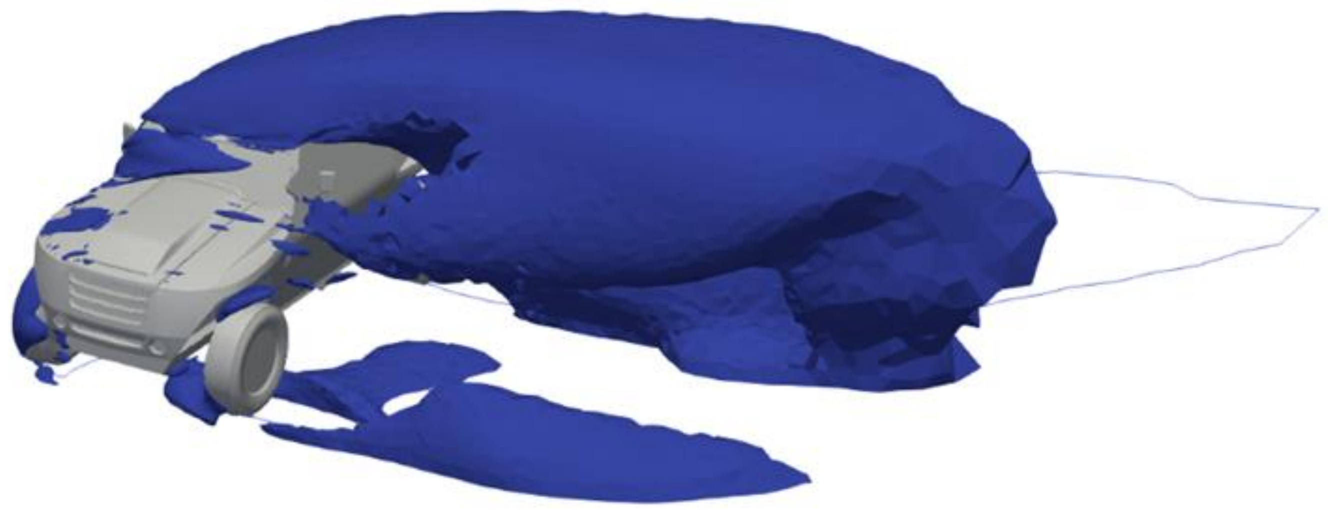
Visualization of Error



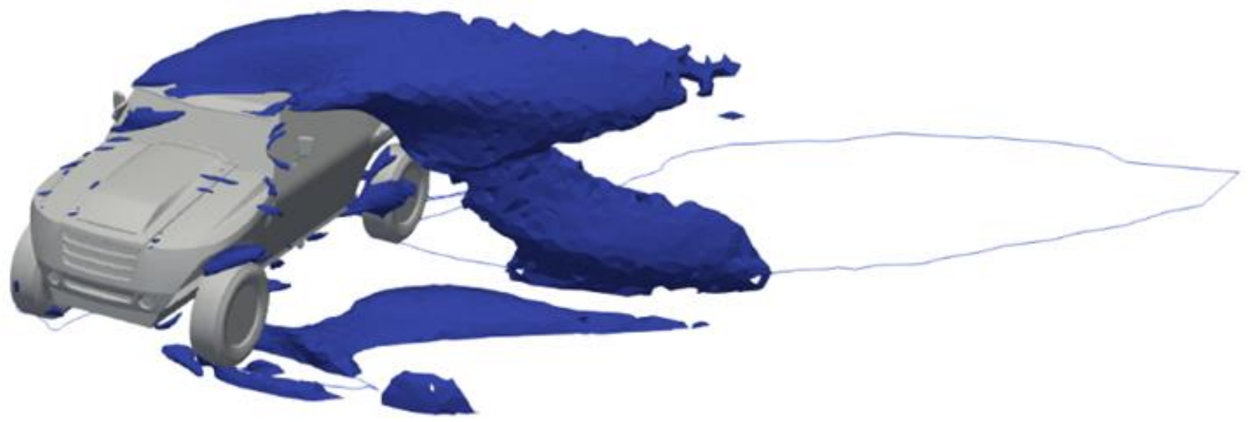
20% cumulative energy



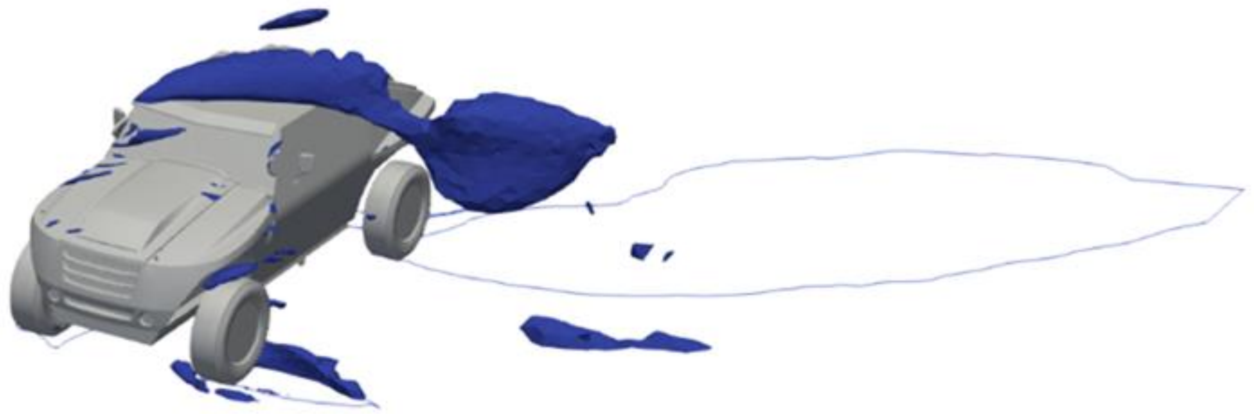
30% cumulative energy



40% cumulative energy



50% cumulative energy

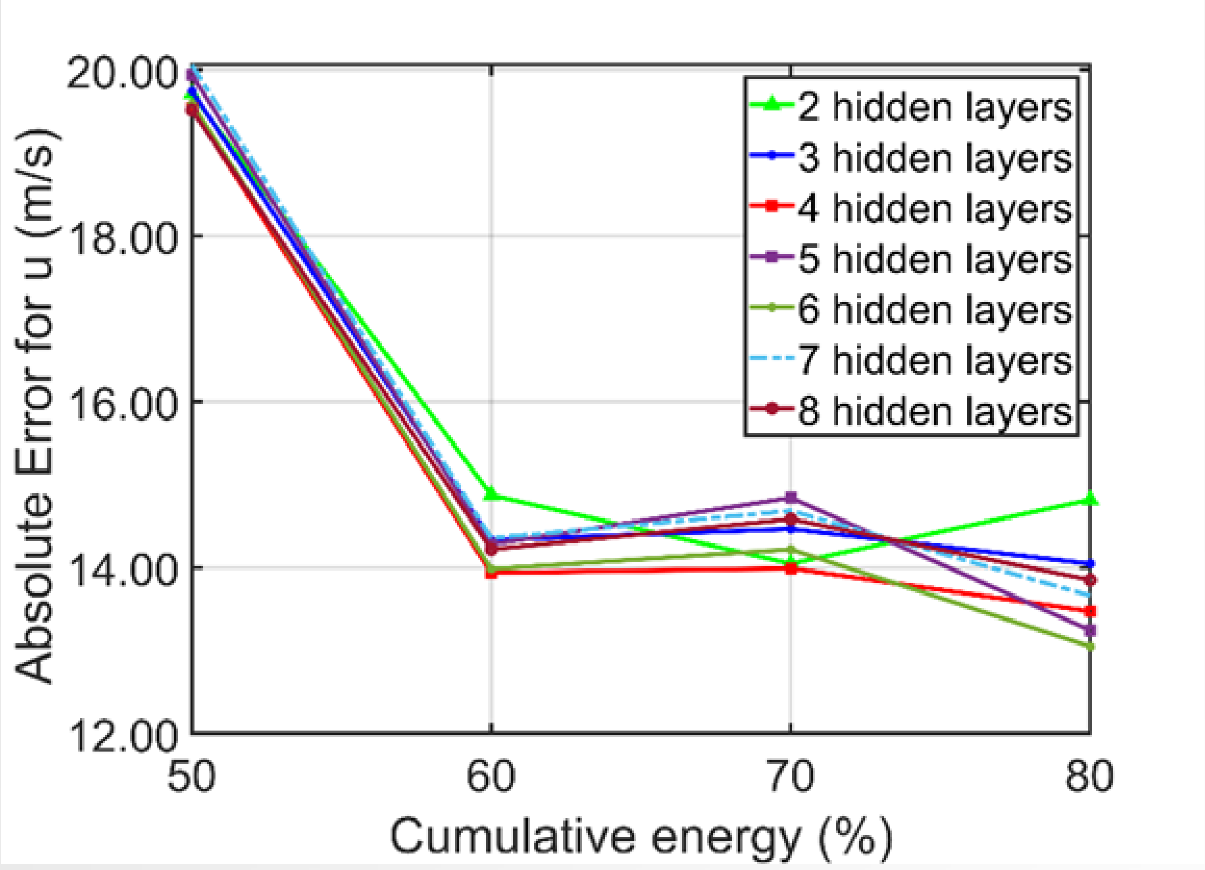


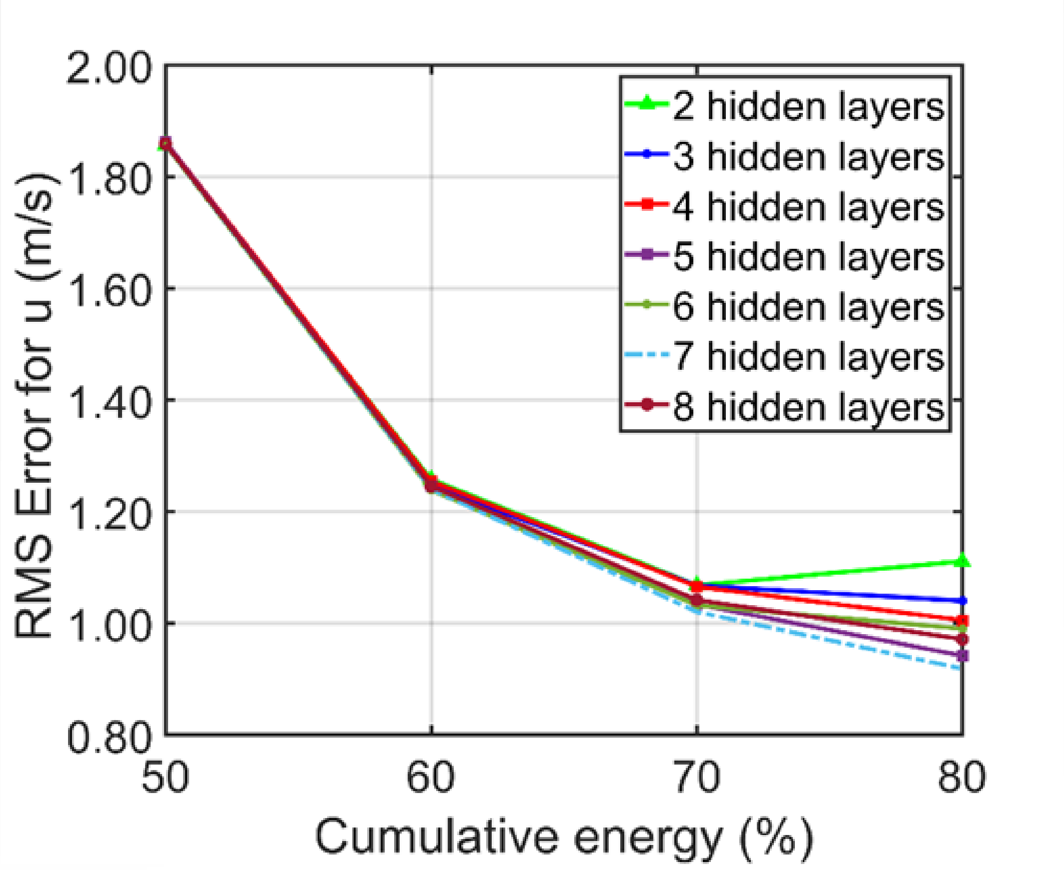
60% cumulative energy

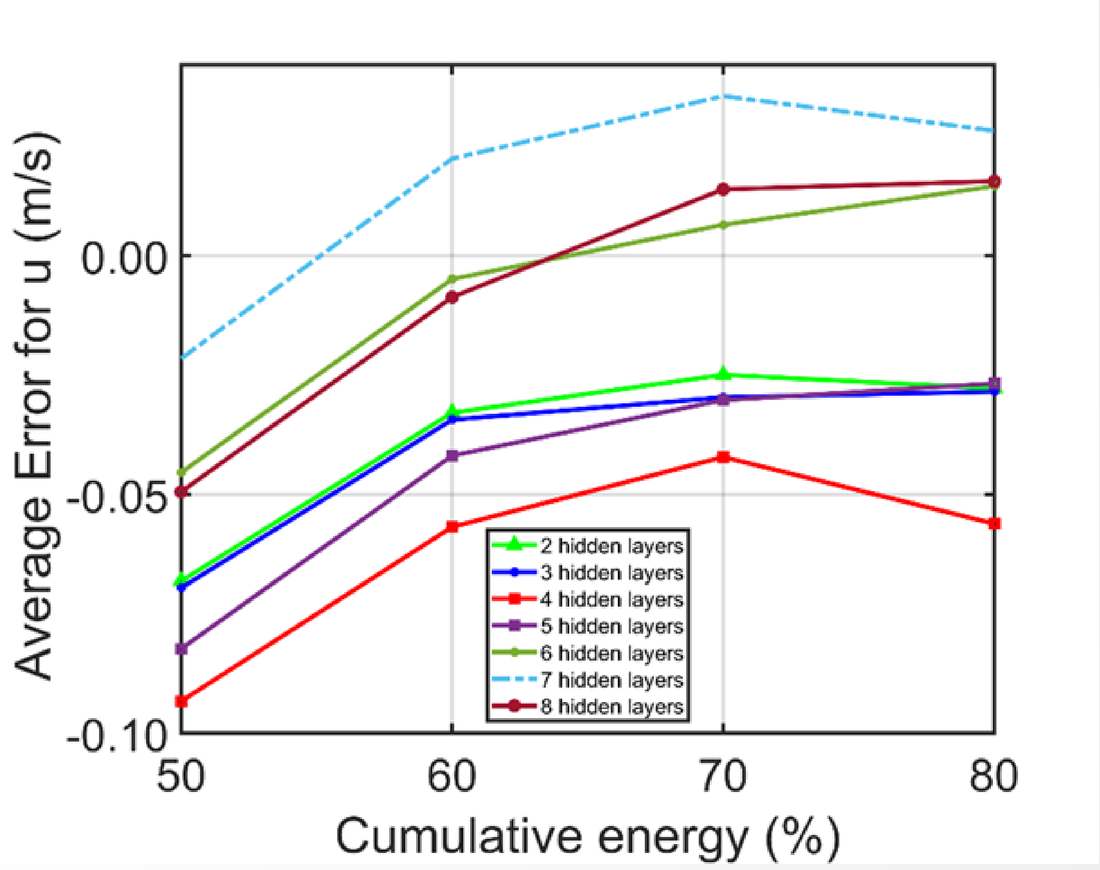
70% cumulative energy

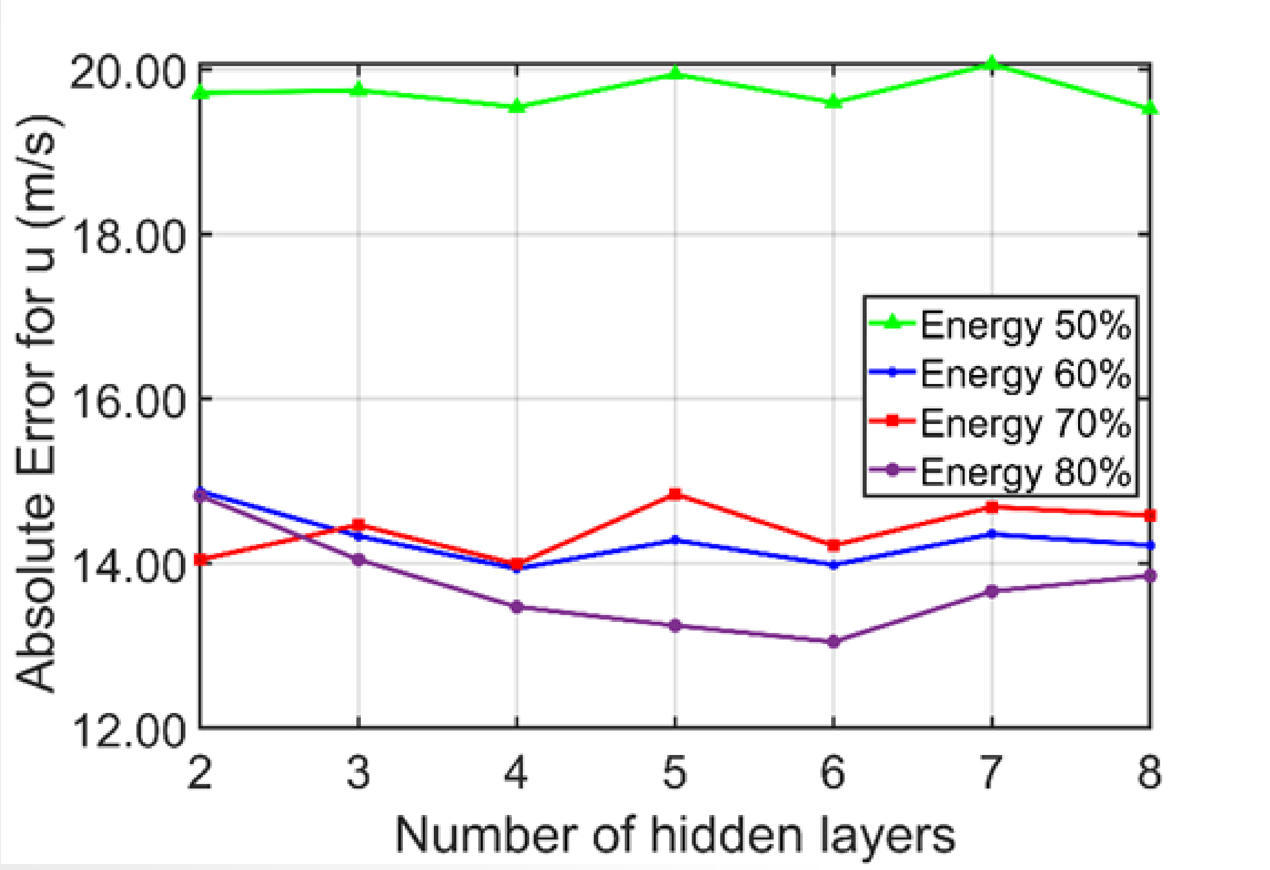
From the x-component of velocity for ML model approach 2 regions with error greater than 5 m/s

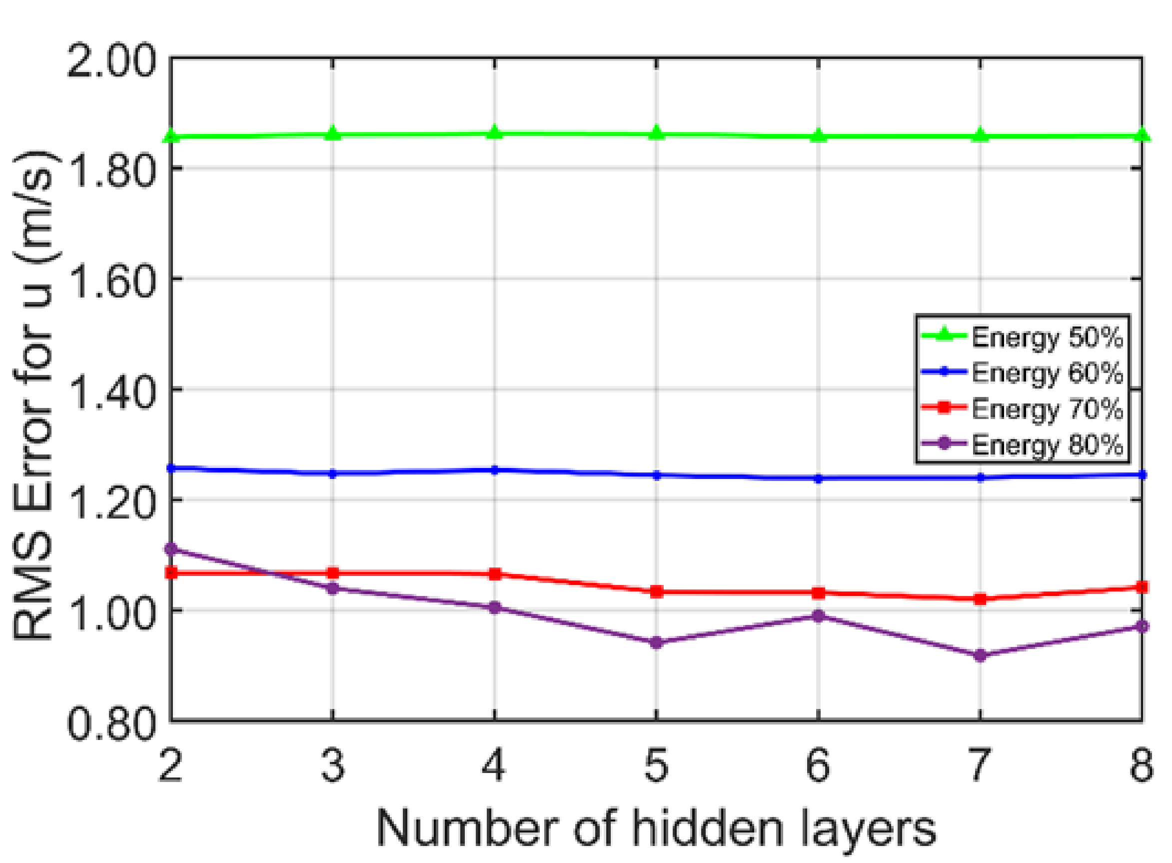
Effect of Hidden Layers on Accuracy

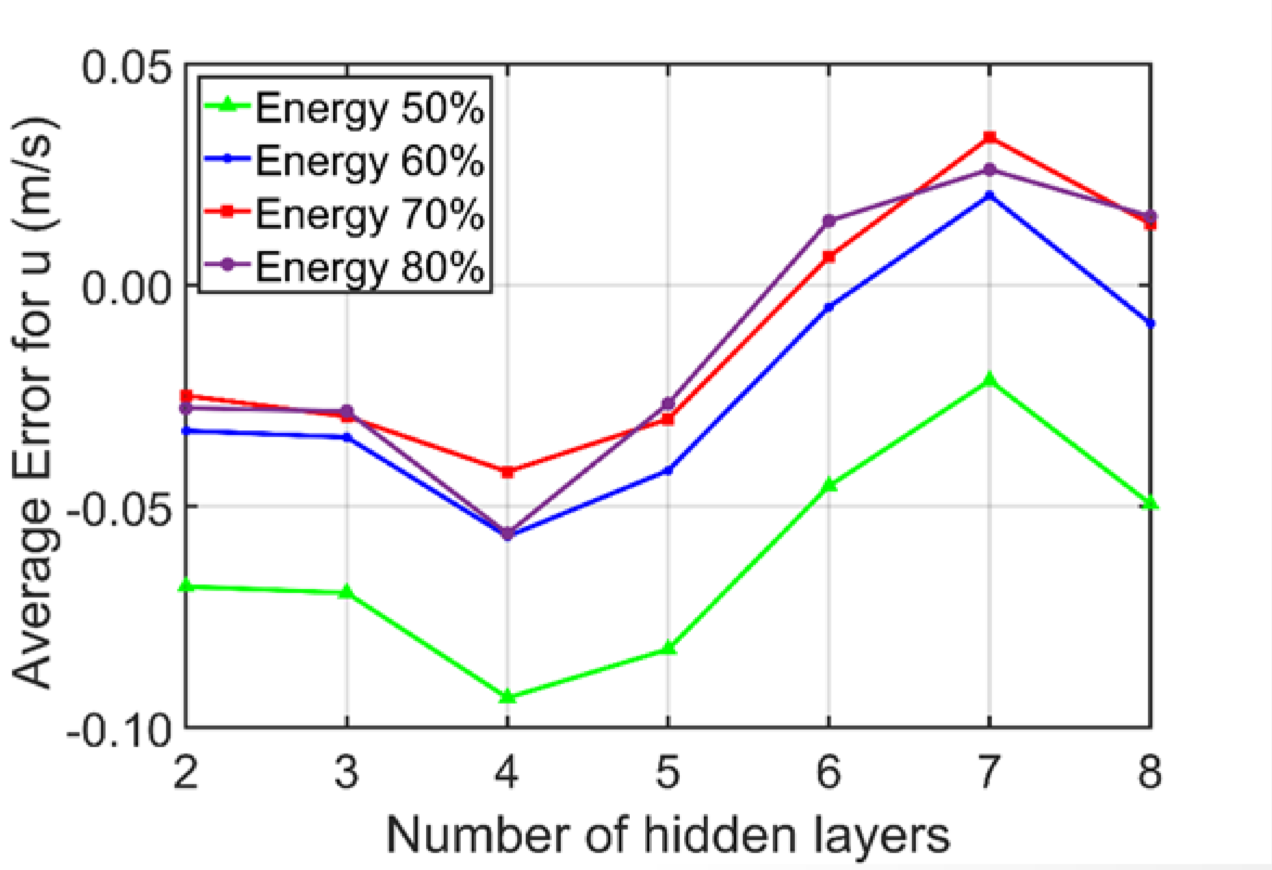








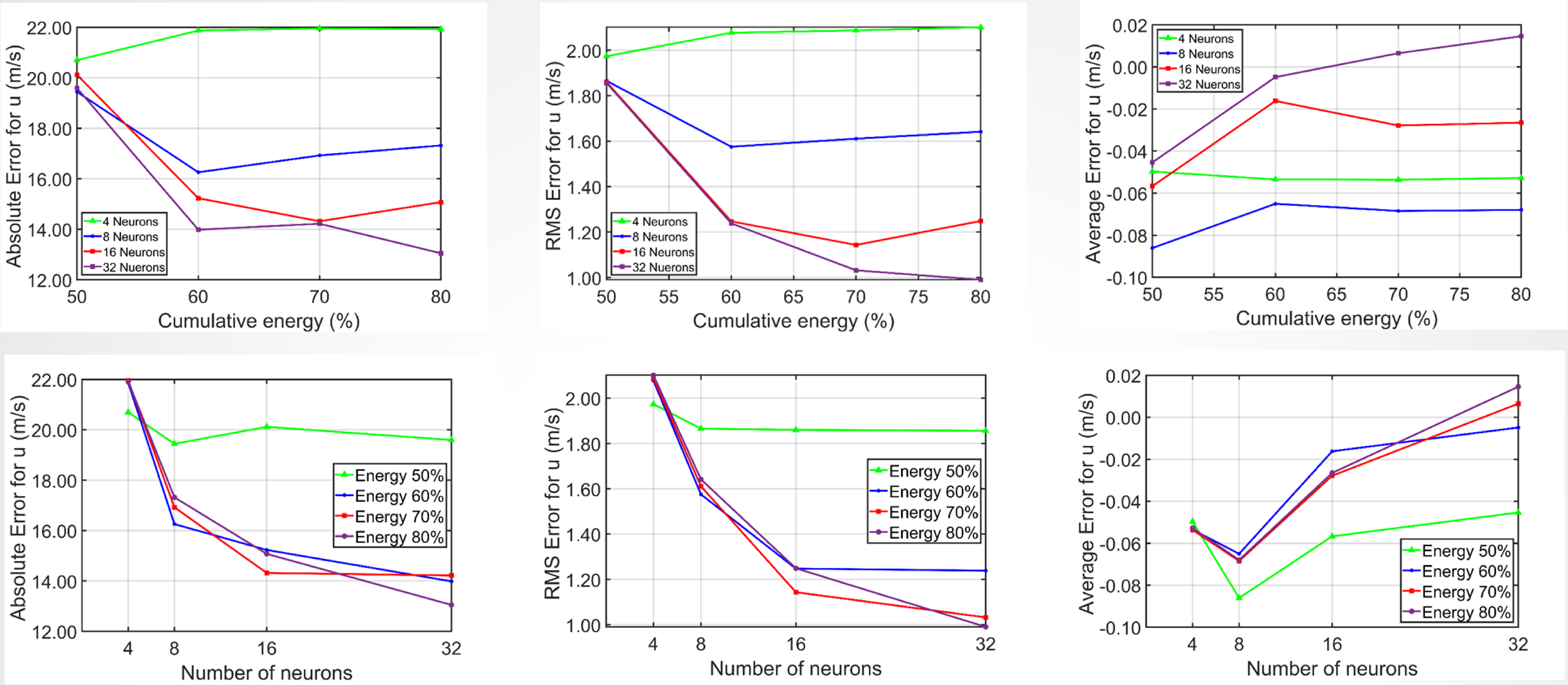




Number of neuron in each layer: 32

No significant effect on RMS or Absolute error
Average error decreases with increasing number of layers
Optimum value ~6

Effect of number of Neurons on Accuracy



Number of hidden layers: 6

Four neuron in the hidden layer has significant error
All errors decreases with increasing number of neurons

Computational Resource Requirements

	Time in seconds				Memory usage (GB)
	SVD	Training	Prediction	Reconstruction	
Approach 1 (91 ML models)	1.08	11486	10.86	0.18	21.02
Approach 2	1.10	117.05	0.15	0.16	16.18
Approach 3	0.81	128.56	0.16	0.20	16.66

The computations were performed using a 2.4 GHz Intel Xeon E5-2680 processor.
The maximum amount of memory used is 21 GB.

Conclusions

- Three different ML models were developed and tested to predict flow fields around a military vehicle for any given wind direction
- POD of the temperature field showed 90% of the cumulative energy is contained in the first mode, indicating only small variation in temperature field
- Modes corresponding to 70 - 80% cumulative energy are needed for accurate prediction of the flow field
  - Adding more modes doesn't improve the accuracy, and in some cases the error increases slightly when adding more modes
- A single ML model with neurons in the output layer for all mode coefficients is found to be more efficient in terms of computational resources and ease of implementation.
- A parametric study showed that a ML architecture with 6 hidden layers and 32 neurons in each layer performed the best

Future Work

- The developed ML model is restricted to FED-Alpha geometry
  - Not useful for other vehicles or change in the geometric shapes
- Explore application of convolutional neural network (CNN) to develop a generalized model applicable to different vehicles

Acknowledgement

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- Ms. Lauren Tetzloff of ThermoAnalytics, Inc. for her help with preparation of simulation model for TAITherm