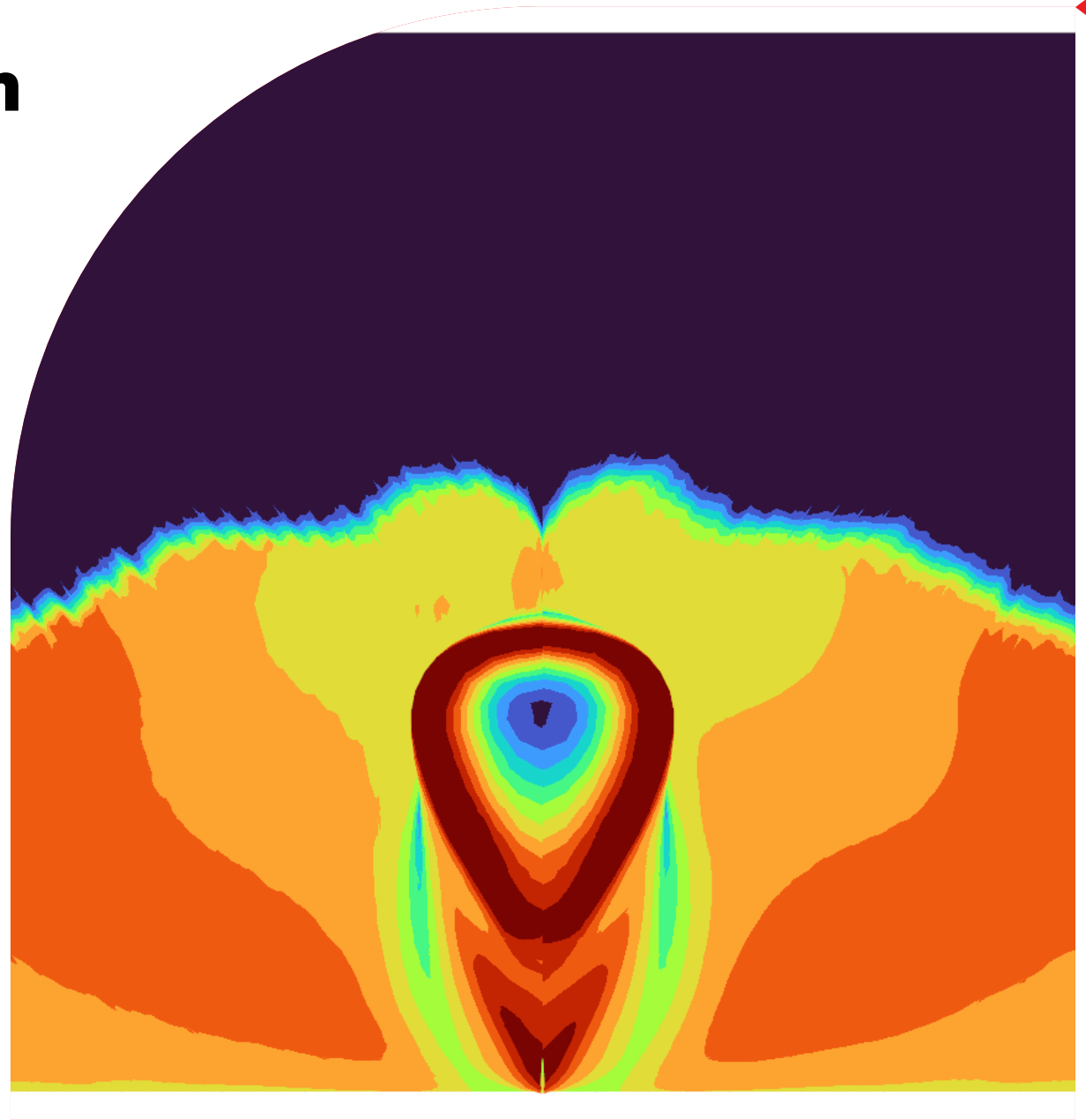
# Enabling Faster Marine Design with GPU-Accelerated HELYX and AI Surrogates

## Ship Hydrodynamics



**I. Shokar** and A. Ghasemi: *NVIDIA*
P. Geremia and E. Costa: *ENGYS*
M. Machowski: *RBF Morph*

ENGYS UGM | 23 October 2026

engys

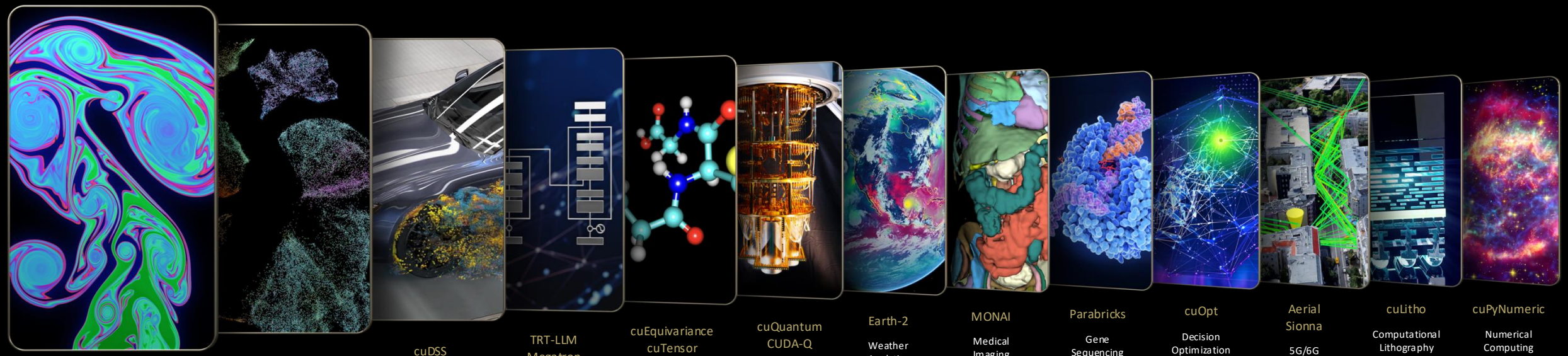
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# NVIDIA Powers AI Factories

Data centers process mountains of continuous data to train and refine AI software. Companies are manufacturing intelligence, and their data centers are becoming giant AI factories. NVIDIA is the engine of the world's AI infrastructure.

# CUDA-X Across Industries



PhysicsNeMo
Warp

AI
Physics

cuDF
cuML

Data Science
and Processing

cuDSS
cuSPARSE
cuFFT
AmgX

Computer Aided
Engineering

TRT-LLM
Megatron
NCCL
cuDNN
CUTLASS
cuBLAS

Deep
Learning

cuEquivariance
cuTensor

Quantum Chemistry

cuQuantum
CUDA-Q

Quantum
Computing

Earth-2

Weather
Analytics

MONAI

Medical
Imaging

Parabricks

Gene
Sequencing

cuOpt

Decision
Optimization

Aerial
Sionna

5G/6G
Signal Processing

cuLitho

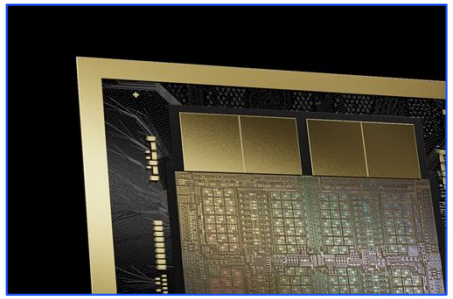
Computational
Lithography

cuPyNumeric

Numerical
Computing

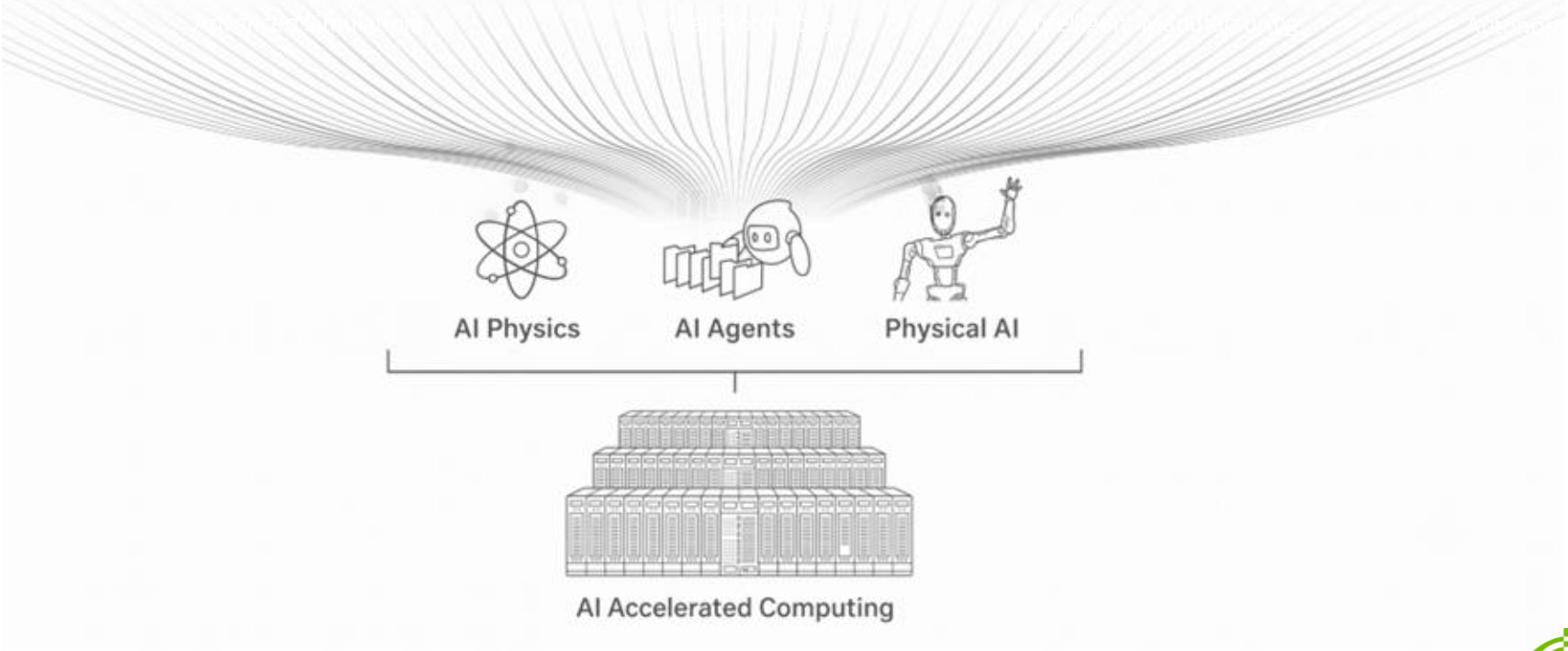
NVIDIA

# AI Revolutionizing Industrial Design and Engineering












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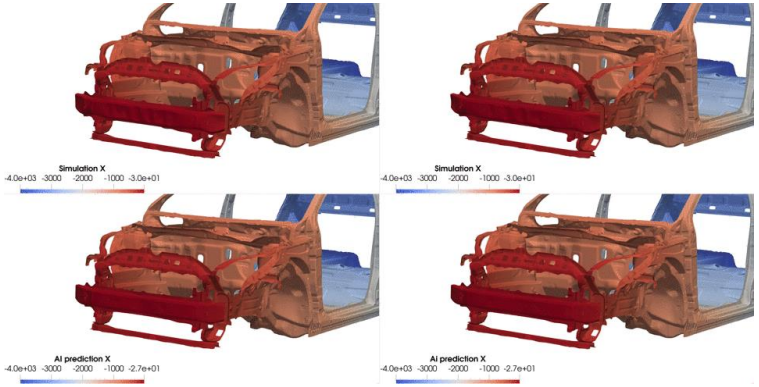
# AI Physics Domains

Use Cases across science and engineering

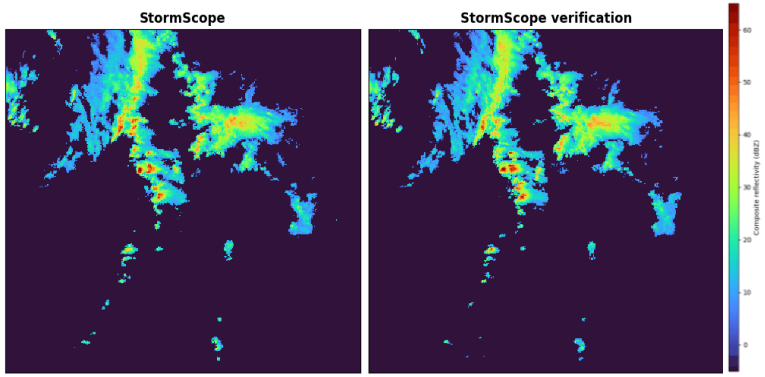
## Computational Fluid Dynamics



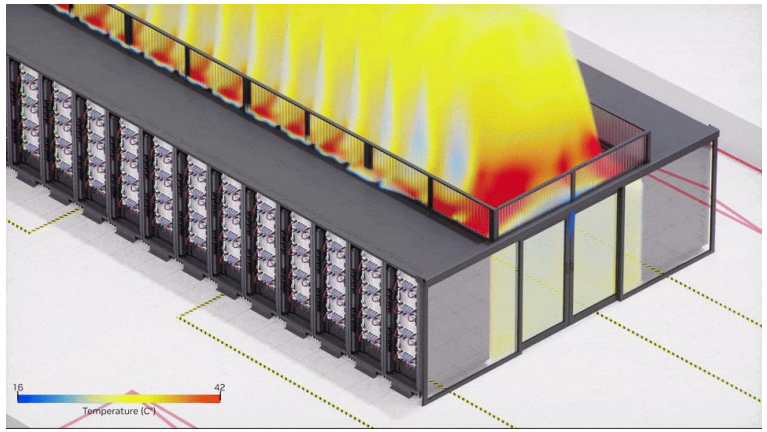

## Structural Mechanics




## Weather & Climate (Earth2)



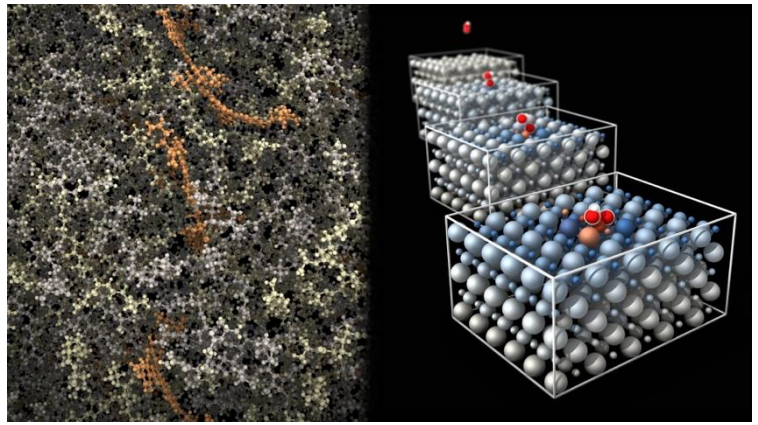

## Thermal




## Energy Generation



## Molecular Dynamics (ALCHEMI)



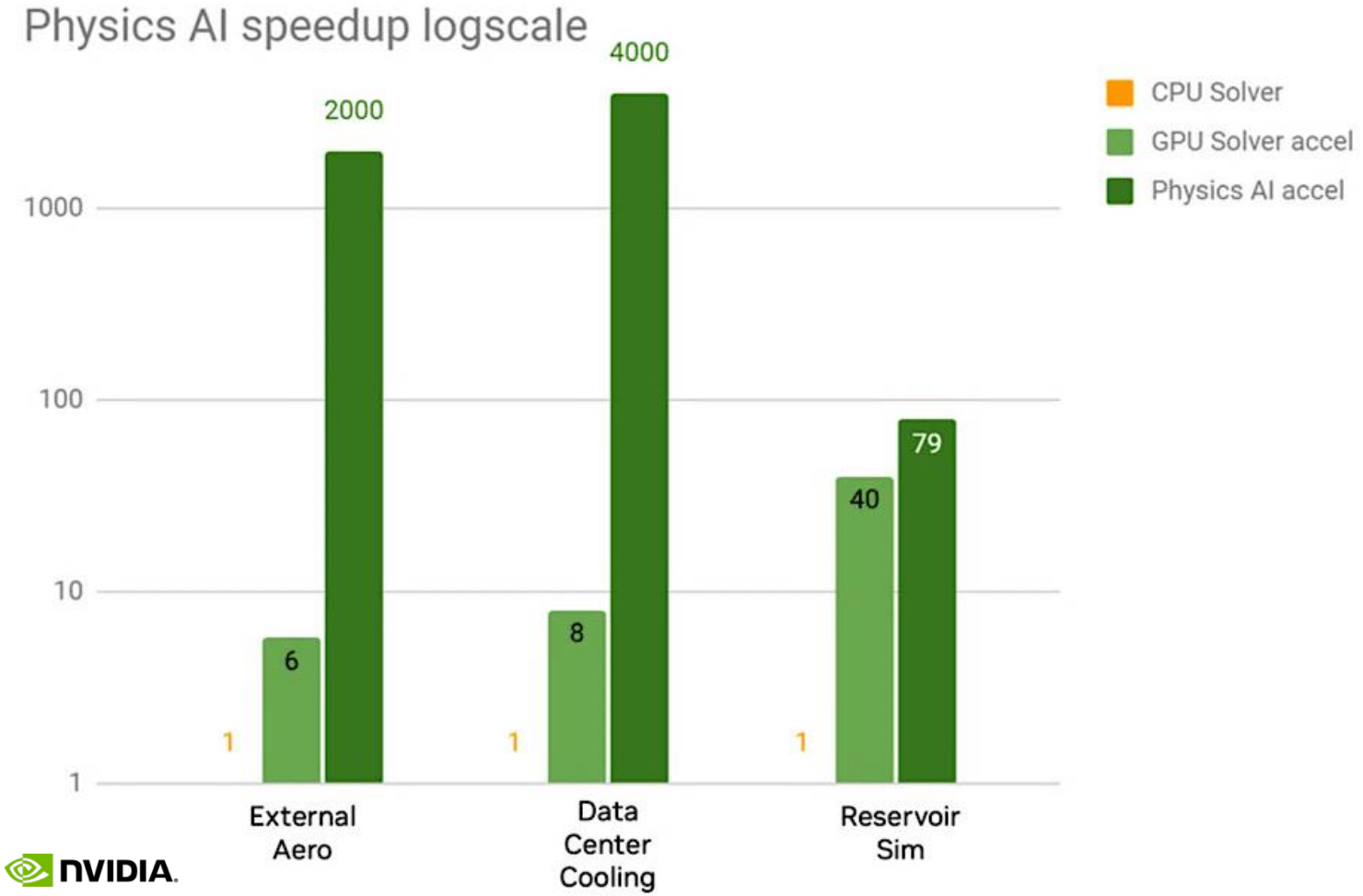
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# NVIDIA PhysicsNemo

## PyTorch++ for AI Physics

Combines first-principles physics AI with enterprise-scale mesh performance to deliver 1000x faster solutions, turning months of low-level infrastructure setup into weeks of rapid, optimized execution.




**Optimized Kernels**

TransformerEngine & NVIDIA Warp

Model Functionals & cuML custom ops

**Scale Up & Scale Out**

Multi-GPU / multi-node parallelism

DistributedManager & ShardTensor

**Physics Fine-Tuning**

Physics-informed loss integration

Grounded solutions & generalization

**Open Models**

Model Zoo across SciML Domain

Pretrained checkpoints on HuggingFace

**Reproducible Recipes**

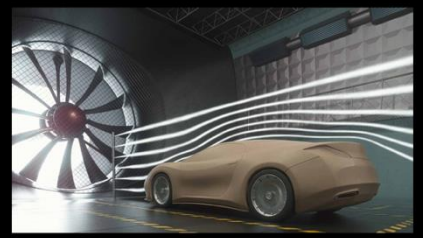
30+ end-to-end NGC workflows

Built-in benchmarking & validation

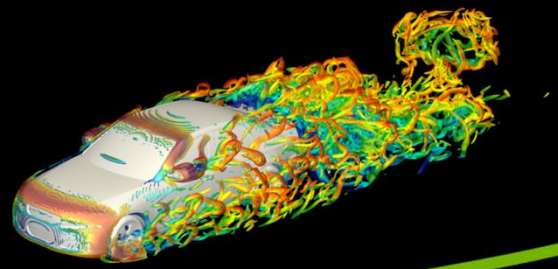
NVIDIA

# Accelerated Computing and AI Physics Revolutionizing Engineering Design

Design Cycles per Time Period



Wind Tunnel
Days-Weeks



CAE Simulation
Hour-Days



Accelerated
Computing
Several hundred/Day




AI Physics
~15,000/Day

NVIDIA

# GPU-Accelerated CFD: HELYX-GPU

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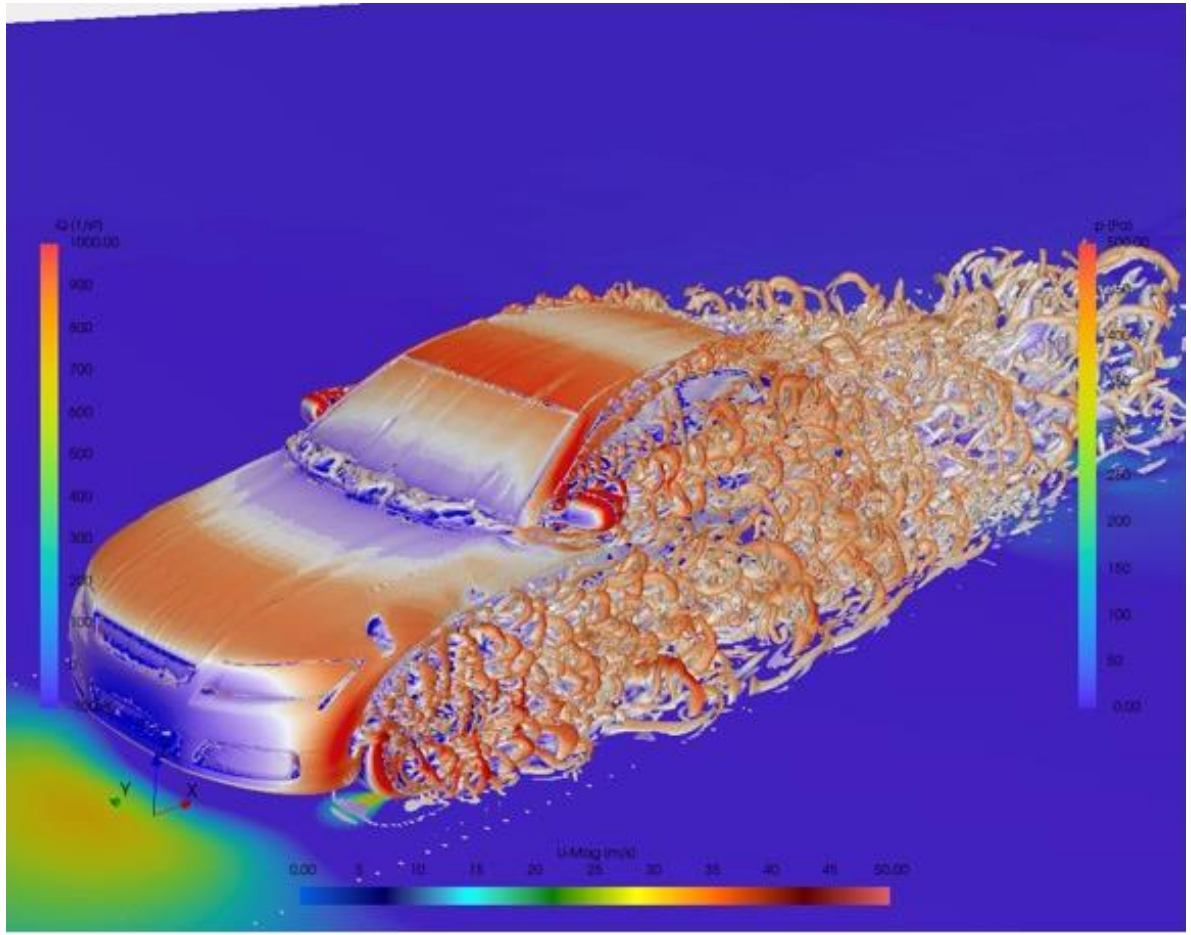
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# HELYX-GPU

## Overview

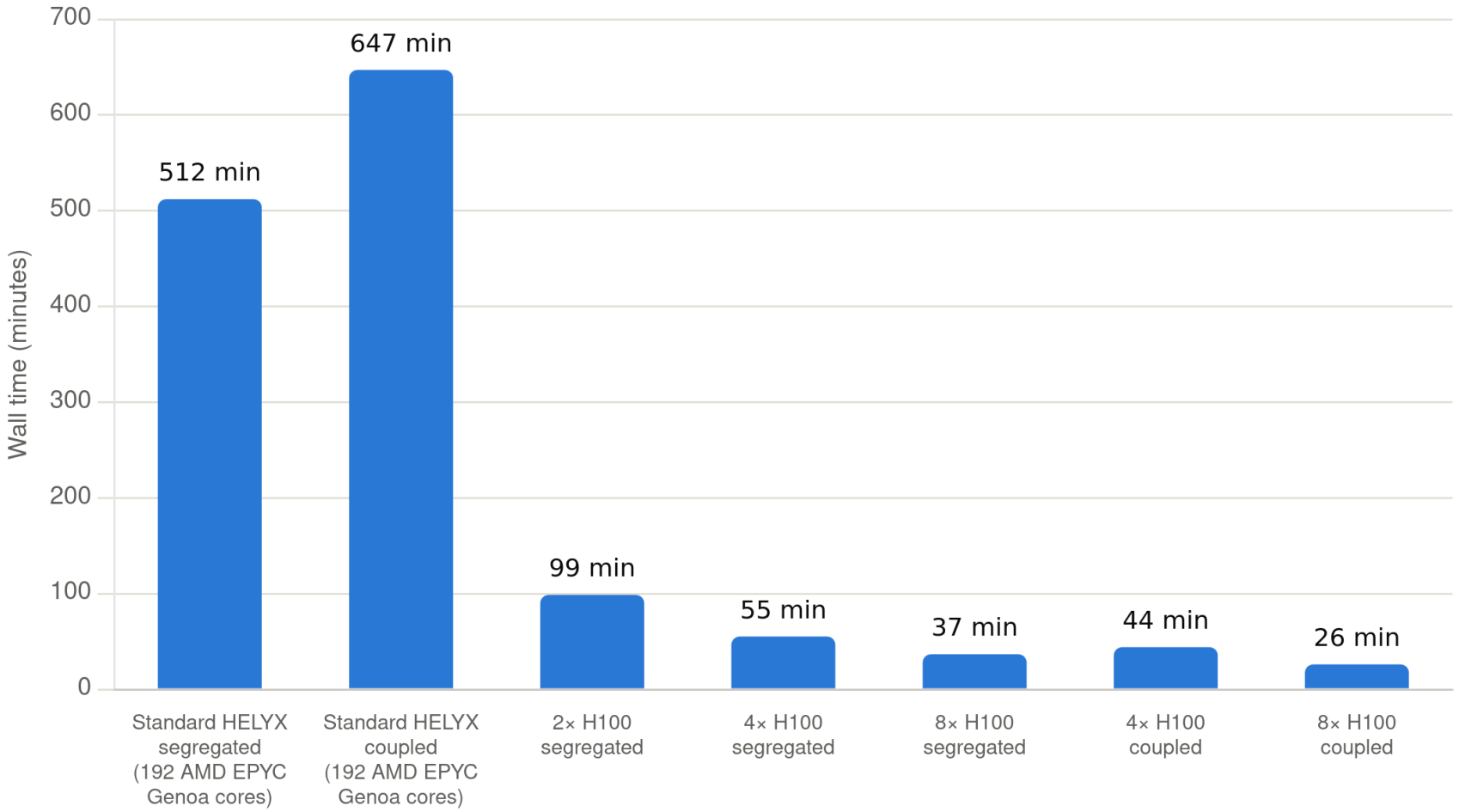
- Product
  - Dedicated GPU solver, released separately from the standard HELYX release stream
  - Current HELYX-GPU version aligned with HELYX 4.6.0
- CUDA support
  - CUDA 11.x up to the latest releases (currently CUDA 13.4)
  - CUDA 13.0 commonly used internally at ENGYS
- Showcase case
  - DrivAer, closed cooling configuration
  - 93 M cells, ENGYS mesh generated with HHM
  - Spalart-Allmaras DDES, single precision
  - Function objects active; optimized code and settings

## Showcase: DrivAer DDES



# HELYX-GPU

## Performance: standard HELYX (CPU) vs HELYX-GPU on NVIDIA H100

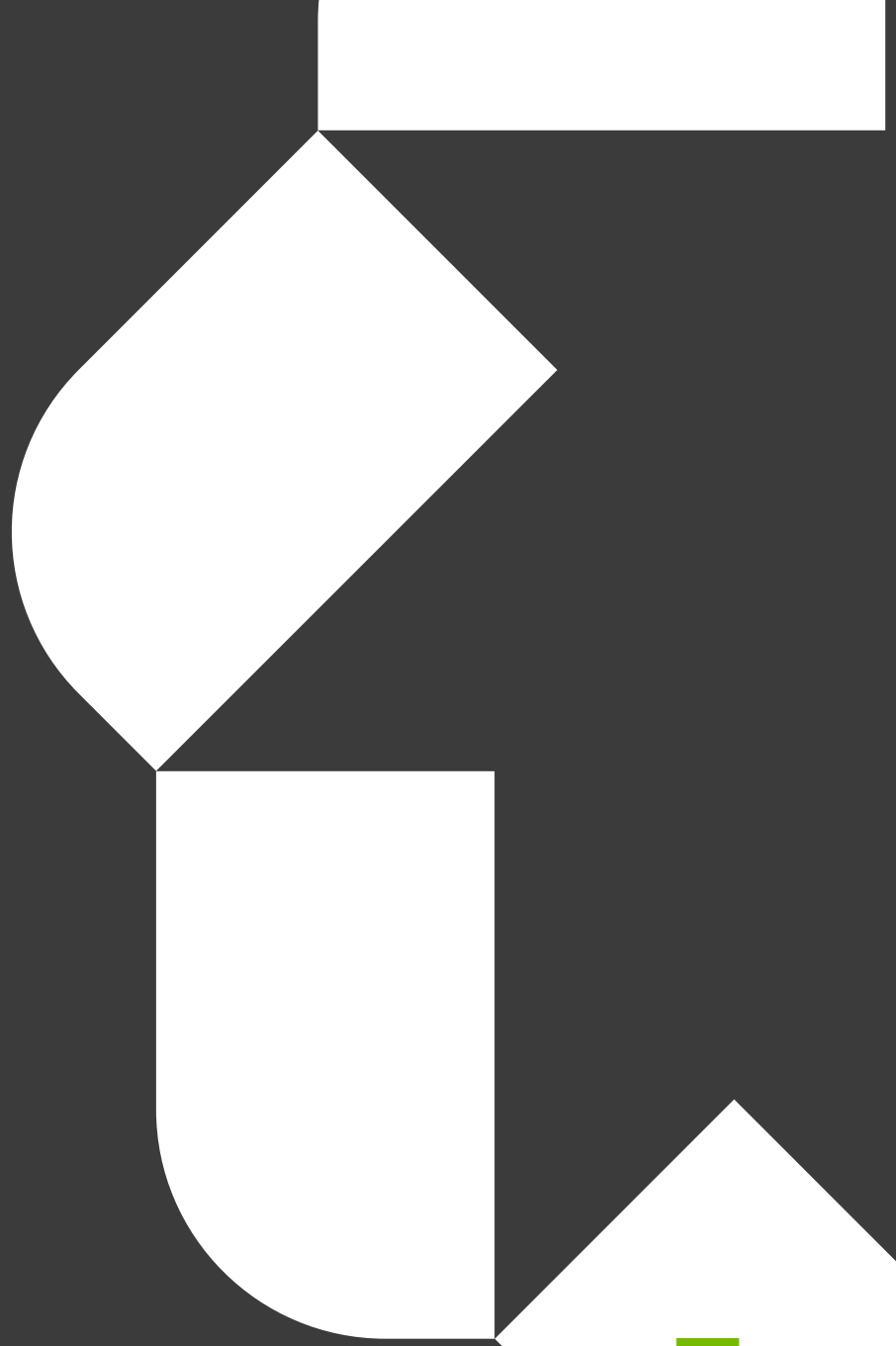



- Wall time reduction
  - Segregated: 512 → 37 min (~14× on 8× H100)
  - Coupled: 647 → 26 min (~25× on 8× H100)
- Scaling (segregated)
  - 2× H100: ~5×
  - 4× H100: ~9×
  - 8× H100: ~14×
- CPU baseline
  - 192 AMD EPYC Genoa cores

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# Linearized Free-Surface Solver



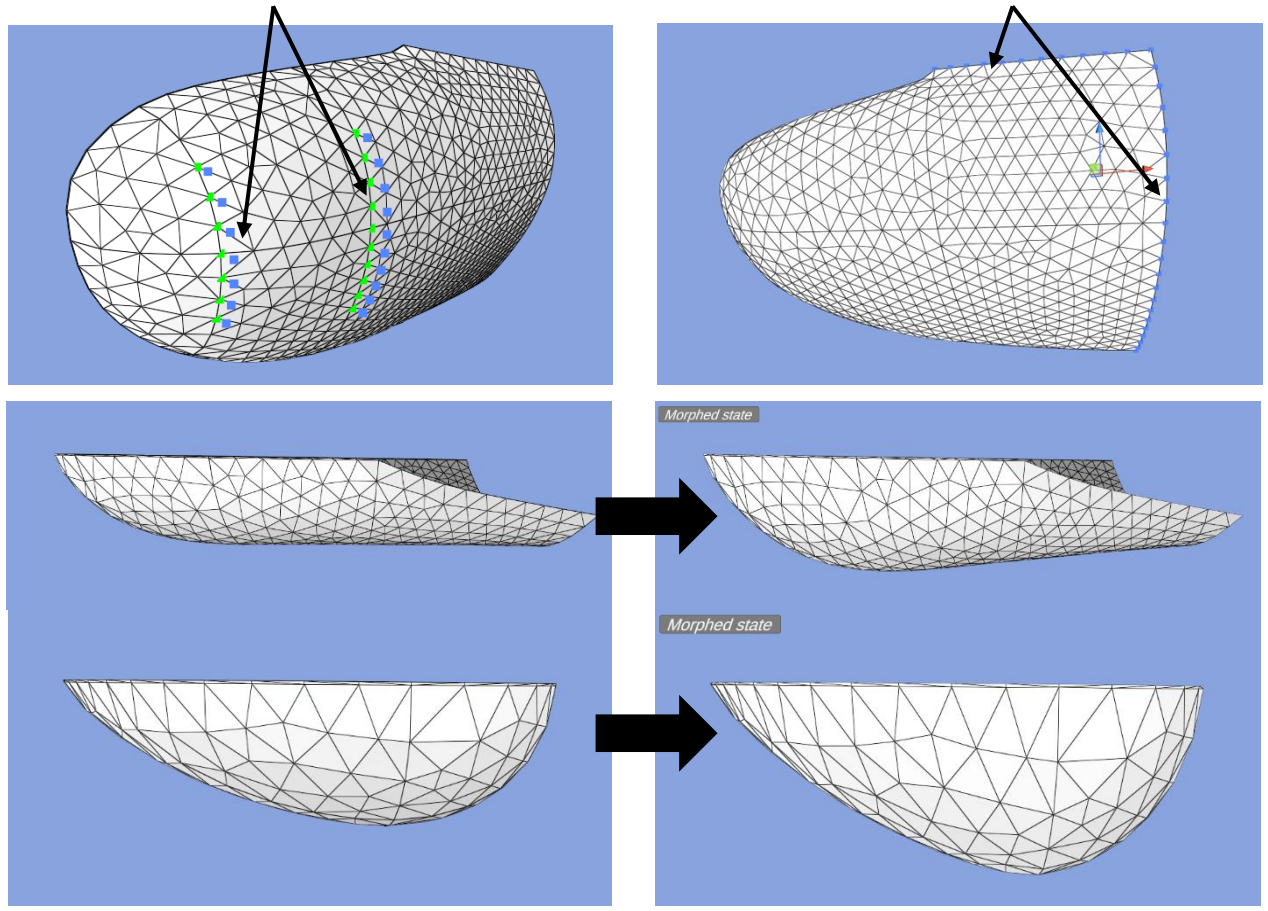
ENGYS

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# Setup

## Morphing Model Setup

- Geometry variation
  - Software → rbfCAE
- RBF shape modifiers set:
  - Bulbous bow → 3 shape modifications (2 in-plane and 1 out-of-plane)
  - Stern → 2 shape modifications (1in-plane and 1out-of-plane)
- DoE generation
  - 101 sample points using LHS (inc. baseline)

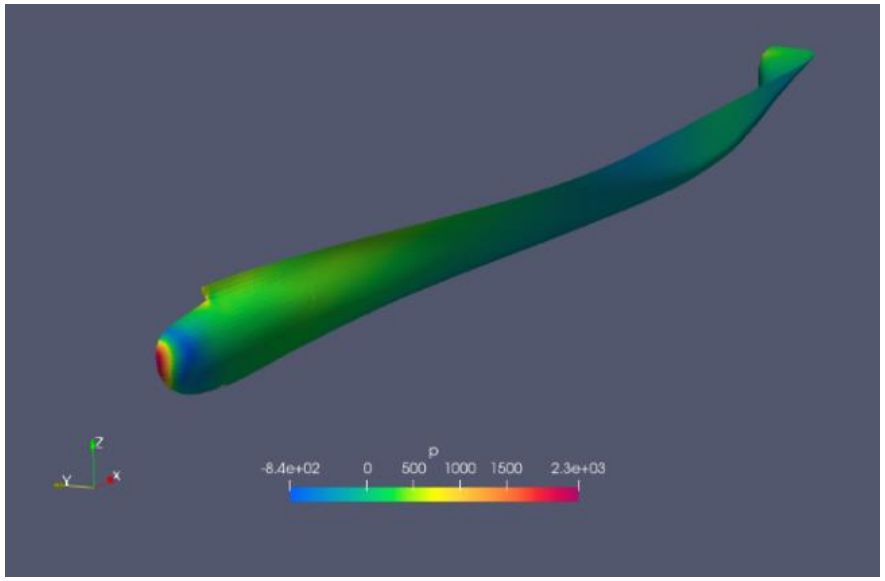



Bow Morphing Preview from Top and Front View

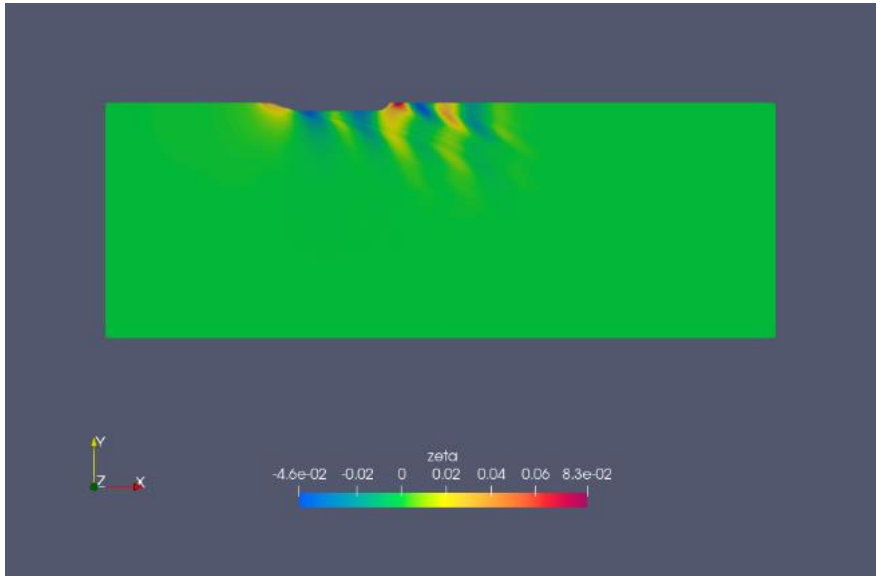
# Setup

## CFD Model Setup

- Mesh
  - Mesh size → 2.5 M cells (half model)
  - Near-wall layers → 5
- Setup
  - Solution → HELYX-Marine Linearized-Free Surface (LFS) solver, steady-state RANS
  - Turbulence → k-ω SST
- Post
  - RTPP → Automatic data export
    - Surface fields → VTK ($p_s$, $\tau_w$ , elevation)




Pressure




Free-surface elevation

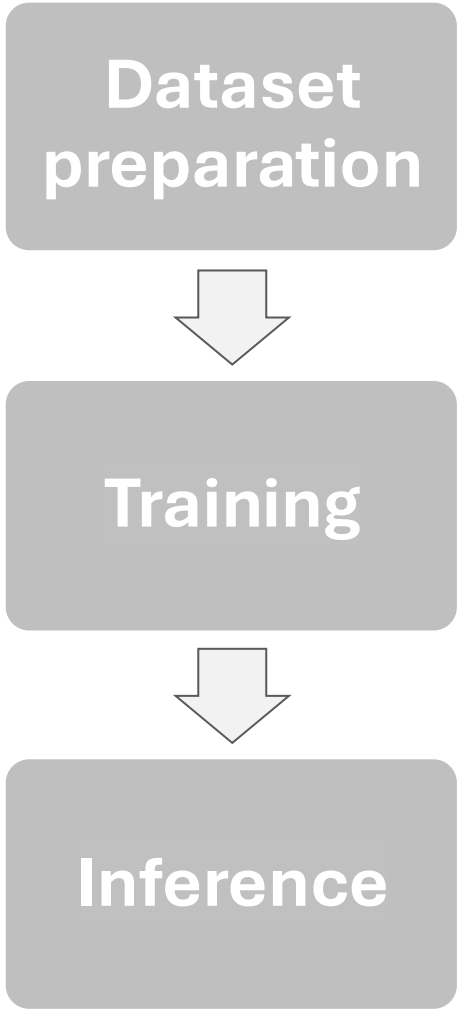
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# Setup

## AI Model Setup

- Dataset Preparation
  - Automated split of dataset into train (81) + validation (10) + test (10) sets via random sampling
- Training
  - Model → Nvidia GeoTransolver
  - No. sampling points → 22k
- Inference on unseen geometries



# Results

## Testing: ship hull total resistance ($R_t$) relative error

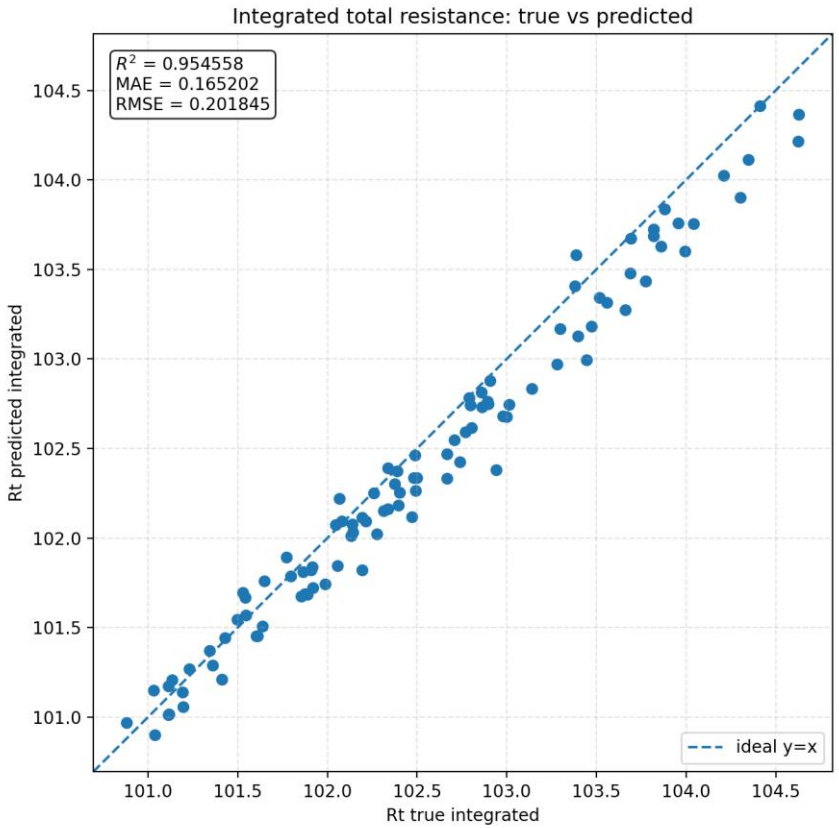
- Rt calculated integrating pressure and WSS results over ship's hull (x2)

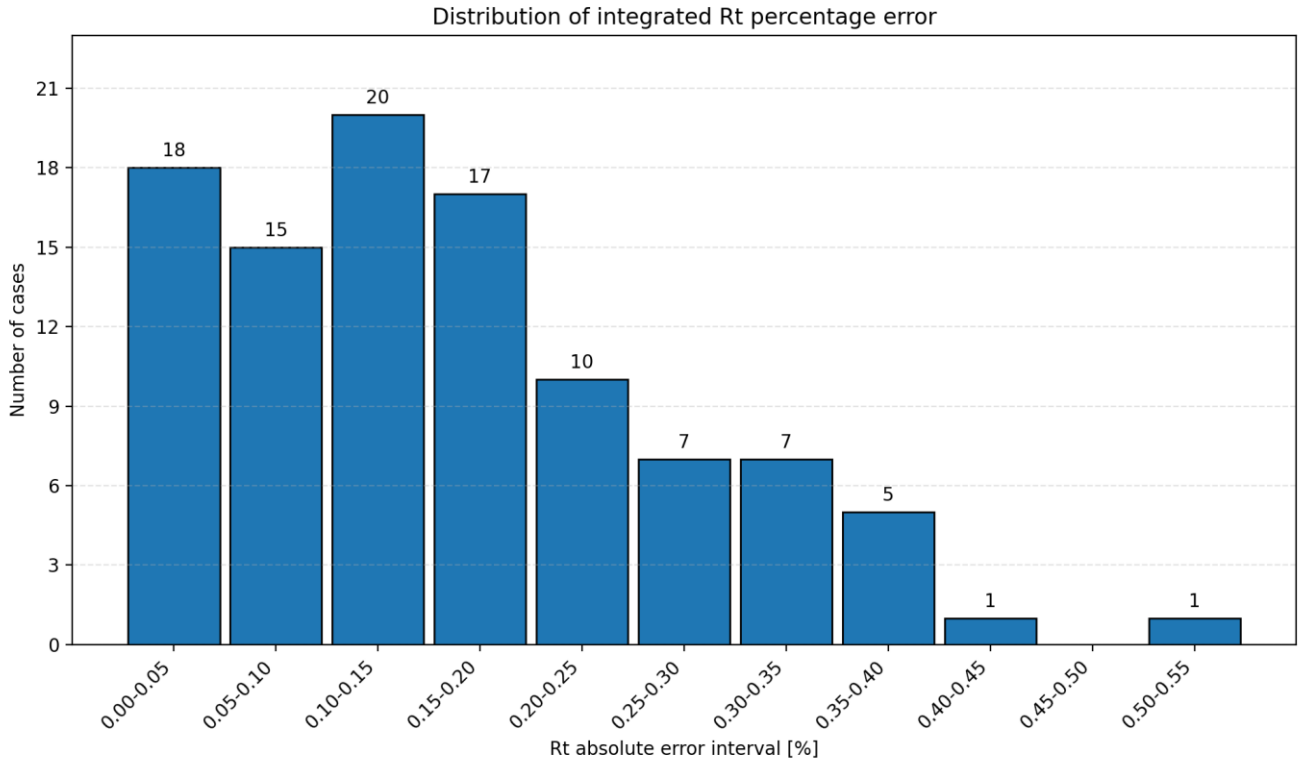
| DP # | RBF Parameters Combination | $R_{t,CFD}$ [N] | $R_{t,AI}$ [N] | Relative Error [%] |
|---|---|---|---|---|
| 91 | 0.00346, -0.0104, 1.31, -1.39, 1.4 | 103.66 | 103.27 | -0.38 |
| 92 | -0.0659, -0.0255, 1.03, -1.97, 1.32 | 102.89 | 102.74 | -0.15 |
| 93 | -0.0277, -0.0432, 1.33, 1.45, 1.27 | 103.47 | 103.18 | -0.28 |
| 94 | -0.093, -0.0441, 1.23, -1.59, 0.825 | 101.11 | 101.17 | 0.06 |
| 95 | -0.0551, 0.0307, 1.38, 0.329, 1.37 | 103.85 | 103.62 | -0.22 |
| 96 | 0.0179, 0.013, 1.01, 0.846, 0.865 | 102.08 | 102.09 | 0.01 |
| 97 | -0.0486, -0.0342, 1.27, -0.85, 1.01 | 101.85 | 101.67 | -0.18 |
| 98 | 0.00992, 0.0359, 0.946, -0.16, 1.48 | 104.20 | 104.02 | -0.17 |
| 99 | -0.0377, -0.0297, 1.01, -1.33,1.17 | 102.38 | 102.37 | -0.01 |
| 100 | -0.0614, 0.0216, 1.25, -1.74, 1.42 | 103.77 | 103.43 | -0.33 |

# Results

## Resistance: statistics

- Rt scattered plot and histograms of relative error (%)

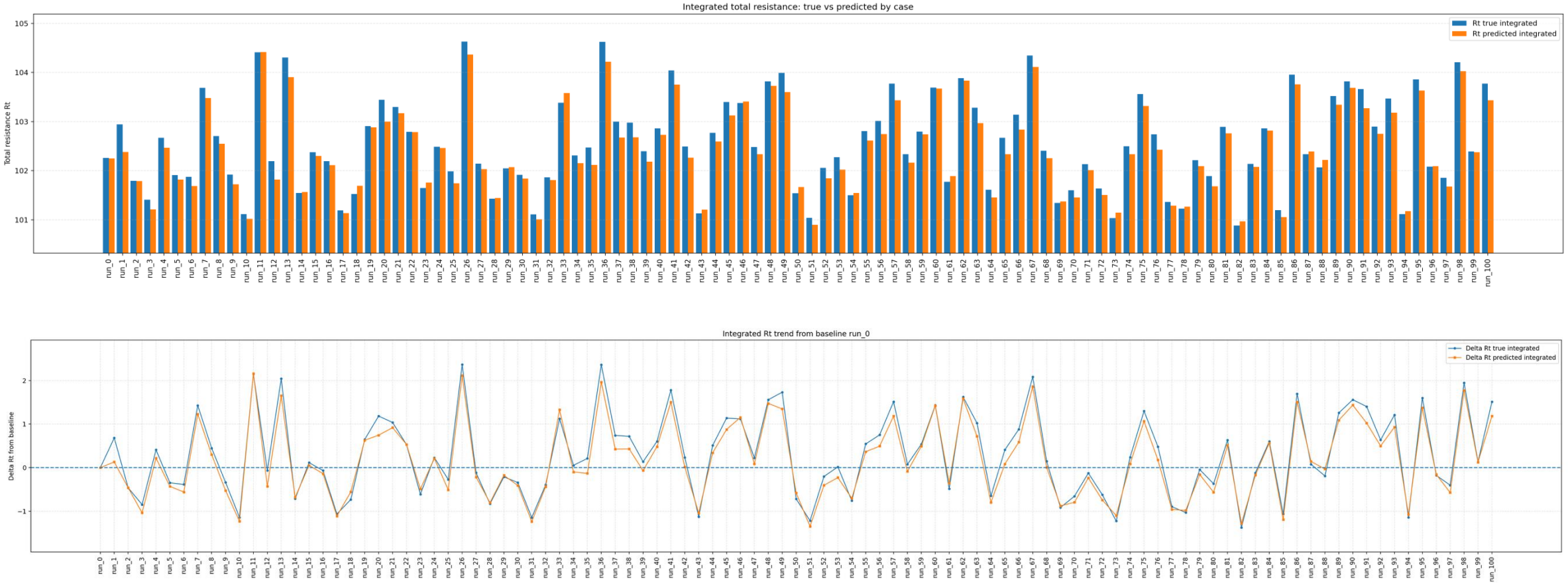


# Results

## Resistance: whole dataset assessment

- CFD / AI predictions: Rt **value** and **delta wrt baseline** over the whole dataset




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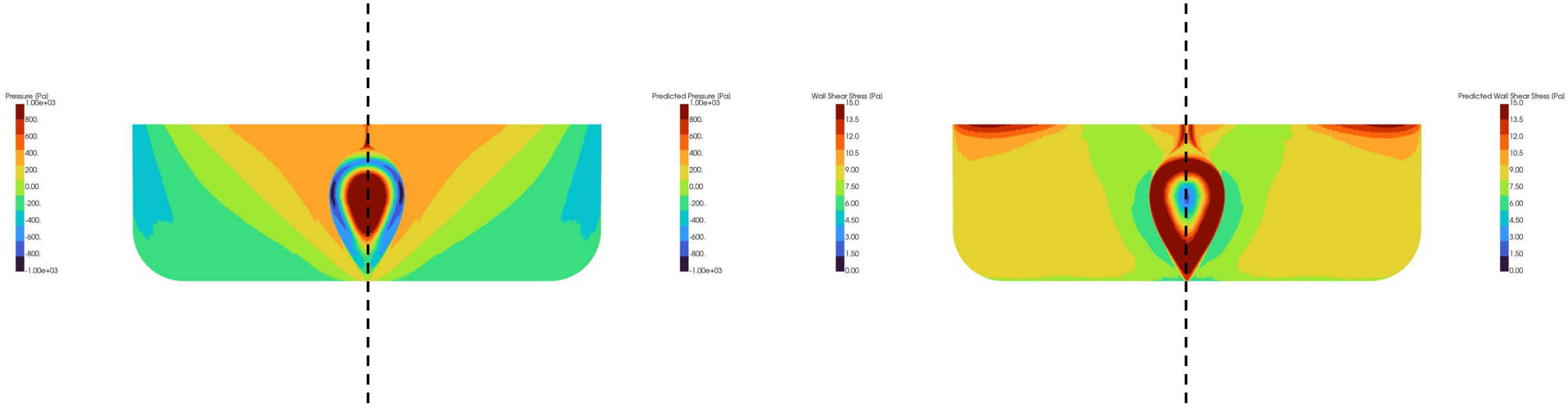
# Results

## GPU Computing: GeoTransolver processing

- **Training** time/epoch: ~ 24.68 s
- **Validation** time/epoch: ~ 0.72 s
- Total time: ~ 11880 s (3 h 30 min)
- **Testing** time/DP: ~ 0.28 s (tot: 28 s)
- Hardware
  - GPU: NVIDIA L40
  - VRAM: 44.418 GB
  - CUDA: 13.0
  - PyTorch:2.9.0a0+145a3a7bda.nv25.10
  - Python: 3.12.3
  - Docker image: NVIDIA PhysicsNeMo 25.11

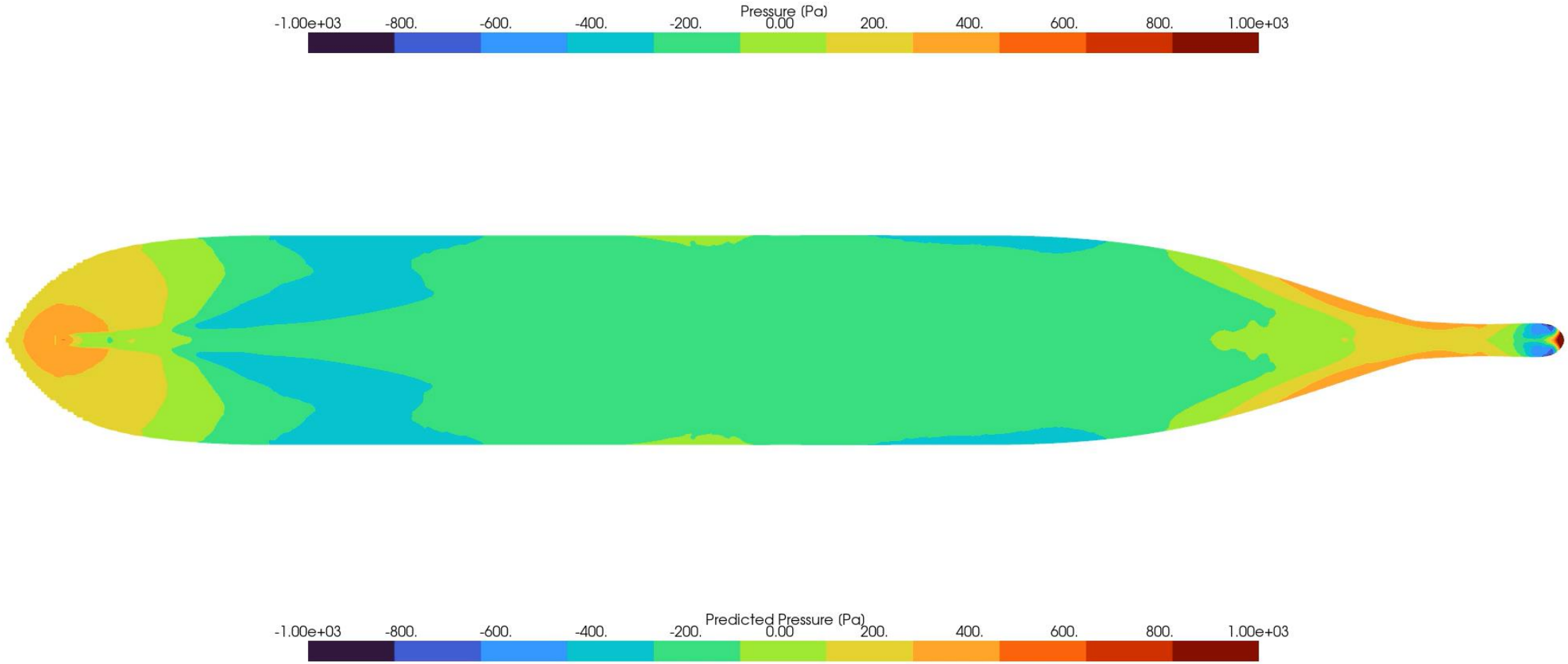
# Results

## Surface Pressure and Wall Shear Stress on Test Set | Front View



# Results

## Surface Pressure Field on Test Set | Bottom View

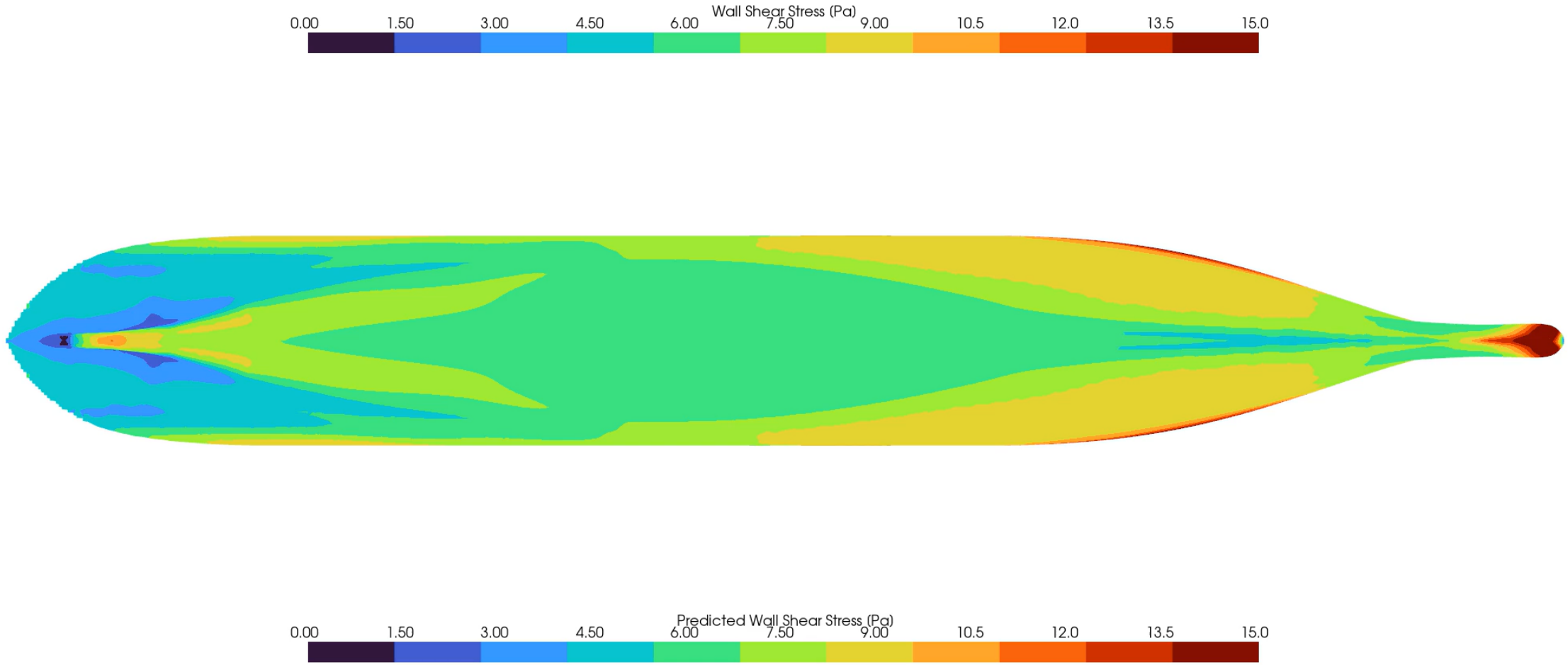



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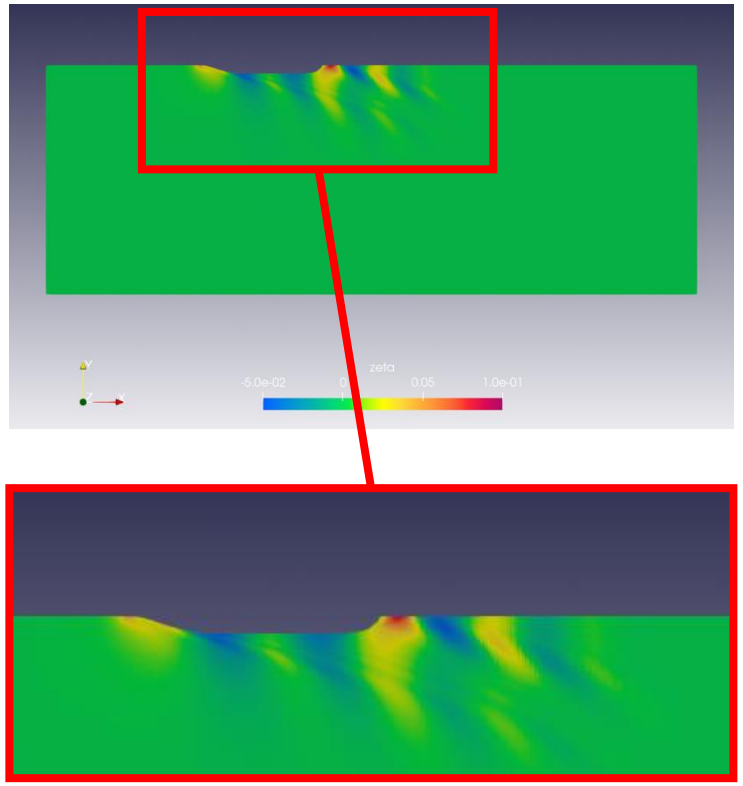
# Results

## Surface Wall Shear Stress on Test Set | Bottom View

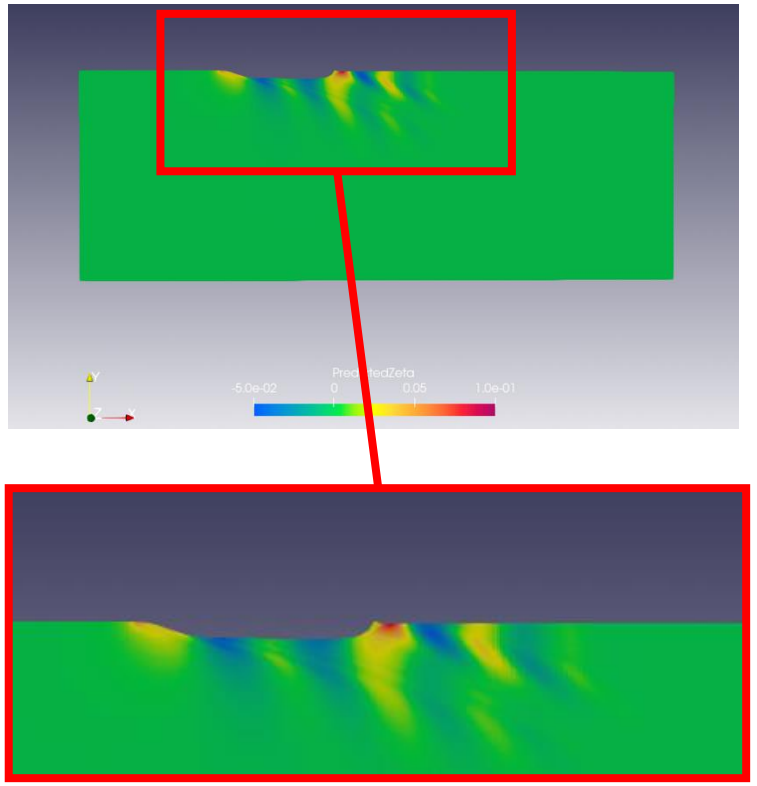


# Results

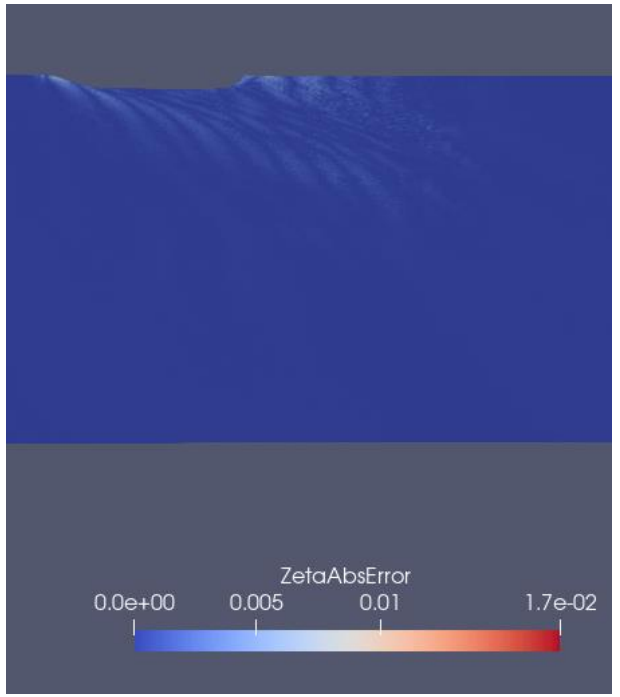
## Free-surface Elevation (DP91)




CFD




AI




Error

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# Multiphase VOF - Training



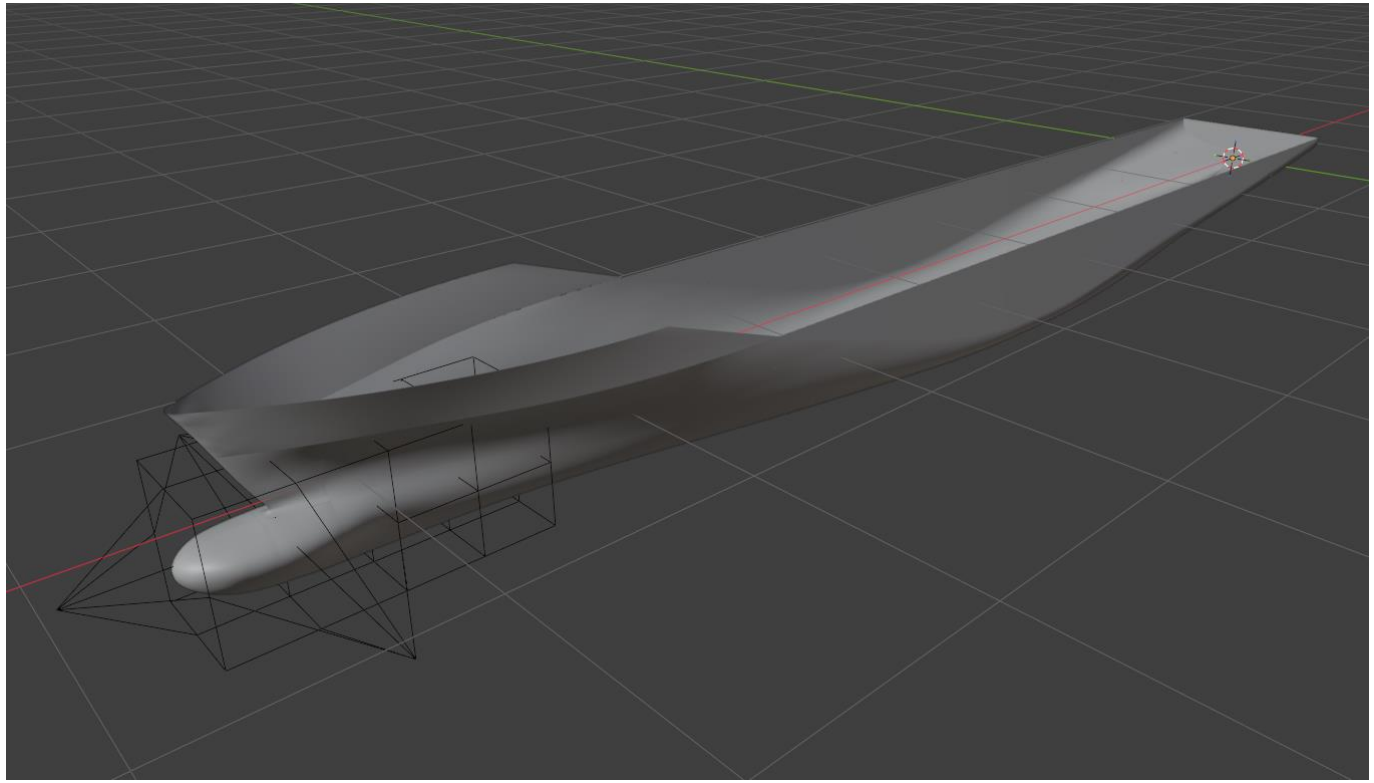
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# Setup

## Morphing Model Setup

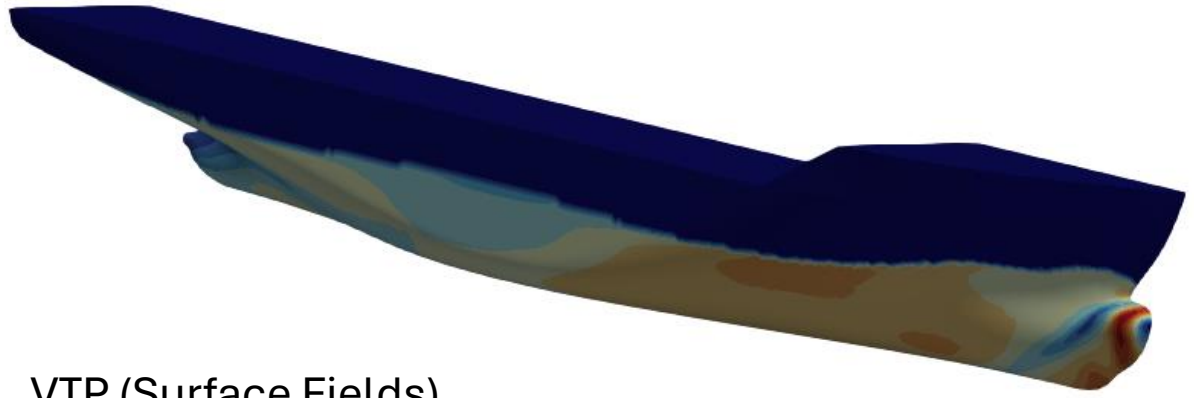
- Geometry variation
  - Software → Blender
  - 3 design variables (bulbous bow)
  - Morphing via harmonic coordinates character articulation algorithm
  - Export to STL via Python API
- DoE generation
  - 133 sample points using LHS



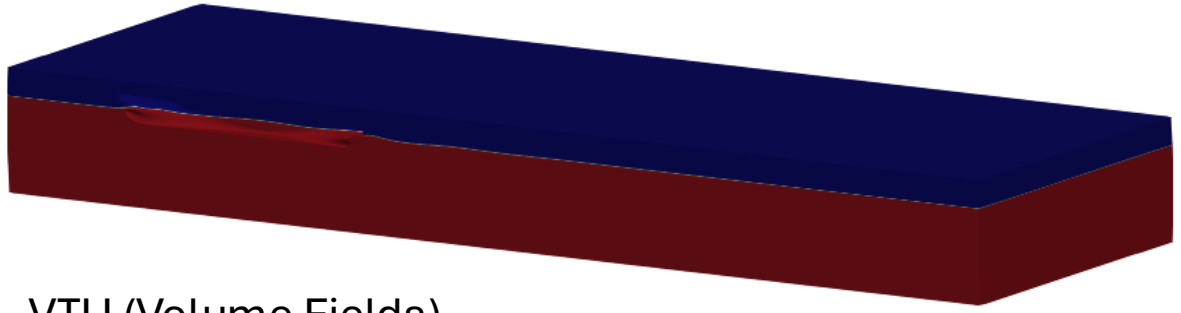
# Setup

## CFD Model Setup

- Mesh
  - Mesh size → 1.8 M cells (half model)
  - Near-wall layers → 5
- Setup
  - Solution → Transient VOF HELYX-Marine
  - Turbulence → k-ω SST
- Post
  - RTPP → Automatic data export
    - Surface fields → VTP ($p_s$, $\tau_w$)
    - Volume fields → VTU (elevation, phase.fraction)



VTP (Surface Fields)



VTU (Volume Fields)

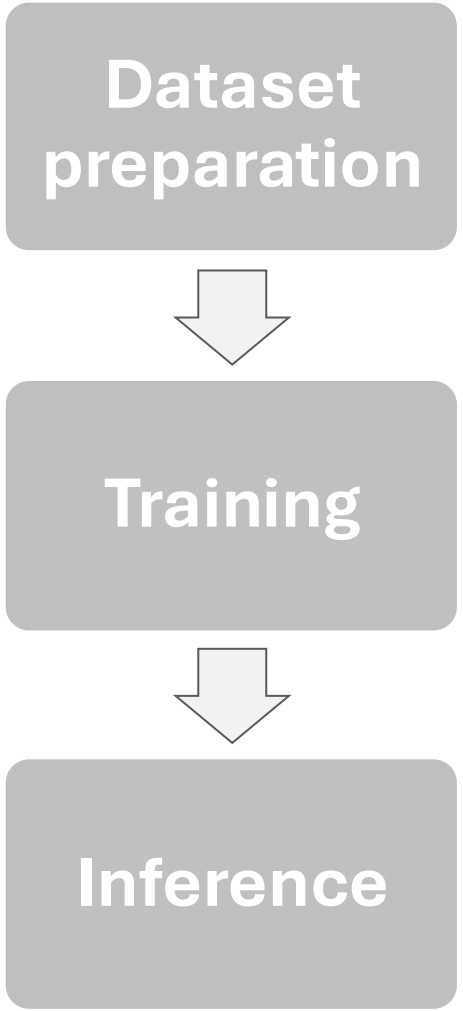
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# Setup

## AI Model Setup

- Dataset Preparation
  - Automated split of dataset into train (119) + validation/test (14) sets via K-Means clustering and stratified sampling
- Training
  - Model → Nvidia GeoTransolver
  - No. sampling points → 30k
  - No. epochs → 500
  - Hardware → 2x Nvidia RTX A5000
- Inference on unseen geometries



# Results

## Results

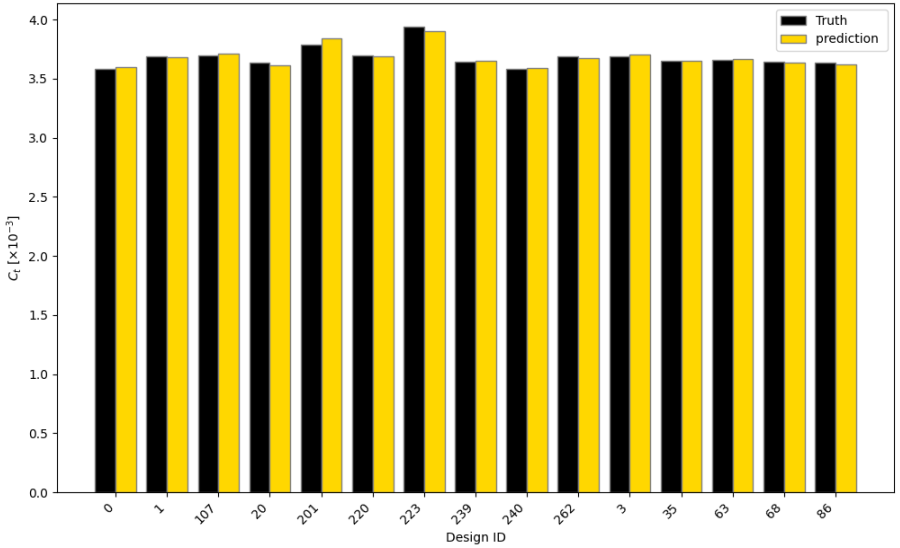
- Validation metrics

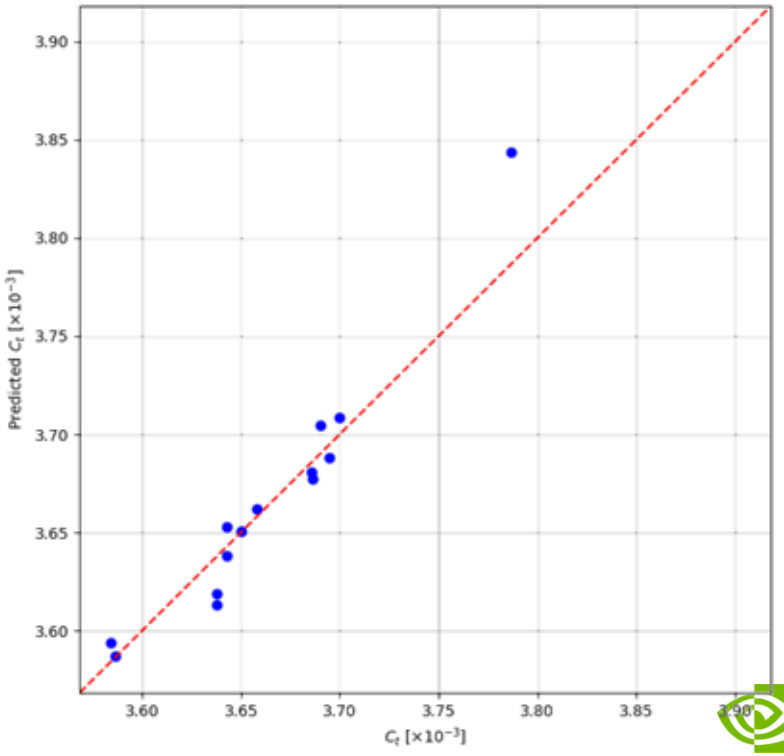
| | Surface | |
|---|---|---|
| | $p_s$ | $\tau_w$ |
| $L_1$ [%] | 0.5 | 0.4 |

| | Volume | |
|---|---|---|
| | Elevation | Phase Fraction |
| MAE | 0.0008 | 0.0009 |

- Regression error

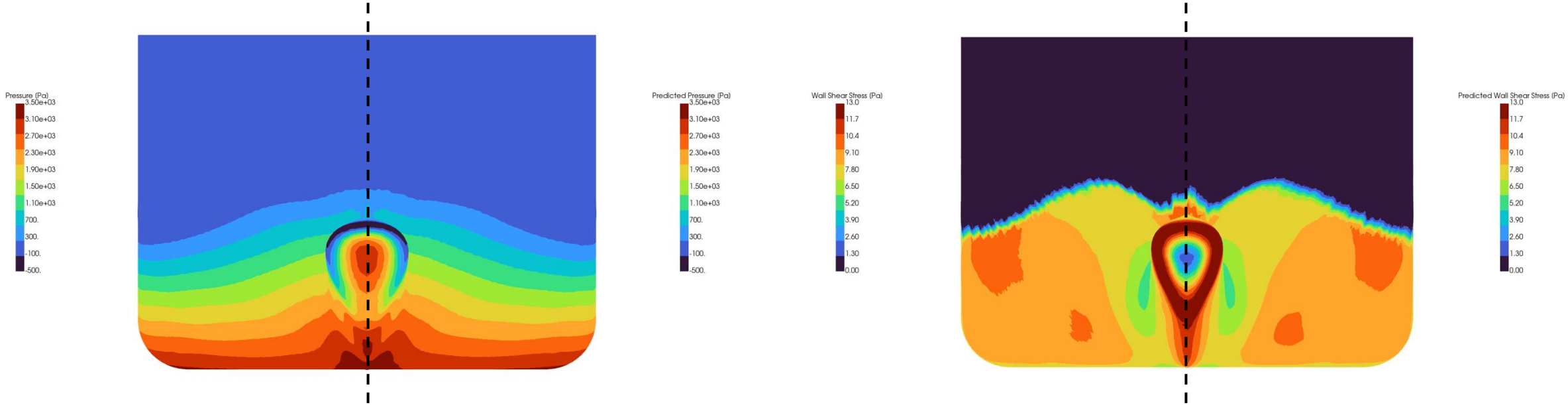
| | $R^2$ $C_t$ |
|---|---|
| Validation Set | 0.940 |



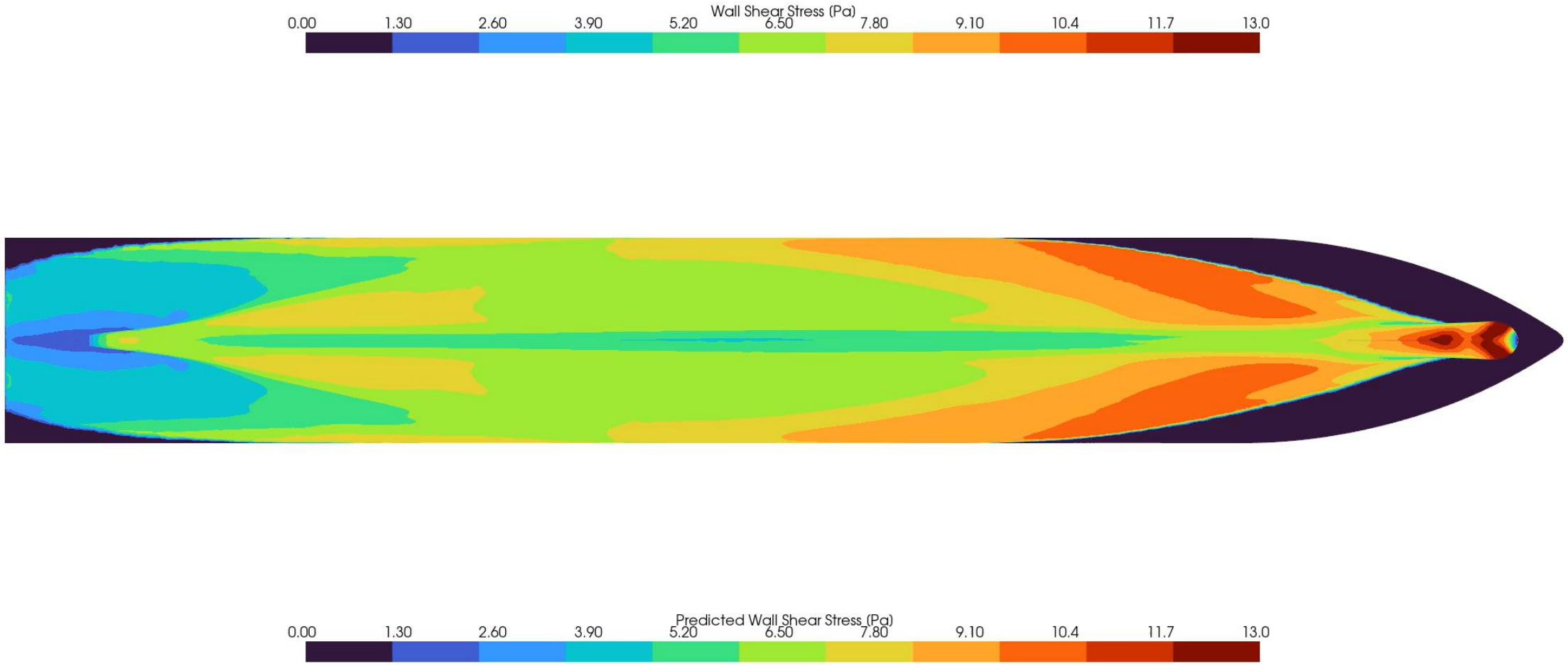
# Results

## Surface Pressure and Wall Shear Stress on Test Set | Front View



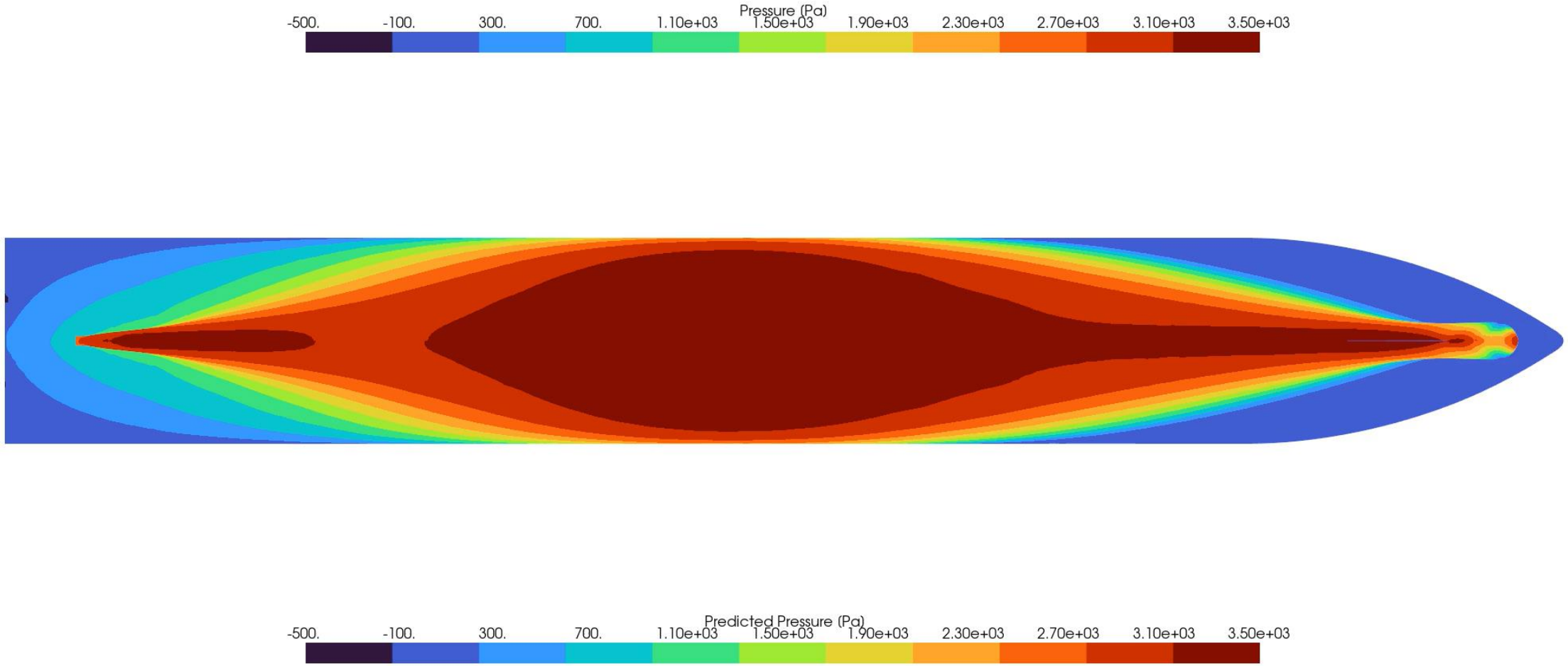
# Results

## Surface Pressure Field on Test Set | Bottom View



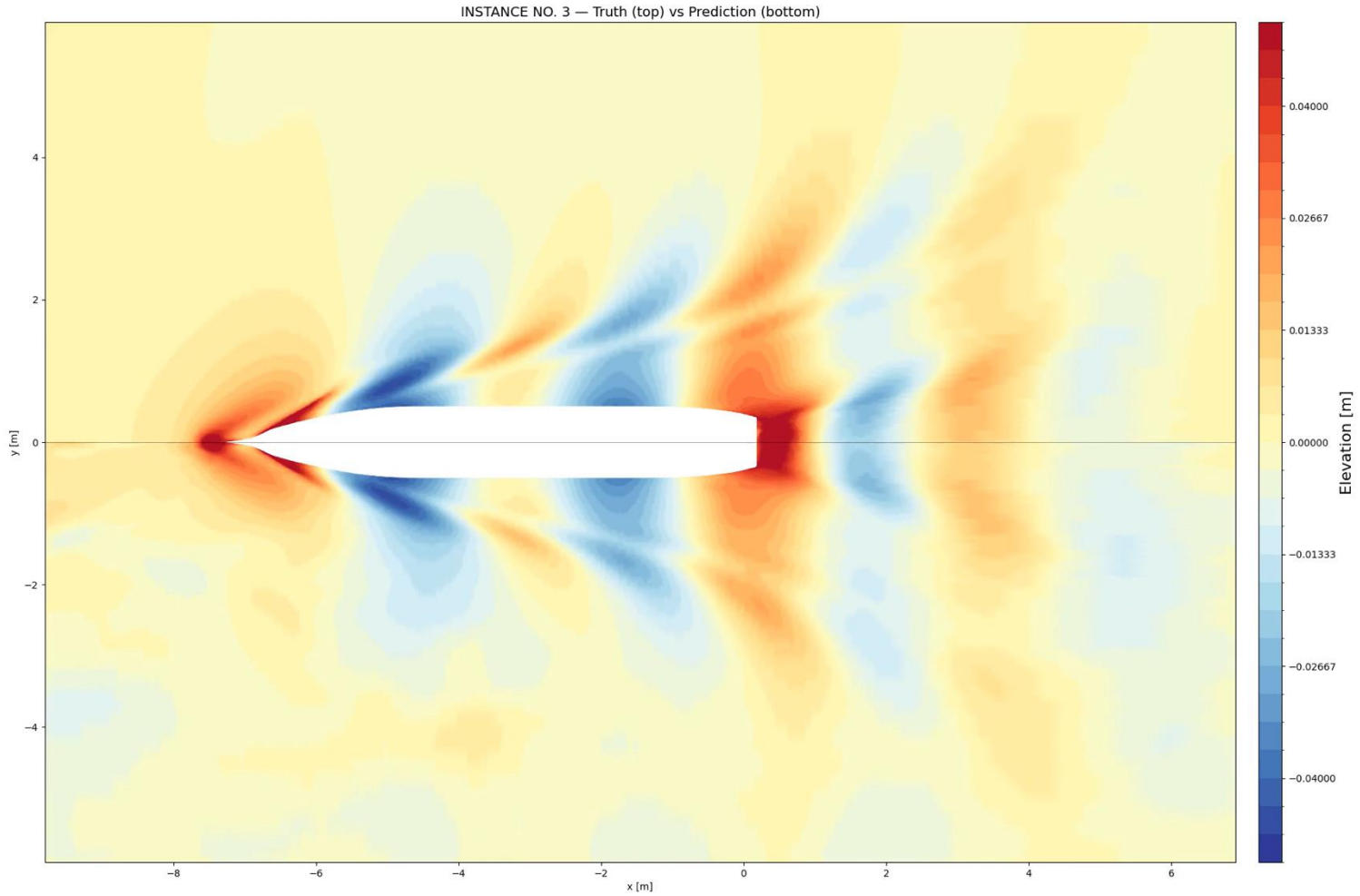
# Results

## Surface Wall Shear Stress on Test Set | Bottom View



# Results

## Free-surface Elevation



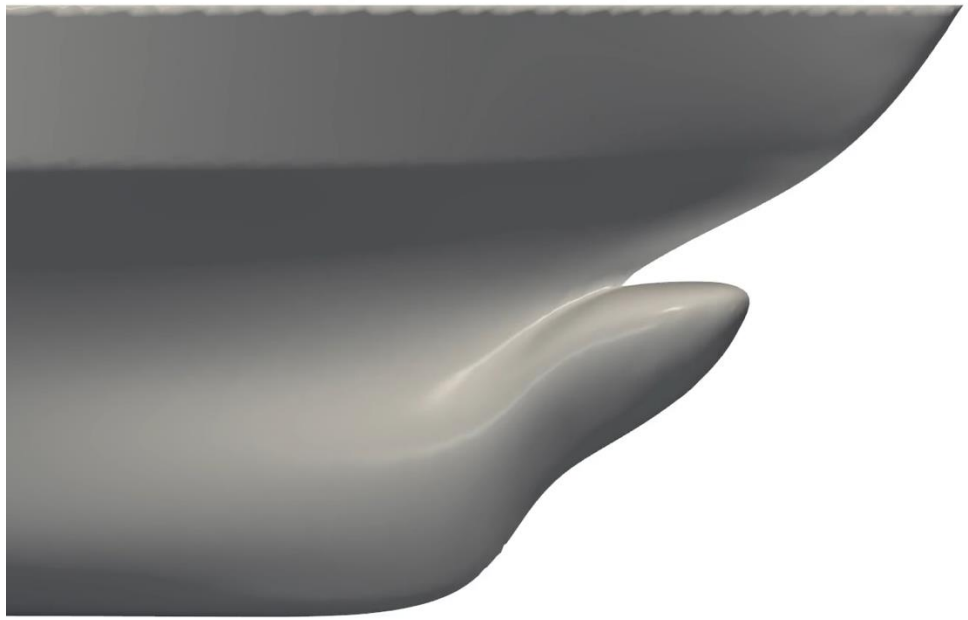
# Multiphase VOF - Optimization

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# Overview

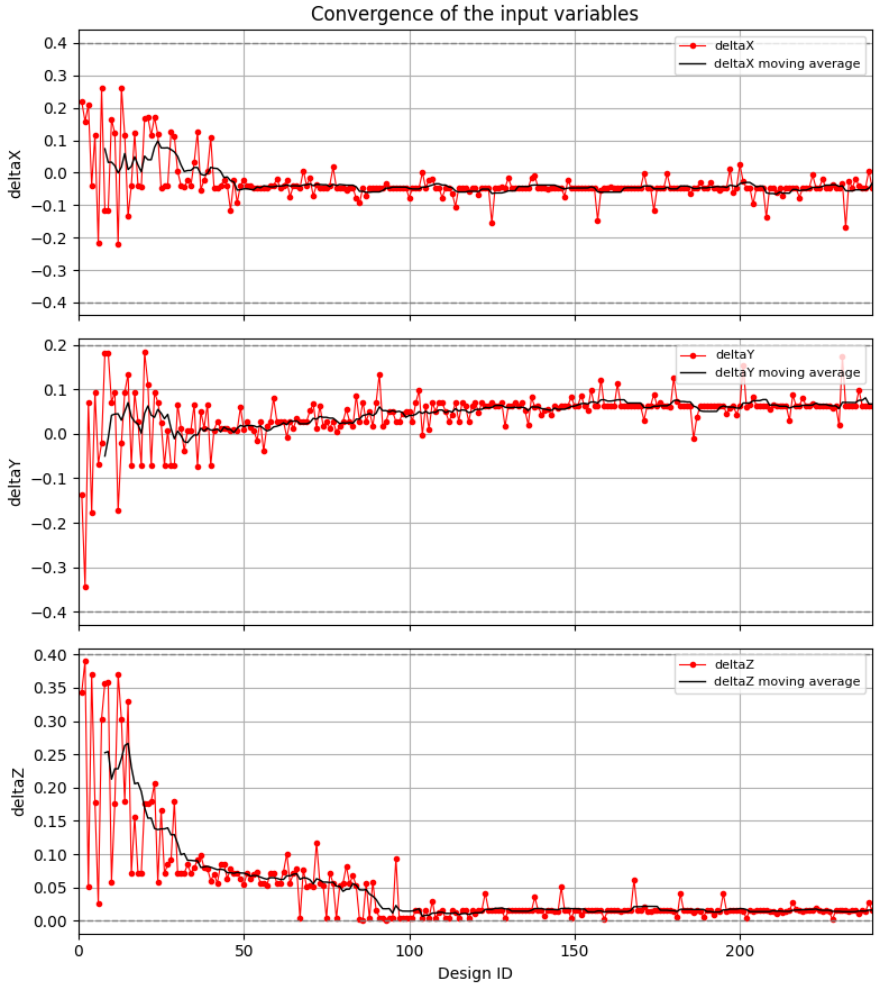
## Optimization Setup

- The AI model created with **GeoTransolver** on the VOF case was used for running a full hull form optimization
- Optimisation setup
  - **Input Variables**
    - 3 morphing control points translation
  - **Design Objective**
    - MIN total resistance force
  - **Algorithm**
    - NSGA-II (30 generations, 8 designs per population)



# Results

## Optimization Results > Convergence





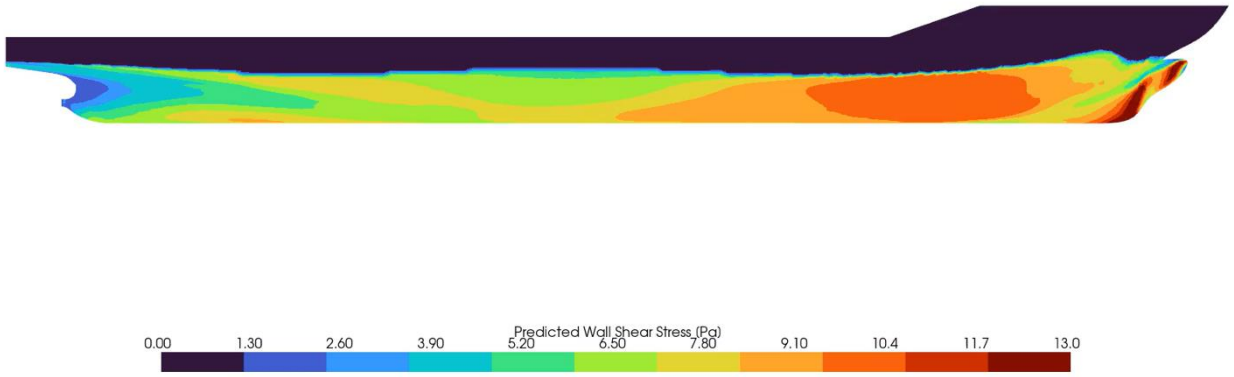


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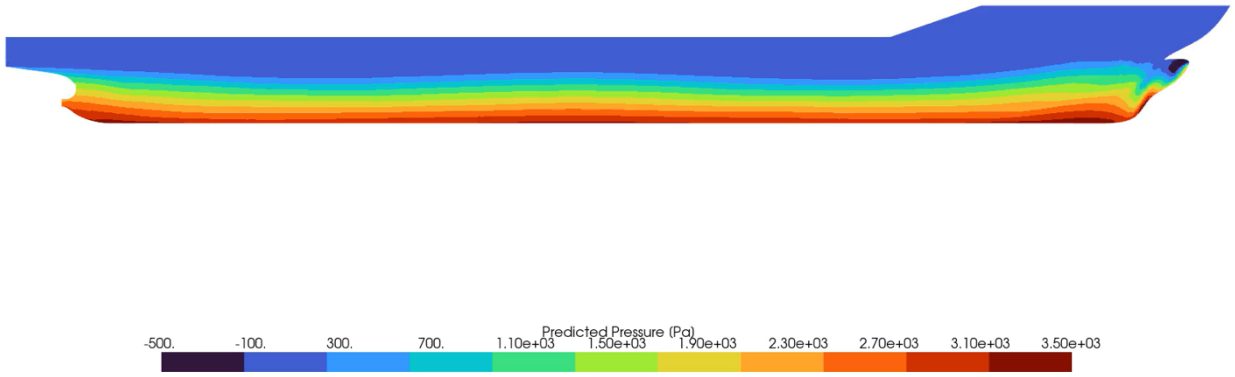
NVIDIA

# Results

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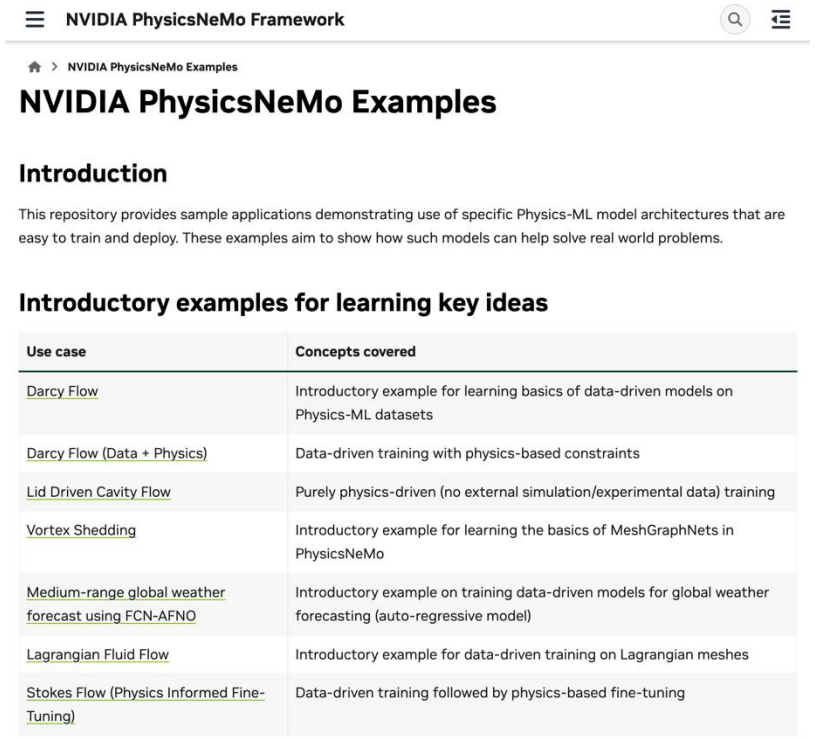

Wall Shear Stress




Pressure

# More details? Open Source Material

Get Start Guides, Training Material, Example recipes, DLIs, build.nvidia.com



NVIDIA PhysicsNeMo Framework

NVIDIA PhysicsNeMo Examples

## NVIDIA PhysicsNeMo Examples

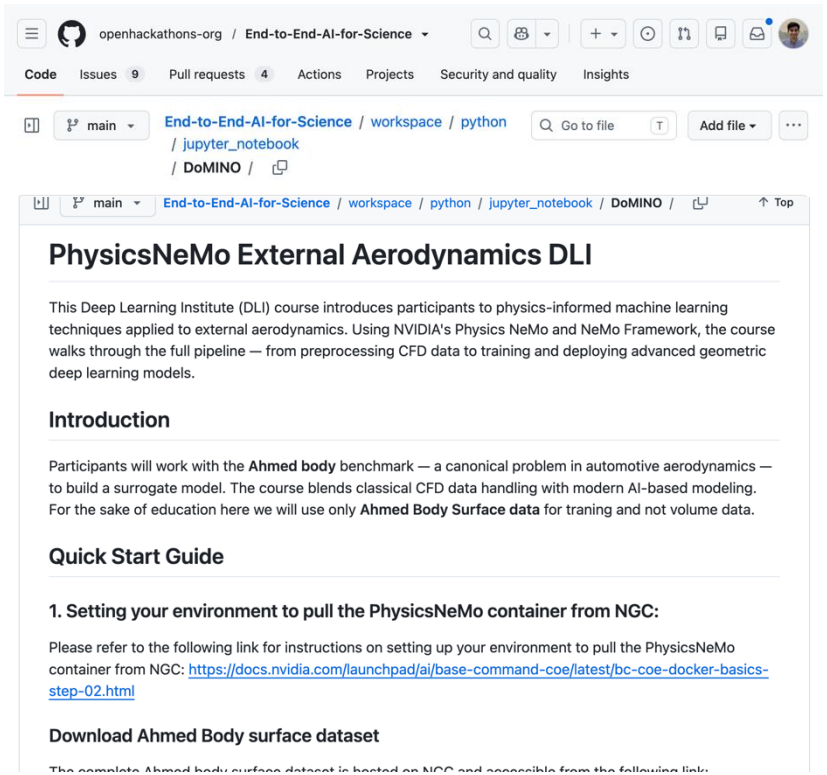
### Introduction

This repository provides sample applications demonstrating use of specific Physics-ML model architectures that are easy to train and deploy. These examples aim to show how such models can help solve real world problems.

### Introductory examples for learning key ideas

| Use case | Concepts covered |
|---|---|
| Darcy Flow | Introductory example for learning basics of data-driven models on Physics-ML datasets |
| Darcy Flow (Data + Physics) | Data-driven training with physics-based constraints |
| Lid Driven Cavity Flow | Purely physics-driven (no external simulation/experimental data) training |
| Vortex Shedding | Introductory example for learning the basics of MeshGraphNets in PhysicsNeMo |
| Medium-range global weather forecast using FCN-AFNO | Introductory example on training data-driven models for global weather forecasting (auto-regressive model) |
| Lagrangian Fluid Flow | Introductory example for data-driven training on Lagrangian meshes |
| Stokes Flow (Physics Informed Fine-Tuning) | Data-driven training followed by physics-based fine-tuning |

https://archive.docs.nvidia.com/physicsnemo/26.03/physicsnemo/examples/README.html



openhackathons-org / End-to-End-AI-for-Science

Code | Issues 9 | Pull requests 4 | Actions | Projects | Security and quality | Insights

main | End-to-End-AI-for-Science / workspace / python / jupyter_notebook / DoMINO / | Go to file | Add file

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## PhysicsNeMo External Aerodynamics DLI

This Deep Learning Institute (DLI) course introduces participants to physics-informed machine learning techniques applied to external aerodynamics. Using NVIDIA's Physics NeMo and NeMo Framework, the course walks through the full pipeline — from preprocessing CFD data to training and deploying advanced geometric deep learning models.

### Introduction

Participants will work with the **Ahmed body** benchmark — a canonical problem in automotive aerodynamics — to build a surrogate model. The course blends classical CFD data handling with modern AI-based modeling. For the sake of education here we will use only **Ahmed Body Surface data** for traning and not volume data.

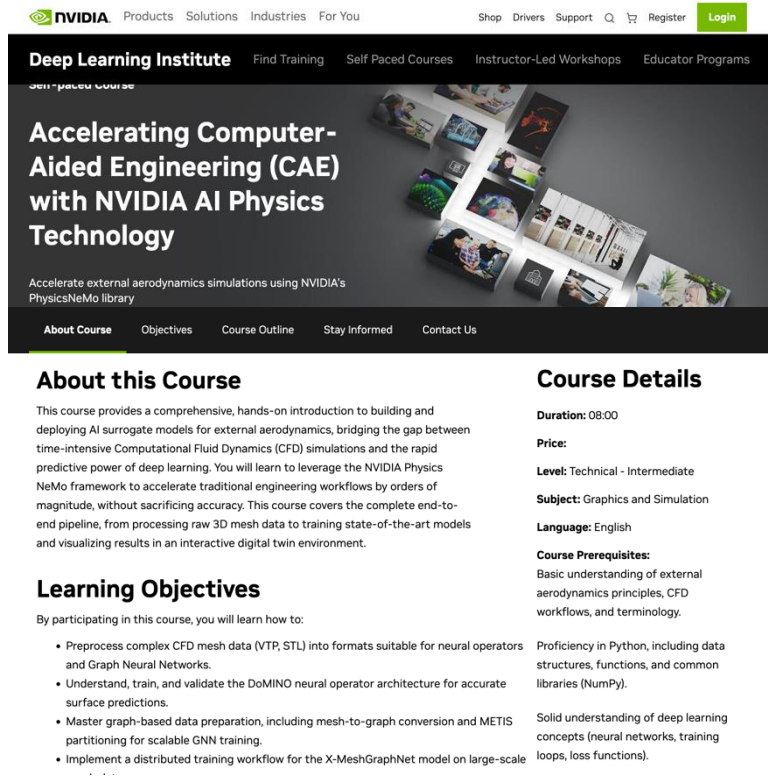
### Quick Start Guide

#### 1. Setting your environment to pull the PhysicsNeMo container from NGC:

Please refer to the following link for instructions on setting up your environment to pull the PhysicsNeMo container from NGC: https://docs.nvidia.com/launchpad/ai/base-command-coe/latest/bc-coe-docker-basics-step-02.html

#### Download Ahmed Body surface dataset

https://github.com/openhackathons-org/End-to-End-AI-for-Science



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Accelerating Computer-Aided Engineering (CAE) with NVIDIA AI Physics Technology

Accelerate external aerodynamics simulations using NVIDIA's PhysicsNeMo library

About Course | Objectives | Course Outline | Stay Informed | Contact Us

## About this Course

This course provides a comprehensive, hands-on introduction to building and deploying AI surrogate models for external aerodynamics, bridging the gap between time-intensive Computational Fluid Dynamics (CFD) simulations and the rapid predictive power of deep learning. You will learn to leverage the NVIDIA Physics NeMo framework to accelerate traditional engineering workflows by orders of magnitude, without sacrificing accuracy. This course covers the complete end-to-end pipeline, from processing raw 3D mesh data to training state-of-the-art models and visualizing results in an interactive digital twin environment.

## Learning Objectives

By participating in this course, you will learn how to:

- Preprocess complex CFD mesh data (VTP, STL) into formats suitable for neural operators and Graph Neural Networks.
- Understand, train, and validate the DoMINO neural operator architecture for accurate surface predictions.
- Master graph-based data preparation, including mesh-to-graph conversion and METIS partitioning for scalable GNN training.
- Implement a distributed training workflow for the X-MeshGraphNet model on large-scale

## Course Details

**Duration:** 08:00

**Price:**

**Level:** Technical - Intermediate

**Subject:** Graphics and Simulation

**Language:** English

**Course Prerequisites:**
Basic understanding of external aerodynamics principles, CFD workflows, and terminology.

Proficiency in Python, including data structures, functions, and common libraries (NumPy).

Solid understanding of deep learning concepts (neural networks, training loops, loss functions).

https://learn.nvidia.com/courses/course-detail?course_id=course-v1:DLI+S-OV-48+V1

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