Reduced Order Models in WT design

Charilaos Kokkinos, Technical Manager, FEAC Engineering

Solution Partner
Digital Industries Software
SIEMENS

Technology Partner
Digital Industries Software
SIEMENS

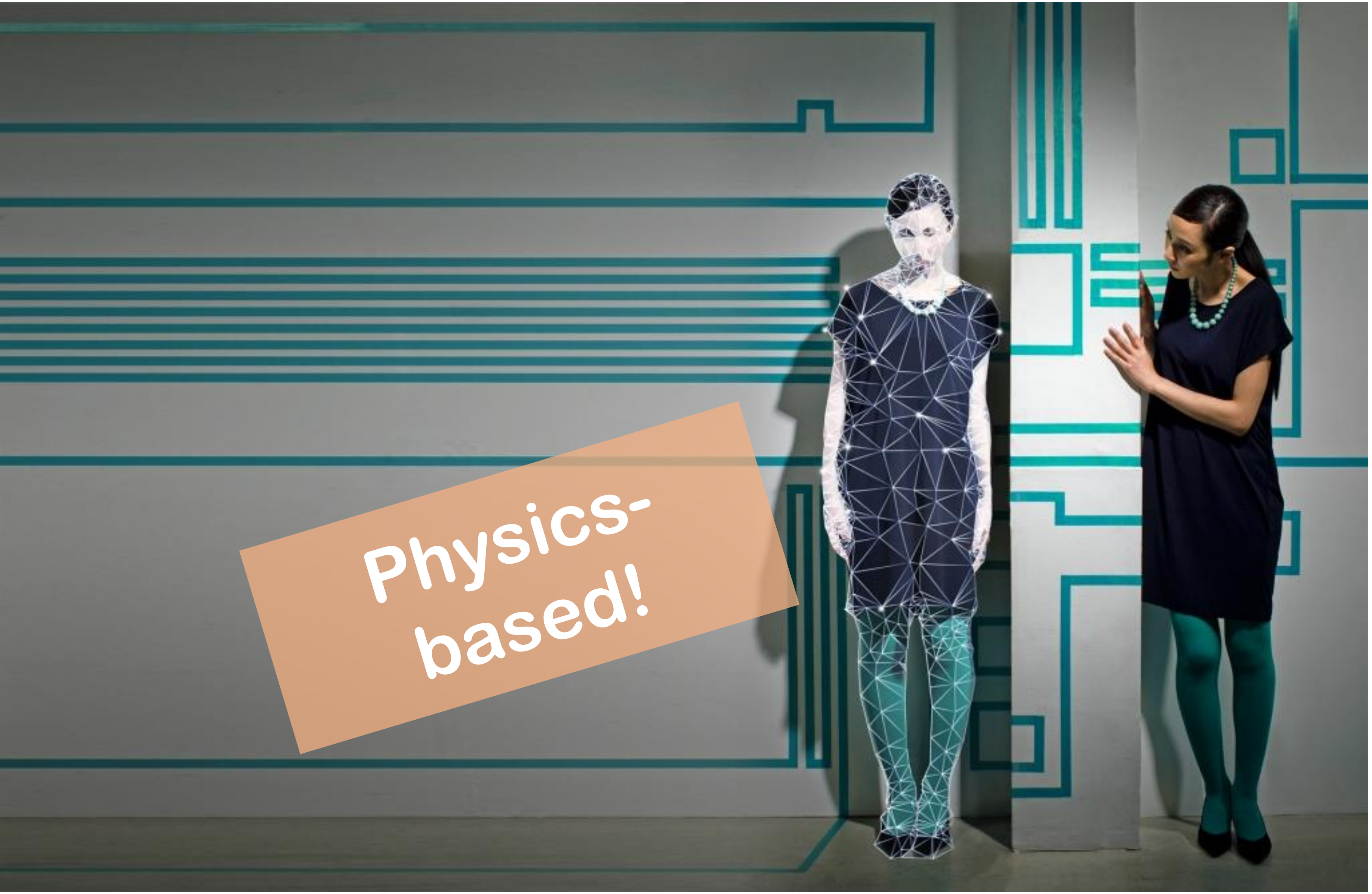
FEAC
ENGINEERING | REALIZE YOUR DIGITAL TWIN

01/07/2022

DAAD Deutscher Akademischer Austausch Dienst
German Academic Exchange Service

KIT Karlsruhe Institute of Technology

UNIVERSITY OF PATRAS



Engineering simulations & Digital Twins is our business

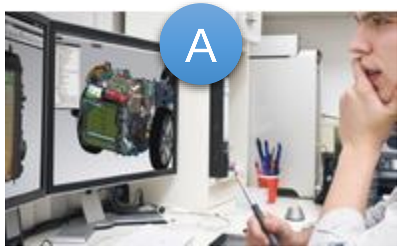
FEAC
ENGINEERING | REALIZE YOUR DIGITAL TWIN

Expert Partner SIEMENS Digital Industries Software

Technology Partner Digital Industries Software SIEMENS

FEAC’s Business Units

A



Consulting Projects & Engineering Expertise

Delivering multi-physics simulation services covering the entire product development process.

B

Solution Partner Digital Industries Software SIEMENS

Software Distribution, Training & Support

Smart Solution, Software & Technology Partner of SIEMENS DISW. Certified Training Partner

C

PITHIA

Software Development

PITHIA, a unique simulation software.

(*Development, Integration, Training & Sales)*

Aerospace/Aeronautics

Marine/Naval

Oil & Gas

Bioengineering

Construction

Renewable Energy

Accelerator Magnets

Defense

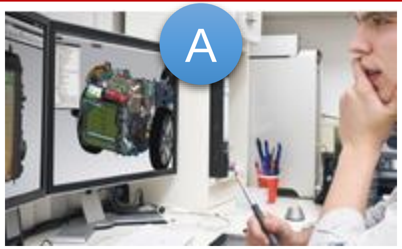
FEAC
ENGINEERING | REALIZE YOUR DIGITAL TWIN

Expert Partner Digital Industries Software SIEMENS

Technology Partner Digital Industries Software SIEMENS

FEAC’s Business Units

A



Consulting Projects & Engineering Expertise

Delivering multi-physics simulation services covering the entire product development process.

B

Solution Partner Digital Industries Software SIEMENS

Software Distribution, Training & Support

Smart Solution, Software & Technology Partner of SIEMENS DISW. Certified Training Partner

C

PITHIA

Software Development

PITHIA, a unique simulation software.
(*Development, Integration, Training & Sales)*

Aerospace/Aeronautics · Marine/Naval · Oil & Gas · Bioengineering · Construction · Renewable Energy · Accelerator Magnets · Defense

FEAC
ENGINEERING | REALIZE YOUR DIGITAL TWIN

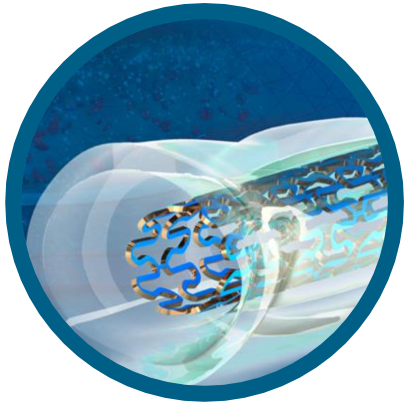
A. Consulting projects

Realize your Digital Twin

Some indicative projects

CERN's
11T magnet

ESA's Juice
Mission



Coronary
Stent

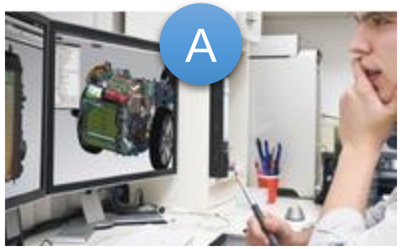
Vessel's
Energy efficiency

Car's
Engine

Some Of Our Partners And Clients

FEAC's Business Units

A



Consulting Projects & Engineering Expertise

Delivering multi-physics simulation services covering the entire product development process.

B

Solution Partner Digital Industries Software SIEMENS

Software Distribution, Training & Support

Smart Solution, Software & Technology Partner of SIEMENS DISW. Certified Training Partner

C

PITHIA

Software Development

PITHIA, a unique simulation software.

(Development, Integration, Training & Sales)

Aerospace/Aeronautics | Marine/Naval | Oil & Gas | Bioengineering | Construction | Renewable Energy | Accelerator Magnets | Defense

B. SIEMENS Partners

Distribution – Technical Support - Training

SIEMENS Portfolio Distribution & Support

Certified SIEMENS Training center

Patras – FEAC Engineering

Athens – Siemens CUBE

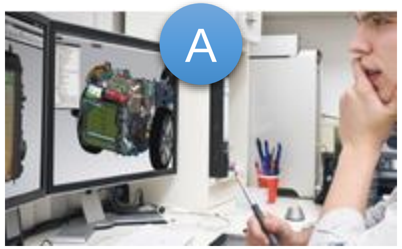
https://feacomp.com/training/

ENGINEERING | REALIZE YOUR DIGITAL TWIN

Expert Partner SIEMENS Technology Partner Digital Industries Software SIEMENS

FEAC's Business Units

A



Consulting Projects & Engineering Expertise

Delivering multi-physics simulation services covering the entire product development process.

B

Solution Partner Digital Industries Software SIEMENS

Software Distribution, Training & Support

Smart Solution, Software & Technology Partner of SIEMENS DISW. Certified Training Partner

C

PITHIA

Software Development

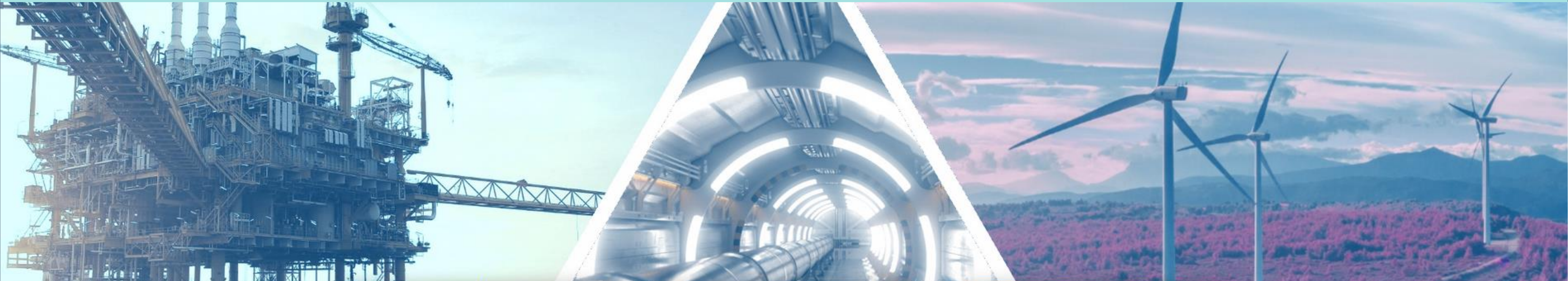
PITHIA, a unique simulation software.

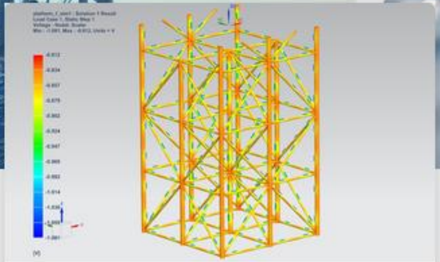
(*Development, Integration, Training & Sales*)

Aerospace/Aeronautics | Marine/Naval | Oil & Gas | Bioengineering | Construction | Renewable Energy | Accelerator Magnets | Defense

C. Software Development

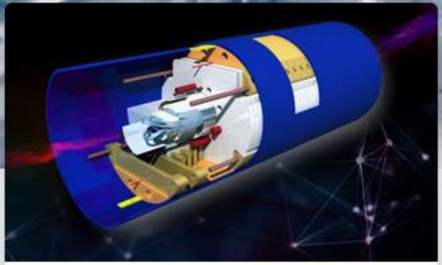
PITHIA-CP for Cathodic Protection





PITHIA-CP

Anti-Corrosion Design via Cathodic Protection



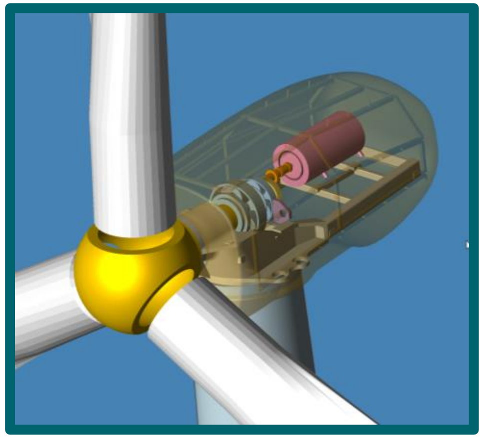
PITHIA-EM

Superconducting Magnets

PITHIA-FSI

Vibro-acoustic Wave Propagation

Holistic Digital twin



DT for Product

DT for Production

DT for Performance

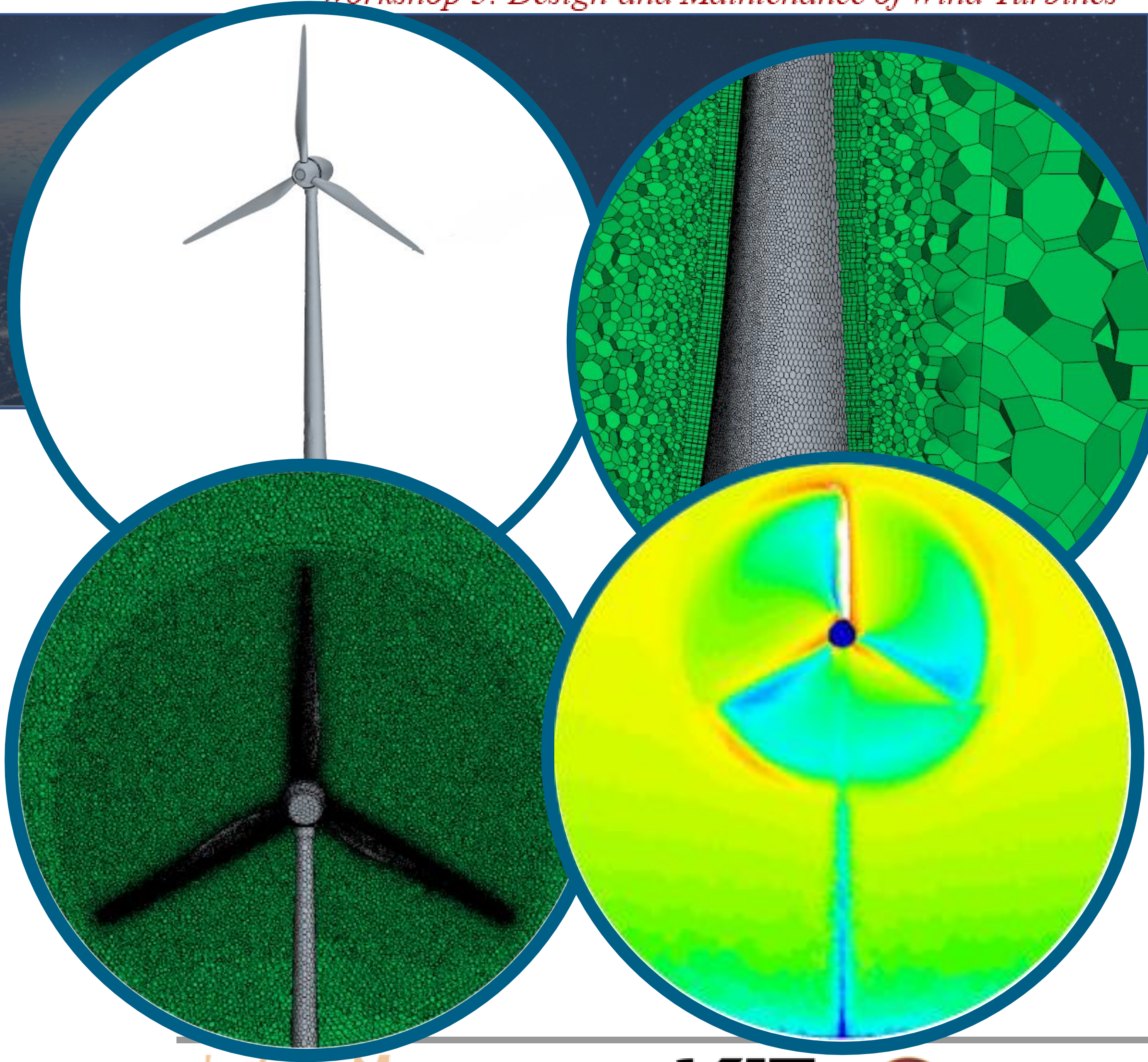
Continuous product/ production improvement

1. Product Design	2. Production Development	**3**. Product Manufacturing	4. Manufacturing Operations	**5**. Product Utilization	6. Plant Performance & Maintenance

High Fidelity Models

GEMINI

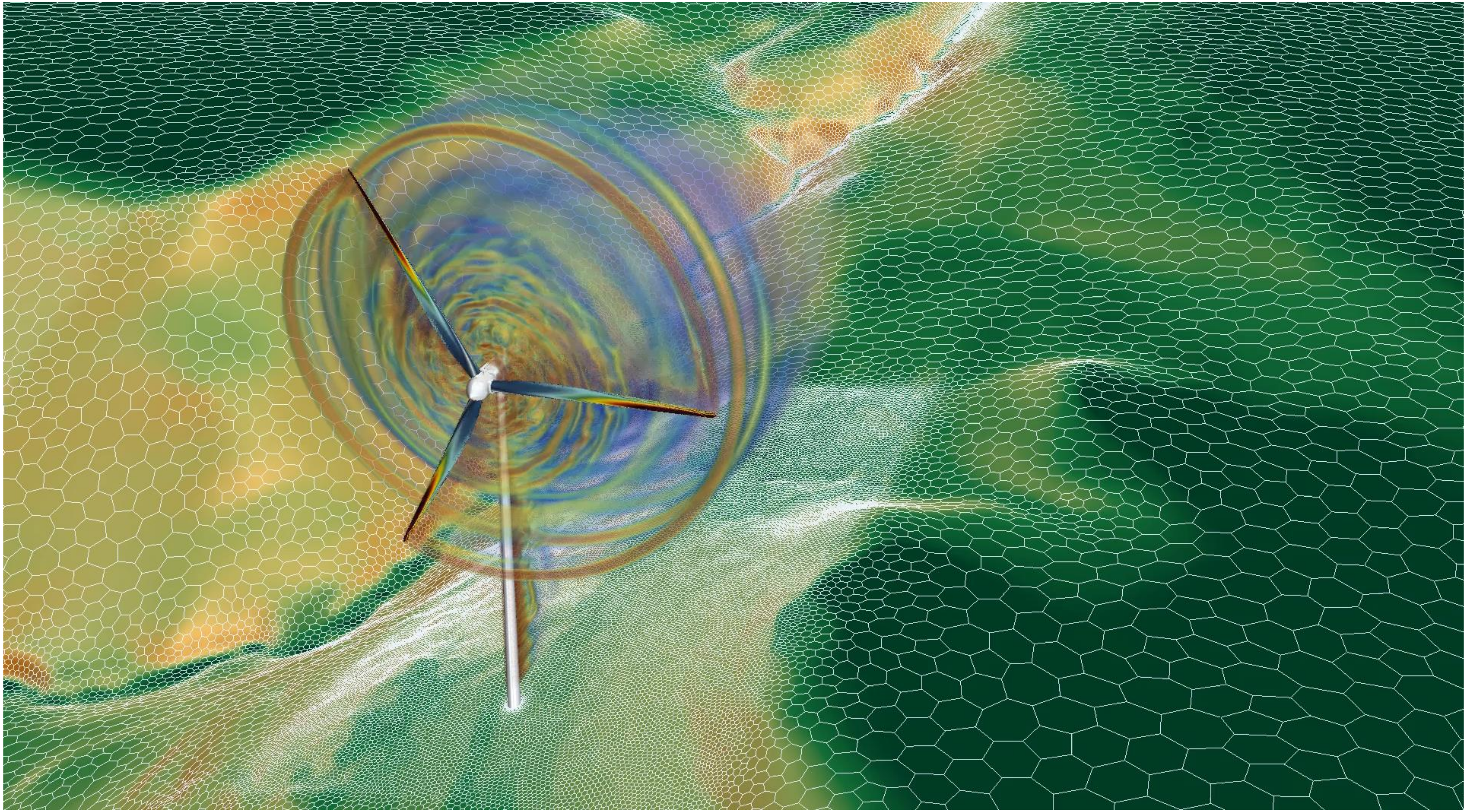
hi**G**h fid**E**lity **M**odeling for small w**IN**d turb**i**ne
(Partners: FEAC & EUNICE)



- **Unsteady Reynolds-averaged Navier-Stokes (URANS) equations with the shear stress transport (SST) k-ω turbulence model are adopted utilizing STAR CCM+.**

- **Total cells 10.1 million (4.0 million for each rotational region and 6.1 million for the stationary region**

- **All simulations were carried out on a parallel computing server with 16 CPU and 64 GB of RAM, and a complete rotational revolution for the WT1 rotor took approximately 20 h.**



Simulation

Advantages/Disadvantages of Simulation

- (+) Can be explained and reconstructed
- (+) Describe Complex multiscale & multiphysics phenomena
- (-) Costly & Time Consuming
- (-) Only numerical experts can create well accurate simulation models

How can we address these challenges?

…with a different technology?

Simulation

Advantages/Disadvantages of Simulation

- (+) Can be explained and reconstructed
- (+) Describe Complex multiscale & multiphysics phenomena
- (-) Costly & Time Consuming
- (-) Only numerical experts can create well accurate simulation models

Artificial Intelligence

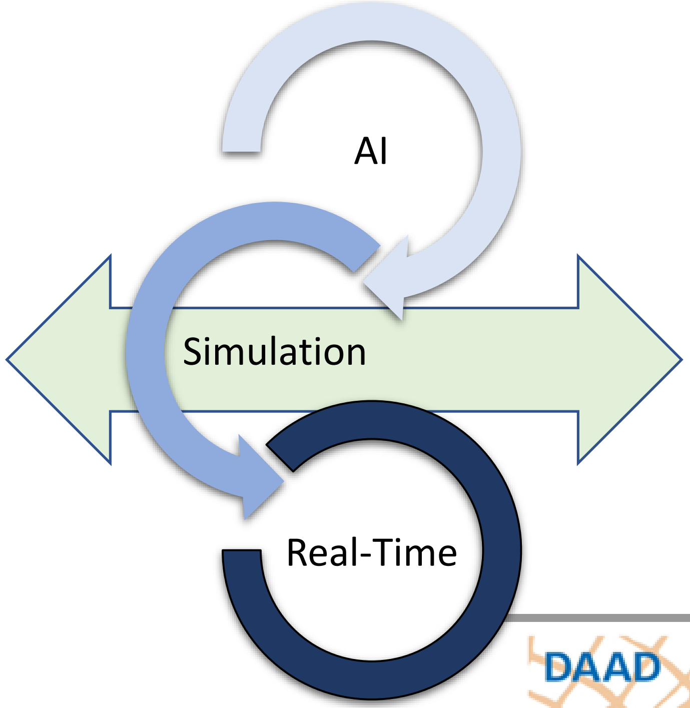
Advantages/Disadvantages of AI

- (+) Can be created easily and quickly with sufficient data
- (-) Can not describe accurately the physics of the system
- (-) Difficult to obtain enough training data
- (-) The mathematical context can not be modified by humans

Simulation

Advantages/Disadvantages of Simulation

- (+) Can be explained and reconstructed
- (+) Describe Complex multiscale & multiphysics phenomena
- (-) Costly & Time Consuming
- (-) Only numerical experts can create well accurate simulation models



Artificial Intelligence

Advantages/Disadvantages of AI

- (+) Can be created easily and quickly with sufficient data
- (-) Can not describe accurately the physics of the system
- (-) Difficult to obtain enough training data
- (-) The mathematical context can not be modified by humans

DAAD Deutscher Akademischer Austausch Dienst German Academic Exchange Service

KIT Karlsruhe Institute of Technology

UNIVERSITY OF PATRAS

Reduced Order Models

Achieve higher ROI

Artificial Intelligence
Engineering workflows optimization for higher ROI

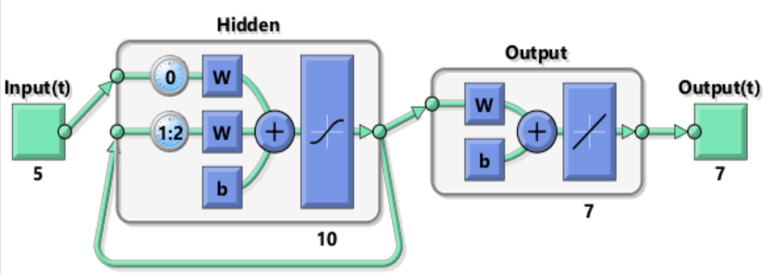
Model Order Reduction

AI to combine physics and data and create physically relevant Reduced Order Models (ROMs)

Set of operating points used as learning data

1. From test
2. From high fidelity models

Neural Network architecture



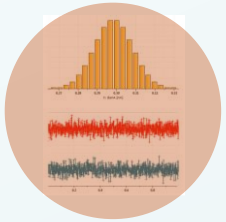
ROMs

Store in library

Export for operational use

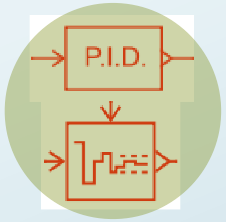
ROM workflow

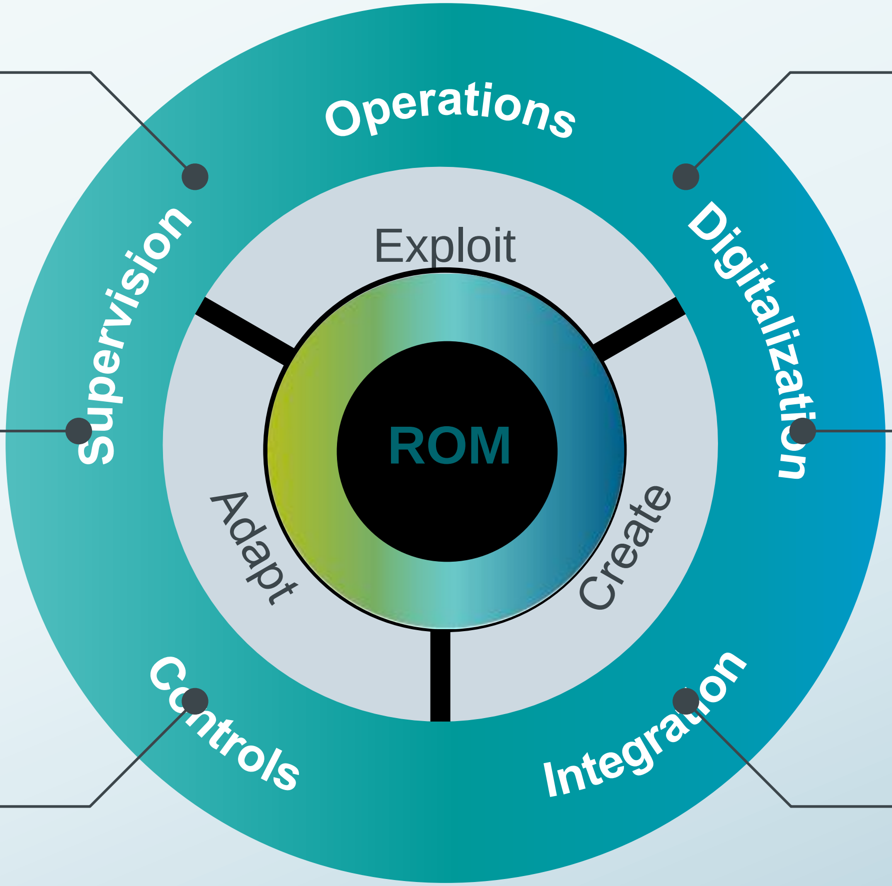
Analyze (batch runs, Monte-Carlo, …)
And export to IoT, Edge computing, ECUs

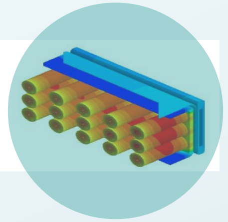


Visualize with dedicated HMI
Dashboard, animation, ...

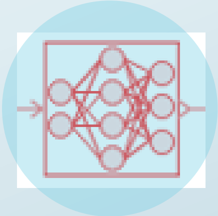
Complete with controls
PID, statechart, ...



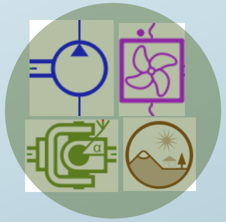




Compute 3D results
From FEM, CFD, ...
Or get test data.



Create the ROM
Digital object like Neural Networks, ...



Add physical components (pumps, ...)
Or subsystems around (cooling, ...)

Example #1

ROM generation

ROM execution

System definition

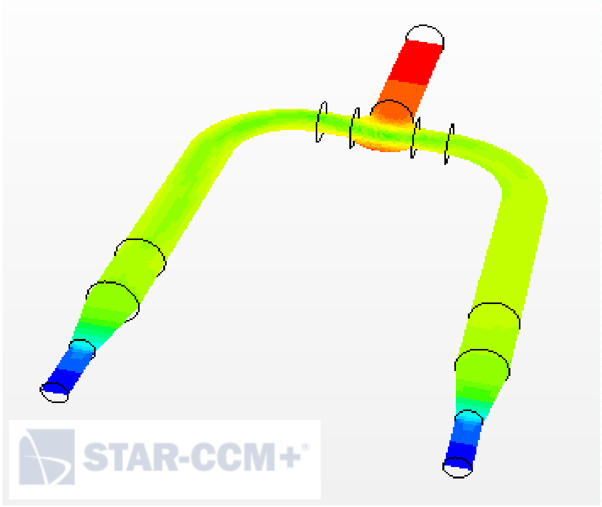
Training data

ROM extraction tools

ROM models

Optimize your system, speed-up your runs, export to real-time

High-fidelity models



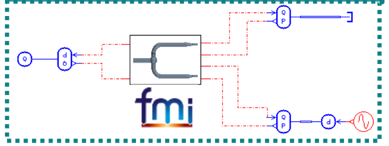
Hours

Design of experiments (DOE)

Design Studies
Design Study

Design#	Name	State	Jun_Pressure_inlet
1	Design 1	✓	126541.6664061...
2	Design 2	✓	117106.0881244...
3	Design 3	✓	102107.8766526...
4	Design 4	✓	139096.3646652...
5	Design 5	✓	133344.0726070...
6	Design 6	✓	6740.281733036...
7	Design 7	✓	108313.7049230...
8	Design 8	✓	140543.6656990...
9	Design 9	✓	30095.00051780...

Digital objects



Minutes

Surrogates with Kriging

SRG
Quadratic, Kriging, RBF, ...
fmu

Surrogates
Junction_M2
Kriging
Junction_M3
Junction_P1

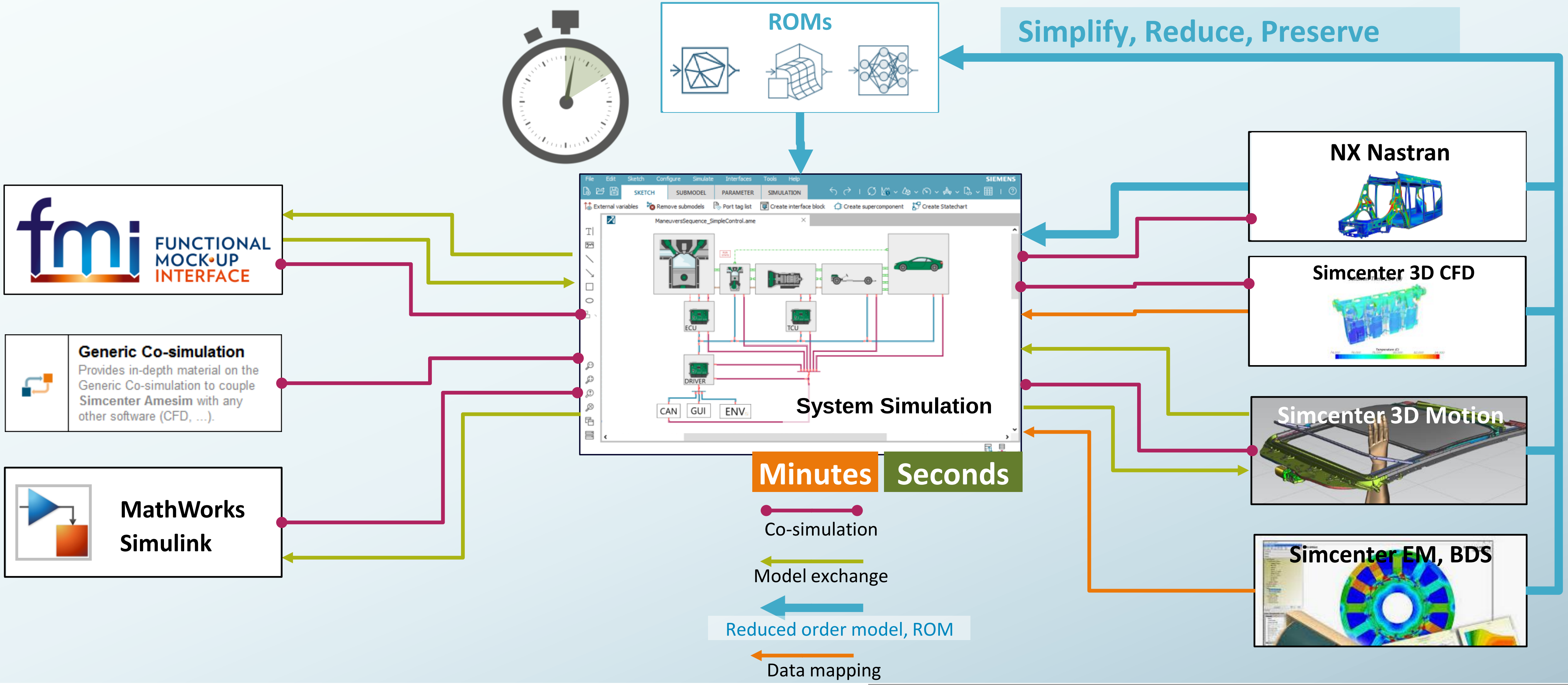
Speed

Efficiency

Seconds

Simcenter Amesim

Example #2



ROMs
Simplify, Reduce, Preserve
FUNCTIONAL MOCK-UP INTERFACE
Generic Co-simulation
Provides in-depth material on the Generic Co-simulation to couple Simcenter Amesim with any other software (CFD, …).
MathWorks Simulink
System Simulation
Minutes
Seconds
NX Nastran
Simcenter 3D CFD
Simcenter 3D Motion
Simcenter EM, BDS
Co-simulation
Model exchange
Reduced order model, ROM
Data mapping

Why ROMs

Simplification

High fidelity
Complex models

Reduction

CPU time
Storage capacity

Preservation

Essential behavior
Dominant effects

3 types of benefits using ROMs

Real-time Digital Twins

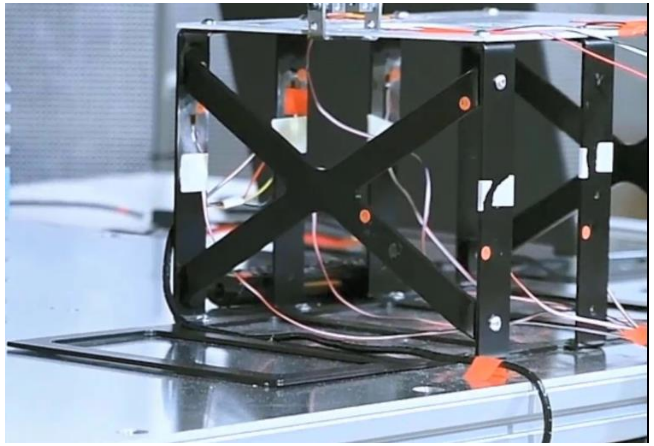
What is an...

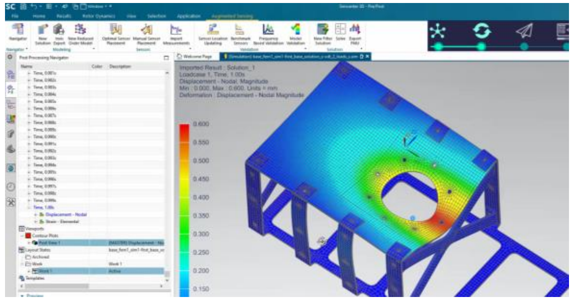
Executable (real-time) Digital Twin

Is a virtual representation connected to a physical product or process, used to understand, predict and monitor the physical counterpart's performance characteristics. It provides simulation results in real-time.

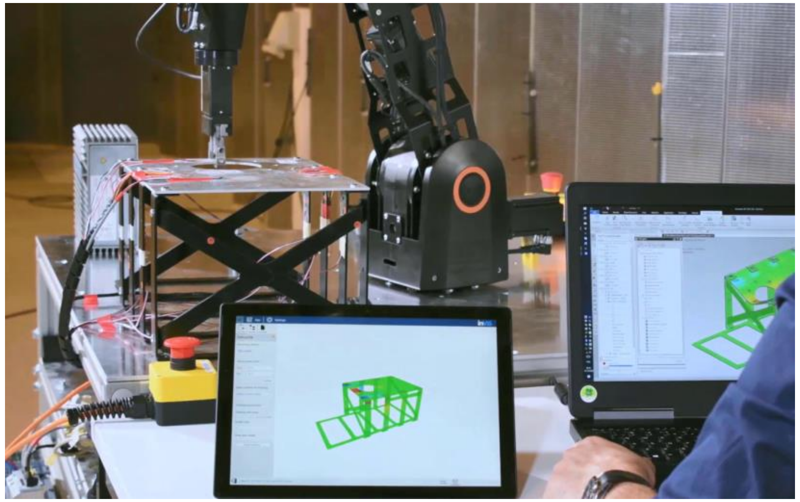
The next era in monitoring…

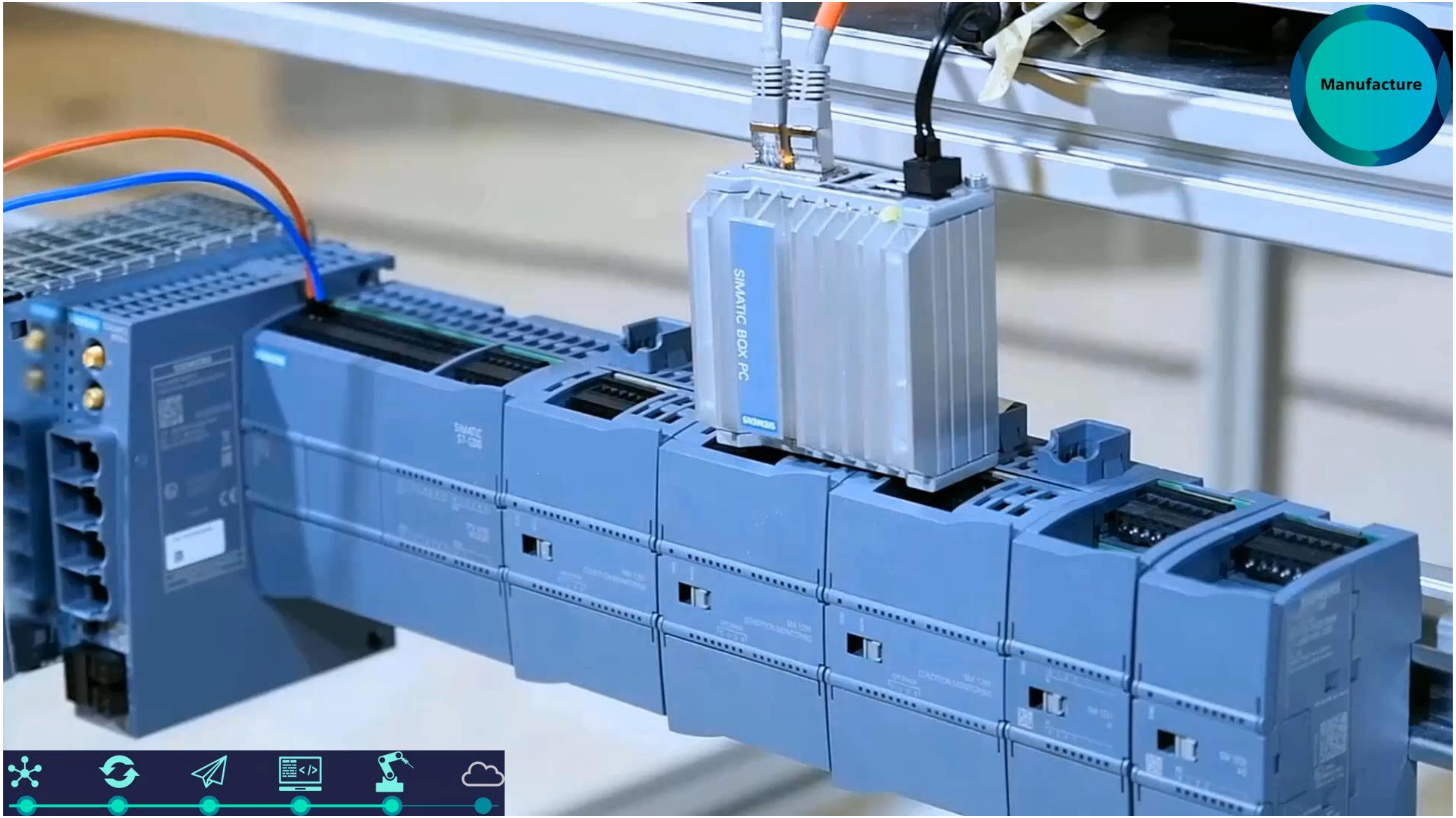
Executable (real-time) Digital Twin





AI & neural networks




Manufacture
SIMATIC BOX PC

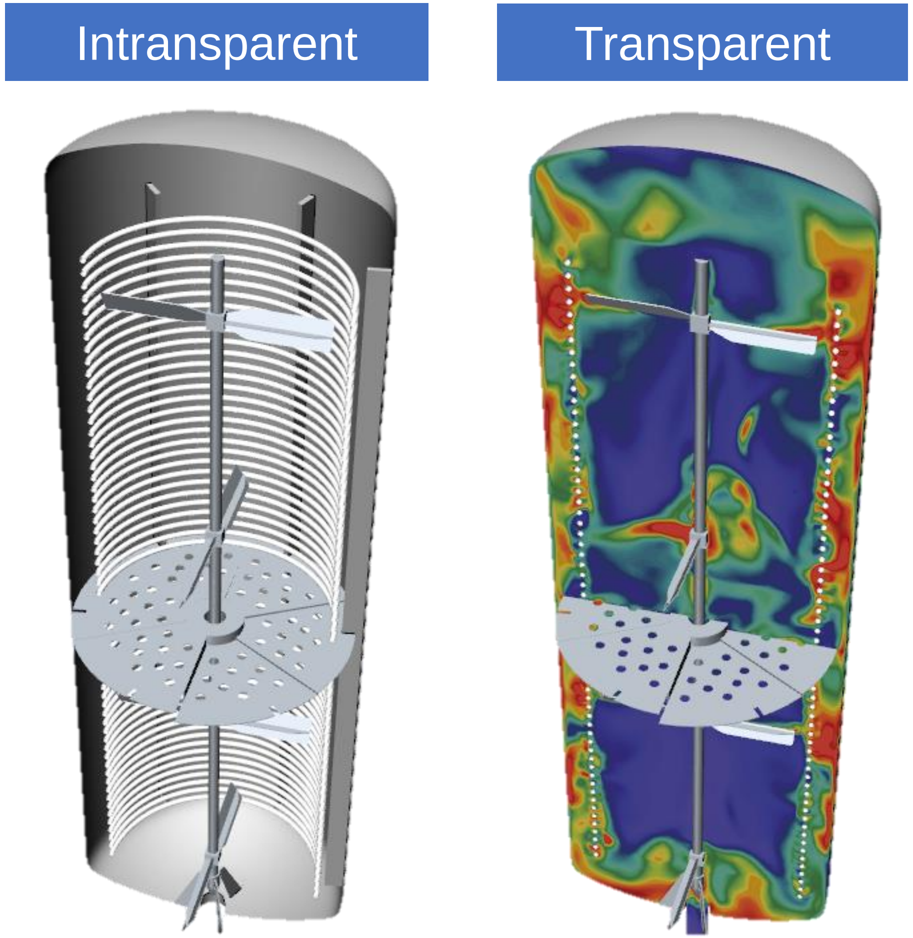
Looking in to the “heart” of the process

Physical Sensors:

- Give you point information, not full 3D picture
- Measure only limited types of quantities
- e.g. Measure T does not tell me yield: but simulation can

Virtual Sensors or Soft Sensors:

- Provides you information in the complete 3D space
- Measure quantities of interest



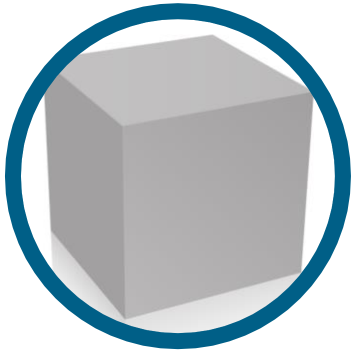
Basic Components of RTDTs

ROMs

Hardware (DAS/Sensors)

Data

Integration Platform



HPC/Cloud

Real-time Digital Twin example

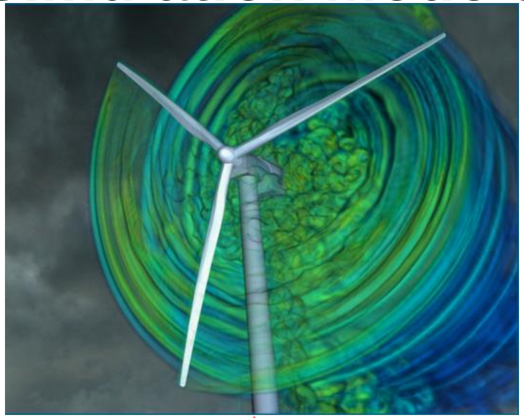
- **Optimize the maintenance planning of the wind turbine fleet**
- **Limit the number of spare parts**
- **Prediction and reduction of failures**
- **Feedback from the field into the development of wind turbine gearboxes**

Sensors & Historical Data

AI & ML to produce ROMs

Simulation Files

Physics-based Simulation Models

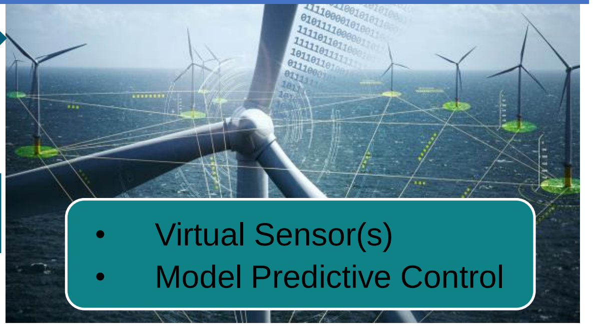


Real Wind Turbine

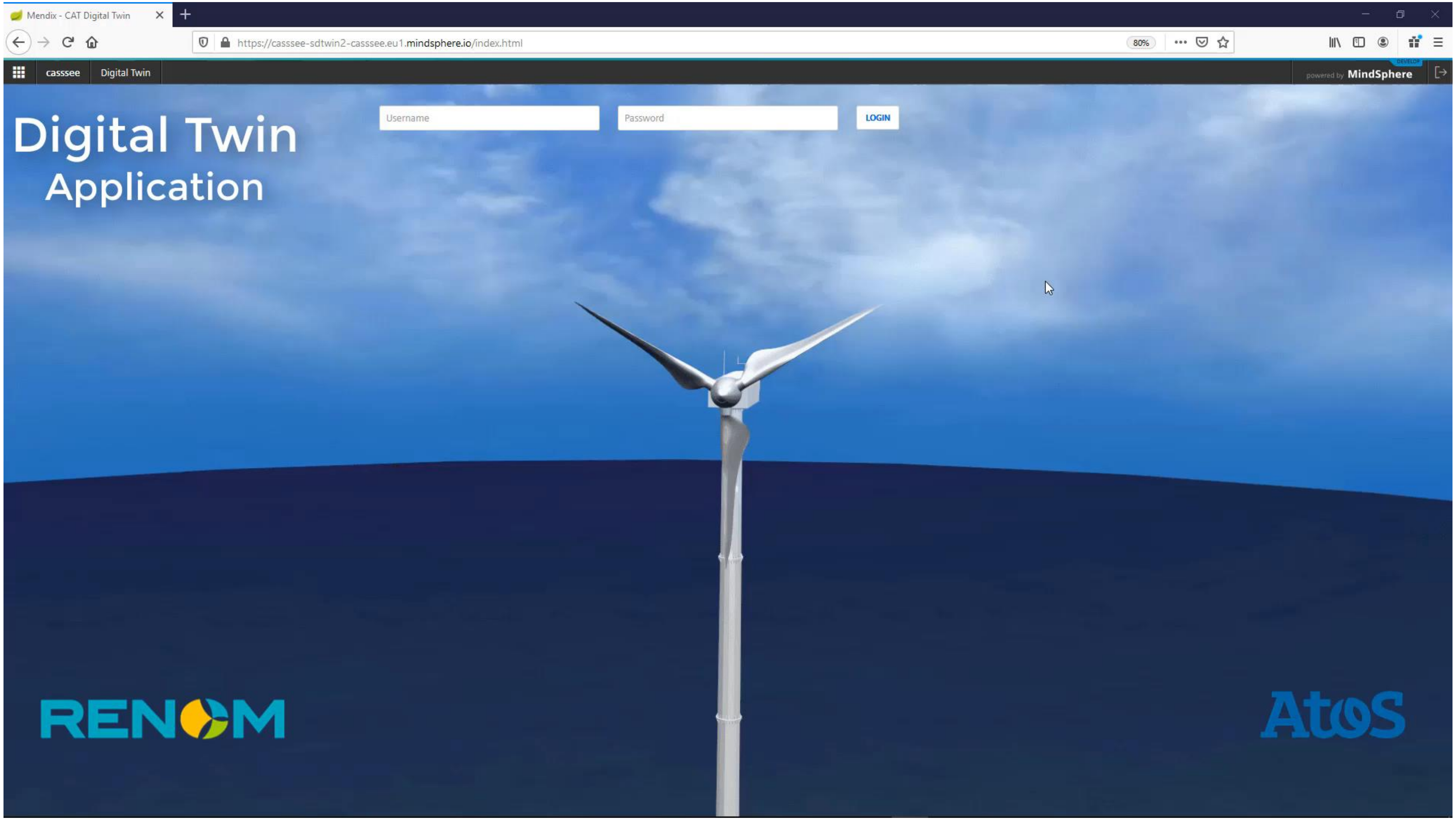
Data

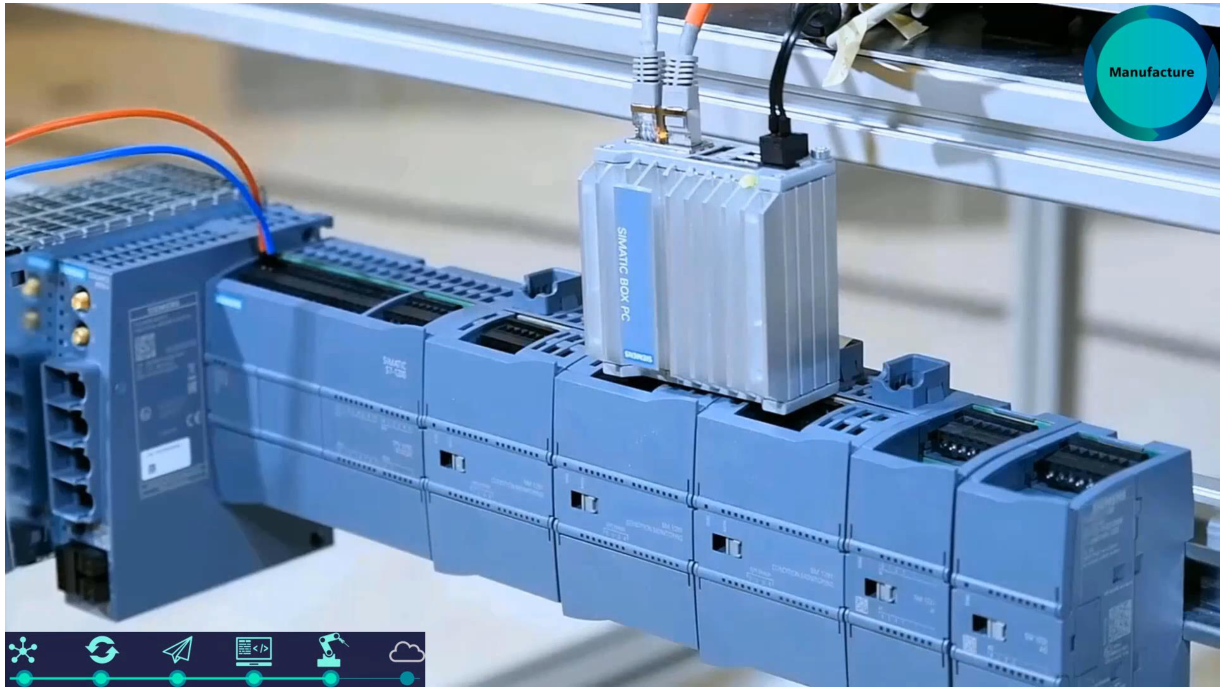
Prediction

Executable Digital Twin



Model Fitting / Validation


Mendix - CAT Digital Twin
https://casssee-sdtwin2-casssee.eu1.mindsphere.io/index.html
casssee
Digital Twin
powered by MindSphere
Username
Password
LOGIN
Digital Twin
Application
RENOM
Atos


Manufacture
SIMATIC BOX PC

Why RT-DT


Transforming asset integrity management through
Maintenance
Accurate & Prioritized inspection programs
Operation
Detailed insights on asset health monitoring
Safety
Data driven life extension decisions

Business

The Business impact of Real-Time Digital Twins

Improved Collaboration

Feedback loop in the performance digital twin connects various teams & organizations across the value chain to enable faster decision making and stronger collaboration

Better Quality

Improved Product & Production Quality leveraging what if scenarios to validate designs and processes virtually

Faster time to Market

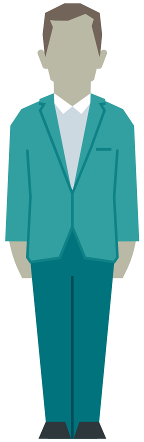
Allows optimization of assets, resources, workflows and processes to prevent costly downtime and faster response to market conditions and needs

New Business Models

The ability to monitor product usage allows customers to implement new Products as a Service (XaaS) Business Models

Who can we help with this solution?

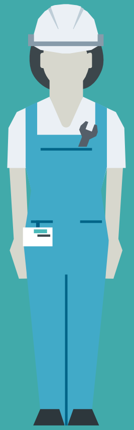
Under what conditions does it perform best?



Need a tool to playback and analyze historical operating conditions to spot my golden batch

Plant Managers

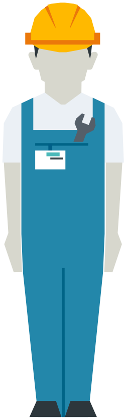
How often was production running at sub-optimal conditions?



Need a tool to identify actual production bottlenecks in the shop-floor

Quality Managers

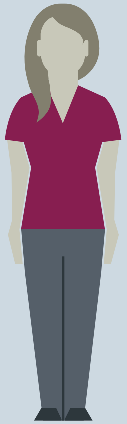
How will actual production be affected if parameters were changed?



Need a tool to understand Actual versus Planned deviations to finetune my production

Production Planners

How accurate is my simulation model to actual production conditions?



Need a tool to validate my design model and simulate new production requirements with higher fidelity

Industrial Engineers

Reduced Order Modelling for Real-Time Digital Twins

George Drakoulas,
Ph.D. Student, University of Patras, Department of Mechanical Engineering & Aeronautics
Simulation Engineer, FEAC Engineering

01/07/2022

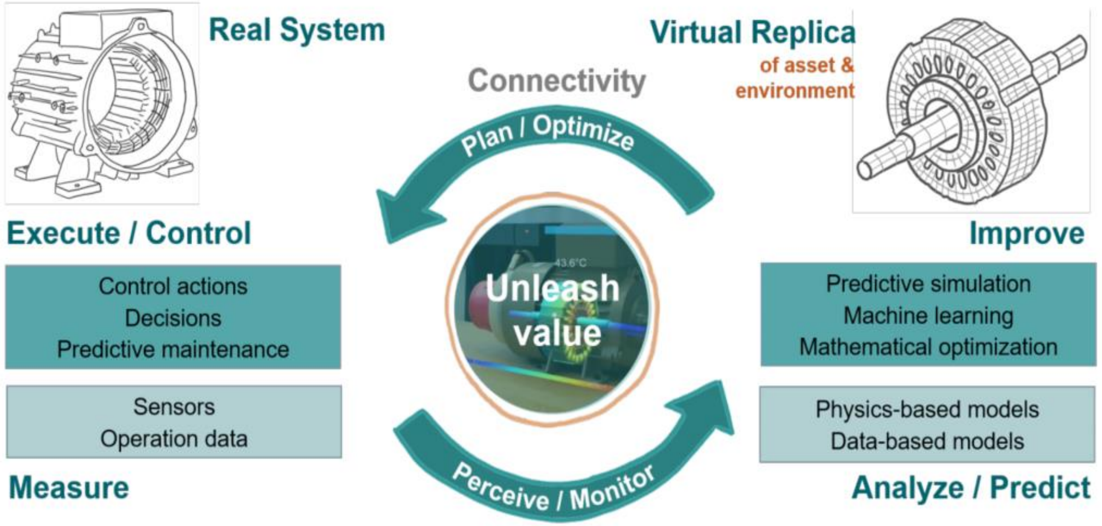
Summary

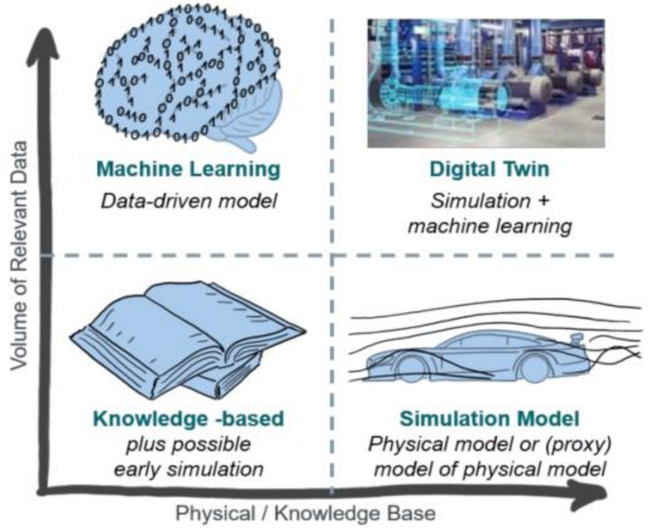
- Brief on the Digital Twin (DT) technology
- Reduced Order Models (ROMs) for real-time DTs
- ROMs Applications/Categories
- Deep Learning-based Non-Intrusive ROMs (NIROMs)
- Test cases - NIROMs

Digital Twins (DT)

- <u>DT</u> is a system that **integrates** physics-based models, with artificial intelligence techniques and data derived from field sensors.

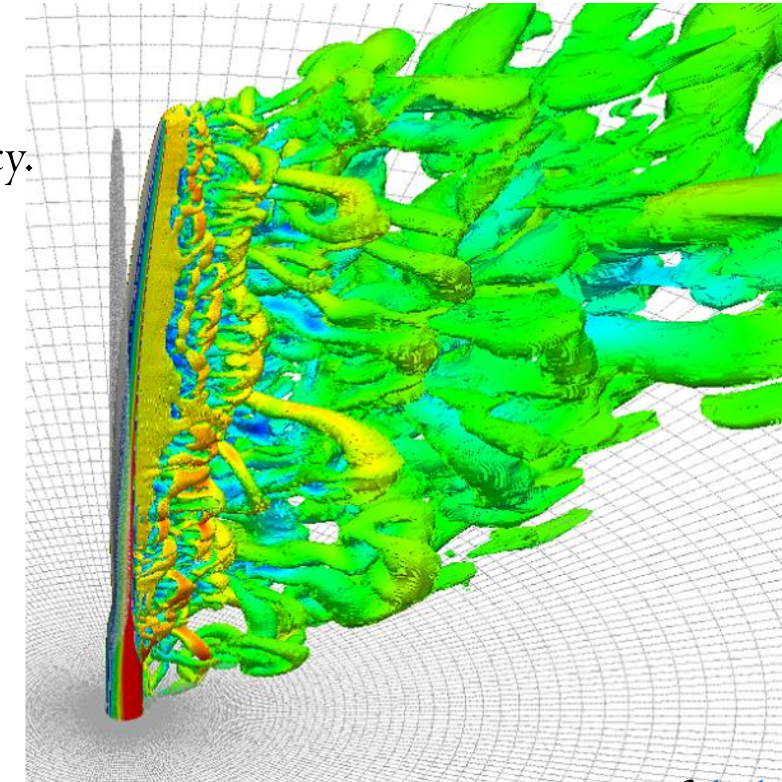
- DT is **composed** of three main elements: the physical world, the virtual world and the connectivity between the two.
-
- DT mainly **includes** sensors to garter information from the real world to the physical twin, edge processing, data security, data processing techniques [e.g. machine learning (ML), big data analytics, etc.] and communication interfaces such as Bluetooth, satellites.





ref: *1)* Digital Twin Technology Challenges and Applications: A Comprehensive Review, Diego M. Botín-Sanabria et al., 2022.
2) Digital twins, Dirk Hartman al., 2020.

HFM towards to ROMs



ref: [link]

(+) High-fidelity models (HFM) can simulate multi-physics phenomena with great accuracy.

(-) Full Order Models (FOM) large-scale dynamic nonlinear phenomena, often require **large computational expense** [e.g. High-Performance Computer (HPC)] & **significant computational time**.

(-) HFMs are **prohibitive for real-time** applications

Data-driven Models — *Real time* ⟷ *Expensive* — Physics-based simulations

Reduced-Order Models (ROMs) are a simplification of a high-fidelity, static or dynamic numerical model that preserves essential behavior, dominant effects and fidelity aiming to:

- Replace the FOM
- Reduce the computational cost
- Provide solutions in a very limited amount of time or even instantaneously

ROMs Applications

ROMs can be applied in various physics based (simulation) models & using multiple numerical schemes:

Physics domains

- Structural mechanics
- CFD
- Thermal
- Electromagnetics
- Multiphysics (e.g. FSI)

Numerical Schemes

- Finite element analysis (FEM)
- Finite volume method (FVM)
- Boundary element method (BEM)
- Finite difference method (FDM)

ROMs can be used to provide real-time solutions for:

On-line Applications

- Digital twins
- Feedback systems
- Critical time decisions
- System identification
- Active control (e.g. flow control)

Off-line Applications

- Speed up numerical simulations, *what-if* scenarios
- Design optimization
- Sensitivity analysis
- Uncertainty quantification

ROMs Categories

Intrusive Reduced Order Models

Require the exact form of the underlying PDEs involved to explain the physics phenomena.

Props (+)

- Maintain stability

Cons (-)

- Necessitate access to the solvers, which is impossible in the industry when commercial softwares are utilized.
- Require complete understanding of the underlying process.
- Non-ideal for convection and transport-dominated problems.

Area of interest

Non-Intrusive Reduced Order Models (NIROMs)

Require data and machine learning techniques to recover low-dimensional, non-linear manifolds.

Props (+)

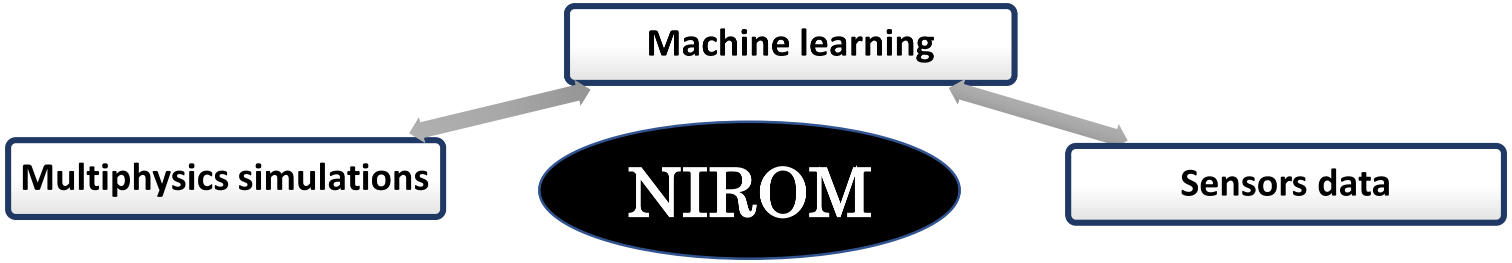
- Can efficiently parallelized on affordable GPUs, giving orders of magnitude speedup.
- Do not require the exact form of the equations.
- Can combine the data derived from experiments, numerical models, sensors, etc.

Cons (-)

- Require big data for training

NIROMs

- **Application agnostic**: Able to provide answers almost in real time in any CAE platform.
- **Numerical method agnostic:** Combine the solutions of various numerical schemes (Finite Element Method (FEM), Finite Volume Method (FVM), Boundary Element Method (BEM), …).
- **Numerical Simulations agnostic :** Provide answers about any physics-based problem (structural, thermal, fluid,..).
- **Industrial applications:** Provide answers for real complex problems: multiscale, multiphysics, non-linear & dynamic.
- **Uncertainty Quantification:** Estimate the noise of the measurements derived from the sensors.



NIROMs Objective

Given a new parameter

CFD: inlet velocity,, angle of attach, fluid viscosity

Structural FEA: Material Properties, Applied Force

Thermal: Temperature

etc.

Reconstruct the FOMS

Reconstruct the requested scalar/vector fields used to train the NIROM

CFD: pressure, velocity

Structural FEA: displacement, stress

Thermal: Temperature

Forecasting

Provide the FOMs of the unsteady & non-linear models for future, unsolved snapshots.

NIROMs tools

1. Dimensionality Reduction

Reduce the dimensional of the snapshot matrix

- **Convolutional Autoencoders (CAE)**
- Variational Autoencoders (CAE)
- Proper Orthogonal Decomposition (POD)
- Kernel Principal Component Analysis (KPCA)

2. Time Predictions & Forecasting

Predict the solutions of the unsteady/transient simulations and forecast to unsolved times

- **Long Short Term Memory (LSTMs)**
- 1D Convolutional Autoencoders

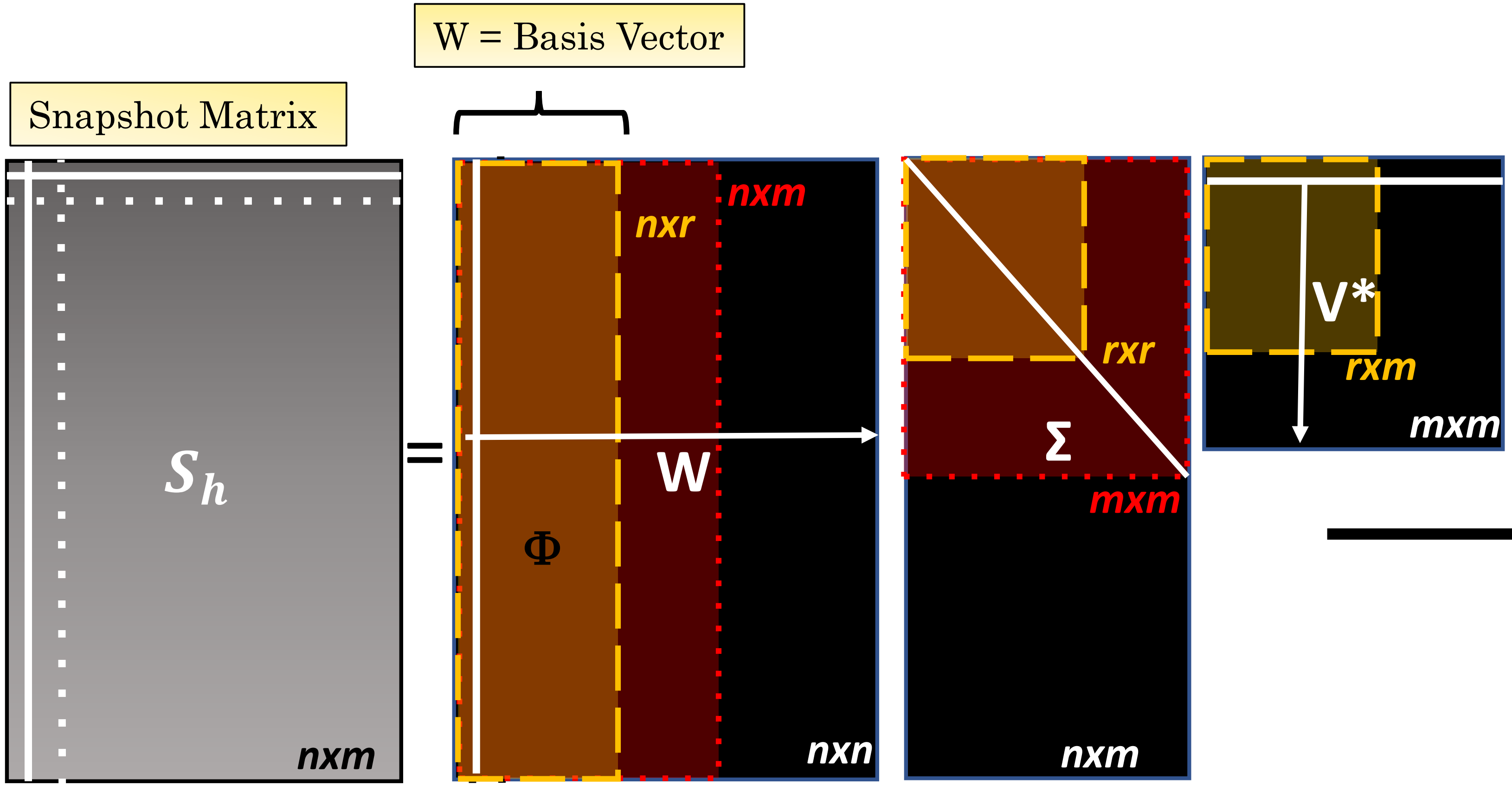
3. Interpolation / Extrapolation

Interpolate & extrapolate in the parameter space

- **Feed Forward Neural Networks (FFNNs)**
- Gaussian Processes (GPs)
- Response Surfaces

Linear dimensionality reduction

Use truncated **Singular Value Decomposition** (SVD) to reduce the size of the snapshot matrix through projection in a linear subspace



Linear projection

$$\begin{pmatrix} \mathbf{u}_1(t_1;\boldsymbol{\mu}_1) & \mathbf{u}_1(t_2;\boldsymbol{\mu}_1) & \cdots & \mathbf{u}_1(t_{N_t};\boldsymbol{\mu}_m) \\ \mathbf{u}_2(t_1;\boldsymbol{\mu}_1) & \mathbf{u}_2(t_2;\boldsymbol{\mu}_2) & \cdots & \mathbf{u}_2(t_{N_t};\boldsymbol{\mu}_m) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{u}_n(t_1;\boldsymbol{\mu}_1) & \mathbf{u}_n(t_2;\boldsymbol{\mu}_2) & \cdots & \mathbf{u}_n(t_{N_t};\boldsymbol{\mu}_m) \end{pmatrix}$$

n<<h

Full SVD
Economy SVD
Truncated SVD

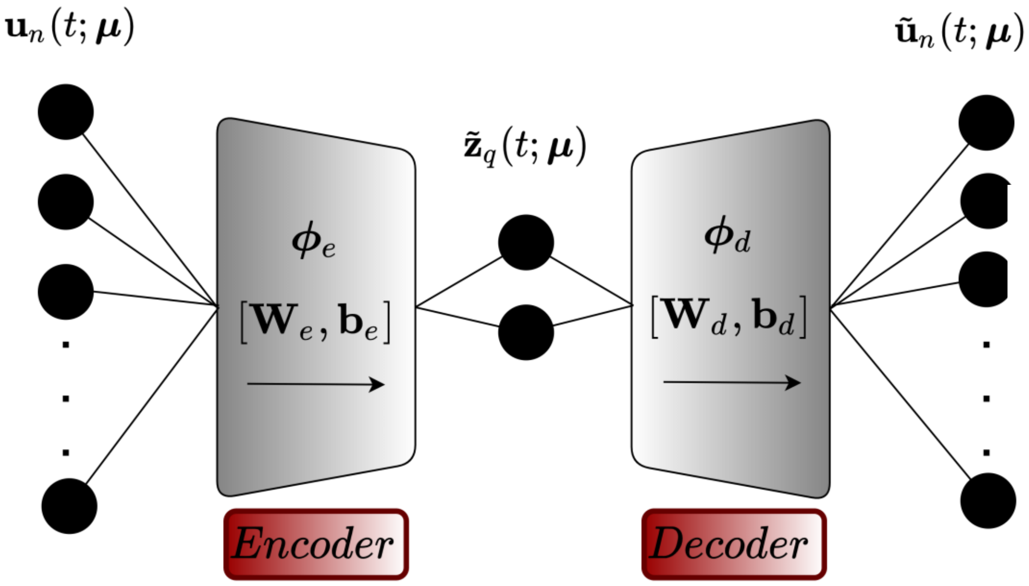
W,V : orthonormal matrices
Σ: diagonal matrix/singular values

Non-linear Dimensionality reduction

- **Convolutional Autoencoder (CAEs)** are neural networks (NN) that approximately learn an identity mapping of the unlabeled input data in an unsupervised manner.

- CAEs are commonly used for pattern recognition, feature extraction, and dimensionality reduction.

- CAEs map the input tensor to a latent space through the encoder, and then they transform the latent representation to the output through the decoder.



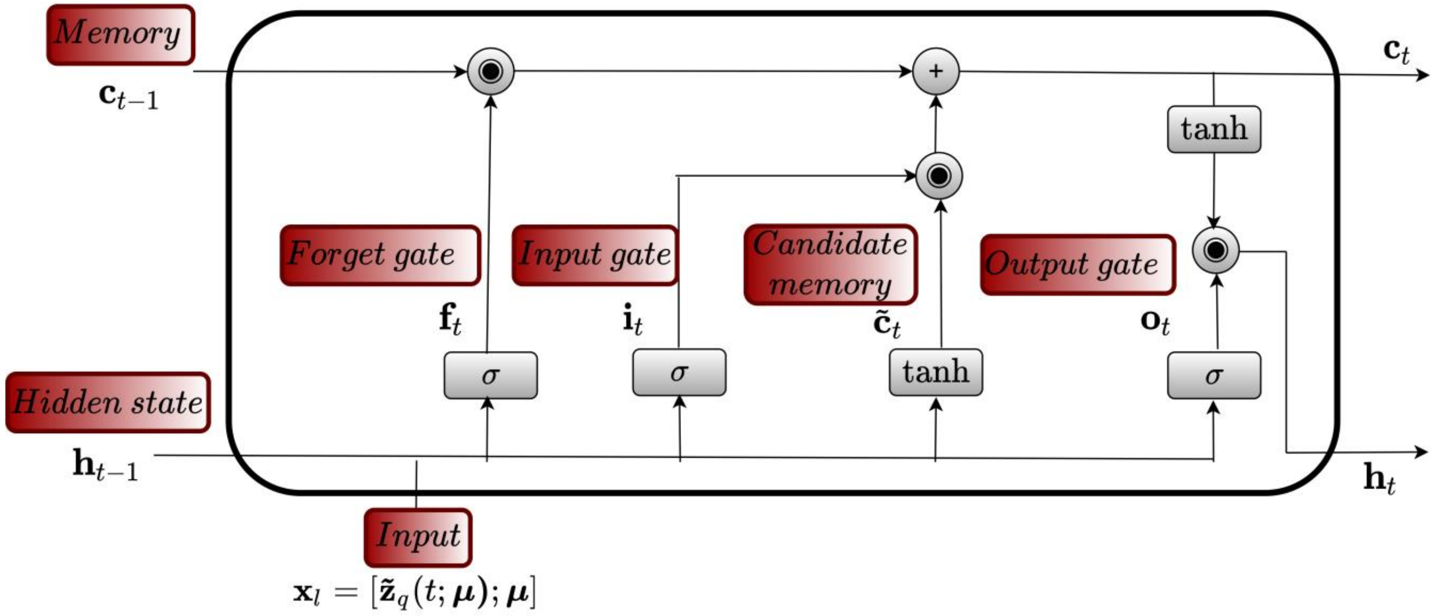
$$\epsilon_{mse} = \frac{1}{mN_t}\sum_{j=1}^{m}\sum_{i=1}^{N_t}\|u_n(t_i;\mu_j^{tr}) - \tilde{u}_n(t_i,\mu_j^{tr})\|_2^2$$

Time Predictions

- **Long Short Term Memory (LSTM)** is a specialized neural network which accounts for "memory" effects in sequential data, like time series (e.g. finance, physics, text).

- LSTM extracts key patterns, trends in the training data and **predicts future data** which acquires these characteristics.

- Internal states explicitly account for memory effects in the data by controlling information flow from past to the future.

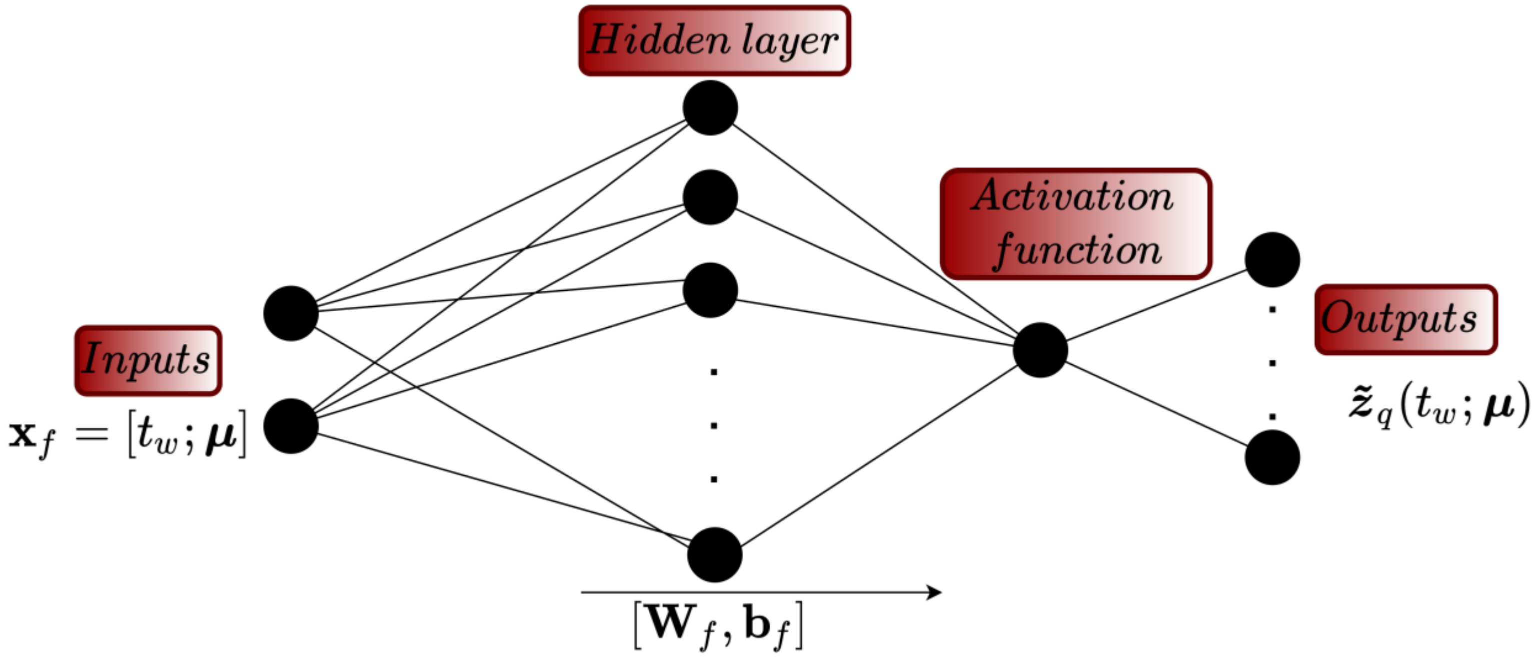


$$
\begin{cases}
\text{Input gate}: \boldsymbol{i}_l = \sigma(\boldsymbol{W}_i[\boldsymbol{h}_{t-1}, \boldsymbol{x}_l] + \boldsymbol{b}_i) \\
\text{Forget gate}: \boldsymbol{f}_l = \sigma(\boldsymbol{W}_f[\boldsymbol{h}_{t-1}, \boldsymbol{x}_l] + \boldsymbol{b}_f) \\
\text{Candidate memory cell}: \tilde{\mathbf{C}}_l = tanh(\boldsymbol{W}_c[\boldsymbol{h}_{t-1}, \boldsymbol{x}_l], \boldsymbol{b}_c \\
\text{Memory cell}: \boldsymbol{c}_t = \boldsymbol{f}_t \cdot \boldsymbol{C}_{t-1} + \boldsymbol{i}_t \cdot \tilde{\boldsymbol{C}}_t \\
\text{Output gate}: \boldsymbol{o}_t = \sigma(\boldsymbol{W}_o[\boldsymbol{h}_{t-1}, \boldsymbol{x}_l], \boldsymbol{b}_o] \\
\text{Hidden state}: \boldsymbol{h}_t = o_t \cdot \tanh(\boldsymbol{C}_t)
\end{cases}
$$

Parameter interpolation

- FFNNs, also known and as multi-layer perceptron, approximate the functional relation among a set of input and output values.

- FFNN are composed of multiple layers with a variable number of nodes while nonlinear activation functions are often applied to the output of each layer.



Test cases

- 2D unsteady convection-diffusion
- Flow past a cylinder
- Structural Dynamics of a cantilever beam
- Wave propagation on a plate

2D unsteady convection-diffusion

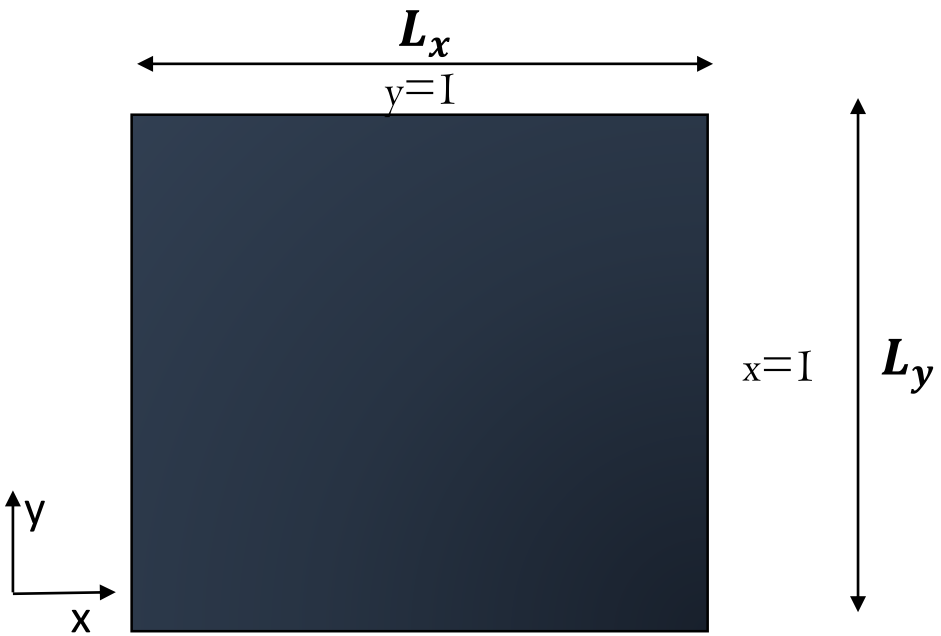
The Convection Diffusion is used to simulate physical phenomena with pollution dispersion, heat flow, chemical reactions, particles and cells transport

Nodes: 16000
dt = 10^{-4}
Timesteps: 75
Parameters = 20
Velocity: 100< u < 200

diffusion | convection | Reaction term

$$\underbrace{\frac{\partial \varphi(\boldsymbol{x},t)}{\partial t}}_{\text{Time derivative term}} = \rho \nabla^2 \varphi(\boldsymbol{x},t) - \boldsymbol{v}\cdot\nabla\varphi(\boldsymbol{x},t) + R(\boldsymbol{x},t)$$

Time derivative term



Boundary Conditions

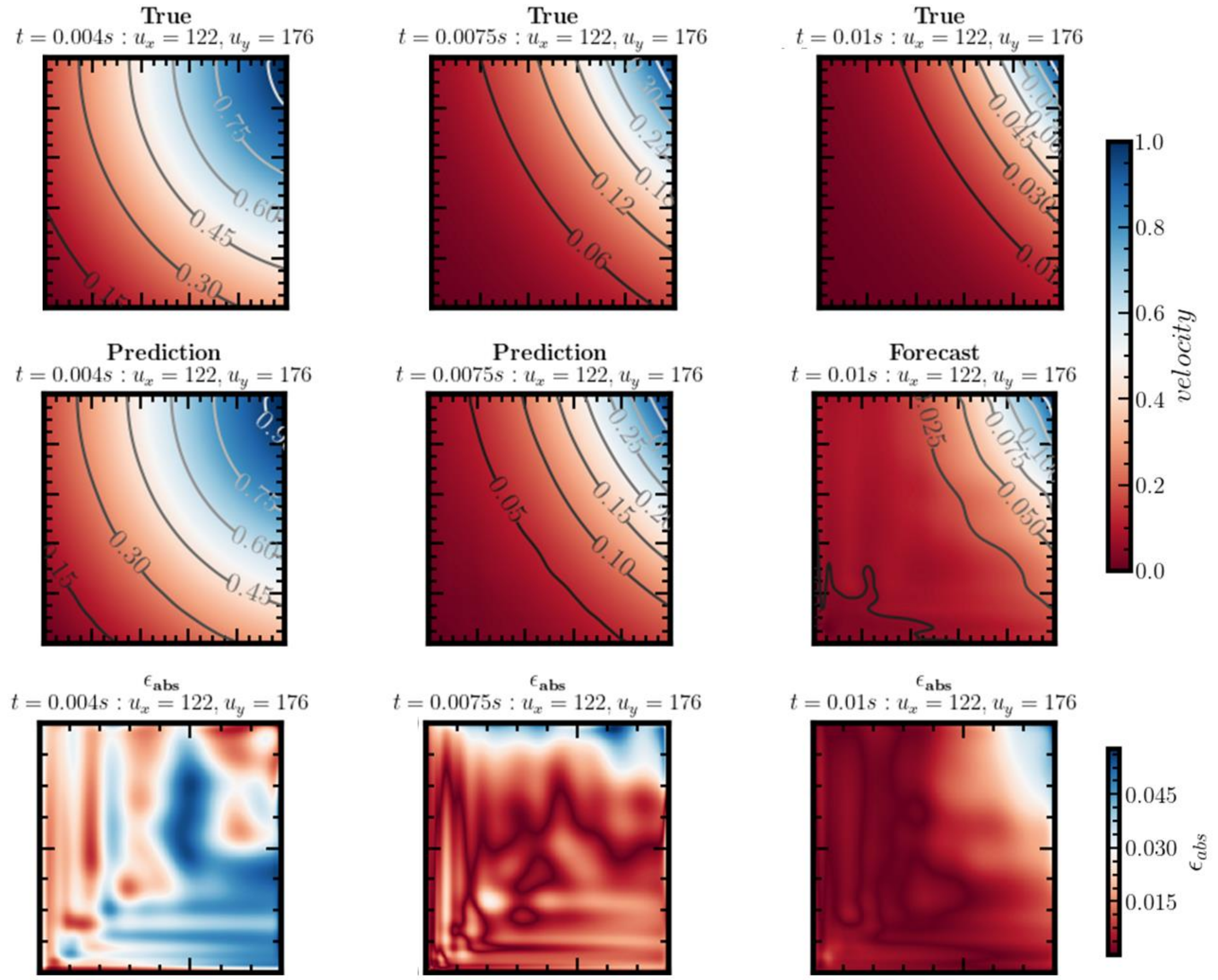
$$\varphi(x,y,t)\Big|_{x=0} = \frac{1}{1+4t} e^{\left[-\frac{(-v_x t-0.5)^2+\left(y-v_y t-0.5\right)^2}{(1+4t)}\right]}$$

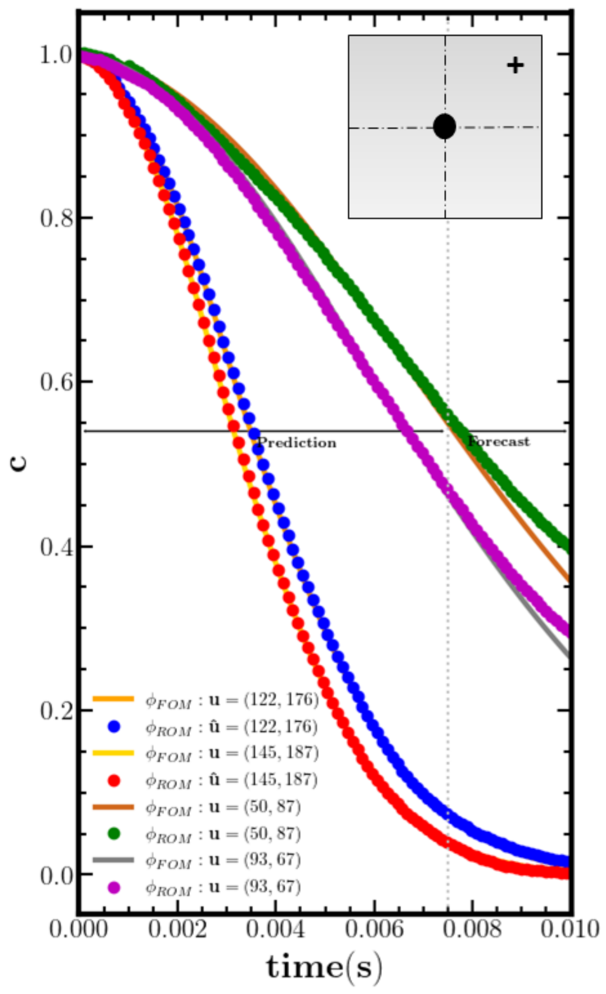
$$\varphi(x,y,t)\Big|_{x=1} = \frac{1}{1+4t} e^{\left[-\frac{(1-v_x t-0.5)^2+\left(y-v_y t-0.5\right)^2}{(1+4t)}\right]}$$

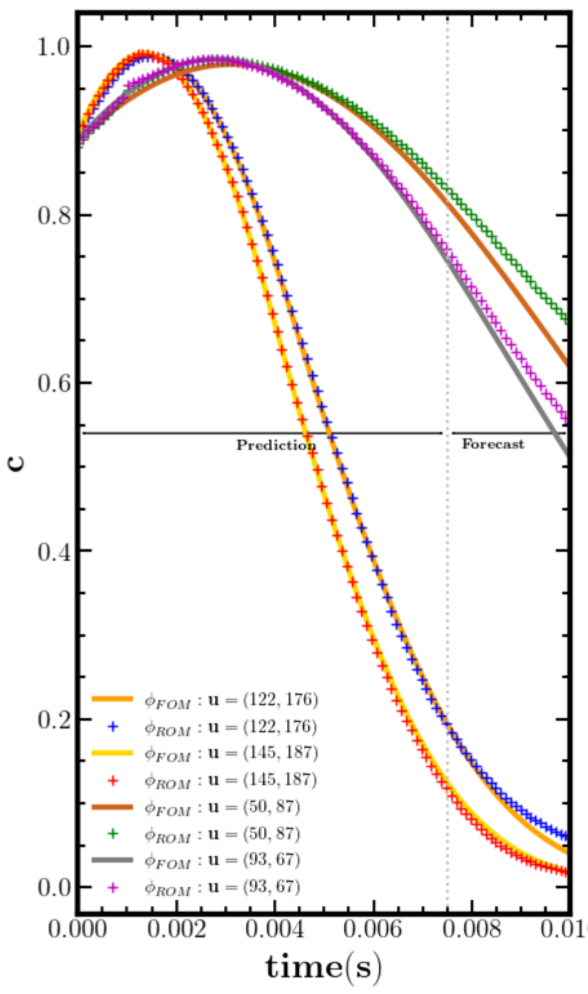
$$\frac{\partial\varphi}{\partial n}(x,y,t)\Big|_{y=0} = 0, \frac{\partial\varphi}{\partial n}(x,y,t)\Big|_{y=1} = 0$$

$$\boxed{\varphi(x,y,t) = \frac{1}{1+4t} e^{\left[-\frac{(x-v_x t-0.5)^2+\left(y-v_y t-0.5\right)^2}{(1+4t)}\right]}}$$

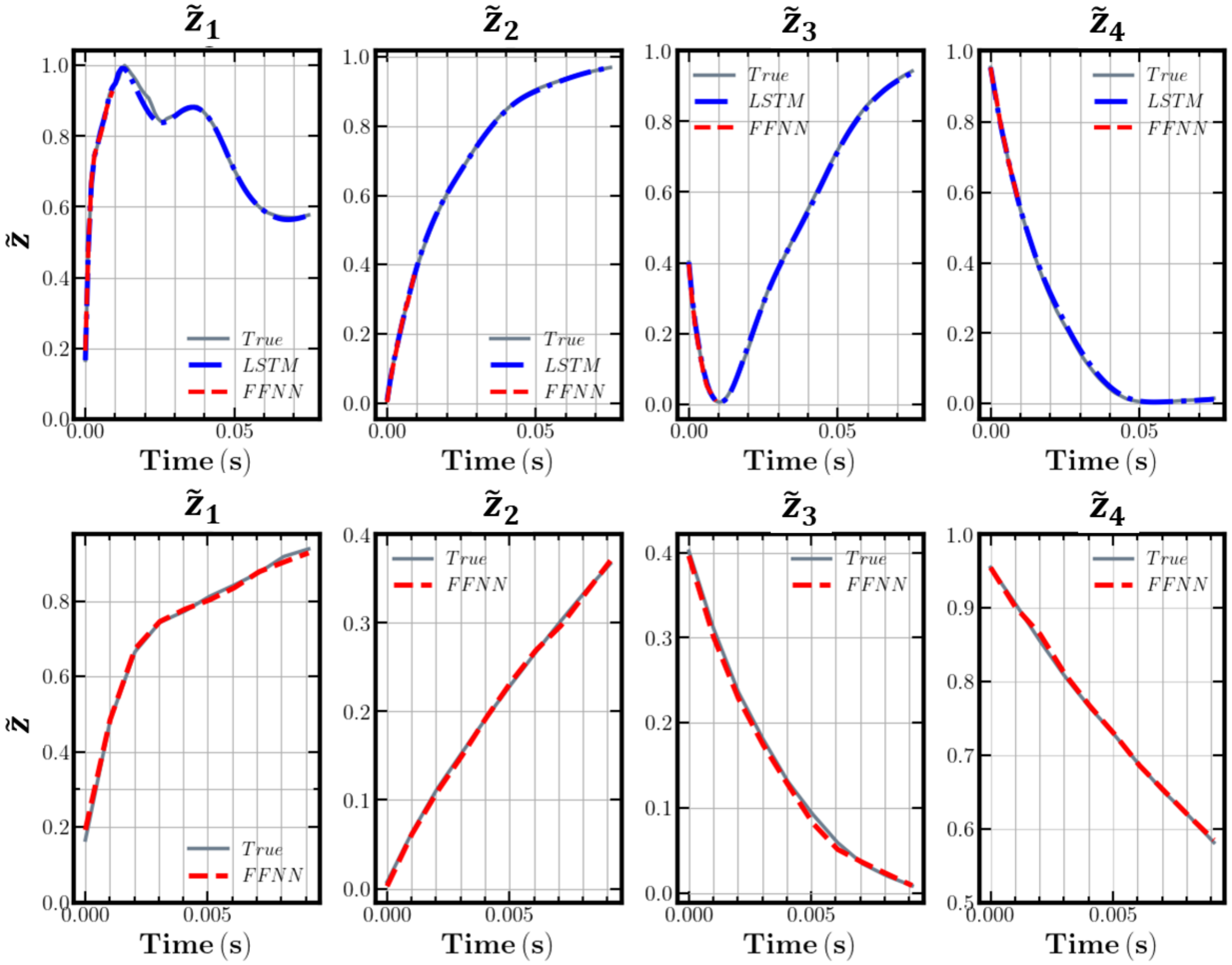
2D unsteady convection-diffusion

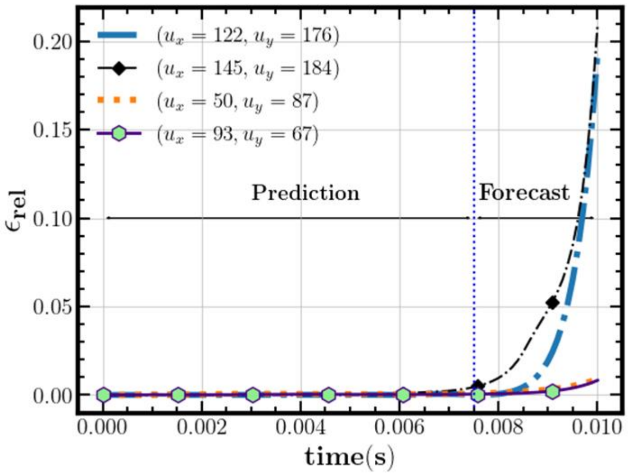


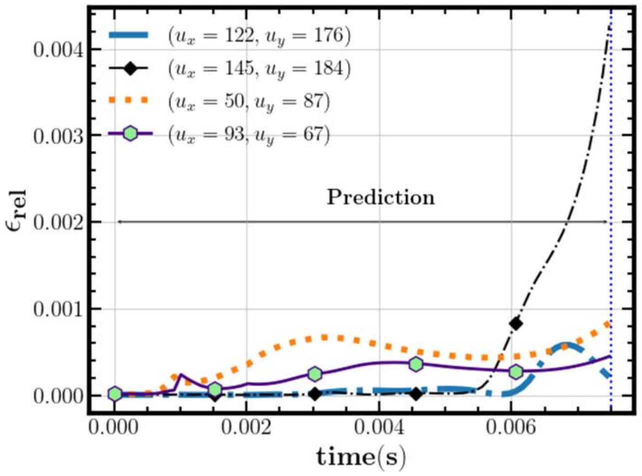




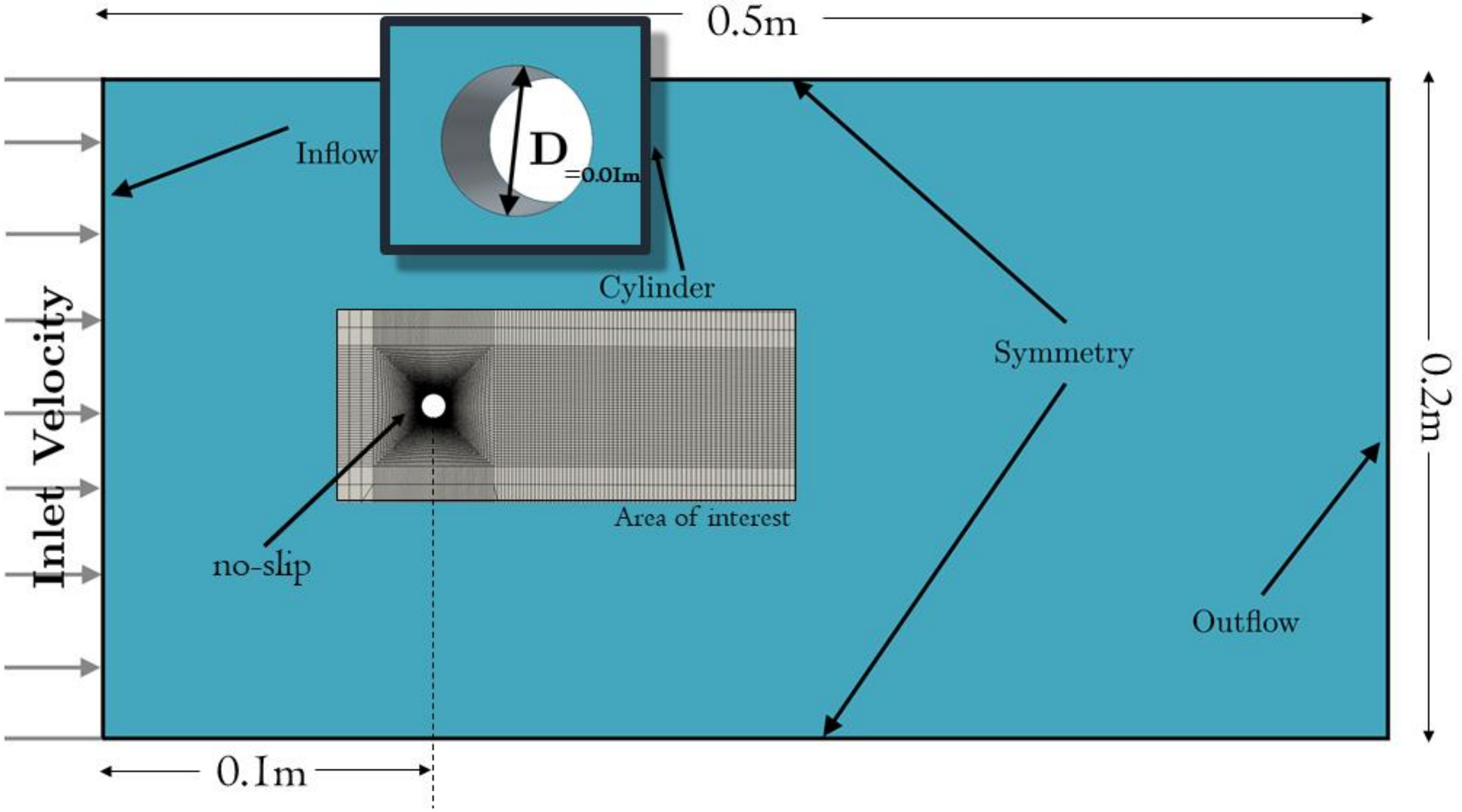
2D unsteady convection-diffusion





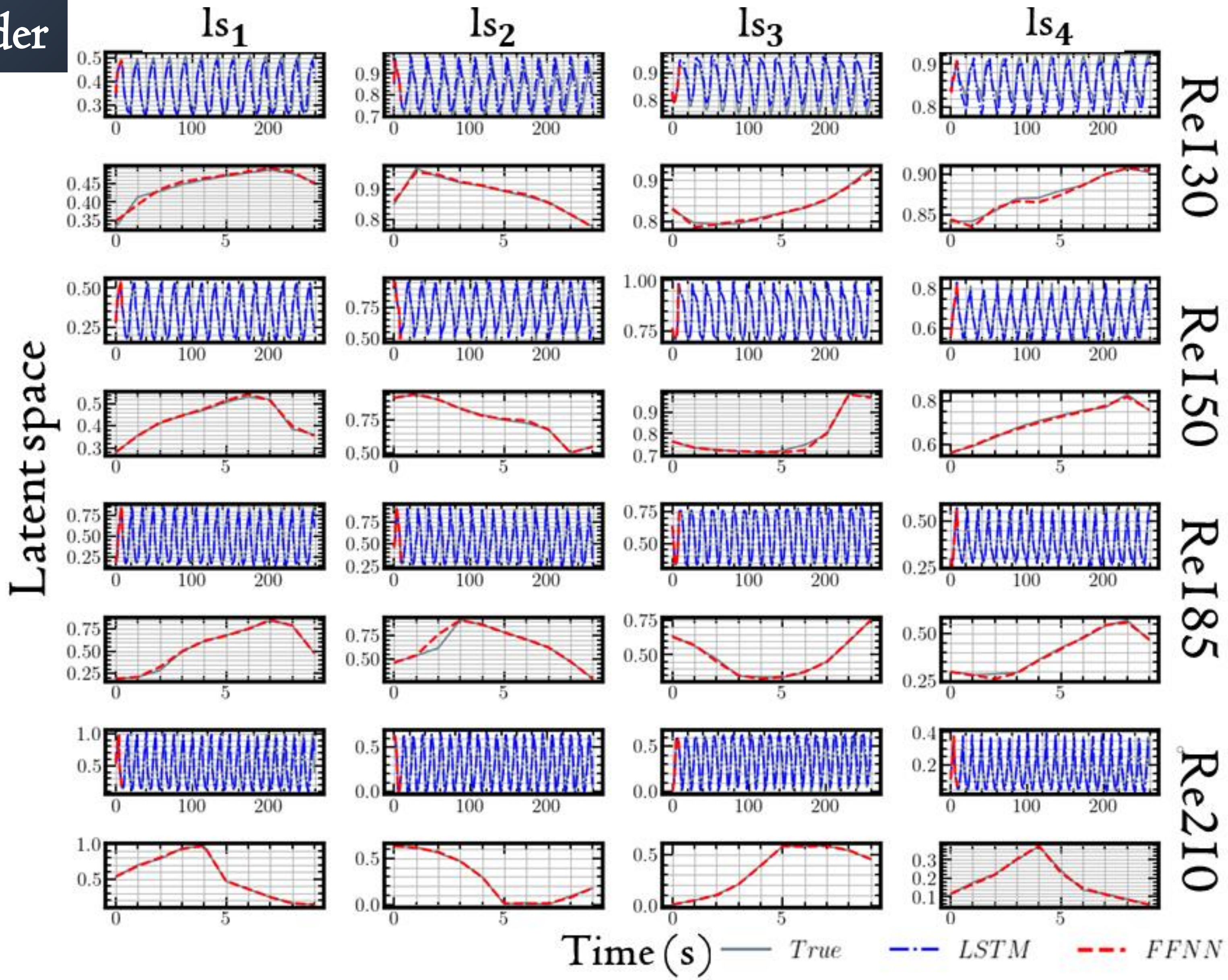


Flow past a cylinder

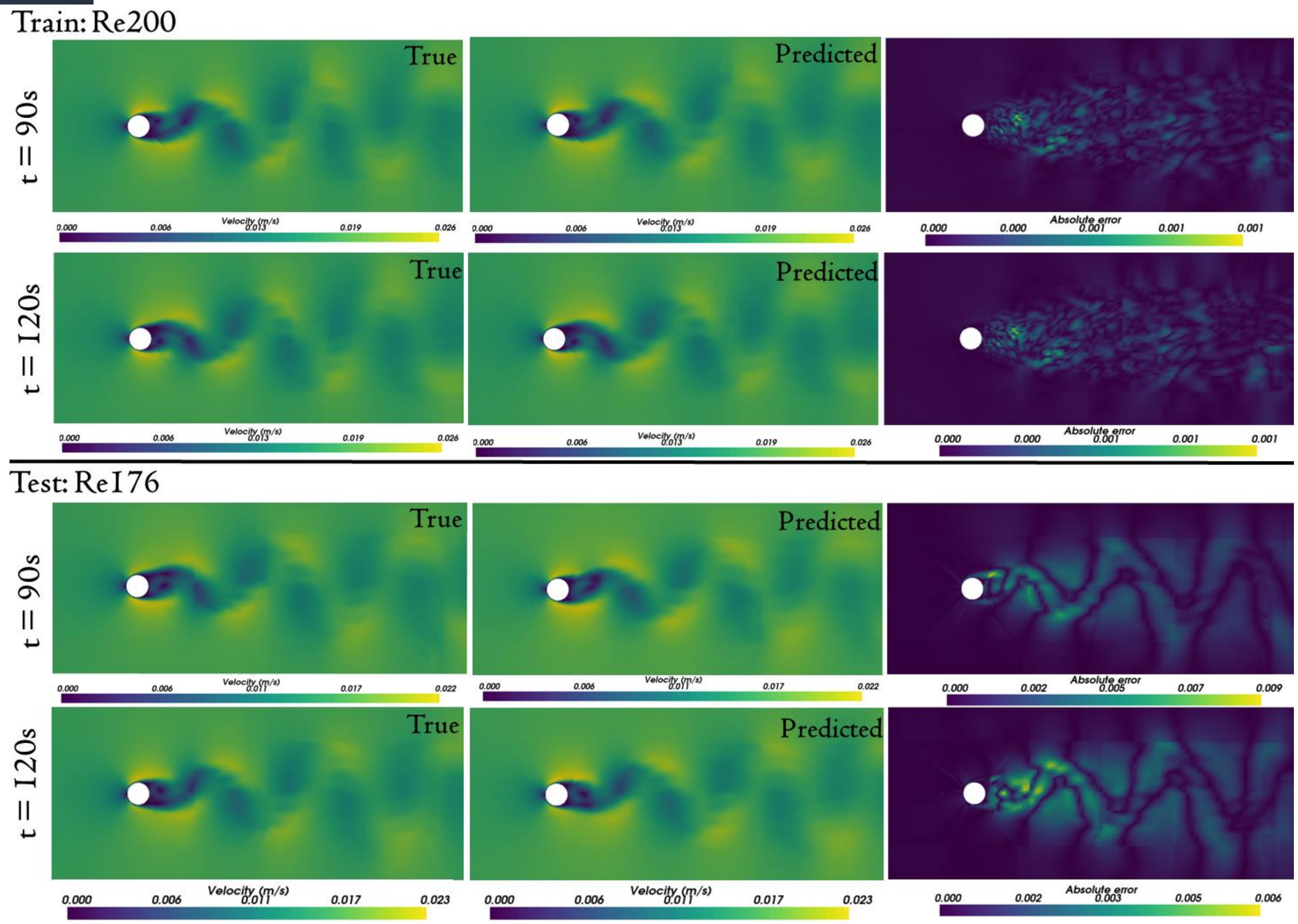


cells: 211000
dt = $5 * 10^{-4}$
Timesteps: 260
Parameters = 10
Velocity: 100< Re < 200

Flow past a cylinder

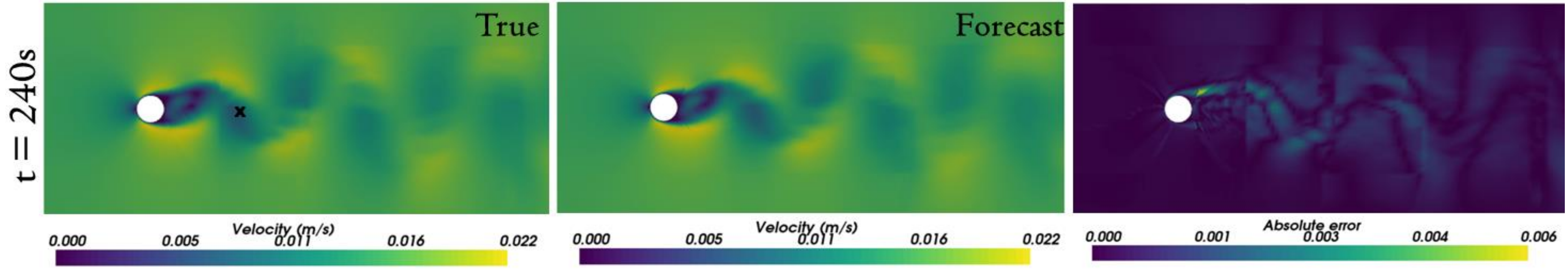


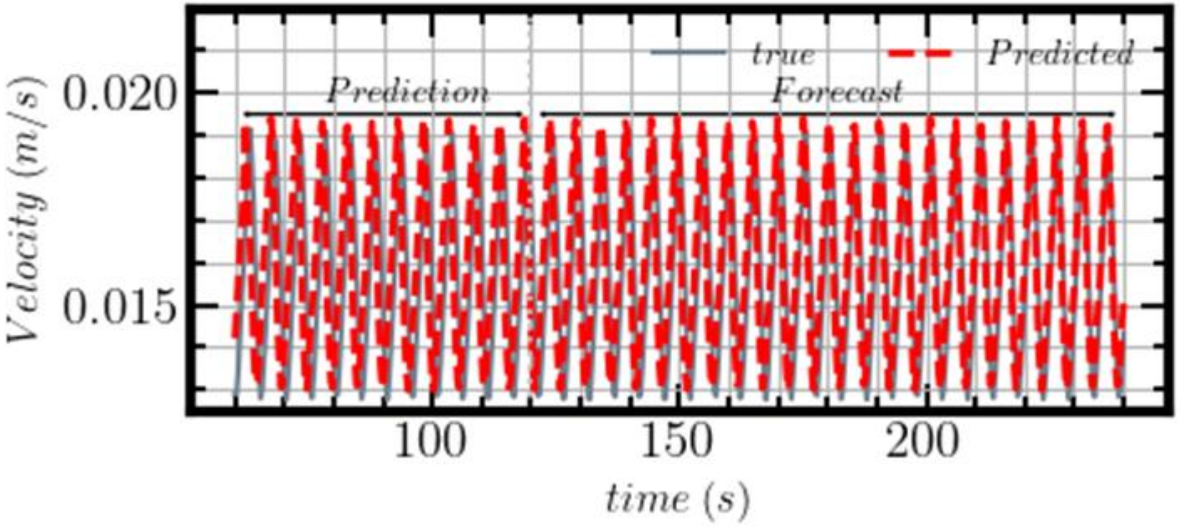
Flow past a cylinder

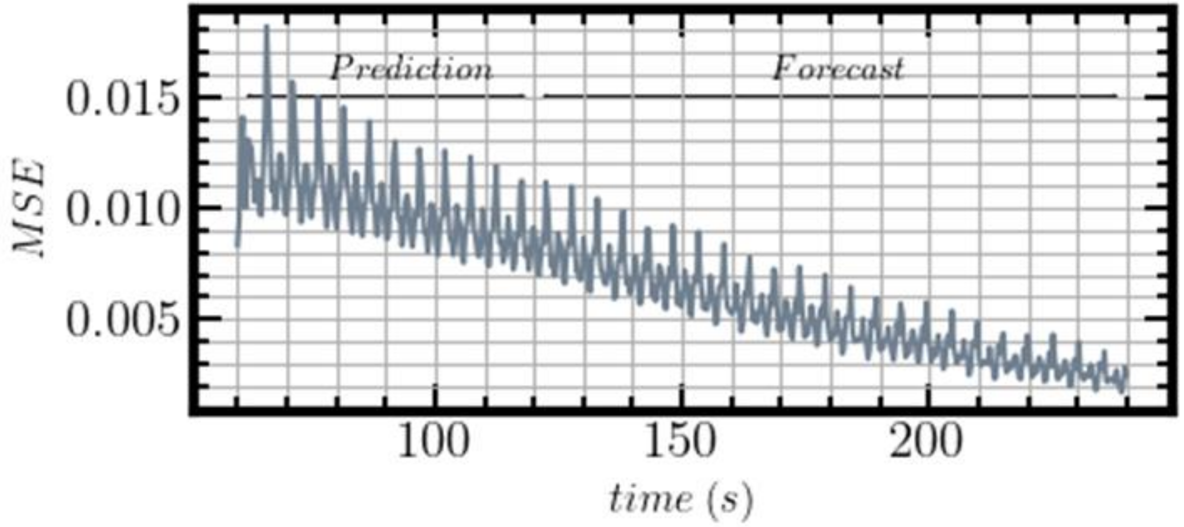


Flow past a cylinder

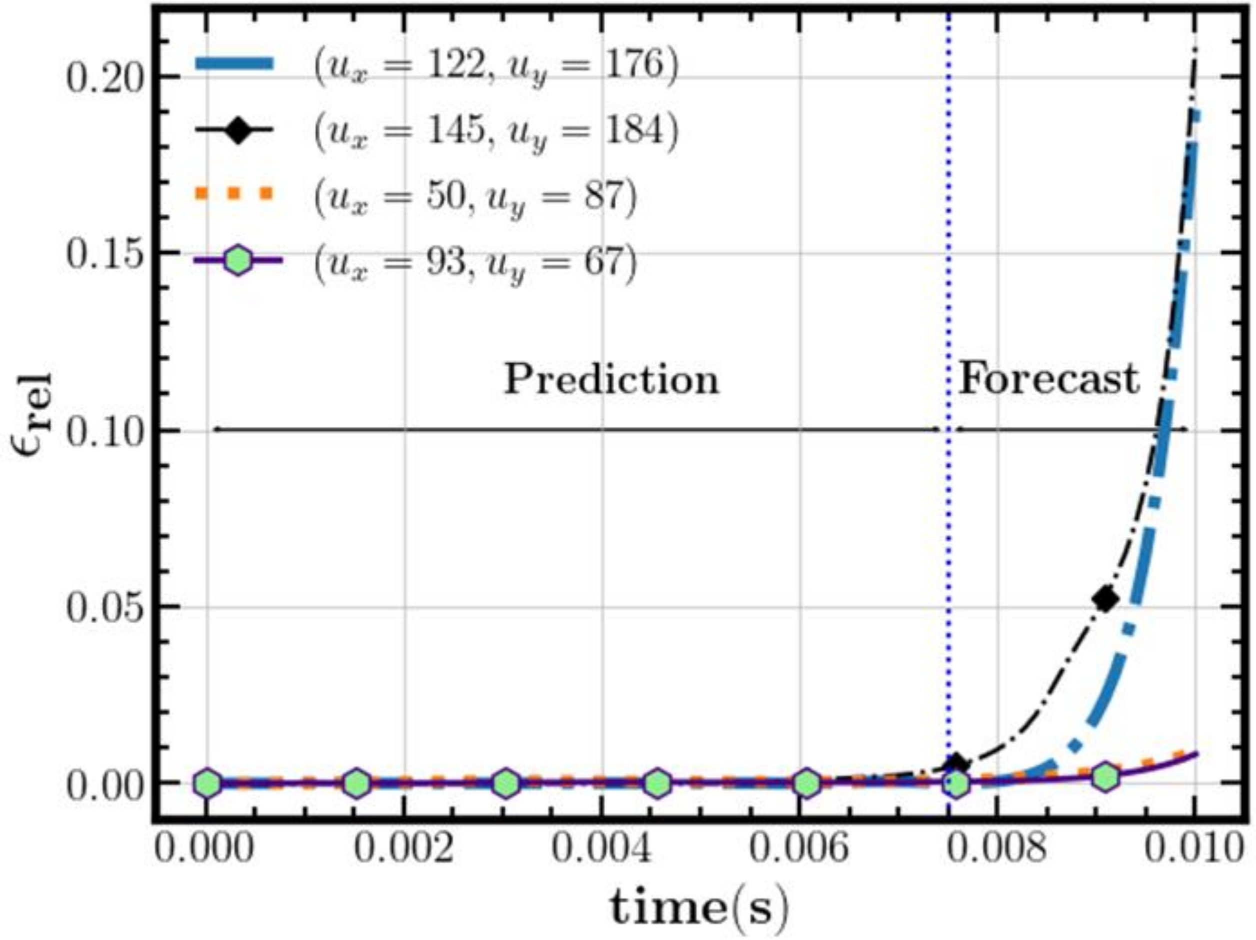
Test: Re176

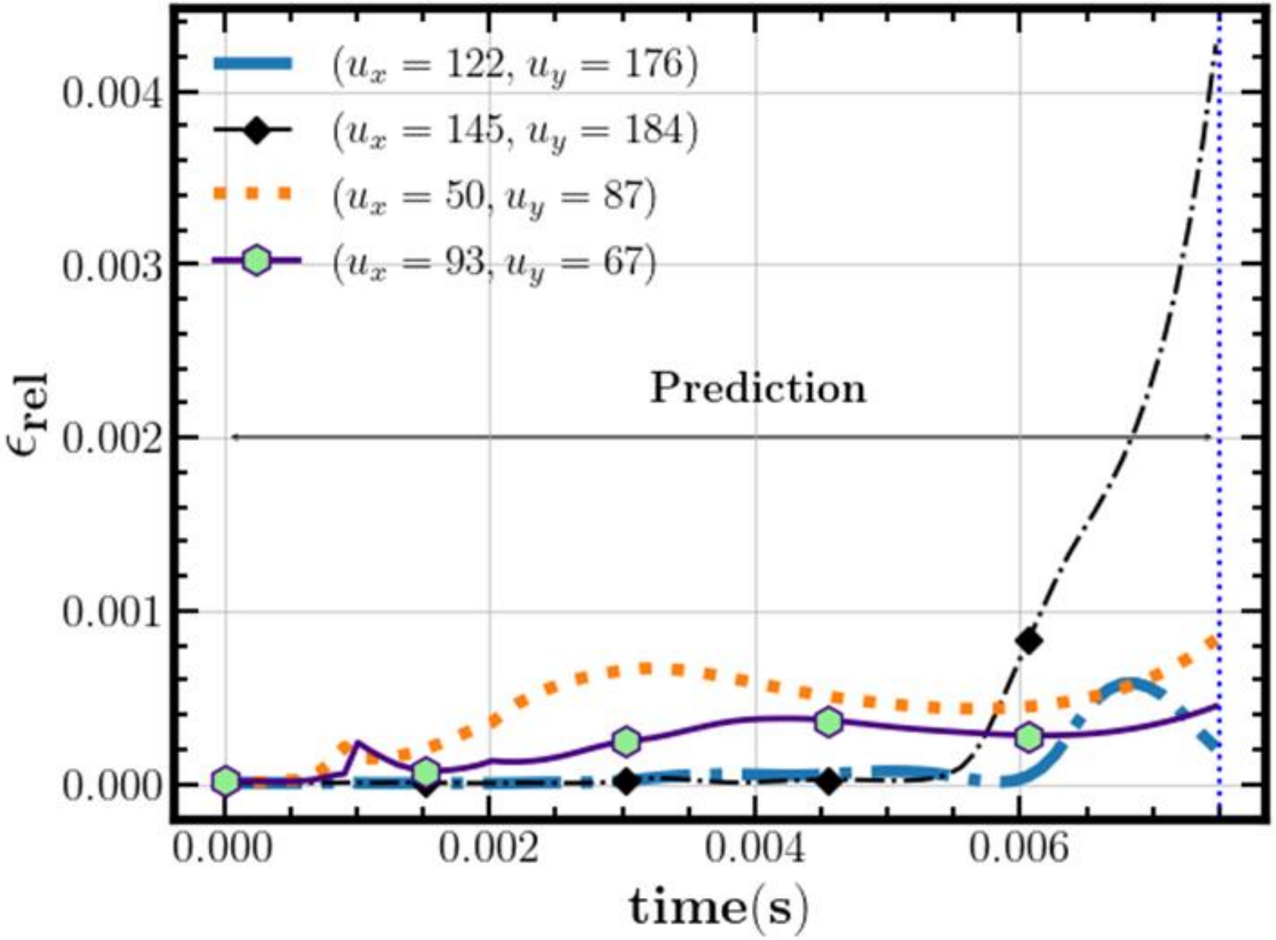






Flow past a cylinder

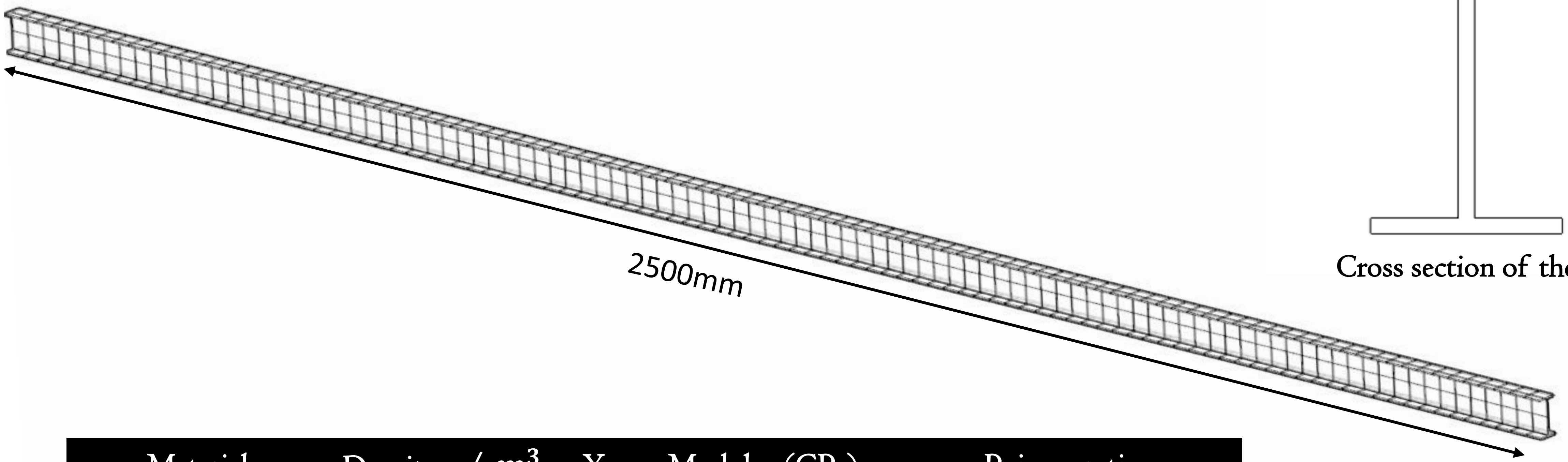


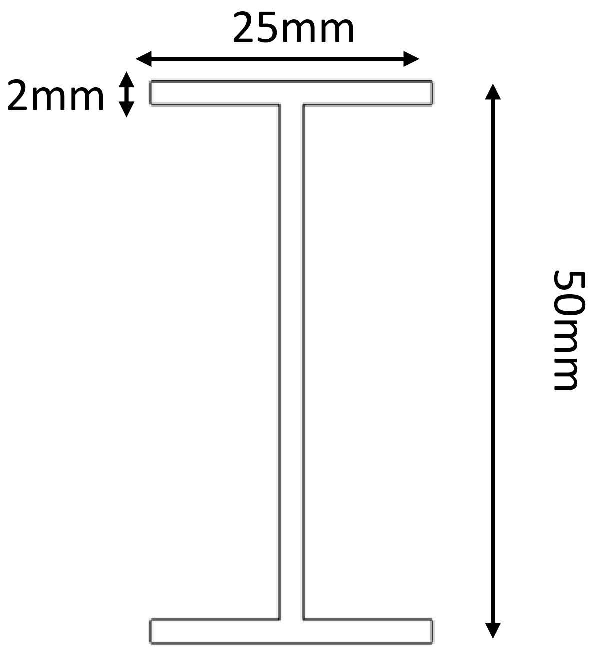


Structural Dynamics of a Cantilever Beam

Mesh grid

Element type	Number of nodes
1D – Bar elements	128





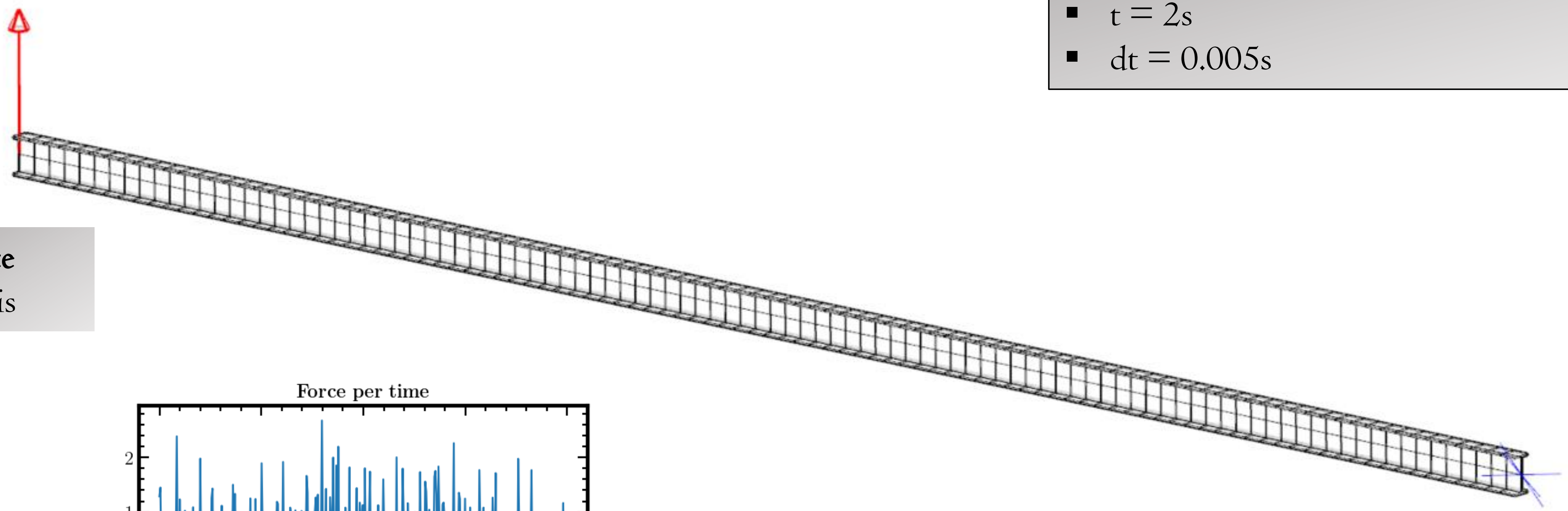
Cross section of the beam

Material	Density g/cm^3	Young Modulus (GPa)	Poisson ratio
Aluminum	2.7	69	0.33

Structural Dynamics of a Cantilever Beam

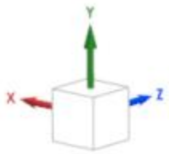
Boundary conditions

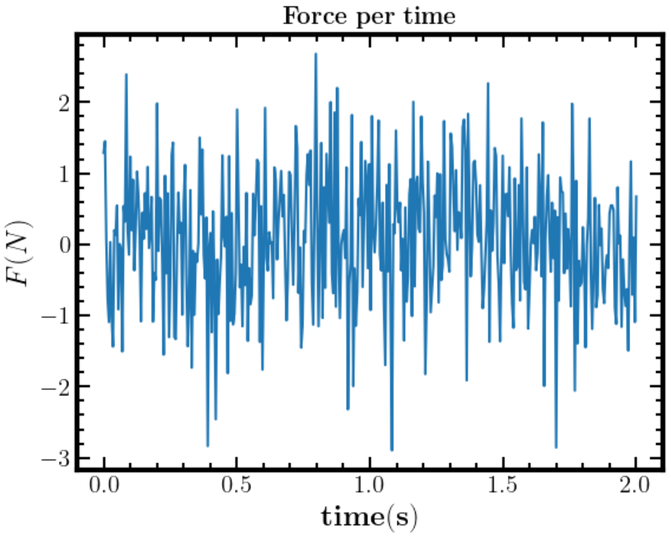
SOL 109 Direct Transient Response
- t = 2s
- dt = 0.005s



Force
z-axis

Fixed
All DoFs



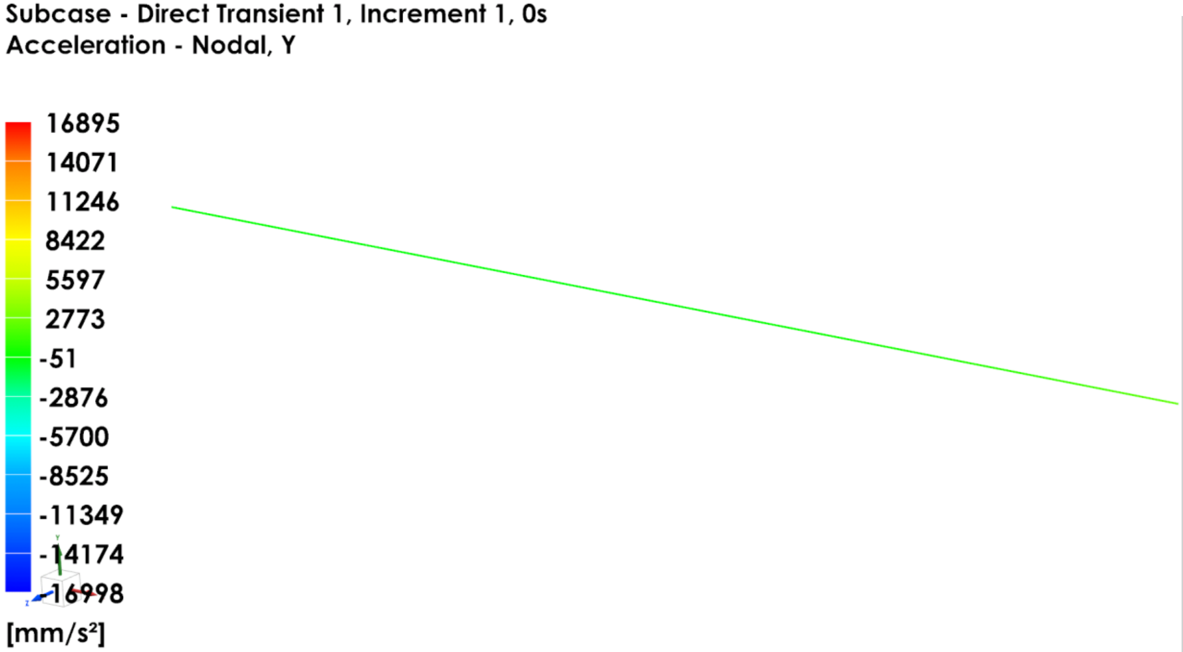


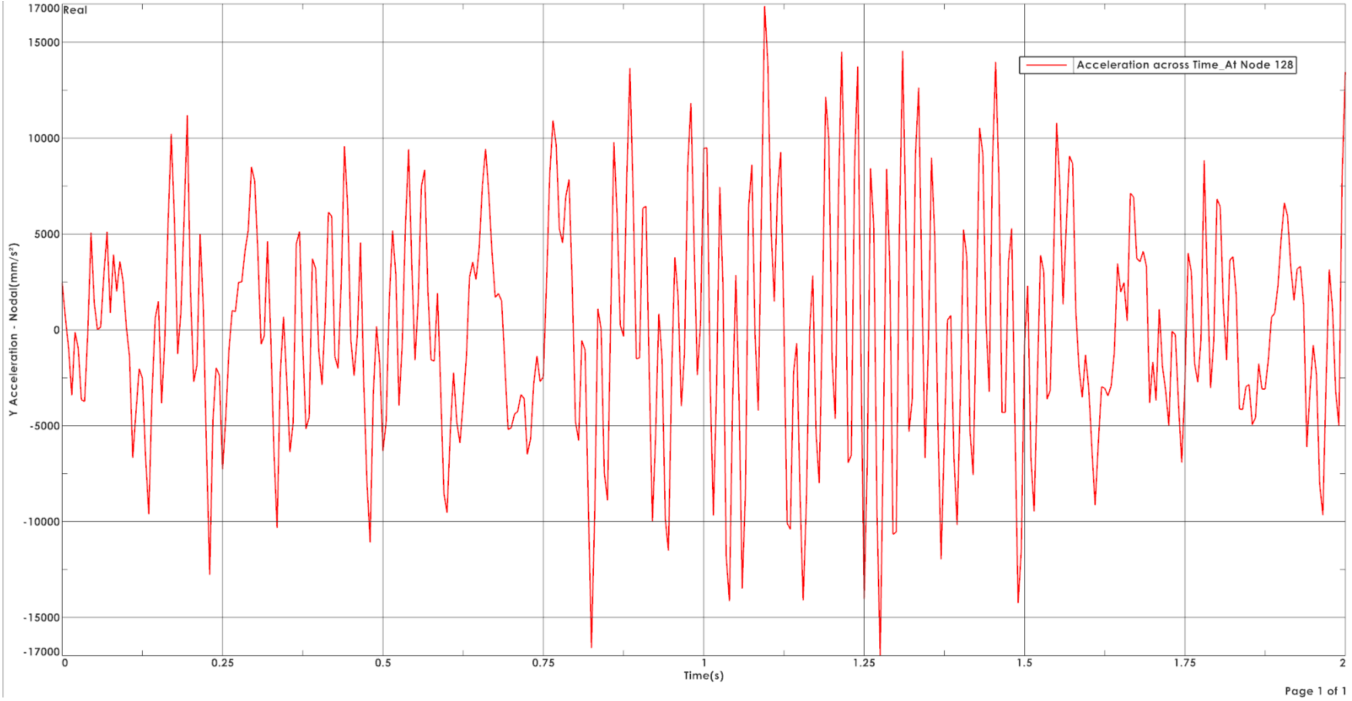
- **External force:** white noise $N\sim(0\ N, 1\ N)$ until **t=2s,** resulting **in 400 timesteps**.

$$dt = \frac{1}{f_{1s}} = \frac{1}{200} = 0.005s$$

Structural Dynamics of a Cantilever Beam

Results





Acceleration along with time (animation)

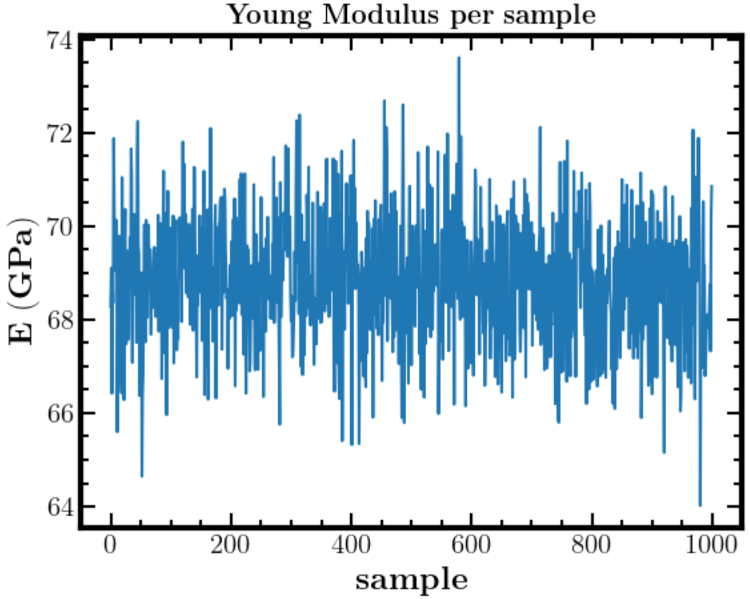
- y-axis

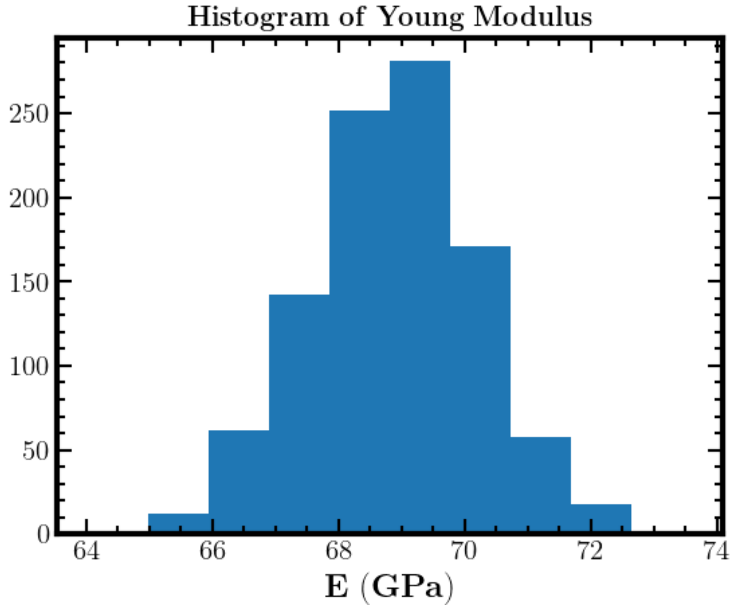
Acceleration along with time for the baseline E value

- y-axis
- Trailing point of the cantilever beam

Structural Dynamics of a Cantilever Beam

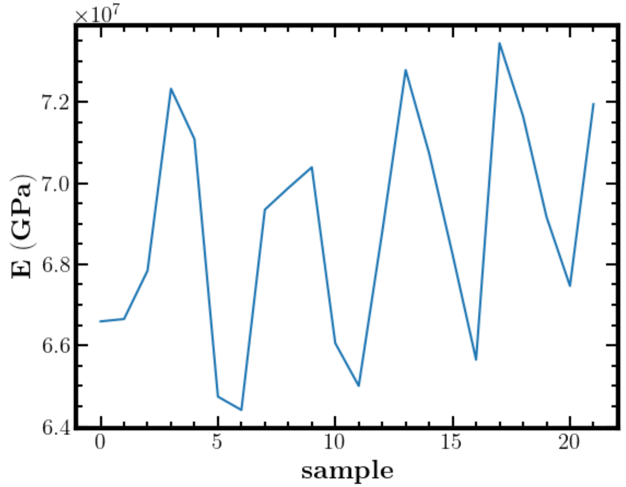
ROM setup





Parameters

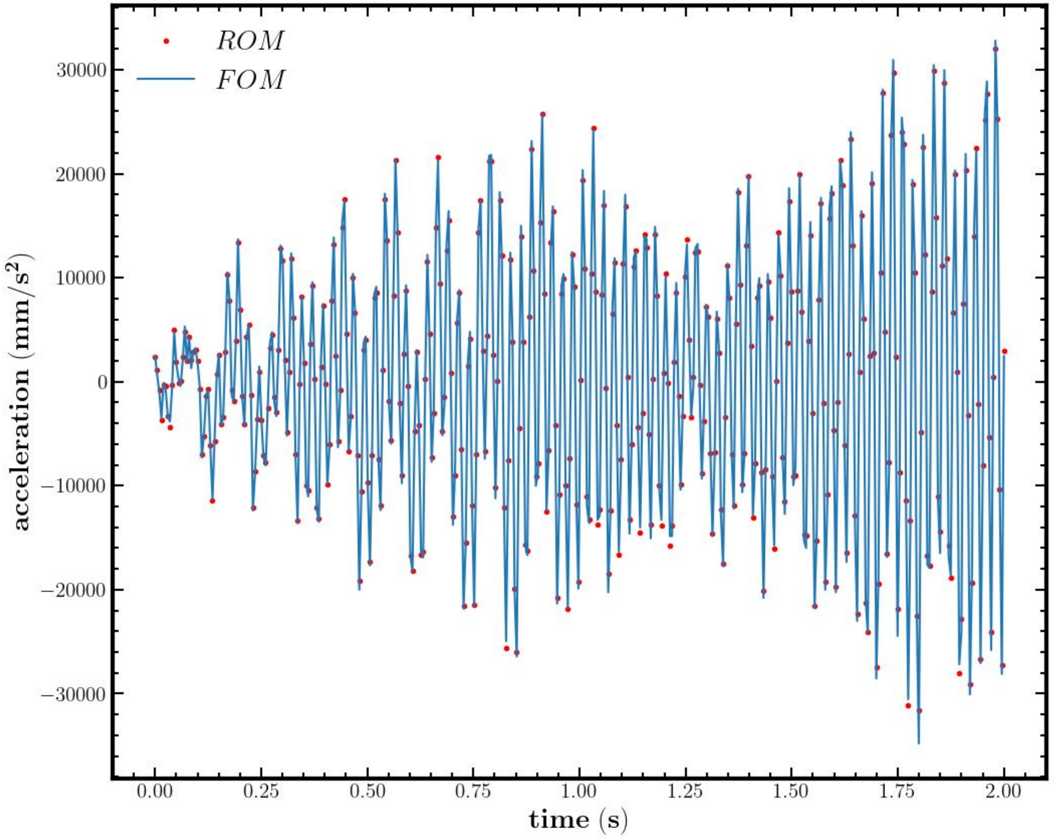
- Young Modulus: $N \sim (68{,}9\ GPa, 1.332\ GPa)$
- Latin hypercube sampling (LHS) methodology
- Train data: 22 samples (20 train, 2 test)
- Time steps: 400
- Nodes: 128
- Field of interest: Acceleration y-axis



Structural Dynamics of a Cantilever Beam

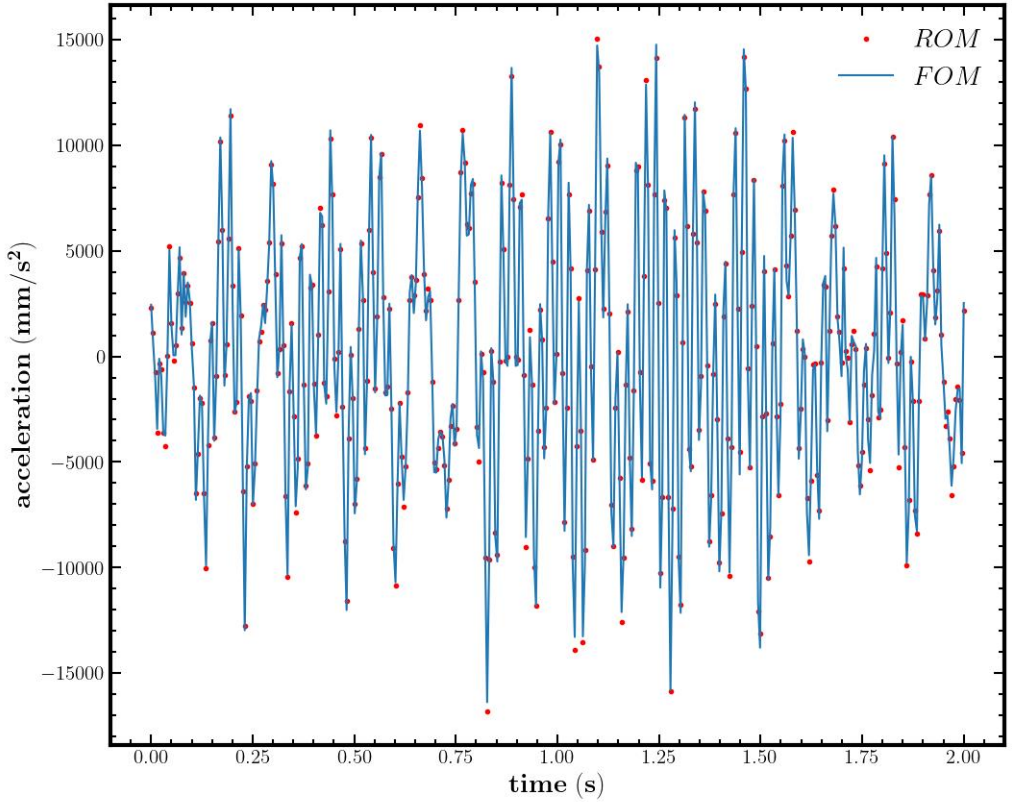
ROM reconstruction

Train data: Young Modulus: E=6.44 GPa



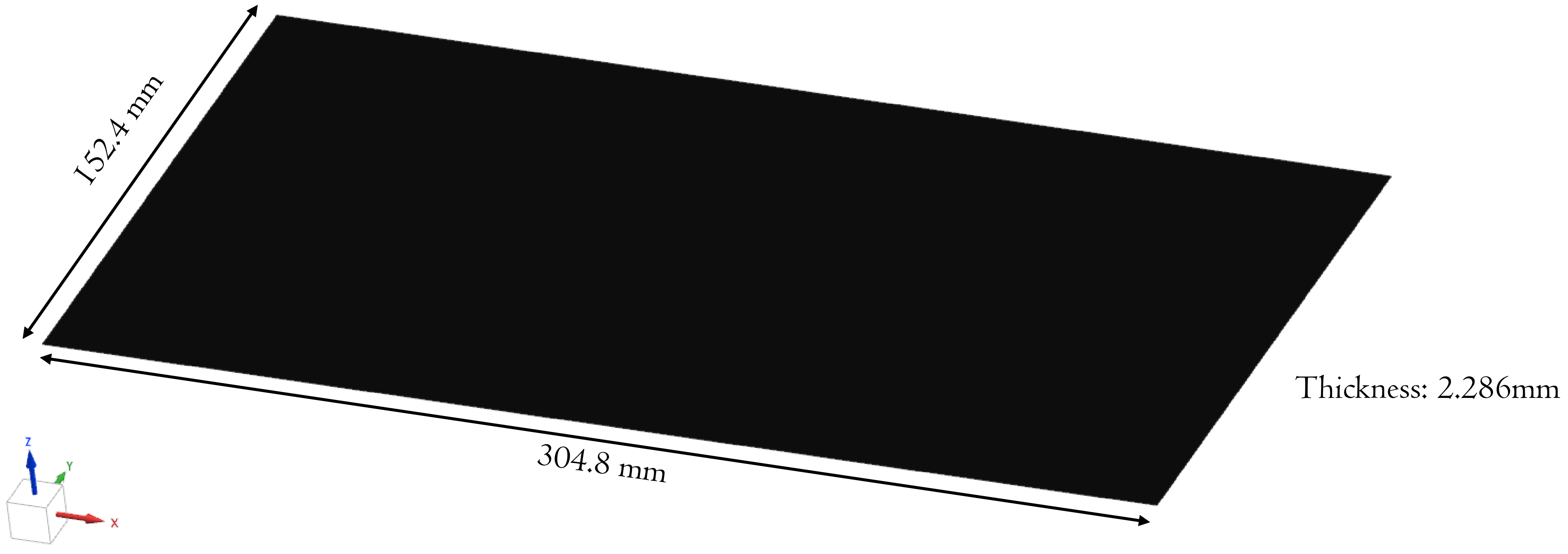
Full order model (FOM) solutions and ROM reconstructed solutions for the trailing node of the beam

Test data: Young Modulus: E=6.82 GPa



Full order model (FOM) solutions and ROM reconstructed solutions for the trailing node of the beam

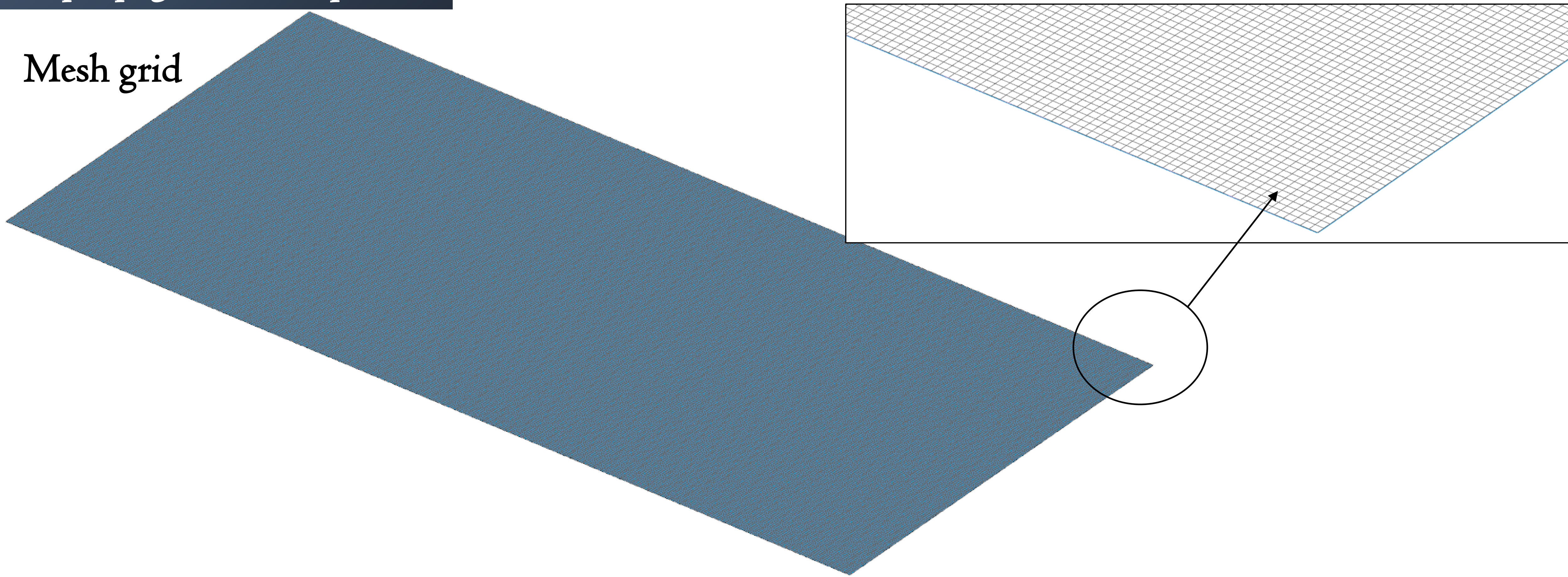
Wave propagation on a plate



Material	Density g/cm^3	Young Modulus (GPa)	Poisson ratio
Aluminum	2.7	68.9	0.33

Wave propagation on a plate

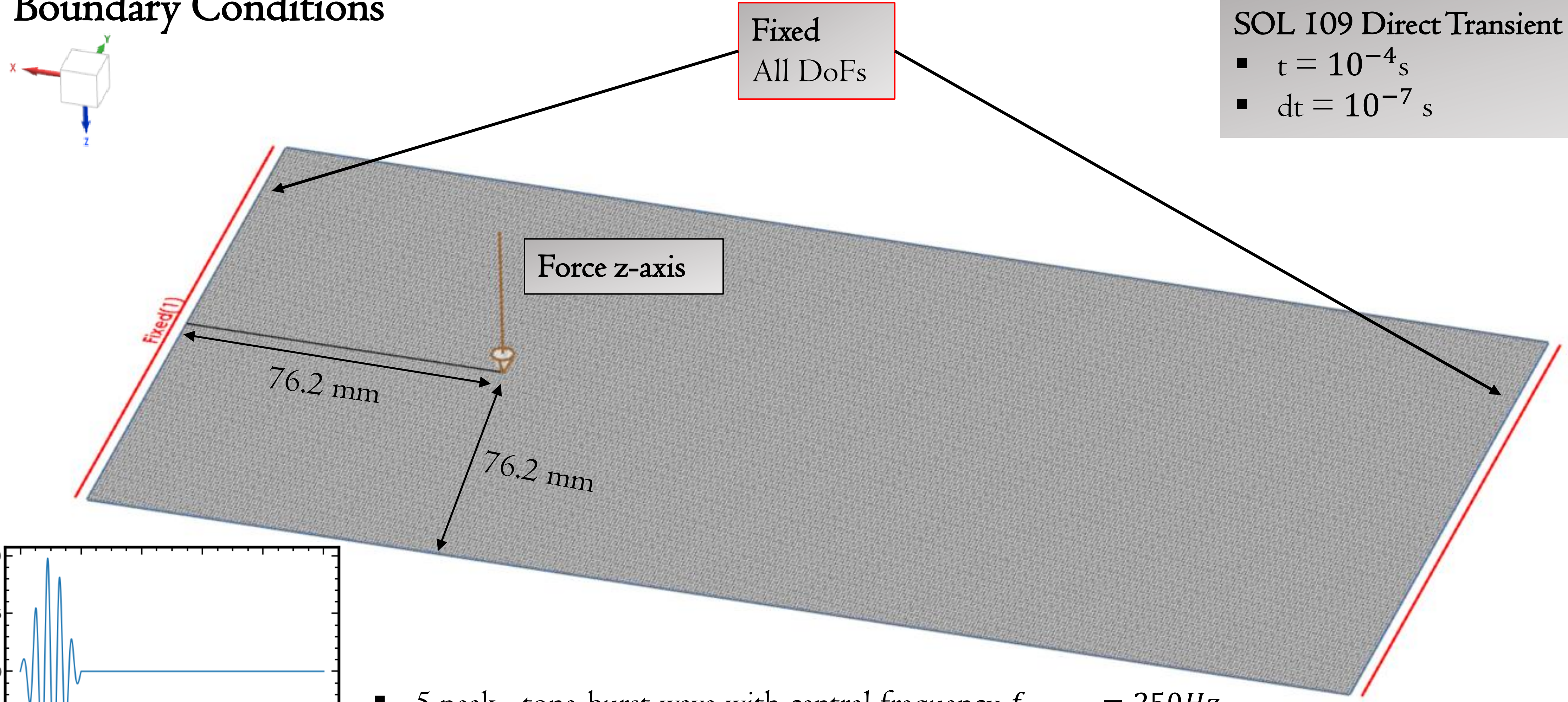
Mesh grid



Type of elements	Element size (mm)	Number of nodes	Number of elements
Shell Element - CQUAD4	0.75	83028	82418

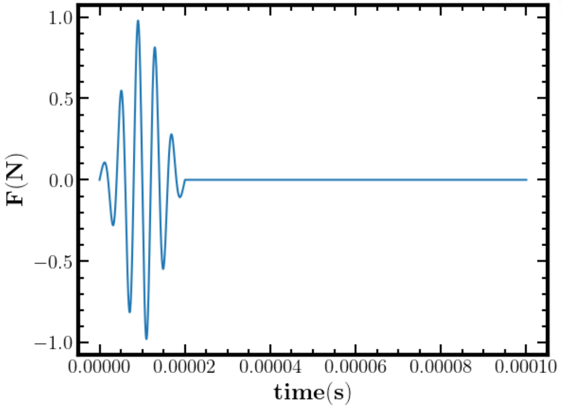
Wave propagation on a plate

Boundary Conditions



SOL 109 Direct Transient Response

- $t = 10^{-4}$s
- $dt = 10^{-7}$ s



- 5 peak –tone-burst wave with central frequency $f_{center} = 250Hz.$
- Amplitude = [-1,1]
- Time range = $[0 - 10^{-4}]$
- Sampling frequency: 24 MHz

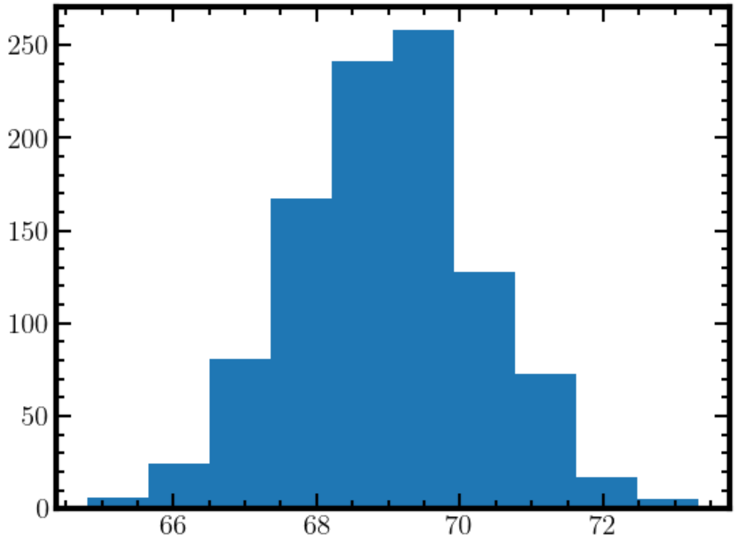
Wave propagation on a plate

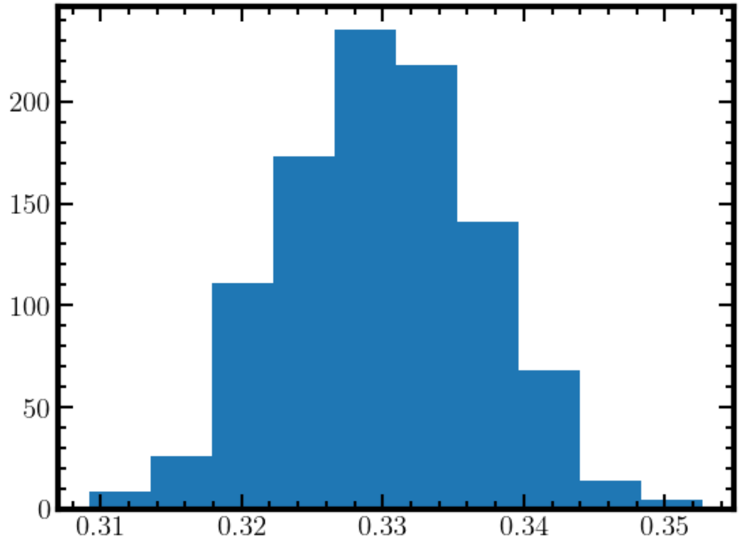
ROM setup

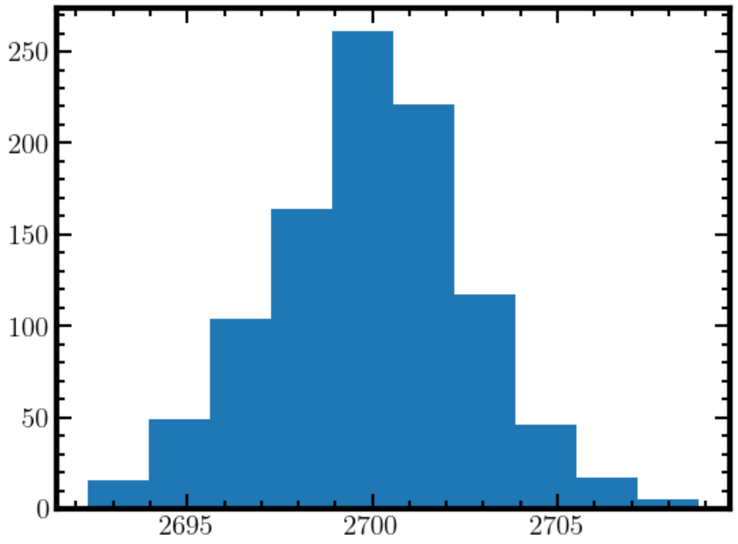
- Time steps: 1000 , skip every 8, resulting in 125 entire time frames. Then, we keep 100 time frames for training the ROM and 25 for testing the forecast/extrapolation of LSTMs to unseen solutions.
- Number of Nodes: 83028

The following uncertainty quantification (UQ) in the material properties is designed with the following configurations:

Young Modulus, E: $\boldsymbol{N\sim(68,9\ GPa, 1,332\ GPa)}$ Poisson's Ratio, ν: $\boldsymbol{N\sim(0.33,\ 0.007\ GPa)}$ Density, ρ: $\boldsymbol{N\sim\left(2700\frac{kg}{m^3},\ 2.70\frac{kg}{m^3}\right)}$

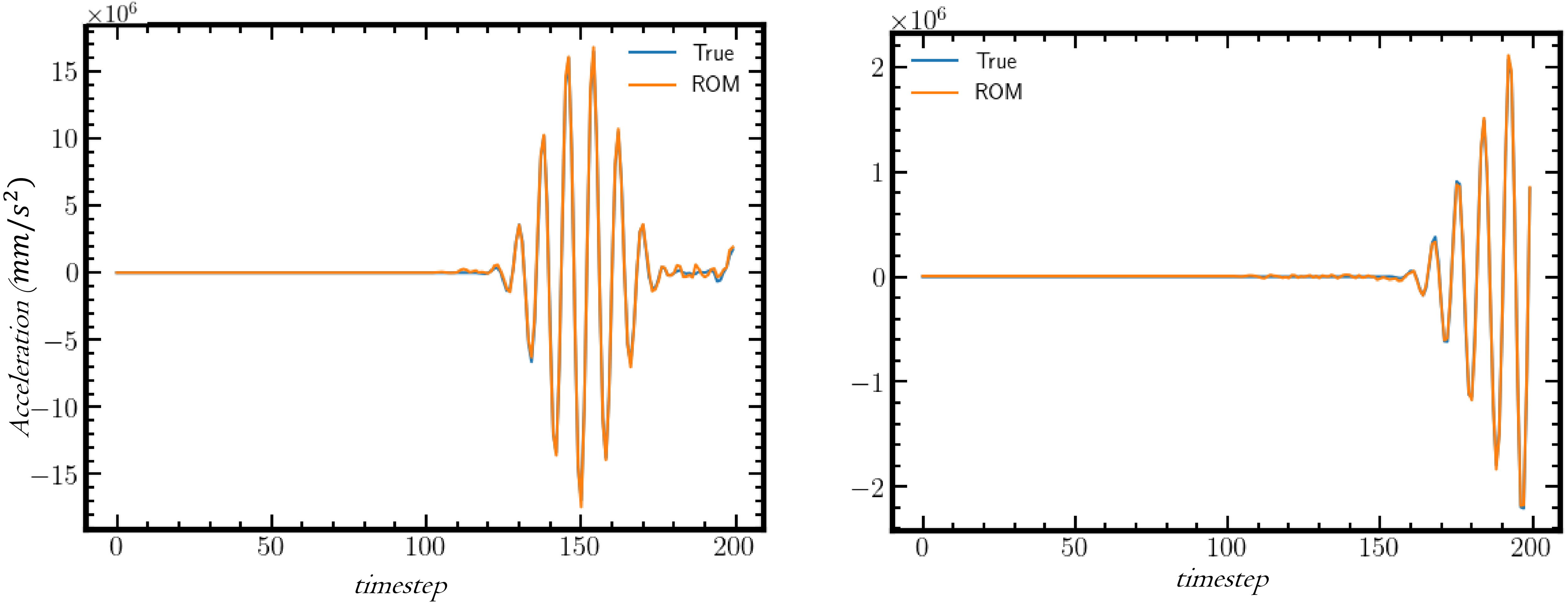






Wave propagation on a plate

ROM reconstruction



Conclusions

An end-to-end framework has been proposed & developed able to:

- Handle data derived through the high-fidelity numerical models
- Reduce the dimensions of snapshot matrixes both with SVD and CAE
- Predict the temporal solutions in time with LSTMs
- Interpolate in the parameter space for a new sample and reconstruct the FOM with FFNN
- Make forecasts in the future with LSMTs providing an estimation of the FOM

Next steps include the application of the proposed methodology in wind energy and wind turbines.