Hype or Reality?

Scalable Reduced Order Modelling For Digital Twins

Dirk Hartmann,
Siemens Digital Industries & Technical University of Darmstadt

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Dirk Hartmann,
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Siemens
Gwendal Jouan, Digital Industries, Belgium
Daniel Berger, Digital Industries, Germany
Stefan Gavranovic[2], Digital Industries, Germany
Birgit Obst, Siemens Technology, Germany
Matthias Schulz, Digital Industries, Germany
Qinyu Zhuang[2], Siemens Technology, Germany

Technical University of Munich
Florian Schnös[2], Mechanical Engineering
Prof. Felix Dietrich, Computer Science

New York University
Prof. Benjamin Peherstorfer, Courant Institute
Wayne Uy, Courant Institute

University of Magdeburg
Prof. Thomas Richter, Mathematics

KU Leuven
Herman van der Auweraer, Mechanical Engineering

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Agenda

1 Digital Twins

2 Digital Twins @ Work

3 Challenges & Opportunities

4 Reduced Order and Surrogate Modeling

5 The Future

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1

Digital Twins

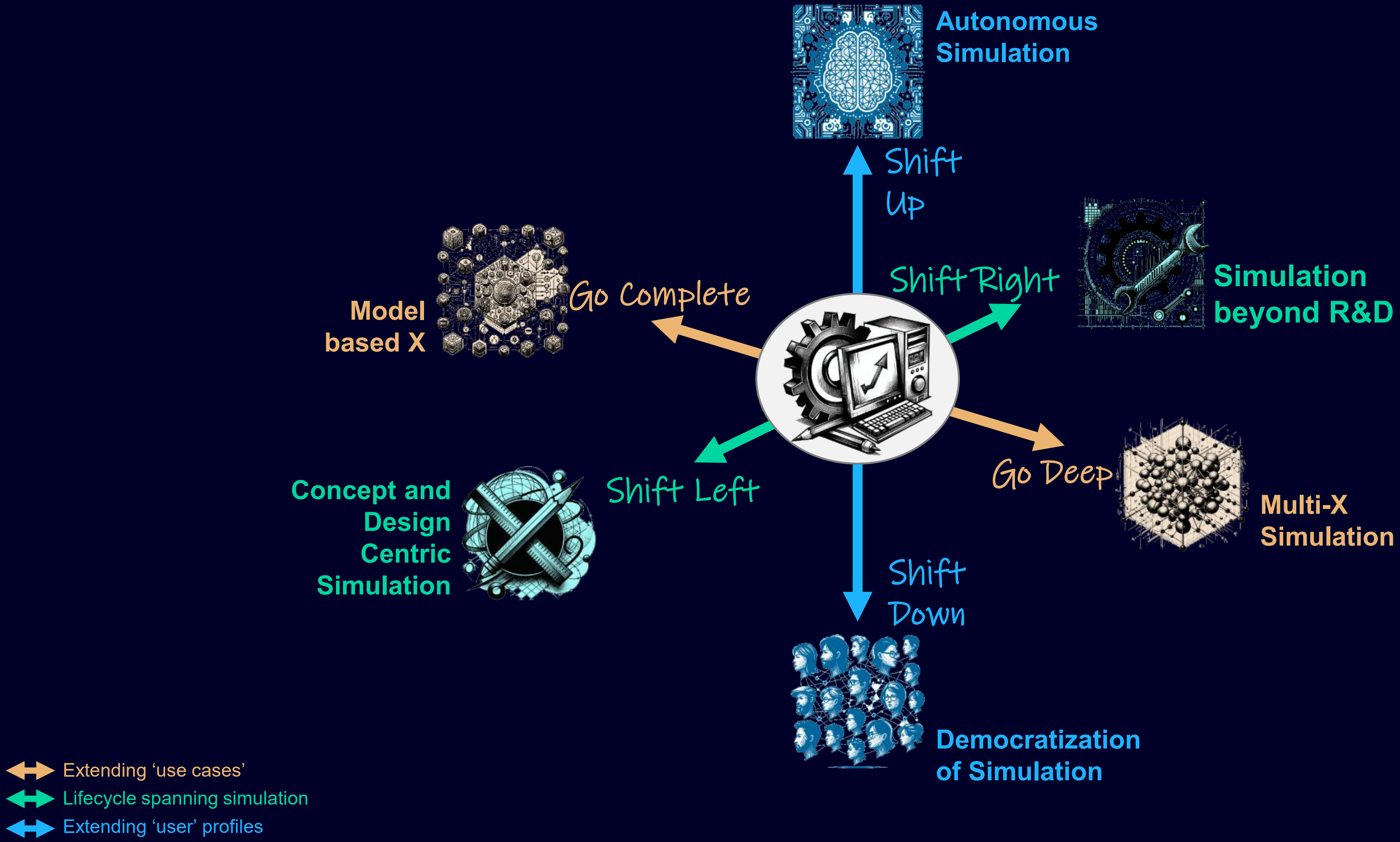
The Digital Twin Paradigm

"A comprehensive set of digital models accepted as full substitutes for reality to understand, predict, and optimize the physical counterpart's performance characteristics for specific purposes. The bidirectional interaction between the digital and the real is central to the digital twin.

Our Vision

"Anyone will be able to easily and robustly predict all relevant behavior of complex systems up to the required realism with compute time and accuracy guarantees.

Digital Twins require a massive expansion of the use of simulation technologies



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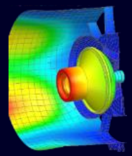
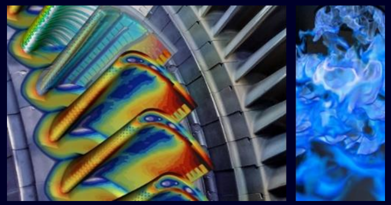
Digital Twins - a golden age for industrial mathematics

Model Pioneers

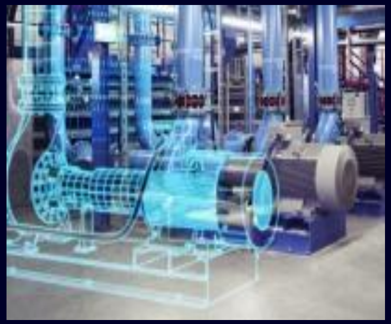


CAx Sunrise



Digital Prototyping

Digital Twin Era



Industrial Metaverse

~1985 ~2000 ~2015 ~2022

CAx: Computer Aided Design, Engineering, & Manufacturing

Source: D. Hartmann, H. Van der Auweraer (2025): Digital Twins - a golden age for industrial. Journal of Mathematics in Industry

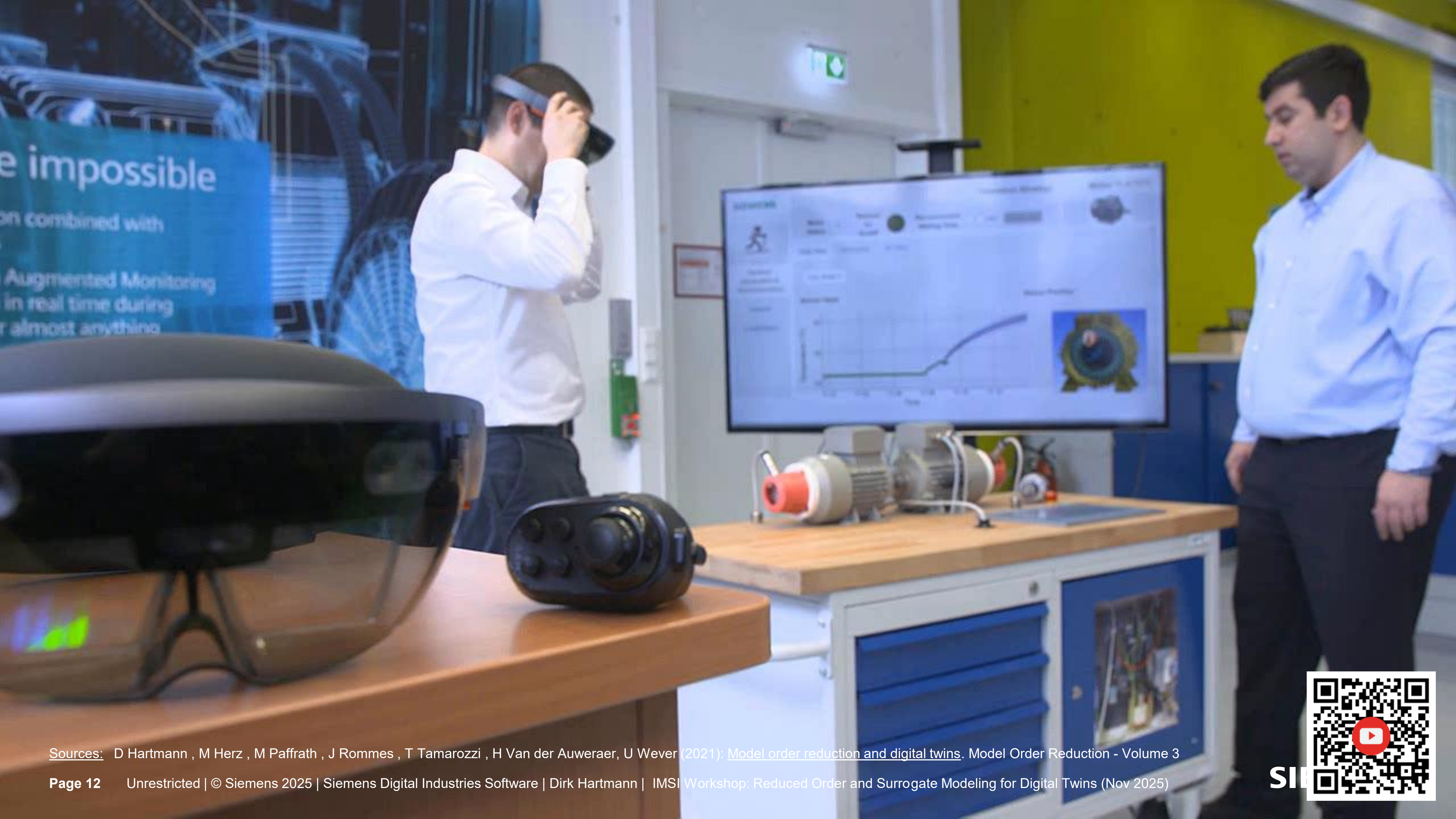
2

Digital Twins @ Work

Major categories of Executable Digital Twin applications

xDT Category	Use this application when you want to…	Examples
Virtual Testing & Commissioning	… prepare for how your asset or system would interact with other assets, systems, or people.	• Testing of automation by virtual commissioning • Testing new control strategies on gas turbines • Operator training
Virtual Sensing	…measure something in your asset or system, but it isn't feasible to put a sensor there.	• Temperature inside electric rotor • Pressure distribution inside a gas turbine • Free-flow inside a sewage network
Diagnosis & Identification	…know why your asset or system is behaving the way it is.	• Unbalance detection of large rotors • Leakage detection in a water distribution network • Predictive maintenance for machine tools
Performance Prediction	…know how your asset or system might behave in future operation.	• Remaining useful lifetime of electric motors • Monitoring of coking in steam cracking furnaces • Movement of people in emergencies
Performance Optimization	…inform actions on how to control the asset or system (with or without a Human-in-the-Loop).	• Model predictive control of a chemical reactor • Pump schedule optimization of oil pipelines • Operating point setting of catalyst modules

Source: D. Hartmann (2021): Real-time Digital Twins.



Sources: D Hartmann , M Herz , M Paffrath , J Rommes , T Tamarozzi , H Van der Auweraer, U Wever (2021): Model order reduction and digital twins. Model Order Reduction - Volume 3

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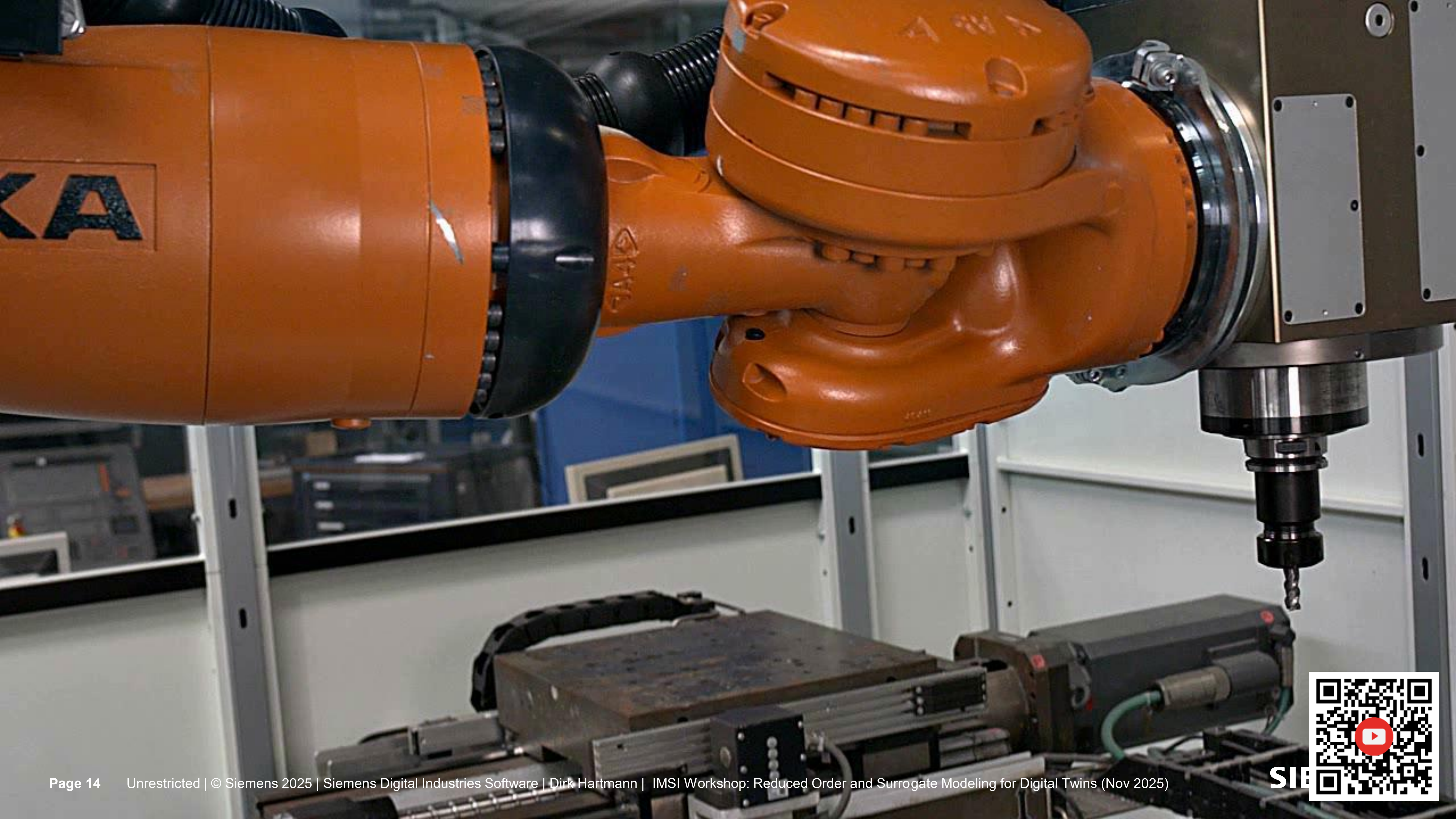
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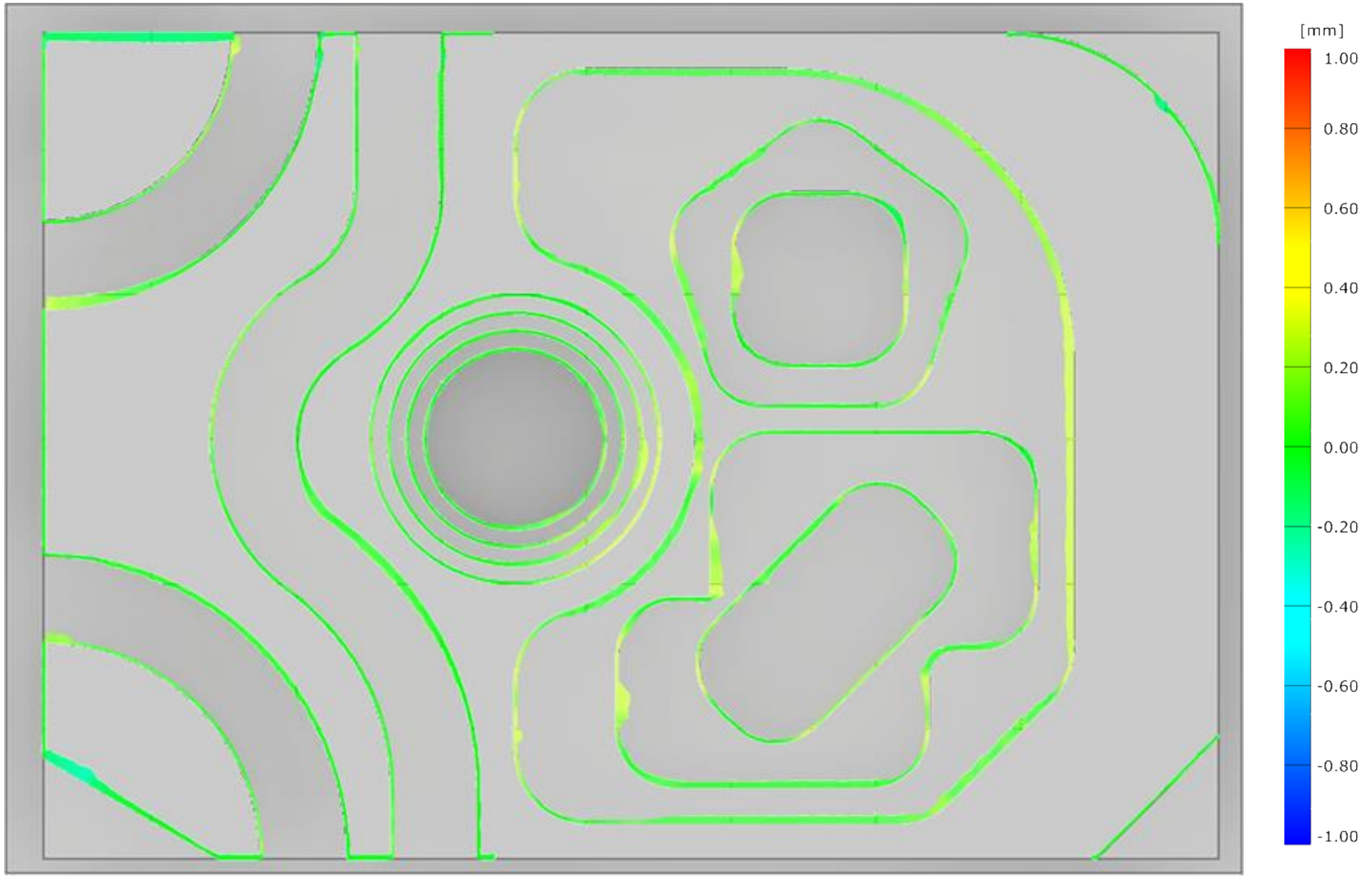

Sources: F Schnös, D Hartmann, B Obst, G Glashagen (2021): GPU accelerated voxel-based machining simulation. Int. J. of Adv. Manufacturing Tech
M Busch, F Schnös, T Semm, MF Zäh, B Obst, D Hartmann (2020): Probabilistic information fusion to model the pose-dependent dynamics of milling robots. Production Engineering
MF Zaeh, F Schnoes, B Obst, D Hartmann (2020): Combined offline simulation and online adaptation approach for the accuracy improvement of milling robots. CIRP Annals

Why do not we see Digital Twins everywhere?

“Despite […] examples of digital twins providing practical impact and value […]
publicity around digital twins […] currently outweighs the evidence base of success.”

Source: National Academies (2024): Foundational Research Gaps and Future Directions for Digital Twins.

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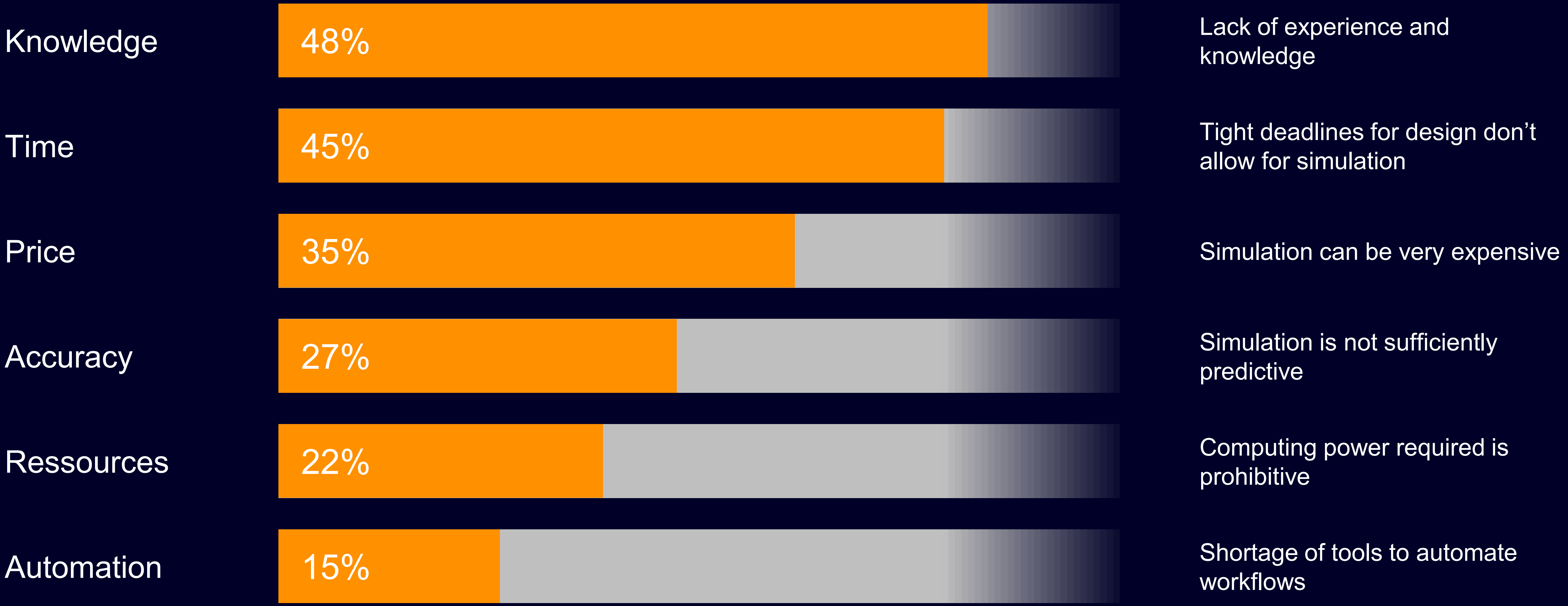
Challenges & Opportunities

Scalability of simulation is limited by the same obstacles since decades.



Source: Engineering.com (2022): Research Report: The State of Simulation, Prototyping and Validation

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Digital Twins are limited by the availability of experts who can realize real-time models in complex software landscapes.

What are the major pain 😣 points for more and broader adoption of #DigitalTwins for #IndustrialOperation and #Service?

Missing calculation power 💻	4%
Missing (real-time) models 📊	32%
Too complex software landscape	28%
Lack of experts 🧓	37%

249 votes

Source: Hartmann D. What are the major pain points for more and broader adoption of Digital Twins for Industrial Operation and Service? 2022.

Key Requirements for a Digital Twin Reduced Order Model

Speed

Accuracy

Workflow Efficiency

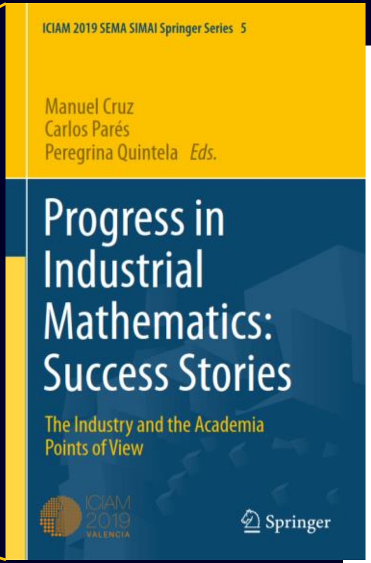
Trustworthiness

Generalizability

Deployability

Usability

Method innovation in predictive technology is key to scale Digital Twins!



Sources: V De Leeuw, D Slansky (2023): The Digital Twin in Industry and Infrastructure, ARC Advisory Group Industry Report
D Hartmann, H van der Auweraer (2020): Digital Twins, Progress in Industrial Mathematics: Success Stories

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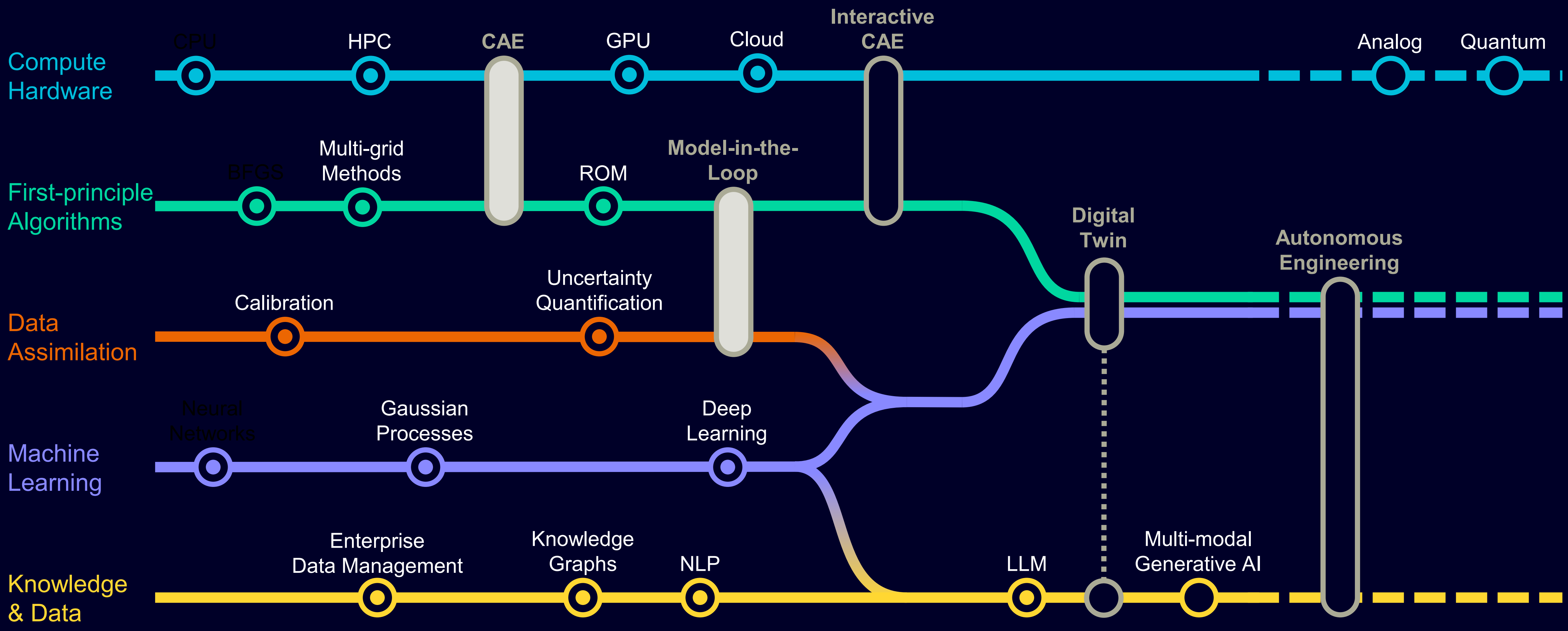
The convergence of technology has driven and will continue to drive innovation – Mathematics is a core element of this!



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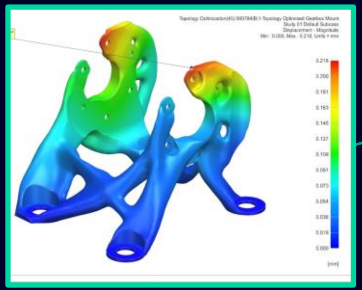
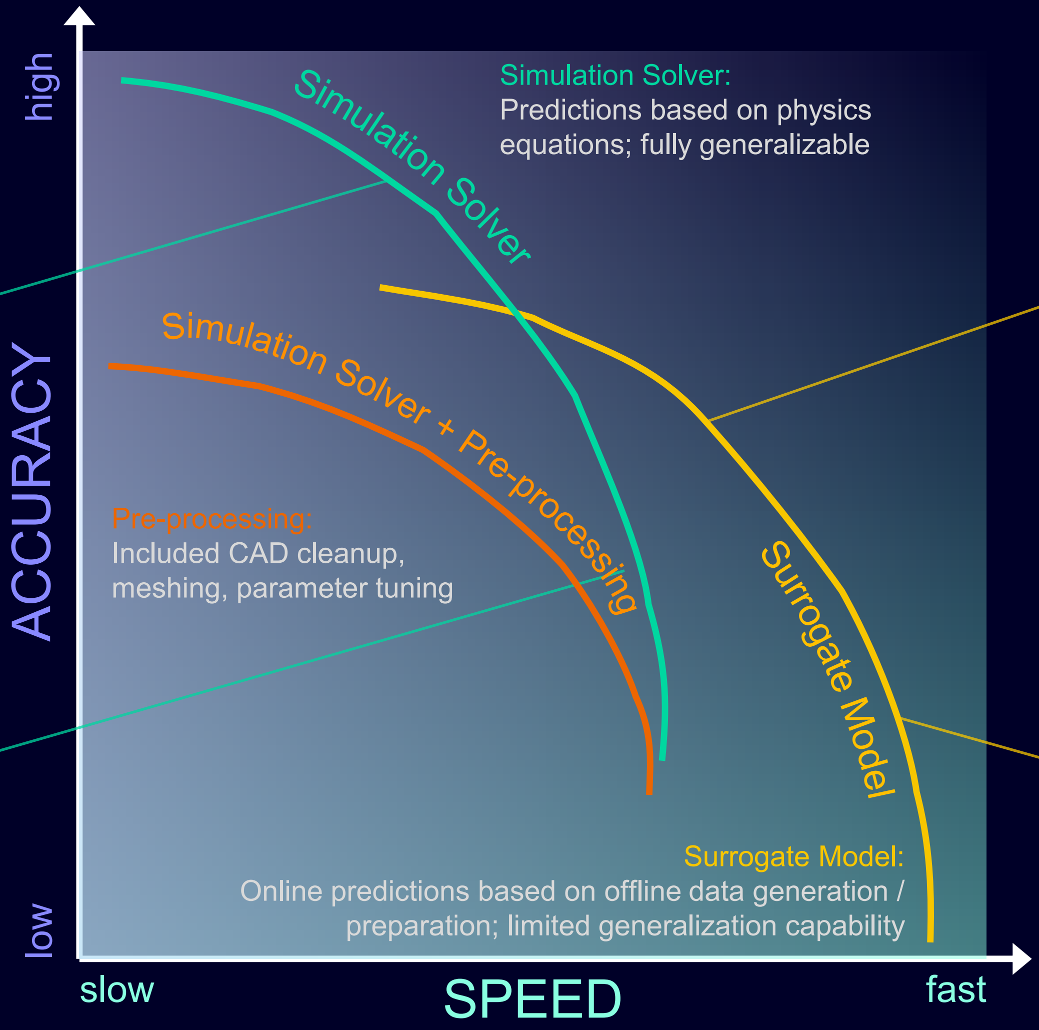
Reduced Order and Surrogate Modeling

Goal: Acceleration of Predictions

High End CFD simulation

Design integrated simulations





Product Configurator

ROM building

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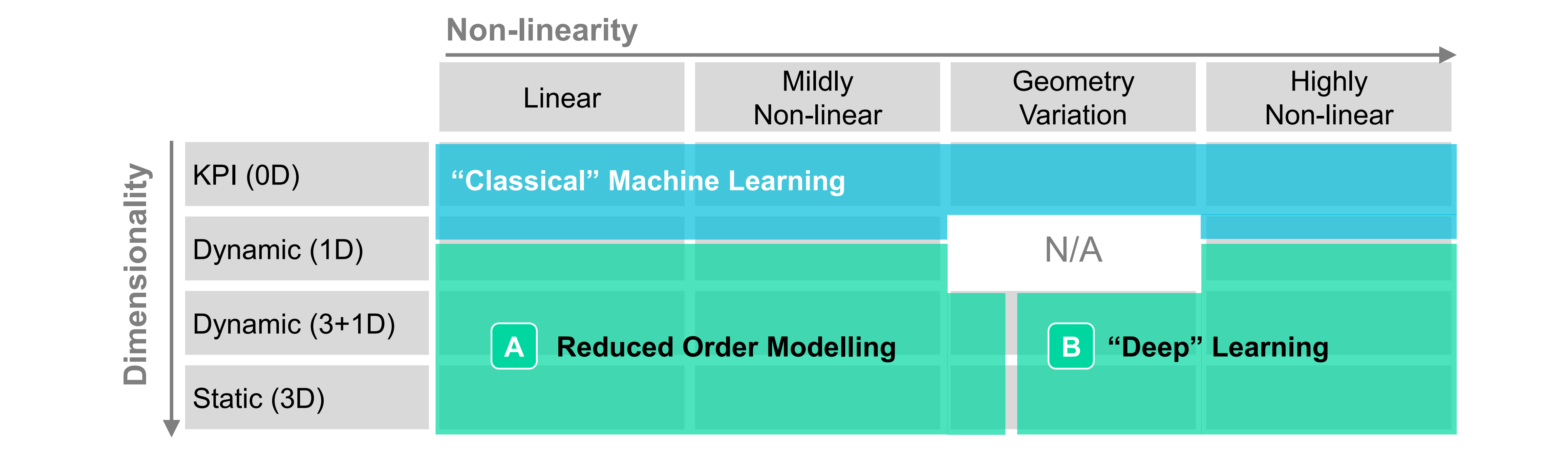
Reduced Order and Surrogate Modeling
Technology Opportunities

There is no one to one mapping between technology and use cases, but the problem categorization in terms of dimensionality & non-linearity can give good guidance.

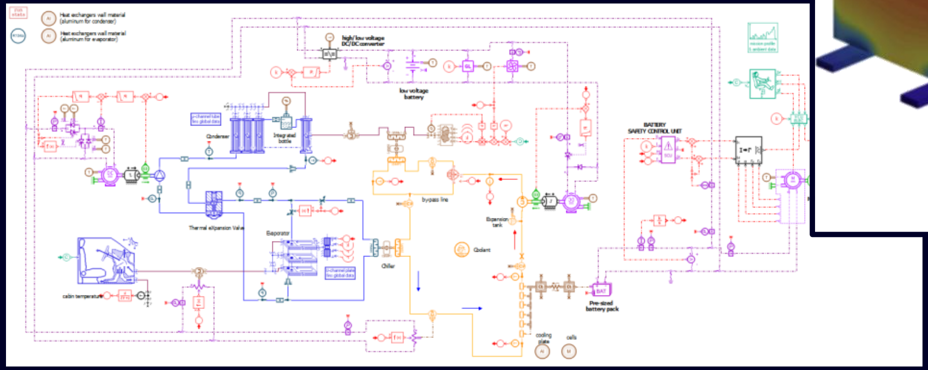


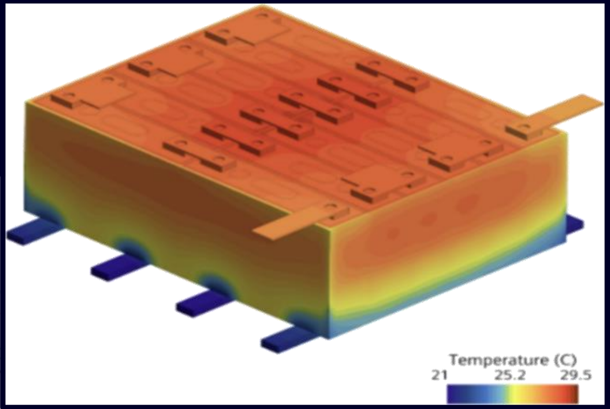
Guideline: Maximize Physical Bias

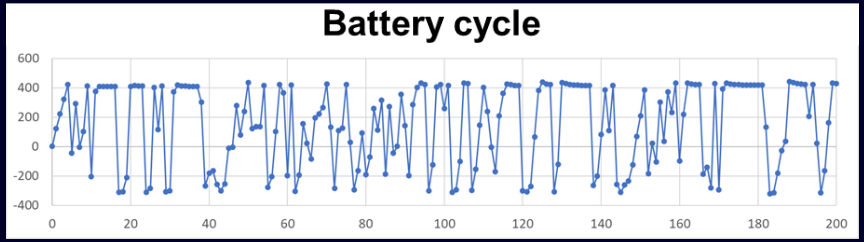
A

Reduced Order Modelling

Battery Thermal Management along the Life Cycle







System Design

Battery Design and 3D Validation

System Validation

…

Monitoring & Control

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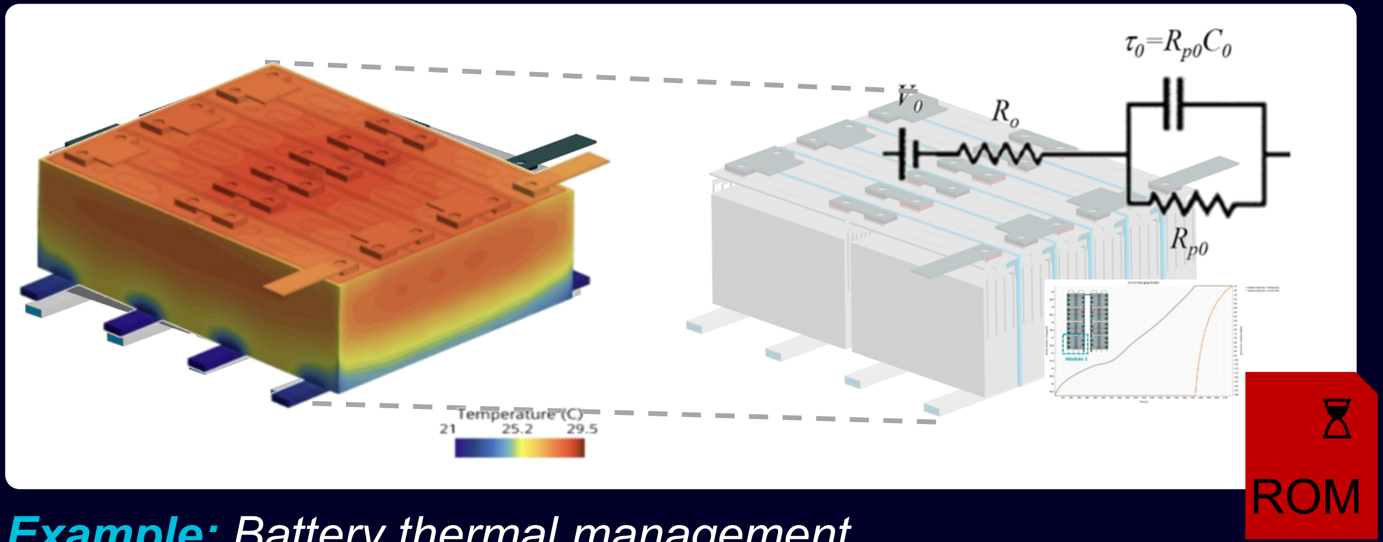
Battery Thermal Management
Reduced Order Modelling



Example: *Battery thermal management*

Challenge:
Controller embedded real-time thermal simulations

Opportunity:
ML-based reduced order modelling technologies

Complex multi-physics model:
- Turbulent fluid flow
- Battery electrochemistry
- Electrical modeling
- ~ 1 million cells

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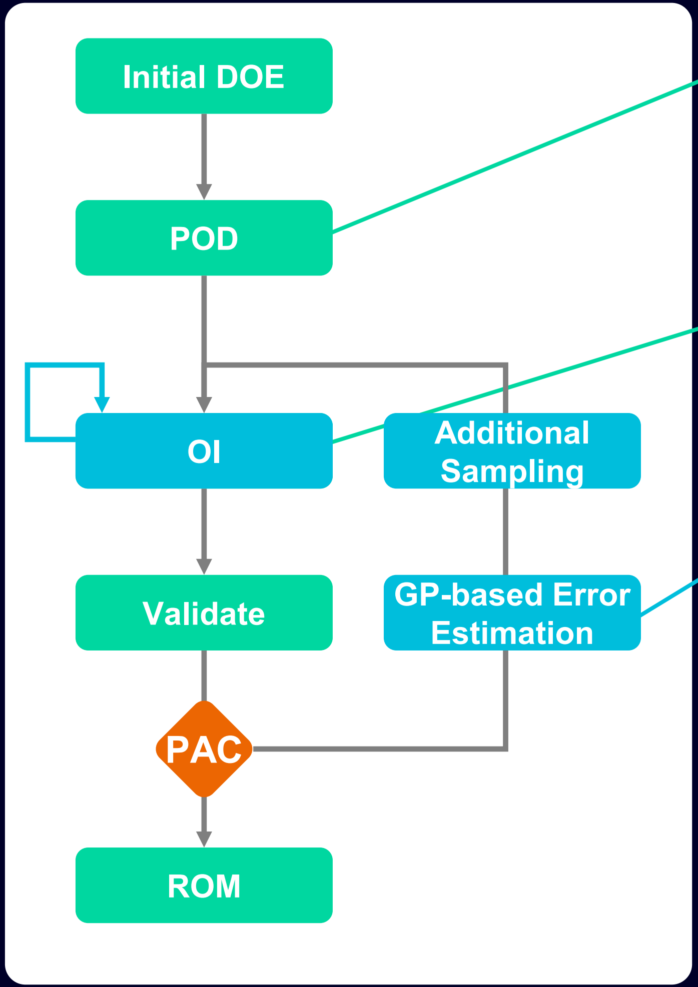
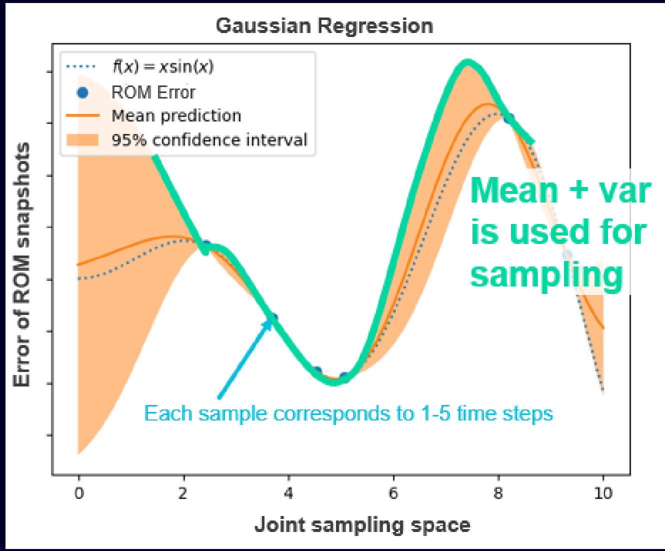
Battery Thermal Management
Technical concept



Latent Dimension Identification, e.g., Autoencoder, Diffusion Maps, Dynamic Mode Decomposition, Proper Orthogonal Decomposition (POD), …

Reduced Model Discovery, e.g., Discrete Empirical Interpolation, Neural Networks, Operator Inference (OI), …
with Trajectory Learning

Active Learning, e.g., classical Design of Experiments



Source: Q Zhuang, D Hartmann, HJ Bungartz, JM Lorenzi (2023): Active-learning-based nonintrusive model order reduction; Data-centric Eng
Q Zhuang, JM Lorenzi, HJ Bungartz, D Hartmann (2021): Model order reduction based on Runge–Kutta neural networks; Data-centric Eng

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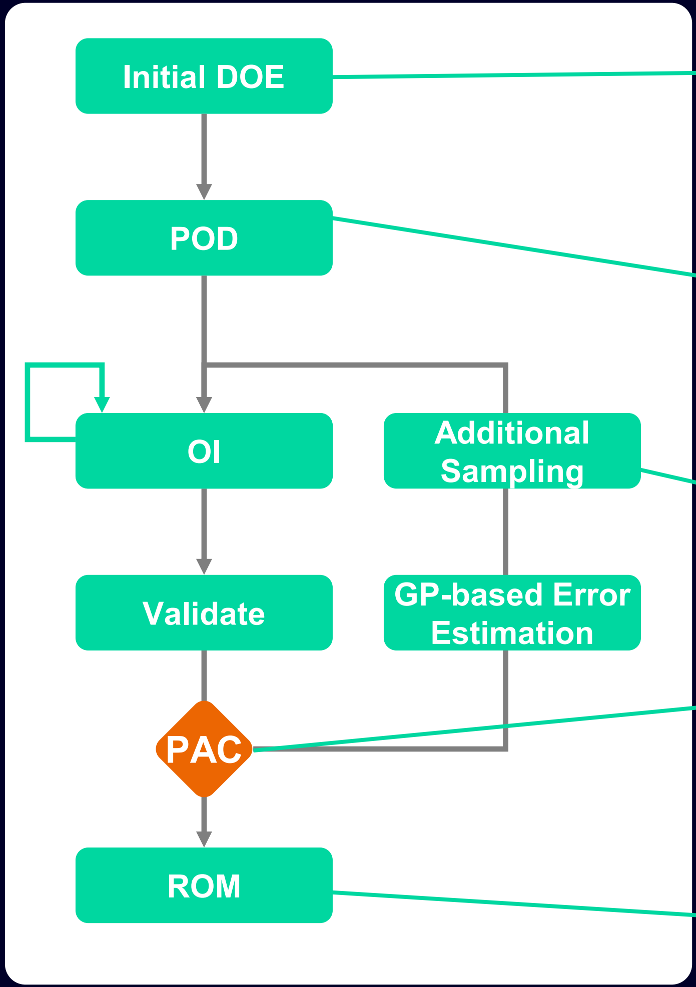
Battery Thermal Management
Results



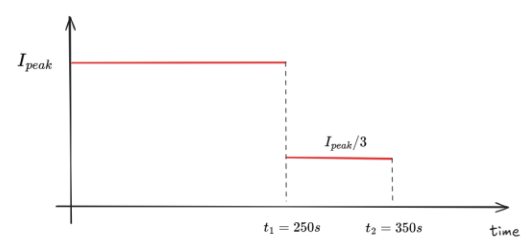
15 long simulations[1] for different parameters
[Time: **4h | **Size on disk: **4.1 GB**]

POD on initial DoE data
[Time: **20' | **Size on disk: **0.7 GB**]

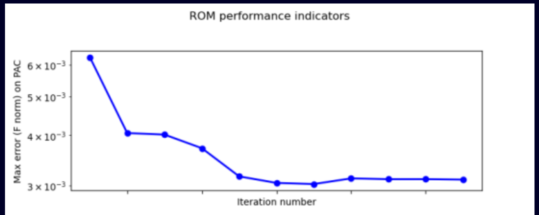
AL loop, 11 iterations with 5 short[2] sim. each
[Time: **2h 20' | **Size on disk: **3.4 GB**]

PAC based on 58 short simulations[2]
[Time: **2h 30' | **Size on disk: **3.6 GB**]

Real-time capable ROM (20 ODEs)



Heating Profile



Error improvement

1) 350 time steps per simulation 2) 5 time steps per simulation

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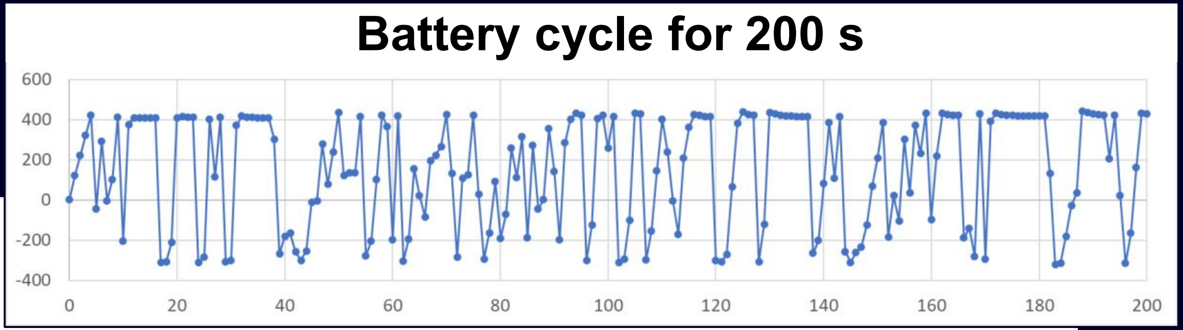
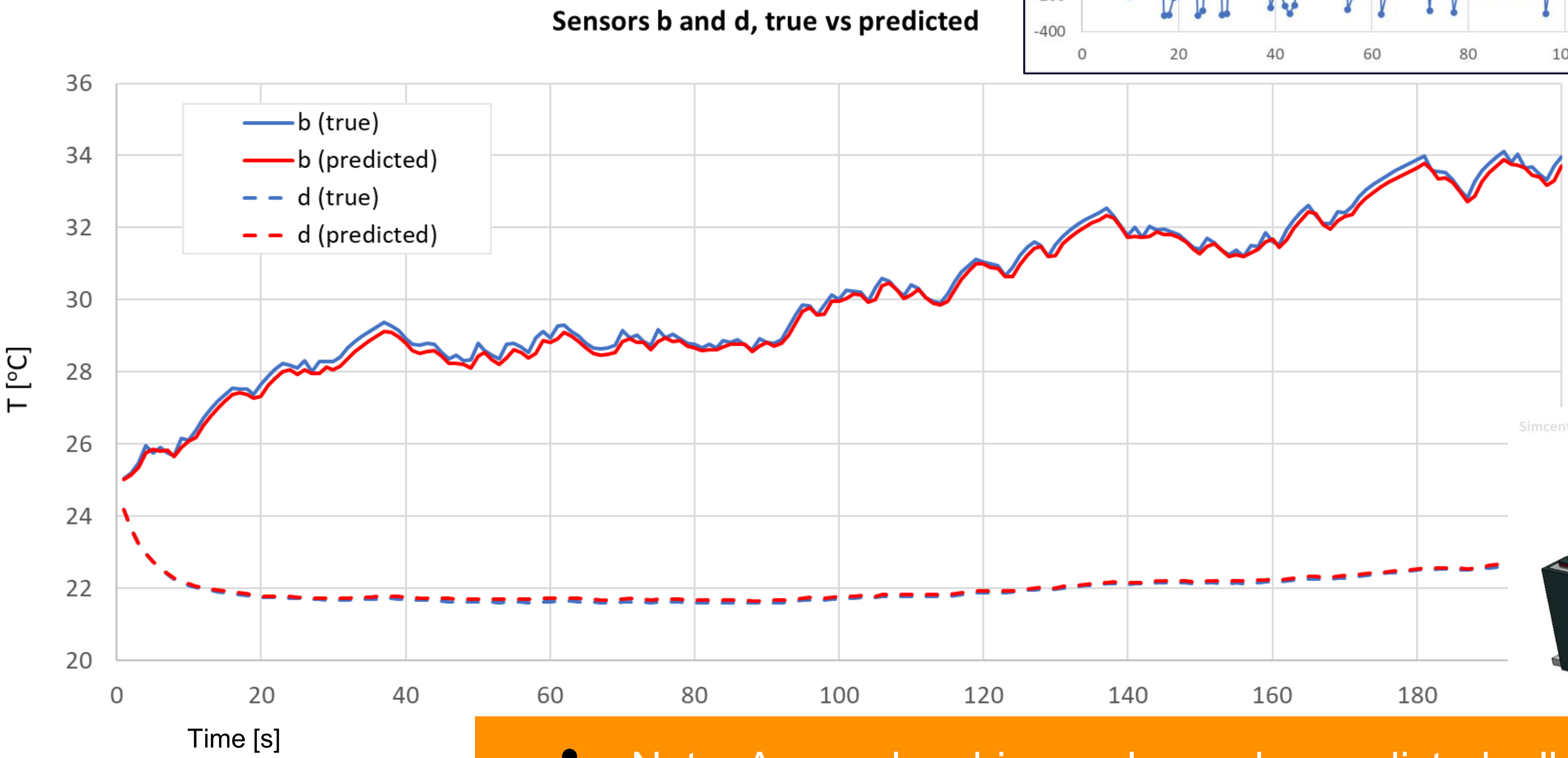
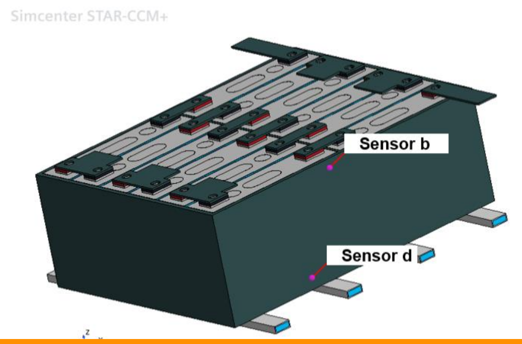
Battery Thermal Management
Results







Note: A complex drive cycle can be predicted, albeit the model has seen only simple step functions in the training phase.

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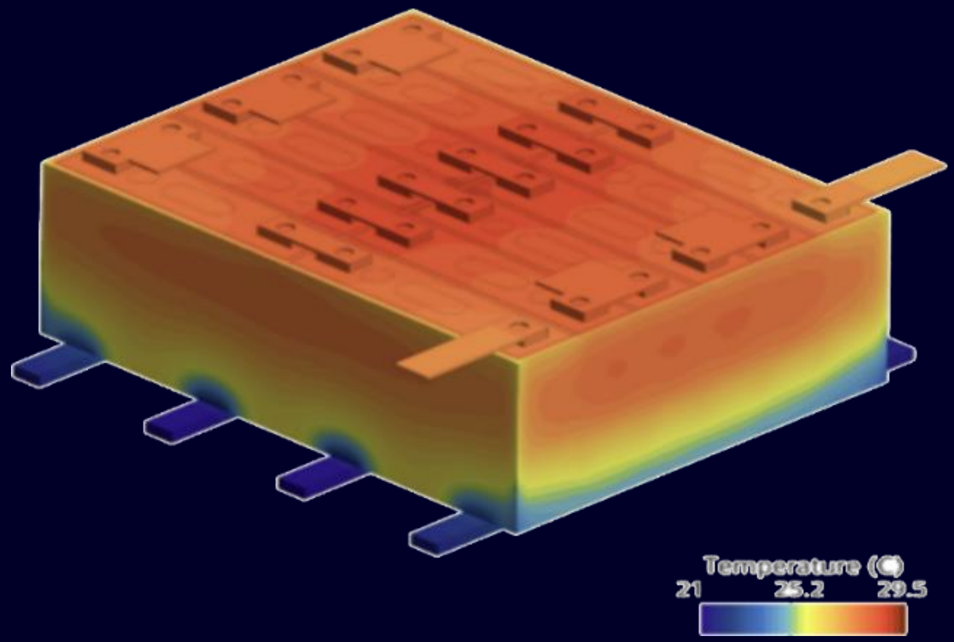
Battery Thermal Management
A fast simulation model isn't everything

There is many more elements to get the Digital Twin working:

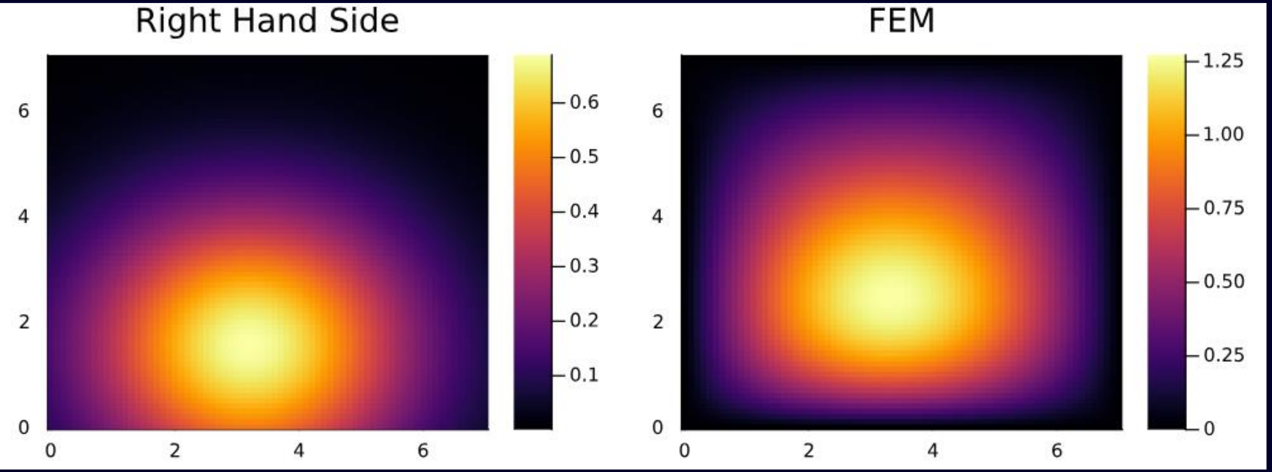
- Data assimilation
- Practical uncertainty quantification
- Integration in control loops
- Digital rights management
- "Obscure" compute hardware
- Required effort & expertise to setup
- …



B

“Brute Force” Surrogate Modelling

Poisson Equation
Brute Force Surrogate Modelling



Example: *Simple Poisson Model*

$$\Delta u = f \text{ on } \Omega, \qquad u = 0 \text{ on } \partial\Omega$$

Challenge:
ML-based surrogate model with limited data requirements, generalizability, trustworthiness

Opportunity:
Domain Decomposition based hybridized Neural Solver

Source: D. Hartmann (2025): Hybridized Data Driven Flux-Conservative Solvers: Towards Foundation Models for PDE-Solving. 1st Workshop on Differentiable Systems and Scientific Machine Learning @ EurIPS 2025

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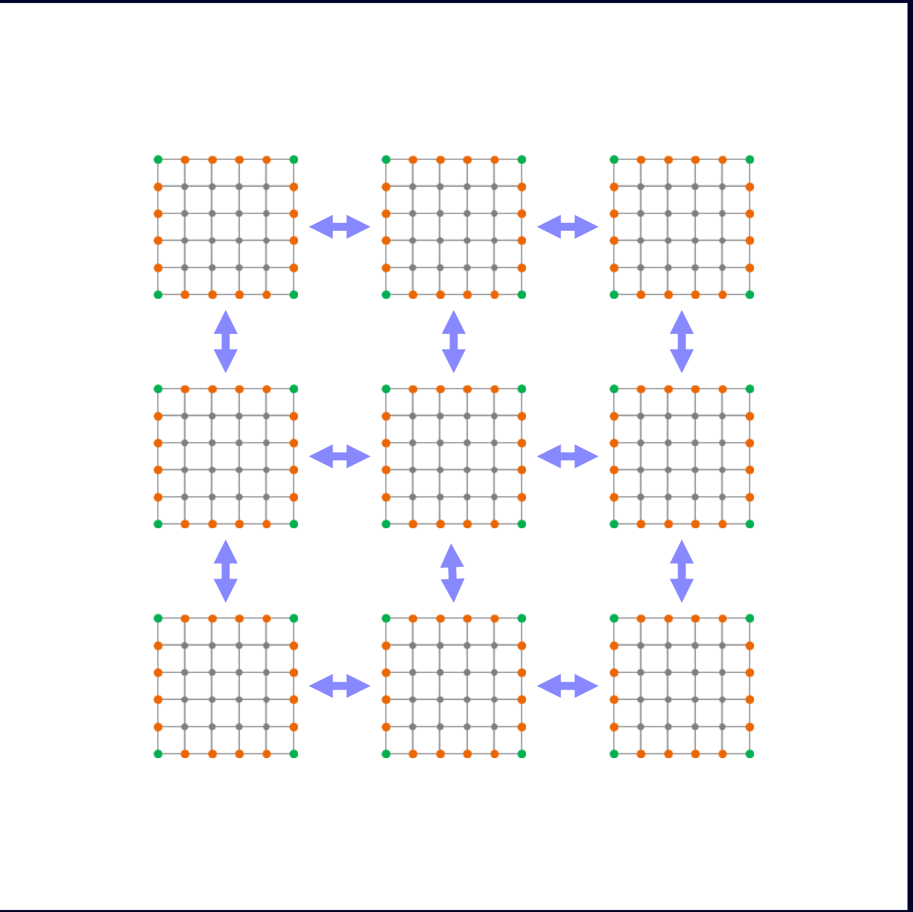
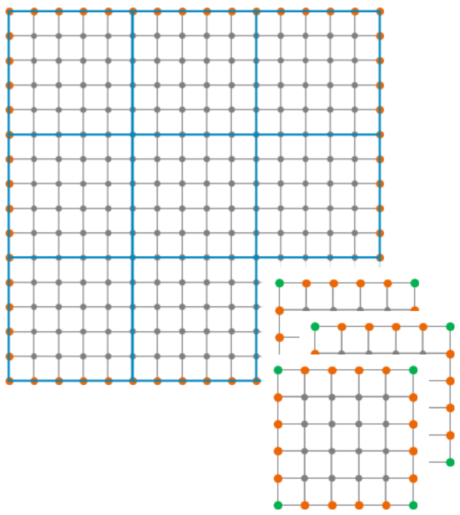
Hybridized Flux Conservative Neural Solver
Ideas



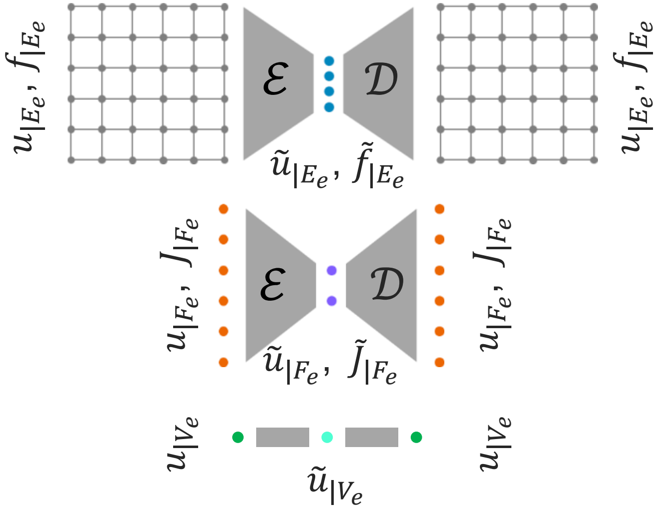
- Domain Decomposition
- Hybridization (Interface variables as main variables)
- Sub-element-based training
- Flux-conservation as coupling condition

Hybridized Flux Conservative Neural Solver
Training Process

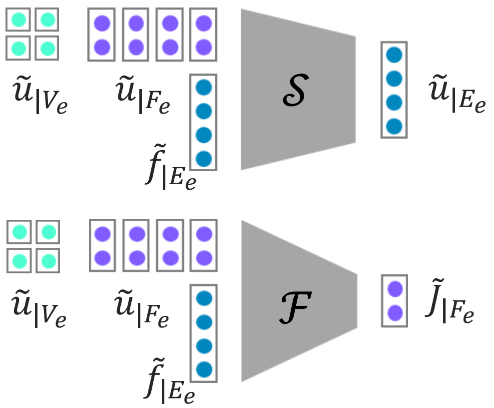
Domain decomposition into **HDD-DG elements**



Encoding of vertex, face, and inner variables



Operator learning of solution and flux operators



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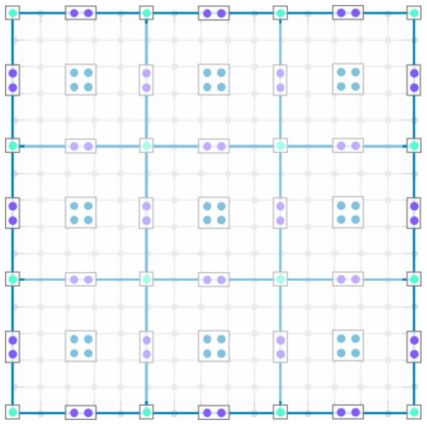
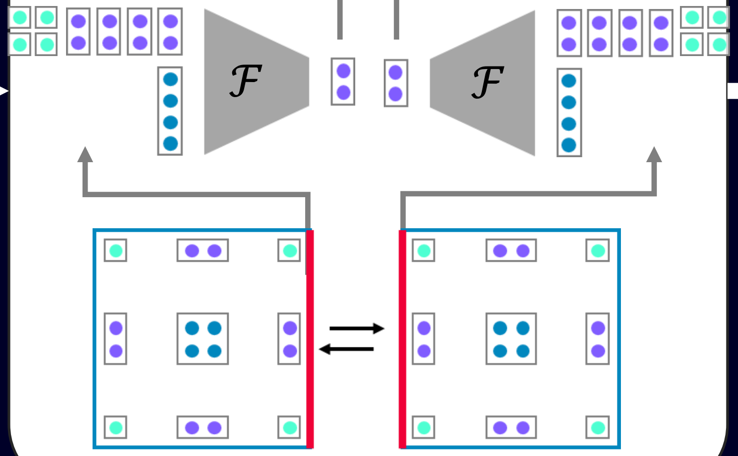
Hybridized Flux Conservative Neural Solver
Inference Process

Encode right hand side and boundary conditions

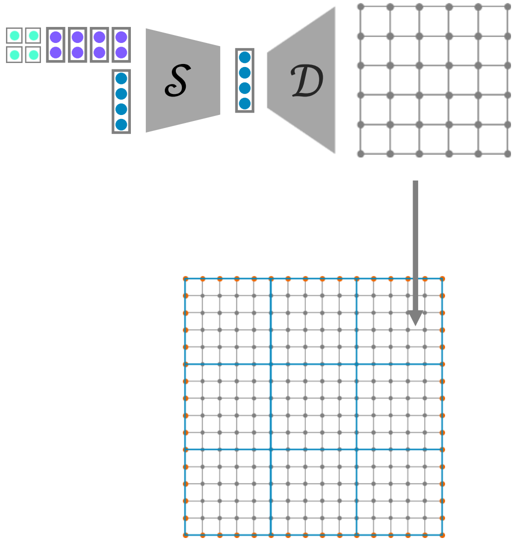


Assemble Δ fluxes for each **face and solve**

$$\min_{\tilde{u}_{|V_e},\tilde{u}_{|F_e}} \sum_i \left\|\Delta J_{|F_i}\right\|^2$$



Recover latent solution **and decode**



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Hybridized Flux Conservative Neural Solver
Results

Setup:

- **Data:** 100 Simulations with 70x70 Finite Elements and random
  $f = a\, \exp(-(x-\mu)^2/2\sigma^2)$
- **Autoencoders:** PCA with 2 / 4 modes for faces / elements respectively
- **Operators:** 4-layer NN
- **Training:** Adams
- **Solution:** BFGS

Results:

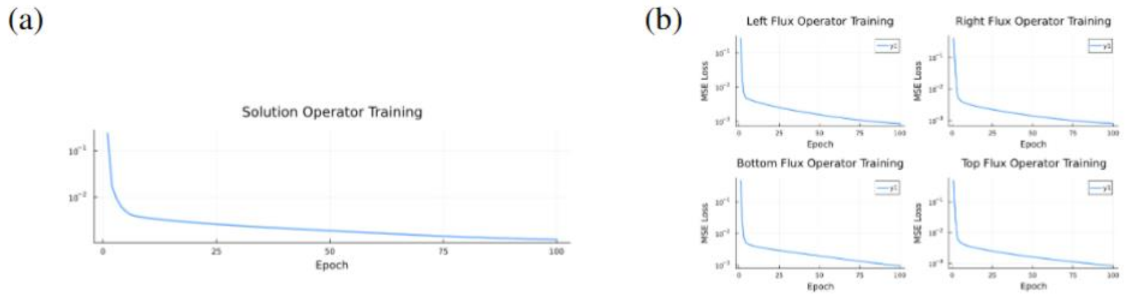


Figure 1: Loss evolution of the operator training (PCA encoding)): (a) solution operator, (b) flux operators.

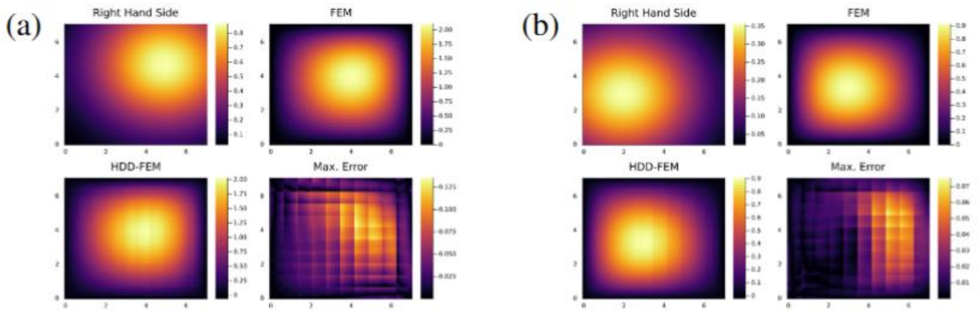
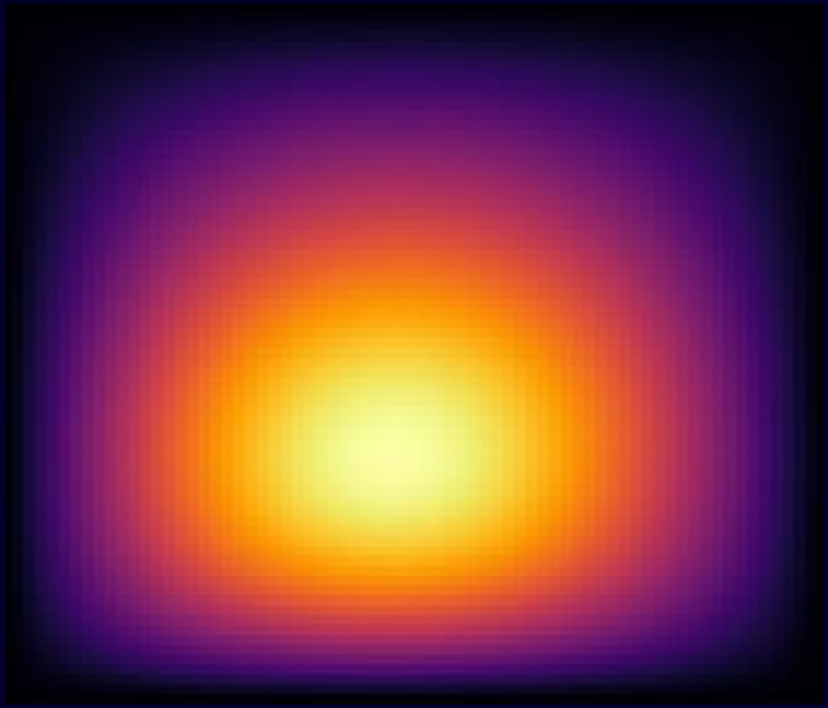


Figure 2: Validation of the method using PCA-encoding for two randomly chosen source functions f which have not been seen during the training.

Hybridized Flux Conservative Neural Solver
Open topics

This is just a first idea, thus there are many open questions

- More complex non-linear cases
- Geometry encoding
- Optimal non-linear solver
- Optimal architectures
- Coupling with other methods
- …



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5

The Future?

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Demo: An AI Companion for Design and Engineering

Source: GradCad (2013): GE jet engine bracket challenge

Aircraft Engine Bracket - Technical Specification

Maximum Size (width x depth x height): 10in x 5in x 3in

Iterface 1: 0.75 inch diameter pin.

Fixation / Inteface 2-5: 4 0.375-24 AS3239-26 machine bolt: Nut face 0.405 in. max ID and 0.558 in. min OD

Minimum material feature size (wall thickness): 0.050 in.

Material: Ti-6Al-4V

Service Temperature: 75 F

Load Conditions:

1. Max static linear load of 8,000 lbs vertical up.

Design Goal

- Maximum yield stress below 131 ksi
- Minimum weight

bracket.md

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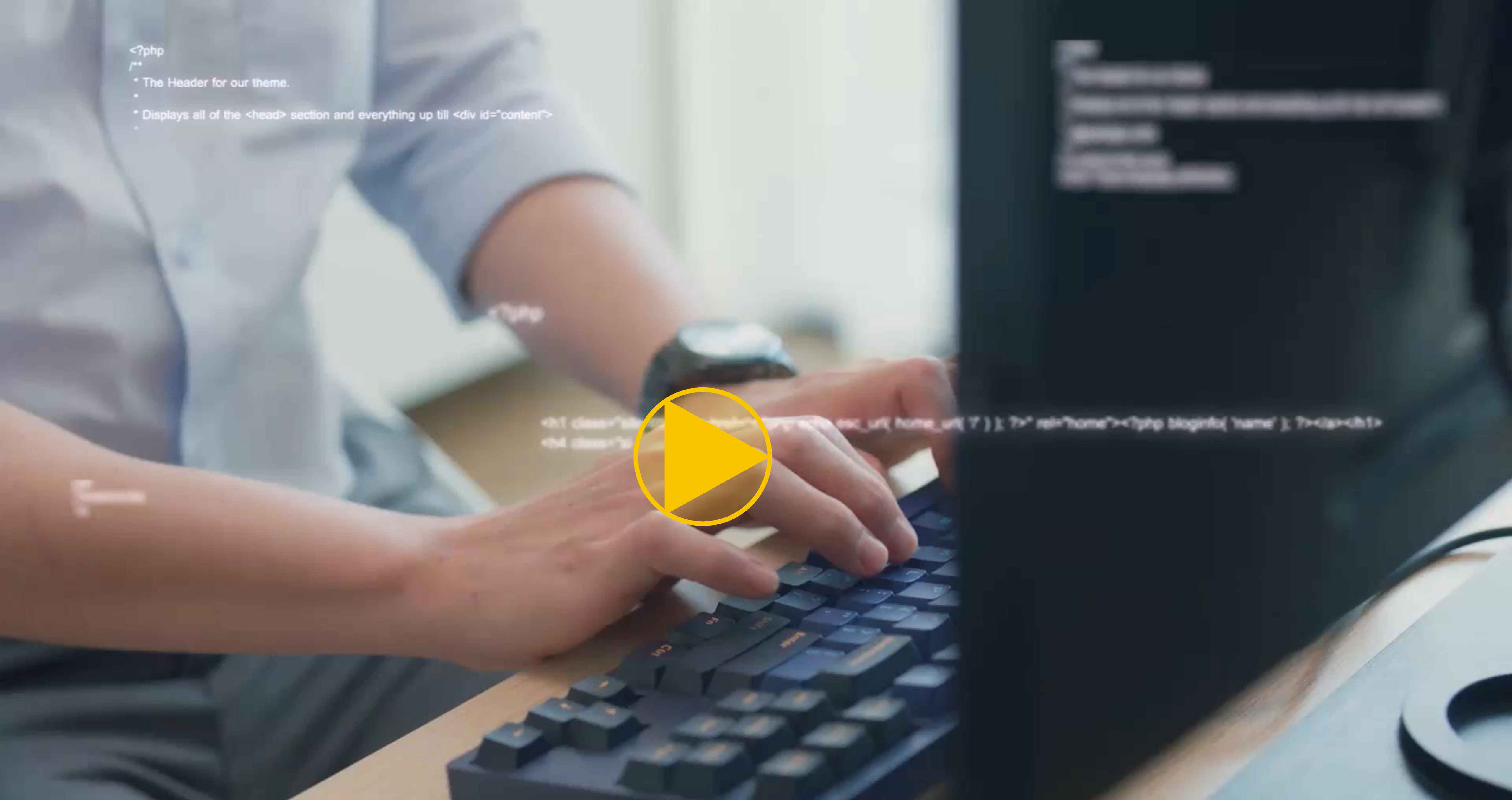
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* The Header for our theme.
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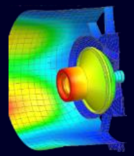
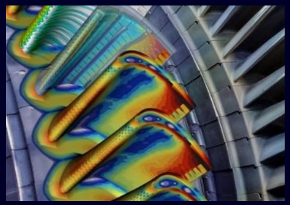
Digital Twins - a golden age for industrial mathematics

Model Pioneers

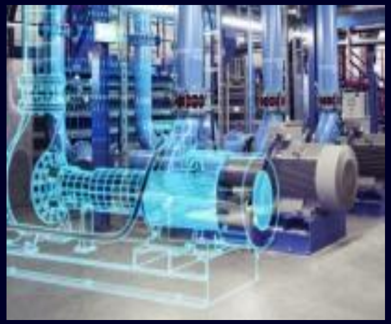


CAx Sunrise



Digital Prototyping

Digital Twin Era



Industrial Metaverse

~1985 ~2000 ~2015 ~2022

CAx: Computer Aided Design, Engineering, & Manufacturing

Source: D. Hartmann, H. Van der Auweraer (2025): Digital Twins - a golden age for industrial. Journal of Mathematics in Industry

Contact

Dr. Dirk Hartmann
Head of Simcenter Technology Innovation
Siemens Digital Industries Software
Simulation and Test Solutions
Otto-Hahn-Ring 6
81739 Munich
Germany

Mobile +49 173 2537709
E-mail hartmann.dirk@siemens.com

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