Powering Innovation That Drives Human Advancement

Hybrid Digital Twins for Operations and Maintenance

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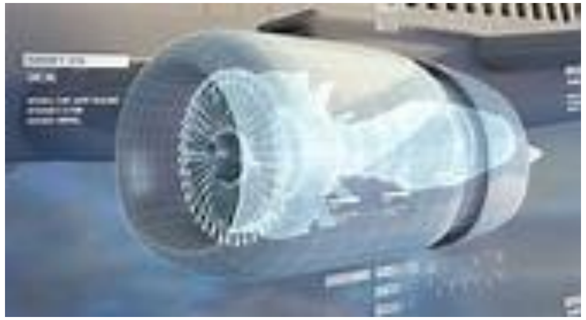
What is a Digital Twin?

digital twin CONSORTIUM : “**Virtual representation** of **real-world entities** and **processes**, **synchronized** at a specified **frequency** and **fidelity**”



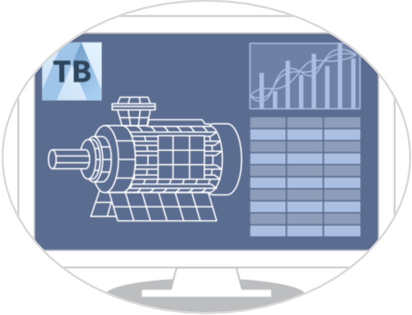
Real Asset, Process or System

Operating variables

Data/info exchange

Actionable Insights

Digital Twin



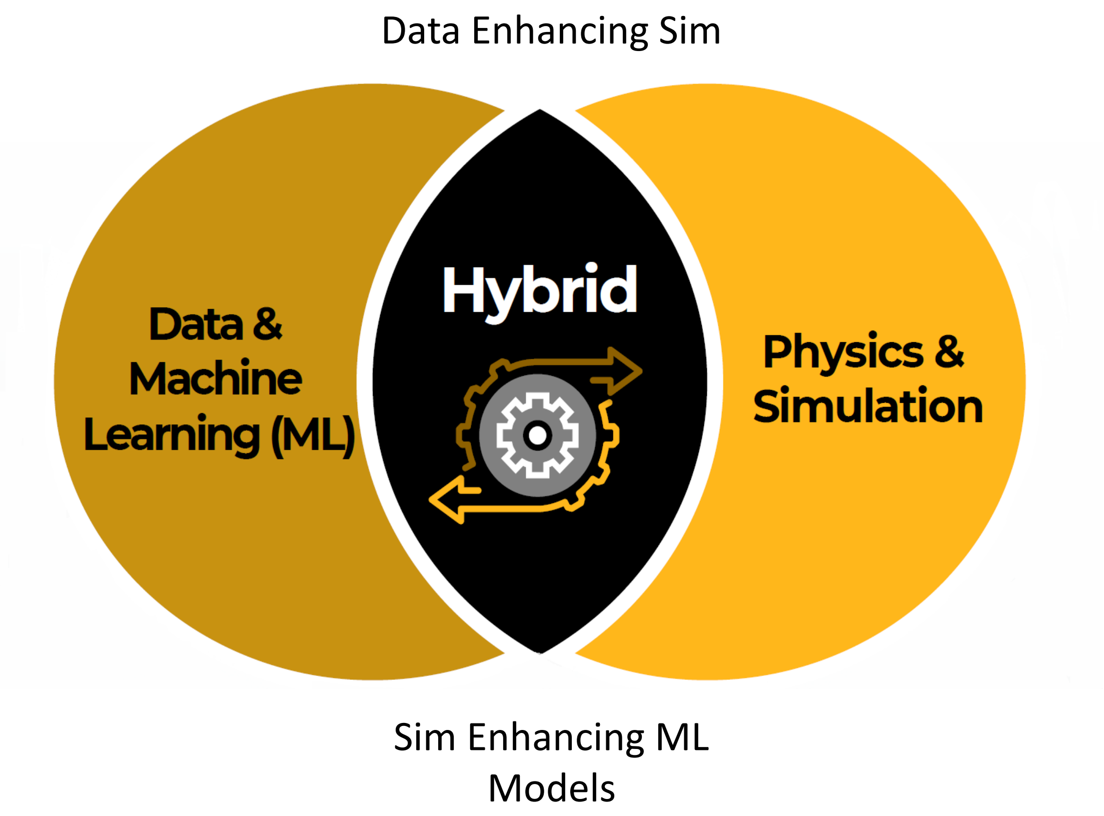
Business Value: Track the past, provide deeper insights into the present, predict and influence future behavior

Hybrid Digital Twins

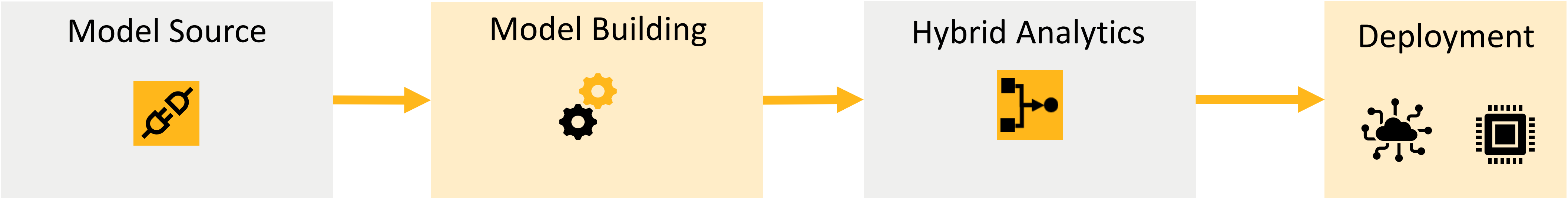
Models based on sensor data are limited to predict within past performance and available training data.

Models based on **physics at times fail** to capture system reality due to equipment aging and/or missing physics.

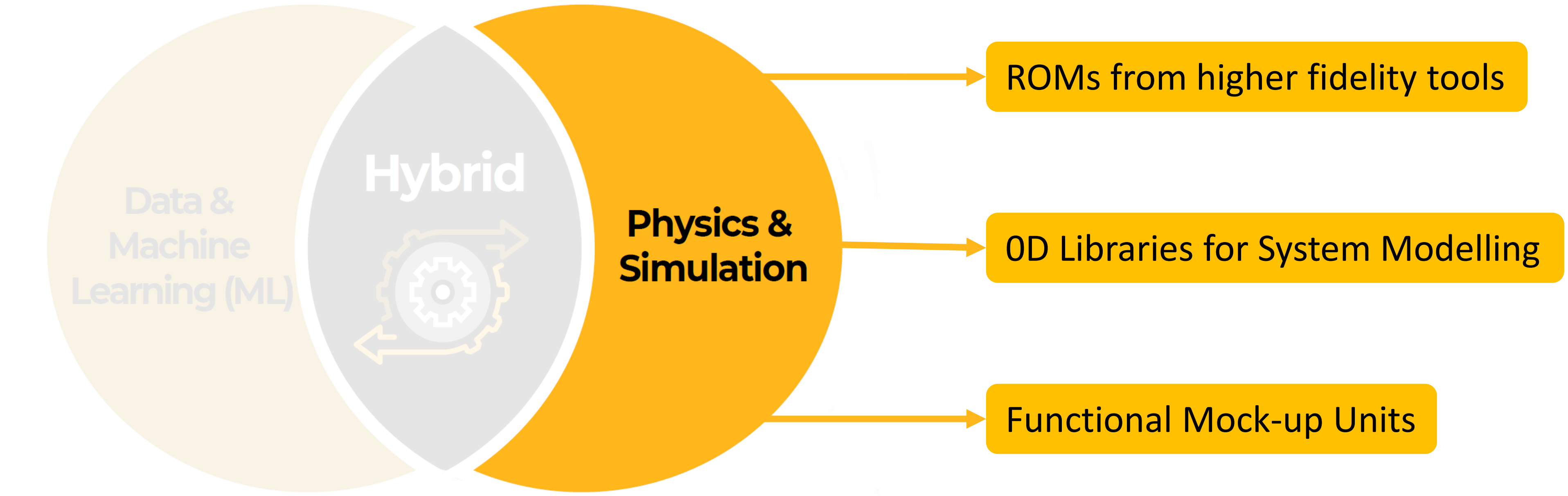
Ansys Hybrid Digital Twins **combines the best of both worlds**, all deployed in platform agnostic containers.



Simplified Digital Twin Workflow



Decoding the Elements of Twin Building



What is a ROM?

Reduced Order Model (ROM)

Model Order Reduction (MOR) is a technique for reducing the computational complexity of mathematical models in numerical simulations.

The output of this technique is a **Reduced Order Model** (ROM).

Benefits of ROM

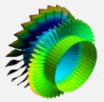
Reduced simulation time (think 10-100x)

- Ideal for Design of Experiments (DoE)/ Parameter sweep
- Integration in Twin Builder for system simulation
- Runtime generation for near real-time applications

Reduced storage size

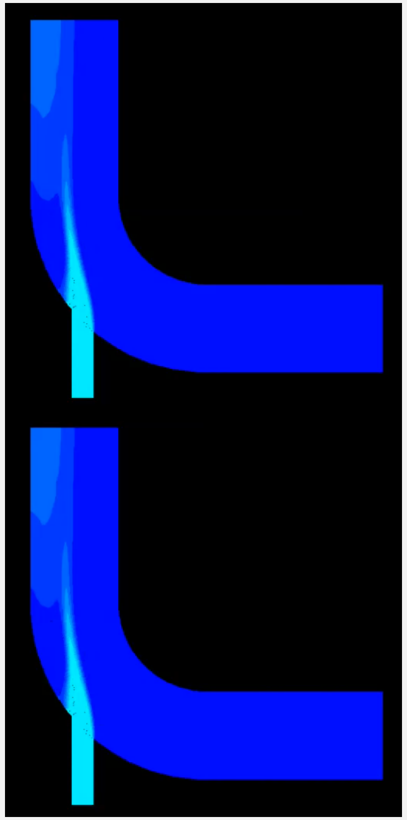
- Reduce the required storage size dramatically

Reuse 3D model



- Utilize validated 3D physics in system model and digital twins

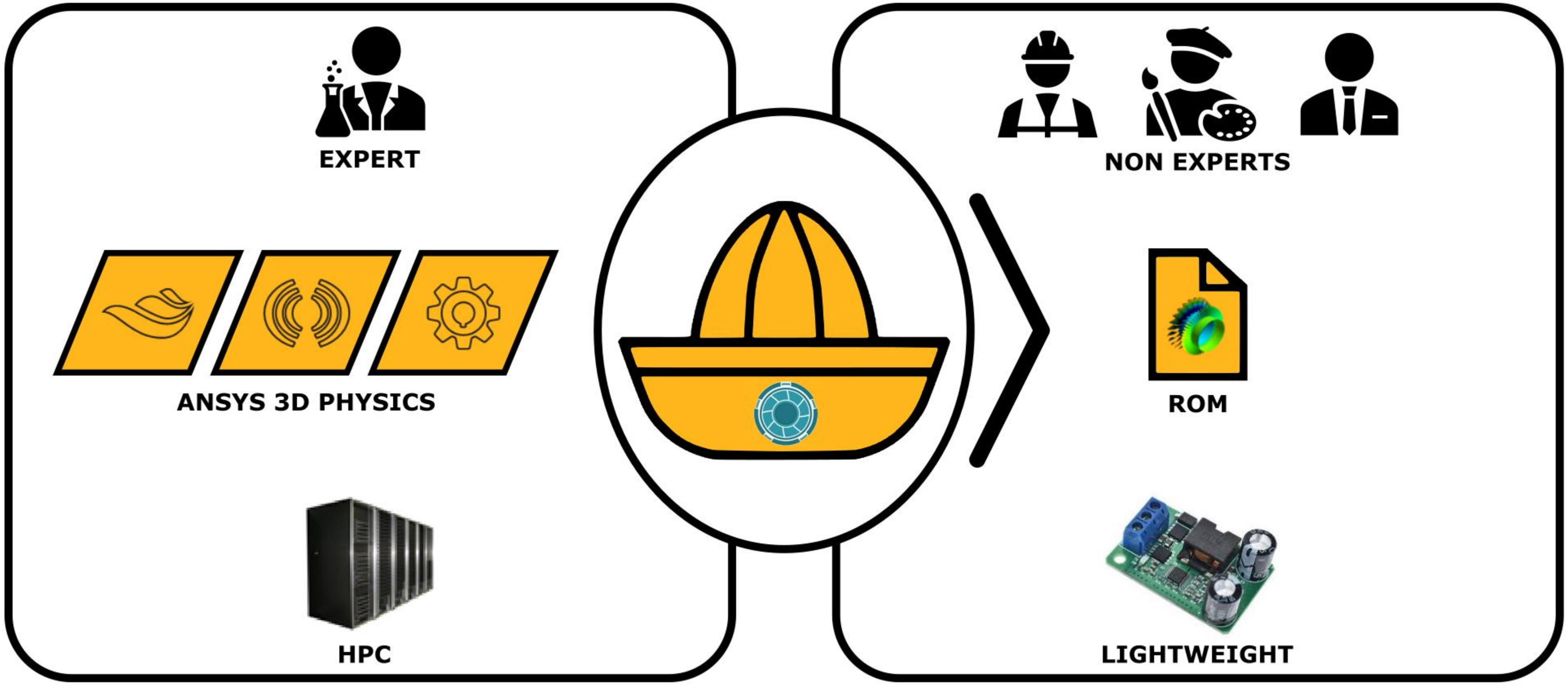
Fluent CFD Simulation: 3 hours on 12 cores



ROM Simulation Realtime

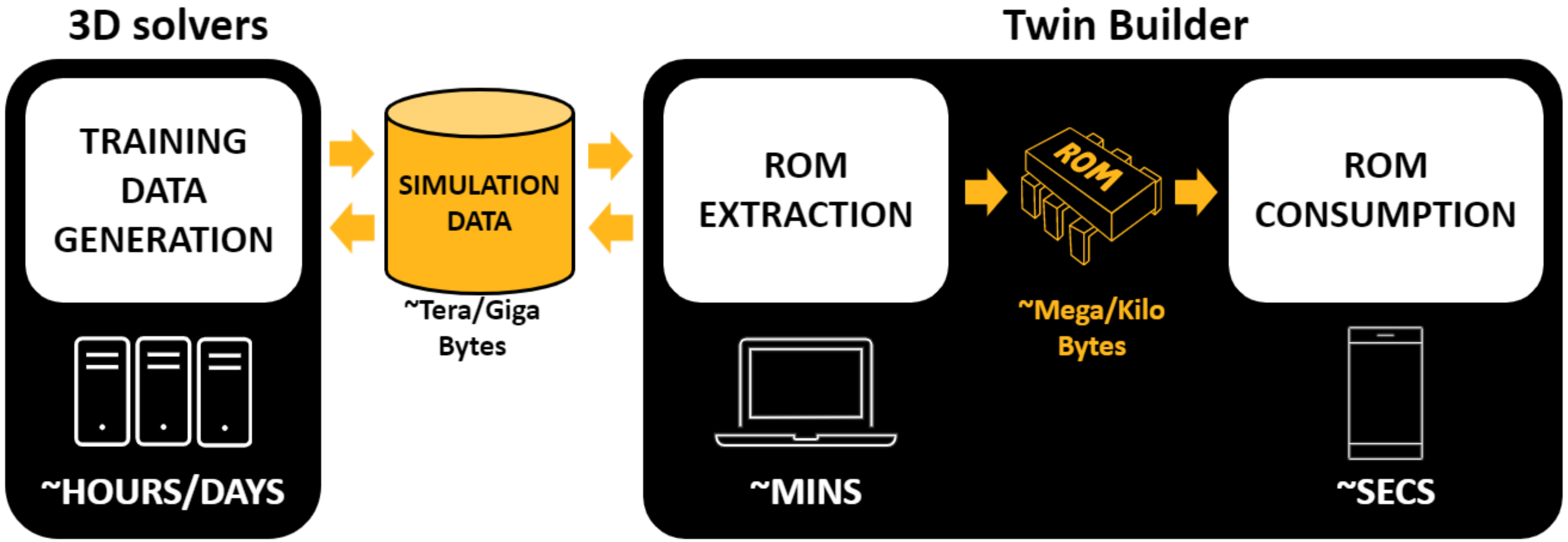
Why ROM is key to your success on digitalization?

Because it brings real-time physical prediction to your digital twin!



ROM Generation workflow – Extract ROM from simulation results

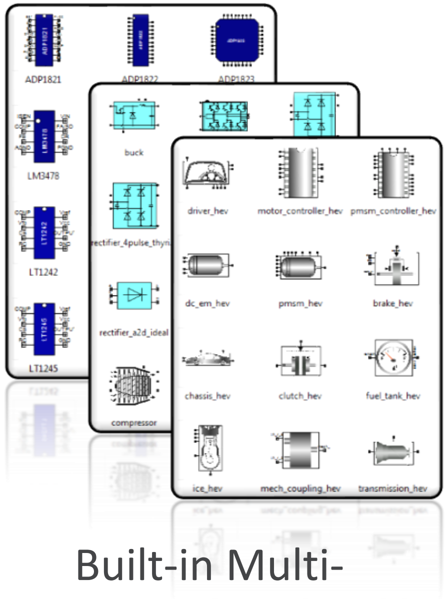
- Non-intrusive technology
  - It works for any mesh-based solvers (Fluent, Mechanical, Maxwell, …) and even Third-party solvers
- Machine learning workflow



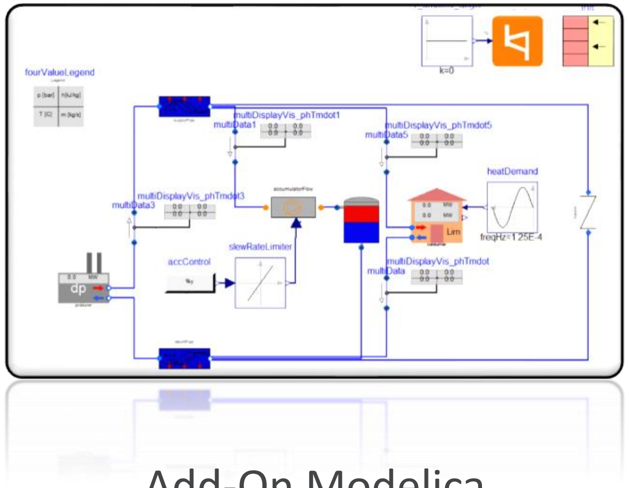
Extensive 0D Application Specific Libraries

Develop multi-domain system models using built-in and add-on libraries

- Develop multi-domain system models using built-in Modelica and specialized Twin Builder libraries.
- Add-on Modelica Libraries:
  - Heating and Cooling Library
  - Fluid Power Library
  - EV Powertrain Library



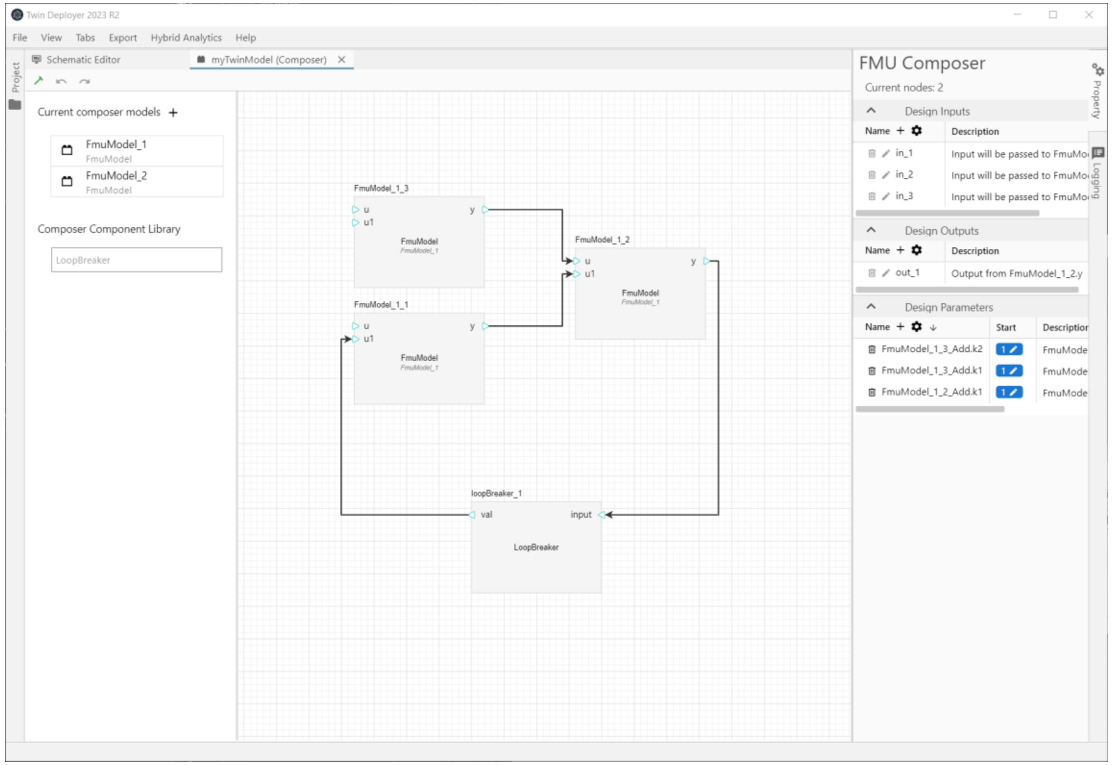
Built-in Multi-Domain System Libraries



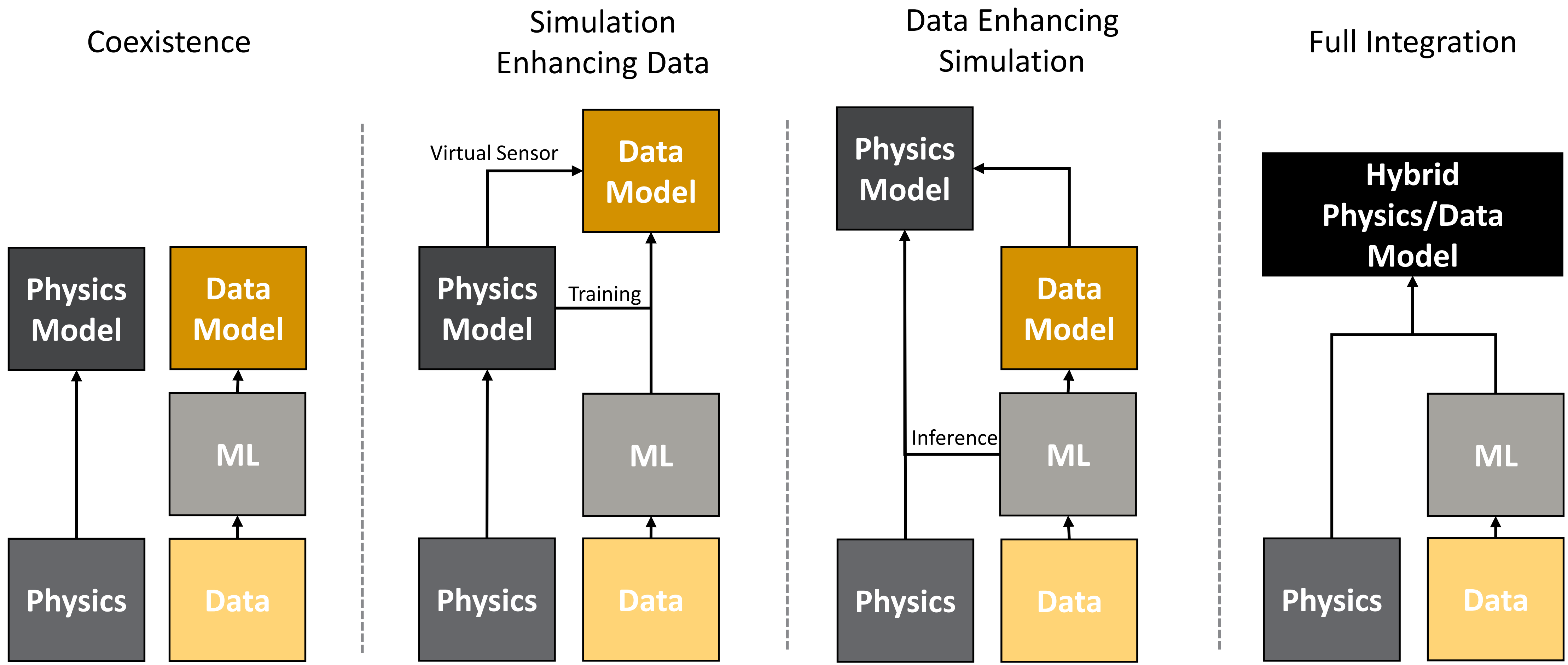
Add-On Modelica Libraries

Compliant with FMI standard

- Compatible with the functional mock-up interface (FMI) for model exchange to import models from FMI-compliant tools and export compatible libraries as FMUs
- Unlock new modeling possibilities by effortlessly combining existing FMUs and exporting as Twin or FMUs
- Seamlessly integrate and interact with internal models (FMUs) through exposed inputs, outputs, and parameters.



The Hybrid Framework



Hybrid Analytics – Techniques

Data Enhancing Physics Simulation

Parameter Estimation

Uncertainty Quantification

Simulation Enhancing ML Models

Virtual Sensors

Explore Failure Modes

Full Integration

Fusion Model: Compensate for any unmodeled physics or other effects by modeling the difference between a physics model and data

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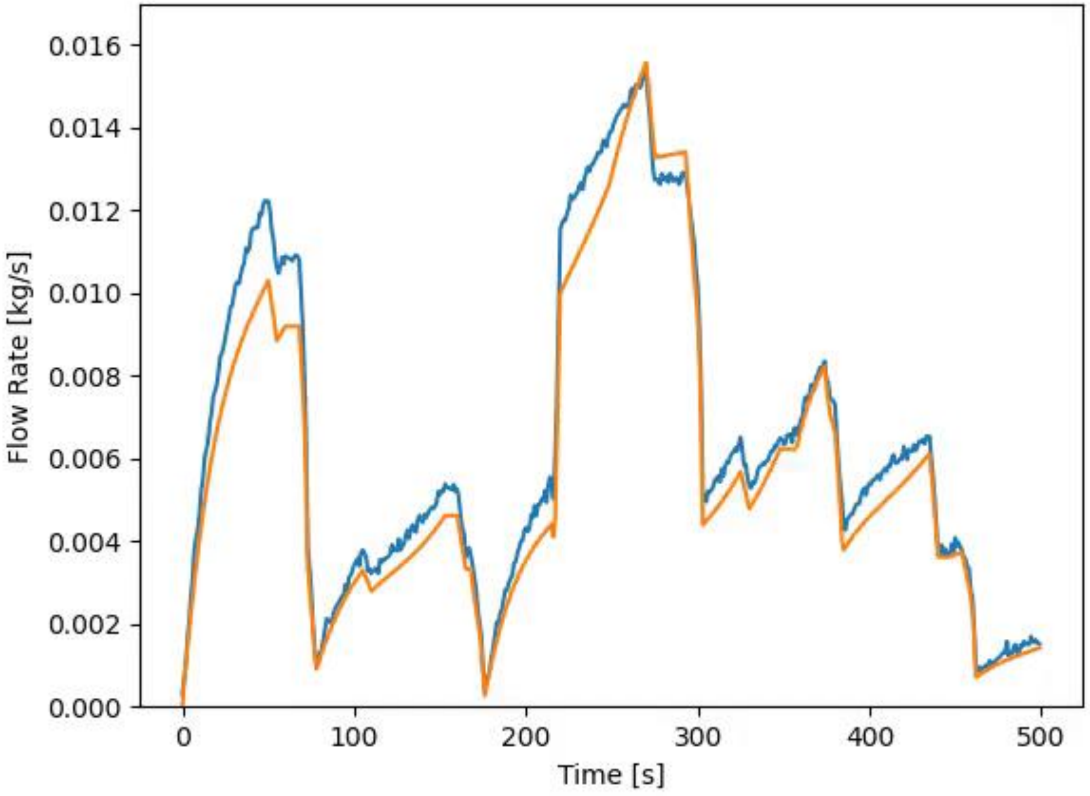
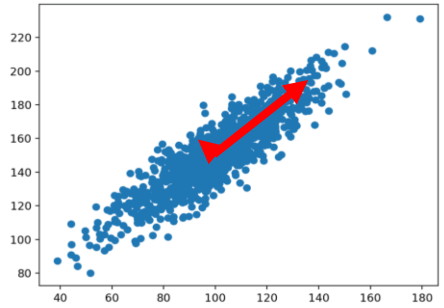
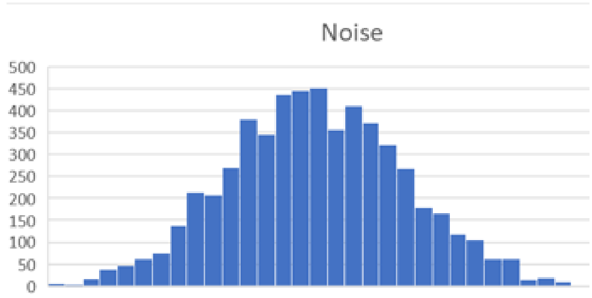
Calibration

Parameter Calibration: Physical model parameters typically represent a physical feature like friction, damping, or mass.

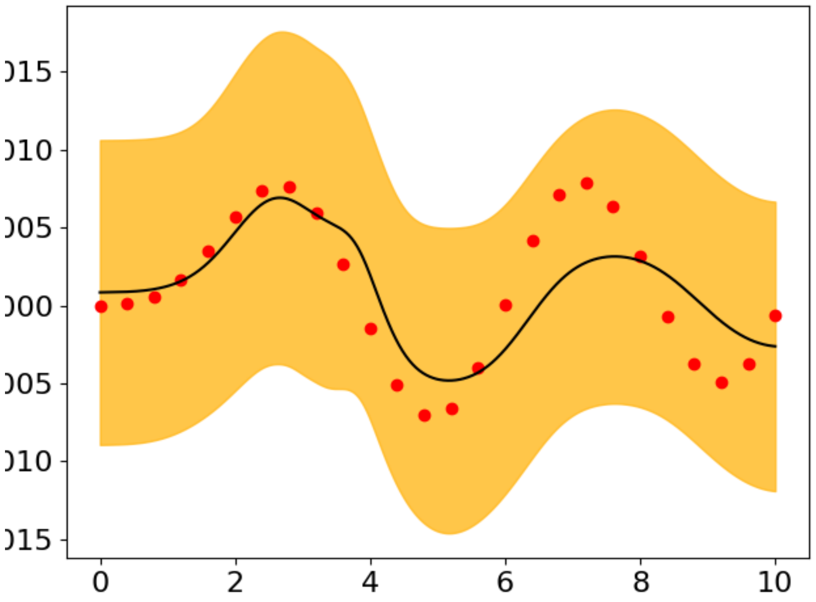
- This parameters can change overtime due to wear and tear and degradation.
- In these cases, the physics model is still good, but the parameters need to be updated to account for environmental changes.
- Parameter calibration allows us to learn from data how these parameters have changed without having to fully understand the processes that led to the changes.



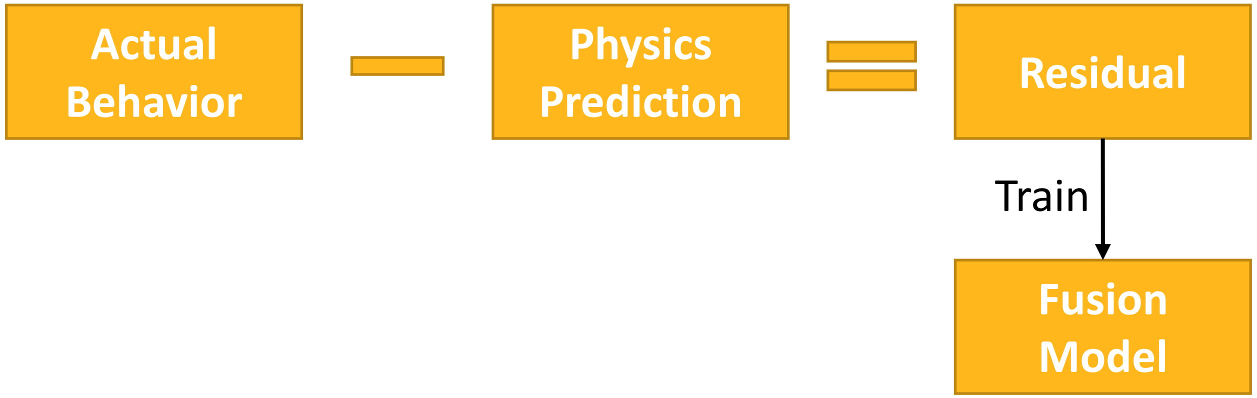


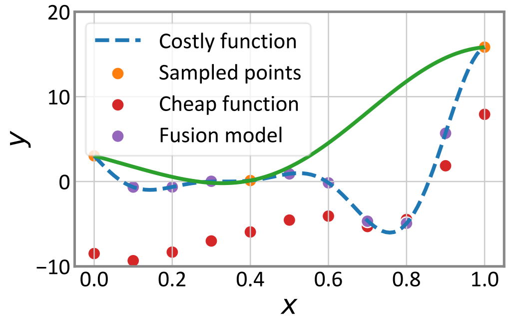


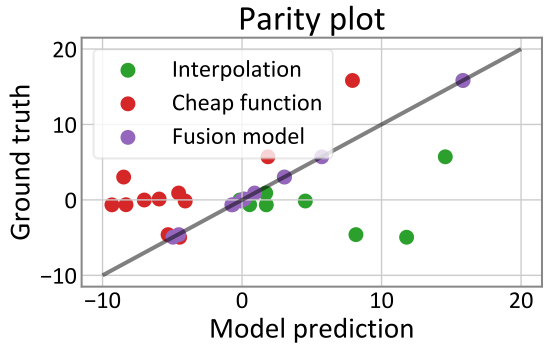
Fusion Modeling



- Build models from two different types of data
  - Simulation and Experimental
  - 3D simulation and 1D simulation
- Returns uncertainty of fit
- Instead of training a full data model, use the most accurate physics model available and train an ML model of the residual







A **Fusion Model** is a machine learning model built from at least two different types of data

Deployment and Scaling of Digital Twins

Automatic Scaffolding Code Generation

- Web-App, Python App, PTC agent, Container Deployment

Quickly Connect to supported IIoT Platforms

- Built-in integration with leading IIoT platform including PTC, AWS, Rockwell and Azure Digital Twin

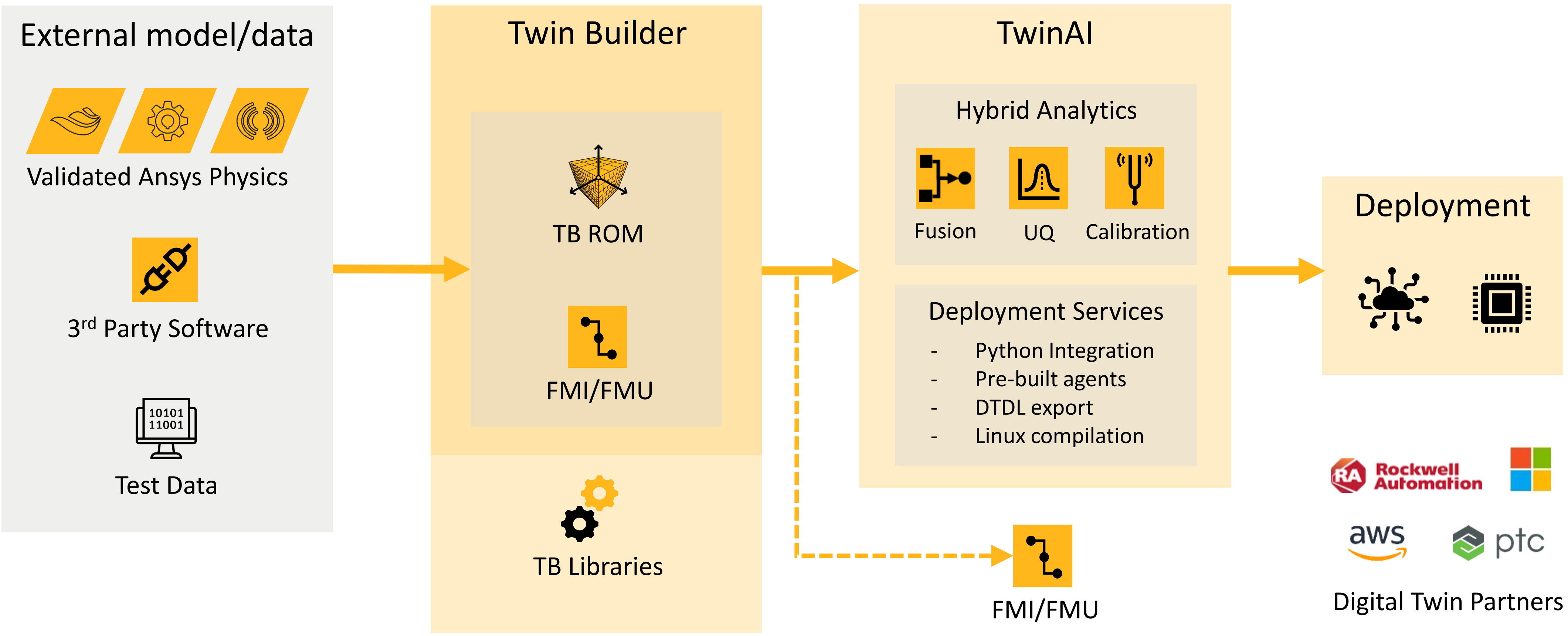
Scalable Licensing

- Scalable licensing is suitable for all kind of small and large projects

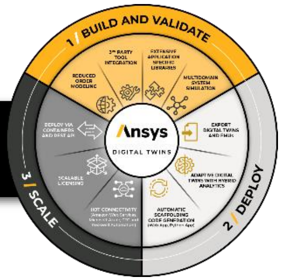
Deploy via Containers and REST API

- Scalable deployments with support of Containers and REST API

Ansys Digital Twin Solution Architecture



Ansys Digital Twin End-to-End Workflow



1/BUILD & VALIDATE | **2/DEPLOY** | **3/SCALE**

Ansys Twin Builder® and Ansys TwinAI for complete end-to-end Digital Twin workflow

Ansys Twin Builder

MODELING & LIBRARIES

Use add-on libraries, including the Twin Builder Heating and Cooling library, Twin Builder Fluid Power library, and EV Powertrain library.

REDUCED ORDER MODELING

Reduced Order Models (ROM) interfaces to generate accurate, compact models from detailed 2D and 3D physics simulations and visualize 3D fields with the ROM viewer.

3rd PARTY INTEGRATION

FMU creation with multi-domain system simulation. FMU composer for fast FMU creation from various sources.

Ansys TwinAI

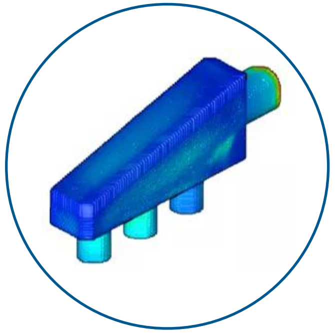
HYBRID ANALYTICS

Hybrid analytics is a set of ML tools for combining physics and data together in different ways.

DEPLOYMENT SERVICES

Microsoft® Azure® IoT, Microsoft Azure Digital Twins, PTC ThingWorx®, Automation Emulate 3D, and Rockwell Studio 5000.

Key Use-cases for Hybrid Digital Twins



Virtual Sensor

Virtual sensors provide missing information

Fleet Deployments

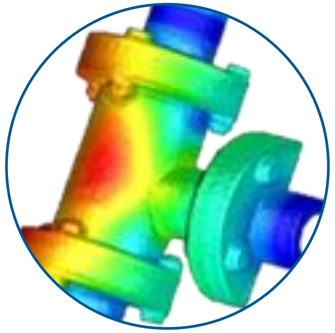
Use data to match the asset's unique behavior and environment

Brownfield Deployments

Learn missing behavior/information my enhancing a model with data

Greenfield Deployments

Decrease cost by replacing physical sensors with virtual sensors



Inverse Problem

Infer what inputs or operating conditions would lead to the desired behavior

Sparse Data

Quantify uncertainty for any amount of data and return meaningful results

Incomplete Physics Modeling

Model the residual between the known/modeled physics behavior and the expected behavior

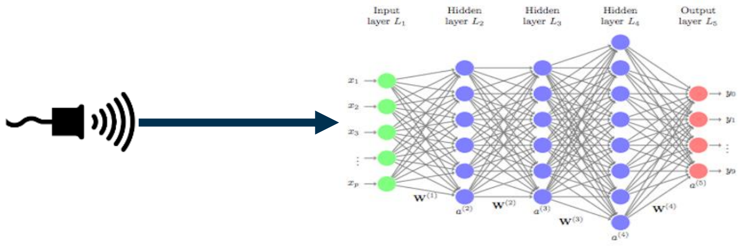
Use Case – Virtual Sensors for Machine Learning

Challenges

- Missing information for data models
- Inability to collect with physical sensors either due to cost or because there is not a sensor for desired information

Solution

- Virtual sensors provide missing information
- Validate Digital Twin with some physics sensors and predict other missing quantities



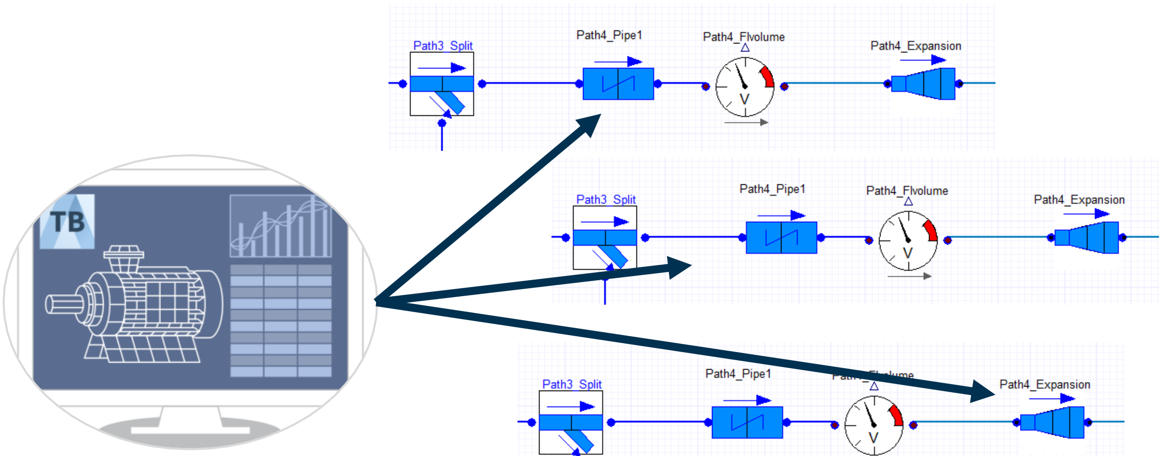
Use Case – Fleet Deployments

Challenges

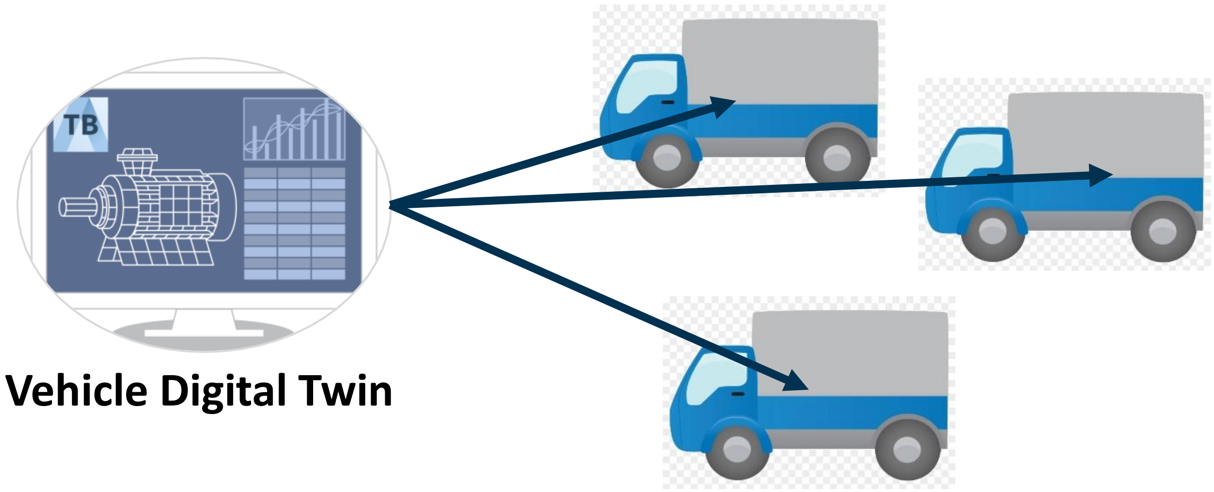
- Deploy the same Digital Twin to multiple assets in a fleet
- Adapt the twin behavior to each asset as it evolves independently of others in the fleet

Solution

- Use data from each asset to update and adjust the twin to match the asset's unique behavior and environment



Asset Digital Twin



Vehicle Digital Twin

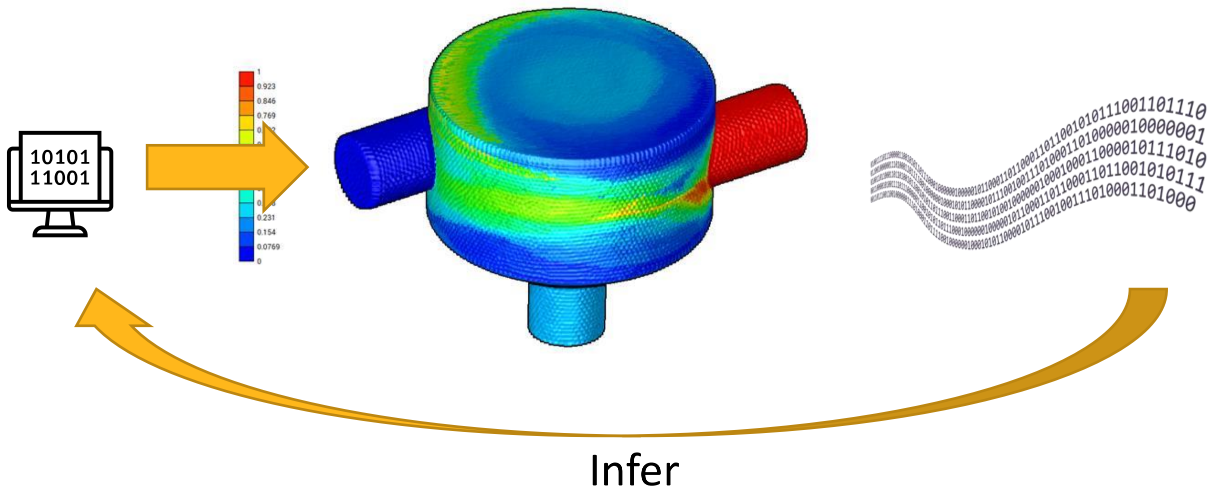
Use Case – Inverse Problem

Challenges

- Understand how to change operation when asset behavior doesn't match desired outcomes

Solution

- Use data and a Hybrid Digital Twin to infer what inputs or operating conditions would lead to the desired behavior



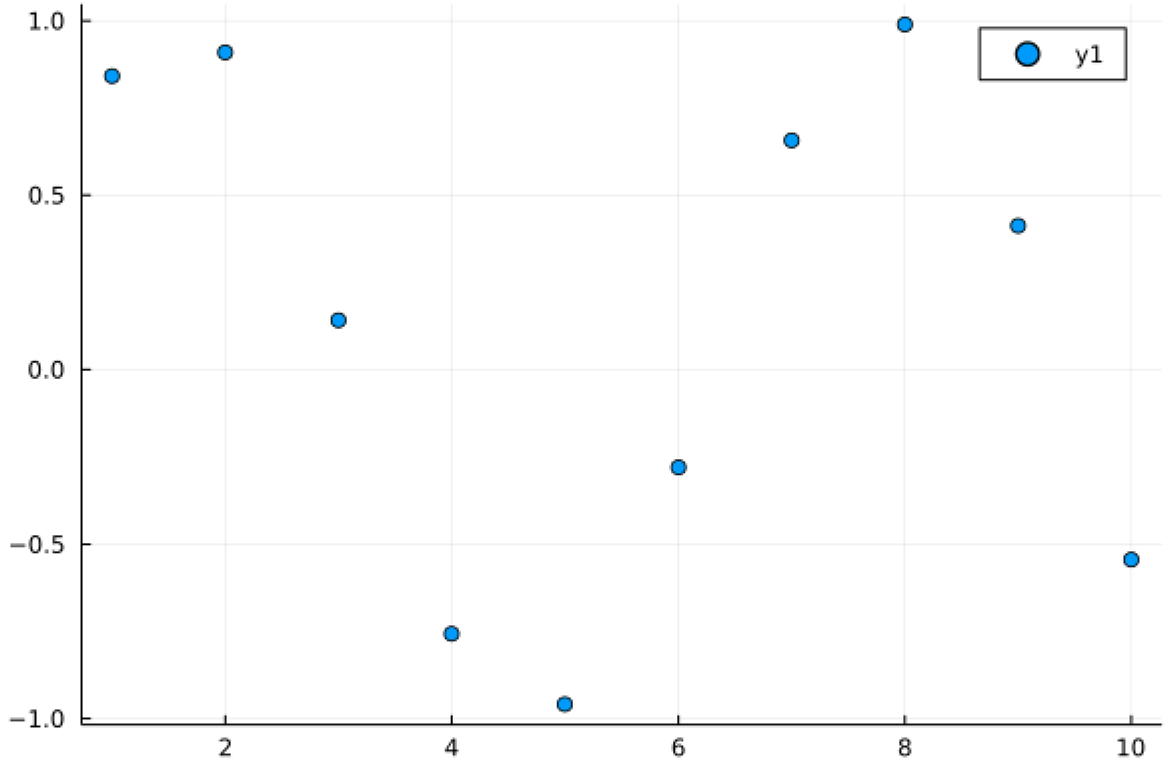
Use Case – Sparse Data

Challenges

- Calibrate a model with limited data
- Too much time/cost in physical testing

Solution

- Use data and a Hybrid Digital Twin to calibrate model parameters
- Amount of data needed is often less than would be needed from a data-based approach



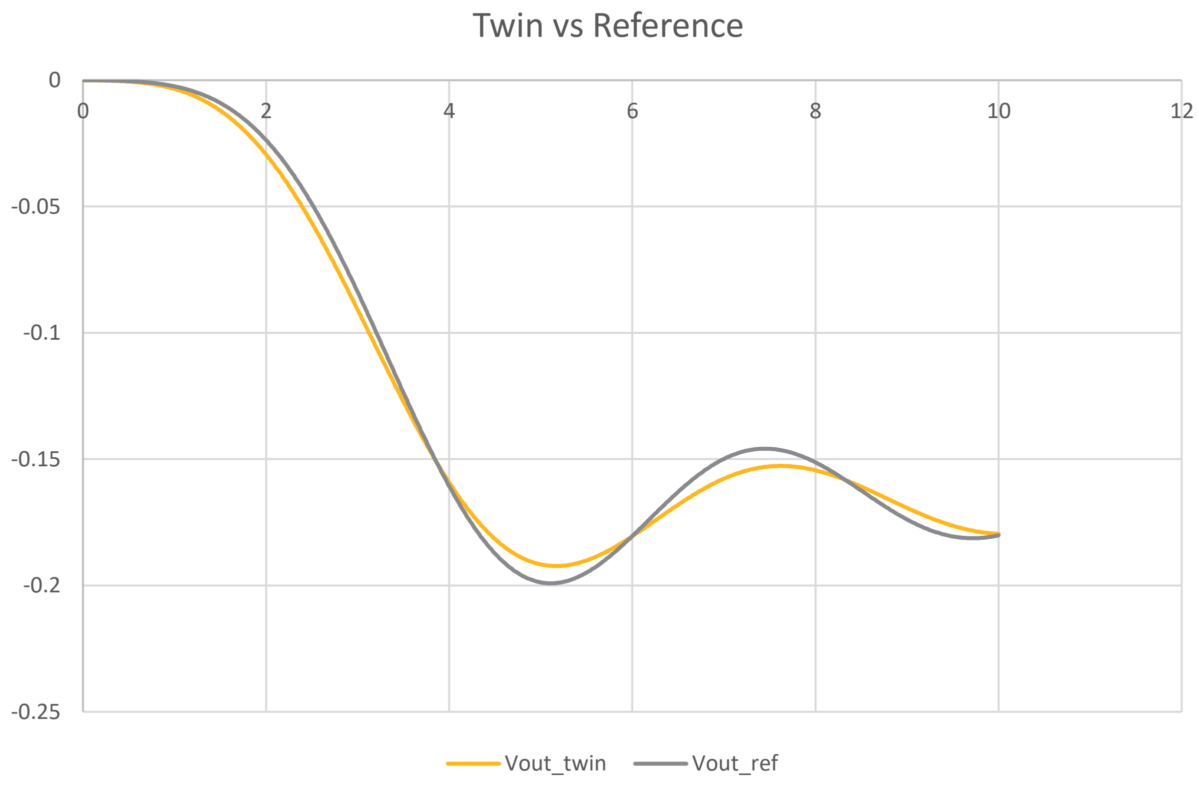
Use Case – Incomplete Physics Modeling

Challenges

- Unknown or unmodeled physics affecting a system behavior

Solution

- Model the residual between the known/modeled physics behavior and the expected behavior
- Add the residual model to the twin model



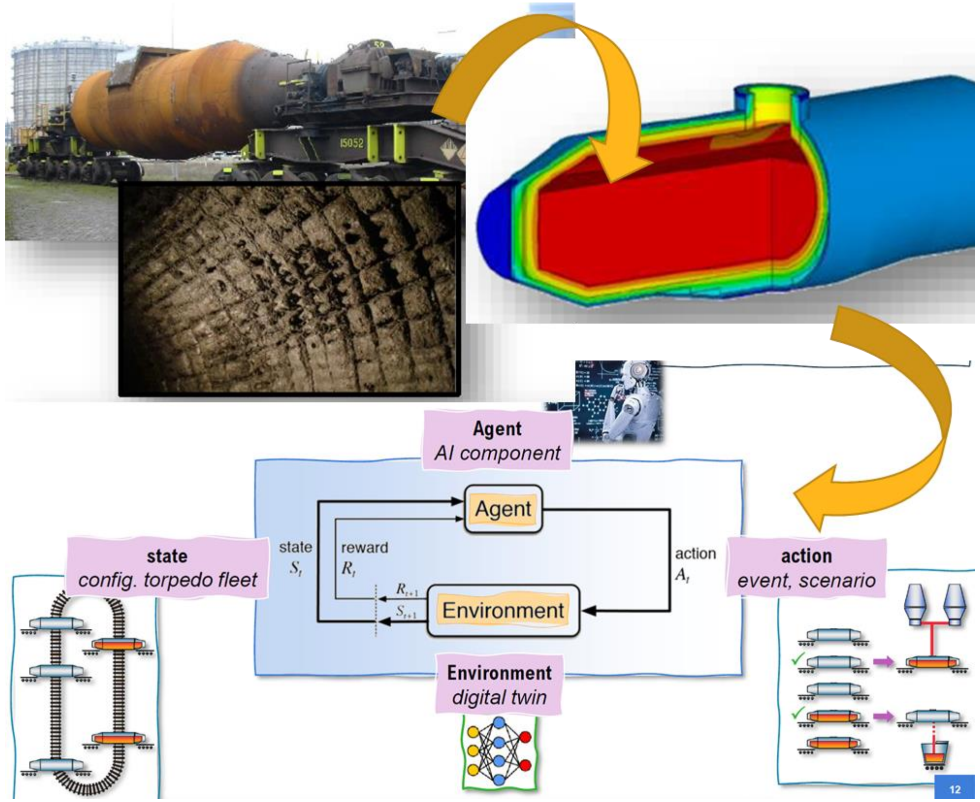
Selected Customer Cases

Improving Maintenance at Tata Steel

Challenge: Higher hot metal temperatures help with yield losses and CO2 emissions but lead to higher wear of insulation of torpedo car linings and higher energy usage. Unplanned torpedo refractory maintenance leads to higher-than-expected downtimes.

Solution: A comprehensive (thermal) digital twin for the entire hot metal (HM) production route. AI based controls to optimize for refractory wear rate and energy consumption.

Result: Facility downtime reduced by 400 hours annually. Additionally, can optimize number of ladles and torpedo cars in use. Finally, in combination with other initiatives, this digital twin is enabling Tata Steel to achieve its target of 30-40% reduction in CO2 emissions by 2030



https://www.ansys.com/blog/simulation-takes-heat-off-tata-steel-during-production

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Verbund Hydro: Minimizing Downtime for Water Turbine

Challenge: Predict turbine component fatigue under actual conditions to avoid failures, unplanned downtime can cost up to $60k/hr

Solution: A hybrid digital twin of the turbine, connected with actual sensor data to predict accurate current stresses of turbine components

Results: Solution in operation and being expanded. Expected to help save **~$100k/year** per turbine by avoiding unplanned downtime and optimizing maintenance schedules

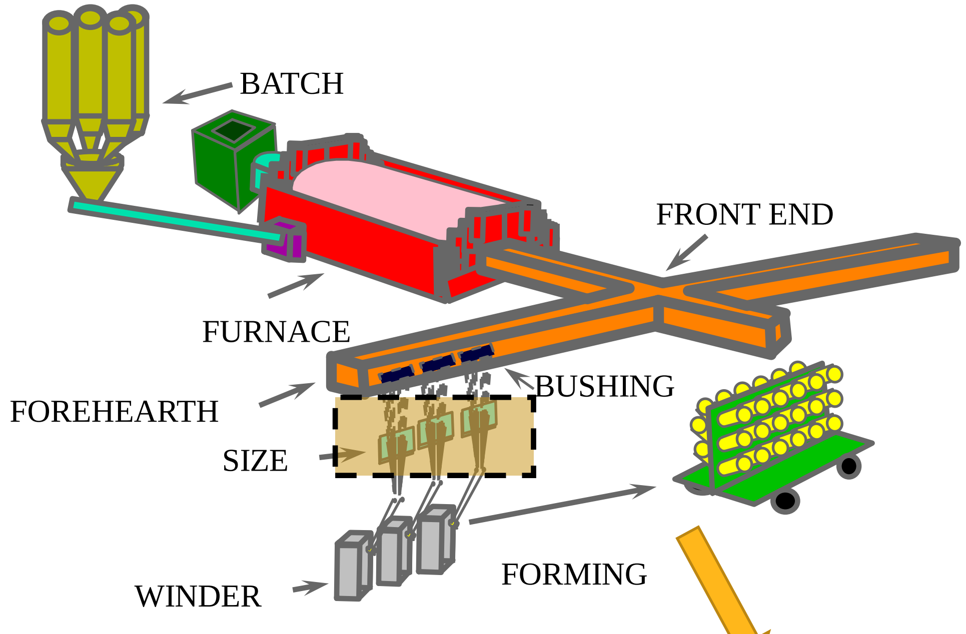
Verbund
in cooperation with
CADFEM
ITficient

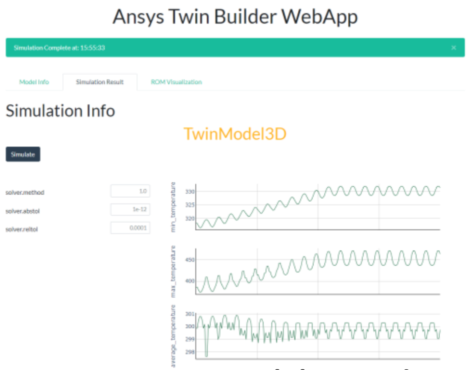
Improving Production Process in Glass Industry

<u>Challenge</u>: For fiberglass manufacturing, consistent temperature (within 2-3 degrees at temperatures in excess of 1400C) in the glass flow path is vital to the quality of the output product. Positioning sensors along the entire flow path is infeasible.

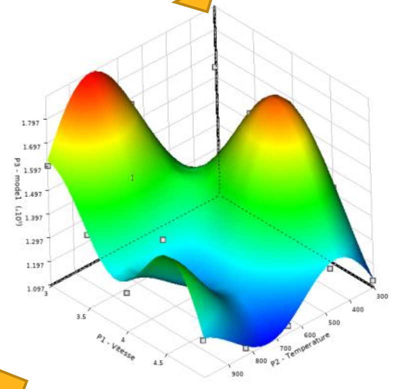
<u>Solution</u>: A reduced order model based digital twin to predict the entire temperature flow field of the forehearth. The reduced order model was created based on available non-linear CFD model and predicts temperatures

<u>Results</u>: Digital twin is deployed on the customer's asset, giving alerts to operators when temperatures are out of bounds. Twin runs in < 5 s, well under the window allowed for the model execution. Real-time product optimization based on the temperature virtual sensor output in the pilot stage.





Operator Dashboard



Field ROM

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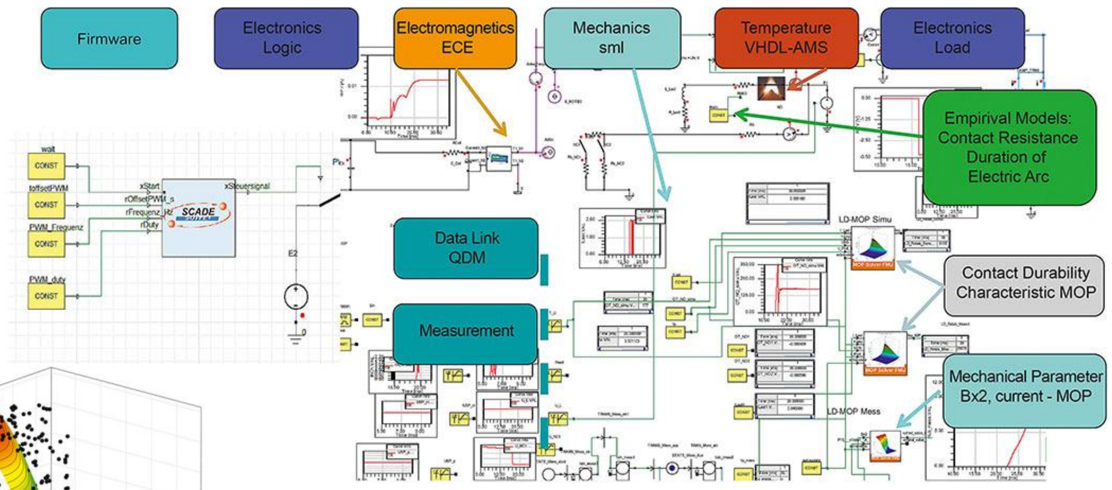
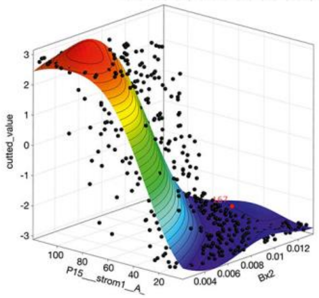
Phoenix Contact: Creating a Fail-Safe Digital Twin

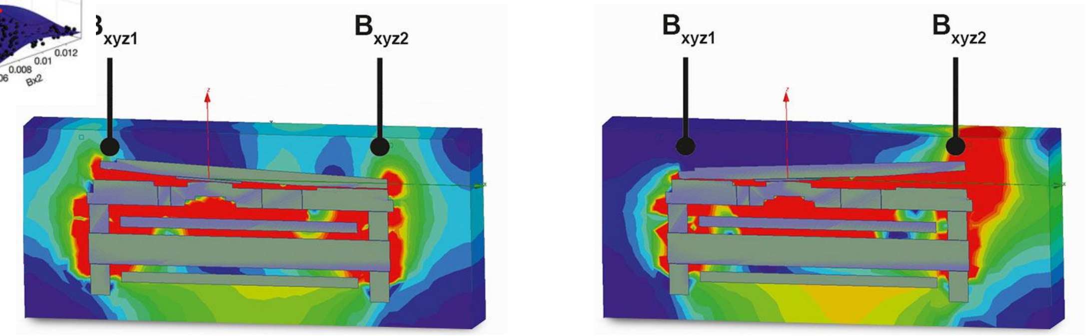
Challenge: Unplanned downtime due to failure of a relay can cost tens of thousands of dollars per hour. It is very hard to predict relay failure as there is no wear sensor.

Solution: To predict component failure before it occurs, a simulation based digital twin was created that predicts the wear based on actual load and sensor data (temperature, switching frequency).

Results: By lowering unplanned downtime, Phoenix Contact's advanced relays can potentially save **tens of thousands of dollars per hour** for their customers.







Ansys Maxwell simulation shows magnetic field at different armature positions.

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