ENTSO-E European R&D meeting

Developing Digital Twins for Accelerator Magnets
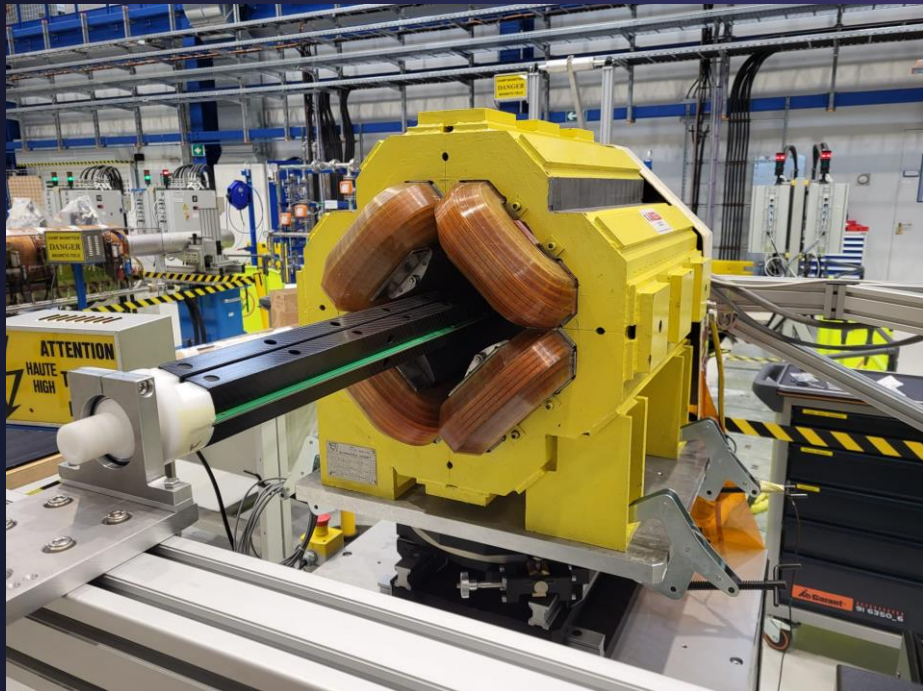
Melvin Liebsch

- TE-MSC-TM -

Agenda

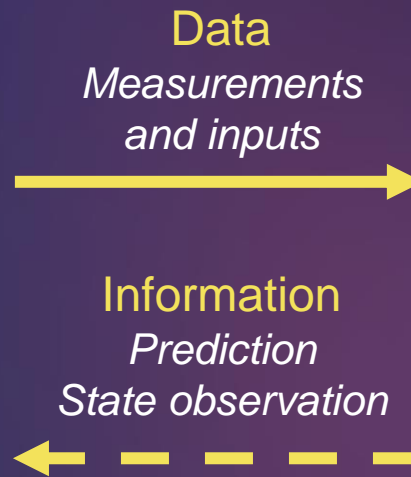*Learning from data through the lens of models is a way to exploit structure in an otherwise intractable problem [6]*

- The digital twin of the accelerator magnet

- Challenges

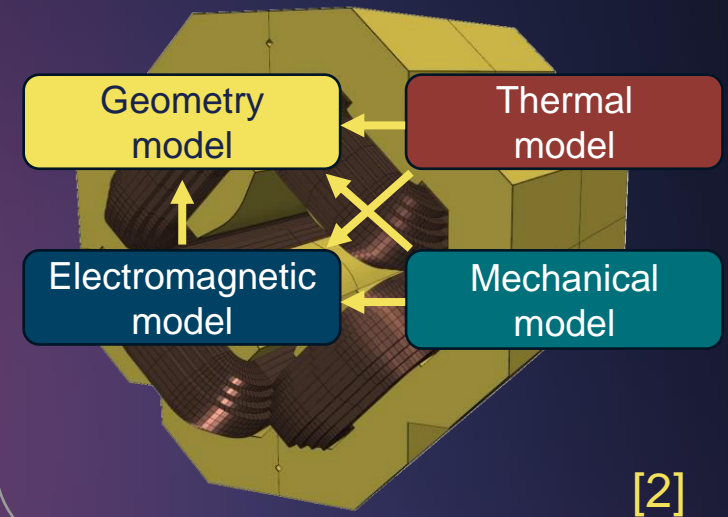- Integration in the life cycle management

- Conclusion

[6] K. Wilcox, Predictive data science for physical systems – from model reduction to scientific machine learning. ICIAM – international congress on industrial and applied mathematics. 2019

The digital twin [1]

Physical object
a.k.a. accelerator magnet

Communication channel

Data
Measurements and inputs

Information
Prediction
State observation

Digital representation
a.k.a. numerical system model

Geometry model

Thermal model

Electromagnetic model
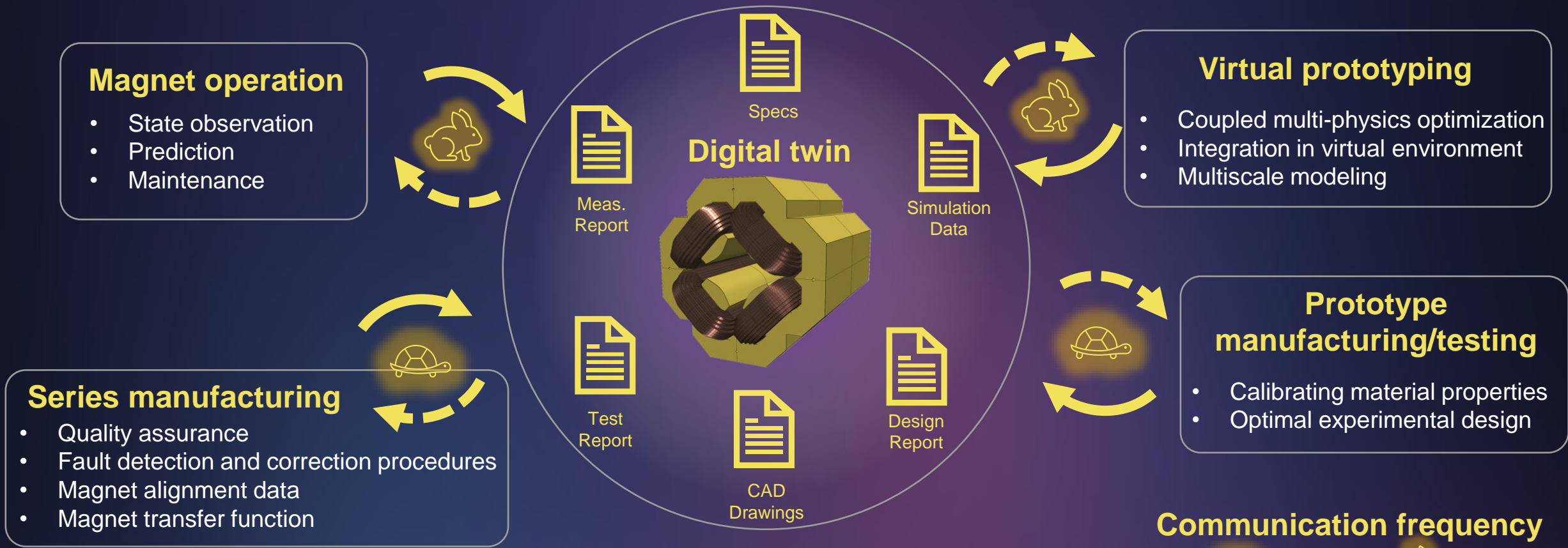
Mechanical model

[2]

→ *The digital twin requires multi-physical modeling*

[1] Piascik, R., et al., *Technology Area 12: Materials, Structures, Mechanical Systems, and Manufacturing Road Map.* 2010, NASA Office of Chief Technologist.
[2] M. Maciejewski, B. Auchmann, D. M. Araujo, G. Vallone, J. Leuthold and J. Smajic, "Model-Based System Engineering Framework for Superconducting Accelerator Magnet Design," in IEEE Transactions on Applied Superconductivity, vol. 33, no. 5, pp. 1-5, Aug. 2023, Art no. 4003105, doi: 10.1109/TASC.2023.3249647

Accelerator magnet life cycle

Magnet operation
- State observation
- Prediction
- Maintenance

Virtual prototyping
- Coupled multi-physics optimization
- Integration in virtual environment
- Multiscale modeling

Series manufacturing
- Quality assurance
- Fault detection and correction procedures
- Magnet alignment data
- Magnet transfer function

Prototype manufacturing/testing
- Calibrating material properties
- Optimal experimental design

Digital twin

Specs

Simulation Data

Meas. Report

Design Report

Test Report

CAD Drawings

Communication frequency

slow   fast

Product life cycle

Development life cycle

→ Document based information exchange
→ Communication frequency depends on the application
→ Data management services → EDMS, EAM, NORMA, PLM

Principles of systems modeling
Communication frequency depends on the application
Data management services → EDMS, EAM, NORMA, PLM

Challenges

- *Complex (non-linear) dynamic system*
  - Interplay of iron saturation, hysteresis and eddy currents
  - Superconductor magnetization
  - Temperature effects

- *Computational costs*
  - A complete 3D magnet simulation does not allow for fast predictions

- *Tough requirements for machine operation*
  - Field stability at 1 unit in 100 000
  - Field quality at 1 unit in 10 000

Digital representation
a.k.a. numerical system model

data

1st principles
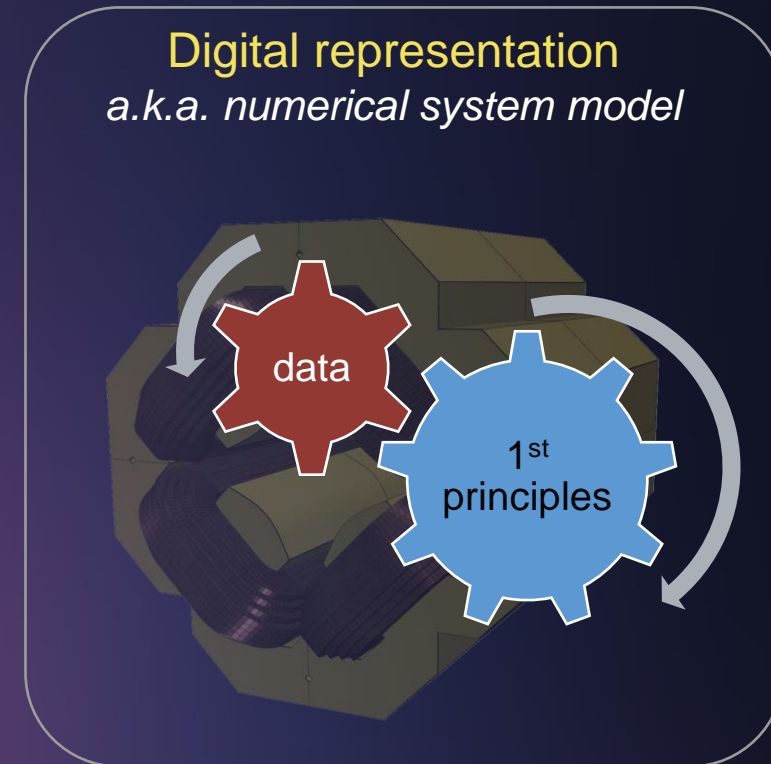
→ ***Measurement data*** *needs to be* ***integrated*** *in the numerical model to enable* ***accurate predictions***
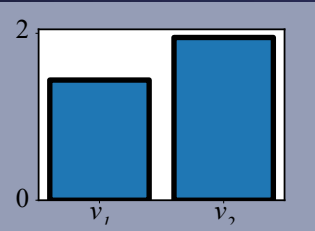
→ *The digital twin is a hybrid model*
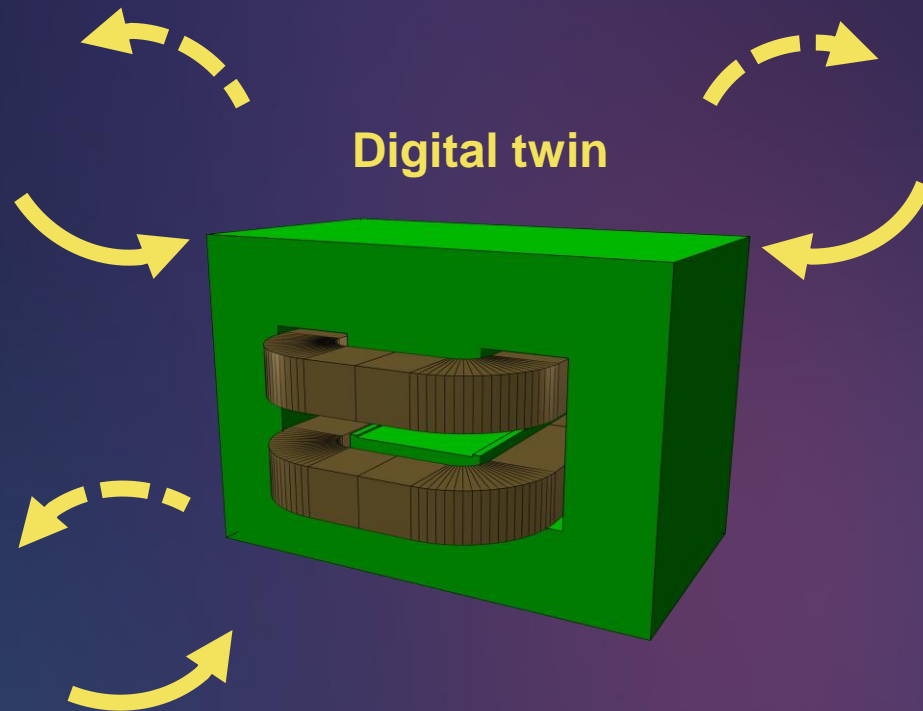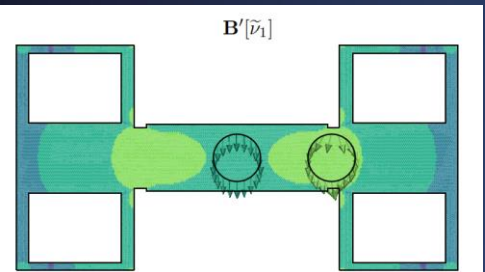
Example – Model Calibration [3]

Magnet manufacturing QA
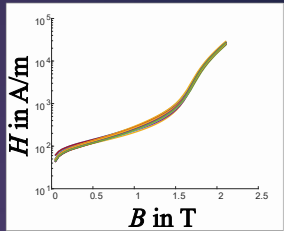
Material Specimen
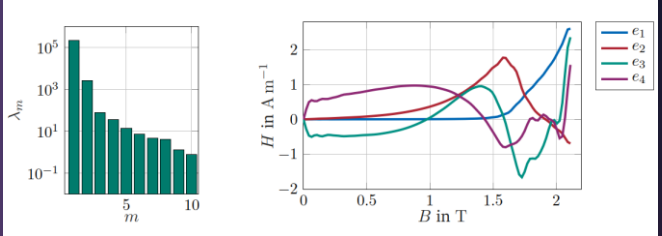
Permeameter

H(B)-curve

H in A/m

B in T

Pattern recognition (KLE)

λ_m

m

H in A m^{-1}

B in T

e_1
e_2
e_3
e_4

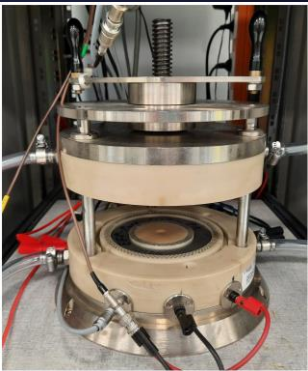**Calibration test campaign**

Resulting parameters

$\tilde{\nu}_1$ $\tilde{\nu}_2$

Design of a test campaign

Design of experiment (DOE)
optimal sensor placement

$\mathbf{B}'[\tilde{\nu}_1]$

Digital twin

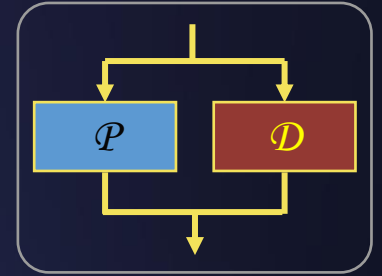[3] L. Fleig, M. Liebsch, S. Russenschuck and S. Schöps, "Identification of B(H) Curves Using the Karhunen Loève Expansion," in IEEE Access, vol. 12, pp. 59441-59449, 2024, doi: 10.1109/ACCESS.2024.3393348

Example – Discrepancy Models

- **Discrepancy** between measurement and simulation **may not vanish** after magnet calibration

- **Discrepancy** drives the delta model

- Delta model **implies Maxwell's equations** in the vacuum domain
  $$\text{curl } \boldsymbol{H} = \boldsymbol{0}, \text{ div } \boldsymbol{B} = 0$$

- **Boundary element** or **volume integral methods** have been used
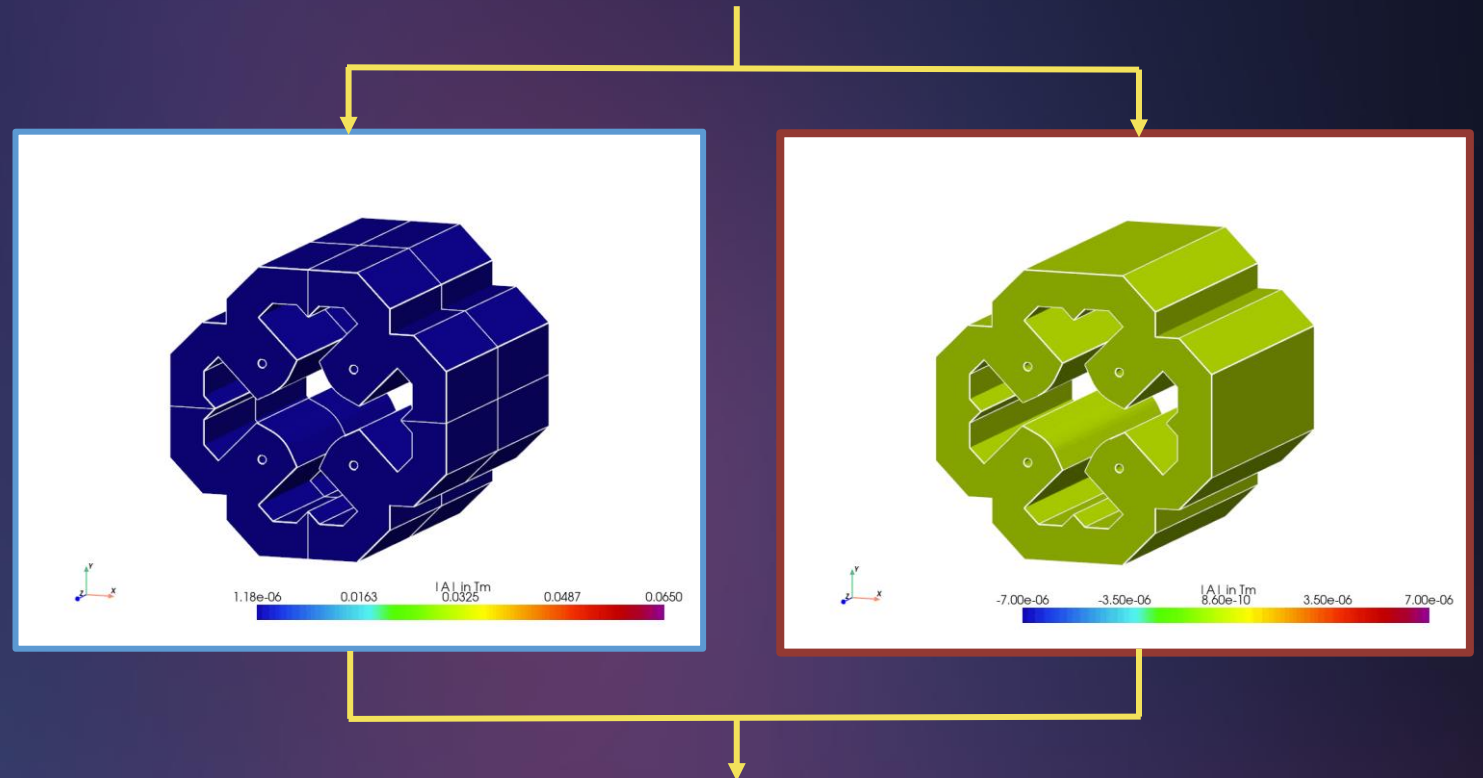
Magnet operation

Requires rapid information exchange

Model order reduction (MOR) [5]

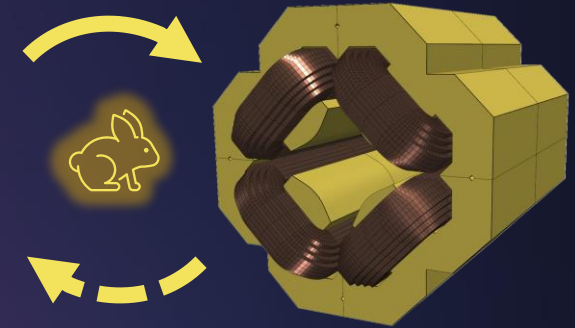$$\dot{x}(t) = A\, x(t) + B\, u(t)$$

High fidelity model

$$\dot{x} = \boxed{A}\; x + \boxed{B}\; u$$

Reduced order model (ROM)

$$\dot{\hat{x}} = \widehat{A}\; \hat{x} + \widehat{B}\; u$$

x: State vector, u: Input vector, $\hat{x}$: ROM state

Magnet operation
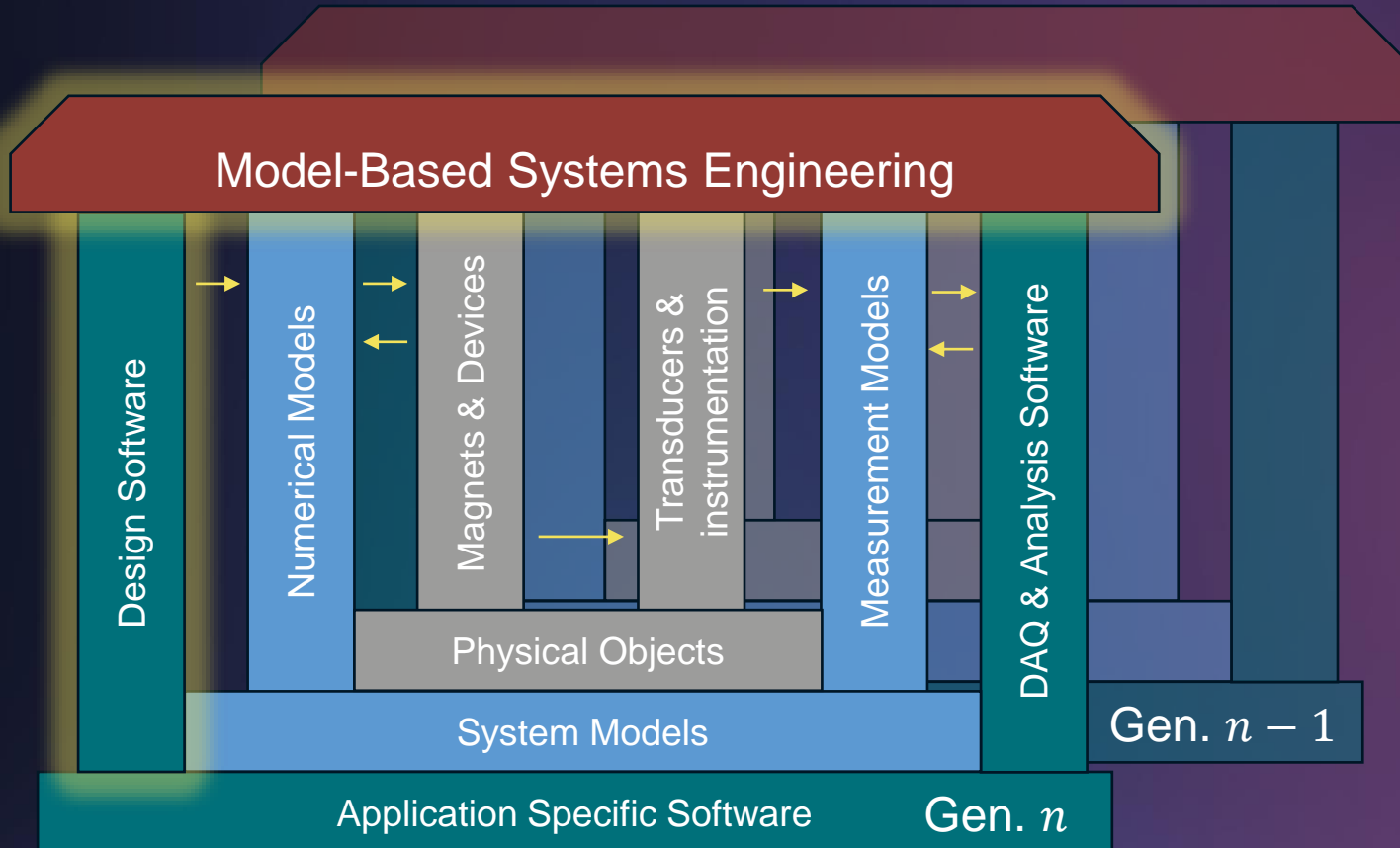
- *State observation*
- *Prediction*
- Maintenance

- *Nonlinear dynamics* and *hysteresis* need to be observed

- *High accuracy* is required
  - *Field integral better than 1 unit in 10 000*

- Objective conflict: ROM is faster, but *less accurate* than the full model!

- *Solution:* Field integrals *are measured at run-time*
  - *c.f. B-train online monitoring systems*

- *Domain knowledge is derived from the digital twin*
  - *e.g. Local versus integral field*

[5] Sorti, S., Petrone, C., Russenschuck, S., Braghin, F.: Data-driven simulation of transient fields in air-coil magnets for accelerators, Nuclear Instruments and Methods in Physics Research Section A, 2021

Integration

*Integrating the digital twin with **M**odel **B**ased **S**ystems **E**ngineering*

ROXIE API for integration in MBSE*

code available

***pyMBSE**: self-contained multi model execution*
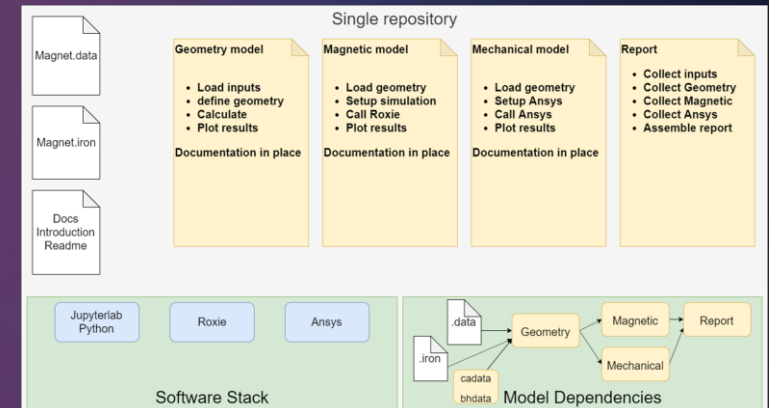
*Developed by M. Bonora (TE-MSC-TM)

Conclusion

Developing the digital twin of the accelerator magnet

- Numerical models and simulation data *need to be integrated* in the *development and product lifecycle management*

- We must use *hybrid modeling* to design *application specific* digital twins

- In doing so we must follow the principles of *model-based systems engineering*
    → *Traceability, platform independence, versioning*

- A *collaborative effort in the ATS sector* is requited to integrate data from various sections and working groups