Hybrid Digital Twins: A Proof of Concept for Reinforced Concrete Beams

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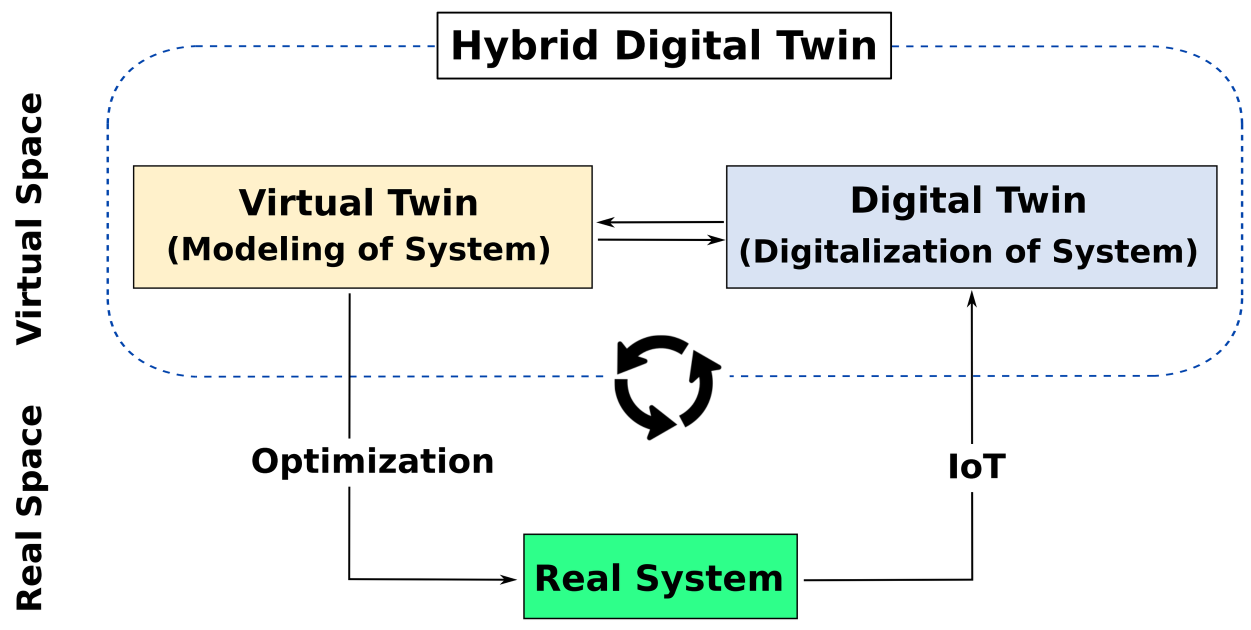
Motivation

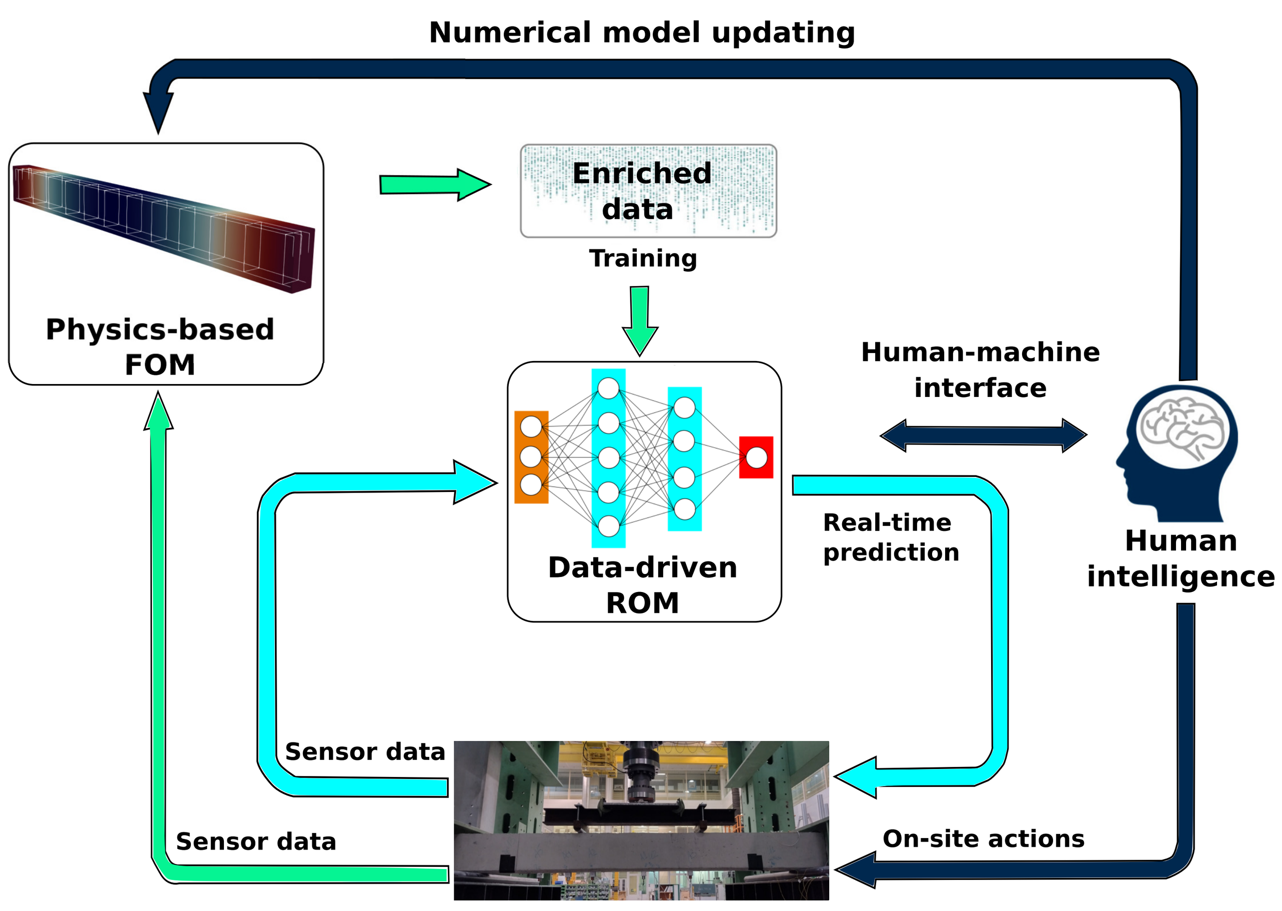
Digital twins map real objects and processes from the physical world into digital space. Going one step further, hybrid digital twins (HDT) combine physics-based modeling (virtual twin) with data-based techniques (digital twin) to form a simulation tool with predictive power.



In light of the increasing digitalization of our world, digital twins have great potential to contribute to protecting and maintaining critical infrastructures. In case of bridges, digital twins can have a crucial role in structural health monitoring (SHM) [1].

Proof of Concept

This contribution provides proof of the concept of a hybrid digital twin for steel-reinforced concrete beams as a representative component of bridges in civil engineering structures.



We combine a physics-based full-order model (FOM) with a fast-to-evaluate data-driven reduced-order model (ROM) interacting with sensor data of the physical asset. The full-order model provides a detailed understanding of the physical behavior and is employed to calibrate the reduced-order model aiming at a reliable digital representation. The combined model has the following capabilities:

- damage, crack and anomaly detection
- "what-if" simulations
- identification of underlying trends

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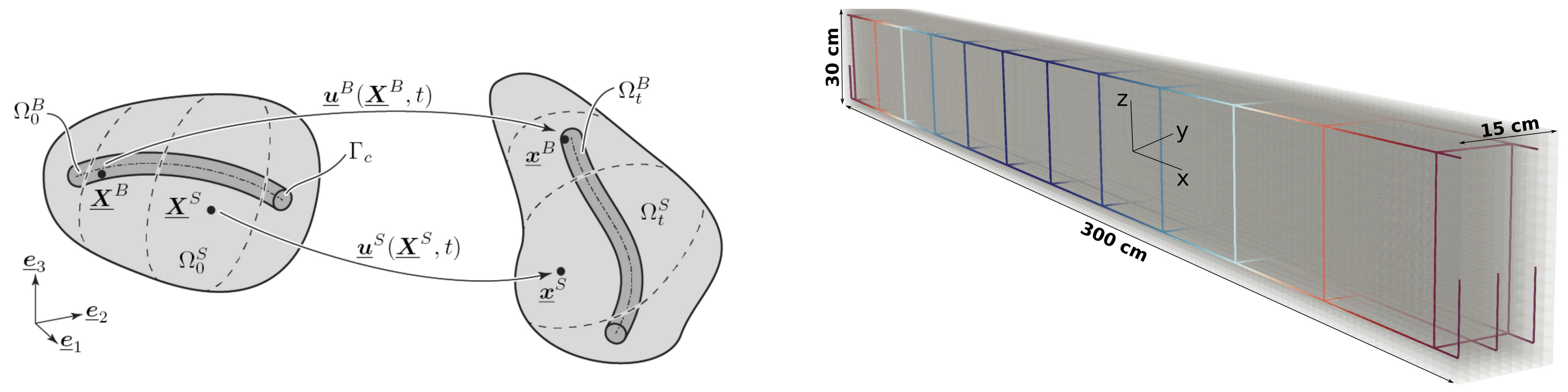
Physics-Based Full-Order Model

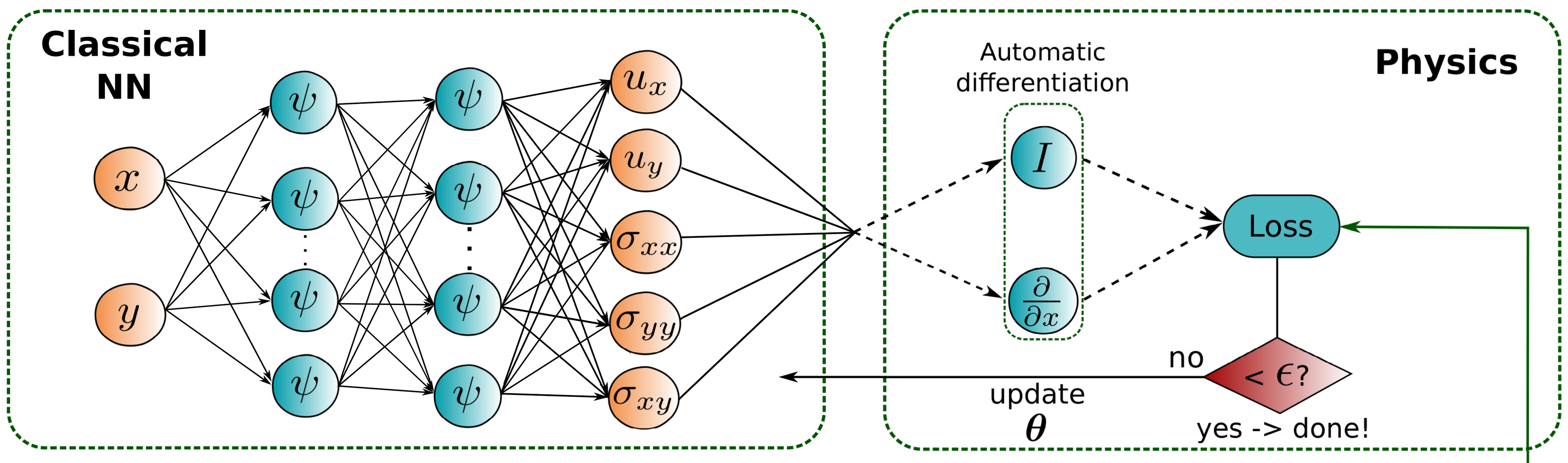
Mixed-dimensional Finite Element model



The physics-based FOM is based on a novel finite element formulation with beam-to-solid mesh tying. We use this method to capture the interaction between the reinforcement components and the concrete matrix of the beam [2].

Data-Driven Reduced-Order Model

Physics-informed neural networks



PDE loss

$$\mathcal{L}_{PDE} := \frac{1}{N_f}\sum_{i=1}^{N_f}\left[\left|\left|\nabla\cdot\boldsymbol{\sigma}\right|\right|_2^2 + \left|\left|\boldsymbol{\sigma} - \lambda tr(\boldsymbol{\varepsilon})\mathbf{I} - 2\mu\boldsymbol{\varepsilon}\right|\right|_2^2\right]_i$$

Boundary loss

$$\mathcal{L}_{BC} := \frac{1}{N_{bc,0}}\sum_{i=1}^{N_{bc,0}}\left[\left|\left|\boldsymbol{\sigma}\cdot\boldsymbol{n}\right|\right|_2^2\right]_i + \frac{1}{N_{bc,l}}\sum_{i=1}^{N_{bc,l}}\left[\left|\left|\boldsymbol{\sigma}\cdot\boldsymbol{n} - \boldsymbol{p}\right|\right|_2^2\right]_i$$

Experiment loss

$$\mathcal{L}_{Exp} := \frac{1}{N_e}\sum_{i=1}^{N_e}\left[\left|\left|\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}^*\right|\right|_2^2\right]_i$$

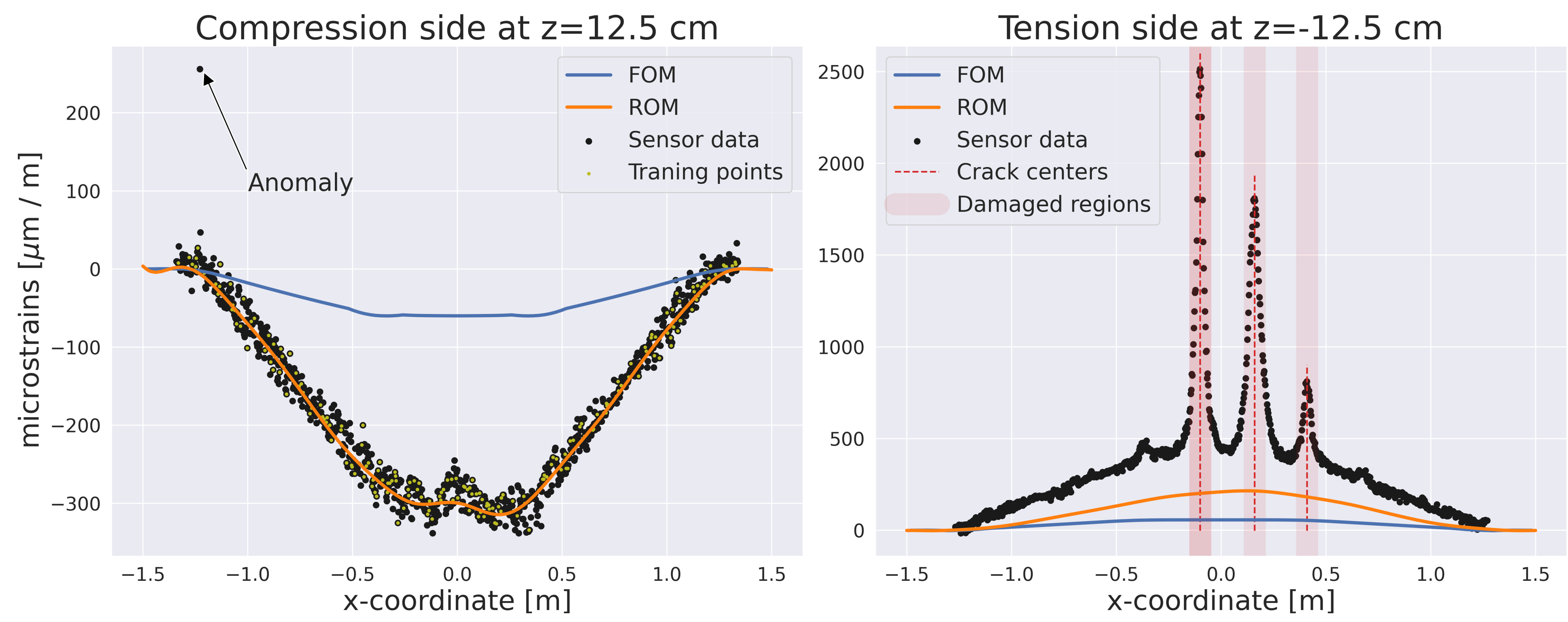
$$\mathcal{L} = \sum_m w_m \mathcal{L}_m$$

where $\boldsymbol{\varepsilon} = \frac{1}{2}(\nabla\boldsymbol{u} + \nabla\boldsymbol{u}^T)$

$\boldsymbol{\theta}$: weights/biases, $\boldsymbol{w}$: loss weights, ψ : activation function

The data-driven ROM is based on **p**hysics-**i**nformed **n**eural **n**etworks (PINNs) that combine differential equations and measurement data in the loss function of neural networks [3].

Use Cases



- Comparison of estimated strains of FOM and ROM with measurements
- Detection of crack centers and damaged regions using purely data-driven ROM
- Anomaly detection in SHM

References

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