

Physics-Informed and Data-Efficient Model Reduction of Thermo-Mechanical Systems

Note: This is a paid opportunity for a master thesis in collaboration with ASML, Veldhoven.

Background: High-fidelity multi-physics simulations are widely used to predict transient temperature and deformation fields in engineering systems. However, repeated simulations can become computationally expensive when exploring different operating conditions, heat-load distributions, or trajectories. Reduced-order models (ROM) and machine-learning-based surrogate models can significantly accelerate these predictions. However, their accuracy often depends on the availability of sufficiently large training datasets generated using high-fidelity simulations. For transient thermo-mechanical systems subjected to localized and moving heat loads, an important question is therefore whether incorporating physical knowledge into the reduced-order modeling framework can reduce the amount of high-fidelity training data required.

Objective: The objective of this project is to investigate whether physics-guided reduced-order models can achieve accurate transient thermo-mechanical predictions using fewer high-fidelity training simulations than purely data-driven approaches. The thesis will develop a baseline data-driven reduced-order model and compare it with a physics-guided alternative under progressively reduced training datasets. The focus is not only on achieving high prediction accuracy, but specifically on interpreting the relationship between physical knowledge, training-data needs and predictive accuracy.

Learning activities

- Develop or use a high-fidelity transient thermo-mechanical reference model subjected to localized and moving heat loads.
- Generate a reference dataset containing multiple heat-load trajectories and their corresponding transient temperature and/or deformation fields.
- Construct reduced representations of the thermal loading and thermo-mechanical response using techniques such as Proper Orthogonal Decomposition (POD).
- Develop a baseline data-driven reduced-order model for predicting the transient response.
- Develop one physics-guided extension of the baseline model by incorporating selected physical knowledge, such as:
 - o known dynamical structure,
 - o conservation principles,
 - o spatial symmetries,
 - o physically meaningful latent variables,
 - o or constraints on the structure of the ROM.
 - o Train both models using progressively smaller subsets of the high-fidelity dataset.
- Evaluate the models on previously unseen heat-load trajectories.

Sample literature

Benner et al. (2015) A Survey of Projection-Based Model Reduction Methods for Parametric Dynamical Systems, *SIAM Review*: <https://doi.org/10.1137/130932715>

Raissi et al. (2018) Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations, *Journal of Computational Physics*: <https://doi.org/10.1016/j.jcp.2018.10.045>

Cenedese et al. (2025) Data-assisted non-intrusive model reduction for forced nonlinear finite elements models, *Nonlinear Dynamics*: <https://doi.org/10.1007/s11071-024-10507-z>