Knowledge- and Data-Driven Model Order Reduction

TRACK Number 4000 Computational AppLied Mathematics

Alaa Armiti-Juber\*, AndrÉ Mielke\*, FElIx Fritzen\*,

Benjamin Unger\*, and Tim Ricken\*

\* University of Stuttgart, 70569 Stuttgart, Germany

[alaa.armiti-juber@isd.uni-stuttgart.de](mailto:alaa.armiti-juber@isd.uni-stuttgart.de); [mielke@isd.uni-stuttgart.de](mailto:mielke@isd.uni-stuttgart.de)[;](mailto:mielke@isd.uni-stuttgart.def) [fritzen@mechbau.uni-stuttgart.de](mailto:fritzen@mechbau.uni-stuttgart.de); benjamin.unger@simtech.uni-stuttgart.de; [tim.ricken@isd.uni-stuttgart.de](mailto:tim.ricken@isd.uni-stuttgart.de);

**Key words:** Asymptotic Analysis, Homogenization, Machine Learning, Artificial Neural Networks (ANN), Projection-based Model Reduction

ABSTRACT

Mathematical models in the form of coupled nonlinear partial differential equations (PDEs) are the classical tool for describing and predicting behavior of multiphysical systems. Discretization of these PDEs leads to high-fidelity models requiring advanced numerical methods to provide high accuracy simulations. Despite the huge advances in computational algorithms and computer chips, simulations might still be time-consuming. This can be problematic for many applications, such as design optimization, model-based predictive control, or clinical-time constraints. Hence, several model order reduction methods have been developed to reduce computational times while capturing important physical features. The most popular reduction approaches can be roughly classified into three main categories: 1) knowledge-driven approaches utilizing tools such as asymptotic analysis [1] and homogenization [2] to simplify the PDEs. 2) Data-driven approaches [2, 3] applying machine learning methods on simulation or experimental data. 3) Projection-based approaches extracting the essential dynamical features from the model or simulation data, then projecting the model onto these features [4].

This mini symposium focuses on novel model order reduction approaches. It aims to explore and exchange recent insights between researchers working in model order reduction. We welcome contributions bringing together the expertise of different reduction methodologies such as asymptotic analysis, homogenization, machine learning, projection-based methods, or hybrid approaches.

**REFERENCES**

[1] Armiti-Juber, A. and Ricken, T., Archive of Applied Mechanics, 2021.

[2] Fritzen, F., Fernández, and M, Larsson, M., Frontiers in Materials 6 (75), 2019.

[3] Mielke, A. and Ricken, T., Mechanics and Applications, 2019.

[4] Black, F., Schulze. P, and Unger, B., ESAIM M2AN 54 (6), 2020.