

## PHYSICS-ENFORCED NEURAL NETWORK-BASED CONSTITUTIVE MODELING AND DISCOVERY

KNUT A. MEYER<sup>1,2</sup>, KARL KALINA<sup>3</sup>,  
JAN N. FUHG<sup>4</sup>, AND D. THOMAS SEIDL<sup>5</sup>

<sup>1</sup>Material and Computational Mechanics,  
IMS, Chalmers University of Technology,  
Gothenburg, Sweden  
[knut.andreas.meyer@chalmers.se](mailto:knut.andreas.meyer@chalmers.se)

<sup>4</sup>University of Texas at Austin,  
Austin, Texas  
[jan.fuhg@utexas.edu](mailto:jan.fuhg@utexas.edu)

<sup>2</sup>Institute of Applied Mechanics,  
TU Braunschweig, Braunschweig,  
Germany

<sup>5</sup>Sandia National Laboratories  
P.O. Box 5800

<sup>3</sup>Institute of Solid Mechanics, TU Dresden  
TU Dresden, 01062 Dresden, Germany  
[karl.kalina@tu-dresden.de](mailto:karl.kalina@tu-dresden.de) and [URL](#)

Albuquerque, NM 87185-1326, USA  
[dtseidl@sandia.gov](mailto:dtseidl@sandia.gov)

### ABSTRACT

Neural network (NN)-based constitutive models can fit arbitrarily complex material behavior due to the universal function approximation theorem. However, without enforcing physical constraints, the extrapolation behavior is unsatisfactory, i.e., the predicted responses outside the training regime remain uncertain and may deviate from fundamental principles. Therefore, a major scientific challenge is how to preserve the expressiveness of NN models while enforcing a priori physical constraints. A second pillar to provide trustworthy predictions is model interpretability, which allows mathematical reasoning of responses for unseen data. In addition to model formulation and discovery, the issue of data acquisition is also critical. In particular, Digital Image Correlation (DIC)-based methods offer great potential in this context. This invited session aims to collect outstanding contributions that address these challenges and to foster discussions on recent advances.

All contributions dealing with the above challenges are welcome for this invited session. Suggested topics include, but are not limited to:

- Constitutive modeling with NNs (elasticity and inelasticity)
- Sparse regression, Bayesian learning, symbolic regression
- Interpretability and fulfillment of physical constraints
- Acceleration of multiscale simulations with NNs
- Identification and parametrization of constitutive models from experiments
- Use of full-field data for data generation/model training
- Data-driven identification for the extraction of stress-strain pairs from experiments