The Euromech Colloquium 650 – Addressing Challenges in Applied Mechanics through Artificial Intelligence Applications, 27 – 29 August 2025, Belgrade, Serbia

New Trends for ML-Based Solution of Solid Mechanics Tasks

Sandra Klinge

Department of Structural and Computational Mechanics,
Technische Universität Berlin, Berlin, Germany
Corresponding Author: sandra.klinge@tu-berlin.de

I. INTRODUCTION

Machine Learning (ML) and Neural Networks (NN) have proven to be highly versatile and applicable to a broad variety of engineering problems in solid mechanics [1, 2]. The present talk gives an overview of recent trends in this field and shows some application examples.

II. EXAMPLE I: CANN-DEM FRAMEWORK

A generic NN-approach consisting of the Deep Energy Method (DEM) and Constitutive Artificial Neural Networks (CANN) has been investigated for elastostatic simulations as an alternative to the traditional Finite Element Method (FEM). No explicit material model is required since the CANN replaces analytical expressions describing the material behavior. The approach is trained based on a small number of deformation states and corresponding boundary conditions and can be used in further simulations on a structural level thereafter. The tests presented have applied a two-, a four- and a twelve-parameter CANN for an incompressible and a compressible Neo-Hookean material. The DEM has been conducted with one, four and six deformation states, respectively on 100 sample points as well as for a three-dimensional T-shaped structure.
The achieved results show that the coupled CANN-DEM architecture works robustly and efficiently. This also applies to the process of automatic material identification. The resulting CANN models generalize well for loading conditions which are not part of the training data. Different than observed in some other approaches, consistently good agreements between the trained CANNs and original material models indicate that there is no influence of the CANN initialization on the final results.

III. EXAMPLE II: oPINN

A new ML architecture, namely the oscillatory Physics-Informed Neural Network (oPINN) has been introduced for the numerical investigation of oscillating continua. The approach carries out a modal analysis of a structure alongside with the transient analysis.
The numerical validation has been carried out on three different test cases of the wave equation with comparison to analytical approximations of the solution as well as to a numerical reference solution based on the conventional Adams predictor-corrector time stepping scheme. The results show that the reference solution and the oPINN can capture the characteristic behavior of continua subjected to free oscillations as well as to harmonic excitation with good agreement and accuracy. In numerically more challenging cases like a saw tooth displacement, the oPINN demonstrates its higher numerical accuracy emphasized by the consistent conservation of energy. This can be attributed to the iterative solution procedure for all time steps in parallel which enables the use of symmetric difference stencils in time, whereas conventional multi-step algorithm only can apply one-sided difference stencils and are bound by the Dahlquist barriers. For the further optimization of accuracy, an additional contribution to the loss term stipulating the conservation of energy has been suggested and demonstrated to be effective. The relative error of the amplitudes for the sawtooth test case amounts to 7.3%, whereas the relative error stays below 5% for the numerically less challenging test cases.
Moreover, the potential of transfer learning has been investigated. This step results in better accuracy and allows to speed up the calculations for a series of related tasks exploiting the similarity between neighbouring solutions and makes use of the adaptive nature of NN training. The results furthermore show its efficacy in calculating solutions for comparatively stiff problems. The suggested architecture of the NN is designed to obtain the modal properties (eigenfrequencies, eigenshapes, amplitudes) of the structure as well as the transient simulation result.

IV. EXAMPLE III: STATISTICAL HOMOGENIZATION

The final example deals with the statistical homogenization methods evaluating the effective response of heterogeneous materials to different cases of loading. A key challenge in applying these methods is the choice of a suitable probability function that accurately captures the material's spatial correlations [5]. To address this open issue, we propose a machine learning based approach to identify a correct two-point correlational descriptor. A combination of neural networks is used to extract the probability functions from the microstructure image focusing purely on the geometry of the given structure. By coupling fully connected neural networks (FCNN) and a convolutional neural network (CNN), both trained simultaneously, our adaptable approach significantly reduces the data requirements, allowing for effective training with a comparably small data set.

V REFERENCES

[1] S. Hildebrand and S. Klinge, "Comparison of neural FEM and neural operator methods for applications in solid mechanics," Neural Comput. & Applic, vol. 11, pp. 16657–16682, 2024. DOI:https://doi.org/10.1007/s00521-024-10132-2
[2] S. Hildebrand and S. Klinge, "Hybrid data-driven and physics-informed regularized learning of cyclic plasticity with neural networks," Mach. Learn.: Sci. Technol., vol. 5, pp. 045058, 2024. URL https://iopscience.iop.org/article/10.1088/2632-2153/ad95da
[3] S. Hildebrand, J. G. Friedrich, M. Mohammadkhah and S. Klinge, "Coupled CANN-DEM simulation in solid mechanics," Mach. Learn.: Sci. Technol., vol. 6, pp. 015038, 2025. URL https://doi.org/10.1088/2632-2153/adaf74
[4] S. Hildebrand, J. Sachsendal and S. Klinge, "Simulating vibrations of continua with oscillatory Physics-Informed Neural Networks (oPINN)," (submitted).
[5] L. Schmollack and S.Klinge, , "A hybrid CNN-FCNN surrogate model for spatial correlations in two-phase composite materials," (submitted).