ML BASED SOLUTION OF SOLID MECHANICS TASKS

Steffan Hildebrand, Luzie Schmollack, Sandra Klinge*

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

Abstract

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.

Example 1: The phasefield-based crack simulation is easy to implement into an ML setup due to the inherently energy-based nature of the problem. However, to avoid divergence and overfitting behavior during training, the conventional techniques requires a very high number of collocation points which is further intensified in cases where the necessary NN expressivity is elevated to model discontinuities such as cracks. The work proposes Quadrature-Based Deep Energy Method (Q-DEM) employing a mesh-based discretization analogous to variational Physics Informed NNs (V-PINNs). The method is validated by a case study on a plate made of Al 7075-T6 subjected to traction loading leading to a mixed mode I-II fracture.

Example 2: A new ML architecture, namely the oscillatory Physics-Informed Neural Network (oPINN) has been suggested for the numerical investigation of oscillating continua [3]. The approach carries out a modal analysis of a structure alongside with the transient analysis. Moreover, the potential of transfer learning has been investigated. This step results in a better accuracy and allows to speed up the calculations for a series of related tasks exploiting the similarity between neighbouring solutions and the adaptive nature of NN training. Among others, the numerical results show the great efficiency of the procedure in calculating solutions for comparatively stiff problems.

Example 3: 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 [4]. 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.

Keywords

Machine Learning; Physics Informed; Neural Networks; Damage; Oscillations; Composites

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. Sachsendal and S. Klinge, "Simulating vibrations of continua with oscillatory Physics-Informed Neural Networks (oPINN)," (submitted).

[4] L. Schmollack and S.Klinge, , "A hybrid CNN-FCNN surrogate model for spatial correlations in two-phase composite materials," (submitted).