Parametric Physics-Informed Neural Networks (PINNs) for Solving Inverse Problems in Mechanics: Viscoplastic Constitutive Model Calibration

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Abstract

Recent advancements in machine learning have transformed numerous fields, including mechanical engineering, by offering powerful tools for data analysis, prediction, and optimisation. In mechanical engineering, constitutive models serve as numerical tools to represent the mechanical behaviour of materials. However, calibrating advanced constitutive models remains a challenging and computationally intensive task. This study leverages Physics-Informed Neural Networks (PINNs) to significantly reduce the computational cost of such calibrations, demonstrated through a case study focused on the Chaboche viscoplastic constitutive model and the prediction to the constitutive response for cyclic tensile tests.
The Chaboche model is recognised for its capability to represent the complex, temperature-dependent mechanical response of metals, capturing phenomena such as viscoplasticity and isotropic-kinematic hardening. Calibrating the model and determining its relatively large number of parameters from experimental time-strain-stress data necessitates the adoption of an inverse analysis approach (1). This typically involves incrementally integrating the evolution equations characteristic for the state variables of the Chaboche model across the experimental loading profile and exploring various combinations of model parameters to achieve the best fit to the available experimental data, thereby identifying the most representative model parameter set by least-squares optimization. This process is computationally expensive, particularly when the model must be calibrated over a wide range of temperatures, based on outcomes from a large number of experiments.

This study utilises PINNs to streamline the calibration process, thereby effectively reducing the computational burden associated with constitutive model calibration. Initially, the Chaboche model formulation is directly incorporated into the neural network framework, and the resulting PINN is trained to construct a parametric solution for the Chaboche model, representing the material deformation behaviour across different loading conditions and various combinations of model parameters. Once the parametric solution is obtained, the trained PINN is employed as a fast surrogate for the Chaboche model in inverse analysis to determine the optimal set of model parameters. This integration enables efficient inverse analysis by leveraging the computational power of GPUs, benefiting from automatic differentiation for calculating required gradients for inverse analysis, and enabling one-shot forward evaluation of PINNs, in contrast to the incremental numerical integration required when using the

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Chaboche model in traditional methods.

In the present contribution, we show that after training the PINNs surrogate model for the typical ranges of the material constants (unsupervised), the Chaboche model parameter identification from a set of synthetic material stress-strain-time curves is successfully completed within an order of 30s. This is a factor of 1000 faster than the traditional approach, based on a numerical integration of the evolution equations within inverse analysis. We hence demonstrate that despite known limitations (2,3), rapid parameter identification for continuum mechanical models of complex, time-dependent material behaviour represents a domain where PINNs can realise their full potential.

Keyeywords: Physics Informed Neural Networks; Constitutive model calibration; Inverse problem; Chaboche model; Parametric solution

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