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Machine learning-accelerated cyclic plasticity simulations

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Abstract

Finite Element (FE) simulations involving many loading cycles with nonlinear material models can lead to high computational costs. One approach to accelerate the cyclic simulations is to use cycle-domain modeling. Such modeling builds upon standard plasticity theory and is formulated as a viscoplastic model for the evolution of plastic deformations in the material over many cycles. A key challenge, however, with cycle-domain material models is to formulate a suitable per-cycle evolution law for the plastic strain. In our earlier work, we investigated the feasibility and accuracy of Machine Learning (ML) to formulate such an equation. The proposed ML-based cycle-domain model was able to produce very accurate results while only taking a single increment per cycle. However, that approach requires a lot of training data even for uniaxial loading. In this contribution, we present an approach to speed up cyclic simulations by taking large time increments in multiaxial loading. This approach takes much larger time steps than standard time integration schemes. Specifically, we propose to use ML to train an explicit model that learns the incremental solutions of the evolution equations for the internal variables. We evaluate different methods for incorporating knowledge from the underlying time- domain model to guide the ML-based model and reduce the amount of needed training data. The physics informed ML models are trained against artificially generated data obtained from a cyclic plasticity model under multiaxial cyclic loading. We prepare training data by varying the strain increment length and direction, enabling training across a wide range of increment sizes and directions without requiring a large number of loading cycles. The trained ML models are applied to finite element simulations, and their accuracy and efficiency are analyzed.

Keywords:

Cyclic plasticity Machine learning Large time increments