A Machine Learning-Based Constitutive Model Incorporating History-Dependent Features for Cyclic Loading Scenarios

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Introduction

Constitutive models are critical for describing and predicting the mechanical behavior of materials under diverse loading conditions. Recent advancements in Machine Learning (ML) have enabled the development of data-driven constitutive models, with particular emphasis on formulating yield functions—a fundamental component of these models [1–3]. While most ML-based yield functions primarily focus on initial yielding, this study extends the approach to account for history-dependent effects, enabling accurate predictions for cyclic loading scenarios, including isotropic, kinematic, and mixed hardening behaviors. The proposed ML-based yield function is formulated using a Support Vector Classification (SVC) model, trained on a feature vector comprising 6 stress components and 6 plastic strain components. These components represent the current state of the material and were sufficient for describing monotonically increasing loading scenarios [4,5]. To extend the applicability of the model to cyclic loading, the feature vector has been extended with two additional components, accumulated plastic strain and signed equivalent stress. The accumulated plastic strain captures the material's deformation history, while the signed equivalent stress, taken from the previous step, provides directional information about the loading. Together, these features enable the trained ML model to effectively capture cyclic loading behaviors. For three cases—isotropic, kinematic, and mixed hardening—the training data included two synthetic datasets with strain amplitudes of 0.004 and 0.008 under a load ratio of R=−1. The synthetic data were generated using monotonic CPFEM simulations as the basis, ensuring an accurate representation of the material's behavior for each hardening scenario. The trained ML model demonstrates the ability to interpolate and extrapolate within and beyond the training strain amplitude range. It can also predict responses for different load ratios (e.g., R=0), and generalize effectively additional cycles when tested on unseen data. The proposed approach allows the ML-based yield function to effectively capture complex cyclic behaviors, including isotropic, kinematic, and mixed hardening. By incorporating history-dependent features and expanding its applicability to diverse loading conditions, this work represents a significant advancement in microstructure-sensitive materials modeling and contributes to the development of digital material twins.

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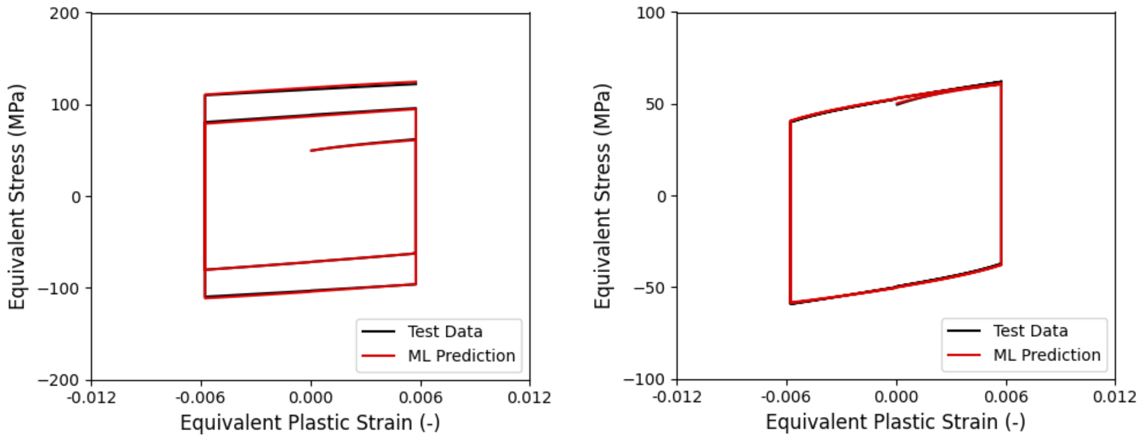

(a) (b)

Figure 1: Interpolation capability of the trained ML model, tested on unseen data with a strain amplitude of 0.006 and R=−1. The real data consists of six stress components and six plastic strain components; the plots illustrate the equivalent stress versus equivalent plastic strain derived from these components. (a) Model trained on purely isotropic hardening data with strain amplitudes of 0.004 and 0.008. (b) Model trained on purely kinematic hardening data with strain amplitudes of 0.004 and 0.008.

References

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