Intelligent surrogate model for the calibration of Hansel-Spittel flow stress model

Thanh Chung Nguyen (1)(2), David Ryckelynck (2), Katia Mocellin (2), Alexis Gaillac (1), Adrien Thierry (1)

(1) Framatome, Components Research Center
(2) CEMEF, Mines Paris PSL

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Within the context of hot forming of metallic alloys and the optimization of process parameters, an intelligent surrogate model would be of interest for the identification of material behavior using industrial data. An accurate constitutive equation aims to improve the ongoing forging process. Furthermore, online calibration of the physical and/or constitutive parameters of the working material enables process monitoring that integrates artificial intelligence and our knowledge of the mechanics of materials [1]. We expect more interpretable process monitoring. To achieve this, the present study proposes comparing a classical deterministic optimization process for finding optimal parameters with the predictions generated by an intelligent surrogate model. The calibration process utilizes a dataset of strain-stress curves obtained at different temperatures and strain rates as input data, where the calibration step's output is the ten coefficients of the Hansel-Spittel flow stress model. Methodologically, the classical approach relies on a two-stage optimization strategy: the parameters are first explored within prescribed bounds using Simplicial Homology Global Optimization (SHGO) to avoid local minima and rigorously explore the broad parameter space, with the mean squared error (MSE) serving as the objective function. The resulting vector is subsequently refined using a Levenberg-Marquardt local optimization procedure to guarantee rapid and highly precise local convergence. In contrast, the intelligent surrogate model is a specialized artificial neural network consisting of fully connected layers. Specifically, the network is designed as a dual-branch Encoder-Decoder Multi-Layer Perceptron (MLP) architecture that independently processes the state variables such as strain, strain rate, and temperature, alongside their finite differentials. These features are concatenated into a dense latent representation before passing through residual skip connections to decode and predict the constitutive coefficients. In this work, the training objective of the surrogate is to perform a direct regression task as in [2], approximating the inverse mapping from multi-condition flow-stress trajectories directly to the ten constitutive parameters. For a preliminary feasibility analysis, the experimental and numerical setup considers a synthetic database containing thousands of parameter vectors generated via a sampling strategy for training. For each vector, the forward Hansel-Spittel model produces a six-curve material signature corresponding to three temperatures and two strain rates. The testing set then evaluates the models using both experimental and synthetic data. The results indicate that for standard flow-stress curves well-described by the Hansel-Spittel formulation, both approaches provide highly reliable calibration, with errors consistently below 5%. However, the main distinction lies in computational efficiency; while the iterative nature of the classical optimization results in a computational cost of several minutes for a single calibration, the trained neural network provides predictions immediately within milliseconds. This discussion also covers cases of experimental data that do not conform to the standard Hansel-Spittel flow model, highlighting a shared limitation. When experimental curves exhibit an abrupt transition from strain hardening to dynamic softening, both the classical optimization and the neural surrogate encounter significantly larger calibration errors. This occurs because the standard formulation intrinsically lacks the mathematical flexibility to reproduce such sharp changes associated with complex metallurgical mechanisms. Ultimately, this study demonstrates that the deep-learning surrogate drastically accelerates parameter identification, making it highly adaptable for online calibration and real-time process monitoring in industrial applications. Future perspectives include enriching the synthetic training dataset with physics-informed trajectories representative of abrupt hardening-softening transitions, which holds the potential to overcome current constitutive limitations while preserving the surrogate's profound computational advantage.

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