

FAST PROBABILISTIC MATERIAL CHARACTERIZATION: AMORTIZED SIMULATION-BASED INFERENCE FOR PHENOMENOLOGICAL MODELS WITH BAYESFLOW

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Abstract

The calibration of phenomenological constitutive models can be formulated as a stochastic inverse problem. In this setting, material parameters are inferred from noise-corrupted observations of structural responses. However, classical inverse analysis typically casts parameter identification as a deterministic optimization problem, thereby neglecting the stochastic nature of experimental observations and model uncertainties. Consequently, measurement noise, model-form discrepancies, and potential non-uniqueness are not rigorously quantified, and the result is often a single best-fit parameter set rather than a probabilistic characterization of the parameters. Moreover, these methods rely on iterative optimization procedures requiring repeated evaluations of nonlinear finite element models, leading to substantial computational cost. Many industrial calibration scenarios are not fully unconstrained but operate in structured settings. Probe geometries, loading protocols, and boundary conditions are typically standardized, while the constitutive model class and its phenomenological parameterization are predefined. The restricted domain induces a learnable mapping between parameters and responses, allowing inverse analysis to be cast as an amortized inference problem. In this work, we employ neural posterior estimation (NPE) implemented with BayesFlow to enable near-instantaneous parameter identification. The model learns a global conditional posterior distribution that maps observed response data directly to the underlying material parameters, thereby eliminating the need to solve a new optimization problem for each material. By combining a stochastic noise prior with forward simulations, the framework defines a simulator-based generative process that captures the full complexity of the inverse solution space. To enable the millions of forward simulations required for posterior amortization, the computationally expensive finite element solver is replaced by a trained surrogate model. The resulting amortized inference model embeds the physics of the constitutive model and acts as a universal inference engine applicable to any material instance within the parameter space. Instead of deterministic point

estimates, the approach produces posterior distributions that explicitly represent parameter uncertainty and non-uniqueness. These posterior distributions enable statistically consistent reasoning about parameter identifiability and material variability, which is essential for robust downstream tasks such as design, simulation, and optimization. Validation on polypropylene recycling blends using experimental observations from a uniaxial tension test and a punch test demonstrates the potential of amortized inference for fast, robust, and uncertainty-aware material characterization in circular economy workflows.