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PHYSICS-CONSTRAINED OPERATOR LEARNING FOR NONLINEAR PATH- AND RATE-DEPENDENT MATERIALS: DISCOVERY AND ACCELERATED SIMULATION

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ABSTRACT

Driven by recent advances in scientific machine learning, operator learning is emerging as a powerful framework for discovering and representing complex material behavior while enabling accelerated prediction and simulation. Material discovery and model prediction remain bottlenecks in engineering design: accurately capturing how materials respond across varying loading conditions, histories, parameters, and microstructures typically requires extensive iterative experiments and simulations. Operator-learning approaches overcome this by learning families of material responses instead of isolated constitutive relations for individual cases. Combined with physical constraints—objectivity, material symmetries, thermodynamic principles, conservation laws, and evolution structures—learned operators enable both rapid discovery of transferable material representations and fast, efficient forward prediction.

This mini-symposium focuses on path- and rate-dependent materials (viscoplasticity, viscoelasticity, creep, damage, stress relaxation), where history dependence is central. We convene researchers from computational mechanics, materials science, and scientific machine learning to exchange developments in physics-constrained operator learning for material discovery and accelerated simulation.

Key Topics:

- Physics-constrained operator learning for material discovery
- Identification of constitutive operators from experimental and computational data
- Learning of history-dependent and path-dependent material response
- Discovery of free energies, dissipation mechanisms, internal variables, and evolution operators
- Neural operators for microstructure–property and process–structure–property relations
- Multiscale and microstructure-sensitive operator learning
- Differentiable simulation and inverse material characterization
- Accelerated prediction and forward simulation: surrogate models, digital twins, parametric studies
- Uncertainty quantification, interpretability, and generalization of learned operators
- Applications to nonlinear, inelastic, multiphysical, and evolving materials

The primary focus is on methods combining learned mappings with physical structure to identify transferable material representations, enable efficient forward prediction across loading paths and scales, and accelerate both model discovery and real-time simulation.