16th World Congress on Computational Mechanics and 4th Pan American Congress on Computational Mechanics

July 21-26, 2024, Vancouver Convention Centre, Vancouver, British Columbia, Canada

MACHINE LEARNING METHODS FOR MULTISCALE AND MULTIPHYSICS MATERIAL MODELING

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MINISYMPOSIUM

The advent of advanced manufacturing and materials technologies now provides the capabilities to architect microstructured materials such as 3D printed lattice structures, fiber-reinforced or multiphase composites, foams, electro- or magneto-active polymers, etc. The mechanical and multifunctional behaviors of these metamaterials can be tailored to their specific engineering applications and are often highly nonlinear, anisotropic, inelastic, and multiphysical. Thus, classical constitutive models are typically not flexible enough to model their effective material behavior in multiscale and multiphysics simulations, while concurrent multiscale approaches are inherently computationally expensive and slow. Thus, in recent years, the formulation of constitutive models using highly flexible machine learning and surrogate modeling methods such as artificial neural networks and deep learning, Gaussian processes, radial basis functions, clustering methods, etc. has gained momentum. Nevertheless, many challenges remain to be addressed for machine learning-based material models, such as their accuracy, reliability, and physical soundness, their efficiency, the consideration of inelastic material behaviors, parametric dependencies or uncertainties, etc.

This minisymposium welcomes contributions on the state-of-the-art of machine learning methods for multiscale and multiphysics materials modeling. In particular, the areas of interest include, but are not limited to:

- Material models based on feed-forward, deep, recurrent, convolutional, graph, and other types of neural networks, or Gaussian processes, radial basis functions, clustering methods, etc.
- Models for elastic, as well as dissipative, inelastic (elasto-plastic, visco-elastic, etc.), and multiphysically coupled (electro, magneto, thermo, chemo, mechanical, etc.) material behaviors
- Physics-guided/informed/augmented machine learning methods for thermodynamically consistent, physically, and mathematically sound material models
- Consideration of parametric dependencies, uncertainties, adaptivity, error estimates, etc. in machine learning methods for material modeling
- Efficient implementation and application of machine learning methods for multiscale and multiphysics simulations