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

CONSTITUTIVE MODELING OF COMPLEX MATERIALS WITH MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

Francisco Sahli Costabal[1] and Adrian Buganza Tepole[2] and Steve WaiChing Sun[3] and Ellen Kuhl[4] and Nikolaos Bouklas[5]*

[1]*Pontificia Universidad Católica de Chile*
[2]*Purdue University*
[3]*Columbia University*
[4]*Stanford University*
[5]*Cornell University*

MINISYMPOSIUM

The recent boom in machine learning (ML) and artificial intelligence (AI) has opened new horizons in computational mechanics. One of the areas in which ML and AI have had tremendous impact is replacing the traditional way in which constitutive models of complex materials are developed. For example, ML and AI have helped solve problems such as: i) Homogenization of the response of multiscale materials with complex microstructure; ii) Discovery of closed-form material models out of a large library of possible models; iii) Posing of inverse problems for identification of heterogeneous model parameters either by replacing the forward solver with ML surrogates or by directly learning the inverse map from imaging data. These advances have been applied to different materials such as soft tissues (heart, skin, arteries, brain, etc), metals, elastomers, soils, among others. Beyond modeling individual material samples, ML tools rooted on a Bayesian formulation have been recently proposed to learn the probability distribution for materials which show inherent variability either because of uncertainty in microstructure or, in the case of soft tissue, due to inherent variability from one individual to another. One major focus for ML and AI constitutive modeling has been the imposition of physics constraints as well as combination of data-driven approaches with established modeling techniques such as micromechanics or microstructure-inspired models. For imposing physics, the loss function can help enforce the constraint, but more recent formulations have architectures that guarantee desired physics for arbitrary parameters. Regarding connection to modeling approaches that use information from the microstructure, there have been recent efforts in interpretable ML models. One of the key advantages of ML and AI constitutive modeling has been the flexibility to capture a wide range of material behavior, from linear elastic, to hyperelastic, viscoelastic and plastic deformation, even in the large deformation non-equilibrium regimes. Finally, in order for data-driven constitutive modeling to be truly useful in practice, implementation into numerical solvers such as finite element packages is needed. This symposium encourages submissions regarding machine learning constitutive models for any kind of materials, and physics (hyperelasticity, viscoelasticity, plasticity, etc…) with a focus on probabilistic frameworks for material property inference, and large scale simulations.