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

BAYESIAN LEARNING OF DYNAMICAL SYSTEMS UNDER UNCERTAINTIES

Rimple Sandhu[1] and Mohammad Khalil[2] and Chris Pettit[3] and Dominique Poirel[4] and Abhijit Sarkar[5]*

[1]*National Renewable Energy Laboratory*
[2]*Sandia National Laboratory*
[3]*United States Naval Academy*
[4]*Royal Military College of Canada*
[5]*Carleton University*

MINISYMPOSIUM

Predictive modeling of complex dynamical systems often involves low- to mid-fidelity mechanistic models being calibrated using data acquired through field experiments or high-fidelity simulations. These calibrated models can replace high-fidelity models for outer-loop applications including design optimization and sensitivity analysis. However, the calibration data required for building a robust predictive model often only span limited sets of modeling configurations and operating conditions. Use of such data warrants careful consideration of model and data uncertainties during model calibration.

Often, a Bayesian model discovery framework is deployed that can automatically extract maximum information from sparse training data by identifying the optimal parametric structure of mechanistic models through Bayesian model comparison and producing uncertainty-aware model parameter distributions through stochastic sampling. Such a framework can help capture data sparseness, model inadequacies, and other modeling simplifications, allowing the end-user to include these post-discovery parametric uncertainties in their applications that involve running these models at conditions different from the ones captured in the field data.

The field of model comparison and Bayesian learning has significantly advanced in the last decade, mostly due to an immense interest in predictive low-fidelity representation of high-fidelity models in situations where large numbers of model runs are required. This symposium will focus on the broad field of Bayesian inverse modeling within the context of dynamical systems, with particular focus on recent advances in the field of Bayesian learning including model comparison, sparse learning, dimensionality reduction and compressive sensing.