MACHINE LEARNING AND UNCERTAINTY QUANTIFICATION FOR COUPLED MULTI-PHYSICS, MULTI-SCALE AND MULTI-FIDELITY MODELING

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ABSTRACT

Due to their substantial computational cost, it remains challenging to use high-fidelity first principles (FP) models for decision support. The situation is particularly grave in applications involving multi-query analyses (e.g., optimization, uncertainty quantification), which require a large number of simulations. This challenge is amplified for coupled multi-physics models, where the computational cost increases markedly with each physics component model incorporated into the system. Data-driven models, such as classical and Machine Learned (ML) surrogates as well as Reduced Order Models (ROMs), are increasingly being adopted to increase the computational efficiency of evaluating an FP model. However, using purely data-driven models credibly in extrapolatory regimes is challenging. This session will present advances in FP, data-driven models, and/or the coupling of the two, which increase the computational efficiency of predicting complex phenomena, while providing estimates of uncertainty.

We are calling for talks that present novel algorithms or application studies that utilize one, or more, time scales, spatial scales, physics, or model fidelity. Specific topics of interest include: algorithms for constructing stable data-driven models for long-time integration of single-physics computational models; stable methods for coupling multiple data-driven and/or FP models with different physics or scales; and multi-fidelity strategies that use data from multiple models (potentially both FP and data-driven models) of varying cost and accuracy to predict complex phenomena at significantly reduced cost.