

RECENT ADVANCES IN DATA-DRIVEN MODELING AND UNCERTAINTY QUANTIFICATION OF COMPLEX DYNAMICAL SYSTEMS

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ABSTRACT

The development of high-fidelity efficient solvers is critical for accurate and reliable simulation of large-scale, multi-physics problems in computational science and engineering applications. However, many-query problems such as inverse design and parameter inference often place a computationally intractable burden on these solvers. Moreover, the characterization and propagation of systemic variability and uncertainties in input parameters are also of fundamental importance in model-based computations of various science and engineering problems. Recent advances in data-driven analysis of systems and machine learning (ML) approaches have revolutionized the modeling of engineering systems by presenting effective ways to tackle the computational bottleneck. Development of fast surrogate models, data-driven augmentation of existing high-fidelity solvers or identification of governing laws, the design of optimized hybrid methods that combine data-driven learning processes with physics-based models, and the integration of ML algorithms with classical solution techniques for inverse problems using tools like learning regularizers and deep generative priors, are some of the exciting new avenues that have helped to address many previously unattainable challenges in modeling and analysis of complex engineering systems and structures.

This minisymposium will be devoted to fundamental developments as well as challenging applications of data-driven methods for such forward and inverse problems in computational fluids and environmental flows, among others. Topics of interest include but are not limited to, advanced physics-informed ML strategies for engineering systems, multi-fidelity training, applications of transfer learning, neural operators, and deep generative modeling.