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# STRUCTURE-PRESERVING DATA-DRIVEN MODELS FOR PREDICTIVE DIGITAL TWINS

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## ABSTRACT

Digital twins are rapidly emerging as a central paradigm for real-time prediction, monitoring, and control of complex engineering systems. A key challenge in constructing reliable digital twins is the development of data-driven models that remain faithful to the mathematical and physical structures governing the underlying systems. These may include positivity, monotonicity, convexity, and other functional constraints, as well as physical invariants such as conservation of mass, momentum, or energy. Digital twins further demand that models respect symmetries, stability characteristics, and geometric structure to promote reliability. Without such structure preservation, learned models may exhibit nonphysical behavior, violate conservation laws, or become unstable, especially when deployed in predictive settings.

This minisymposium focuses on methodologies for building structure-preserving data-driven models that enable robust, interpretable, and trustworthy digital twins. We will bring together researchers developing and applying novel methods involving structure-preserving model reduction, operator inference, physics-constrained scientific machine learning, and related areas. Topics of interest include: physics-constrained dynamical systems learning, data-driven reduced-order models for digital twins, data-driven variational integration, equivariant machine learning, structure-preserving neural operators, constrained system identification, and other techniques for ensuring invariant preservation, stability and passivity in learned models. We welcome contributions from a variety of science and engineering applications, including but not limited to fluid dynamics, solid mechanics, quantum mechanics, fluid-structure interactions, energy systems, advanced manufacturing, and Earth system modeling.