

## MODELING AND LEARNING OF STRUCTURED DYNAMICAL SYSTEMS

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### MINISYMPOSIUM

Accurate dynamical models of real-world phenomena have become indispensable tools in numerous scientific and industrial applications such as vibrational analysis and control of mechanical systems, shape optimization, and digital twins. In some cases, one has access to explicit representations of these models resulting from, for example, a semi-discretization of the corresponding partial differential equations (PDEs). Due to the need for greater accuracy, the resulting models are generally rather complex with millions of degrees of freedom, making their simulation a formidable challenge to be used in real-time applications. This motivates the need for model reduction: Given the large-scale model, construct easy-to-simulate reduced models whose behavior is guaranteed to approximate the original one.

These large-scale mathematical models (dynamical systems) naturally inherit many physical properties of the phenomena they represent, encoded in the internal differential and nonlinear structures of these dynamical systems. Typical differential structures include higher-order time derivatives occurring in structural mechanics and acoustics, time delays that account for incompleteness in the modeling process, or integral terms that are often used in conservation laws. Therefore, it is vital that the resulting reduced models retain these properties so that they are physically meaningful surrogate representations. A typical approach for the reduction process is the use of a Petrov-Galerkin projection of the original dynamics. This is referred to in the literature as “projection-based (intrusive) structure-preserving model order reduction”.

However, in some settings one does not have access to an explicit (state-space) representation of the underlying dynamics. Instead, one has an abundant amount of input-output data, either in the time or frequency domain. In these instances, the goal is to “learn a structured model” directly from the data such that the learned model inherits the relevant differential structures (without having explicit access to them). This is what we refer to as “data-driven (non-intrusive) structure-preserving modeling”.

This minisymposium (MS) will focus on both intrusive as well as non-intrusive (data-driven) approaches for approximating structured dynamical systems. Talks in this MS will focus on both theory and real-world applications and will bring together the classical engineering modeling knowledge with state-of-the-art approaches from numerical analysis for the efficient design of structured dynamical systems. Topics covered by this MS will be:

- Structural modeling of dynamical systems,

- Intrusive (projection-based) structure-preserving model order reduction,
- Data-driven (non-intrusive) structure-preserving modeling,
- Modeling of structured nonlinearities,
- Hamiltonian and port-Hamiltonian systems,
- Data-driven vibrational and system analysis.