Low-Dimensional Identification of Port-Hamiltonian Systems by Combining Model Order Reduction and Machine Learning

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Complex technical systems are frequently modeled by coupled multiphysics equations and are subsequently subject to virtual multiobjective optimization. The energy-based port-Hamiltonian (pH) framework in combination with structure-preserving model order reduction is an ideal approach for modeling such systems in a hierarchical manner [1, 2]. Unfortunately, the derivation of pH systems is not trivial, and often a universal transformation into a pH system is not available at all. A possible approach to circumvent this problem is data-based system identification. Modeling with the help of data, e.g. from measurements or artificially generated, can usefully supplement the classical approach where the system is obtained from discretizing partial differential equations. Existing identification approaches discover pH systems in the frequency-domain [3] and time-domain [4] by optimization. In contrast, we aim to discover a low-dimensional pH-system using a deep learning based framework.

Deep neural networks have attracted much attention for their flexibility and performance in many fields. For example, in [5] autoencoders were used to find low-dimensional system coordinates in which a system can be described with ODEs based on a library of ansatz functions. In this work, we propose a new approach to discover pH systems from data obtained from multiphysics systems to usefully complement existing classical linear pH modeling approaches and identification by optimization. In detail, we combine a (variational) autoencoder with a multi-layer perceptron (MLP) for the identification of dynamics in latent space. Consequently, the autoencoder not only reduces the dimensionality of the underlying system but also nonlinearly transforms the system states to a low-dimensional manifold in which the system is describable in the pH formulation. The MLP is constrained to learn a dynamical system that follows the description of the pH framework based on the reduced coordinates as well as their time derivatives. A high-fidelity multi-physics model of a thermoelastic disc brake is an illustrative example where the high-dimensional system data is obtained from a finite element (FE) discretization of both the thermal and mechanical domains.

References

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