NON-INTRUSIVE PARAMETRIC MODEL REDUCTION VIA DATA-DRIVEN OPERATOR INFERENCE

Parisa Khodabakhshi[1], Shane McQuarrie[2] and Karen Willcox[2]

[1] Lehigh University
[2]University of Texas at Austin

ABSTRACT

Numerical simulation of dynamical systems is a primary means of understanding their behavior. However, simulations of large-scale systems impose significant computational expenses for outer-loop applications, such as uncertainty quantification, optimization, and inverse problems. Model reduction seeks to alleviate this burden by constructing reduced-order models (ROMs) that accurately approximate the dynamics of the underlying system but are significantly cheaper to evaluate. Such ROMs are key enablers for outer-loop applications on large-scale dynamical systems. One major challenge in developing ROMs is the limited training data for large-scale systems. This issue is aggravated in situations where, in addition to having a high-dimensional state space, the governing equations are parameterized. In this presentation, the authors present a novel framework for model reduction of parameterized time-dependent partial differential equations (PDEs) with affine parametric dependence, which combines the rigor of projection-based model reduction with the convenience of machine-learning methods [1]. The parametric structure of the ROM is directly embedded into the ROM. The operators of the ROM are learned using the Operator Inference (OpInf) method [2]. OpInf is a scientific machine learning method that combines data-driven learning and physics-based modeling. The resulting ROM can map parameter values to approximate PDE solutions efficiently.

REFERENCES

[1] S. McQuarrie, P. Khodabakhshi, and K. Willcox, Non-intrusive reduced-order models for parametric partial differential equations via data-driven operator inference, arXiv preprint arXiv:2110.07653, 2021.

[2] B. Peherstorfer, and K. Willcox, Data-driven operator inference for non-intrusive projection-based model reduction, *Computer Methods in Applied Mechanics and Engineering*, **306**, 196-215, 2016.