Model reduction for modeling, analysis and control – Methods and applications

Open Invited Track Code: mip4p

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Abstract

Model reduction methods are established tools in the field of automatic control. Conversely, automatic control has traditionally been a driver for the advancement of model reduction methods. We invite both, contributions that require model reduction as an enabling step for automatic control, and contributions on the advancement of model reduction methods for use in systems and control. Contributions that involve learning or other data-driven approaches, or compare data-driven approaches to model reduction methods that require physical models are particularly welcome.

Handling Committee

TC 2.6 Distributed parameter systems

The organizers stress the open invited track is not restricted to applications to distributed parameter systems. The open invited track is organized in collaboration with TC 1.1 Modelling, Identification and Signal Processing, and TC 6.1 Chemical Process Control.

Description of the topic

Due to the ever-growing complexity of technical systems, automatic control has evolved from a set of techniques for simple control loops to methodologies for complex systems. This evolution to more and more complex systems is evident, for example, from the shifts from lumped parameter to distributed parameter systems, from isolated to networked systems, or from the use of simple models to multiphysics simulation models.

Whenever working with a complex system, it is an obvious question to ask if there is a low-dimensional set of particularly suitable ("latent") coordinates that describe the system sufficiently precisely for the given purpose.

Apart from a fundamental interest in such a low-dimensional description or approximation, a reduced order model enables a wider choice of control methods that would otherwise be unavailable or simply impractical, due to their scaling in computational complexity, for example.

A broad variety of model reduction methods has successfully been used in the field of automatic control. Conversely, automatic control has been a driver for advancements in model reduction methods throughout. In projection-based model reduction methods (see, e.g., [1, 3]), for example, the understanding of observable and controllable subspaces has helped to advance proper orthogonal decomposition to balanced truncation. Similarly, dynamic mode decomposition, originally developed for autonomous systems, has been extended to systems with inputs, and, arguably, the popularity of DMD is to a considerable extent due to its successful application to control in fluid dynamics [8]. More recently, learning-based methods have challenged established reduction and identification methods. (see, e.g., [4]). In contrast to projection-based approaches, learning-based methods require no physical model, a property they have in common with many identification approaches. Learning-based methods are also often claimed to be superior because it is natural to incorporate nonlinear mappings into neural networks. Finally, recent developments in Koopman operator theory [7] have created additional impetus for model reduction methods, both in combination with system theoretic and learning-based approaches (see, e.g., [2, 6] and [5], respectively).

It is the purpose of this open invite track to collect contributions that either present methodological advances in model reduction methods tailored to the field of control, or involve model reduction as a crucial enabling step for subsequent application of systems and control methods. We particularly invite contributions that benchmark model reductions based on learning and neural networks, or that compare such methods to established ones.

References

[1] A. C. Antoulas. *Approximation of Large-Scale Dynamical Systems.* Society for Industrial and Applied Mathematics, 2005.

[2] H. Arbabi, M. Korda, and I. Mezić. A Data-Driven Koopman Model Predictive Control Framework for Nonlinear Partial Differential Equations. In *2018 IEEE Conf. Decis. Control CDC*, pages 6409–6414, 2018.

[3] P. Benner, S. Gugercin, and K. Willcox. A survey of projection-based model reduction methods for parametric dynamical systems. *SIAM Review*, 57(4):483–531, 2015.

[4] S. L. Brunton and J. N. Kutz. *Data-driven science and engineering: Ma-*

chine learning, dynamical systems, and control. Cambridge University Press, 2022.

[5] C. Folkestad, D. Pastor, I. Mezic, R. Mohr, M. Fonoberova, and J. Burdick. Extended Dynamic Mode Decomposition with Learned Koopman Eigenfunctions for Prediction and Control. In *2020 Am. Control Conf. ACC*, pages 3906–3913, July 2020.

[6] M. Korda and I. Mezić. Optimal Construction of Koopman Eigenfunctions for Prediction and Control. *IEEE Trans. Autom. Control*, 65(12):5114–5129, Dec. 2020.

[7] A. Mauroy, I. Mezic, and Y. Susuki, editors. *The Koopman Operator in Systems and Control: Concepts, Methodologies, and Applications*. Lecture Notes in Control and Information Sciences. Springer International Publishing, 2020.

[8] J. Proctor, S. Brunton, and J. Kutz. Dynamic mode decomposition with control. *SIAM J. Applied Dynamical Systems*, 15(1):142–161, 2016.