Guest Editorial Introduction to the IEEE Control Systems Letters Special Section on Data-Driven Analysis and Control

MATHEMATICAL models play a crucial role in systems and control theory. They can take various forms, including ordinary or partial differential equations, difference equations, transfer matrices, and their combinations with logic elements. There are several ways to obtain a mathematical model for a physical system. The most common approach is to apply the basic physical laws that govern the variables in the system, known as first principles modeling. An alternative method is system identification, which uses data collected from the physical system by setting certain external variables to specific values and measuring other variables.

However, classical model-based approaches can face several challenges when dealing with complex systems that combine different subsystems. Obtaining precise mathematical models for such systems can be difficult, if not impossible, and the models obtained may be too complex. To address these problems, data-driven analysis and control offers an alternative approach to system analysis and control design. This method avoids the step of finding a mathematical model of the to-be-controlled complex system and instead focuses on designing control laws directly using only measured data.

Data-driven control has a rich history within systems and control theory. Dating back to Ziegler and Nichols' work in the 1940s on tuning PID controllers, data-driven control methods have been investigated within various contexts and under different names, such as adaptive control, iterative feedback tuning, unfalsified control, predictive control, and model reference control. Very recently and parallel to the rise of data-intensive methodologies in other scientific and engineering disciplines, data-driven control has established itself as a more systematic and more pronounced subfield of systems and control theory.

Moreover, one could of course argue that also the combination of classical system identification followed by model-based control as described above is an instance of data driven control design. Indeed, methods using this combination are often called indirect methods of data-driven control, as they consist of the two-step process of data-driven modeling (i.e., system identification) followed by model-based control. In contrast to these indirect methods, there exist direct methods that focus on directly mapping data to controllers without an intermediate step of system identification. Both paradigms have different pros and cons. For example, identification might be expensive and the obtained model may not always be useful for the intended control design problem. In comparison to the maturity of system identification, the theory of direct data-driven control is still in its infancy.

The goal of this special section is to provide a snapshot of the recent developments as well as the state-of-art within data-driven control. This special section consists of 10 papers that deal with several topics related to data-driven approaches, and present new results on challenging theoretical as well as practical aspects. Indeed, the set of papers allow to have an overview of different aspects related to learning (as in [A1], [A3], [A5], and [A7]), control design (as in [A2], [A4], [A6], [A8], and [A9]) and identification (as in [A10]). A brief description of the different contributions is provided below.

In [A1], the authors present a direct minimum-variance (MV) data-driven safe control design approach for uncertain linear discrete-time stochastic systems. The superiority of the direct MV approach is shown by developing and comparing direct versus indirect learning approaches and MV versus certainty-equivalence (CE) approaches.

In [A2], the authors study the possibility to synthesize a stabilizing feedback control, in the complete absence of a model, starting from the open-loop control generated by an expert operator, capable of driving a system to a specific set-point. The system under consideration is linear and discrete time and two different controls: a linear dynamic controller and a static, piecewise linear one, are investigated.

In [A3], the authors investigate the reinforcement learning (RL) framework in the context of non-deterministic finite transition systems (FTSs), whose solutions are non-unique but not endowed with a probability measure. RL controllers are designed for maximizing the best-case and worst-case return obtained from a trajectory (run) of the model, assuming full-state information.

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In [A4], the authors propose a data-driven approach to derive explicit predictive control laws by exploiting the prior knowledge about the fact that the optimal solution is a piecewise affine controller. Lyapunov techniques to perform a prior stability check for safe controller deployment are used.

In [A5], the authors address backward reachability as a framework for providing collision avoidance guarantees for systems controlled by neural network (NN) policies. They introduce a formulation that allows to obtain closed-form representations of polytopes to bound the backprojection sets tighter than prior work, which required solving linear programs and using hyper-rectangles.

In [A6], the authors design switching control law for switched affine systems, ensuring that a neighborhood of a given operating point is stable. After proposing a model-based control design, a systematic method is exhibited to translate a model-based condition expressed using the framework of Linear Matrix Inequalities (LMI), into a data-driven condition.

In [A7], the authors propose a framework for training a neural ODE using barrier functions and improve robustness for classification problems. Robustness against adversarial attacks using a wait-and-judge scenario approach is also considered.

In [A8], the authors study data-driven regional stabilization problem for input-saturated systems. By using Lyapunov functions and a generalized sector condition, a convex design algorithm based on linear matrix inequalities for obtaining a regionally stabilizing data-driven static state-feedback gain is provided.

In [A9], the authors address the problem of providing a data-driven solution to the local stabilization of linear systems subject to input saturation. A systematic method to transform model-driven into data-driven LMI conditions is presented. Although this technical solution is equivalent to some recent advanced results based on S-procedure or Peterson Lemmas, its advantage relies on its simplicity and its potential applicability to a broad class of problems.

In [A10], the authors deal with model parameter identification method via a hyperparameter optimization scheme (MI-HPO). The proposed method adopts an efficient strategy to identify the parameters of dynamic models in a data-driven optimization manner. Such a method is used in a dedicated platform of a full-scaled autonomous race vehicle.

Appendix: Related Articles

[A1] H. Modares, "Minimum-variance and low-complexity data-driven probabilistic safe control design," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1598–1603, 2023.

[A2] F. Blanchini, F. Dabbene, G. Fenu, F. A. Pellegrino, and E. Salvato, "Model-free feedback control synthesis from expert demonstration," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1604–1609, 2023.

[A3] A. Borri and C. Possieri, "Reinforcement learning for non-deterministic transition systems with an application to symbolic control," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1610–1615, 2023.

[A4] V. Breschi, A. Sassella, and S. Formentin, "Data-driven design of explicit predictive controllers with structural priors," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1616–1621, 2023.

[A5] M. Everett, R. Bunel, and S. Omidshafiei, "DRIP: Domain refinement iteration with polytopes for backward reachability analysis of neural feedback loops," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1622–1627, 2023.

[A6] A. Seuret, C. Albea, and F. Gordillo, "Practical stabilization of switched affine systems: Model and data-driven conditions," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1628–1633, 2023.

[A7] R. Yang, R. Jia, X. Zhang, and M. Jin, "Certifiably robust neural ODE with learning-based barrier function," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1634–1639, 2023.

[A8] V. Breschi, L. Zaccarian, and S. Formentin, "Data-driven stabilization of input-saturated systems," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1640–1645, 2023.

[A9] A. Seuret and S. Tarbouriech, "A data-driven approach to the L_2 stabilization of linear systems subject to input saturations," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1646–1651, 2023.

[A10] H. Seong, C. Chung, and D. H. Shim, "Model parameter identification via a hyperparameter optimization scheme for autonomous racing systems," *IEEE Contr. Syst. Lett.*, vol. 7, pp. 1652–1657, 2023.

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