Advanced Data-Driven Control Frameworks for Nonlinear Systems

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Abstract:

Contemporary automation, manufacturing, and cyber-physical systems are increasingly characterized by complex, nonlinear, and high-dimensional dynamics operating under uncertain and time-varying conditions. In such systems, unmodeled dynamics, strong coupling effects, actuator nonlinearities, and external disturbances are frequently encountered, making the derivation of accurate analytical models either extremely expensive or entirely impractical. As a consequence, the effectiveness of classical model-based control approaches, such as PID and Model Predictive Control (MPC), is often compromised, since their performance critically depends on the accuracy of the underlying mathematical model. Even small deviations between the nominal model and the true process dynamics may lead to performance degradation or instability. To overcome these difficulties, there has been an increasing shift toward control paradigms that rely on data, rather than explicit models, for system analysis and controller design [1-4]. The ongoing digital transformation of industry has resulted in the accumulation of vast amounts of process and operational data, which inherently encode the dynamic behavior of physical systems. This abundance of data has inspired the emergence of data-driven control, a research direction that constructs control laws directly from measured input–output data without resorting to detailed plant identification [5]. Such an approach aims to exploit the descriptive power of data to model, predict, and regulate system behavior, effectively bridging the gap between traditional control theory and modern data science. Data-driven methods are particularly attractive for large-scale or nonlinear systems where model uncertainty and external perturbations are unavoidable. They enable real-time adaptability and robustness while reducing reliance on prior physical modeling assumptions. However, the development of rigorous and generalizable data-driven control frameworks that can guarantee closed-loop stability and robustness remains an open and highly active research area. Several notable methodologies have been proposed to formalize the concept of data-driven control, each grounded in distinct theoretical principles. One of the foundational developments in this field is the Willems' Fundamental Lemma [6], which establishes that for any unknown linear time-invariant system, all possible system trajectories can be represented using a sufficiently rich, or "persistently exciting," dataset of input–output measurements. This result has inspired the Data-Enabled Predictive Control (DeePC) algorithm, which eliminates the need for explicit model identification by constructing the predictive control problem directly from Hankel matrices built from data [7]. DeePC provides strong performance for linear systems but typically assumes persistently exciting data and can be computationally demanding due to its optimization structure. Building upon the same foundation, the Willems–Koopman Predictive Control (WKPC) framework extends DeePC to nonlinear systems by incorporating the Koopman operator theory, which maps nonlinear dynamics into a higher-dimensional linear space [8]. Although the Koopman-based approach offers a promising means of addressing nonlinearities, its performance relies on accurate approximation of Koopman eigenfunctions, which is a nontrivial task in practice. Moreover, both DeePC and WKPC assume time-invariant system behavior and often exhibit sensitivity to noise or nonstationary dynamics in real-world data [9].

In parallel, the Model-Free Adaptive Control (MFAC) family of methods has evolved as another major branch of data-driven control [10]. Unlike DeePC or WKPC, which utilize predictive optimization frameworks, MFAC focuses on adaptive learning through dynamic linearization of the nonlinear system's input–output behavior.

The key concept in MFAC lies in the estimation of pseudo-partial derivatives (PPDs), which act as time-varying sensitivity coefficients that can be recursively updated using real-time data. This formulation enables the controller to maintain adaptability and stability without requiring explicit knowledge of system parameters or structure. While MFAC is conceptually simple and computationally efficient, it may experience difficulties in high-noise environments or under rapid operating condition changes, where accurate online estimation of PPDs becomes challenging [2]. Furthermore, MFAC frameworks often lack mechanisms to explicitly handle input/output constraints or performance optimization criteria, which are critical in safety-sensitive or resource-limited applications. Despite significant progress, current data-driven control strategies still face several theoretical and practical limitations. DeePC and WKPC methods, while effective in structured or quasi-linear settings, are computationally demanding and dependent on persistently exciting datasets that may not always be available in industrial contexts. They also lack inherent adaptability to nonstationary or time-varying systems. Conversely, MFAC and its predictive extensions are more adaptive but provide limited means for constraint handling and multi-objective optimization. Hence, there exists a pressing need for unified frameworks that combine the adaptivity of MFAC with the predictive, optimization-oriented capabilities of modern control architectures, while maintaining theoretical guarantees of stability and robustness. Addressing these challenges requires the development of scalable algorithms that can learn and adapt directly from data, handle nonlinearities, and operate reliably in uncertain, dynamic environments.

Accordingly, the overarching goal of this Ph.D. study is to develop a comprehensive data-driven control framework for nonlinear systems that integrates adaptive learning principles with predictive and optimization-based control mechanisms. The research aims to formulate algorithms capable of ensuring closed-loop stability and robust performance without relying on explicit plant models or persistent excitation assumptions. The study will explore the use of dynamic linearization and online parameter adaptation to construct pseudo-linear predictive models directly from streaming data, complemented by optimization-based tuning and stability analysis using Lyapunov and control barrier function methodologies. By combining theoretical analysis with simulation-based validation and potential experimental implementation, this work seeks to advance the frontier of data-driven control and establish a rigorous foundation for real-time, model-free regulation of complex nonlinear processes. The expected outcome is a generalized framework that enhances adaptability, robustness, and computational efficiency, bridging the gap between existing model-free and predictive control paradigms and paving the way for novel intelligent control systems.

Literature:

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Study Program Board´s opinion:

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Training Centre´s opinion:

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