A multi-level framework for intelligent control of dynamical systems with unknown physics

Abstract

Modern engineering systems are designed to achieve high standards of safety, stability, and efficiency, yet their performance is frequently challenged by environmental uncertainties, operational disturbances, and complex real-world dynamics. Phenomena such as wind-induced vibrations in skyscrapers or flow-induced oscillations in bluff bodies illustrate how unsteady aerodynamic forces and structural fatigue can compromise performance of a system. Sustaining desired functionalities in such conditions requires active control strategies capable of sensing disturbances, reasoning about system behavior, and deploying corrective actions in real time, capabilities that passive control mechanisms cannot offer in rapidly varying environments. However, the design of effective active controllers is often hindered by two major limitations. First, classical active control frameworks depend on accurate physics-based models, which are difficult to derive for systems influenced by high-dimensional, nonlinear, or partially unknown dynamics. Second, modern data-driven control approaches, including reinforcement-learning-based methods, face challenges related to sample inefficiency, safety concerns during trial-and-error exploration, and the computational cost associated with learning or simulating complex dynamical systems. This work addresses these challenges by developing machine-learning-driven tools for model-agnostic predictive control of systems with unknown or partially known physics. The talk will highlight three central contributions toward intelligent control of dynamical systems with incomplete physical knowledge: (a) Handling systems where governing physics in unknown or partially known: Novel algorithms have been developed to extract interpretable governing equations of dynamical systems directly from data, enabling principled reasoning about system evolution even when governing physics are a-priori unavailable., (b) Accelerated solution of the discovered dynamical system: To enable fast predictive evaluation within a control loop, a new family of neural operators, termed the Wavelet Neural Operator, is introduced to provide rapid and accurate solutions of the discovered dynamical models., (c) Real-time control law learning: A Deep RL framework that leverages developments in (a) and (b), is proposed to learn control policies suitable for real-time deployment without requiring explicit system models. The individual components of the framework are benchmarked against several canonical problems from literature. The applicability of the overall framework is illustrated on two problems, a 76-storey building subjected to wind load and flow past a cylinder. Overall, these developments contribute to a unified and computationally efficient paradigm for active control of dynamical systems with unknown or partially known physics.