Dynamic model Learning for Model Predictive Control of Nonlinear Systems

Porteur : Madiha Nadri-Wolf, madiha.nadri-wolf@univ-lyon1.fr
Partenaires : Pascal Dufour pascal.dufour@univ-lyon1.fr
Laboratoire : LAGEPP / Dycop https://lagepp.univ-lyon1.fr/les-equipes/dycop
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Résumé : (200 mots)
This position explores the intersection of Control Theory (CT) and Machine Learning (ML) to enhance the control of nonlinear systems. While CT employs model-based strategies for stabilization and estimation, it struggles with the complexities of nonlinear models, especially regarding noisy data and uncertainties. This research proposes leveraging ML advancements to create data-driven representations of dynamic systems, integrating these with traditional control methods.
The proposition focuses on improving model predictive controllers (MPC), known for their effectiveness but high computational demands. In contrast, model-free methods like reinforcement learning are less computationally intensive but lack robust theoretical foundations. The goal is to simplify nonlinear MPC optimization using coordinate transformations, facilitated by ML algorithms, to yield linear or affine representations.
The research will initially focus on finding transformations to represent nonlinear systems in a latent linear space.
The work can continue as part of a PhD by demonstrating that these representations can support MPC controller design with reduced complexity. Collaborations with industrial partners will apply the findings to real-world energy system challenges, validating the effectiveness of the proposed strategies and contributing to advancements in both fields.

Scientific field: Control theory and Machine Learning
Keywords: control theory, model predictive control, identification, machine learning, optimization

Research Project:

Scientific context: In the context of control of nonlinear systems, this PhD position addresses fundamental contributions on the crossroads between Control Theory (CT) and Machine Learning (ML). The two fields, while being distinct, have a long history of interactions between them and as both fields mature, their overlap is more and more evident. CT aims to provide differential model-based approaches to solve stabilization and estimation problems. However, nonlinear models usually need to be simplified and they have difficulty accounting for noisy data and non modeled uncertainties. This work proposes to take advantage of progress in ML for the design of representations of the model from data from various trajectories of complex dynamic systems. This will be coupled with more traditional approaches from advanced control.

General objective of the internship and expected contributions: One of the famous control strategies is the model predictive controller (MPC) based on a nonlinear model and classical analysis as theory for stability, feasibility and robustness, management of constraints; but has a high on-line implementation complexity. On the other hand, model-free approaches such as reinforcement learning have low online complexity, but a theory of closed-loop stability, feasibility, robustness are almost "non-existent". Here, to simplify the resolution of the optimization problem (through for example convexification) of the nonlinear MPC, we will use coordinate changes to obtain a linear/affine representation. Under conditions on the nonlinear model and the observations, the transformation will not require an explicit calculation but the representation will be given by a machine learning algorithm. We will work on a unified theory of controller stability and robustness.

Research program: As first step we will consider the question of finding (for example by learning) a change of coordinates which transforms a representation of a strongly nonlinear controlled dynamic system into a latent linear system which will be able to predict the future state of the system in the original coordinates and therefore allow the synthesis of an MPC controller for the nonlinear system. One possible approach is based on the Koopman operator [KOR18], [BRU16]. Then, we have to show that the system in latent space (often of higher dimension but can be reduced [Jan22]) can be used to design an MPC controller for the dynamic system of complex nonlinear origin, but with a complexity of computation comparable to an MPC controller for a linear dynamic system with the same number of inputs, controls and states. Finally, in collaboration with our industrial partners [GAL19], the obtained results will be applied to concrete problems to energy systems [PER20], [PER17] and experimentally on a new LAGEPP pilot [DAD22].

Perspectives:- This research program will continue for a period of three years at Lagepp/ the Campus de la Doua of Université Lyon 1 in Villeurbanne, France

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