3 year funded PhD thesis Position
"Reinforcement learning based-economic predictive control for nonlinear systems
(Machine Learning & Control Theory)

Where
Lyon, France
Univ. Lyon 1 (https://www.univ-lyon1.fr), LAGEPP Laboratory (https://lagepp.univ-lyon1.fr)

When
Applications are now open until May, 15th
If successful, the candidate is expected to start the PhD in October 2021.

Funding
French Ministry of Higher Education and Research : about 1950 € gross salary/month x 3 yrs
Possibility to add a teaching assistant contract

Hiring process
First leg: supervisors select the candidate
Send the files: CV, motivation letter, official grades at the University, MSc report, github account if available, recommendation letter of the Msc thesis professor
to: pascal.dufour@univ-lyon1.fr madiha.nadri-wolf@univ-lyon1.fr

Second leg: an oral presentation will take place in front of the EEA Doctoral School committee.

Supervisors
Control Theory: Madiha Nadri (https://scholar.google.fr/citations?user=KOXesIUAAAAJ&hl=fr&oi=ao , https://lagepp.univ-lyon1.fr/membre/nadri-madiha/)
Control Theory: Pascal Dufour (https://sites.google.com/site/dufourpascalsite)

Topic
In the context of control of nonlinear systems, this PhD thesis position addresses fundamental contributions on the crossroads between Artificial Intelligence (AI) / Machine Learning (ML) and Control Theory (CT). These fields, while being distinct, have a long history of interactions between them and as both fields mature, their overlap is more and more evident [9]. CT aims to provide differential model-based approaches to solve stabilization and estimation problems. These model-driven approaches are powerful because they are based on a thorough understanding of the system and can leverage established physical relationships. 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 deep learning for the design of representations of the model from data from various trajectories of complex dynamic systems (*Figure 1)*. This will be coupled with more traditional approaches to advanced automation.

One of the famous control strategy in CT is the economic predictive controller (EMPC), which is based on a nonlinear model, with a strong theory for stability, feasibility, robustness and management of constraints; but may have 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 almost "non-existent". Indeed, only the convergence of the learning algorithm is guaranteed. Here, to reduce the complexity of the nonlinear EMPC, we will consider an algorithm based on adaptive models via recurrent neural networks. These methods can generally only be used online for small-scale systems. To overcome this, we will use coordinate changes to have 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.

As first step we will consider the question of finding 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 EMPC controller for the non-linear system. Two approaches will be considered : an approximation by N-multi-models [8], [4] and a transformation by the Koopman operator [9],[1],[6]. In both cases, the objective is to show that the system in latent space (often of greater dimension) can be used to design an EMPC controller for the dynamic system of complex nonlinear origin, but with a complexity of computation comparable to an EMPC controller for a linear dynamic system with the same number of inputs, controls and states.

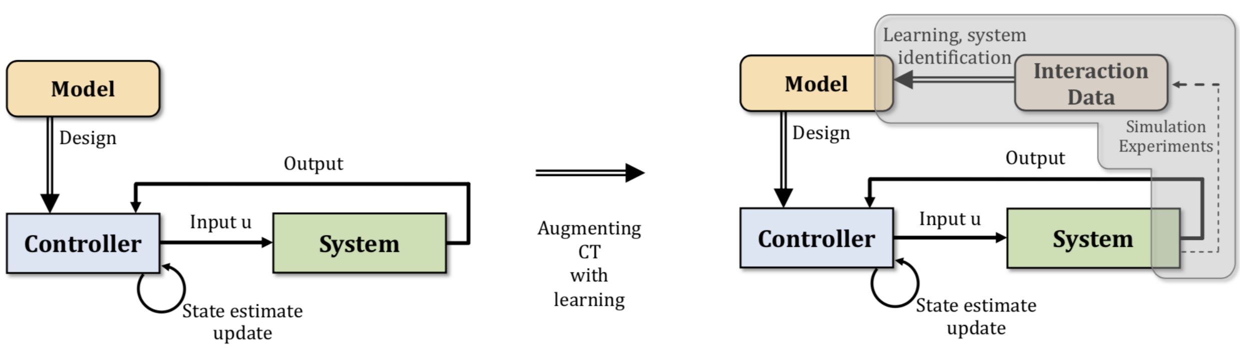

Figure 1: we address combining machine learning and control theory, for instance by augmenting control theory with learned components.

In collaboration with our industrial partners [7],[5], the obtained results will be applied to concrete problems in complex environments requiring planning as well as fine-grained control. In the current context, energy systems are among the fields of application most concerned by the problems linked to the complexity of models (non-linearities, phase changes, coupling of physico-chemical phenomena) and the lack of robust sensors, with increasingly stringent standards and control if necessary. The obtained results will be applied to concrete problems i) experimentally on a new LAGEPP pilot [2]. ii) on a heat pump model that we have already used [3]. The PhD candidate will participate in the ongoing collaboration between the LAGEPP and University of Liège (Ulg) for the experimental side. Research exchanges (multi month stays) with international partners are planned and encouraged.

References

[1] S. L. Brunton, B. W. Brunton, J. L. Proctor, and J. N Kutz, Koopman invariant subspaces and finite linear representations of nonlinear dynamical systems for control, PLoS ONE, 11(2):150-171, 2016.

[2] https://lagepp.univ-lyon1.fr/materiel/dady-demonstrateur-pour-la-recherche-en-automatique-appliquee-au-genie-des-procedes

[3] B. Dechesne, V. Lemort, M. Nadri, P. Dufour, Impact of suction and injection gas superheat degrees on the performance of a residential heat pump with vapor injection and variable speed scroll compressor, 17th International Refrigeration and Air Conditioning Conference at Purdue, july 9-12, 2018, OAI : hal-01896056.

[4] V.Grelet, P. Dufour, M. Nadri, V.Lemort, T. Reiche, "Explicit multi model predictive control of a waste heat Rankine based system for heavy duty trucks", 54th IEEE Conference on Decision and Control (CDC), Osaka, Japan, pp. 179-184, december 15-18, 2015. DOI : 10.1109/CDC.2015.7402105, OAI : hal-01265059.

[5] https://twitter.com/hashtag/InnoTherMS.

[6] M. Korda and I. Mezic," Linear predictors for nonlinear dynamical systems: Koop- man operator meets model predictive control", Automatica, 93:149–160, 2018.

[7] J. Peralez, M. Nadri, P. Dufour, P. Tona, A. Sciarretta, "Organic Rankine Cycle for Vehicles: Control Design and Experimental Results", IEEE Transactions on Control Systems Technology, Institute of Electrical and Electronics Engineers, 25 (3), pp.952 - 965., 2017

[8] J. Peralez, F. Galuppo, P. Dufour, C. Wolf, M. Nadri, "Data-driven multimodel control waste for heat recovery system on a heavy duty truck engine", IEEE Conference on Decision and Control (CDC),Paper FrA10.1, Jeju Island, Republic of Korea, December 14-18, 2020.

[9] M.O. Williams, I. G. Kevrekidis, and C. W. Rowley, "A data-driven approximation of the Koopman operator: Extending dynamic mode decomposition". Journal of Nonlinear Science, 25(6):1307–1346, 2015.