M2 Internship Opportunity

Opportunity to pursue a PhD

Title: Robust Data-Driven Predictive Control with Online Learning for Complex Industrial Systems under Bounded Uncertainties

Supervisors:

Tarek RAISSI (Cnam, tarek.raissi@cnam.fr)

Franco FALCONI (Schneider Electric, franco.falconi@se.com)

The rapid development of Industry 4.0 has led to the digitalization of industrial processes, enabling the collection of large volumes of operational data. Such data can be used to optimize production, reduce energy consumption, and extend equipment lifetime through predictive maintenance. However, industrial systems such as Air Handling Units, Pasteurizers/Sterilizers, and Waste-to-Energy plants are highly nonlinear, multivariable, and subject to significant uncertainties, making classical model-based control approaches often insufficient. Air Handling Units (AHU) regulate heating, cooling, humidification, and air purification for industrial or tertiary buildings. The primary challenges are achieving high control performance while ensuring energy efficiency under varying operating conditions. Pasteurizers and Sterilizers are Food-processing units with strongly nonlinear thermal dynamics, where precise temperature and timing are critical to ensure product safety and maintain quality. Multivariable interactions and nonlinearities make real-time control challenging. Waste-to-Energy Units convert municipal waste into energy via incineration. The main challenge is controlling steam production and energy output while minimizing pollutant emissions and adapting to variable input waste composition and flow rates.

These systems exhibit complex dynamics, strong nonlinearities, interactions among multiple variables, and measurement/process uncertainties, motivating the use of data-driven control techniques that can adapt in real time.

The scientific challenges of this proposal are threefold: (i) Robust control design ensuring stability, performance, and constraint satisfaction in the presence of bounded measurement noise and process uncertainties. (ii) Online adaptation of the control policies incrementally as new operational data becomes available to handle system variability and changing modes of operation. (iii) Set-membership representation of uncertainties using for instance zonotopes

and ellipsoids to efficiently model bounded errors and integrate them into the predictive control design.

The central focus of this work is the design of a robust DeePC framework that incorporates bounded uncertainties, and that is enhanced through online learning in order to progressively improve control performance, robustness, and adaptability in complex industrial systems.

Objectives:

- Conduct a comprehensive literature review on robust DeePC, set-membership estimation techniques, and AI-based online learning for industrial control.

- Develop a robust DeePC controller capable of accounting for bounded uncertainties.

- Implement AI-based online learning to incrementally update uncertainty sets and adapt control policies in real time.

- Validate the approach on simulated and real industrial datasets, including AHU, Pasteurizer/Sterilizer, and Waste-to-Energy systems, evaluating performance metrics such as robustness, constraint satisfaction, adaptability, and control accuracy.

References

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