

An in-context learning framework for control

Riccardo Busetto^{1,3}, Valentina Breschi², Marco Forgione¹, Dario Piga¹, Simone Formentin³

¹IDSIA Dalle Molle Institute for Artificial Intelligence

²Department of Electrical Engineering, Eindhoven University of Technology

³Dipartimento di Elettronica, Bioingegneria e Informazione, Politecnico di Milano

Contact us



In-context learning approach

- Design of a **unified model, estimator or controller** from data $\mathcal{D} = \{D^{(i)}\}_{i=1}^M$ of a class of *similar* systems $\mathcal{S} = \cup_{i=1}^M \mathcal{S}^{(i)}$
- Transformers** are trained for the class, but can **adapt** to the **specific system** extrapolating the **context** from data

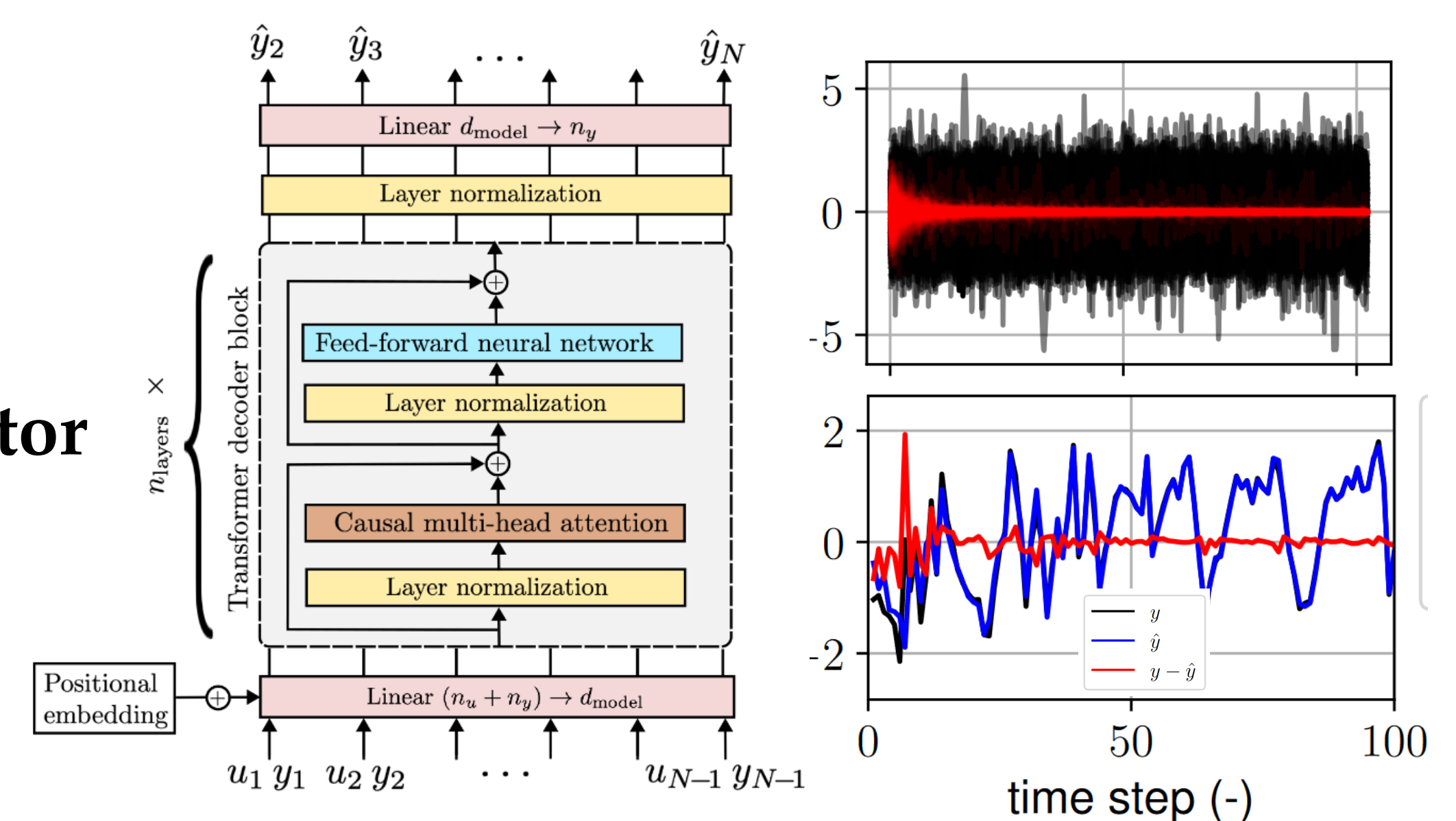


Paper link

System Identification

- Goal:** one-step prediction $\hat{y}_{k+1} = \mathcal{M}_\phi(u_{1:k}, y_{1:k}), \forall S \in \mathcal{S}$
- Context** is understood from input/output data $D^{(i)} = (u_{1:N}^{(i)}, y_{1:N}^{(i)})$
- Learning** from (potentially infinite) set of similar systems through a **simulator**
- Excellent performance** on nonlinear systems (Class of WH systems)

Original work of Marco Forgione, Filippo Pura, and Dario Piga. "From system models to class models: An in-context learning paradigm." *IEEE Control Systems Letters* (2023).



Paper in preparation.. stay tuned

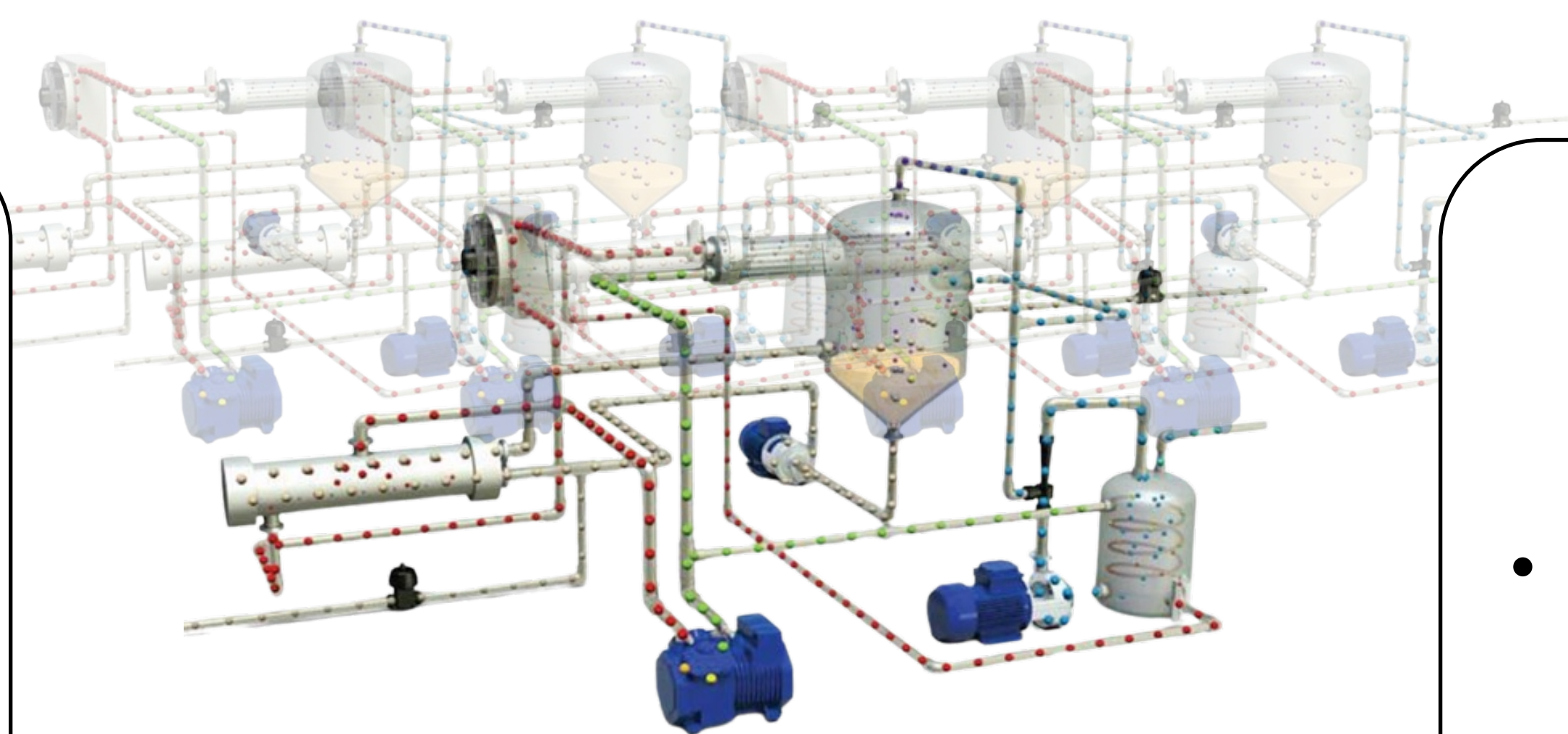
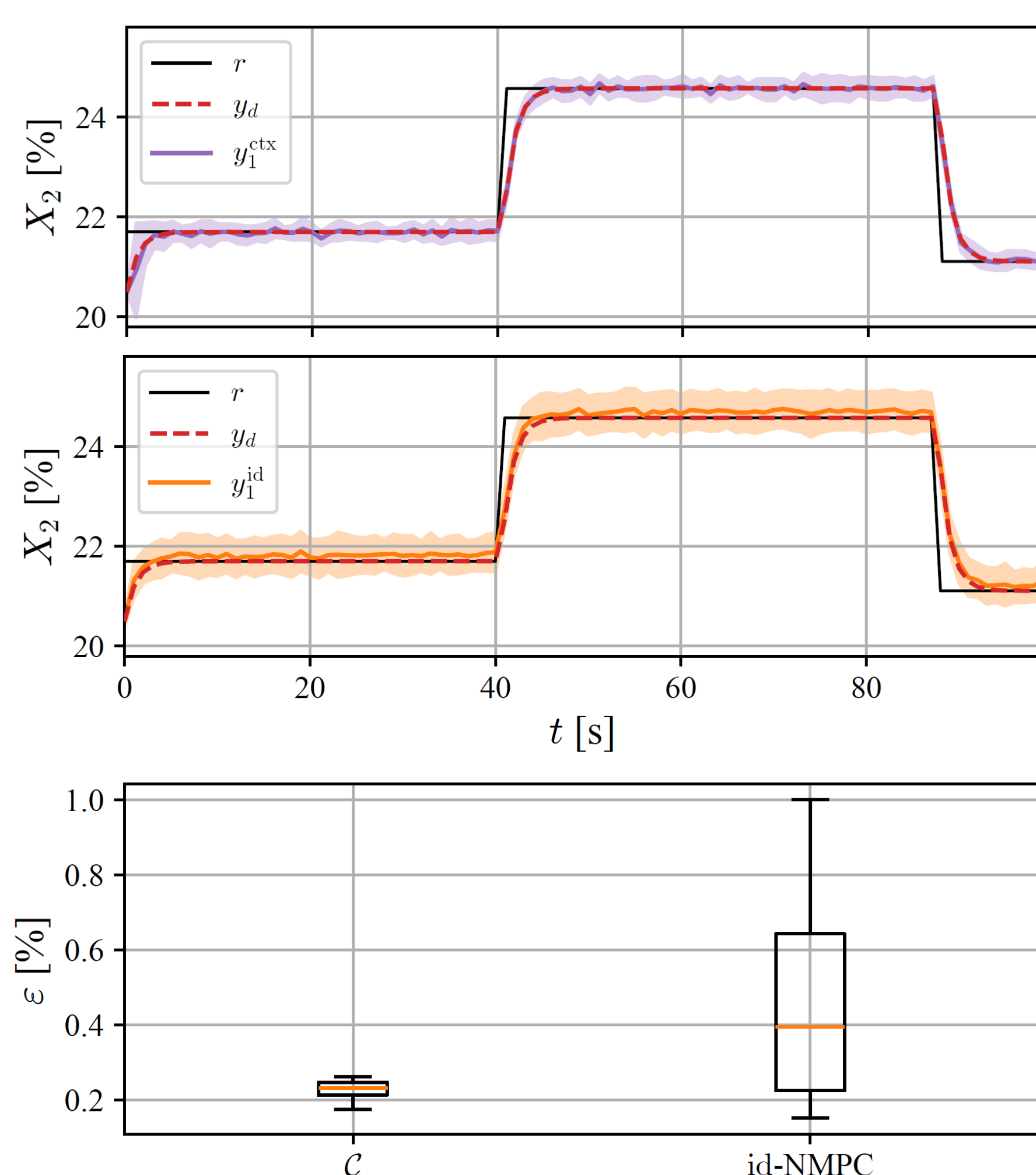
Control

$$\hat{u}_k = \mathcal{C}_\phi(e_{1:k}, u_{0:k-1})$$

- Goal:** model reference control

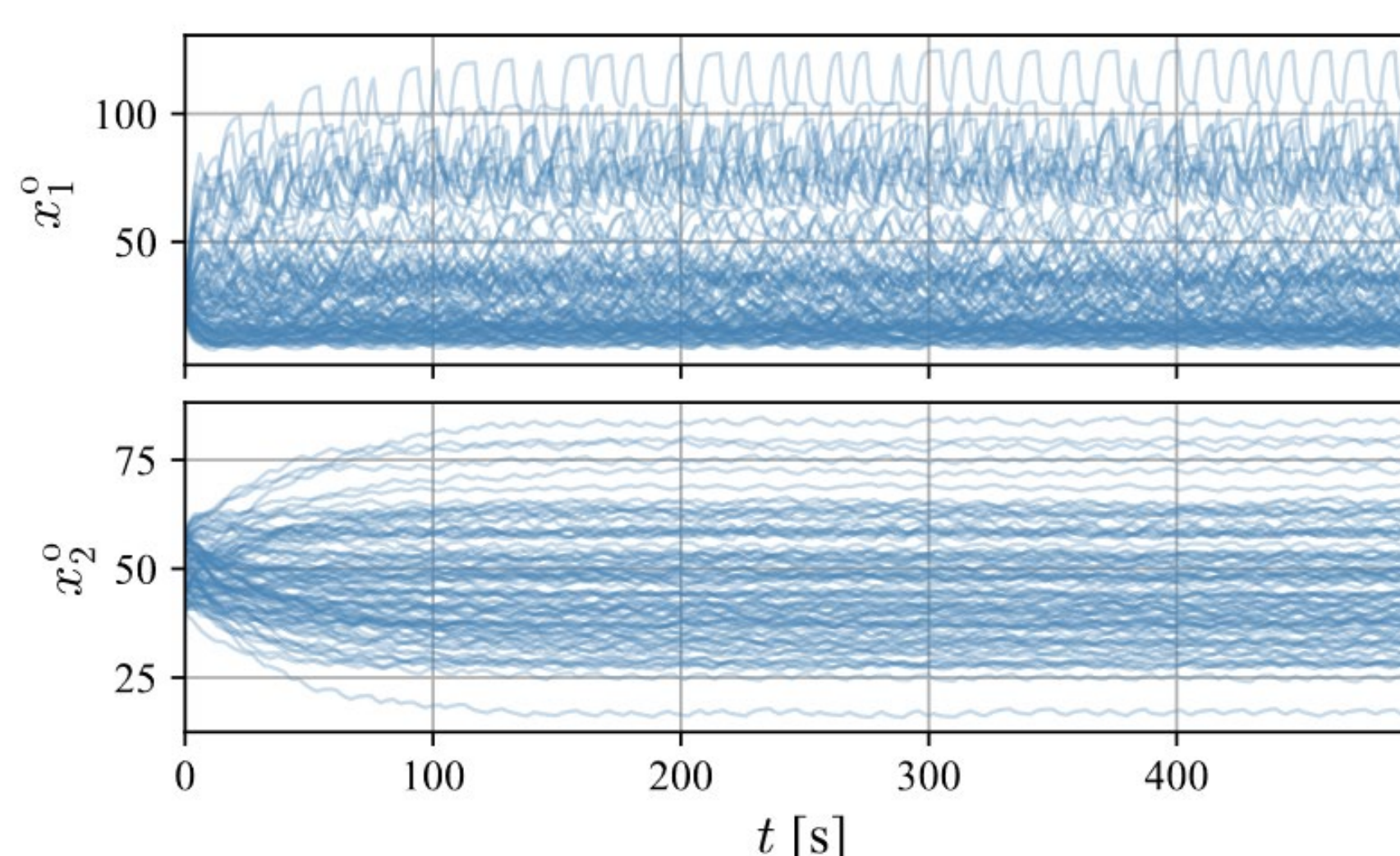
$$\min_{\phi} \mathbb{E}_{p(\mathcal{D})} \left[\sum_{k=1}^{N-1} \|u_k^* - \mathcal{C}_\phi(e_{1:k}, u_{0:k-1})\|_2^2 \right]$$

- Context** is understood from errors $e_{1:k}$ and inputs $u_{0:k-1}$
- Matching error is reduced** with respect to NMPC



Example: evaporation process

- Nonlinear benchmark
- Class \mathcal{S} described by 19 parameters, each perturbed by 5-20%



Future works

- Experimental validation** on applications
- Architectural modifications to **speed up learning**
- Formal results** on properties of the approach (stability, effect of noise)

Paper link



State Estimation

$$\hat{x}_k = \mathcal{F}_\phi(u_{1:k}, y_{1:k}),$$

- Goal:** state estimation

$$\min_{\phi} \mathbb{E}_{p(\mathcal{D})} \left[\sum_{k=1}^{N-1} \|x_k^o - \mathcal{F}_\phi(u_{1:k}, y_{1:k})\|_2^2 \right]$$

- Context** is understood from inputs $u_{1:k}$ and outputs $y_{1:k}$
- Estimation error is reduced** with respect to EKF

