Data - driven control for thermal process

CONTROL SYSTEMS AND INSTRUMENTATION ENGINEERING PROGRAM

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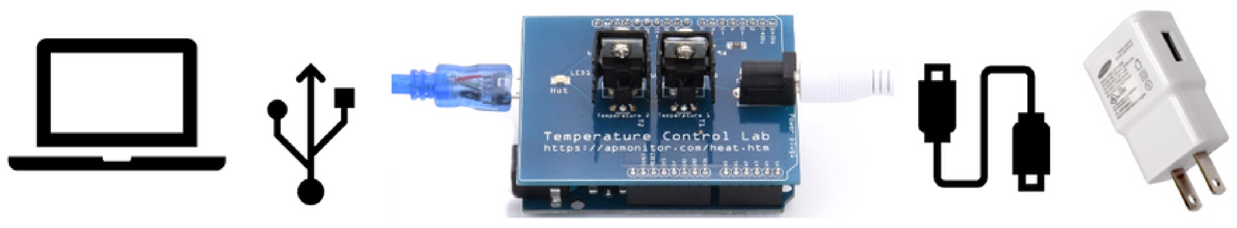
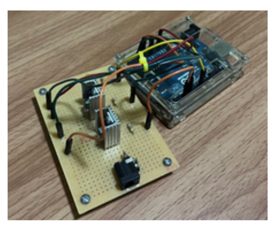
Introduction

This work explores the efficacy of a data-driven deep learning (DL) approach for continuous control. We propose a framework utilising Long-Short Term Memory (LSTM) networks for system identification and Deep Deterministic Policy Gradient (DDPG) for control. This framework is evaluated on the TCLab platform, offering a versatile testbed for nonlinear Single-Input Single-Output (SISO) and Multiple-Input Multiple-Output (MIMO) control problems. Hyperparameter optimisation revealed that the proposed DL-based controller outperforms the conventional approach employing a linear First-Order Plus Dead Time (FOPDT) model for prediction and a DRL controller.

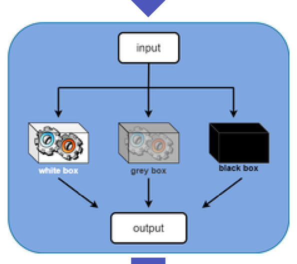
Methods



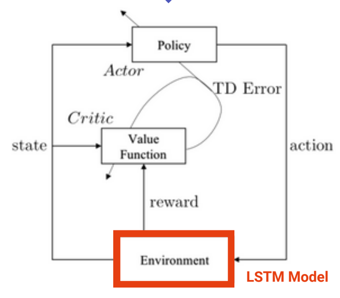
In this project we use TCLab (temperature control lab)[1] as thermal process and control by connect TCLab with computer with serialport to comunication



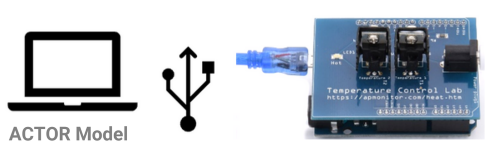
TCLab development and test : Build TClab and test to collect data.



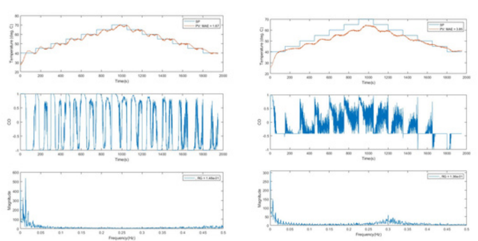
System identifcation and hyperparameter tunning for LSTM : use data collected to train LSTM model of TCLab and select optimal structure of the LSTM model



DDPG training in simulation : use LSTM model of TCLab as Environment to train DDPG controller and test in simulation



Deployment of DDPG on actual system : Implement DDPG model to actual system to test performance of the model



Performance evaluation: evaluate performance data-driven model with FOPDT model

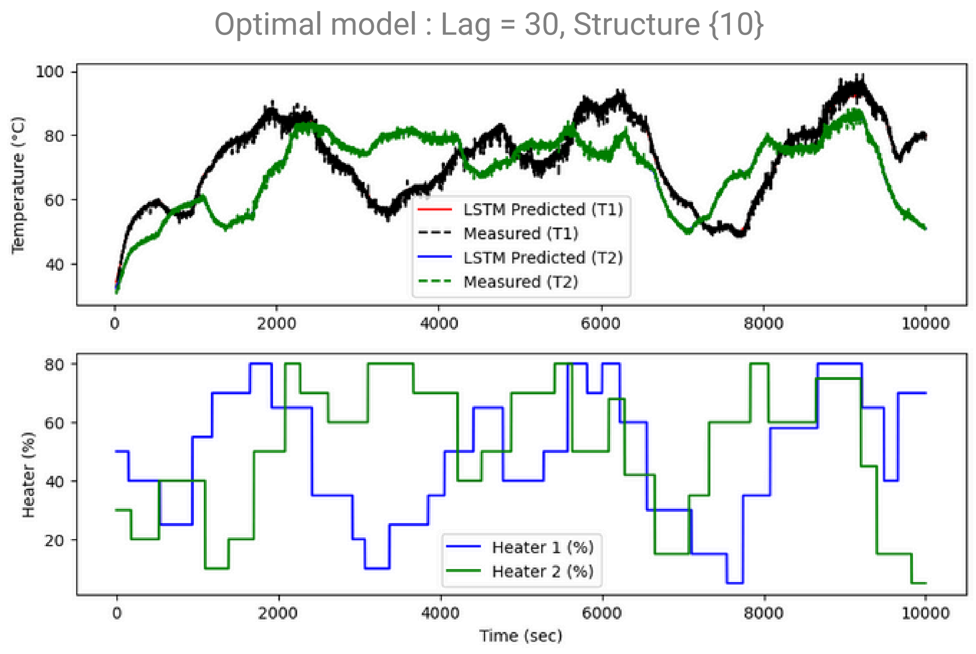
LSTM Model

Collect data from TCLab and creat model of TCLab : search optimal structure of LSTM model

Lags	15	30	45	60

Model Structure
{10}
{25}
{50}
{10, 10}
{25, 25}
{50, 50}
{10, 10, 10}
{25, 25, 25}
{50, 50, 50}

Optimal model : Lag = 30, Structure {10}



Conclusion

- This project successfully demonstrated the superiority of a data-driven deep learning approach for continuous control. Our framework, leveraging LSTMs and DDPG, outperformed conventional methods in various control scenarios.

Future Work:

- Reduced Training Time: Investigate methods to accelerate training (e.g., efficient algorithms, transfer learning).
- MIMO DDPG with Single Actor: Explore implementing MIMO DDPG with a single actor for improved efficiency.
- Adaptive Control: Develop adaptive control mechanisms using transfer learning and online training for dynamic systems.

DDPG Training

Config	MAE	Roughness	Training Time (s)
ε_t = 5, n_h = 32	2.66	7.91e-03	1950.07
ε_t = 0.5, n_h = 32	1.30	5.80e-02	2038.20
ε_t = 5, n_h = 16	1.37	9.20e-03	2057.63
ε_t = 0.5, n_h = 16	1.40	5.09e-02	2077.19
ε_t = 5, n_h = 8	1.55	9.99e-03	1915.05
ε_t = 0.5, n_h = 8	1.56	7.81e-03	1984.02
ε_t = 5, n_h = 4	2.63	2.74e-02	1217.20
ε_t = 0.5, n_h = 4	1.27	2.87e-02	1222.15
ε_t = 5, n_h = 2	1.52	2.20e-02	1804.09
ε_t = 0.5, n_h = 2	1.20	1.44e-02	1862.58

Training DDPG : search structure of DDPG in model training By adjusting the number of nodes in each layer of the actor network (n_h) and the value of ε_t or the tolerance of the system. to train actor and test in simulation

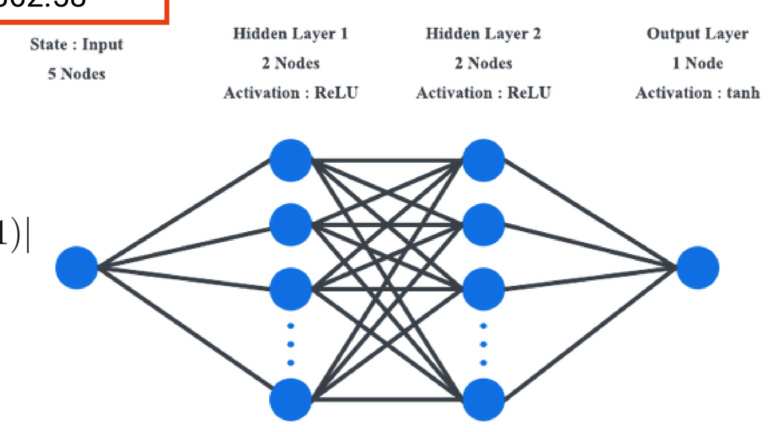
- **STATE**

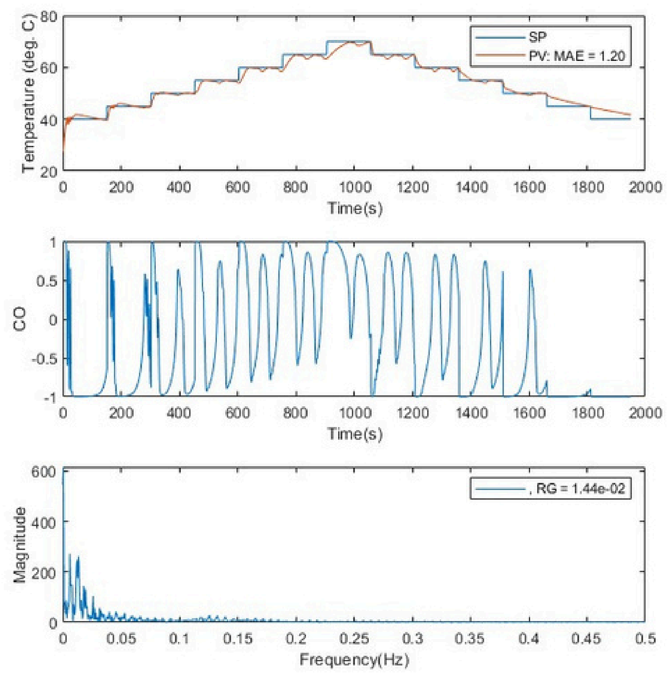
$$\text{STATE} = \{u(t-1), u(t-2), e(t), e(t-1), e(t-2)\}$$

- **REWARD**

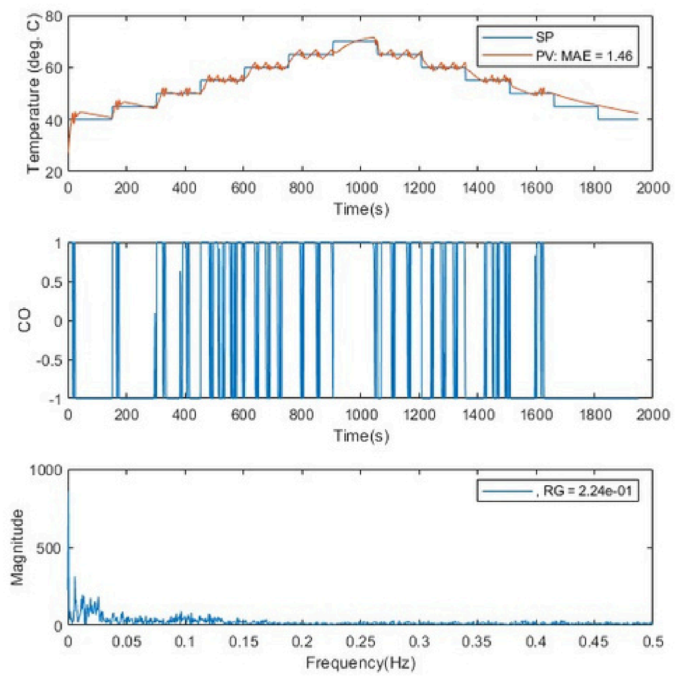
$$\text{Reward} = w_1 \cdot (|e(t)| < \varepsilon_t) - w_2 \cdot |e(t)| - w_3 \cdot |u(t) - u(t-1)|$$

u = control signal
e = error signal
w_i = weight
ε_t = error tolerances





Trained with LSTM Model



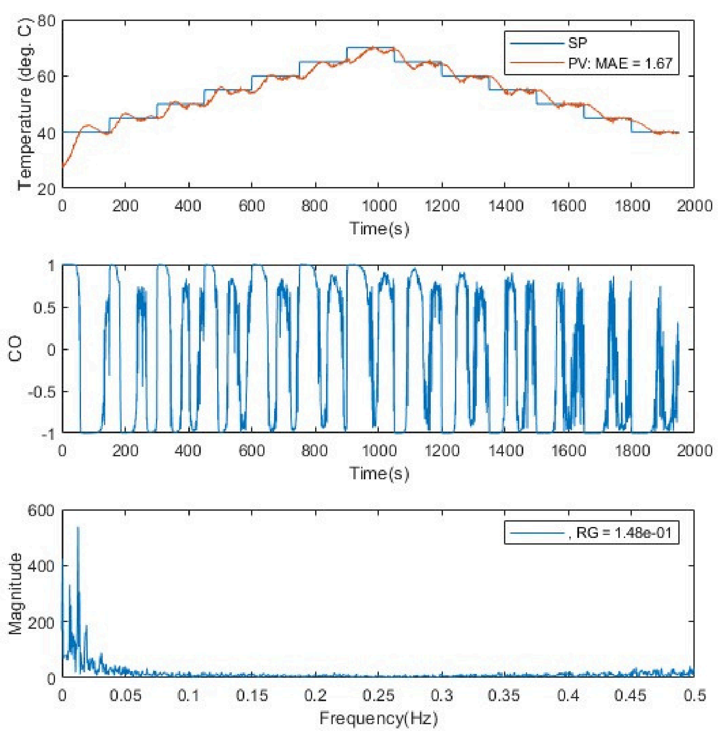
Trained with FOPDT Model

Control Method	MAE	Roughness
LSTM + DDPG	**1.20**	**1.44e-02**
FOPDT + DDPG	1.46	2.24e-01

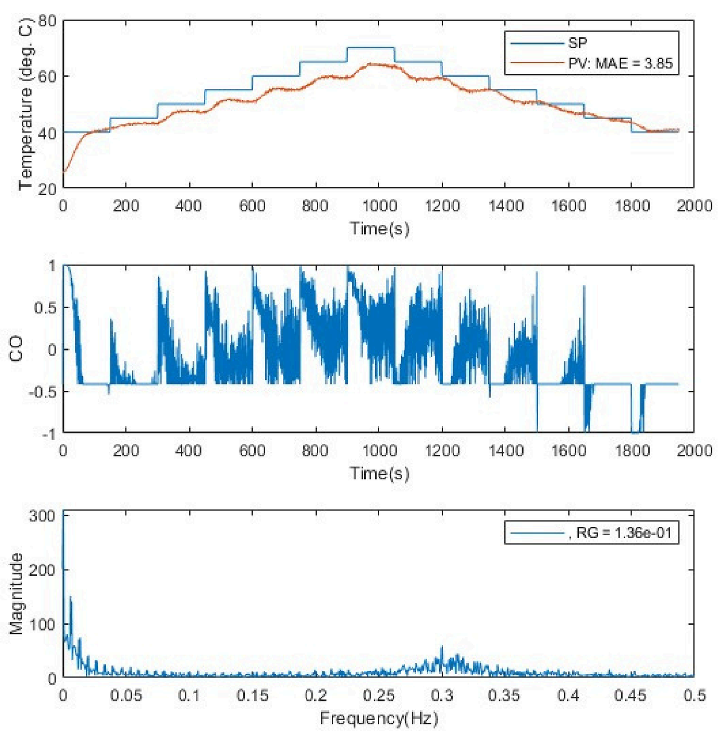
Implement on Actual system

Implement on Actual system : transfer actor model and test on actual system

- **SISO**



LSTM Model

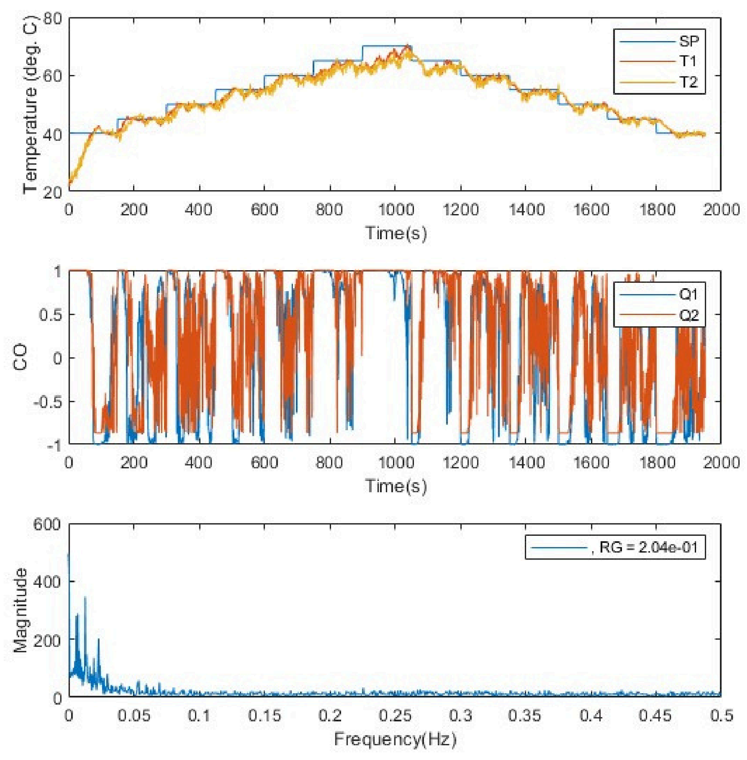


FOPDT Model

Control Method	MAE	Roughness
LSTM + DDPG	**1.67**	1.48e-01
FOPDT + DDPG	3.85	**1.36e-01**

- **MIMO :** in this version, we separate the controller into 2 actor models to control 2 actuators of TCLab

Control Method	MAE	Roughness
MIMO V1	2.16	2.04e-01



MIMO

References

[1] Junho Park, R. Abraham Martin, Jeffrey D. Kelly and John D. Hedengren., 2020,"Benchmark temperature microcontroller for process dynamics and control", Computers and Chemical Engineering, Vol.135, pp.106736-106748.

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