Hybrid Model Predictive Control of Chiller Plant with Thermal Energy Storage Evaluated with Modelica-Python Co-Simulation

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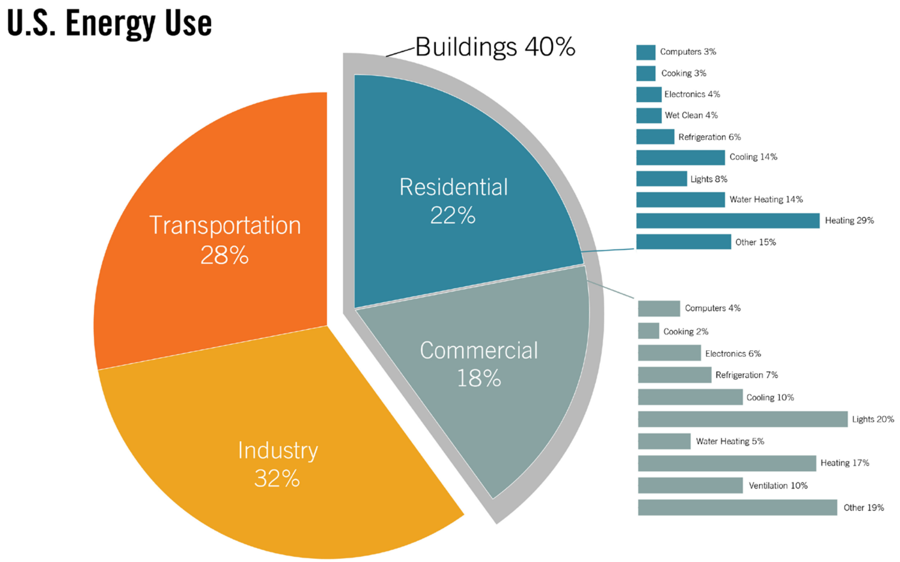
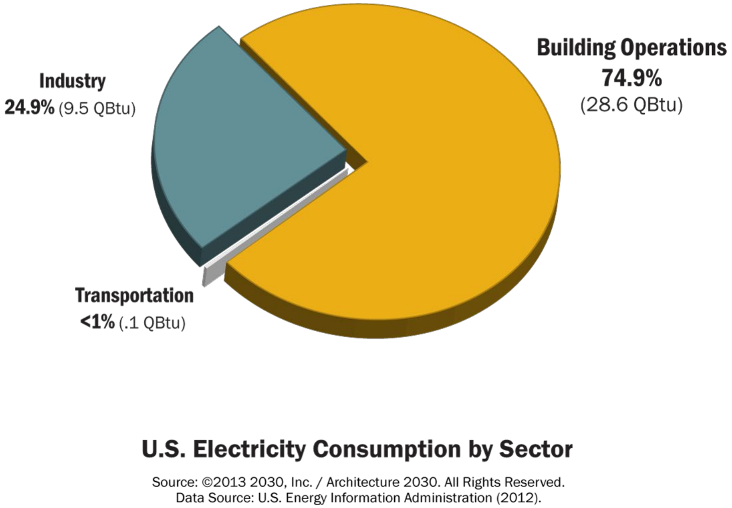
Outline

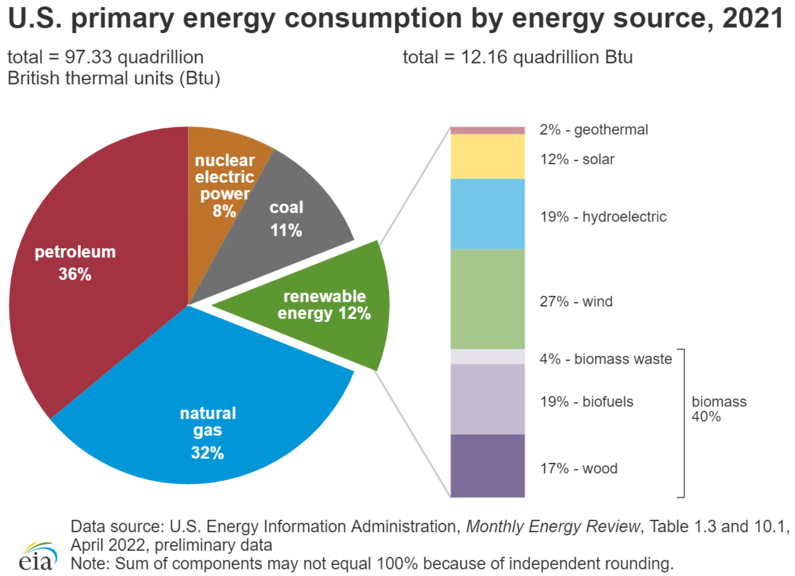
- Background: Demand Response for Chiller Plant System
- Challenges and Proposed Work
- Chiller Plant with Water Storage: System Configuration & Modelica Dynamic Simulation Model
- Control-oriented Modeling: Koopman Models & Model Selection
- Hybrid Model Predictive Control for Demand Response Operation
- Simulation Study with Python-Modelica Co-Simulation Platform

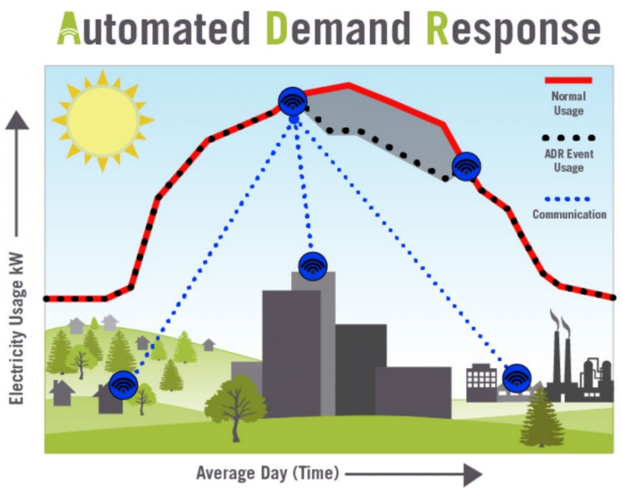
Background





- Significant share of building energy consumption and electricity use
- Grid stability under increasing penetration of renewable energy





- Development of Grid-interactive Efficient Buildings
- Demand response and ancillary services by building HVAC operation

Review of Existing Work

Two key challenges:

- significant nonlinearities of plant characteristics are present;
- continuous and discontinuous manipulated variables coexist, due to the on/off and/or staged operation of some actuating devices in addition to the continuously adjustable devices.

Existing solution:

- Conventional scheduling techniques
- Operation shift with Thermal Energy Storage

➢ Piecewise linearization

➢ Mixed-integer linear programming model predictive control (MILP-MPC) strategy

M. Fadzli Haniff, H. Selamat, R. Yusof, S. Buyamin, and F. Sham Ismail, "Review of hvac scheduling techniques for buildings towards energy-efficient and cost-effective operations," Renewable and Sustainable Energy Reviews, vol. 27, pp. 94–103, 2013.

M. J. Risbeck, C. T. Maravelias, J. B. Rawlings, and R. D. Turney, "A mixed-integer linear programming model for real-time cost optimization of building heating, ventilation, and air conditioning equipment," Energy and Buildings, vol. 142, pp. 220–235, 2017.

Proposed Work

Motivations:
- Demand responds for energy saving
- Global optimization with mixed-integer nonlinear programming MPC

- Chiller plant with thermal energy storage (TES) system

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- Data-driven control-oriented model with Koopman operators for different operation modes

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- Hybrid dynamical system with mode switch (mixed-integer bilinear term)

↓

- Model predictive control on temperature regulation and minimization power consumption

↓

- Convexification for mixed-integer bilinear term (facilitate computing)

Mixed-integer bilinear programming $\rightarrow$ mixed-integer linear programming

Dynamic Simulation Plant

- Modelica dynamic simulation plant: a chiller plant with thermal energy storage

Components

- Scroll compressor (4 L displacement)
- A counter flow wet cooling tower
- A shell and tube condenser
- A shell and tube evaporator
- A stratified tank for thermal energy storage
- Refrigerant: R134a

1: EEV opening → superheat
2: compressor speed → leaving water temperature

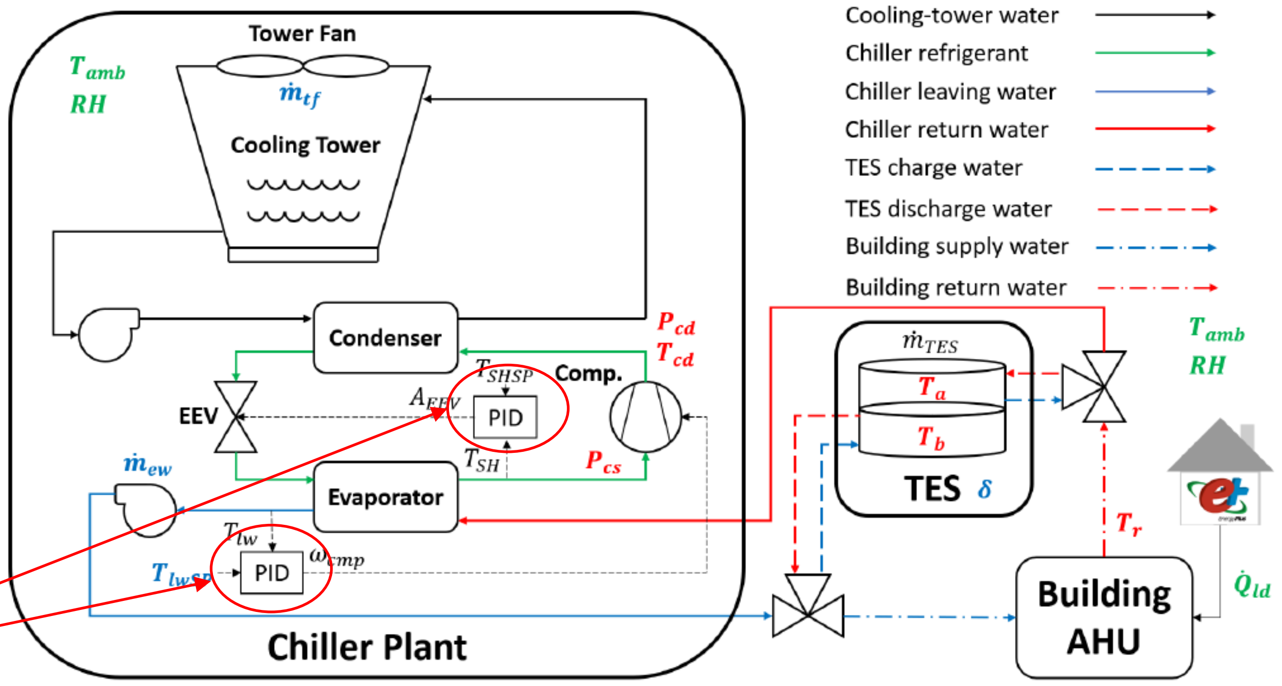
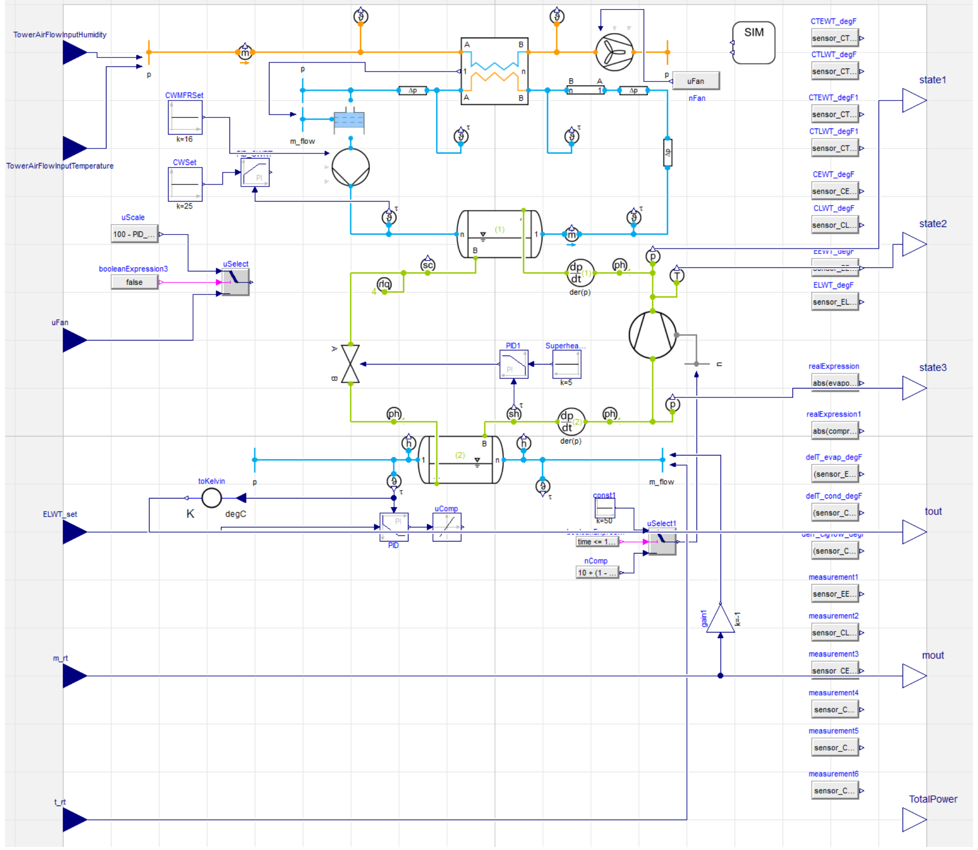
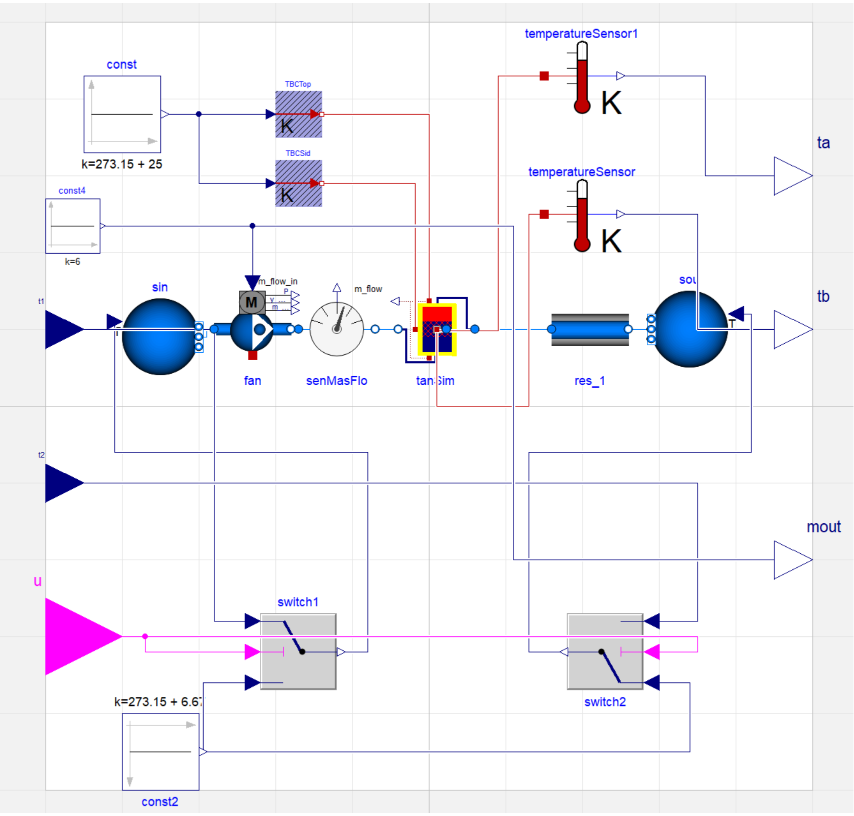


Fig. 1. Schematic for Chiller Plant Coupled with Thermal Energy Storage

Dymola Layout for Chiller Plant and TES



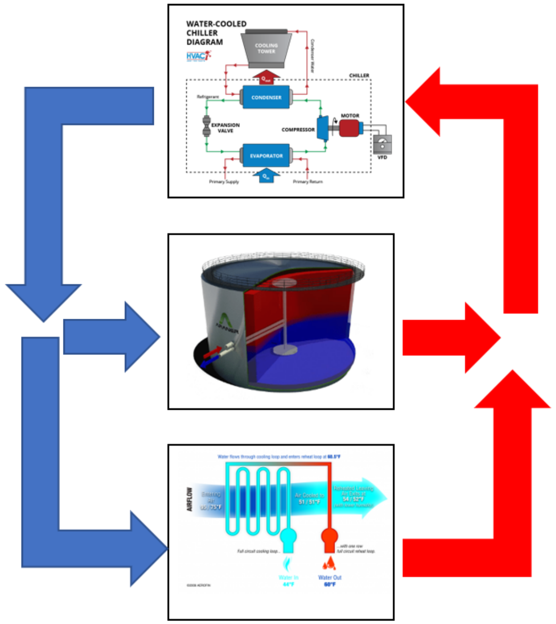
Base on TLK library:
T.-T. GmbH. TIL Suite. [Online]. Available: https://www.tlk-thermo.com/index.php/en/til-suite

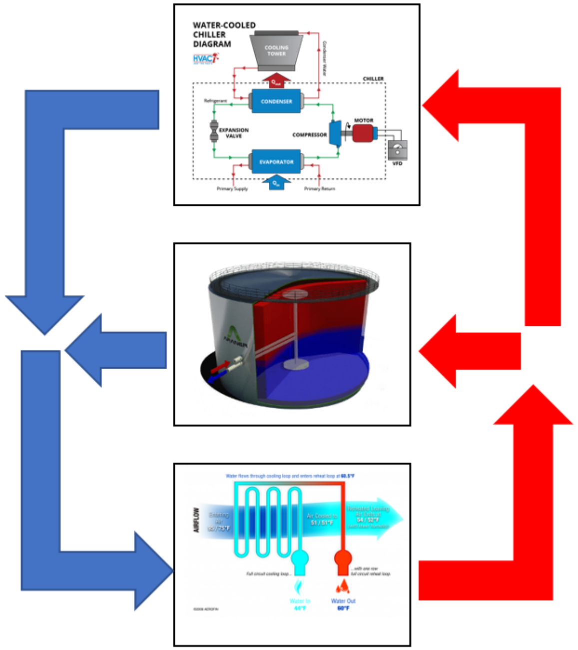


Base on Building library:
M. Wetter, W. Zuo, T. S. Nouidui, and X. Pang, "Modelica Buildings library," Journal of Building Performance Simulation, vol. 7, no. 4, pp. 253–270, 2014.

Dassault Systèmes, (2019), *Dymola*. Available: http://www.3ds.com/products/catia/portfolio/dymola.

Illustration for Two Operation Modes





Mode 1: TES Charging

- TES charged by chiller water from chiller plant
- Building load (AHU) handled by chilled water from chiller plant
- Building/AHU return water + TES outlet water, → chiller plant

Mode 2: TES Discharging

- TES discharges chiller water to AHU
- AHU supplied chill water comes from Chiller Plant and TES
- The AHU return water → the TES and Chiller Plant

Control-oriented Model for Chiller Plant with Water Storage

States:

- Chiller plant related states:
  - compressor discharged pressure (P_{cd})
  - compressor discharge temperature (T_{cd})
  - compressor suction pressure (P_{cs})
- Building load/AHU related state:
  - chilled-water return temperature (T_r)
- Thermal energy storage related states:
  - top- and bottom-layer water temperatures (T_a and T_b)

Inputs:

- tower fan speed ($\dot{m}_{tf}$)
- chiller evaporator leaving water setpoint (T_{lwSP})
- chiller evaporator water mass flow rate ($\dot{m}_{ew}$),

mode switch input: $\delta \in \{0, 1\}$,

where 0 represents Mode 1 and 1 represents Mode 2

Disturbance:

- ambient temperature (T_{amb})
- building load ($\dot{Q}_{ld}$),

Power consumption(P_t):

- compressor power (P_{cmp})
- tower fan power (P_{tf})
- evaporator liquid pump power(P_{pmp})

Data-driven model with Koopman operators for Mode 1&2

Original States:

$$x = [P_{cd},\ T_{cd},\ P_{cs},\ T_r,\ T_a,\ T_b]^T$$

Inputs:

$$u = [\dot{m}_{tf},\ T_{lwSP},\ \dot{m}_{ew}]^T$$

Disturbance:

$$w = [T_{amb},\ \dot{Q}_{ld}]^T$$

Discrete-time dynamic system: $x_{k+1} = \mathrm{F}(x_k, u_k, w_k)$

Koopman operator

$$\mathcal{K}g = g \circ \mathrm{F}$$

infinite-dimensional function space

finite-dimensional lifted space

$$z_{k+1} = Az_k + B_u u_k + B_w w_k$$

$$\hat{x}_k = Cz_k$$

Kernel function $z \triangleq \boldsymbol{\psi}(x) = [\psi_1(x) \quad \cdots \quad \psi_N(x)]^T$

- In this study, the original states x are affined into the 1st-order, 2nd-order polynomial functions and their cross terms.

$$z = [x_1,\ \ldots,\ x_6,\ x_1^2,\ \ldots,\ x_6^2,\ x_1x_2,\ \ldots,\ x_5x_6]^T$$

Sparse Identification of Nonlinear Dynamics with Control (SINDYc)

$$z = [x_1, \ \ldots, \ x_6, \ x_1^2, \ \ldots, \ x_6^2, \ x_1 x_2, \ \ldots, \ x_5 x_6]^T$$

$$\underset{A,B}{\operatorname{argmin}} \|\Xi_+ - A\Xi - B_u \mathbf{U} - B_w \mathbf{W}\|_2$$

Mode 1: $z_{k+1}^1 = A^1 z_k^1 + B_u^1 u_k^1 + B_w^1 w_k^1$

LASSO: $\underset{\xi^j}{\operatorname{argmin}} \left\|\Xi_+^j - \xi_j (A^j \Xi^j - B^j \mathbf{U}^j)\right\|_2 + \lambda^j \|\xi^j\|_1$

Mode 2: $z_{k+1}^2 = A^2 z_k^2 + B_u^2 u_k^2 + B_w^2 w_k^2$

- Typical Akaike Information Criterion (AIC) for polynomial functions

Akaike, H. (1969). Fitting autoregressive models for prediction. *Annals. Inst. Stat. Math.*, *21*(1), 243–247.

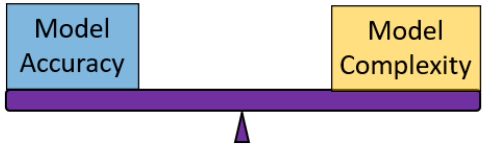
Residual Sum of Squares for fitting error

\# of model parameters

AIC Score $\longrightarrow AIC = \rho \cdot \ln \left(\boxed{\frac{RSS}{\rho}} \right) + 2p$

Sample size

Maximum likelihood function



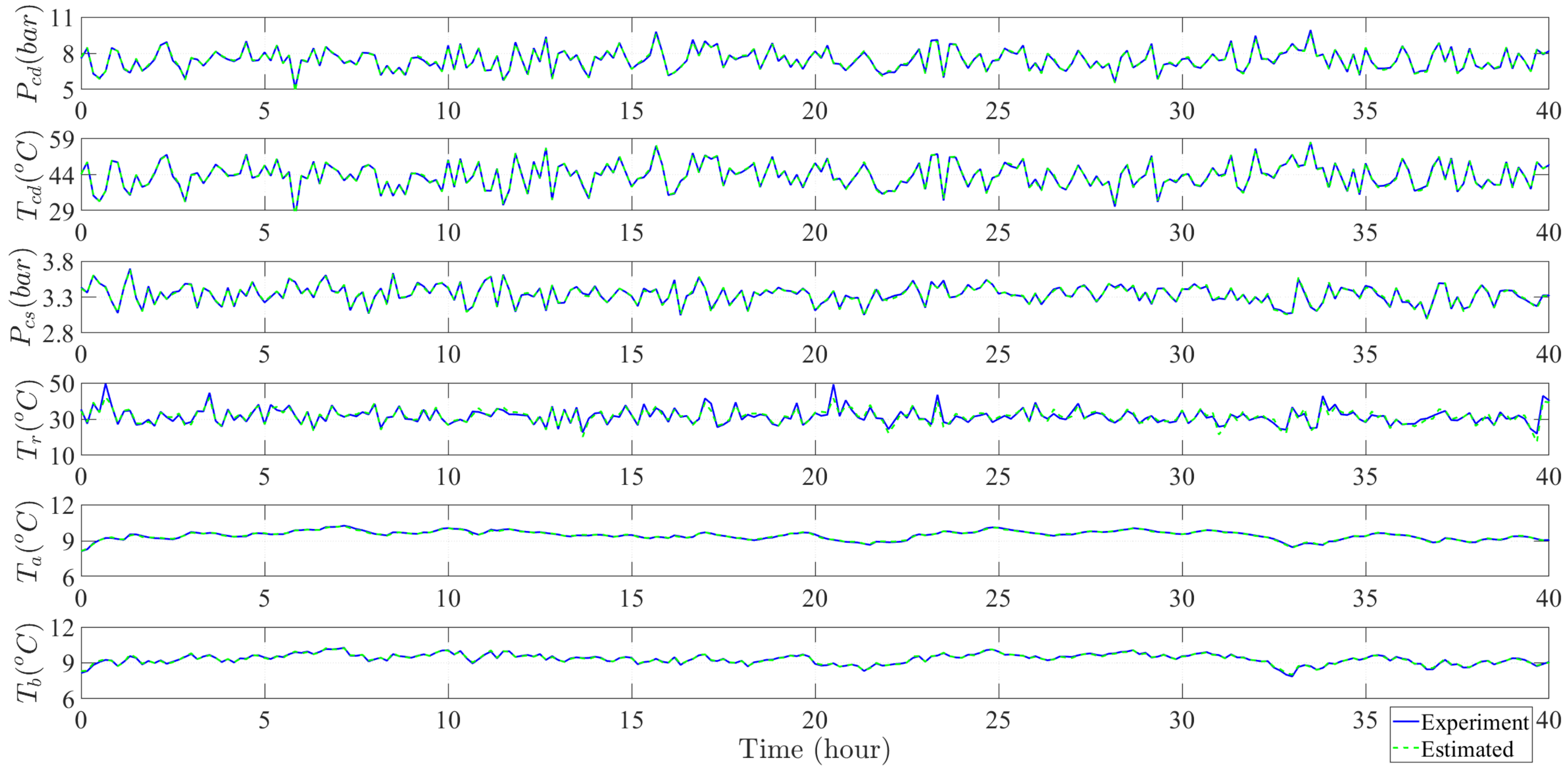
- AIC with correction (AICc) for small sample size: $AIC_c = AIC + \dfrac{2(p+1)(p+2)}{(p-\rho-2)}$

- The total power model for two modes is identified as a static map of all states, inputs and disturbances.

Mode 1: $y_k^1 = C^1 z_k^1 + D_u^1 u_k^1 + D_w^1 w_k^1$

Mode 2: $y_k^2 = C^2 z_k^2 + D_u^2 u_k^2 + D_w^2 w_k^2$

Model Selection Results for Mode 1 (600s sampling time)

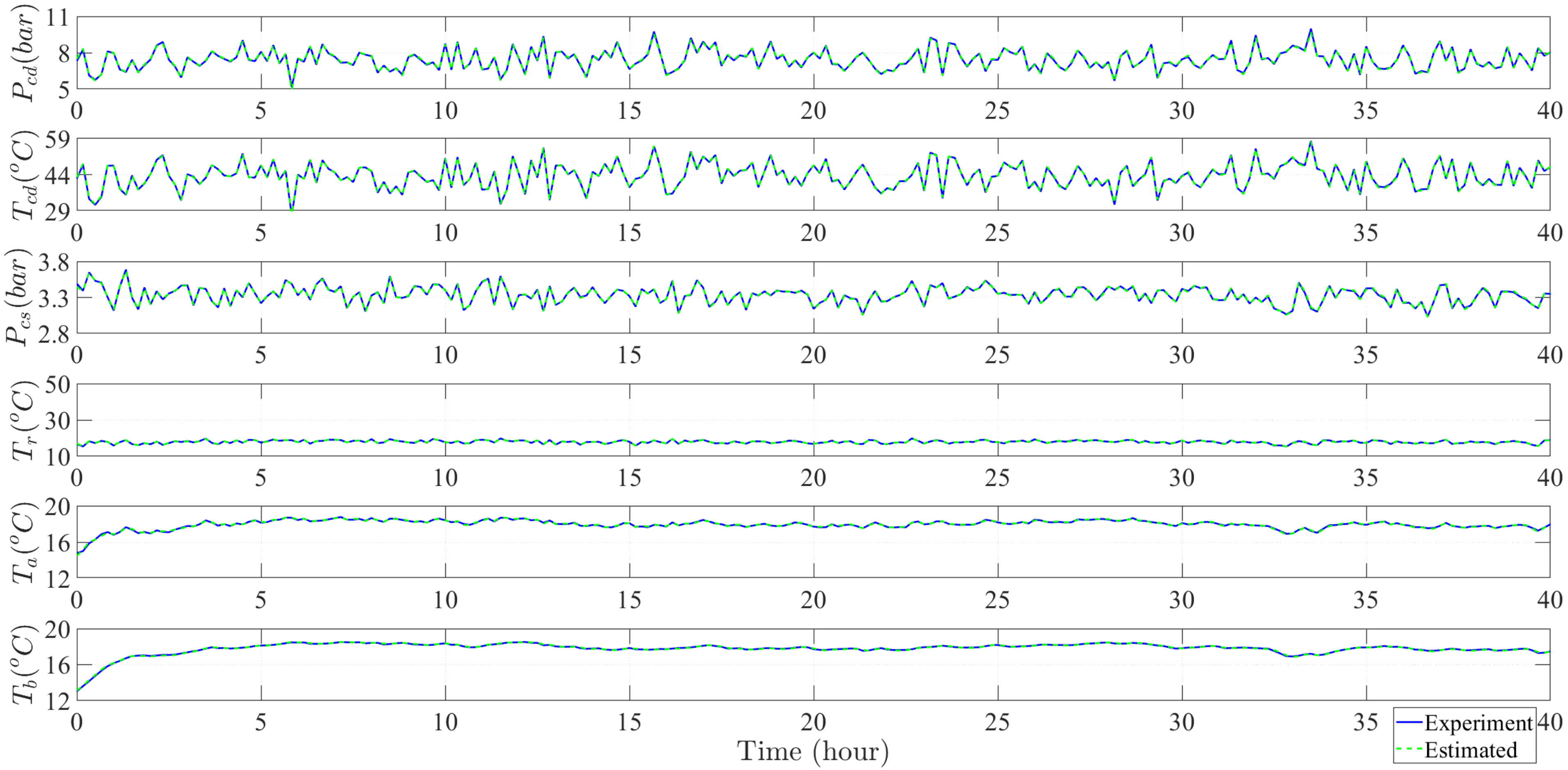


Variable	RMSE
P_{cd} (bar)	0.0167
T_{cd} (°C)	0.0111
P_{cs} (bar)	0.0183
T_r (°C)	0.0482
T_a (°C)	0.0035
T_b (°C)	0.0038
-	N_0*
A^1	333
B_u^1	6
B_w^1	5

* The number of null elements in identified coefficients

About half elements in A

Model Selection Results for Mode 2 (600s sampling time)



Variable	RMSE
P_{cd} (bar)	0.0157
T_{cd} (°C)	0.0088
P_{cs} (bar)	0.0138
T_r (°C)	0.0033
T_a (°C)	0.0048
T_b (°C)	0.0040
-	N_0*
A^1	267
B_u^1	4
B_w^1	5
* The number of null elements in identified coefficients	

Hybrid system model by mixed dynamical system

$$z_{k+1} = \begin{cases} A^1 z_k + B_u^1 u_k + B_w^1 w_k, & \delta_k = 0, \\ A^2 z_k + B_u^2 u_k + B_w^2 w_k, & \delta_k = 1. \end{cases}$$

$$y_k = \begin{cases} C^1 z_k + D_u^1 u_k + D_w^1 w_k, & \delta_k = 0, \\ D^2 z_k + D_u^2 u_k + D_w^2 w_k, & \delta_k = 1. \end{cases}$$

Mixed-integer dynamic model with bilinear terms

$$\begin{aligned} z_{k+1} =& (A^1 - A^2)\boxed{z_k \delta_k} + (B_u^1 - B_u^2)\boxed{u_k \delta_k} + \\ & (B_w^1 - B_w^2)\boxed{w_k \delta_k} + A^2 z_k + B_u^2 u_k + B_w^2 w_k \end{aligned}$$

$$\begin{aligned} y_k =& (C^1 - C^2)\boxed{z_k \delta_k} + (D_u^1 - D_u^2)\boxed{u_k \delta_k} + \\ & (D_w^1 - D_w^2)\boxed{w_k \delta_k} + C^2 z_k + D_u^2 u_k + D_w^2 w_k \end{aligned}$$

HMPC for Chiller Plant with Water Storage

HMPC design problem: minimizing energy cost while regulating AHU return water temperature requirements, assuming perfect knowledge of future ambient temperature and cooling load

Electricity rate

$$\min_{u,\delta}\Big[\sum_{k=0}^{N_p}\|z_k - z_k^r\|_Q + \sum_{k=0}^{N_p-1} c_k y_k\Big]$$

s.t.

$$\begin{aligned}
z_{k+1} &= A^3 z_k\delta_k + B_u^3 u_k\delta_k + B_w^3 w_k\delta_k \\
&\quad + A^2 z_k + B_u^2 u_k + B_w^2 w_k \\
y_k &= C^3 z_k\delta_k + D_u^3 u_k\delta_k + D_w^3 w_k\delta_k \\
&\quad + C^2 z_k + D_u^2 u_k + D_w^2 w_k \\
& z_k^{lb} \le z_k \le z_k^{ub}, u_k^{lb} \le u_k \le u_k^{ub} \\
& z_0 = z_{ini} \\
& k \in \mathbb{I}_{[0,N_p)}
\end{aligned}$$

Power model can be substituted into cost function

Quadratic programming with mixed-integer bilinear terms

$$\min_{u,\delta}\Big[\sum_{k=0}^{N_p-1}(q_\delta^T z_k\delta_k + r_\delta^T u_k\delta_k + p_\delta^T w_k\delta_k + q_z^T z_k + r^T u_k + p^T w_k + p_m^T) + (q_m^T z_{N_p} + p_m^T)\Big]$$

$$\begin{aligned}
\dot{m}_{tf} &\in [30, 60]Hz \\
T_{lwSP} &\in [6.67, 12.22]^\circ C \\
\dot{m}_{ew} &\in [8, 12]kg/s
\end{aligned}$$

Convexification for bilinear programming

Define the new variables of bilinear functions

$$f_z(z,\delta) = z\delta \qquad f_u(u,\delta) = u\delta$$

Convex hulls

$$conv(\mathcal{S}_{z,i}) = \{(z_i, \delta, f_{z,i}) \in (\mathbb{R} \times \mathbb{I} \times \mathbb{R}) | \mathcal{F}_{z,i}\}$$
$$conv(\mathcal{S}_{u,j}) = \{(u_j, \delta, f_{u,j}) \in (\mathbb{R} \times \mathbb{I} \times \mathbb{R}) | \mathcal{F}_{u,j}\}$$

McCormick inequalities

$$\mathcal{F}_z = \begin{cases} f_z \geq z^{lb}\delta + \delta^{lb}z - z^{lb}\delta^{lb} \\ f_z \geq z^{ub}\delta + \delta^{ub}z - z^{ub}\delta^{ub} \\ f_z \leq z^{lb}\delta + \delta^{ub}z - z^{lb}\delta^{ub} \\ f_z \leq z^{ub}\delta + \delta^{lb}z - z^{ub}\delta^{lb} \end{cases}$$

$$\mathcal{F}_u = \begin{cases} f_u \geq u^{lb}\delta + \delta^{lb}u - u^{lb}\delta^{lb} \\ f_u \geq u^{ub}\delta + \delta^{ub}u - u^{ub}\delta^{ub} \\ f_u \leq u^{lb}\delta + \delta^{ub}u - u^{lb}\delta^{ub} \\ f_u \leq u^{ub}\delta + \delta^{lb}u - u^{ub}\delta^{lb} \end{cases}$$

MILP-MPC

$$\min_{u,\delta,f_z,f_u} \Big[\sum_{k=0}^{N_p-1} (q_\delta^T f_{z,k} + r_\delta^T f_{u,k} + p_\delta^T w_k \delta_k + q_z^T z_k + r^T u_k + p^T w_k + p_m^T) + (q_m^T z_{N_p} + p_m^T) \Big]$$

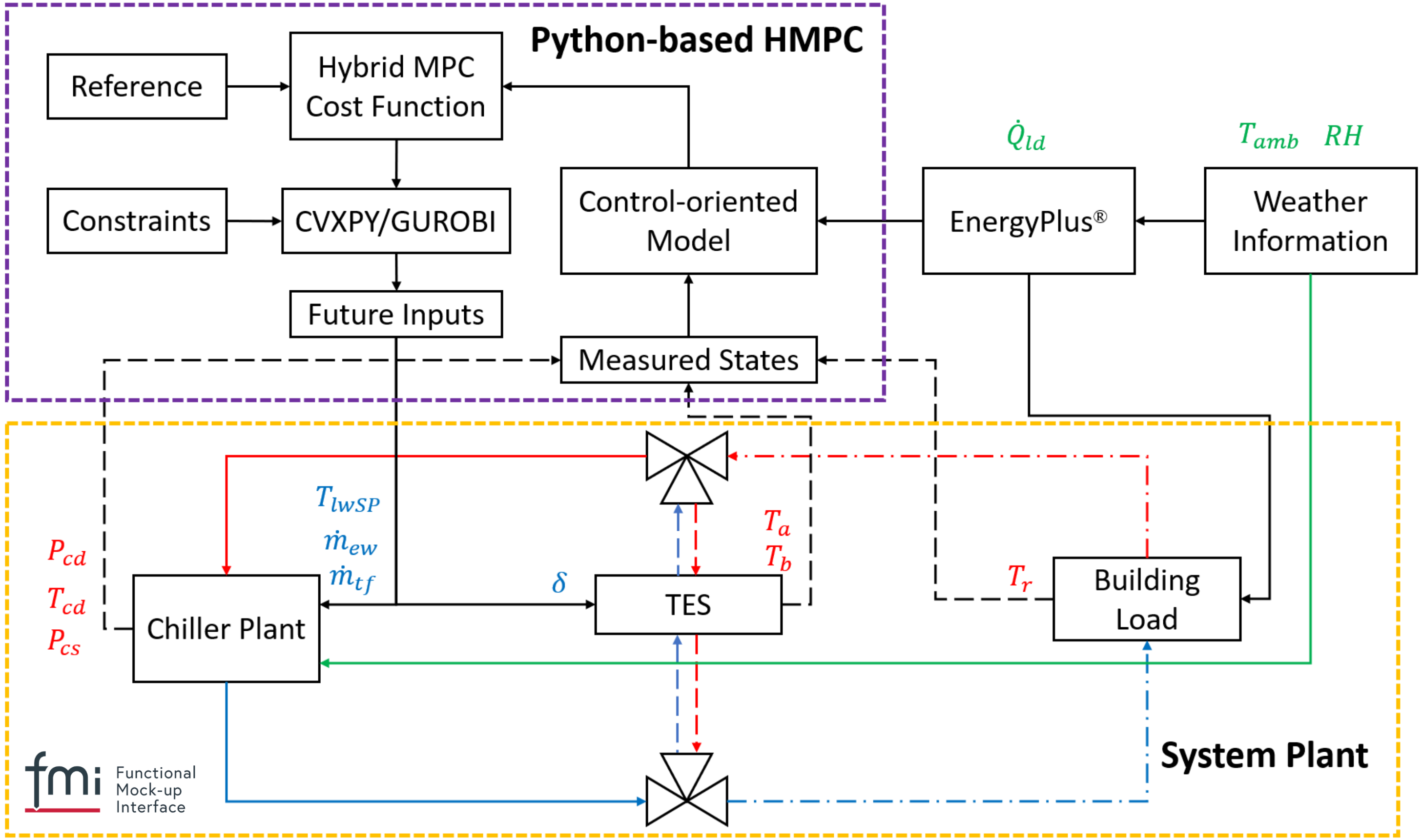
s.t.

$$z_{k+1} = A^3 f_{z,k} + B_u^3 f_{u,k} + B_w^3 w_k \delta_k + A^2 z_k + B_u^2 u_k + B_w^2 w_k$$
$$z_k^{lb} \leq z_k \leq z_k^{ub},\ u_k^{lb} \leq u_k \leq u_k^{ub}$$
$$z_0 = z_{ini}$$
$$k \in \mathbb{I}_{[0,N_p)}$$

Hybrid Model Predictive Control with mixed-integer bilinear programming (HMPC-MIBLP)

- Dymola: Modelica model of Chiller Plant with Water Storage
- Python: MPC design and implementation

FMI 2.0
Co-simulation



https://fmi-standard.org/

Co-Simulation Results for HMPC Operation

Simulation setting

- Sampling time : 600s
- Predictive horizon : 2 hours
- Initial tower fan speed: 40 Hz
- Initial chiller leaving water temperature setpoint: 10 °C
- Initial chiller plant water mass flow rate: 11 kg/s
- Initial TES charging/discharging mode: 1 (discharging)
- Initial ambient temperature: 28 °C
- Initial cooling load on AHU cooling coil: 360 kW

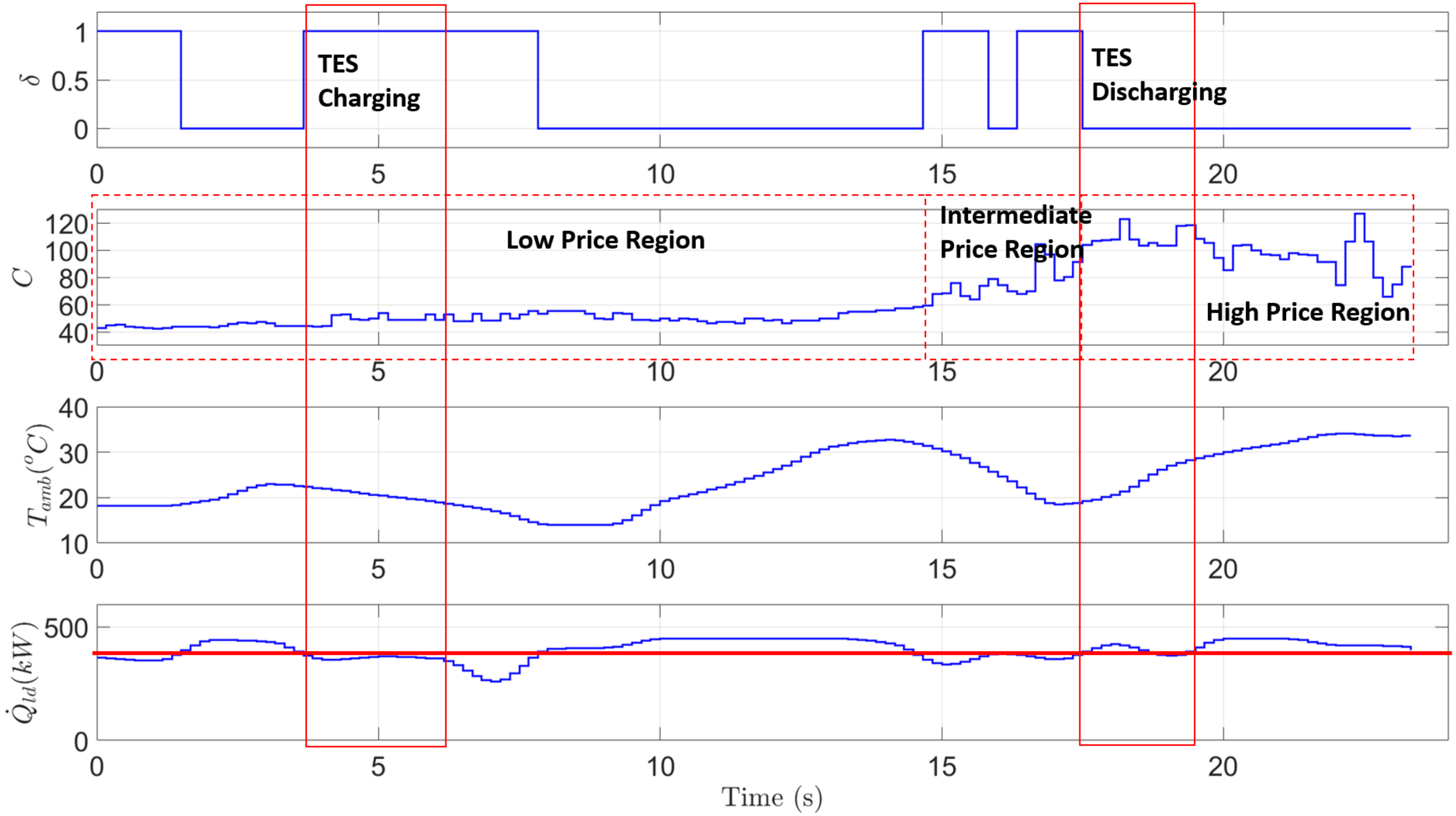
Utilized Python package:

```
"""
Created on Sat Sep 17 14:54:36 2022

@author: cxp161130
"""

import cvxpy as cp
import numpy as np
import scipy as sp
from scipy import sparse
import matplotlib.pyplot as plt
# from matplotlib.patches import StepPatch
import shutil
import scipy.io as scio
import time
from fmpy import read_model_description, extract
from fmpy.fmi2 import FMU2Slave
```

Diamond, S., & Boyd, S. (2016). CVXPY: A Python-embedded modeling language for covex optimization. *J. Machine Learning Res.*, 17(83), 1–5. https://doi.org/10.48550/arXiv.1603.00943.

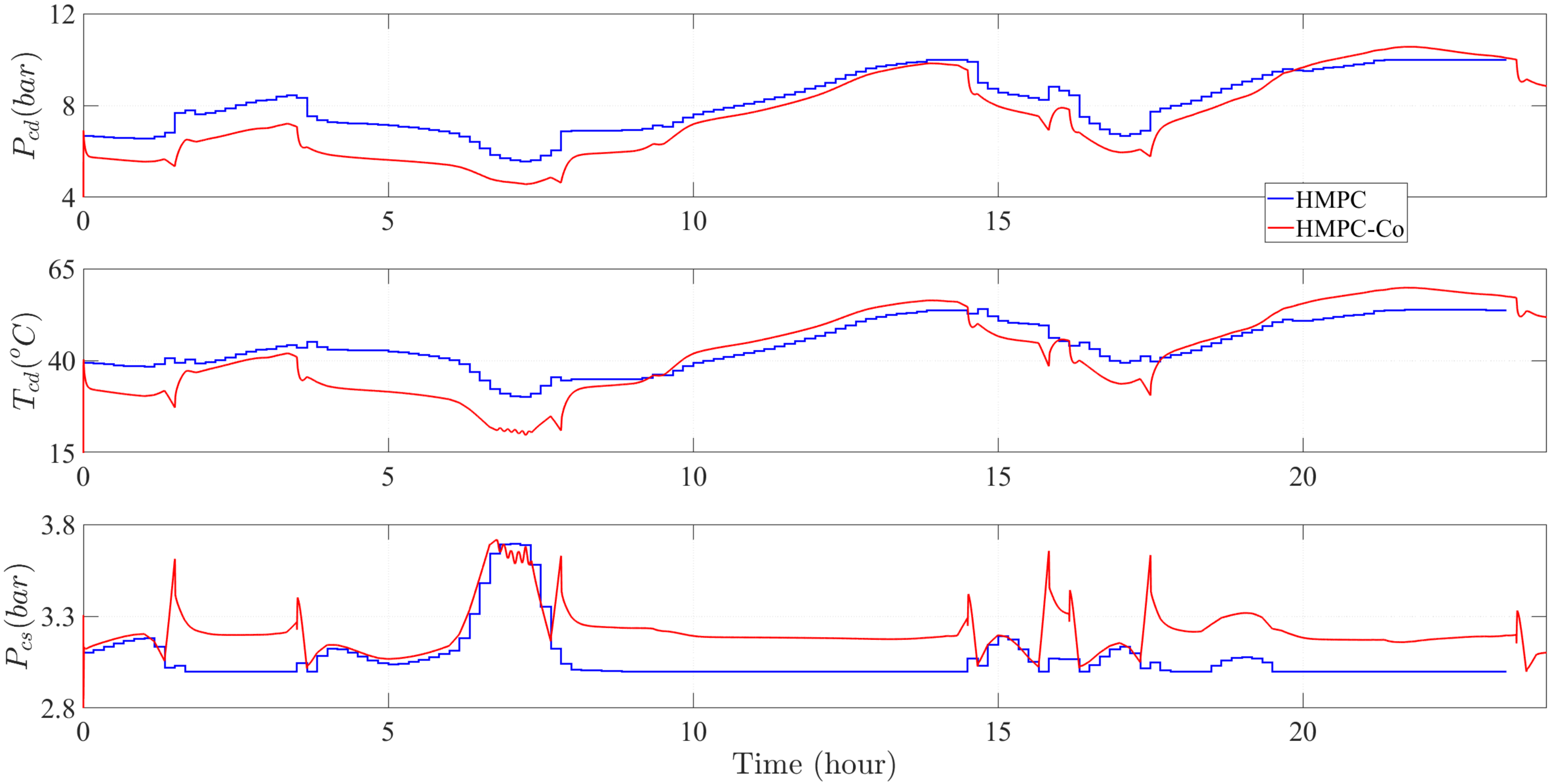
T. Sommer, *FMPy*, (2020). Available online: https://github.com/CATIA-Systems/FMPy.

Co-simulation Results for HMPC Operation



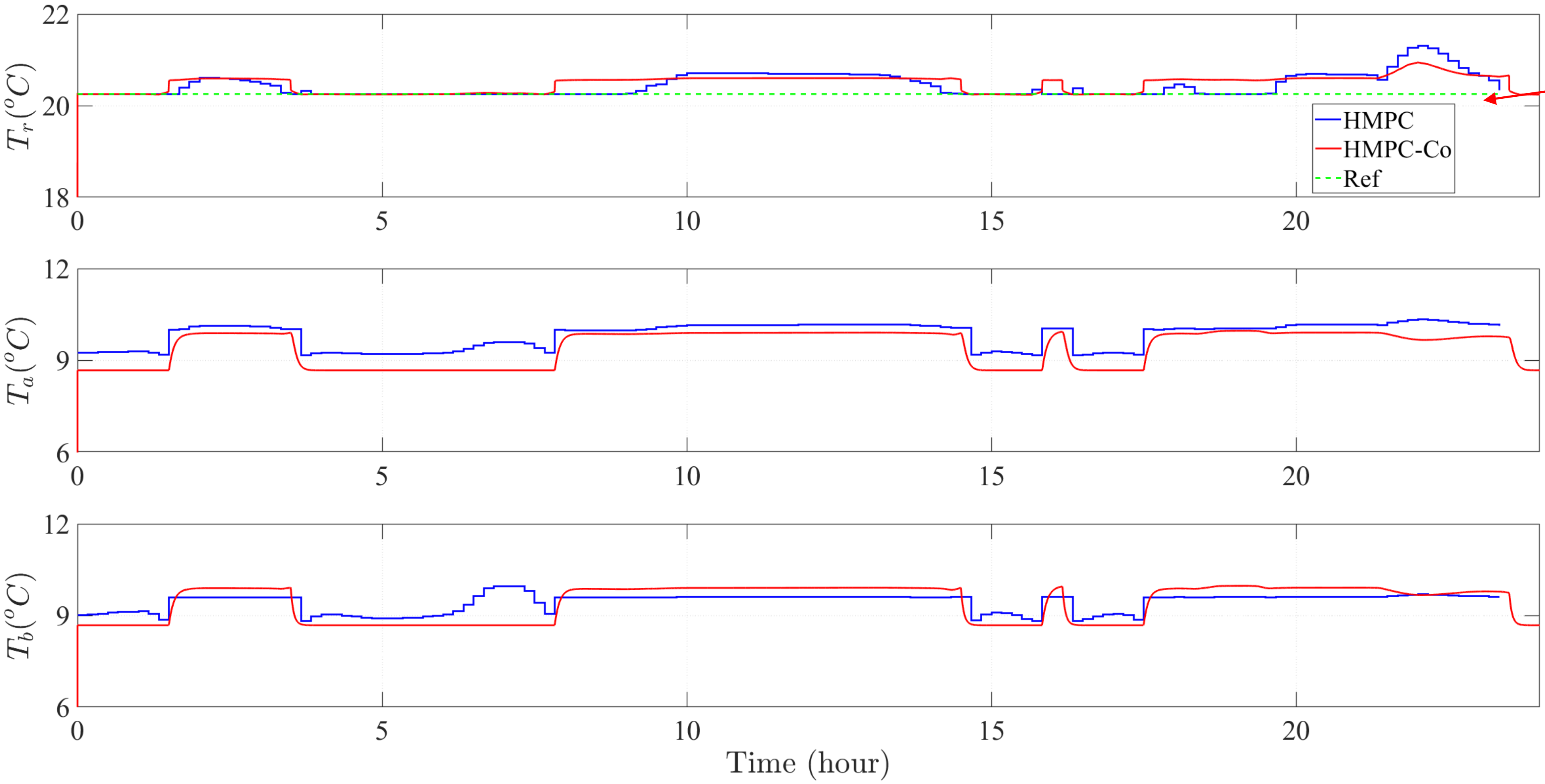
low-price region
(LPR: [0, 14.5] hour)
medium-price region
(MPR: [14.5, 17.5] hour)
high-price region
(HPR: [17.5, 24] hour)

Co-simulation Results for HMPC Operation



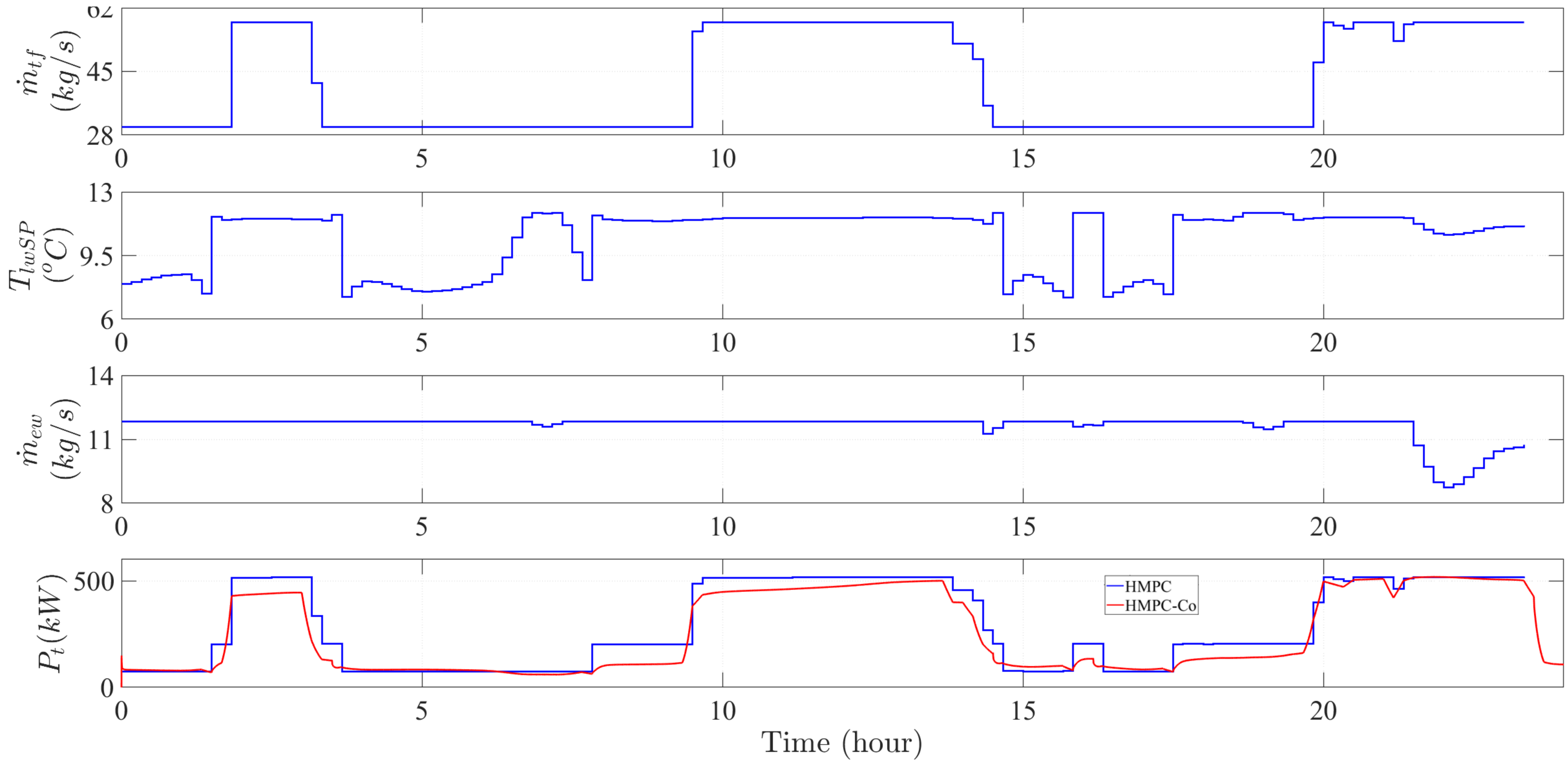
Oscillation due to mode switch and inner PI controllers

Co-simulation Results for HMPC Operation



Regulated target: 20.25 °C

Co-simulation Results for HMPC Operation



Mean total power:

HMPC: 288 kW

HMPC-Co: 252 kW

Conclusion

- We propose a data-driven method of Chiller plant coupled with chilled-water storage.
- The SINDYc-based Koopman-invariant subspace models are identified with simulations data from Modelica-based dynamics model.
- A MIBLP-MPC is formulated for global optimization of energy saving and satisfication of cooling rate demand.
- To solve this optimization problem, a convexification with McCormick envelopes is implemented and transformed the MIBLP into MILP.
- The proposed control strategy is evaluated with Python-based co-simulation framework.

Acknowledgments

- TLK-Thermo is appreciated for their permission to access TIL Suite software and technical assistance

Thanks!

Any Questions?