Self-Learning Backlash Inverse Control of Cooling or Heating Coil Valves Having Backlash Hysteresis

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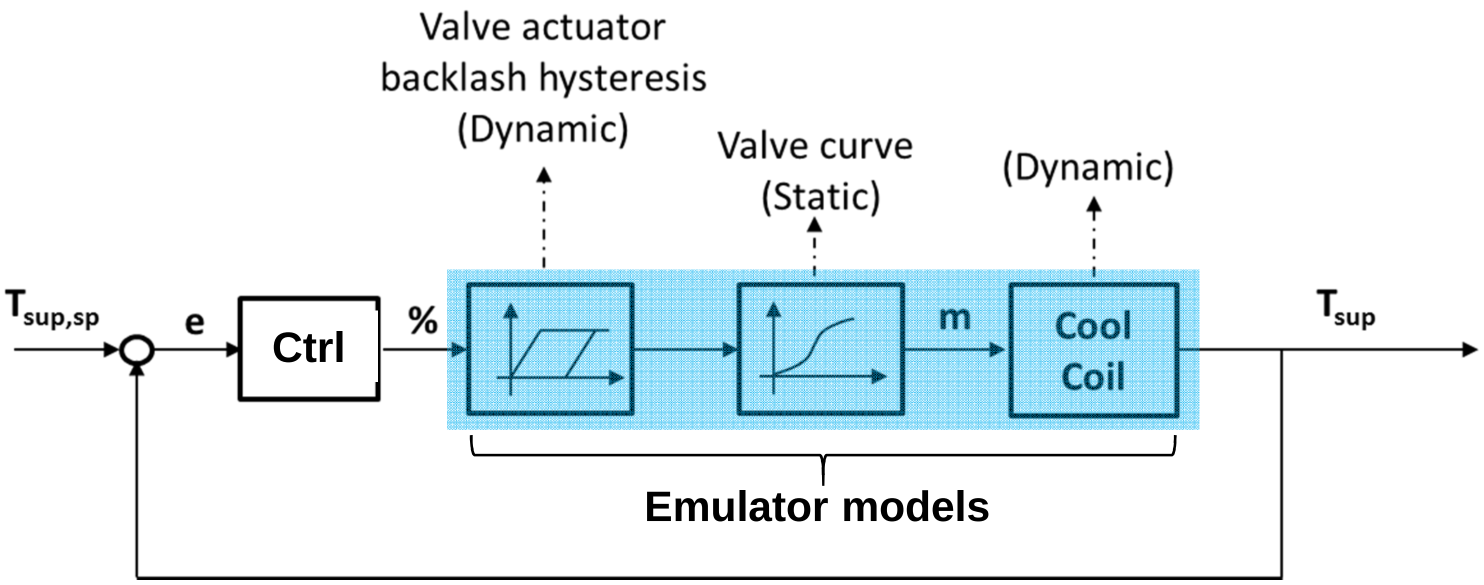
Motivations

- HVAC valves often suffer from backlash type hysteresis
- Valve hysteresis leads to unsatisfactory control performance
  - Ref: Cai, J., Kurtulus, O. and Braun, J.E., “Experimental Performance Investigation of Cooling or Heating Coil Valves and Their Impact on Temperature Controls”, *International Ref. and AC Conference at Purdue*, 2016
- Unsatisfactory control leads to
  - Control variable fluctuation (comfort)
  - Plant chattering and cycling (efficiency and unit life span)
  - Higher power peaks (demand cost)

Approach

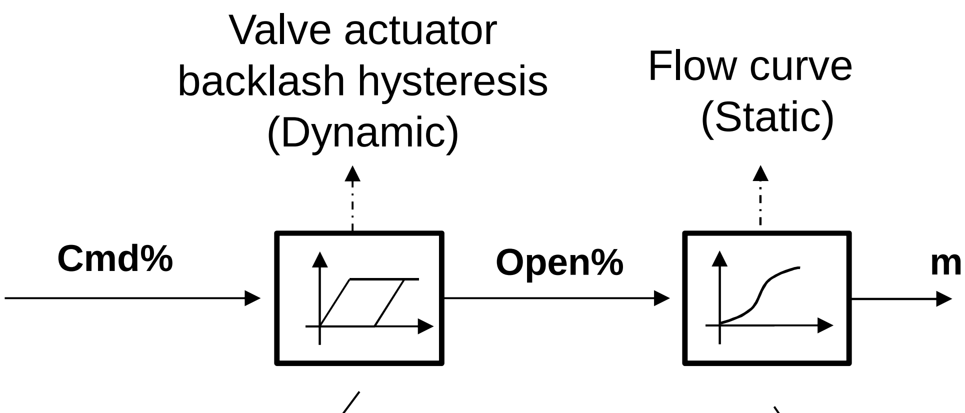
- Dynamic cooling coil + valve model as a test bed (trained with Living Lab AHU cooling coil data)
- Backlash inverse control implemented on top of a conventional PI controller
- Self-learning procedure to estimate the backlash magnitude

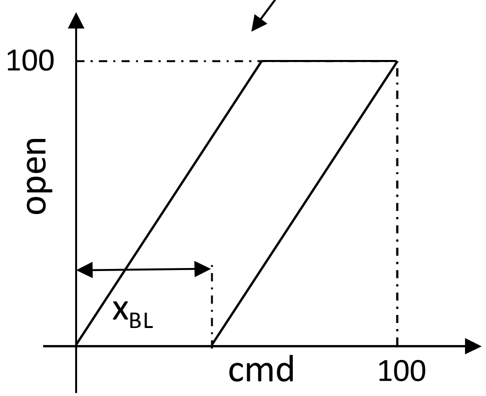
Valve Control System

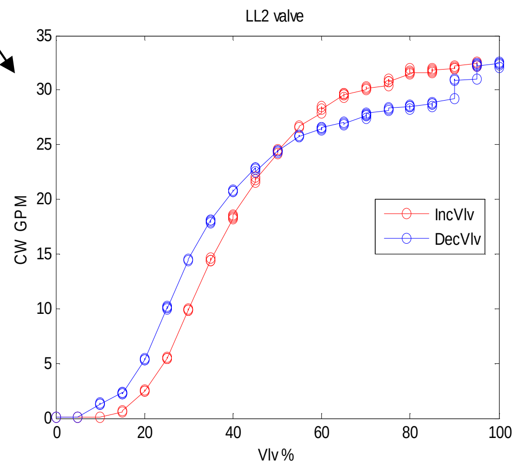


- Data-driven valve and cooling coil models
- A feedback controller to maintain the supply air temperature setpoint
  - Conventional PI controller
  - Backlash inverse controller on top of an existing PI controller
- Resetting $T_{sup,sp}$ strategy

Valve Model







- Backlash type hysteresis is dominant (at least locally)
- From manufacturing tolerance of the actuator gearbox

- Relationship between opening and fluid flow
- Depend on valve design

Valve Model – Hysteresis Sub-model

- Backlash model is *dynamic*
- Input: cmd[t-1], cmd[t]
- State: x[t] (backlash position)
- Output: open[t] (valve opening)
- *Parameter*: x_{BL} (backlash magnitude)

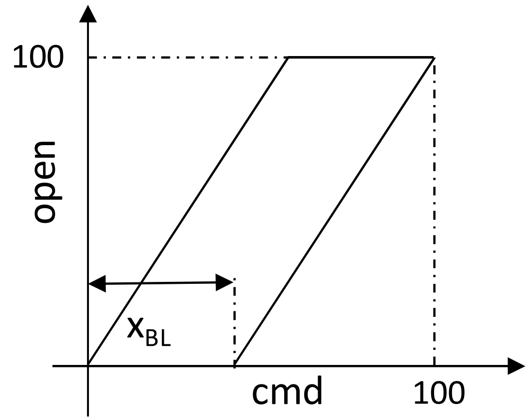


Fig. Backlash hysteresis

If $\{cmd[t]-cmd[t-1] \geq x_{BL} - x[t-1]\}$

$$x[t] = x_{BL}$$
$$open[t] = \alpha \times (cmd[t] - x_{BL})$$

Elseif $\{cmd[t]-cmd[t-1] < x_{BL} - x[t-1]\}$ **and** $\{cmd[t]-cmd[t-1] \geq -x[t-1]\}$

$$x[t] = x[t-1] + cmd[t] - cmd[t-1]$$
$$open[t] = \alpha \times (cmd[t-1] - x[t-1])$$

Else

$$x[t] = 0$$
$$open[t] = \alpha \times cmd[t]$$

Valve Model – Flow Sub-model

- Flow model is *static* correlating the opening and the fluid flow
- Input: open
- Output: mass flow

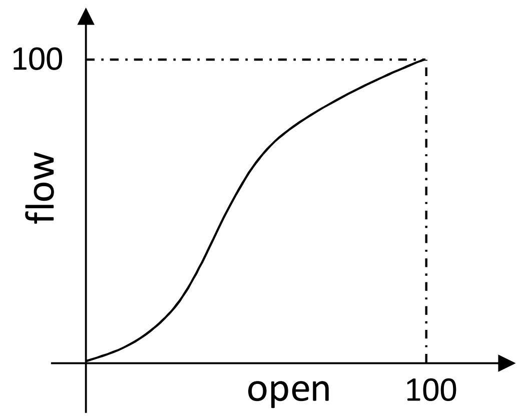


Fig. Flow relationship

For flow equal percentage control

- Flow increases exponentially in the low end
- Flow saturates in the high end due to loss of authority
- Generalized logistic model is used
- *Parameters*: a, b, c

$$m = \frac{m_{max}}{\left(1 + a \cdot e^{-b(open-c)}\right)^{1/a}}$$

Valve Model – Training

- AHU cooling coil valve opening was randomly perturbed in the Living Lab #3 to generate training data
- Parameters in the hysteresis and flow sub-models were estimated simultaneously
- Estimated backlash magnitude = 7%

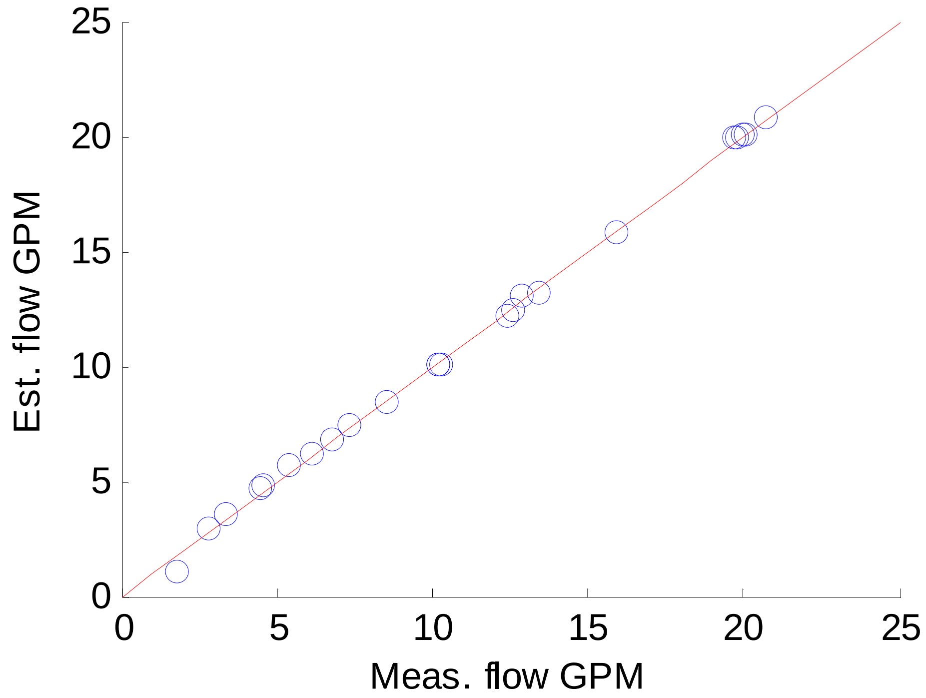


Fig. Model training results

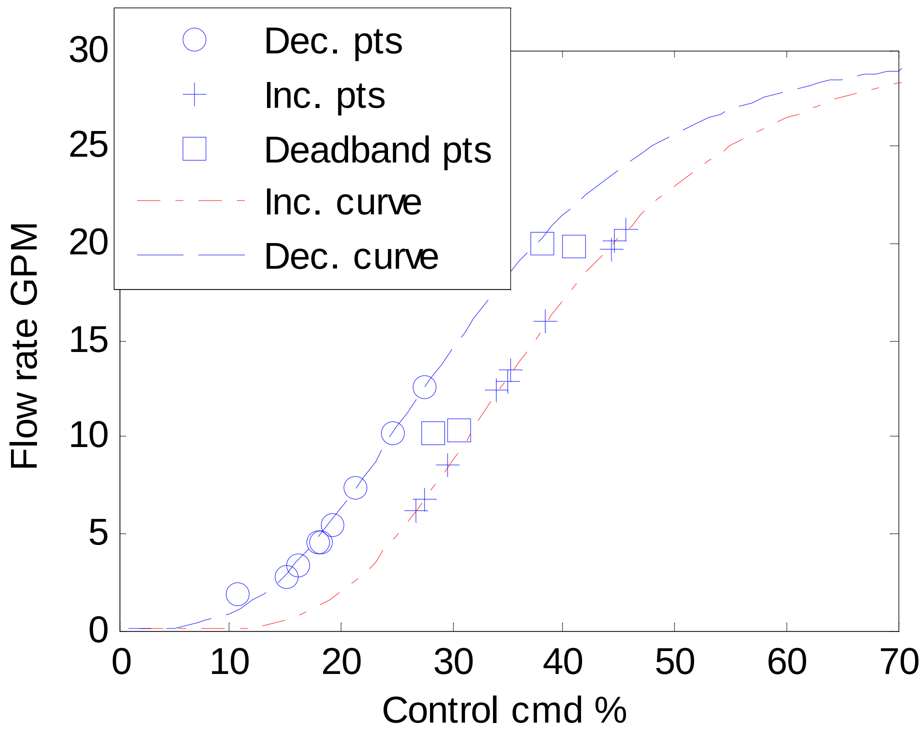


Fig. Estimated model curves with training points

Cooling Coil Model

Method and assumptions

- Counter-flow assumption
- Energy balance for each CV
- Explicit solution scheme to avoid iterations
- Time step = 1 sec.
- Coil divided into 8 CVs
- Effective-NTU method to determine heat rate
- Neglect air dynamics

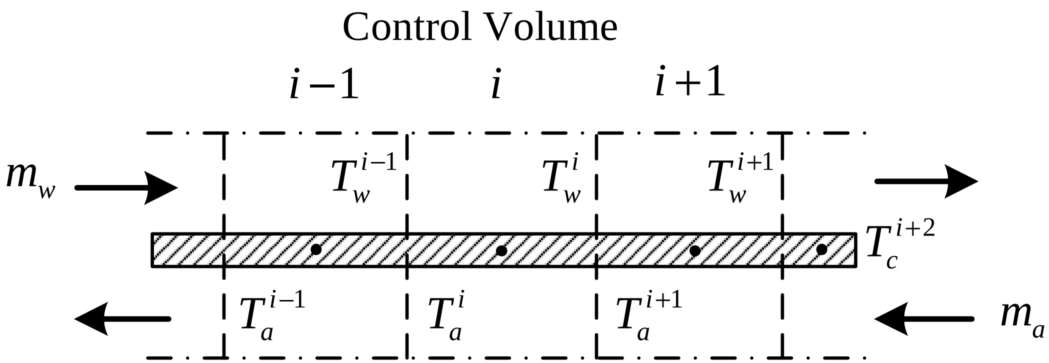


Fig. Finite volume cooling coil model

$$C_w \frac{T_w^i[t+1]-T_w^i[t]}{\Delta t} + m_w c_{p,w}\left(T_w^i[t]-T_w^{i-1}[t]\right) + \frac{T_w^{i-1}[t]-T_c^i[t]}{R_w} = 0$$

$$(Dry) \quad C_c \frac{T_c^i[t+1]-T_c^i[t]}{\Delta t} + \frac{T_c^i[t]-T_a^{i+1}[t]}{R_a} + \frac{T_c^i[t]-T_w^{i-1}[t]}{R_w} = 0$$

$$(Wet) \quad C_c \frac{T_c^i[t+1]-T_c^i[t]}{\Delta t} + \frac{h_{s,c}^i[t]-h_a^{i+1}[t]}{R_a^*} + \frac{T_c^i[t]-T_w^{i-1}[t]}{R_w} = 0$$

$$R_a = \frac{1}{\varepsilon_a m_a c_{p,a}}, \qquad R_w = \frac{1}{\varepsilon_w m_w c_{p,w}}, \qquad R_a^* = \frac{1}{\varepsilon_a^* m_a}$$

$$\varepsilon_w = 1-\exp\left(-\beta_1 m_w^{\beta_2}\right)$$

$$\varepsilon_a = 1-\exp\left(-\beta_3 m_a^{\beta_4}\right)$$

$$\varepsilon_a^* = 1-\exp\left(-\beta_5 m_a^{\beta_6}\right)$$

Cooling Coil Model

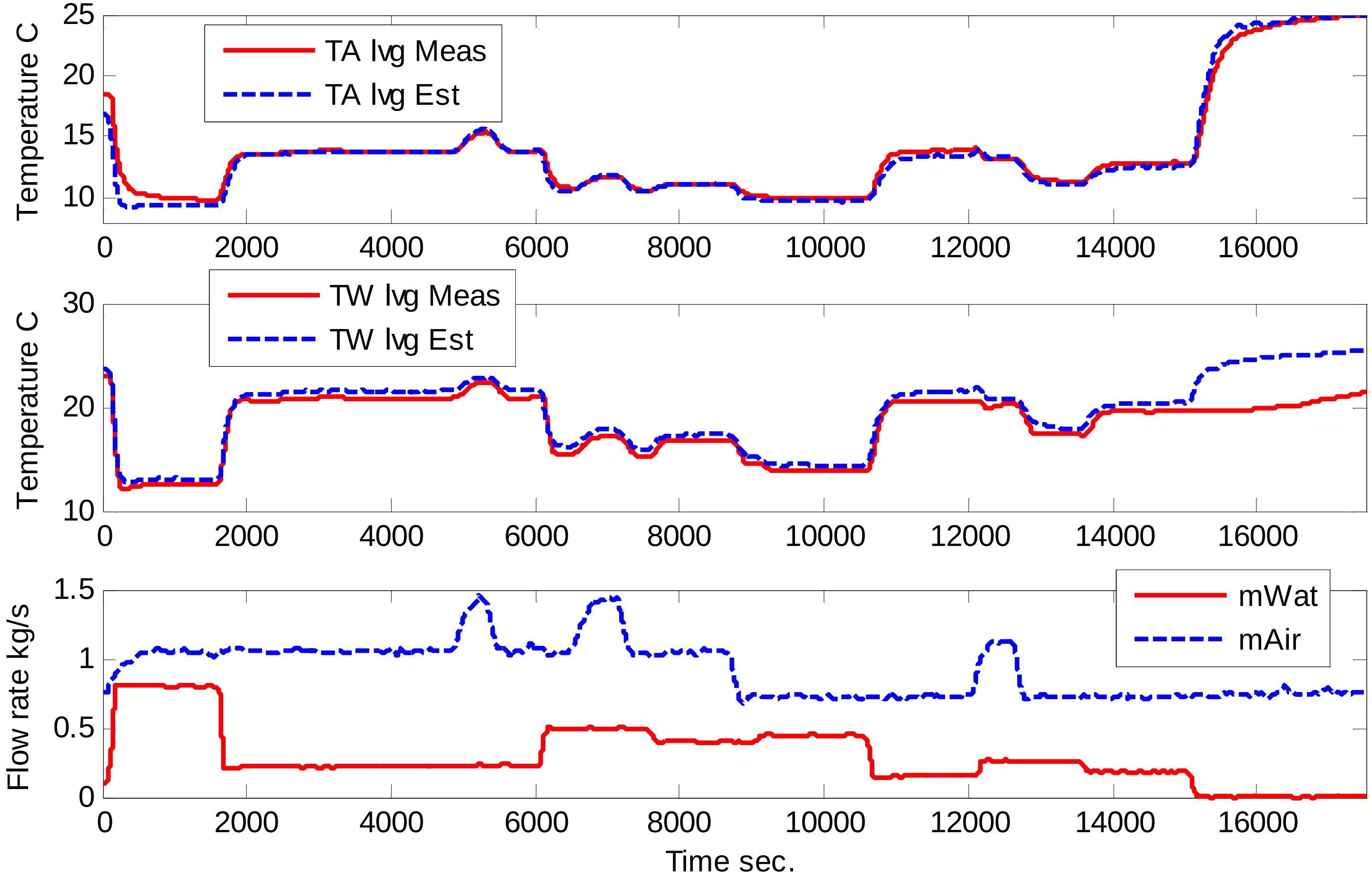


Fig. Model training results

- Training data with random step changes in the air and water flow was collected for the Living Lab #3 cooling coil
- Regression was performed to match leaving air temperature

Cooling Coil Model

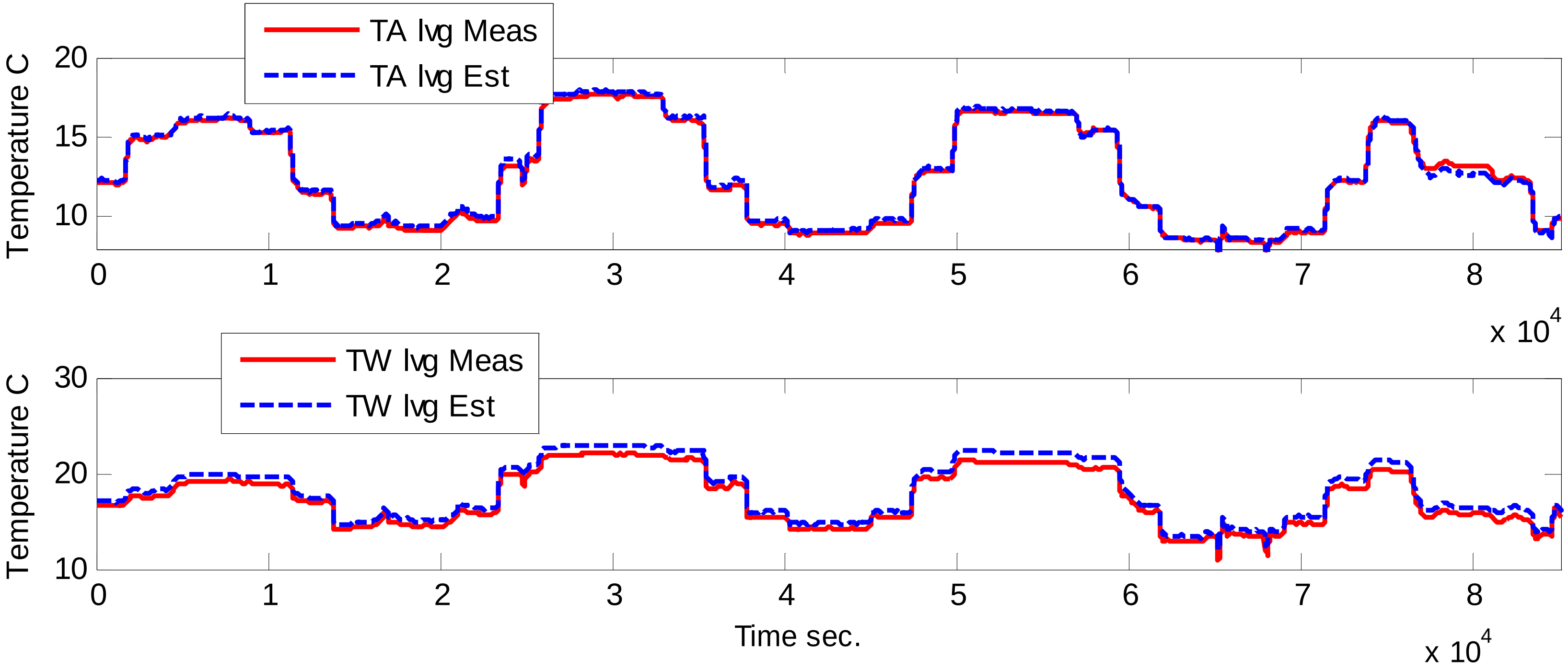
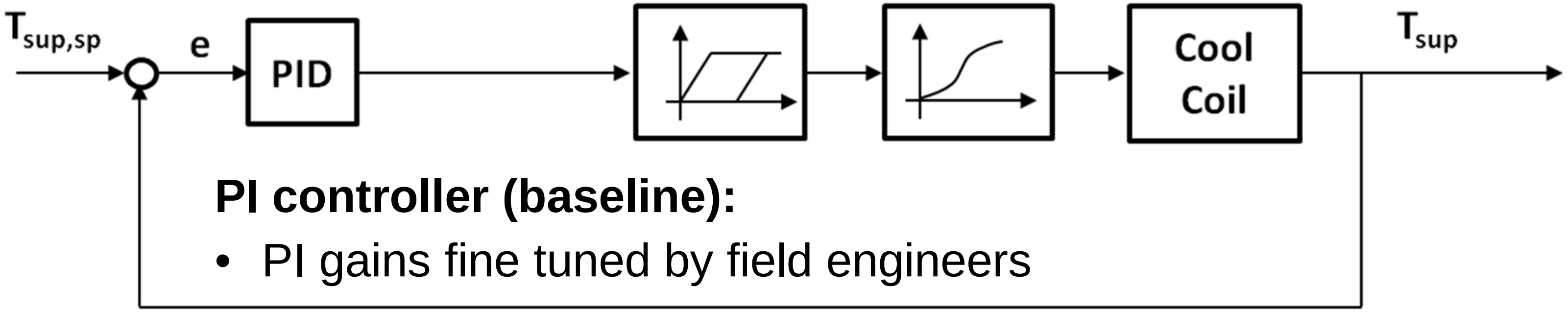


Fig. Model validation results

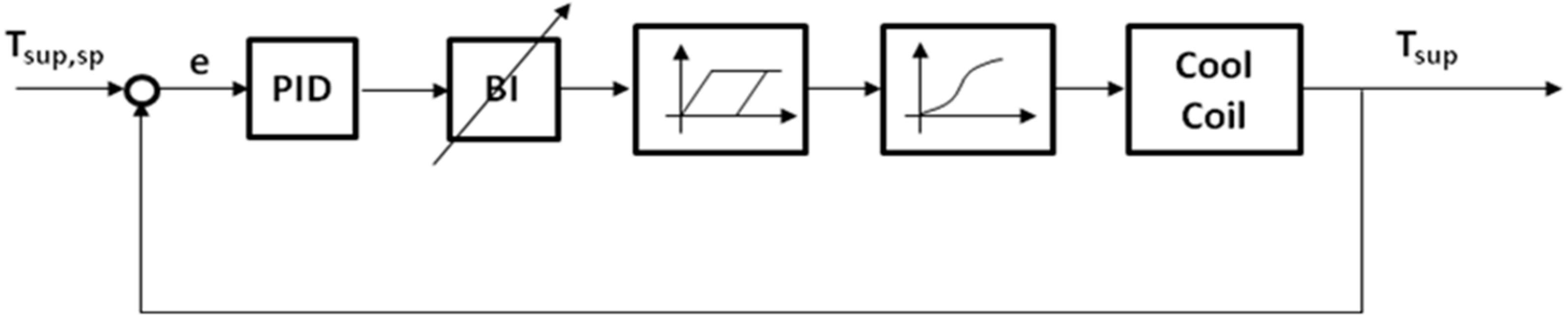
- Validation data was collected from a different period of time
  - under normal operation;
  - and with SAT resetting strategy to reduce VAV reheat

Valve Controllers



PI controller (baseline):

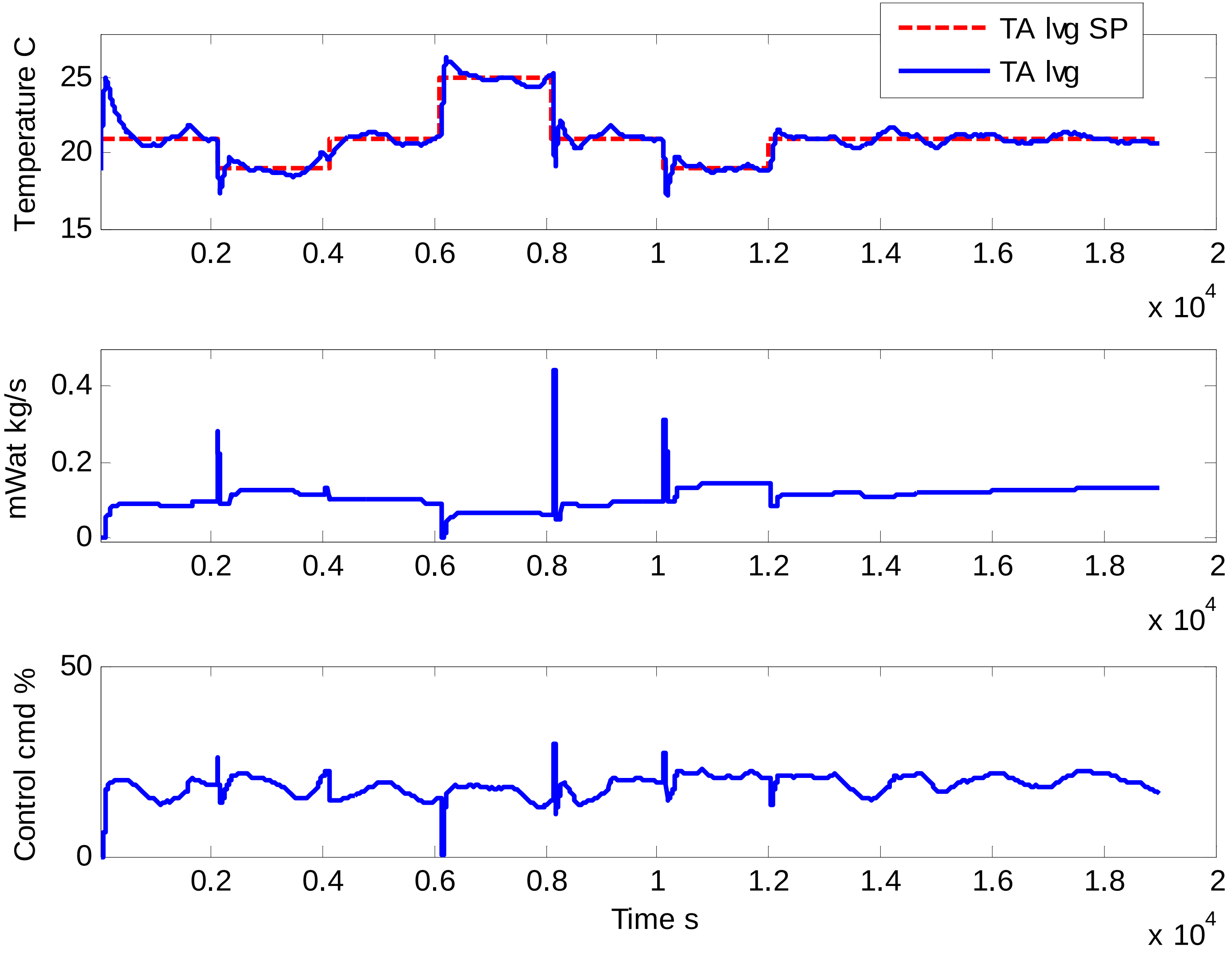
- PI gains fine tuned by field engineers



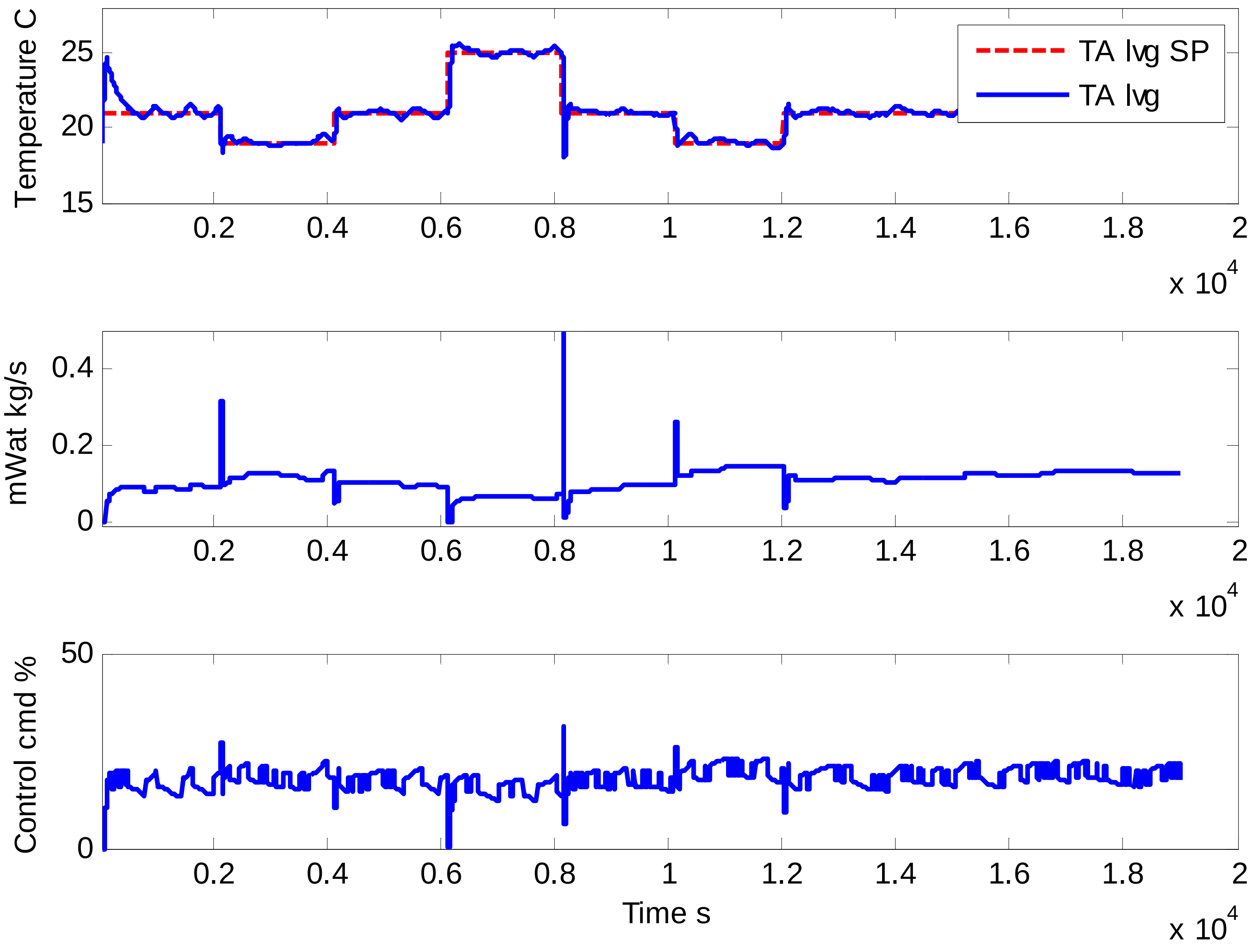
BI controller:

- Same PI settings
- Estimated backlash magnitude in the BI block

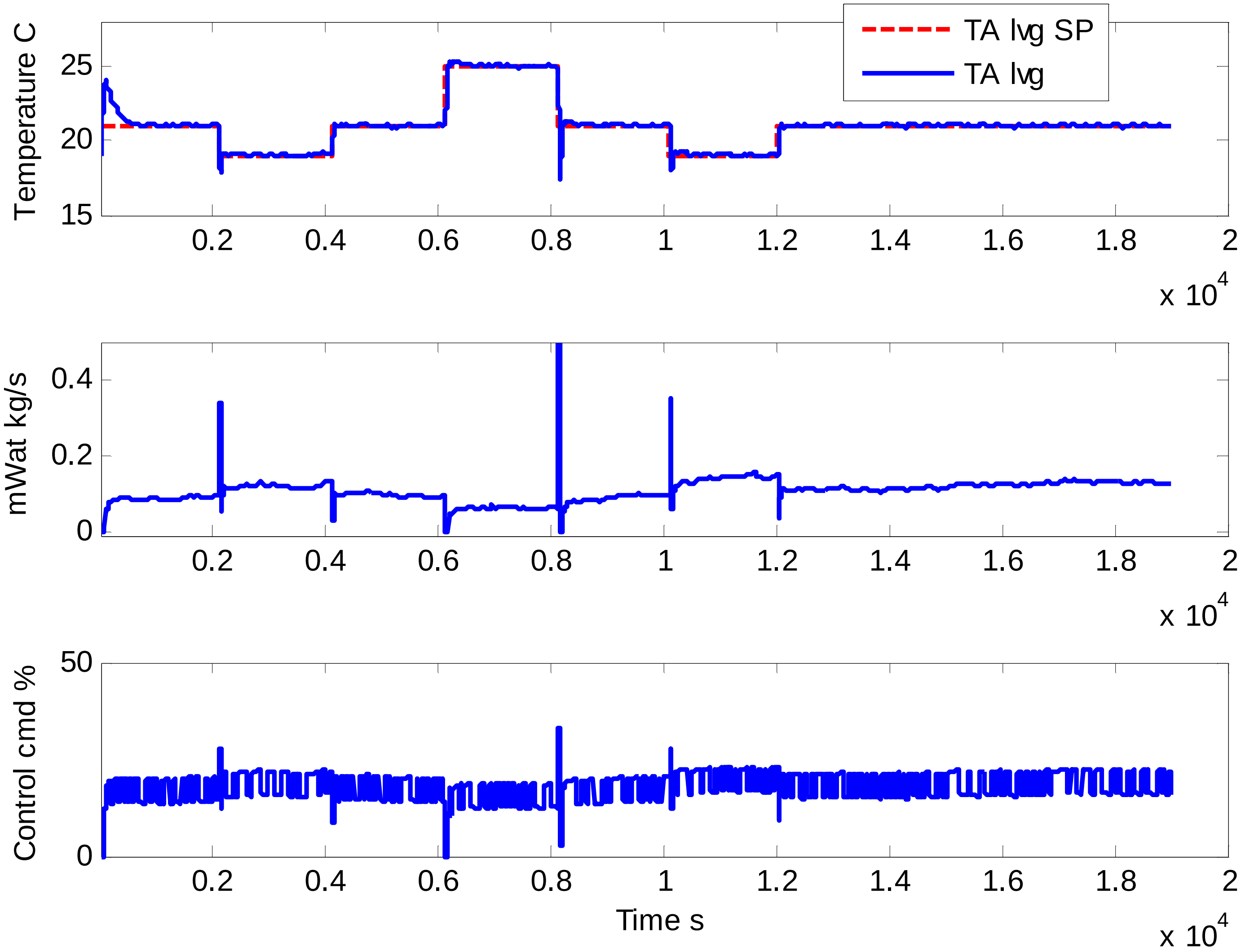
Baseline PI Control Simulation Results



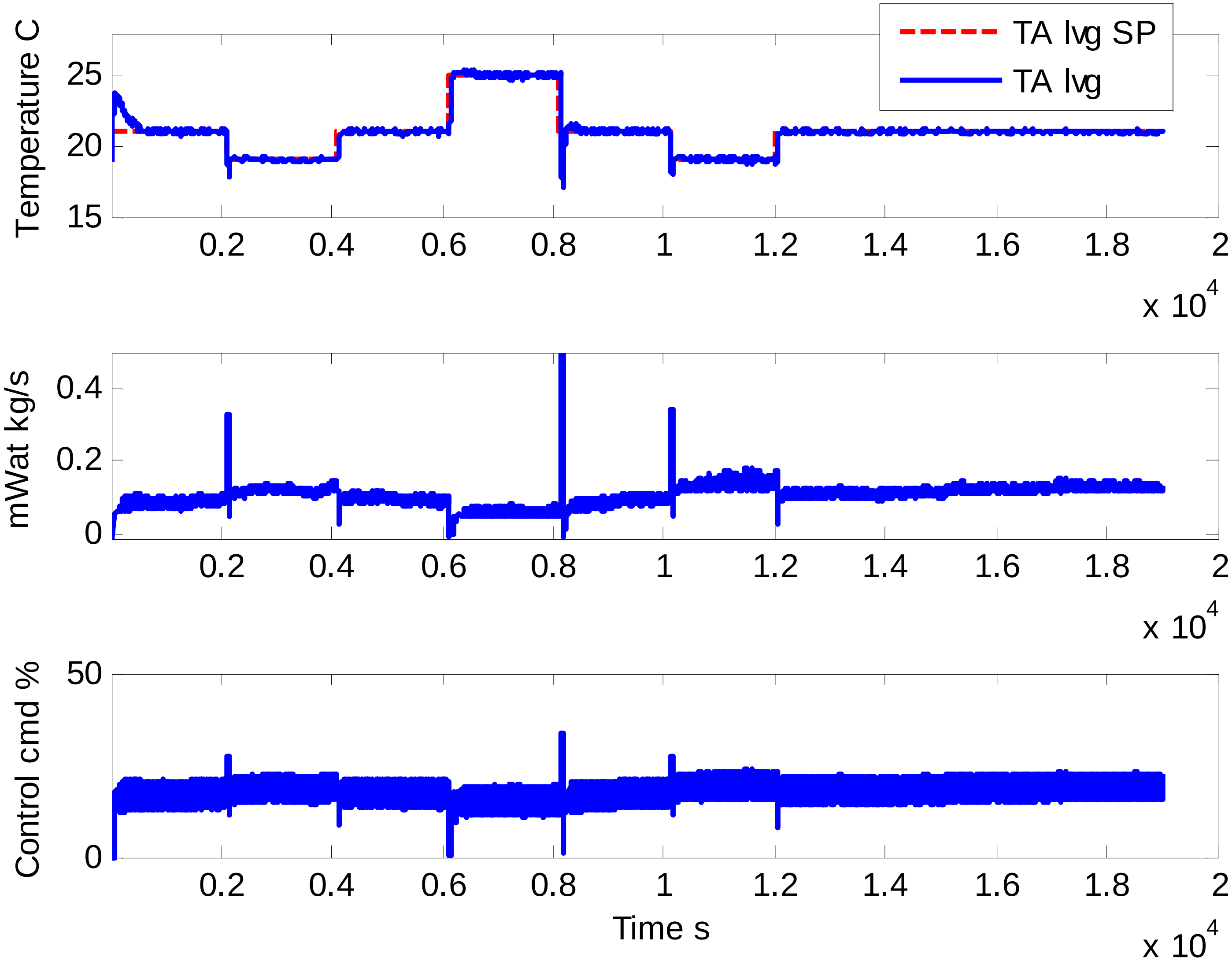
BI Control with 60% Backlash Estimate



BI Control with 95% Backlash Estimate



BI Control with 110% Backlash Estimate



Self-Learning BI Control

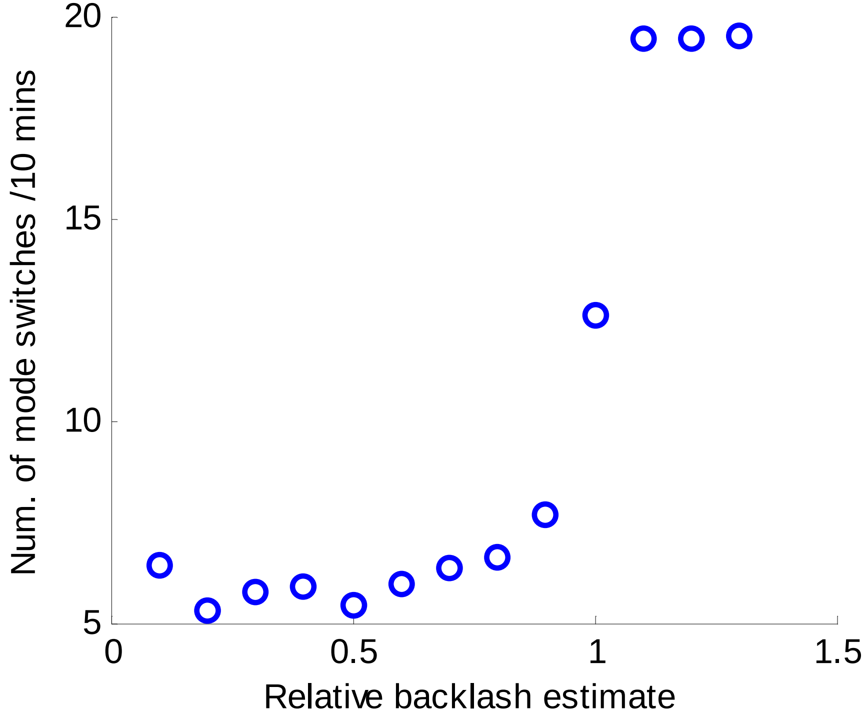
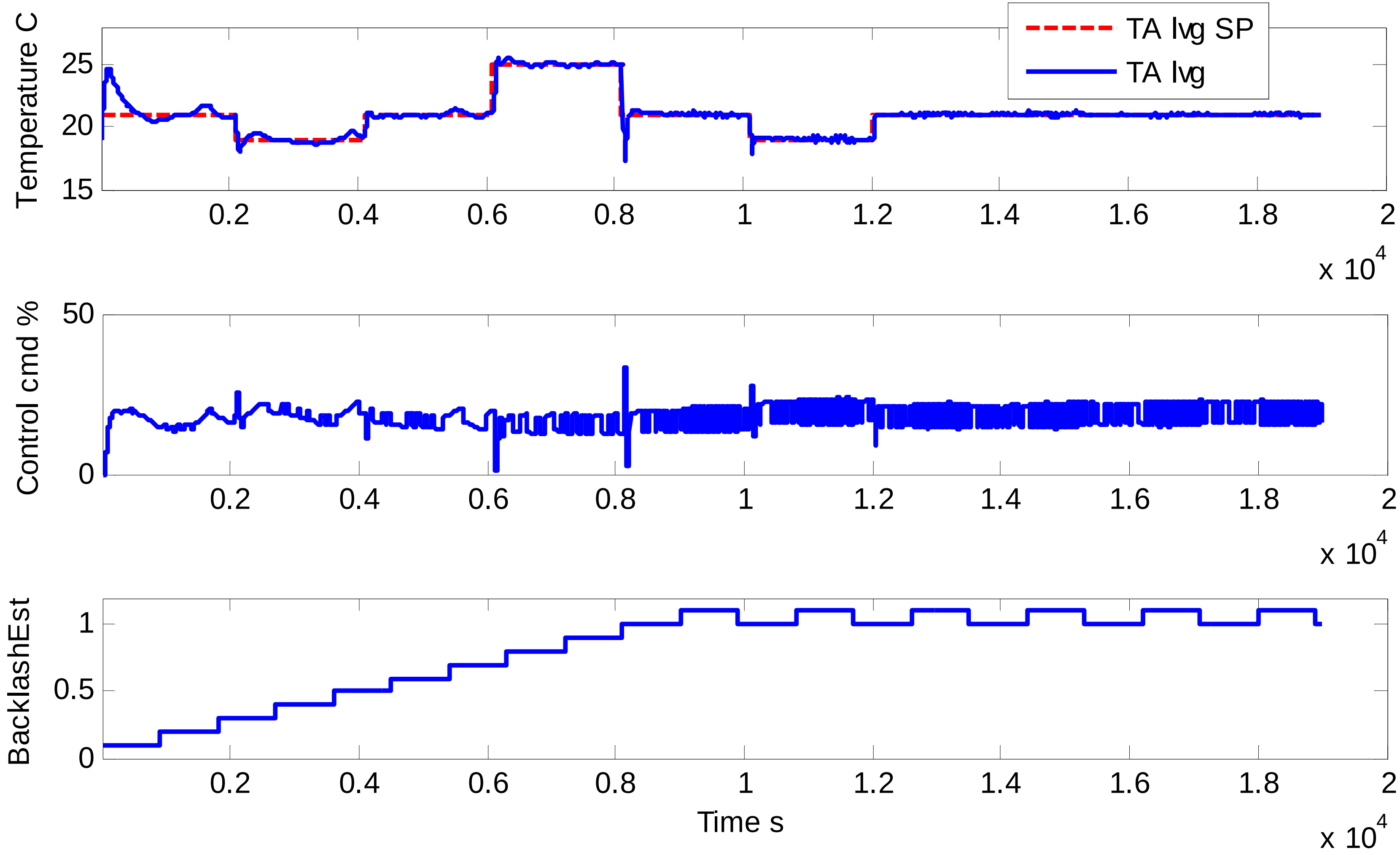


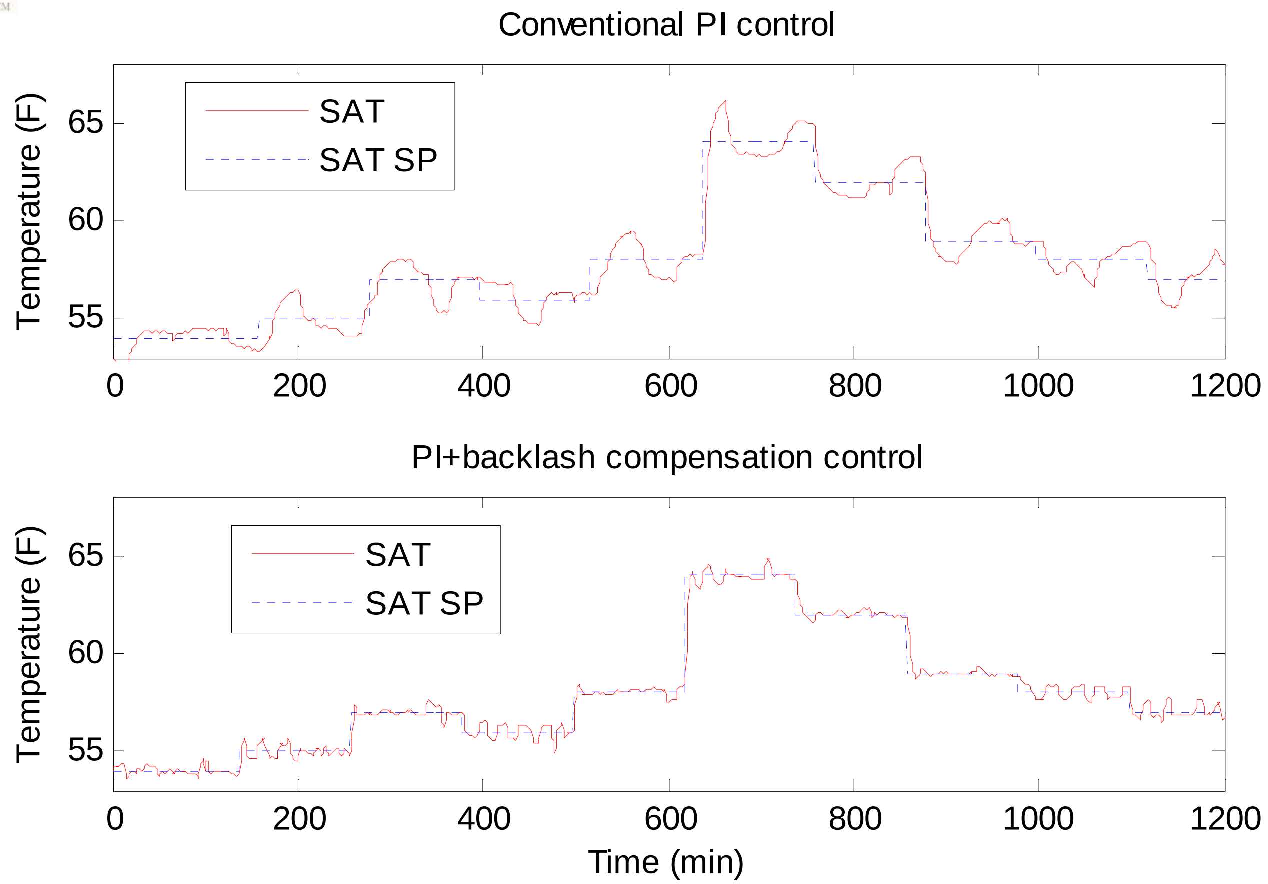
Fig. Chattering frequencies for BI controllers with different backlash estimates

- Self-learning algorithm: increase backlash estimate until chattering frequency shows a significant jump

Self-Learning BI Control



Experimental Test Results



- Tested with the same cooling coil valve to train the models
- Resetting SAT strategy

Conclusions & Discussions

- A companion paper showed most HVAC valves suffer from hysteresis effects
- Valve and cooling coil models were developed as a simulation test bed to study valve control performance
- A backlash inverse controller was proposed with limited modification from a conventional PI controller
- A self-learning method was proposed to estimate the backlash magnitude used in a backlash inverse controller
- Significant control improvement was achieved with the proposed backlash inverse control approach in simulation and field tests
- Potential benefits:
  - Improved comfort delivery (stable temperature control)
  - Enhanced unit efficiency and longer life span (less chattering)
  - Reduced electricity demand cost (reduced power peak)

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Thank you!

Q&A