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Managing Communication Delays and Model Error in Demand Response

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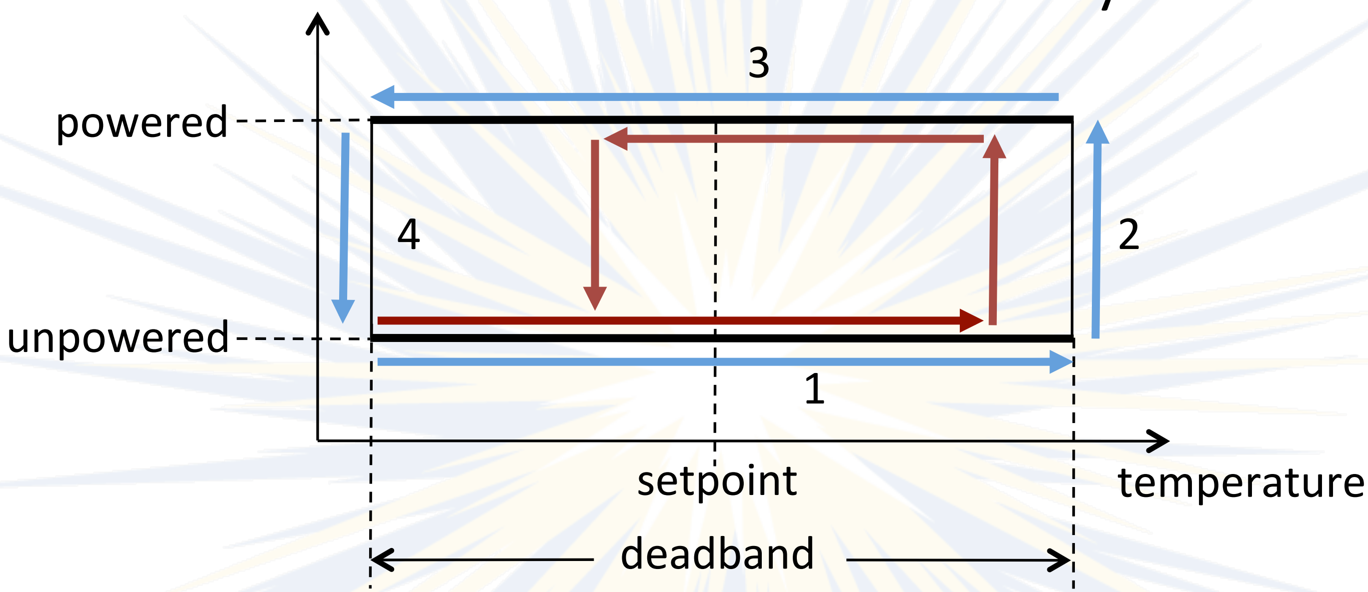
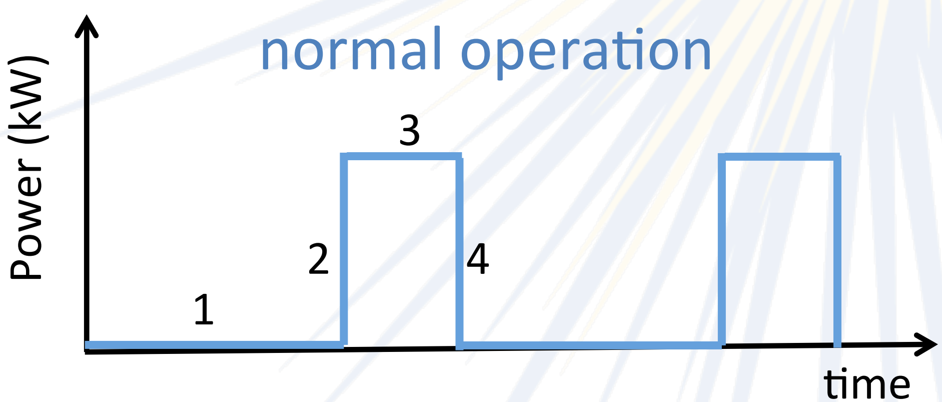
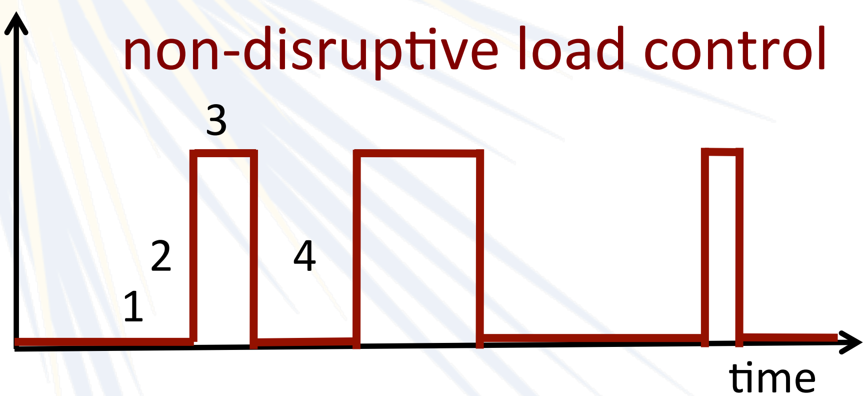
How can loads provide reserves?

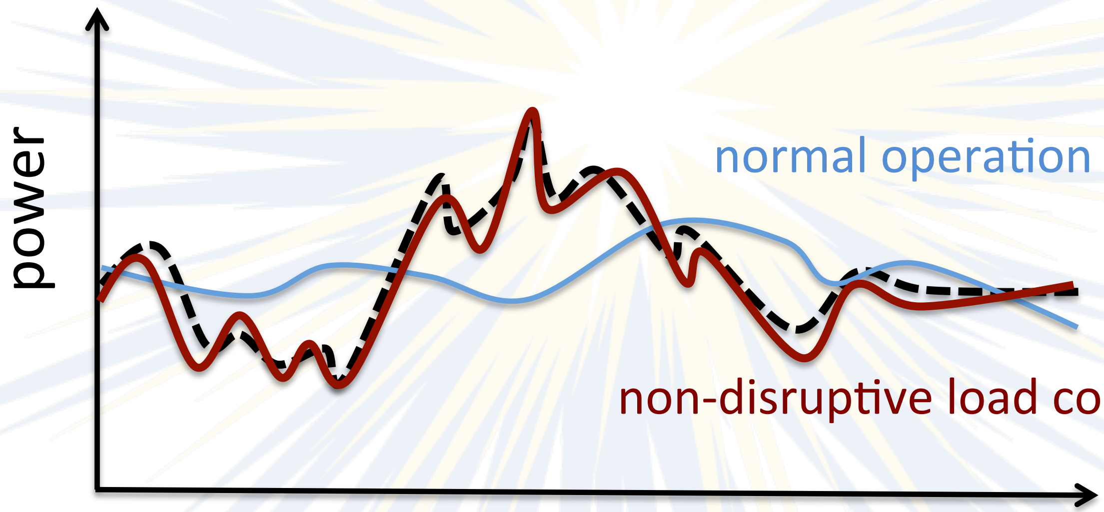
→ your refrigerator, air conditioner, and water heater are already flexible







Thousands of thermostatically controlled loads (TCLs) can track signals and provide reserves



[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

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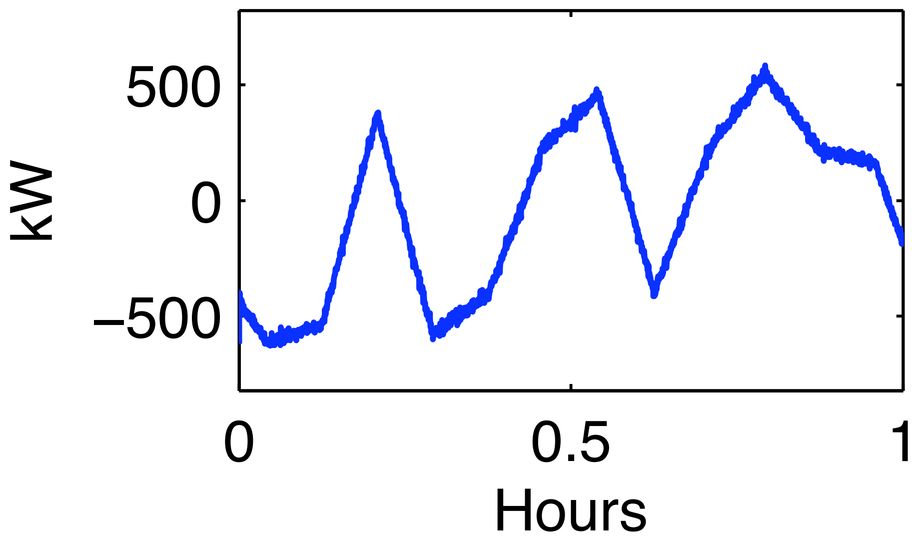
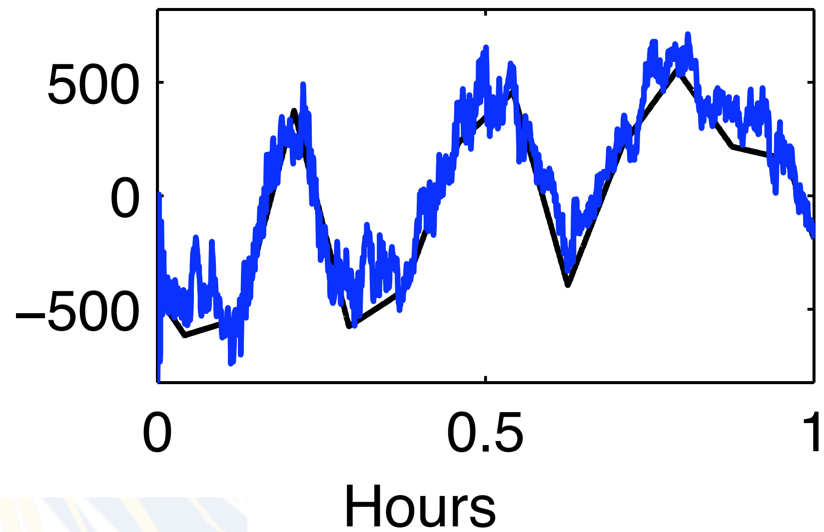
Simulation results:

1000 ACs tracking 5-minute market signal

Controller gets temperature/state of each load every 2 seconds



Controller infers TCL behavior from power measurements at the substation



→The more the controller knows about the loads, the better it can track a signal

[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

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Data from loads

- Parameters
  - the make/model of the load?
  - its temperature setpoint/dead-band width?
  - some information about the household?

→ Modeling

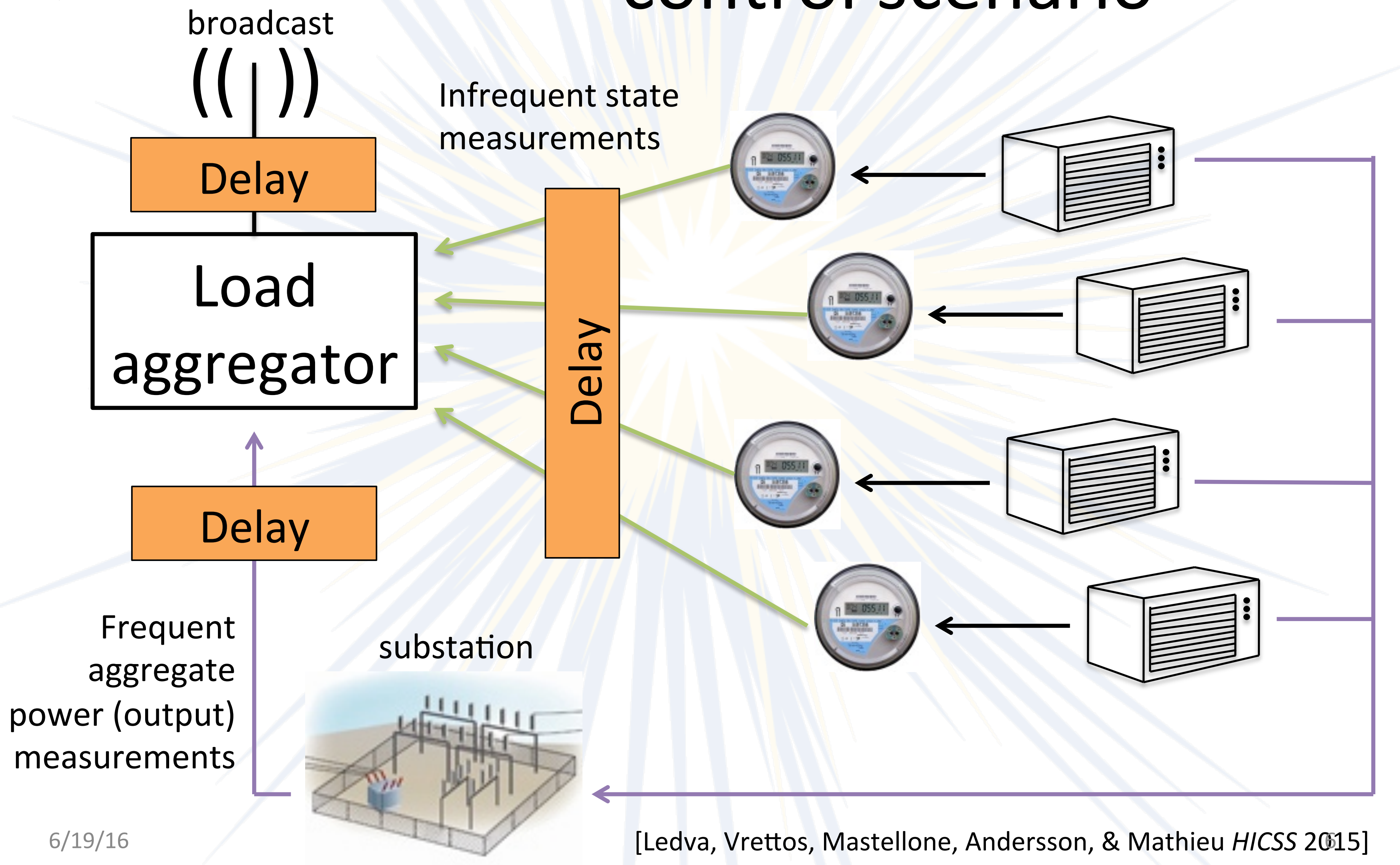
- Real-time data
  - Measurements of the on/off state and/or internal temperature?
  - Household smart meter data? → High quality, infrequent
  - Power measurements from the distribution network? → Low quality, frequent

→ Feedback control

- Recorded data
  - high resolution power measurements of each load?

→ Auditing

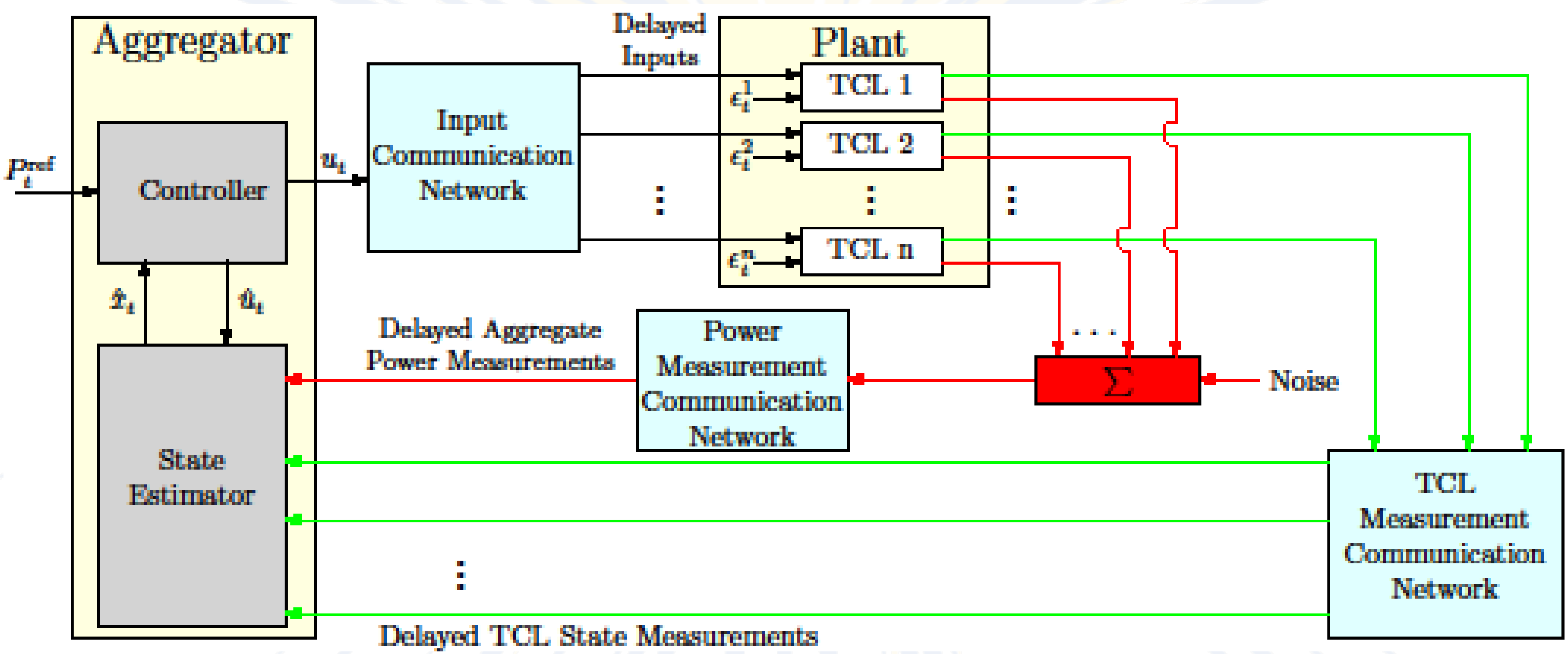
Communication and control scenario



[Ledva, Vrettos, Mastellone, Andersson, & Mathieu *HICSS* 2015]

System block diagram

Delays cause unsynchronized arrivals of inputs at the loads and measurements at the estimator

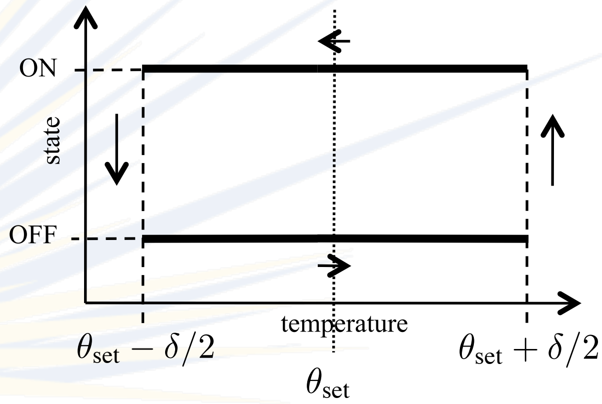


The challenge

- Design an estimator and controller to enable loads to track a signal *despite delays*
- Assuming…
  - Control inputs & measurements are time-stamped
  - Delay statistics are known
  - State measurements are taken frequently; measurement *histories* are transmitted infrequently
  - Aggregate power measurements are *very* noisy (though the noise is normally distributed, zero-mean, and the standard deviation is known)

Two-state TCL model

Each TCL i is modeled with a stochastic hybrid difference equation:



Temperature of the space

$$\theta_i(k+1) = a_i\theta_i(k) + (1-a_i)(\theta_{\text{a},i} - m_i(k)\theta_{\text{g},i}) + \epsilon_i(k)$$

On/off state

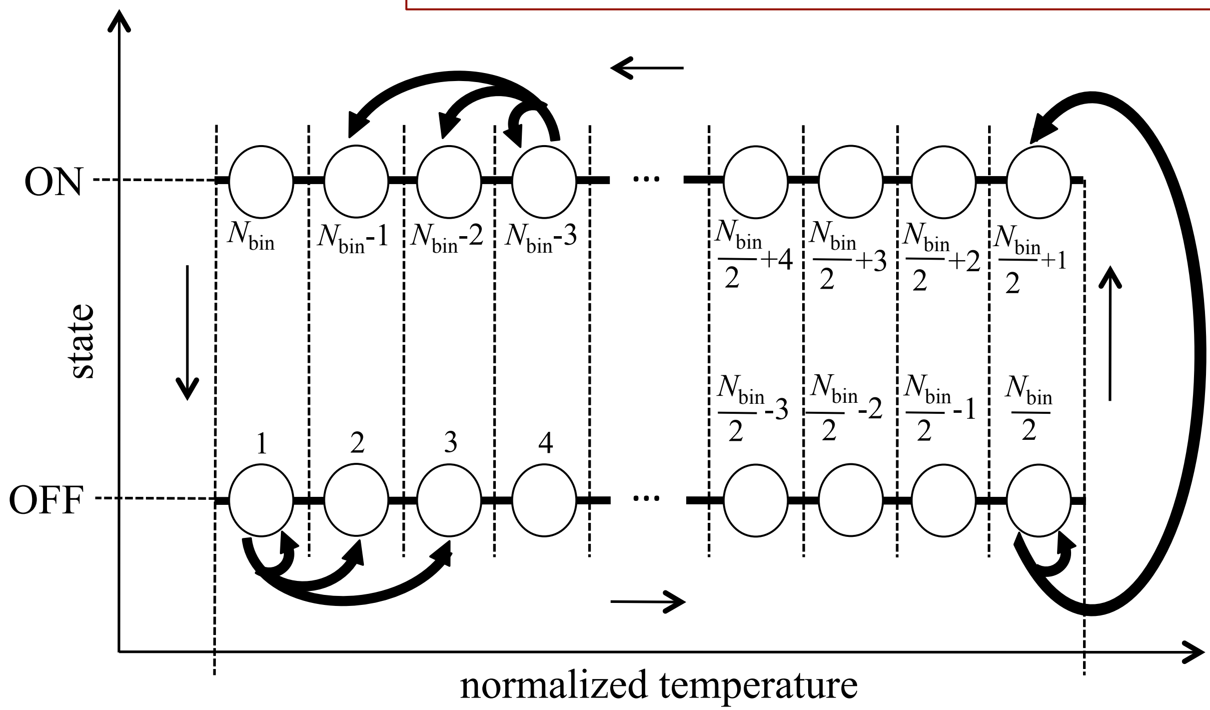
$$m_i(k+1) = \begin{cases} 0, & \theta_i(k+1) < \theta_{\text{set},i} - \delta_i/2 \\ 1, & \theta_i(k+1) > \theta_{\text{set},i} + \delta_i/2 \\ m_i(k), & \text{otherwise} \end{cases}$$

a, thermal parameter
θ_{g}, temperature gain
θ_{a}, ambient temperature
ϵ, noise
θ_{set}, set point
δ, dead-band width

[Ihara & Schweppe 1981, Mortensen & Haggerty 1990, Uçak & Çağlar 1998]

Aggregate System Model

$$x(k+1) = Ax(k) + Bu(k) + B_\omega \omega(k)$$
$$y(k) = Cx(k) + \nu(k)$$



Similar models in the literature:

- Lu & Chassin 2004/2005
- Bashash & Fathy 2011/2013
- Kundu & Hiskens 2011
- Zhang et al. 2013

[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

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Estimator Designs

- Based on Kalman Filtering
  - Estimator 1: Parallel filter estimator
    - One Kalman Filter per load
    - Each time a measurement arrives, filter it
    - Synthesize aggregate estimate from individual estimates
  - Estimator 2: Single Kalman Filter Using Aggregate State Predictions
    - Use state measurement histories to estimate *individual* load parameters (two-state model)
    - Use individual load models to predict current state
    - Use predictions as "measurements" in Kalman Filter

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Controller Design

- Based on Model Predictive Control
  - Use knowledge of delay distributions and past control inputs

First control sequence: $u_1, u_2, u_3, \ldots, u_n$

Second control sequence: $u_2, u_3, \ldots, u_{n+1}$

Third control sequence: $u_3, u_4, \ldots, u_{n+1}$

$\mathcal{U}_k$

Input estimate: $\widehat{u}_k = \mathcal{U}_k \mathcal{P}$

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Control Formulation

$$\underset{u,\delta}{\text{minimize}} \sum_{k=t}^{t+N^{\text{mpc}}-1} \left[c^y \left(y_k^{\text{err}}\right)^2 + c^\delta (\delta_k^- + \delta_k^+) + \sum_{m=k-N^{\text{mpc}}+1}^{k} c^u (u_{k|m}^\top u_{k|m}) \right]$$

Tracking error — State constraint deviations — Control effort

$$\text{s.t.} \quad x_{k+1} = A\, x_k + B\, \widehat{u}_k$$

$$\widehat{u}_k = \mathcal{U}_k \mathcal{P}$$

$$y_k^{\text{err}} = y_k^{P,\text{ref}} - C^{\text{P}} x_k$$

$$u_{k|m}^i \leq x_k^i \qquad i \in \{1, \ldots, N^{\text{x}}/2\}$$

$$-u_{k|m}^i \leq x_k^{N^{\text{x}}+1-i} \qquad i \in \{1, \ldots, N^{\text{x}}/2\}$$

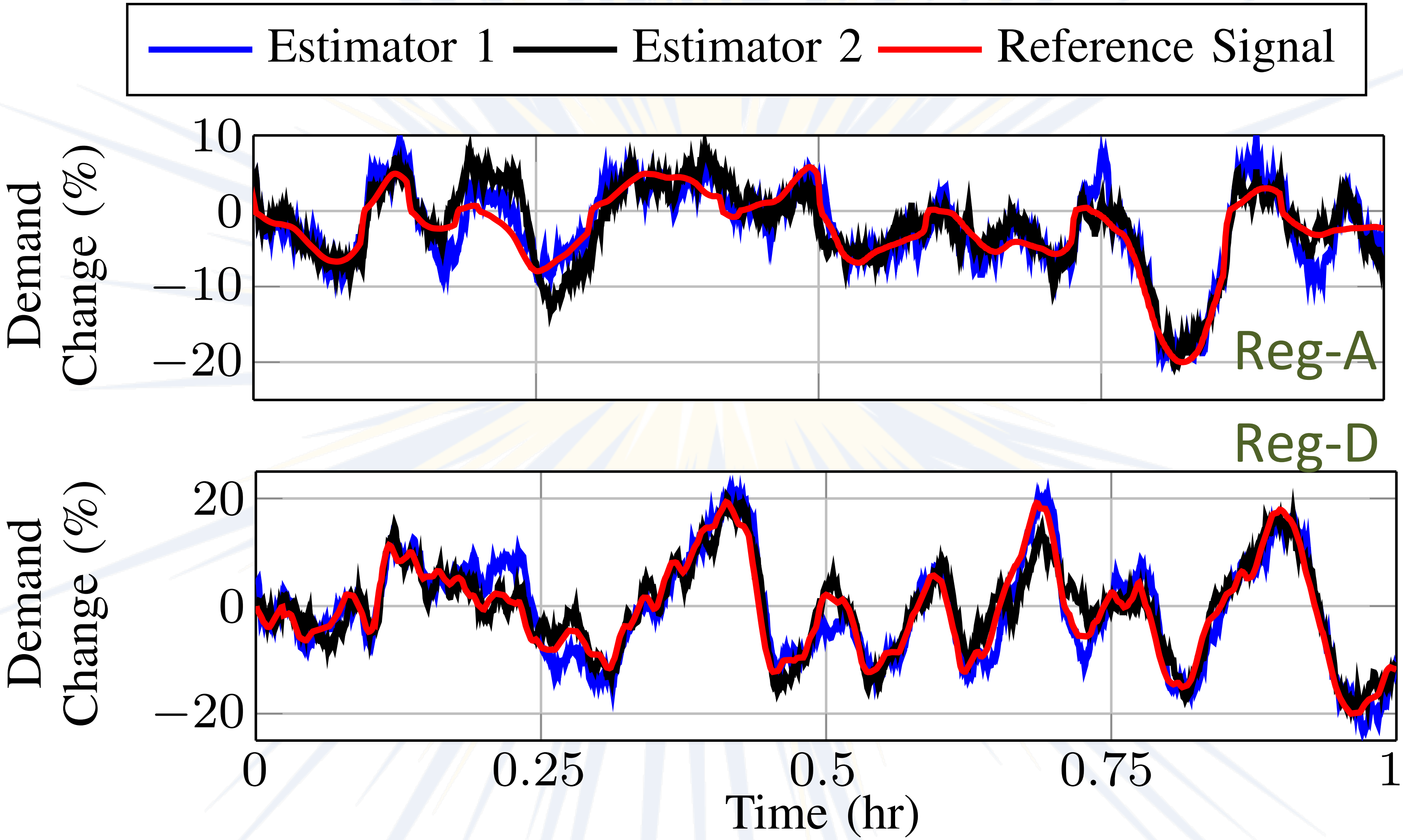
$$0 - \delta_k^- \leq x_k \leq 1 + \delta_k^+$$

$$0 \leq \delta_k^-, \delta_k^+.$$

Case Studies

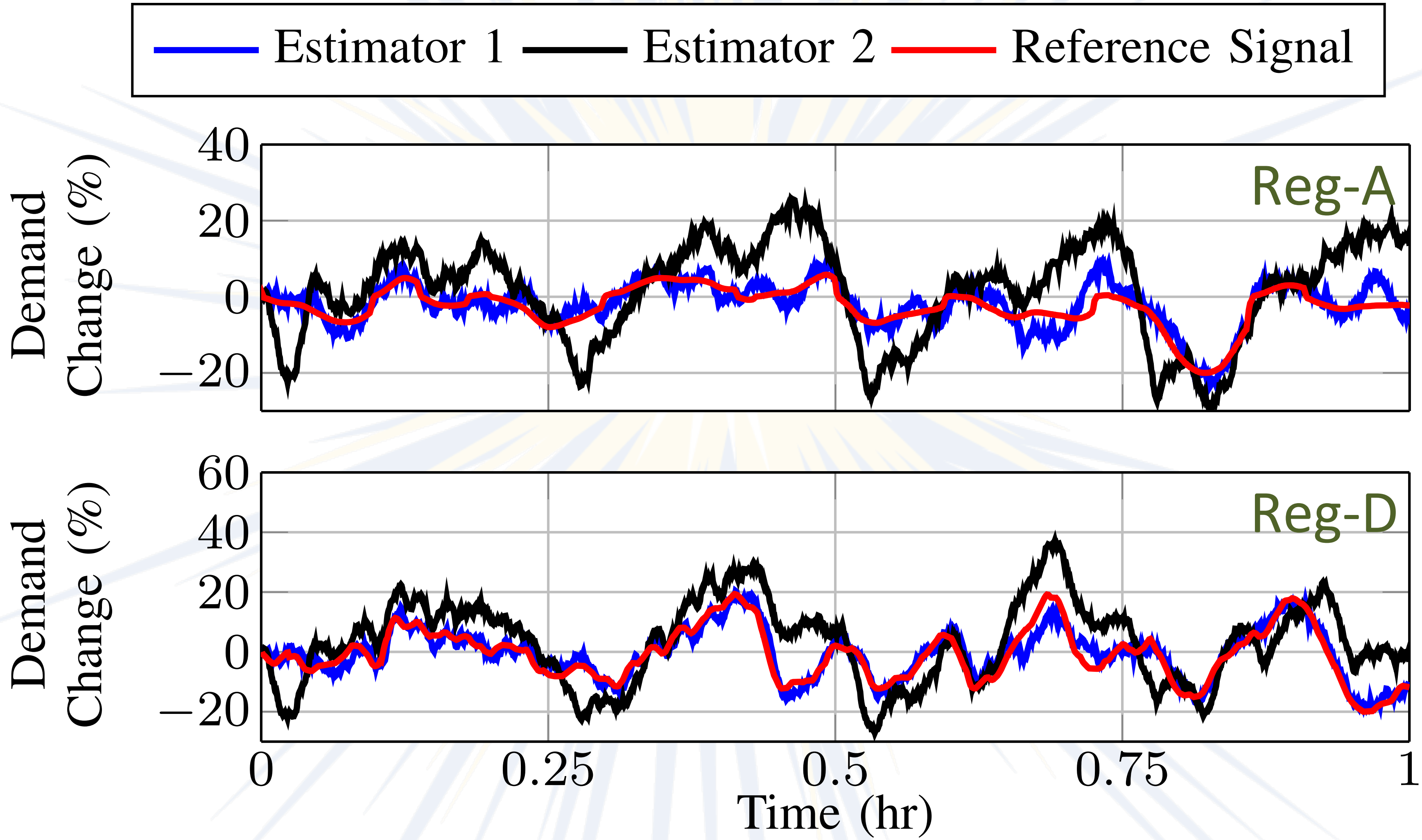
- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- (Delayed) state histories arrive every 15 minutes

Results

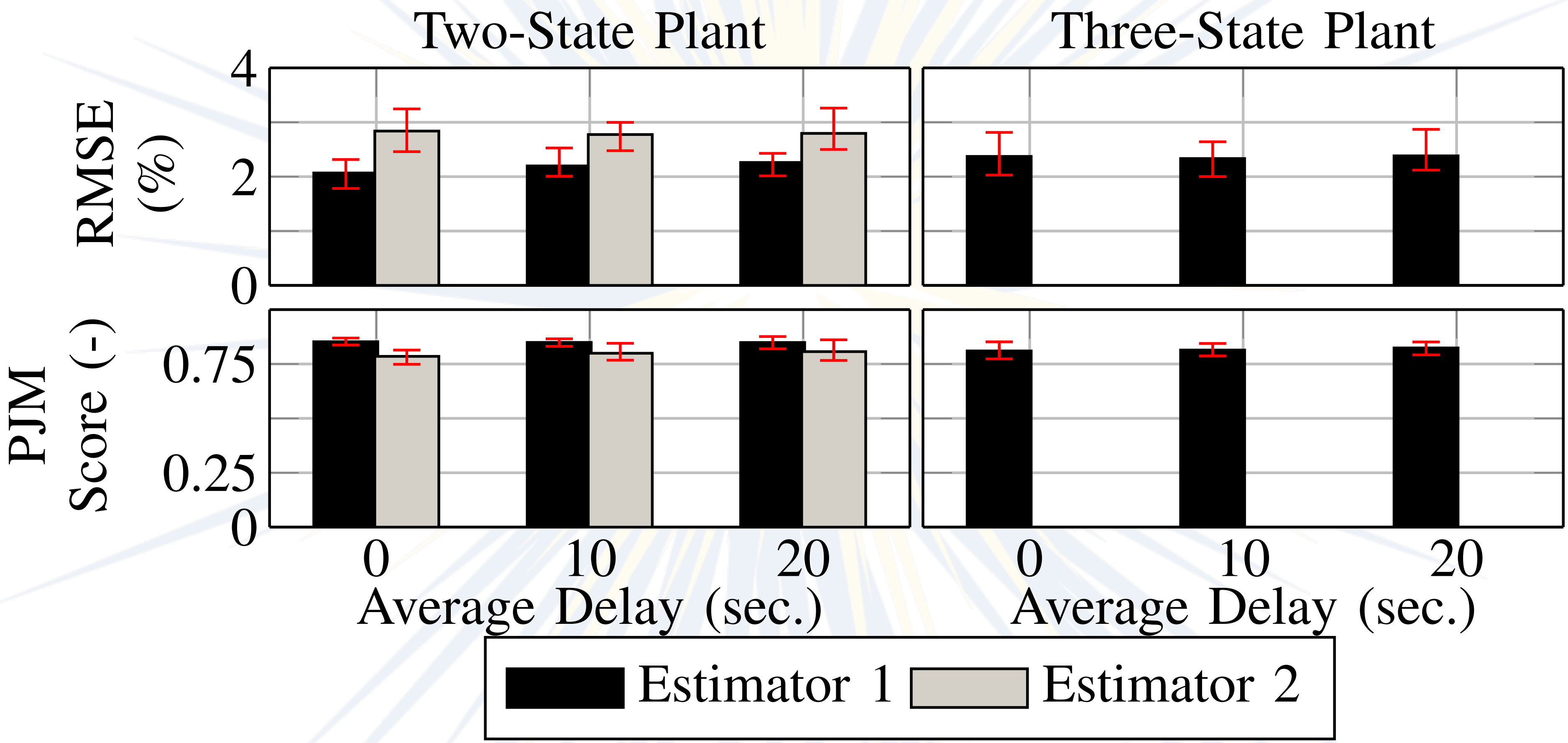


Estimator 1
Estimator 2
Reference Signal
10
0
−10
−20
Demand Change (%)
Reg-A
Reg-D
20
0
−20
Demand Change (%)
0
0.25
0.5
0.75
1
Time (hr)

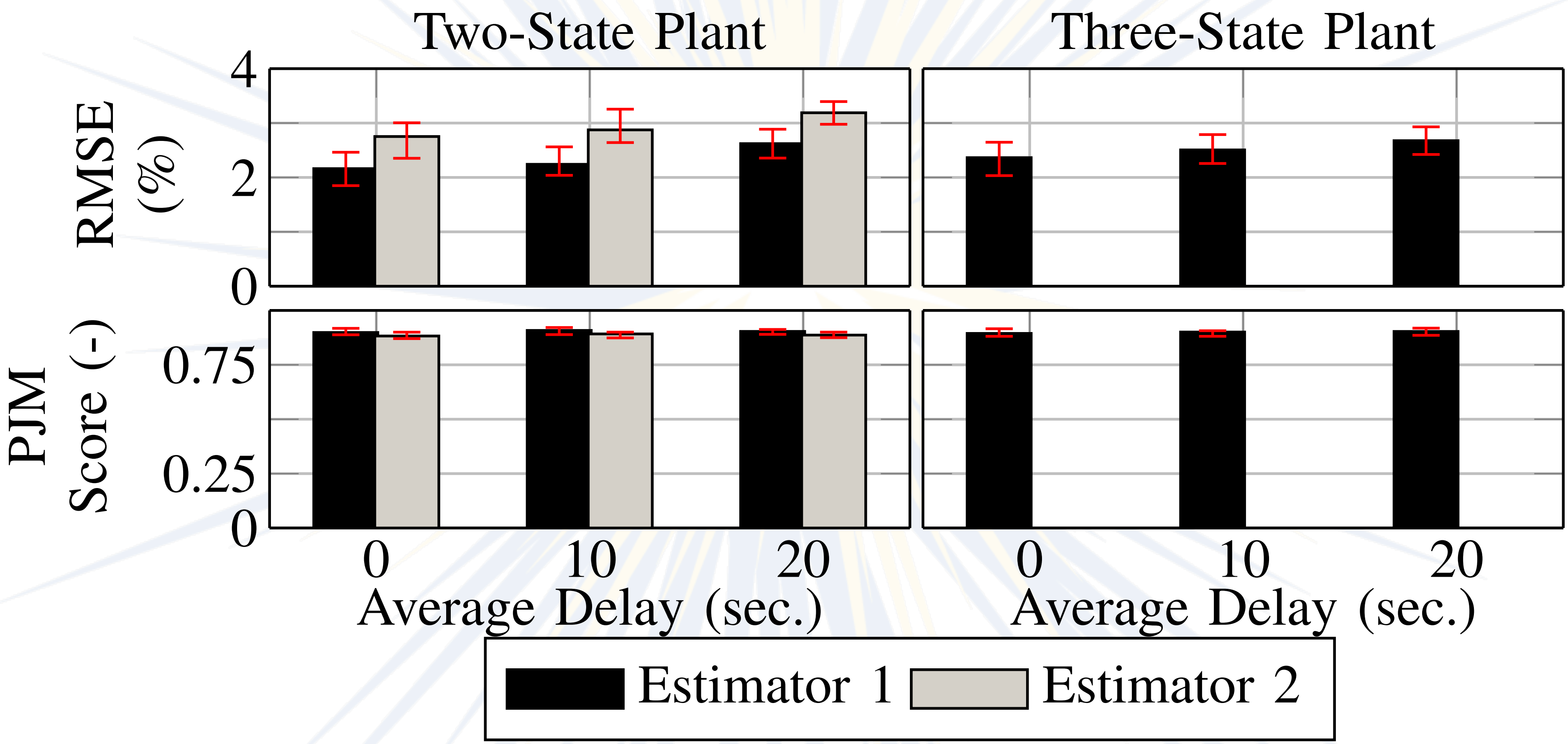
Results: Model Mismatch



Control Results: Reg-A



Control Results: Reg-D



Controller Reformulation

Original Model
$$x_{k+1} = A\,x_k + B\,u_k$$
$$y_k = C\,x_k.$$

Modal Model
$$\begin{bmatrix} 1 \\ \widetilde{x}_{k+1} \end{bmatrix} = \overbrace{\begin{bmatrix} 1 & 0 \\ 0 & \widetilde{A} \end{bmatrix}}^{A^*} \overbrace{\begin{bmatrix} 1 \\ \widetilde{x}_k \end{bmatrix}}^{x_k^*} + \overbrace{\begin{bmatrix} 0 \\ \widetilde{B} \end{bmatrix}}^{B^*} u_k$$
$$y_k = \underbrace{\begin{bmatrix} y_{\text{ss}} & \widetilde{C} \end{bmatrix}}_{C^*} \begin{bmatrix} 1 \\ \widetilde{x}_k \end{bmatrix}$$

Reduced-Order Model
$$\widetilde{x}_{k+1} = \widetilde{A}\,\widetilde{x}_k + \widetilde{B} u_k$$
$$\widetilde{y}_k = \widetilde{C}\,\widetilde{x}_k.$$

Controller Reformulation

The linear controller uses constant gains generated from an output-regulating Linear Quadratic Regulator (LQR) with reference feedforward.

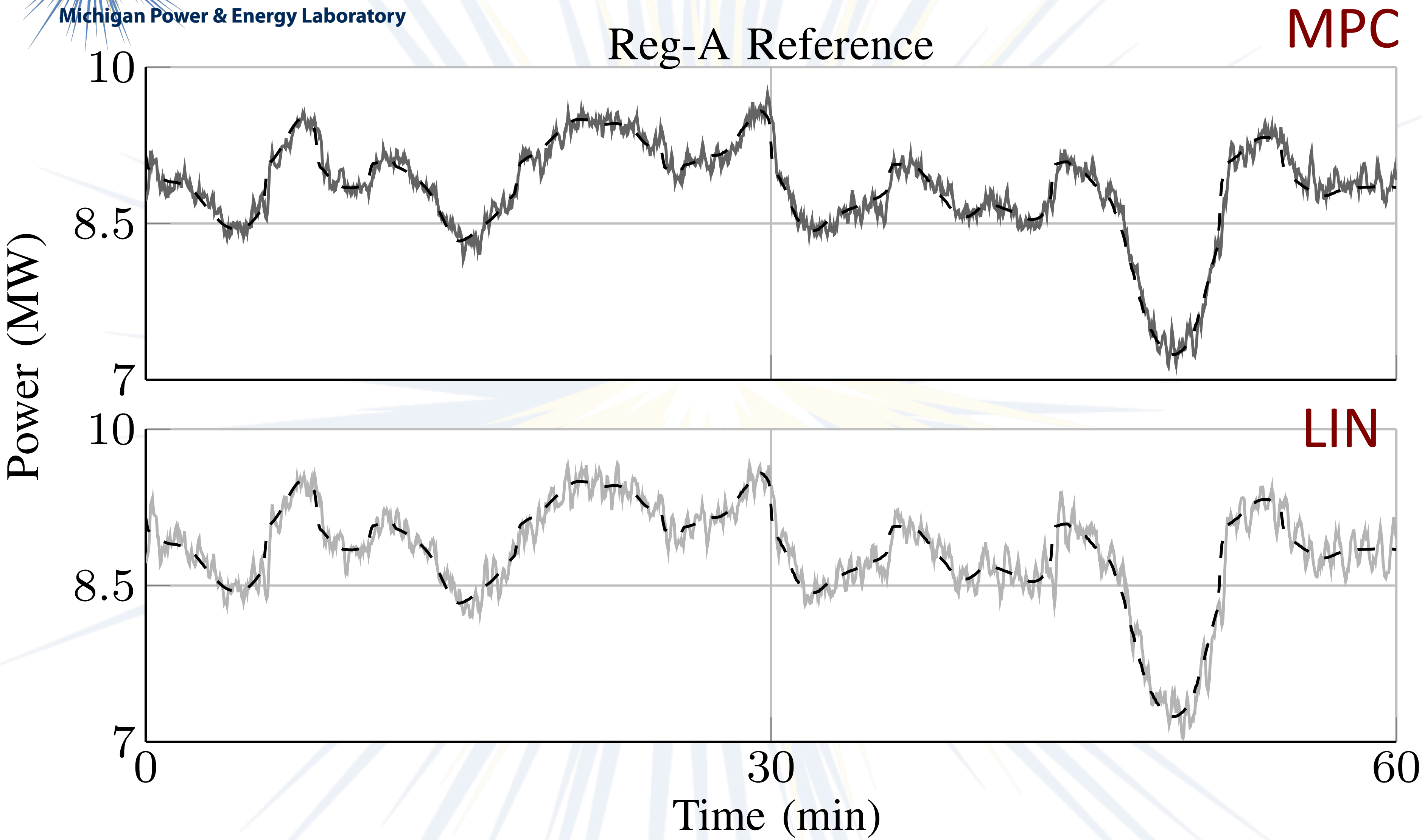
Linear Controller $u_t^{\text{seq}} = -K_\infty^{\text{x}}\,\overline{x}_t - K_\infty^{\text{w}}\,w_t + K_\infty^{\text{y}}\,y_t^{\text{des}}$

LQR Formulation
$$\min_u \sum_{k=t}^{\infty} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix}^T \begin{bmatrix} \widetilde{\overline{C}}^T q^{\text{y}} \widetilde{\overline{C}} & 0 \\ 0 & q^{\text{w}} \end{bmatrix} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix} + (u_k^{\text{seq}})^T R\, u_k^{\text{seq}}$$
$$\text{s.t.} \quad \begin{bmatrix} \widetilde{\overline{x}}_{k+1} \\ w_{k+1} \end{bmatrix} = \begin{bmatrix} \widetilde{\overline{A}} & 0 \\ \widetilde{\overline{C}} & 0 \end{bmatrix} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix} + \begin{bmatrix} \widetilde{\overline{B}} \\ 0 \end{bmatrix} u_k^{\text{seq}}$$

Feedforward Gain $K_\infty^{\text{y}} = \left(\widetilde{\overline{C}}\{zI - \widetilde{\overline{A}} + \widetilde{\overline{B}}\widetilde{K}_\infty^{\text{x}}\}^{-1}\widetilde{\overline{B}}\right)^{-\dagger}$

Case Studies

- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- Full state feedback, no measurement delay
- Three-state models used for the plant


Reg-A Reference
MPC
LIN
Power (MW)
10
8.5
7
10
8.5
7
0
30
60
Time (min)

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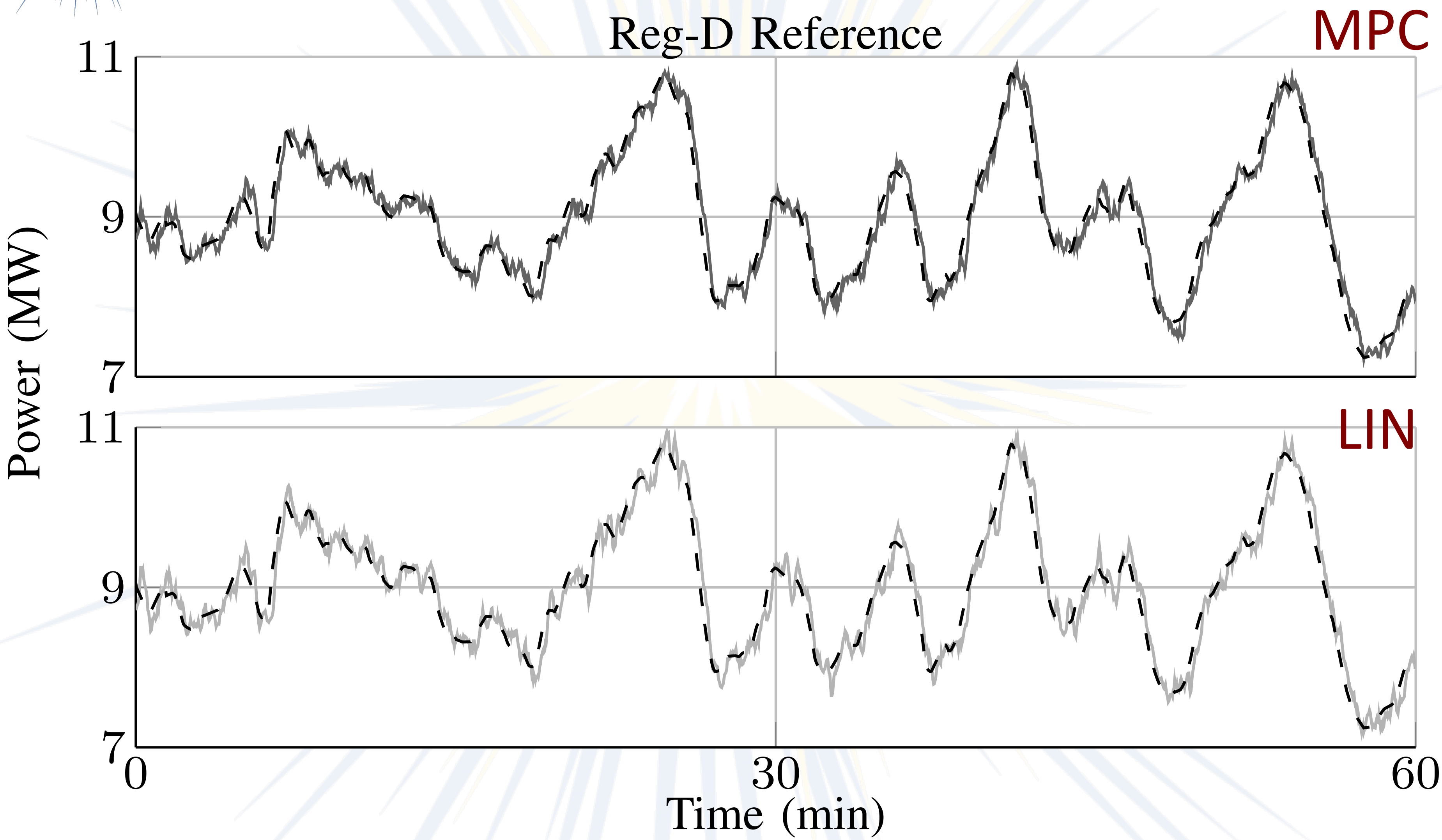
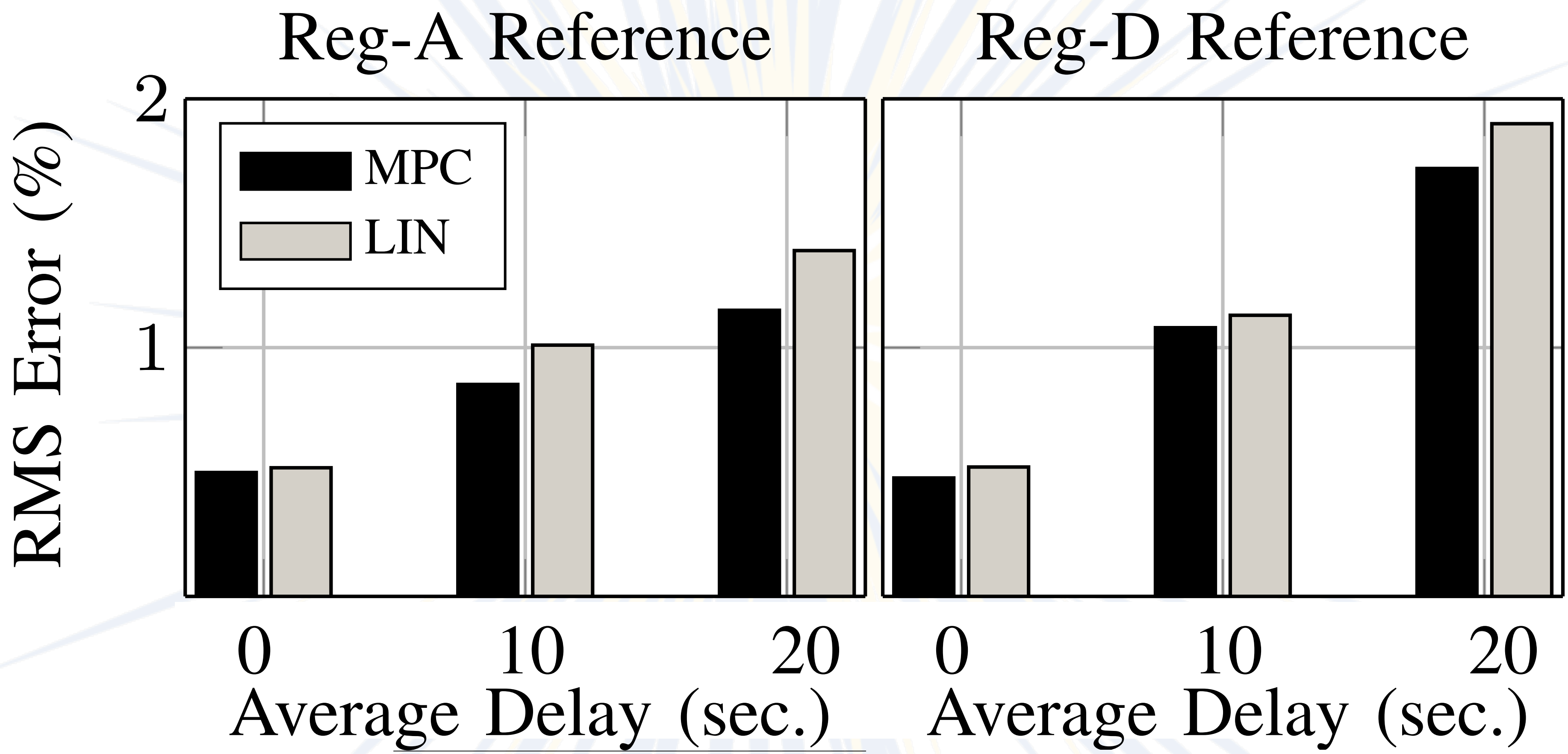


Results Summary



→ LIN is 100 times faster than MPC

Key takeaways

- Communication network limitations necessitate controller/estimator designs that cope with delays, bandwidth limitations, etc.
- Delays make loads less capable of providing fast services, but we can mitigate these impacts through delay-aware control and estimation.