Inference and control of electric loads given sparse measurements and communications delays

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Benefits and Challenges of the Modern Electric Grid

- Grid sensing and communication systems are becoming more prevalent
  - Cost & privacy concerns
  - Need methods to infer grid/load information from existing measurements
- Renewable energy resources are also becoming more prevalent
  - Most (e.g., wind and solar) are intermittent and uncertain
  - Need new sources of power system reserves

Overview

- **Inference:** Inferring the behavior of distributed energy resources with sparse measurements
  [Ledva, Balzano, & Mathieu *Allerton* 2015]

- **Control:** Controlling distributed electric loads to provide power system services with sparse measurements and input/measurement delays
  [Ledva, Vrettos, Mastellone, Andersson & Mathieu *HICSS* 2015]
  [Ledva & Mathieu CDC *(in review)* 2016]

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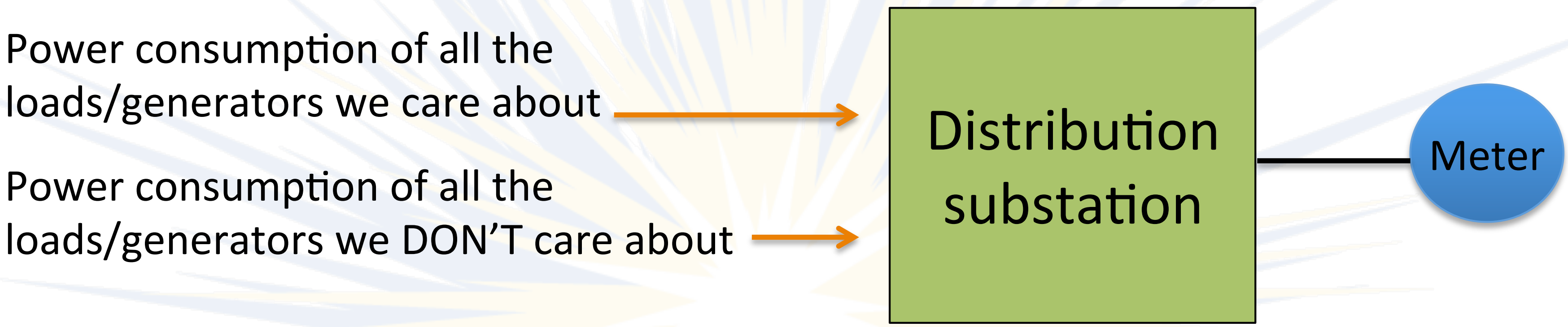
Disaggregating substation load data



Why do we want to disaggregate resources at the substation?

- Energy efficiency via conservation voltage reduction
- Contingency planning
- Optimal reserve contracting
- Demand response event signaling
- Demand response bidding
- Load coordination feedback

Disaggregation methods

e.g., [Berges et al. 2009; Kolter et al. 2010; Dong et al. 2013]

- State estimation
  - Linear techniques require LTI system models
  - Nonlinear techniques can be computationally demanding

- Online learning
  - Optimization formulations
  - Model-free

- Hybrid approach: Dynamic Mirror Descent [Hall & Willet 2015]
  - Admits dynamic models of arbitrary forms
  - Optimization-based method to choose a weighted combination of the estimates of a collection of models

Outline: Part 1

- Dynamic Mirror Descent
- Problem setting: Plant data/models
- Algorithm Models
- Results
- Next steps

Dynamic Mirror Descent

- Mirror Descent: online algorithm to estimate a fixed state

- Dynamic Mirror Descent: online algorithm to estimate a dynamic state using a *collection of models* [Hall & Willet 2015]
  1. Compute the error between the model predictions and the measured data (i.e., loss function)
  2. Update the state in the direction of the negative gradient of the loss function

$$\widetilde{\theta}_t^i = \underset{\theta \in \Theta}{\arg\min}\, \eta_t \left\langle \nabla \ell_t(\widehat{\theta}_t^i, y_t),\ \theta \right\rangle + D\left(\theta \| \widehat{\theta}_t^i\right)$$

Dynamic Mirror Descent

3. Use the estimated states to evaluate the models for the next time step

$$\widehat{\theta}^i_{t+1} = \Phi^i_t(\widetilde{\theta}^i_t)$$

4. Compute a weighted version of the estimates

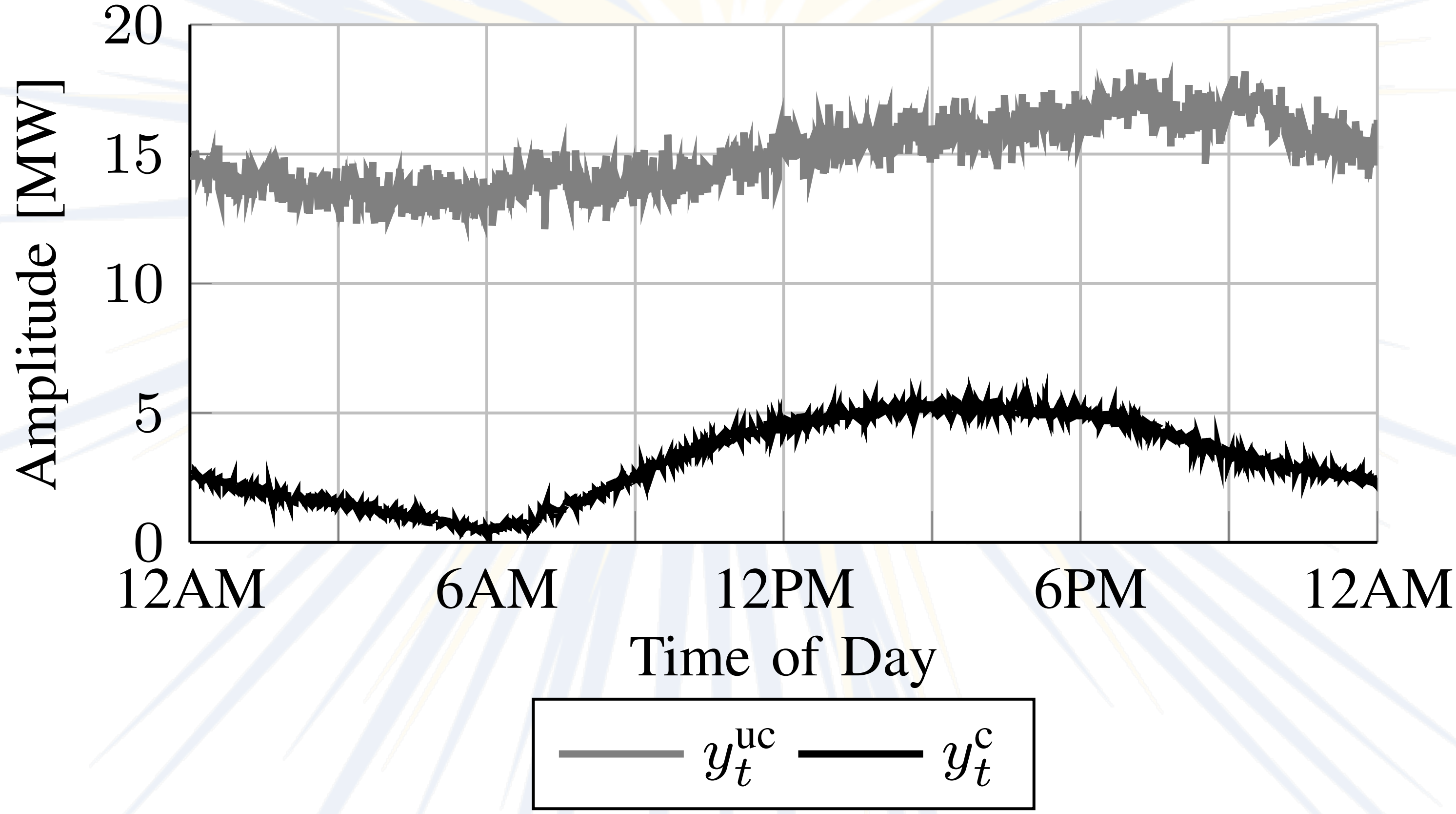
$$\widehat{\theta}_{t+1} = \sum_{i=1}^{N^{\text{mdl}}} w^i_{t+1} \widehat{\theta}^i_{t+1}.$$

5. Update the model weights

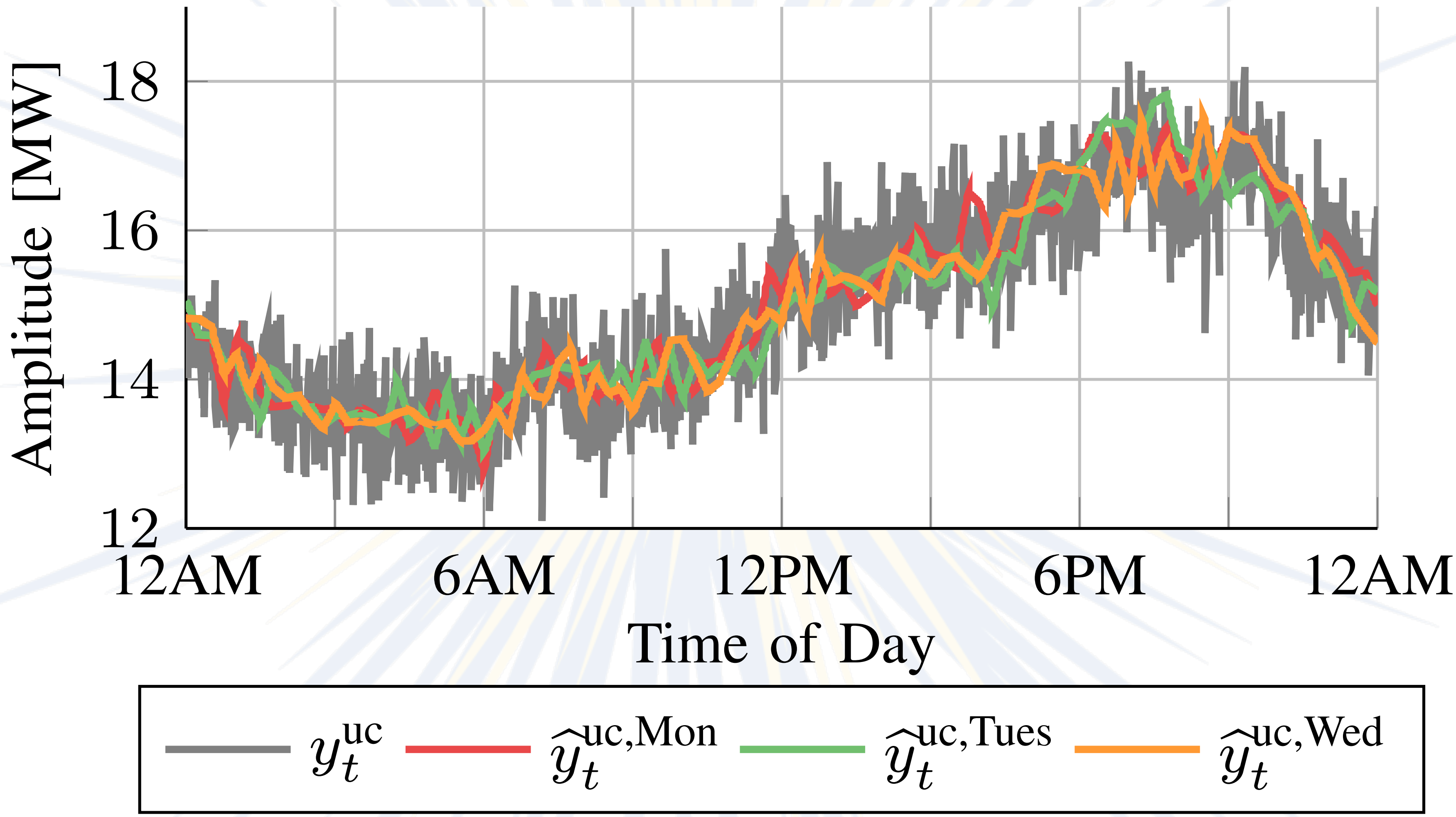
$$w^i_{t+1} = \frac{\lambda}{N^{\text{mdl}}} + (1-\lambda) \frac{w^i_t \exp\left(-\eta^r \ell_t \left(\widehat{\theta}^i_t, y_t\right)\right)}{\sum_{j=1}^{N^{\text{mdl}}} w^j_t \exp\left(-\eta^r \ell_t \left(\widehat{\theta}^j_t, y_t\right)\right)}$$

Problem Setting: Plant Data/Models

- Uncontrollable loads: data from Pecan Street Inc. Dataport
- Controllable loads: three-state hybrid models of air conditioners [Sonderegger 1978]



Algorithm Models: Uncontrollable loads



Algorithm Models: Controllable loads

- Two-state hybrid models of air conditioners [Mortensen & Haggerty 1988]
  - Temperature and ON/OFF mode
- Sets of Linear Time Invariant (LTI) aggregate system models [Mathieu et al. 2013]

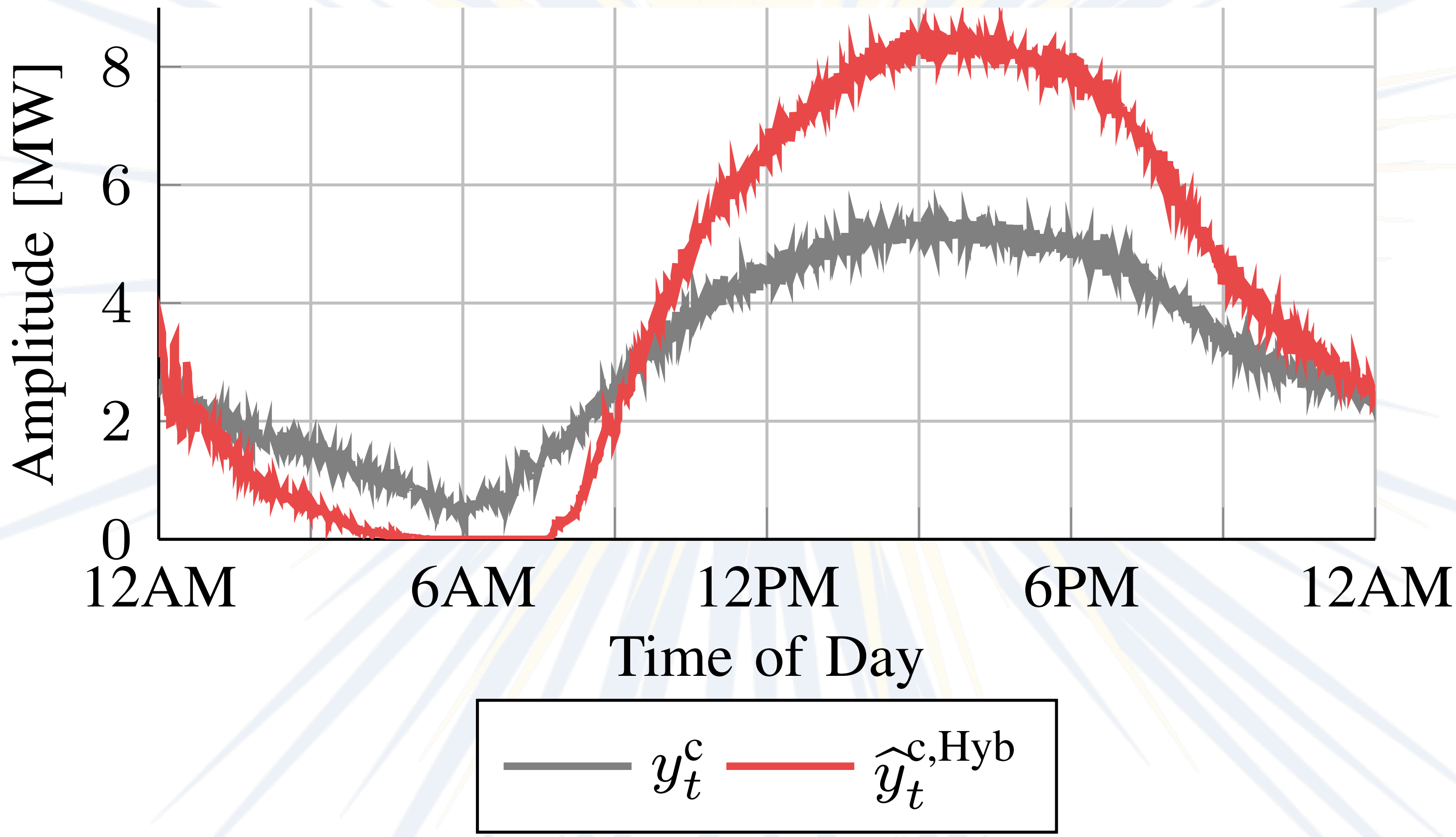
$$x_{t+1}^{i} = A^{i}\, x_t^{i} \qquad i \in \mathbb{N}^{\text{temps}}$$
$$\widehat{y}_t^{\text{c,LTI},i} = C^{i}\, x_t^{i} \qquad i \in \mathbb{N}^{\text{temps}}.$$

- Sets of Linear Time Varying (LTV) aggregate system models

$$x_{t+1} = A_t\, x_t$$
$$\widehat{y}_t^{\text{c,LTV}} = C_t\, x_t.$$

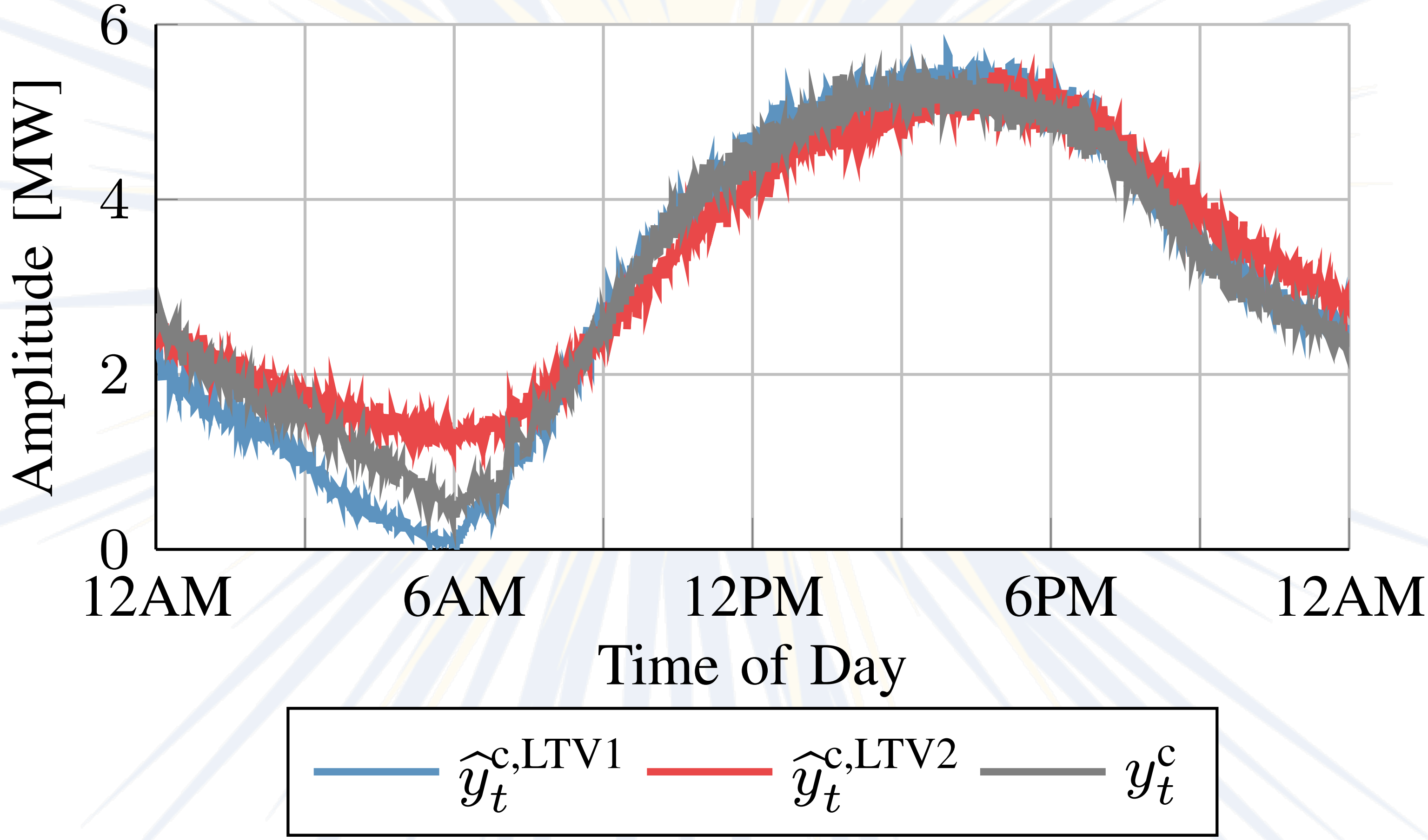
Algorithm Models: Controllable loads

- Two-state hybrid AC models do not work well.



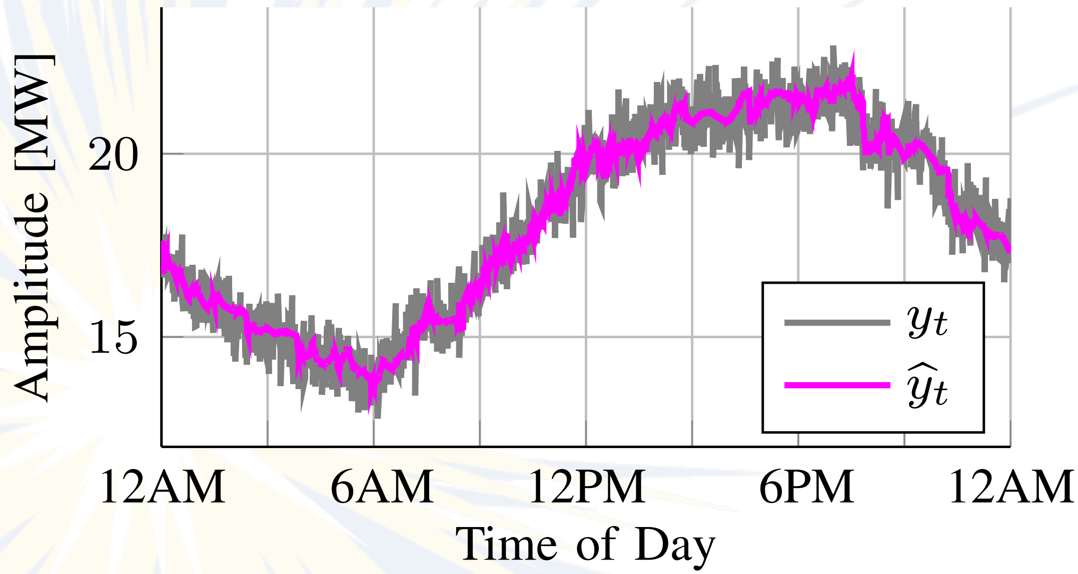
Algorithm Models: Controllable loads

- LTV models work better.

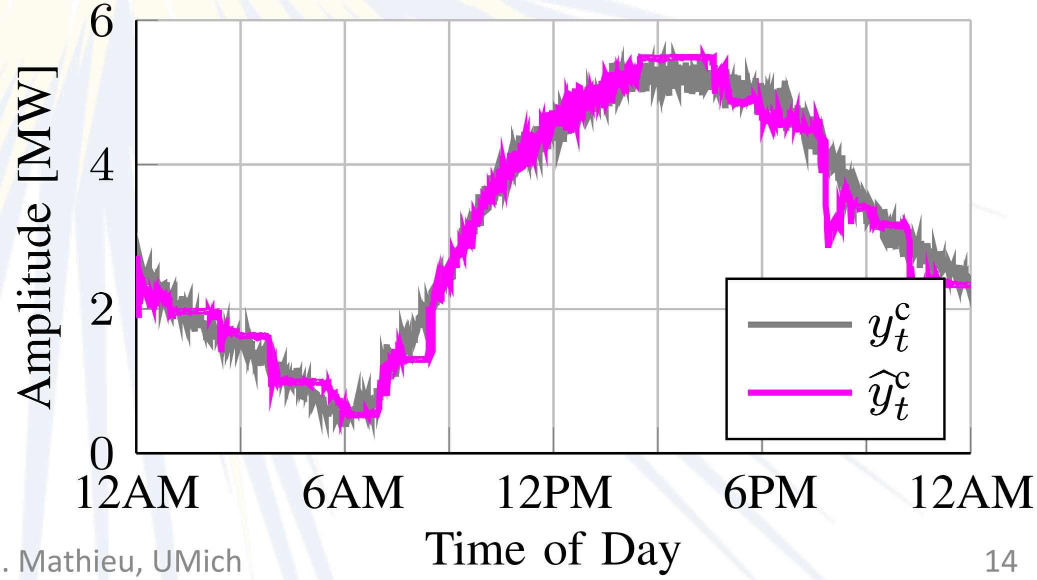


Results: All combinations of models

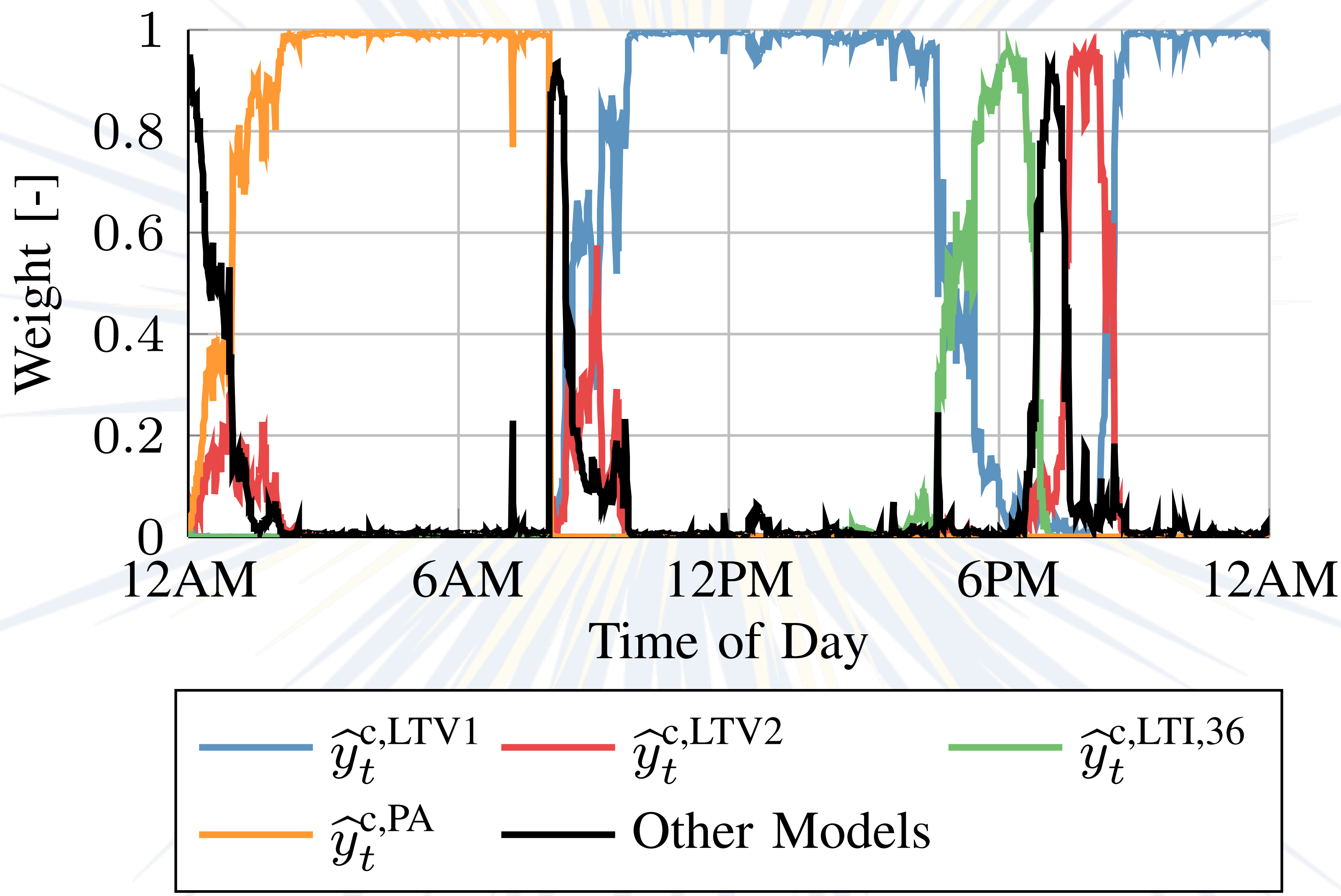
Total Load



Controllable Load

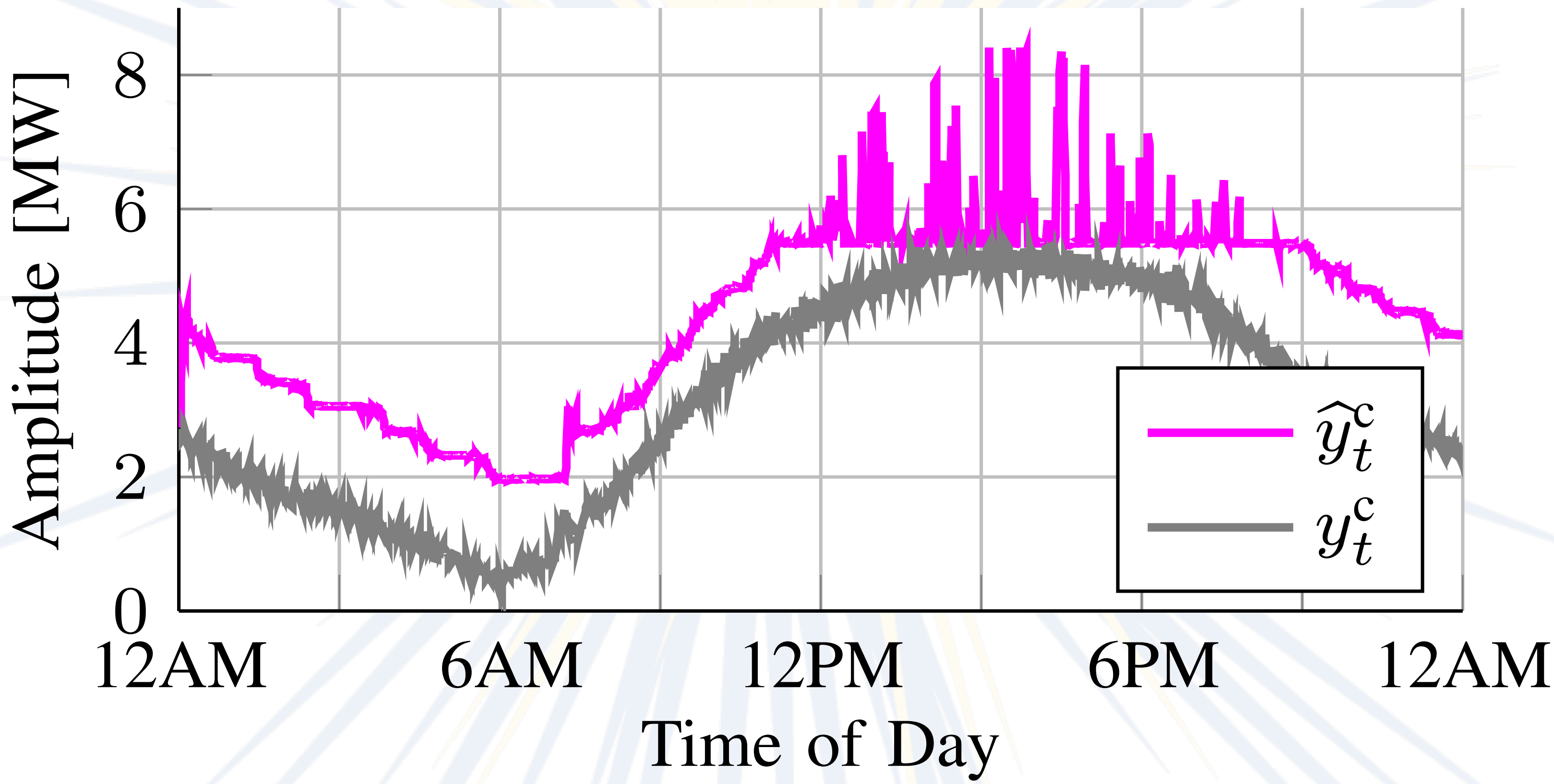


Results: Weightings



Results: Bad Models

- All uncontrollable load models are too low.

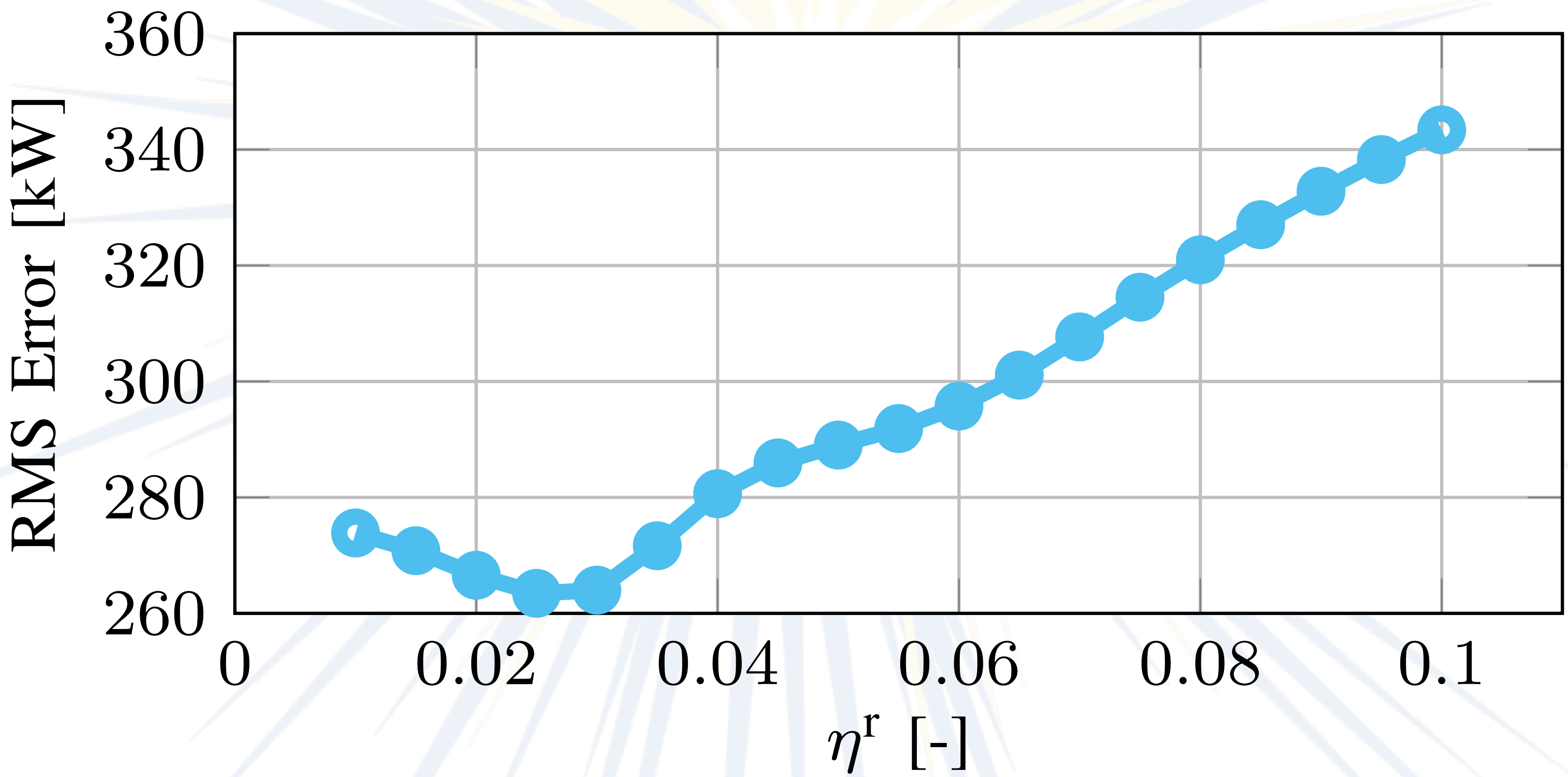


Results: Summary

Case	RMS Error (kW)
Benchmark: Use current outdoor temperature to evaluate simple controllable load model	738
DMD Case 1: Includes every combination of uncontrollable and controllable models	264
DMD Case 2: Case 1 models plus a smoothed version of the actual uncontrollable load	211
DMD Case 3: Case 2 models plus more accurate model of the controllable load over time periods where the other models are less accurate	175
DMD Case 4: Includes uncontrollable load models that underestimate the uncontrollable load	1392

Results: Varying Algorithm Parameters

Recall: $$w_{t+1}^{i} = \frac{\lambda}{N^{\text{mdl}}} + (1-\lambda) \frac{w_t^i \exp\left(-\eta^r \ell_t\left(\widehat{\theta}_t^i, y_t\right)\right)}{\sum_{j=1}^{N^{\text{mdl}}} w_t^j \exp\left(-\eta^r \ell_t\left(\widehat{\theta}_t^j, y_t\right)\right)}$$



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Next steps

- Investigate more realistic settings (using more real data)
- Develop better load models
- Improve the algorithm, e.g., alternative weighting functions
- Investigate identifiability
- Incorporate additional measurements (reactive power, voltage) into the approach

Key findings

- Dynamic Mirror Descent (DMD) enables us to solve the substation disaggregation problem leveraging dynamical models of arbitrary form
- DMD can work well (on simple examples); however, it is easy to find instances where it does not work well

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Overview

- **Inference:** Inferring the behavior of distributed energy resources with sparse measurements
  [Ledva, Balzano, & Mathieu *Allerton* 2015]

- **Control:** Controlling distributed electric loads to provide power system reserves with sparse measurements and input/measurement delays
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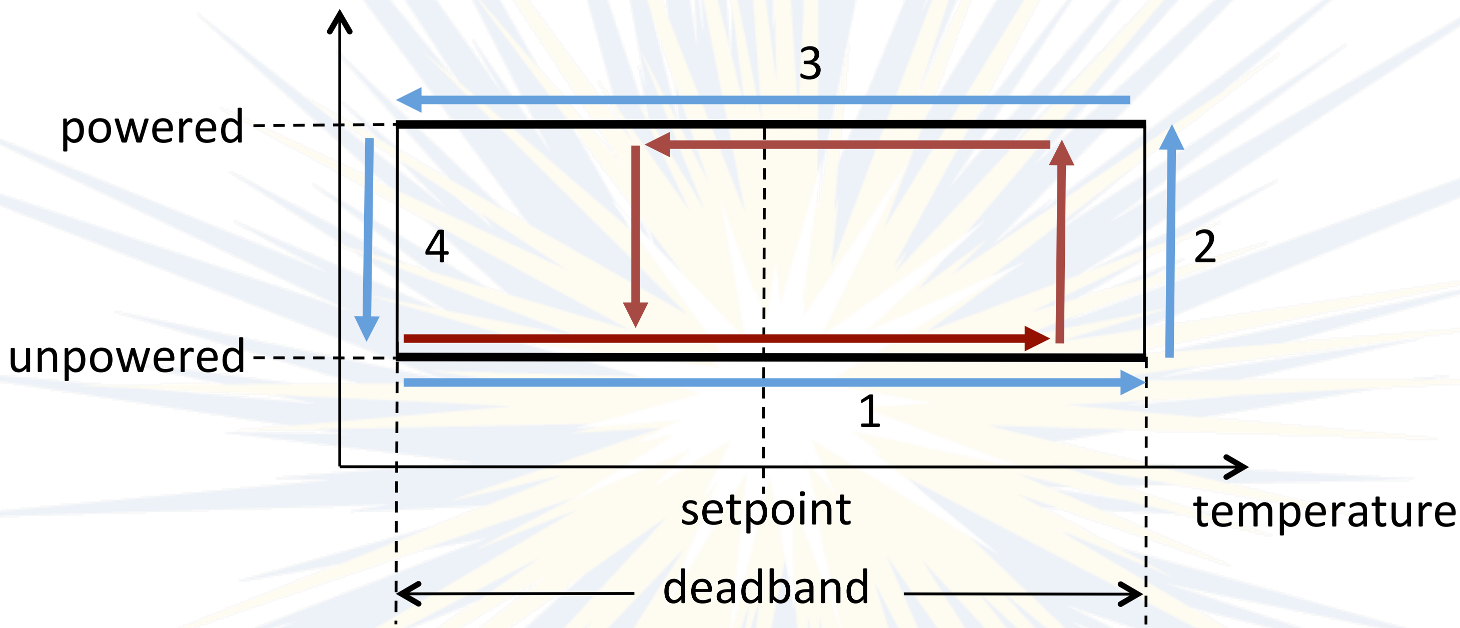
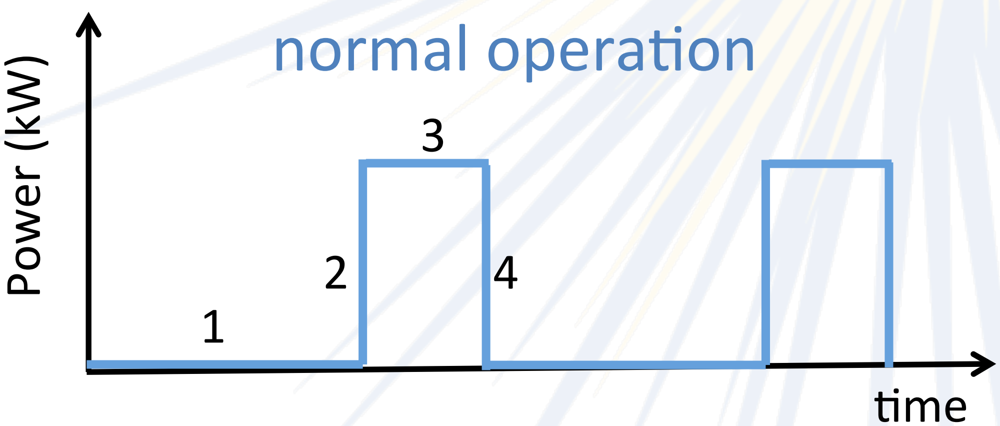
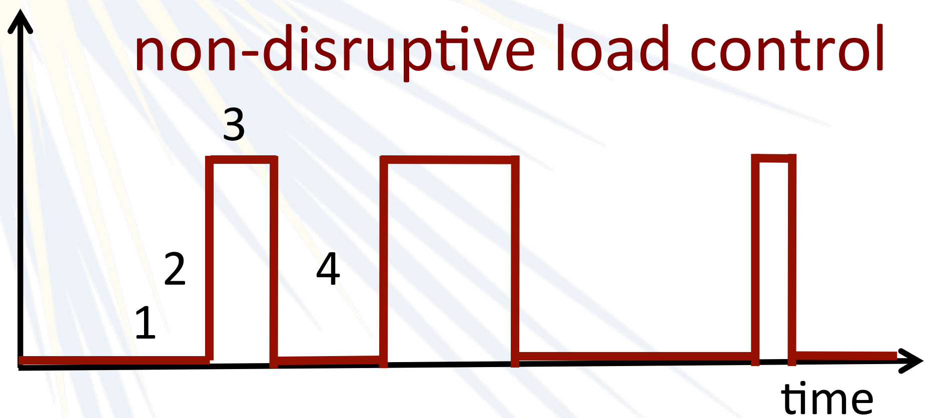
How can loads provide reserves?
→ your refrigerator is already flexible

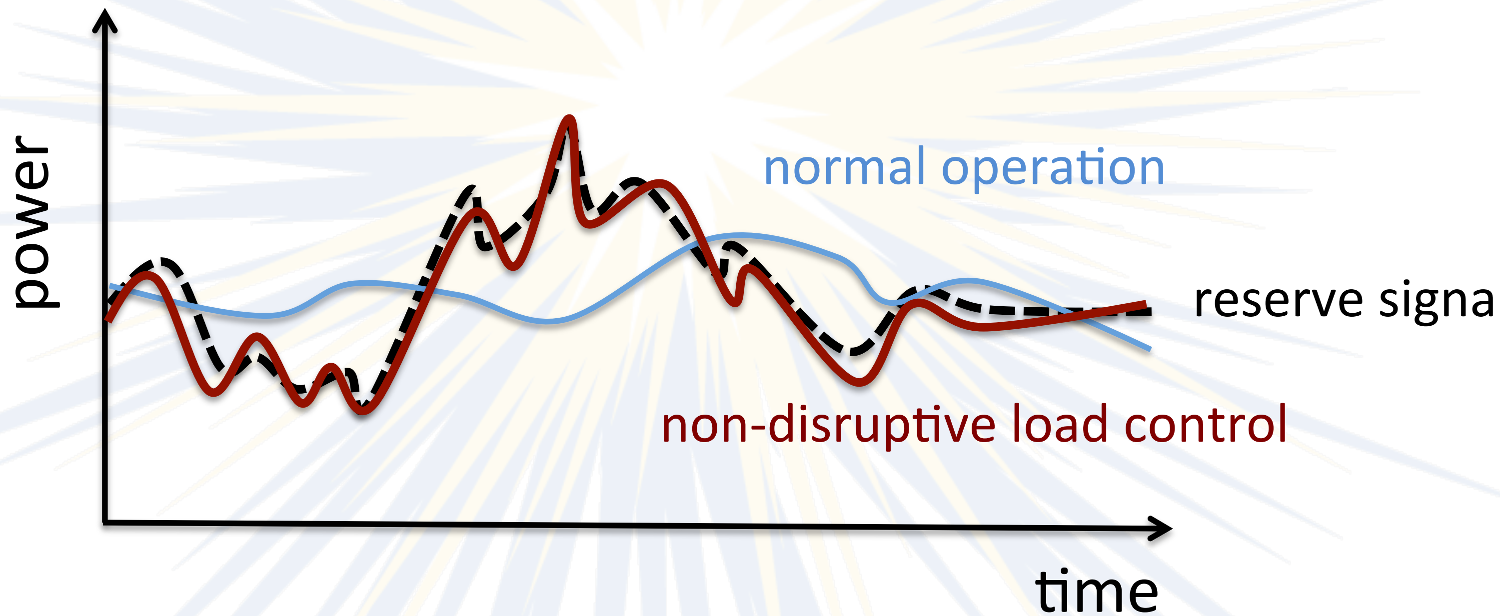






Thousands of thermostatically controlled loads (TCLs) can track signals and provide reserves

TCLs: air conditioners, heat pumps, space heaters, electric water heaters, refrigerators

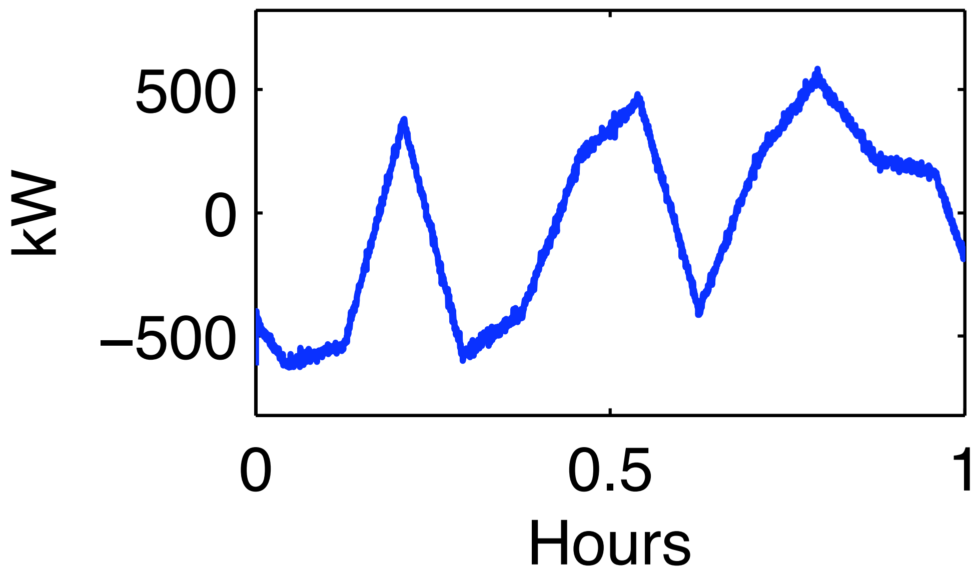


[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

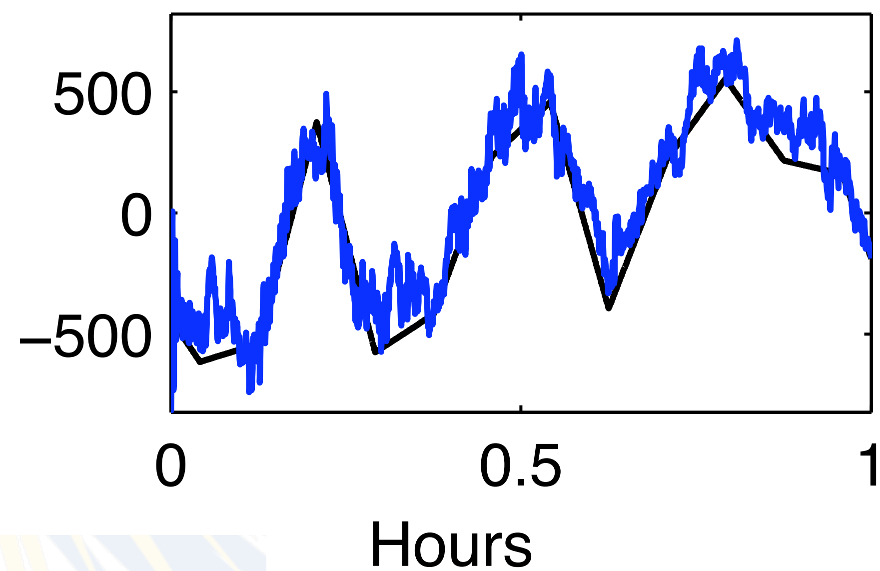
Simulation results:

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]

Data from loads

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

→ Modeling

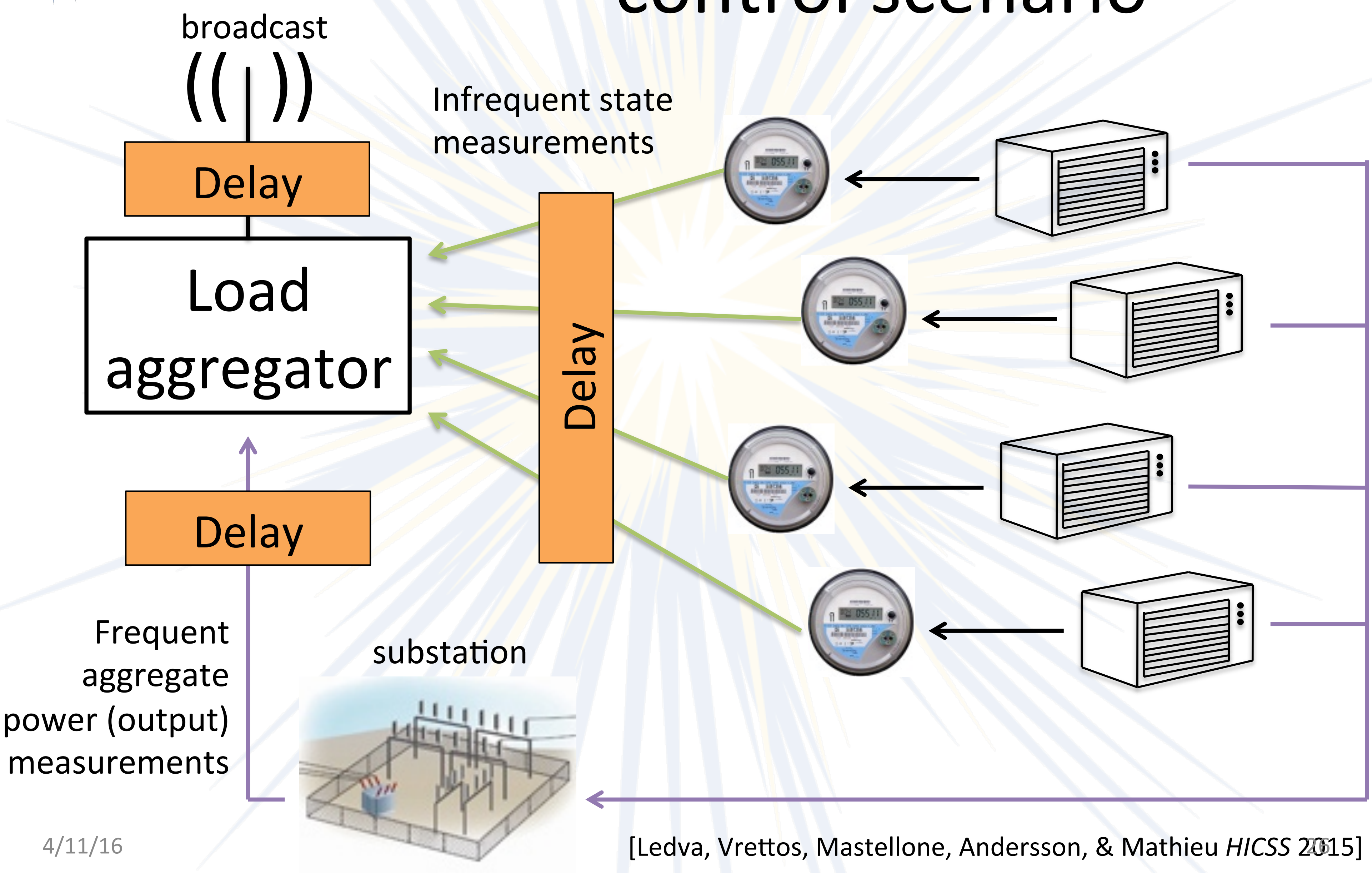
- Real-time data
  - Measurements of the on/off state and/or internal temperature?
  - Household smart meter data? → High quality, infrequent
  - Power measurements from the distribution network? → Low quality, frequent

→ Feedback control

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

→ Auditing

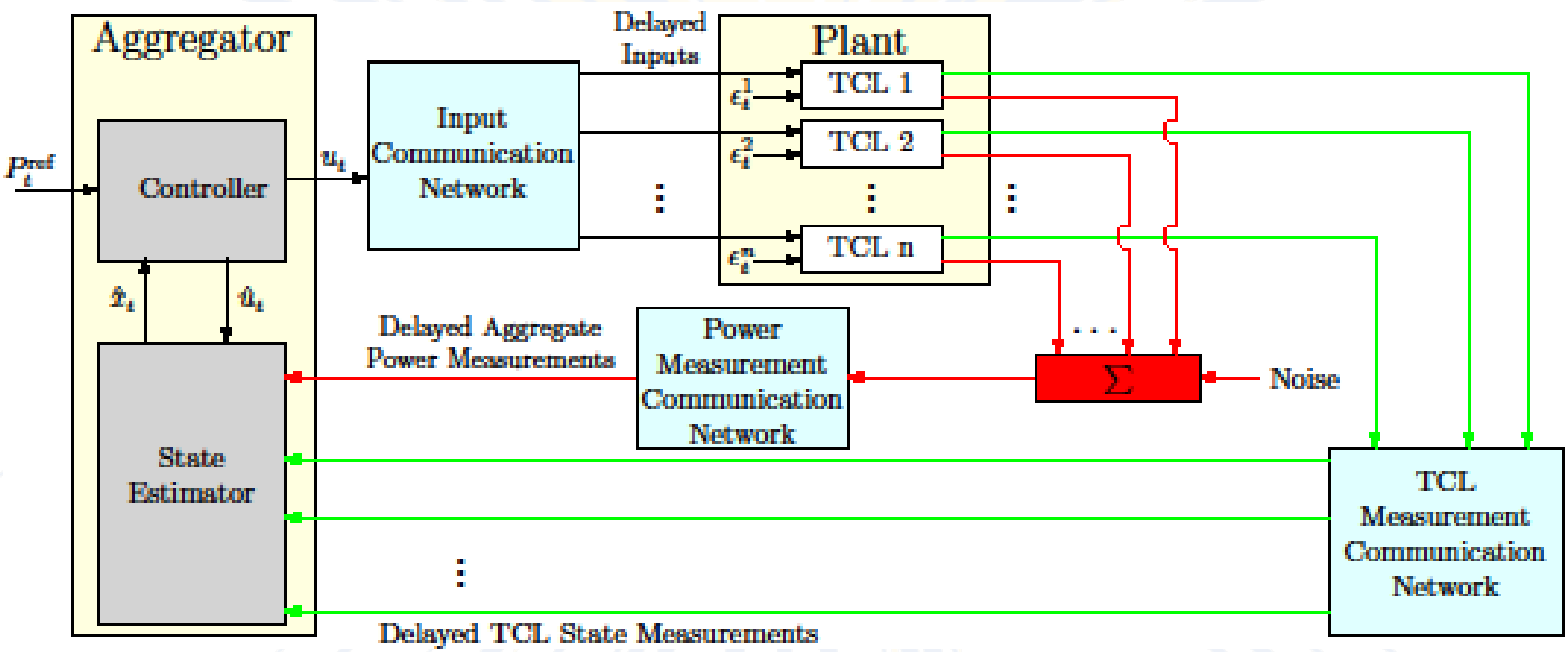
Communication and control scenario



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

System block diagram

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

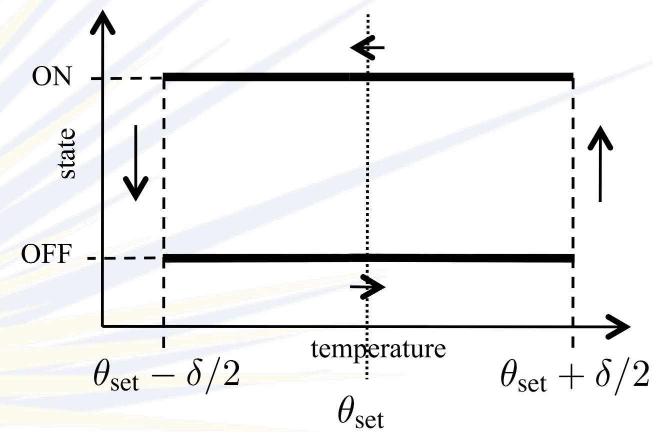


The challenge

- 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

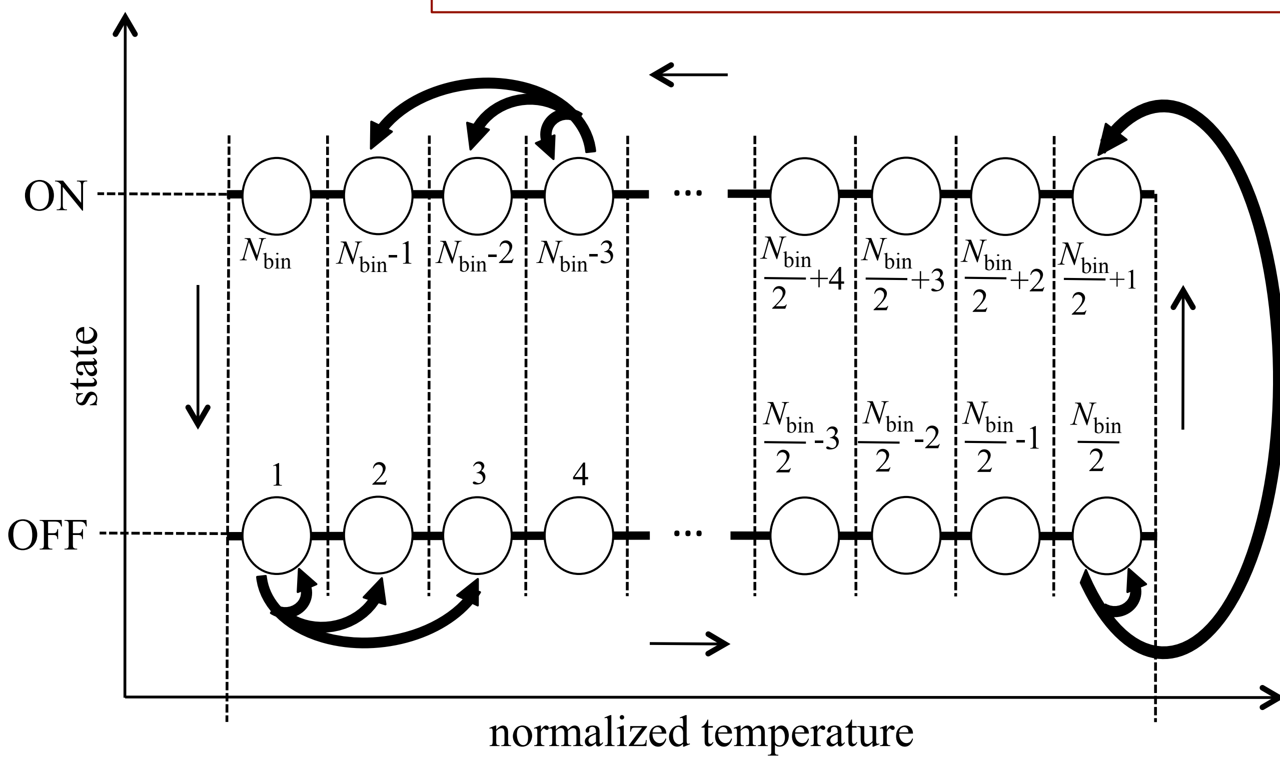
$$m_i(k+1) = \begin{cases} 0, & \theta_i(k+1) < \theta_{\text{set},i} - \delta_i/2 \\ 1, & \theta_i(k+1) > \theta_{\text{set},i} + \delta_i/2 \\ m_i(k), & \text{otherwise} \end{cases}$$

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

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) + \boldsymbol{B}_{\omega}\boldsymbol{\omega}(k)$$
$$\boldsymbol{y}(k) = \boldsymbol{C}\boldsymbol{x}(k) + \boldsymbol{\nu}(k)$$



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]

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 in Kalman Filter

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

Control Formulation

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

Tracking error

State constraint deviations

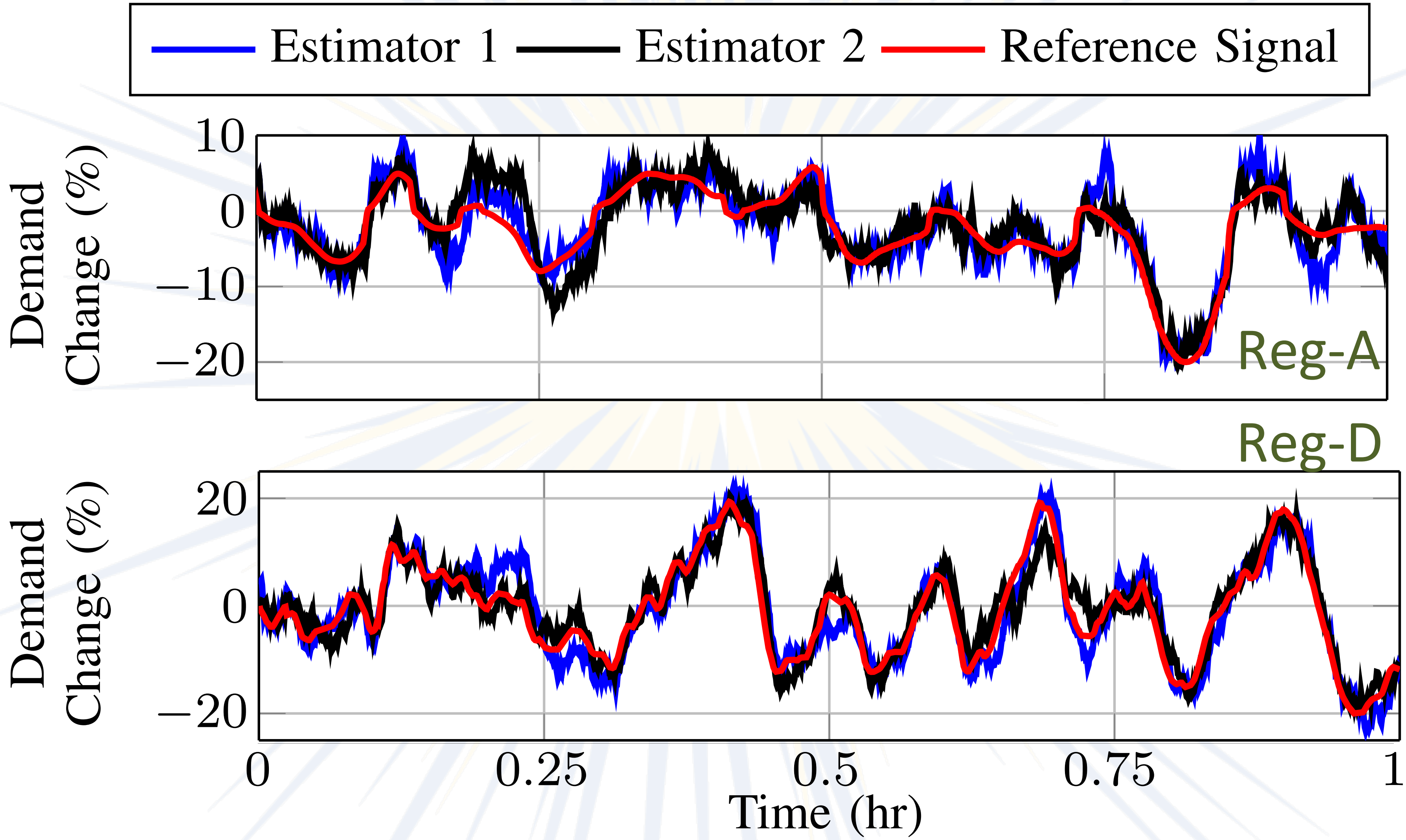
Control effort

$$\begin{aligned} \text{s.t.} \quad x_{k+1} &= A\, x_k + B\, \widehat{u}_k \\ \widehat{u}_k &= \mathcal{U}_k \mathcal{P} \\ y_k^{\text{err}} &= y_k^{P,\text{ref}} - C^{\text{P}} x_k \\ u_{k|m}^i &\le x_k^i & i \in \{1, \ldots, N^{\text{x}}/2\} \\ -u_{k|m}^i &\le x_k^{N^{\text{x}}+1-i} & i \in \{1, \ldots, N^{\text{x}}/2\} \\ 0 - \delta_k^- &\le x_k \le 1 + \delta_k^+ \\ 0 &\le \delta_k^-, \delta_k^+ . \end{aligned}$$

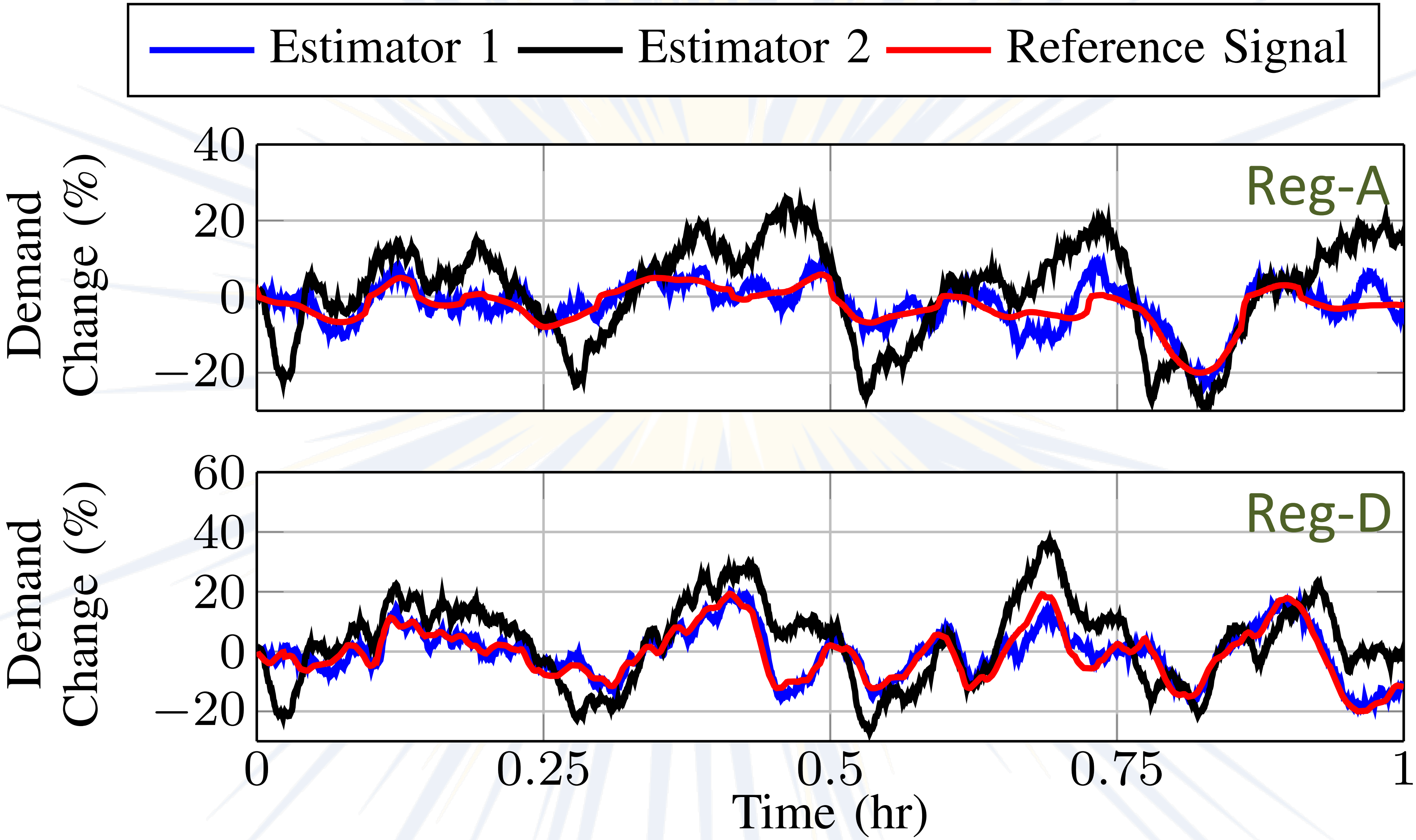
Case Studies

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

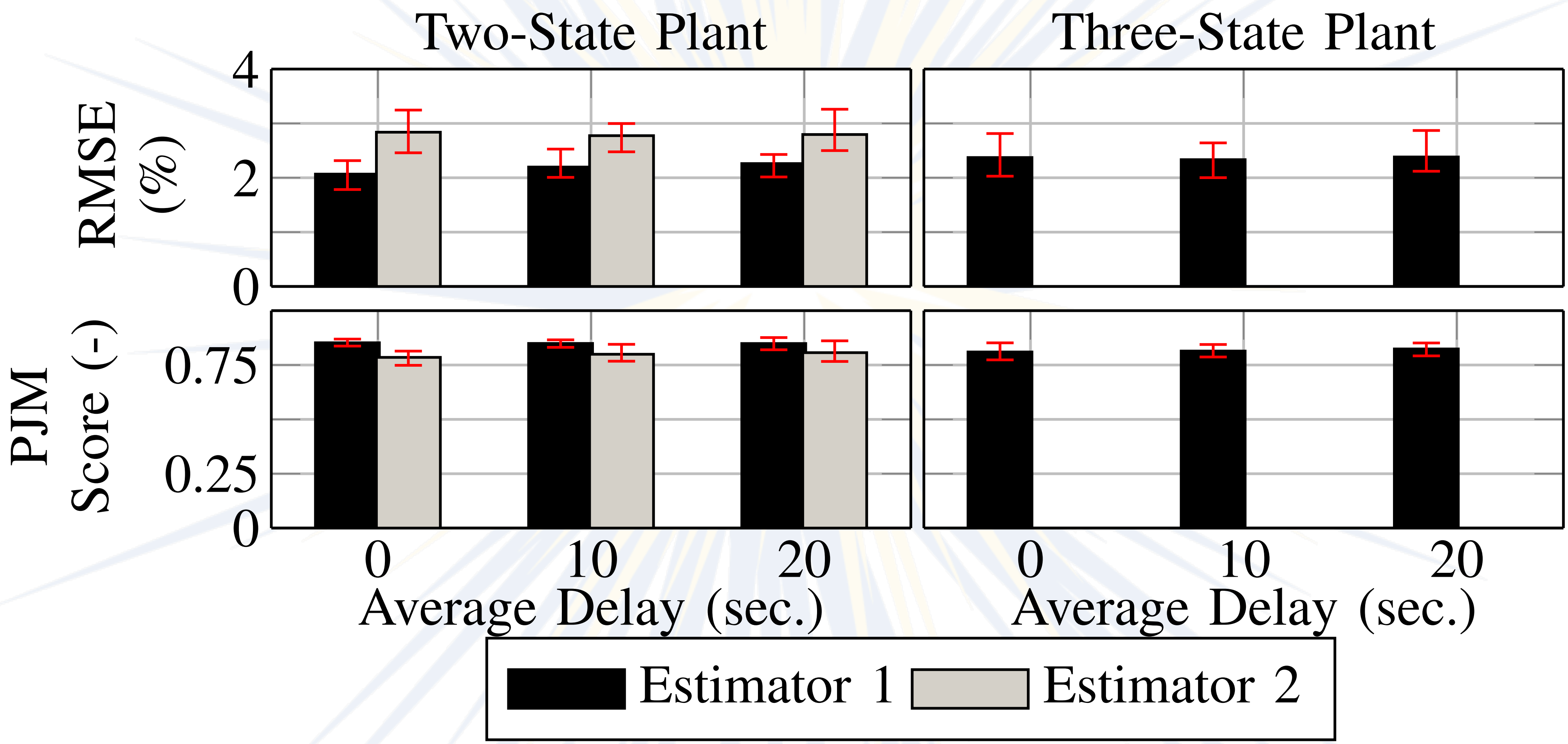
Results


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)

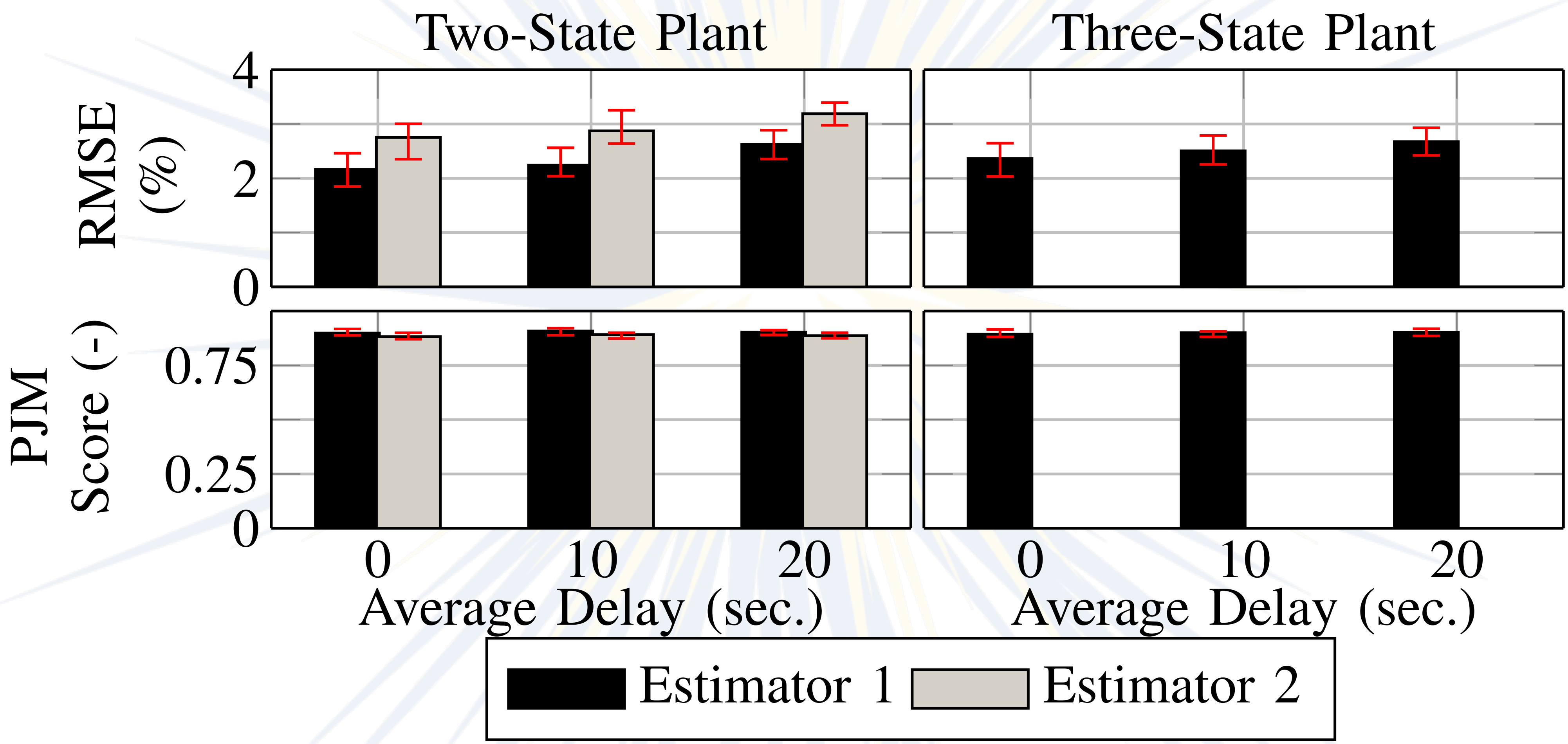
Results: Model Mismatch



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

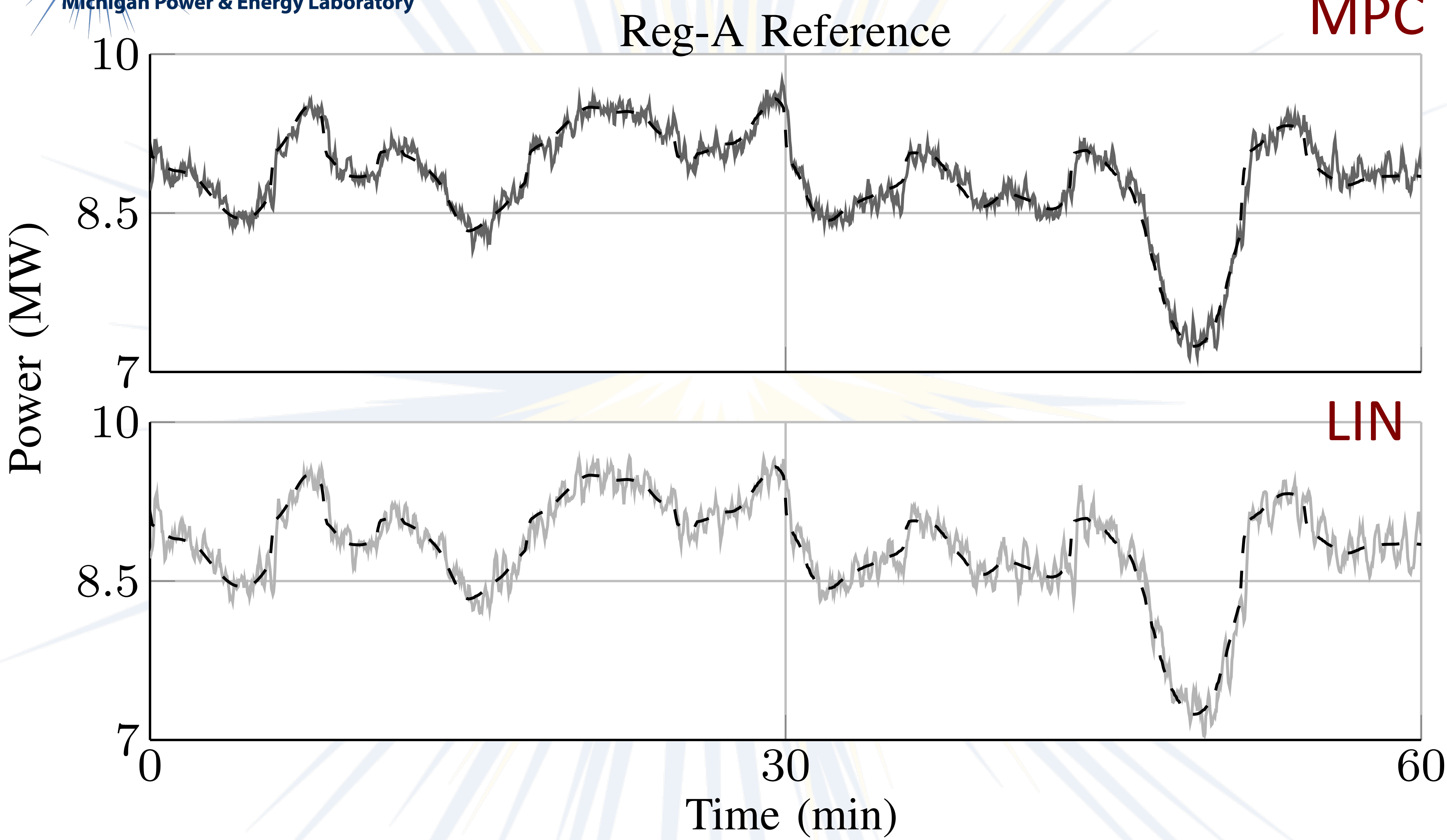
LQR Formulation $\min_u \sum_{k=t}^{\infty} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix}^T \begin{bmatrix} \widetilde{\overline{C}}^T q^{\text{y}} \widetilde{\overline{C}} & 0 \\ 0 & q^{\text{w}} \end{bmatrix} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix} + (u_k^{\text{seq}})^T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

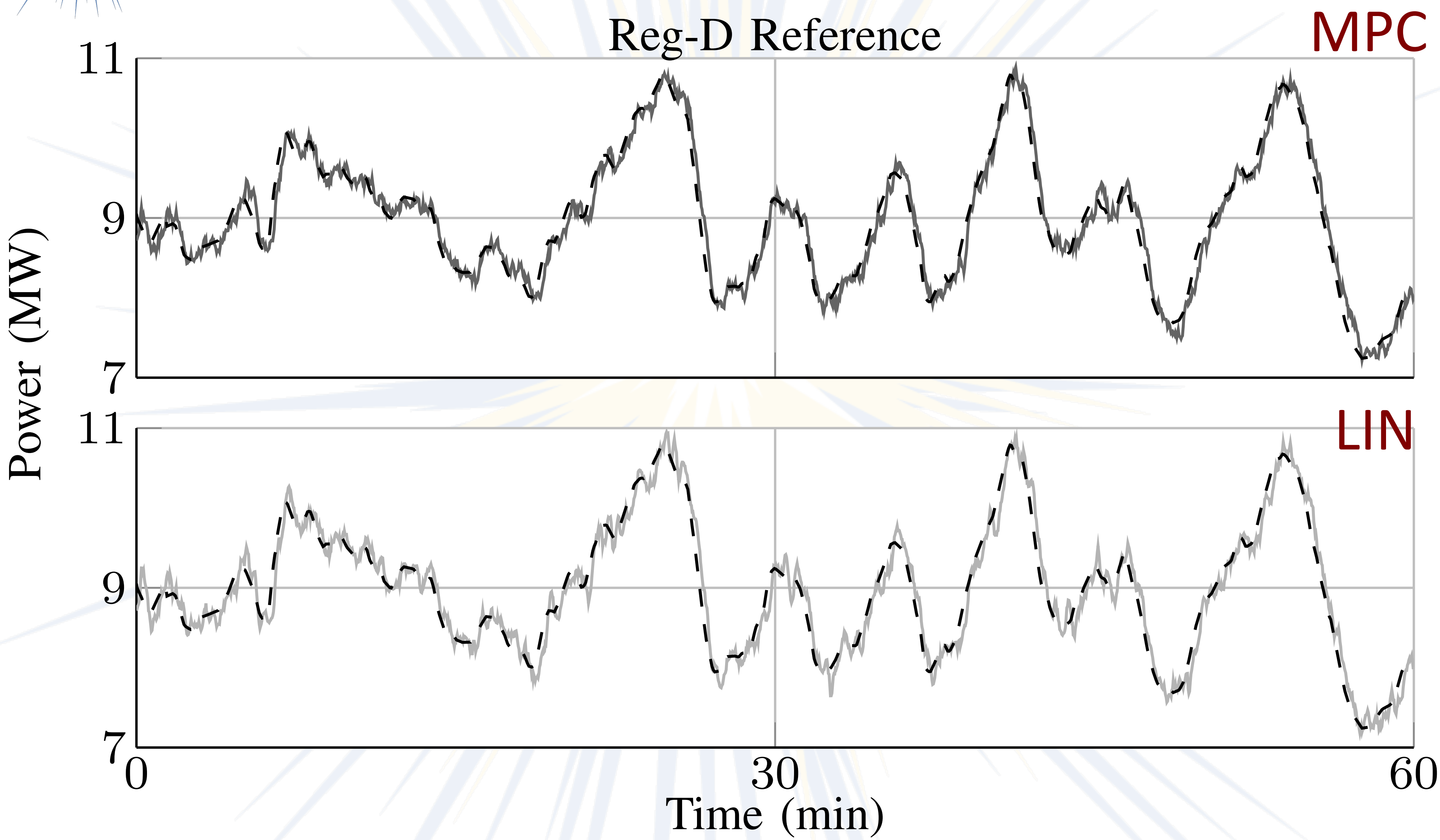
$$\text{s.t.} \quad \begin{bmatrix} \widetilde{\overline{x}}_{k+1} \\ w_{k+1} \end{bmatrix} = \begin{bmatrix} \widetilde{\overline{A}} & 0 \\ \widetilde{\overline{C}} & 0 \end{bmatrix} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix} + \begin{bmatrix} \widetilde{\overline{B}} \\ 0 \end{bmatrix} u_k^{\text{seq}}$$

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

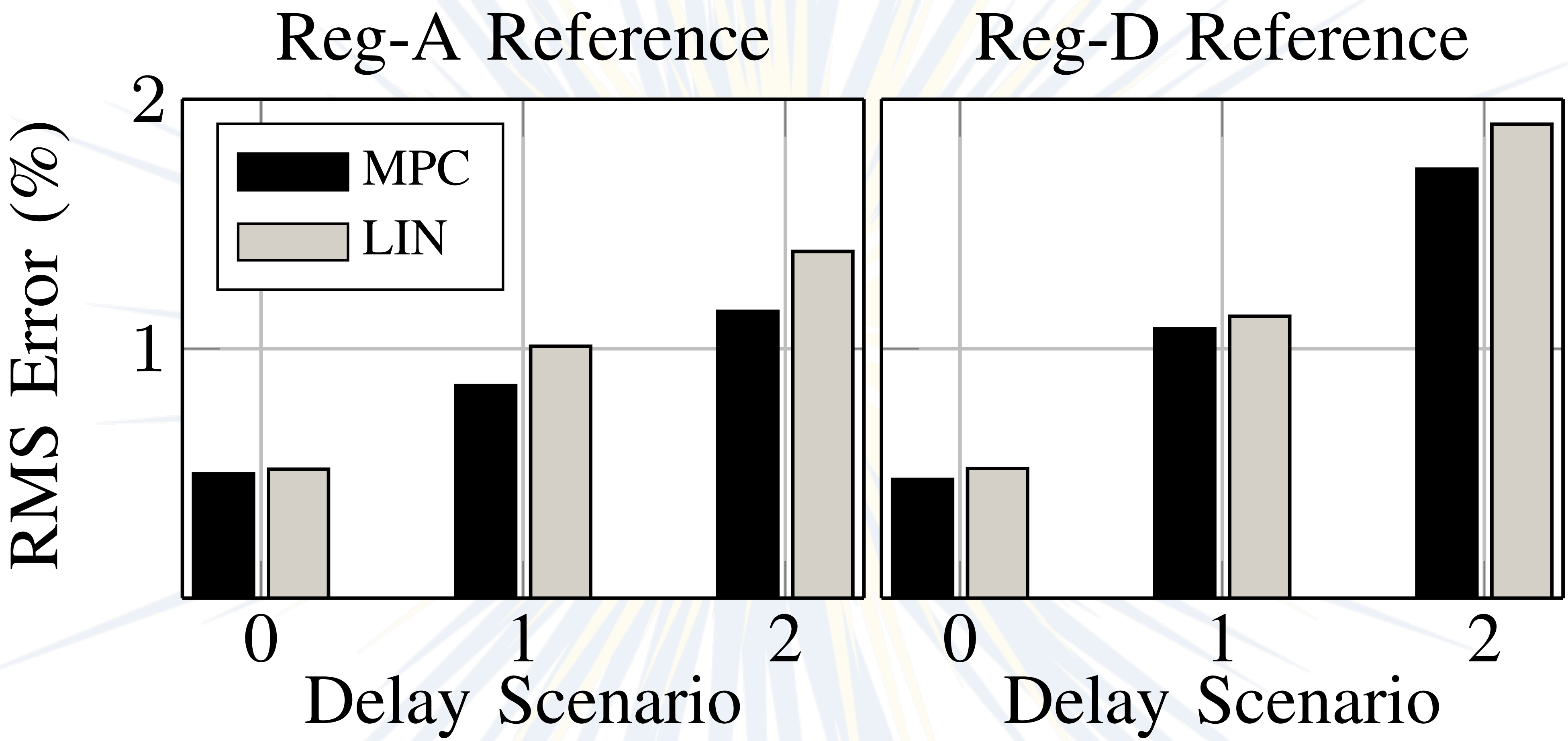
- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- Full state feedback, no measurement delay
- Three-state models used for the plant


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



Reg-D Reference
MPC
LIN
11
9
7
Power (MW)
0
30
60
Time (min)

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.

Conclusions

- Need methods to infer electric load behavior from existing measurements
  - Dynamic mirror descent applied to distribution substation measurements
- Need new sources of power system reserves
  - Coordination of distributed electric loads using delay-aware control/estimation

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