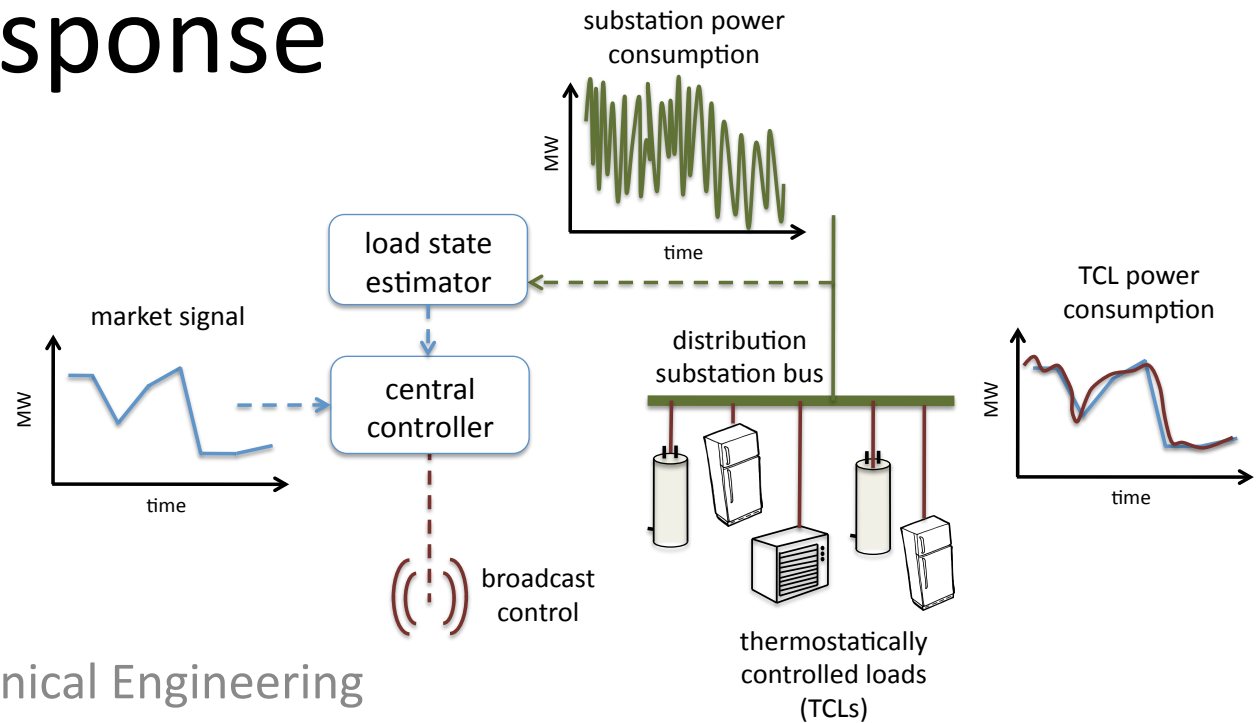


The value of real-time data in controlling electric loads for demand response



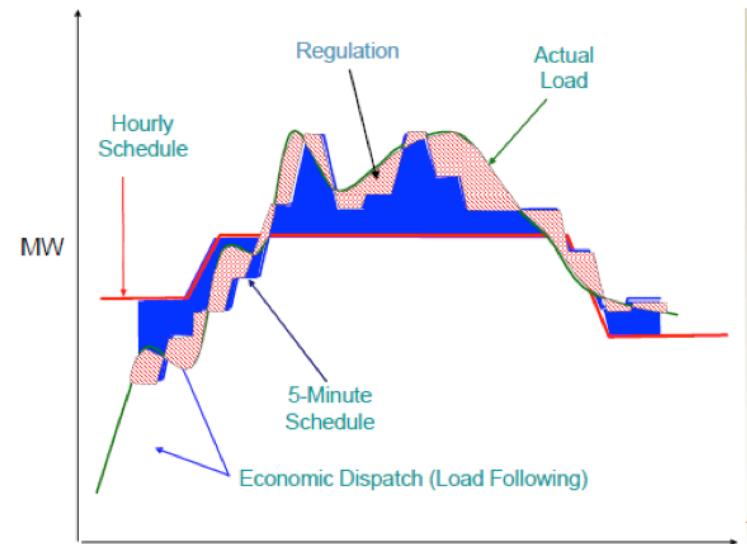
Johanna Mathieu, Mechanical Engineering
Duncan Callaway, Energy & Resources Group
University of California, Berkeley

Carnegie Mellon Conference on the Electricity Industry: March 12-14, 2012

As more wind and solar are added to the grid there is more need for **load following** and **regulation**.

[Makarov et al., "Operational Impacts of Wind Generation on California Power Systems," 2009]

- These services could be provided by new generators, energy storage, and/or **demand response**.
- We usually think of using **LARGE loads** for Demand Response (DR).
- In our work, we simulate **small residential loads**.



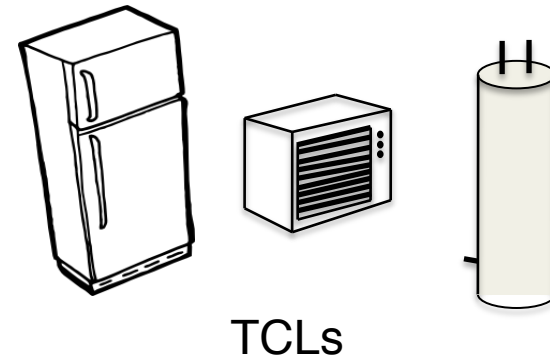
[source: CAISO]

Why small??

- more reliable
- simple local controls
- spatially distributed
- continuous, not discrete, control response

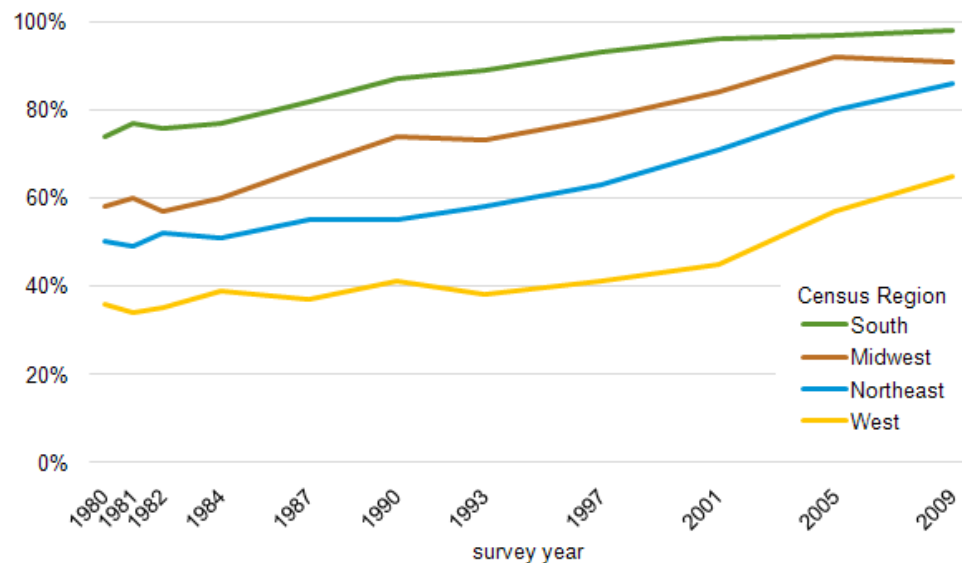
Thermostatically Controlled Loads (TCLs)

- Refrigerators, water heaters, air conditioners, electric space heaters, etc.



- Hysteretic ON/OFF control (dead-band)
- Store thermal energy like batteries store chemical energy

Figure 1. Steady rise in air conditioned homes in all regions of the U.S.
percent of homes with AC



Source: U.S. Energy Information Administration, 2009 Residential Energy Consumption Survey

Two Options for Revenue

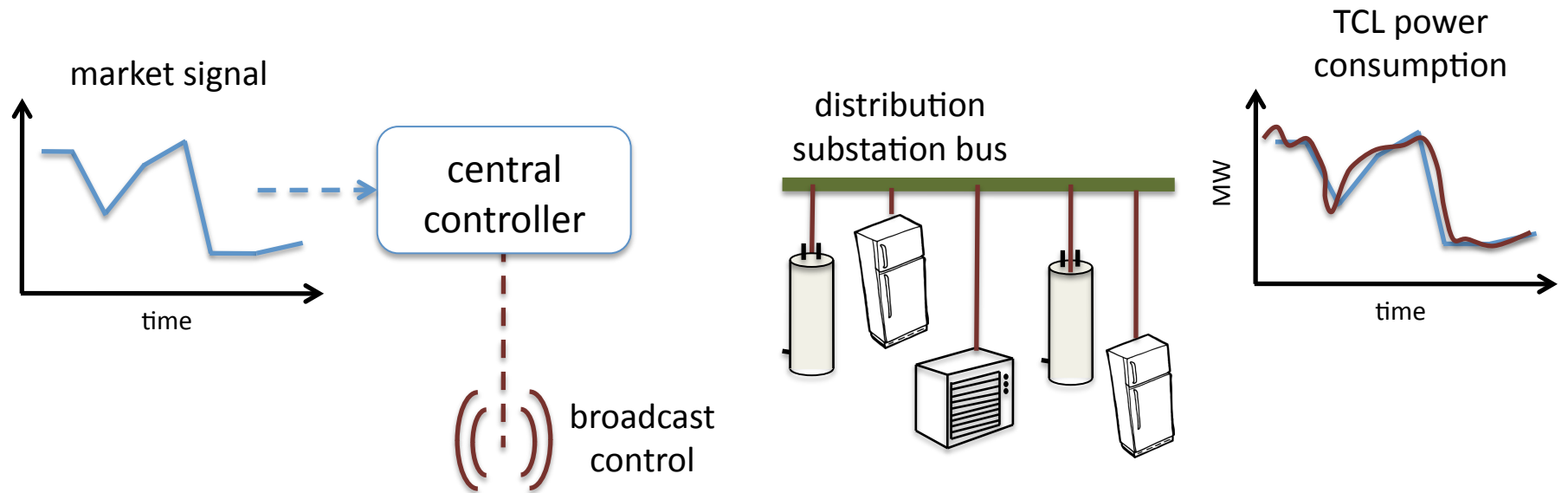
1. Participation in ancillary services markets & fast timescale energy markets

GOAL: market signal tracking

2. Energy arbitrage: buy more low, buy less high

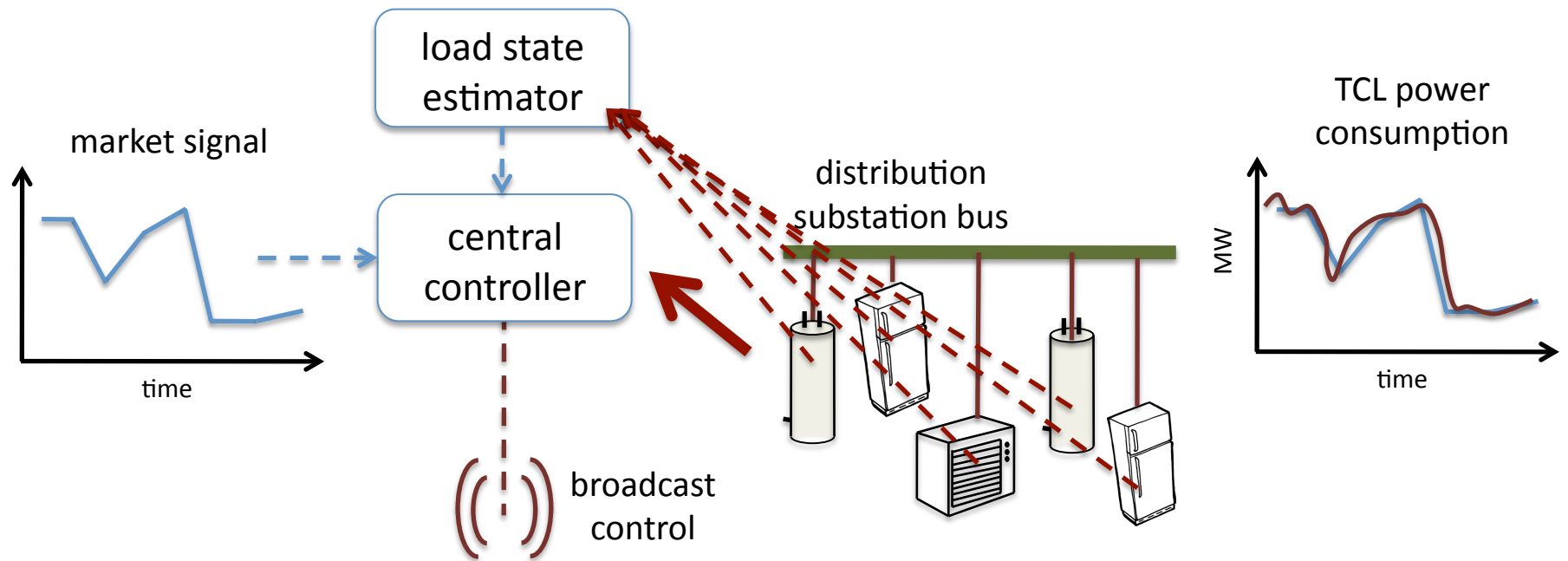
GOAL: minimize energy costs

Market Signal Tracking



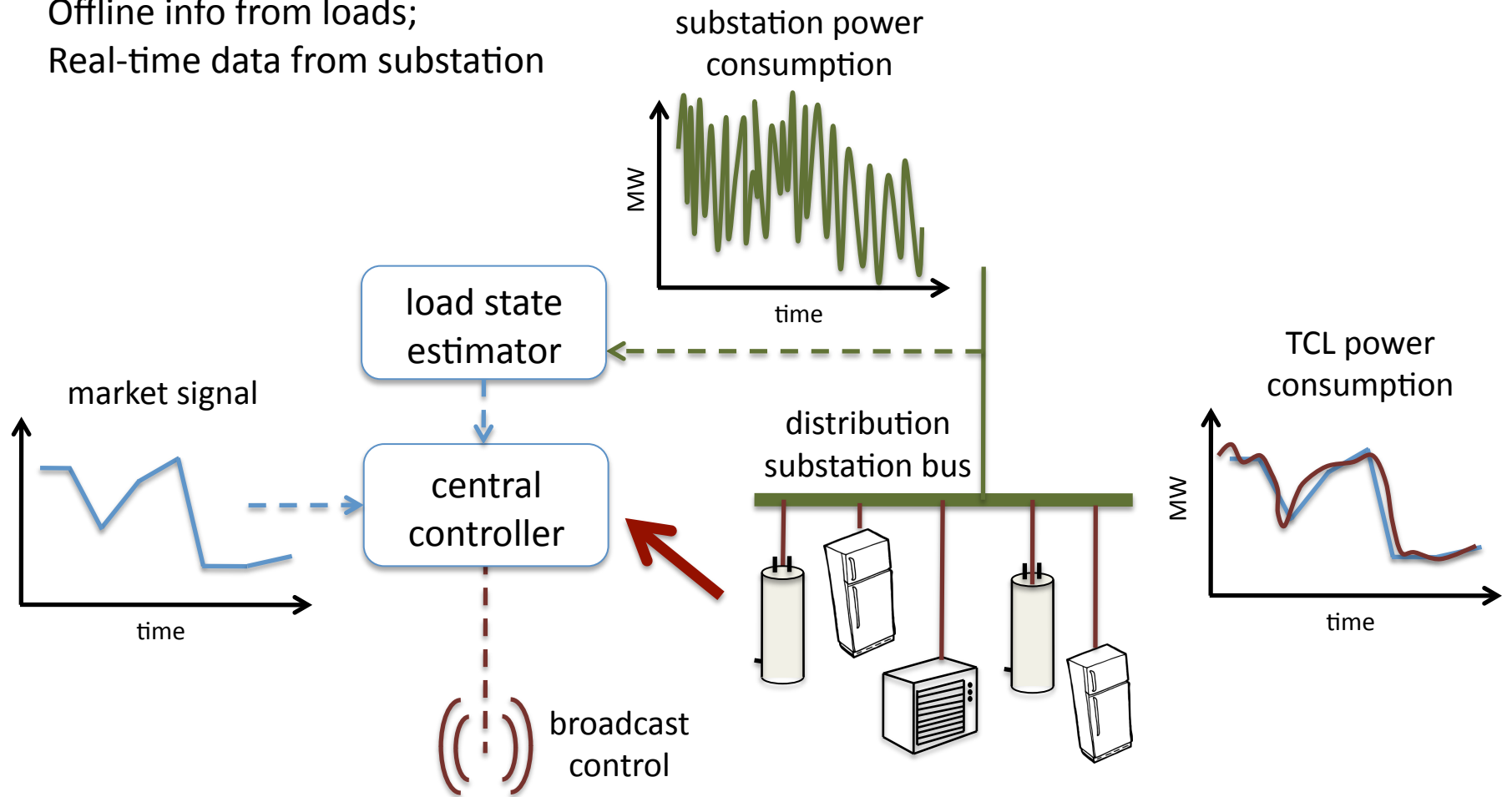
Market Signal Tracking

Offline and real-time info/data from loads



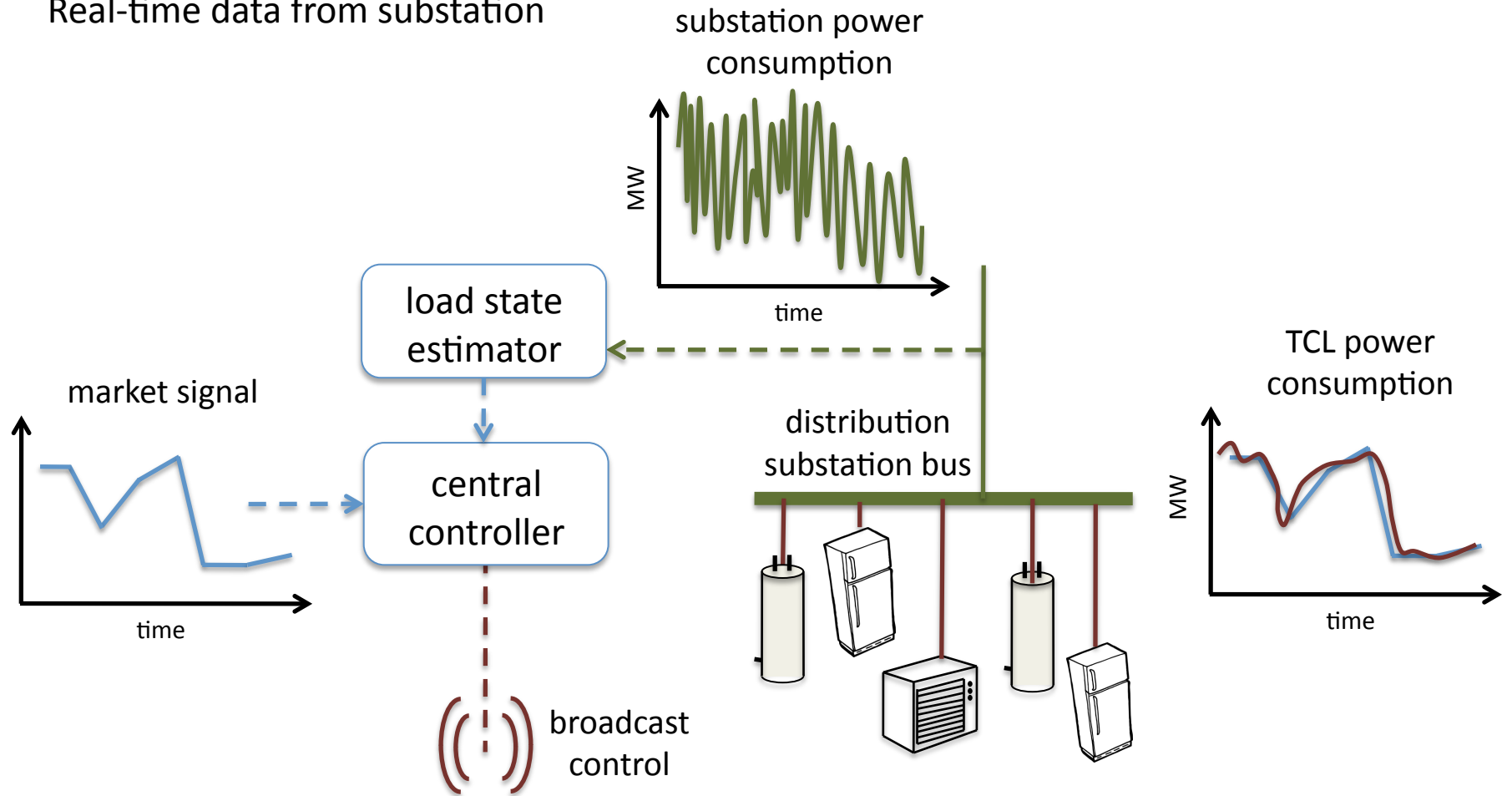
Market Signal Tracking

Offline info from loads;
Real-time data from substation



Market Signal Tracking

Real-time data from substation



Heterogeneous TCL Population Model

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k$$

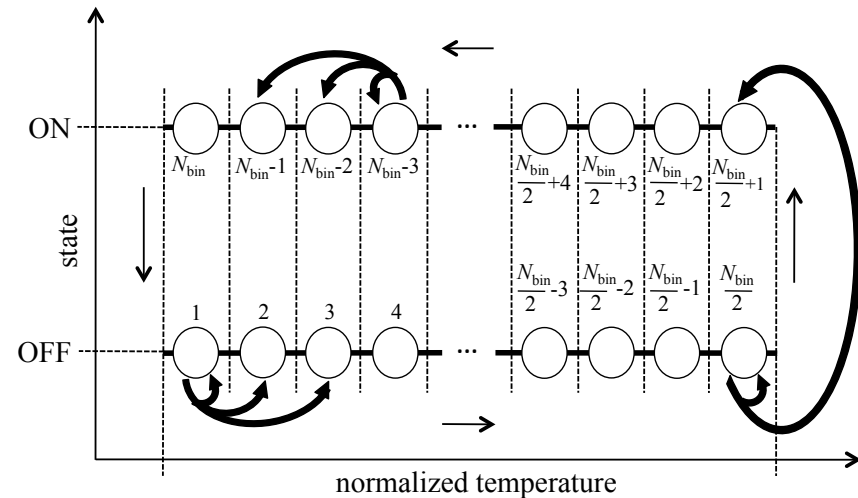
$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k$$

\mathbf{x} - fraction of TCLs in each state bin

\mathbf{A} - transition matrix

\mathbf{u} - input vector that allows us to switch TCLs ON or OFF

\mathbf{y} - aggregate power (and possibly a measurement of \mathbf{x})



Key control assumptions:

- We can only switch TCLs on or off, not change the temperature set point, etc.
- We broadcast same control to all TCLs, which switch on or off probabilistically based on their current state.
- We can't switch TCLs outside of the dead-band.

[Mathieu & Callaway HICSS 2012; Koch, Mathieu, & Callaway PSCC 2011]

Tracking Results: 5-minute market signal

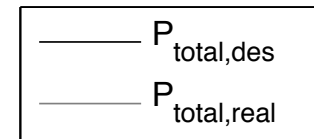
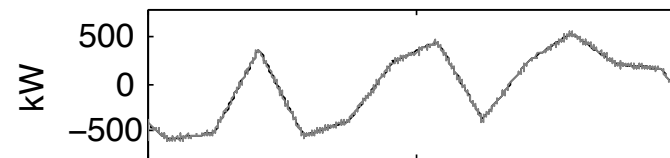
One-step look-ahead proportional predictive controller

1,000 heterogeneous TCLs

Scenario 1

- real-time data: full state
- offline parameter estimation

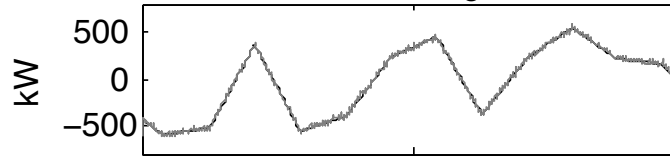
Scenario 1: Reference Case



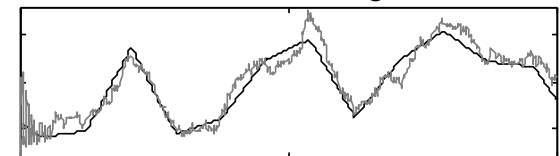
Scenario 2

- real-time data: on/off state
- offline parameter estimation

Scenario 2: 100% Metering



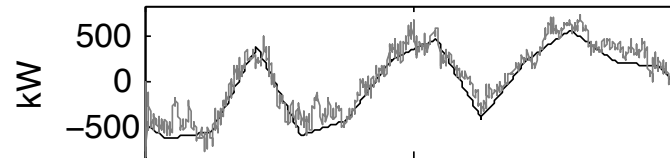
30% Metering



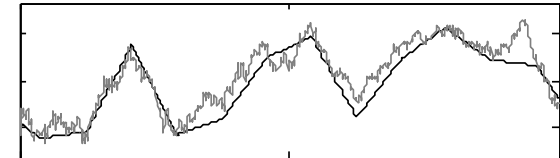
Scenario 3

- real-time data: substation power
- offline parameter estimation

Scenario 3: 5% Forecast Error



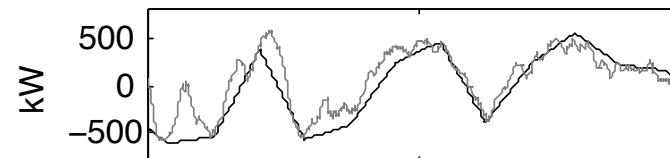
10% Forecast Error



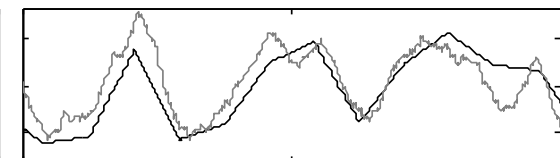
Scenario 4

- real-time data: substation power
- online parameter estimation

Scenario 4: 5% Forecast Error



10% Forecast Error



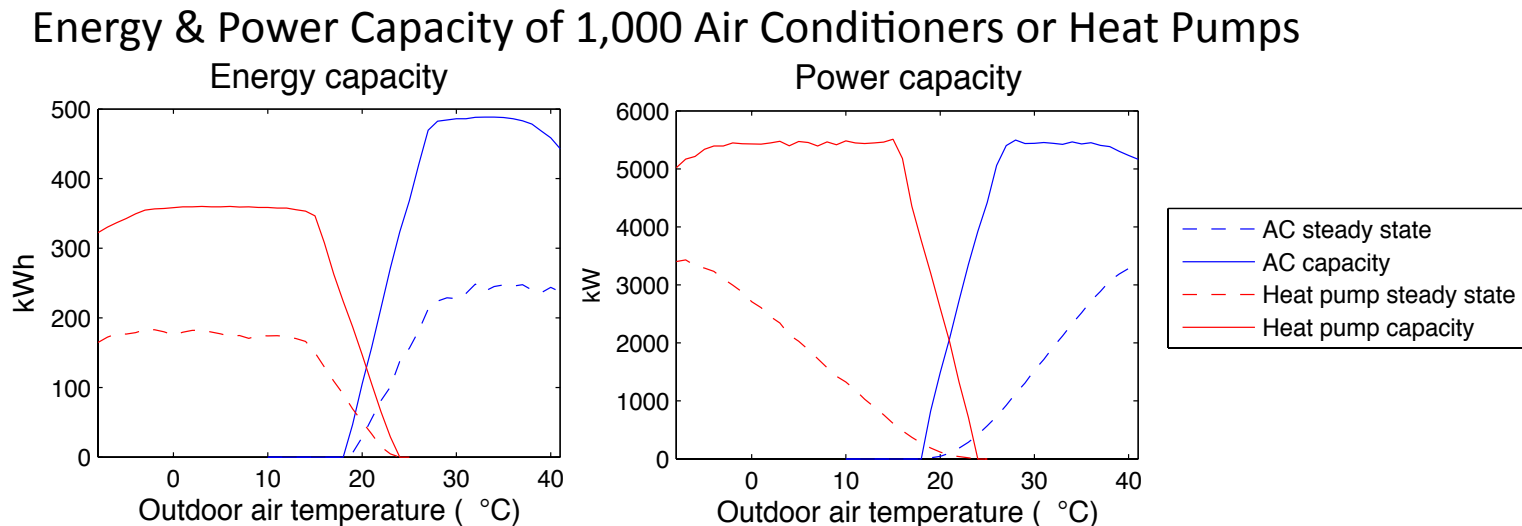
0 0.5 10
Hours

0 0.5 1
Hours

Energy Arbitrage

(Preliminary Approach & Results)

- Three Levels of Control:
 1. Linear program to solve for the optimal trajectory
 2. TCL population controller (currently, a proportional controller)
 3. a population of individual TCLs, each with its own local controller
- Ambient temperature is very important:



LP Set-up

Goal: minimize energy cost

$$J = l(1)p(1)\Delta T + l(2)p(2)\Delta T + \dots + l(N)p(N)\Delta T$$

subject to:

$$e(k+1) = e(k) + (p(k) - p_{ss}(k))\Delta T$$

$$0 \leq e(k) \leq e_{\max}(k)$$

$$0 \leq p(k) \leq p_{\max}(k)$$

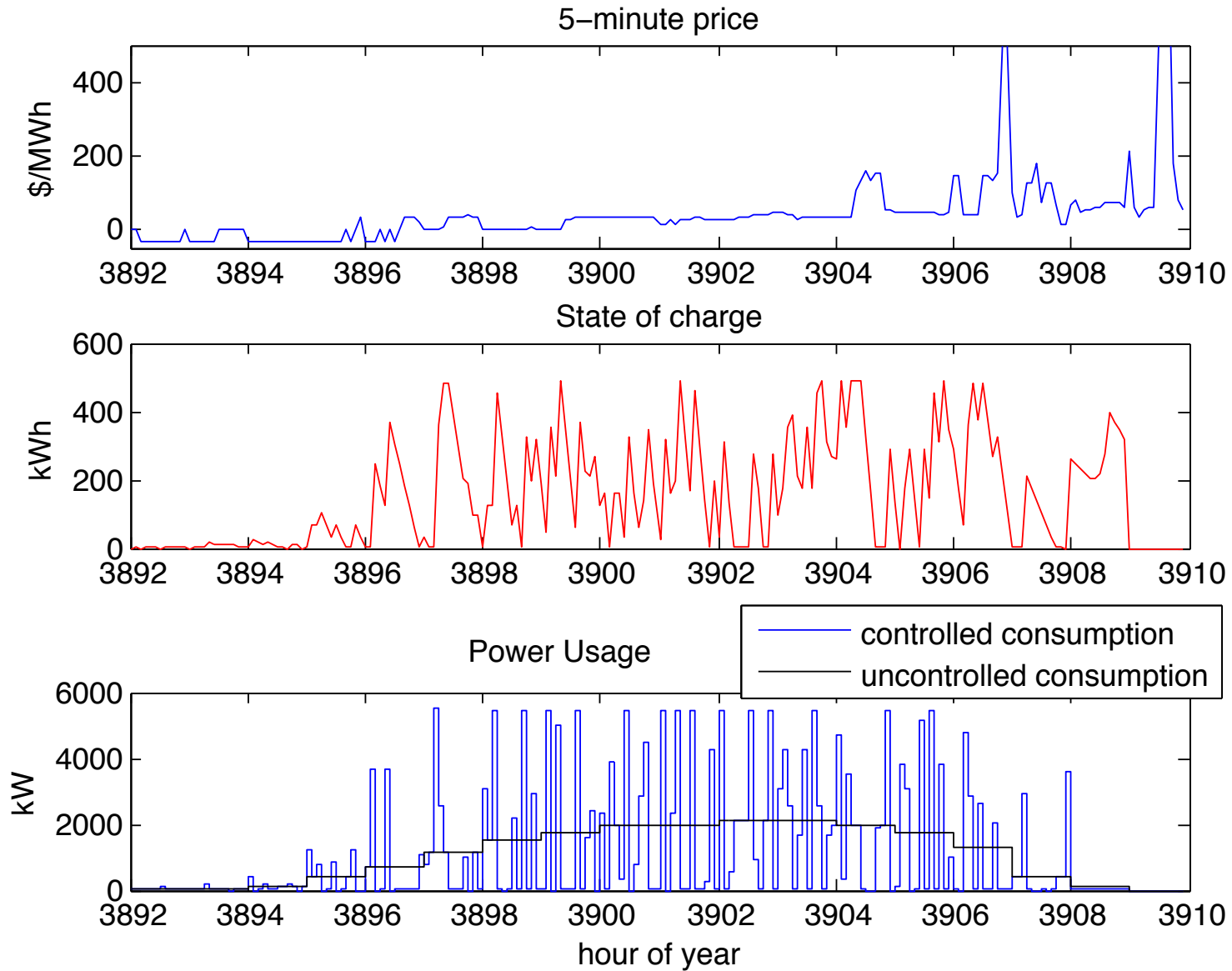
Iterative set-up:

- re-run LP at each time-step
- implement only the first control

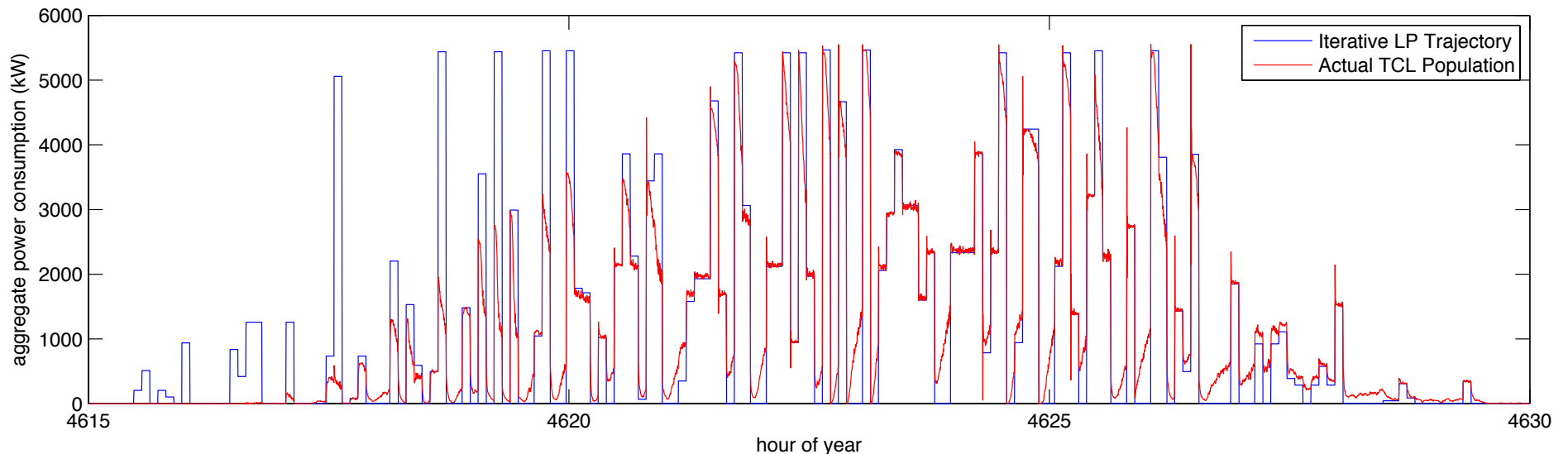
Price forecast error model: $\omega(k+1) = \gamma\omega(k) + \alpha\varepsilon(k)$

Temperature forecast error standard deviation: β

LP Trajectory: 1 hour prediction horizon, iterative



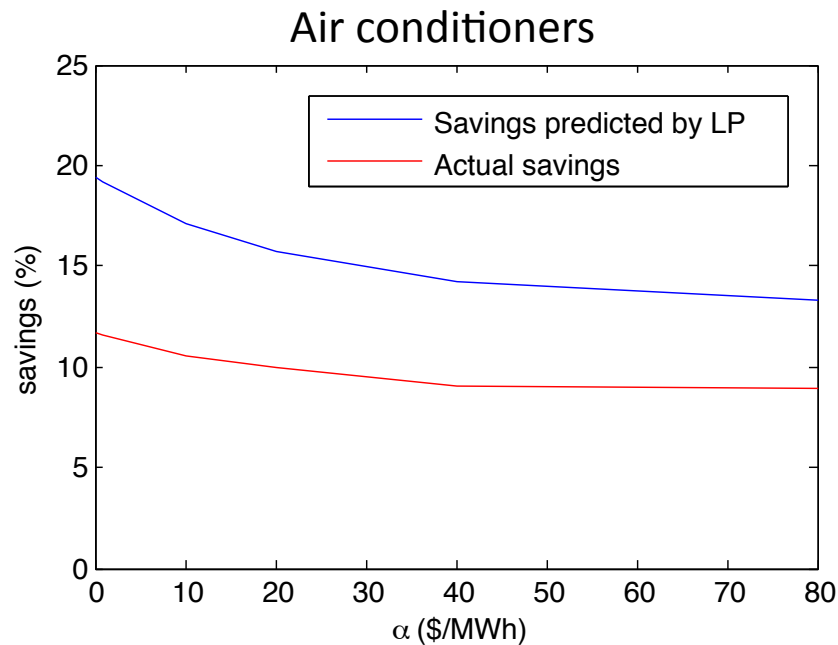
Tracking Performance: P-controller (for now)



Issues:

- the resource is over-estimated in the morning: power and energy capacity is a function of current and PAST ambient temperature
- the proportional controller isn't great, plus some TCLs are outside of the dead-band and uncontrollable

Energy Cost Savings



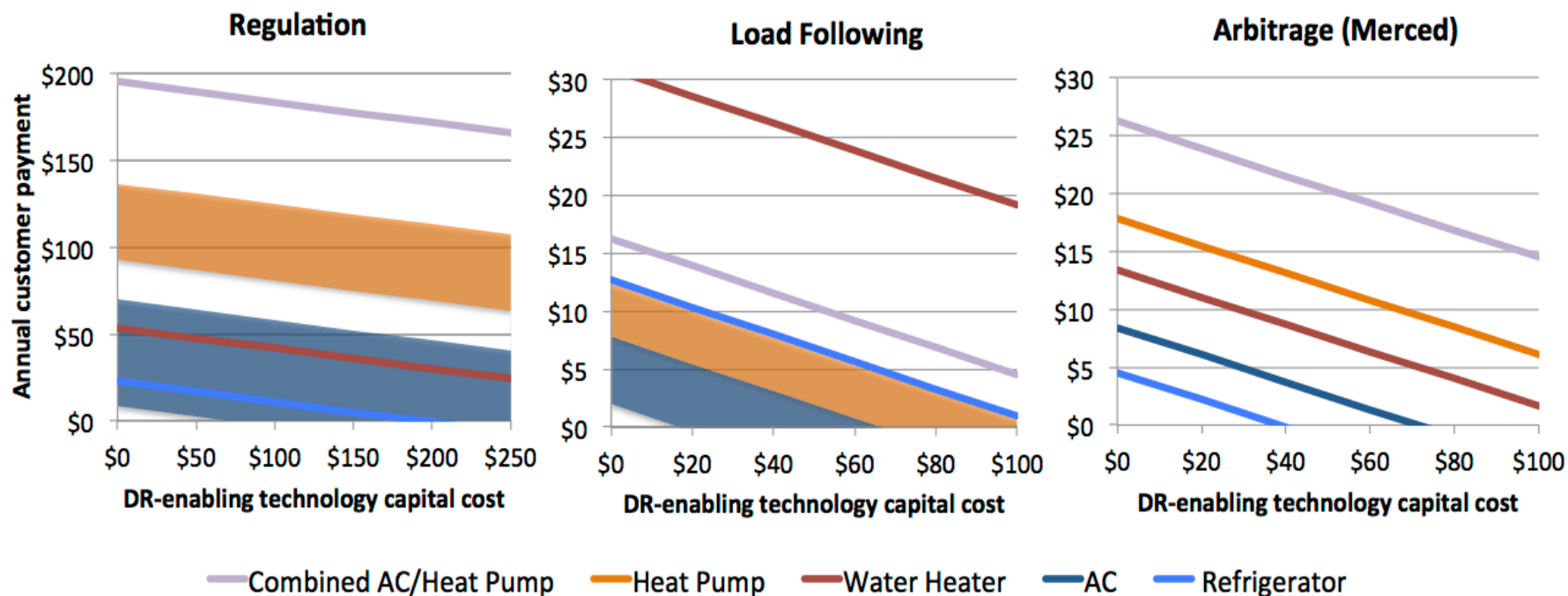
$\beta = 3^\circ\text{C}$
 $\gamma = 0.3$

Actual savings

	Perfect forecasts	Noisy forecasts*
Air conditioners	12.2%	9.0%
Heat Pumps	10.2%	6.7%
Water Heaters	41.0%	16.4%
Refrigerators	27.1%	13.6%

* $\alpha = 40\$/\text{MWh}$
 $\beta = 3^\circ\text{C}$
 $\gamma = 0.3$

Per-TCL Capital and Annual Costs Required to Break Even

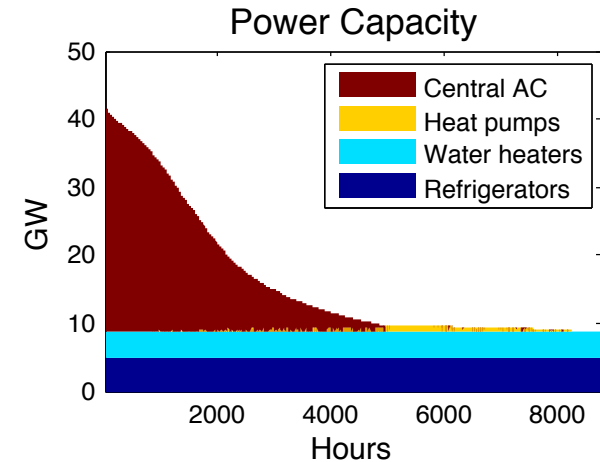
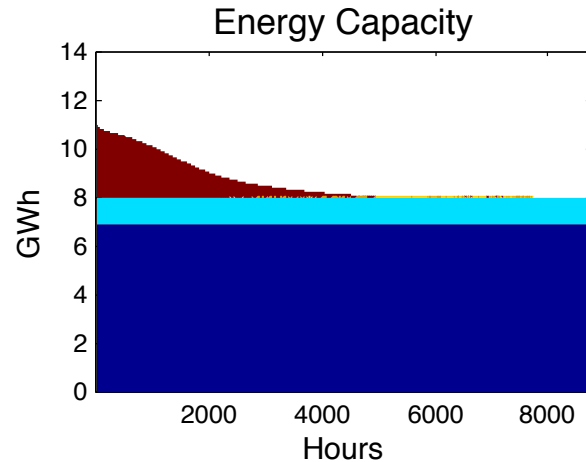


[Regulation and load following revenues estimated with data from Eyer & Corey 2010 (SAND2010-0815). Arbitrage revenue estimated with interval LMP data from California's Merced node. Details in Mathieu et al. ACEEE 2012 (forthcoming).]

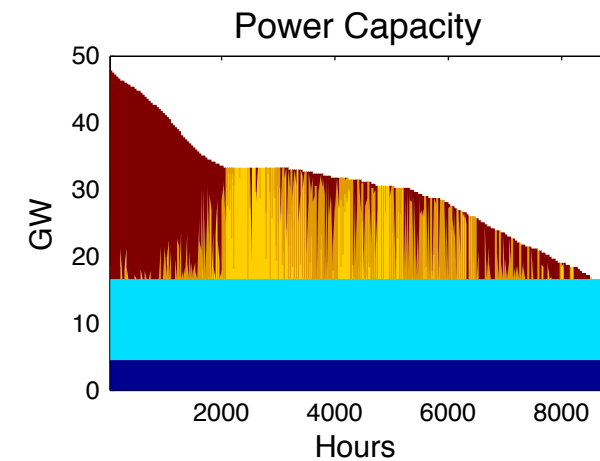
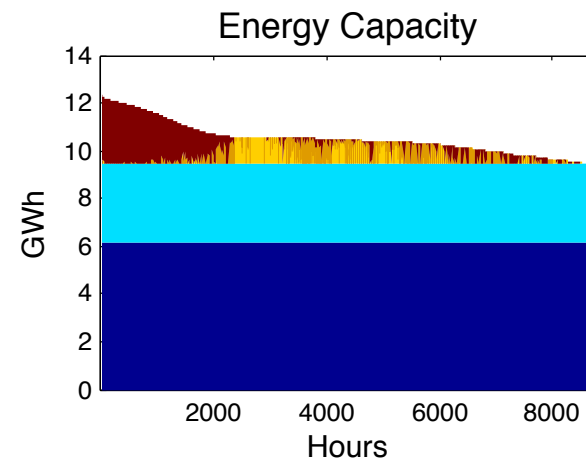
How BIG is the resource potential?

Estimates for most of California (5 largest utilities) based on RECs and CEC data.

2012 Resource
Duration Curve



2020 Resource
Duration Curve,
assuming increased
efficiency and 30% of
water/space heaters
converted to electric



[Mathieu et al. ACEEE 2012 (forthcoming)]

Key Takeaways

- TCLs can be controlled to follow signals *and* still provide the service requested by the consumer.
- Possible revenue sources are participation in energy/ancillary services markets or energy arbitrage.
- The revenues may cover the costs.
- The resource potential is large.

Thank you! Questions?

The value of real-time data in controlling
electric loads for demand response

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