Scheduling and coordinating uncertain electric loads to provide power system reserves

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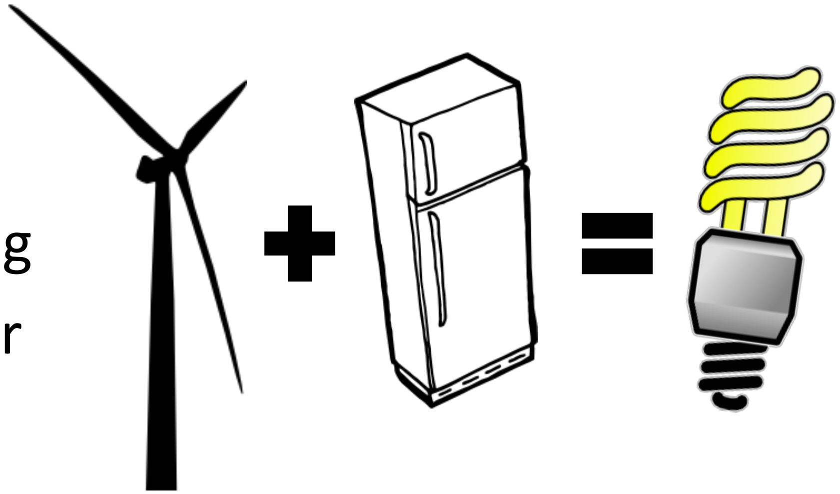
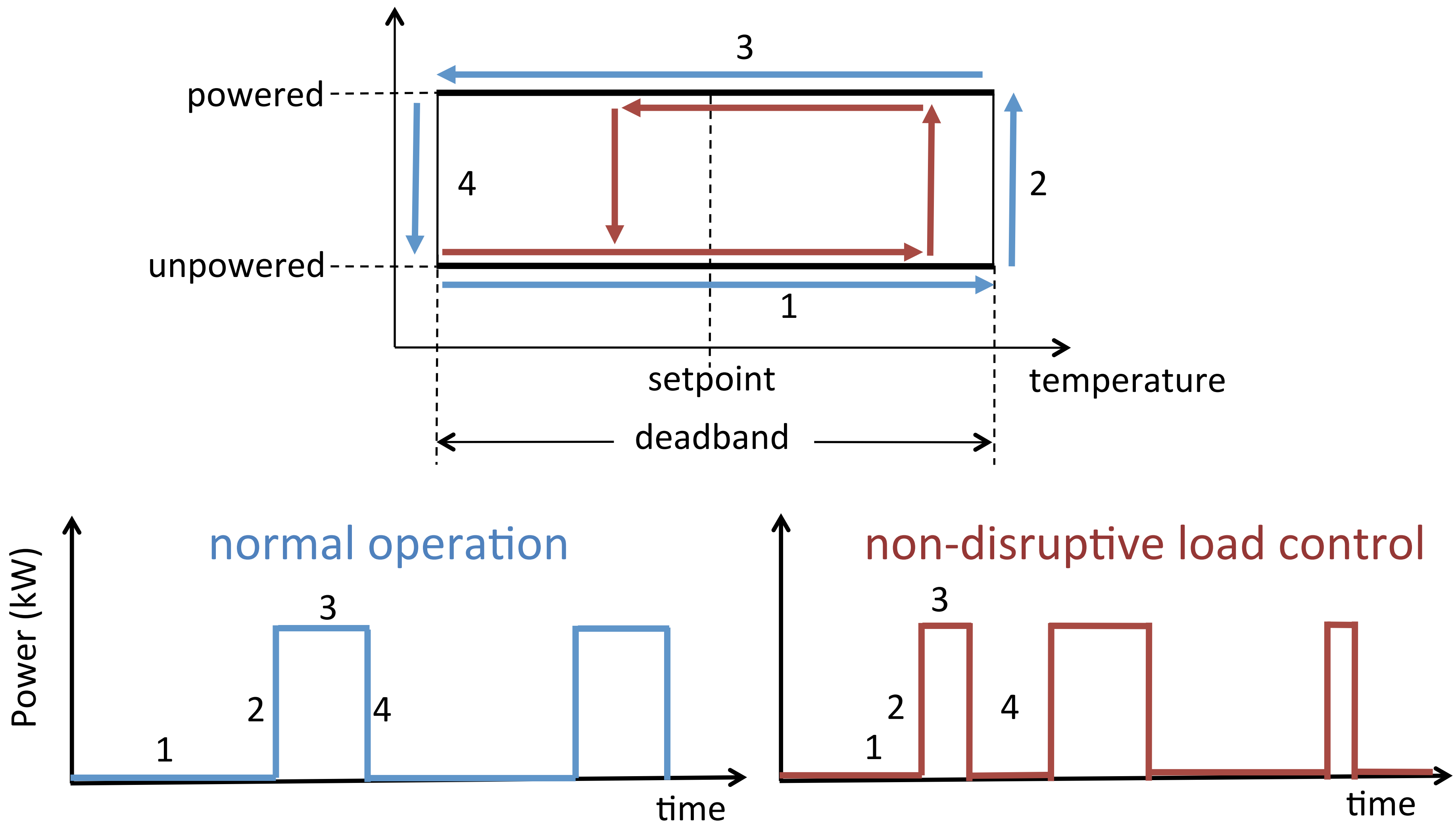


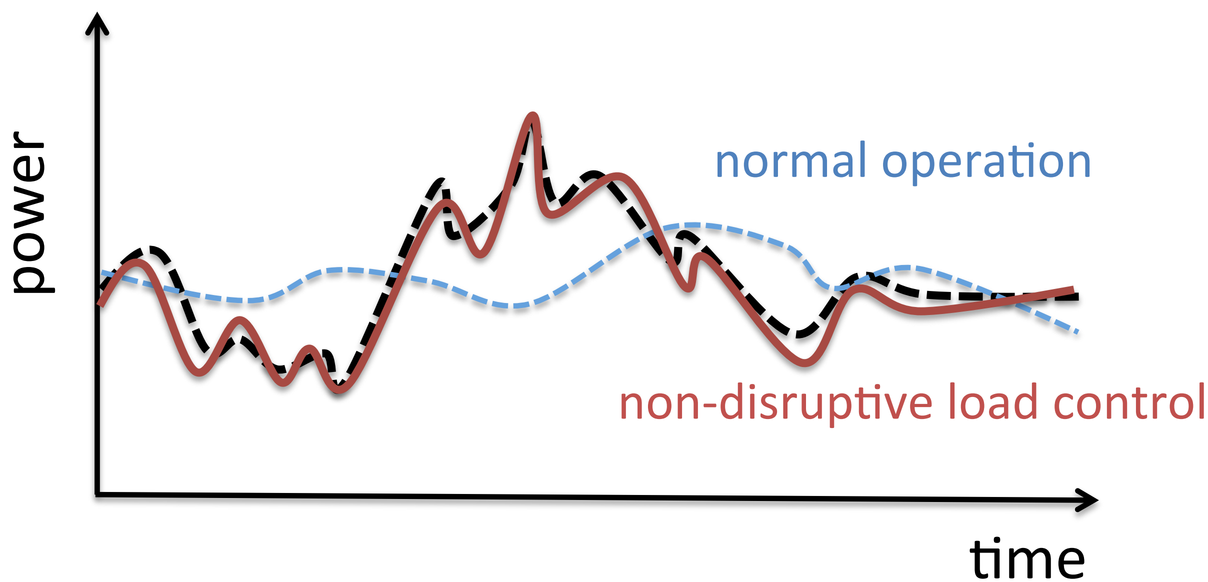
March 6, 2015

How can loads provide reserves?
→ your refrigerator is already flexible



Thousands of coordinated thermal loads (TCLs) can track signals and provide reserves

→ Air conditioners, heat pumps, space heaters, electric water heaters, refrigerators



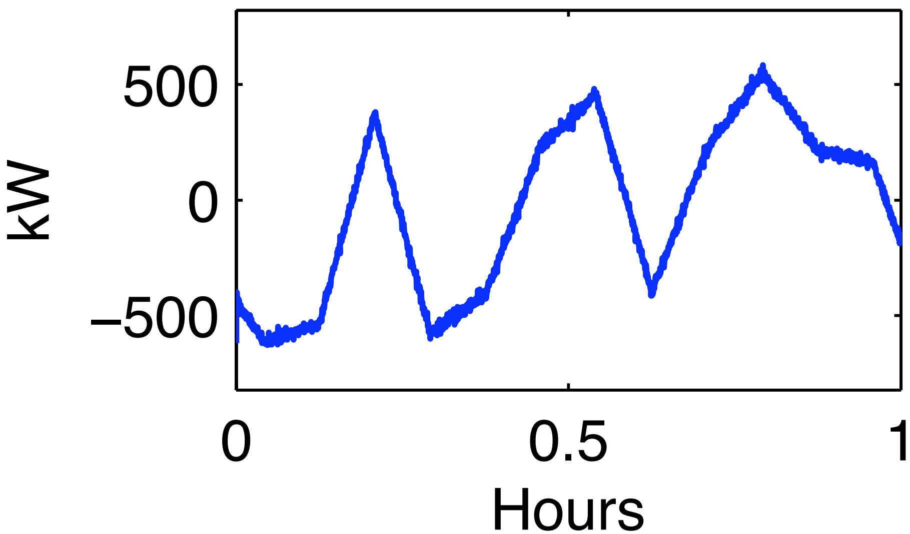
[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

Thousands of coordinated thermal loads (TCLs) can track signals and provide reserves

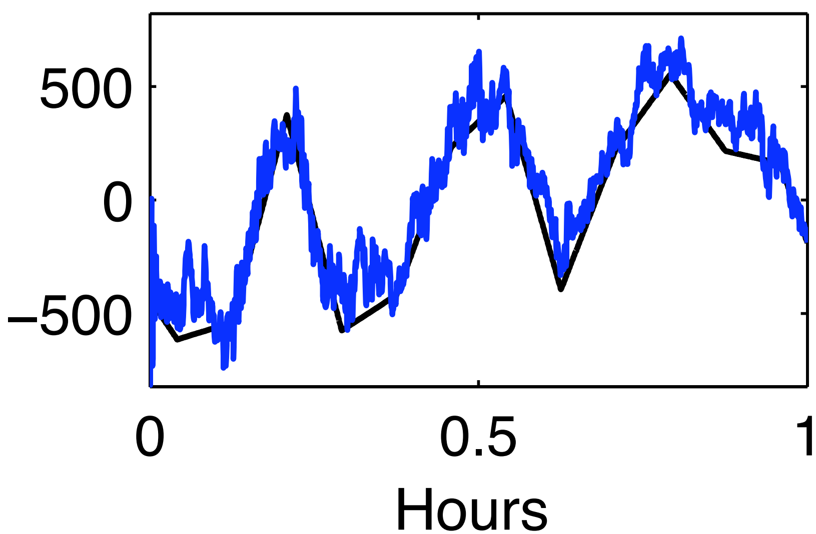
→ Air conditioners, heat pumps, space heaters, electric water heaters, refrigerators

→ The more the controller knows about the load, the better it can coordinate them

Controller gets temperature/state of each load every 2 seconds



Controller infers TCL behavior from power measurements at the substation



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

Data from loads

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

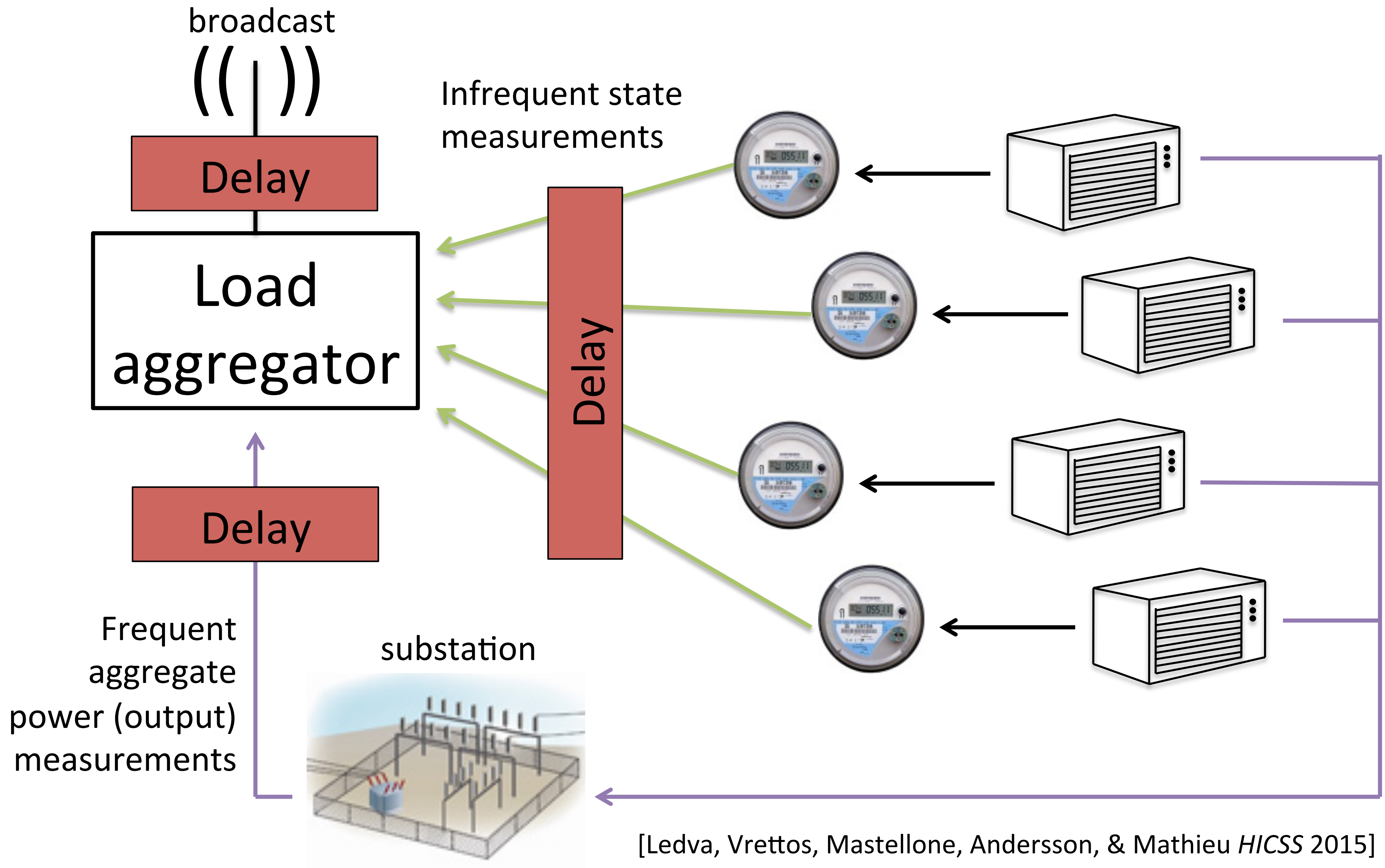
→ Auditing

Research Questions

- How can we leverage existing imperfect communication networks for load coordination?

- How can we schedule loads to provide reserves when the reserve capacity available from load aggregations is inherently uncertain?

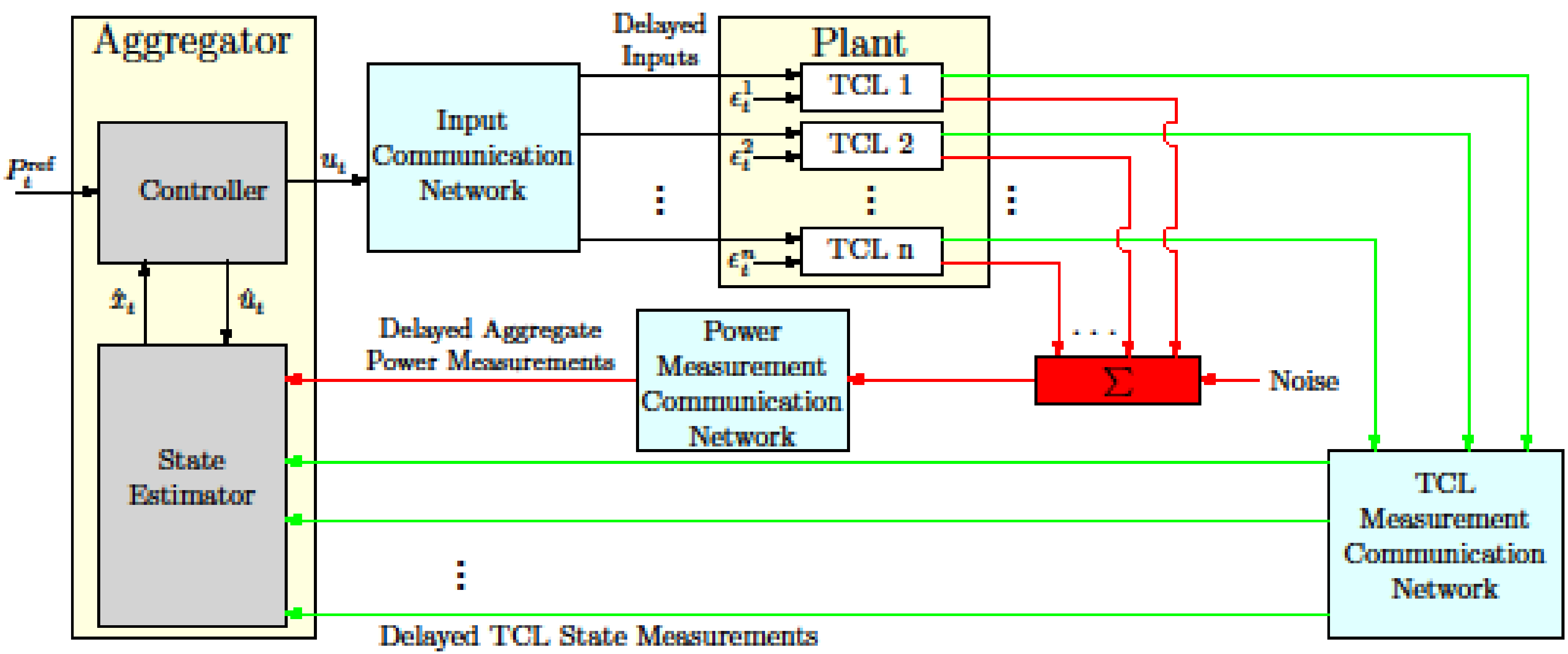
Communication & Control Scenario



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

System block diagram

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

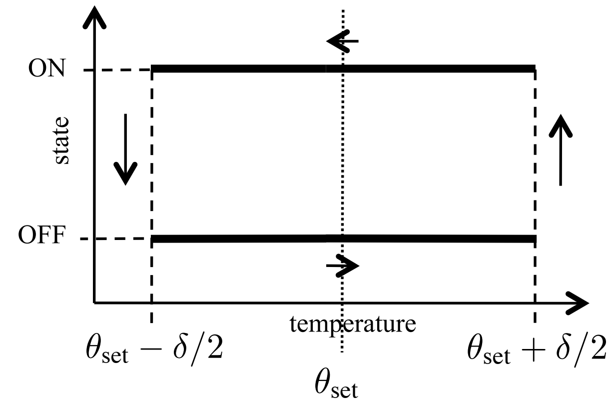


The challenge

- 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)

Individual TCL Model (Plant)

Each TCL, i, can be 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

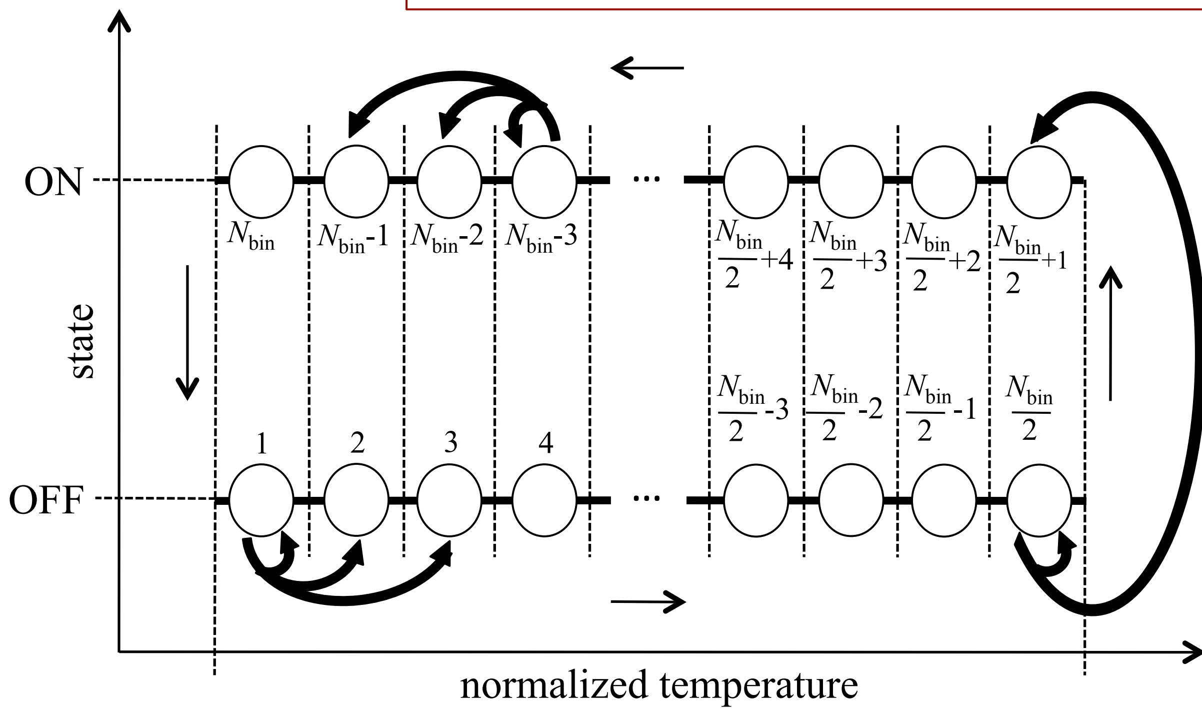
$$m_i(k+1) = \begin{cases} 0, & \theta_i(k+1) < \theta_{\text{set},i} - \delta_i/2 \\ 1, & \theta_i(k+1) > \theta_{\text{set},i} + \delta_i/2 \\ m_i(k), & \text{otherwise} \end{cases}$$

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:

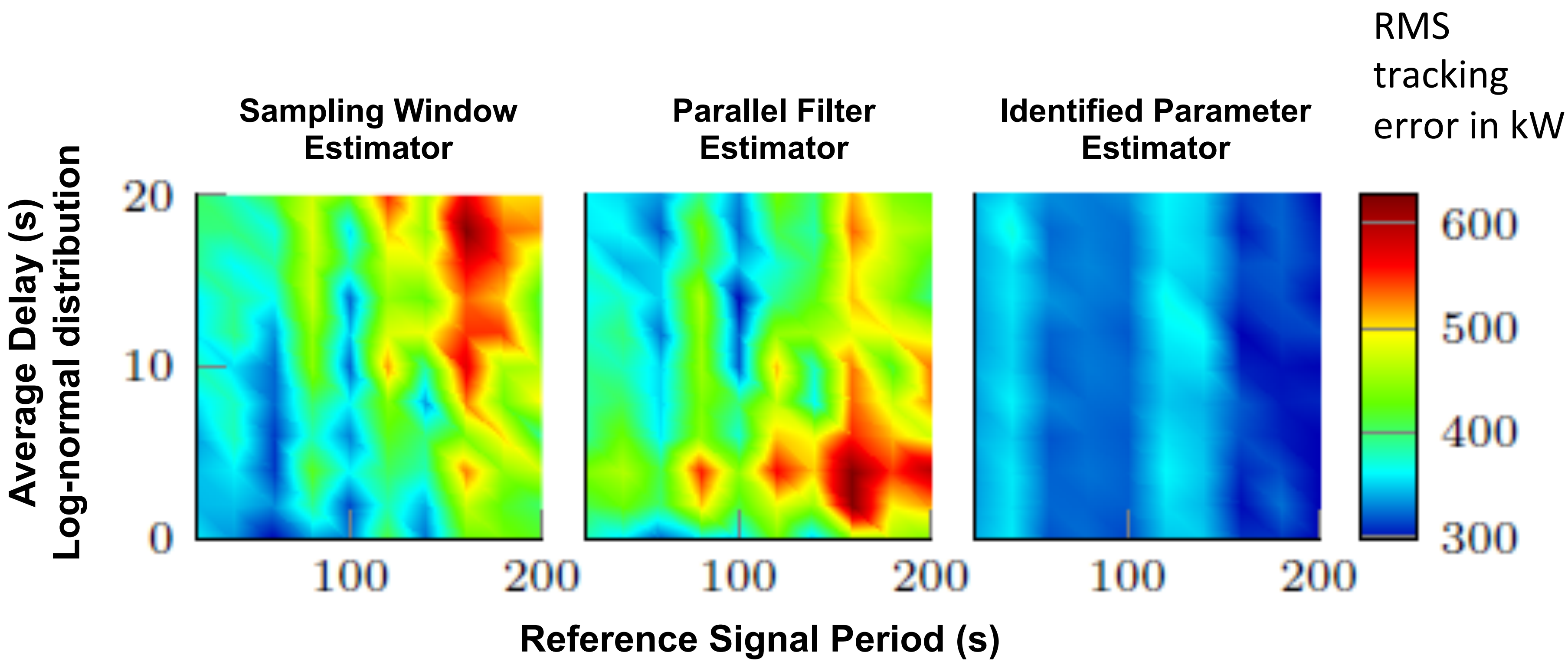
- Lu & Chassin 2004/2005
- Bashash & Fathy 2011/2013
- Kundu & Hiskens 2011
- Zhang et al. 2013

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

Estimator designs

- Based on Kalman Filtering
- Options
  - Sampling window estimator
    - Wait, collect, estimate
  - Parallel filter estimator
    - One Kalman Filter per load
    - Each time a measurement arrives, filter it
    - Synthesize aggregate estimate from individual estimates
  - Identified parameter estimator
    - Use state measurement histories to estimate *individual* load parameters
    - Use individual load models to predict current state
      → pseudo-measurements
    - Use pseudo-measurements in Kalman Filter

Estimator Results



→ Estimators relies on infrequent state estimates *much more* than noisy, frequent aggregate power measurements

Controller designs

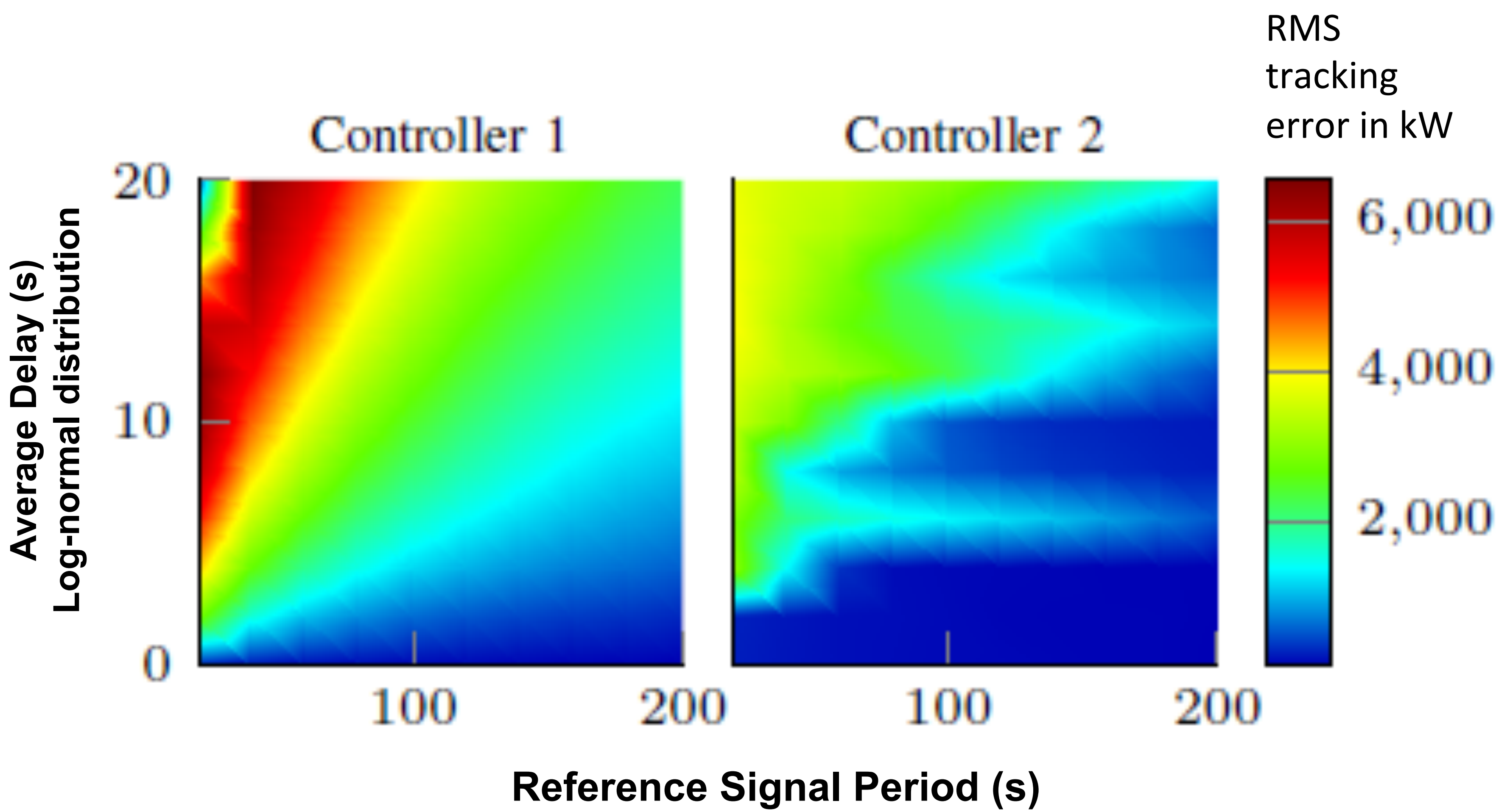
- Based on Model Predictive Control
- Options
  - Use the mean delay – “Mean Delay Controller”
  - Use knowledge of delay distributions and past control inputs – “Full Distribution Controller”

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

Controller Results



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 some control/estimation approaches we've developed mitigate these impacts.

Research Questions

- How can we leverage existing imperfect communication networks for load coordination?

- How can we schedule loads to provide reserves when the reserve capacity available from load aggregations is inherently uncertain?

Power system operation – in two slides

- Day-head electricity markets schedule:
  - hourly power output of generators
  - reserve capacity, i.e., how much capacity is kept in "reserve" to balance real-time supply-demand mismatches
- Real-time energy markets reschedule the power output of *a small fraction* of the generators every 5 or 15-minutes

*Disclaimer – this is VERY simplified; it only applies to the U.S. markets; each electricity market in the U.S. works differently.

The day-ahead scheduling problem
i.e., Optimal Power Flow (OPF) problem

minimize *generation costs + reserve costs*

subject to *power flow equations*

generation constraints

line constraints

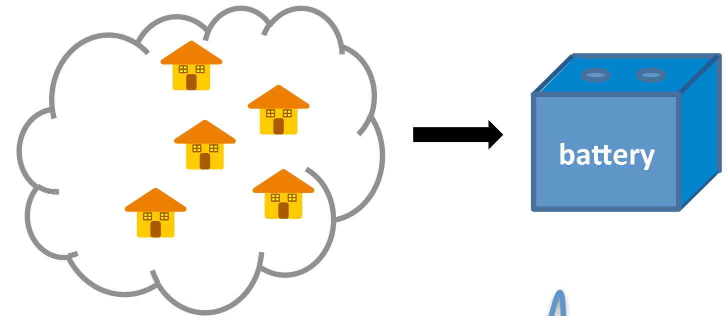
…

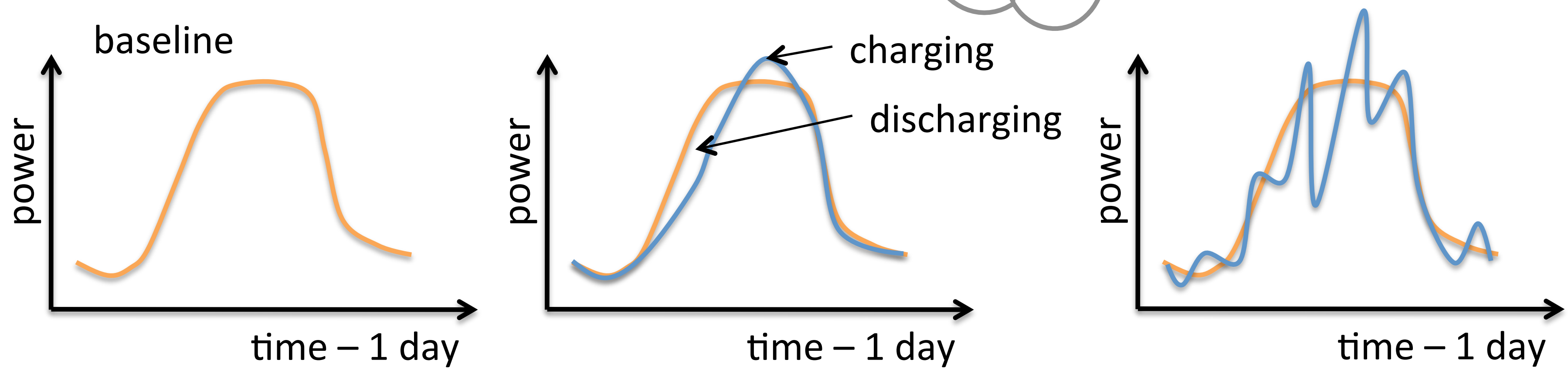
Decision variables: generator power set points, generator reserve capacity

"But load control will never be reliable enough to provide trustworthy reserves!"

- Why?
  - Too much uncertainty: People! Weather! etc.
- Two options:
  - Be conservative in how much reserve you schedule
  - Explicitly consider reserve uncertainty in the planning algorithm

Time-varying “thermal battery” model





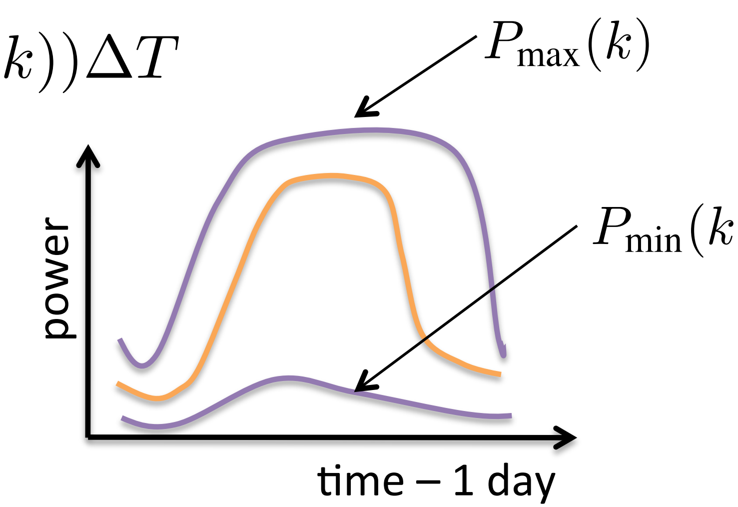
$$S(k+1) = S(k) + (P(k) - P_{\text{baseline}}(k))\Delta T$$

Mean power over an interval

$$P_{\min}(k) \leqslant P(k) \leqslant P_{\max}(k)$$

State of charge

$$S_{\min}(k) \leqslant S(k) \leqslant S_{\max}(k)$$

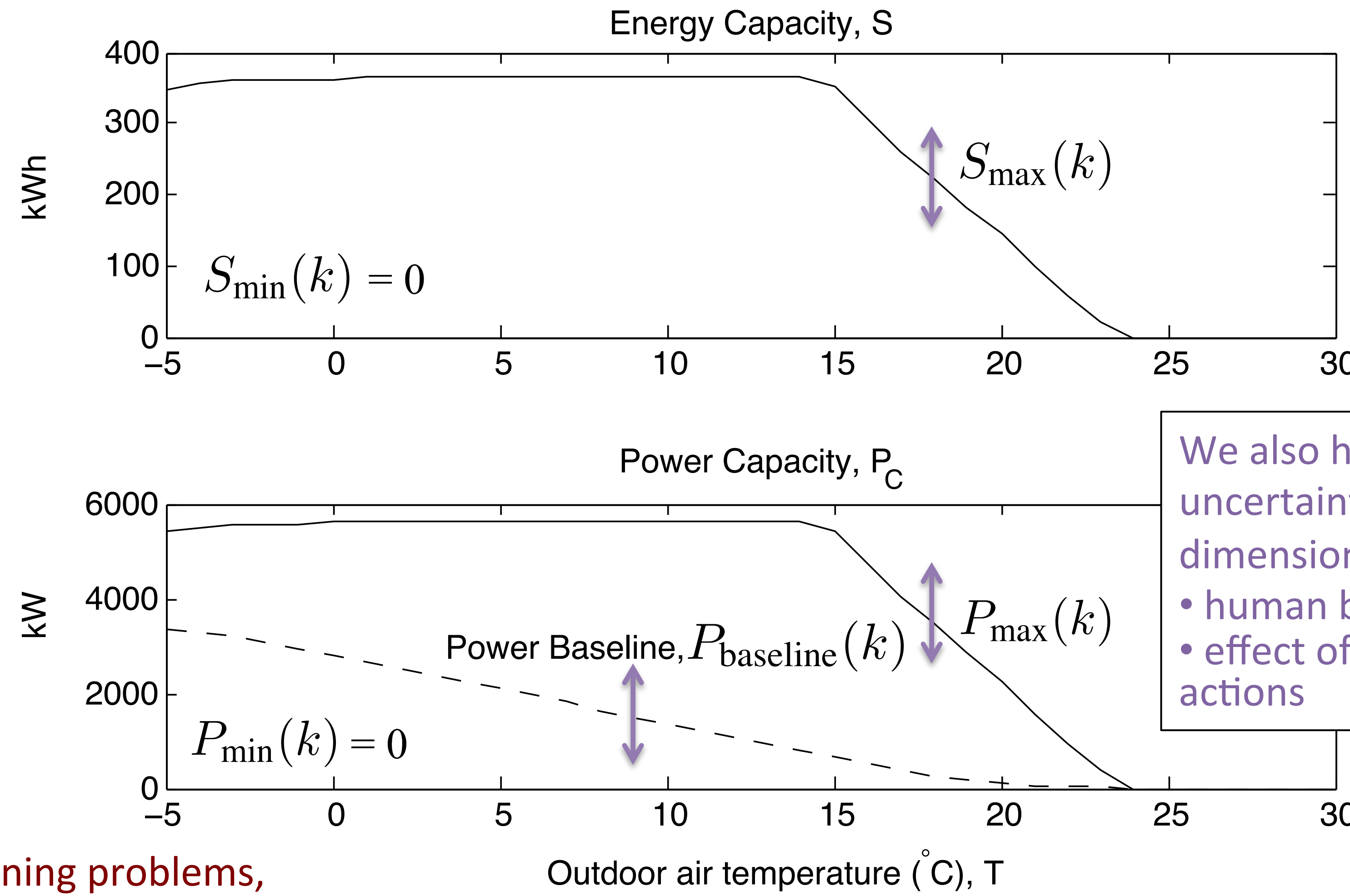


Other similar models: Croft et al. *IECON* 2013; Hao et al. *TPWRS* 2015; etc.

[Mathieu, Kamgarpour, Lygeros, Andersson, & Callaway *IEEE Transactions on Power Systems* 2015]

Time-varying power & energy capacities

1000 electric space heaters



We also have uncertainty in this dimension!

- human behavior
- effect of past DR actions

In planning problems, we have temperature forecast uncertainty

The (original) day-ahead scheduling problem

minimize *generation costs + reserve costs*

subject to *power flow equations*

generation constraints

line constraints

…

Decision variables: generator power set points, generator reserve capacity

The (new) day-ahead scheduling problem

minimize *generation costs + generator reserve costs + load reserve costs*

subject to *power flow equations* ← wind uncertainty

generation constraints

line constraints

controllable load constraints ← load control uncertainty

…

Decision variables: generator and load power set points, generator and load reserve capacity, distribution vectors

Building on recent work

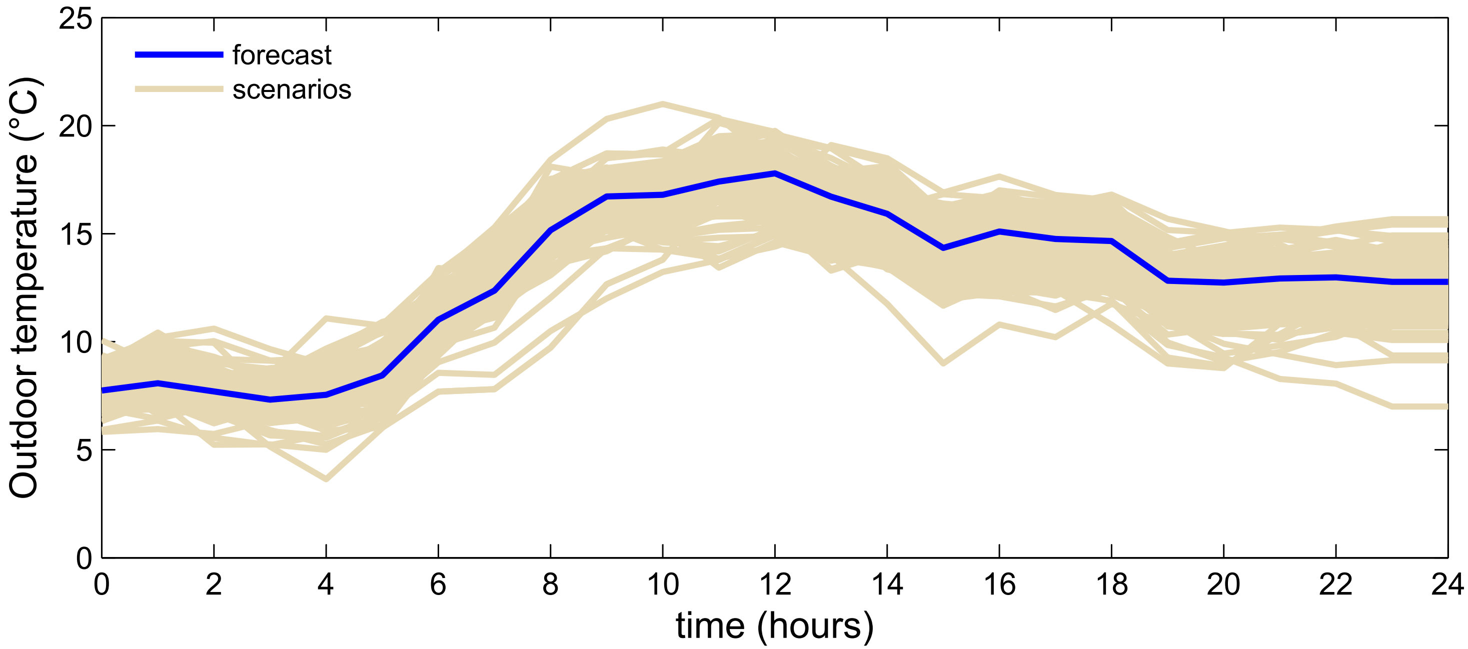
- Stochastic optimal power flow
  - Bouffard and Galiana 2008
  - Papavasiliou et al. 2011
  - Vrakopoulou et al. 2013
- Power flow with loads and storage
  - Gayme and Topcu, 2011
  - Mount et al. 2011
  - Papavasiliou and Oren 2012
  - Gonzalez Vaya and Andersson 2013
  - Anderson and Cardell 2013

Uncertainty Modeling

- Wind power production uncertainty
- Outdoor air temperature uncertainty

  → load uncertainty → load control capacity uncertainty

  → reserve capacity uncertainty



Reserve Modeling

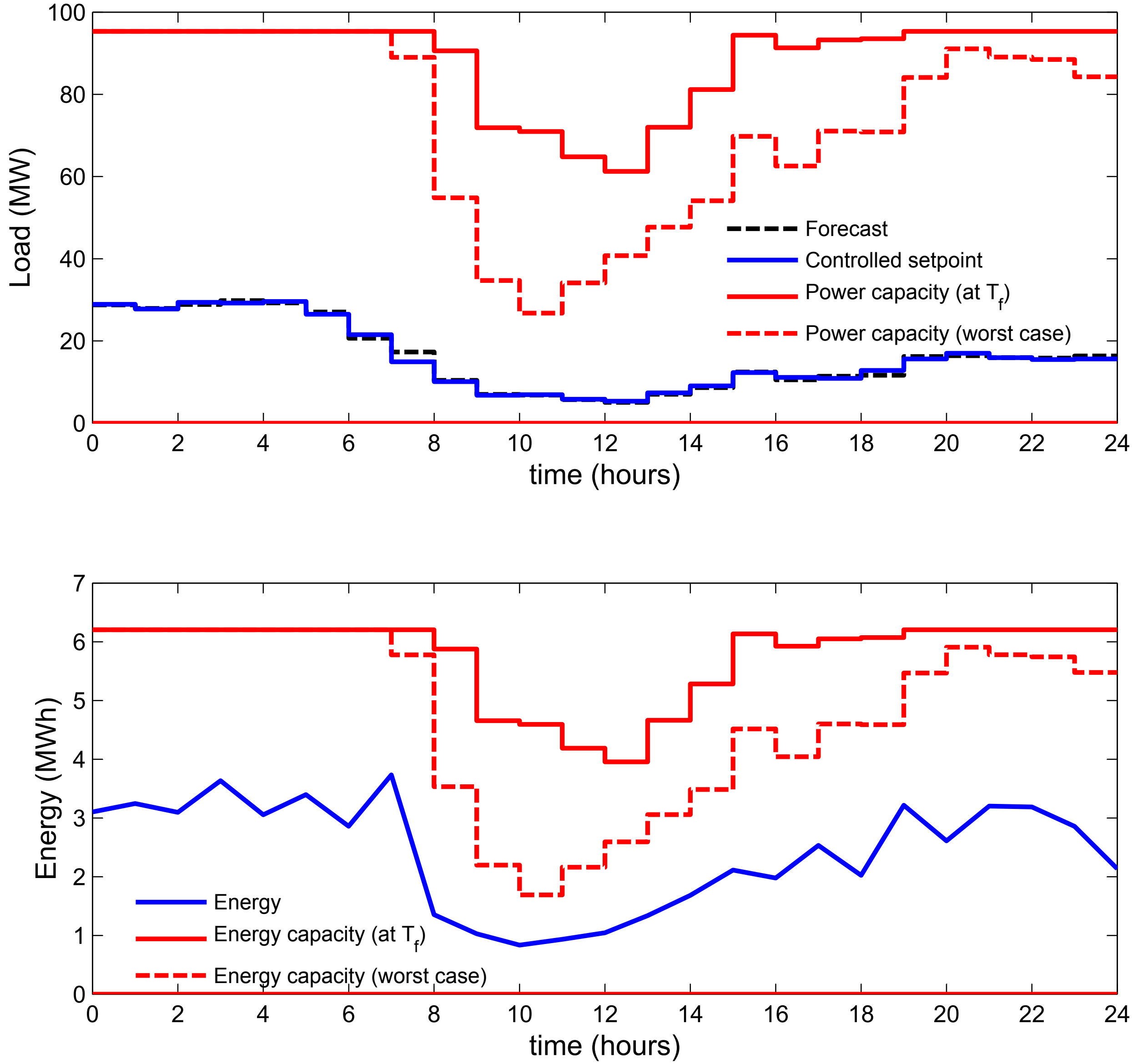
- Secondary frequency control (AGC) provided by loads and generators
  - Assumes loads are cheaper!

- Re-dispatch (15-minute market, Tertiary control) provided by generators
  - Covers power mismatch between expected and actual generation (as it does today)
  - Provides energy to return loads to their scheduled energy state

Solution Approach

- Linearized power flow (DC-OPF)
- Chance-constraints: $\mathrm{P}(Ax \geq b) \geq 1\text{-}\varepsilon$
- Solved with probabilistically robust design [Margellos, Goulart, and Lygeros 2014], inspired by a scenario-based approach [Calafiore and Campi 2006]
  - assumes no a priori knowledge of uncertainty distributions
  - provides probabilistic guarantees

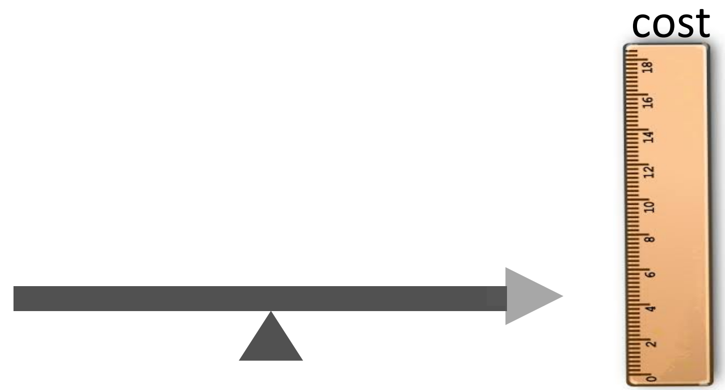
How much does outdoor temperature uncertainty really matter?

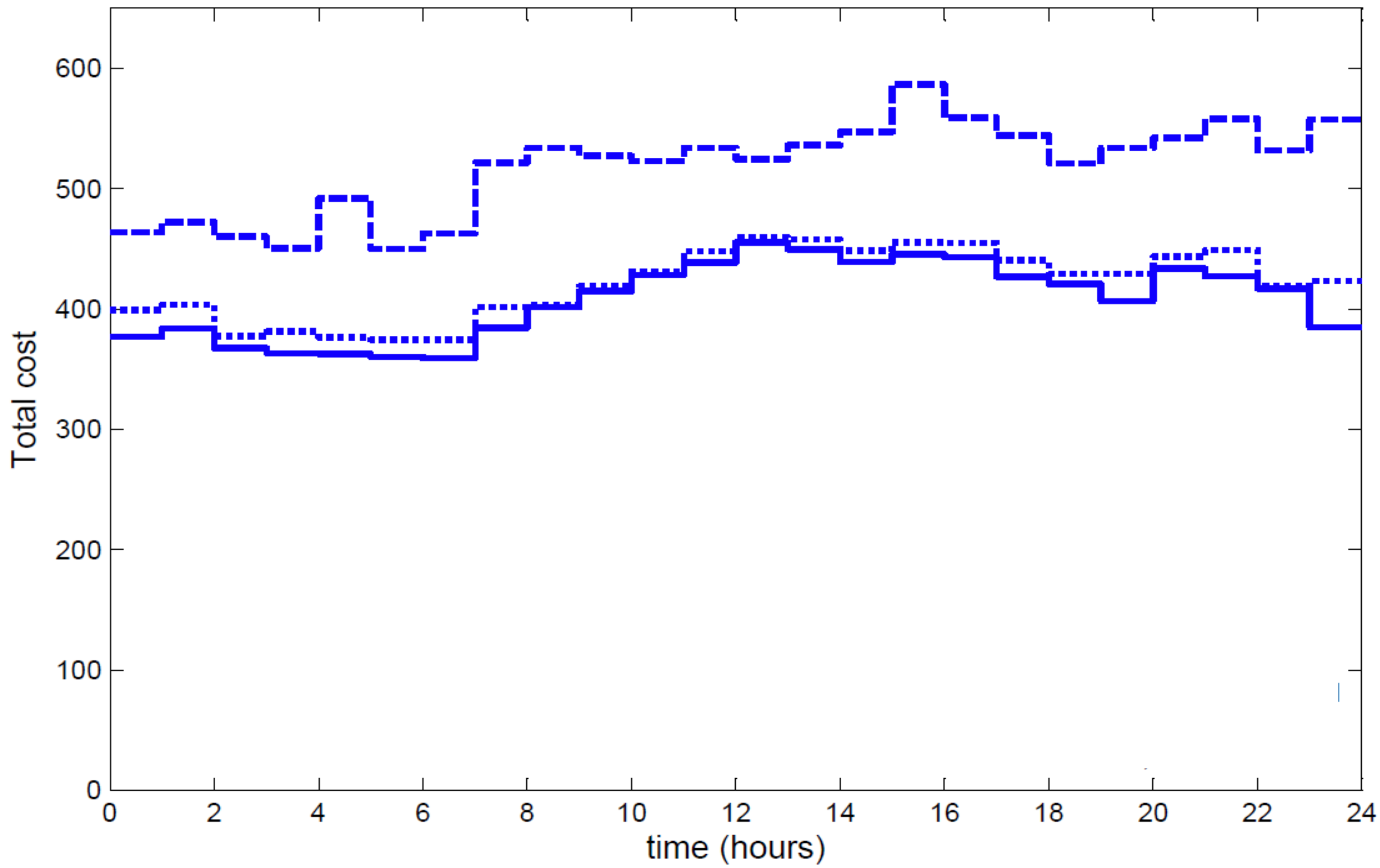


[Vrakopoulou, Mathieu, and Andersson *HICSS* 2014]

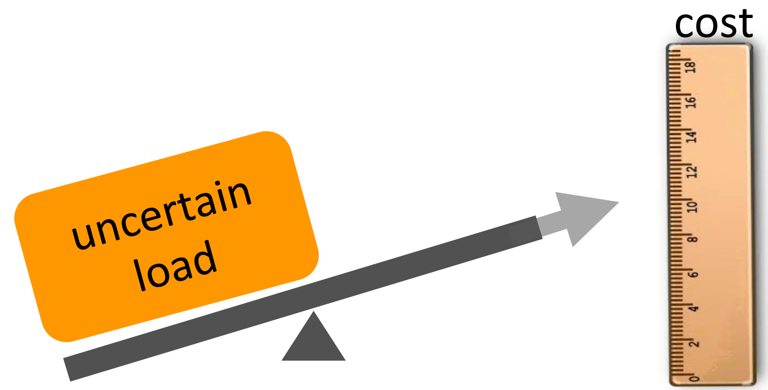
Operational costs

no load uncertainty, no load control

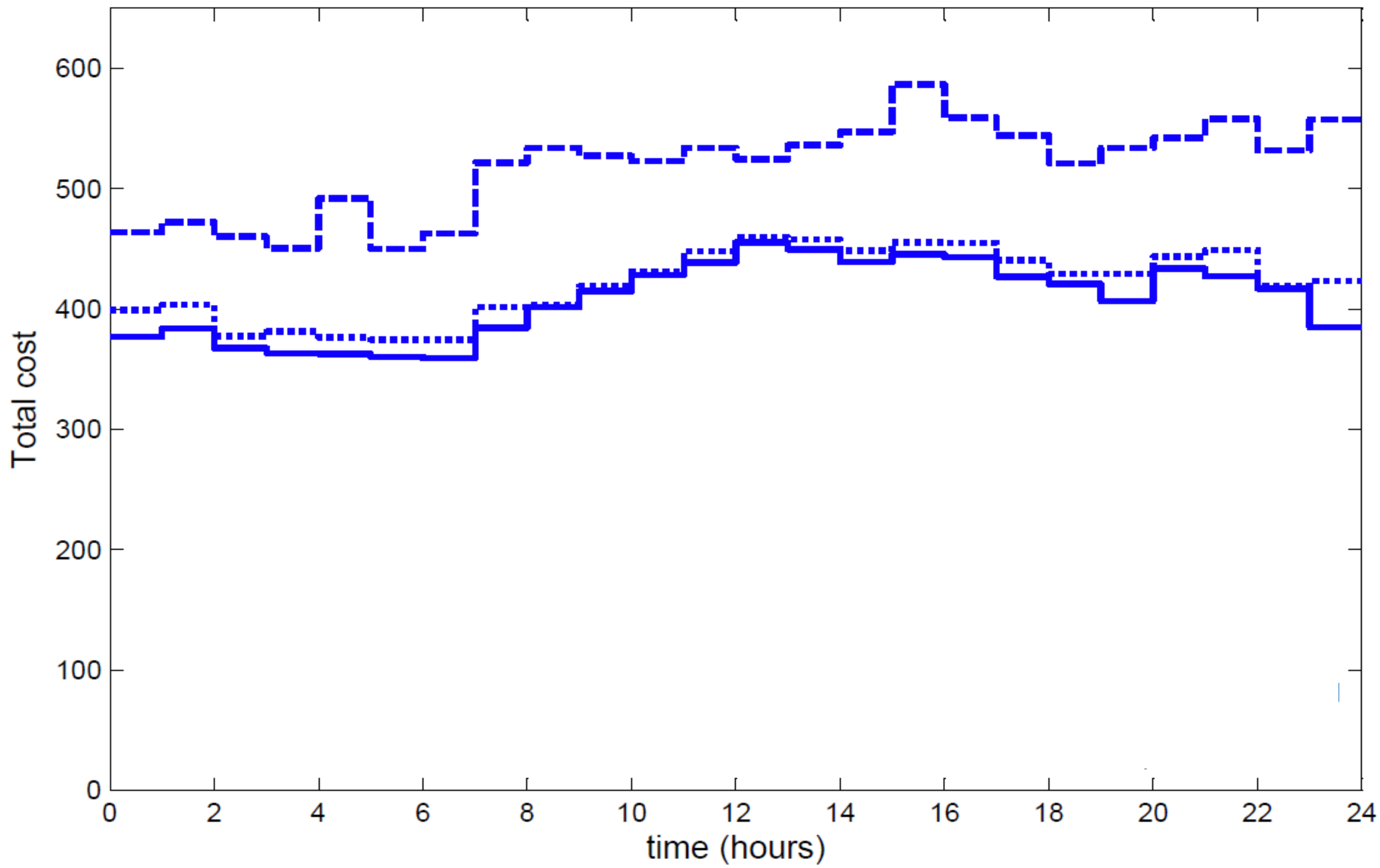




Operational costs

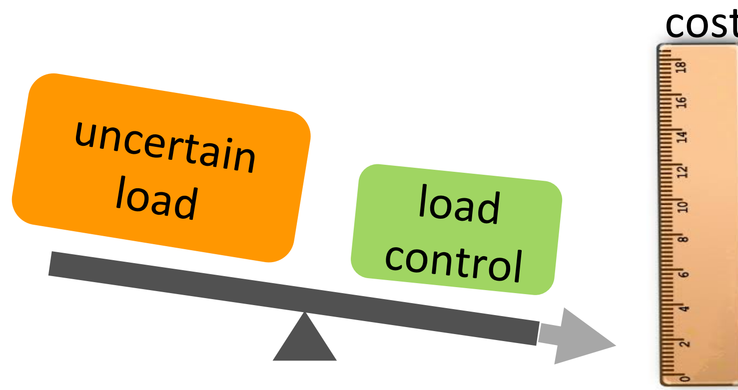


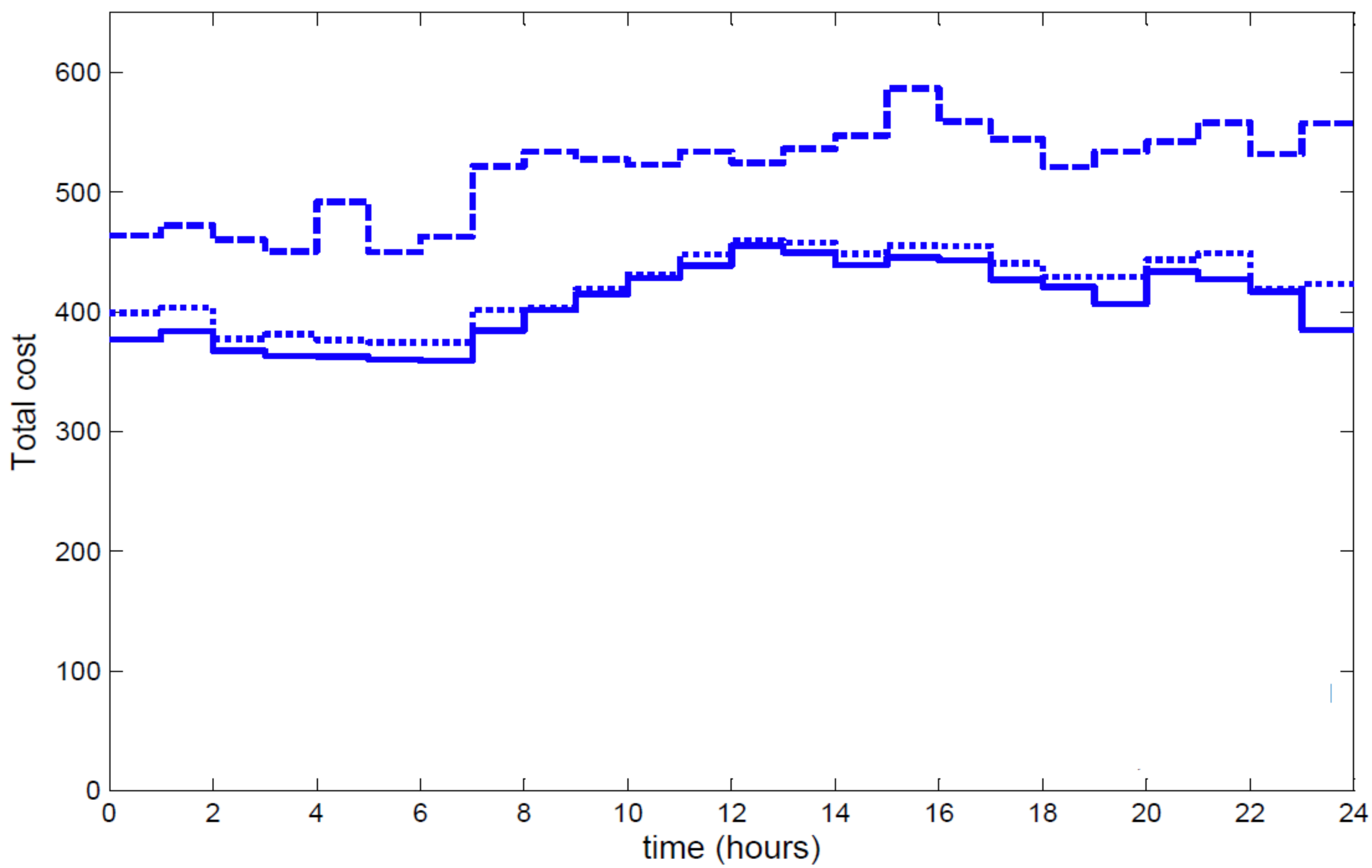
no load uncertainty, no load control
uncertain load, no load control



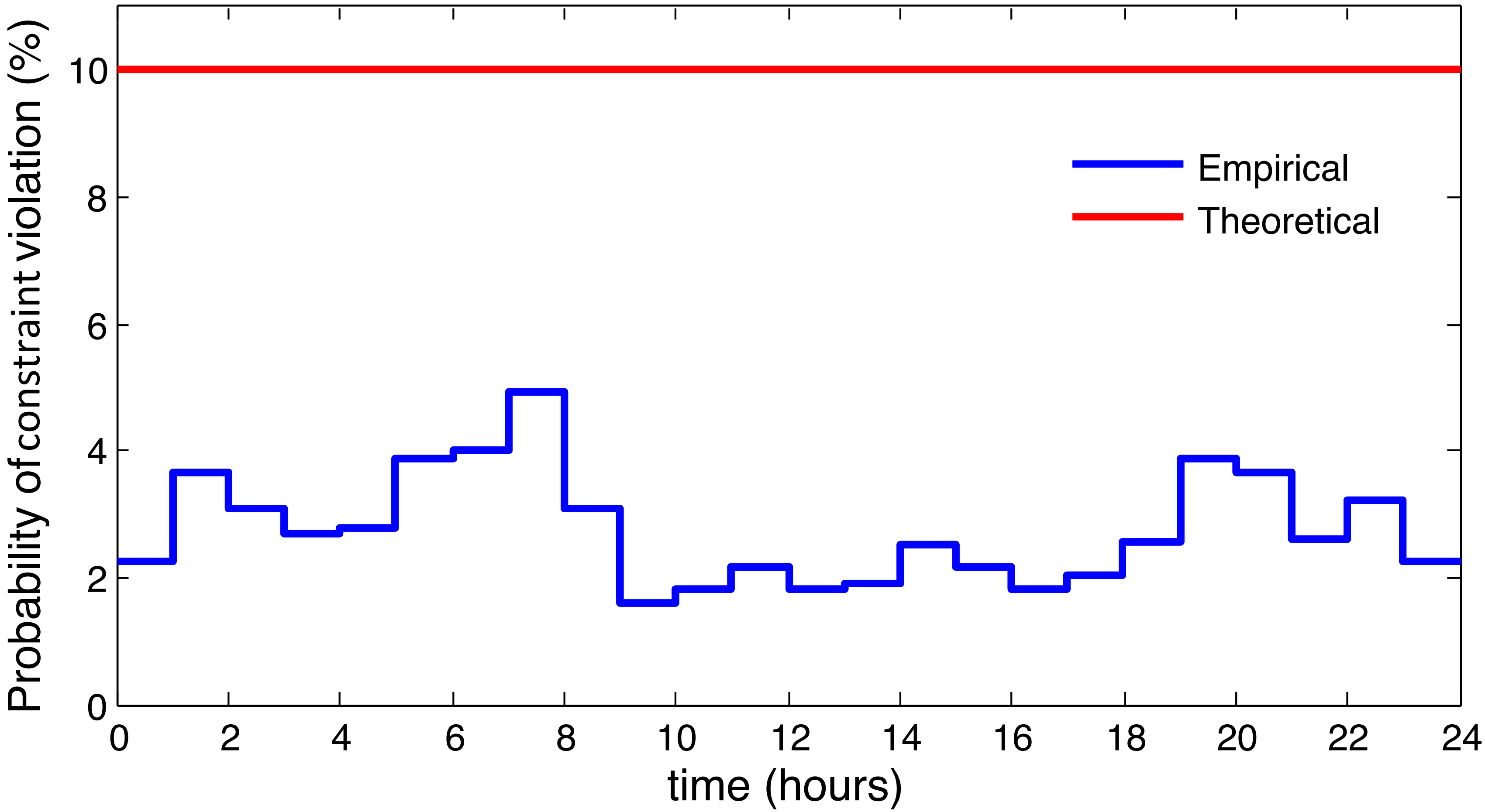
Operational costs

no load uncertainty, no load control
uncertain load, no load control
uncertain load, load control





How well do the probabilistic guarantees work?



Key Takeaway

Reserves from loads may not be of the same "quality" as those provided by generators, BUT we can *plan* for load uncertainty by explicitly considering it in our problem formulation

New directions…

- How do uncertainty and reserve costs interact?

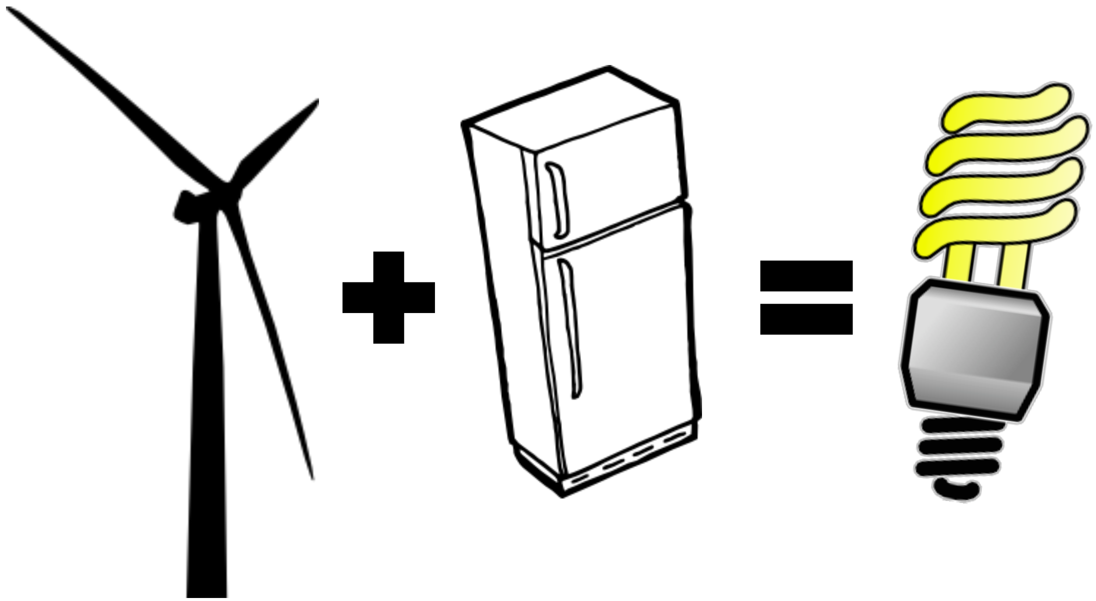
- How can we handle the full complexity of load control uncertainty?
  - Multi-dimensional
  - Exogenous and endogenous
  - Non-stationary
  - Insufficient data!

Scenario-based approaches Vs. Distributionally robust optimization Vs. Analytical reformulation

- Distributionally robust optimization
  - Use available data to build a confidence set to bound the pdf of the uncertainty distribution
  - Moment matching: [Zhang, Shen, & Mathieu, ACC 2015 (to appear)]

- Analytical reformulation
  - Assume knowledge of uncertainty distributions and reformulate chance-constraints to solve a deterministic problem for a specific choice of ε
  - Gaussian approximation: [Li and Mathieu; in preparation for PowerTech 2015]

THANK YOU! QUESTIONS?



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