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Coordinating Distributed Energy Resources Without Breaking the Bank, or the Grid

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What principles should we follow when coordinating distributed energy resources (DERs) to provide services to the power grid?

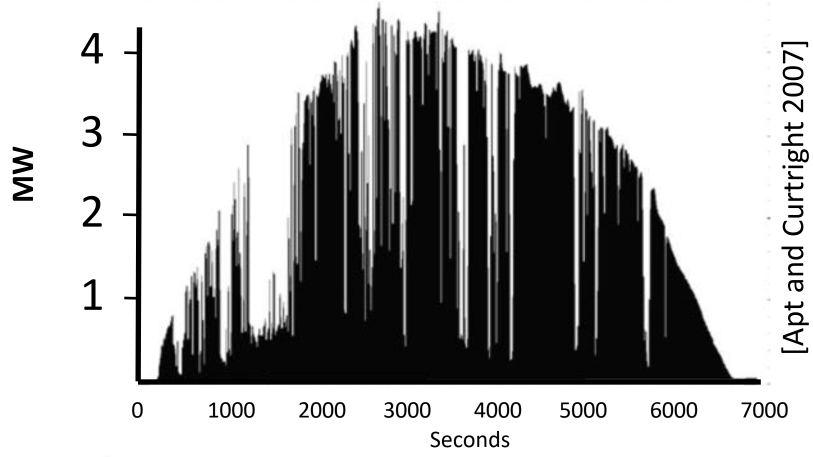
Outline

- Context – what does it mean to coordinate DERs and how do we do it?
- My favorite DERs
- 7 Principles … with examples!
- Concluding thoughts

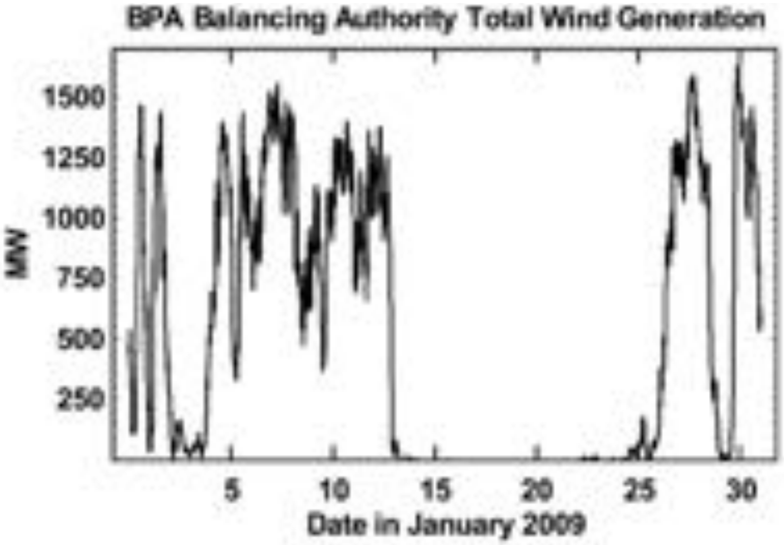
Challenges & Opportunities in Modern Power Systems

- Challenges
  - Renewables
  - Load growth (electrification)
  - Aging system
- Opportunities
  - More sensing and communications systems
  - More controllable resources in the distribution network: DERs

One day – AZ Solar Power Plant



[Apt and Curtright 2007]



[Katzenstein and Apt 2009]

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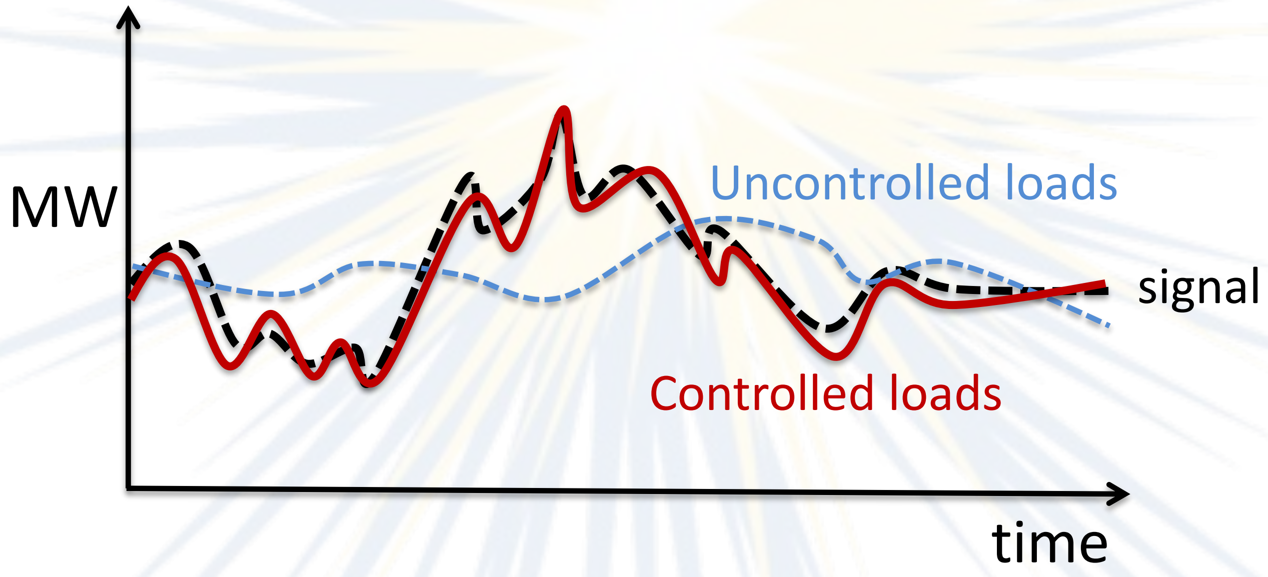
DER Coordination

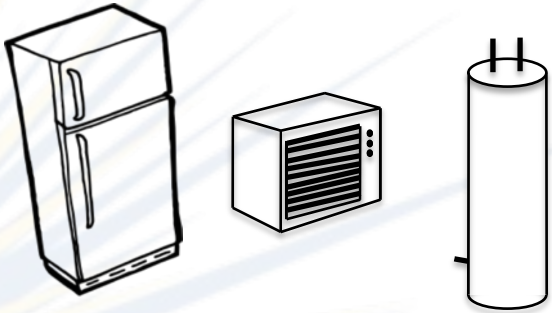
- DERs: distributed generation, storage, and responsive loads
- DER coordination can provide a variety of services to power systems
  - Frequency regulation and other ancillary services
  - Synthetic inertia and droop control
  - Transmission/distribution network constraint management, e.g., voltage control
  - Load shifting for peak load management
  - etc. etc.

DER Coordination: This Talk

- Thousands of "small" (a few kW) devices coordinated to provide frequency control



My Favorite DERs



- Thermostatically Controlled Loads (TCLs)
  - Refrigerators, water heaters, air conditioners, space heaters
  - On/Off control within a temperature dead-band
  - Store thermal energy
- Existing, small-scale distributed batteries
- (Water pumping)

Other DERs

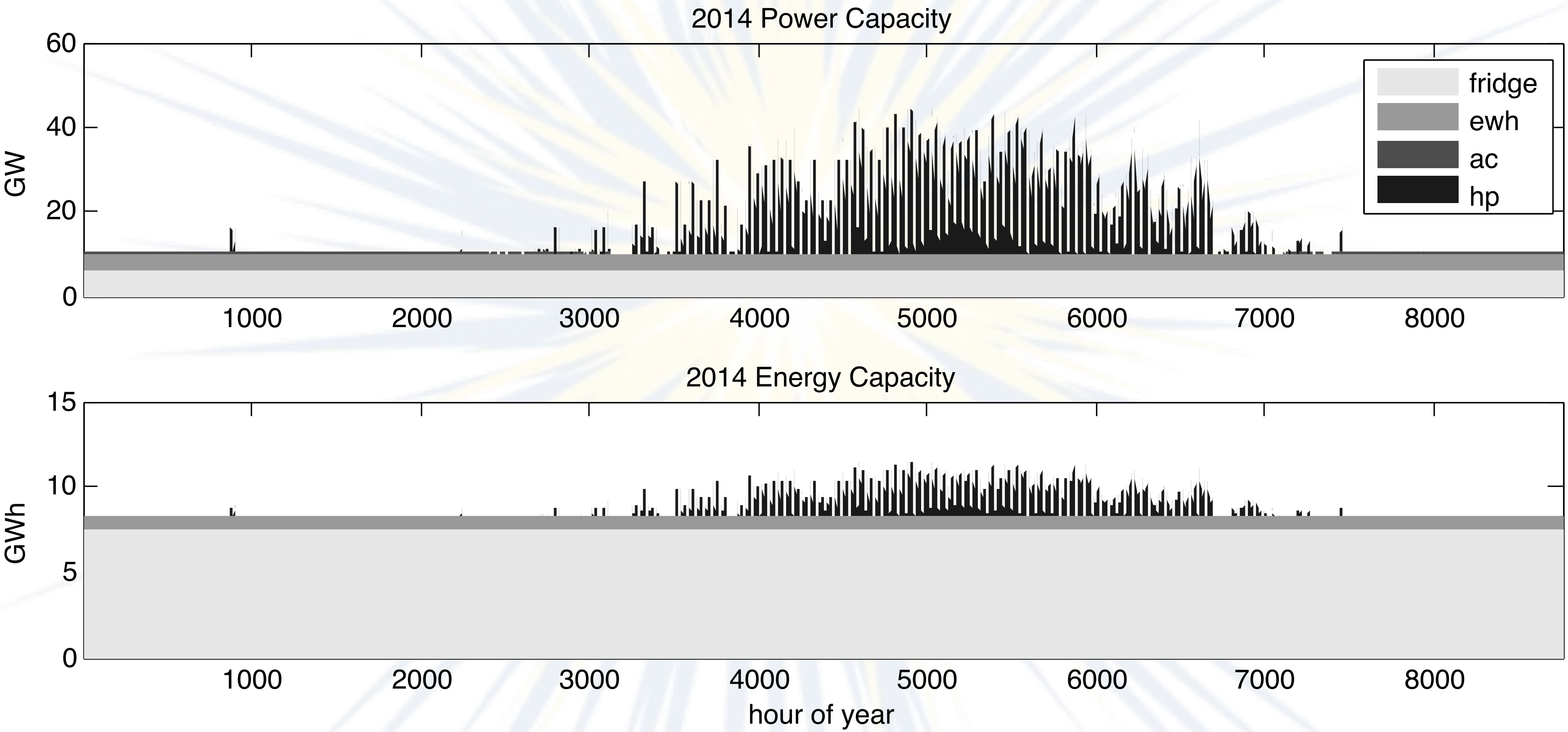
DERs I'm less fond of…

- Commercial buildings
- Purpose-built storage

DERs I won't talk much about (directly)

- Distributed solar and wind

Principle 1: Use what we've already got



[Mathieu, Dyson, Callaway 2015]

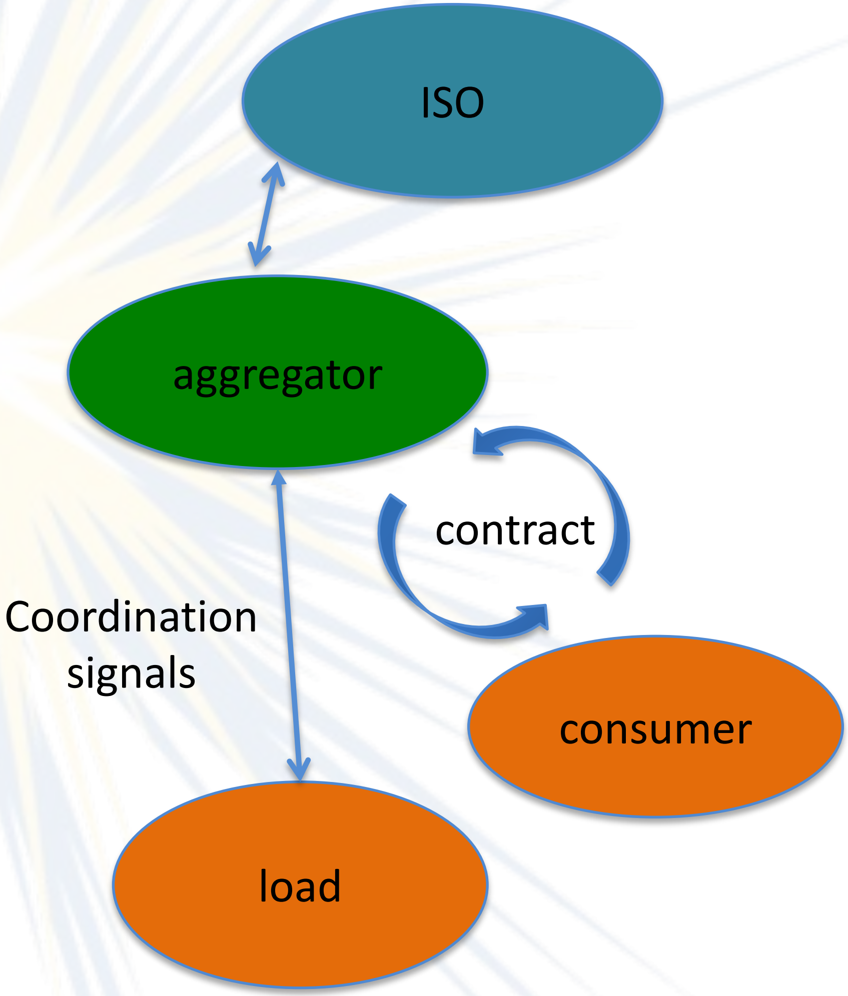
But this is hard!

- Need to coordinate A LOT of relatively small DERs
- Each DER has something it needs to do, e.g.,
  - TCLs providing heating/cooling
  - Distributed batteries powering cars, smoothing solar photovoltaic power, etc.

and we must ensure it can still do it, while additionally doing something for the grid

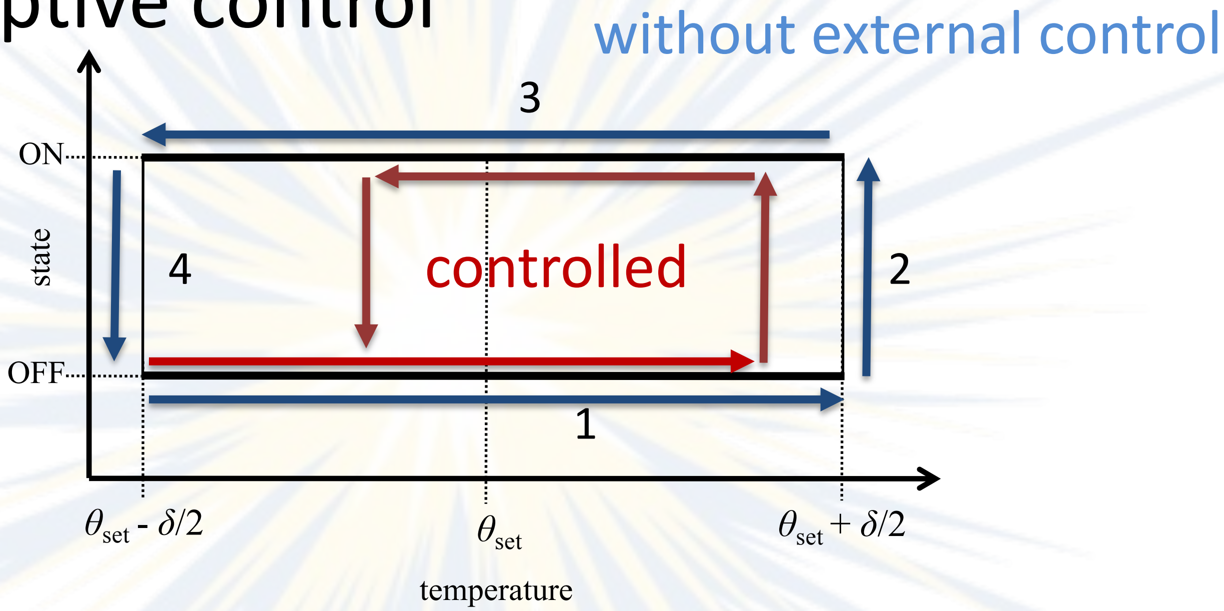
Principle 2: Don't annoy the consumers

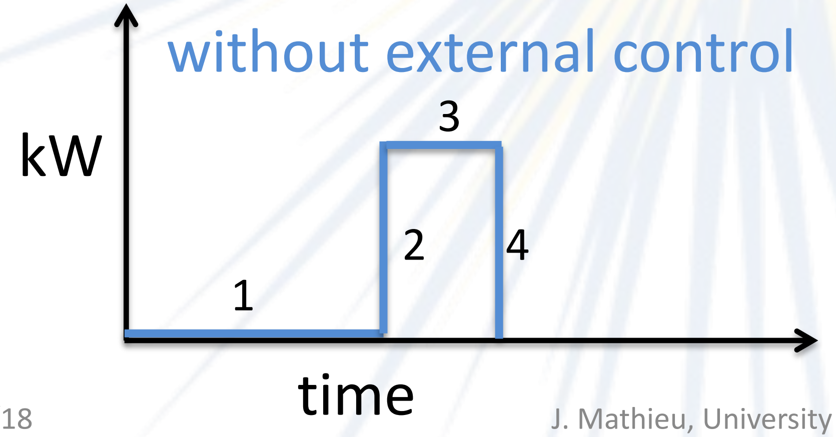
- Contracts, not prices to devices (or transactive energy?)

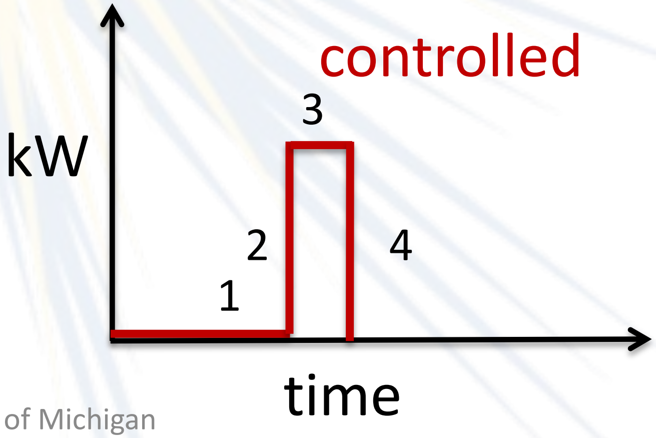


Principle 2: Don't annoy the consumers

- Nondisruptive control

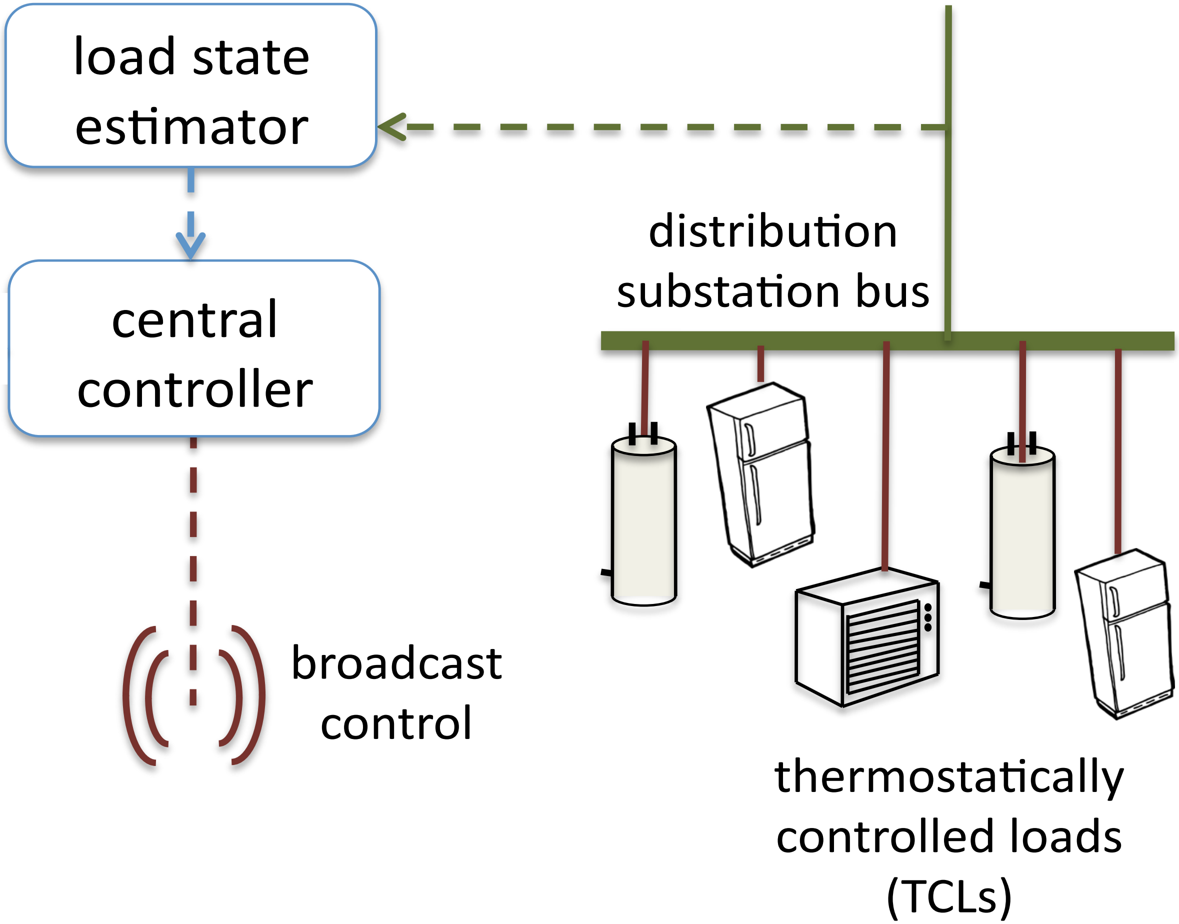






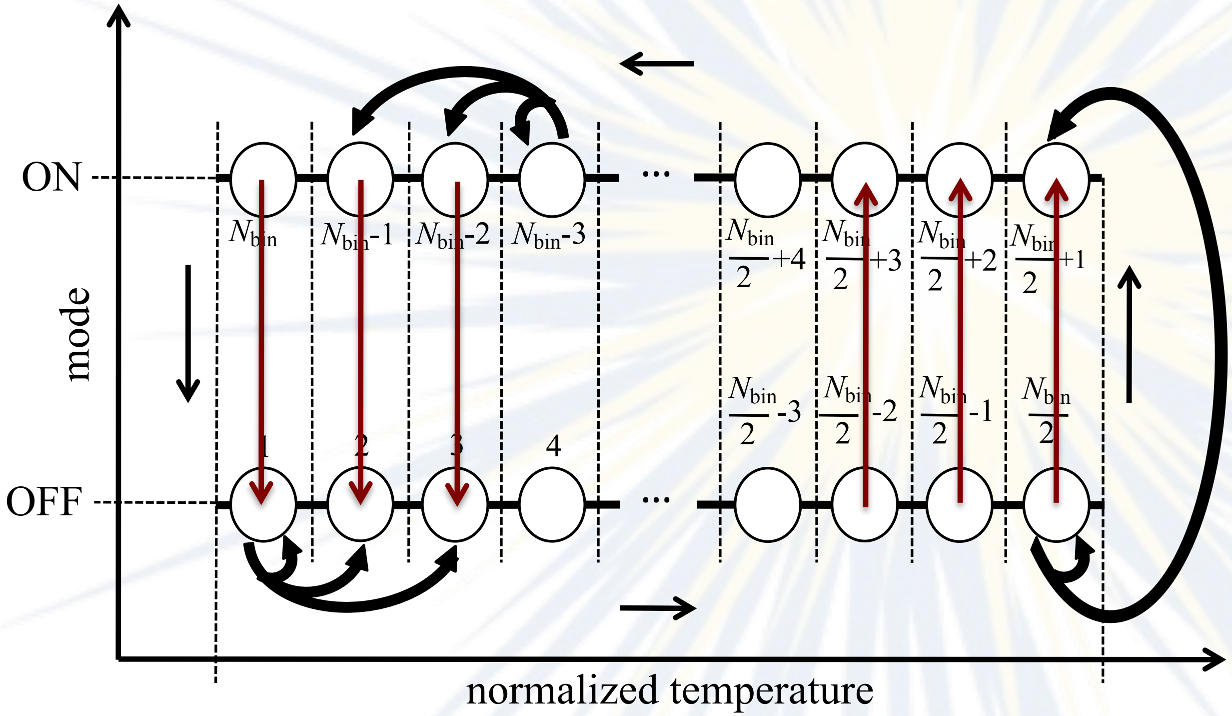
Principle 2: Don't annoy the consumers

- Consumer privacy



Principle 3: Minimize measurement & communication requirements

- Example A: [Mathieu, Koch, Callaway 2013]



[Similar to that proposed by Lu & Chassin 2004; Lu et al. 2005; Bashash & Fathy 2011; Kundu et al. 2011]

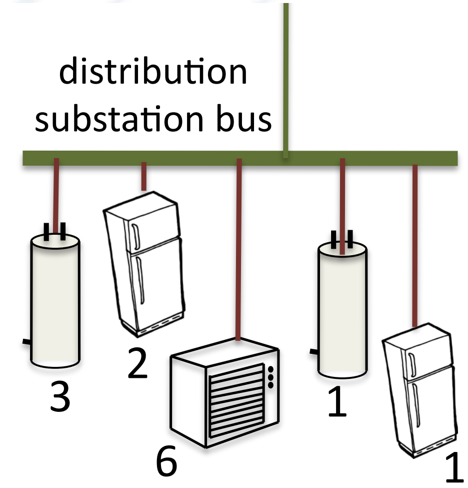
- Divide the dead-band into temperature intervals.
- Divide each temperature interval into two bins.
- A Markov Transition Matrix describes the movement of *thousands of heterogenous TCLs* around the dead-band.
- We can force the system to consume:
  - less power
  - more power

→ Linear time varying system model!

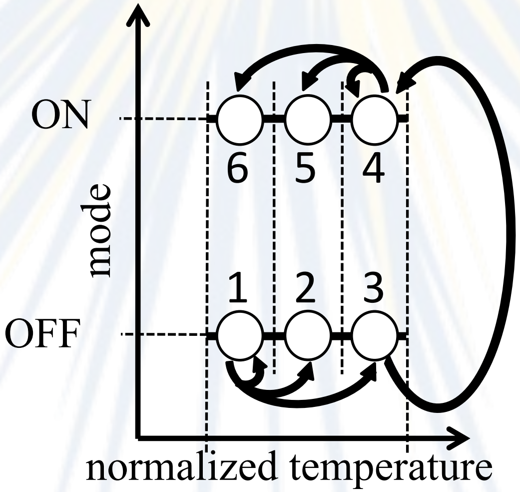
Probabilistic Control via Broadcasts

broadcast control

mode	state	input
OFF	1	0.2
	2	0.1
	3	0.3
ON	4	0
	5	0
	6	0



thermostatically controlled loads (TCLs)



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Control performance across different sensing/communication scenarios

Scenario 1:

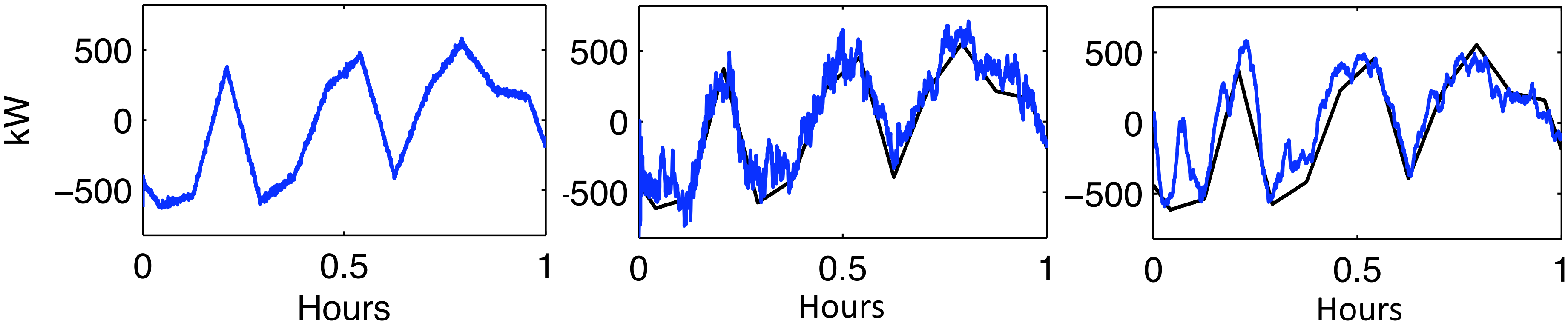
- Identify model with historical data
- Measure/communicate state in real-time

Scenario 2:

- Identify model with historical data
- Estimate state from substation power measurements

Scenario 3:

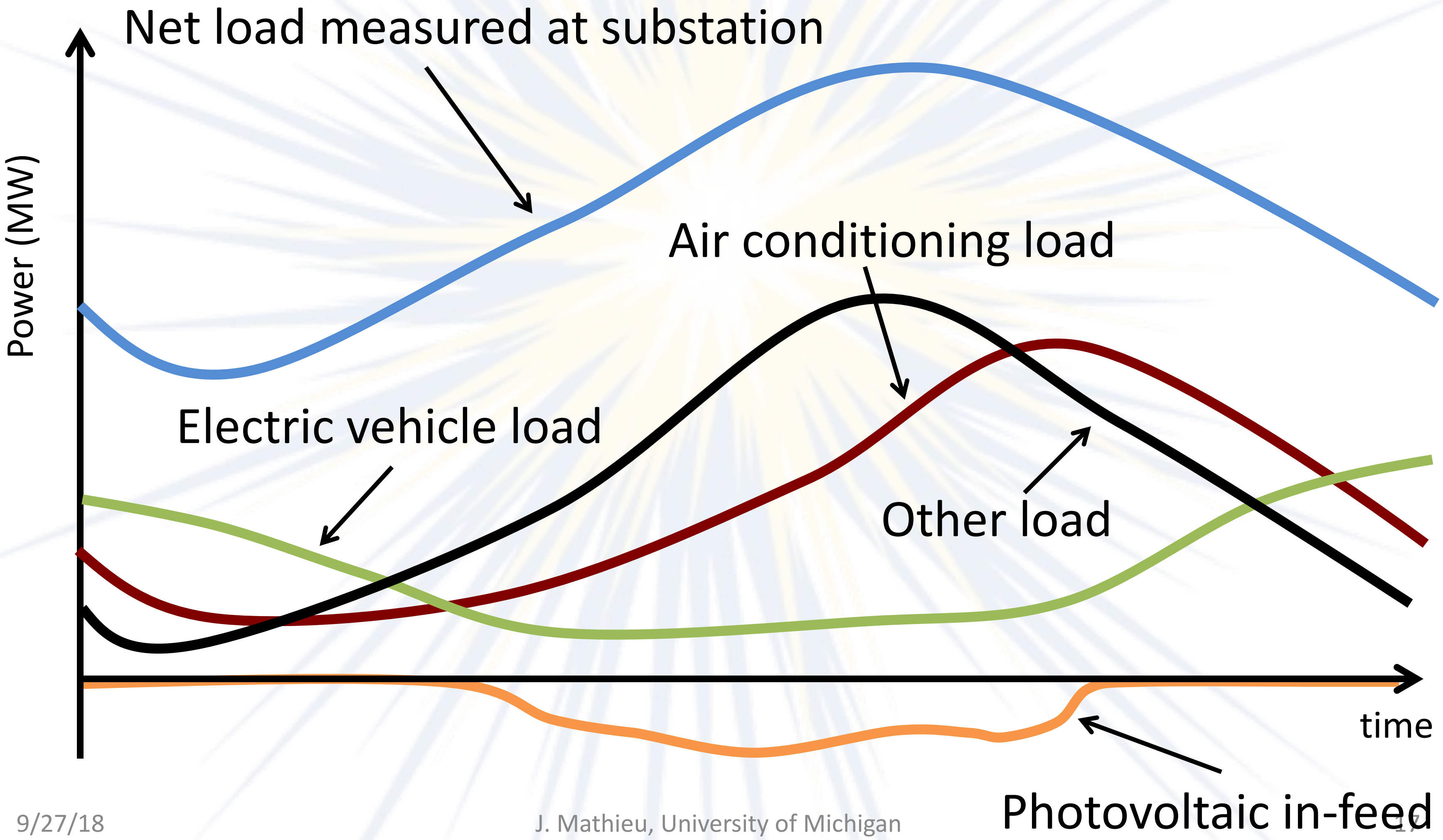
- Model learned in real-time
- Estimate state from substation power measurements



How do we ”measure” TCL aggregate power at the substation?

Principle 3: Minimize measurement & communication requirements

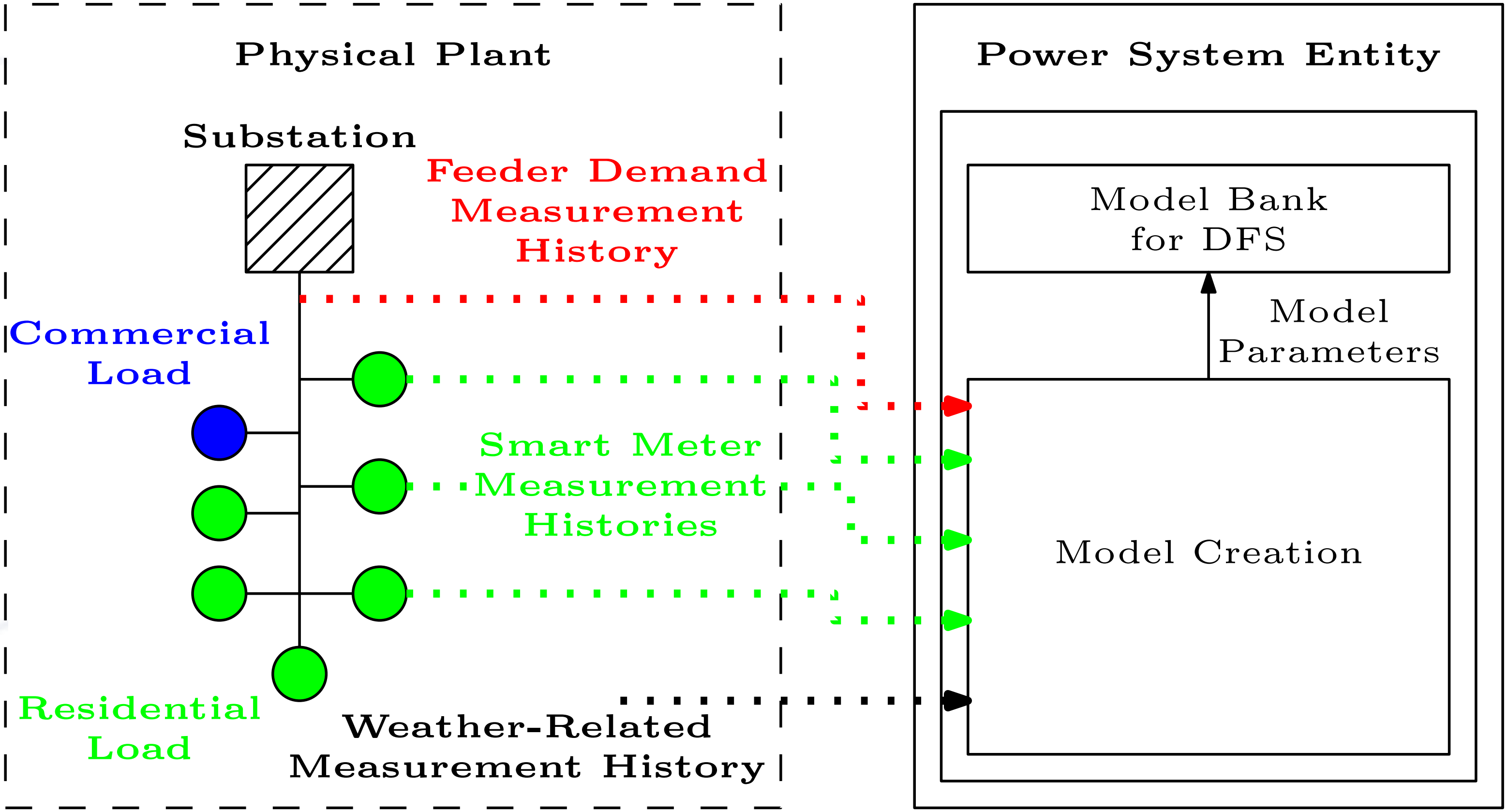
- Example B: [Ledva, Balzano, Mathieu 2018]



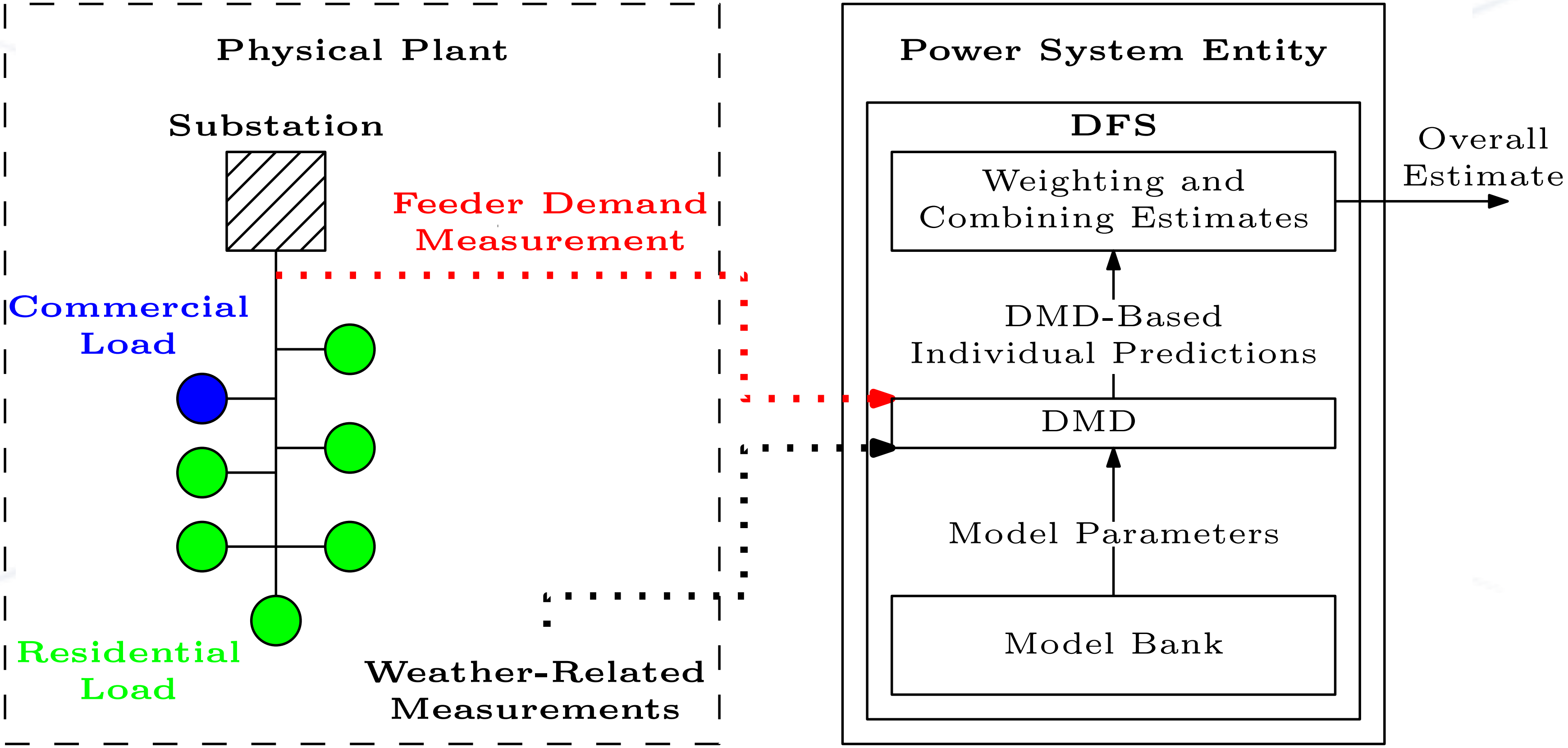
Possible methods

- Short-term load (component) forecasting
  - Doesn’t incorporate real-time feedback
- State estimation
  - Linear techniques require linear system models
  - Nonlinear techniques can be computationally demanding
- Online learning
  - (Typically) data-driven, “model-free”
- Hybrid approach: Dynamic Fixed Share & 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

Problem Framework: Offline Model Generation



Problem Framework: Real-time Estimation



Dynamic Mirror Descent

[Hall & Willet 2015]

For each model m we compute

1. an observation-based update

$$\widetilde{\theta}_t^m = \arg\min_{\theta\in\Theta} \eta^{\mathrm{s}} \left\langle \nabla \ell_t(\widehat{\theta}_t^m),\ \theta \right\rangle + D\left(\theta \| \widehat{\theta}_t^m\right)$$

where $\ell_t(\widehat{\theta}_t^m)$ is a convex loss function and D is a Bregman divergence function

2. a model-based update

$$\widehat{\theta}_{t+1}^m = \Phi^m(\widetilde{\theta}_t^m)$$

Dynamic Fixed Share

[Hall & Willet 2015]

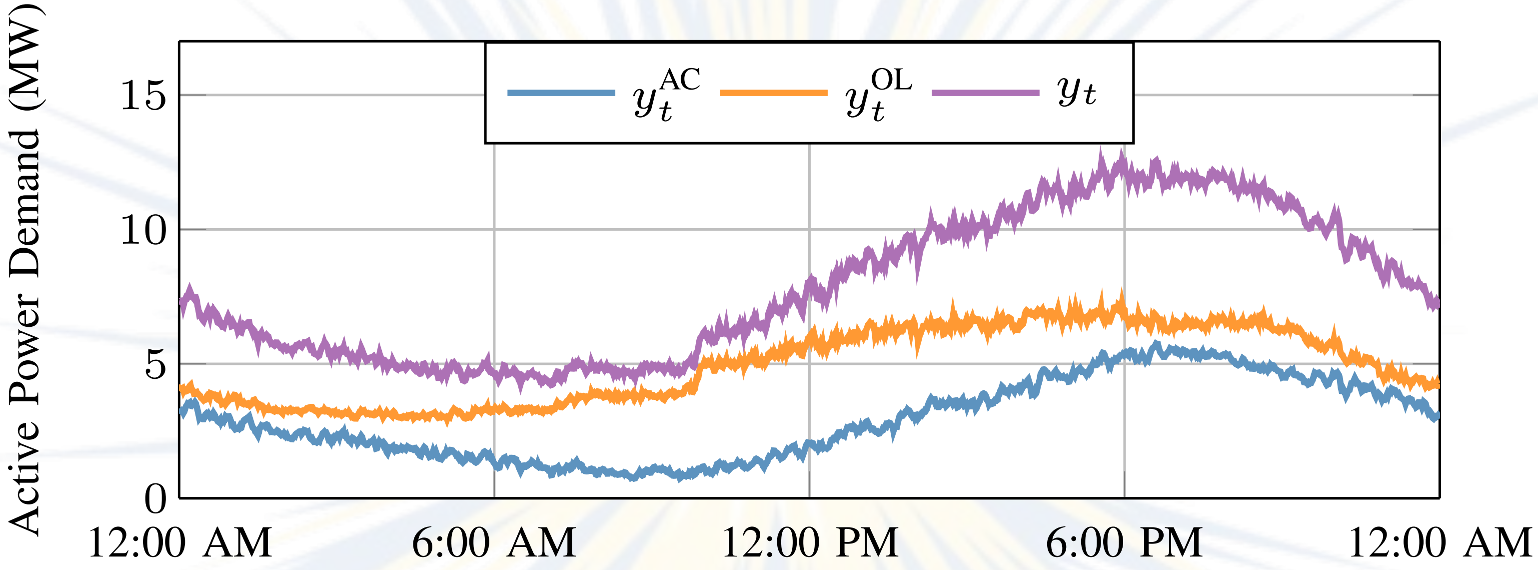
3. Next, we update the weight of each model

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

4. and compute the overall estimate.

$$\widehat{\theta}_{t+1} = \sum_{m \in \mathcal{M}^{\text{mdl}}} w_{t+1}^m \, \widehat{\theta}_{t+1}^m$$

Load models

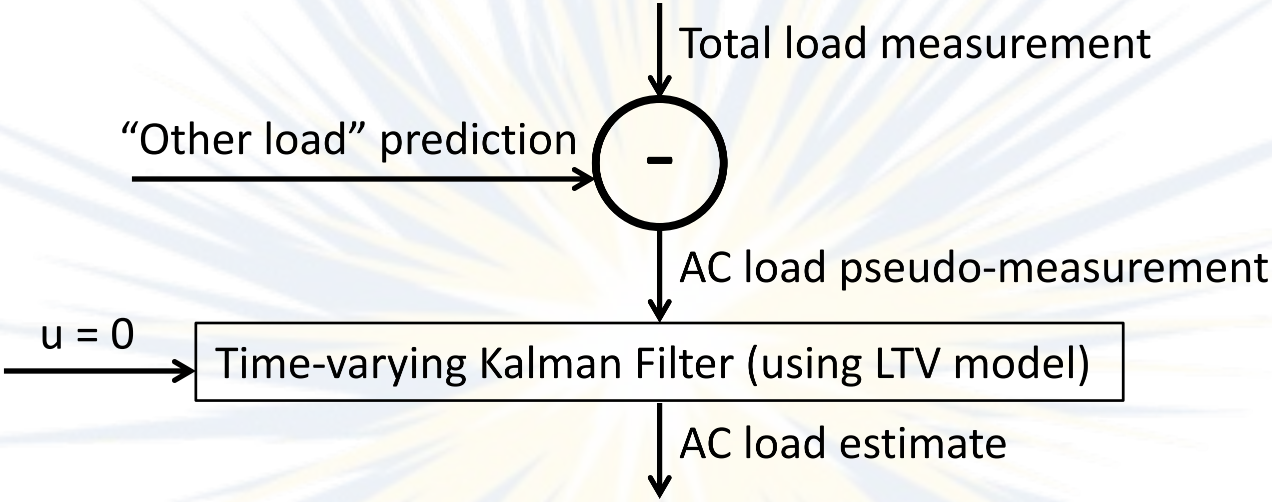


- 29 aggregate air conditioning load (AC) models
- 6 “other load” (OL) model
- 1 AC model + 1 OL model = 1 total load model
  → 174 total load models

Case study data

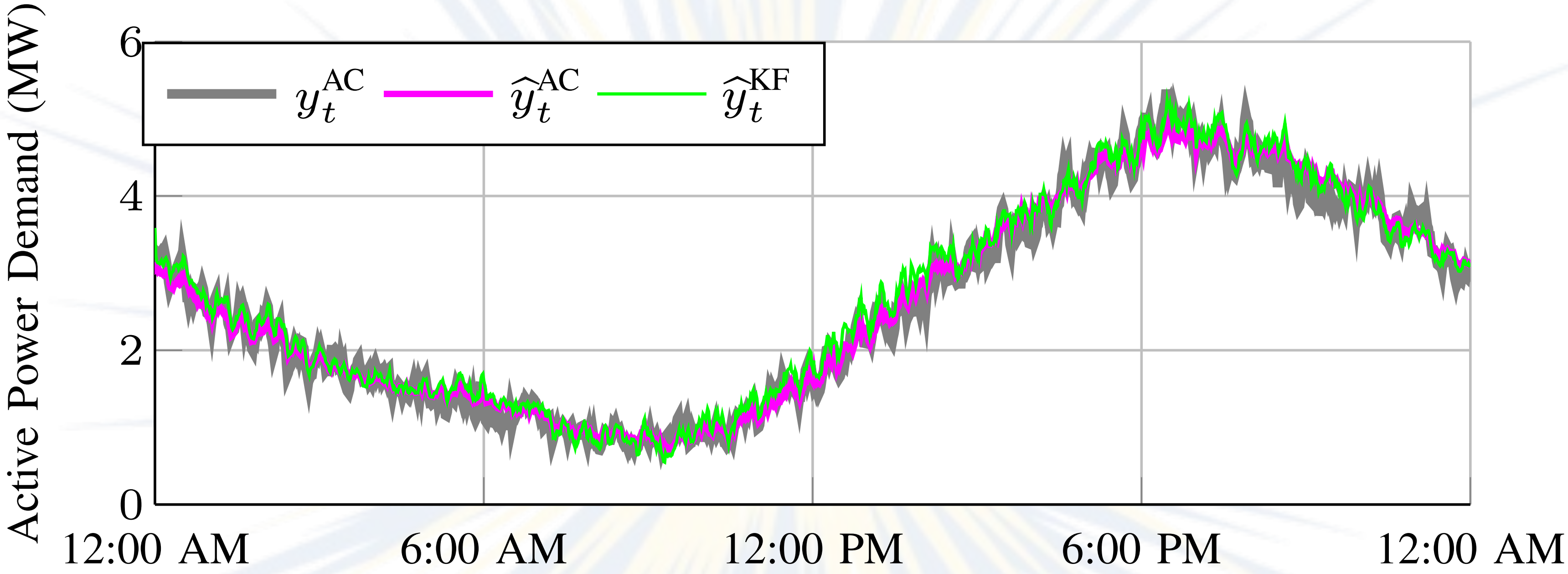
- Residential load and weather data from Pecan Street Dataport (Austin, TX)
- Commercial load data from Pacific Gas & Electric Company; weather data from NOAA (Bay Area, CA)
- GridLab-D feeder used to size the load

Case study benchmark



- Each "other load" model + LTV AC model combination is used to compute one AC load estimate.
- We obtain the estimates from all Kalman filters and compute the a posteriori best and average results.

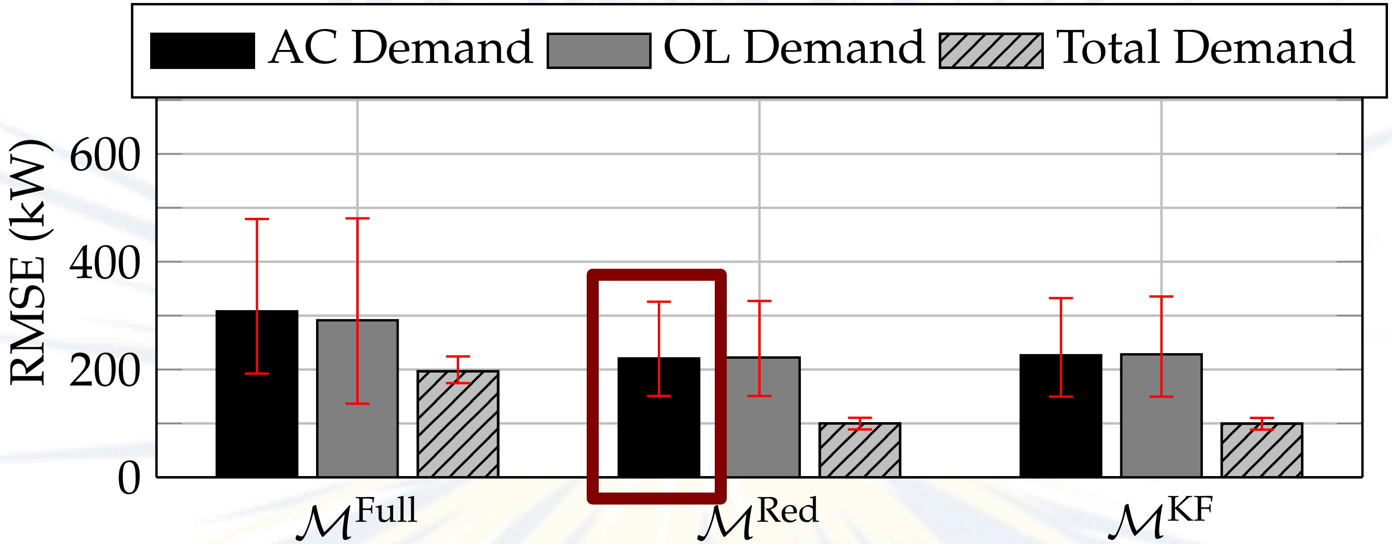
Example results



RMSE

DFS/DMD	151 kW
a posteriori best KF	177 kW
average KF	214 kW

Summary results



RMSE

	a posteriori best KF	average KF
Mean	195 kW	259 kW
Min	148 kW	173 kW
Max	319 kW	358 kW

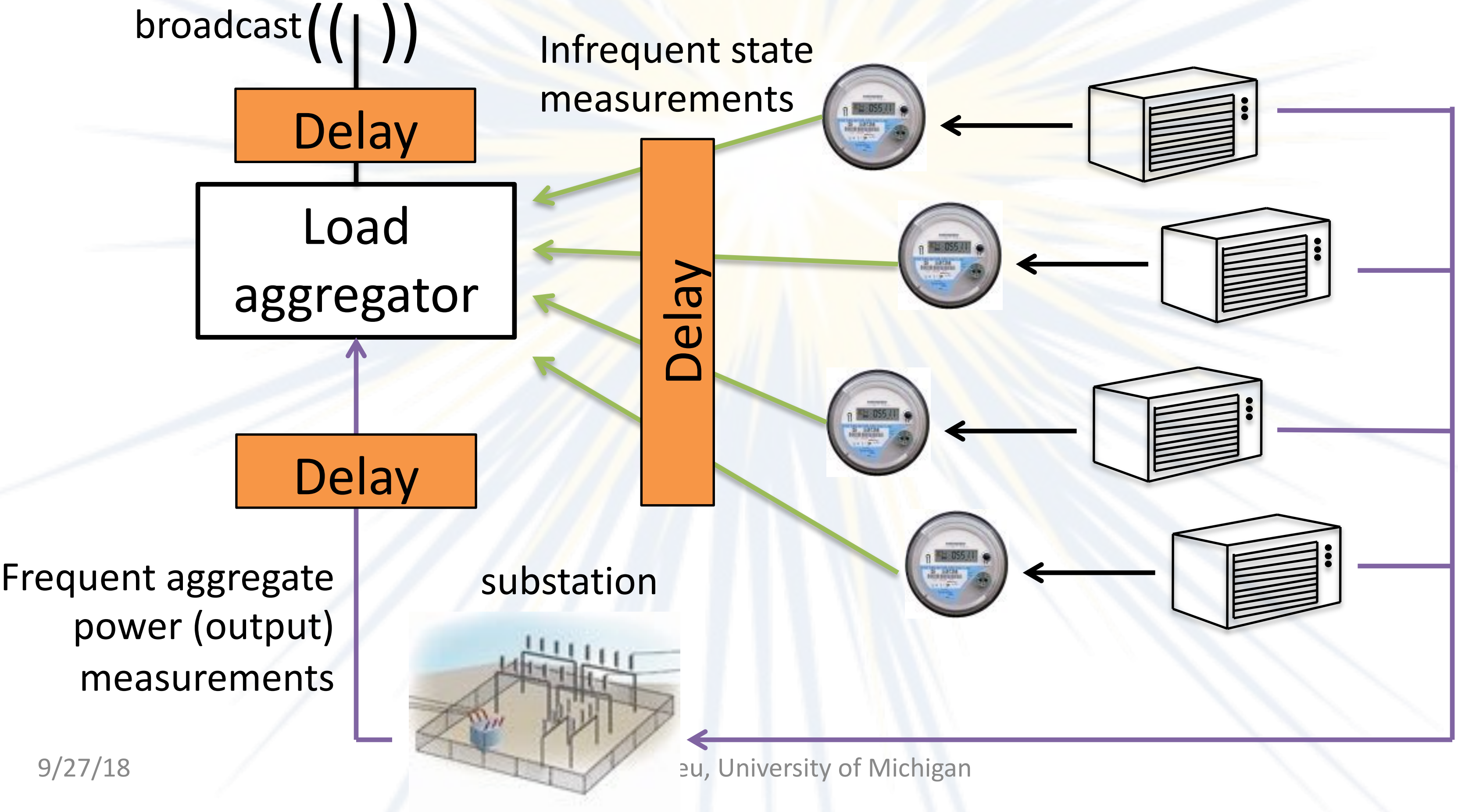
Back to the principles…

- “Estimation and learning is all well and good but your control approach still uses comm!”
  - From the aggregator to the loads (control input)
  - From the substation to the aggregator (output)

- Do we need communication?

Principle 4: If you use comm, make sure your approach works even with faulty comm

- Example C: [Ledva, Vrettos, Mastellone, Andersson, Mathieu 2018]



broadcast

Delay

Load aggregator

Delay

Infrequent state measurements

Delay

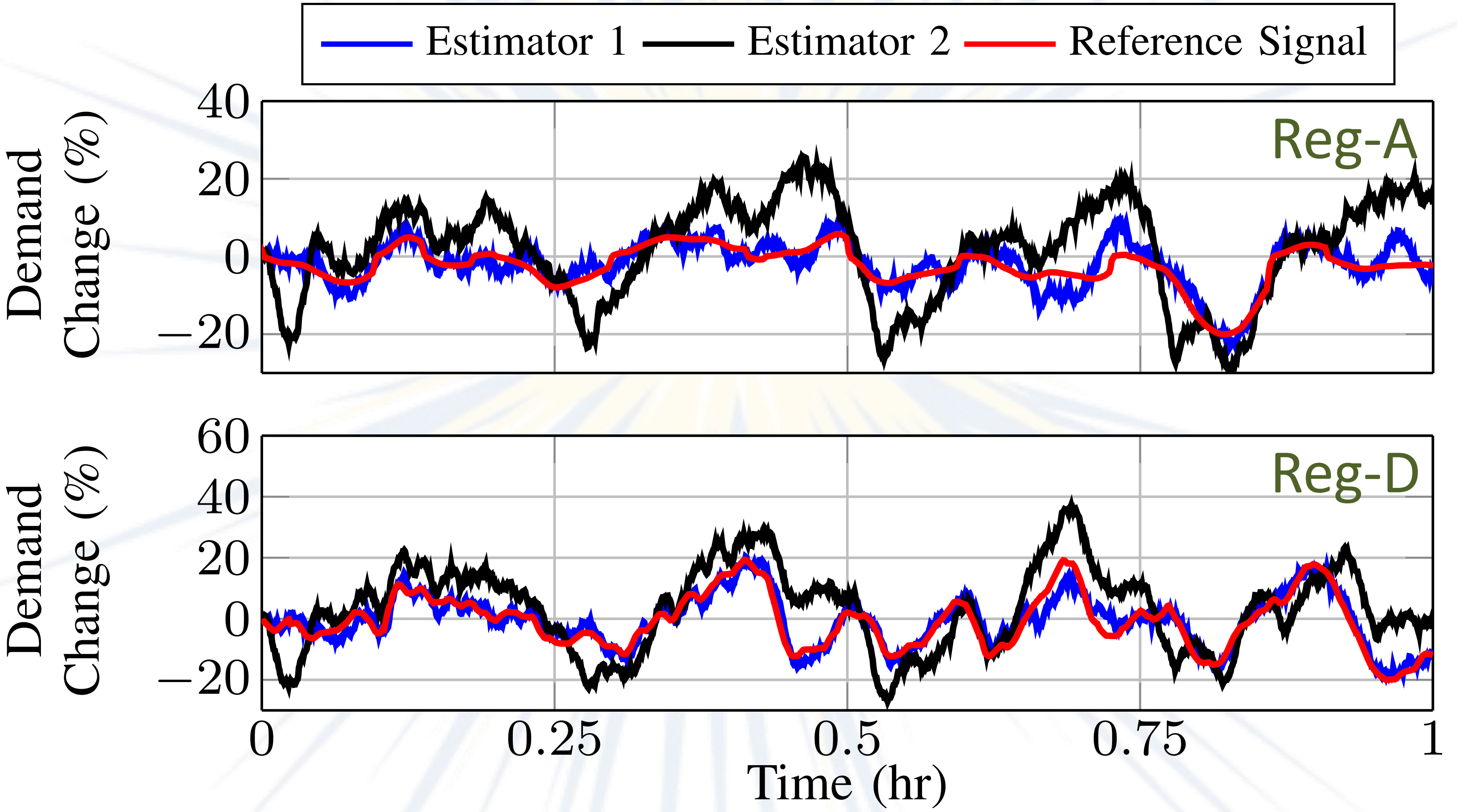
Frequent aggregate power (output) measurements

substation

Methods

- Estimation: Kalman filtering with asynchronous measurements
  - Estimator 1: Uses one Kalman filter per load
  - Estimator 2: Uses individual load models for predictions and a single Kalman filter
- Control: model predictive control using knowledge of delay distributions and past control inputs

TCLs tracking PJM regulation signals (20 second input delay, delayed state measurements every 15 minutes)

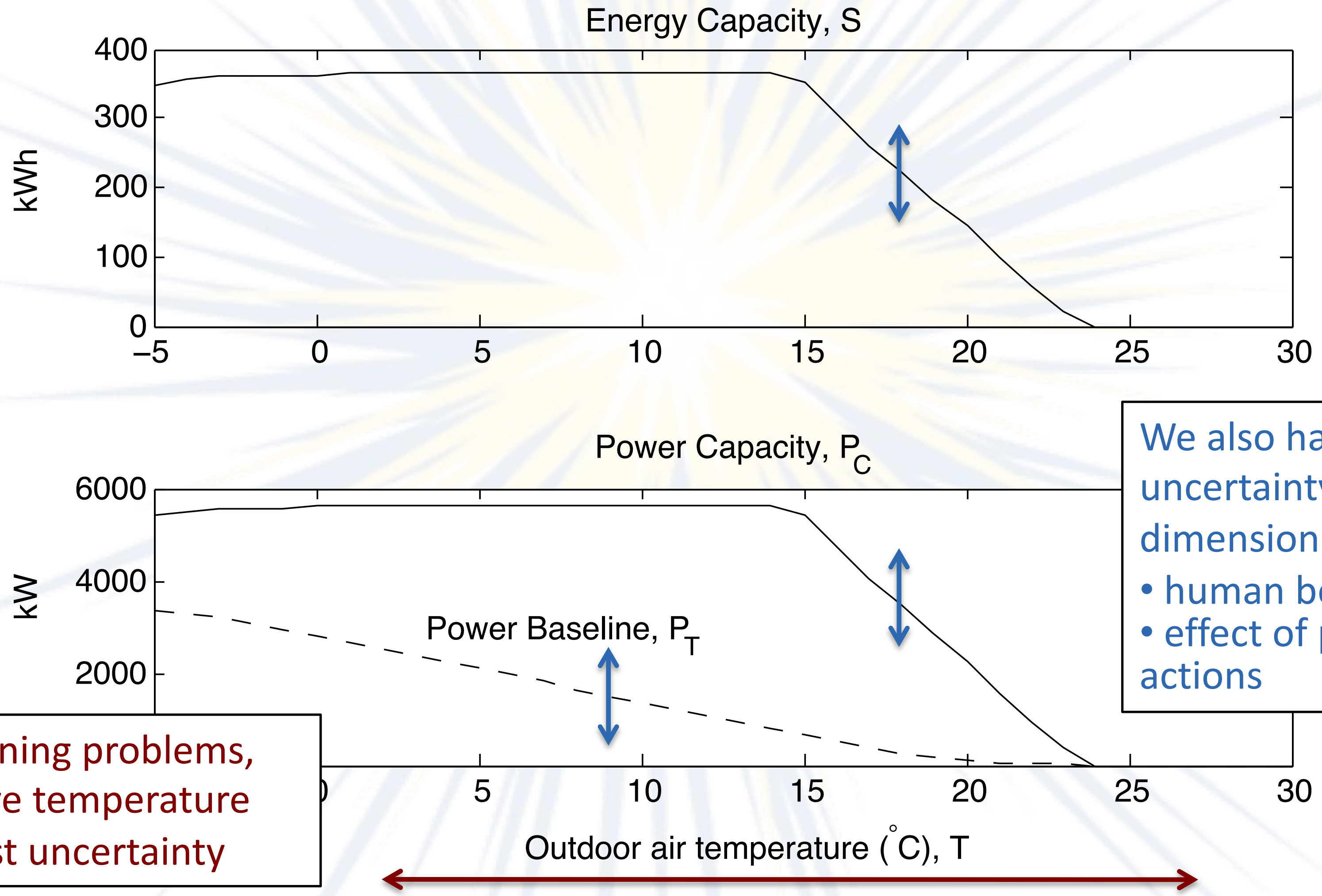


Principle 5: Plan for uncertainty

- Weather, people, …
- Uncertain control responses
  - Use feedback control
- Uncertain capacity: System operator’s perspective
  - Example D: [Vrakopoulou, Li, Mathieu (in press); Li, Vrakopoulou, Mathieu (in press)]
- Uncertain capacity: Aggregator’s perspective
  - Example E: [Mégel, Mathieu, Andersson 2015]

An uncertain and time-varying thermal battery

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

Stochastic Optimal Power Flow with Uncertain Reserves

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

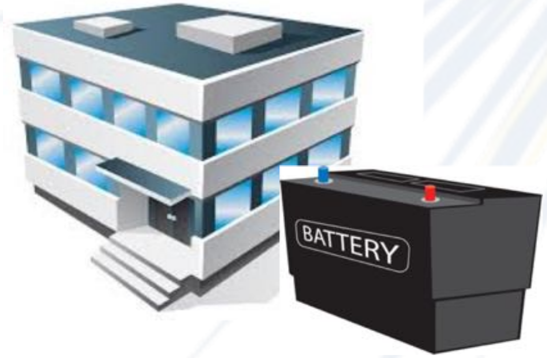
subject to *power flow equations* ← wind uncertainty
generation constraints
line constraints
controllable load constraints ← load control uncertainty
…

Decision variables: generator and load power set points, generator and load reserve capacity, participation factors

Storage Multitasking & Aggregation

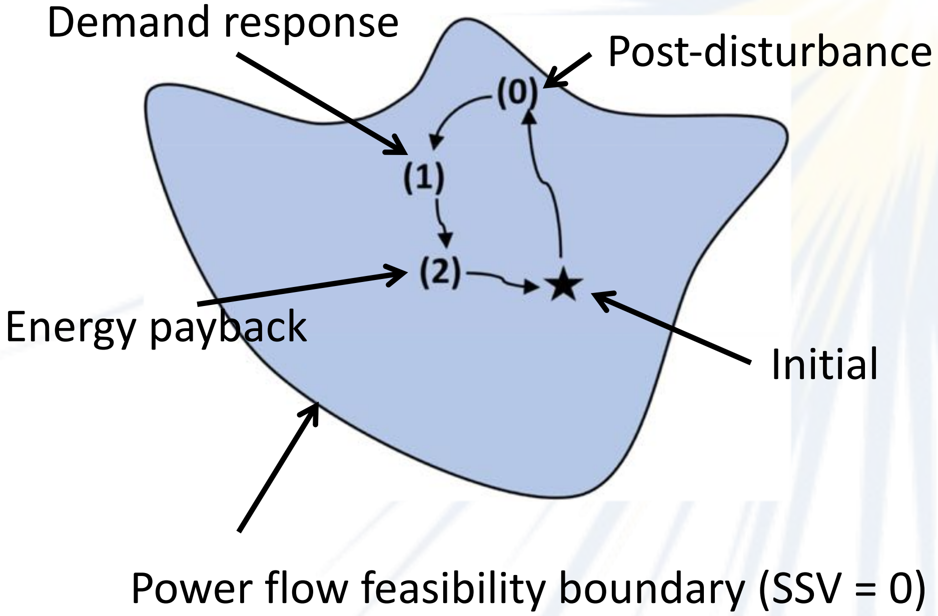
How much energy/power capacity should be allocated to each local service (individually) and to frequency regulation (in aggregate)?

Methods: model predictive control, stochastic dual dynamic programming



Principle 6: Once you have a population of coordinated DERs, do as much as you can with it

- Leverage multiple value streams
- Example F: [Yao, Molzahn, Mathieu 2017]



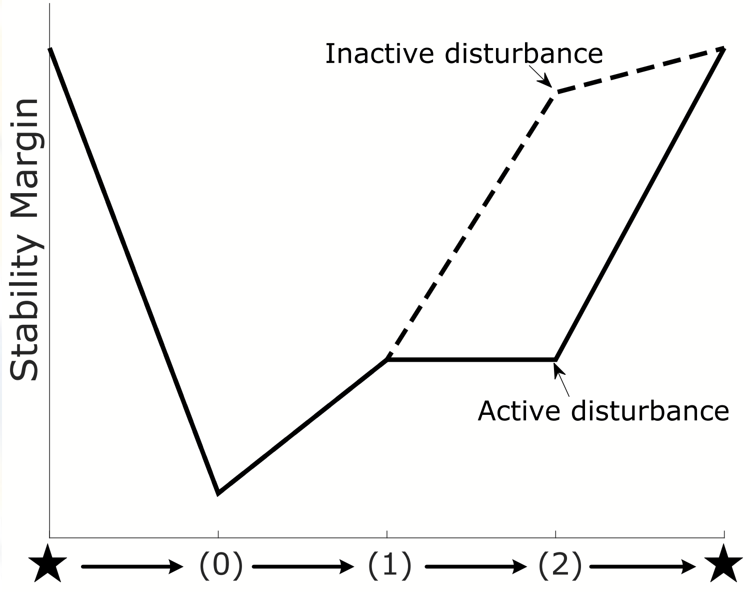
Demand response

Post-disturbance

Energy payback

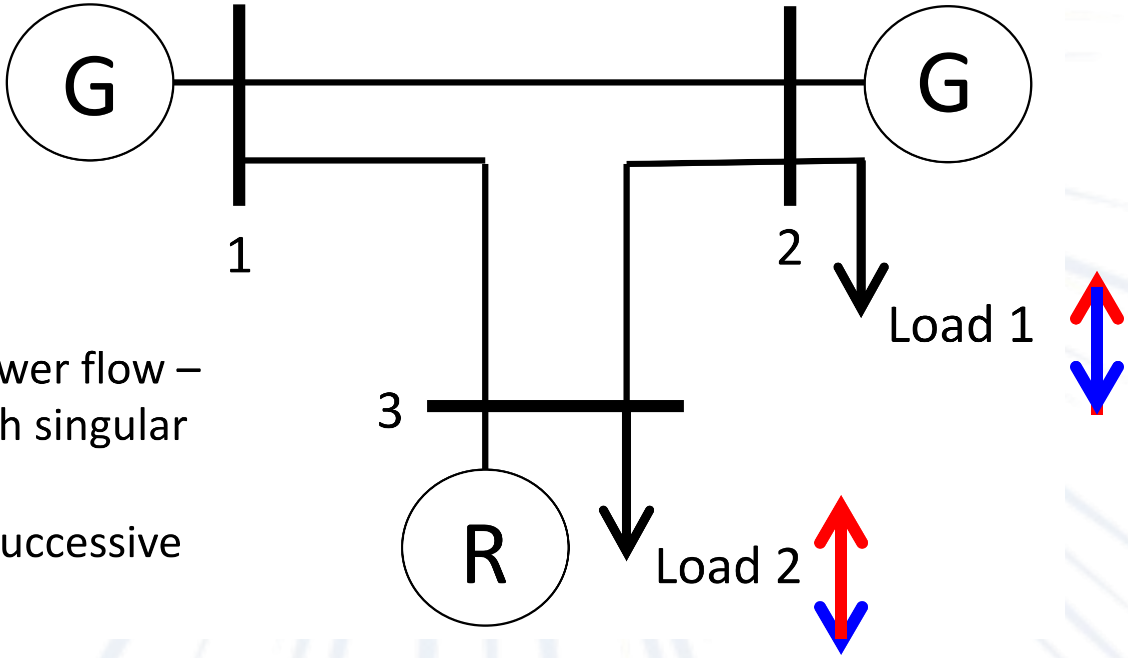
Initial

Power flow feasibility boundary (SSV = 0)



Using Demand Response to Improve Voltage Stability

- Objective: maximize the smallest singular value (SSV) of the power flow Jacobian via spatial shifting of flexible load
- Constraint: total demand held constant over time to maintain frequency stability



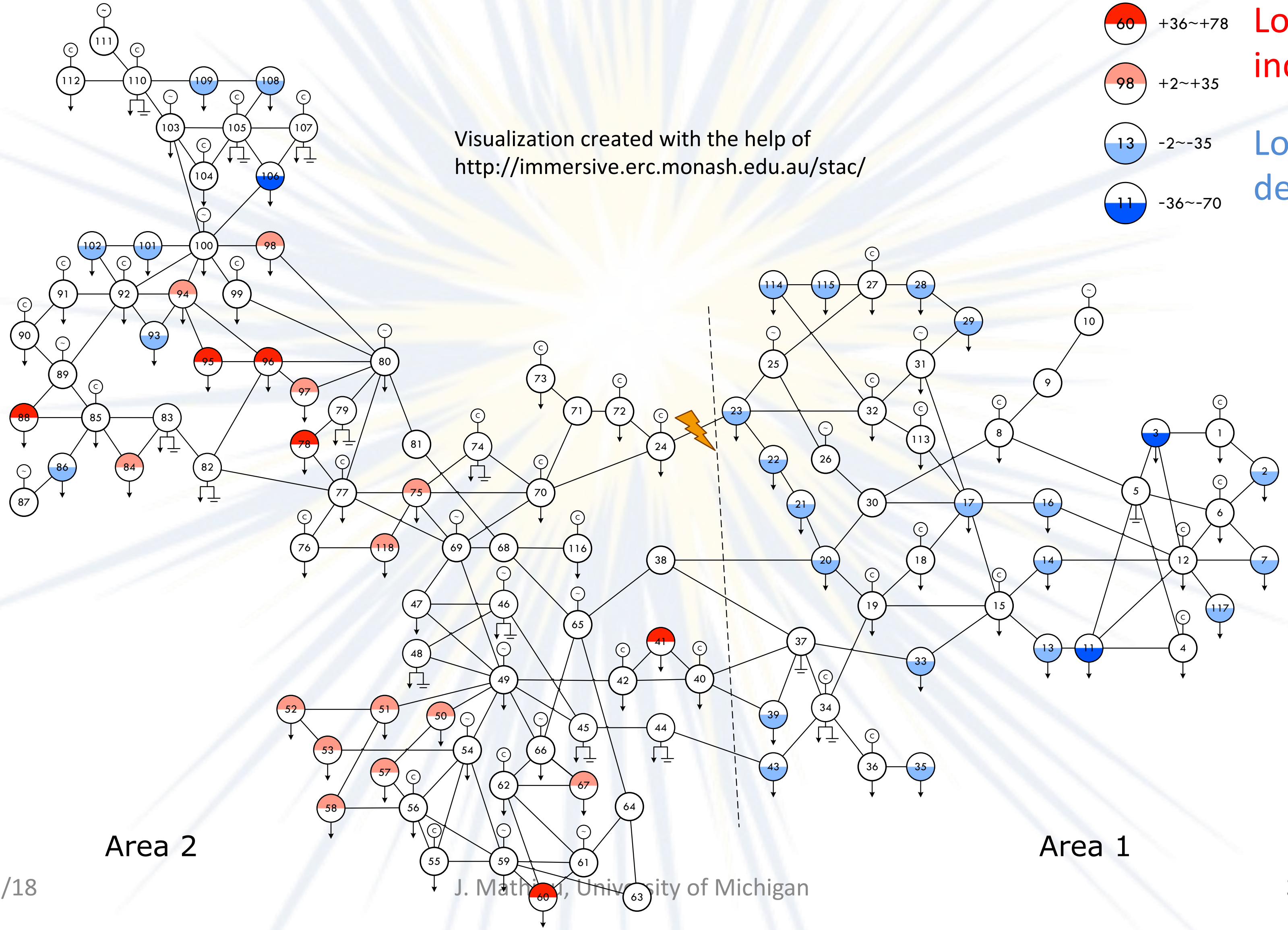
Method: Optimal power flow – type formulation with singular value sensitivities

Solution approach: Successive linear programming

Loading changes in IEEE 118-Bus System

Visualization created with the help of
http://immersive.erc.monash.edu.au/stac/

🟥 60	+36~+78	Load increase
🟥 98	+2~+35	
🟦 13	-2~-35	Load decrease
🟦 11	-36~-70	



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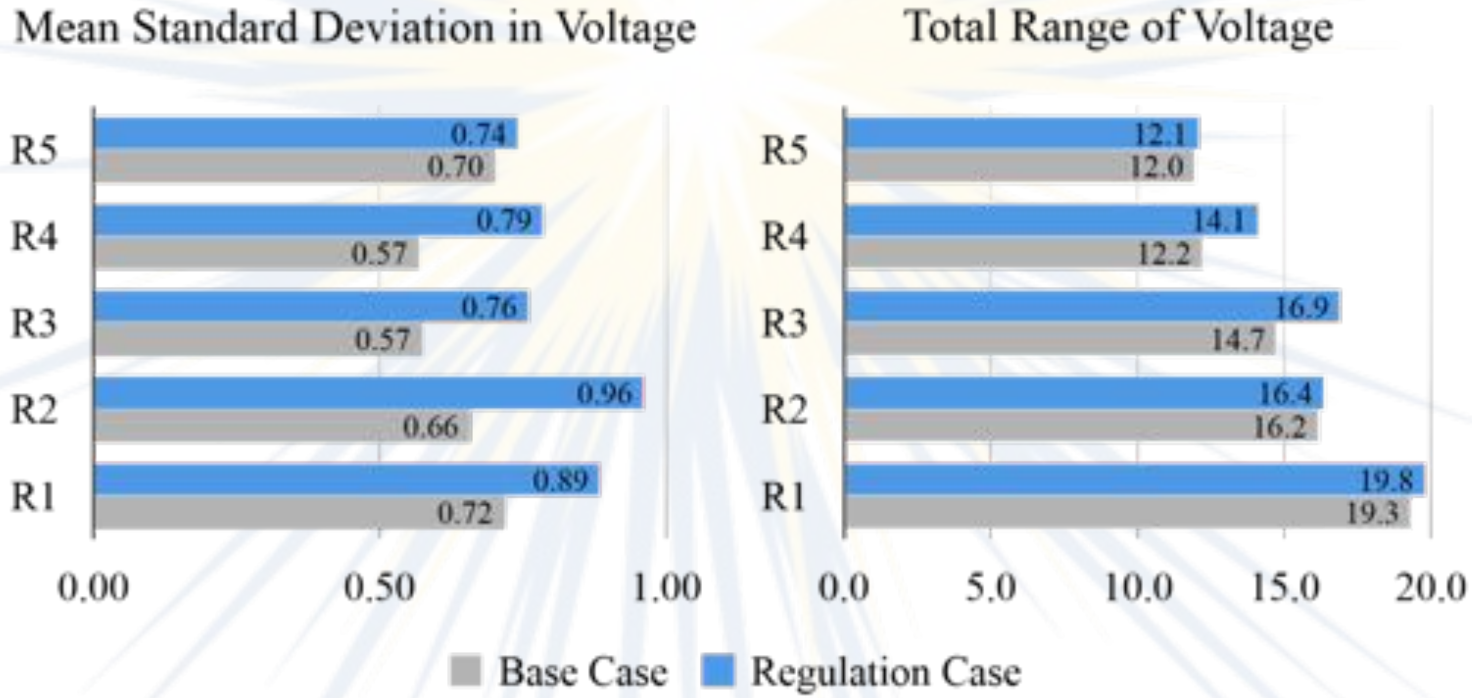
Principle 7: Do no harm

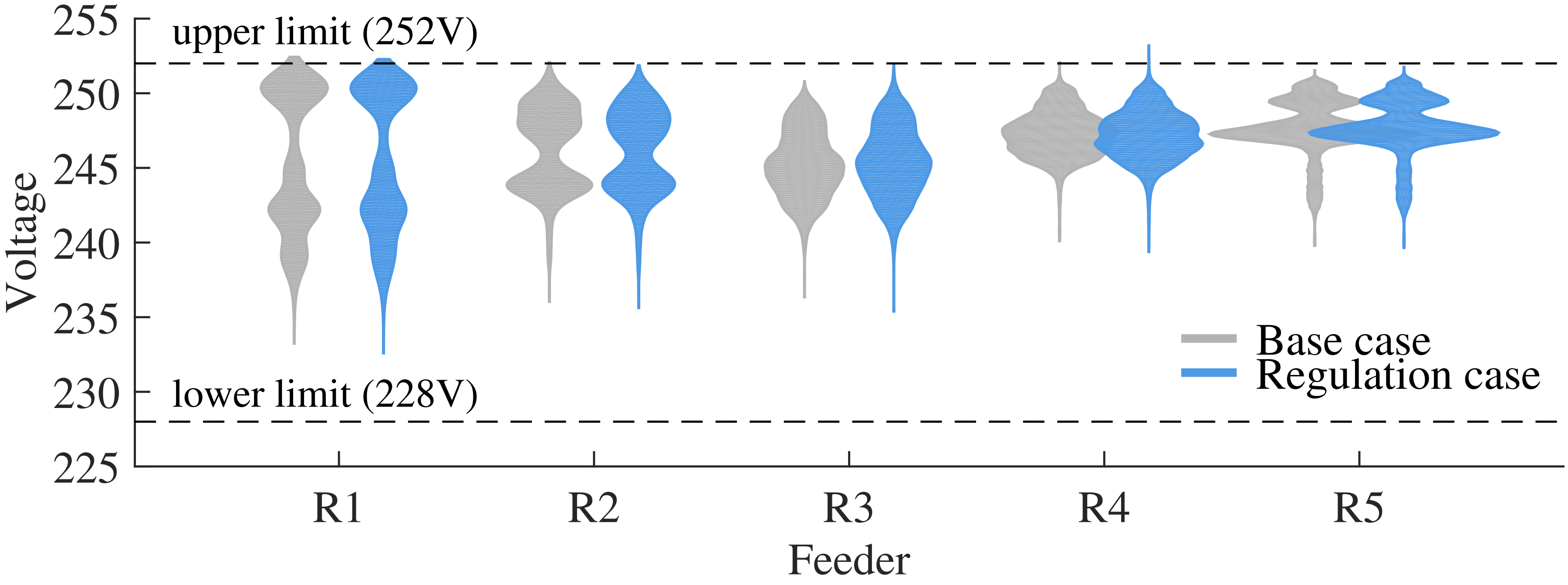
- Network impacts: constraints, nonlinear dynamics
- Example G: [Ross, Vuylsteke, Mathieu (in press)]



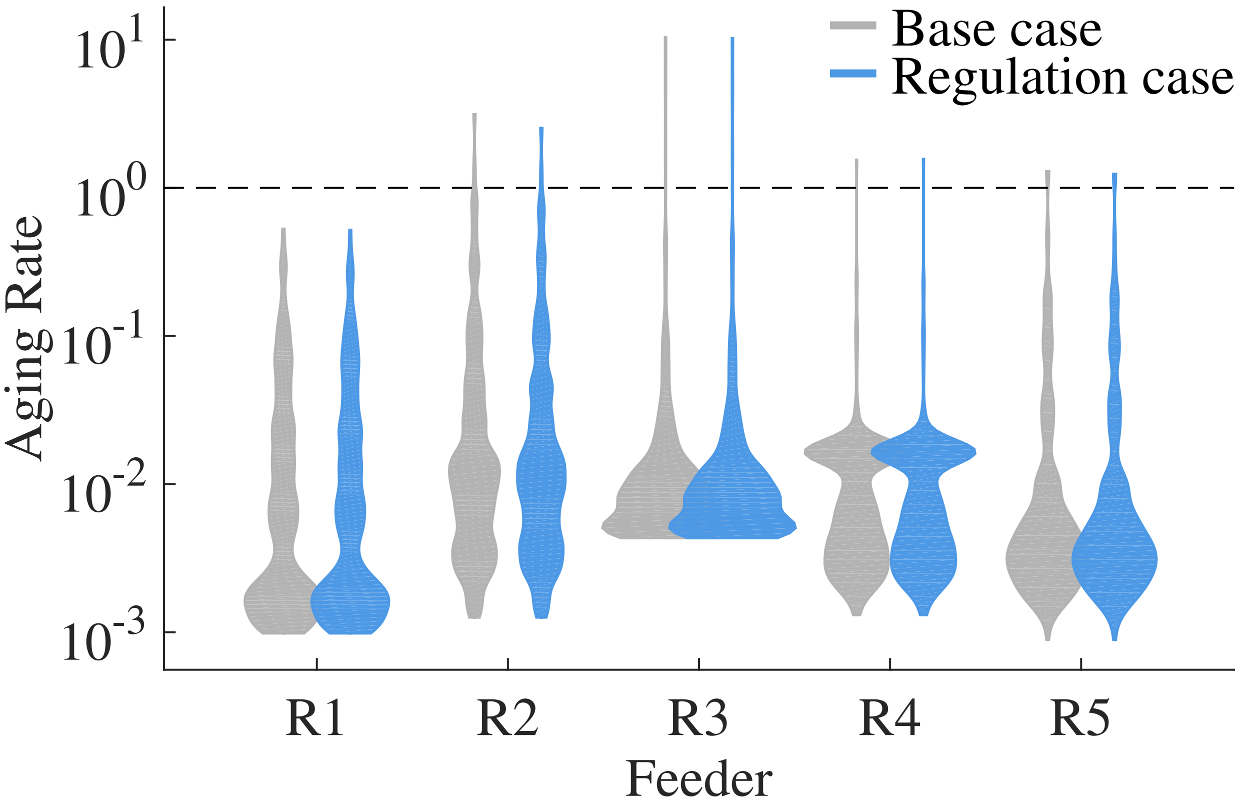
Mean Standard Deviation in Voltage

Total Range of Voltage

Voltage distributions



Transformer Aging



Summary

1. Use what we've already got
2. Don't annoy the consumers
3. Minimize measurement & communication requirements
4. If you use comm, make sure your approach works even with faulty comm
5. Plan for uncertainty
6. Once you have a population of coordinated DERs, do as much as you can with it
7. Do no harm

Concluding thoughts

- This list isn’t exhaustive – regulatory, political, practical, social issues…
- Some of these things might be controversial

- What’s our true goal here?
  - Environment + health, economics, reliability
  - Is DER coordination necessary? If so, how do we do it right?