A Survey of Control Techniques for Distributed Electric Load Management with Implications to Market Design

Sean Meyn

COGNITION & CONTROL IN COMPLEX SYSTEMS

Department of Electrical and Computer Engineering — University of Florida

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Acknowledgements

Fun with randomized policies is all with Ana Bušić!

Going back a dozen years, beggining with intelligent swimming pools (!) [14]

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Acknowledgements

More on markets in this new survey

ANNUAL REVIEWS

Annual Review of Control, Robotics, and Autonomous Systems

Control Engineer Roles in the Next Power Market Transition

Hala Ballouz,[1] Joel Mathias,[2] Sean Meyn,[3] Robert Moye,[4] and Joseph Warrington[5]

[1]Electric Power Engineers, Austin, Texas, USA

[2]Midcontinent Independent System Operator (MISO), Carmel, Indiana, USA

[3]Department of Electrical and Computer Engineering, University of Florida, Gainesville, Florida, USA; email: meyn@ece.ufl.edu

[4]Tyr Energy, Overland Park, Kansas, USA [5]AstraZeneca, Cambridge, United Kingdom

https://www.annualreviews.org/content/journals/10.1146/annurev-control-030323-023057

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And this old survey, *electricity rates for the zero marginal cost grid*, [9]

The electricity industry is rapidly changing: costs are increasingly dominated by capital and technology is turning loads into resources. This is similar to the early days of the Internet. Building on rate-structures used in the communications industry, utilities of the future should offer customers a portfolio of service contract options that provide a signal to the utility regarding the type and amount of infrastructure that should be deployed.

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Mathematical Economics today is in the state of Control Theory when I was a graduate student. In those days, "important men "would declare that one approach is pristine and the others tainted—fights among the three flavors in vogue: robust, optimal, and adaptive. It wasn't always explicit in public, but I remember some passionate conversations. I moved away from my advisor's doctoral topic precisely because one of his colleagues (a compelling "great man") declared that adaptive control was nonsense.

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They could fight like this, claiming superiority via their theorems, only because there was no unbiased umpire to pick a winner. When computers became practical for realistic simulations we had the judge we needed so we could test theory against the closest thing to practice. We now know there is no winner, but lots of great alternatives for controlling complex systems. We need to test lots of alternatives because our mathematical models are always flawed.

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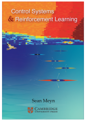
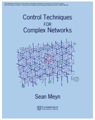
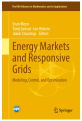
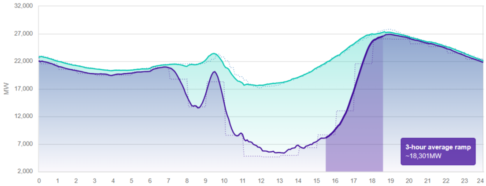
Mathematical Economics cannot survive in its current echo chamber.
The field needs to find its own umpire.

1. Load Control ... Blah Blah Blah
2. Distributed Control
3. Controlling the Fleet
4. Conclusions
5. References









What's most critical to Zibelman is the creation of liquidity and transparency in the marketplace, as well as erasing barriers to entry. "Regardless of whether it's one distributed platform provider or multiple utilities," she said, "I want—from the customer-facing and market-facing approach—for everything to be very consistent."

Unpacking the value of demand

One of the most radical ideas in the REV is that New York is having demand—as opposed to generation—be the state's primary energy resource.

"Rather than demand being the last resource you manage in the system, it's the first resource," Zibelman said. "Demand can respond much more quickly than any other resource."

Like many other regions in the country, New York has slowing overall demand for electricity, but a growing gap between peaks and non-peaks, which diminishes the overall efficiency of the electricity system.

Blah Blah Blah ...

Demand Dispatch **IS** the Answer

That's what everyone has been saying the past 100 years 🤣

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Look around the room, or consider your home.
Most energy consumption is flexible

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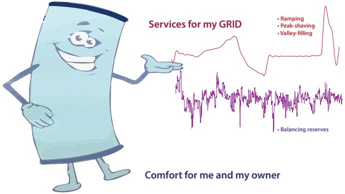
Image from IHP 2018:



Example: water heaters are inherently *energy storage devices*

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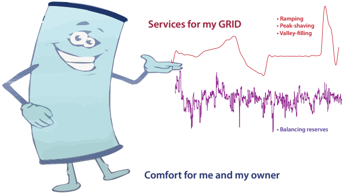

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We (engineers) can harness this flexibility to supply grid services.

Demand Dispatch

- Services from deferrable loads are **free** [aside from one-time fixed costs]

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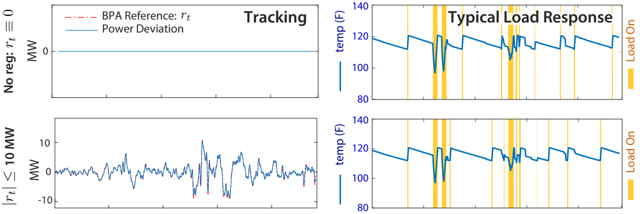
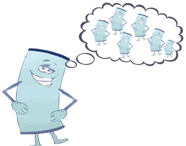
- With appropriate control architecture, they provide grid services surpassing utility scale storage [20, 18]





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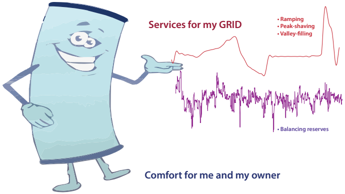
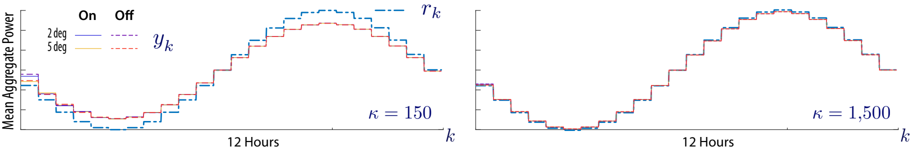


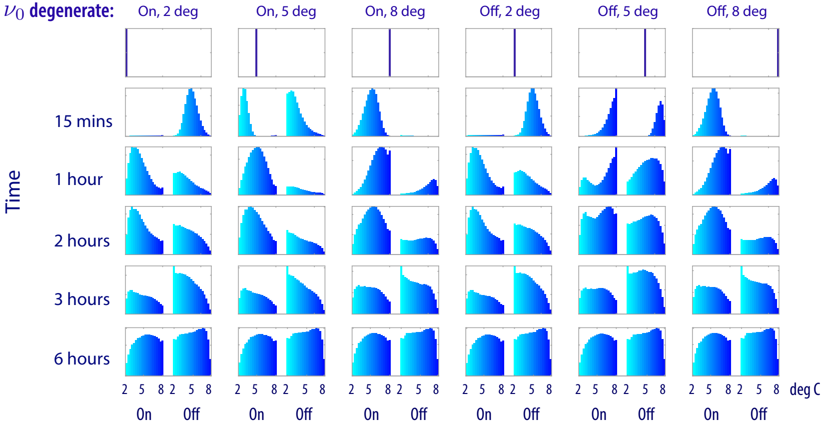
Arguments apply to other deferrable loads,

such as fans in commercial buildings, irrigation, ...



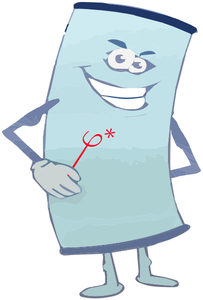
Tracking for a refrigerator model from four different initial conditions, with two different values of κ. The aggregate power consumption nearly coincides after about three hours with $\kappa = 150$, and coupling occurs much faster when κ is increased to 1,500.

Distributed Control



Distributed Control

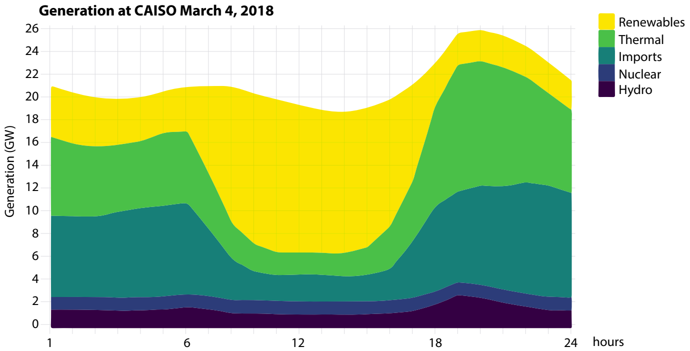
$$D(p\|p^0) + \frac{\kappa}{2}\sum_{k=1}^{T}\big(\langle \nu_k, u\rangle - r_k\big)^2$$



Distributed Control

Energy Challenge In California Today

How do we make use of forecasts of weather and usage?



March 4: nearly 50% of demand was served by solar at 1pm

March 5: record solar production, over 10GW at 10am

Energy Challenge In California Today

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KLQ objective

$$J^*(\nu_{t_0}) = \min_p \Big\{ D(p \| p^0) + \frac{\kappa}{2} \sum_{k=t_0+1}^{t_0+T} \big(y_k - r_k\big)^2 \Big\}$$

subject to given initial marginal ν_{t_0}

- $\{r_k\}$ reference to be tracked (estimate at time t_0 based on system conditions)
- $\{\nu_k\}$ marginals of p
- $y_k = \langle \nu_k, \mathcal{U} \rangle$ mean power consumption (or deviation) at time k
- Nominal is Markov: $p^0(x) = \nu_0(x_0)P_0(x_0, x_1) \cdots P_{T-1}(x_{T-1}, x_T)$

(model based estimates at time t_0)

WLOG $t_0 = 0$

KLQ solution

$$J^*(\nu_0) = \min_p \Big\{ D(p\|p^0) + \frac{\kappa}{2} \sum_{k=1}^{T} \big(y_k - r_k\big)^2 \Big\}$$

WLOG $t_0 = 0$

Solution: $\check{p}(x_0, \ldots, x_T) = p^0(x_0, \ldots, x_T) \exp\Big(\sum_{k=1}^{T} \beta_k^* \mathcal{U}(x_k) - \Lambda_{\beta^*}(x_0) \Big)$

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- Λ_{β^*} normalizing constant

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- Λ_{β^*} normalizing constant
- $\beta^* =$ Lagrange multiplier

KLQ solution

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- Λ_{β^*} normalizing constant
- $\beta^* = \arg\max \varphi^*(\beta)$

$$\varphi^*(\beta) = -\frac{1}{2\kappa} \|\beta\|^2 - \langle \nu_0, \Lambda_\beta \rangle + \beta^T r$$

(strictly concave and smooth)

- $\beta_k^* = \kappa e_k, \qquad e_k = r_k - y_k^* = r_k - \langle \nu_k^*, \mathcal{U} \rangle$
- Solution is Markovian $\Longrightarrow$ randomized policy at each load

General Architecture

Approach:

- Construct a family of transition matrices $\{P_\zeta : \zeta \in \mathbb{R}\}$
- ζ_k is broadcast to all loads of a given class at time k
- A load in state x transitions to state x' with probability $P_{\zeta_k}(x, x')$.

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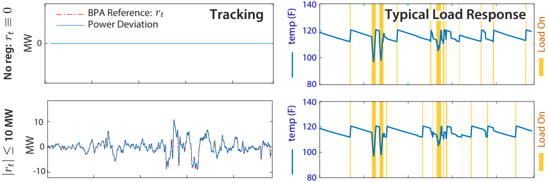
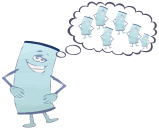
A particular construction led to these amazing results:





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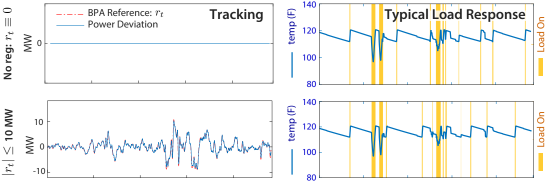
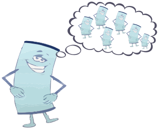
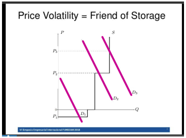


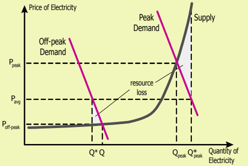
Construction: Essentially equivalent to infinite-horizon KLQ with $r_k \equiv \zeta$.



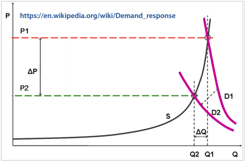
VI SIMPOSIO EMPRESARIAL INTERNACIONAL FUNSEAM:
RIESGOS Y OPORTUNIDADES DE LA TRANSICIÓN ENERGÉTICA
22 de feb de 2018



Keynote Speaker
Frank Wolak, Stanford Economics

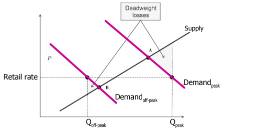


Benefits of demand response in electricity markets and recommendations for achieving them **DoE report**, 2006.



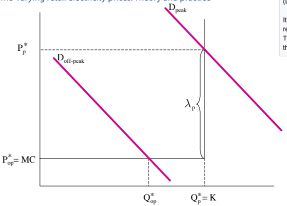
Explanation of demand response effects on a quantity (Q) - price (P) graph. Under inelastic demand (D1) extremely high price (P1) may result on a strained electricity market.
If demand response measures are employed the demand becomes more elastic (D2). A much lower price will result in the market (P2).

It is estimated[16] that a 5% lowering of demand would result in a 50% price reduction during the peak hours of the California electricity crisis in 2000/2001. The market also becomes more resilient to intentional withdrawal of offers from the supply side.



H-P Chao 2010,
Price-Responsive Demand Management for a Smart Grid World

S. Borenstein 2005
Time-varying retail electricity prices: Theory and practice



https://energyathaas.wordpress.com/2019/08/19/priing-for-the-short-run/

Hogan, 2019
3.2. *Smart Technology*
... technology that automatically monitors and adjusts consumption based on price signals, without active intervention by the consumer. **Even intelligent technologies are less likely to encourage smart charging if they are not coupled with dynamic pricing schemes.**

Controlling the Fleet

A single residential water heater

$$\frac{d}{dt}\Theta(t) = -\lambda(\Theta(t) - \Theta_a) + \gamma M(t)\mathcal{P}_m\,, \qquad \Theta_- \le \Theta(t) \le \Theta_+$$

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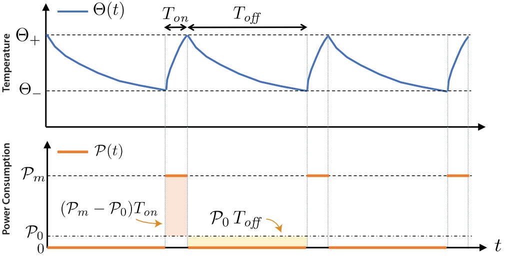
$\Theta(t)$: tank water temperature

$M(t)$: power mode (1 or 0)

Θ_a: ambient temperature

$\mathcal{P}_m$: power consumption (5kW typical)



Virtual Battery Model

N water heaters $\quad \frac{d}{dt}\Theta^i(t) = -\lambda(\Theta^i(t) - \Theta_a) + \gamma M^i(t)\mathcal{P}_m \quad \mathcal{P}_0 = \frac{\lambda}{\gamma}(\Theta_0 - \Theta_a)$

Virtual battery model of Hao et. al. [21] is based on an ODE for *deviation*. Normalized deviations from baseline (homogeneous population):

$$x^i(t) = \frac{1}{\gamma}[\Theta^i(t) - \Theta_0], \quad z^i(t) = -[M^i(t)\mathcal{P}_m - \mathcal{P}_0]$$

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A bit of algebra: $$\frac{d}{dt}x^i(t) = -\lambda x^i(t) - z^i(t)$$

Virtual Battery Model

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Definitions for the aggregate:

- State of charge (SoC) : $x(t) = \sum_{i=1}^{N} x^i(t)$
- Power discharge : $z(t) = \sum_{i=1}^{N} z^i(t)$ $\frac{d}{dt}x(t) = -\lambda x(t) - z(t)$

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- *Bounds on SoC* : $\dfrac{N}{\gamma}[\Theta_- - \Theta_0] \le x(t) \le \dfrac{N}{\gamma}[\Theta_+ - \Theta_0]$

Recall: $\Theta_- \le \Theta(t) \le \Theta_+$

Virtual Battery Model

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Similar model for irrigation/pool cleaning in [14, 15]
Distributed control of batteries in [20]

Cheap control

Consider M assets (real or virtual batteries) with SoC $\{x_i(t) : 1 \le i \le M\}$

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Convex formulation over time-period $[0, \mathcal{T}]$*:*

$$\begin{aligned} \underset{g,x}{\text{minimize}} \quad & \int_0^{\mathcal{T}} \big[c_g(g(t)) + c_d(g'(t)) + c_{\mathsf{X}}(x(t))\big]\, dt \qquad c_{\mathsf{X}}(x) \stackrel{\text{def}}{=} \sum_i c_i(x_i) \\ \text{subject to} \quad & g(t) = \ell(t) - \sum_i z_i(t) \quad \textit{Supply = Demand}, \\ & \frac{d}{dt} x_i(t) = -\alpha_i x_i(t) - z_i(t), \\ & \frac{d}{dt} z_i(t) = u_i(t), \qquad i \in \{1, ..., M\} \end{aligned}$$

c_i : penalty or barrier functions for SoC

Cheap control

Consider M assets (real or virtual batteries) with SoC $\{x_i(t) : 1 \le i \le M\}$
Convex formulation over time-period $[0, \mathcal{T}]$*:*

$$\underset{g,x}{\text{minimize}} \quad \int_0^{\mathcal{T}} \big[c_g(g(t)) + c_d(g'(t)) + c_X(x(t))\big]\, dt \qquad c_X(x) \stackrel{\text{def}}{=} \sum_i c_i(x_i)$$

$$\text{subject to} \qquad g(t) = \ell(t) - \sum_i z_i(t) \quad \textit{Supply = Demand},$$

$$g'(t) = \ell'(t) - \sum_i u_i(t) \quad \textit{model cost of ramping},$$

$$\frac{d}{dt} x_i(t) = -\alpha_i x_i(t) - z_i(t),$$

$$\frac{d}{dt} z_i(t) = u_i(t), \qquad i \in \{1, \dots, M\}$$

Cheap control

Consider M assets (real or virtual batteries) with SoC $\{x_i(t) : 1 \le i \le M\}$
Convex formulation over time-period $[0, \mathcal{T}]$*:*

$$\min_{g,x} \quad \int_0^{\mathcal{T}} \left[c_g(g(t)) + c_d(g'(t)) + c_X(x(t)) \right] dt \qquad c_X(x) \stackrel{\text{def}}{=} \sum_i c_i(x_i)$$

$$\text{subject to} \qquad g(t) = \ell(t) - \sum_i z_i(t) \quad \textit{Supply = Demand},$$

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$$\frac{d}{dt} x_i(t) = -\alpha_i x_i(t) - z_i(t),$$

$$\frac{d}{dt} z_i(t) = u_i(t), \qquad i \in \{1, \dots, M\}$$

Cost on $\sum u_i \quad \Longrightarrow \quad$ *Singular optimal control problem [27, 28]*

Consequences

1. Power consumption is not a continuous function of price

   There is no meaningful price for power deviation, or energy deviation over an interval Δ

2. State space collapse
3. Fragility

Consider consumer preference for hot water

Consequences

1. Power consumption is not a continuous function of price
2. State space collapse: $x^*(t)$ evolves in a two-dimensional manifold
3. Fragility

Lagrangian relaxation of supply/demand constraint

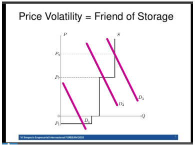
Consequences

1. Power consumption is not a continuous function of price
2. State space collapse
3. Fragility

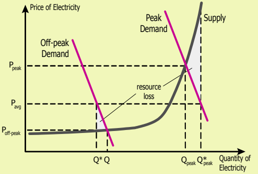
Just one example of fragility in an optimal solution

Blowing Up The Grid

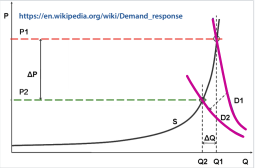
VI SIMPOSIO EMPRESARIAL INTERNACIONAL FUNSEAM:
RIESGOS Y OPORTUNIDADES DE LA TRANSICIÓN ENERGÉTICA
22 de feb de 2018



Keynote Speaker
Frank Wolak, Stanford Economics

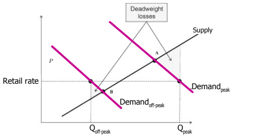


Benefits of demand response in electricity markets and recommendations for achieving them **DoE report**, 2006.



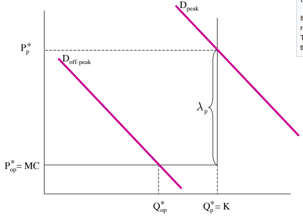
Explanation of demand response effects on a quantity (Q) - price (P) graph. Under inelastic demand (D1) extremely high price (P1) may result on a strained electricity market.
If demand response measures are employed the demand becomes more elastic (D2). A much lower price will result in the market (P2).

It is estimated[16] that a 5% lowering of demand would result in a 50% price reduction during the peak hours of the California electricity crisis in 2000/2001. The market also becomes more resilient to intentional withdrawal of offers from the supply side.



H-P Chao 2010,
Price-Responsive Demand Management for a Smart Grid World

S. Borenstein 2005
Time-varying retail electricity prices: Theory and practice



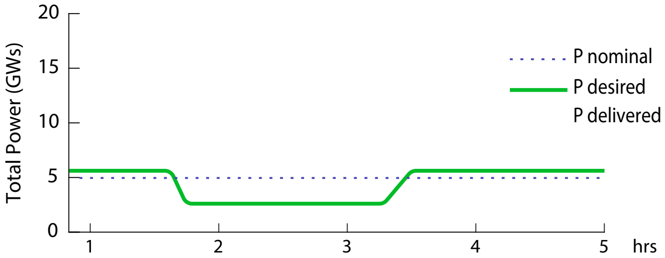
https://energyathaas.wordpress.com/2019/08/19/priing-for-the-short-run/

Hogan, 2019
3.2. Smart Technology
... technology that automatically monitors and adjusts consumption based on price signals, without active intervention by the consumer. **Even intelligent technologies are less likely to encourage smart charging if they are not coupled with dynamic pricing schemes.**

Axiom I of power economics: Demand is a continuous function of price

Blowing Up The Grid

Aggregator-consumer model



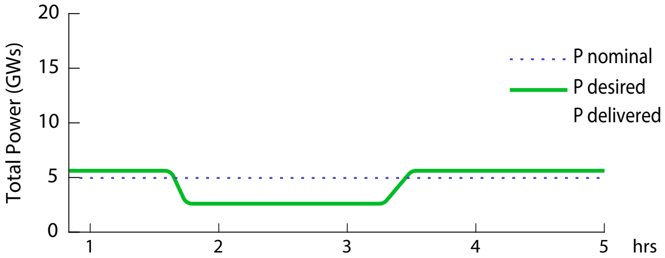
Example: Aggregator has contracts with consumers

7 million residential ACs
700,000 water heaters
700,000 commercial water heaters
17 million refrigerators
All the pools in California

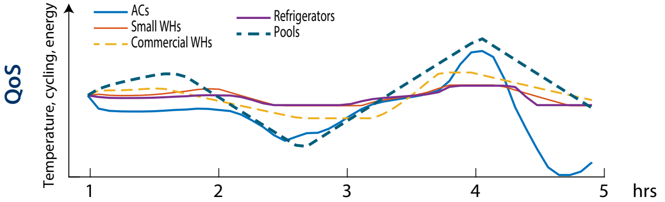
Promises strict bounds on QoS for each customer

Blowing Up The Grid

Aggregator-consumer model



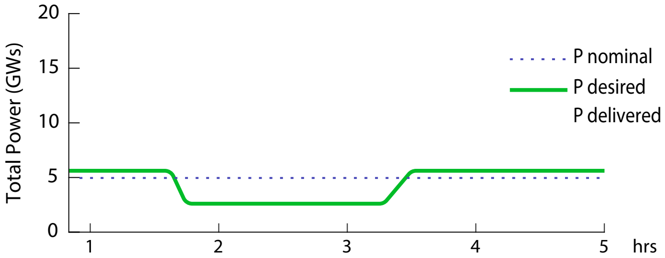
Example: Aggregator has contracts with consumers



Promises strict bounds on QoS for each customer

Blowing Up The Grid

Power consumption is not continuous as a function of price



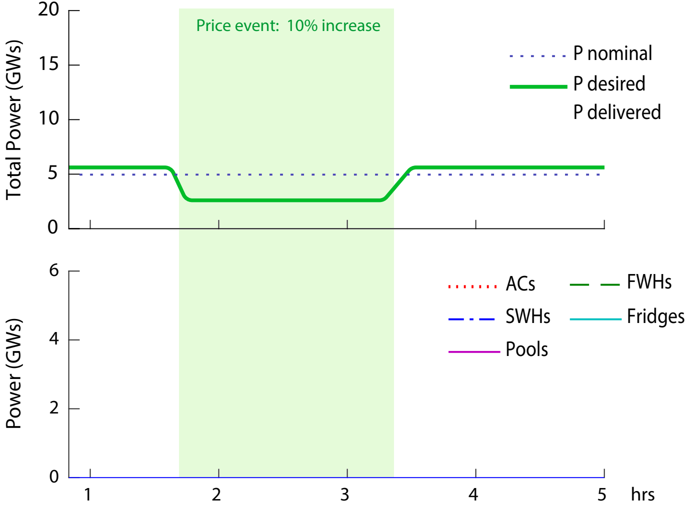
Example: Aggregator has contracts with consumers

Balancing authority desires power reduction over 2 hours
Sends PRICE SIGNAL: 10% increase
Aggregator optimizes subject to QoS constraints

Promises strict bounds on QoS for each customer

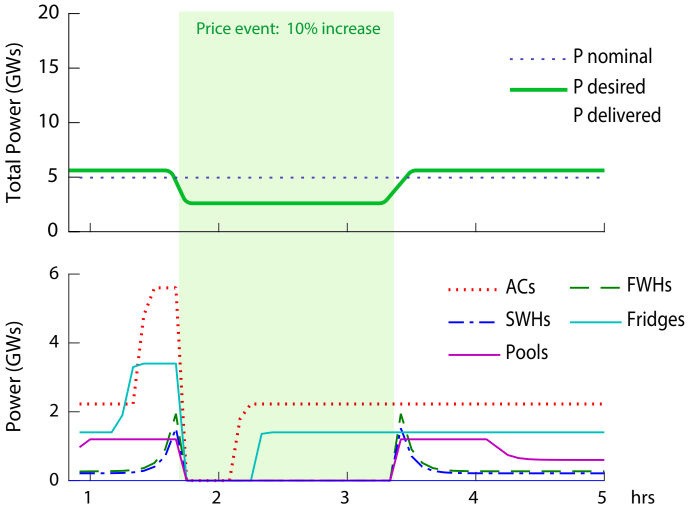
Blowing Up The Grid

Power consumption is not continuous as a function of price



Blowing Up The Grid

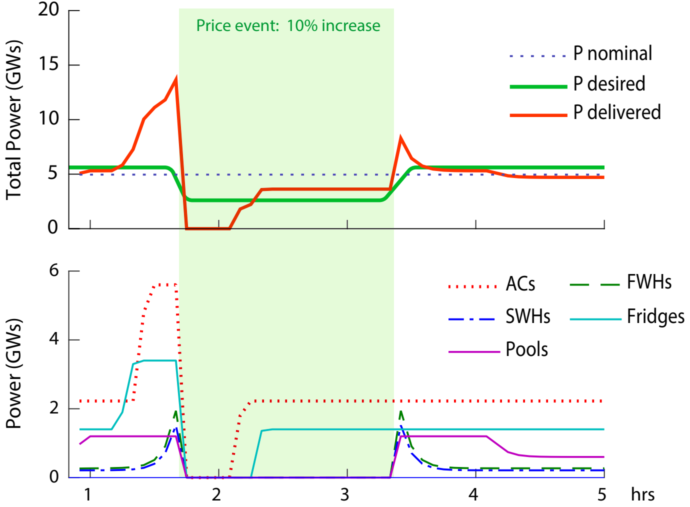
Power consumption is not continuous as a function of price



Promises strict bounds on QoS for each customer

Blowing Up The Grid

Power consumption is not continuous as a function of price



No QoS promises to Balancing Authority!

Evolution of Marginal Cost Optimal Solution

Consideration of dual functional: (relaxing supply/demand constraint)

$$\phi^*(\varrho) = \inf_{g,u} \int_0^{\mathcal{T}} \Big\{ c_g(g(t)) + c_d(g'(t)) + c_{\mathsf{X}}(x(t)) + \varrho(t)[\ell(t) - g(t) - z_\sigma(t)] \Big\} \, dt$$

Evolution of Marginal Cost Optimal Solution

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Assume maximizer ϱ^* exists

$$\phi^*(\varrho^*) \geq \phi^*(\varrho) \text{ for all } \varrho,$$

and ϱ^* is smooth

Evolution of Marginal Cost — Optimal Solution

Consideration of dual functional: (relaxing supply/demand constraint)

$$\phi^*(\varrho) = \inf_{g,u} \int_0^{\mathcal{T}} \Big\{ c_g(g(t)) + c_d(g'(t)) + c_{\mathsf{X}}(x(t)) + \varrho(t)[\ell(t) - g(t) - z_\sigma(t)] \Big\}\, dt$$

Assume maximizer ϱ^* exists

$$\phi^*(\varrho^*) \ge \phi^*(\varrho) \text{ for all } \varrho,$$

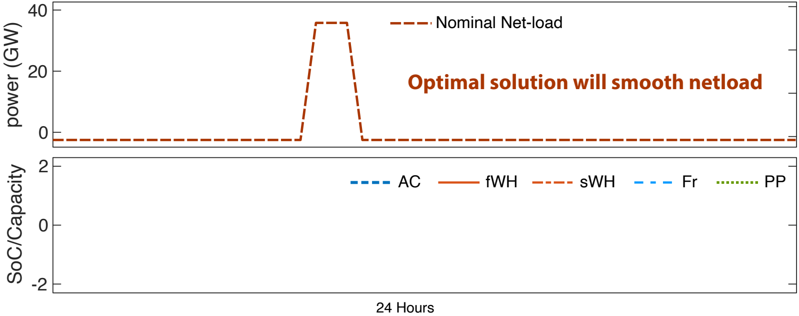
and ϱ^* is smooth

State space collapse:

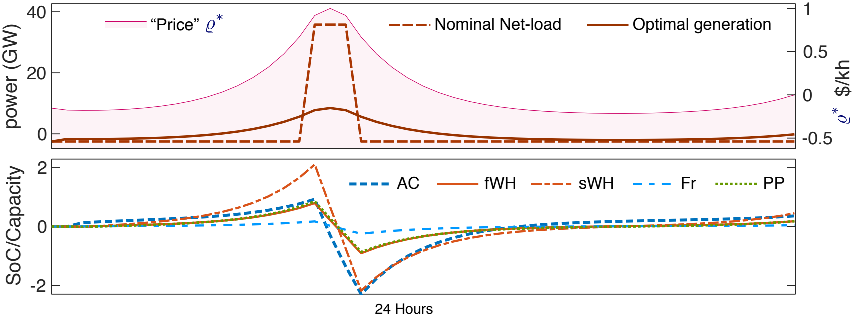
$$c_i'\,(x_i^*(t)) = -\alpha_i \varrho^*(t) + \frac{d}{dt}\varrho^*(t)$$

Marginal costs evolve on a two-dimensional subspace

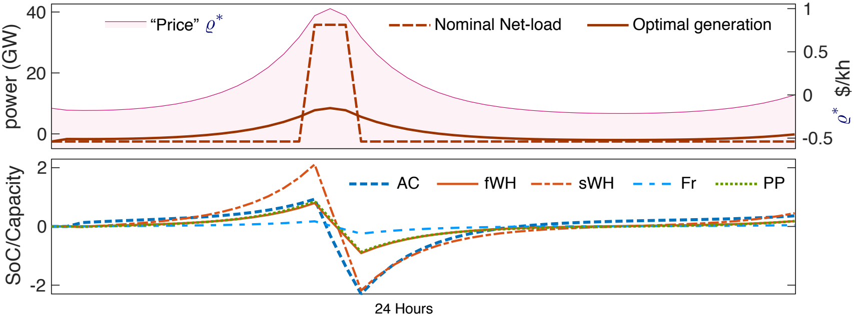
Optimal Solution to Economist's Problem



Optimal Solution to Economist's Problem

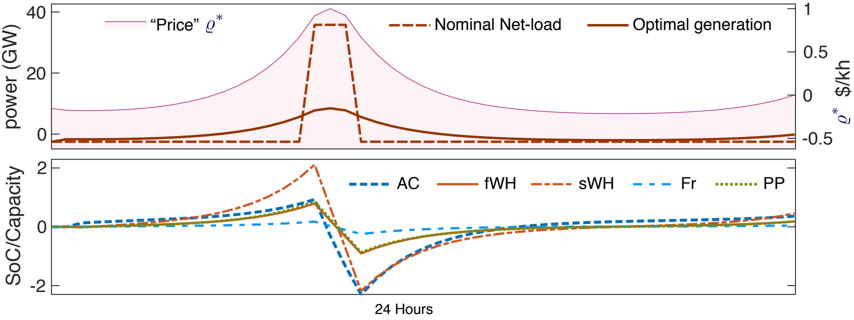


Optimal Solution to Economist's Problem



ϱ^* is the Lagrange multiplier for supply/demand balance

Optimal Solution to Economist's Problem

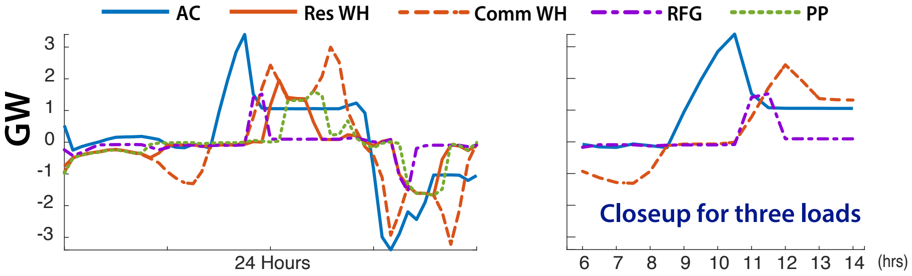


ϱ^* is the Lagrange multiplier for supply/demand balance

Please believe me, it is not really a price signal!

Fragility

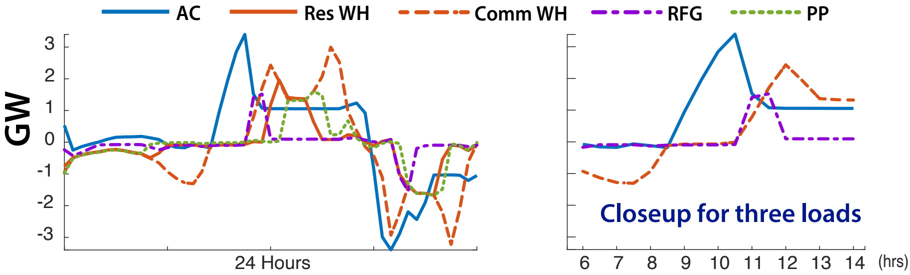
This is what collapse looks like:



- Power trajectories of each class have sharp ramps
- "Spaghetti" phenomenon is a concern

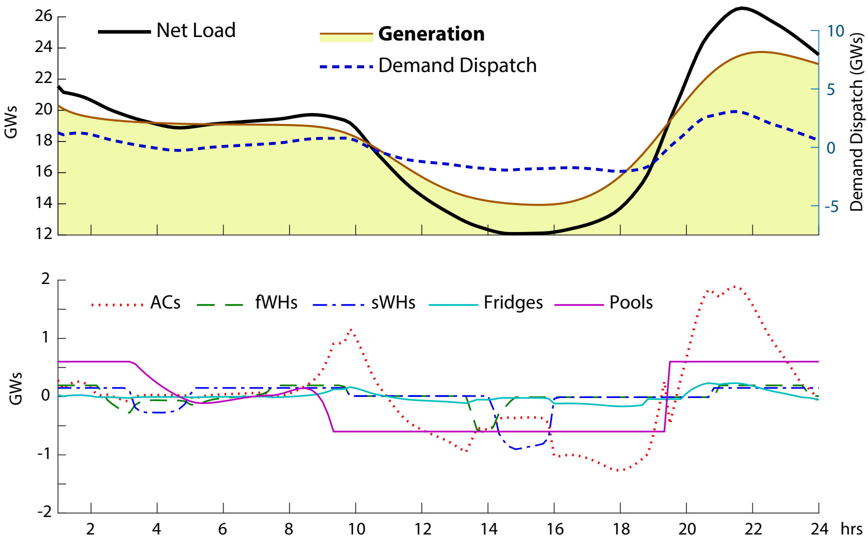
Fragility

This is what collapse looks like:



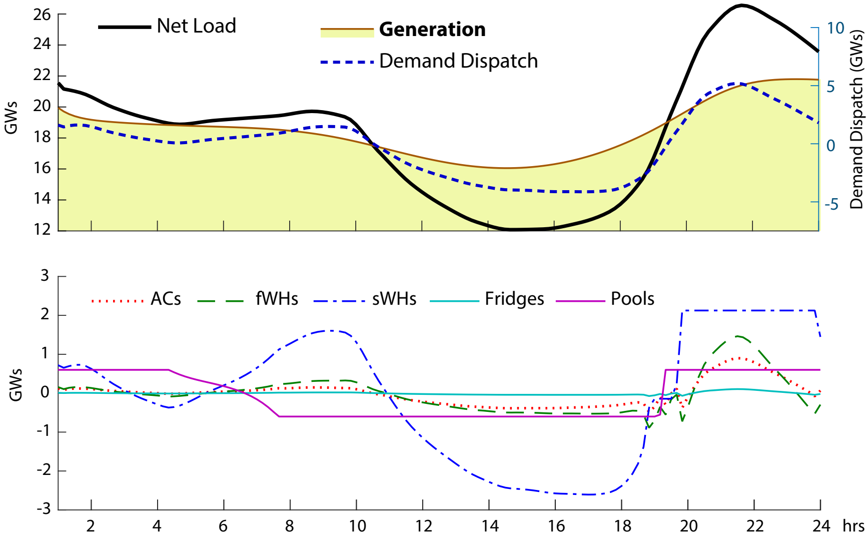
- Power trajectories of each class have sharp ramps
- “Spaghetti” phenomenon is a concern

What is possible today



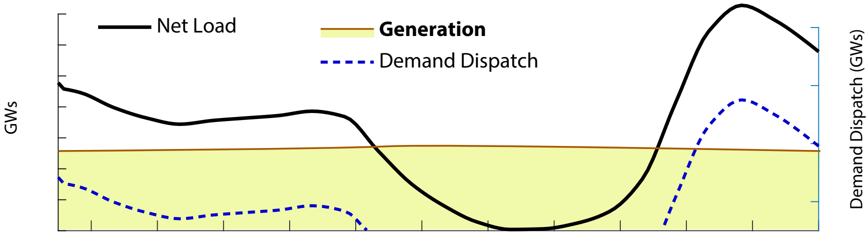
Conclusions

What is possible in 2050



Conclusions

There are many loads that are deferrable



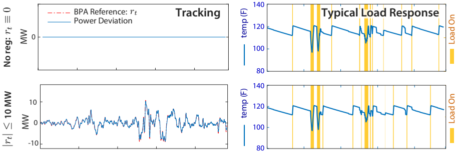
ACs fWHs sWHs Fridges Pools

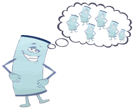
and
Irrigation
Cow cooling
Plug-in electric vehicles
Commercial HVAC

Conclusions

Conclusions

- The power of distributed control is remarkable.






DIVE BRIEF

ERCOT drops plans to add 3 GW for winter reliability after 'zombie' power plants fail to bid

Looking ahead, the grid operator said it believes there is "tremendous potential in expanding demand response capabilities" to help keep the Texas grid reliable.

Published Nov. 20, 2023

Robert Walton
Senior Reporter

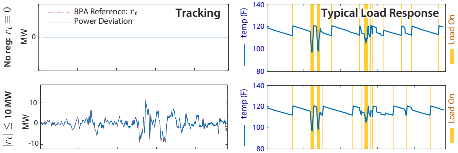
www.utilitydive.com/news/ercot-cancels-3-gw-winter-capacity-request-texas-demand-response/700266/

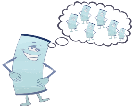
I am not aware of any economic theory that supports real time pricing

Conclusions

- The power of distributed control is remarkable.
  Recent work introduces approaches to address fragility:

  Convex Q-Learning in Continuous Time with Application to Dispatch of Distributed Energy Resources   Paper WeB15.4 IEEE CDC, 2023






DIVE BRIEF

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Senior Reporter

TEXAS

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Conclusions

- The power of distributed control is remarkable.
  Recent work introduces approaches to address fragility:

  Convex Q-Learning in Continuous Time with Application to Dispatch of Distributed Energy Resources   Paper WeB15.4 IEEE CDC, 2023

- Please stop talking about price signals!

See Spence [10, 11] for another take on *Naïve energy markets*.


DIVE BRIEF

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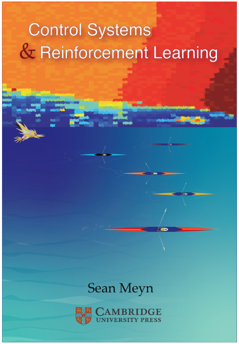
I am not aware of any economic theory that supports real time pricing

Farewell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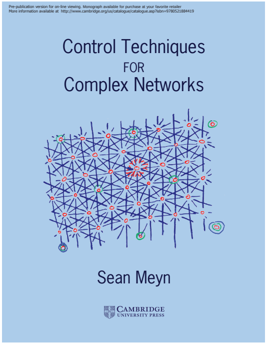
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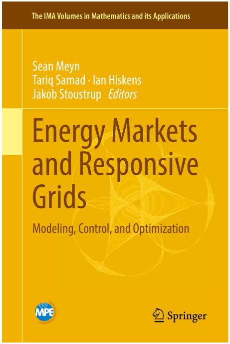
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Sean Meyn
Tariq Samad · Ian Hiskens
Jakob Stoustrup Editors
Energy Markets and Responsive Grids
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