Ancillary Service to the Grid Using Intelligent Deferrable Loads

PGMO Days 2015

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Inria, DI ENS

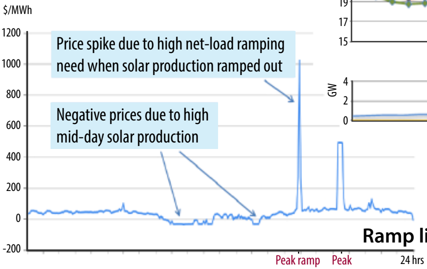
In collaboration with S. Meyn and P. Barooah

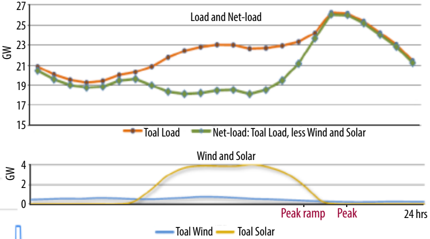
Thanks to PGMO, NSF, and Google

Electrical and Computer Engineering
University of Florida

Outline

March 8th 2014: Impact of wind and solar on net-load at CAISO



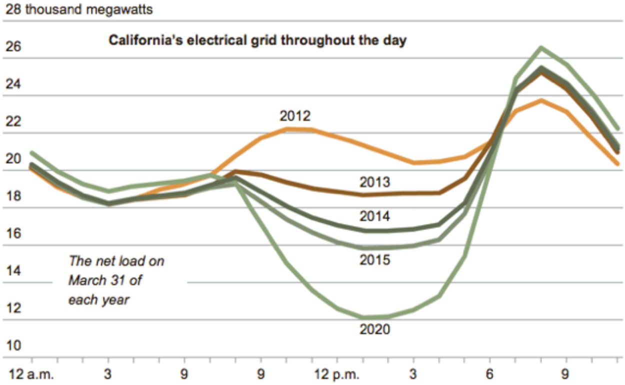


Ramp limitations cause price-spikes

Challenges

Some of the Challenges

1. Ducks

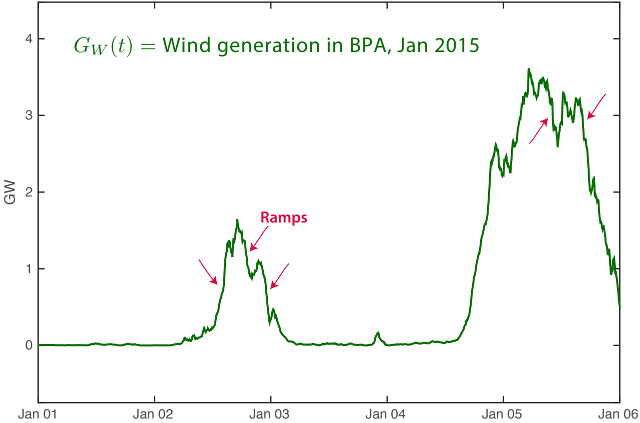


Source: CalISO

MISO, CAISO, and others: seek markets for *ramping products*

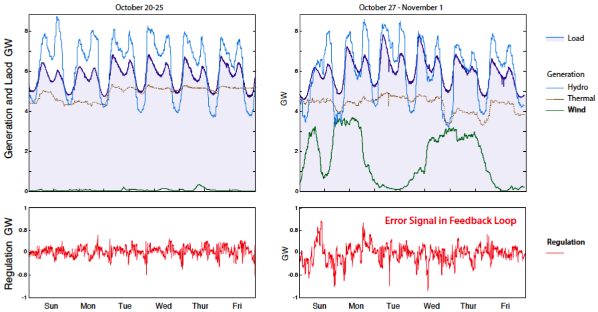
Some of the Challenges

1. Ducks
2. Ramps



Some of the Challenges

1. Ducks
2. Ramps
3. Regulation



Some of the Challenges

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2. Ramps
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One potential solution:

Large-scale storage with fast charging/discharging rates

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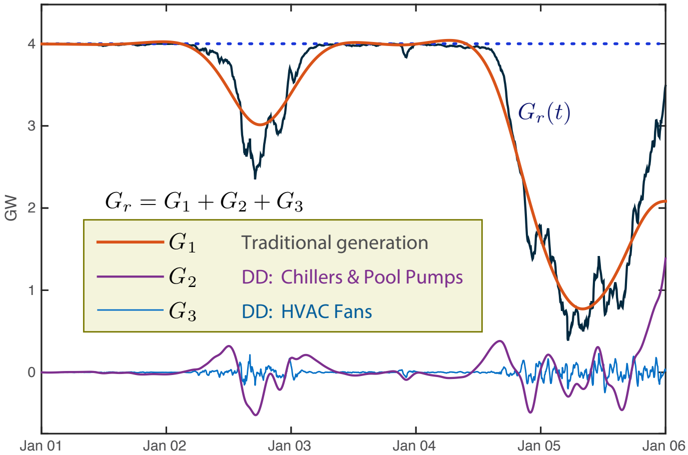
One potential solution:

Large-scale storage with fast charging/discharging rates

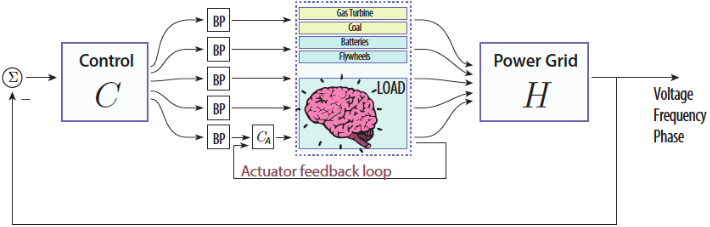
Let's consider some alternatives



Virtual Energy Storage

Control Architecture

Frequency Decomposition



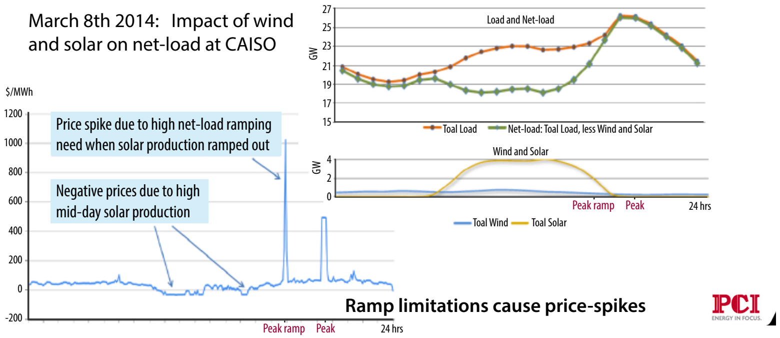
Today: PJM decomposes regulation signal based on bandwidth,

$$\mathrm{R} = \mathrm{RegA} + \mathrm{RegD}$$

Proposal: Each class of DR (and other) resources will have its own bandwidth of service, based on QoS constraints and costs.

Frequency Decomposition

Taming the Duck

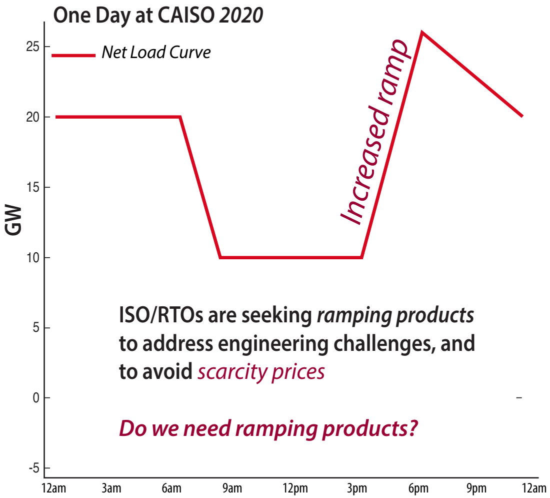


ISOs need help: ... *ramp capability shortages could result in a single, five-minute dispatch interval or multiple consecutive dispatch intervals during which the price of energy can increase significantly due to scarcity pricing, even if the event does not present a significant reliability risk*

http://tinyurl.com/FERC-ER14-2156-000

Frequency Decomposition

Taming the Duck



Frequency Decomposition

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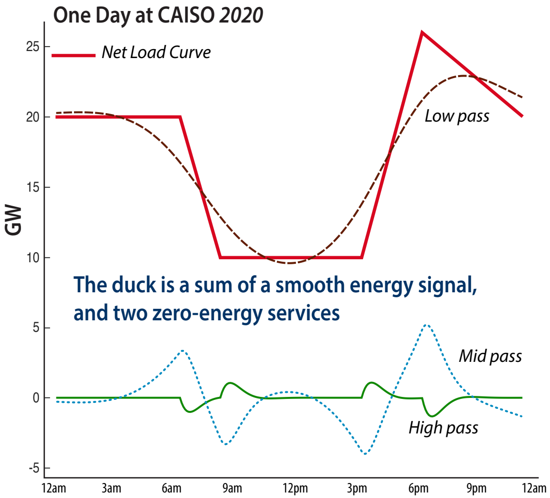
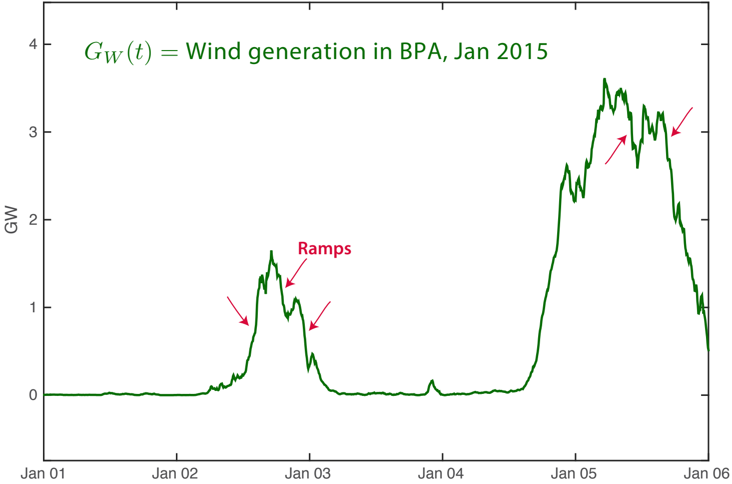


Frequency Decomposition

Regulation



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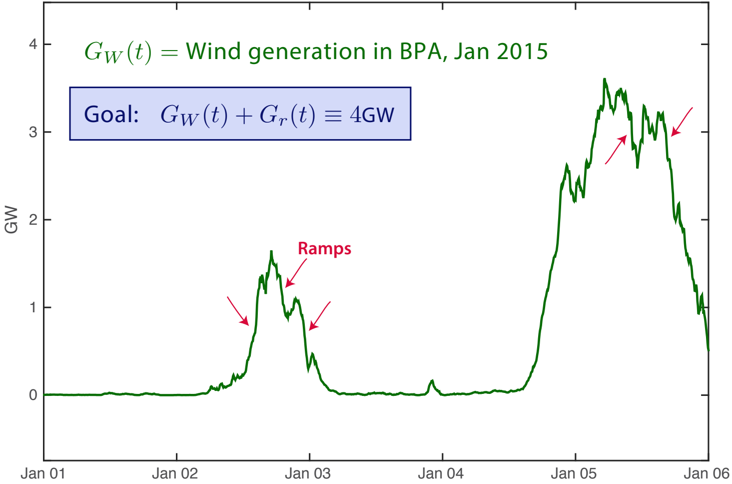

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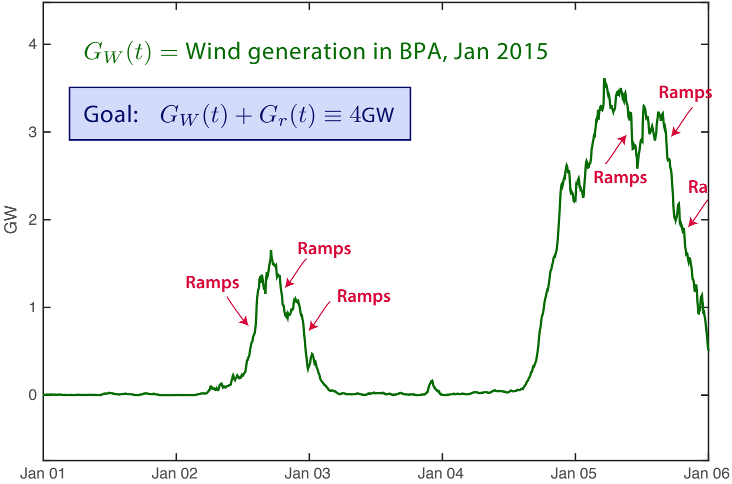

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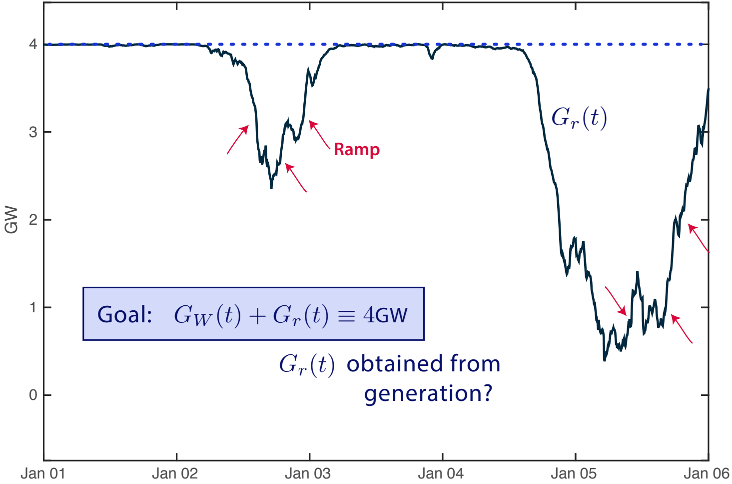

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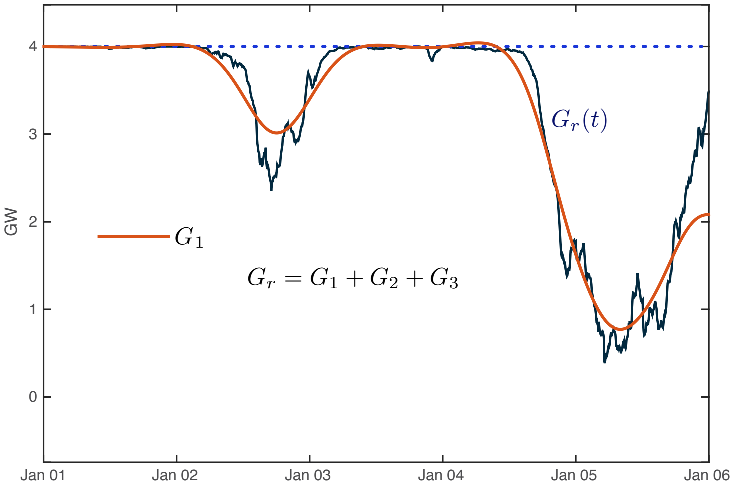

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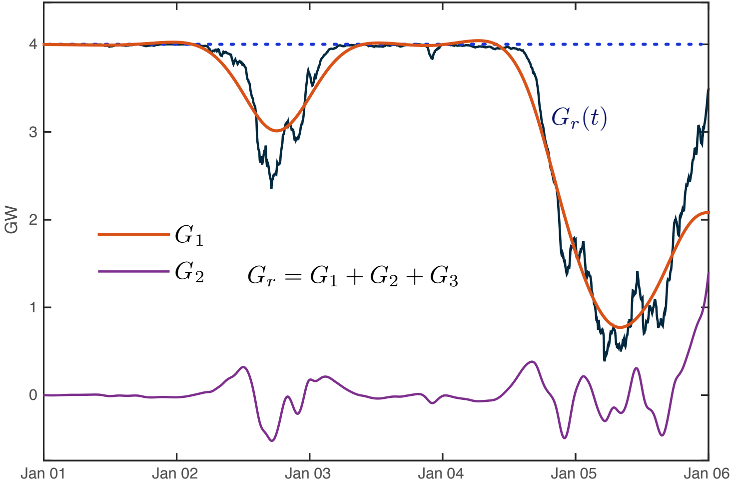

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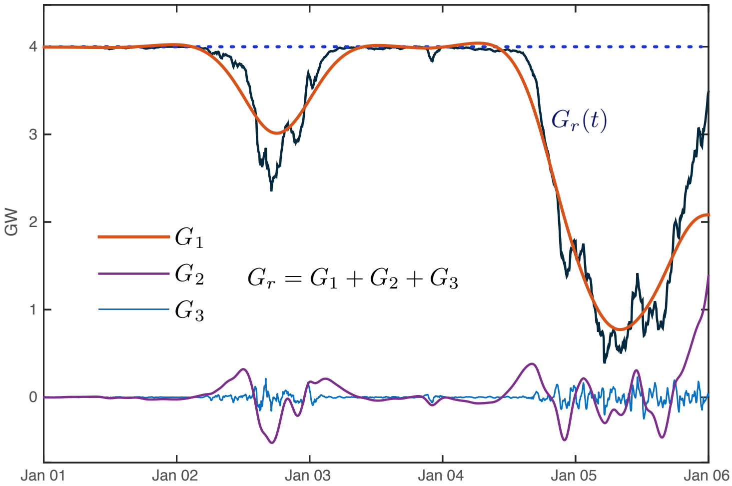

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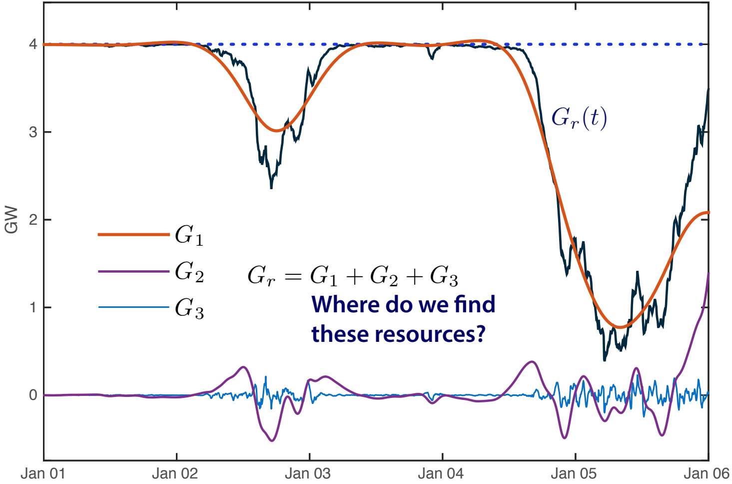
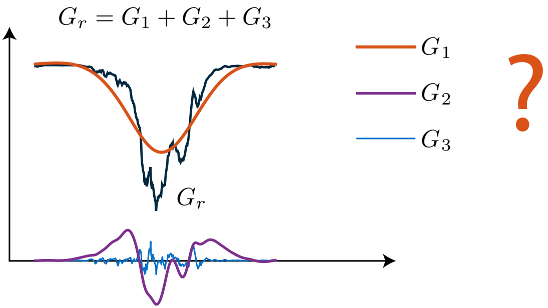


Demand Dispatch

Responsive Regulation *and* desired QoS



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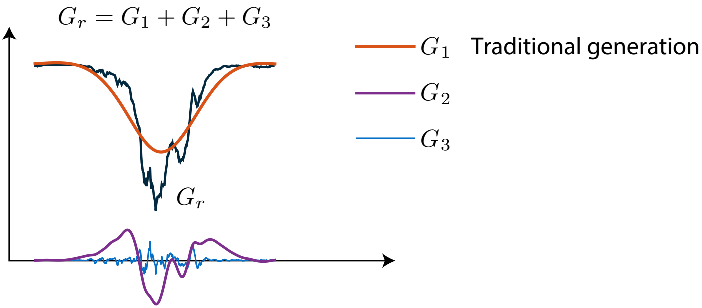

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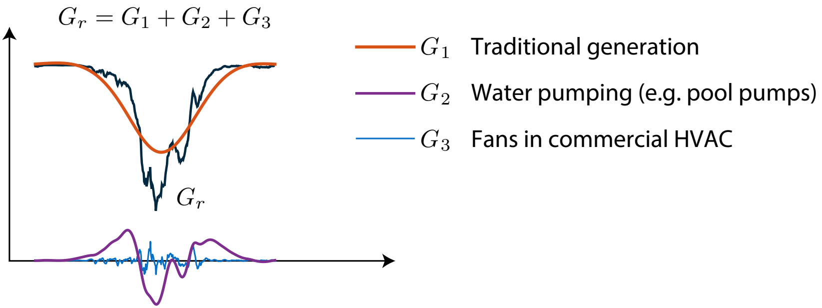

Demand Dispatch: Power consumption from loads varies automatically and continuously to provide service to the grid, without impacting QoS to the consumer

Demand Dispatch

Responsive Regulation *and* desired QoS
– A partial list of the needs of the grid operator, and the consumer

- High quality Ancillary Service? Does the deviation in power consumption accurately track the desired deviation target?

Demand Dispatch

Responsive Regulation *and* desired QoS
– A partial list of the needs of the grid operator, and the consumer

- High quality Ancillary Service?
- Reliable?
  Will AS be available each day?
  It may vary with time, but capacity must be predictable.

Demand Dispatch

Responsive Regulation *and* desired QoS
– A partial list of the needs of the grid operator, and the consumer

- High quality Ancillary Service?
- Reliable?
- Cost effective?
  This includes installation cost, communication cost, maintenance, and environmental.

Demand Dispatch

Responsive Regulation *and* desired QoS
– A partial list of the needs of the grid operator, and the consumer

- High quality Ancillary Service?
- Reliable?
- Cost effective?
- Customer QoS constraints satisfied?
  The pool must be clean, fresh fish stays cold, building climate is subject to strict bounds, farm irrigation is subject to strict constraints, data centers require sufficient power to perform their tasks.

Demand Dispatch

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- Reliable?
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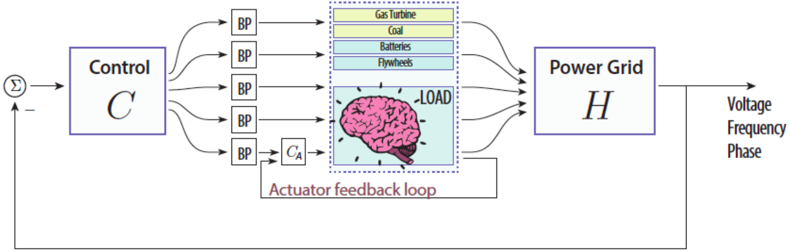
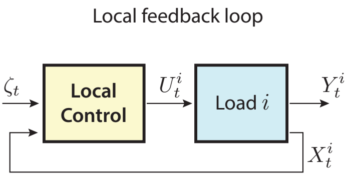
Virtual energy storage: achieve these goals simultaneously through distributed control

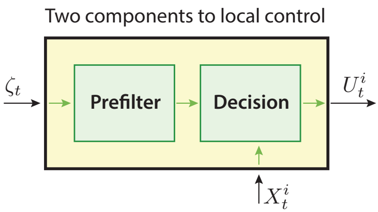


Control of Deferrable Loads

Control Goals and Architecture

Prefilter and decision rules designed to respect needs of load and grid





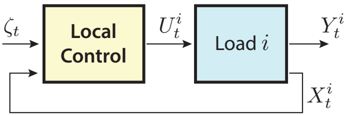
Requirements

- **Minimal communication:** Each load monitors its state and a regulation signal from the grid
- **Aggregate must be controllable:** *Randomized policies* required for finite-state loads

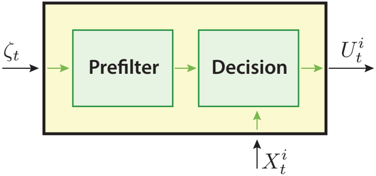
Control Goals and Architecture

Prefilter and decision rules designed to respect needs of load and grid

Local feedback loop



Two components to local control



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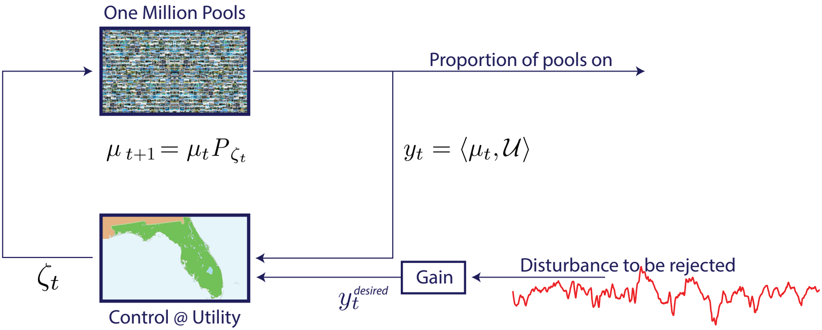
Questions

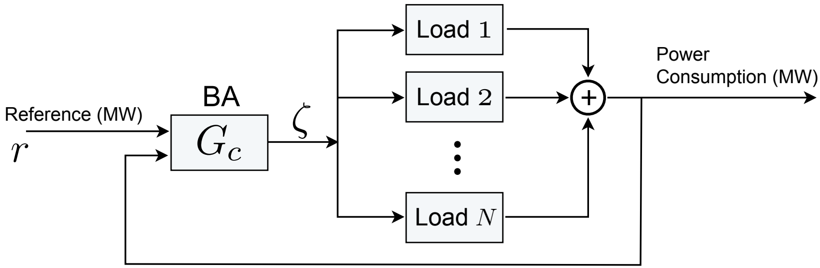
- How to analyze aggregate of similar loads?
- Local control design?



Aggregate of similar deferrable loads

Control Architecture

Aggregate of similar deferrable loads

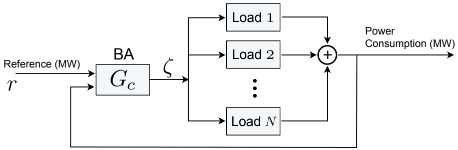


Examples: Chillers in HVAC systems, water heaters, residential TCLs, ...

... residential pool pumps

Load Model

Controlled Markovian Dynamics



Assumptions:

Load Model

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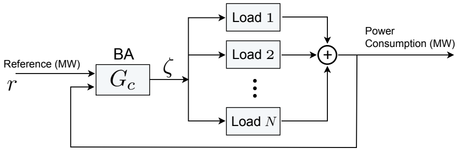

Assumptions:

- Discrete time: ith load $X^i(t)$ evolves on finite state space X

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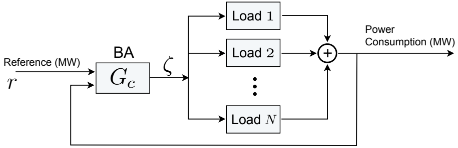

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Signal $\zeta = \{\zeta_t\}$ is broadcast to all loads

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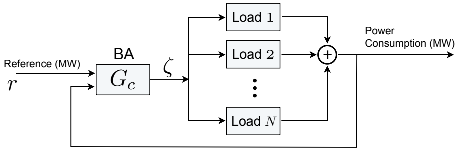

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- Controlled transition matrix $\{P_\zeta : \zeta \in \mathbb{R}\}$:

$$\mathsf{P}\{X^i_{t+1} = x' \mid X^i_t = x,\, \zeta_t = \zeta\} = P_\zeta(x, x')$$

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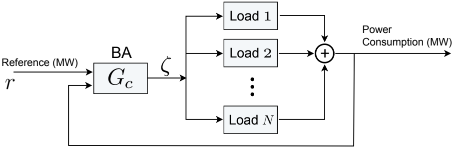

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- $\mathcal{U} \colon \mathsf{X} \to \mathbb{R}$ models the needs of the grid

Aggregate Model

N loads running independently, each under the command ζ.

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Empirical Distributions:

$$\mu_t^N(x) = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}\{X^i(t) = x\}, \qquad x \in \mathsf{X}$$

$$y_t^N = \frac{1}{N}\sum_{i=1}^{N}\mathcal{U}(X_t^i) = \sum_x \mu_t^N(x)\mathcal{U}(x)$$

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Limiting model:

$$\mu_{t+1} = \mu_t P_{\zeta_t}, \quad y_t := \sum_x \mu_t(x)\mathcal{U}(x)$$

via Law of Large Numbers for martingales

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Mean-field model:

$$\mu_{t+1} = \mu_t P_{\zeta_t}, \qquad y_t = \mu_t(\mathcal{U})$$

$$\zeta_t = f_t(\mu_0, \dots, \mu_t) \quad \textit{by design}$$

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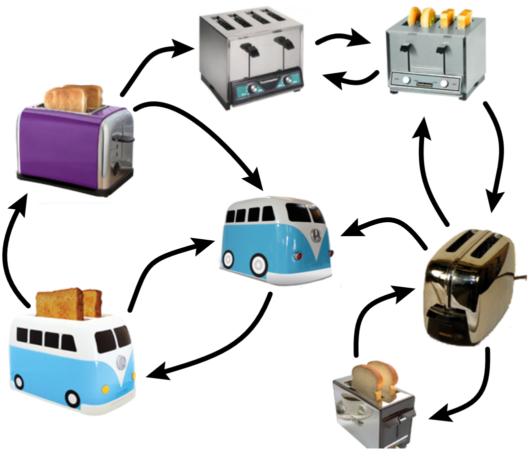
Question: *How to design* P_ζ*?*



Local Design

Local Design

Goal: Construct a family of transition matrices $\{P_\zeta : \zeta \in \mathbb{R}\}$

Design: Consider first the finite-horizon control problem:

$$p_\zeta(x_1, \dots, x_T) = \prod_{i=0}^{T-1} P_\zeta(x_i, x_{i+1}) \,, x_0 \in \mathsf{X}$$

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Choose distribution p_ζ to *maximize*

$$\zeta \mathsf{E}_{p_\zeta}\Big[\sum_{t=1}^{T} \mathcal{U}(X_t)\Big] - D(p \| p_0)$$

D denotes relative entropy.

p_0 denotes nominal Markovian model.

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Explicit solution for finite T:

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Markovian, but not time-homogeneous.

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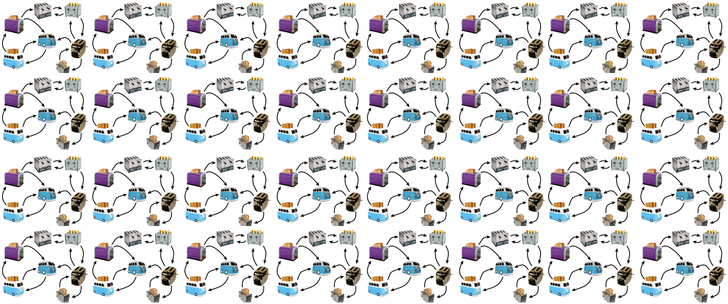
Explicit construction via eigenvector problem:

$$P_\zeta(x,y) = \frac{1}{\lambda} \frac{v(y)}{v(x)} \hat{P}_\zeta(x,y) \, , \qquad x, y \in \mathsf{X},$$

where $\hat{P}_\zeta v = \lambda v, \qquad \hat{P}_\zeta(x,y) = \exp(\zeta \mathcal{U}(x)) P_0(x,y)$

Extension/reinterpretation of [Todorov 2007] + [Kontoyiannis & M 200X]



$$\mu_{t+1} = \mu_t P_{\zeta_t}$$
$$y_t = \langle \mu_t, \mathcal{U} \rangle$$

$$\Phi_{t+1} = A\Phi_t + B\zeta_t$$
$$\gamma_t = C\Phi_t$$

Linearized Dynamics

Mean Field Model

Linearized Dynamics

Mean-field model: $\mu_{t+1} = \mu_t P_{\zeta_t}, \qquad y_t = \mu_t(\mathcal{U})$

Linear state space model:

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Interpretations: $|\zeta_t|$ is small, and π denotes invariant measure for P_0.

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$$\Phi_t(x) \approx \mu_t(x) - \pi(x),\ x \in \mathsf{X}$$

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- $\gamma_t \approx y_t - y^0$; deviation from nominal steady-state

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Linear state space model:
$$\begin{aligned}\Phi_{t+1} &= A\Phi_t + B\zeta_t \\ \gamma_t &= C\Phi_t\end{aligned}$$

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- $\Phi_t \in \mathbb{R}^{|\mathsf{X}|}$, a column vector with
$$\Phi_t(x) \approx \mu_t(x) - \pi(x),\ x \in \mathsf{X}$$
- $\gamma_t \approx y_t - y^0$; deviation from nominal steady-state
- $A = P_0^{\mathsf{T}}$, $C_i = \mathcal{U}(x^i)$, and input dynamics linearized:

Mean Field Model

Linearized Dynamics

Mean-field model: $\mu_{t+1} = \mu_t P_{\zeta_t}, \qquad y_t = \mu_t(\mathcal{U})$

Linear state space model:

$$\Phi_{t+1} = A\Phi_t + B\zeta_t$$
$$\gamma_t = C\Phi_t$$

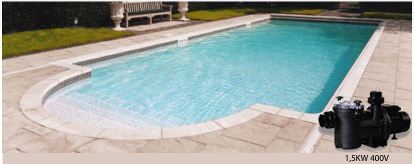
Interpretations: $|\zeta_t|$ is small, and π denotes invariant measure for P_0.

- $\Phi_t \in \mathbb{R}^{|\mathsf{X}|}$, a column vector with
$$\Phi_t(x) \approx \mu_t(x) - \pi(x),\ x \in \mathsf{X}$$
- $\gamma_t \approx y_t - y^0$; deviation from nominal steady-state
- $A = P_0^{\mathsf{T}}$, $C_i = \mathcal{U}(x^i)$, and input dynamics linearized:

$$B^{\mathsf{T}} = \frac{d}{d\zeta} \pi P_\zeta \Big|_{\zeta=0}$$

Example: One Million Pools in Florida

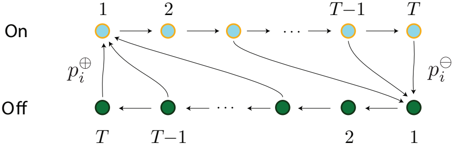
How Pools Can Help Regulate The Grid



Needs of a single pool

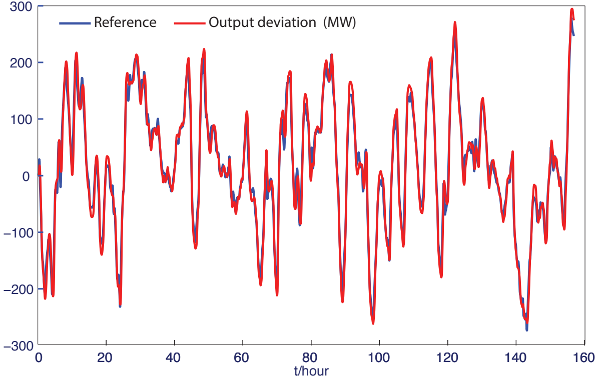
- Filtration system circulates and cleans: Average pool pump uses 1.3kW and runs 6-12 hours per day, 7 days per week
- Pool owners are oblivious, until they see *frogs and algae*
- Pool owners do not trust anyone: *Privacy is a big concern*

Single pool dynamics:



Pools in Florida Supply G_2 – BPA regulation signal*

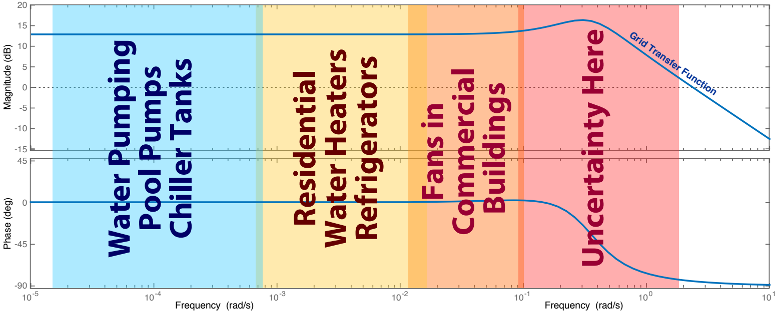
Stochastic simulation using $N = 10^5$ pools



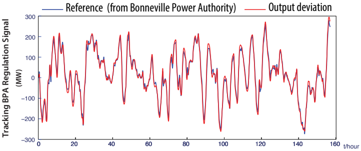
PI control: $\zeta_t = 19 e_t + 1.4 e_t^I, \quad e_t = r_t - y_t$ *and* $e_t^I = \sum_{k=0}^{t} e_k$

Each pool pump turns on/off with probability depending on 1) its internal state, and 2) the BPA reg signal

*transmission.bpa.gov/Business/Operations/Wind/reserves.aspx



10,000 pools



Bandwidth
centered around
its natural cycle

Conclusions and Future Directions

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Challenges: intermittence and volatility of renewable generation
In the absence of grid-level efficient storage, increased need for responsive fossil-fuel generators, negating the environmental benefits of renewables

Approach: creating Virtual Energy Storage through direct control of flexible loads - helping the grid while respecting user QoS
(MDP on the local level and mean-field analysis of the aggregate)

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Current and future research directions

- Extending local control design to include disturbance from the nature
- Investigating needs for communication and forecast
(minimizing communication and computation costs while providing reliable service to the grid)
- Integrating VES with traditional generation and batteries (resource allocation optimization problems involving different time scales)

Conclusions

Thank You!

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