Challenges of renewable power generation

Virtual energy storage from flexible loads

Workshop EDF Lab'

gestion centralisée/décentralisée des systèmes électriques

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University of Florida

INVENTEURS DU MONDE NUMÉRIQUE

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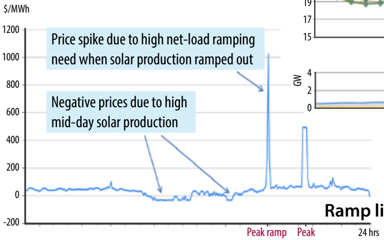
COGNITION & CONTROL IN COMPLEX SYSTEMS

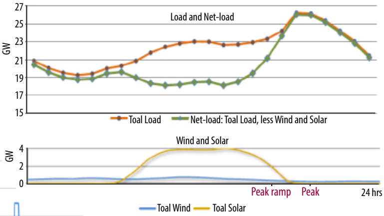
Electrical and Computer Engineering

University of Florida

Challenges of Renewables: ducks & ramps

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





Ramp limitations cause price-spikes

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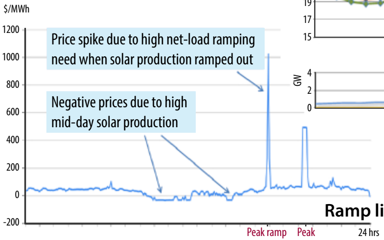

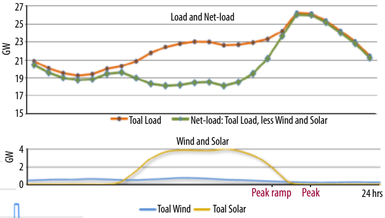

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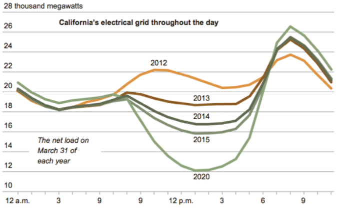

Source: CalISO

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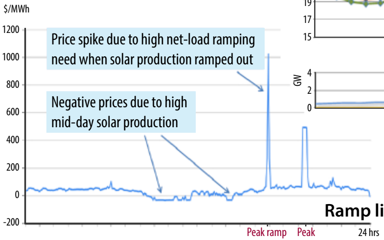

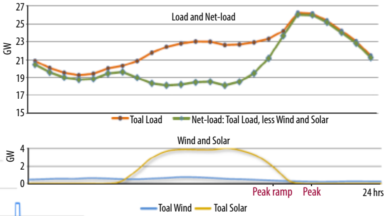

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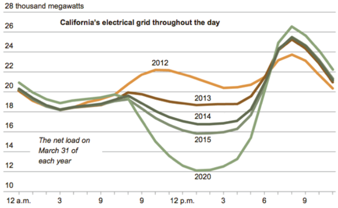
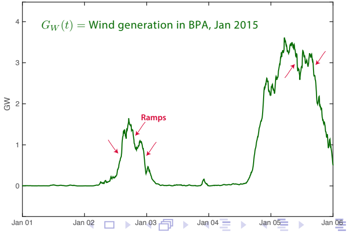
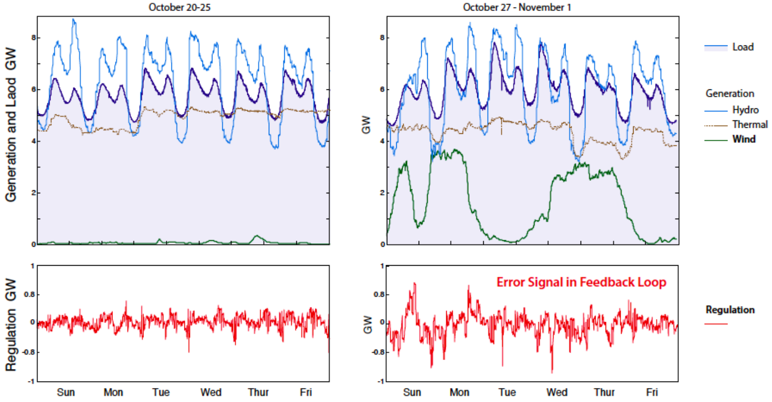


Source: CallSO



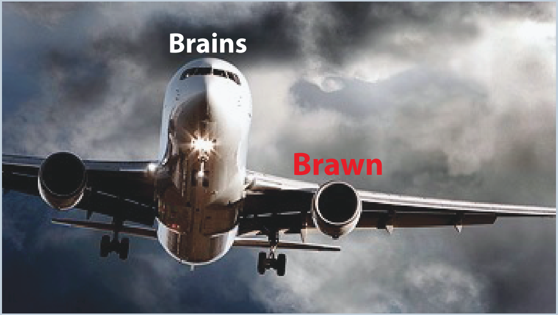
Challenges: regulation



Lack of large-scale storage with fast charging/discharging rates

Comparison: Flight control

How do we fly a plane through a storm?

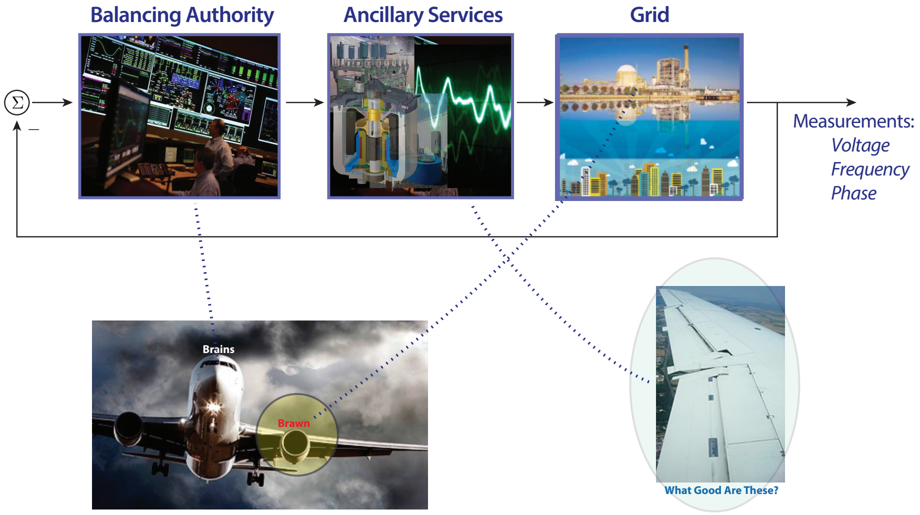


Comparison: Flight control

How do we fly a plane through a storm?

Comparison: Flight control

How do we operate the grid in a storm?

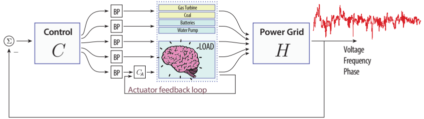


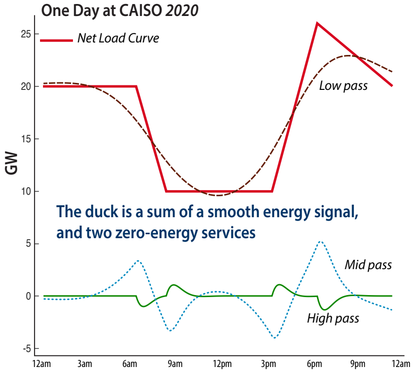
Demand Dispatch

Frequency Decomposition

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

Approach: Frequency decomposition
Each class of flexible loads allocated to its own *bandwidth of service*, based on *QoS constraints* and *costs*





Today: PJM regulation signal:
R = RegA + RegD

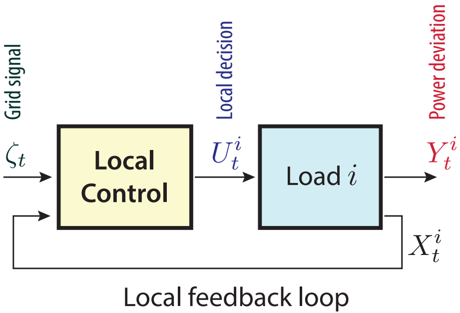
Demand Dispatch

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

- High quality Ancillary Service?
- Customer QoS constraints satisfied?
- Cost effective?
  Includes installation cost, communication cost, maintenance, and environmental.
- Reliable?
  Will AS be available each day?
  (may vary with time, but capacity must be predictable)
- Is the incentive to the consumer reliable?
  If a consumer receives a $50 payment for one month, and only $1 the next, will there be an explanation that is clear to the consumer?

Control Goals and Architecture

Local Control: decision rules designed to respect needs of load and grid



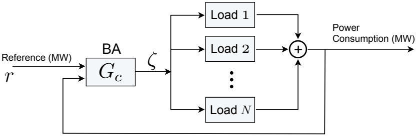
- Min. communication: each load monitors its state and a regulation signal from the grid.
- Aggregate must be controllable: **randomized policies** for finite-state loads.

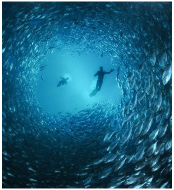
Questions

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

Load Model

Controlled Markovian Dynamics & Mean Field Model of the Aggregate





- Discrete time: ith load $X^i(t)$ evolves on finite state space X
- Each load is subject to *common* controlled Markovian dynamics.

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

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

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

- Mean-field analysis for the aggregate of loads
(R. Malhame et. al. 1984 –)

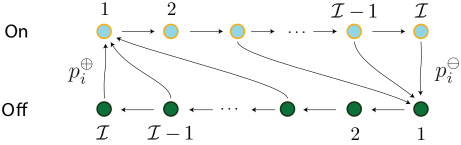
Example: pool pumps

How Pools Can Help Regulate The Grid

Needs of a single pool

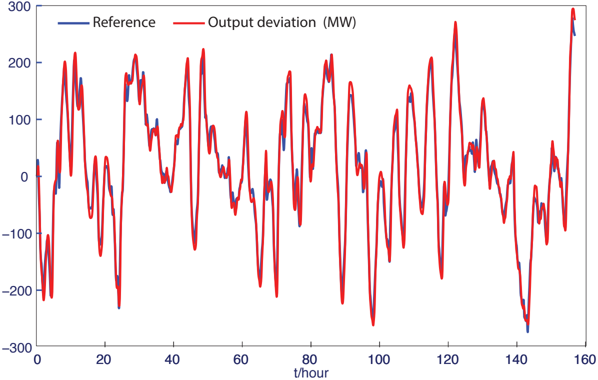
- Filtration system circulates and cleans: Average pool pump uses 1.3kW and runs 6-12 hours per day, 7 days per week
- Pool owners are oblivious, until they see *frogs and algae*
- Pool owners do not trust anyone: *Privacy is a big concern*

Single pool dynamics:



Pools in Florida Supply G_2 – BPA regulation signal*

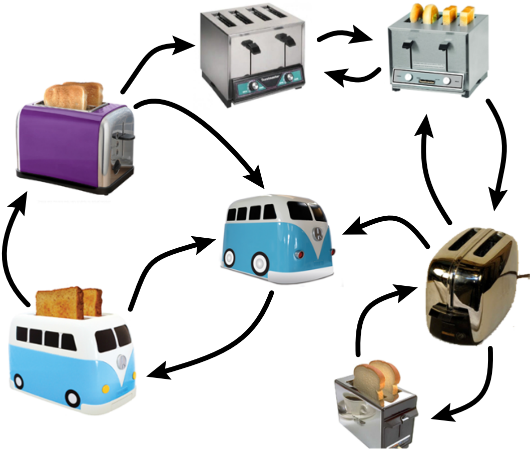
Stochastic simulation using $N = 10^6$ pools



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

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`



Local Control Design

Local Design

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

Individual Perspective Design

Local welfare function: $\mathcal{W}_\zeta(x, P) = \zeta\mathcal{U}(x) - D(P\|P_0)$,

where D denotes relative entropy: $D(P\|P_0) = \sum_{x'} P(x, x') \log\big(\frac{P(x,x')}{P_0(x,x')}\big)$.

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Markov Decision Process: $\limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} E[\mathcal{W}_\zeta(X_t, P)]$
Local control is a solution of AROE:

$$\max_P \Big\{ \mathcal{W}_\zeta(x, P) + \sum_{x'} P(x, x') h_\zeta^*(x') \Big\} = h_\zeta^*(x) + \eta_\zeta^*$$

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Explicit construction via eigenvector problem:

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

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

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

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Myopic Design
(one step optimization)

$$P_\zeta(x, x') := P_0(x, x') \exp\big(\zeta \mathcal{U}(x') - \Lambda_\zeta(x)\big)$$

with $\Lambda_\zeta(x) := \log\Big(\sum_{x'} P_0(x, x') \exp\big(\zeta \mathcal{U}(x')\big)\Big)$ the normalizing constant.

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System Perspective Design

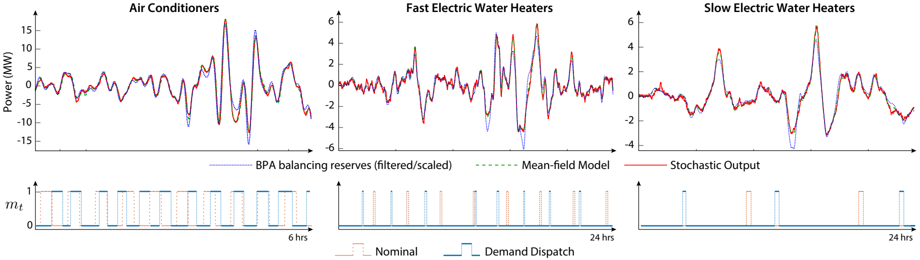
Linearized aggregate model is passive: $\sum_{t=0}^{\infty} u_t y_{t+1} \geq 0, \ \forall \{u_t\}$.

Tracking performance

and the controlled dynamics for an individual load

Heterogeneous setting:

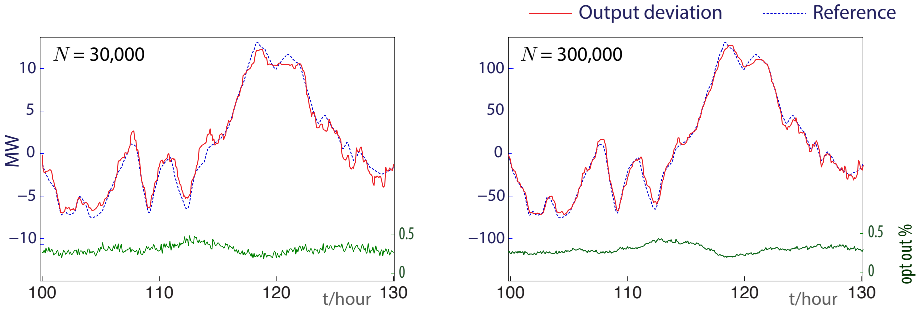
- 40 000 loads per experiment;
- 20 different load types in each case



Unmodeled dynamics

Setting: 0.1% sampling, and

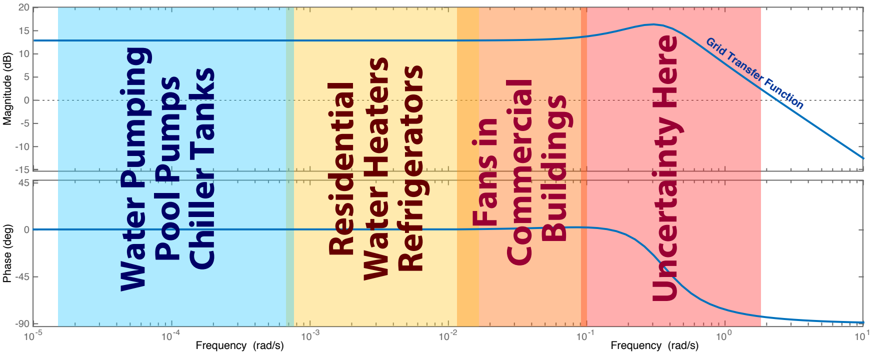
1. *Heterogeneous* population of loads
2. Load i overrides when QoS is out of bounds



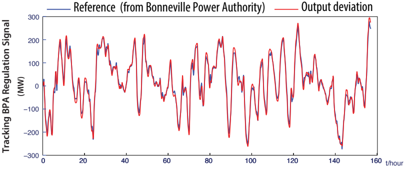
Closed-loop tracking

Control Architecture

Frequency *Allocation* for Demand Dispatch



10,000 pools



Bandwidth
centered around
its natural cycle

Conclusions

The virtual storage capacity from demand dispatch is enormous

Approach: creating Virtual Energy Storage through direct control of flexible loads - helping the grid while respecting user QoS

These resources are **free!** Fans, Irrigation, pool pumps, ...

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But, of course: Zero marginal cost $\neq$ **free**

- VES is cheaper than batteries. However, there is *significant sunk-cost*
- **Challenge:** economic theory for a zero marginal cost market
- **Solutions:** *Contracts for services*, as mandated in FERC Order 755, or practiced by EDF or in FP&L's On Call program since the 1980s

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Ongoing and future work:

- Information Architecture: $\zeta_t = f(?)$
  Different needs for communication, state estimation and forecast.
- Resource optimization & learning:
  Integrating VES with traditional generation and batteries.

Conclusions

Thank You!

References: Demand Dispatch

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