Coordinated Aggregation of Distributed Energy Resources

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August 6, 2013

Our Research Group

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CERTS Research Activities

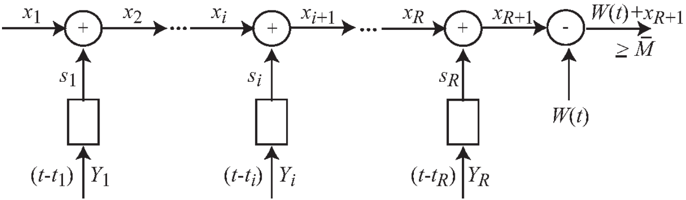
- Network case of Risk-Limiting Dispatch
- Improved Load Forecasting with fine-grain measurements
- Coordinated Aggregation of Distributed Resources

Risk Limiting Dispatch

Risk Limiting Dispatch (RLD)

- Main Idea: exploit recourse opportunities
  - purchase reserves in a sequence of forward markets (one day, six hours, one hour, 5 minutes ahead of delivery time)
- Key Issue: Information-cost trade-off
  - better forecasts available closer to delivery time
  - increased price risk closer to delivery time
- Objective: minimize expected cost of reserves + imbalance penalty.
- Decision at each market:
  - is based on all available information (from the current and previous markets)
  - takes into account the statistics of future information and future recourse decisions

RLD – Previous Result



- s_i forward purchase or sale made at market time $t - t_i$
- Decisions based on information Y_i
- Cost $= \mathbb{E}\{$energy $+$ reserve capacity $+$ imbalance penalty$\}$

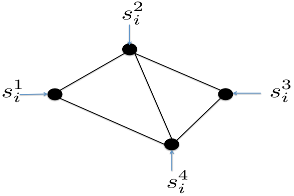
Theorem

Single bus case. Optimal decision s_i satisfies threshold rule:

$$s_i + \sum_{j<i} s_j \in [\phi_{i+}, \phi_{i-}]$$

RLD – New Results

Network case: n buses, m transmission lines



- Transmission constraints and flows modeled with DC power flow
- $\mathbf{s}_i = (s_i^1, s_i^2, \ldots, s_i^n)$ is the purchase *decision vector* at market time $t - t_i$

Theorem

Optimal decision vector $\mathbf{s}_i$ *still satisfies threshold rule:*

$$\mathbf{s}_i = \Phi_i - \sum_{j<i} \mathbf{s}_j \quad \textit{where } \Phi_i \textit{ is the n-dimensional threshold vector}$$

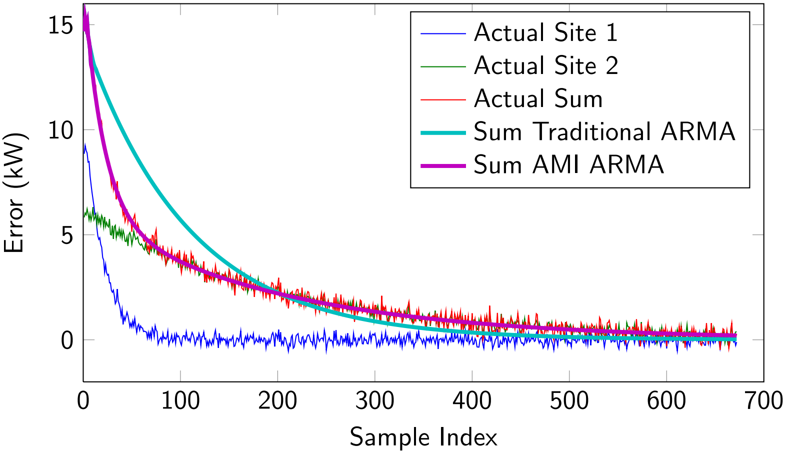
Load Forecasting

Problem Formulation

- Accurate load forecasts are important
  - Load management and infrastructure investments
  - Decrease reserve requirements
- AMI is widespread – can we use this data to improve forecasts?
- Problem setup:
  - AMI time-series $y^k(t), k = 1, \cdots, N$
  - Aggregate power time-series $p(t) = \sum_k y^k(t)$
- Compare two approaches:
  - Traditional: forecast $p(t+T)$ given $p(s), s \leq t$
  - AMI based: forecast $p(t+T)$ given $y^k(s), s \leq t$
- Modeling method:
  - model each time-series as baseline + ARMAX for residual
  - Baseline $b(t)$ from intelligent averaging
  - ARMAX model parameters from traditional system ID

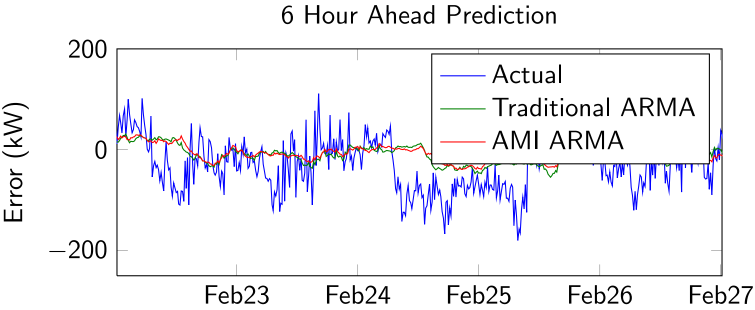
Results: Synthetic Data

- Two AMI sites: different nominal, residual is first order ARX
- Example shows AMI data can improve prediction



Preliminary Results: Real Data

- 18 buildings selected from LoCal project at UC Berkeley
  - Test forecasting for 0.25h, 1h, 6h prediction horizon
  - AMI prediction does not show improvements



- Problem: too much noise in data, makes modeling $y^k(t)$ difficult
- Need to understand noise sources in building level data (chiller events, abrupt load changes)

Aggregate Flexibility

A Paradigm Shift

- Today: tailor generation to meet random load
- Tomorrow: tailor load to meet random generation
- Enabling ingredient: flexible loads
  - residential HVAC
  - commercial HVAC
  - deferrable appliance loads
  - electric vehicles
- Flexible loads will enable deep renewable penetration without large increases in reserves

The Sound-bite

“Flexible loads can absorb variability in renewable generation”

- Devil is in the details, and the sound-bite is vague ...
- What variability?
  - variability in wind or rooftop solar?
  - what time scales? wind ramps or routine fluctuations?
- What product can be provided?
  - load-following capacity?
  - frequency regulation ancillary service?
- Architecture?
  - direct load control or load control through price proxies?
  - degree of decentralization?
  - hardware infrastructure?
- Where is the economic value?

An Example of What is Possible

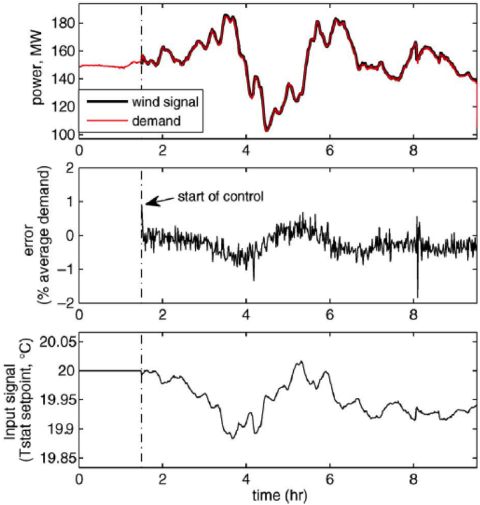
- Direct load control: 60,000 diverse AC units

Control	$u(t)$ = common setpoint change
Measurements	$P(t)$ = aggregate power
Objective	$P(t)$ tracks command $r(t)$
	high freq part of power from wind farm

- Result: $\pm 0.1^\circ C$ setpoint changes can track high freq part of $w(t)$!

Callaway, *Energy Conversion and Management*, 2009
Flexibility in TCL's can firm wind generation

Results



- $P(t) \approx w(t)$
- Tracking error $\approx 1\%$
- Set-point changes $\approx 0.1^\circ C$
- Proof-of-concept result
- Two key problems with implementation
  - measuring agg power
  - defining nom power

Callaway, *Energy Conversion and Management*, 2009

Two Central Problems

- Consider collection of flex loads
- ex ante Modeling Aggregate Flexibility
  - characterize the set of admissible power profiles
    i.e. profiles that meet the needs of flex loads
  - want a simple, portable model
  - System Operator uses model for procuring AS or load following
- run-time Control Algorithms
  - aggregator or cluster manager controls flex loads
  - allocation available generation to loads
  - allocation must be causal
  - not traditional control, more like CS scheduling

Two Business Cases

- Selling aggregate flexibility capacity as an AS
  - ex: residential HVAC
  - loads pay fixed price per MW
  - flexibility is sold as a regulation service
- Using aggregate flexibility to minimize operating costs
  - ex: shopping mall EV charging
  - loads pay low-cost bulk power + expensive reserves
  - flexibility can minimize reserve cost

Aggregate Flexibility

- Collection of flexible loads, indexed by k
  - For each load, define a nominal power profile $P_k^o(t)$
  - Many perturbations e from nominal satisfy the load

$$\mathbb{E}_k = \{e : \ e + P_k^o \text{ satisfies load } k\}$$

- Aggregate nominal power $n(t) = \sum_k P_k^o$
- Aggregate flexibility

$$\mathbb{E} = \sum_k \mathbb{E}_k$$

- Key problem: characterize $\mathbb{E}$

Generalized Electricity Storage

- Models a set of power profiles

$$u(t) \in Batt(\phi) \iff \begin{cases} u(t) \in [-m^-, m^+] \\ \dot{x} = -ax + u \\ x(0) = \xi \implies x(t) \in [-C^-, C^+] \end{cases}$$

Parameters ϕ

parameter	meaning
m^-, m^+	discharge/charge rate limits
C^-, C^+	up/down capacity
a	dissipation
ξ	init condn

- Effective capacity

$$C^+_{eff} = \min\{C^+, m^+/a\}, \quad C^-_{eff} = \min\{C^-, m^-/a\}$$

- Compact, portable model

Result Summary

- Consider collection of flex loads: TCLs, EVs, etc
- Aggregate flexibility can be well modeled as a stochastic battery:

$$Batt(\phi_1) \subseteq \mathbb{E} \subseteq Batt(\phi_2)$$

- Battery parameters are random processes
  - depend on exogenous variables
  - ex: ambient temp, arrival/departure rates, charging needs, etc
- For TCLs:
  - battery must have dissipation
  - gap between ϕ_1, ϕ_2 because of diversity
  - agg flex is small at low θ_a because no participation
  - agg flex is small at high θ_a because short-cycling

Result Summary ...

- Consider sufficient model

  $$Batt(\phi_1) \subseteq \mathbb{E}$$

- Scheduling problem:
  Given $u \in Batt(\phi_1)$, allocate u to flex loads
  - $u = \sum_k e_k, \quad e_k \in \mathbb{E}_k$
  - algorithms must be causal
- For TCLs, proportional allocation works
- For EVs, without rate limits, EDF, LLF, etc work
- For EVs with rate limits, scheduling algorithms do not exist

Aggregate Flexibility from TCLs

Some Related work

- Callaway, *Energy Conversion and Management 2009*
- Koch, Zima, Andersson, *IFAC PP+PSC, 2009*
- Papavasiliou, Oren, *PES 2010*
- Galus, la Fauci, Andersson, *PES 2010*
- Ilic, Xie, Joo, *IEEE TPS 2011*
- Mathieu, Kamgarpour, Lygeros, Callaway, *ECC 2013*
- Koch, Mathieu, Callaway, *IEEE TPS, 2013*
- Meyn, Barooah, Busic, Ehren, *preprint, 2013*

Comments:

– Markov chain models for aggregate

– Population-bin-transition model

– SO imposes tight audit requirements on AS provision

Simple Model of a TCL (Cooling Load)

- Dead-band model

$$\dot{\theta} = \begin{cases} -\frac{1}{CR}(\theta - \theta^a + P^m R) + w & \text{ON state} \\ -\frac{1}{CR}(\theta - \theta^a) + w & \text{OFF state} \end{cases}$$

- State-switching boundaries

$$\overline{\theta} = \theta^r + \Delta, \quad \underline{\theta} = \theta^r - \Delta$$

  - Control input = setpoint θ_r
  - Process disturbance w for model uncertainty
  - Simplified model, ignoring many details

C	thermal capacitance	2 kWh/$^\circ$C
R	thermal resistance	2 $^\circ$C/kW
P^m	power consumption when ON	5.6 kW
Δ	deadband	1 $^\circ$C

Even Simpler Model

- Continuous-power model

$$\dot{\theta} = -\frac{1}{RC}(\theta - \theta_a + Re(t)) + w$$

  - Control input $e(t)$ is power supplied to TCL
  - Constraint: $e(t) \in [0, P^m]$

- We use this model for analysis
- Use better dead-band model for simulations
- Need to show that for a large population,
aggregate behavior of TCLs is same under either model

Nominal Average Power

- Average power consumption to maintain $\theta(t) = \theta_r$

$$P^o = \frac{\theta_a - \theta_r}{R}$$

- Nominal average power P^o
  - function of HVAC, ambient temp, set-point
  - slowly-varying random process
- Measuring P^o is critical: firmware solution
  - know θ_r from thermostat
  - measure $\theta(t)$
  - run-time ID of R, θ_a

Aggregate Flexibility – Diverse TCLs

Theorem

(a) $Batt(\phi_1) \subset \mathbb{E} \subset Batt(\phi_2)$

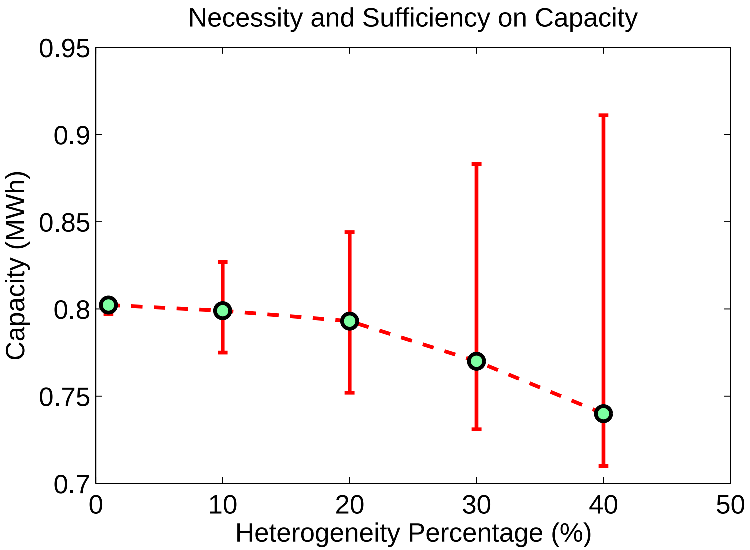
parameter	ϕ_1	ϕ_2
dissipation	$\frac{1}{N}\sum_k a_k$	$\frac{1}{N}\sum_k a_k$
charge rate limit n^+	$\sum_k (P_k^m - P_k^o)$	$\sum_k (P_k^m - P_k^o)$
discharge rate limit	$n^+ \min_k \frac{P_k^o}{P_k^m - P_k^o}$	$\sum_k P_k^o$
capacity	$n^+ \min_k \frac{C_k \Delta_k}{P_k^o (1+\frac{\lvert a-a_k \rvert}{a_k})}$	$\sum_k (1 + \frac{\lvert a-a_k \rvert}{a}) C_k \Delta_k$

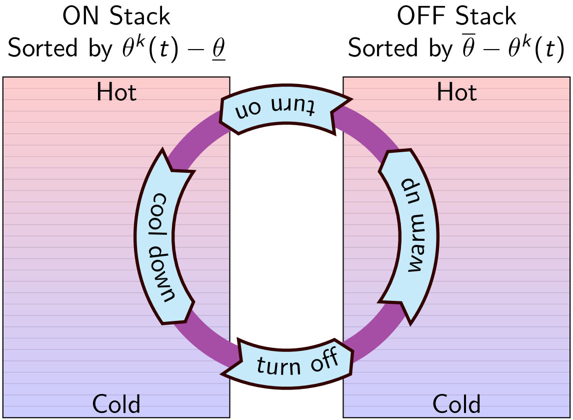
(b) *If* $u \in Batt(\phi_1)$, *proportional allocation keeps* $\theta_k(t)$ *in deadband.*

No diversity $\implies$ $Batt(\phi_1) = Batt(\phi_2)$

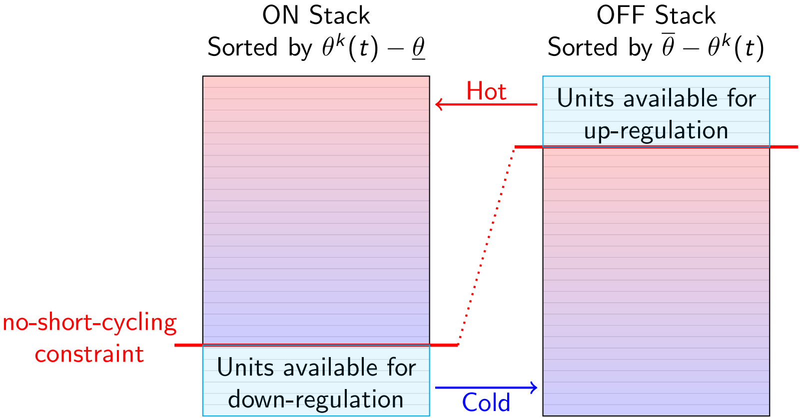
Aggregate flexibility of TCLs can be modeled as a stochastic battery

How Tight are the Battery Models?



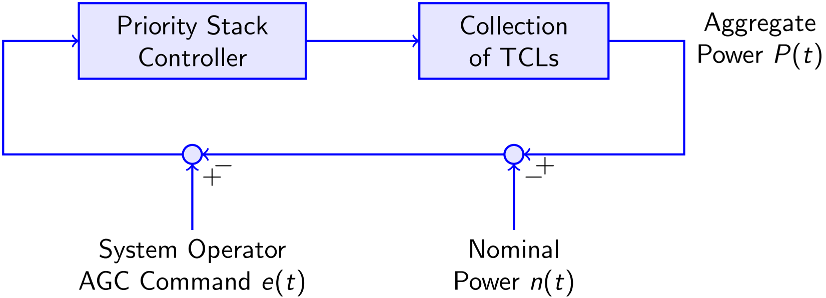

ON Stack
Sorted by $\theta^k(t) - \underline{\theta}$
OFF Stack
Sorted by $\overline{\theta} - \theta^k(t)$
Hot
Cold
Hot
Cold
turn on
cool down
warm up
turn off

Priority Stack Controller



- turn OFF colder units to provide power
- turn ON warmer units to absorb power
- no-short-cycling constraints

Control Architecture



- Nominal aggregate power $n(t) = \sum_k P_k^o$
  Contractually agreed on with SO when delivering freq regulation
- Two key problems:
  - Measuring aggregate power $P(t)$
  - Computing nominal aggregate power $n(t)$

Control Architecture Details

- Centralized control, sampling rate 0.25 Hz
- Each TCL:
  1. during installation calibration of P^m (hopefully $\approx$ const)
  2. measure $\theta_k(t), \theta^r$ (already available)
  3. estimate R, C, θ^a, Δ (standard system ID)
  4. compute and transmit to cluster manager

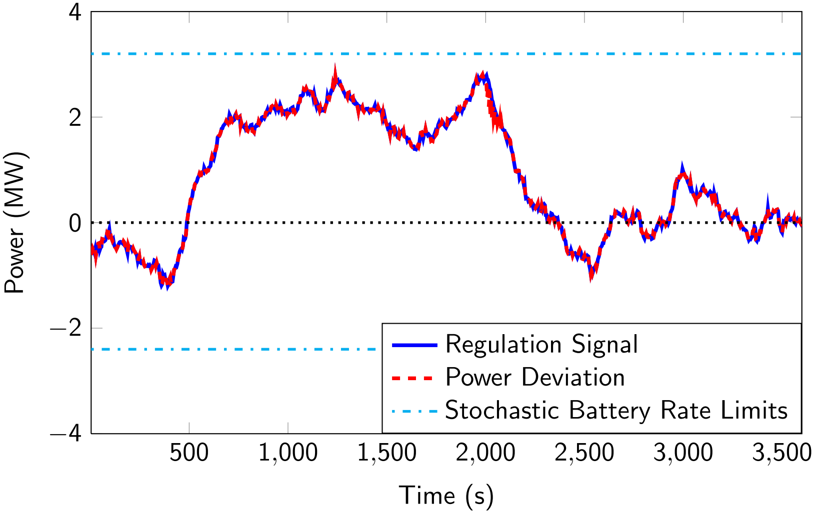
$$P_k^o, P_k(t), \text{priority} = \pi_k(t)$$

- Cluster manager:
  1. computes nominal aggregate power $n(t)$
  2. computes aggregate power $P(t)$
  3. updates priority stack
  4. receives AGC command, computes control action
  5. broadcasts control action to TCLs

Simulations

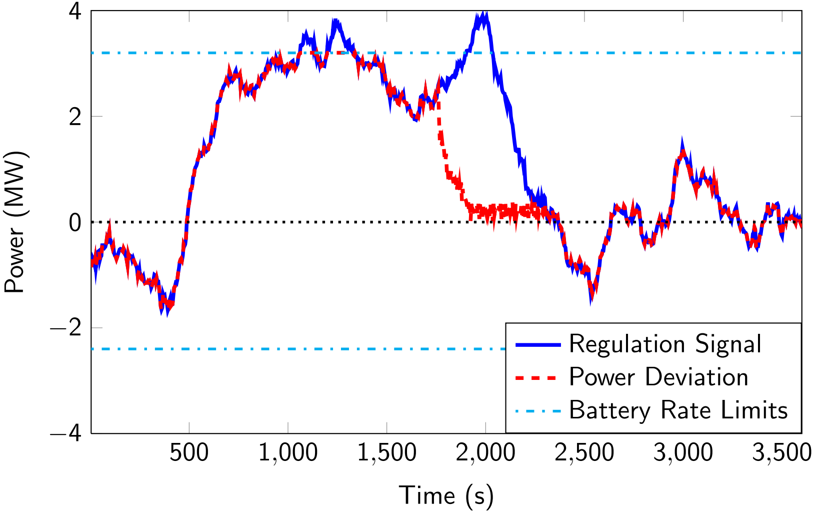
- Heterogenous Population of 1000 TCLs
  - nominal power $= 2.4$ MW
  - peak power (all units ON) $= 5.6$ MW
  - randomized model parameters R, C, P^m, a
  - common ambient temperature θ_a
  - synthetic process noise
  - no-short-cycling constraint
- Stochastic Battery Model
  - charge-rate constraints $[-2.4, 3.2]$ MW
  - capacity 0.8 MWh
  - dissipation time const 4 h

Excellent Tracking of AGC Command



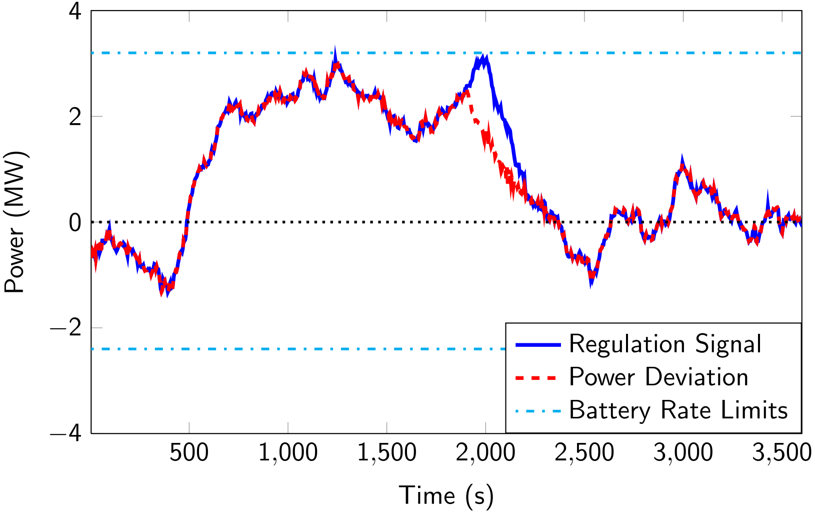
AGC command within stochastic battery limits

Asking for too much power!



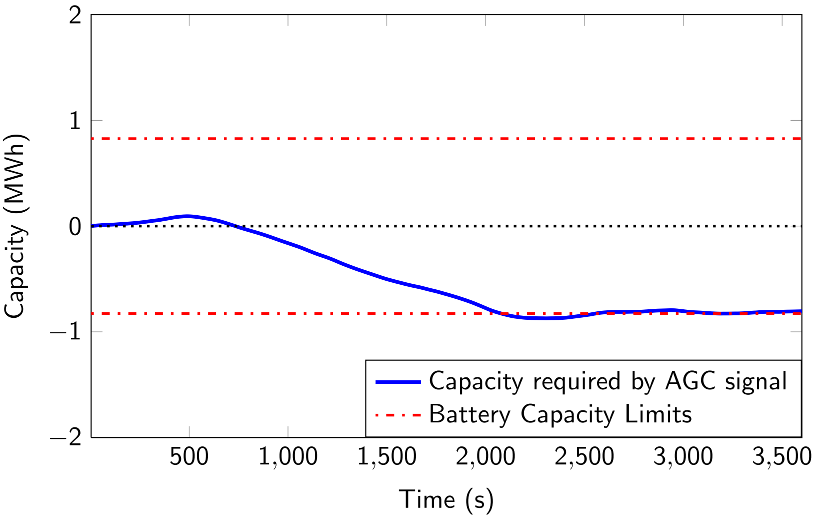
AGC command exceeds stochastic battery rate limits

Asking for too much capacity!



AGC command within stochastic battery rate limits, but ...

Asking for too much capacity!



AGC command exceeds stochastic battery capacity limits

Summary

- Residential HVACs – large capacity bcz units can be phase shifted
- Commercial HVACs – small capacity bcz of efficiency droop in chillers
- Plenty of flexibility
  - San Diego, summer months
  - 25% participation from residential AC
  - Agg flexibility offers 2 $\times$ currently needed regulation
- Battery models can be used to screen for participation
  - cluster similar TCLs into battery model
  - good TCLs: large Δ, P^m
- The gaming issue!

Aggregate Flexibility from EVs

Modeling Electric Vehicles

- Simple model
  - arrival a, departure d, needs energy E, max rate m

$$\int_a^d p(t)dt = E, \quad 0 \leq p(t) \leq m$$

  - Ignoring many details: range for E, quantized power levels, minimum rate during charging, ...
- Each EV load is a task parametrized by (a, d, E, m)
- EV announces task parameters on arrival
- Task are pre-emptive: can interrupt and resume servicing
  else problems become bin packing (NP Hard)

Some Simple Concepts

- Energy state of task at time t:

$$e(t) = E - \int_a^t p(\tau)d\tau = \text{remaining energy needed}$$

- Task is active at time t if $a \leq t \leq d$
- $\mathbb{A}(t)$ = set of all active tasks at time t
- Nominal load profile $n(t)$
  - Service task at a constant rate $E/(d-a)$
  - Don't exploit flexibility

Adequacy

- Many power profiles can meet EV needs
- Available generation $g(t)$
- σ allocates available generation $g(t)$ to tasks
  - σ is causal if allocations at time t depend only on:
    info from past tasks , past generation
  - $g(t)$ is adequate if $\exists\ \sigma$ that completes all tasks
  - $g(t)$ is exactly adequate if adequate + no surplus
- Agenda:
  - When is g exactly adequate?
  - If it is, what policy σ will complete the tasks?
  - If it isn't, we have at times shortfall/surplus generation
    What are the minimum energy reserves we need?

Common Scheduling Policies

- Build priority stack
- Earliest Deadline First [EDF]: Prioritize tasks by deadline d
- Least Laxity First [LLF]: Prioritize tasks by laxity λ

$$\text{Laxity} \quad \lambda(t) = \overbrace{(d_i - t)}^{\text{time remaining}} - \overbrace{(e_i(t)/m_i)}^{\text{time required}}$$

- Very easy to implement!
- Inspired by Processor-Time-Allocation research [ex: Liu ('73), Dertouzos ('74)]

Aggregate Flexibility of EVs

Theorem

Assume no rate limits

(a) *Agg flexibility* $\mathbb{E} = Batt(\phi)$.
Battery has no dissipation, no rate limits, and time-varying capacities:

$$C^- = \sum_{i \in \mathbb{A}(t)} E^i \frac{t - a^i}{d^i - a^i} \quad C^+ = \sum_{i \in \mathbb{A}(t)} E^i \frac{d^i - t}{d^i - a^i}$$

(b) *If* $u \in Batt(\phi)$, *EDF scheduling satisfies all tasks.*

- $x(t) > C^+ \implies$ have surplus, need down-regulation
- $x(t) < -C^- \implies$ have shortfall, need up-regulation

Aggregate flexibility of EVs can be modeled as a stochastic battery

Intuition

- Flexibility captured by battery capacity $[-C^{-}(t), C^{+}(t)]$
  - time-varying
  - depends only on active task info
  - easily computed causally from $\mathbb{T}$
  - ex: Bernoulli arrival of identical tasks

$$C^{-} = C^{+} \approx 0.5 \sum_{i \in \mathbb{A}(t)} E^{i} = C(t)$$

- Aggregate Flexibility $C(t)$
  - $C(t) =$ half energy needs of active tasks at time t
  - keep cumulative deviation x in sleeve $\pm C(t)$

Minimum Energy Reserve Policy

- Suppose available generation is not exactly adequate
  - shortfall $\rightarrow$ up-regulation $r^{up}(t)$
  - surplus $\rightarrow$ need down-regulation $r^{down}(t)$
- How much reserves are needed? How to schedule in real-time?

Theorem

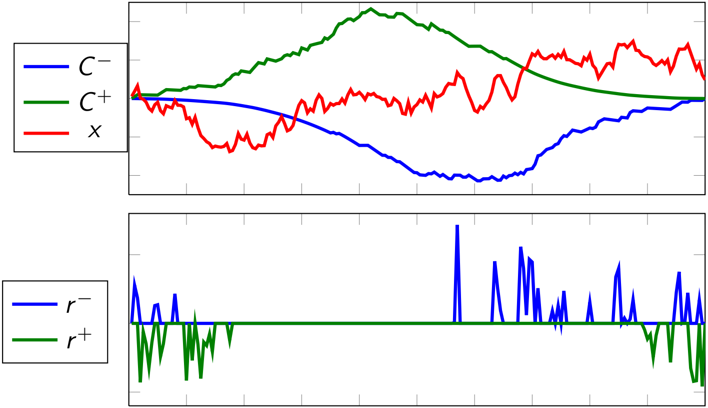
Define the random process $y(t)$ with $y(0) = 0$ and

$$dy = \begin{cases} v(t) & \textit{if } |y(t)| \leq C \\ 0 & \textit{else} \end{cases}$$

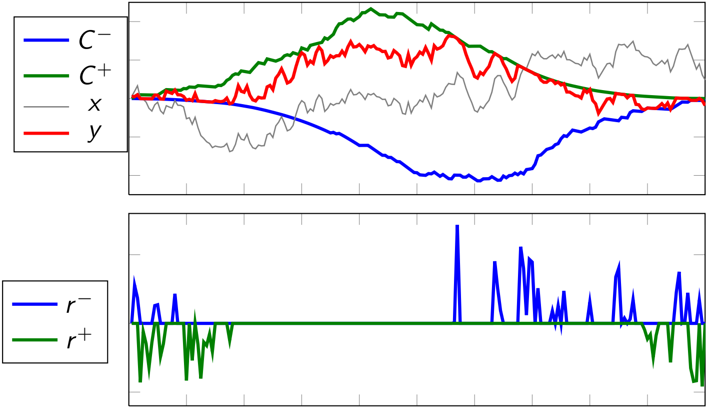
The minimum energy reserve policy to complete the tasks is

$$\begin{aligned} r^{up}(t) &= (y(t) + v(t) - C)^{+} \\ r^{down}(t) &= (-C - y(t) - v(t))^{+} \end{aligned}$$

Illustration



Illustration



ex: Green Garage

- Car statistics

Average EV arrivals	50 per hour
Average time parked	h hours
Average charge rate	4 kW
Nominal load $n(t)$	$\approx 50 \times h \times 4$ kW

- Aggregate Flexibility
  - Average energy needed at any time

$$\overset{\text{ave num of cars}}{50h} \times \overset{\text{charge rate}}{4} \times \overset{\text{ave stay}}{h} = 200h^2 \ \text{kWh}$$

  - Cars behave like nominal + stochastic battery:
  - Battery capacity $\approx \pm 100h^2$ kWh

What happens with Rate Limits?

Theorem

Assume rate limits. Suppose g is adequate.
Causal scheduling policy may not exist.

- Must use forecasts of generation $g(t)$ and loads $\mathbb{T}$
- Model predictive control works well, but may be overkill
- Simulation studies reveal
  - Reserve energy: all scheduling policies are comparable
  - Reserve capacity: MPC is better
  - In many metrics, EDF/LLF work very well for $\approx$ 100 EVs

A. Subramanian *et al*, [ACC 2012, CDC 2012]

Looking Forward ...

- Computing battery models
  - Deferrable appliance loads?
  - Commercial buildings?
  - Can we use data from AMIs directly to build battery models?
- Regulation resources: conventional generation, flex loads, storage
  - Differentiated by reliability, duration, performance
  - Different prices
- Generalized regulation procurement
  - What resource mix should SO use?
  - Network case?
  - Connections to RLD?
- Incentivizing Participation
  - Discounts? Lotteries?