The Grid with Intelligent Periphery

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Renewable Integration

Renewables: Drivers and Targets

- Increased interest and investment in renewable energy sources
- Drivers:
  - Environmental concerns, carbon emission
  - Energy security, geopolitical concerns
  - Nuclear power safety after Fukushima
- Ambitious targets:
  - CA: RPS 33% energy penetration by 2020
  - US: 20% wind penetration by 2030
  - Denmark: 50% wind penetration by 2025

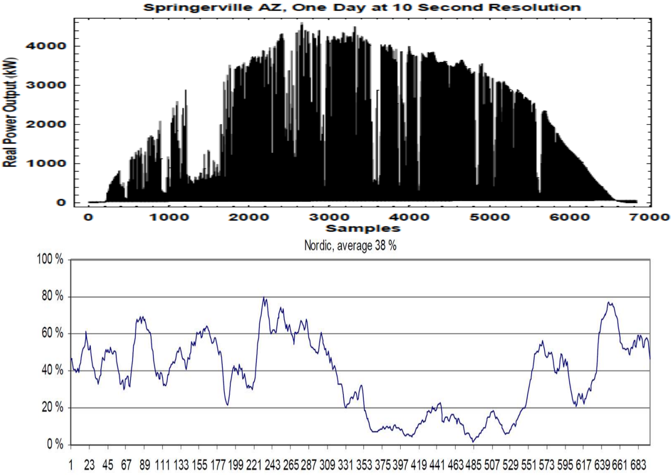
How will we *economically* meet these aggressive targets?

Renewables: where and how much?

- Grid-side wind farms, large PV facilities, thermal-solar plants
  - away from population centers
  - need transmission investment
  - centralized dispatch
- Distribution-side small rooftop PV at $\sim 10^6$ locations
  - power generated and consumed locally
  - decentralized control

Large fraction of renewable investments will be on distribution-side

Renewable Generation is Variable



Solar data – Jay Apt and Aimee Curtright, CMU, 2009

Wind data – Hourly power from Nordic grid for Feb. 2000 P. Norgard et al, 2004

Integration Costs

- Increased variability is *the* problem!
  - Operational challenges: ± 3 GW/h wind ramps
  - Reserve requirements: $3X$ increases needed
- Reserve capacity increases needed with current practice under 33% penetration in CA [Helman 2010]

  Load following: 2.3 GW $\rightarrow$ 4.4 GW

  Regulation: 227 MW $\rightarrow$ 1.4 GW

  Excess reserves defeat carbon benefits
- Added costs due to reserves at 15% renewable penetration

  $\approx$ \$2.50 - \$5 per MWh of renewable generation

  EWITS study, NREL, 2010

Reserves are a significant cost for renewable integration

Mitigating Reserve Costs – Approaches

Supply-side Better use of Information	Improved forecasting Risk limiting dispatch
Demand-side Exploiting Flexibility	Storage, HVACs Electric vehicles
Market-side Novel Instruments	Intraday markets New incentive strategies

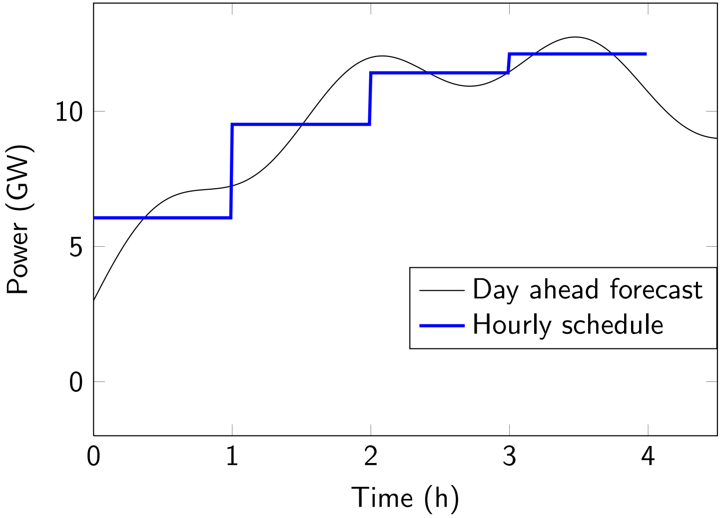
Power System Operations

- The Core Problem: Balancing Supply and Demand
  - economically through markets
  - with transmission constraints
  - while maintaining power quality (voltage, frequency)
  - and assuring reliability against contingencies
- Today
  - All renewable power taken, treated as negative load
    subsidies: feed-in tariffs, etc
  - Net load $n(t) = \ell(t) - w(t)$
  - Tailor supply to meet random demand
- Tomorrow
  - Renewables are market participants
  - Tailor demand to meet random supply

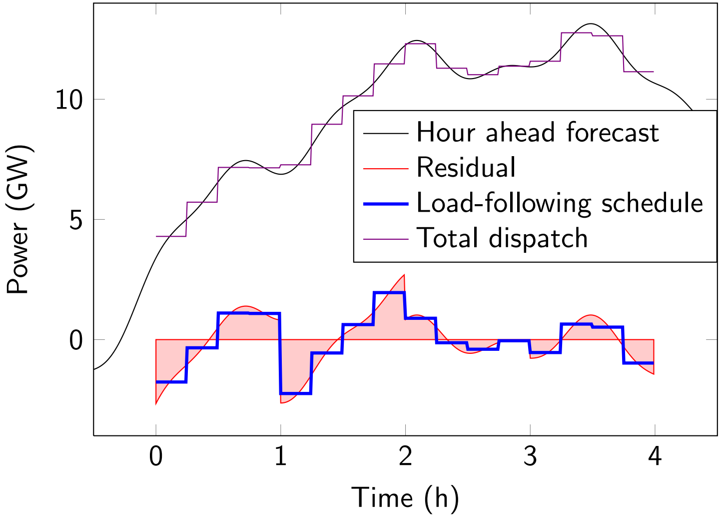
System Operations Today

- Complex, vary immensely across regions, countries
- Constructing the supply to meet random demand
  - Feed-forward: use forecasts of $n(t)$ in markets
  - Feedback: use power & freq measurements for regulation
- Markets (greatly simplified)
  - Day ahead: buy 1 hour blocks using forecast of $n(t)$
  - "Real-time": buy 5 min blocks using better forecast of $n(t)$
- Regulation
  - For fine imbalance (sub 5-min) between supply and demand
  - Must pay for regulation capacity
  - Various time-scales

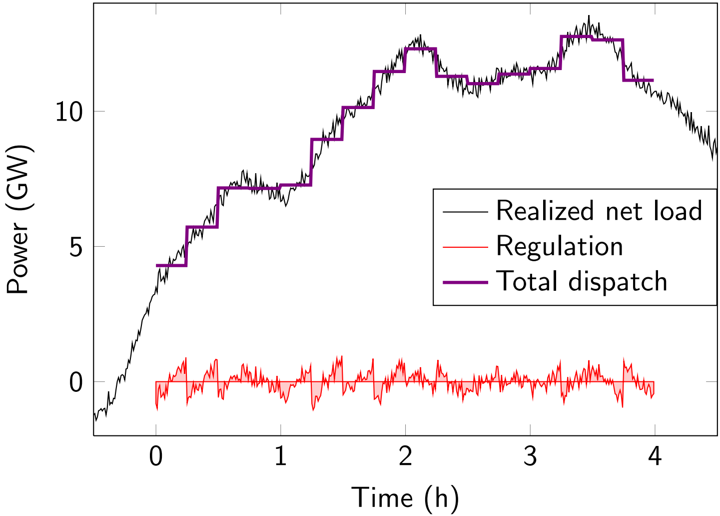
Day Ahead Market Dispatch



Real Time Market Dispatch

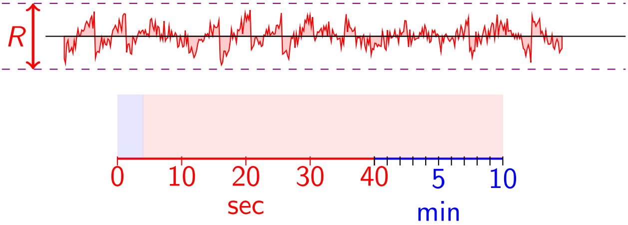


Regulation



Power (GW)
10
5
0
0
1
2
3
4
Time (h)
Realized net load
Regulation
Total dispatch

Regulation Time-scales



Capacity R for various regulation services procured in advance

time-scale	ancillary service	detail
$<$ 4s	governor control	decentralized
4s to 10m	AGC automatic generation control	centralized control generators on call respond to SO commands

Tomorrow: Things Fall Apart

- Myopic decision-making
  - ignores forecast error
  - doesn't exploit that there is a recourse opportunity

  Approach: Risk-limiting-dispatch Rajagopal *et al* 2012

- Too much variability
  - 33% renewables $\rightarrow$ lots of variability $\rightarrow$ 3X reserves
  - variability at many time-scales and magnitudes
    need distinct regulation services

    solar $\rightarrow$ more frequency regulation
    wind $\rightarrow$ more operating reserves
    large wind ramps $\rightarrow$???

  Solution: tailor demand to meet random supply by
  exploiting flexible loads

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 Ancillary Services can be provided?
  - load-following regulation?
  - frequency regulation?
- Architecture?
  - direct load control or load control through price proxies?
  - degree of decentralization?
  - hardware infrastructure?
- Where is the economic value?

The Value of Flexible Loads

Player	*Value*
Flexible Loads	discounted electricity price
Utilities	better forecasting
Aggregator	minimizing operating costs
Renewable Generators	firming variable power
System Operator	displacing reserve capacity

An Example of What is Possible

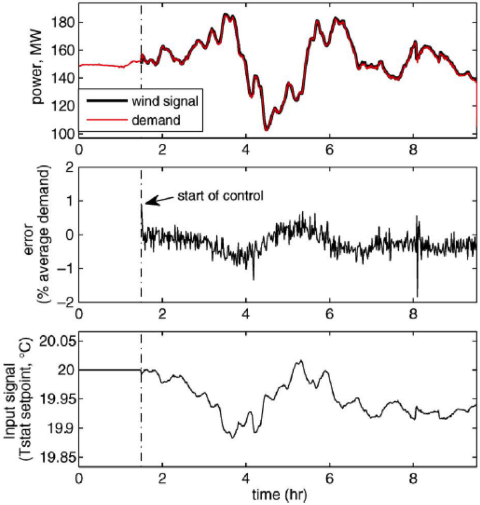
- Direct load control: 60,000 diverse AC units

Control	$u(t)$ = common setpoint change
Measurements	$\theta_k(t)$ = temperatures of unit k
Objective	total power $P(t)$ tracks command $r(t)$
	high freq part of power from wind farm
Model	collection of TCLs: stochastic hybrid system
	Malhamé and Chong, *IEEE TAC*, 1985

- 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 Central Problems

- Consider collection of flex loads
- Modeling Aggregate Flexibility
  - characterize the set of admissible power profiles that can meet the needs of flex loads
  - want a simple, portable model
  - System Operator uses model for procuring AS
- 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 as an AS
  - ex: residential HVAC
  - loads pay fixed price per MW
  - flexibility is sold as load-following 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

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

- 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

- 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
- Simple scheduling algorithms:
  Given $u \in Batt(\phi_1)$, can allocate u to flex loads
  - $u = \sum_k e_k, \quad e_k \in \mathbb{E}_k$
  - algorithms are causal

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)]

Testing Adequacy

$g(t)$	available generation
$n(t)$	nominal load profile
$v(t)$	deviation $g - n$
$x(t)$	cumulative deviation $\int_0^t v(\tau) d\tau$

Theorem

Assume no rate limits

g is exactly adequate $\iff$

$$-C^- \leq x(t) \leq C^+ \quad \textit{where} \begin{cases} C^- & = & \sum_{i \in \mathbb{A}(t)} E^i \frac{t - a^i}{d^i - a^i} \\ C^+ & = & \sum_{i \in \mathbb{A}(t)} E^i \frac{d^i - t}{d^i - a^i} \end{cases}$$

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

Aggregate Flexibility of EVs

- An equivalent view ...

Theorem

Assume no rate limits

g is exactly adequate $\iff$ $g = n + u$ *where* $u \in Batt(\phi)$.

Battery has no dissipation, no rate limits, and time-varying capacities:

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

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

- Capacities are random processes
  - depend on arrival/departure rates, charging needs, etc

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

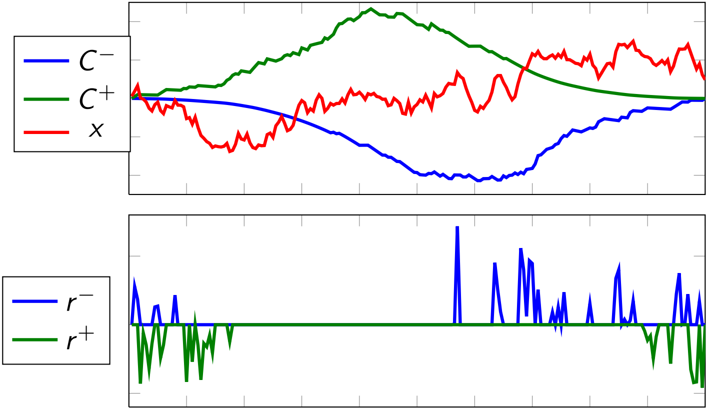
Define the random process $y(t)$ with $y(0) = 0$ and

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

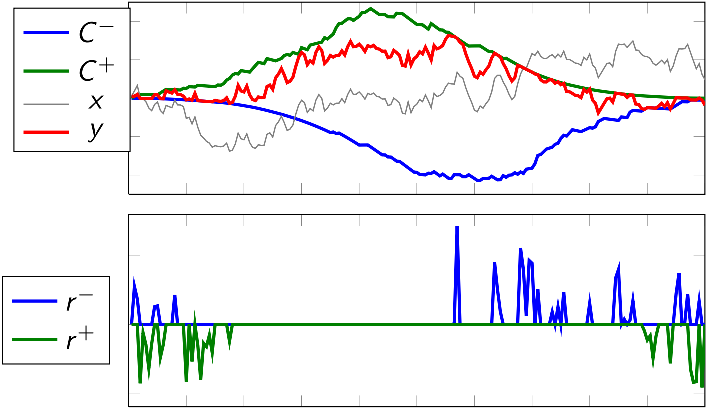
The minimum energy reserve policy to complete the tasks is

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

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!
- Simulation studies reveal
  - Reserve energy: all scheduling policies are comparable
  - Reserve capacity: MPC is much better

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

Aggregate Flexibility from TCLs

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/°C
R	thermal resistance	2 °C/kW
P^m	power consumption when ON	5.6 kW
Δ	deadband	1 °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
- Later need to show that for a large population, aggregate behavior of TCLs is same under either model

Nominal Average Power

- Assume $\theta_a \approx$ const
- 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

Collection of TCLs

- N diverse TCL loads
- Each modelled by $\{\theta_k^r, \Delta_k, R_k, C_k, P_k^m\}$
- Nominate aggregate power

$$n(t) = \sum_k P_o^k = \text{fn of ambient, TCLs, set-points}$$

- Some constants

$$\begin{aligned} \bar{a} &= \frac{1}{N}\sum_k 1/(R_k C_k) = \text{ ave time constant} \\ m^- &\approx \sum_k P_k^o = \text{ agg nominal power} \\ m^+ &\approx \sum_k (P_k^m - P_k^o) = \text{ agg peak - agg nominal power} f_k \end{aligned}$$

Adequacy

- Many power profiles can keep TCLs within user-specified comfort bounds $\theta_r \pm \Delta$
- Available generation $g(t)$
- Scheduling policy σ allocates $g(t)$ to TCLs

– σ is causal if allocations at time t depend only on:

  past info from TCLs , past generation

– $g(t)$ is adequate if $\exists$ σ such that

$$|\theta^k(t) - \theta_r^k| \leq \Delta^k$$

– $g(t)$ is exactly adequate if adequate + no surplus

Aggregate Flexibility

$g(t)$	available generation
$n(t)$	nominal aggregate power

Theorem

g is exactly adequate $\Longrightarrow g = n + u$ where $u \in Batt(\phi_1)$.
Battery has dissipation $\bar{a}$, rate limits $[m^-, m^+]$, and capacity:

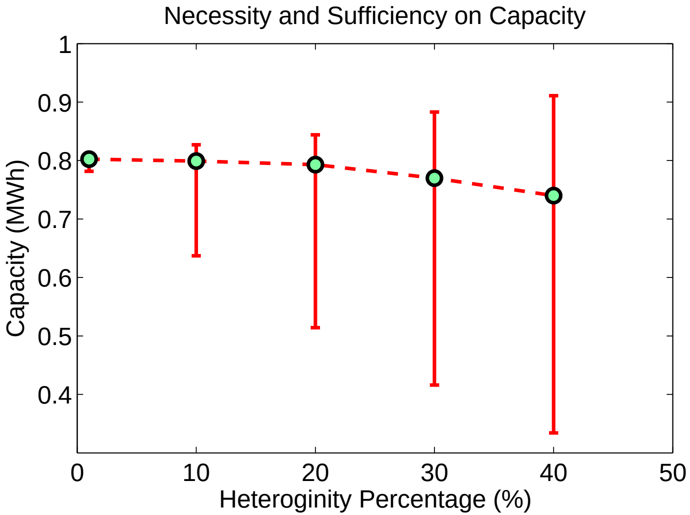
$$C \approx \sum_k \Delta_k (1 + f_k)$$

g is exactly adequate $\Longleftarrow g = n + u$ where $u \in Batt(\phi_2)$.
Battery has dissipation $\bar{a}$, rate limits $[m^-, m^+]$, and capacity:

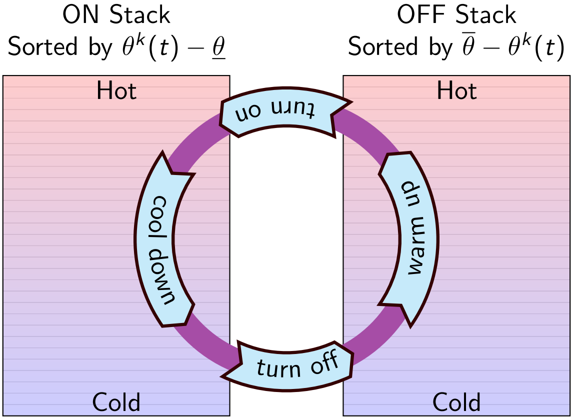
$$C \approx \sum_k \Delta_k (1 - f_k)$$

Aggregate flexibility of TCLs can be modeled as a stochastic battery

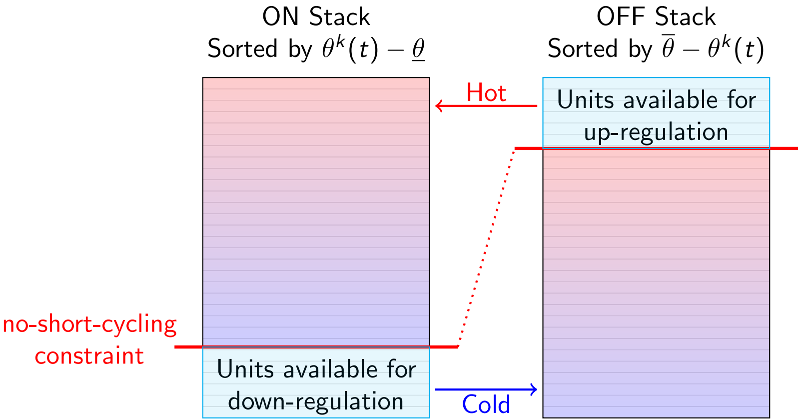
How Tight are the Battery Models?



Priority Stacks

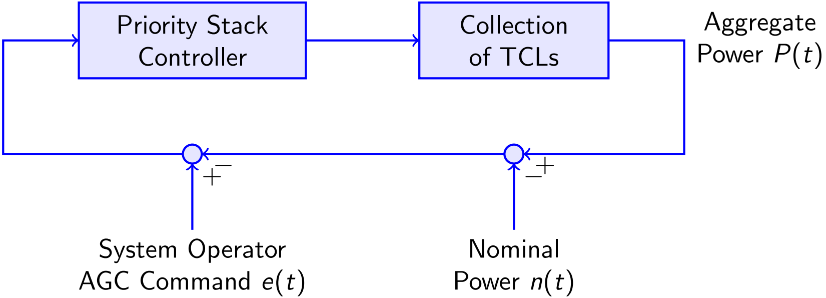


Priority Stack Controller



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

Control Architecture



- 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

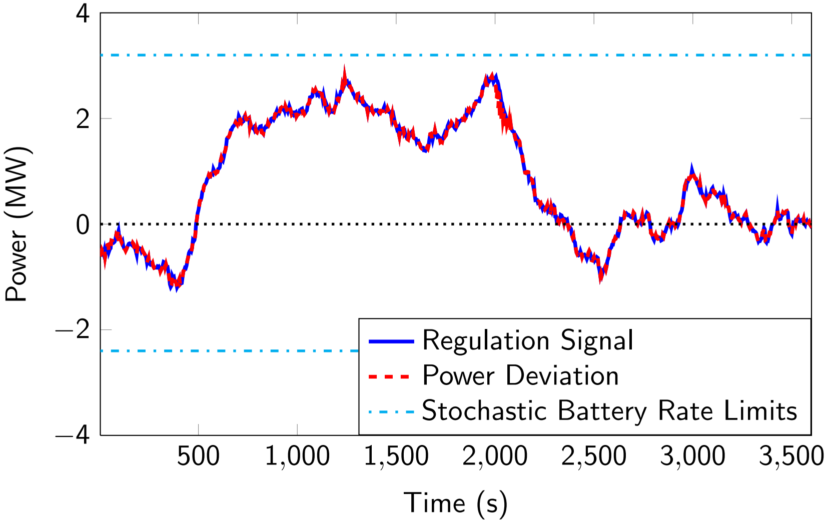
$$P_k^o, P_k(t), \text{priority} = \pi_k(t)$$

- 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

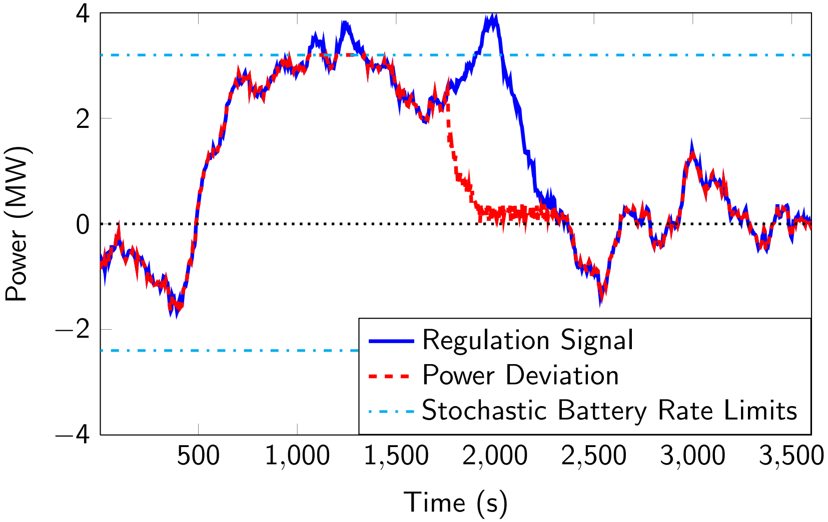
- Heterogenous Population of 1000 TCLs
  - nominal power = 2.4 MW
  - peak power (all units ON) = 5.6 MW
  - randomized model parameters R, C, P^m, a
  - common ambient temperature θ_a
  - synthetic process noise
  - no-short-cycling constraint
- Stochastic Battery Model
  - charge-rate constraints $[-2.4, 3.2]$ MW
  - capacity 1 MWh
  - dissipation time const 4 h

Excellent Tracking of AGC Command



AGC command within stochastic battery limits

Asking for too much!



AGC command exceeds stochastic battery limits

Reserves:
Procurement and Payment

Regulation Reserves: today and tomorrow

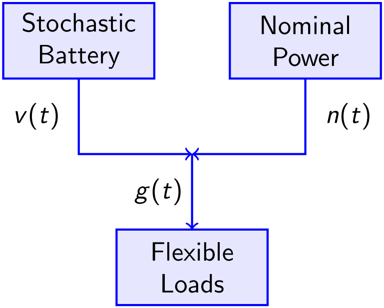
- Focus on regulation reserves
  - Capacity procured in forward market
  - *ex post* energy (mileage) payment
  - Reserves follow AGC command from system operator
  - 4 sec to 10 min time-scale
- *status quo:*
  - Historically, all uncertainty was from loads
  - Load-serving entities pay
  - Costs passed on to rate-payer
- *Tomorrow:* 33% renewable penetration
  - Much more variability injected
  - Much more reserve capacity needed with current practice
    227 MW $\rightarrow$ 1.4 GW in CA [Helman 2010]

Two Problems

- Procurement
  - Generator resources for reserves defeat carbon benefit of renewables
  - Can we use load flexibility for regulation reserves?
- Payment
  - It is a big problem! *status quo* is being challenged
  - ERCOT: Nov 2012, BPA: Sep 2012
  - Paying wind to curtail, utilities object to paying more for regulation
  - Who should pay fairly?
- Principle: Flexible loads are like electricity storage
- Principle: Cost-allocation for cost-causation

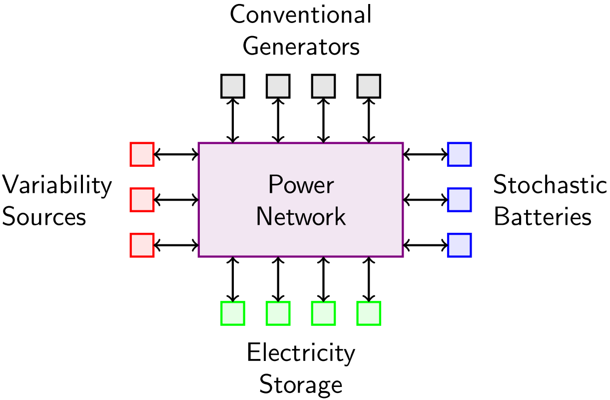
Flexible Loads as Stochastic Batteries

- Universal model of flexibility
- Nominal power:
  arranged through dispatch
- High-frequency residual:
  regulation AS
- Flexible loads
  - Electric vehicles (done)
  - Residential HVACs (done)
  - Commercial HVAC (open)



- Residential HVACs – large capacity bcz units can be phase shifted
- Commercial HVACs – small capacity bcz of efficiency droop in chillers

Generalized Regulation Procurement



- Sources: load forecast errors, wind farms, solar PV
- Sinks: generators, storage, flex loads
- Network: line capacities, losses

Generalized Regulation Procurement ...

- *ex ante* problems
  - Flexible loads forecast their capability
  - SO conducts optimal economic stochastic procurement
- *run time* problems
  - Flexible loads deliver contracted regulation
  - System operator conducts verification
- Single-bus case: optimal procurement reduces to a linear program
- General Problem: open

Incentivizing Participation

The Problem of Small Rewards

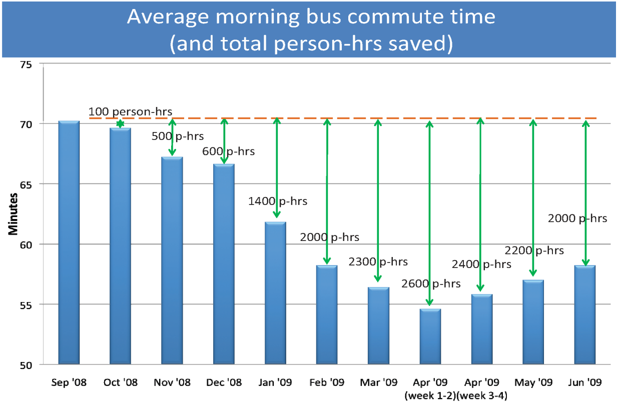
- Want: consumers to turn off AC for $\sim$ 10 min on request
  - Big value to grid: lower reserve costs $\approx$ \$15 M/month in CA
  - Small value per household: $\approx$ \$20/month
  - Reward is too small to get people excited
- A cognitive bias: [Kahneman & Tversky, 1979]
  - People prefer low prob large reward over a guaranteed small reward
  - ex: 5¢ for recycling a can vs. \$5 with prob 0.01
  - Extensive empirical evidence validating this bias
- Idea: Pool system benefit, raffle few large rewards
- Applications to social networks: transportation, health care, energy

Ex: Lottery Incentives for Transportation

- The INSTANT Project: Balaji Prabhakar [Stanford]
  - Change commuter behavior in Bangalore, India
  - Road congestion $\Longrightarrow$ added fuel cost, lost man-hours
  - No incentive to shift to off-peak commute times
- IExpt details
  - 14,000 commuters
  - Credits for off-peak commute
  - Credits qualify for raffle
  - Average winnings = 28$
  - Expected payoff = 24¢/week
    too small to attract participation

Results

- Large reduction in average commute times
- 70 min $\rightarrow$ 55 min, saving fuel cost, and 2500 man-hrs/day



D. Merugu et al., *Proc. of ACM NetEcon Workshop*, 2009

Singapore-UCB Experiment

- Goal: show demand flexibility can be induced by lottery incentives
  - More effective than fixed-rebate incentives
  - Target: 5000 households by 2014
- Protocol: indirect load control
  1. Utility broadcasts SMS flexibility request to consumers
  2. Users return SMS with intent to participate
  3. Smart plugs validate intent
  4. Credits allocated to consumers
  5. Weekly lottery draw
- Minimal technology infrastructure

  Smart phones, wi-fi enabled plugs, software

Selling Random Energy

Re-thinking the Product

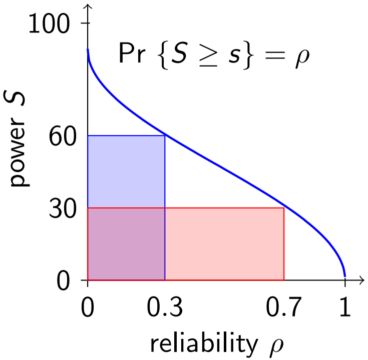
- Today $\rightarrow$ utilities must supply on-demand power
- But, some customers will accept flexible power
- Two paradigms:
- Reliability differentiated: Tan & Varaiya, *J. Econ Dyn Cont*, 1993
  - Get constant power s with probability $> \rho$
  - Price depends on ρ
- Deadline differentiated: Bitar & Low, *CDC*, 2012
  - Get energy E on service window $[t, t+h]$
  - Price depends on h

h (hrs)	0	0.5	1
price (\$/KWh)	0.35	0.3	0.2

Product: differentiated service, not undifferentiated good

Generation Availability Curve

- Generator has random supply S
- Generation availability curve
  - $\Pr\{S \geq s\} = \rho$
  - Constructed from historical data
- ex: 100 MW wind farm
  - 30% of the time, $S > 60$ MW
  - 70% of the time, $S > 30$ MW

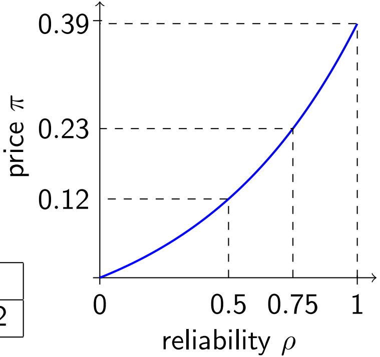


- How can we sell this random supply?

Reliability Differentiated Contracts: Supply

- Product sold: (s, ρ, π)
  - power s with prob $> \rho$ at price π
  - menu of products: $\mathbb{M} = \{s_k, \rho_k\}$

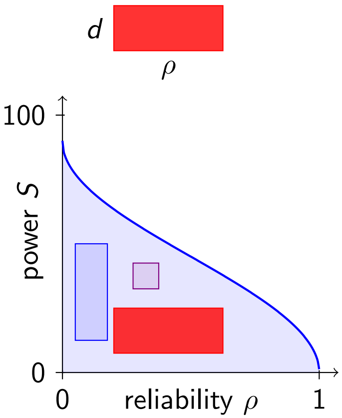
reliability ρ	0.99	0.75	0.5
price π (\$/KWh)	0.39	0.23	0.12



- Supplier sells lower reliability ρ at lower price π

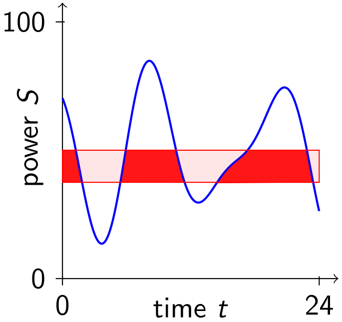
Reliability Differentiated Contracts: Demand

- Consumer purchase
  - Buy power d with reliability $> \rho$
  - Represent by rectangle $R(d, \rho)$
- Balancing supply and demand
  - rectangles must not overlap
  - must place $R(d, \rho)$ below generation availability curve
- Theorem: $\exists$ equib prices that fill available supply
- Drawbacks
  - Difficult to audit
  - Consumers must plan consumption with uncertain supply



Duration Differentiated Contracts

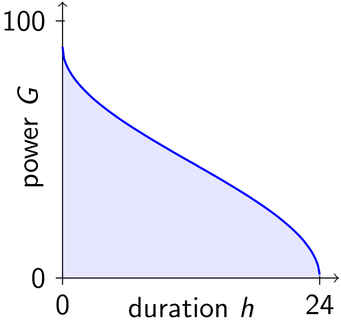
- Consider generation for next 24 hrs
- Idea: sell slices (x, h) of x MW for h hrs
- Availability period is chosen by supplier
- Issues
  - Supply is random
  - Auditing is easy
  - Consumers must plan consumption with uncertain supply
- Negrete-Pincetic, Poolla, Varaiya [2013]



Adequacy

- Consumer purchase
  - (x_k, h_k), $k = 1 \cdots n$
  - h_k sorted in descending order
  - Assume $x_k = 1, \forall k$
- Is the available generation adequate?
- Idea: generation duration curve $G(h)$ (sorted supply curve)
- Theorem: Generation is adequate $\iff$

$$\sum_{1}^{j} G^{-1}(k) \geq \sum_{1}^{j} h_k \quad \text{for } j = 1 \cdots n$$



Contract Pricing

- How should we price (x_k, h_k)?
- Prices serve to balance supply and demand
- Approach
  - identical consumers
  - consumer utility $u(h, x) = h \cdot b(x) - xp$, b is concave
  - supplier utility

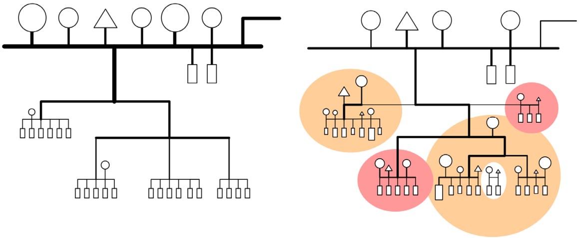
$$v = \sum_k p_k x_k - \ell(x, h)$$

  - two player game for each commodity
- Theorem: $\exists$ equib prices that fill available supply
- Open problem: dealing with randomness in supply $G(h)$

A Vision of Grid 2050

Grid2020 vs Grid2050

- $>30\%$ renewables, mainly in distribution system
- reduces need for investing in high-voltage transmission infrastructure
- power generated and consumed locally
- core grid diminishes in function
- DERs organised into resource clusters



The GRIP Architecture

GRids with Intelligent Periphery

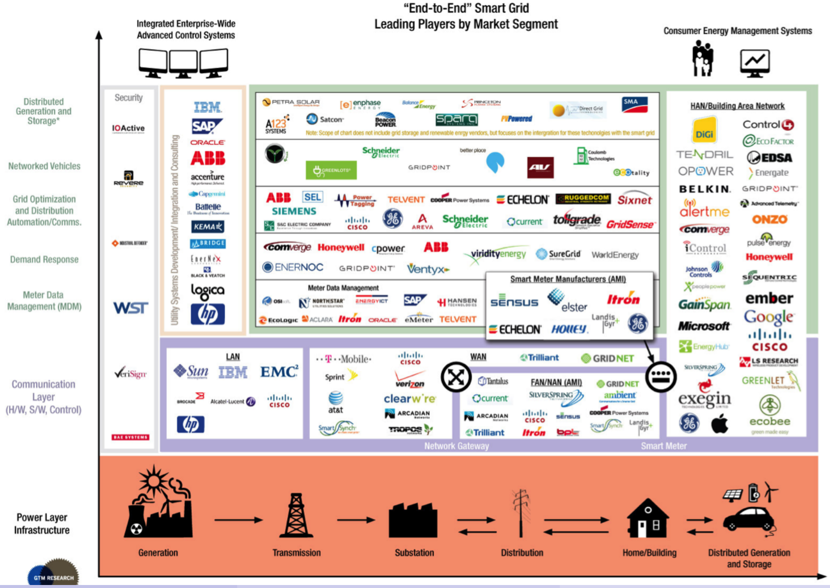
- Resource clusters: storage, micro-generation, flexible loads
  - likely to be below a large (100 MW) substation
  - because of constraints: voltage support, phase balance
- Cluster manager conducts coordinated aggregation
  - *ex ante* represents aggregated resource capability to system operator
  - *ex post* coordinates resources to deliver services

Necessary Technology

- Many critical problems:
  - Power quality and reliability
  - Feeder automation
  - Monitoring and protection
- Need common technology infrastructure:
  - Programmable switches [ex: many vendors]
  - Novel, inexpensive sensors/actuations [ex: Varentek]
  - Communication and computation [ex: internet-of-things]
  - Inter-operability standards [ex: OpenADR]

A $200B market opportunity

Future Energy Systems: Players



Innovation at the Periphery

- Why the periphery? lower regulatory hurdles
- Obstacles
  - Complexity: 10^6 devices to be controlled!
  - Architecture: appropriate degree of decentralization?
  - Trust: will control make things worse? ex: IEEE Standard 1547
  - Who is responsible for reliability?
- Key innovations from: control, modeling, optimization
  - Our community has a vital role to play
  - The problems are of a scale and importance like no other ...
  - Seize the day !!

Some References

Pricing flexibility	Bitar & Low (CDC, 2012)
Risk limiting dispatch	Varaiya et al (Proc. of the IEEE, 2011)
	Rajagopal et al (Int. J. of Elec. Pow. & En. Sys., 2013)
Wind contracts	Bitar et al (IEEE TPS, 2012)
Scheduling	Subramanian et al (CDC, 2012, ACC, 2012)
Aggregate flexibility	Nayyar et al (in prep.)
Risk sharing	Nayyar et al (ECC 2013, submitted),
	Baeyens et al (IEEE TPS, 2012 submitted)
Storage	Taylor et al (Trans. on Pow. Sys., 2012)
TCLs	Callaway (En. Conv. & Mgmt., 2009)

stay hungry, stay foolish

Thank You!

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