Demand Smoothing Through Resource Buffering

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Supported by NSF PFI and NYSTAR TIPP, and Gaia Power Technologies

October 4, 2008

Outline

1. Motivation
2. Offline problem
3. Online problem
4. Conclusion

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High energy demand

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- Key challenge for providers in electricity markets:
  - High simultaneous demand
  - Limited supply (per unit time)
- ConEd wants to sell you lots of energy... but not all right now
- Extreme simultaneous usage is a challenge for the provider
- Difficult to prepare for, puts strain on grid, causes blackouts...

Demand charges

- One response by utilities: disincentivize peak usage
  - *peak* for the individual client
  - (other models: client incentives based on *total* current usage)
  - though this could be reposed from the provider's pt of view

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- Some large clients' energy bills are based on both:
  - How much — kWh — electricity — usage charges
  - How fast (at peak) — $kWh/h = kW$ — power — peak charges

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How much	kWh	electricity	usage charges
How fast (at peak)	kWh/h = kW	power	peak charges

- Per-kW peak charge $\approx$ 100x per-kWh usage charge
  - Incentive: spread out usage over time
  - But not always possible - stores have customer surges, etc.

Alternative energy sources

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- but typically unpredictable.
- How to rely on them?

Solution to both: batteries

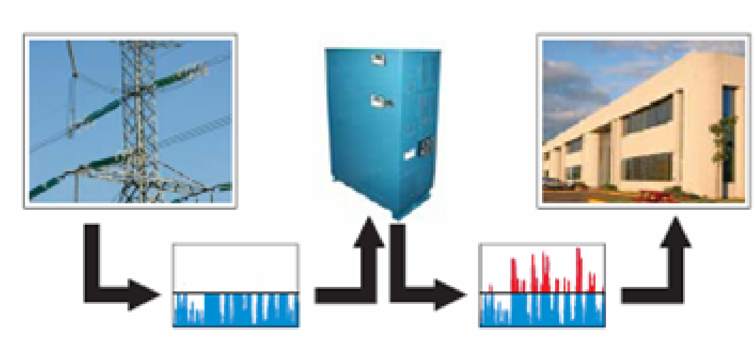

Figure: Gaia PowerTower

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The Xbox shortage of 2005

"[T]he Xbox 360 can be produced only gradually, but all the demand is there at once. Plentiful supply would be possible only if Microsoft made millions of consoles in advance and stored them without releasing them, or if it built vast production lines that only ran for a few weeks–both economically unwise strategies. ... The steady supply can't match peak December demand." (http://www.slate.com/id/2132071/)

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- *Or can it?*

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Model and notation

- At each time: How much extra to request? Or how much less?
- Goal: make request curve as smooth as possible (min max)
  - While always satisfying demand
  - Ideally without wasting any energy
- A dilemma:
  - Request nothing extra: waste the battery
  - Request too much extra: introduce new peaks
- Obj ftn is *max*, not sum
  - “strict liability”

Offline problem definition

Notation

- n discrete timesteps
- d_i: demand at time i (demands = input)
- r_i: request at time i (requests = output)
- $D = \max_i d_i$
- $R = \max_i r_i$
- b_i: battery level at start of time i ($b_1 = 0$ or $b_1 = B$)

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Goal: choose requests r_i to minimize R

- i.e., make request curve as smooth as possible
  - *all demands must be satisfied*
  - with no underflow: $\forall i \;\; b_i \geq 0$
- NB: $b_{i+1} = b_i + r_i - d_i$ (except when underflow/overflow)

Incorporating the free source

- At each time may also have free source amount f_i
- In this case, effective demand is $\hat{d}_i = d_i - f_i$
- As long as negative demands make sense, can ignore free source wlog

Optimal solution (offline, unbounded battery)

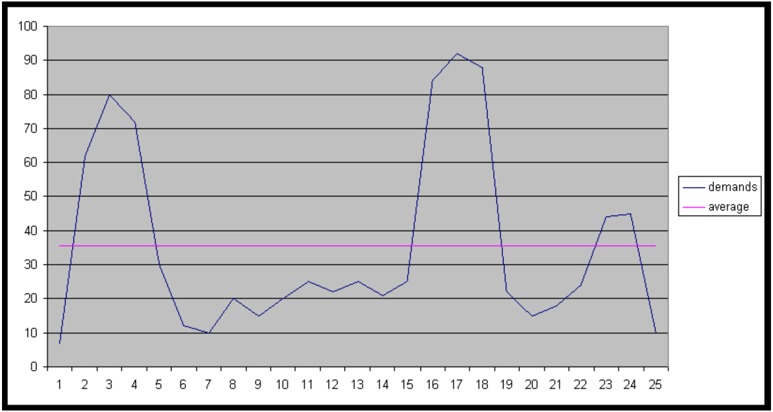

Figure: Demands and mean

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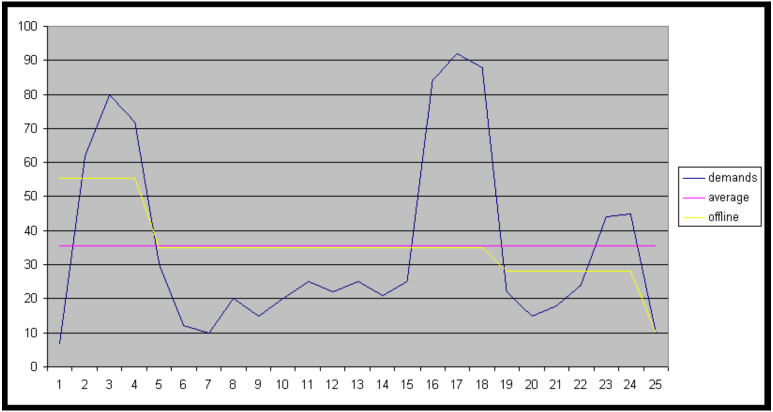

Figure: Demands, mean, and optimal

Threshold algorithms

- All our algorithms are based on *thresholds*
  - Threshold = amount the algorithm tries to request
  - Offline: global threshold T
  - Online: threshold T_i at timestep i
- At each time, (try to) request T_i, and charge/discharge the rest (based on d_i & b_i)

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Two issues:

- Overflow: battery too full: ok, just lose the energy
  - Or just request less
- Underflow: battery below empty: forbidden ("crash")

Threshold algorithms

$$\begin{array}{l} \textbf{for} \text{ each timeslot } i \\ \quad \textbf{if } T_i > d_i \\ \qquad \text{charge } min(T_i - d_i, B - b_i) \\ \quad \textbf{else} \\ \qquad \text{discharge } d_i - T_i \end{array}$$

Figure: Threshold algorithm schema (assumes $b_i \geq d_i - T_i$)

Offline problems

- Two subsettings: unbounded and bounded batteries
- Both solvable by LP
  - But we seek efficient combinatorial algorithms
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  - Initial/final conditions: slightly preprocess input (demands)
- Unbounded battery: find hardest prefix (average) of demands
  - For $b_1 = 0$ case
  - Easy in linear time

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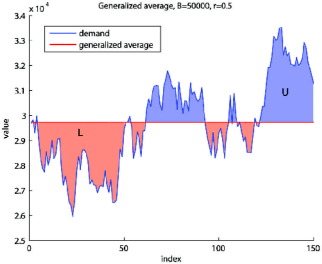

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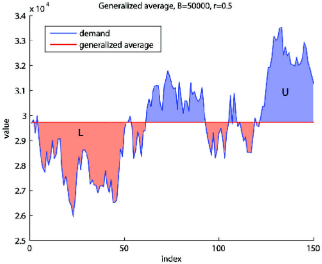

- Can easily find this region in quadratic time

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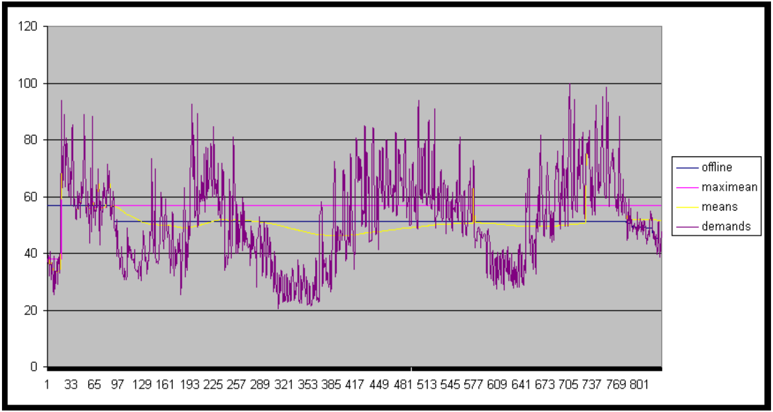
$\rightarrow$ at each moment, run OPT on the full history up until now

- Then choose accordingly
  - i.e., request OPT's *max-so-far* (times some $\alpha \geq 1$)
  - unbounded case: just the maximum prefix mean

Request graph



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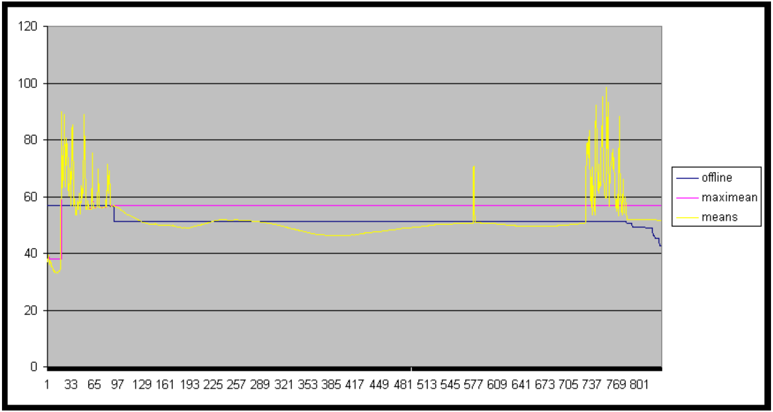
Request graph: means



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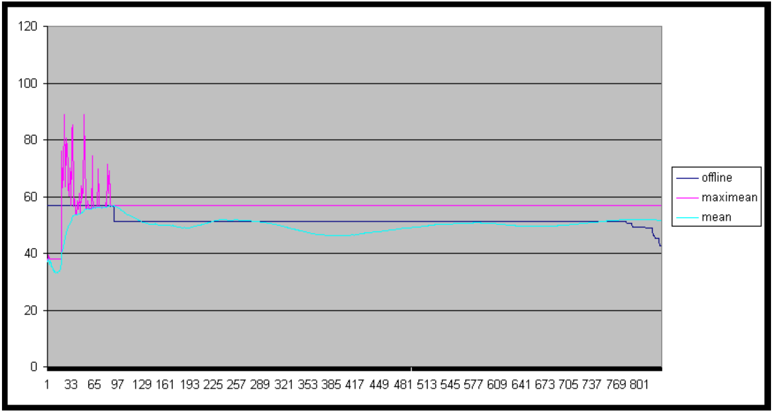
Request graph: maximean



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Competitive online algorithm?

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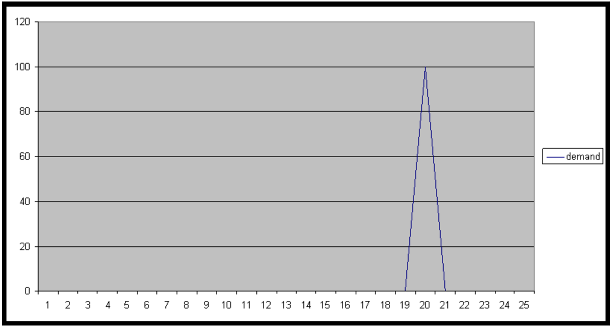

Figure: Competitiveness counterexample for $b_1 = 0$ case

Semi-online algorithms

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- Since opt savings is $D - R_{opt}$
  - Always request so that savings is exactly $1/H_n$ of "optimal savings so far" (compared to D)
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    - Alg 2.a: $T_i \leftarrow D - \frac{D-\hat{\mu}(1,i)}{H_n}$
- H_n-competitive by construction, *assuming it's correct*
    - i.e., assuming battery never crashes
    - i.e., request T_i always suffices, with no underflow

Semi-online algorithms

Lemma

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NB: applies to both bounded and unbounded battery.

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Proof sketch: If ALG is c-competitive ($c \geq 1$) and $b_1 = B$, can force it to discharge:

- B/c at time 1,
- $B/(2c)$ at time 2,
- $B/(3c)$ at time 3, etc.

Total discharge: $\sum_i B/(i \cdot c) = H_n \cdot B/c$.

The demand sequence is just: $(D, D, D, ..., D)$, for some $D \geq B$.

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For unbounded battery, have lower bound of $H_n - 1/2$.

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- Alg 2.a can be $O(n^2)$
  - Basically computing OPT over time
  - At each time, extend $O(n)$ GAs
- Turns out (lemma) we can do better with less work: $O(n)$
  - Suffices to find the GA back to last time battery was full (for us)
  - Forget about prefix: $n \rightarrow n' < n$
  - More importantly: only one GA to extend each time
  - Alg 2.b: $T_i \leftarrow D - \frac{D-\mu(s_i,i)}{H_{(n-s_i+1)}}$
- Analysis same as for Alg 2.a

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Summary

- Gave poly-time offline algorithms for bounded and unbounded batteries
- Unfortunately, many online problem settings here are intractable, but not all
- Gave $O(1)$-per-unit-time online algorithms for two of them

Future directions

Problem extensions:

- Entry loss
  - Corresponding online algorithm also appears to be H_n-competitive (WEA '08), but no proof
- Self-discharge (batteries draining over time)
- 30-minute rolling averages

Experimental work:

- Tuning more aggressive algorithms to empirical data (WEA '08)

Other models:

- E.g. dynamic pricing based on total current demand

Thanks!

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