Efficient Algorithms for Renewable Energy Allocation to Delay Tolerant Consumers





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A STORY calculating **II**

- Feynman Point

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A STORY

calculating **II**

- Feynman Point



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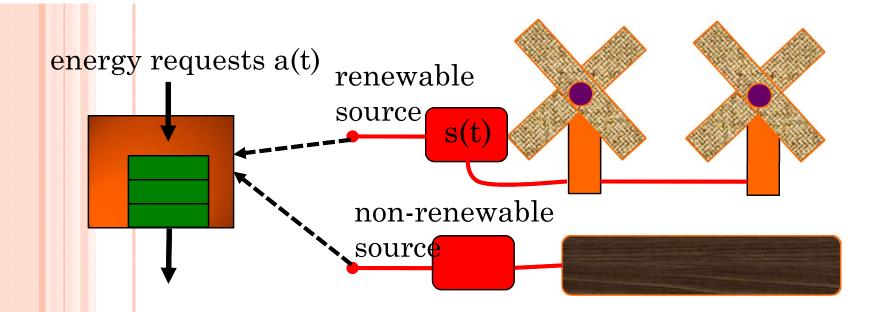
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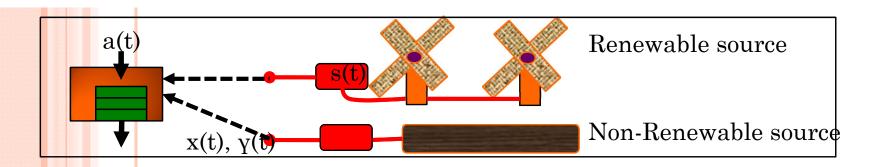
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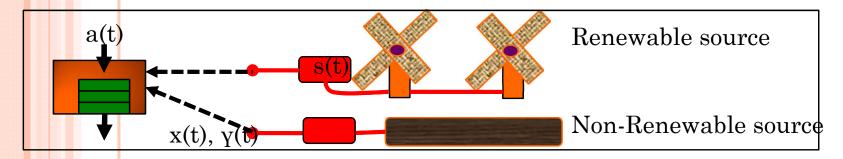


- •Renewable sources of energy can have *variable* and *unpredictable* supplies s(t).
- •We can integrate renewable sources more easily if consumers tolerate service within some maximum allowable delay D_{max} .
- •Might sometimes need to purchase energy from non-renewable source to meet the deadlines, and purchase price can be highly variable.



Outline:

- •<u>First Problem</u>: Minimize time average cost of purchasing non-renewable energy
- •<u>Second Problem</u>: Joint pricing of customers and purchasing of non-renewables

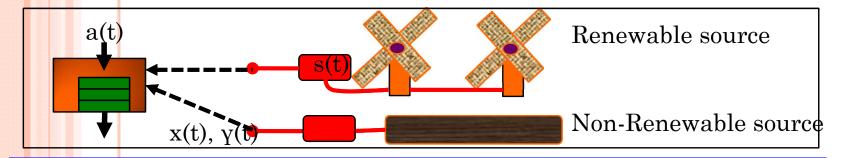


- •Slotted Time: $t = \{0, 1, 2, ...\}$
- •a(t) = energy requests on slot t (serve with max delay D_{max}).
- •s(t) = renewable energy supply on slot t. ("use-it-or-loose-it")
- •x(t) = amount of non-renewable energy purchased on slot t. requests (random)
- $Q(t) = \frac{\$\$}{\text{max}} Q(t) = \text{s(t)} \text{x(t)}, 0 + \text{a(t)}, cost(t) = \text{x(t)} = \text{x(t)} = \text{x(t)}$

Renewable supply (random) (use-it-or-loose-it)

Non-Renewables purchased (decision variable)

purchase price
(random)



$$Q(t+1) = \max[Q(t) - s(t) - x(t), 0] + a(t) , \quad \cos t(t) = x(t)\gamma(t)$$

Assumptions:

• For all slots t we have:

$$0 \le a(t) \le a_{max}$$
, $0 \le s(t) \le s_{max}$, $0 \le \gamma(t) \le \gamma_{max}$, $0 \le x(t) \le s_{max}$

- x_{max} units of energy always available for purchase from non-renewable (but at variable price $\gamma(t)$).
- •a_{max} ≤ x_{max} (possible to meet all demands in 1 slot at high co
- •(a(t), s(t), $\gamma(t)$) vector is i.i.d. over slots with *unknown distr*

$$Q(t+1) = \max[Q(t) - s(t) - x(t), 0] + a(t)$$
, $cost(t) = x(t)y(t)$

Possible formulation via Dynamic Programming (DP):

"Minimize average cost subject to max-delay D_{max} ."

• This can be written as a DP, but requires distribution know

We will not use DP. We will take a different approach...

$$Q(t+1) = \max[Q(t) - s(t) - x(t), 0] + a(t) , \quad \cos t(t) = x(t)\gamma(t)$$

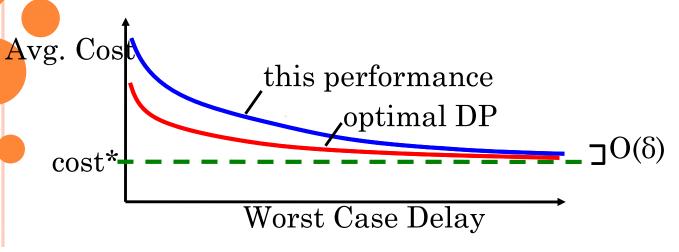
Relaxed Formulation via Lyapunov Optimization for Queue Ne

Minimize: E{cost} (time average)

Subject to: (1) $E{Q} < infinity$ (a "queue stability" constrain

(2) $0 \le x(t) \le x_{max}$ for all t

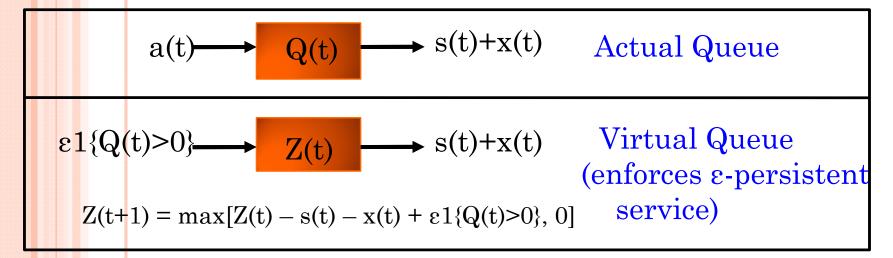
- •Define cost* = min cost subject to stability
- •By definition: $cost* \le cost$ delivered by any other alg (includit
- •We will get within $O(\delta)$ of cost*, with worst-case delay



Advantages of Lyapunov Optimization for Queueing Networks:

- No knowledge of distribution information is required.
- Explicit $[O(\delta), O(1/\delta)]$ performance guarantees.
- Robust to changes in statistics, arbitrary correlations ...
- Worst case delay bounds

Virtual Queue for Worst-Case Delay Guarantee (fix ε>0



Theorem: Any algorithm with bounded queues $Q(t) \leq Q_{max}$, $Z(t) \leq Z$ for all t yields worst-case delay of:

$$D_{\max} = Q_{\max} + Z_{\max}$$

Proof Sketch: Suppose not. Consider slot t, a(t):

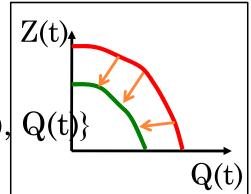
Then:
$$\sum_{\tau=t}^{t} [s(\tau)+x(\tau)] \leq Q_{max}$$

Implies:
$$Z(t+D_{max}) > Z_{max}$$
 (contradiction)

Stabilize Z(t) and Q(t) while minimizing average cost co

Lyapunov Function: $L(t) = Z(t)^2 + Q(t)^2$

Lyapunov Drift: $\Delta(t) = E\{L(t+1) - L(t) \mid Z(t),$



Take actions to greedily minimize "Drift-Plus-

Weighted-Penalty":

$$\frac{\text{Minimize: } \Delta(t) + V_{Y}(t)x(t)}{}$$

where V is a postiive constant that affects the [O(1/V), O(V)]

Cost-delay tradeoff.

(using V=1/ δ recovers the [O(δ), O(1/ δ)] tradeoff.)

Resulting Algorithm: Every slot t, observe $(Z(t), Q(t), \gamma(t))$.

- Choose $x(t) = \{ 0, \text{ if } Q(t) + Z(t) \le V\gamma(t) \}$ $\{ x_{\text{max}}, \text{ if } Q(t) + Z(t) > V\gamma(t) \}$
- •Update virtual queues Q(t) and Z(t) according to their equation

Define:
$$Q_{max} = V_{Y_{max}} + a_{max}$$
, $Z_{max} = V_{Y_{max}} + \varepsilon$

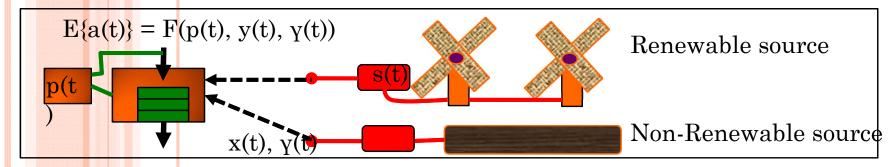
Theorem: Under the above algorithm:

- (a) $Q(t) \le Q_{max}$, $Z(t) \le Z_{max}$ for all t.
- (b) Delay $\leq (Q_{max} + Z_{max})/\epsilon = O(V)$

Further, if $(s(t), a(t), \gamma(t))$ i.i.d. over slots, and if $\epsilon \le \max[E\{a(t)\}]$ Then:

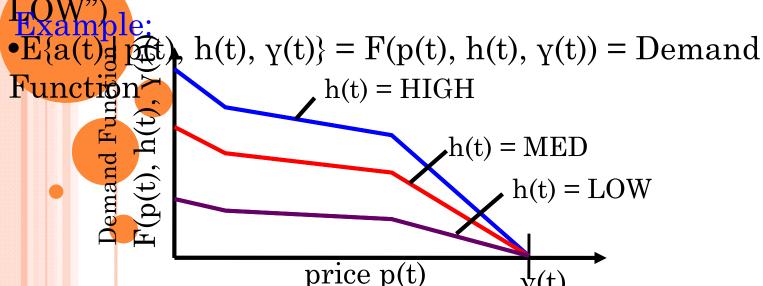
$$E\{cost\} \le cost* + B/V$$

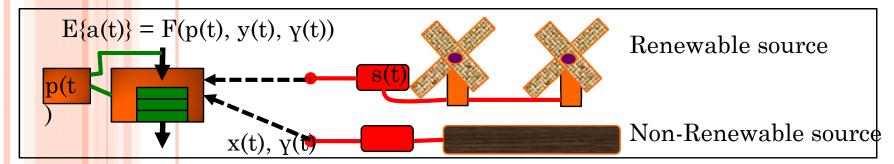
[where $B = (s_{max} + x_{max})$



Same system model, with following extensions:

- •a(t) = arrivals = Random function of pricing decision p(t)
- •h(t) = additional "demand state" (e.g. "HIGH, MED,



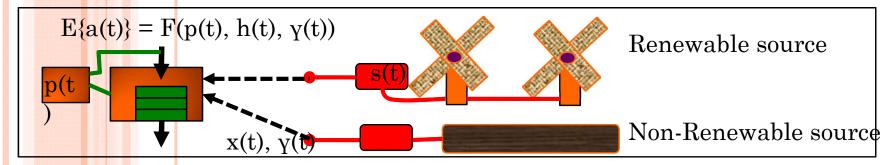


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New Problem:

- FE (a(t), p(t), h(t), y(t)) = F(p(t), h(t), y(t)) = Demand Function
- •Maximize Time Average Profit!
- •Profit* Optimal Time Avg. Profit Subject to Stability



Drift-Plus-Penalty for New Problem:

$$\Delta(t) - VE\{Profit(t) \mid Z(t), Q(t)\} = \Delta(t) - VE\{a(t)p(t) - x(t)\gamma(t) \mid Z(t)\}$$

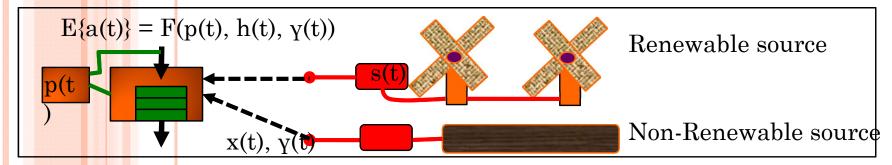
Resulting Algorithm:

Every slot t, observe (h(t), Z(t), Q(t), $\gamma(t)$). Then:

• (Pricing) Choose p(t) in [0, p_{max}] to solve:

Maximize: $F(p(t),h(t),\gamma(t))(Vp(t)-Q(t))$ Subject to: $0 \le p(t) \le p_{max}$

- •(Purchasing) Choose x(t) same as before.
- •Update queues Q(t), Z(t) same as before.



Drift-Plus-Penalty for New Problem:

$$\Delta(t) - VE\{Profit(t) \mid Z(t), Q(t)\} = \Delta(t) - VE\{a(t)p(t) - x(t)\gamma(t) \mid Z(t)\}$$

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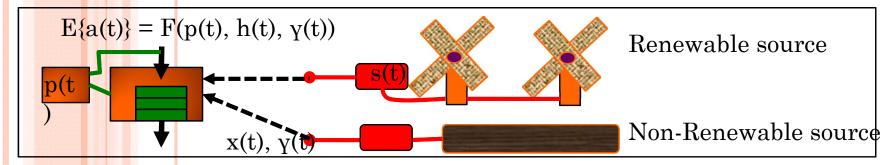
Maximize: $F(p(t),h(t),\gamma(t))(Vp(t)-Q(t))$

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*If $F(p,h,y) = \beta(h)G(p,y)$, don't need to know demand state



Drift-Plus-Penalty for New Problem:

$$\Delta(t) - VE\{Profit(t) \mid Z(t), Q(t)\} = \Delta(t) - VE\{a(t)p(t) - x(t)\gamma(t) \mid Z(t)\}$$

Resulting Algorithm:

Every slot t, observe (h(t), Z(t), Q(t), $\gamma(t)$). Then:

•(Pricing) Choose p(t) in [0, p_{max}] to solve:

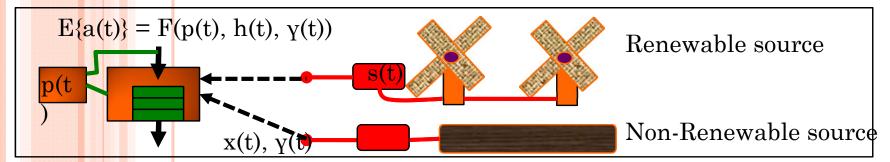
Maximize: $\beta(h(t))G(p(t),\gamma(t))(Vp(t)+Q(t))$

Subject to: $0 \le p(t) \le p_{max}$

•(Purchasing) Choose x(t) same as before.

•Update queues Q(t), Z(t) same as before.

*If $F(p,h,y) = \beta(h)G(p,y)$, don't need to know demand state

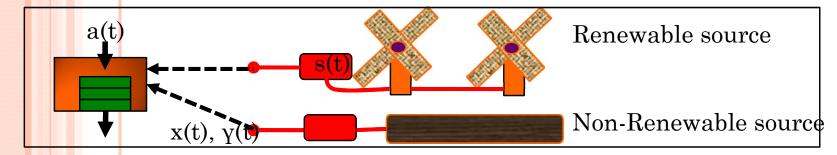


Theorem: Under the joint pricing and energy allocation algor

- (a) Worst case queue bounds Q_{max} , Z_{max} same as before.
- (b) Worst case delay bound D_{max} same as before, i.e., O(V).
- (c) If (s(t), $\gamma(t)$, h(t)) i.i.d. over slots, and $\epsilon \leq E\{s(t)\}$, then:

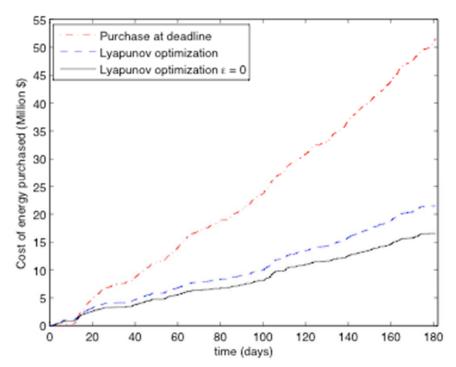
$$E\{profit\} \ge profit^* - O(1/V)$$

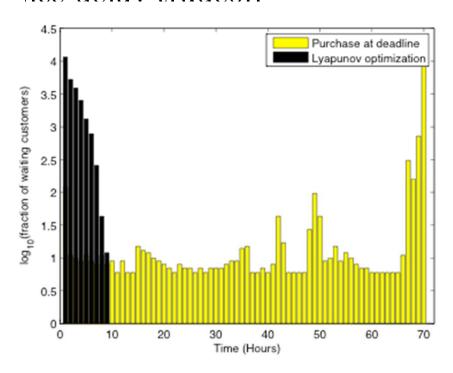
Concluding Slide:



- •Lyapunov Optimization for Renewable Energy Allocation
- •No need to know distribution. Robust to arbitrary sample paths.

-P--1::-: [O(1/N) O(N) ---------nce-delay tradeoff





THANK YOU!

Explanation of Why Delay is small even with $\varepsilon=0...$

Even with $\varepsilon=0$, we still get the same Q_{max} bound. $(Q(t) \leq Q_{max}$ for all t).

Delay of requests that arrive on slot t is equal to the smallest integer T such that:

$$\sum_{\tau=t}^{t+T} [s(\tau)+x(\tau)] \ge Q(t)$$

So delay will be less than or equal to T whenever:

$$\sum_{\tau=t}^{t+T} s(\tau) \ge Q_{max}$$

There is no guarantee on how long this will take for arbitrary s(t) processes, but one can compute probabilities of exceeding a certain value if we try to use a stochastic model for s(t).