A Method for Storing Energy Requests in Large Scales Instead of Storing Electricity

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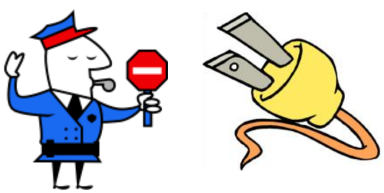
Outline

- Overview of work on Demand Side Management
- Research objective in the context of Smart Grid efforts
- Proposed architecture for DSM
  - Model for demand reservoir
  - Dispatch optimization
- Numerical results
- Conclusions

Background

- Energy demand is intrinsically "elastic" but:
  - Customers today are shielded from price-aware market decisions
  - Balance requirement: The market is biased towards controllable generation
- Vision: Control the load more so that it can use less predictable and controllable (green) generation
- Demand Side Management and Demand Response
- Two prominent ideas – two opposite sides of the control spectrum:
  - Load Control Through Curtailment



    - Advancing but not new
  - Priced Based Load Control / Real Time Pricing

Direct Load Control

- Goal: keep the generation/demand balance in emergencies
- Interruptible Load Programs (since the 70s)
  - Only good for appliances that **can be interrupted** (HVAC)
  - Signal to turn off for a pre-determined interval in emergency situations and peak load hours
- Events cannot happen frequently as decisions are not accounting for the inconvenience of the customers

Various pricing schemes

- Time of Use: predetermined (variable during the day)
  - Designed years beforehand – no actual real-time control over demand
- Critical Peak Pricing: TOU except for the duration of critical peak events (only emergency!)
- Real-time Pricing:

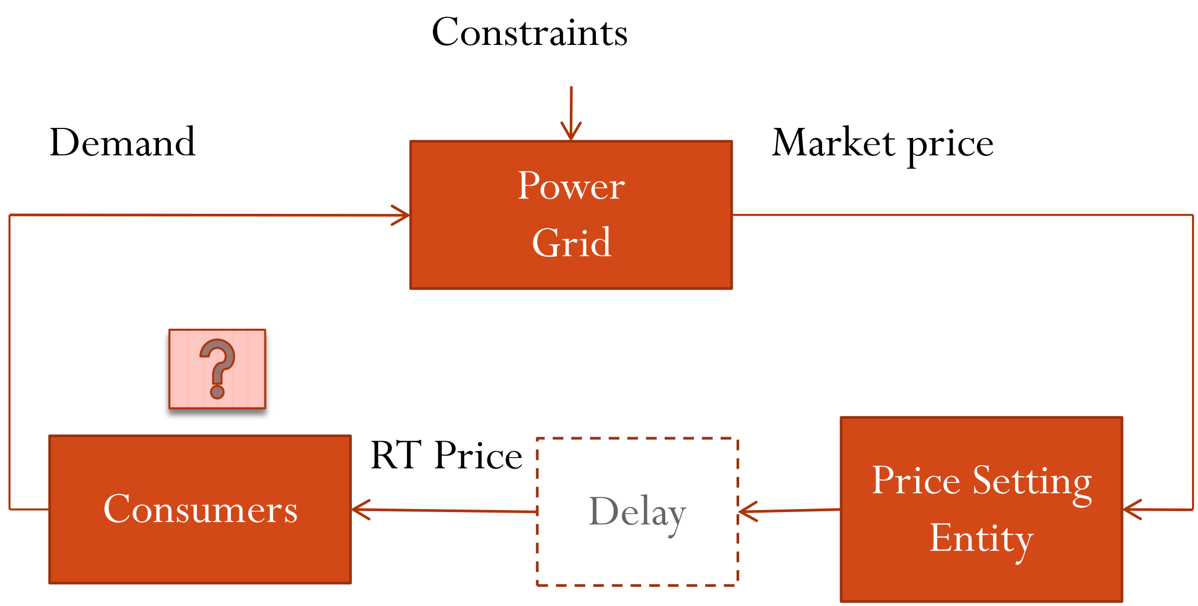
→Requires communication of a price signal

(see e.g.,[Choi et al,98],[Samadi et al,10]…)

→Requires Home Energy Management Systems (HEMS)

(see e.g., [Han and Lim,2010],[Paradiso et. Al, 2011])

Drawback: Real-time price feedback



- Requires extensive knowledge about customer behavior: On flat rates, customers are much more predictable
- Energy is not delivered instantly in packets, current price will affect usage for the next few hours (complexity!)

Research Objective

In the context of popular DSM efforts

Objective of the work

- Pricing is complex and requires extensive research
- Direct control is good for emergencies only
- The gap:
  - A control architecture that accounts for the quality of the service delivered, while guaranteeing to balance load and generation under transmission constraints
- Instead of interrupting the job of appliances, we choose to schedule when they start their jobs while accounting for the QoS.

Classification of loads for scheduling

- Type 1: Delay insensitive – known duration
  - Electrical Vehicles (EVs), washers, dryers
  - Inconvenience is proportional to delay
- Type 2: Delay sensitive – duration unknown
  - Lighting, entertainment systems
- Type 3: Dynamical systems – duration varies depending on state evolution
  - HVAC

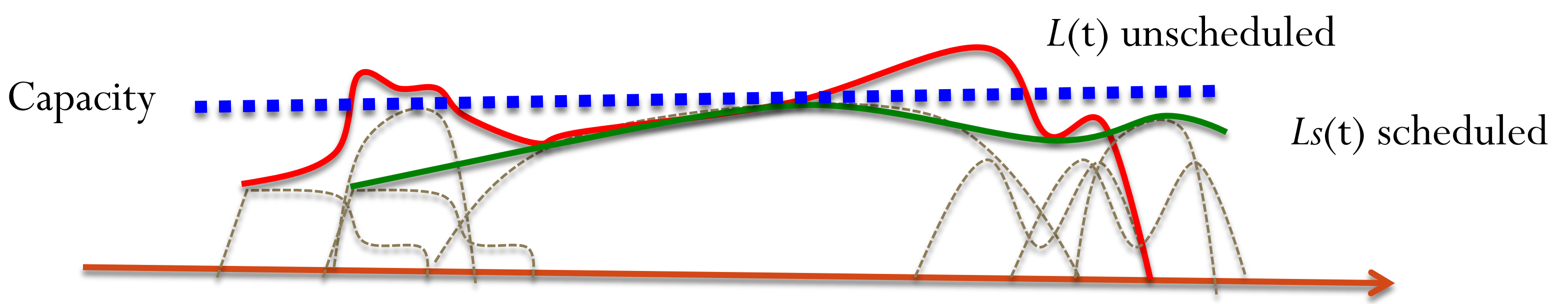
- In this presentation we will only talk about type 1
  - Type 3, requires a different control scheme
  - Type 2, requires local energy storage

Digital Direct Load Scheduling

Model for the network control interaction

Key Idea: Unbundle the load and schedule

- The load offered to the grid (complex phasor) is the sum of random contributions from each appliance



- Basic assumptions
  - Smart loads last a finite time, with random shape that has finite degrees of freedom → lossy compression in a finite number of codes per load type
- Basic idea:
  - Delay and reassemble appliance contributions optimally to shape the load
  - Unlike curtailing there is no interruption here

Main characteristics of our solution

- How? Customers agree to release the control of the time at which their delay insensitive smart appliances turn on
- Voluntary program where customers join to:
  - Receive cheap green energy, cheaper than TOU or RTP
  - They are also rewarded directly for their inconvenience (proportionally to their delay)
- Energy is cheap because the DSM allows to opportunistically use local renewables
- Cellular Architecture for scalability

Modeling appliance energy use

- The evolution of energy use by any type-1 smart appliance is specified in a parameter vector C
- For a given C the load phasor corresponding to an appliance that starts its job at time 0 is represented by the function

$$g(t; C)$$

- For EVs $g(t; C)$ is approximately real and with a nearly rectangular shape that depends on the charge amount to fill
- Our ideas are valid for arbitrary $g(t; C)$

Model for the aggregate load

- The load can be decomposed in two parts

$$L(t) = L_S(t) + L_T(t)$$

Smart Load $\;\;\;$ Traditional Load

- SMART LOAD ARRIVAL PROCESS (non-stationary) +code

$$a(t) = \sum_i u(t - t_i^a) \qquad C_i \;\; i.i.d. \sim f(C)$$

- The scheduled load has the optimal $t_i^d \geq t_i^a$

$$L_S(t) = \sum_i g(t - t_i^d; C_i)$$

Digital Direct Load Scheduling: Step 1 - Analog to Digital Load Mapping

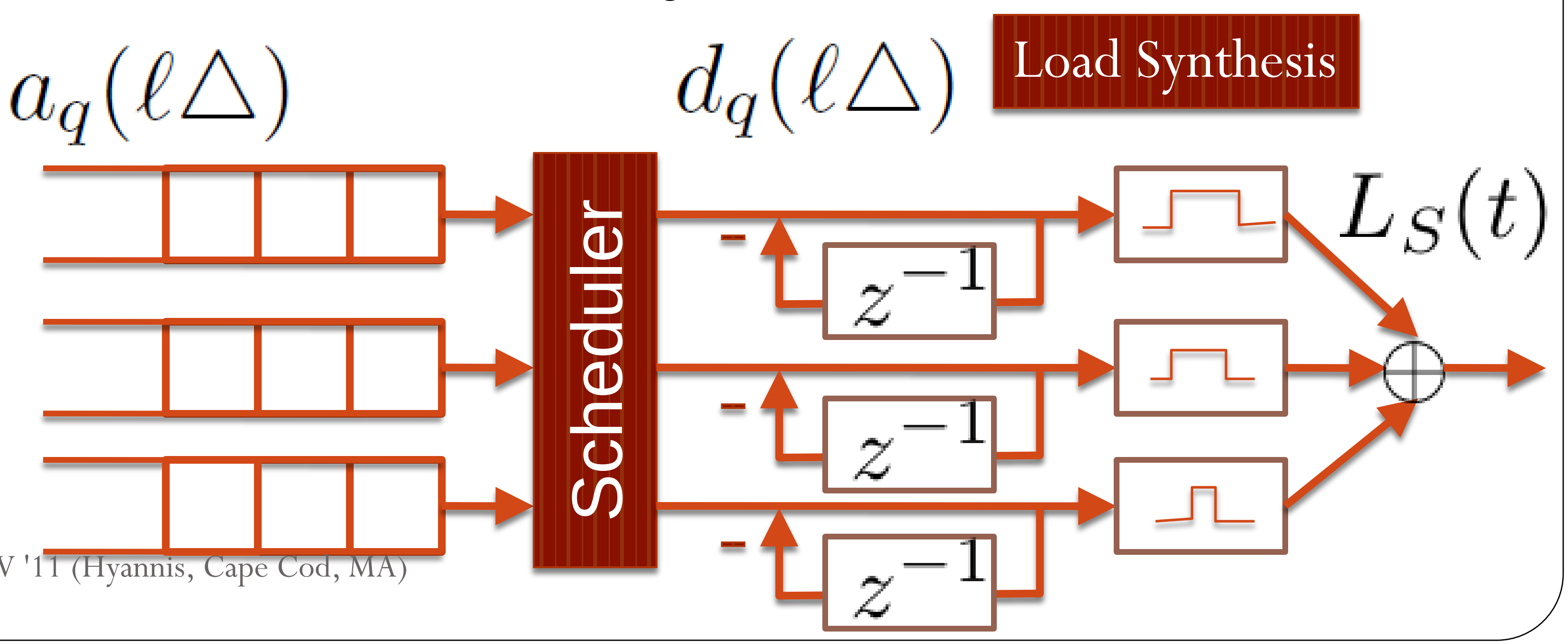
- Goal: Find a tractable model to communicate control information and reassemble the optimal load process
- Uplink: Communicate (t_i^a, C_i)
- Quantize in time: step $\triangle$
- C_i's are quantized through a mapping $\Psi(C_i)$ onto Q codes $C_q,\ q = 1, \ldots, Q$
- Appliances divided into queues based on C_q
- The control unit decides the departures from the queues: FIFO
- Discrete arrival and departure processes $a_q(\ell\triangle)$ and $d_q(\ell\triangle)$ corresponding to queue "q"

Synthesis of the load from departures

The load corresponding to activating the scheduled appliances is approximately

$$\hat{L}^S(t) = \sum_{q=1}^{Q} \sum_{\ell=\ell_0}^{\infty} [d_q(\ell\triangle) - d_q((\ell-1)\triangle)] g(t - \ell\triangle; C_q).$$

First upcoming epoch



Rates of Uplink and Downlink are Modest

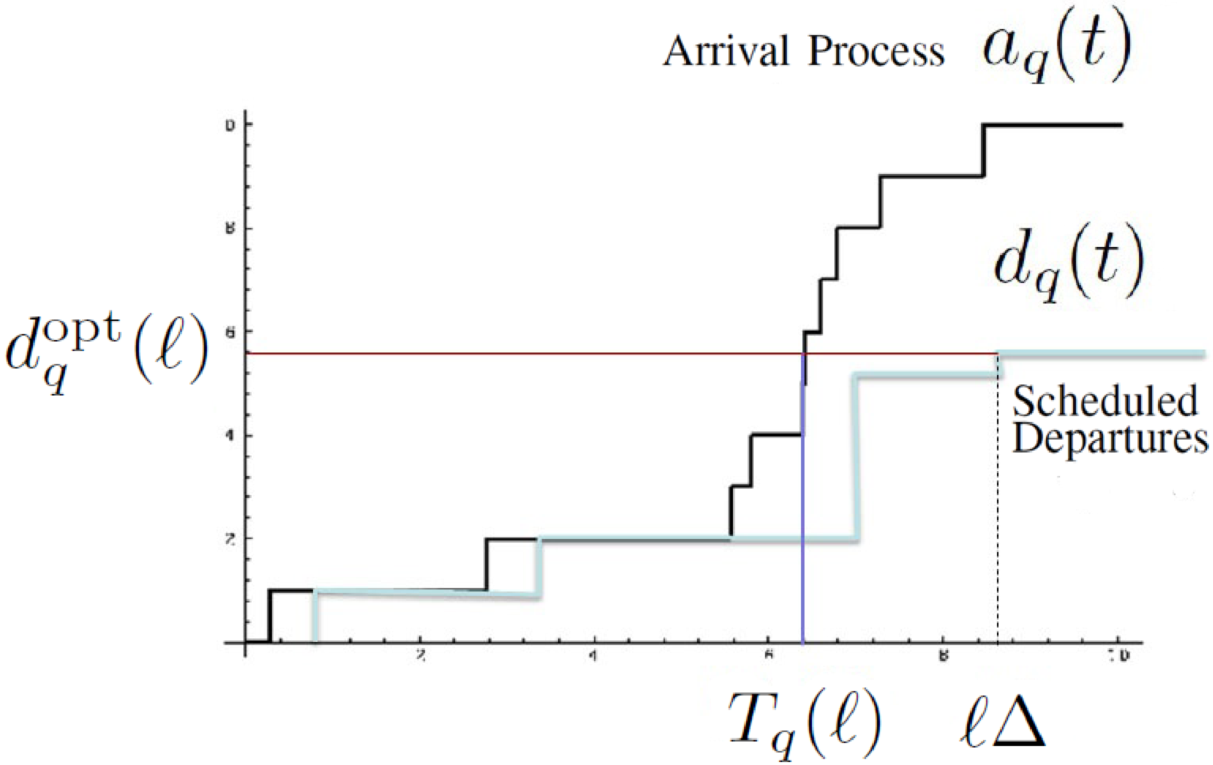
- Suppose that the network delay is *D* discrete epochs
- *Then the appliance arrival can be coded using as side information the message arrival index* ℓ_i^n
- The code:

$$p_i^a = \ell_i^a - [\ell_i^a]_D = \ell_i^a - [\ell_i^n]_D$$

$$p_i^a \in \{0, \ldots, D-1\}$$

$$R_{\mathrm{HEMS}}(\ell) = \frac{1}{\Delta}\lambda(\ell\Delta)\log_2(DQ).$$

EV activation: Downlink Feedback



$$T_q(\ell) = \max\{\tau \leq \ell : a_q(\tau) \leq d_q^{\text{opt}}(\ell)\}.$$

Messages are completely anonymous (uplink and downlink)

How do we choose Q? Finally a new rate distortion problem!

- Per queue distortion in the load synthesis

$$\chi_q = \int_{t=0}^{\infty} \int_{x \in Q^{-1}(C_q)} \left| g(t;x) - g(t;C_q) \right|^2 f_C(x) dt dx$$

- The total average distortion is

$$\chi_{tot} \leq \sum_{q=1}^{Q} \lambda_q^{\max} \chi_q$$

- A reasonable optimization

$$\min Q, \quad \text{s.t.} \quad \sum_{q=1}^{Q} \lambda_q^{\max} \chi_q \leq \chi*,$$

Decision model

What does the optimization take into account?

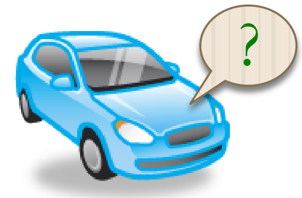
Costs

- Inconvenience cost (experienced by the community, not individuals)
$$\mathrm{DCI}(t) = \int_t^{\infty} \left\| C_T(\bar{a}(\tau) - \bar{d}(\tau)) \right\|_1 d\tau.$$
- $C_T = \mathrm{diag}[C_{D,1}, \ldots C_{D,Q}]$ weighs queues differently (different QoS)
- When time is discretized:
$$\mathrm{DCI}(\ell_0 \triangle) = \left\| C_T \sum_{\ell=\ell_0}^{\infty} [\bar{a}(\ell\triangle) - \bar{d}(\ell\triangle)] \right\|_1 .$$
- Cost of deviation from available power (power purchased on the day ahead + renewables)

The Scheduling Optimization

- A sequential decision maker that determines the schedules for the appliances over a sliding finite horizon ($N\Delta$)
- Objective: minimize the expected increment in the accumulated cost of operation over the time horizon
- Uncertainty: arrival of smart loads, traditional load, renewables, price
- The DDLS has:
  - Predictions of local marginal prices (LMP) for deviating from the day ahead bid at the particular load injection bus
  - The statistics of both smart and traditional loads
  - Predictions of available local (green) generation
- Output: a decision matrix $D = [\bar{d}(\ell_0), \bar{d}(\ell_0+1), \ldots, \bar{d}(\ell_0+N)]$
- N-1 dummy decision vectors to account for the future

Mathematical formulation of the DDLS:



$$D^* = \underset{D}{\operatorname{argmin}} \; E_A[\text{Cost of retail entity in real time}] =$$

Day ahead bid

Renewable

$$\underset{D}{\operatorname{argmin}} \sum_{\ell=\ell_0}^{\ell_0+N} E_A \{ \underbrace{\mathcal{C}_\ell \left(L_T(\ell) + L_S(\ell, D), B^*(\ell), R(\ell) \right)}_{\text{Power cost}} + \mathrm{DCI}(\ell_0, D) \}$$

Delay cost

$$\text{s.t.} \quad d_q(\ell - 1) \le d_q(\ell) \le a_q(\ell); \quad d_q(N) = a_q(N)$$

$$d_q(\ell) \in \mathbb{N} \quad q = 1, \ldots, Q, \;\; \ell = \ell_0, \ldots, \ell_0 + N$$

Example of typical deviation cost :

$$\mathcal{C}_\ell(L_T + L_S, B, R) = \$_{up}(B + R - L_T - L_S)^+ + \$_{down}(L_T + L_S - B + R)^+$$

Linear Programming Approximation

- Certainty Equivalent Controller → LP

$$\min_{D} \|C_{DV}[P - \Gamma vec(D^T)]\|_1 + \|(C_T \otimes I)[vec(A^T) - vec(D^T)]\|_1$$

$$s.t. \quad vec(D^T) \preceq vec(A^T), \; (I \otimes J^T)vec(D^T) \succeq 0, \; vec(D^T) \succeq 0,$$

where

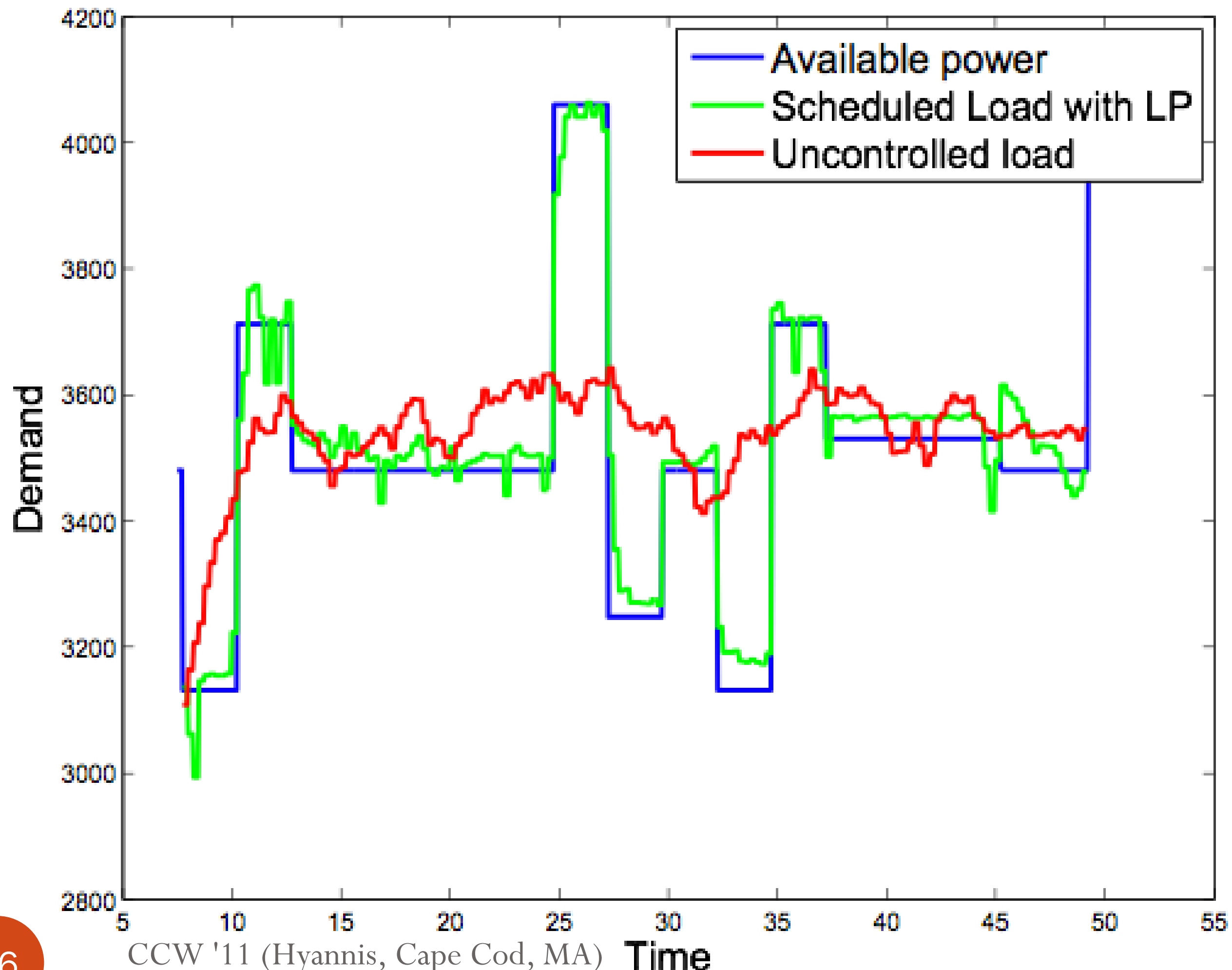
$$D = [\bar{d}(\ell_0), \ldots, \bar{d}(\ell_0 + T)], \quad A = [\bar{a}(\ell_0), \ldots, \bar{a}(\ell_0 + T)], \quad P = [P(\ell_0), \ldots, P(\ell_0 + T)]'$$

$$C_{DV} = \mathrm{Diag}[C_{dv}(\ell_0), C_{dv}(\ell_0 + 1), \ldots, C_{dv}(\ell_0 + T)], \quad C_T = \mathrm{Diag}[C_{D,1}, \ldots, C_{D,Q}].$$

Preliminary results

A few simulations….

Numerical Results – LP



18k Electric Vehicles

0 ≤ Charge time ≤ 8 hours

Optimization is run every 15 minutes

Charge code quantization step = 15 minutes

Arrival process is Poisson with constant rate λ =3 arrivals/each 15 minutes for each queue (32 queues)

Solver: Certainty equivalent controller that uses LP to schedule the Electric Vehicles

Look-ahead horizon = 8 hours

For fairness, the number of scheduled appliances is equal in the two profiles and no arriving appliances is delayed beyond t = 50 h

Wrap up!

Components of our architecture

- Communication and modeling portion
  - Traffic model
  - A way of communicating requests and receiving feedback digitally
  - We capture inconvenience
- Control portion:
  - Optimize the schedule by grouping a number of loads that are scheduled together in service queues. Based on:
    - Wholesale market price
    - Safety constraints
    - Available local green generation
    - Inconvenience of customers
- Generation Market Interface:
  - Interacts with the central power grid

Conclusions

- We described a method to realize efficiency for the customer by allowing the smart loads requests to be scheduled
- Basic principle:
  - Unbundle and digitize the load – do not store energy, store requests!

Future Work

- How does the cell participate in the wholesale energy market
  - Optimum Day-ahead Bid - Dispatch strategy by ISO
  - Real-time Bids
  - Game model to study the equilibrium
- Currently, we only cover certain types of loads that have a pre-known job cycle like EVs and Washing Machines
  - HVAC – we think we can do better than interrupting
  - Televisions and Hair Dryers?
- Questions we want to answer
  - What is the optimum size of these cells?
  - Do they cooperate with each other?
  - Who owns the cell?

Thank you!!