Signal Processing and Communication Challenges for the Internet of Energy

Anna Scaglione

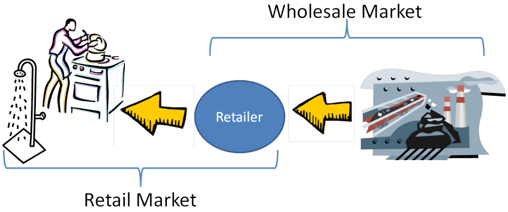
collaborators: M. Alizadeh, X. Li, T.H. Chen, Z. Wang
R.J. Thomas, G. Kesidis, K. Levitt, A. Goldsmith, M. Van Der Schaar

ICNC 2015

February 17, 2015

Power is produced "just in time"

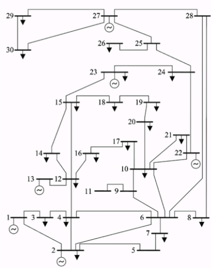
A daily dispatch managed by retailers and whole sale markets:

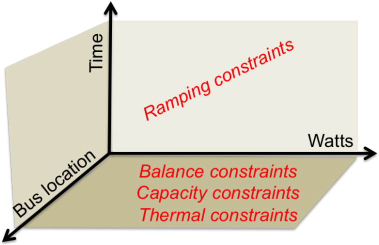


1. Retail electricity market → public utility, regulated monopoly
2. Wholesale electricity market → emulates perfect competition
   - To have a reliable balance the market equilibrium price is the output of a centralized optimization
   - The amount is adjusted through multiple settlements

Unit Commitment and Day-ahead Market (hourly intervals) → Hour-ahead Adjustment Market (hourly intervals) → Real-time Market (5-10 minute intervals)

Whole Sale Market





- Non-profit Coordinator: Independent System Operator (ISO) determines the Optimal Power Flow (OPF) (bid based auction)

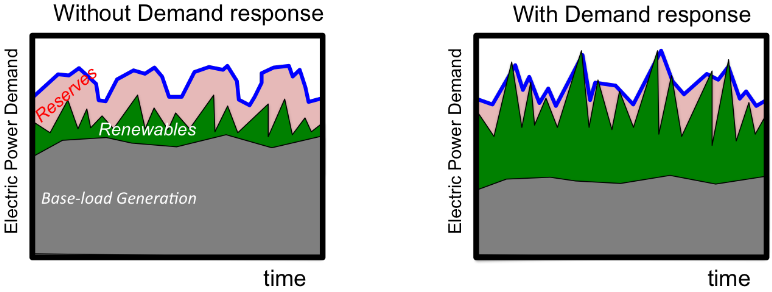
$$\min_{G_i} \sum_i \mathrm{Cost}_i(G_i)$$

$$\text{subject to} \quad \text{Balance, Capacity, Ramping, etc.}$$

- Balance means: Demand (L_i)=Supply (G_i)+Loss
- Lagrange multipliers of the balance constraints at each bus are Local Marginal Price of resource \$ (LMP for short)

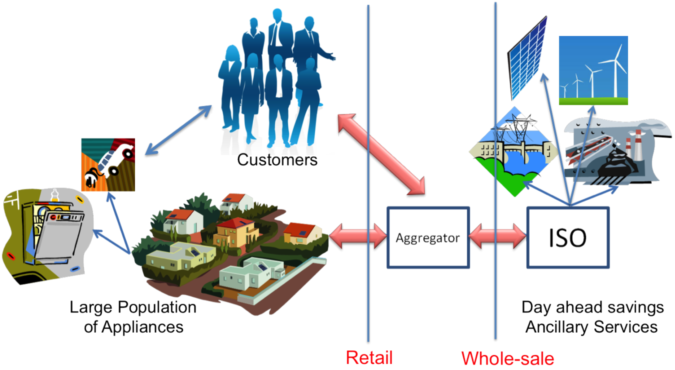
The role of flexible demand

- Large generator ramps + reserves for dealing with uncertainty blow up costs and pollution



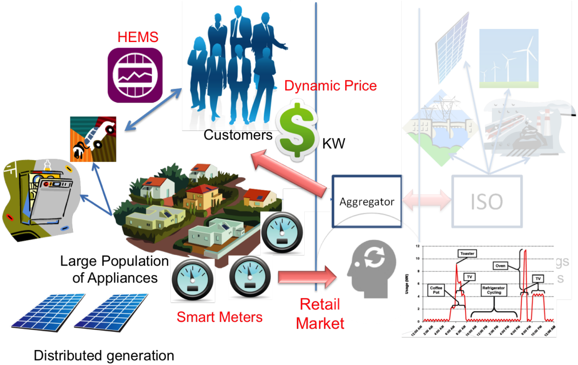
If we can modulate the load (via Demand Response Programs), we can increase renewables and reduce reserves (cleaner, cheaper power)

Challenges for Demand Response (DR)



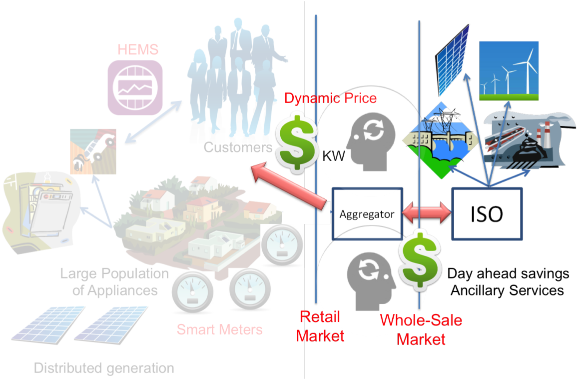
- Aggregation is needed (Whole Sale Market blind below 100MW)
- Challenge 1: Heterogenous population of appliances
- Challenge 2: Real time control of millions of them
- Challenge 3: Modeling their aggregate response in the market

Research on coordinating Distributed Resources



- Most of the work is on the home price response side
- Detailed model: Model each individual appliance constraints *[Joo,Ilic,'10], [Huang, Walrand, Ramchandran,'11], [Foster,Caramanis,'13]*
  - Hard to predict the aggregate response, invasion of privacy

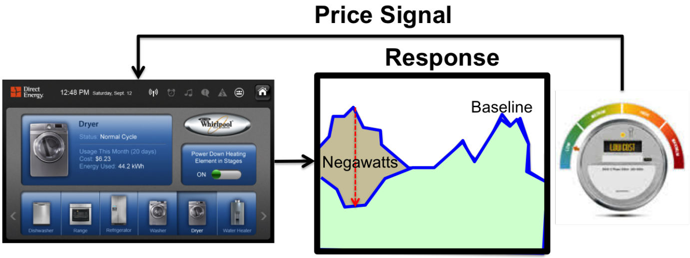
The Smart Grid system level challenge



- Tank model: Flexible demand requires a certain amount of energy. Fill the flexible demand tank by the end of the day... *[Lambert, Gilman, Lilienthal,'06], [Lamadrid, Mount, Zimmerman, Murillo-Sanchez, '11],[Papavasiliou, Oren '10]*
    - Inaccurate representation of what customers want

The Smart Grid model that *was* really emerging

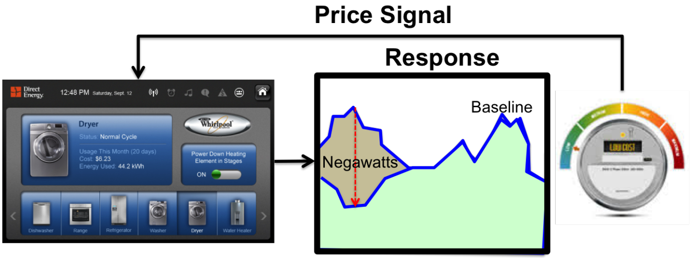
- Price sensitive demand and *Measurement & Verification*



  - Customers have a baseline load (measured with smart-meters)
  - LMP prices are communicated (via smart-meters)
  - Customers shed a certain amount of the baseline
  - The diminished demand is verified with smart-meters
  - Customers are paid LMP for the Negawatts (or punished)
- This is what the Smart-Grid was going to be
  - Advocated by utilities, promoted by a FERC order (law) 745...
  - ....blocked by the courts (DC Circuit Court)

The Smart Grid model that *was* really emerging

- Price sensitive demand and *Measurement & Verification*



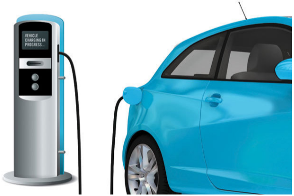
  - Customers have a baseline load (measured with smart-meters)
  - LMP prices are communicated (via smart-meters)
  - Customers shed a certain amount of the baseline
  - The diminished demand is verified with smart-meters
  - Customers are paid LMP for the Negawatts (or punished)
- This is what the Smart-Grid was going to be
  - Advocated by utilities, promoted by a FERC order (law) 745...
  - ....blocked by the courts (DC Circuit Court)

Why we should be relieved...

- The notion of baseline and negawatts price is ill posed:
  - How can I measure what you will be able to not consume and verify that you have not consumed it?
  - What is a good model for a price for lack of demand?

- Alternatives? Differentiating via Quantized Population Models
  - Cluster appliances and derive an aggregate model
  - The Internet of Energy: appliances that say what they want

[Chong85],[Mathieu,Koch, Callaway,'13],[Alizadeh, Scaglione, Thomas,'12]...



Population Load Flexibility

Definition of Flexibility

The potential shapes that the electric power consumption (load) of an appliance or a popoulation of appliances can take while providing the sought economic utility to the customer

Categories of appliances covered

1. Interruptible rate constrained EVs with deadlines and V2G ✓
2. Thermostatically Controlled Loads ✓
3. Deferrable loads with dead-lines ✓

Example of Load flexibility: Ideal Battery

One ideal battery indexed by i

- Arrives at t_i and remains on indefinitely
- No rate constraint
- Initial charge of S_i
- Capacity E_i

The flexibility of battery i is defined as

$$\mathcal{L}_{\mathrm{i}}(\mathrm{t}) = \{\mathrm{L}_{\mathrm{i}}(\mathrm{t}) | \mathrm{L}_i(\mathrm{t}) = \mathrm{dx}_{\mathrm{i}}(\mathrm{t})/\mathrm{dt}, \mathrm{x}_{\mathrm{i}}(\mathrm{t}_{\mathrm{i}}) = \mathrm{S}_{\mathrm{i}}, 0 \le \mathrm{x}_{\mathrm{i}}(\mathrm{t}) \le \mathrm{E}_{\mathrm{i}}, \mathrm{t} \ge \mathrm{t}_{\mathrm{i}}\}.$$

In English:

Load (power) = rate of change in state of charge $x(t)$ (energy)

- Set $\mathcal{L}_i(\mathrm{t})$ characterized by appliance category v (ideal battery) and 3 continuous parameters:

$$\boldsymbol{\theta}_i = (t_i, S_i, E_i)$$

But how can we capture the flexibility of thousands of these batteries?

Aggregate flexibility sets

We define the following operations on flexibility sets $\mathcal{L}_1(\mathrm{t})$, $\mathcal{L}_2(\mathrm{t})$:

$$\mathcal{L}_1(t) + \mathcal{L}_2(t) = \left\{ L(t) | L(t) = L_1(t) + L_2(t), (L_1(t), L_2(t)) \in \mathcal{L}_1(t) \times \mathcal{L}_2(t) \right\}$$

$$n\mathcal{L}(t) = \left\{ L(t) | L(t) = \sum_{k=1}^{n} L_k(t),\ (L_1(t), .., L_n(t)) \in \mathcal{L}^n(t) \right\},$$

where $n \in \mathbb{N}$ and $0\mathcal{L}_1(t) \equiv \{0\}$.

- Then, the flexibility of a population $\mathcal{P}^v$ of ideal batteries is

$$\mathcal{L}^v(\mathrm{t}) = \sum_{\mathrm{i} \in \mathcal{P}^{\mathrm{v}}} \mathcal{L}_{\mathrm{i}}(\mathrm{t}) \tag{1}$$

flexibility of population = sum of individual flexibility sets

What if we have a very large population?

Quantizing flexibility

- Natural step $\rightarrow$ quantize the paramaters: $\boldsymbol{\theta}_i = (t_i, S_i, E_i)$

$$\boldsymbol{\theta} \ \mapsto \ \boldsymbol{\vartheta} \in \text{Finite set } \mathcal{T}^v$$

- Quantize state and time uniformly with step $\delta t = 1$ and $\delta x = 1$
- Discrete version (after sampling + quantization) of flexibility:

$$\mathcal{L}_i(t) = \{L_i(t) | L_i(t) = \partial x_i(t), x_i(t_i) = S_i, x_i(t) \in \{0, 1, \ldots, E_i\}, t \geq t_i\}.$$

- $\mathcal{L}^v_{\boldsymbol{\vartheta}}(t)$ = Flexibility of a battery with discrete parameters $\boldsymbol{\vartheta}$
- Let $a^v_{\boldsymbol{\vartheta}}(t) \triangleq$ number of batteries with discrete parameters $\boldsymbol{\vartheta}$

$$\mathcal{L}^v(t) \ = \ \sum_{\boldsymbol{\vartheta} \in \mathcal{T}^v} a^v_{\boldsymbol{\vartheta}}(t) \mathcal{L}^v_{\boldsymbol{\vartheta}}(t), \qquad \sum_{\boldsymbol{\vartheta} \in \mathcal{T}^v} a^v_{\boldsymbol{\vartheta}}(t) = |\mathcal{P}_v|. \qquad (2)$$

Bundling Batteries with Similar Constraints

- Population $\mathcal{P}_E^v$ with homogenous E but different (t_i, S_i)
- Define arrival process for battery i

$$a_i(t) = u(t - t_i) \rightarrow \text{indicator that battery } i \text{ is plugged in}$$

- We prefer not to keep track of individual appliances
- Random state arrival process on aggregate

$$a_x(t) = \sum_{i \in \mathcal{P}_E^v} \delta(S_i - x) a_i(t), \quad x = 1, \ldots, E$$

- Aggregate state occupancy

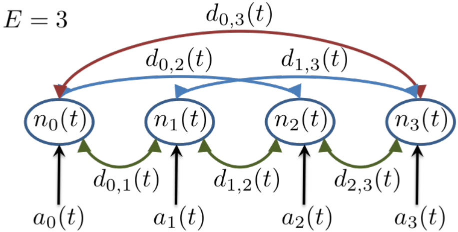
$$n_x(t) = \sum_{i \in \mathcal{P}_E^v} \delta(x_i(t) - x) a_i(t), \quad x = 1, \ldots, E$$

Control Actions

Activation process from state x' to x :

$d_{x,x'}(t) = \#$ **batteries that go from state x to state x' up to time t**

Naturally, $\partial d_{x,x'}(t) \leq n_x(t)$.



Controlled Aggregate Load flexibility

Lemma

The relationship between occupancy, control and load are:

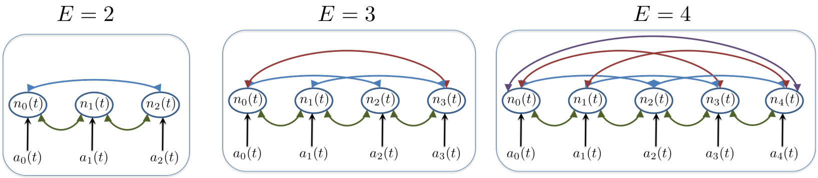
$$n_x(t+1) = a_x(t+1) + \sum_{x'=0}^{E} [d_{x',x}(t) - d_{x,x'}(t)]$$

$$L(t) = \sum_{x=0}^{E} \sum_{x'=0}^{E} (x' - x) \partial d_{x,x'}(t)$$

Notice the linear and simple nature of $L(t)$ in terms of $d_{x,x'}(t)$

Bundling Batteries with Non-homogeneous Capacity

- Results up to now are valid for batteries with homogenous capacity E
- The capacity changes the underlying structure of flexibility
- We divide appliances into **clusters** $q = 1, \ldots, Q^v$ based on the quantized value of E_i



Quantized Linear Load Model

Load flexibility of heterogenous ideal battery population

$$\mathcal{L}^v(t) = \left\{ L(t) | L(t) = \sum_{q=1}^{Q} \sum_{x=0}^{E^q} \sum_{x'=0}^{E^q} (x' - x) \partial d^q_{x,x'}(t) \right.$$

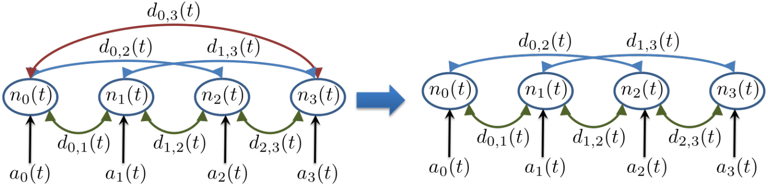
$$\left. \partial d^q_{x,x'}(t) \in \mathbb{Z}^+, \sum_{x'=1}^{E^q} \partial d^q_{x,x'}(t) \leq n^q_x(t) \right\}$$

$$n^q_x(t) = a^q_x(t) + \sum_{x'=0}^{E^q} [d^q_{x',x}(t-1) - d^q_{x,x'}(t-1)]$$

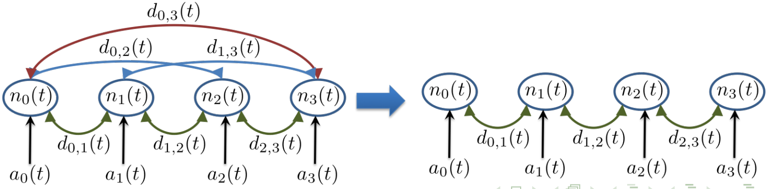
Linear, and scalable at large-scale by removing integrality constraints

Aggregate model= Tank Model *[Lambert, Gilman, Lilienthal,'06]*

- The canonical battery can go from any state to any state and has no deadline or other constraints.
- What about real appliances? Some are simple extensions
- Rate-constrained battery chage, e.g., V2G



- Interruptible consumption at a constant rate, e.g., pool pump, EV 1.1kW charge



Deadlines

- You can add deadlines using the same principle: cluster appliances with the same deadline χ^q
- Then, you simply express the constraint inside the flexibility set

$$\mathcal{L}^v(t) = \Bigg\{ L(t) | L(t) = \sum_{q=1}^{Q^v} \sum_{x=0}^{E^q} \sum_{x'=0}^{E^q} (x' - x) \partial d^q_{x,x'}(t)$$
$$\partial d^q_{x,x'}(t) \in \mathbb{Z}^+, \forall x, x' \in \{0, 1, \dots, E^q\}$$
$$\sum_{x'=1}^{E^q} \partial d^q_{x,x'}(t) \leq n^q_x(t), \forall x < E^q \rightarrow n_x(\chi^q) = 0 \Bigg\} \tag{3}$$

Thermostatically Controlled Loads - Individual Flexibility

- $x_i(t)$ temperature in comfort band $[x_i^* - B_i/2, x_i^* + B_i/2]$ in the time window $[\chi_i^s, \chi_i^e)$ of the day.
- TCL cycles on and off $b_i(t) \in \{0, 1\}$ within a time frame $[t_i^s, t_i^e)$ larger or equal than $[\chi_i^s, \chi_i^e)$. TCL i arrival and departure events:

$$a_i(t) = u(t - t_i^s), \quad r_i(t) = u(t - t_i^e).$$

For unit i we have:

$$\mathcal{L}_i(t) = \Big\{ L_i(t) | \partial x_i(t) = -k_i x_i(t) + \alpha_i(t) + b_i(t)\xi_i, \\ b_i(t) \in \{0, 1\}, L_i(t) = b_i(t)\Xi_i, \forall t \in [t_i^s, t_i^e) \\ |x_i(t) - x_i^*| \leq B_i/2, \ \forall [t]_{24H} \in [\chi_i^s, \chi_i^e) \Big\}$$

where ξ_i = rate of heat gain Btu/h, Ξ_i is ξ_i in KW/h and the ambient noise $\mathbb{E}[\alpha_i(t)] = x_{\text{amb}}(t) k_i$, $x_{\text{amb}}(t)$ = ambient temperature

- Since $\alpha_i(t)$ is random, switching the control $b_i(t) \in \{0,1\}$ changes the probability that the appliances move from one state x to x'

$$P_i(x'|x;t;b_i(t)) = \text{Prob}\Big(\alpha_i(t) = x' - x(1-k_i) - b_i(t)\xi_i\Big).$$

- We need to cluster based on these probabilities

$$P_i(x'|x;t;b) \mapsto P^q(x'|x;t;b), \quad q = 1,\dots,Q^v$$

- Occupancy of a temperature bin includes those OFF + those ON

$$\begin{aligned} n_x^q(t) &= n_{x,0}^q(t) + n_{x,1}^q(t) \\ &= a_x^q(t) - r_x^q(t) + \sum_{x' \in \mathcal{S}^q} D_{x',x}^q(t-1) - D_{x,x'}^q(t-1) \end{aligned}$$

$$D_{x,x'}^q(t) = \#\ \textbf{appliance moved from } x \textbf{ to } x' \textbf{ at time } t$$

$$\mathbb{E}\{D_{x,x'}^q(t)|n_x^q(t)\} = n_{x,0}^q(t)P^q(x'|x;t;0) + n_{x,1}^q(t)P^q(x'|x;t;1)$$

TCLs - Aggregate Flexibility

- The comfort band constraint translates into

$$\forall |x - x^{*q}| > B^q/2 \quad \rightarrow \quad \Pr(n_x^q(t) = 0) \geq \eta,$$

where η is close to one (violations rare)

- Aggregate flexibility of heterogeneous TCLs

$$\begin{aligned} \mathcal{L}^v(t) = \Big\{ L(t) | L(t) = \sum_{q=1}^{Q^v} \sum_{x \in \mathcal{S}^q} \Xi^q n_{x,1}^q(t),\ n_x^q(t) &= \sum_{b=0}^{1} n_{x,b}^q(t), \\ n_x^q(t) = a_x^q(t) - r_x^q(t) + \sum_{x' \in \mathcal{S}^q} D_{x',x}^q(t-1) - D_{x,x'}^q(t-1) &, \\ \mathbb{E}\{D_{x,x'}^q(t) | n_x^q(t)\} = \sum_{b=0}^{1} n_{x,b}^q(t) P^q(x'|x;t;b); \\ \forall x : |x - x^{*q}| > B^q/2, \quad \forall [t]_{24H} \in [\chi^{s,q}, \chi^{e,q}) \\ \rightarrow \ \Pr(n_x^q(t) = 0) \geq \eta \Big\} \end{aligned}$$

Real time TCL control: simplified model

- The complexity grows linearly with # of quantization points but exponentially with # of parameters
- Simplified myopic policies based on EV deadlines: Least Laxity First (LLF) and Earliest Deadline First (EDF) [S. Caron and G. Kesidis, '10], [S. Chen, Y. Ji, and L. Tong, '12], [A. Subramanian, M. Garcia, A. Dominguez-Garcia, D. Callaway, K. Poolla, and P. Varaiya, '12], [G. O' Brien and R. Rajagopal, '13]
- TLC deadlines based control: TCL communicates quantized deadline instead of temperature state and switch value $(\tau_i(t), b_i(t))$

$$\tau_i(t) = \frac{1}{k_i} \ln \left(\frac{x_i(t) - b_i(t)\frac{\Xi_i}{k_i} - \frac{\alpha_i(t)}{k_i}}{x_i^* - (-1)^{b_i(t)}\frac{B_i}{2} - b_i(t)\frac{\Xi_i}{k_i} - \frac{\alpha_i(t)}{k_i}} \right).$$

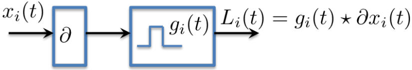
- An EDF scheduler maximizes residual future flexibility

Non-interruptible Appliances - Individual flexibility

- Loads that can be shifted within a time frame but cannot be modified after activation, e.g., washer/dryers
- $x_i(t) \in \{0, 1\}$ = state of appliance i (wainting/activated)
- Impluse response of appliance i if activated at time $0 = g_i(t)$
- Laxity (slack time) of χ_i

$$\begin{aligned}\mathcal{L}_i(t) = &\{L_i(t) | L_i(t) = g_i(t) \star \partial x_i(t), x_i(t) \in \{0, 1\}, \\ &x_i(t) \geq a_i(t - \chi_i),\ x_i(t-1) \leq x_i(t) \leq a_i(t)\}.\end{aligned} \tag{4}$$

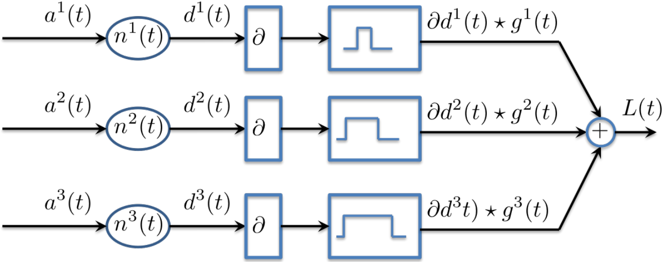
Load = change in state convolved with the load shape $g_i(t)$



Note: $d^q_{0,1}(t) \equiv d^q(t) \equiv x^q(t)$

Non-interruptible Appliances - Aggregate flexibility

- We assign appliances to cluster q based on quantized pulses $g^q(t)$
- $a^q(t)$ = total number of arrivals in cluster q up to time t
- $d^q(t)$ = total number of activations from cluster q up to time t



$$\mathcal{L}^v(t) = \Big\{ L(t) | L(t) = \sum_{q=1}^{Q^v} g^q(t) \star \partial d^q(t), \, d^q(t) \in \mathbb{Z}^+ \qquad (5)$$

$$d^q(t) \geq a^q(t - \chi^q), \; d^q(t-1) \leq d^q(t) \leq a^q(t) \Big\}$$

How to generalize the information model

1. State-space parametric description of the set $\mathcal{L}_i(t)$ of possible load injections of specific appliance i
2. Event-driven: Appliances are available for control after t_i with initial state S_i; (arrival is $a_i(t) = u(t - t_i)$ unit step)
3. Divide and conquer: Define a representative set $\mathcal{L}_q^v(t)$ for a given appliances cathegory (v), quantizing possible parameters (q) and, if continuous, quantize the state (x)
4. Aggregate and conquer: Describe total flexibility $\mathcal{L}^v(t)$ using: Aggregate arrival and state occupancy

$$a_x^q(t) = \sum_{i \in \mathcal{P}^{v,q}} \delta(S_i - x) a_i(t), \quad n_x^q(t) = \sum_{i \in \mathcal{P}_E^v} \delta(x_i(t) - x) a_i(t)$$

Aggregate control knob

$$d_{x,x'}^q(t) = \# \textbf{ appliance moved from } x \textbf{ to } x' \textbf{ before time } t$$

$$\partial d_{x,x'}^q(t) = d_{x,x'}^q(t+1) - d_{x,x'}^q(t) = \# \textbf{ ... at time } t$$

How to generalize the information model

1. State-space parametric description of the set $\mathcal{L}_i(t)$ of possible load injections of specific appliance i
2. Event-driven: Appliances are available for control after t_i with initial state S_i; (arrival is $a_i(t) = u(t - t_i)$ unit step)
3. Divide and conquer: Define a representative set $\mathcal{L}_q^v(t)$ for a given appliances cathegory (v), quantizing possible parameters (q) and, if continuous, quantize the state (x)
4. Aggregate and conquer: Describe total flexibility $\mathcal{L}^v(t)$ using: Aggregate arrival and state occupancy

$$a_x^q(t) = \sum_{i \in \mathcal{P}^{v,q}} \delta(S_i - x) a_i(t), \quad n_x^q(t) = \sum_{i \in \mathcal{P}_E^v} \delta(x_i(t) - x) a_i(t)$$

Aggregate control knob

$$d_{x,x'}^q(t) = \# \textbf{ appliance moved from } x \textbf{ to } x' \textbf{ before time } t$$

$$\partial d_{x,x'}^q(t) = d_{x,x'}^q(t+1) - d_{x,x'}^q(t) = \# \textbf{ ... at time } t$$

How to generalize the information model

1. State-space parametric description of the set $\mathcal{L}_i(t)$ of possible load injections of specific appliance i
2. Event-driven: Appliances are available for control after t_i with initial state S_i; (arrival is $a_i(t) = u(t - t_i)$ unit step)
3. Divide and conquer: Define a representative set $\mathcal{L}_q^v(t)$ for a given appliances cathegory (v), quantizing possible parameters (q) and, if continuous, quantize the state (x)
4. Aggregate and conquer: Describe total flexibility $\mathcal{L}^v(t)$ using: Aggregate arrival and state occupancy

$$a_x^q(t) = \sum_{i \in \mathcal{P}^{v,q}} \delta(S_i - x) a_i(t), \quad n_x^q(t) = \sum_{i \in \mathcal{P}_E^v} \delta(x_i(t) - x) a_i(t)$$

Aggregate control knob

$$d_{x,x'}^q(t) = \# \text{ appliance moved from } x \text{ to } x' \text{ before time } t$$

$$\partial d_{x,x'}^q(t) = d_{x,x'}^q(t+1) - d_{x,x'}^q(t) = \# \ldots \text{ at time } t$$

How to generalize the information model

1. State-space parametric description of the set $\mathcal{L}_i(t)$ of possible load injections of specific appliance i
2. Event-driven: Appliances are available for control after t_i with initial state S_i; (arrival is $a_i(t) = u(t - t_i)$ unit step)
3. Divide and conquer: Define a representative set $\mathcal{L}_q^v(t)$ for a given appliances cathegory (v), quantizing possible parameters (q) and, if continuous, quantize the state (x)
4. Aggregate and conquer: Describe total flexibility $\mathcal{L}^v(t)$ using: Aggregate arrival and state occupancy

$$a_x^q(t) = \sum_{i \in \mathcal{P}^{v,q}} \delta(S_i - x) a_i(t), \quad n_x^q(t) = \sum_{i \in \mathcal{P}_E^v} \delta(x_i(t) - x) a_i(t)$$

Aggregate control knob

$$d_{x,x'}^q(t) = \#\ \textbf{appliance moved from } x \textbf{ to } x' \textbf{ before time } t$$

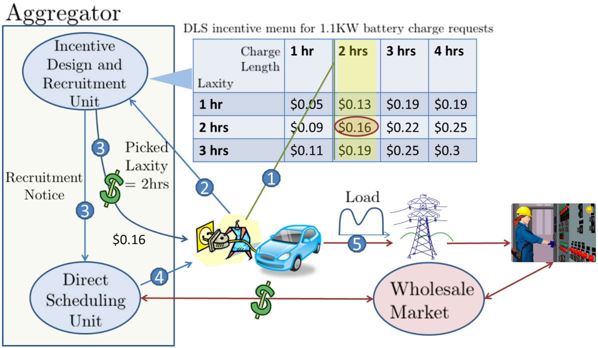
$$\partial d_{x,x'}^q(t) = d_{x,x'}^q(t+1) - d_{x,x'}^q(t) = \#\ \textbf{... at time } t$$

Pricing specific flexible uses

Dynamically Designed Cluster-specific Incentives

- Characteristics in ϑ have 2 types: intrinsic and customer chosen
- We cluster appliances based on intrinsic characteristics
- Customer picks operation mode m, e.g., laxity χ based on price

We design a set of incentives $c_m^{v,q}(t), m = 1, \ldots, M^{v,q}$ for each cluster



DLS incentive menu for 1.1KW battery charge requests

Laxity \ Charge Length	1 hr	2 hrs	3 hrs	4 hrs
1 hr	$0.05	$0.13	$0.19	$0.19
2 hrs	$0.09	$0.16	$0.22	$0.25
3 hrs	$0.11	$0.19	$0.25	$0.3

[Alizadeh, Xiao, Scaglione, Van Der Schaar 2013], see also [Bitar, Xu 2013], [Kefayati, Baldick, 2011]

The advantage of differentiating pricing...

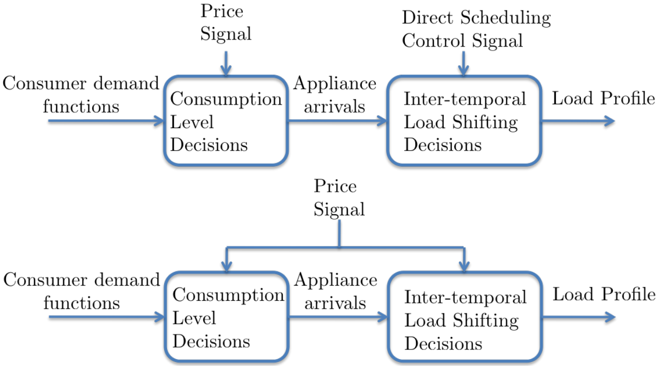


Figure : Differentiated Pricing and Scheduling (top) and Dynamic Retail Pricing (bottom).

Both schemes harness a subset of the *true* flexibility of demand

$$\mathcal{L}^{DR}(t) \subseteq \mathcal{L}(t)$$

Differentiated pricing

- An aggregator hires appliances and directly schedules their load
- Set of differentiated prices based on flexibility

$$\boldsymbol{c}^v(t) = \{c^v_{\vartheta}(t), \forall \boldsymbol{\vartheta} \in \mathcal{T}^v\}$$

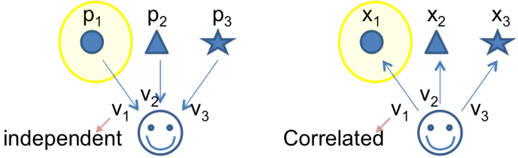
- Differentiated discounts $\boldsymbol{c}^v(t)$ from a high flat rate → incentives
- Appliances choose to participate based on incentives → $a^v_{\boldsymbol{\vartheta}}(\boldsymbol{c}^v(t))$

$$\mathcal{L}^{DR}(t) = \sum_{v=1}^{V} \sum_{\boldsymbol{\vartheta} \in \mathcal{T}^v} a^v_{\boldsymbol{\vartheta}}(\boldsymbol{c}^v(t)) \mathcal{L}^v_{\boldsymbol{\vartheta}}(t). \quad (6)$$

- Reliable: aggregator observes $a^v_{\boldsymbol{\vartheta}}(\boldsymbol{c}^v(t))$ after posting incentives and before control - no uncertainty in control

Incentive design

- Optimal posted prices? The closest approximation is the "optimal unit demand pricing"
- Customers valuation for different modes correlated (value of EV charge with 1 hr laxity vs. value of EV charge with 2 hrs laxity)



The Incentive Design Problem

- Independent incentive design problem for different categories v and clusters q $\rightarrow$ Let's drop q, v for brevity
- Aggregator designs

$$\mathbf{c}(t) = [c_1(t), c_2(t), \ldots, c_M(t)]^T, \tag{7}$$

- From recruitment of flexible appliances, the aggregator saves money in the wholesale market (utility):

$$\mathbf{u}(t) = [U_1(t), \ldots, U_M(t)]^T \tag{8}$$

- Aggregator payoff when interacting with a specific cluster population:

$$Y(\mathbf{c}(t); t) = \sum_{m \in \mathcal{M}} \overbrace{(U_m(t) - c_m(t))}^{\text{Payoff of mode } m} \sum_{i \in \mathcal{P}(t)} \overbrace{a_{i,m}(\mathbf{c}(t); t)}^{\text{indicator of mode } m \text{ selection}} \quad . \tag{9}$$

$a_{i,m}(\mathbf{c}(t); t) = 1$ if load i picks mode m given incentives $\mathbf{c}(t)$

- Goal: maximize payoff $Y(\mathbf{c}(t); t)$
- Problem: we don't know how customers pick modes

Probabilistic Model for Incentive Design Problem

- At best we have statistics → Maximize expected payoff
- Probability of load i picking mode m:

$$P_{i,m}(\mathbf{c}(t);t) = \mathbb{E}\{a_{i,m}(\mathbf{c}(t);t)\}. \tag{10}$$

- Incentives posted publically - Individual customers not important
- Define the *mode selection average probability* across population:

$$P_m(\mathbf{c}(t);t) = \frac{\sum_{i\in\mathcal{P}(t)} P_{i,m}(\mathbf{c}(t);t)}{|\mathcal{P}(t)|} \tag{11}$$

$$\mathbf{p}(\mathbf{c}(t);t) = [P_0(\mathbf{c}(t);t),\ldots,P_M(\mathbf{c}(t);t)]^T \rightarrow \text{what we need} \tag{12}$$

- Maximize expected payoff across cluster population

$$\max_{\mathbf{c}(t)\succeq\mathbf{0}} \mathbb{E}\left\{\sum_{m\in\mathcal{M}} (U_m(t)-c_m(t)) \sum_{i\in\mathcal{P}(t)} a_{i,m}(\mathbf{c}(t);t)\right\} =$$

$$\max_{\mathbf{c}(t)\succeq\mathbf{0}} \overbrace{(\mathbf{u}(t)-\mathbf{c}(t))^T}^{\text{known}} \overbrace{\mathbf{p}(\mathbf{c}(t);t)}^{\text{unknown}} \tag{13}$$

Modeling the customer's decision

Approaches to model $\mathbf{p}(\mathbf{c}(t);t)$? (average probability that the aggregator posts $\mathbf{c}(t)$ and a customer picks each mode m)

1. Bayesian model-based method: rational customer - $\max(V_i(t))$
   Risk-averseness captured by *types*

$$\text{customer utility} \quad V_i(t) = \sum_{v,q} c_m^{v,q}(t) - R_{i,m}^{q,v}(t)$$

   $R_{i,m}^{q,v}(t) = \gamma_i^{v,q} r_m^{v,q}(t)$, γ_i random variable drawn from one PDF
2. Model-free learning method: customers may only be boundedly rational. We need to learn their response to prices

The whole picture

Pricing Incentive design:

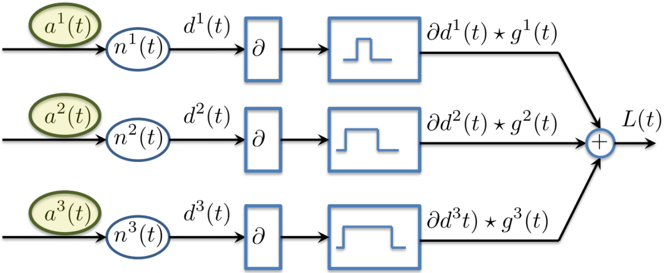
- Design incentives to recruit appliances

Pricing Incentive design:

- Design incentives to recruit appliances

Planning:

- Forecast arrivals in clusters for different categories
- Make optimal market decisions based on forecasted flexibility



The whole picture

Pricing Incentive design:

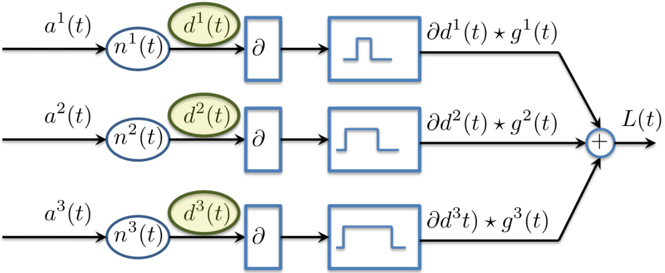
- Design incentives to recruit appliances

Planning:

- Forecast arrivals in clusters for different categories
- Make optimal market decisions based on forecasted flexibility

Real-time:

- Observe arrivals in clusters
- Decide appliance schedules $d^q(t)$ to optimize load

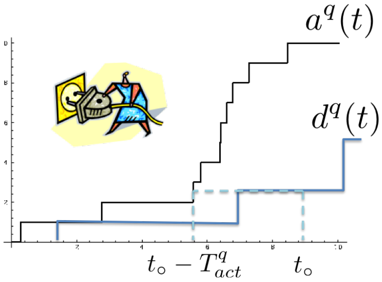


Real-time: How do we activating appliances?

Arrival and Activation Processes

$a_q(t)$ and $d_q(t)$ $\rightarrow$ total recruited appliances and activations before time t in the q-th queue

- Easy communications: Broadcast time stamp T_{act}:
  $a_q(t - T_{act}) = d_q(t)$

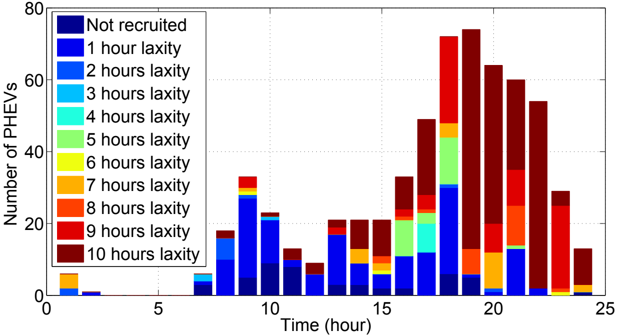


- Appliance whose arrival is prior than $T_{act.}$ initiate to draw power based on the broadcast control message

How does it perform?

Residential charging...

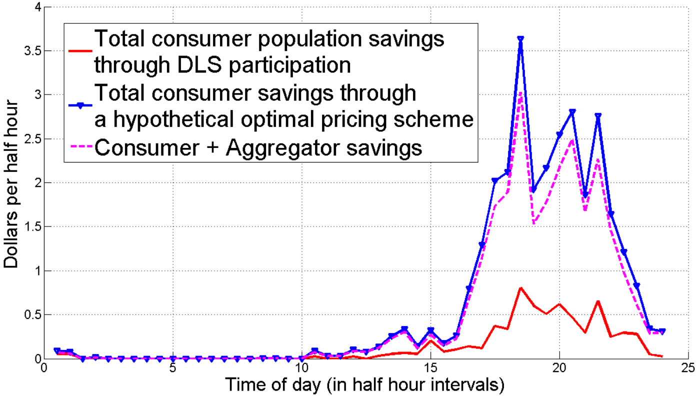
- Aggregator schedules 620 uninterruptible PHEV charging events
- Prices from New England ISO DA market - Maine load zone on Sept 1st 2013
- How many do we recruit (out of 620) and with what flexibility?



- More savings in the evening...

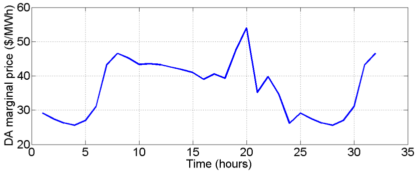
Welfare Effects in Retail Market

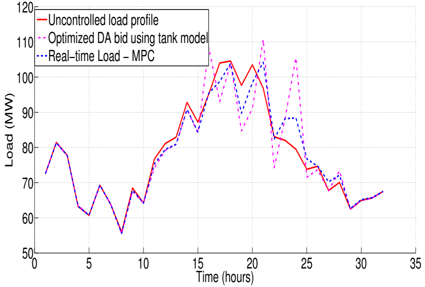
- Welfare generate via Direct Load Scheduling (DLS) vs. idealized Dynamic Pricing (marginal price passed directly to customer - no aggregator)
- Savings summed up across the 620 events (shown as a function of time of plug-in)



Day Ahead Market with the Tank Model

- Population of 40000 PHEVs + 1.1 kW non-interruptible charging
- Tank model = PHEVs effectively modeled as canonical batteries

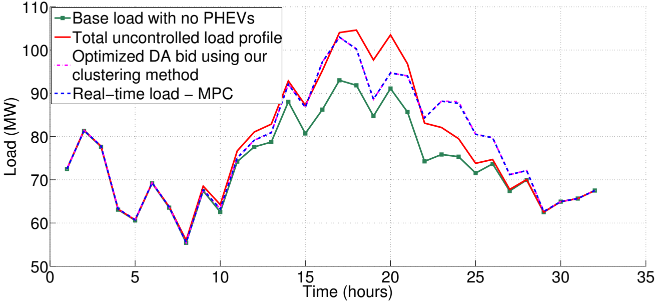




- Real-world plug-in times and charge lengths
- 15 clusters (1-5 hours charge + 1-3 hours laxity)
- PHEV demand = 10% of peak load
- DA= Day Ahead
- PJM market prices DA 10/22/2013 • Real time prices = adjustments cost 20% more than DA
- DA = LP + SAA with 50 random scenarios + tank model
- RT = ILP + Certainty equivalence + clustering

Proposed scheme

- Quantized Deferrable EV model
- Load following dispatch very closely when using our model



- Same setting
- DA = LP + Sample Average $\approx \mathbb{E}\{a^q(t)\}$ (50 random scenarios) + clustering
- Real Time Control = ILP + Certainty equivalence + clustering

Regulation through TCL loads

Regulation market:

- To participate the aggregator must be able to
  1. Increase/decrease demand by a certain step of variable height m from the baseline
  2. Hold the demand at that value for a certain duration ξ (follow the AGC signa)
- We evaluated ξ to be the 97 % quantile of the zero-crossing time from historical AGC signals (19 min. based on PJM signals)
- Capacity estimated for the population of 10000 home air conditioners is 2.05 MWs

$$M' = \sum_{q=1}^{Q} \min_t M^q(t)$$

where $M^q(t)$ is the maximum deviation m from the baseline that a load in cluster q can tolerate at time t with $0.05m$ error (determined simulating the response of each cluster using $\mathcal{L}^q(t)$)

Regulation through TCL loads

- Real Time the TCLs are controlled for 6 h based on *clustering deadlines* (60 clusters)
- Temperature is Jan 29th 2012 in Davis;
- $\Xi_i = \xi_i \sim U([2000, 4000])$ Btu/h, $k_i = \sim U([50, 200])$ W/C, $x_i^* \sim$ U([69, 75]), $B_i \sim U([2, 4])$ F

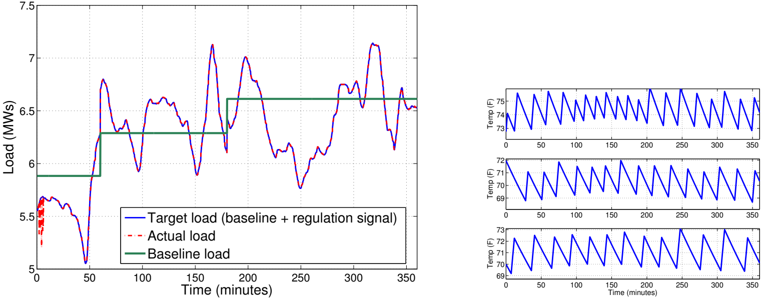
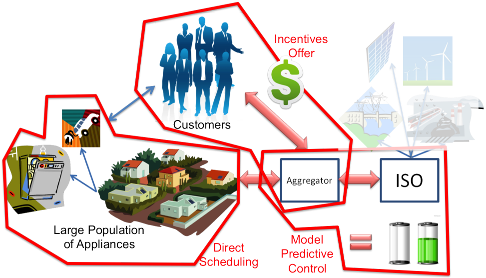


Figure : Simulated response of the TCL population (10000) to regulation signals and three 2 ton A/C units temperatures. The y-axis range i= comfort band.

Conclusion

- We have discussed an information, decision, control and market models for responsive loads
- We left out reliability and verification: can you prevent the users from cheating, avoid cyber attacks....
- Also how to sell renewables power as a result of this *See work on Risk Limiting Dispatch (RLD) [Varaiya, Wu, Bialek,2011],[He, Murugesan, Zhang 2011], [Rajagopal, Bitar, Varaiya, Wu, 2013],...*
- How much risk can one hedge in generation with load flexibility?...many questions left



Conclusion

- We have discussed an information, decision, control and market models for responsive loads
- We left out reliability and verification: can you prevent the users from cheating, avoid cyber attacks....
- Also how to sell renewables power as a result of this *See work on Risk Limiting Dispatch (RLD) [Varaiya, Wu, Bialek,2011],[He, Murugesan, Zhang 2011], [Rajagopal, Bitar, Varaiya, Wu, 2013],...*
- How much risk can one hedge in generation with load flexibility?...many questions left