Signal Processing and Communication Challenges for the Internet of Energy

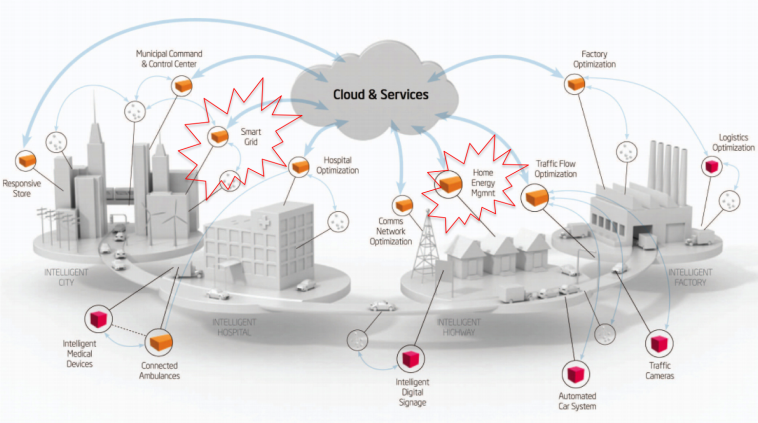
Anna Scaglione

acknowledgement: **M. Alizadeh**
R.J. Thomas, G. Kesidis, K. Levitt, A. Goldsmith, M. Van Der Schaar

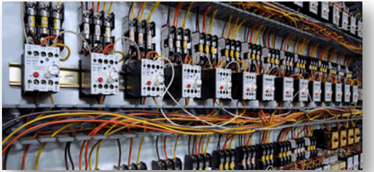
April 8, 2015

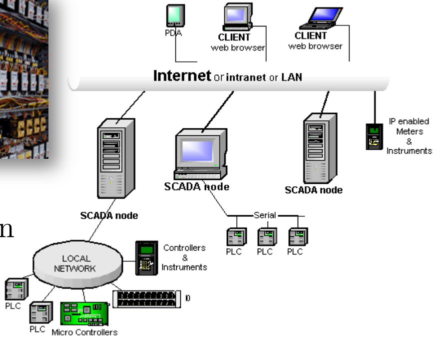
The Internet of Things Age

- A world where *everything* is tagged, monitored and remotely controllable via the Internet



- Let's look at the past and what we can do with it in the future, focusing on Energy Delivery



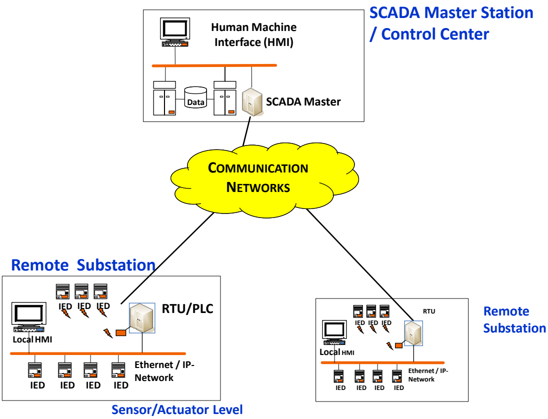


Industrial Automation

- Electric Power Systems, Pipelines (Water, Fuel), Building Control, Manifacturing plants...
- Monitoring: Sensor telemetry and databases
- Automation: The discipline focused on the design of automation software is called Hybrid Control

Supervisory Control And Data Acquisition

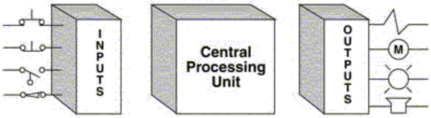
- "SCADA " widely used Industrial Control (IC) reference model
- Its birth nest: the Electric Power sector



- Very wide area systems (the size of a country) → hierarchical control = “divide and conquer”

The Programmable Logic Controller

PLC/Digital Relay: an industrial computer control system

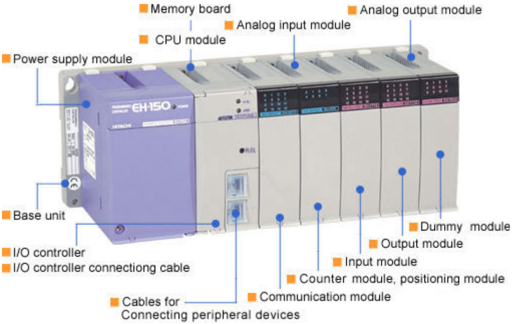


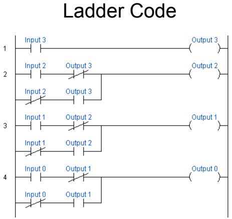
- Data Items are identified by object (o), property (p) and time (t). The value (v) is a function of o, p and t

$$v = F(o, p, t)$$

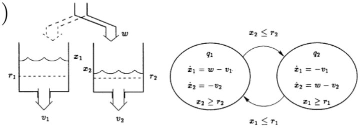
- Typical values for PLC are input/output single bit (coils) and registers (16/32 bits, analog values)
- PLC activity:
  1. Input Scan: Scans the state of the Inputs
  2. Program Scan: Executes the program logic
  3. Output Scan: Energize/de-energize the outputs
  4. Housekeeping: Update the state

Communications among PLCs

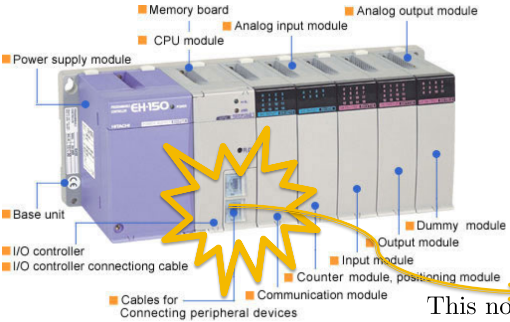


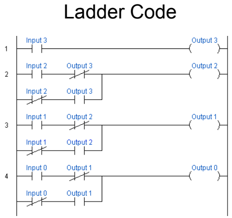


- Programmable Logic Controller (PLC)
- Remote Terminal Units (RTU)
- Intelligent Electr. Devices (IED)



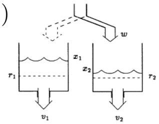
- Originally most controllers used serial communications

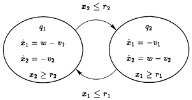




This now can surf the Internet

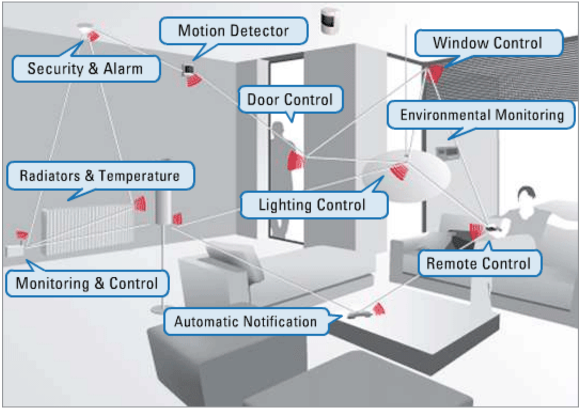
- Programmable Logic Controller (PLC)
- Remote Terminal Units (RTU)
- Intelligent Electr. Devices (IED)





- Today most of them are Ethernet based, but this is changing, wireless being the next big contender

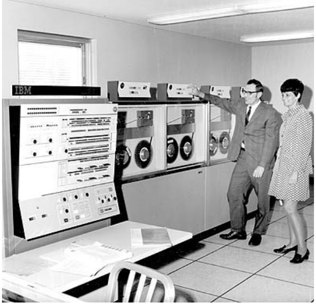
ZigBee: Industrial Control Gets Personal...



- ZigBee was conceived for low power, low rate, sensor networking in a variety of applications
- Embedded computer are like personal computers...

A watershed moment?

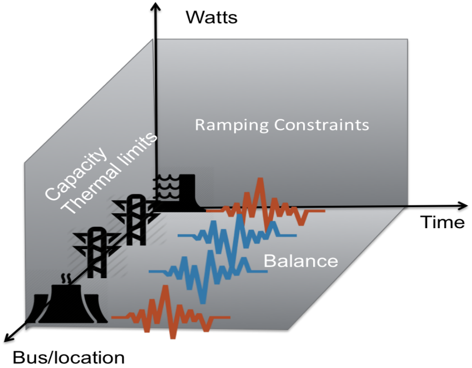
- The transition from Mainframe to PC changed computation



- In Power Systems SCADA was meant for the grid core
- IoT ⇒ intelligence at the edge of the grid
  - Example: ZigBee Smart Energy V2.0 specifications define an IP-based protocol to monitor, control, inform and automate the delivery and use of energy and water
  - Huge opportunity for change...

Cognitive Power Systems

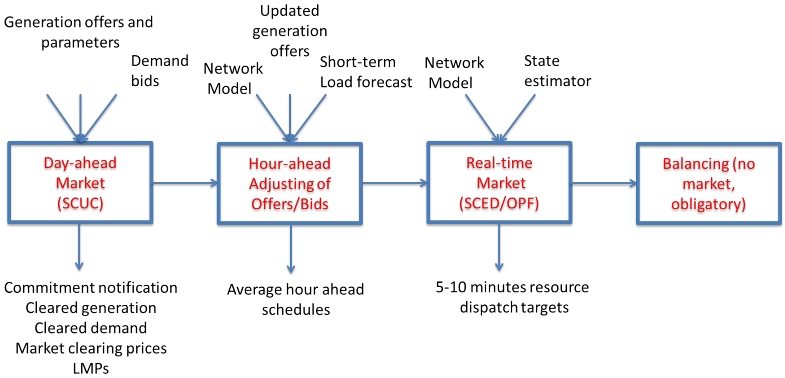
Decision Space for the Grid



- Plan the generation *signal* $G_i(t)$ to be equal exactly to the demand for electricity $L_i(t)$ (load) (sold on a Retail Market)
- Today tens of large generators serve millions of homes (2 orders of magnitude difference)
- Whole sale optimization objective: over a future horizon Ω
  $\rightarrow \min \sum_i \int_\Omega Cost(G_i(t))dt$ subject to
  (1) Power Balance, (2) $G_i(t)$ and $G_i'(t)$ bounds, (3) Thermal constr.

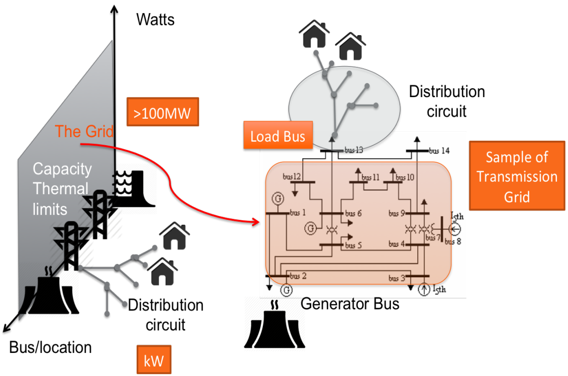
Multi-settlement optimization/market structure

1. Wholesale electricity market → a centralized optimization (run by an Independent System Operator – ISO)



SCUC = Security Constrained Unit Commitment (who we buy from)
LMP = Local Marginal Prices (at what price at each bus and time)
OPF = Optimal Power Flow (how much)

Optimizing the power flow

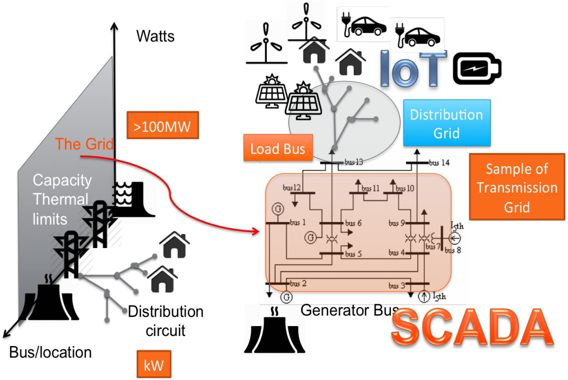


- Suppose $\Omega = t$ one time instant. We have the Optimal Power Flow (OPF) problem:

  $\rightarrow \min C(G_i(t))$ subject to

  (1) Demand = Supply + Losses, (2) $G_i(t)$ and $G_i'(t)$ below capacity, (3) Thermal constr.

IoT = millions of control knobs



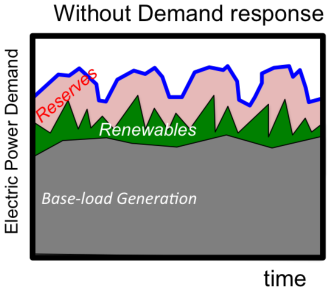
- Everything works without controlling them....why do we need to do it?

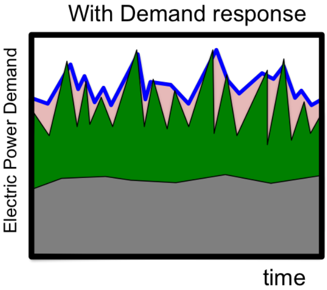
Cognitive Electric Consumption

- For consumers the grid is *plug and play* → at most good appliances reduce energy consumption
- The moment at which we draw power is chosen carelessly
  → we need to generate just in time
  → we depend on fossil fuels to do that
- Demand is random but not truly inflexible, but today there is no widespread standard appliance interface to modulate it

- Demand Response (DR) programs tap into the flexibility of end-use demand for multiple purposes

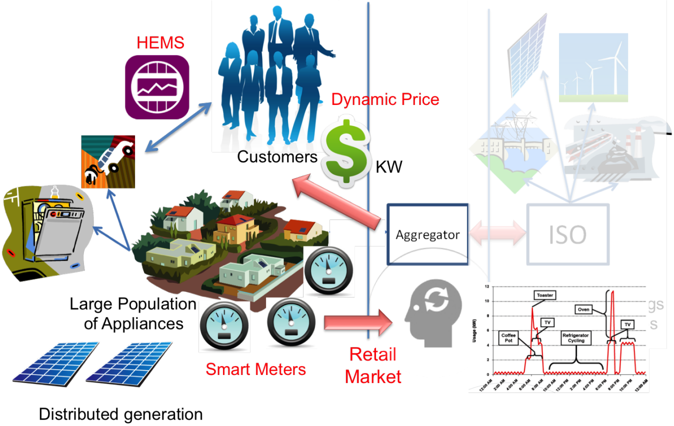
- Large generator ramps + reserves for dealing with uncertainty blow up costs and pollution





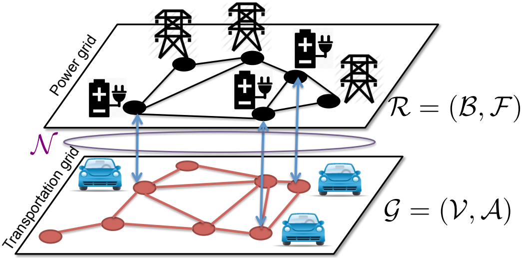
If we can modulate the load (via Demand Response Programs), we can increase renewables and reduce reserves (cleaner, cheaper power)

The Smart Grid vision



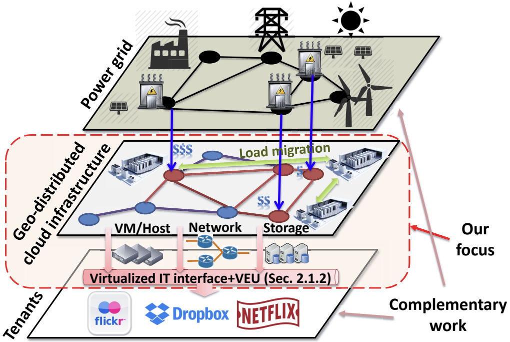
- Intelligent homes will be price responsive

- Electric Vehicles!
  Where and when they charge can be modulated...

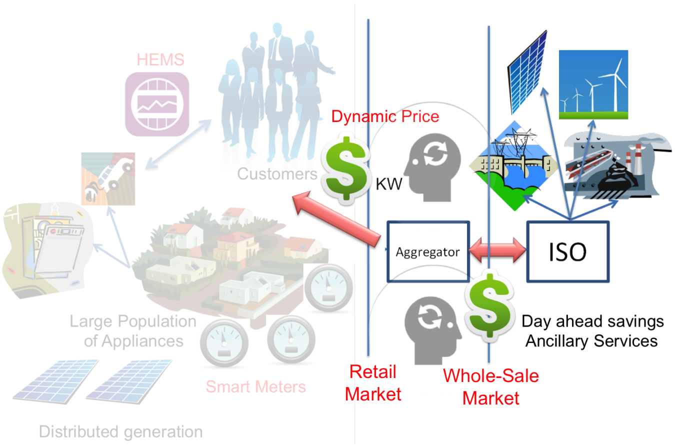


IoT that shifts demand in space and time

- Clouds!
  Computation can shift swiftly where renewable power is abundant and power is cheap...

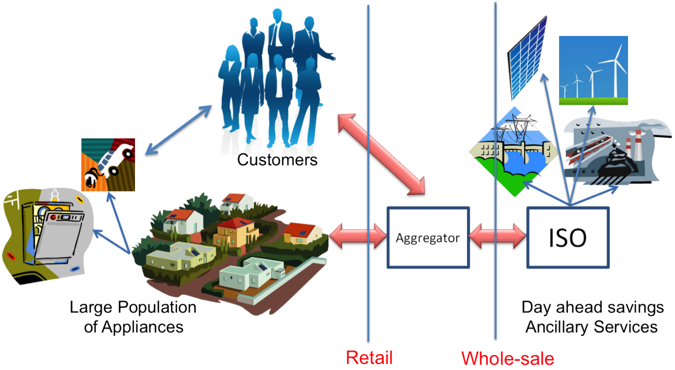


The Smart Grid System Challenge



- Designing the price...

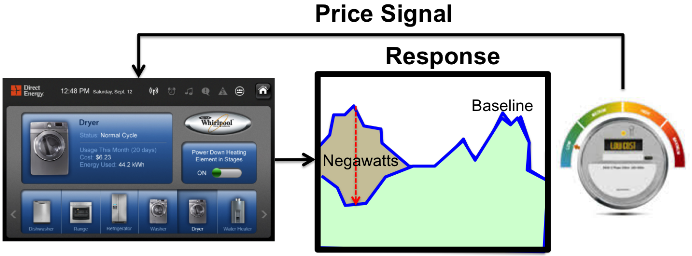
Challenges for Demand Response (DR)



- 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

The Smart Grid model that *was* really emerging

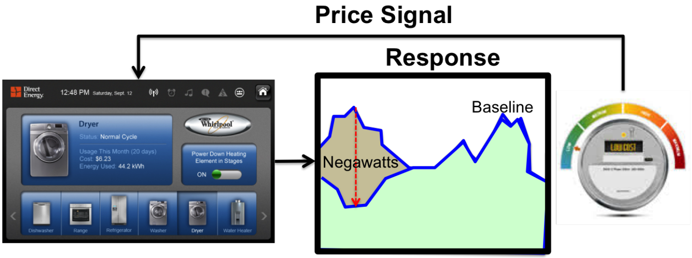
- Price sensitive demand and *Measurement & Verification*



  - 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

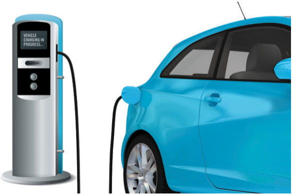
- Price sensitive demand and *Measurement & Verification*



  - 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)

- 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
  - (Hide customers with differentially private codes)

[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

$$\mathcal{L}_\mathrm{i}(\mathrm{t}) = \{\mathrm{L_i(t)}|\mathrm{L}_i(\mathrm{t}) = \mathrm{dx_i(t)/dt, x_i(t_i) = S_i, 0 \leq x_i(t) \leq E_i, t \geq t_i}\}.$$

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 → 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 $\boldsymbol{\vartheta}$

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

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

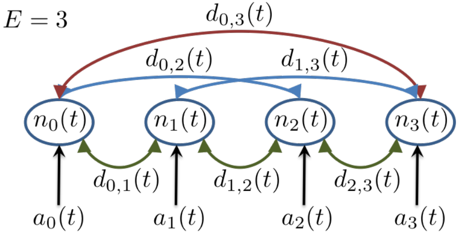
$$n_x(t) = \sum_{i \in \mathcal{P}_E^v} \delta(x_i(t) - x) a_i(t), \quad x = 1, \ldots, E$$

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:

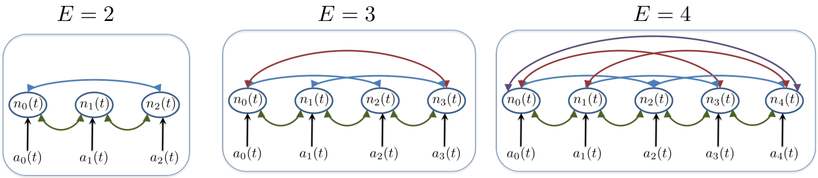
$$n_x(t+1) = a_x(t+1) + \sum_{x'=0}^{E} [d_{x',x}(t) - d_{x,x'}(t)]$$

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

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

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

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

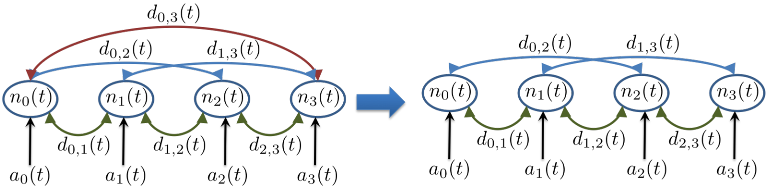
$$n^q_x(t) = a^q_x(t) + \sum_{x'=0}^{E^q} [d^q_{x',x}(t-1) - d^q_{x,x'}(t-1)]$$

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

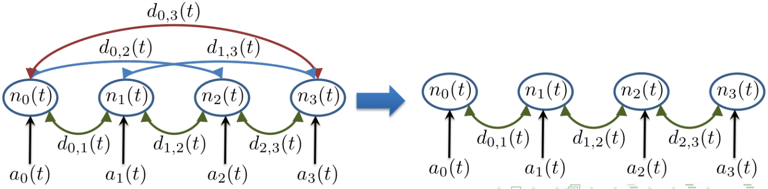
Aggregate model= Tank Model *[Lambert, Gilman, Lilienthal,'06]*

Rate controlled, Interruptible charge, V2G (EVs)

- 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

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

$$\partial d^q_{x,x'}(t) \in \mathbb{Z}^+, \forall x, x' \in \{0, 1, \ldots, E^q\}$$

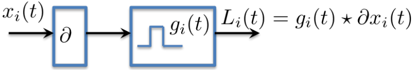
$$\sum_{x'=1}^{E^q} \partial d^q_{x,x'}(t) \leq n^q_x(t), \forall x < E^q \rightarrow n_x(\chi^q) = 0 \Bigg\} \tag{3}$$

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

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

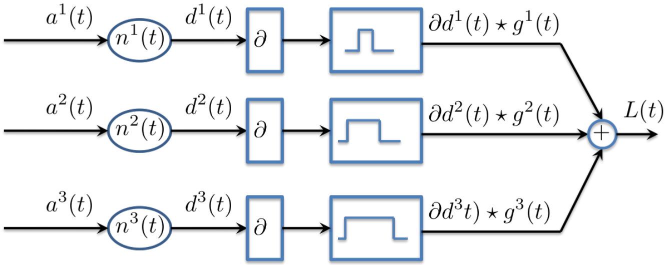
Load = change in state convolved with the load shape $g_i(t)$



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

$d^q_{x,x'}(t) = \#$ **appliance moved from** x **to** x' **before time** t

$\partial d^q_{x,x'}(t) = d^q_{x,x'}(t+1) - d^q_{x,x'}(t) = \#$ **... 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 $\mathcal{L}^v_q(t)$ 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

$$a^q_x(t) = \sum_{i \in \mathcal{P}^{v,q}} \delta(S_i - x) a_i(t), \quad n^q_x(t) = \sum_{i \in \mathcal{P}^v_E} \delta(x_i(t) - x) a_i(t)$$

Aggregate control knob

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

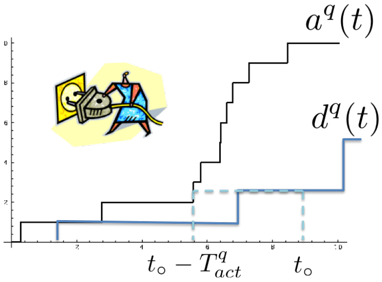
$$\partial d^q_{x,x'}(t) = d^q_{x,x'}(t+1) - d^q_{x,x'}(t) = \#\ \textbf{... at time } t$$

Real-time: How do we activating appliances?

Arrival and Activation Processes

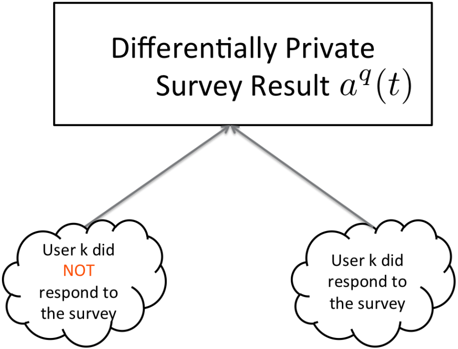
$a_q(t)$ and $d_q(t)$ $\rightarrow$ total recruited appliances and activations before time t in the q-th queue

- 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

- One can use a biased coin to add *noise* to the activation of a certain appliance in cluster q
- This will hide the identity of who is active at a certain time
- With large aggregation the bias can be easily removed

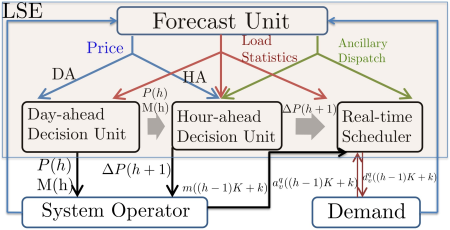


Ex-ante Planning

1. From historical data forecast statistics of arrivals in clusters (e.g. *[Alizadeh, Scaglione, Kurani, Davies 2013] for PHEVs*)
2. Use a Model Predictive Control (MPC) framework with Sample Average Approximation (SAA) to make market purchase decisions

Real-time Control

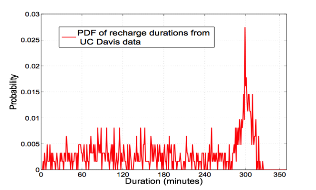
1. We perform DLS
2. Decide the profit maximizing schedule
3. Activate appliances
4. Refresh future arrival forecasts based on new observations

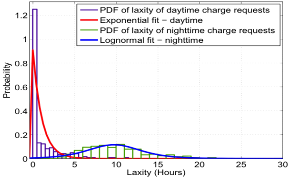


Ex-ante Stochastic Population Models

- In DLS, appliance arrival event is explicitly communicated
- Modeling challenge is similar to that of forecasting and serving non-stationary traffic for a call-center...
  PHEV charging events studied in [Alizadeh, Scaglione, Davies, Kurani 2013]

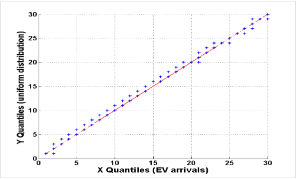
Charge and Laxity → Clusters



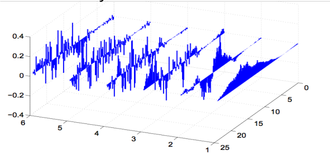


Arrival counts → Traffic

KS test confirms Poisson arrivals

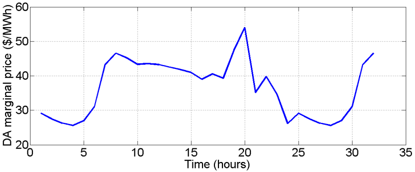


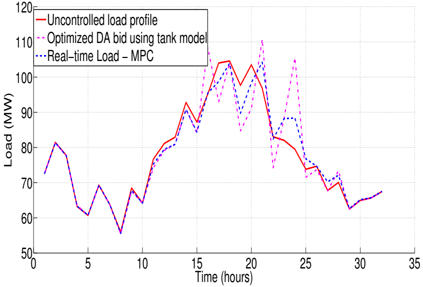
6 Principal components of daily arrival rate vectors



Day Ahead Market Level Simulation

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

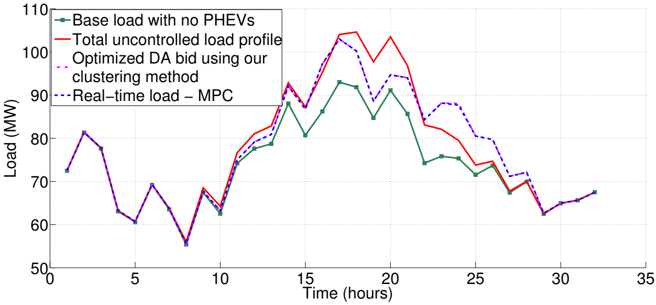




- Real-world plug-in times and charge lengths
- 15 clusters (1-5 hours charge + 1-3 hours laxity)
- PHEV demand = 10% of peak load
- DA= Day Ahead
- PJM market prices DA 10/22/2013
- Real time prices = adjustments cost 20% more than DA
- DA = LP + SAA with 50 random scenarios + tank model
- RT = ILP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

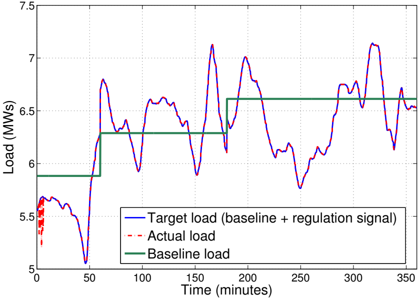
- To participate the aggregator must be able to
  1. Increase/decrease demand by a certain step of variable height m from the baseline
  2. Hold the demand at that value for a certain duration ξ (follow the AGC signa)
- We evaluated ξ to be the 97 % quantile of the zero-crossing time from historical 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



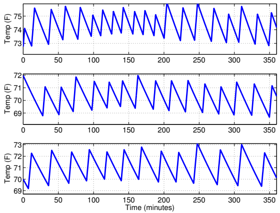


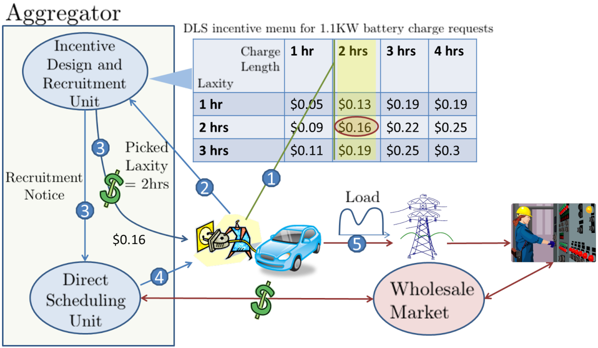
Figure : Simulated response of the TCL population (10000) to regulation signals and three 2 ton A/C units temperatures. The y-axis range i= comfort band.

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



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...

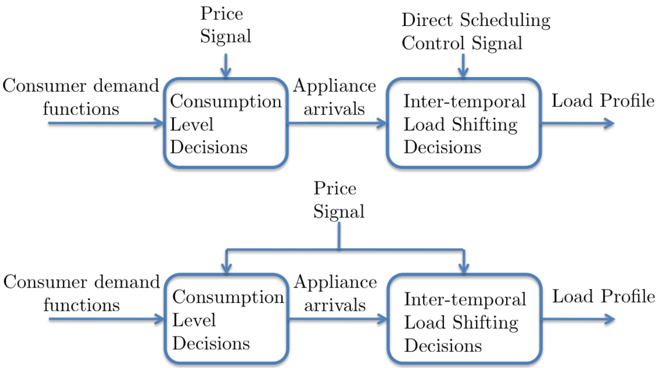
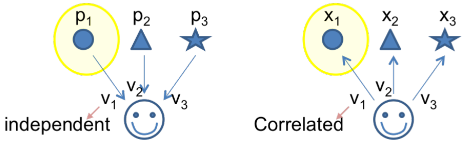


Figure : Differentiated Pricing and Scheduling (top) and Dynamic Retail Pricing (bottom).

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

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

- Optimal posted prices? The closest approximation is the "optimal unit demand pricing" (modes are correlated)



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

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

- Customers respond by *arriving* in a cluster. The Aggregator profit depends on the *mode selection average probability*:

$$P_m(\mathbf{c}(t); t) = \frac{\mathbb{E}\{a_m(\mathbf{c}(t); t)\}}{|\mathcal{P}(t)|}$$

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

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 – good for simulations and theory
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

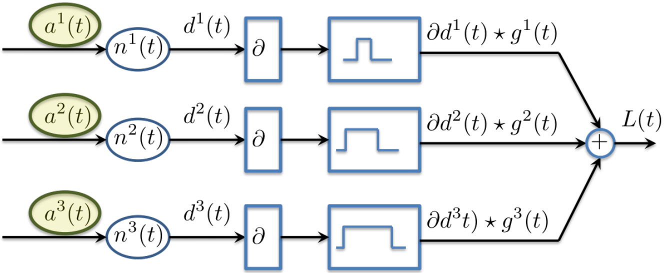
The whole picture

Pricing Incentive design:

- Design incentives to recruit appliances

Planning:

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



The whole picture

Pricing Incentive design:

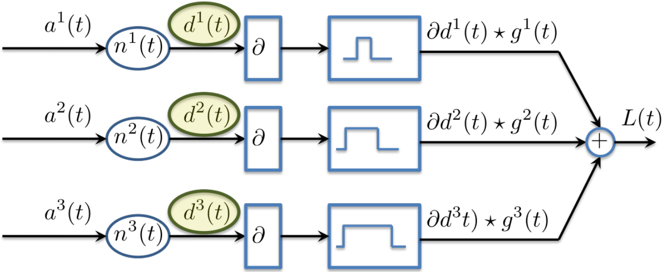
- Design incentives to recruit appliances

Planning:

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

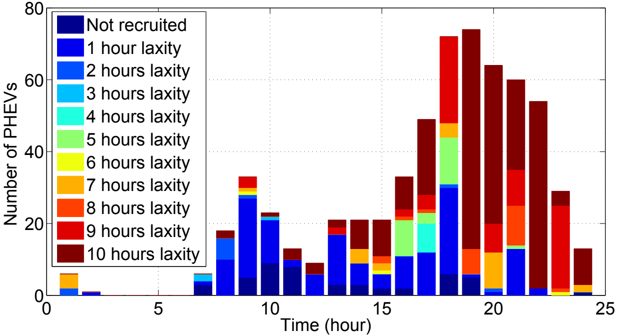
Real-time:

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



Residential charging...

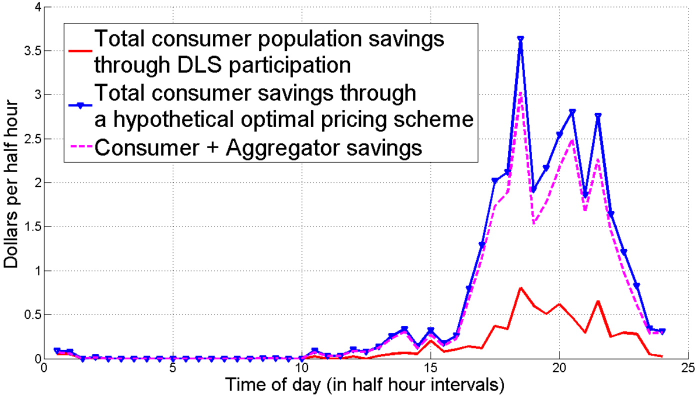
- Aggregator schedules 620 uninterruptible PHEV charging events
- Prices from New England ISO DA market - Maine load zone on Sept 1st 2013
- How many do we recruit (out of 620) and with what flexibility?



- More savings in the evening...

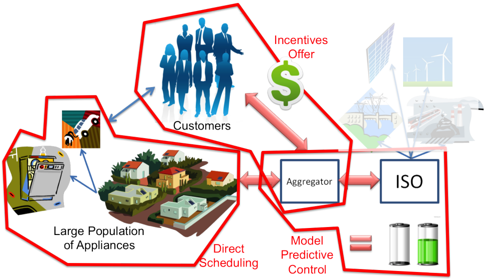
Welfare Effects in Retail Market

- 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)



Conclusion

- We have discussed an information, decision, control and market models for responsive loads
- These models allow to use high level data and convert them in models of load flexibility for mapping data into models and for scalable simulations
- Extension: Model prosumers assets such as distributed renewable resources, like roof-top solar



Conclusion

- We have discussed an information, decision, control and market models for responsive loads
- These models allow to use high level data and convert them in models of load flexibility for mapping data into models and for scalable simulations
- Extension: Model prosumers assets such as distributed renewable resources, like roof-top solar