

# Demand Response

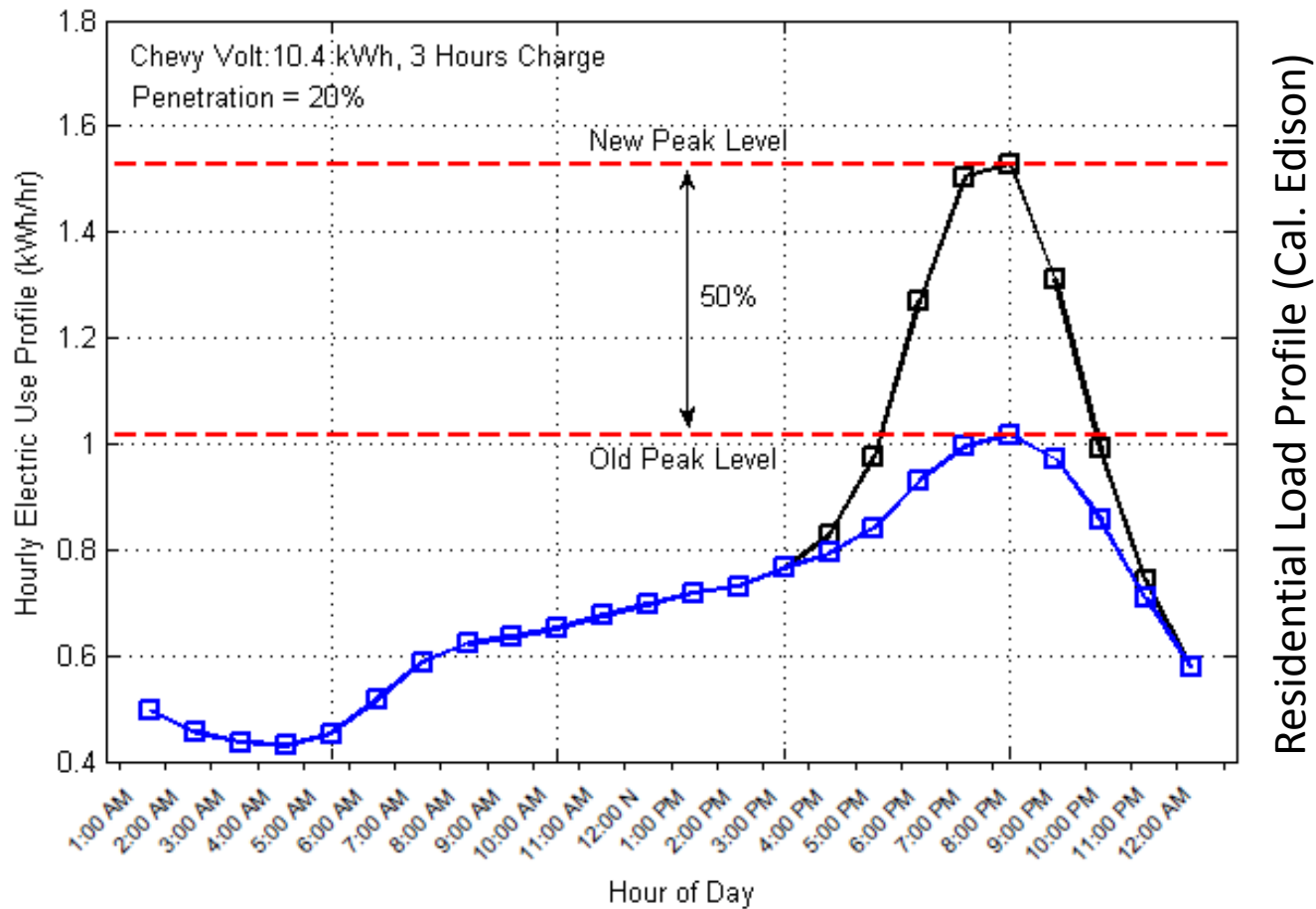
Department of Electrical & Computer Engineering  
Texas Tech University

Spring 2012



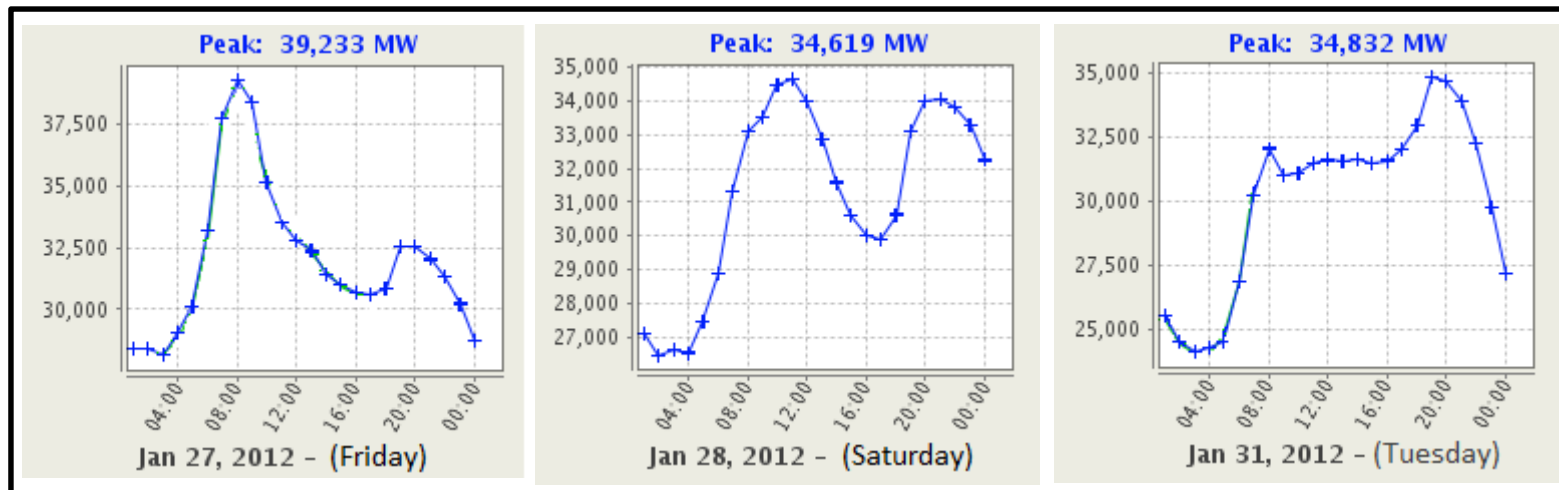
# Residential Load Profile

- A typical residential load profile with and without PHEVs in California:



# Residential Load Profile

- The **overall load** profile in various days in the state of Texas:



Source: ERCOT

- The overall load may significantly change during the day and week.

# Residential Load Profile

- The practical load profile is very unbalanced:
  - Residential Peak Load (afternoon)
  - Industrial / Office Peak Load (morning)
- We define:
  - Peak-to-average ratio (PAR):  $\frac{\text{Peak Daily Load}}{\text{Average Daily Load}}$
- It is desirable to have PAR close to 1. (Q: Why?)

# Definition of Demand Response

- According to the U.S. Department of Energy:

Demand response (DR) is defined as changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.

Q: What is the difference between DR and Load Shedding done by utility?

# Two Approaches to Demand Response

- There are two general approaches to DR:
  - Direct Load Control (DLC)
  - Indirect Load Control / Pricing
  
- Direct load control programs have been around for decades.
  
- **Q:** What is the difference between the two approaches?

- In DLC:
  - The utility has remote access to certain load of users
    - Air conditioner
    - Water heater.
  - It remotely turns on or off the load when ever needed.
  - DLC is tried to be transparent to users. (Q: Why?)

# DLC Example

- Baltimore Gas and Electric (BGE) has been involved in DLC:
  - Since April 1988.
    - For residential and small commercial customers
  - Participants/users are offered \$10 per months
    - During the summer: June - September
  - BGE installed DLC switches on air conditioner



# DLC Example

- Baltimore Gas and Electric (BGE) has been involved in DLC:
  - Compressor cycle is controlled remotely:
    - To operate a **max of 30 min** at any one time.
  - In 1990, they also added DLC for **water heaters**.
- Currently [after 20 years]:
  - The program has about **250,000** customers enrolled

# DLC Example

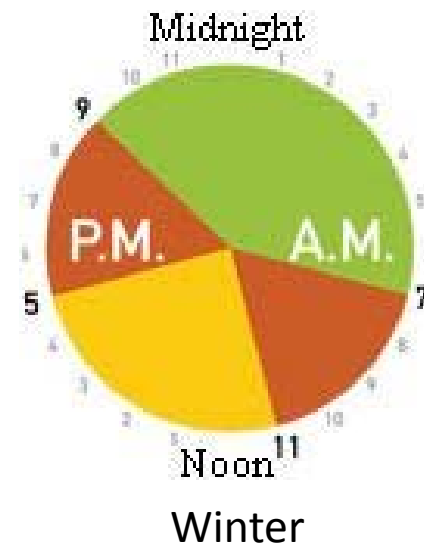
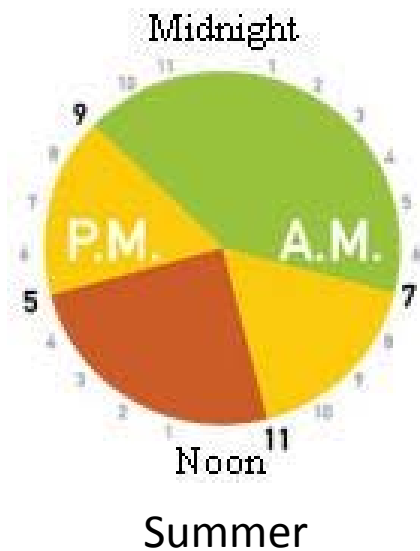
- The DLC program in the city of New Bern, NC:
  - Total number of residential customers: 17,210
    - Total DLC participants: 10,500 (61%).
  - Key idea:
    - Reduce the load at **peak hours**.
- DLC programs require special equipment and maintenance.

# Smart Pricing

- An alternative for DLC is **smart pricing**.
  - Instead of directly controlling customers' load,
  - Let them know about the **price changes**:
    - They will **naturally** try to avoid higher price hours:
      - This will reduce the load at peak hours.
  - Users are **directly involved in decision making**.

# Smart Pricing Models

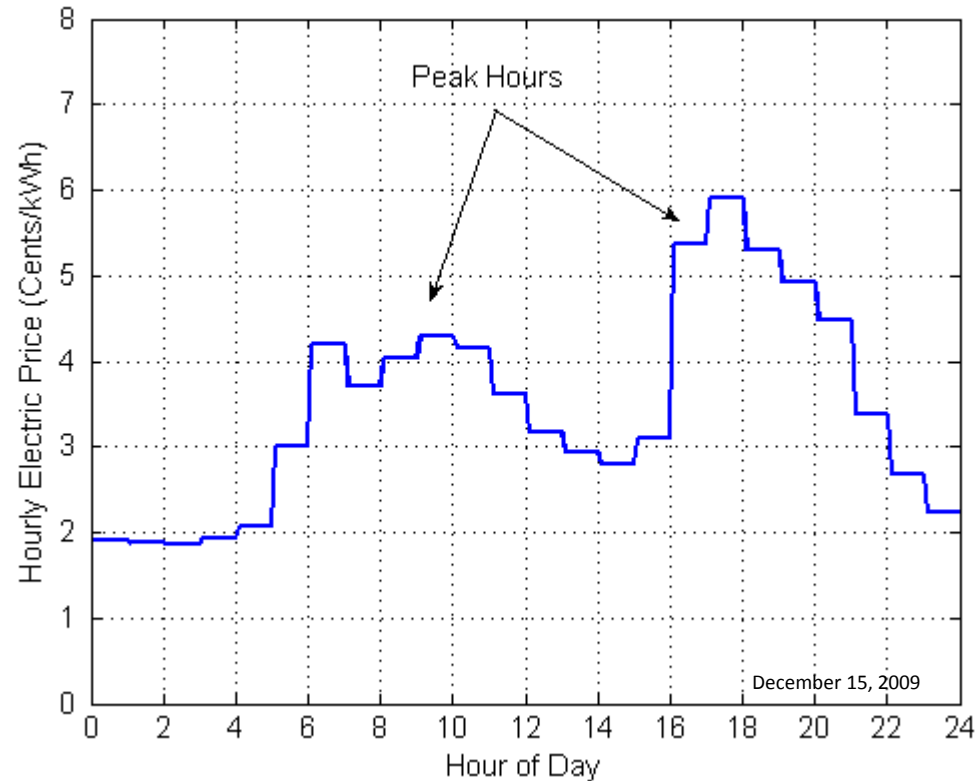
- Time-of-Use (TOU) Pricing in Toronto, Ontario:



- On - Peak / Highest Price
- Mid - Peak / Mid Price
- Off - Peak / Lowest Price

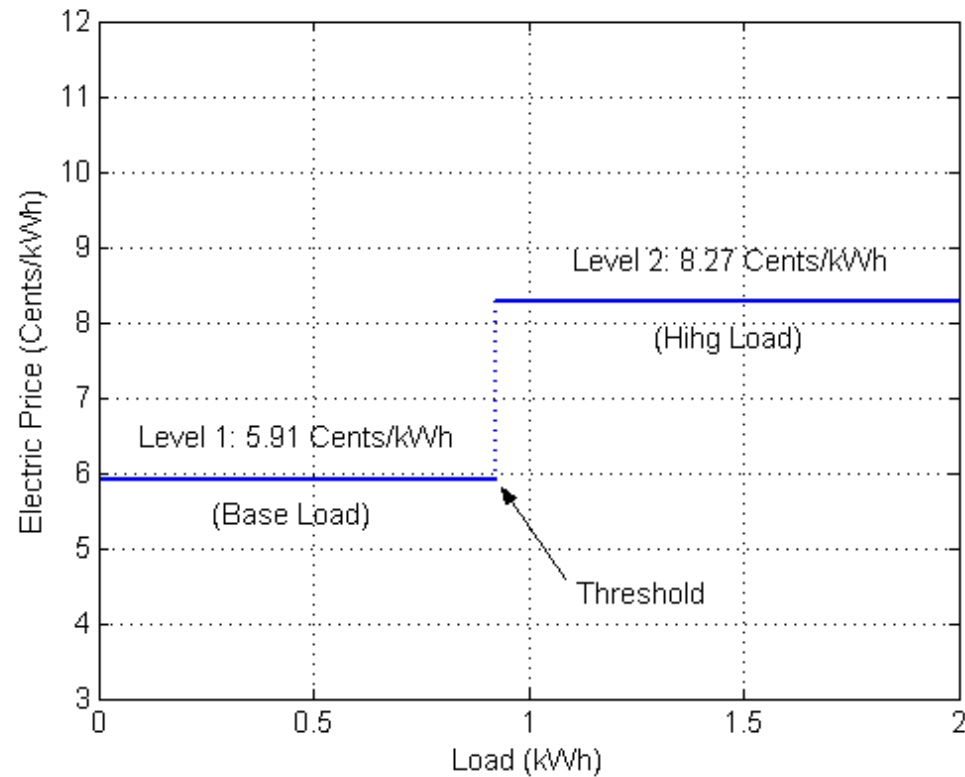
# Smart Pricing Models

- Day-Ahead Pricing (DAP) / Real-Time Pricing (RTP) in Chicago, IL:



# Smart Pricing Models

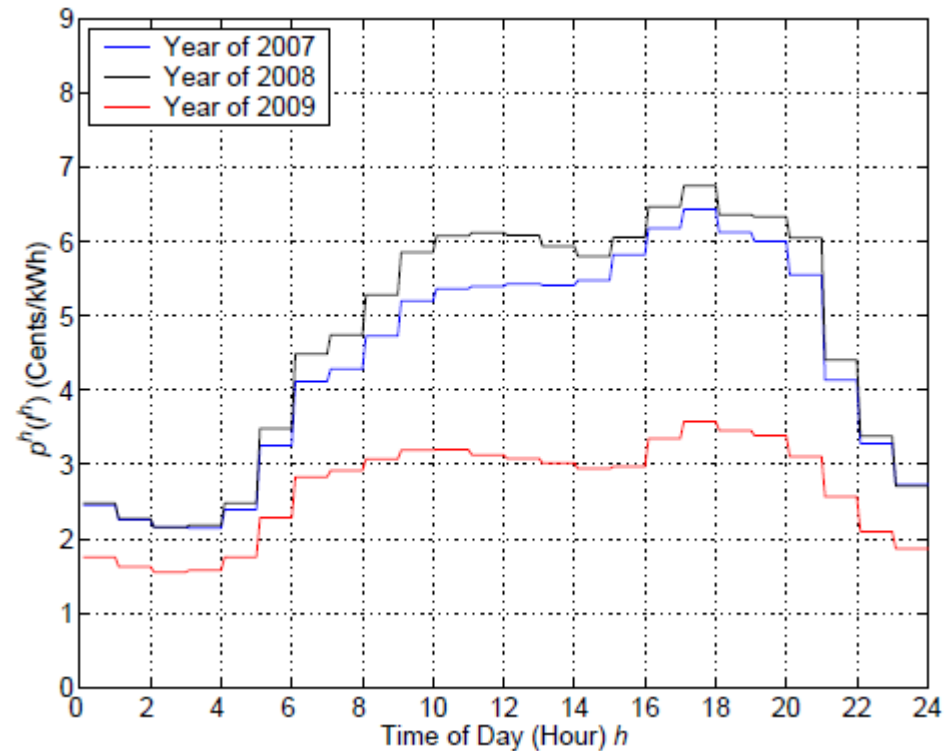
- **Inclining Block Rates (IBR)** in Vancouver, British Columbia:



**Q:** What is the benefit of using IBR?

# Closer Look at DAP

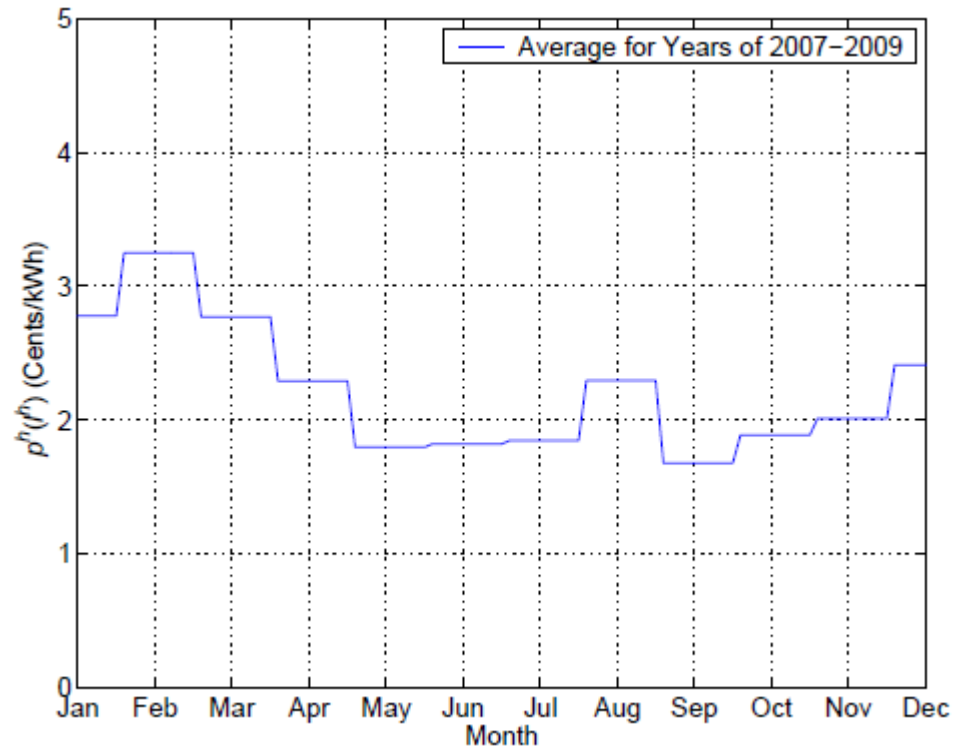
- The overall **daily trend** is somehow the same over the past few years:



- We have higher prices at peak load hours. (Q: Why?)

# Closer Look at DAP

- Prices can change at **different months** of the year:

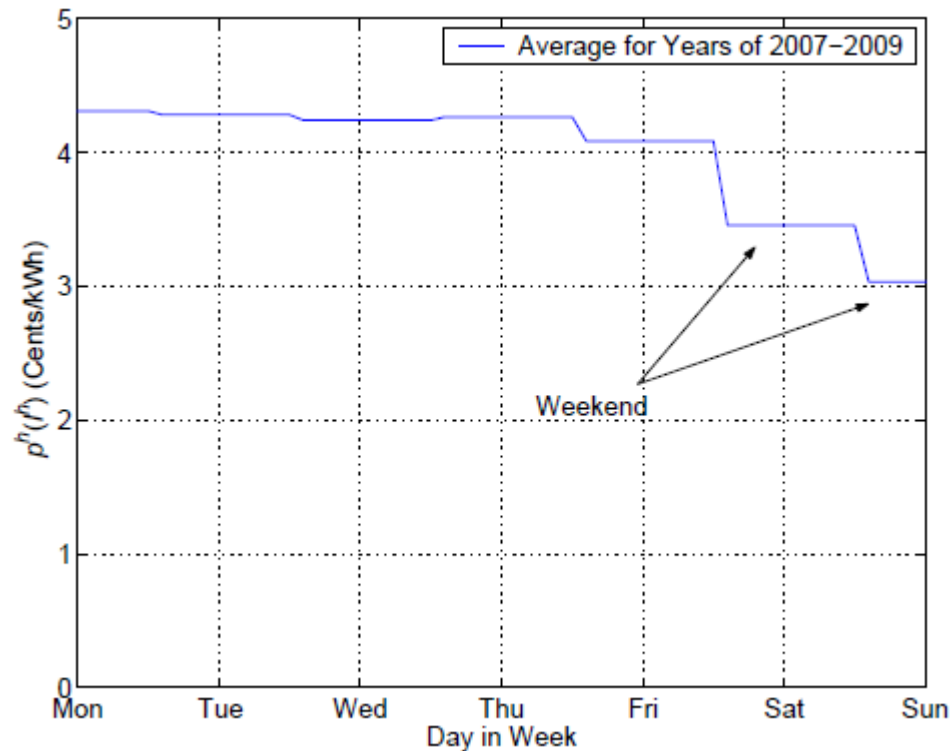


- In Chicago, the prices are higher in Winter. (Q: Why?)



# Closer Look at DAP

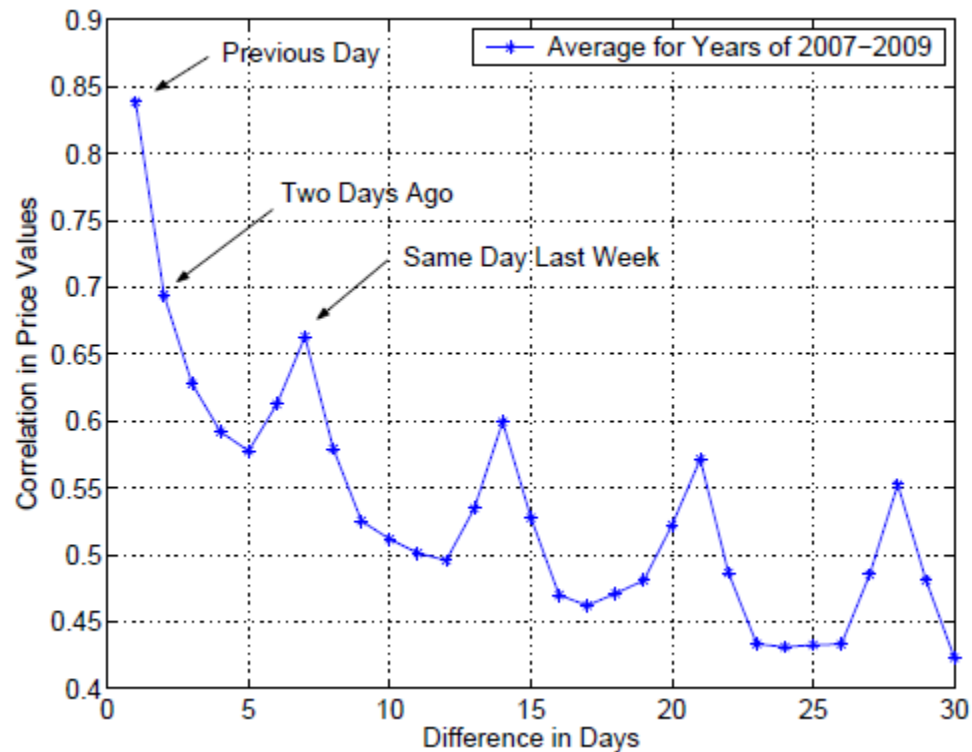
- Prices are different on **week days vs. weekend**.



- The prices are usually less on weekends. (Q: Why?)

# Closer Look at DAP

- Today's price is usually **correlated** with prices on previous days:



- **Q:** Can you explain why the correlations are like this?

# Informing Users

- The users should be informed about prices (price changes):
  - Utility Website
  - Email
  - Text Message
  - Automated Voice Calls
  - Energy Orbs [We will learn about it soon]
  - Smart Meter

# Informing Users

- **Energy Orb: A Light to Visualize Electricity Consumption.**
  - Used by BGE, PJM, ...
  - BGE Setup:
    - Colors: **Green, Yellow, and Red**
    - They indicate off-peak, mid-peak, and on-peak hours.
  - People **react** to price changes and reduce consumption.
  - Saved each user an average of **\$100** on the **summer bill!**

# Informing Users

- **PJM** Energy Orb Codes: **Alert** Users about DR Events.



**Solid Blue** Standby / No event is currently underway.



**Solid Yellow** Warning / Day-ahead event warning has been issued.



**Pulsing Yellow** Warning / An event will occur later in the day.

Ref: [www.pjm.com](http://www.pjm.com)

# Informing Users

- PJM Energy Orb Codes: **Alert** Users about DR Events.

	<b>Solid Red</b> Activation / Event has been activated and is currently in progress.
	<b>Pulsing Red</b> Activation / Event in progress and another declared for the following day.
	<b>Solid Green</b> Testing / Demand response notification system is being tested.

Ref: [www.pjm.com](http://www.pjm.com)

# User Response

- **Q:** Can users/consumers properly react/respond to smart pricing?
- **A:** Not Really!
- Reason 1) Too much information to follow!
  - In Chicago users **did not have time** to check the real-time prices.
- Reason 2) Complicated Decision Making.
  - Think of a **combined** RTP and IBR model!!!
- The “Energy Orb” is **not** enough! We need more...

# User Response

- An interesting commercial product is **Energy Detective<sup>(R)</sup>**:



Source: [www.theenergydetective.com](http://www.theenergydetective.com)



# User Response

- It can be interfaced with your PC or Smart Phone:



Source: [www.theenergydetective.com](http://www.theenergydetective.com)

# User Response

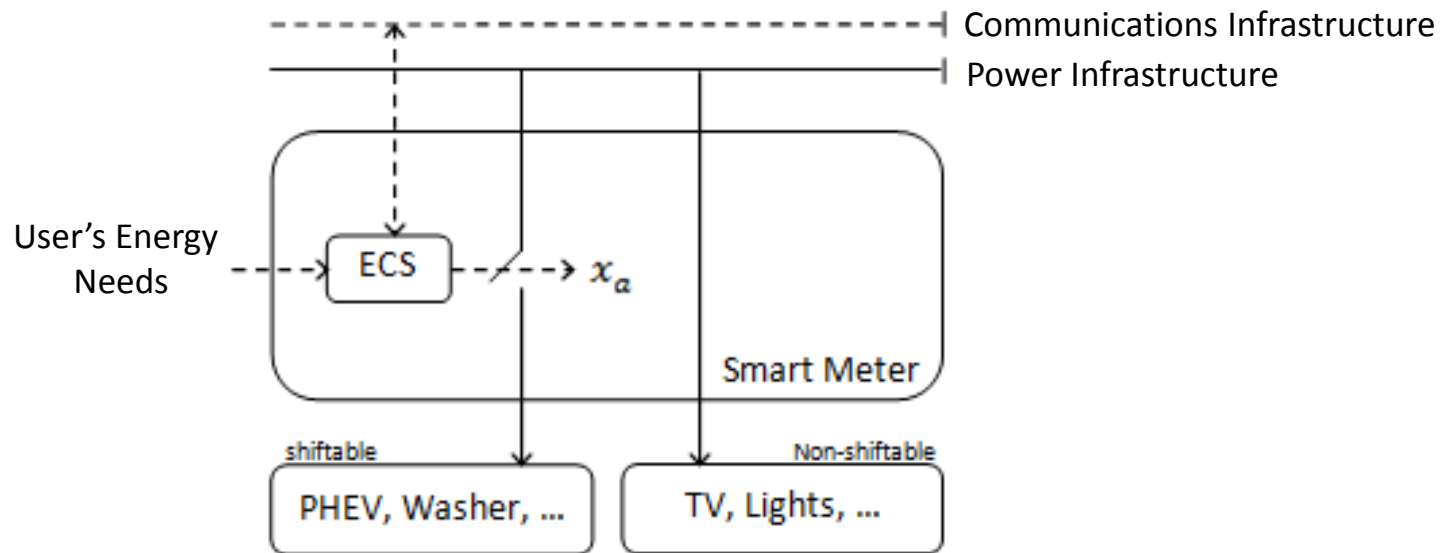
- Provides users with **analyzed** information about:
  - Real time power **consumption** measurements
  - Real time electricity **price** values
- It is essentially interfaced with **Smart Meter** to obtain such info.
- It can also support **behind-the-meter** renewable generation.
  - More Info: <http://www.theenergydetective.com/support/installation>

# Energy Consumption Scheduling

- Energy Orb, Energy Detective, and similar products:
  - Can help users **understand** smart pricing and DR
- But DR **decision making** can still be difficult task for users.
- Solution: **Automated Energy Consumption Scheduling (ECS)**
  - Could be Part of Smart Meter
  - Could be Part of Energy Detective Device
  - Could be a Separate Device

# Energy Consumption Scheduling

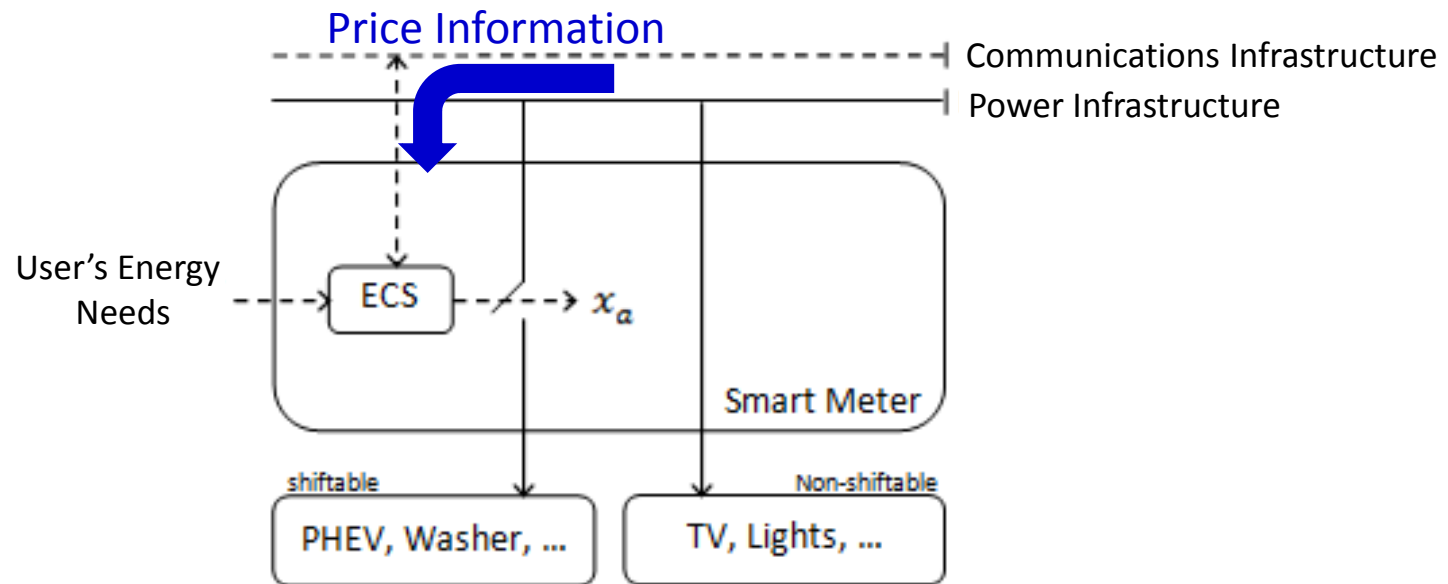
- Smart meter with an embedded ECS:



- $x_a$  : Energy consumption schedule for appliance  $a$ .

# Energy Consumption Scheduling

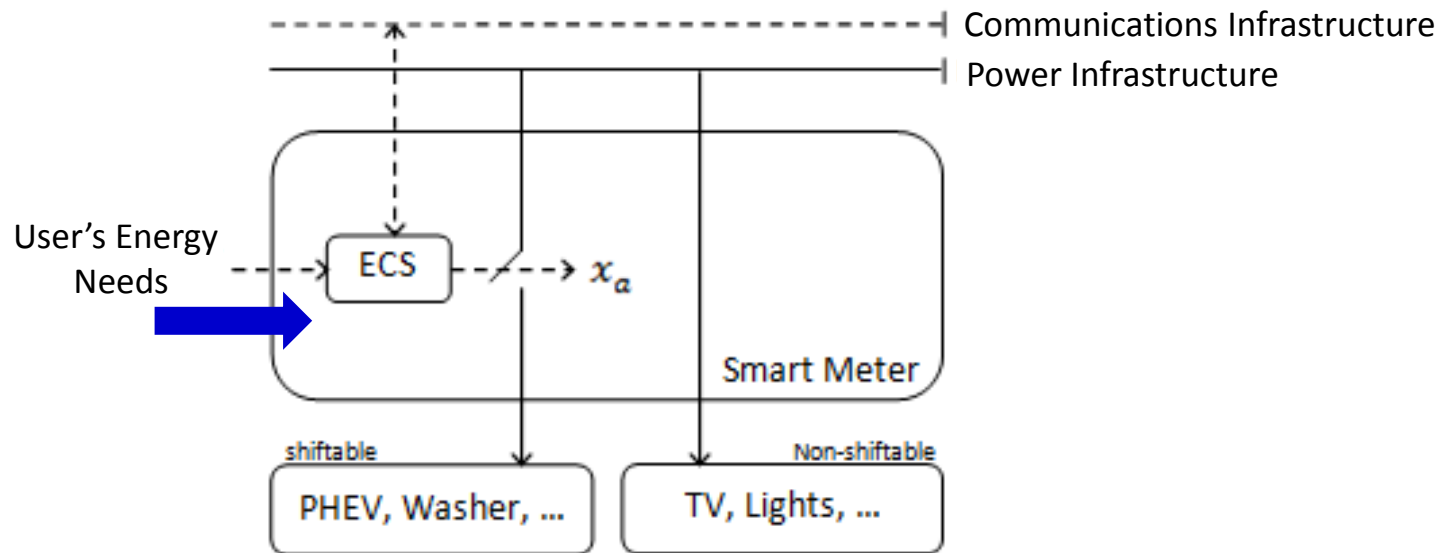
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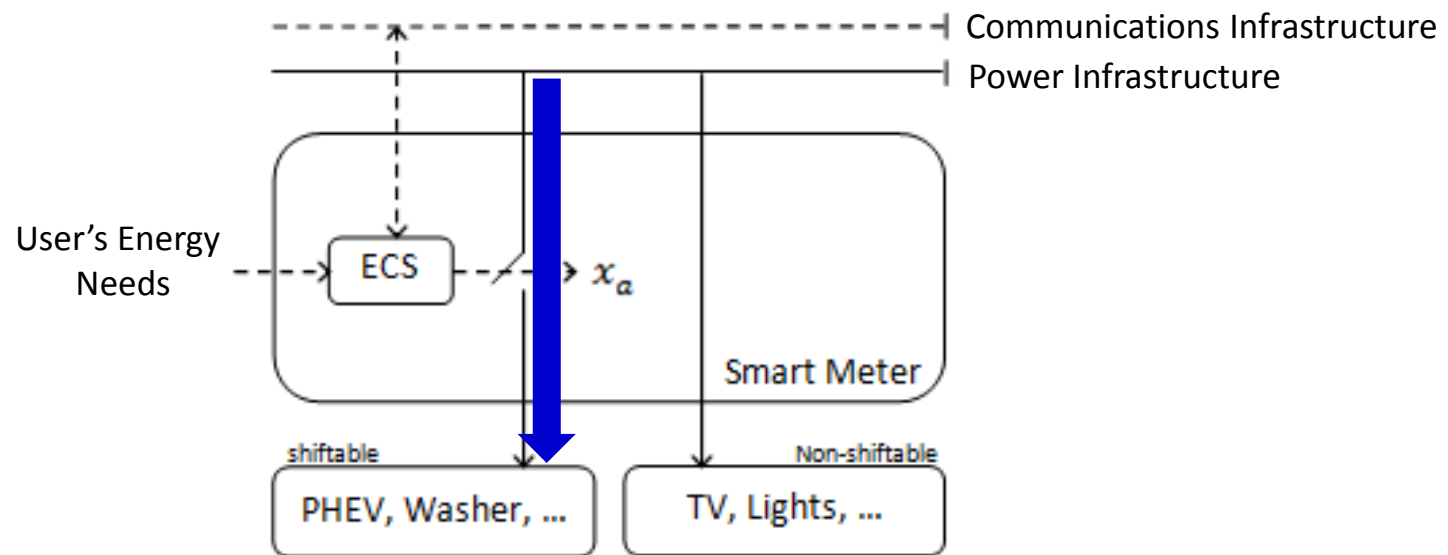
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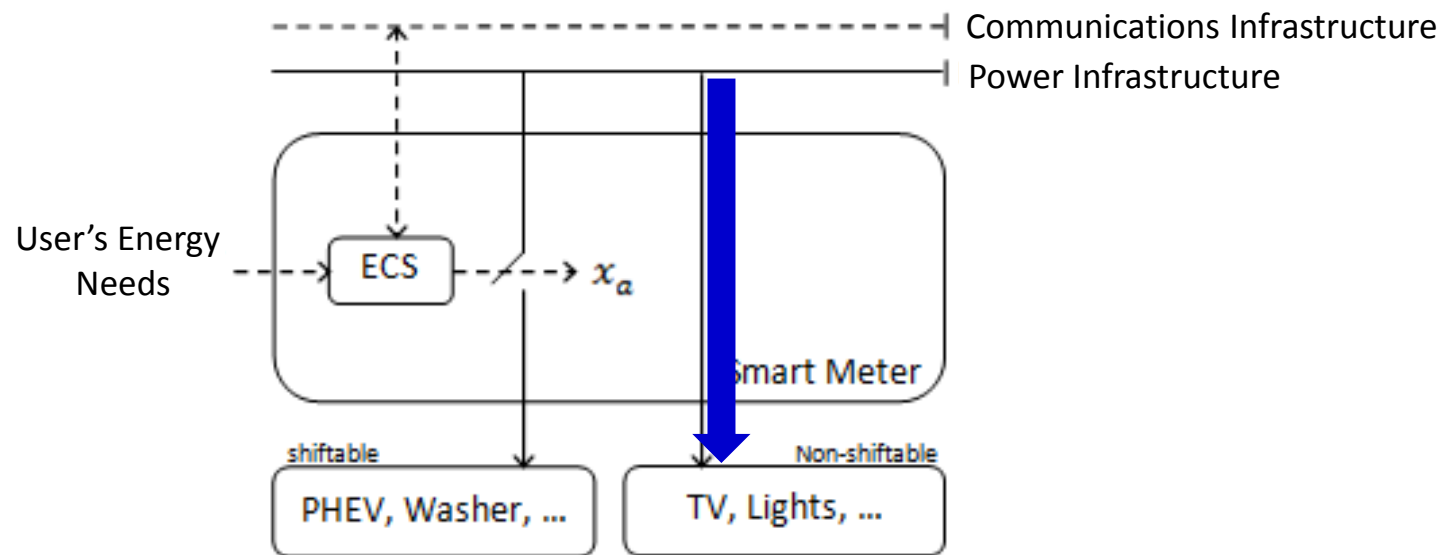
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# Energy Consumption Scheduling

- Smart meter with an embedded ECS:

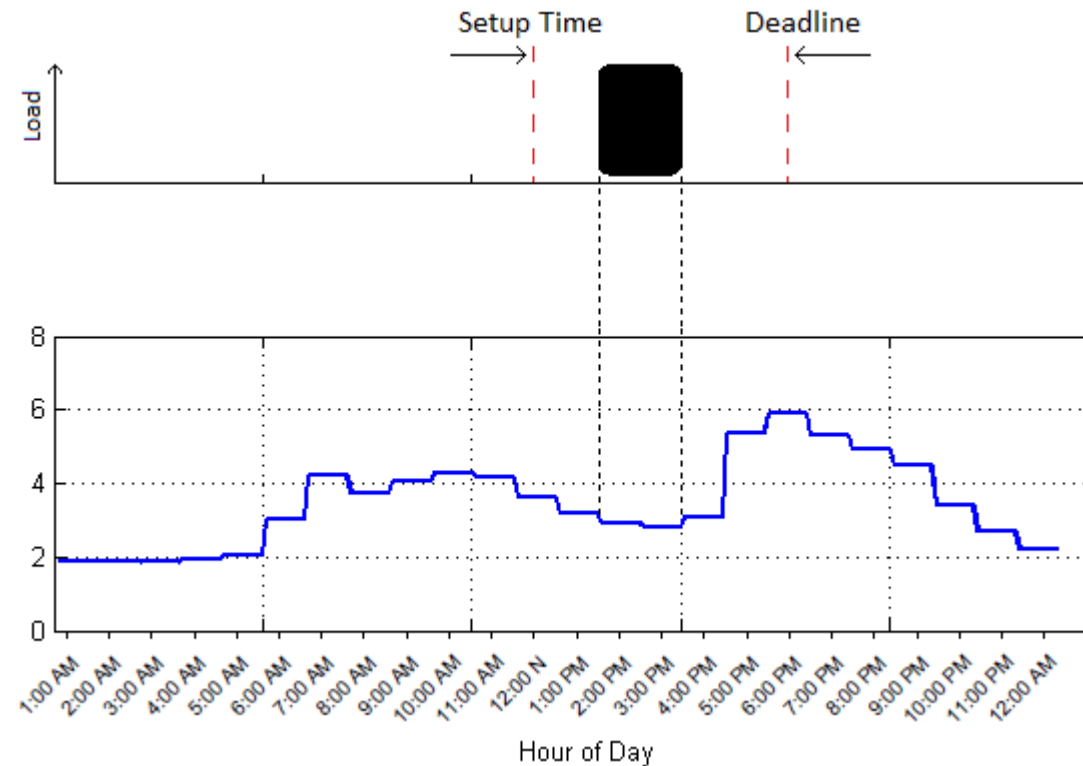


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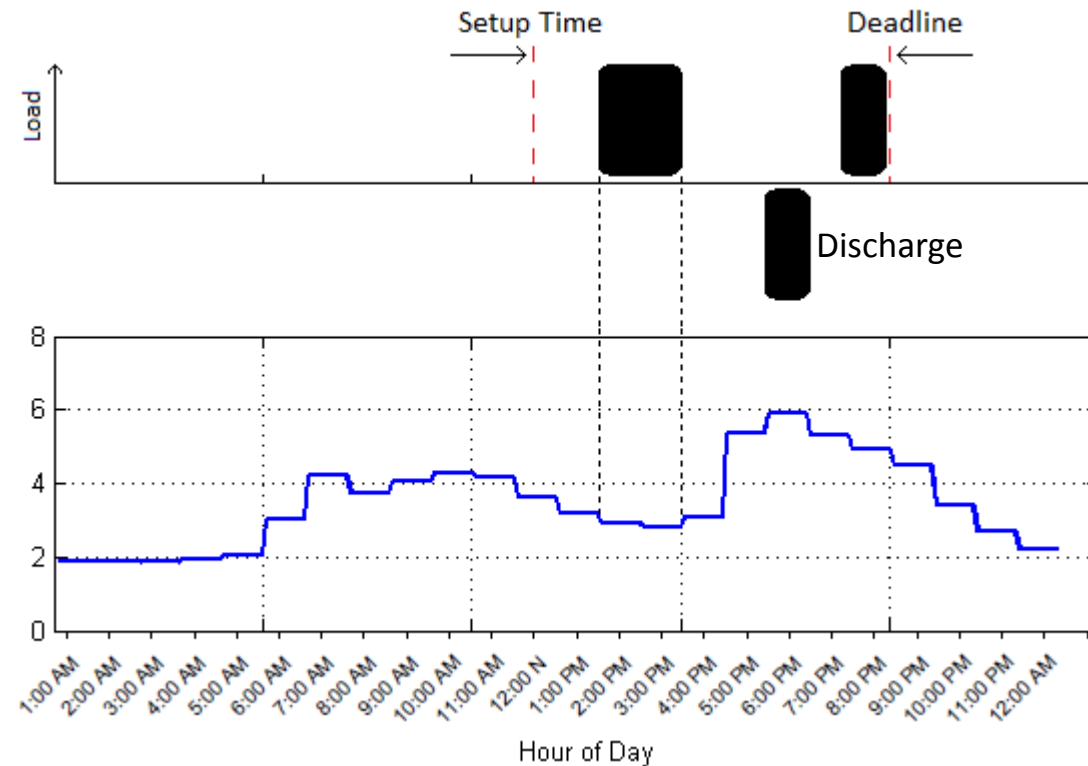
# Energy Consumption Scheduling

- **Simple Example:** Dishwasher (after lunch):



# Energy Consumption Scheduling

- **Another Example:** A Parked Electric Vehicle:



Q: Why would you ever want to **discharge** your battery?

# Energy Consumption Scheduling

- ECS Devices should:
  - Be Compatible with Smart Appliances
  - Be Easy-to-understand and Easy-to-use
  - Be Plug-and-Play
  - Satisfy users' energy consumption needs
  - Help reduce not only PAR but also users' bills (Q: Why?)

# ECS Decision Making

- **Q:** Given the price values how should ECS schedule the load?
  - ECS should have CPU/Microcontroller to analyze:
    - Price values
    - User's energy consumption needs
  - The schedule should basically be an optimal solution
    - To **minimize the cost** while **maintain comfort**.

# ECS Decision Making

- Let  $A$  denote the set of appliances:
  - Washer, Dryer, Dish-washer, PHEVs, ...
  - For each appliance  $a \in A$ , we define an **energy consumption scheduling vector**  $x_a$  as follows:

$$x_a = [x_a^1, \dots, x_a^H]$$

- where  $H \geq 1$  is the **scheduling horizon** that indicates the number of hours ahead which are taken into account for decision making in energy consumption scheduling ( $H = 24$ ).

# ECS Decision Making

- A real-valued scalar  $x_a^h \geq 0$  denotes the corresponding **one-hour** energy consumption that is scheduled for appliance  $a \in A$ .
- Let  $E_a$  denote the **total** energy needed for the operation of appliance  $a \in A$ .
  - **PHEV**:  $E_a = 16$  kWh to charge the battery for a 40-miles driving range
  - **Front-loading washing machine**:  $E_a = 3.6$  kWh per load
  - **Q**: Other examples?

# ECS Decision Making

- For each  $a \in A$ , the user should indicate:
  - $\alpha_a$ : Beginning of the **acceptable operation time**.
  - $\beta_a$ : End of the acceptable operation time (**deadline**).
    - **Dish washer** after lunch table:  
 $\alpha_a = 2 \text{ PM}$  and  $\beta_a = 6 \text{ PM}$  (make dishes ready for dinner)
    - **PHEV** after plugging in at night:  
 $\alpha_a = 10 \text{ PM}$  and  $\beta_a = 7 \text{ AM}$  (make PHEV ready in the morning)

# ECS Decision Making

- The ECS should finish operation for appliance  $a \in A$  by deadline.
  - Operation should be scheduled within **interval**  $[\alpha_a, \beta_a]$
- Given the pre-set parameters  $E_a$ ,  $\alpha_a$ , and  $\beta_a$ , it is required that

$$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \quad a \in A.$$

- It is also required:  $x_a^h = 0$  for any  $h < \alpha_a$  and  $h > \beta_a$ . (Q: Why?)



# ECS Decision Making

- Each appliance  $a \in A$  usually has a **maximum** power level  $\gamma_a^{\max}$ .
  - **PHEV**: May be charged only up to  $\gamma_a^{\max} = 3.3$  kW per hour
- Each appliance  $a \in A$  may also have a **minimum** power level  $\gamma_a^{\min}$ .
- Therefore, for each appliance  $a \in A$ , it is required that

$$\gamma_a^{\min} \leq x_a^h \leq \gamma_a^{\max}, \quad h \in [\alpha_a, \beta_a]$$

# ECS Decision Making

- Depending on the **type of meter** and **load subscription**:
  - We may need to limit the total hourly load:

$$\sum_{a \in A} x_a^h \leq E^{\max}, \quad h = 1, \dots, H.$$

- **Q:** Is there any other constraint that we should consider?
- [For PHEVs, for now, we do not consider discharging]

# ECS Decision Making

- Putting these constraints together
  - We can introduce a **feasible scheduling set** for the ECS:

$$X = \left\{ x \mid \begin{aligned} & \sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, & \forall a \in A, \\ & \gamma_n^{\min} \leq x_a^h \leq \gamma_n^{\max}, & \forall a \in A, h \in [\alpha_a, \beta_a], \\ & x_a^h = 0, & \forall a \in A, h \notin [\alpha_a, \beta_a], \\ & \sum_{a \in A} x_a^h \leq E^{\max}, & \forall h = 1, \dots, H \end{aligned} \right\}.$$

# ECS Decision Making

- Any energy consumption schedule  $x \in X$  is **acceptable** for user.
  - Acceptable in terms of fulfilling the user's energy **needs**:
- **Q**: Do we have any preference over a particular schedule?
- Some of the ECS design objective:
  - Minimize the cost of electricity
  - Maximize user's comfort

} **Tradeoff**

# ECS Decision Making: Cost Minimization

- Let  $p^h$  denote the price of electricity at hour  $h$ .
  - Could be RTP, TOU, DAP, etc.
- Q: How can we calculate a user's total daily cost of electricity?
- [Assume that  $H = 24$ .]

# ECS Decision Making: Cost Minimization

- Energy Consumption Scheduling Problem to **Minimize** Cost:

$$\min_{x \in X} \sum_{h=1}^H p^h \times \left( \sum_{a \in A} x_a^h \right)$$

- **Q:** Is this a **convex** optimization problem?
- You can use **CVX** to solve this problem.
- You can also implement the right code in a **microcontroller**.

# ECS Decision Making: Cost Minimization

- **Q:** What if **IBR** pricing tariffs are used by the utility?
- Let  $p^h(l^h)$  denote a DAP model with IBR as a function of load:

$$p^h(l^h) = \begin{cases} a^h, & \text{if } 0 \leq l^h \leq c^h \\ b^h, & \text{if } l^h > c^h. \end{cases}$$

- Based on the choice of parameters  $a^h$ ,  $b^h$ , and  $c^h$ , the above pricing model reduces to DAP-only or IBR-only tariffs (**Q:** How?).

# ECS Decision Making: Cost Minimization

- Q: What is the ECS Problem to **Minimize** Cost for TOU+IBR prices?

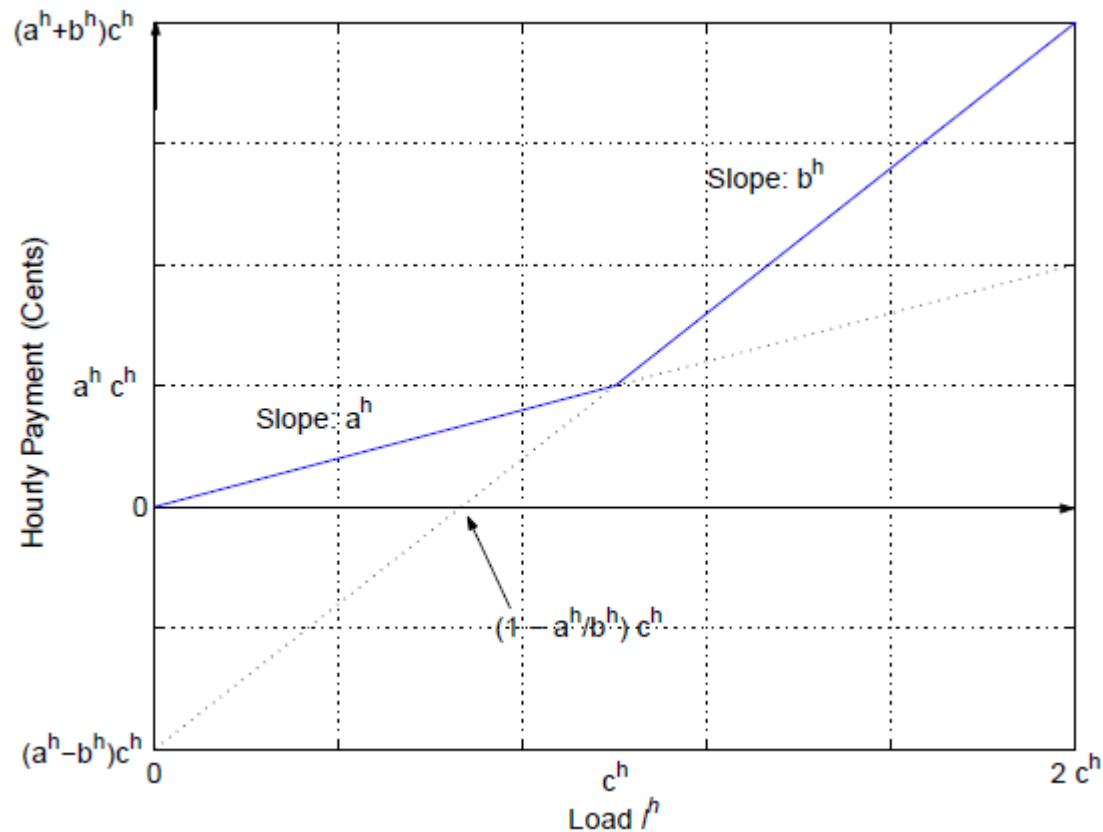
$$\min_{x \in X}$$

- Q: Is this a **convex** optimization problem?
- Q: Is the objective function **differentiable**?



# ECS Decision Making: Cost Minimization

- We can plot the **hourly payment** at hour  $h$  with IBRs as follows:



# ECS Decision Making: Cost Minimization

- The **hourly payment** is formed based on two **intersecting lines**:

$$\text{Payment} = a^h l^h$$

and

$$\text{Payment} = b^h l^h + (a^h - b^h)c^h.$$

- In fact, we have (Q: Why?)

$$p^h(l^h) \times l^h = \max\{a^h l^h, b^h l^h + (a^h - b^h)c^h\}$$

# ECS Decision Making: Cost Minimization

- The ECS Problem to **Minimize** Cost for TOU+IBR becomes:

$$\min_{x \in X} \sum_{h=1}^H \max \left\{ a^h \sum_{a \in A} x_a^h, b^h \sum_{a \in A} x_a^h + (a^h - b^h) c^h \right\}$$

- To get rid of max term, we introduce **auxiliary variables**  $v^h$  :

$$v^h = \max \left\{ a^h \sum_{a \in A} x_a^h, b^h \sum_{a \in A} x_a^h + (a^h - b^h) c^h \right\}$$

- Next, we replace the above with multiple inequality constraints.

# ECS Decision Making: Cost Minimization

- The ECS Problem to **Minimize** Cost for TOU+IBR becomes:

$$\begin{aligned} \min_{x \in X} \quad & \sum_{h=1}^H v^h \\ \text{s.t.} \quad & a^h \sum_{a \in A} x_a^h \leq v^h, & h = 1, \dots, H, \\ & b^h \sum_{a \in A} x_a^h + (a^h - b^h)c^h \leq v^h & h = 1, \dots, H. \end{aligned}$$

- The above problem is linear and differentiable: easy to solve.

# ECS Decision Making: Optimization Trade-off

- What if, we also incorporate user's comfort in the model?
- For each appliance  $a \in A$ , user is OK:
  - If the job is done before the deadline  $\beta_a$ .
- But he may still prefer if the job is done sooner.
  - The preference is relative to how much extra money he may need to pay!
  - Q: How can we model this trade-off in the ECS optimization problem?

# ECS Decision Making: Optimization Trade-off

- For each appliance  $a \in A$ , let us define:

$$\rho_a^h = \frac{(\delta_a)^{h-\beta_a}}{E_a}, \quad h = [\alpha_a, \beta_a],$$

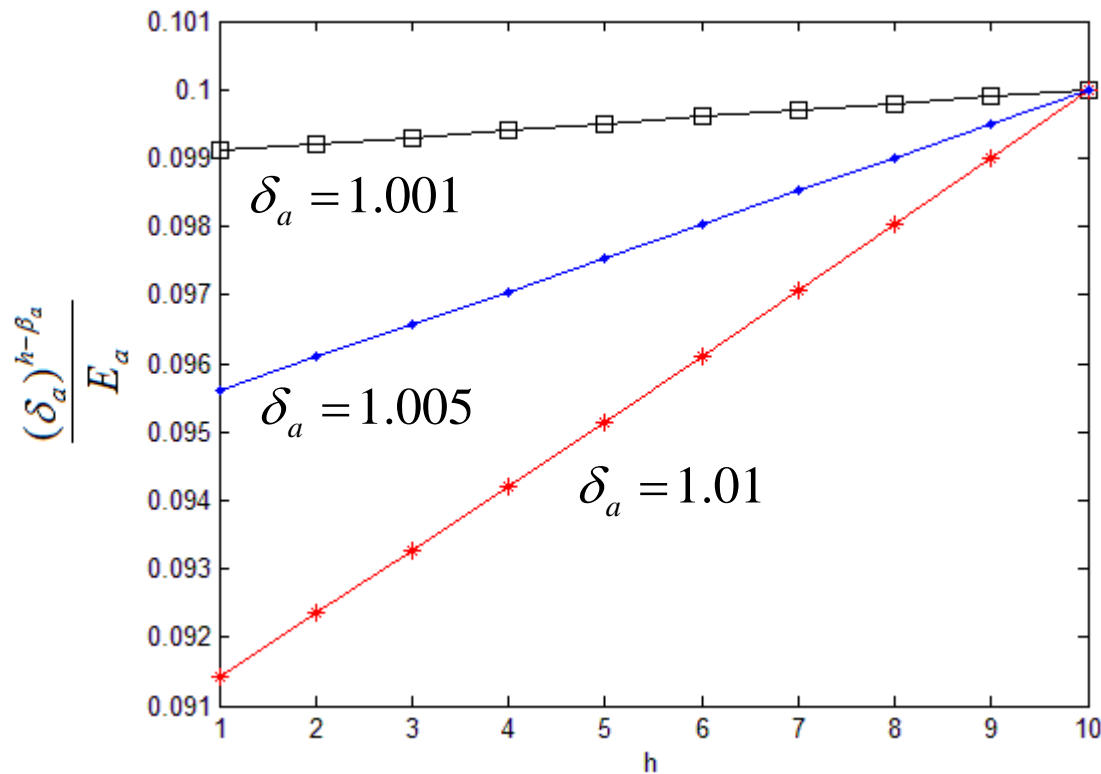
where  $\delta_a \geq 1$  is selected by the user.

- We have (Q: Why?):

$$\rho_a^{\alpha_a} < \dots < \rho_a^{\beta_a}$$

# ECS Decision Making: Optimization Trade-off

- Example:  $E_a = 10$ ,  $\alpha_a = 1$ , and  $\beta_a = 10$ :



Q: Any idea how this can this model help us?

# ECS Decision Making: Optimization Trade-off

- The new ECS Problem to find the **optimal trade-off**:

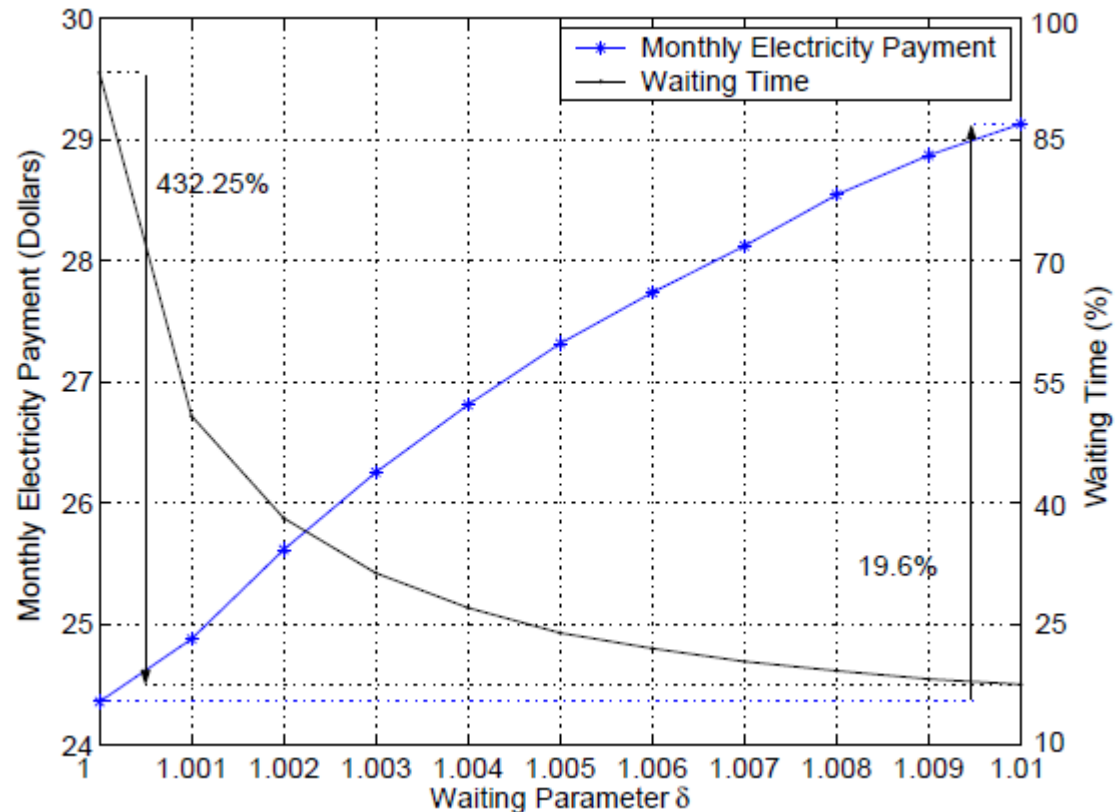
$$\min_{x \in X} \sum_{h=1}^H \max \left\{ \underbrace{a^h \sum_{a \in A} x_a^h, b^h \sum_{a \in A} x_a^h + (a^h - b^h)c^h}_{\text{Cost Term}} \right\} + \lambda_{\text{comfort}} \underbrace{\left( \sum_{a \in A} \frac{(\delta_a)^{h-\beta_a}}{E_a} x_a^h \right)}_{\text{Comfort Term}}$$

- Parameter  $\lambda_{\text{comfort}}$  is also set by the user.
  - Higher  $\lambda_{\text{comfort}}$ : The user cares more about comfort than cost!
- Again, we can use auxiliary variables to solve this problem.



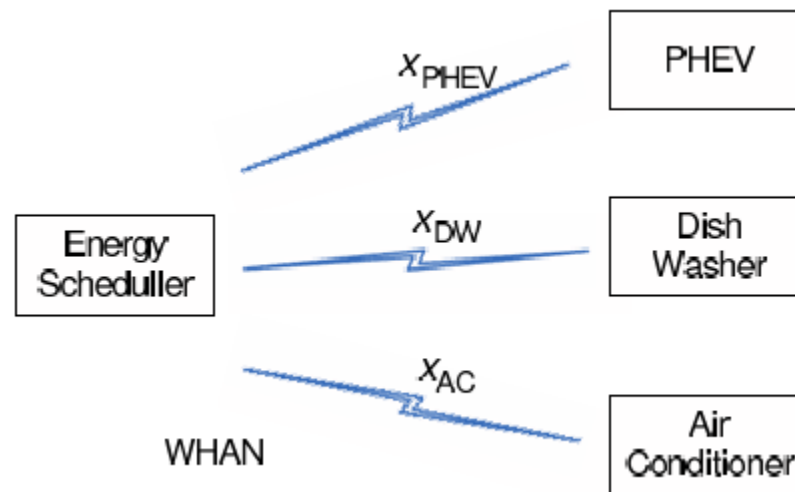
# ECS Decision Making: Optimization Trade-off

- For a typical residential load:



# ECS Decision Making: Notifying Smart Appliances

- One the optimal energy consumption schedule is obtained:



- The smart meter can talk to smart appliances over [ZigBee](#) WHAN.

# ECS: Handling Different Types of Load

- What we have seen so far applies to relative simple load types.
- We also look at three other types of load:
  - PHEV with **discharging** to participate in V2G systems
  - **Air Conditioner**
  - **Water Heater**
- Demand Response can be more complicated for the these load.

# ECS: Handling Different Types of Load

- Consider the case when a PHEV can **discharge** its battery:
  - Clearly,  $x_a^h$  is no longer restricted to **non-negative** numbers.
  - The battery may not be discharged if it is **empty**.
  - The battery may not be charged if it is **full**.
- We need to add some additional constraints together with:

$$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \quad a \in A.$$

# ECS: Handling Different Types of Load

- Let  $C_a^{\text{full}}$  denote the **full charging capacity** of the PHEV battery.
- Let  $C_a^{\text{init}}$  denote the **initial charging level** of the PHEV battery.
- The following constraints will fix the problem:

$$-C_a^{\text{init}} - \sum_{s=\alpha_a}^{h-1} x_a^s \leq x_a^h, \quad h = \alpha_a, \dots, \beta_a,$$

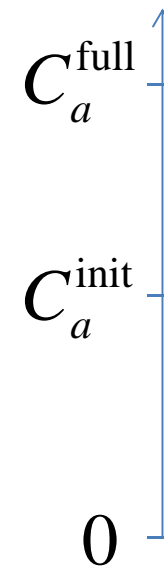
$$C_a^{\text{full}} - C_a^{\text{init}} - \sum_{s=\alpha_a}^{h-1} x_a^s \geq x_a^h, \quad h = \alpha_a, \dots, \beta_a,$$

# ECS: Handling Different Types of Load

- Assume that  $\alpha_a = 1$ .
- For  $h = \alpha_a = 1$ , the constraints on last slide can be written as:

$$-C_a^{\text{init}} \leq x_a^1 \leq C_a^{\text{full}} - C_a^{\text{init}}.$$

- **Q:** Why is it correct?

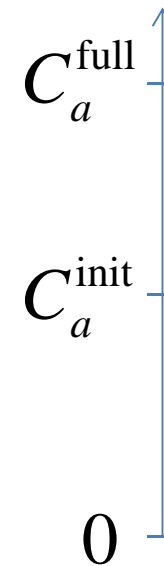


# ECS: Handling Different Types of Load

- For  $h = \alpha_a + 1 = 2$ , the constraints become:

$$-C_a^{\text{init}} - x_a^1 \leq x_a^2 \leq C_a^{\text{full}} - C_a^{\text{init}} - x_a^1$$

- **Q:** Why is it correct?
- **Scenario 1:**  $x_a^1 \geq 0$  (Charge)
- **Scenario 2:**  $x_a^1 < 0$  (Discharge)

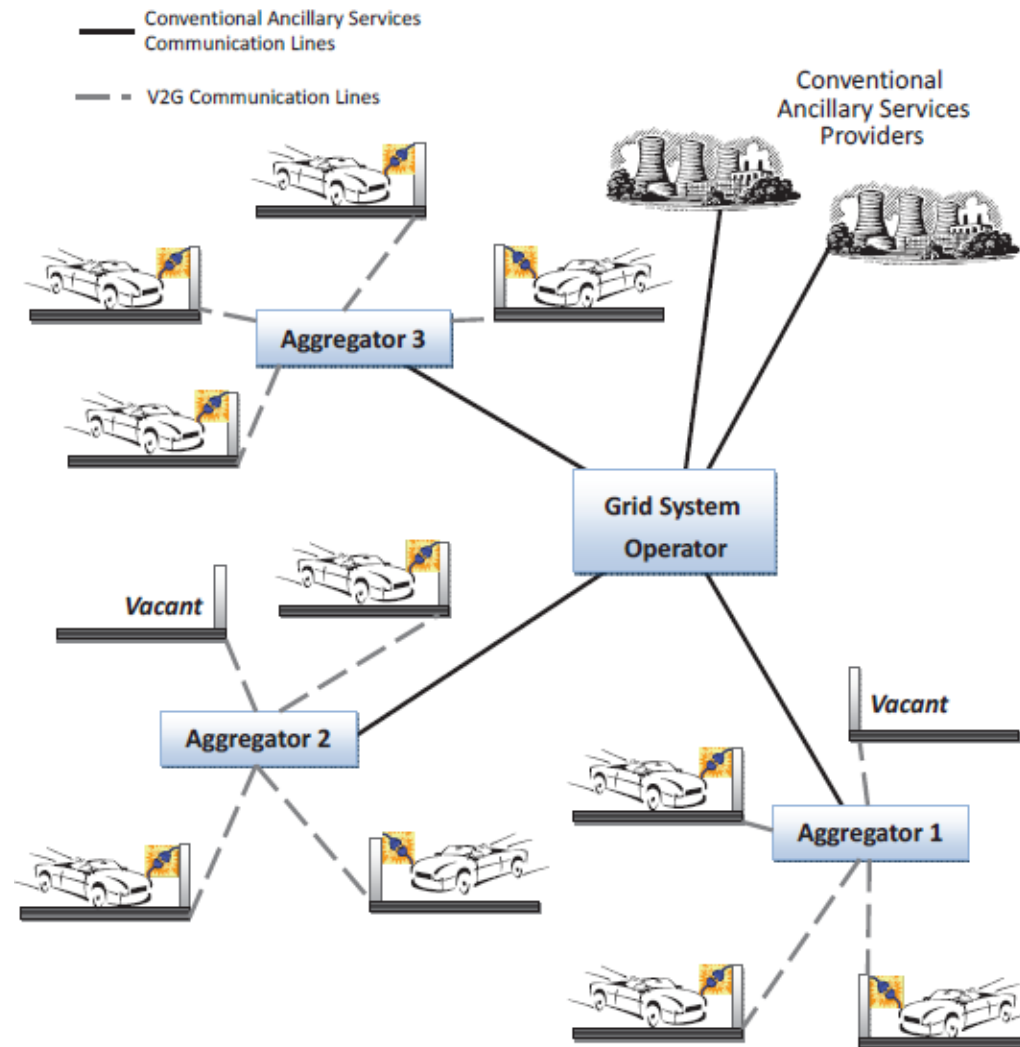


# ECS: Handling Different Types of Load

- Once an ECS can support discharging:
  - The PHEV can participate in [Vehicle-to-Grid \(V2G\)](#) systems.
- V2G: Batteries of parked vehicles are used as source of power.
  - The PHEVs discharge their battery when the [grid lacks generation](#).
  - The PHEVs are [paid](#) to compensate for their contribution.
- Each group of PHEVs is usually coordinated by an [aggregator](#).



# ECS: Handling Different Types of Load



V2G

# ECS: Handling Different Types of Load

- Air Conditioner:
  - For air conditioner, you do **not** have a need for a certain amount of power.
  - Instead, you want to make sure that the **indoor temperature**
    - Remains as closely as possible to the **set point** by the user.
  - Therefore, you are actually dealing with a **closed-loop control system**.
  - The key question is:
    - How can we relate **energy consumption** to the **indoor temperature**?

# ECS: Handling Different Types of Load

- We define:
  - $v$ : Indoor temperature
  - $\epsilon$ : Thermal time constant of the building
  - $\gamma$ : Air conditioner efficiency factor
  - $K$ : A factor depends on total thermal mass.
  - $u$ : Electricity consumption (same as  $x$  so far, but it is shown as  $u$  for input)

# ECS: Handling Different Types of Load

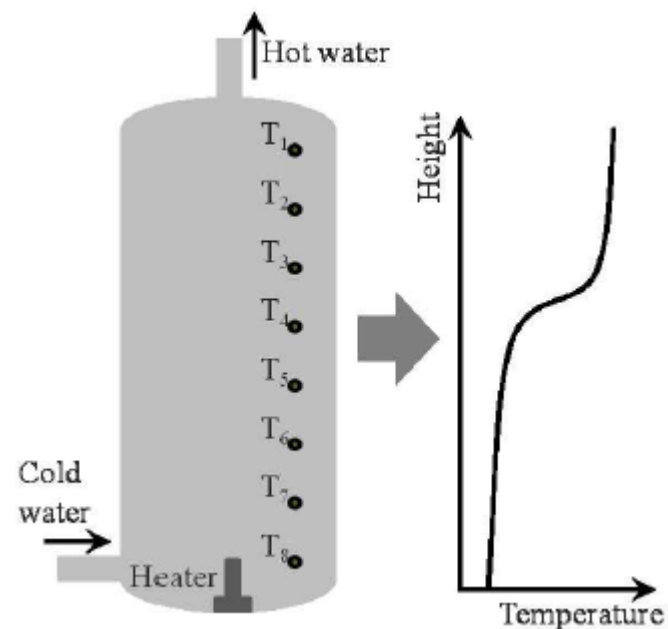
- We can show that, when it comes to cooling, we have:

$$\dot{v} = \varepsilon v - \gamma (1 - \varepsilon) K u + (1 - \varepsilon) t_{OD}$$

- Therefore, the ECS design for the air-conditioner will be:
  - Designing a closed-loop controller to maintain  $v$  close to its set-point.
  - The set point will be chosen by the user.

# ECS: Handling Different Types of Load

- Residential hot water system is a major power consumer.
  - Cold water enters at the bottom.
  - Hot water leaves at the top.
  - Heater is an electric resistor.
  - Designed to avoid mix of water.
  - We have  $n$  layers of water:
    - Layer  $i$ : Uniform temperature  $T_i$  and volume  $V_i$ .



# ECS: Handling Different Types of Load

- Two comfort settings:
  - $T_{\max}$ : The maximum temperature of water in the tank.
  - $T_{\min}$ : The minimum temperature at which water is allowed to leave.
- Another comfort parameter is the volume of hot water available:
  - At temperature  $T_{\min}$ .
  - You should always have enough warm water to reach user's needs.

# ECS: Handling Different Types of Load

- Mathematically, this last item can be modeled based on SoC:
- State-of-charge (SoC):
  - The ratio of the energy content of the **available water with higher than  $T_{min}$**  temperature, versus the energy content of a full tank reaching  $T_{max}$ .

$$SoC = 100 \left[ \frac{\sum_{i=1}^n V_i (T_i - T_{min}) \varphi(T_i, T_{min})}{\sum_{i=1}^n V_i (T_{max} - T_{min})} \right]$$

Indicator function

# ECS: Handling Different Types of Load

- The third comfort parameter can be in form of  $SoC_{\min}$ :

$$SoC \geq SoC_{\min}$$

- ECS should make sure that the above condition always holds.
- The **control variable**: turning the heater 'on' and 'off'.
- **Q**: When and for how long should we switch 'on' for **TOU** prices?



# ECS: Handling Different Types of Load

- We define:
  - $P$  : The power consumption of the heater when it is 'on'.
  - $\eta$  : Electricity efficiency of the heater.
- The time it takes to reach  $T_{\max}$  from current temperatures  $T_i$ :

$$t_{\max} = \frac{4.186}{\eta \cdot P} \sum_{i=1}^n V_i (T_{\max} - T_i)$$

- Cost of reaching this point:  $P \times \sum_{h=t}^{t_{\max}} \text{Price at hour } h.$

# ECS: Handling Different Types of Load

- Every time we switch on the heater:
  - The heater **stays on** until we reach  $T_{\max}$  .
  - The **cost** will depend on the time of switching on and the TOU price values.
  - Due to the heat loss and usage, the temperature will **gradually** go down.
- ECS should decide:
  - Select the switching on cycles to **minimize cost** and **assure**  $SoC \geq SoC_{\min}$  .

# ECS: Handling Different Types of Load

- Appliances may or may not be **interrupted**.
- In either case they may have some flexible load.
- You can turn on and off interruptible load any time you want.
  - Example: PHEV, Dryer
- You can **postpone** the operation for a non-interruptible load:
  - But when you start operation, you cannot stop it until the work is done.

# ECS: Handling Different Types of Load

- Some loads may be modeled using **utility functions**.
  - Utility value: user's level of satisfaction about energy consumption
- Key idea: Users will benefit from **consuming more**.
- Could represent industrial load:
  - More power consumed, more products will be manufactured.
  - Example:  $U(x_a^h) = \log(1 + x_a^h)$

# Demand Response: Data Centers



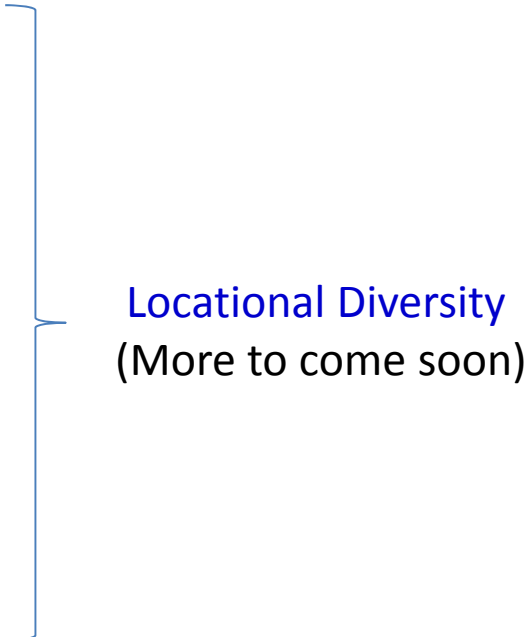
Ref: R. H. Katz, 2009

Google's Data Center next to Columbia River in The Dalles, Oregon.

# Demand Response: Data Centers

- Google has data centers in:

- The Dalles, Oregon
- Atlanta, Georgia
- Reston, Virginia
- Lenoir, North Carolina
- Goose Creek, South Carolina



Locational Diversity  
(More to come soon)

- In other countries: Netherlands, Belgium, Australia, etc.

# Demand Response: Data Centers

- Data centers are **huge** energy consumers.
- Take Microsoft's data center in Quincy, WA:
  - 43,600 square meters of space.
  - 4.8 kilometers of chiller piping
  - 965 kilometers of electric wire
  - 1.5 metric tons of batteries for backup power
  - Total load = **48 megawatts: enough power for 40,000 homes!**



# Demand Response: Data Centers

- Data centers pay a lot on their **electricity bills!**

Company	Servers	Electricity	Cost
eBay	16K	$\sim 0.6 \times 10^5$ MWh	$\sim \$3.7$ M
Akamai	40K	$\sim 1.7 \times 10^5$ MWh	$\sim \$10$ M
Rackspace	50K	$\sim 2 \times 10^5$ MWh	$\sim \$12$ M
Microsoft	>200K	$> 6 \times 10^5$ MWh	$> \$36$ M
Google	>500K	$> 6.3 \times 10^5$ MWh	$> \$38$ M
USA (2006)	10.9M	$610 \times 10^5$ MWh	$\$4.5$ B

Ref: Qureshi, 2009

Annual electricity cost at \$60 / MWh

- Therefore, DR and ECS can significantly help data centers.
- Key question:** how can we model the load in data centers?



# Demand Response: Data Centers

- Let  $P_{cluster}$  be the **power usage** of a server cluster.
- Let  $n$  be the number of servers in the cluster.
- Let  $u_t$  be its average CPU utilization (between 0 and 1) at time  $t$ :

$$P_{cluster} = F(n) + V(u_t, n) + \varepsilon$$

The diagram illustrates the components of the power usage equation. Three blue arrows point from the terms in the equation to their respective labels:  $F(n)$  points to "Fixed Power",  $V(u_t, n)$  points to "Variable Power", and  $\varepsilon$  points to "Empirically Derived Correction Constant".

# Demand Response: Data Centers

- We have:

$$F(n) = n \times (P_{idle} + (PUE - 1) \times P_{peak})$$

$$V(u_t, n) = n \times (P_{peak} - P_{idle}) \times (2u_t - u_t^r)$$

where

- $P_{idle}$ : average idle power draw of a single server
- $P_{peak}$ : average peak power draw of a single server
- $r$ : empirically derived constant, accurate:  $r = 1.4$ , OK: 1

# Demand Response: Data Centers

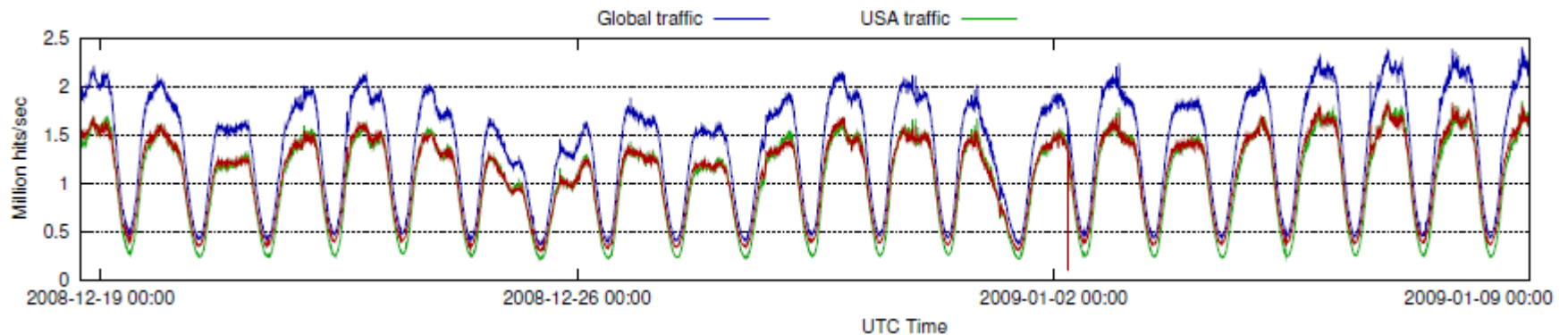
- PUE: Data center power usage effectiveness.
- Some typical numbers:
  - $P_{\text{idle}} = 150$  watts
  - $P_{\text{peak}} = 250$  watts
  - $PUE = 1.3$
- Therefore, we can model the electric load in terms of  $n$  and  $u_t$ .

# Demand Response: Data Centers

- Similarly, the **quality-of-service** can be modeled in  $n$  and  $u_t$ .
  - Depending on the data center workload:
    - We may turn on more / less computer clusters and servers
    - We may need to run servers at higher / lower utilization
  - We can decide to serve better / more workload:
    - But then it will be at the cost of higher electric bills!

# Demand Response: Data Centers

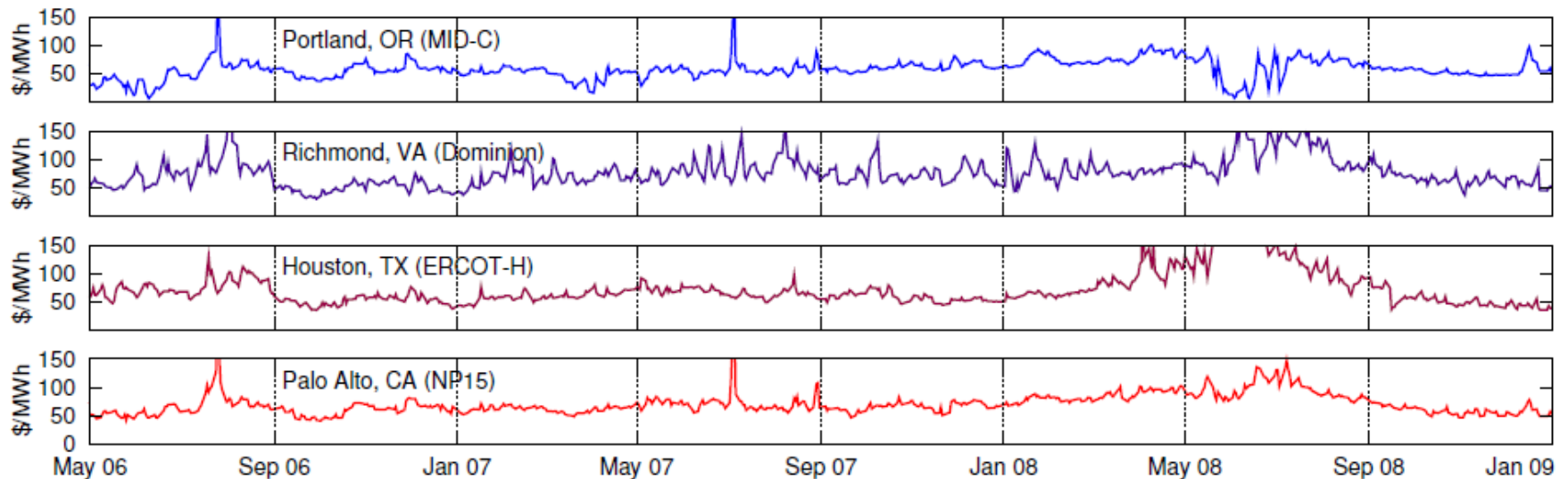
- Sample **workload** trend on Akamai (content distribution) servers:



- The workload varies over time and over different days.
- **Q:** How can we design an ECS unit for data centers?

# Demand Response: Data Centers

- The key is to benefit from **locational diversity!**



Daily averages of day-ahead peak prices at different regions

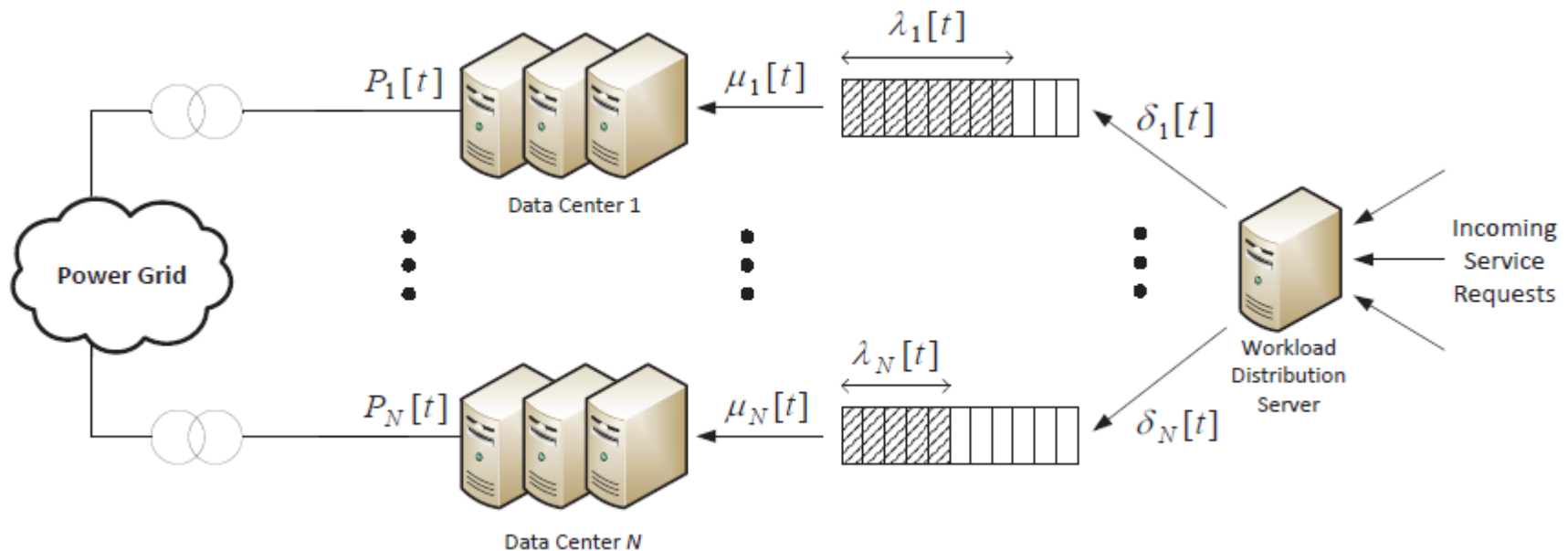
- The price of electricity varies over time and over different days.

# Demand Response: Data Centers

- For most load, ECS unit **diversifies** load across **time**.
- For data centers, ECS unit also **diversifies** load across **regions**.
  - Part of ECS is placed in a task distribution server.
  - More workload is forwarded to data centers:
    - That face cheaper electricity in their region
    - Each data center may be favored at part of day

# Demand Response: Data Centers

- For data centers, ECS unit also **diversifies** load across **regions**.

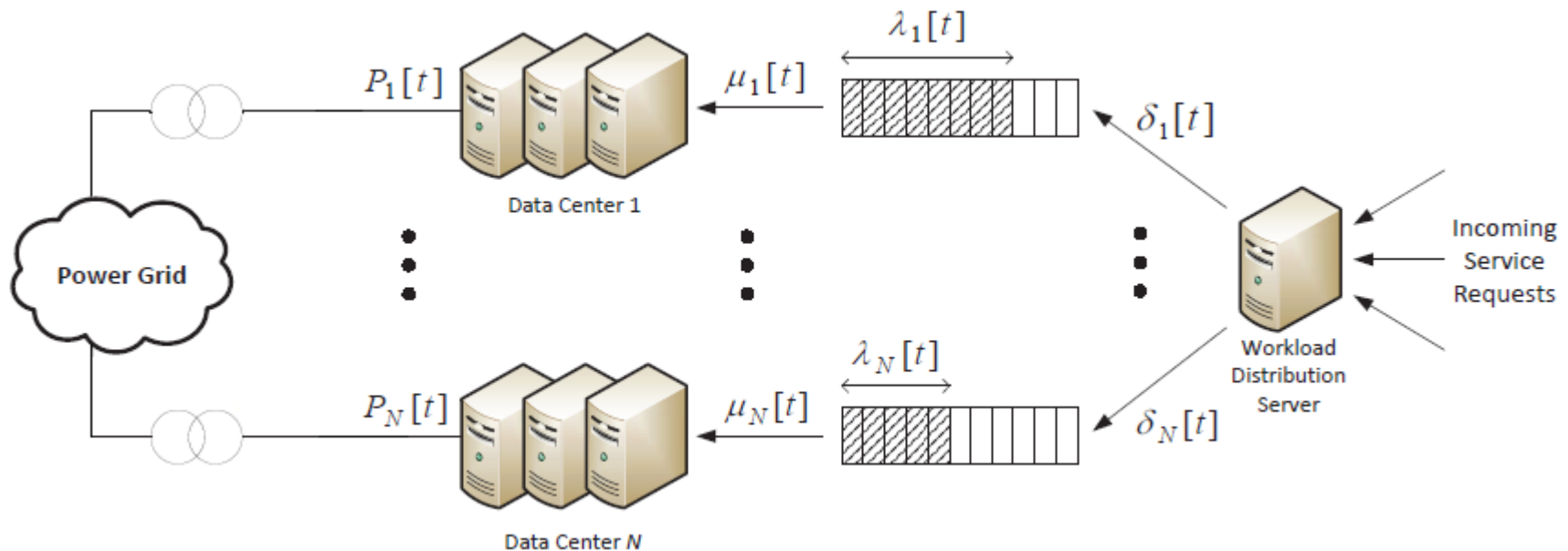


- The total workload =  $\sum_{i=1}^N \delta_i[t]$ .



# Demand Response: Data Centers

- For data centers, ECS unit also **diversifies** load across **regions**.

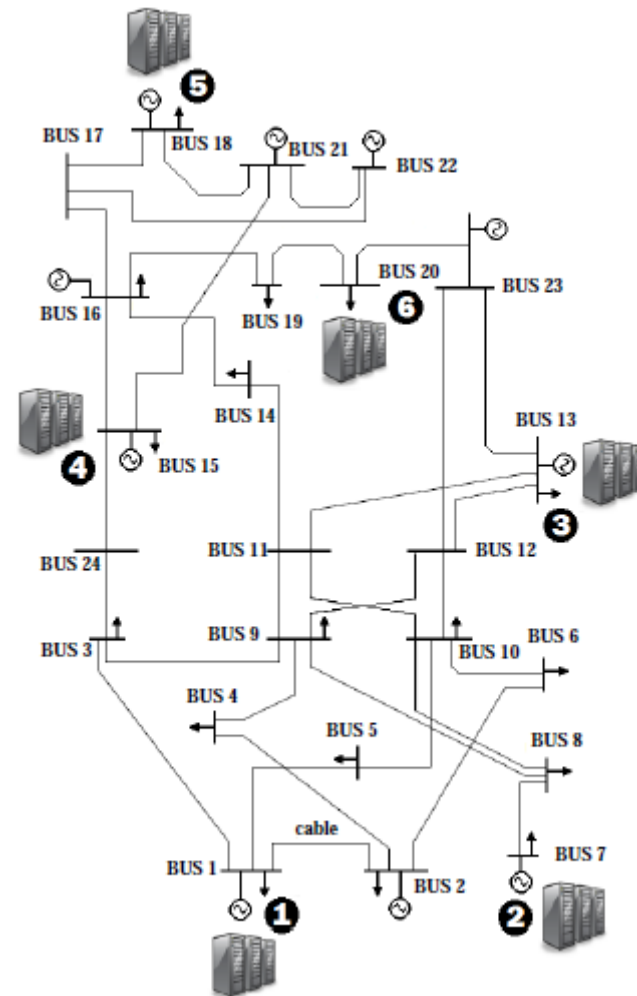


- The **power consumption**  $P_i[t]$  is proportional to **service rate**  $\mu_i[t]$ .
  - $\mu_i[t] \sim n u_t$

# Demand Response: Data Centers

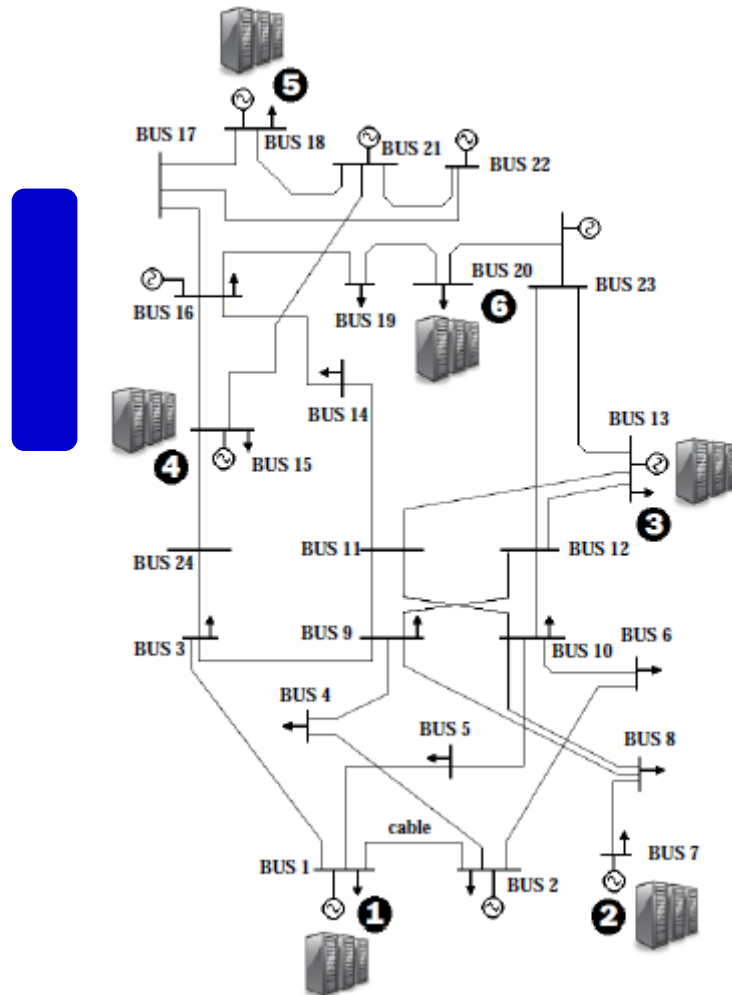
- For data centers, ECS unit also **diversifies** load across **regions**.

- We can **redistribute** the **workload**.
- This will move the power load
  - From one **bus**
  - To another **bus**
- Combine with power flow analysis
- You can solve congestion problems.



# Demand Response: Data Centers

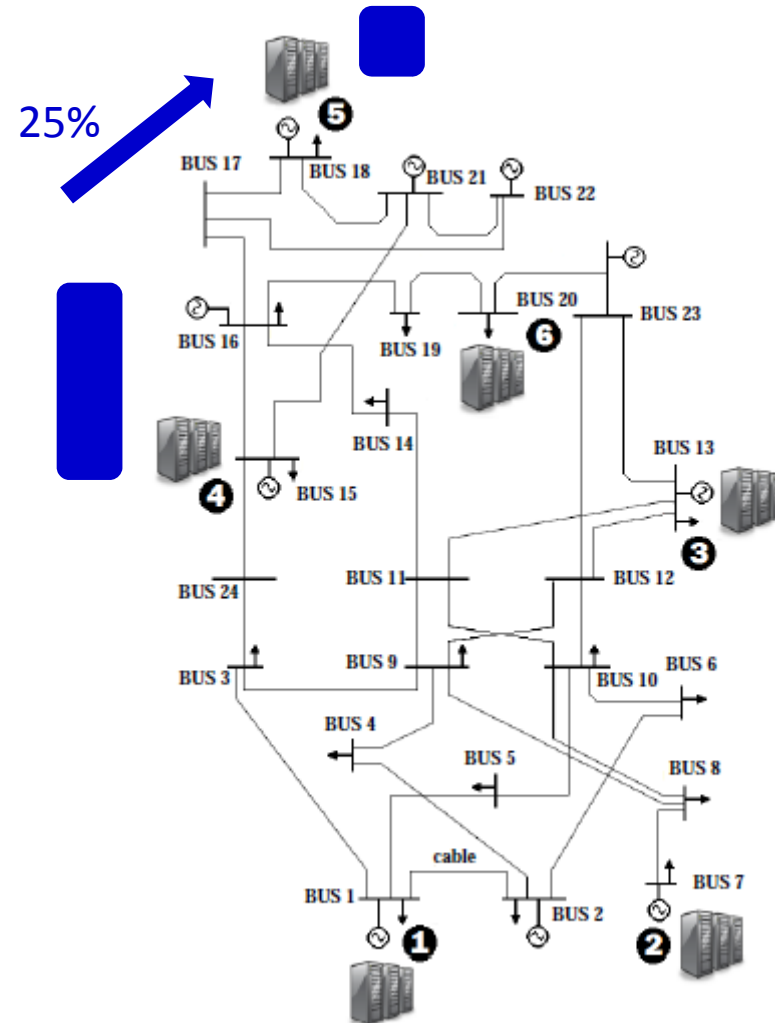
- For data centers, ECS unit also **diversifies** load across **regions**.
- Assume **Bus 15** is congested.



# Demand Response: Data Centers

- For data centers, ECS unit also **diversifies** load across **regions**.

- Assume **Bus 15** is congested.



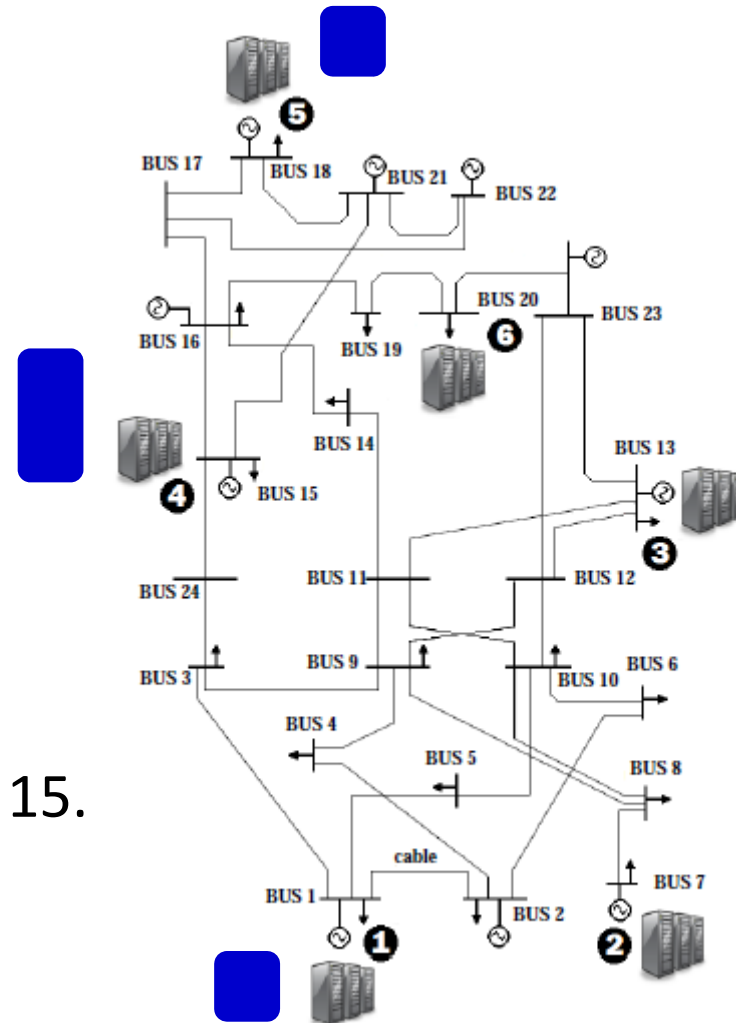


# Demand Response: Data Centers

- For data centers, ECS unit also **diversifies** load across **regions**.

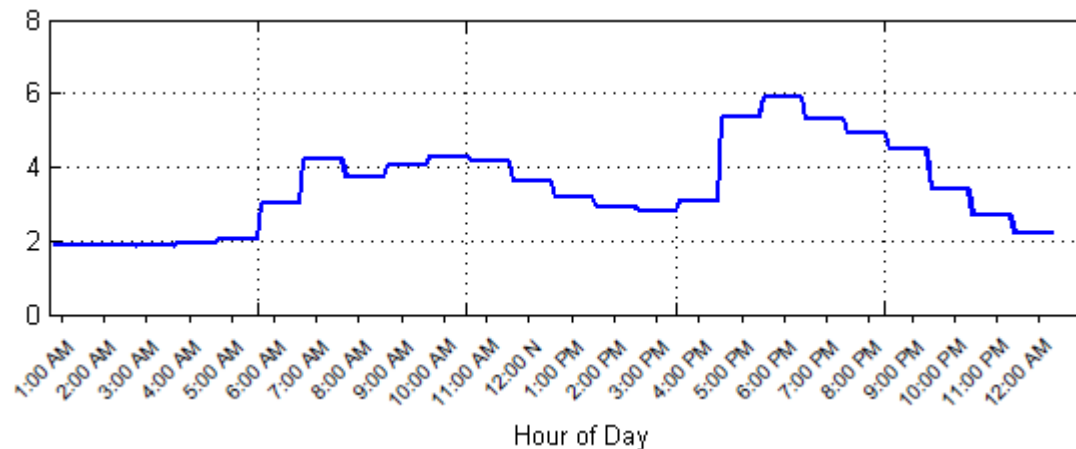
- Assume **Bus 15** is congested.

- We can reduce the load on Bus 15.



# Demand Response: Load Synchronization Problem

- Consider the following time-of-use prices:



- For an ECS, it is reasonable to shift the load from 6 PM to 3 PM.
- **Q:** But what if **every** ECS does the same?

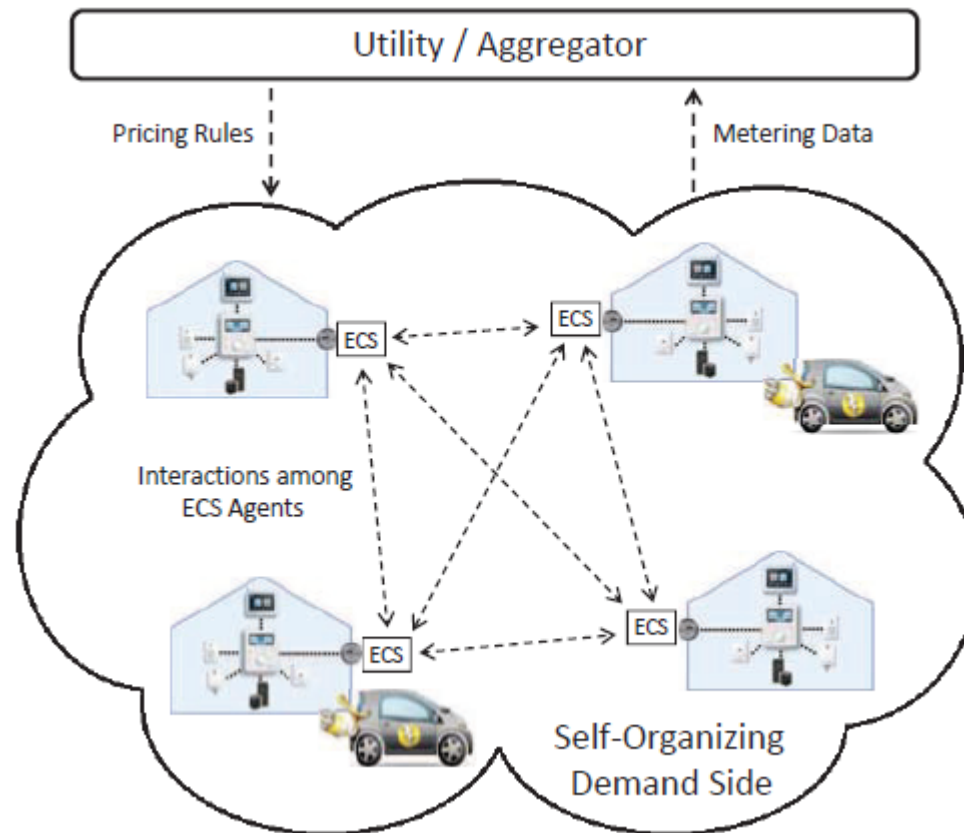
# Demand Response: Load Synchronization Problem

- **Load Synchronization:**
  - Shifting away a major load from an on-peak hour to an off-peak hour.
  - Creating a **new peak load**, just at a different hour!
- If demand response is **manual**, load synchronization is unlikely.
- However, with major ECS penetration, this is a possible problem.
  - **Q:** How can we **avoid** load synchronization?



# Demand Response: Load Synchronization Problem

- Self-organizing demand response:



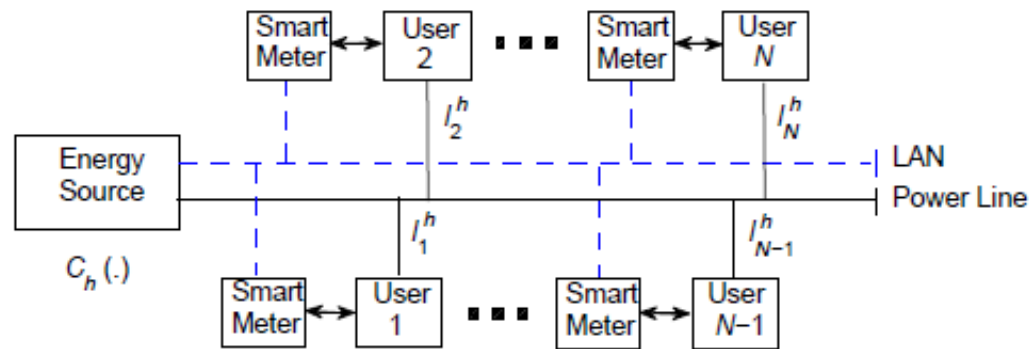
**Key aspect:** ECS units / smart meters communicate with the utility and with each other.

# Demand Response: Load Synchronization Problem

- Self-organizing demand response:
  - Users in a neighborhood make a collaborative effort:
    - To minimize the energy expenditure for **all** participating users.
  - The ECS devices will still implement the decisions.
  - The ECS decisions are made using
    - Optimization and
    - **Game Theory!**

# Demand Response: Load Synchronization Problem

- Self-organizing demand response:



- Instead of announcing the price values:
  - Let users know about the **energy cost function**  $C_h(\cdot)$  at each hour.
  - Distribute the cost **fairly** among users.

# Demand Response: Coexistence Problem

- Assume we have 50% penetration of ECS units in a neighborhood
  - This means that half of the users consume energy just the way they like.
- Those who participate in demand response:
  - Work hard (Q: how?) to reduce the peak-load.
  - This will bring down the cost of generation and price of electricity.
- But those who did not participate will also benefit.
  - Q: Why should you participate, if you could benefit with no participation?

# Demand Response: Coexistence Problem

- Key challenge:
  - Set the prices to assure **rewarding** those who
    - Contribute in reducing the peak load.
- The reward should be proportional to the user's **contribution**.
- **Q:** How can we measure a user's contribution?
- **Q:** Do we need new pricing models?

# Demand Response: Offering Ancillary Services

- According to the Federal Energy Regulatory Commission:

Ancillary services are necessary to support the transmission of power from sellers to buyers given the obligation of control areas and transmission utilities to maintain a reliable operation of the interconnected transmission system / grid.

- On average, ancillary services account for about 10% of the total generation and transmission costs of the power system.

# Demand Response: Offering Ancillary Services

- **Example:** Regulation (Frequency Response) as Ancillary Service
  - To help the grid maintain the balance between supply and demand:
    - To tackle the **moment-to-moment variations** in
      - Customer demand
      - Scheduled generation (e.g., renewable generation)
  - **Q:** Can demand response help in regulation?
  - **Q:** How about we charge or discharge a group of PHEVs?

# Demand Response: Final Words

- PJM has an interesting way to **reward** consumers to **reduce load**.
- They count your load at the five peak hours every day.
  - They take the average over a year or a season.
- The number is compared with a **similar number last year**.
- You will get rewards if:
  - You have **reduced** your load at peak hours compared to last year.



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