Demand Response Research

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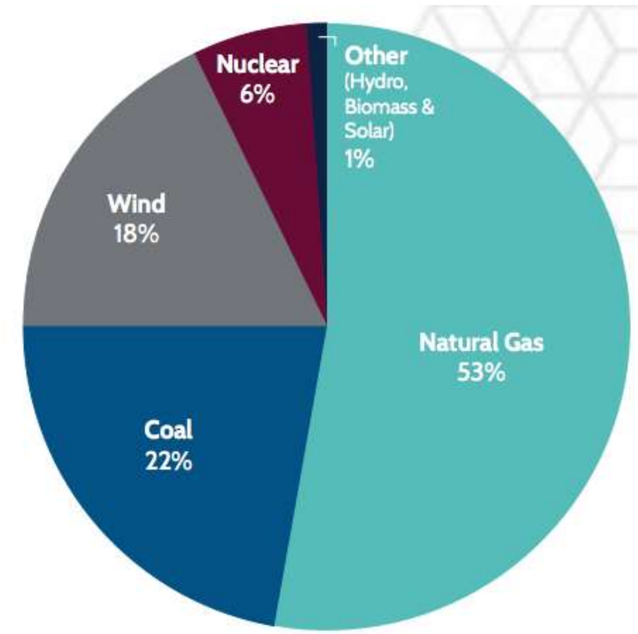
Acknowledgement

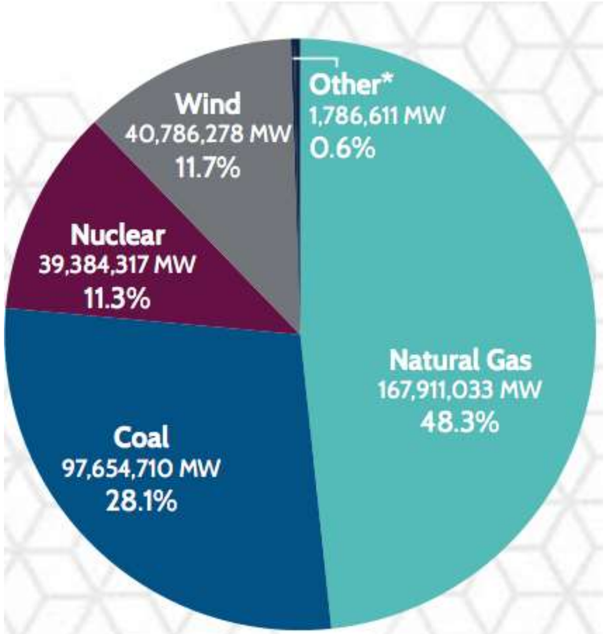
- Collaborators
  - P. R. Kumar, M. Ilic, S. Shakkottai, S. Puller, P. Varaiya, A. Halder, NDR Sarma
- Students
  - J. An, H. Ming, X. Geng, Y. Li, Y. Zhou, A. Thatte, H. Zhong, K. Ma
- Sponsors
  - Power Systems Engineering Research Center
  - National Science Foundation

Electric Reliability Council of Texas (ERCOT) 2016

- ❑Peak demand: 69,877 MW (August 10, 2015)
- ❑Wind capacity: > 16,000 MW (*highest* of any state in the U.S.)
- ❑Wind generation record: 13,883 MW (12/20/2015), ~***45%*** of load at that time



2015 Generation Capacity
(Total Installed Summer Capacity as of December 31, 2015)



Energy Use 2015
*Includes solar, hydro, petroleum coke, biomass, landfill gas, and DC Ties

http://ercot.com/content/news/presentations/2016/ERCOT_Quick_Facts

Exploiting Demand Side Flexibility

- Modeling DR in Wholesale Markets [1][2]
- Market Revenue Inadequacy with DR [3]
- New ISO Design to Account for Stochastic Dynamic DR [4]
- Internet-of-things inspired Energy Coupon DR [5]
- Privacy-preserving retail services while exploiting DR [6]

Quantifying Actual Demand Response in ERCOT

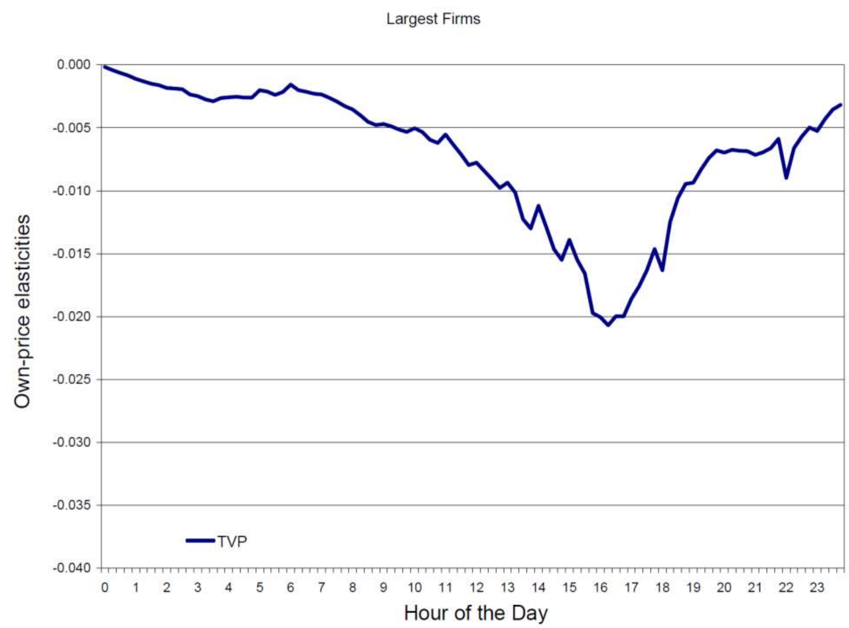
- ERCOT provided us with customer-level data for each "large" C&I customer:
  - Customer location
  - Information on whether retail contract uses time-varying prices (TVP)
    - TVP includes e.g. real-time pricing, critical peak pricing. Excludes simple time-of-use
  - Consumption (every 15-min for summer of 2008-2010)
  - 8537 customers (23% of ERCOT load)
    - 1250 are exposed to time-varying wholesale prices

5

Econometric Approach: Elasticity Estimation

- Econometric estimation generates "substitution matrix" elasticity

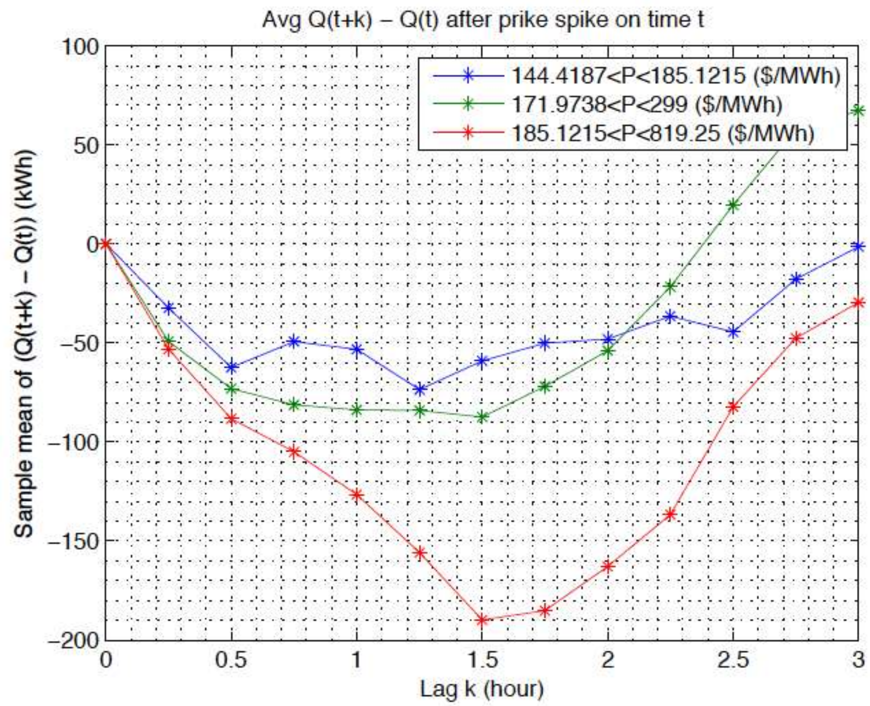
$$\varepsilon = \frac{\frac{\mathrm{d}q}{q}}{\frac{\mathrm{d}\pi}{\pi}} = \frac{\pi}{q}\frac{\mathrm{d}q}{\mathrm{d}\pi}$$



L. Xie, S. Puller, M. Ilic, and S. Oren, "Quantifying Benefits of Demand Response and Look-ahead Dispatch in Systems with Variable Resources," *PSERC Final Report M-26*, Aug 2013.

A Closer Look from an Engineering Perspective

- Nonlinearity (Two-regime)
  - Very small response when price is low-to-moderate
  - Observable response when price is *very high* (P > 95%-quantile)
- (Almost Consistent) Delay in response
  - Maximum DR response occurs up to several intervals after price spike



J. An, P. R. Kumar, L. Xie, "On Transfer Function Modeling of Price Responsive Demand: An Empirical Study," *IEEE PESGM 2015*.

Problem Formulation

- Given an ARX Model of Demand Q(t) with respect to price P(t) and Q(t)

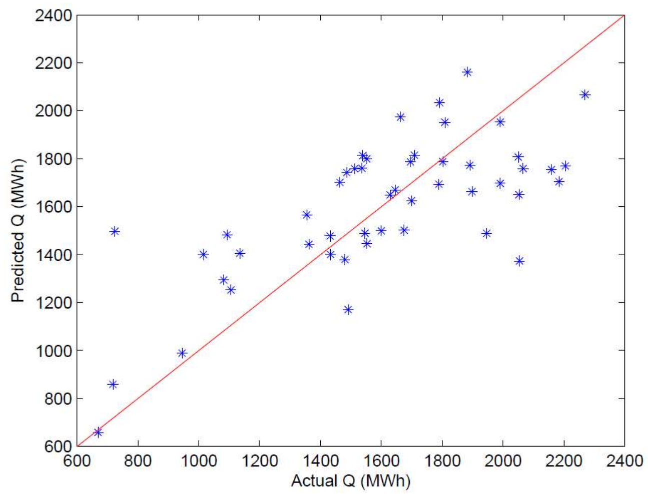
$$Q(t) = (\sum_{i=1}^{m} \hat{\alpha}_i z^{-i})Q(t) + (\sum_{i=1}^{n} \hat{\beta}_i z^{-i})f(P(t)) + \epsilon_t$$

- Estimate parameters $\hat{\alpha}$ and $\hat{\beta}$, and characterize the residual ϵ_t
  - Moderate price regime
  - Peak price regime: *f(P(t))* may be nonlinear

TF Model of a Commercial Load under High Price Regime (P>95%-quantile)

Delay effect of demand response w.r.t. price spikes (60 min)

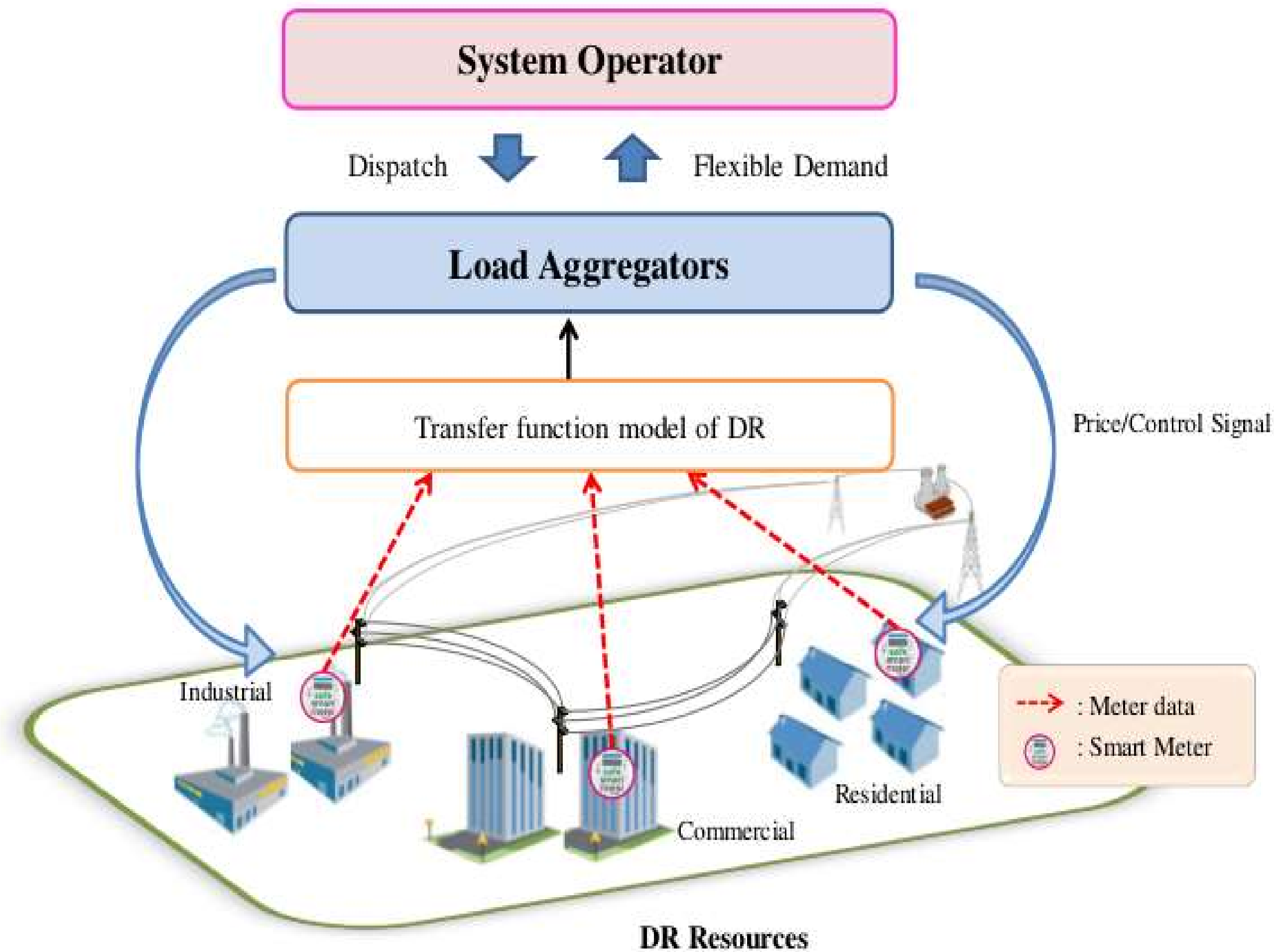
$$TF_{\text{Peak}}^{2:15pm} = \frac{Q(z)}{P(z)} = \frac{-220.1z^{-4}}{1 - 0.4015z^{-1} + 0.2383z^{-2} - 0.2512z^{-4}}$$



Correlation: 72%

J. An, P. R. Kumar, L. Xie, "On Transfer Function Modeling of Price Responsive Demand: An Empirical Study," *IEEE PESGM 2015*.

DR for Providing Flexibility



Key References

[1] L. Xie, S. Puller, M. Ilic, and S. Oren, “Quantifying Benefits of Demand Response and Look-ahead Dispatch in Systems with Variable Resources,” PSERC Final Report M-26, Aug 2013.

[2] J. An, P. R. Kumar, L. Xie, “On Transfer Function Modeling of Price Responsive Demand: An Empirical Study,” IEEE PESGM 2015.

[3] H. Ming and L. Xie, “Revenue Adequacy of Wholesale ElectricityMarkets with Demand Response Providers,” IEEE PESGM 2016

[4] R. Singh, P. R. Kumar, and L. Xie, “Decentralized Control via Dynamic Stochastic Prices: The Independent System Operator Problem,” submitted to IEEE Tran. On Automatic Control

[5] H. Zhong, L. Xie, and Q. Xia "Coupon Incentive-based Demand Response: Theory and Case Study, " IEEE Transactions on Power Systems Vol. 28, No. 2, pp. 1266 - 1276, May 2013.

[6] A. Halder, X. Geng, G. Sharma, L. Xie, and P.R. Kumar, “A Control System Framework for Privacy Preserving Demand Response of Thermal Inertial Loads,” IEEE SmartGridComm 2015

Thank You!

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Demand Response via Privacy Preserving Thermal Inertial Load Management by an LSE

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Joint work with X. Geng, F.A.C.C. Fontes, P.R. Kumar, and L. Xie

How smart is your smart thermostat

SECTIONS HOME SEARCH The New York Times

STYLE

Nest Thermostat Glitch Leaves Users in the Cold

Disruptions
By NICK BILTON JAN. 13, 2016

The Nest Learning Thermostat is dead to me, literally. Last week, my once-beloved "smart" thermostat suffered from a mysterious software bug that drained its battery and sent our home into a chill in the middle of the night.

Although I had set the thermostat to 70 degrees overnight, my wife and I were woken by a crying baby at 4 a.m. The thermometer in his room read 64 degrees, and the Nest was off.

This didn't happen to just me. The problems with the much-hyped thermostat, which allows users to

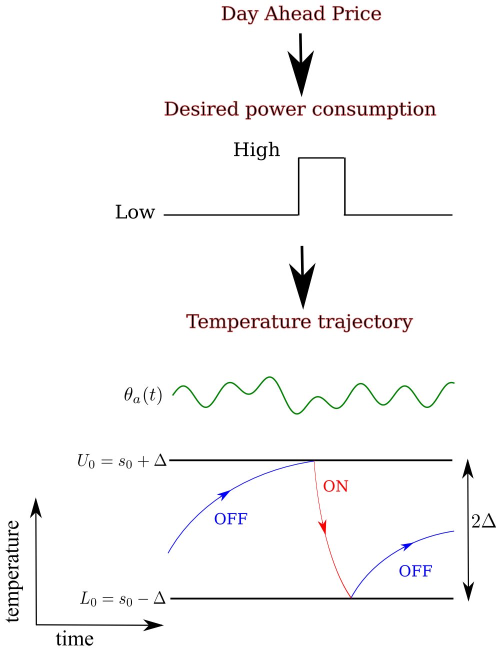
American Thinker

January 4, 2008

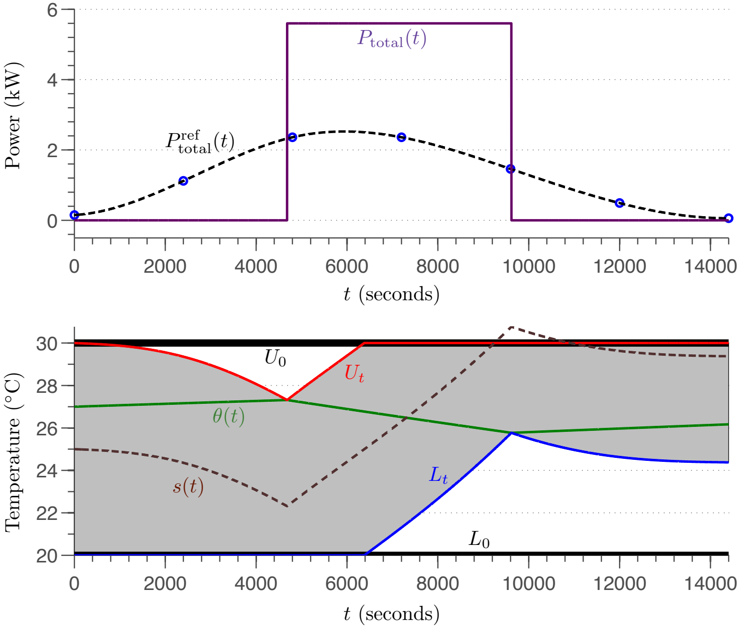
Who Will Control Your Thermostat?

By Joseph Somsel

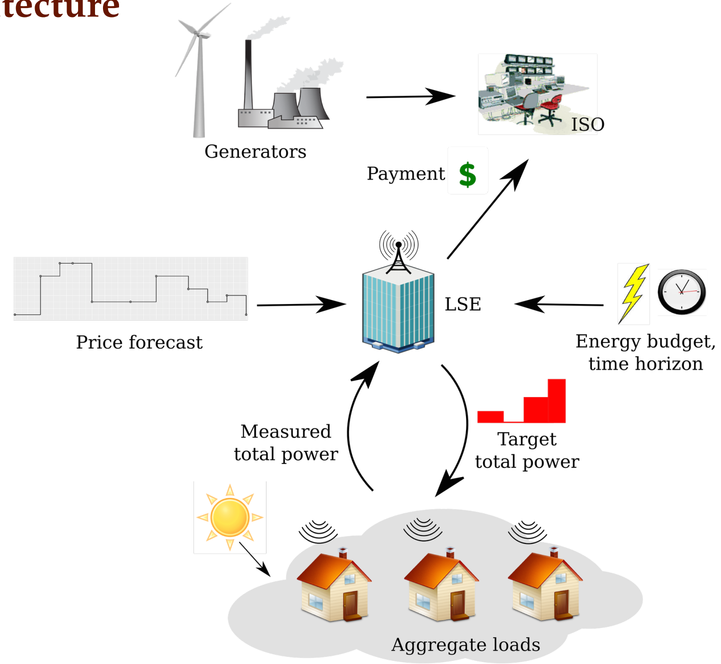
"We repeat, there is nothing wrong with your thermostat. You are about to participate in a great adventure. You are about to experience the awe and mystery which reaches from the inner mind to ... SACRAMENTO!"



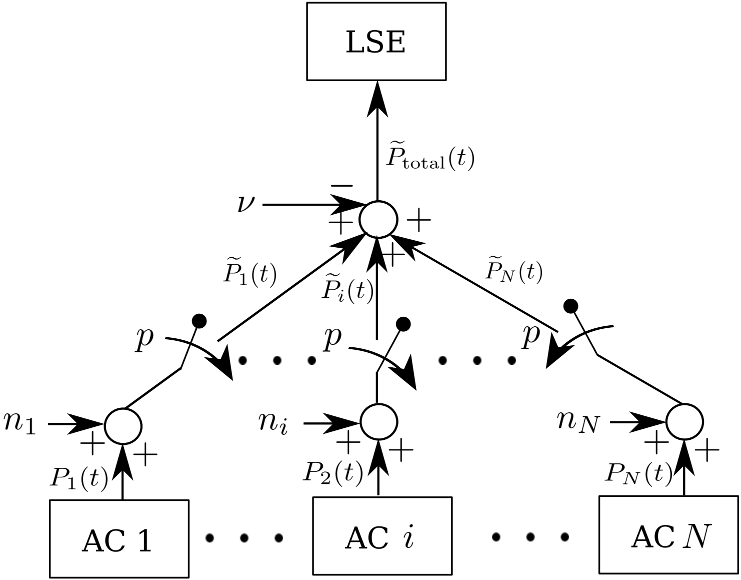
Deadband → Liveband



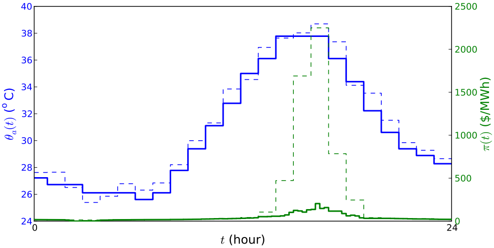
Architecture

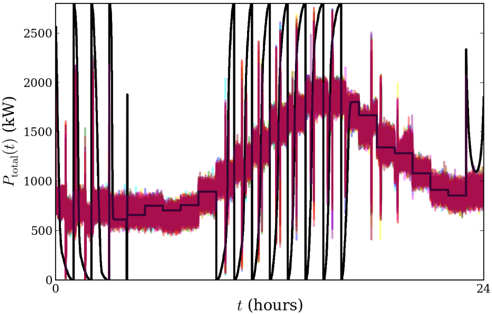


Privacy preserving sensing of total power

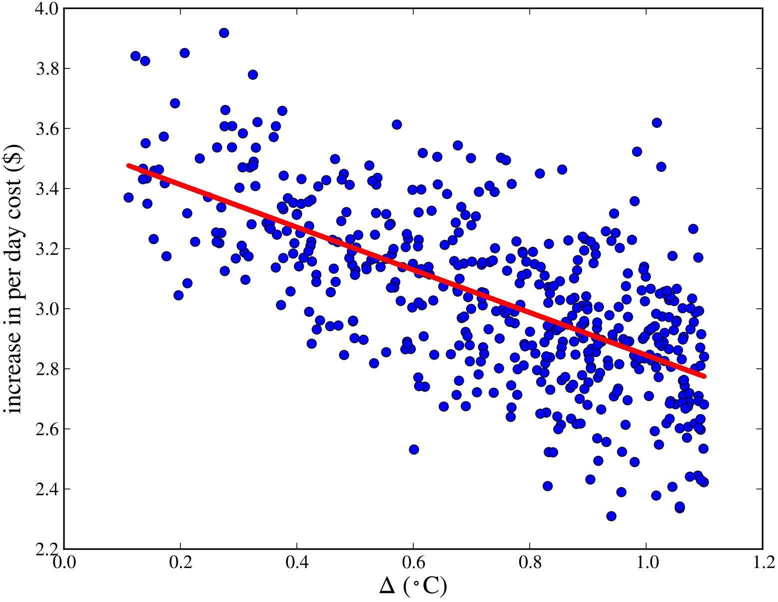


Simulation for 500 homes + ERCOT DA price





How can the LSE price a contract



Summary

1. Privacy preserving aggregate sensing
2. Individual comfort guarantees
3. Contract cost $\propto$ QoS
4. Mathematically optimal, no ad-hoc fix

Wishlist

1. Hardware implementation of thermostatic control
2. Pilot project to implement the architecture

EnergyCoupon: Demand Response in Retail Markets

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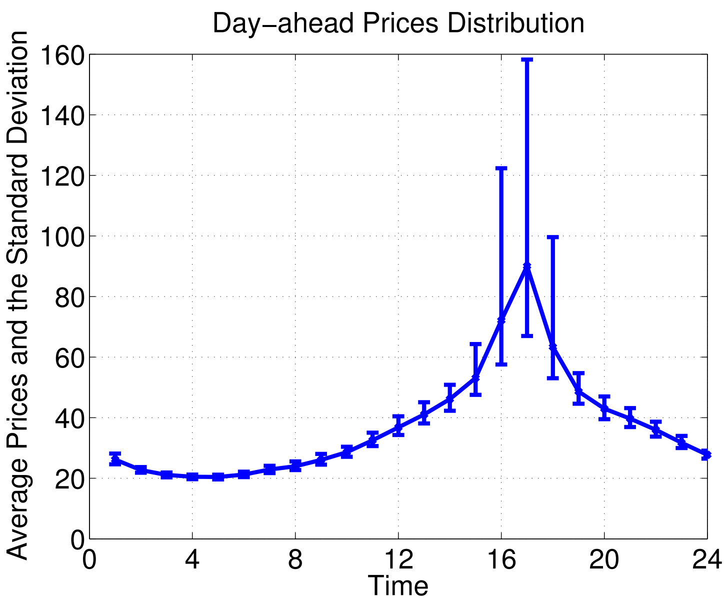
System Model

- LSE pays a variable price in the energy market.
- AC usage of about 3 kWh per home at 5:00-6:00 PM.
- Nudge users into changing their usage pattern by offering Energy Coupons?



- When do we offer coupons?
- What kind of incentive scheme to motivate adoption?
- How much savings to the LSE?

Simulation: Texas Homes

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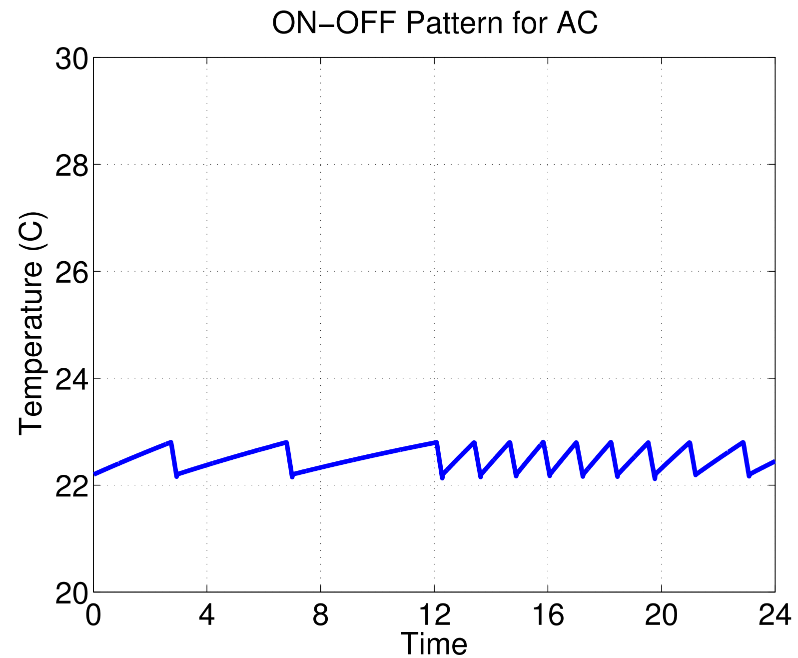
- Home air conditioning is a major part of electricity usage in Texas.
- Typical 2500 sq ft home consumes of the order of 30 kWh per day, and about 12 kWh in the peak period.
- Can we incentivize users to move some energy consumption from the peak period to off-peak?



Index	Period	Energy	ON Time	No. of units
1	3 – 4 PM	0.45	4	0.8
2	4 – 5 PM	3.4	30	6
3	5 – 6 PM	3.85	34	6.8
4	6 – 7 PM	0	0	0
5	7 – 8 PM	3.57	31.5	6.3

Simulation: Texas Homes

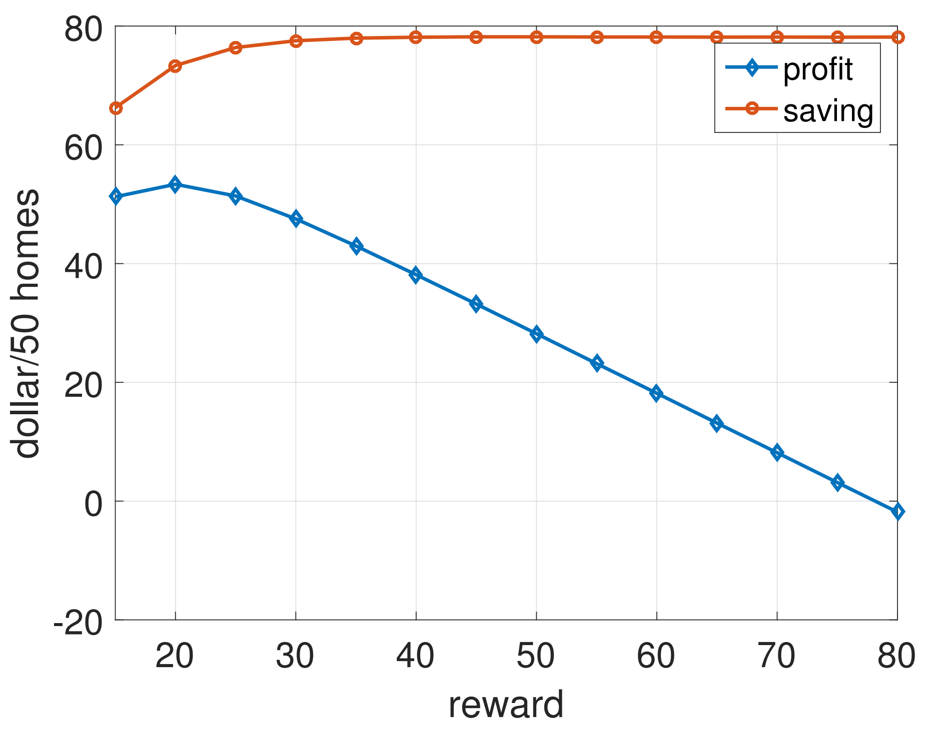
- Hazard to LSE measured as **mean plus standard deviation in price**.
- Coupons assigned heuristically to promote consumption in off peak.
- Reasonable set of action vectors chosen
- Cost is the difference in mean plus standard deviation of home temperature.

Index	Period	Hazard/MWh	Coupons/unit
1	3 – 4 PM	\$61.2	15 if $x_1 > 0.8$; 1 otherwise
2	4 – 5 PM	\$120.2	1
3	5 – 6 PM	\$154.2	0
4	6 – 7 PM	\$101.3	2
5	7 – 8 PM	\$54.05	30 if $x_5 > 6.3$; 1 otherwise

Index	Action Vector	Cost	Coupons
0	$(0, 0, 6, 0, 0)$	0.05	13.92
1	$(1, 0, 0, 0, 5)$	1.719	243.92
2	$(2, 0, 0, 0, 4)$	1.547	233.92
3	$(3, 0, 0, 1, 2)$	0.934	187.92
4	$(4, 0, 0, 1, 1)$	0.874	177.92
5	$(3, 0, 0, 2, 1)$	0.525	151.92

Simulation: Texas Homes

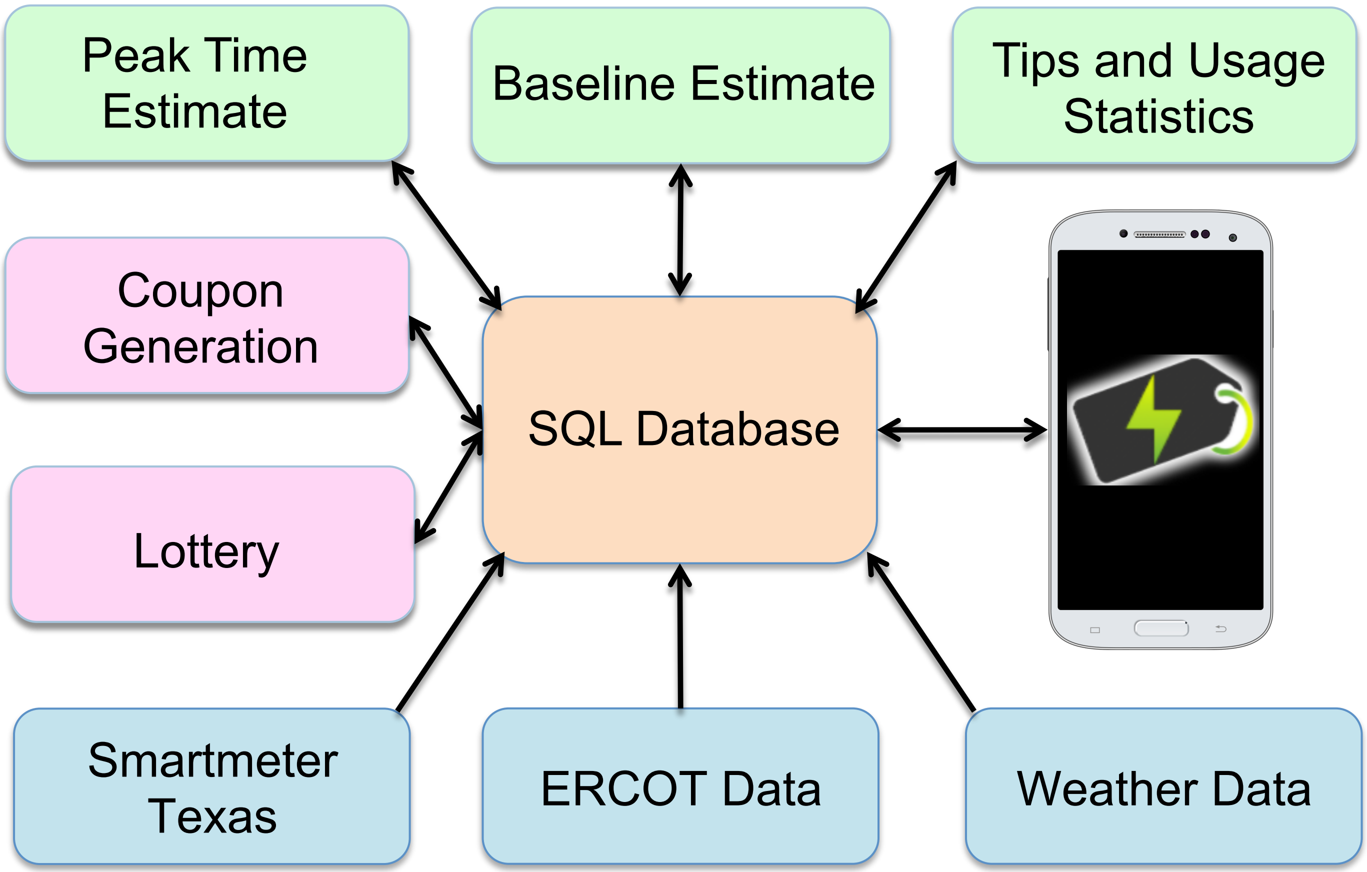
- Win: Reward $x
- Lose: -$1
- Stay in the system for an average of 50 lotteries.
- Prospect utility representing response to lotteries.
- **Net reduction in hazard to the LSE for 50 homes is $116 per week.**
- System could be self sustaining.



- 50 simulated homes.
- Price data from ERCOT: Summer 2014
- Weather Data: Variation in daily temperature.
- Rational customer model.
- Conservative actions (only move energy from 5:00 PM – 7:00 PM; less than 1 degree temperature variation).
- Simulation run over 12 weeks.
- **Average savings to LSE is about $85 per week.**

J. Li, B. Xia, X. Geng, H. Ming, S. Shakkottai, V. Subramanian and L. Xie, "Energy Coupon: A Mean Field Game Perspective on Demand Response in Smart Grids, ACM SIGMETRICS'15.

System Architecture



Android App

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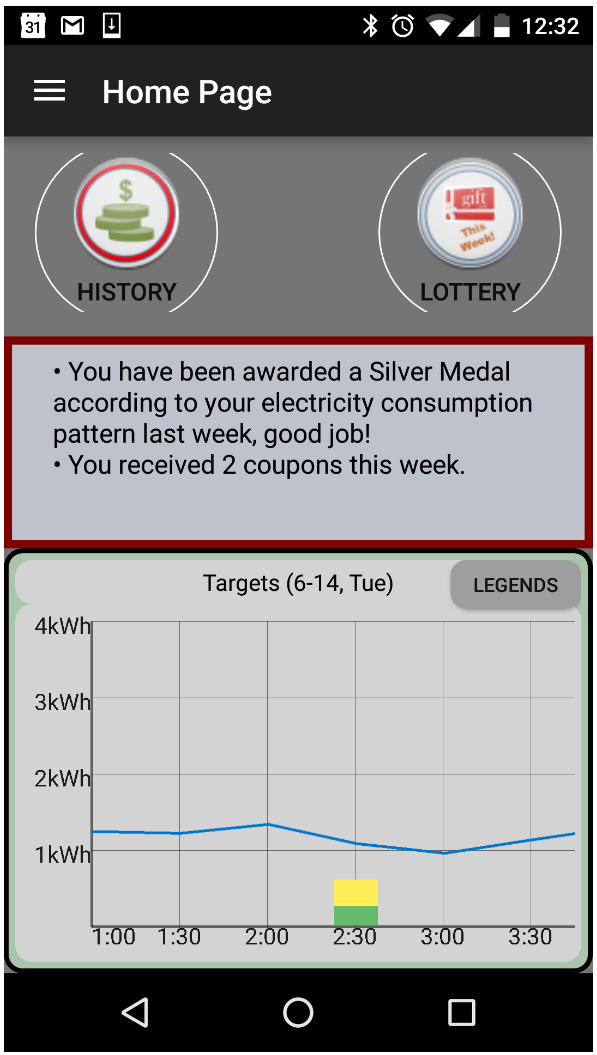

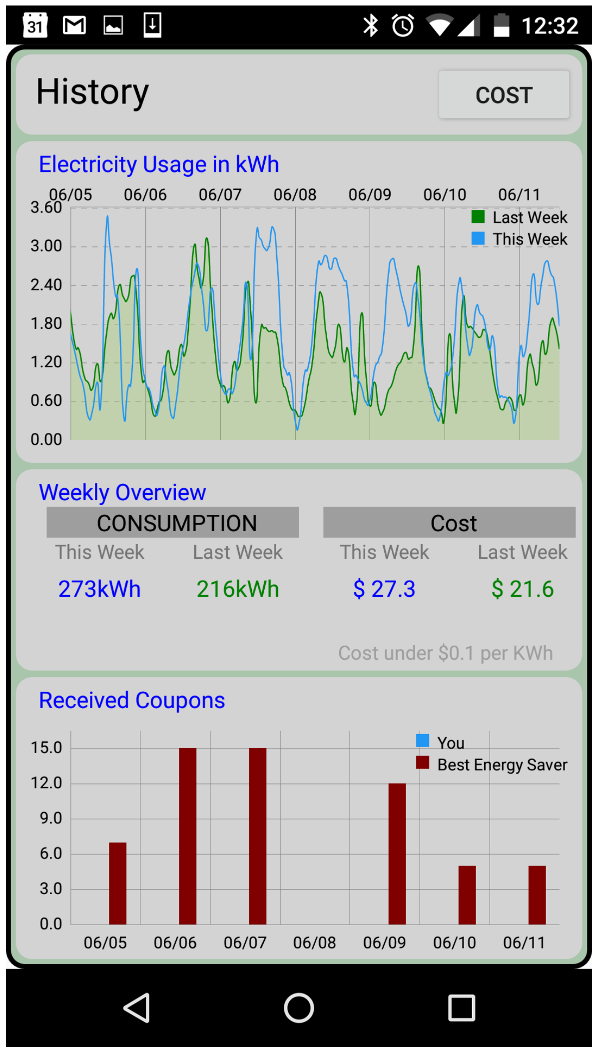

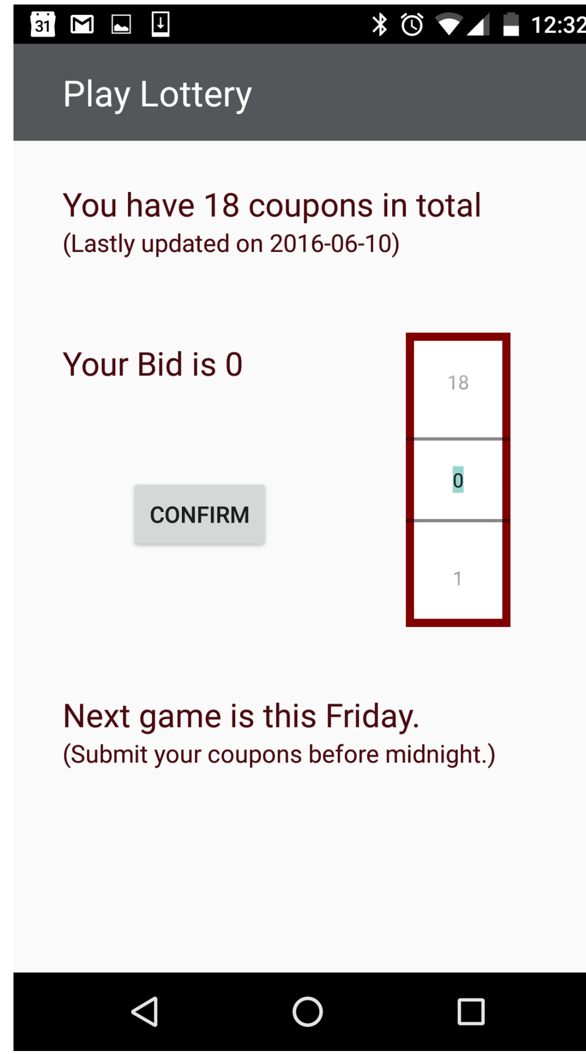

Trial Details

- 10 Homes in Houston Texas.
- Trial is in its second week currently.
- Provide users with candidate thermostat settings to maximize their rewards.
- Response has been very positive, both on the incentive scheme, as well as on home usage data.
- Users appreciate receiving home electricity usage statistics and comparisons with other homes.

Concluding Remarks

- Demand response of the order of 5 to 6 kWh per residential customer (~ 0.5 MWh with 100 users) appears to be feasible in a sustainable manner.

- **Wish List**
  - Partner with LSE(s) to conduct trial at a larger scale.
  - Obtain data on response to differentiated pricing:
    - What is the usage when peak/off peak pricing is used?
    - Obtain data on response to block pricing.

Thank you!