

Two-Settlement Electric Power Markets with Dynamic-Price Contracts

Huan Zhao, Auswin Thomas, Pedram Jahangiri,
Chengrui Cai, Leigh Tesfatsion, and Dionysios Aliprantis

27 July 2011

IEEE PES GM, Detroit, MI

Last Revised: 24 July 2011

Presentation Outline

- Overview of Integrated Retail/Wholesale (IRW) project at Iowa State University
- Two Dynamic-Pricing Studies:
 - First Study: Effects of price-responsive retail consumer demand on LSE demand bidding and profit outcomes, both with and without LSE learning.
 - Second Study: Determination of a household resident's optimal comfort-cost trade-offs by a smart HVAC system conditional on contract terms, prices, outdoor temperature, and other forcing terms
- Conclusion

IRW Project: Integrated Retail/Wholesale Power System Operation with Smart-Grid Functionality

Project Directors: Leigh Tesfatsion (Professor of Econ, Math, & ECpE, ISU)
Dionysios Aliprantis (Assistant Prof. of ECpE, ISU)
David Chassin (Staff Scientist, PNNL/Department of Energy)

Research Assoc's: Dr. Junjie Sun (Fin. Econ, OCC, U.S. Treasury, Wash, D.C.)
Dr. Hongyan Li (Consulting Eng., ABB Inc., Raleigh, NC)

Research Assistants:

Huan Zhao (Econ PhD student, ISU)
Chengrui Cai (ECpE PhD student, ISU)
Pedram Jahangiri (ECpE PhD student, ISU)
Auswin Thomas (ECpE M.S. student, ISU)
Di Wu (ECpE PhD student, ISU)

Current Government & Industry Funding Support:

PNNL/DOE, the Electric Power Research Center (an industrial consortium), and the National Science Foundation

Industry Advisors: Personnel from PNNL/DOE, XM, RTE, MEC, & MISO

Meaning of “Smart Grid Functionality”?

For our project purposes:

Smart-grid functionality =

Market design & resource enhancements permitting more responsiveness to the needs, preferences, and decisions of retail energy consumers.

Examples: Introduction of advanced metering and other technologies to support

- flexible dynamic-price contracting between suppliers (“Load-Serving Entities”) and retail energy consumers
- integration of distributed renewable energy resources, e.g., consumer-owned photovoltaic (PV) panels

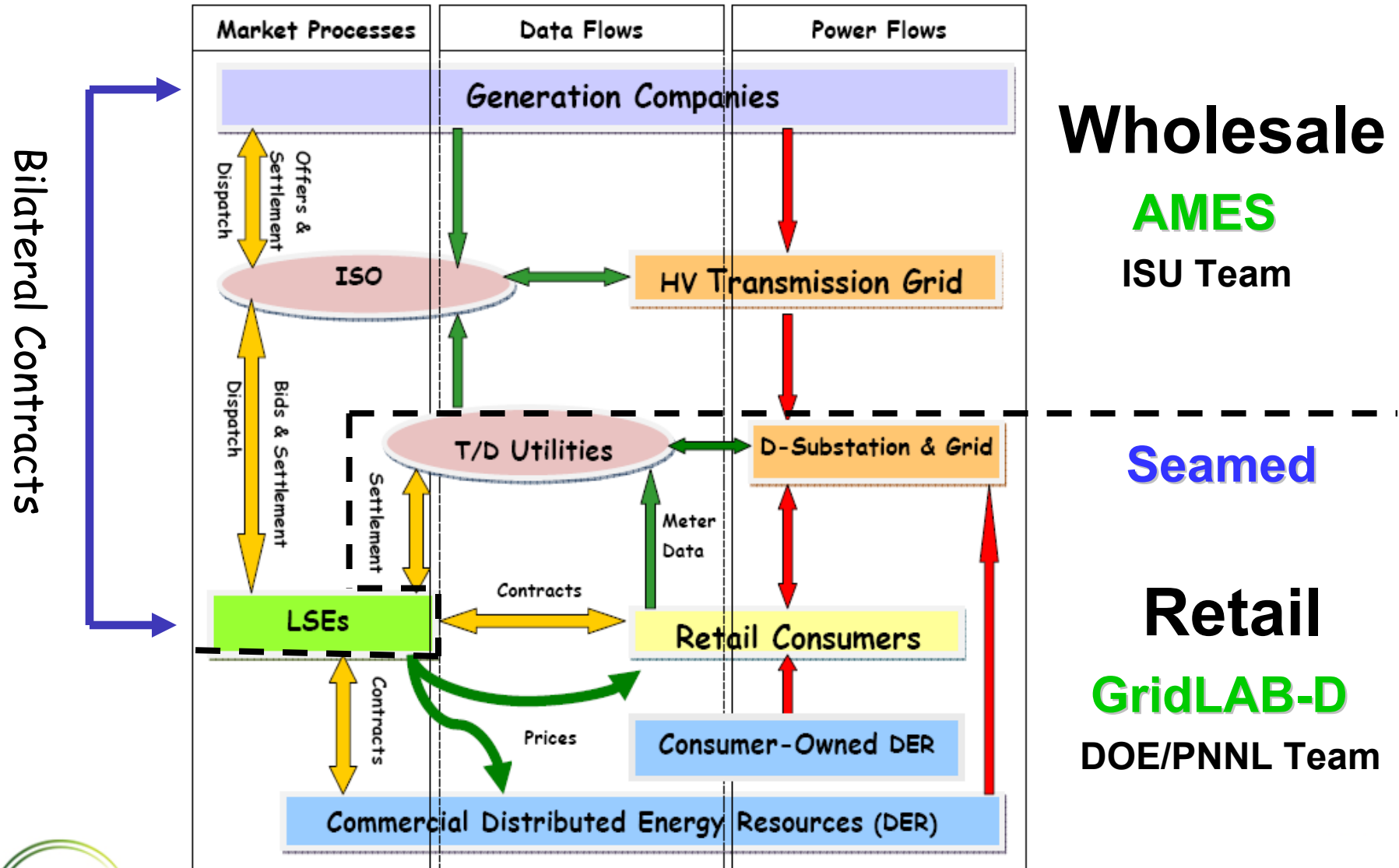
Principal IRW Project Research Topics

- Dynamic retail/wholesale reliability and efficiency implications of **integrating demand response resources** as realized thru
 - Top-down demand response (e.g., emergency curtailment)
 - Automated demand dispatch (continuous signaling)
 - Price-sensitive demand bidding by demand resources
- Dynamic retail/wholesale effects of increased penetration of consumer-owned distributed energy resources, such as **photovoltaic (PV) generation & plug-in electric vehicles (PEV)**
- Development of agent-based algorithms for **smart device implementation** (e.g., “smart” HVAC systems)

Primary Project Tool: The IRW Power System Test Bed

- An agent-based computational laboratory
 - “Culture dish” approach to complex dynamic systems
 - Permits systematic computational experiments
 - Permits sensitivity testing for changes in physical constraints (e.g., grid configuration), market rules of operation, and participant behavioral dispositions
- Seams empirically grounded test beds (AMES/GridLAB-D)
 - Market rules based on business practices manuals for restructured North American electric power markets
 - Realistically rendered transmission/distribution networks
 - Retail contracting designs based on case studies (e.g., ERCOT) and pilot studies (e.g., Olympic Peninsula 2007)
- Open source software release planned.

IRW Power System Test Bed: AMES & GridLAB-D



Wholesale

AMES

ISU Team

Seamed

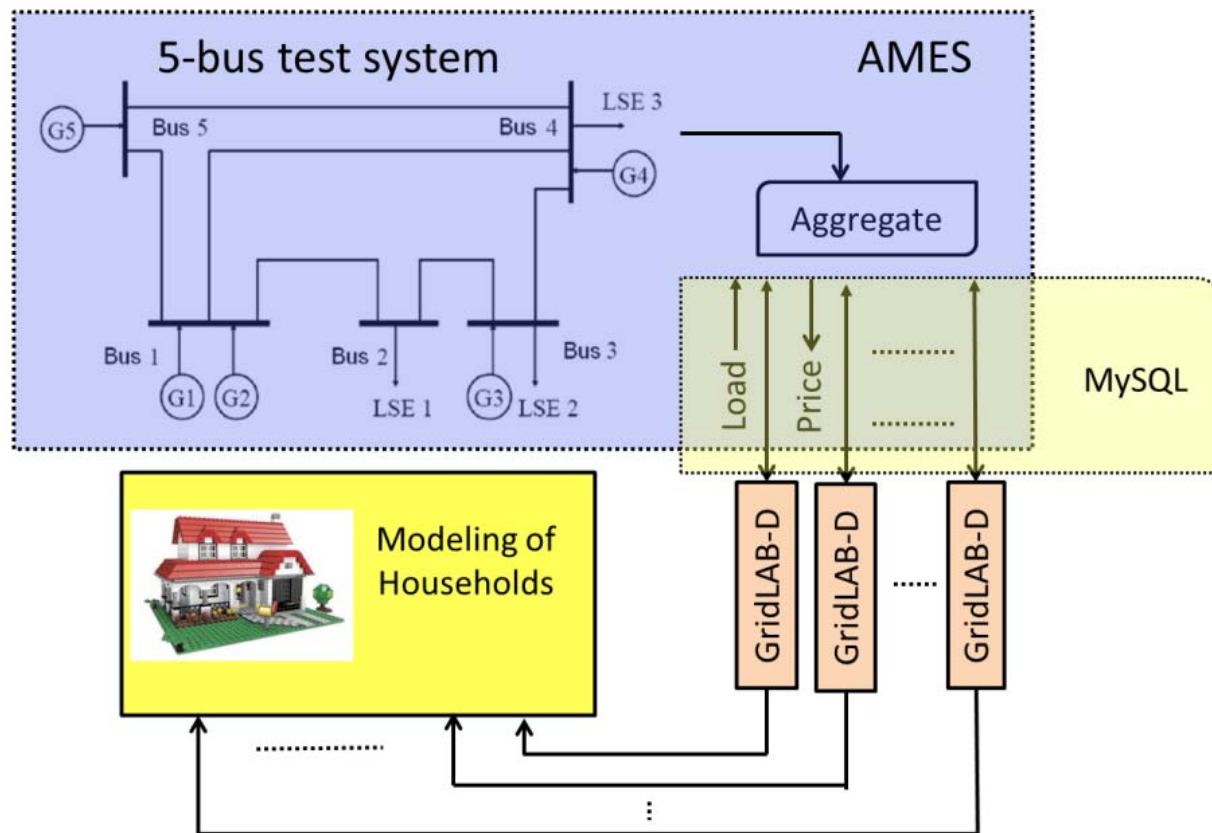
Retail

GridLAB-D

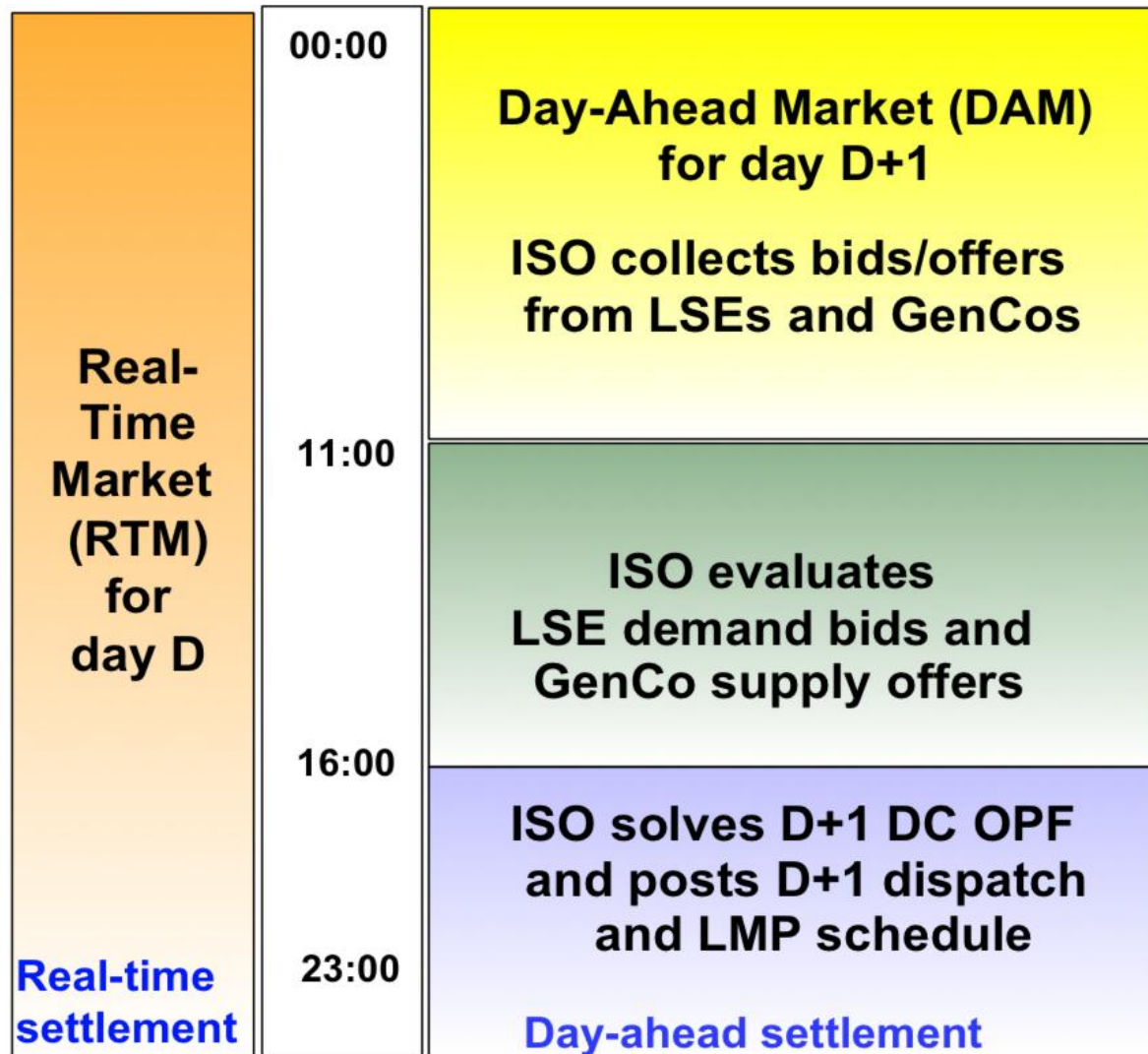
DOE/PNNL Team

IRW Power System Test Bed (Version 1.0)

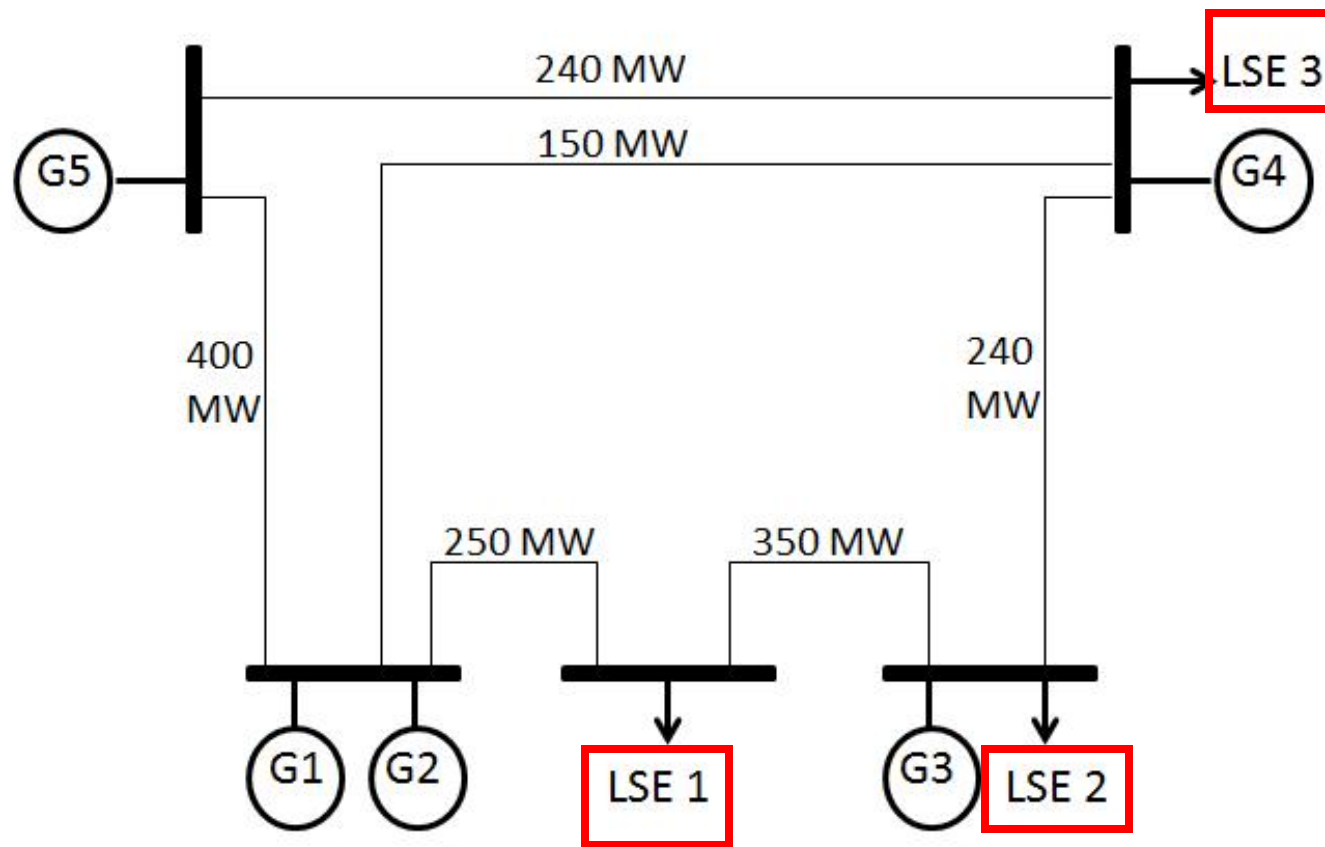
Seams AMES (wholesale) & GridLAB-D (retail) with a retail focus on households with price-sensitive loads



Typical Day-D Market Operator (ISO) Activities



First Study: LSEs Servicing Residential HVAC Loads



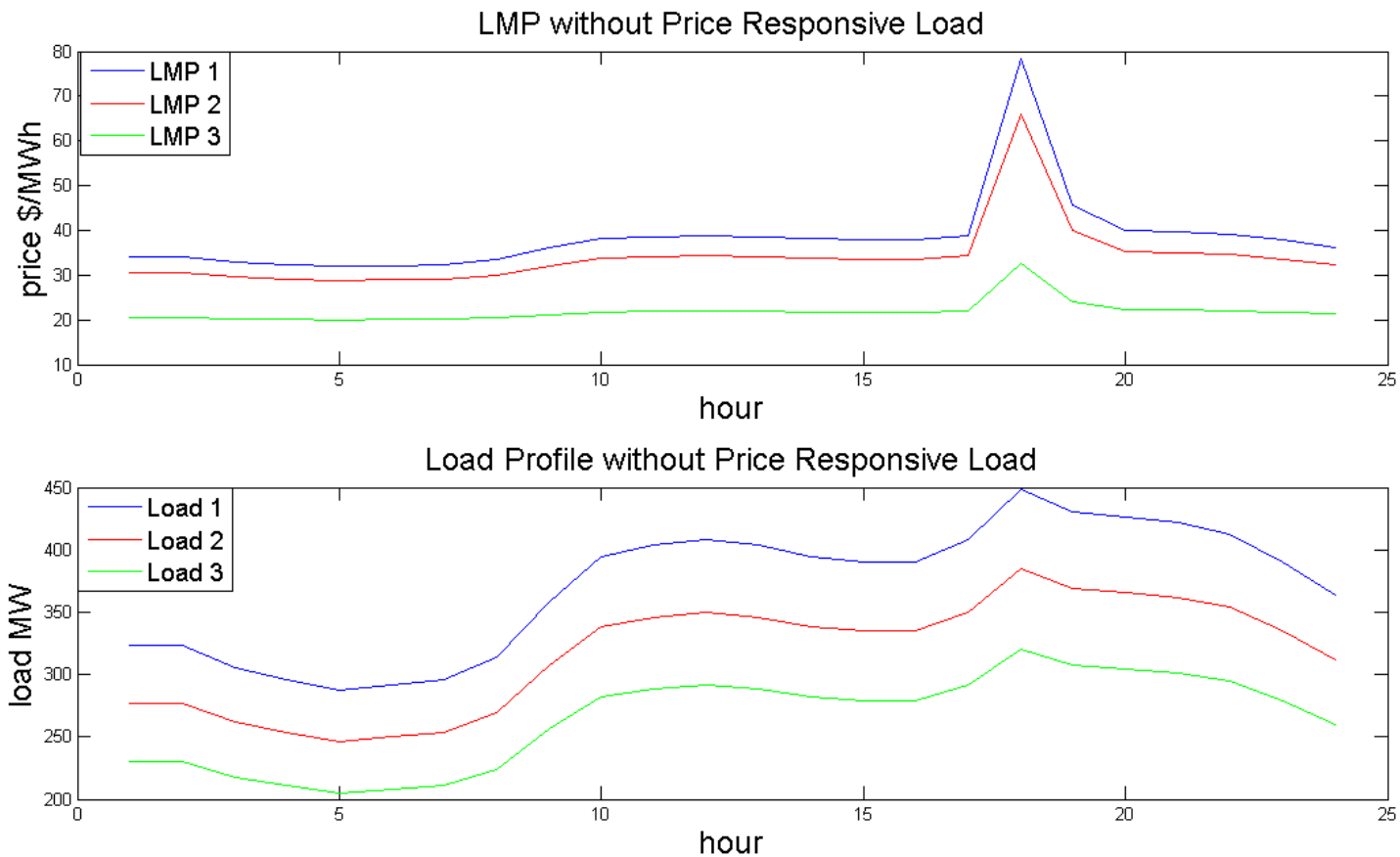
Five-Bus Grid Configuration with Three LSEs

Residential HVAC Model

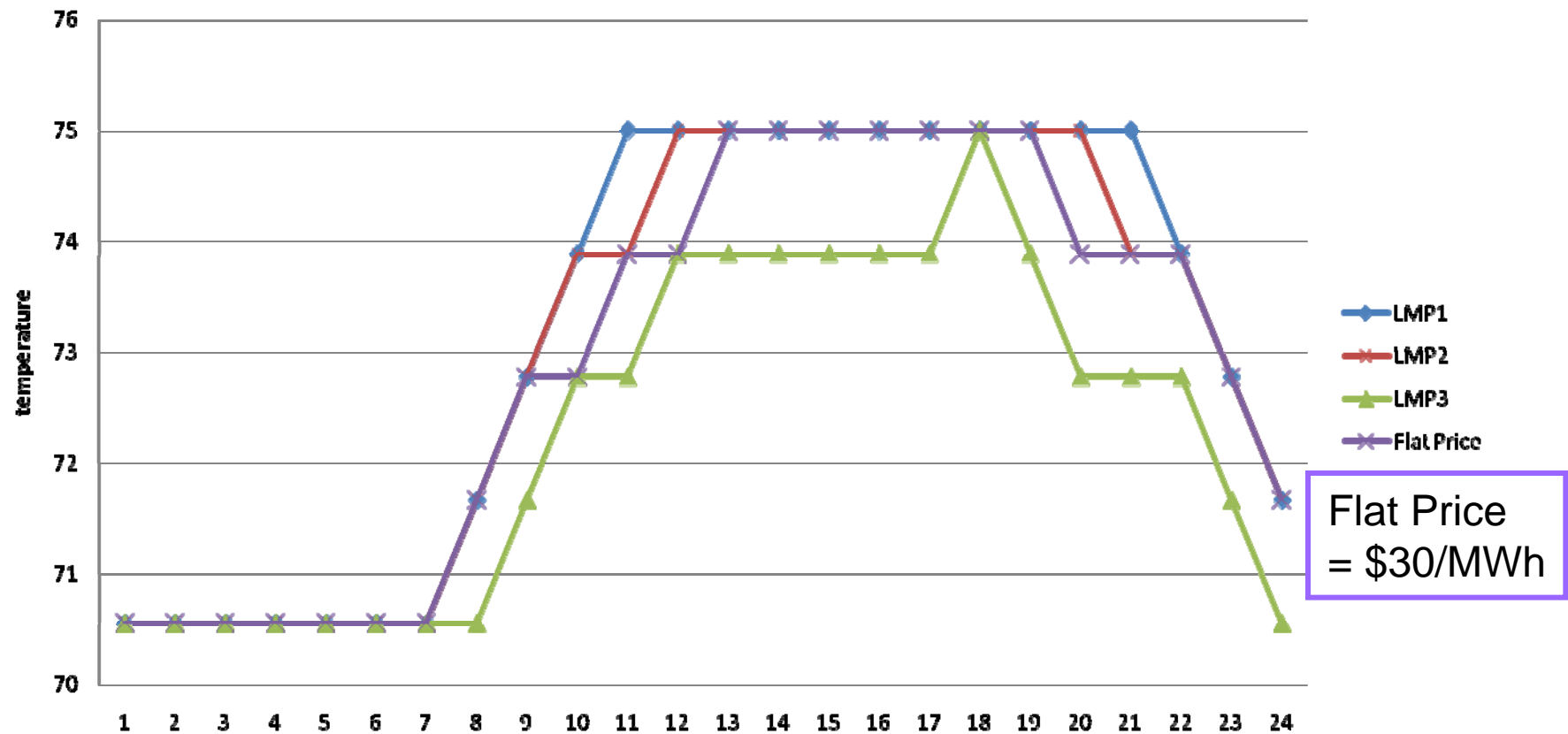
- **TRADITIONAL HVAC CASE:** Houses have traditional HVAC systems
Inside air/mass temps controlled by HVAC to achieve **optimal comfort** for resident, conditional on outside air temp
- **SMART HVAC CASE:** Houses have smart HVAC systems
Inside air/mass temps controlled by HVAC to achieve **optimal comfort/cost trade-offs** for resident, conditional on outside air temp **and on day-ahead market prices (LMPS)**
- Inside air/mass state equations for residential HVAC systems are modeled using a simple version of the **Equivalent Temperature Parameter (ETP) Model**

Benchmark Outcomes:

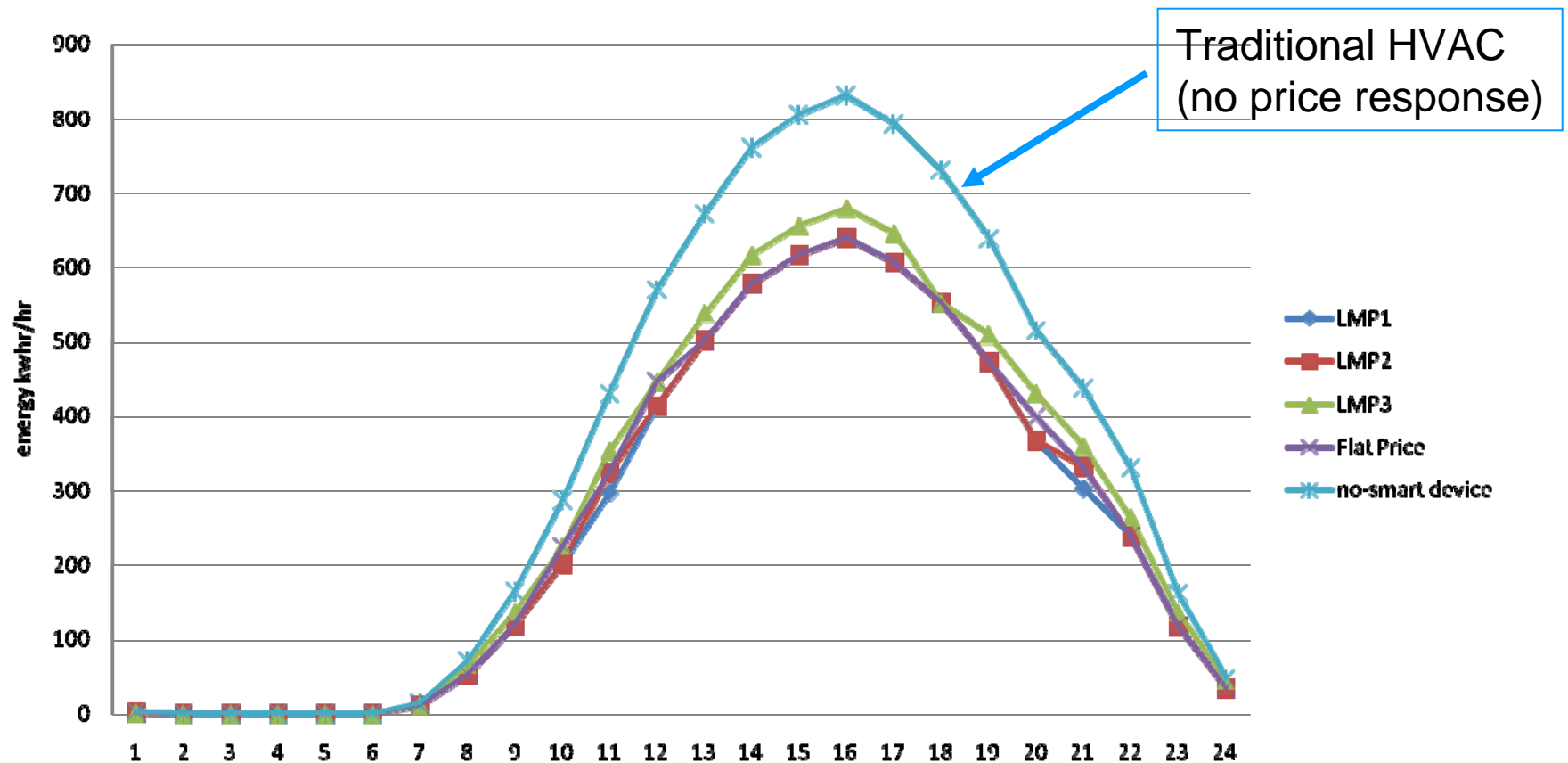
LMP and Fixed Load Profiles for Traditional HVAC Case



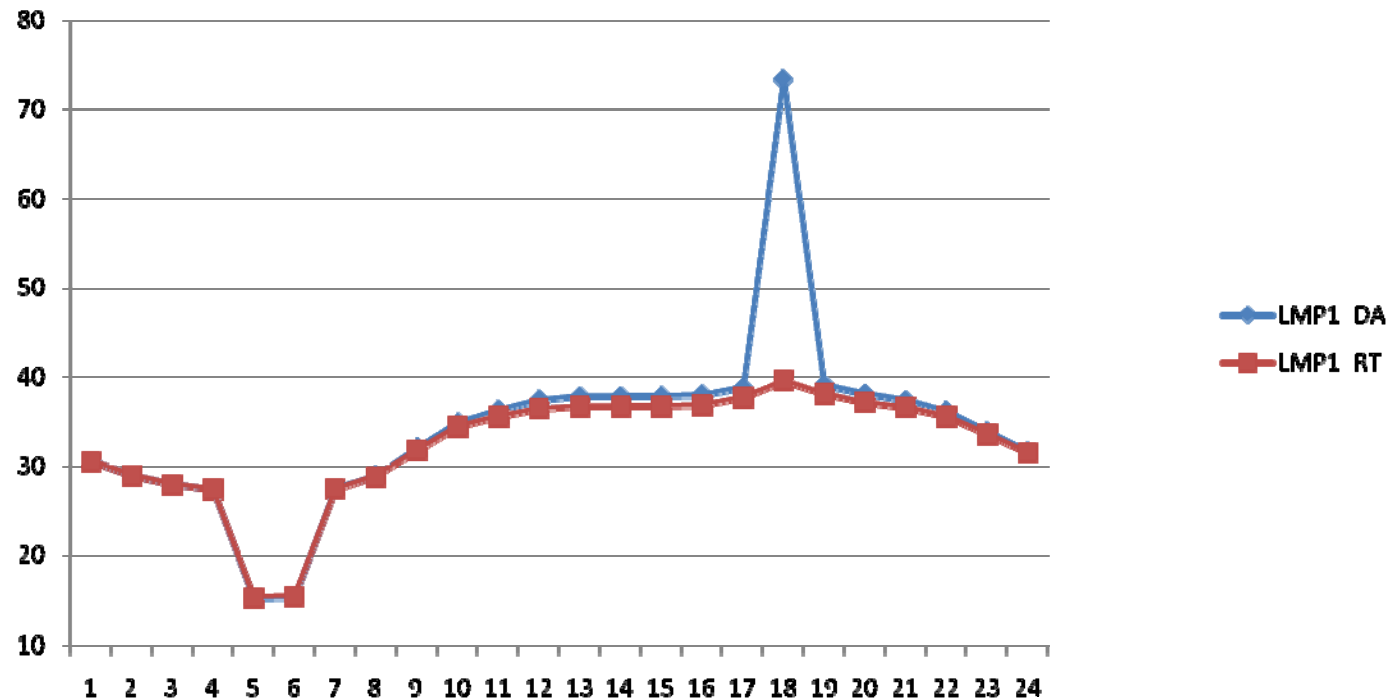
How the smart HVAC system controls inside air temperature under four price scenarios



Household Energy Consumption for Traditional HVAC Case and for Smart HVAC Case (four price scenarios)



Day-Ahead vs. Real-Time LMPs at Bus 1 for the Smart HVAC Case



- Traditional HVAC Case: HVAC load is not price responsive
- Smart HVAC Case: HVAC load responds to dynamically changing DA LMPs.

LSE Profits are Negative for Smart HVAC Case

- Profit for LSE daily operation
 - LSE1: (1582)
 - LSE2: (2665)
 - LSE3: (555.7)
- Explanation for Operation Loss
- $\pi = P_{DA} * Q_{RT} - (P_{DA} * Q_{DA} + P_{RT} * (Q_{RT} - Q_{DA}))$
 $= -(P_{RT} - P_{DA}) * (Q_{RT} - Q_{DA})$

Given price error caused by load deviation,

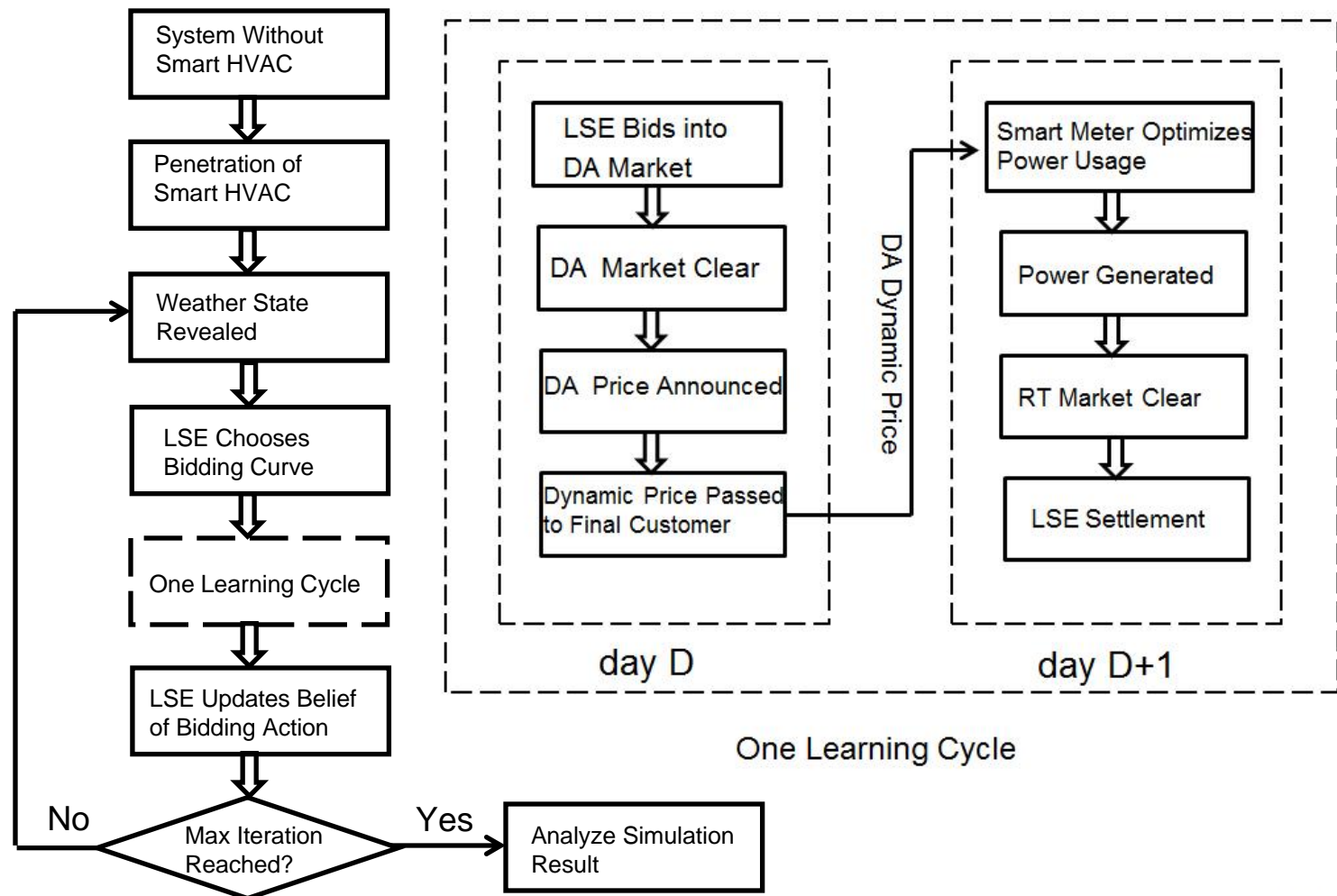
$corr(\Delta P, \Delta Q) > 0$, therefore loss for LSE operation.

Market Robustness

- Key Issues:
 - Does changing from the traditional HVAC case (fixed load) to smart HVAC case (price-responsive load) result in
 - peak load shift?
 - discrepancies between day-ahead and real-time prices?
 - How does this change affect the demand bidding behavior of the LSEs in the DA market?

Market Robustness Test

Flow Diagram



Learning Experiments for the Three LSEs

- **State**
 - Outdoor temperature spread, which is drawn from [small, large]
 - Outdoor temperatures differ across the bus locations of the three LSEs
- **Action**
 - LSE bids into the day-ahead market with fixed load and price-sensitive load
 - LSE strategizes price-sensitive load capacity limit. The discretized actions are chosen from the set $[0, 0.2, 0.4, 0.6, 0.8, 1] * P_{Max}$
 - LSE makes decision every hour and updates belief every day
- **Payoff**
 - LSE payoff $\pi = -(P_{RT} - P_{DA}) * (Q_{RT} - Q_{DA})$
 - In general, $\pi < 0$ as discussed previously

Suppose each LSE is a Q-Learner

- The LSE updates the anticipated profit (“Q value”) associated with each state-action pair, based on past profit outcomes

If $x = x_n$ and $a = a_n$,

$$Q_n(x, a) = (1 - \alpha_n)Q_{n-1}(x, a) + \alpha_n[r_n + \gamma V_{n-1}(y_n)]$$

Otherwise,

$$Q_n(x, a) = Q_{n-1}(x, a)$$

where $V_{n-1}(y) \equiv \max_b \{Q_{n-1}(y, b)\}$

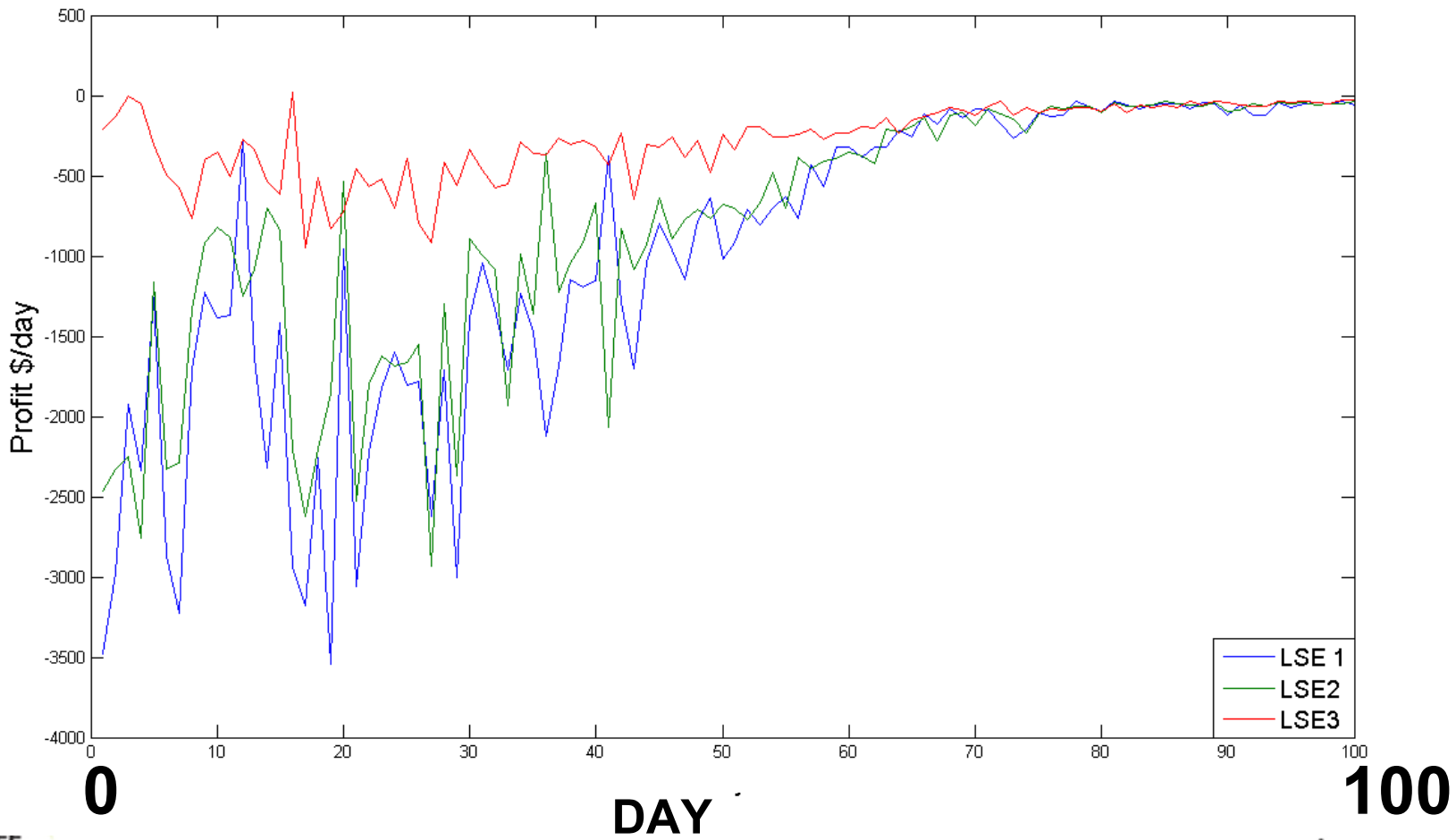
- LSE chooses next day’s action (demand bid) according to

$$p_D(x, a) = e^{Q(x,a)/T_D} / \sum_{b \in AD_i} e^{Q(x,b)/T_D}$$

- LSE explores the action space in an attempt to find an action yielding highest possible anticipated profits

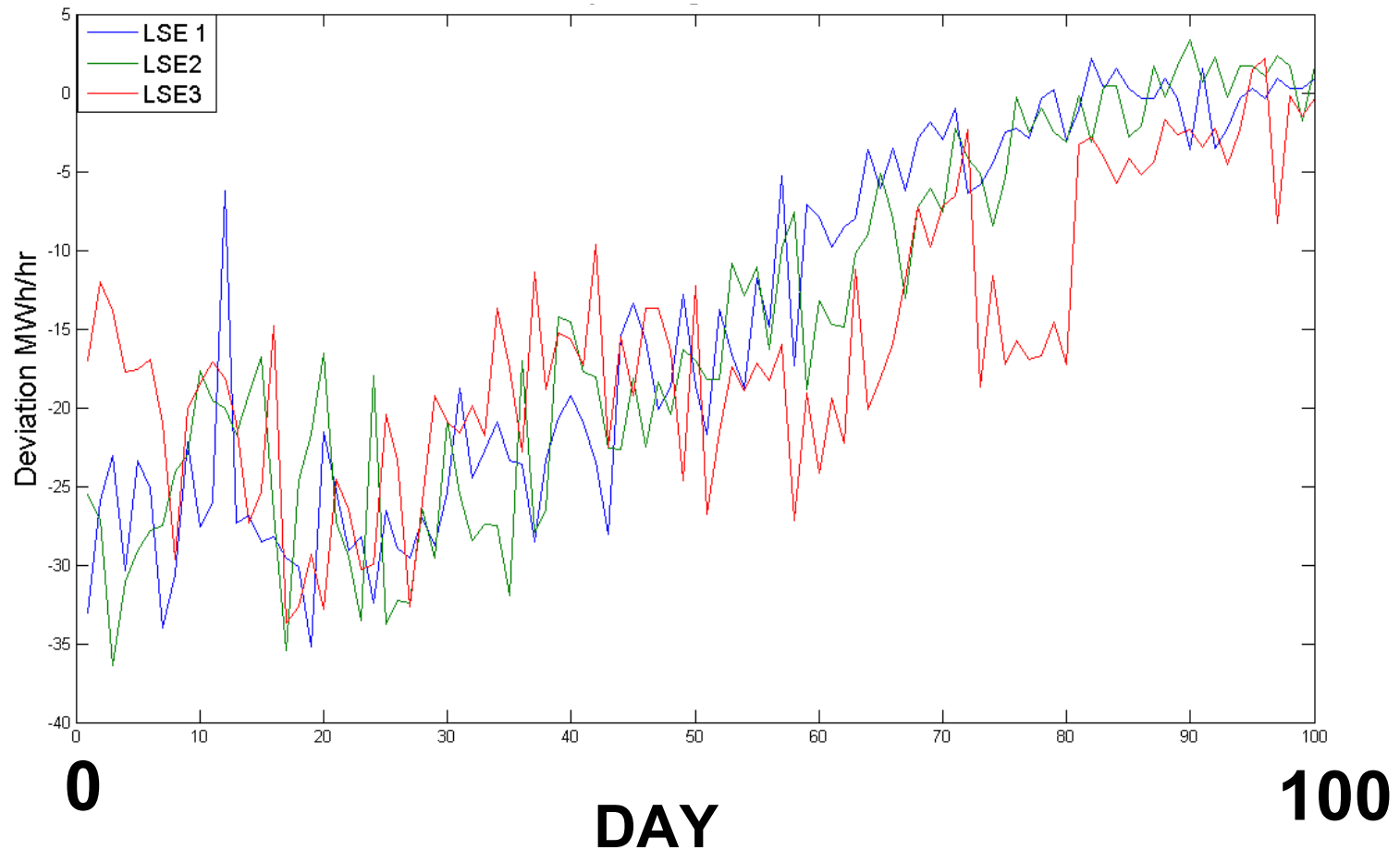
Simulation Results (100 Days)

Daily Average Profits for the Three Learning LSEs



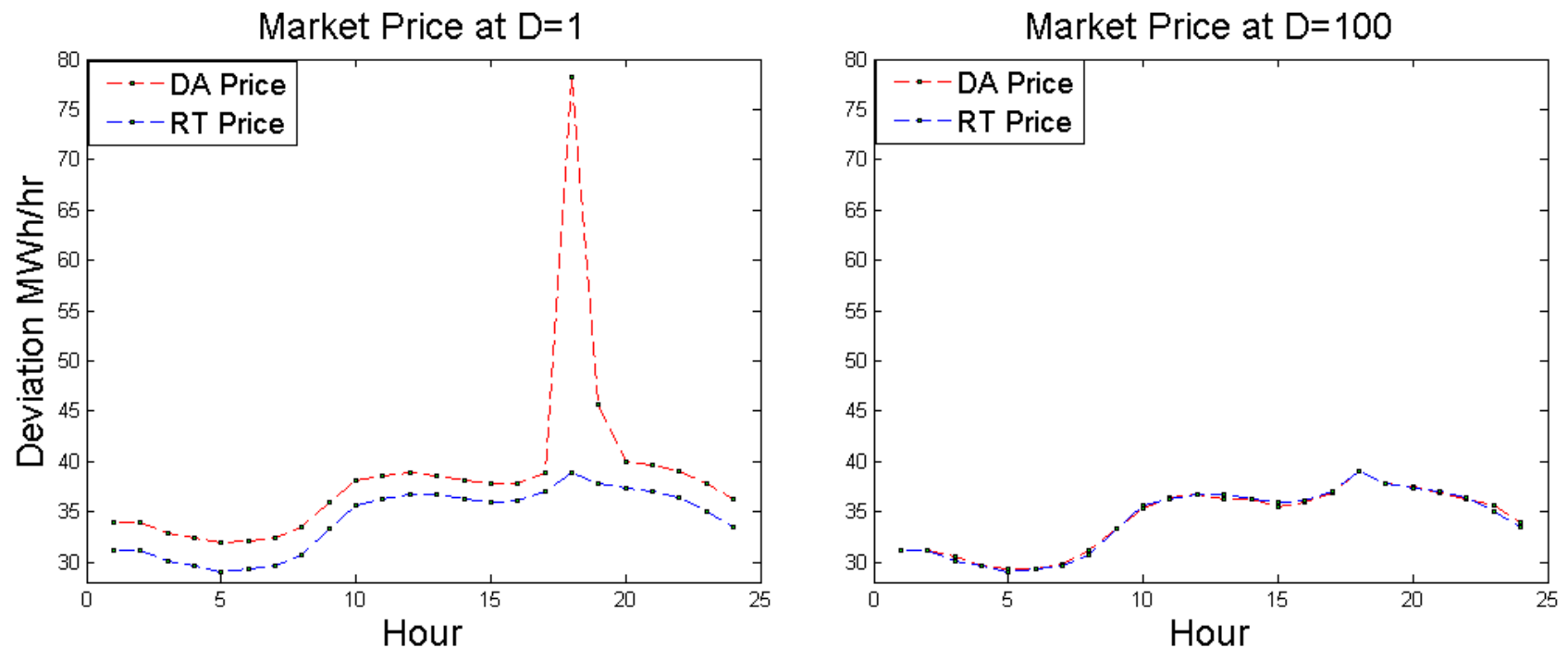
Simulation Results (100 Days)...Continued

Hourly Average Load Deviations for the Three Learning LSEs



Simulation Results...Continued

Market Performance Comparison

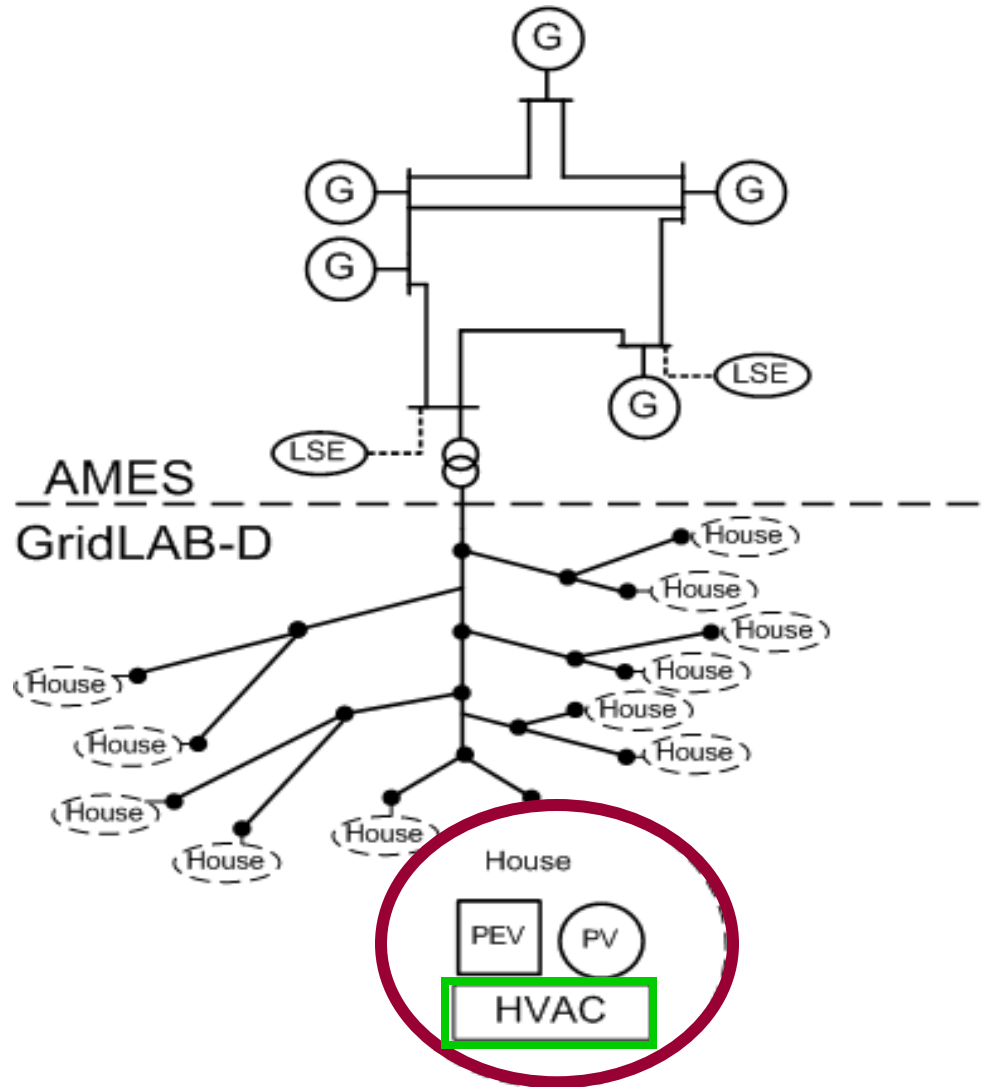


- On day D=1, smart HVAC replaces traditional HVAC. LSEs do not have enough information to estimate smart HVAC price responsiveness
- During next 100 days, LSEs use learning to adjust their DA market demand bids in an attempt to maximize their profits
- By day D=100, the LSEs have learned how to make DA market demand bids that more properly account for smart HVAC price responsiveness.

Market Robustness Findings

- Over time the LSEs learn how to adjust to smart HVAC demand response and select their DA market demand bids to maximize their profits.
- By day 100, LSE demand bids appear to have stabilized.
- By day 100, the DA and RT markets have evolved to a coordinated outcome where the prices in the two markets are essentially the same.

Second Study: Controller Design for Smart HVAC System



Modeling of a Smart HVAC System (HVAC = Heating-Ventilation-Air-Conditioning)

- Inputs include:
 - **Preferences** of a household resident trying to achieve optimal daily trade-offs between comfort and costs
 - **Structural home attributes** (e.g., square footage & insulation level)
 - **Electricity prices** (e.g. fixed regulated price, market-based LMPs)
 - **Forcing terms** (outdoor temp, solar radiation, control actions)
 - **State equations** for a two-dimensional state vector $x(t)$ consisting of (1) Indoor air temp $T^a(t)$ and (2) indoor mass temp $T^m(t)$, e.g. for furniture and walls.

ETP Modeling of HVAC State Equations

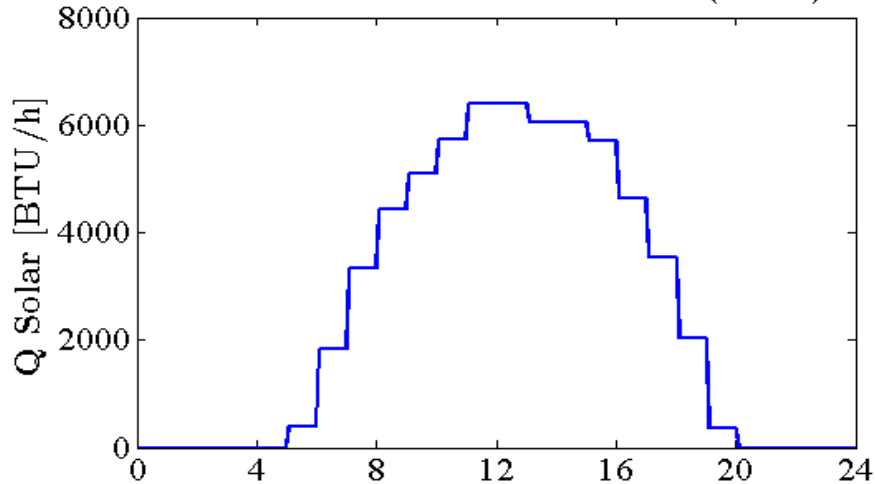
$$\frac{dT^a}{dt} = \frac{1}{C^a} [(T^o - T^a)U^a + (T^m - T^a)U^m + Q + Q^a]$$

$$\frac{dT^m}{dt} = \frac{1}{C^m} [(T^a - T^m)U^m + Q^m]$$

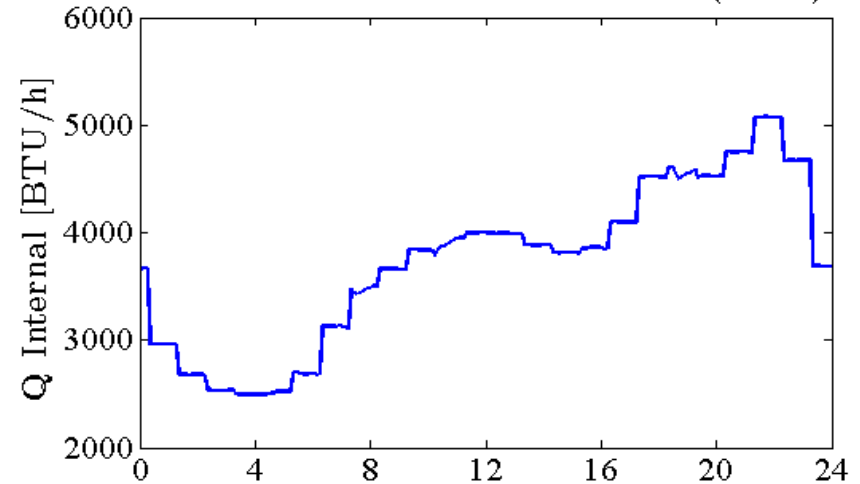
- The house resident has a “bliss” temp (e.g., 72°F)
- Using a discretized form of ETP state equations, HVAC sets its status levels (from cooling to heating) to achieve optimal comfort/cost trade-offs for the resident over time, conditional on forecasted prices, outdoor temp, & other forcing terms.
- HVAC status levels derived via dynamic closed-loop control.

External and Internal Forcing Terms

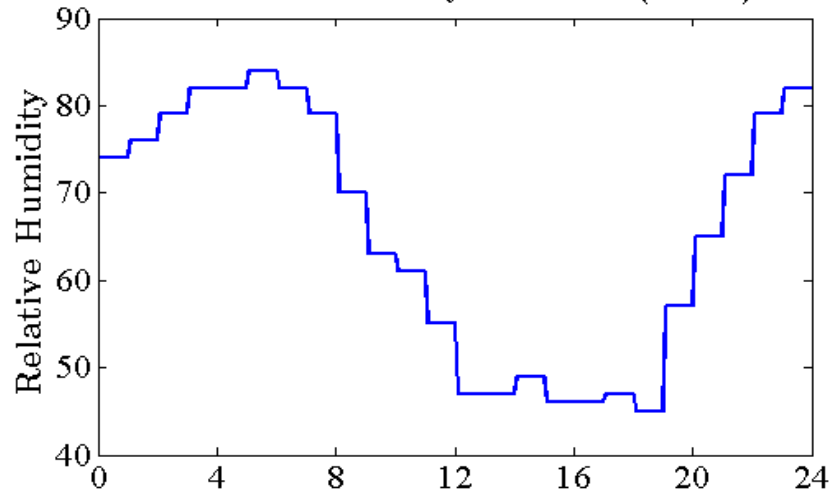
Solar Heat Flow Rate vs Time (Hour)



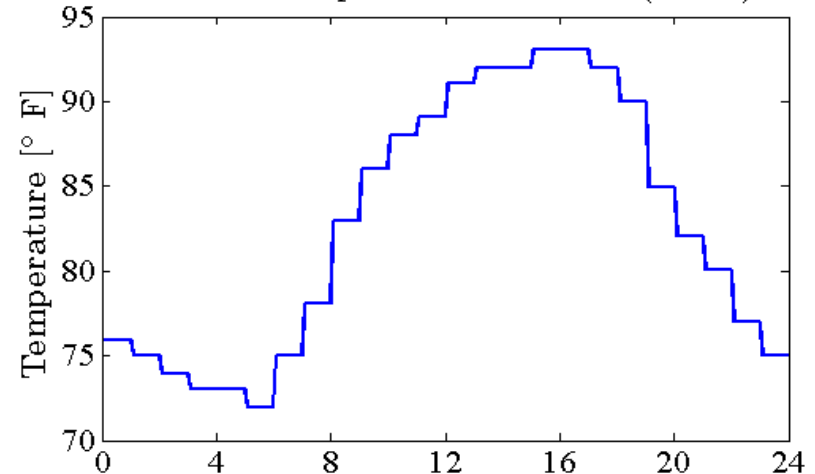
Internal Heat Flow Rate vs Time (Hour)



Relative Humidity vs Time (Hour)

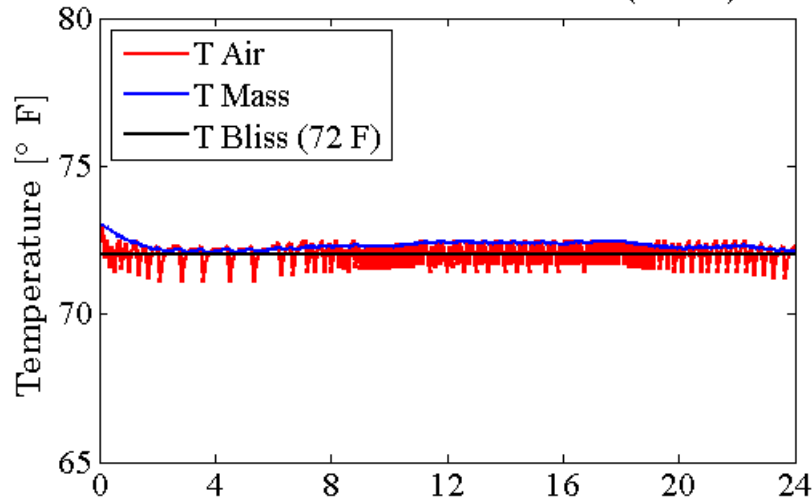


Outside Temperature vs Time (Hour)

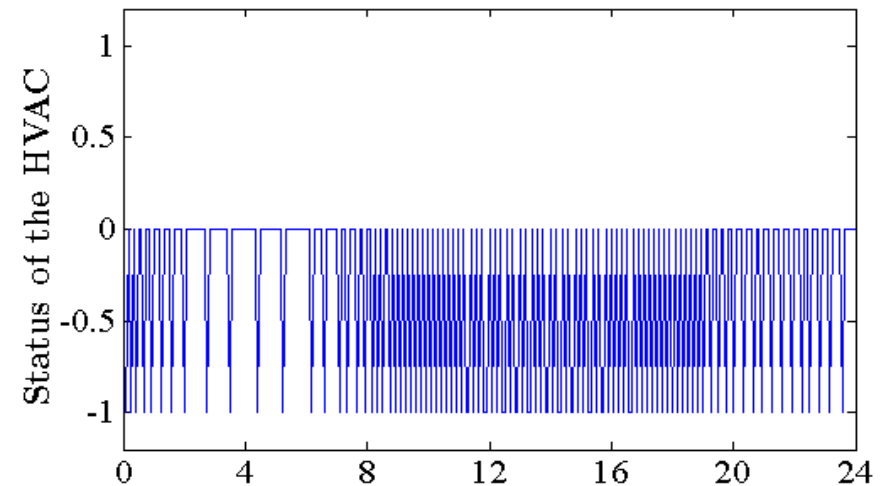


Sample Output of HVAC when Resident cares most about comfort

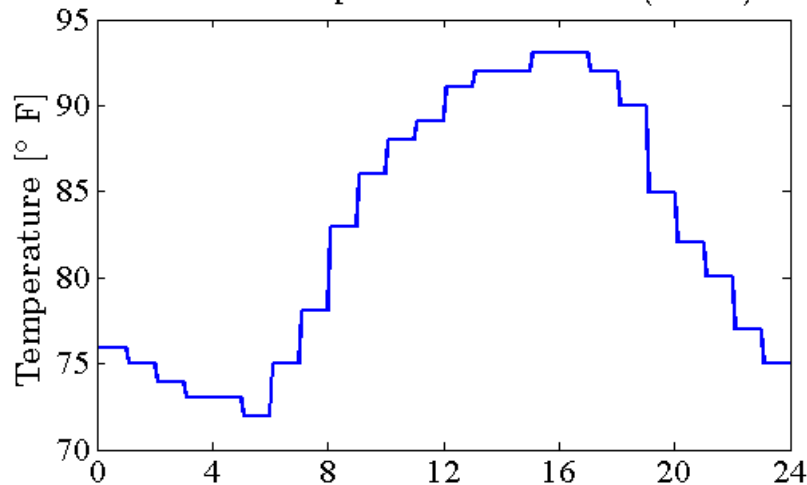
T Air and T Mass vs Time (Hour)



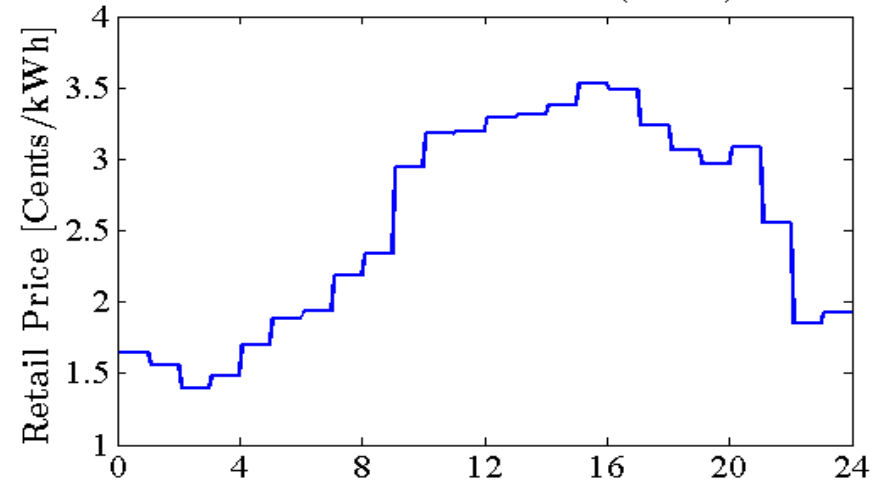
Status of the HVAC vs Time (Hour)



Outside Temperature vs Time (Hour)



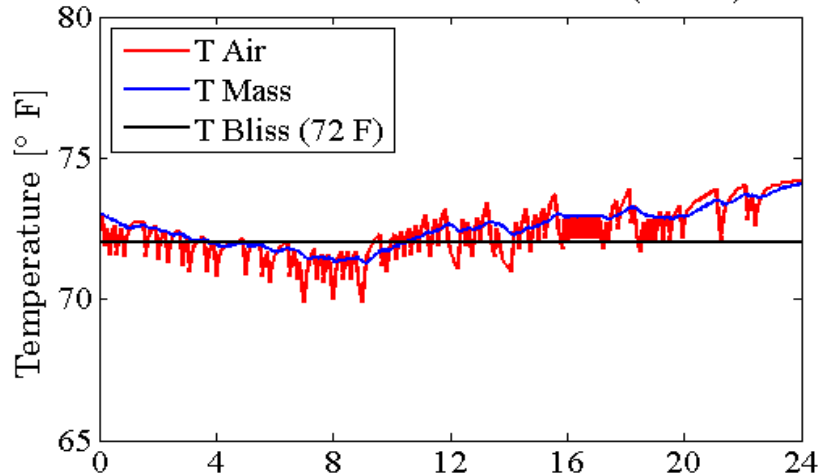
Retail Price vs Time (Hour)



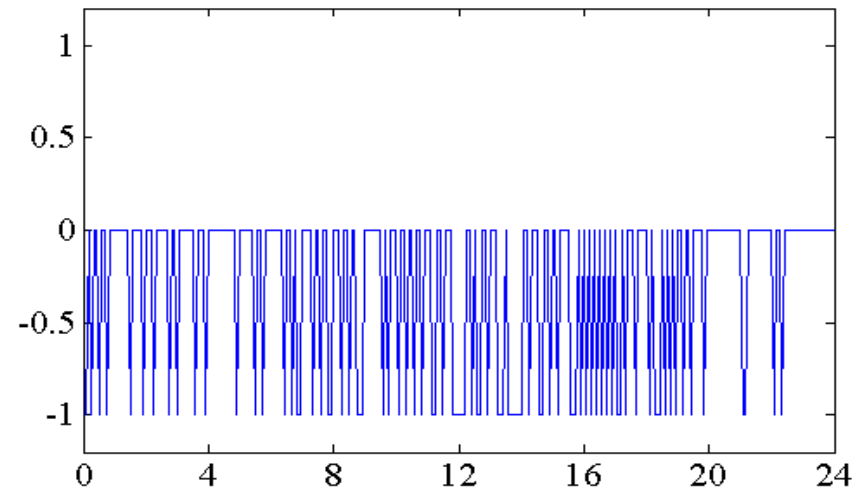
$\alpha=1$, 24-Hour Cost = \$0.6572, 24-Hour Comfort = 1435.3 Utils

Resident has a balanced concern for comfort and cost

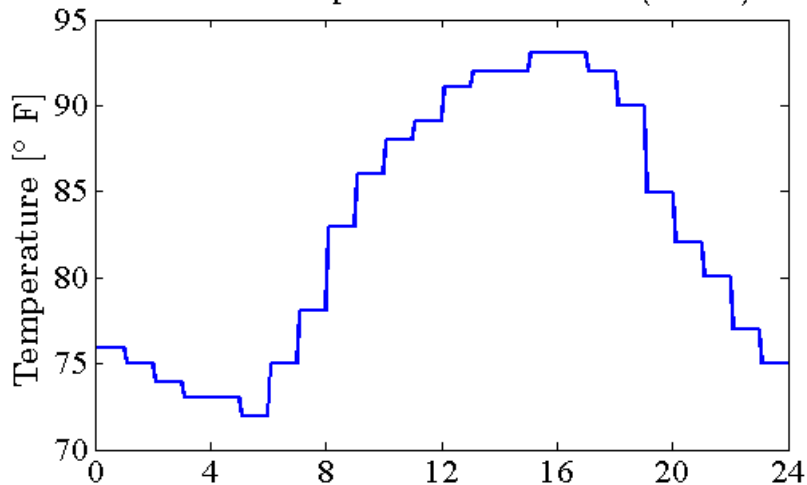
T Air and T Mass vs Time (Hour)



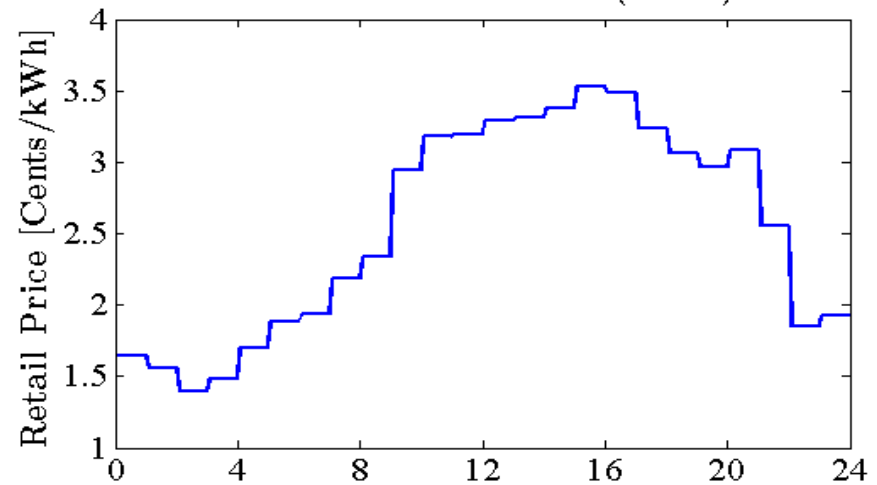
Status of the HVAC vs Time (Hour)



Outside Temperature vs Time (Hour)

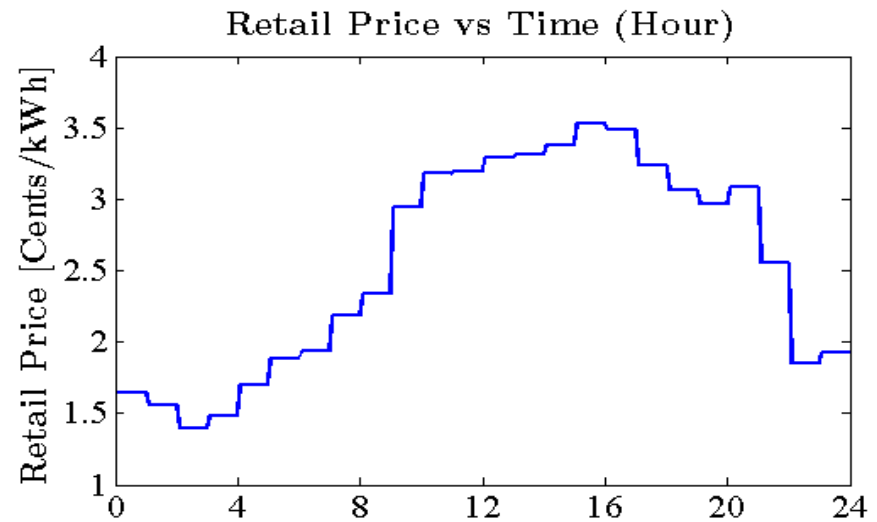
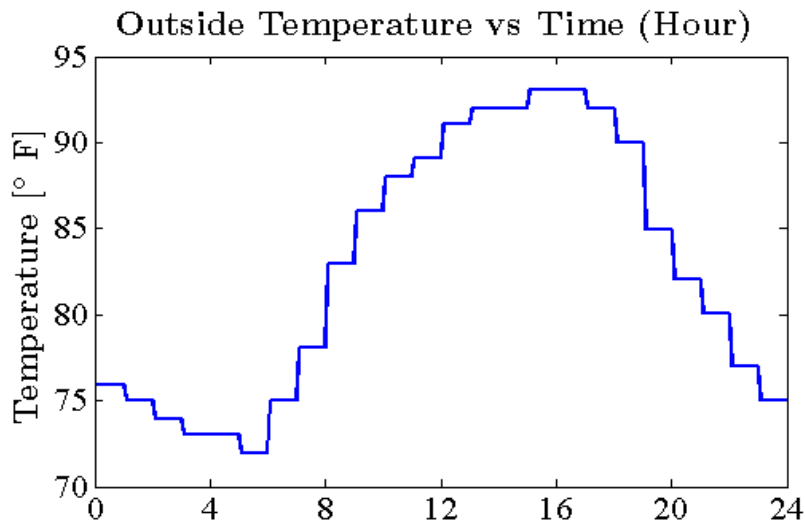
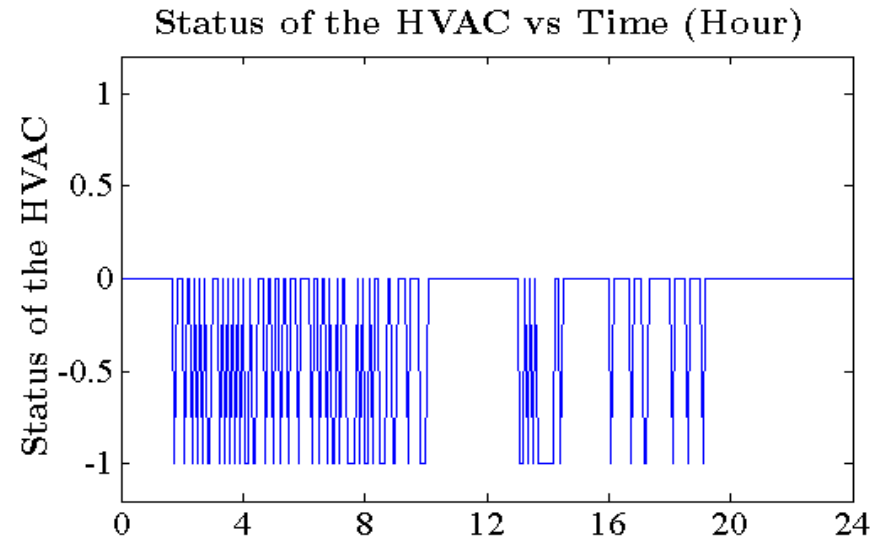
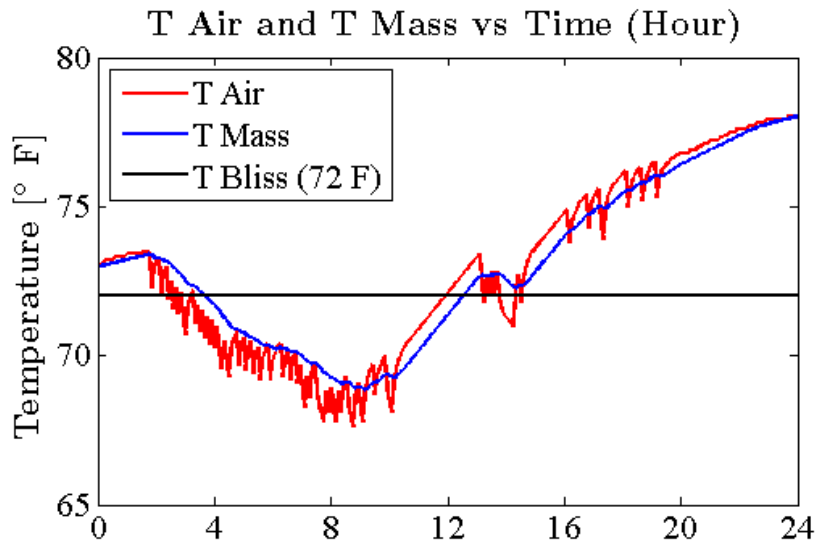


Retail Price vs Time (Hour)



$\alpha=500$, 24-Hour Cost = \$0.5333, 24-Hour Comfort = 1412.4 Utils

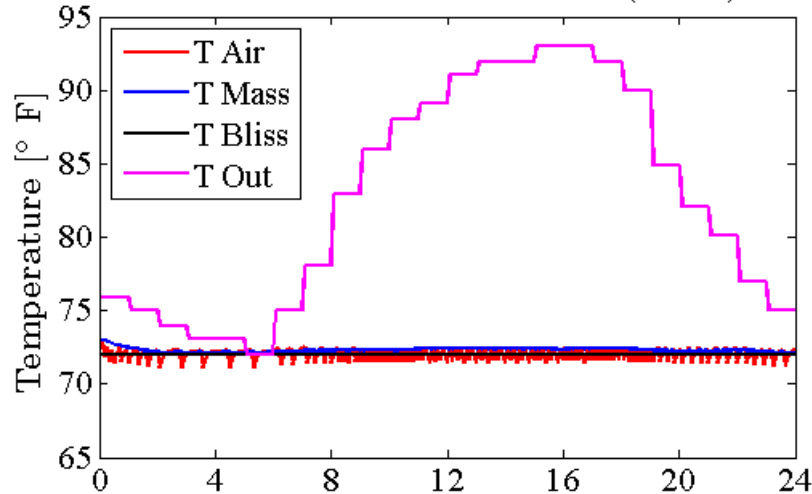
Resident cares most about cost



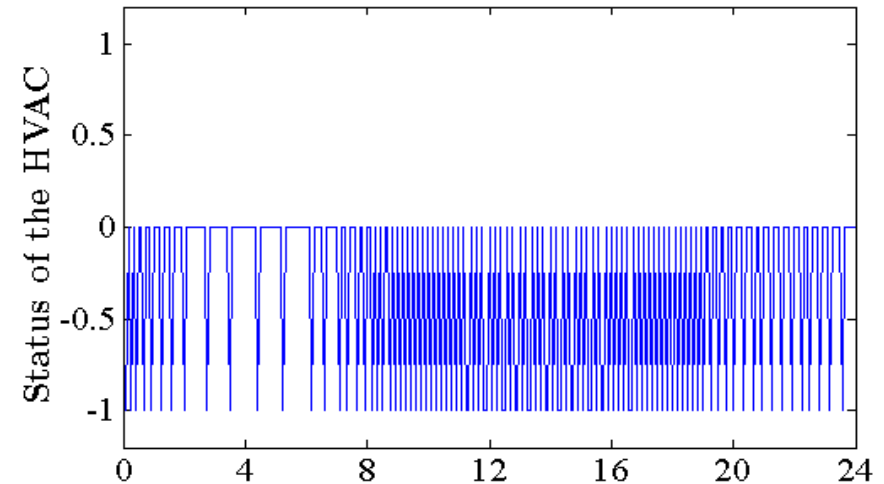
$\alpha=2000$, 24-Hour Cost = \$0.3190, 24-Hour Comfort = 1149.4 Utils

Sample Output of HVAC when Resident cares most about comfort

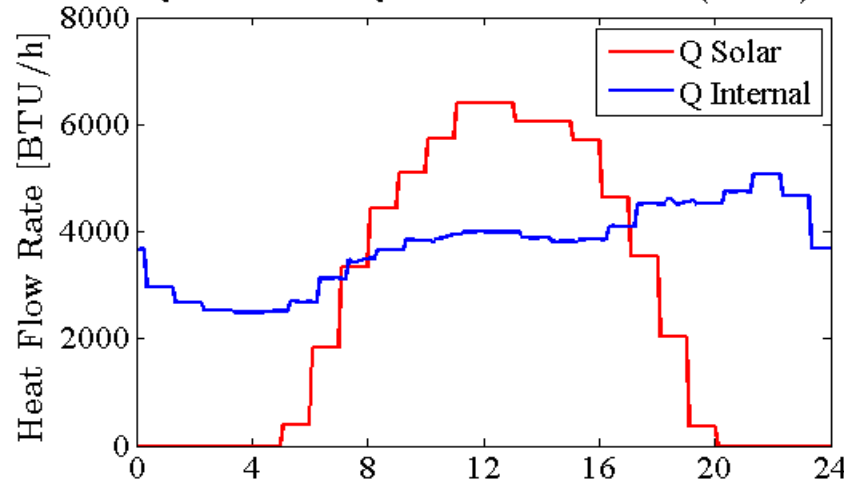
T Air and T Mass vs Time (Hour)



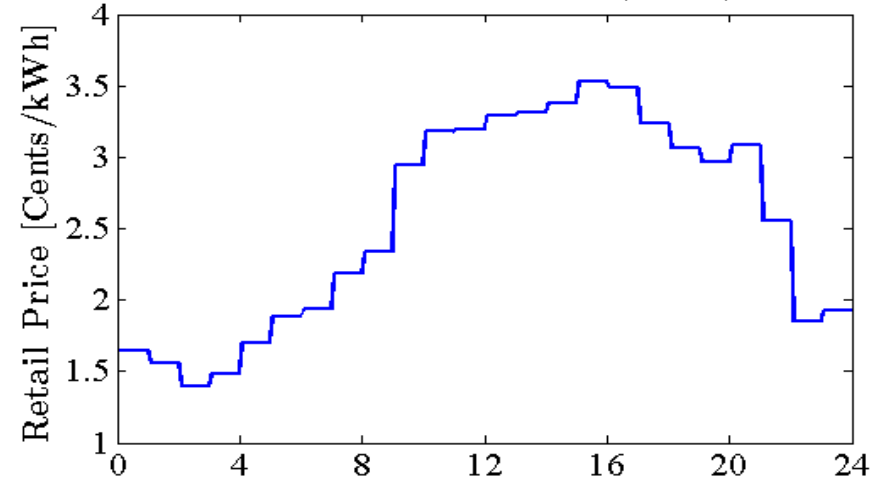
Status of the HVAC vs Time (Hour)



Q Solar and Q Internal vs Time (Hour)



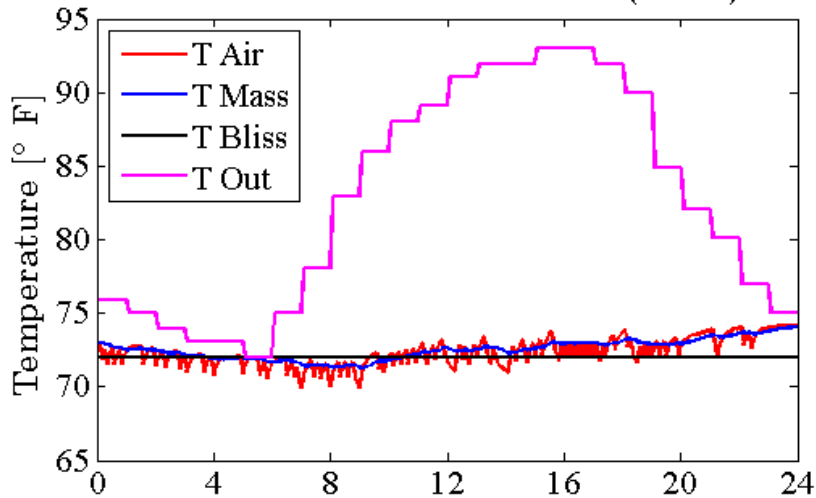
Retail Price vs Time (Hour)



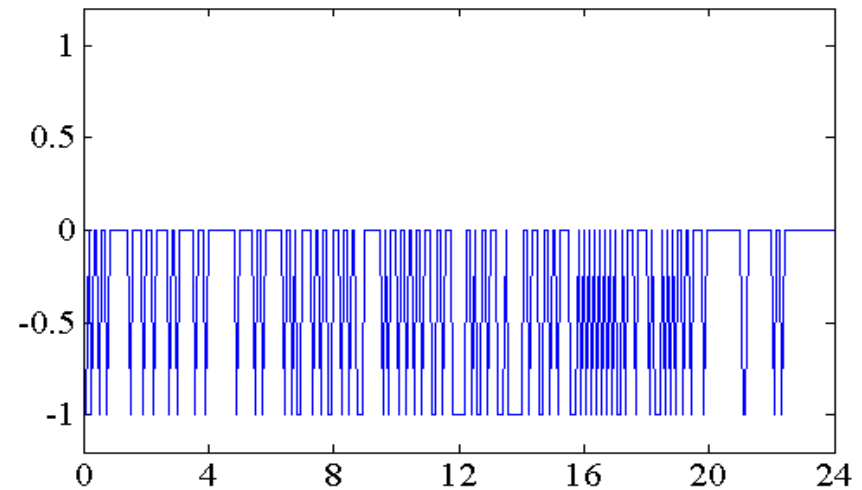
$\alpha=1$, 24-Hour Cost = \$0.6572, 24-Hour Comfort = 1435.3 Utils

Resident has a balanced concern for comfort and cost

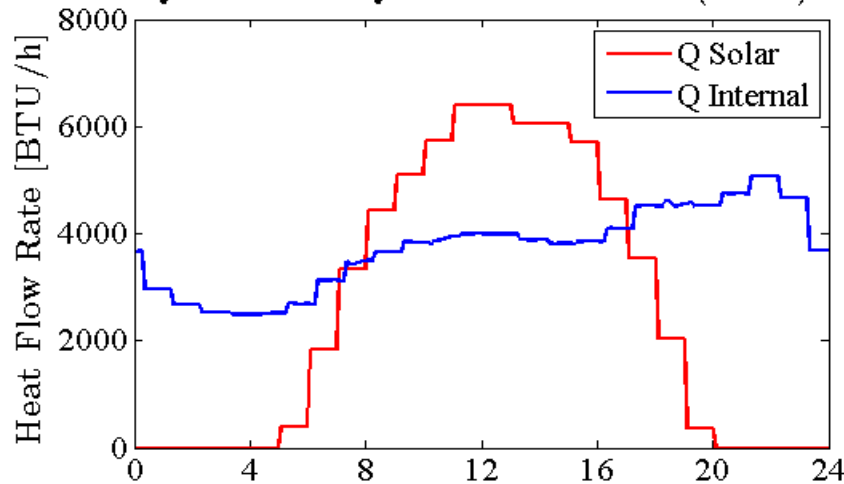
T Air and T Mass vs Time (Hour)



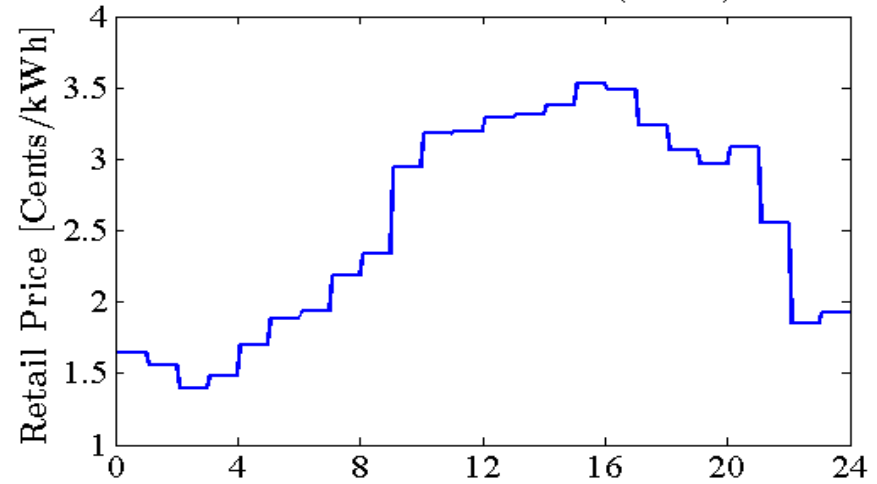
Status of the HVAC vs Time (Hour)



Q Solar and Q Internal vs Time (Hour)



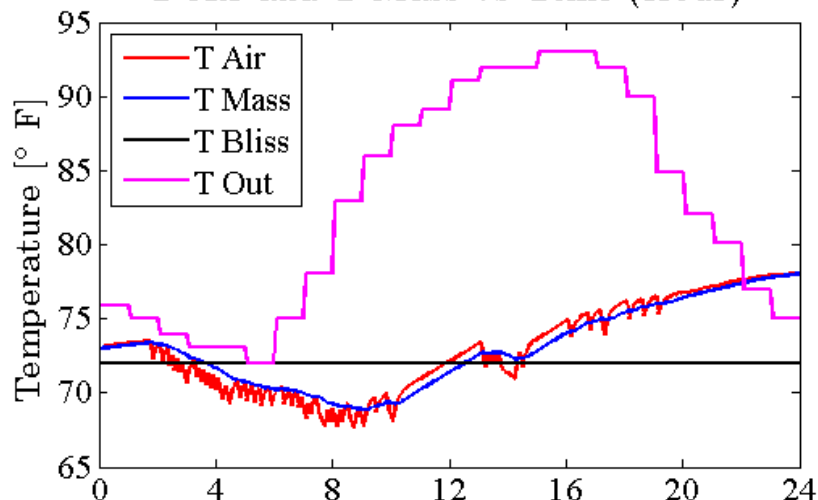
Retail Price vs Time (Hour)



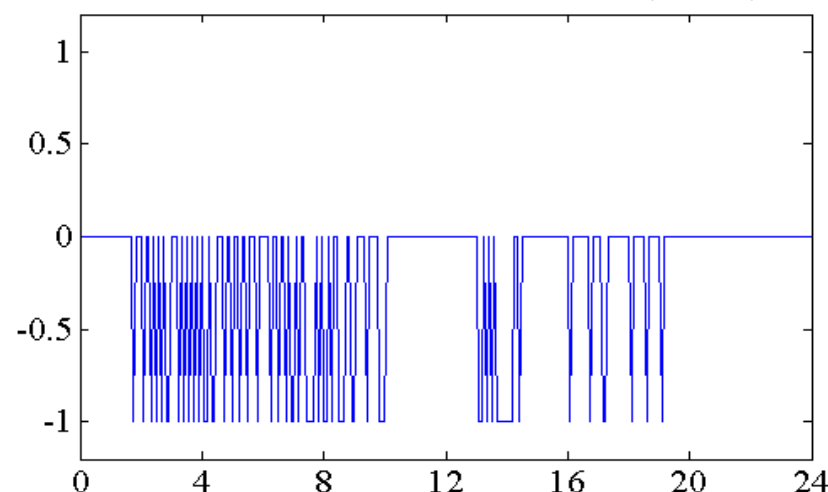
$\alpha=500$, 24-Hour Cost = \$0.5333, 24-Hour Comfort = 1412.4 Utils

Resident cares most about cost

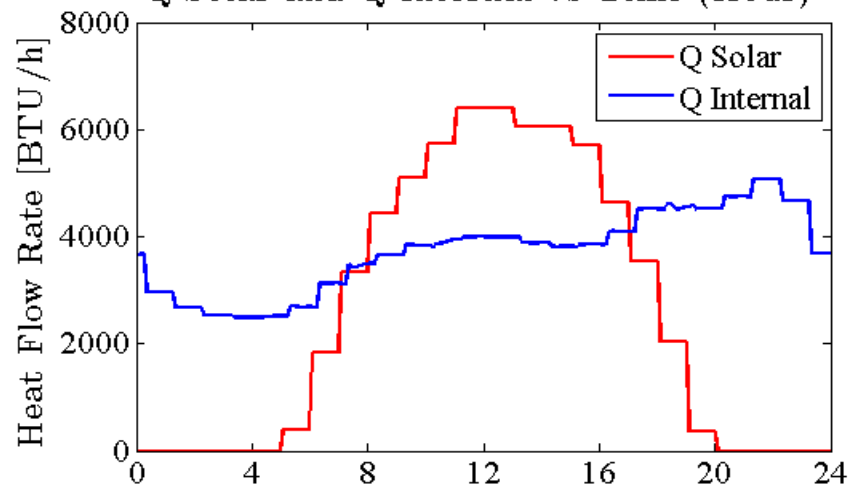
T Air and T Mass vs Time (Hour)



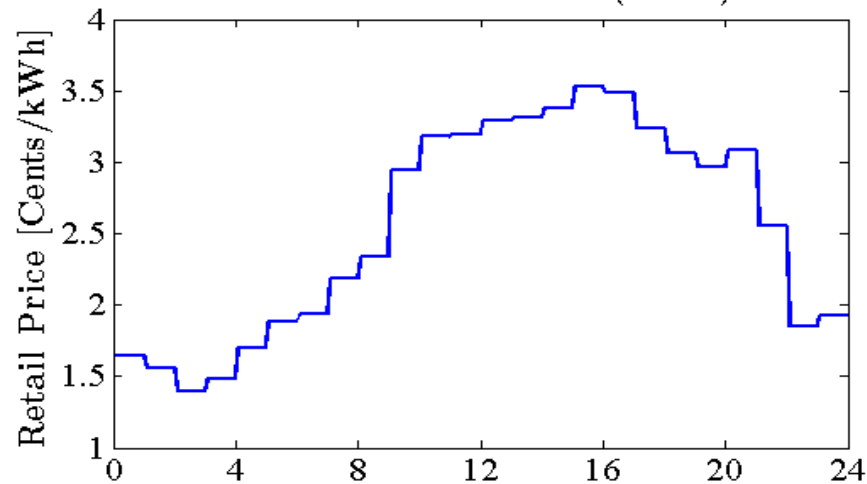
Status of the HVAC vs Time (Hour)



Q Solar and Q Internal vs Time (Hour)



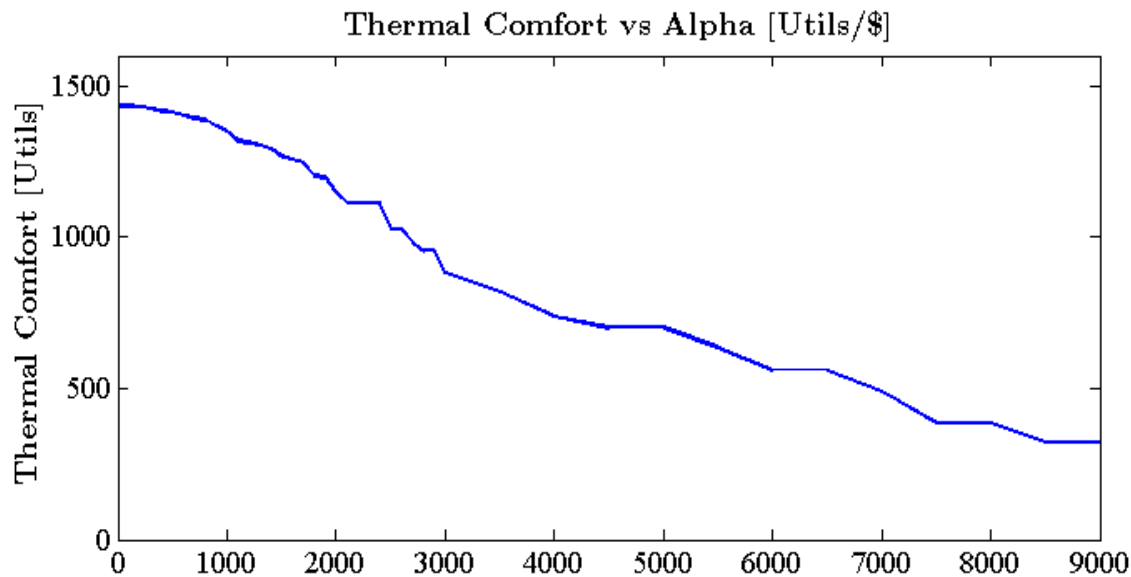
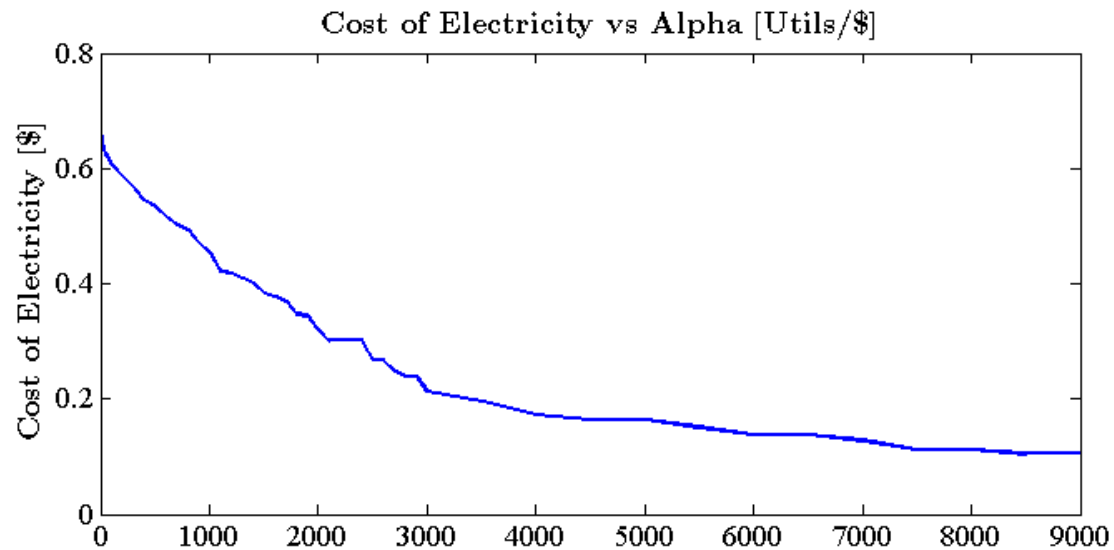
Retail Price vs Time (Hour)



$\alpha=2000$, 24-Hour Cost = \$0.3190, 24-Hour Comfort = 1149.4 Utils

Variation of Cost and Comfort with Alpha

(Low Alpha → Stress On Comfort, High Alpha → Stress on Cost)



Dynamic Pricing Studies: Summary and Future Planned Work

- Impact of retail consumer price-responsive demand on LSE demand bidding and LSE profit outcomes, both with and without LSE learning.
- Design of a smart residential HVAC controller to achieve optimal comfort-cost trade-offs conditional on prices and forcing terms (e.g., outdoor temp)
- Goal: Use IRW Test Bed to study carefully the effects of various types of Demand Response (DR) on retail and wholesale power system operations