

**Development and Application of a Control Analytic Tool
for Evaluating Automated Residential Smart Grid Control
Strategies**

by

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B.S., Clemson University, 2007

A thesis submitted to the
Faculty of the Graduate School of the
University of Colorado in partial fulfillment
of the requirements for the degree of
Masters of Science

Department of Civil, Environmental and Architectural Engineering

2011

This thesis entitled:
Development and Application of a Control Analytic Tool for Evaluating Automated Residential Smart
Grid Control Strategies
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Development and Application of a Control Analytic Tool for Evaluating Automated Residential Smart Grid
Control Strategies

Thesis directed by Prof. Gregor Henze, PhD, P.E.

This research project describes the development and application of a control analytic tool for evaluating the effectiveness of automated residential smart grid control strategies at shifting and reducing energy consumption during peak pricing periods. The development of this control analytic tool was completed through collaboration between Tendril and the Building Energy Research Group (BERG) from the University of Colorado at Boulder. This tool is able to evaluate control strategies that take into effect varying hourly device consumption and set point schedules with building and weather interactions. This research project provides insight into the most effective approaches for reducing peak energy consumption and lowering energy cost for homeowners and utilities. This tool can be used to help homeowners understand and utilize control enabling devices, and can guide utilities in implementing incentives for energy reduction that are beneficial to both them and the individual needs of their customers.

Acknowledgements

First, I would like to thank Tendril who has been a perfect partner for this research project. Kent Dickson and the engineering team at Tendril have helped to guide and support this project from beginning to end. Their knowledge and expertise in residential smart grid applications have made this analytic tool and research project both relevant and applicable to the real world in a way that would not have been possible without their partnership. Second, I would like to thank the Building Energy Research Group at the University of Colorado at Boulder for contributing extensive knowledge and expertise to make the creation of this analytics tool possible. Specifically, I would like to thank Chad Corbin and Peter May-Ostendorp for their prior work in creating the MATLAB - EnergyPlus environment and their constant guidance throughout this project. I would also like to thank Dr. Henze, who has been instrumental in bringing this research project to life, and for his motivation and vision for this tool. His wisdom in control strategies and direction have been critical in the development and implementation of this analytic tool and I am thankful to have him as my advisor. I would also like to thank the homeowners, who allowed me to measure their energy information as part of this project, for their patients and availability as well as everyone who has contributed to this project with ideas, advice, time, and encouragement. Thank you

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Chapter 1

Introduction

1.1 Motivation

According to the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability the United States' electric grid is currently built to transport more than 1,000,000 megawatts of generating capacity from over 9,200 generation units across more than 300,000 miles of transmission lines [25]. It can be considered the largest interconnected machine on earth and has been identified by the National Academy of Engineering as the single most important engineering achievement of the 20th century with other critical distribution and transportation based achievements such as water supply and distribution, the Internet, and the U.S. highway system receiving 4th, 11th, and 13th respectively [27].

Yet there are many reasons a "smarter" grid is needed. More and more consumers are demanding increasing amounts of electricity due to the digitalization of our society. Since 1982 growth in peak demand for electricity has exceed transmission growth by 25% every year. Blackouts and brownouts are increasing due to capacity limitations, the slow response times of mechanical switches, and a lack of visibility into what is happening in the electrical grid and where potential problems are pending. Five *major* blackouts have occurred in the past 40 years, three of which have happened in the past nine, and unless the grid is upgraded, more are likely. The cost of outages and power quality issues are estimated to cost American businesses over \$100 billion on average every year. [25]

Our electricity grid not only needs to be upgraded for reliability reasons, but also to improve national security, energy efficiency, and environmental impacts. A smarter grid will allow for distributed generation

plants to be integrated more effectively creating a decentralized and safer electricity grid. Efficiency can be increased by preventing blackouts, reducing peak loads met by the least efficient power plants, increasing the utilization of existing grid infrastructure and integration of renewable sources, and controlling the quality of the power that is generated and distributed. It is estimated that smart grid enhancements could increase our grid utilization anywhere from 50 to 300% and reduce the need to build more infrastructure for which raw material prices have increased tremendously in recent years. Electricity generation is responsible for 40% of the carbon dioxide produced in the United States and many more pollutants harmful to human health such as NO_x and SO_x, yet according to the European Wind Energy Association integrating wind and solar power at levels higher than 20% is not possible without advanced energy management techniques. Furthermore, if the quality of the power transported through the grid were 5% more efficient, the energy savings would be equivalent to eliminating the emissions from 53 million cars. [25]

Moving forward with smart grid technology will allow for higher renewable integration and the possibility to transfer the use of millions of barrels of oil from transportation over to these renewable sources of energy through the applications such as electric vehicles. Electric vehicles have been making a lot of noise in the media and even earned their own “avenue”, a 37,000 ft² space on the main floor of the 2010 North American International Auto Show this year in Detroit known as “Electric Avenue”[31]. Their arrival could create opportunities to reduce spinning reserves and peaking loads, while enhancing renewable integration and greatly reducing transportation emissions and our nation’s dependency of foreign oil. According to the Pacific Northwest National Laboratory, our current generation capacity can support 73% of light duty vehicles if they are controlled to charge at night and reduce current oil imports by 52%. Even without using renewable sources the emissions from driving on electricity are less and the cost are cheaper than with gasoline. [23]

The Department of Energy is in charge of leading our country’s upgrade to a more reliable, secure, efficient, and environmentally responsible “smart” grid. This effort is headed by the Office of Electricity Delivery and Energy Reliability in conjunction with the newly formed multi-agency ‘Smart Grid Task Force’ responsible for coordinating efforts including standards development, aiding research and development projects, and supporting the agendas of a wide range of stakeholders such as utilities, regulators, providers,

vendors, and consumers. [49]

The upgrade of our nations electrical grid can be thought of as simply applying the advancements in communication technology and information management brought about in recent years from digitalization and the adoption of the Internet to our electricity grid. This massive project is entirely possible with the introduction of enabling technologies, interoperability based on standards, and low-cost electronics and communication. Many demonstration projects are already in existence all over the country[11]. The first step needed in creating a smart grid, technologically, is an upgrade to the existing tools for gathering and communicating energy consumption information. At the customer level this requires the implementation of an advanced metering infrastructure which can gather more detailed energy consumption data and transfer this to utilities immediately. This step has been energized by the recent American Recovery and Reinvestment Act which has awarded \$3.4 billion in smart grid matching grants to 100 companies, \$2.8 billion of which is for advanced meter infrastructure projects [48] [50].

The Department of Energy is investing heavily in the modernization of the U.S. electrical grid[50]. This investment will help create a market for platforms that can access, manage, and analyze energy data and implement control strategies based on the needs of the customers and the electrical grid. Tendril is one of many companies entering the space created by the advancement of modern grid technology. Their goal is to create a two way dialog between utilities and consumers, to enable real time pricing and price based device control, and allow the deployment of smart energy conservation programs based on individual customer scenarios. Tendril's software platform combined with any number of in-home, control enabled devices will allow energy management strategies to be implemented seamlessly, automatically, and immediately as needed. [44]

This research project, completed through collaboration between Tendril and the Building Energy Research Group (BERG) at the University of Colorado at Boulder, focuses on designing a control analytic tool for evaluating the effectiveness of different energy control strategies to shift/reduce energy consumption during peak pricing periods and lower energy cost for residential homeowners and utilities. This tool is intended to evaluate control strategies in the presence of varying occupant behavior with building and weather interactions and provide insight into the most effective approaches for saving peak energy consumption and

overall cost for both homeowners and utilities.

1.2 Desired Knowledge

- (1) Quantify energy savings potential in residential home applications based on changes in device operation and specific smart grid control strategies.
- (2) Quantify realistic cost saving potential for energy customers and utilities based on real time pricing and time-of-use structures through the application of control enabling technology.
- (3) Develop a simulation tool that is able to guide homeowners and utilities in decision making related to reducing peak energy loads and creating incentives that benefit both homeowners and utilities.
- (4) Provide a methodology for accurately simulating smart grid residential control strategies with consideration for variance in hourly schedules.

1.3 Thesis Organization

The following thesis first presents a review of relevant research and the results of demonstration projects focused on reducing residential energy consumption and shifting demand loads. The review investigates the potential for residential energy load shifting and peak reduction focusing on large home appliances and devices as well as the integration of electric vehicles.

Next, a description of Tendril's device and platform capabilities which will be examined in regards to building energy control and management. Background on Tendril's specific control and communication capabilities is discussed briefly to give context to the development work completed in this thesis.

A case study on a home with Tendril's smart grid enabling technology is discussed next. The process of equipping this home with detailed energy measurement equipment and creating a tool to collect and analyze detailed consumption data from the home's smart meter is discussed. Also, details on the construction and energy characteristics for this home are presented.

The measured circuit data from this house is presented in graphical format and hourly energy consumption and operation schedules are examined in detail. An analysis on the peak reduction potential for

individual energy end-uses is conducted for varying peak periods and pricing rate differences. Furthermore, the energy data obtained from the smart meter is processed and displayed as average energy consumption schedules by month and used to make conclusions about the practicality of certain residential control strategies.

Next, the creation and calibration of a building energy model is explained. The process for obtaining and applying historical data from a local weather station is presented along with the process for applying and manipulating device schedules to meet the measured energy consumption schedule for a specific month.

The Tendril Control Analytic Tool (TCAT) developed with the purpose of evaluating automated control strategies is then introduced. The numerical computing and building energy simulation software tools utilized in this control analytic tool are examined with reasoning for their selection. The simulation inputs and processes executed in this control simulation environment are described. Also, the design reasoning for control implementation capabilities and resulting calculation outputs are given.

Next, the simulation results are presented and discussed with a focus on both the customer and utility perspective. The process of using TCAT to answer important smart grid control questions is demonstrated and discussed. A benchmark study is designed and TCAT is applied to gathering, simulating, and analyzing the results.

Lastly, conclusions on the knowledge gained from this research project and suggestions for future research methodology for evaluating and validating smart grid residential control strategies are discussed. Future work and applications for this simulation tool are discussed with comments on the flexibility and scalability.

Chapter 2

Literature Review

2.1 Rate Structures and Demand Response

Borenstein, et al., [2] explains the procedures and trade-offs of different advanced pricing structures such as real time pricing (RTP) and time of use (TOU) pricing. RTP is not used much today, but TOU pricing structures have been used extensively. TOU structures typically have an on-peak, off-peak, and possibly a shoulder period. They usually only change two or three times a year with the seasons. An element of RTP that has been introduced in some rate structures to help capture the price variation within a price block is critical peak pricing (CPP). This allows for a very high price to be issued to customers upon response to critical periods when the whole sale price of electricity becomes extremely high. This typically would apply during peak hours of the peak season on select days when the “critical” situation occurs, but these events, unlike the on-peak TOU period, are not scheduled in advance.

RTP structures would require that the price of energy be announced at fixed time intervals, such as one hour. The price would be evaluated and presented at the beginning of each period. It is possible to set RTP further in advance but the accuracy of the predictions degrade because it is more difficult to forecast weather and other grid factors. RTP with a very long lag time essentially becomes a TOU structure. TOU rates are based mostly on historical averages and create incentive for demand shift due to behavioral modification to take effect, either manually through formed habits, or set as an automatic control on a particular device. After this occurs savings potential can diminish greatly, especially for devices that are simply set either on or off. Savings potential also diminish after a customer has reached his/her perceived

comfort limit in set point controls. This phenomenon was perceived in a study conducted by Erikson, et al.,[24], examined later in this chapter, when CPP prices were doubled from one year to the next, yet load reduction for residential customers remained relatively the same.

RTP and TOU pricing structures are useful because they do not require individual contracts with thousand of customers as required for demand response events to occur.

In the Hammerstrom, et al., Olympic Peninsula Project [15], described in more detail later in this chapter, residential TOU participants actually showed greater peak load reductions than RTP participants. This makes sense as RTP structures will not create a great effect unless the market price dictates such measures. In this study the RTP structure was extremely effective at reducing load congestion in the distribution system when needed even though it did not always create higher savings for customers. It was also found that the loads from TOU customers changed more abruptly at the beginning and end of peak periods which could have adverse effects on the electrical grid without some form of mitigation strategy.

An alternative, or addition, to charging customers higher prices during certain periods of the day, is to allow for a demand response program in which customers are given incentive to reduce energy consumption by being payed if they respond to a demand response event. For this to happen, a baseline consumption value must first be determined and then the price offered for demand reduction will determine the economic incentive for the customer to reduce demand. Without demand response programs utilities suffer from underutilization of infrastructure due to the requirement to have the capacity to meet the infrequent peak demands. Furthermore, without the ability to reduce demand during periods when the generation capacity is being reached, the price of energy increases exponentially during these periods causing higher prices to be transferred to the customers. With the ability to reduce demand during the extremely high periods, price spikes can be reduced or eliminated. [2]

According to M.Violette [7] the potential benefits of demand response in organized electrical markets include more efficient resource allocation, driving technology innovation, and increasing industry productivity. He suggest that it will not be possible to prevent large electricity price increases without further adoption of demand response mechanisms due to the growing electrical loads and increased capital cost of additional plants and infrastructure.

Borenstein, et al., [2] also notes that demand charges have been used for years in commercial and industrial markets to charge customers for their peak loads and contribution to the need to build more power plants. The natural progression from demand charges as technology allows more detailed energy measurements is CPP which can be implemented in all electricity markets including residential. A tremendous benefit of RTP and TOU pricing structures, that makes them very suitable for residential markets, is that they do not require individual contracts as needed for demand response mechanisms to be put in place. Demand response programs usually involve tricky preliminary decisions such as determining the baseline in a way that does not promote higher use during non event periods and determining where to draw funds to pay out incentives for demand reduction. There are many system benefits that can result from demand response mechanisms as will be discussed throughout this chapter. The Federal Energy Regulatory Commission (FERC) has even endorsed the concept as a counterpart to generation reserve, meaning the number of backup and idle plants can be reduced, which will in turn reduce energy cost and have positive environmental impacts.

There are certainly many issues that must be considered when implementing changes in rate structures or demand response programs. They will not be discussed here but are covered thoroughly in other papers such as that of Hist, et al [20].

2.2 Thermostats

Erikson, et al.,[24] concludes from the results of a two-year residential demand response pilot program with customers of Public Service Electric and Gas Company (PSE&G) using two way communicating meters and communication thermostats that technology does make a difference in aiding energy savings. The pilot program gave communicating thermostats to half of the participants to test the effect of TOU rate structures and CPP events with and without technology enabled response. The technology enabled customers reduced their on-peak summer demand by 21% and CPP event demand by 47% while the information only customer reductions were 3% and 17%, respectively. The thermostats were set to react to pricing signals by adjusting the temperature set point. The on-peak and CPP rates were significantly higher than the base rate during summer months. The on-peak rate ranged from two to three times higher than the base and the CPP rate

was 15 times higher in certain months. The CPP rate was nearly doubled from the first year to the second, yet no significant increase in reduction was found from this increase. The original CPP rate of \$0.69 was sufficiently high to lead customers into action; there was either no ability or will to reduce consumption further, even when the rate was doubled.

The ability to reduce load was hindered in the winter because there were few electric heaters in the population and the technology enabled customers showed only a tiny amount, 3%, of peak use reduction during on-peak periods. They were, however, willing to shed additional load, 27% more, during CPP events. The information only customers shed more load during the TOU peak periods, 7%, and an additional, 14% during CPP event.

A second finding in this study was that the information only customers had larger year-round energy use reductions on a percent basis. Due to the nature of the thermostat control, little overall reduction was found in either customer group during summer months, as consumption was simply shifted, but the information only customers showed higher reduction overall and especially higher reduction during the on-peak winter months when technology was less effective at creating energy savings. This suggests that while technology certainly aids reduction when it can, energy information may lead to higher energy conscientiousness in customers and more energy saving habits. However, it was also observed in the customer satisfaction survey that the customers with the technology enabling devices were more excited about the program.

From this study it is clear that technology enabling devices provide greater energy reduction when possible, and provide a “cool factor” to the customer, but the energy information helps create energy conscientiousness in customers that can lead to greater energy savings by creating an energy reduction habit. While the variability in occupancy behavior and differences in day to day savings are briefly mentioned, this study does not use this data to develop a method of predicting future load reduction for a specific period.

Nevius, et al.,[29] examines the impact of simply installing programmable thermostats in customers homes. This study concludes that installing these devices in the homes of an energy conscience customers does not lead to savings because it is likely that they already practice temperature setbacks, and installing these devices in the homes of non energy conscience customers does not lead to energy savings because they are unlikely to set back their temperature. This conclusion, while more of a social then technology study,

supports the effort to provide energy information and technology enabling devices coupled with energy rate structures that allow for bill savings due to energy reducing behavior in order to encourage and enable all customers to reduce energy use.

In one of the Pacific Northwest GridWise™ Testbed Demonstration Projects, the Olympic Peninsula Project, Hammerstrom, et al.,[15] evaluated a complete smart grid demonstration involving demand response mechanisms controlled by wholesale market prices to manage feeder overload and curb peak energy consumption. Many possibilities of smart grid technology were demonstrated and valuable insight into customer interactions and acceptance of demand response programs were gained. In relation to thermostat control the project created custom algorithms based on user comfort specifications that controlled the set point of the residential thermostats during changing grid conditions and corresponding price fluctuations. Interestingly, less than 1% of customers chose comfort over economy, while 67% chose balanced comfort and economy and 10% preferred economy (22% had no price reaction). The most common customer chosen heating and cooling preferred set points were 72 and 78 respectively, though the range of selections, especially the maximum and minimum settings, varied by much more. The results of the study showed that it is possible to maintain customer comfort with minimal interaction after the initial setting of control conditions, and that the thermostats can effectively act as a resource for load shed. This project used the market price to determine the importance of different request and thus the thermostatic loads were not simply reduced during peak hours to a preset comfort constraint, but were shifted into the hours when the market price was the lowest. In effect, preloading occurred, heating or cooling beyond the set point when real time market prices were low, due to the logic of the control algorithm. Interestingly there was higher overall consumption and a higher peak demand due to the controls, yet this allowed the peak loads to be reduced while better maintaining comfort conditions. Residential customers were very accepting of the control enabling technology and associated price reductions in general, although excessive preloading was met with less favor. A large part of the customer acceptance was probably due to their ability to see their historical energy use in 15 minute intervals and to set thermostat schedules to override the demand response control for future periods giving the customers full control of their comfort when it mattered most.

This project also clearly demonstrated that Internet based control was highly successful and that

despite sporadic connectivity at times the resources performed well in default modes until communications were re-established. The thermostats themselves were also used in some cases as signaling devices for high electricity prices. There were also cases in which wireless repeaters were needed due to distance or materials and additional thermostats were installed to serve this purpose only . The project did note the difficulty in finding qualified electricians, knowledgeable of thermostat control wiring, to install these devices.

While these projects and research studies demonstrate the effectiveness of thermostatic demand response controls and price signaled temperature set points at lowering demand, they do not provide a predictive model that may be used to evaluate the effectiveness of similar controls in separate populations and locations. A tool, such as the one being developed by this research project will allow preliminary simulation of situations similar to those evaluated in these projects and allow utilities to develop strategies that best meet the needs of their customer population. It will also be able to predict energy and cost savings for an individual customer given their specific decisions for automatic control of devices based on energy prices.

2.3 Electric Vehicles

Hadley, et al.,[14] simulates the effect of a growing electric vehicle fleet on utility demands over the next 20 years. The simulations, using data from the US Department of Energy (DOE), were completed with the Oak Ridge Competitive Electricity Dispatch (ORCED) model which has been developed over the last 12 years. The simulations analyze 13 different regions for the effects on emissions, cost, load, and other utility factors. Of the many simulation results, two trends stand out as important related to this research. First, it is expected that additional generation capacity will be required in most regions to accommodate vehicle charging by 2020 and in almost all regions by 2030 unless technology is used to control charging via demand response mechanisms. Also, it is concluded that with demand response mechanisms in place it is possible to actually lower the overall generation cost of electricity. This is due to the utilization of more efficient plants and optimization of load profiles. Hadley, et al., also makes the point that current electricity infrastructure is under-utilized, especially during off-peak times. The addition of PHEVs will not effect peak loads, if charged at night, but, instead, will increase the utilization of the electricity infrastructure. However,for this case to be realized it will be necessary to integrate new technology allowing the grid to respond more quickly to

changes in supply and demand to ensure reliability.

The charging profile of a PHEV can vary greatly in peak demand and length depending on the size of the battery pack and the charge rate. It is expected to see charge rates between 1.4 and 6 kW depending on the circuit it is charged on and a wide range of charge times from just a couple hours to over 10 hours depending on many factors. The preferred charging time for the utilities is during nighttime, off-peak hours, for the reasons discussed above, yet it is predicted that the customers will prefer to plug in as soon as they are near an outlet because they will be by the vehicle and will want to charge as soon as possible in case the vehicle is needed later. It will require a price incentive, or regulations, and smart charging technology to encourage the customers to charge in the nighttime hours. If cars are charged in the evening (beginning between 5 and 6 PM) , they will increase the peak demand in the summer requiring additional generation capacity, and increase the evening peak in the winter requiring more drastic ramping of power plants.

Parks, et al.,[36] examined the effect of 4 different PHEV charging schedules on the Xcel utility grid concerning energy cost, emissions, and load. The charging schedules were 1) Uncontrolled, 2) Delayed, 3) Optimized, and 4) Continuous. Cases 1-3 assumed all charging happened at the house. Case 1 assumed cars were plugged in when the driver arrived home and the car charged till full. This case was based on GPS tracking of a real car fleet. Case 2 assumed a simple delay or timer device was used, and case 3 assumed a more technically advanced system allowing the utility to turn cars on and off when optimal. Case 4 assumed charging stations were placed around the city so cars could be topped-off whenever they were not in use. The real Xcel generation mix was used and the simulations were completed using a utility forecasting software to create the base case and alternate cases.

It was found that by replacing 30% of the current vehicle fleet with PHEV-20s (20 mile electric range) that achieved 39% of their miles from electricity would increase the total load by less than 3%. However, there would be an increase in generation capacity needed in the cases without delay or optimization. Also by optimizing (case 3), the utility can better utilize the most efficient power plants during off-peak hours and support a massive penetration of PHEVs without needing to increase generation capacity.

The cost and emissions are sensitive to the generation mix of the utility but in all cases there is significant reduction in emissions of CO₂ and the overall \$/mile compared to current vehicle standards. The

best case for reducing emissions, cost, and utility burden requires technology to allow the utility to optimize the charging of vehicles with their load profile and generation availability while also allowing daytime charging to ensure the maximum miles traveled via electricity.

Kintner-Meyer, et al., [23] from Pacific Northwest National Laboratory also performed an analysis of the effect of PHEVs on electric utilities and regional power grids. The results showed that up to 73% of the US light duty fleet (cars, pickup trucks, SUVs, and vans) could be supported by the existing infrastructure with varying regional percentages. This would displace 6.5 million barrels of oil equivalent per day, which equates to 52% of U.S. oil imports. The scenario used involved electric vehicles with 33 miles driven per day on electricity and charged during off-peak utility hours. Kintner-Meyer, et al., also notes that under this scenario the grid will be fully loaded for most hours of all days, meaning maintenance will be more difficult and required more often, system reliability will be reduced because of lower reserve capacities thus making “smart” charging systems important for mitigating the extent and severity of any grid emergencies.

Electric vehicles equipped with the ability to feed energy back into the grid from their batteries could allow peak load reduction and act as a spinning reserve. Studies have been performed on this technology, but it is unsure at this time if such technology will be widely adopted by battery manufactures and utilities alike and thus Kintner-Meyer, et al., [23] focus only on the life cycle cost of PHEVs, without vehicle to Grid (V2G) technology, compared to other types of vehicles and their impacts on customer and utility cost.

The cost effectiveness of owning a PHEV depends on the price of electricity and gas, and the fuel efficiency of the car that would be driven instead. Their results stated that at \$0.12/kWh and \$2.5/gallon, given the driving and charging assumptions stated above, there is no premium associated with the purchase of a PHEV over a hybrid electric vehicle (HEV) with fuel efficiency of 56mpg such as the Toyota Prius (assuming an average vehicle life of 9 years and no resale value). Yet for any higher gas price, lower electricity price, or comparison with a vehicle of fuel efficiency less than 56mpg the PHEV is more cost effective. This means there are many cases in which a PHEV can save an owner thousands of dollars which will likely be a strong driving force for these vehicle in many markets where utility prices are low or where RTP or TOU pricing structures are offered. The analysis also concluded that the introduction of PHEV charging at night (a valley filling charging scenario) will lower the average price per MW of power generation for utilities and

thus they will have increased profit margins which can in turn be used as incentives for nighttime charging or put towards other grid upgrade program cost. [23]

In almost all practical future outlook scenarios for electric vehicles, a smart charging control platform to connect utilities and consumers is necessary. Without such technology peak loads will increase, additional generating capacity will be needed, and grid reliability will surely decline. However with such technology, the grid reliability can be maintained or improved (with V2G technology allowing flow from cars into the grid), and the overall utility prices can be reduced by utilizing more efficient plants and the existing grid infrastructure. The tool being developed in this project can aid in predicting the effects of electric vehicles on individual customer and specific utility population load profiles as these vehicles reach the market over the next few years.

2.4 Electric Domestic Hot Water Heaters

The Hammerstrom, et al., Olympic Peninsula Project [15] also evaluated demand response enabling control technology for residential electric water heaters. This project demonstrated the ability of water heaters to be used as a demand response resource via two way wireless communicating load switches. It also sheds light on customer energy preferences concerning water heaters, which interestingly were largely weighted toward comfort rather than economy with no users choosing maximum economy.

A load control switch was installed by a professional technician between the water heater and power supply. The load control switch was equipped with wireless communication capabilities allowing it to respond to curtailment commands and relay current status information to the utility system dashboard. This did not allow for the actual water temperature to be measured or controlled by set point so a probabilistic function was developed to control the water heaters based on the market electricity price. If the market price was ever below the previous 24 hour average the water heaters were not shut off, but if the price was higher than the average market price the probability of shutting of the water heater was increased according to the price standard deviation and the comfort requirement of the user. The market price evaluations occurred every five minutes. Users were allowed to set the on/off status of the water heater during any period of the day to override the demand response controls. The overall effect of the control enabled water heaters and

thermostats was the ability to reduce peak load by 5 to 20%, depending on the scenario for the maximum feeder capacity, without compromising customer comfort.

While this study proves the technology is able and collaboration is possible, it does not provide a predictive simulation model for determining the energy impacts of controlling water heaters via automatic customer controls or demand response events. The logical next step in the progression of evaluating smart grid control strategies is to create a way to predict what will happen in different utility populations with similar enabling technology.

In another of the Pacific Northwest GridWise™ Testbed Demonstration Projects, the Grid Friendly™ Appliance Project, Hammerstrom, et al.,[16] 50 electric water heaters were equipped with a Grid Friendly™ appliance controller, a small electronic controller board that autonomously detects underfrequency events and request that load be shed. This technology was used to stabilize grid performance during events when the frequency fell below 59.95 Hz. A drop in grid frequency indicates a mismatch between generation and load which may be caused due to failure of a large generator or sudden large spikes in load for which resource side controllers and spinning reserves cannot immediately counteract. Similar devices are installed in some substations and will create an area wide blackout if the frequency drops below a specified criteria in order to prevent more widespread outages. This situation is not ideal for many reason and the use of devices as immediate load shedding resource has many benefits.

This experiment was run for 1 year in different areas of Washington and Oregon. All appliances reacted to the frequency trigger reliably for periods ranging from 1/4 second to 10 minutes. Customers reported that they were not inconvenienced or that they did not even notice the device curtailment. Events requiring device curtailment occurred once a day on average. The load controllers were also used successfully to receive and act upon demand response signals sent during peak load periods. The water heater load peaks were closely related to the Pacific Northwest grid electric load peaks and the water heaters provided much higher load shed potential during curtailment events than the dryers used in the experiment, 0.1 to 0.7 kW, depending on when the event occurred making these appliances a prime demand response resource. Future cost effectiveness of such controls could be optimized by having the controlling devices installed in the appliances at the manufacturing sites. [16]

Depending on occupancy behavior and comfort constraints the effectiveness of electric water heaters as a demand response resource can vary. To correctly predict these effect of load control devices on these appliances the stochastic nature of occupancy behavior must be considered and the nature of the water heater modeled correctly.

2.5 Other Appliances

In the Hammerstrom, et al., Grid FriendlyTM Appliance Project [16] 150 dryers were also included as load shedding appliances. This is one of the first demonstrations of interactive “smart” appliances equipped to announce a load shed request. These dryers were manufactured for the project by Whirlpool Corporation and during the demand response event would request audibly and visually the request to shed load. The customer could press the start button a second time if they wanted to continue dryer use during this time. The study observed that the load profile for the dryer population was relatively flat during daytime hours and allowed between 0.02 and 0.2 kW to be shed per dryer during curtailment events depending on the time of day, day of week, and season. To address inconvenience issues the load of the heaters in the dryers was the only thing that was stopped during the curtailment events. The dryers continued to spin and cycle as normal until the power was restored to the heater, thus the events were mostly unnoticed by customers. Hammerstrom, et al., notes that to best provide innocuous demand response functionality appliance manufacture cooperation and collaboration will be needed.

2.6 Conclusions

The literature suggest that control enabling technology can help customers reduce peak energy consumption and that energy information can increase customer approval of control technology. Controls on large energy consuming devices and thermostats can have a significant impact on peak energy loads. Yet there are many factors that influence the effect of automatic control strategies. In order for a simulation environment to accurately model the effect of hourly residential control strategies it should consider specific location information, occupant behavior, building interactions, and variable pricing rates simultaneously. This review affirms the practicality and usefulness of a simulation tool such as the one developed in this

research project.

Chapter 3

Background and Methodology

3.1 Who is Tendril?

Tendril is an energy management technology provider offering energy management software, hardware, and services to customers and utilities. Tendril has developed a unique software platform with a suite of in-home devices that allow for the implantation of many energy management services. This section introduces Tendril's platform capabilities, devices, and applications relevant to the implementation of automated smart grid control strategies.

3.1.1 Platform

Tendril's platform, shown in Figure 3.1, connects utilities and their customers, allowing for the communication of real-time energy information and implementation of energy management strategies for reducing and shifting energy use.

In-home devices with wireless communication capabilities are connected to a home area network with a gateway allowing data to be transferred over the Internet. The utility back office and energy management platforms can also be connected via smart meter networks. Tendril's platform, positioned between utilities and customers, allows for energy information to be shared and controls to be planned and implemented by utilities and consumers. A communication platform between customers and utilities is critical for the implementation of reliable, real-time, and accurate controls on in-home devices. It is also important to emphasize that this platform allows for the mitigation of many problems related to comfort, utilization, and management that can arise with the attempt at controlling devices without a reliable two-way communication

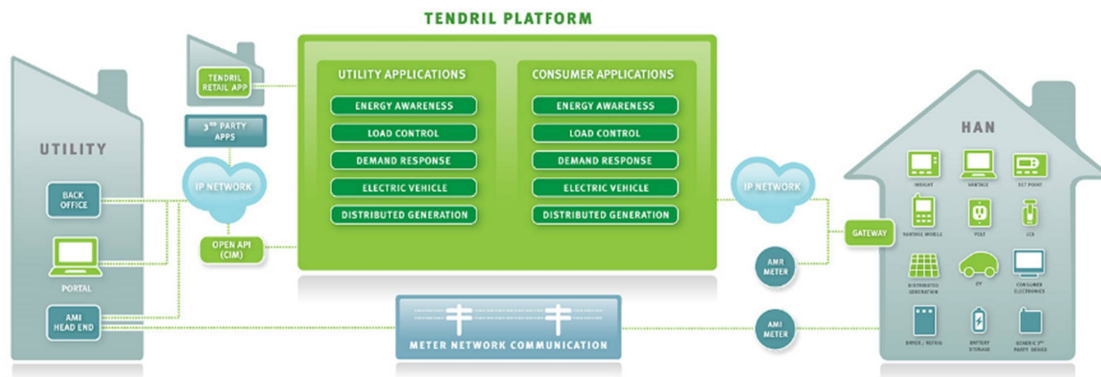


Figure 3.1: Diagram of Tendril's platform connecting utilities and customers

platform.

3.1.2 Devices

Tendril has many devices and software tools that make home energy management possible. These can be grouped into three main categories based on their primary function: communication, control, and network. Each of these layers is crucial to effectively share energy information and implement controls. They are currently sold only to utilities but are designed to be installed or implemented in homes and used by the utilities' customers.

Tendril offers three different interface options, shown in Figure 3.2 for viewing energy consumption and price information and for setting control strategies for individual devices. Vantage is a web-based portal where consumers can access their personal energy consumption history and price information. This portal allows homeowners to connect to all devices on the network and set price based control strategies that will be implemented automatically as the price of energy changes. Customers can use Vantage from any computer that has Internet access, even away from the home. Insight is an in-home device that relays utility messages to customers and allows customers without computers to participate in energy reducing and shifting strategies. Also, portable devices such as the iphone or ipad can be used to view and control energy consumption.

Tendril has three devices, shown in Figure 3.3, that can be installed in the home to control any device



(a) Vantage

(b) Insight

Figure 3.2: Communication Portals

or appliance. The Volt plugs into a normal 110/120V wall outlet and records energy information. It also allows for devices to be shut off by the customer via the web-portal, by automated price rules set in advance by the customer, or cycled by a utility signaled demand response event. The load control switch allows the same control as the Volt but for larger 240 volt appliances. It is installed between the device and the circuit breaker. The Set Point is a thermostat that allows the temperature set point to be changed based on the price of energy, or by the utility if the customer participates in a demand response program. It can also be controlled from anywhere by the customer via the web-portal. These devices are connected via a wireless sensor network to allowing communication with homeowners and utilities using the network display devices or web based portals.

Tendril also offers a variety of devices, shown in Figure 3.4 for creating a home area network. The Transport connects smart meters with Tendril's devices and servers to transfer and manage energy information. The Relay allows the home area network to be extended to reach devices out of range or in places that are hard for wireless signals to reach. The Translate allows homes with AMR meters to be included in control strategies and integrated with AMI solutions.

3.1.3 Services

Tendril's platform and devices allow for advanced energy applications such as energy awareness, load control, demand response, smart electric vehicle charging, and distributed generation to become a reality for residential customers. These different services are in varying stages of development. Highlighted below are a few of the applications that Tendril provides. In the Vantage Web portal homeowners can log in and see their current usage, expected monthly bill, and messages from the utility concerning load control events or price changes as seen in Figure 3.5. They can also view their historical energy use by month, week, day, or hour and compare their consumption to the average value of other similar homes as seen in Figure 3.6. This web portal also serves as one of the platforms for setting device controls. Figure 3.7 shows the temperature set point control allowing the set point to change automatically if the price of energy increases above a certain amount.

Tendril also has a utility web portal that allows for demand response load control events to be initiated



(a) LCS



(b) Set Point



(c) Volt

Figure 3.3: Control Devices



Figure 3.4: Network Devices

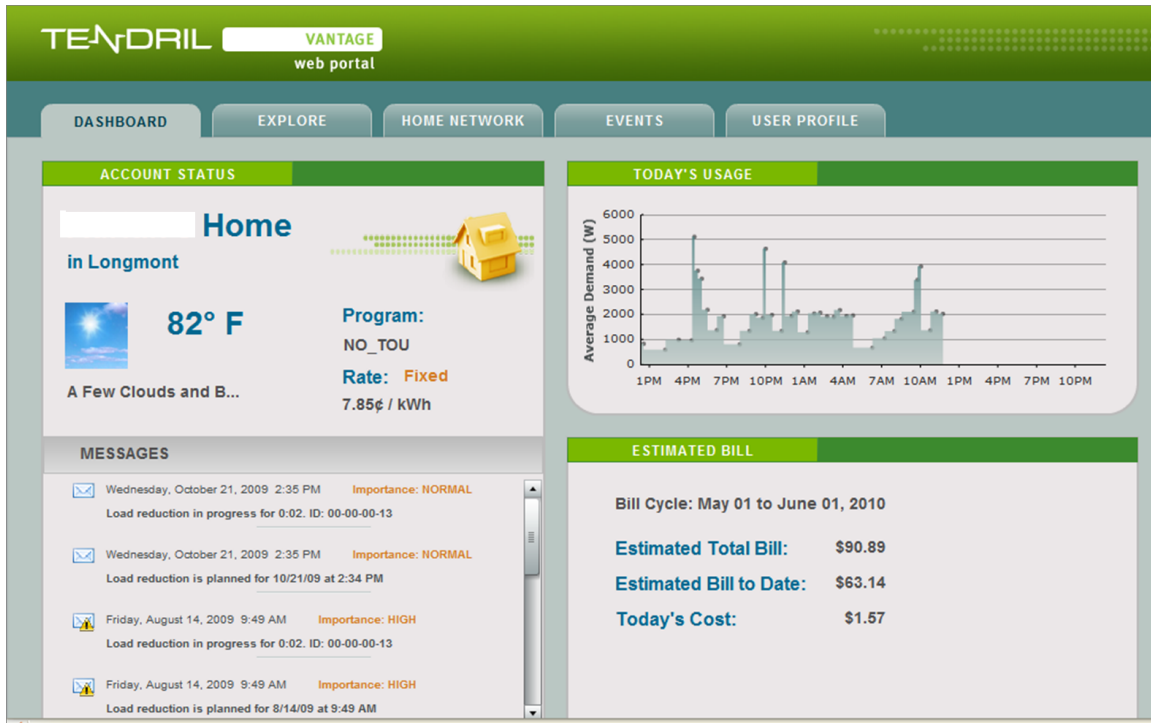


Figure 3.5: Dashboard on Tendril's Vantage web portal

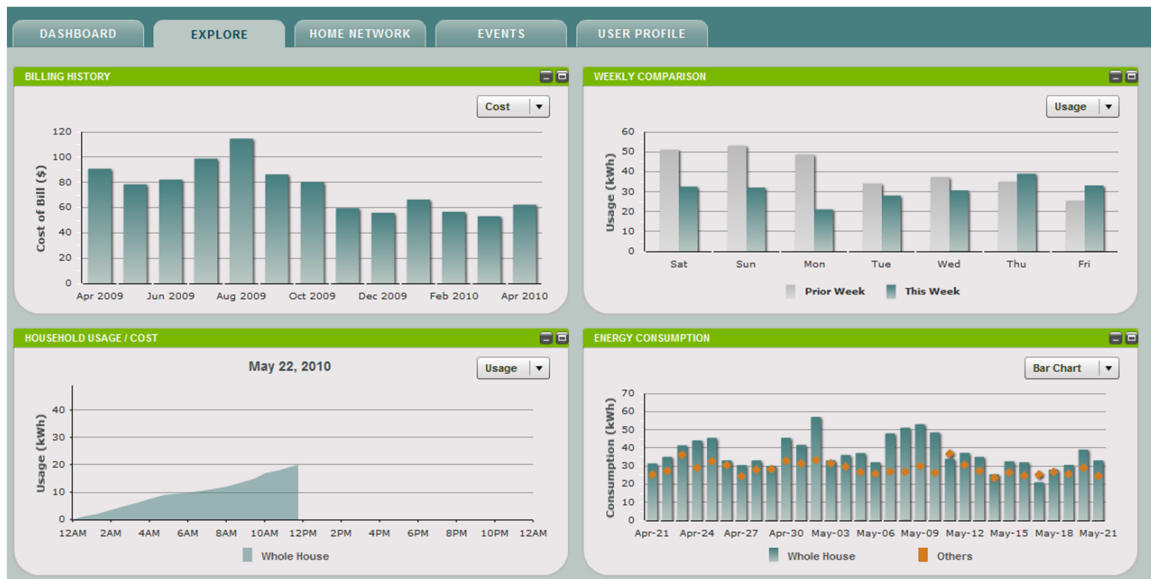


Figure 3.6: Consumption history on Tendril's Vantage web portal

The screenshot displays the Tendril's Vantage web portal interface. At the top, there is a navigation bar with five tabs: DASHBOARD, EXPLORE, HOME NETWORK, EVENTS, and USER PROFILE. The 'HOME NETWORK' tab is currently selected. Below this, a sub-header bar shows 'HOME NETWORK' and 'DEVICE SETUP'. The main content area is titled 'Control Adrians Tstat' and features three tabs: Heating, Cooling, and Manual. The 'Heating' tab is active. The interface includes two conditional rules for setting the thermostat temperature based on electricity prices. The first rule states 'When price of electricity is equal to or above 15 ¢/kWh set my device to 78°F'. The second rule states 'When price of electricity is below [blank] ¢/kWh set my device to --Select--'. A 'SAVE RULE' button is positioned to the right of the second rule. A 'CLOSE' button is located at the bottom center of the window.

DASHBOARD EXPLORE HOME NETWORK EVENTS USER PROFILE

HOME NETWORK DEVICE SETUP

Control Adrians Tstat

Heating Cooling Manual

When price of electricity is equal to or above 15 ¢/kWh set my device to 78°F

When price of electricity is below [blank] ¢/kWh set my device to --Select--

SAVE RULE

CLOSE

Figure 3.7: Controls on Tendril's Vantage web portal

in individual homes or entire populations of homes for all control enabled devices.

Tendril has the technology to control any device in the home. In the future Tendril would like to be able to suggest controls to individual customers and to be able to predict the effect of specific controls on energy consumption and cost. To do this, Tendril needs to understand individual device consumption as it relates to the variability of occupancy behavior and other factors such as home construction type and weather. It would also be helpful for Tendril to guide utilities in creating rate structures that incentivize peak energy reduction but do not significantly increase the total energy cost if the customer does not reduced energy consumption during peak hours. This requires knowledge of how control strategies affect the overall energy consumption when building thermal interaction and other variable factors are considered.

3.2 Research Methodology

The following research methodology was followed to develop the Tendril Control Analytic Tool used to gain the desired knowledge for this research project.

- (1) Obtain devices consumption and set point schedules
- (2) Build a home energy model
- (3) Obtain local historical weather data
- (4) Build a simulation environment to evaluate control strategies that take into account variable occupant behavior, weather changes, variable rate structures, and automatic control rules
- (5) Calibrate the building energy model to hourly consumption data measured by a smart meter
- (6) Conduct control simulations to answer customer and utility based questions and obtain the desired knowledge to improve future residential control strategy implementations, customer specific incentive programs, and development of cost equivalent rate structures.
- (7) Apply TCAT to a regional benchmark study in which control strategy scenarios are systematically varied to inform utilities of the most effective way to reduce peak energy consumption using a thermostat set point offset and time-of-use program

Chapter 4

Case Study Design

Device schedules in the home of a Tendril employee were measured over the course of several weeks during the months of October and November, 2009. The collection of detail energy consumption schedules from these devices was used to:

- (1) Discover the most practical path to peak energy savings and overall cost reduction.
- (2) Quantify the bounds of the potential energy and cost savings for individual devices and appliances.
- (3) Provide typical energy consumption schedules for the development of the Tendril Control Analytics Tool (TCAT)

4.1 Home Description

The house chosen for this experiment is a single family residence located in Longmont, CO. The house is approximately 15 years old, with a total floor area of 5470ft² (4720ft² of living space) including a three car garage and finished basement. The front of the house shown in Figure 4.1 faces southeast. The main floor contains the living and dining rooms, kitchen, study, family room, laundry room, half bath, and the garage. The living and dining rooms, as well as the entry way, have vaulted ceilings. The second floor has three bedrooms and two bathrooms. The basement contains a bathroom, bedroom, studio, and games room. The walls are wood frame construction, with vinyl and stone siding, and the roof is tile. All glazing, including the sliding glass doors, is clear double pane. Blown-in fiberglass insulation of approximately 8 thickness is installed in the attic, fairly evenly.



Figure 4.1: Picture of home used in Tendril Case Study

The house is occupied by a family of four, two adults and two children. One adult works from home while the other works out of the home and is often traveling for work. The two children attend school. The house is served by a DX air conditioning unit for cooling, and a natural gas furnace for heating. Domestic hot water is provided by a natural gas water heater.

A variety of lamp types are used in the residence. Many bulbs are incandescent because they are wired to dimming switches. The most common lamp type found in the house is a 60 W incandescent bulb. This house has two large entertainment areas and an office with desktop computers. There are two full size refrigerators. The homeowners installed an outdoor heated swimming pool in 2008 which operates from April to October. The pool pump is scheduled to run during evening hours, usually from 9PM to 5AM on weekdays, but runs throughout the day on weekends during the swimming season. There is an electric dryer and stove as well as dish and clothes washers.

4.2 Circuit Measurement

Power consumption data was collected on the following circuits/devices in the home: 1) pool pump, 2) dishwasher, 3) dryer 4) oven, 5) refrigerator, 6) furnace fan, 7) family room with entertainment center, and 8) office with computer equipment. The current in the circuit was measured at 1 minute intervals from Oct 9 to Nov 20 (43 days) using current transducer clamps on wires in the circuit breaker. The Hobo CTV-A 20Amp CT clamp[35] was used with the Hobo U12-006 4-port external data logger[33] shown in Figure 4.2 to collect circuit data. Temperature in the home was measured using the Hobo U10-001 temperature logger[32]. Measured data was transferred to a personal laptop using a USB data cable and a .csv file was created with the Hoboware Lite software[34].

Once collected, the data was imported into MATLAB[26] (version R2009a) and readings from separate read periods were combined into a single data array for each device. Circuit noise and other devices on the circuit, if present, were filtered out using algorithms and criteria specific to each device. Date stamps were also combined into an array for each device. Data was collected for 1-2 week periods between each successive download. For missing data periods, caused by the need to download the data off the Hobo's, an average value for similar days and hours was used to create a continuous data array. Hourly consumption and on/off



(a) Current Transducer Clamp

(b) Hobo Measuring Device

Figure 4.2: Measurement equipment

schedules were created for each day, as well as weekend, weekday and average day.

4.3 Meter Data Collection

Energy consumption data from smart meters is stored on Tendril's servers. To obtain this data in a manageable format a function was written in MATLAB that opens and runs a Curl script through the windows command prompt to retrieve the data from the servers. Inputs to this function include, 1) the specific location of the data on the Tendril servers, 2) the network ID of the home area network for them home, 3) the start and end date of the meter reads that are desired, 4) a user name and password to either the specific home area network or the server on which the data is stored, 5) a name for the file to which the data will be written. When this script is executed, an .xml file is created with accumulated consumption and cost data beginning with 0 at the start date given.

To pull this data into MATLAB another function was created to open and parse the .xml file and create a data array of accumulated consumption, accumulated cost, and date stamp for each meter read. The meter reads vary in decimal and time accuracy depending on the meter technology. The house used in this case study has a smart meter with 1 kW granularity with reads occurring at 15 minute intervals. The time stamps of the reads vary for a variety of known (and unknown) reasons. It is important to note that the reads only change as the meter steps by 1 kW so during periods of low consumption the meter read may not change over a period greater than 1 hour.

A MATLAB function was created to manipulate this meter data and create an hourly consumption schedule. This function, first, adjusts the meter reads from the Greenwich mean time stamp to local time and adjust for daylight savings time using a stored data structure of DST begin and end times for past years. Consumption and cost data is then linearly interpolated across the hour time stamps to calculate the total consumption and cost for each hour. This function then applies an algorithm that checks for periods with missed reads and removes this data from the array so the average hourly schedules are not effected by inaccurate data interpolation. In the initial data collection procedures, without this check, missed read periods during some months significantly skewed the data. When reads are missed the data is linearly interpolated across the time period and as a result all hours receive the same amount of energy consumption which causes the average daily schedule to become increasingly flat. A separate MATLAB function was used

to create the average hourly schedule for the recorded period. An hour vector array was used to average the hourly consumption for different days and hours allowing a 24-hour, average day schedule to be created for each day of the week.

These hourly consumption schedules give significant insight in to the consumption habits and trends of the homeowners. This data allows actual days, or typical days (e.g. weekends, weekdays, or Mondays) to be compared or analyzed individually. This hourly data also allows for peak consumption periods to be identified and targeted for energy reduction control strategies. Measured device schedules can be compared to the overall energy consumption for the home for any day or hourly period to calculate the percentage of energy use associated with each measured device. This is especially important when evaluating peak reduction potential for individual devices and control capabilities.

Chapter 5

Case Study Results

5.1 Measured Circuit Data

Data was recorded for 43 days in October and November 2009. Two weeks into this recording period the family shut down the pool for the winter. This action had a very significant effect on the total energy use for the home yet did not effect the individual appliances. Also, during this recording period the thermostat was set to the heating mode, so fan energy associated with heating was measured for this period. Cooling energy was not collected at the circuit level in this case study, but it is possible to infer upon the cooling energy use from the meter data as explained in the next section.

The consumption data was collected with the Hobo's and CT clamps, imported onto a personal laptop, and stored in a .csv file via the Hoboware Lite software. This data was then processed using MATLAB as described previously.

The CT clamps measured the current at one minute intervals. This value was multiplied by 120 to calculate power in Watts. A power meter was used to measure the voltage in the circuits. On multiple occasions the voltage was measured at approximately 120 V. For each appliance or circuit, two groups of charts are shown. The first group displays the actual power measured in the circuit for the recording period and a histogram of the power readings. The histogram gives a more clear view of the variability in device power consumption for different operating modes or tasks. For example, the power consumption of the dishwasher differs by more than a factor of five when heating water vs. when cycling.

A second group of charts shows the average energy consumption for each hour on typical days (e.g.

weekend, weekday, and the average day) as well as the average operating time for each hour. It is clear that some devices/circuits are used differently by the occupants on weekends and weekdays. Also it can be seen in some cases that the runtime and energy consumption schedules differ due to the variability in power consumption.

The dryer is run infrequently sometimes with entire days between operation. There are two distinct operating modes that on a few occasions overlap. The histogram shows the electric heating element uses approximately 1.2 kW when on. The motor for rotating the load and any other loads (e.g. electronic display) may use anywhere between .1 and .8 kW. It appears that the cycling and heating loads usually occur separately but on a few occasions seem to be combined.

The consumption and operation schedules vary only slightly despite the large variance in power consumption, likely because the loads often happen within the same hour when the dryer is run. Though the heating element in the dryer is a significant load, on average the consumption schedule is much more moderate with a peak of just over .25 kWh at 1pm on weekends. The dryer is run most often in the morning and mid-day hours and less in the evening or typical on-peak hours. It is evident from this graph, and also shown in many others, that one family member works from home and often runs completes chores through out the day. It is interesting thought to see that on weekdays the peak dryer load occurs in the early morning, while on weekends it does not even start until 10AM and peaks in the afternoon.

The charts and description of the other appliances and circuits is provide in Appendix A. Insight into the occupant behaviors and schedules are inferred from the graphs.

Summing all of these average energy consumption profiles together accounts for the majority of energy use in the home. Yet, there are still other miscellaneous plug loads, lighting loads, and a few appliances such as an old fridge in the garage and the dishwasher that are were not measured. Figures 5.3 and 5.4 show the aggregate consumption of all the average day schedules for the appliances measured during the recording period. The first shows the average day schedules under the total energy consumption measured from the meter for the period with out the pool pump. The second includes the pool pump to show the drastic difference the pool pump makes on the total energy consumption profile. The average day schedule with the pool pump is much flatter as the pool pump runs through the night.

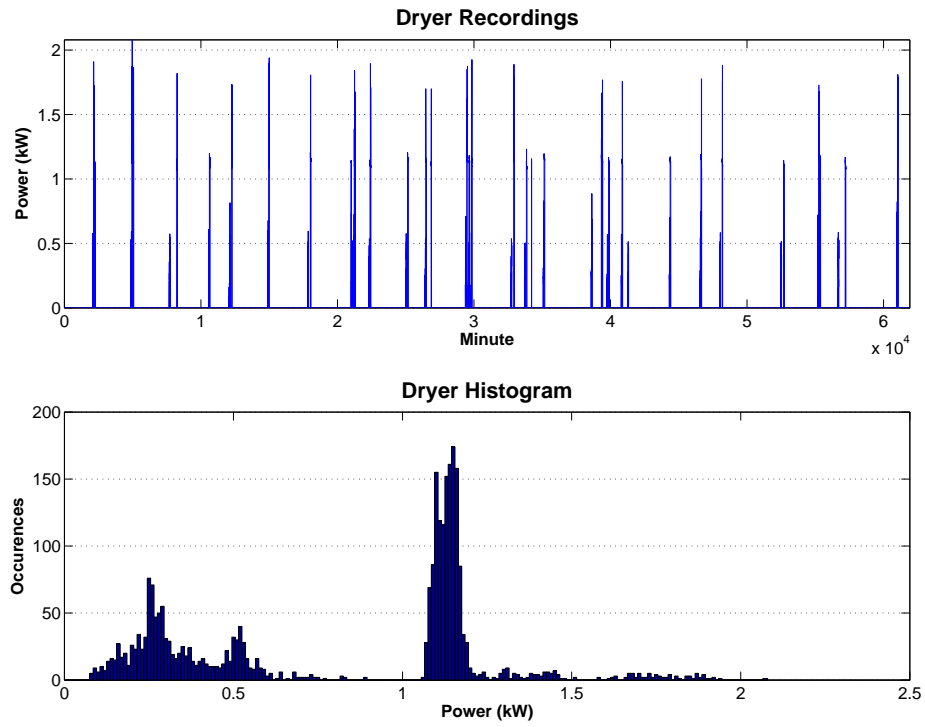


Figure 5.1: Dryer recorded data

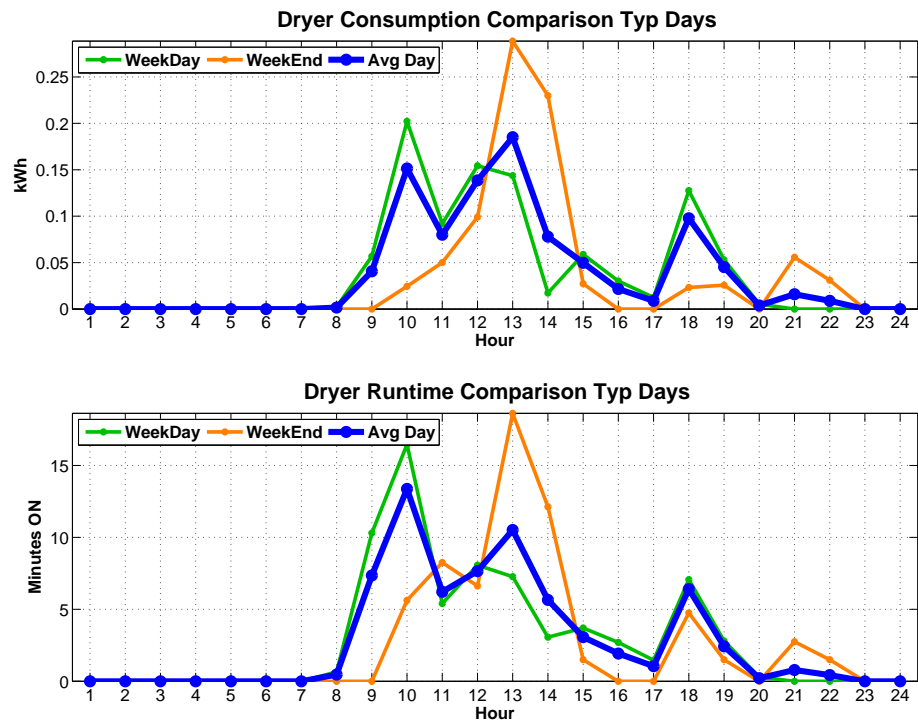


Figure 5.2: Dryer average schedules

The pool pump accounts for 36.2% of the energy consumption during this period. The study room and family room are the next highest at 10.8% and 8.7%. The appliances all consume between 1.5 and 3.6%, while the oven is slightly higher at 4.1%, and the furnace fan consumes 5.3% of the total energy use.

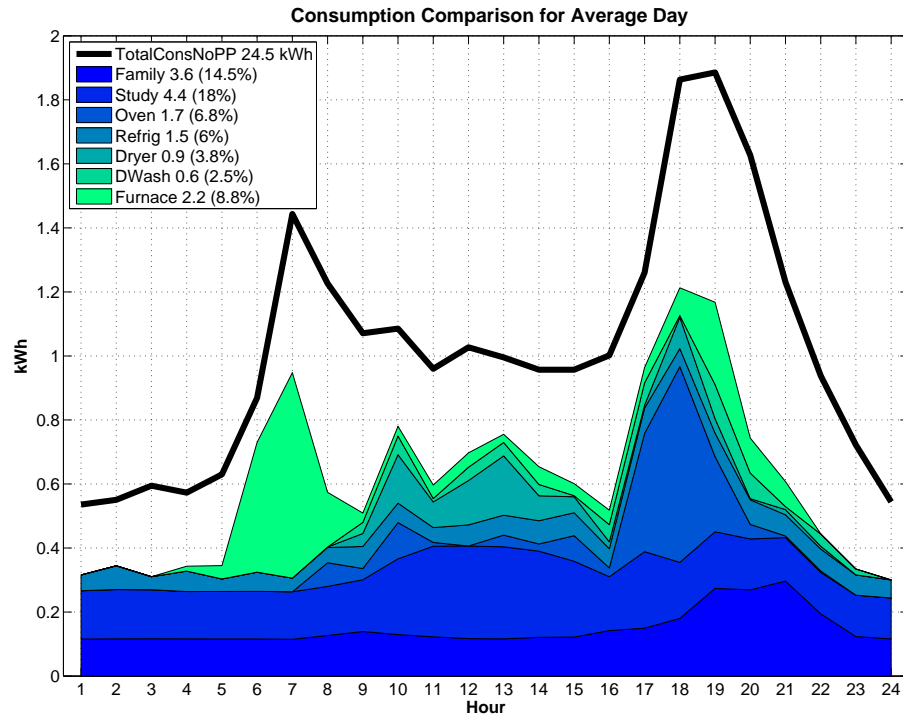


Figure 5.3: Measured Energy Consumption in Tendril Home with no Pool Pump

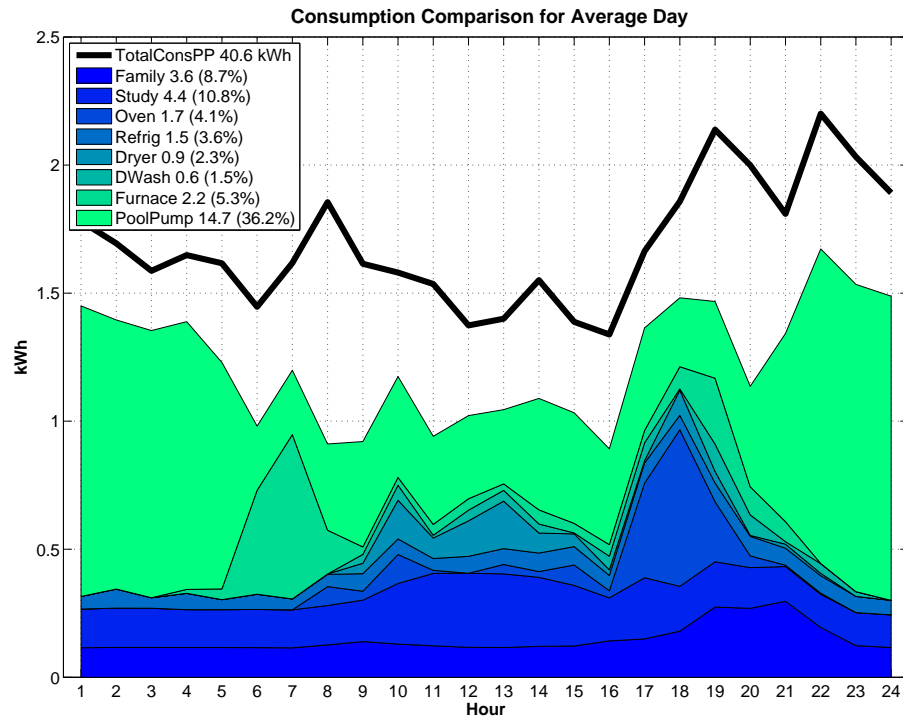


Figure 5.4: Measured energy consumption in Tendril home with pool pump

5.2 Peak Reduction Potential

This study was intended, in part, to gain knowledge about on the potential for peak energy reduction for individual appliances. Figure 5.5 shows the portion of the consumption that occurs between 16 and 22 o'clock. This period covers the peak appliance loads and a portion of the typical pool pump evening run time. Compared to the overall energy use, the percentages during this period for all appliances are similar in distribution, but slightly lower, at less than 4%. The oven is an exception, because most of its total energy use occurs during this period its percentage has increased to 10%. The pool pump is by far the largest energy consumer during this period at 28.4% with the family and study rooms also contributing significantly to the total peak load at roughly 10%.

Figure 5.6 shows the total energy use for each appliance and circuit during this period in a bar format. The appliances/circuits have been ordered from left to right with the most intrusive control scenarios being on the left. This chart also shows the amount of money that could be saved per month if the appliance or circuit were shut off completely during the peak period and the energy use were completely shifted to off-peak hours. This first case assumes a \$0.06/kWh difference between on-peak and off-peak rates. Under these circumstances, the family room, study room, and oven, have a moderate savings of between \$1.00 and \$1.50 yet these are all far to intrusive to be used in a control event. The appliances will all save less than \$.50/month even if shut off completely between 16 and 22 o'clock for this recording period. The pool pump however is a device that causes no inconvenience to shut off and can save almost \$7 per month under this specific rate difference and peak-period.

Another case for peak reduction potential is evaluated to see how the appliance fair under different circumstances. The next case involves a 4 hour peak period between 16 and 20 o'clock but with a much higher rate difference between on and off-peak periods. This peak period significantly reduces the pool pump energy consumption percentage because it cuts out the typical time the pump starts every evening. However it is still the largest energy user on average for this period. The oven is also higher in the scenario as the peak period ends closer to its typical boundaries. In this scenario the appliances still offer almost no incentive, even when completely shifting all energy use to off-peak periods. The family, study, and oven are all above

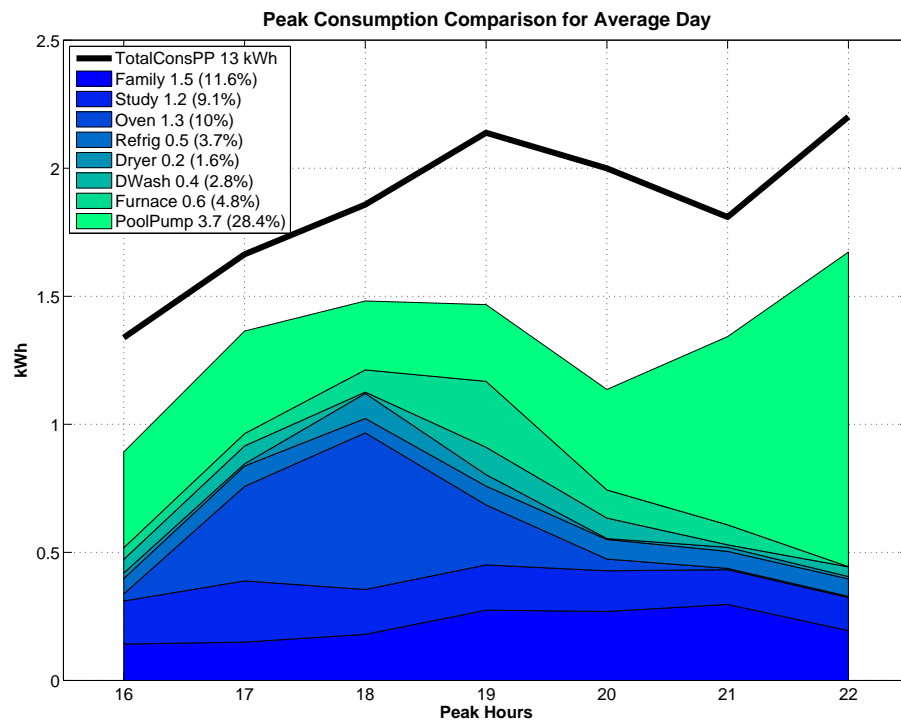


Figure 5.5: Peak measured energy consumption in Tendril home with pool pump (6 hr peak)

\$1/month, but that is not worth the intrusion a control event would cause. The pool pump offers nearly \$11 in peak reduction cost savings despite much of its consumption being removed from the peak period.

From this analysis, it is clear that there is little cost incentive to invest in smart appliances for the owners of this home. This is a very important finding because Tendril currently invest resources in developing control capabilities and network integration for smart appliances. This study suggests that this should not be done in hopes to offer home owners the chance to save money from peak energy reductions. There are other reasons to invest in smart appliance technology, but based on this study, for these homeowners, cost payback should not be a reason. There are some other energy use applications such as the oven and entertainment equipment that could be controlled during peak periods that would offer moderate savings but at a high inconvenience making it unlikely to ever happen.

These finding show that the most effective and cost efficient methods to deploy smart grid control technology is to focus on a few major energy consuming devices, such as a pool pump. In this case study the pool pump was already set to run in the evening, yet it still offered potential for peak energy savings based on the assumed peak periods. If the pool pump were run during peak periods as it is in the night hours, it would have the potential for approximately \$14 in the first scenario and \$30/month savings in the second scenario.

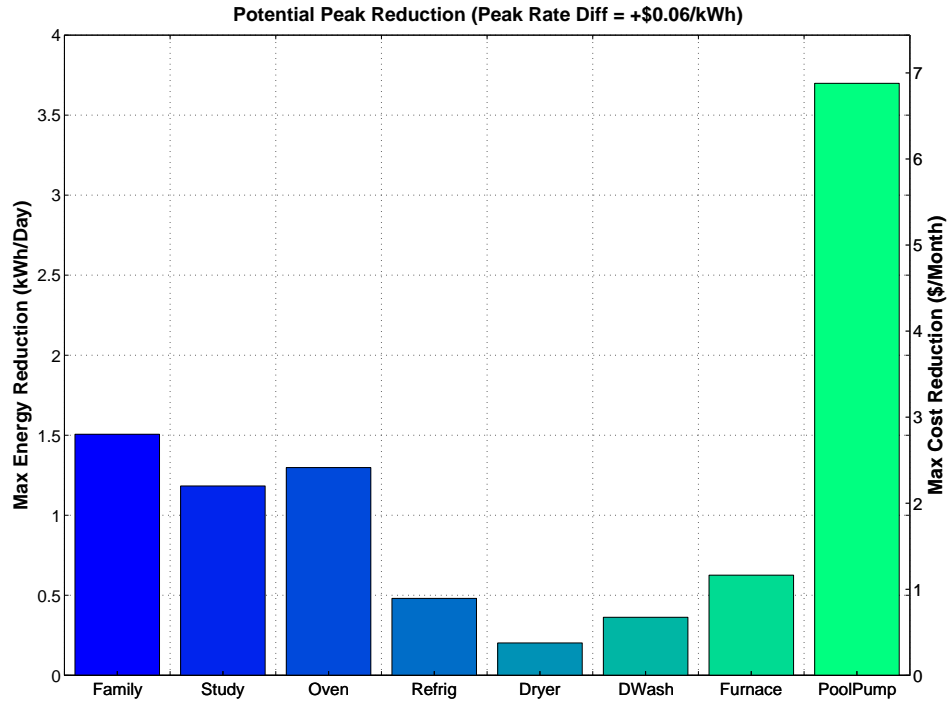


Figure 5.6: Potential energy and cost reduction for all measured appliances(6 hr peak)

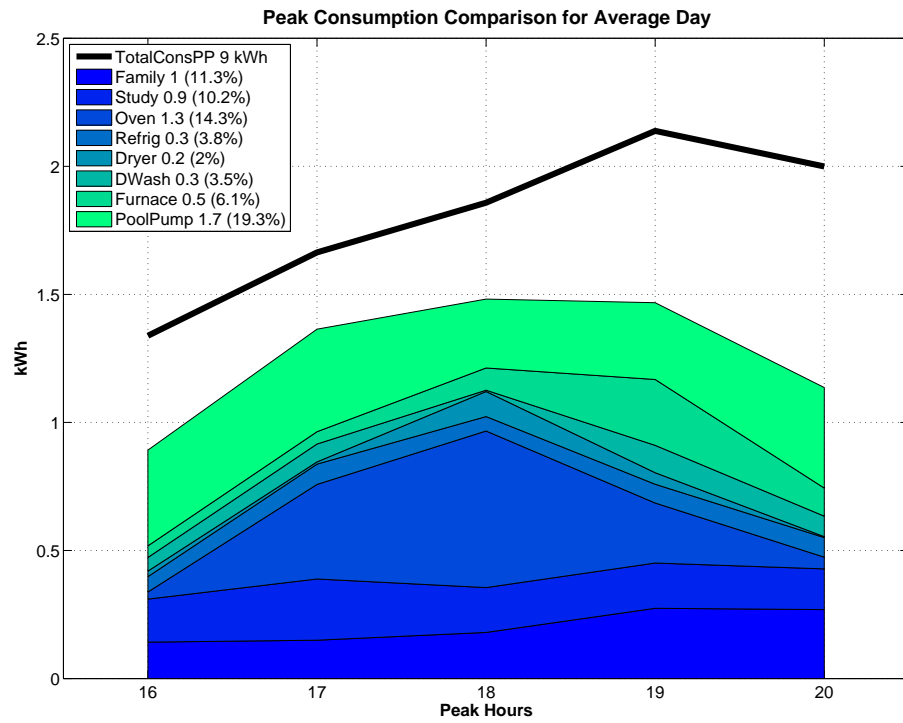


Figure 5.7: Peak measured energy consumption in Tendril home with pool pump (4 hr peak)

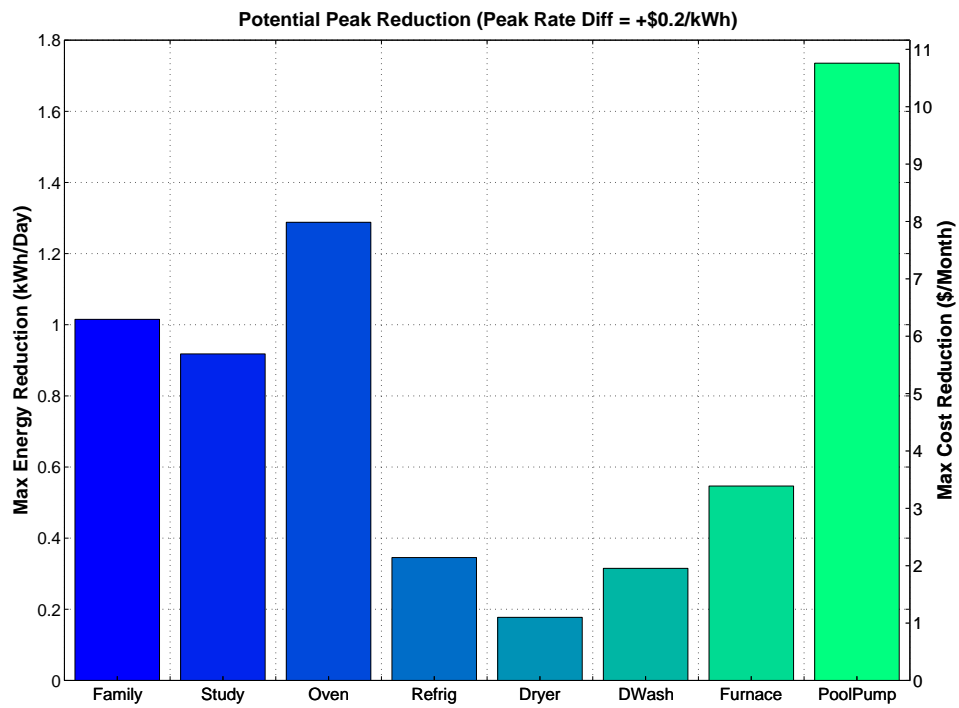


Figure 5.8: Potential energy and cost reduction for all measured appliances (4 hr peak)

5.3 Meter Data Analysis

Using the meter data to gain insight into peak reduction potential offers some significant conclusions and direction in formulating a plan for evaluating peak energy control strategies. As part of the study for peak reduction potential meter data was collected for the entire year of 2009. For each month an average day schedule was created. Figure 5.9 shows the average consumption schedule for each month in 2009 and also sums the total energy use for the average day as, shown in the legend. This chart reveals significantly more energy consumption potential in the summer months, but more importantly there is also much more potential for peak energy reduction. It is possible that the schedules for appliances may change for these months but more likely that these additional loads are due to cooling loads. There is also a known addition of the pool pump consumption starting in March and ending in October for the year of 2009. This is evident in the night time energy loads as seen most clearly between 1 and 5 AM.

For comparison, a similar chart is shown in Figure 5.10 for a comparable home of a different Tendril employee that does not have an air conditioner or a pool pump. The winter months have nearly the same total energy use and schedules besides a little more energy use during the day for heating. For this home the energy use in the spring and summer months the total energy use is less than the winter months. It appears that the schedules are roughly the same other than for the decrease in heating energy. This suggests that the main difference between heating and cooling months for the home in the case study is the added cooling load for the DX coil air conditioner and the pool pump energy in the evenings.

This is the most compelling case for tool to evaluate peak energy reduction and cost savings having the capability to simulate the effect of cooling temperature set point changes on a home's energy use. Yet this is not easily done as many different factors must be considered to accurately evaluate energy consumption as a result of temperature set point. An entire building energy model must be considered with weather and thermal interactions from other appliance controls if accurate energy and cost savings are to be calculated.

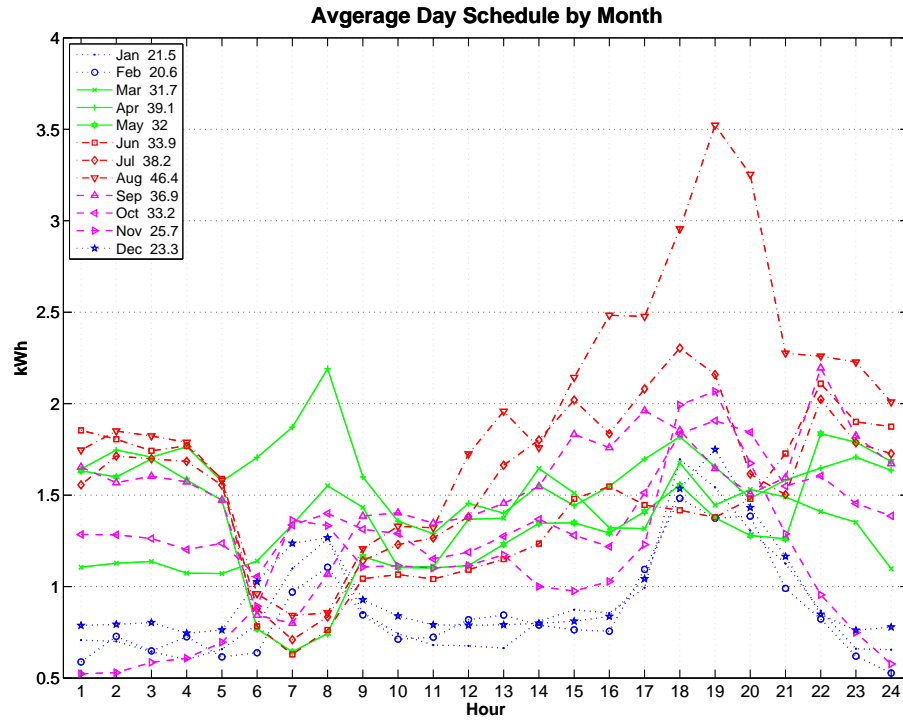


Figure 5.9: Average day schedule for all months in 2009 for case study home

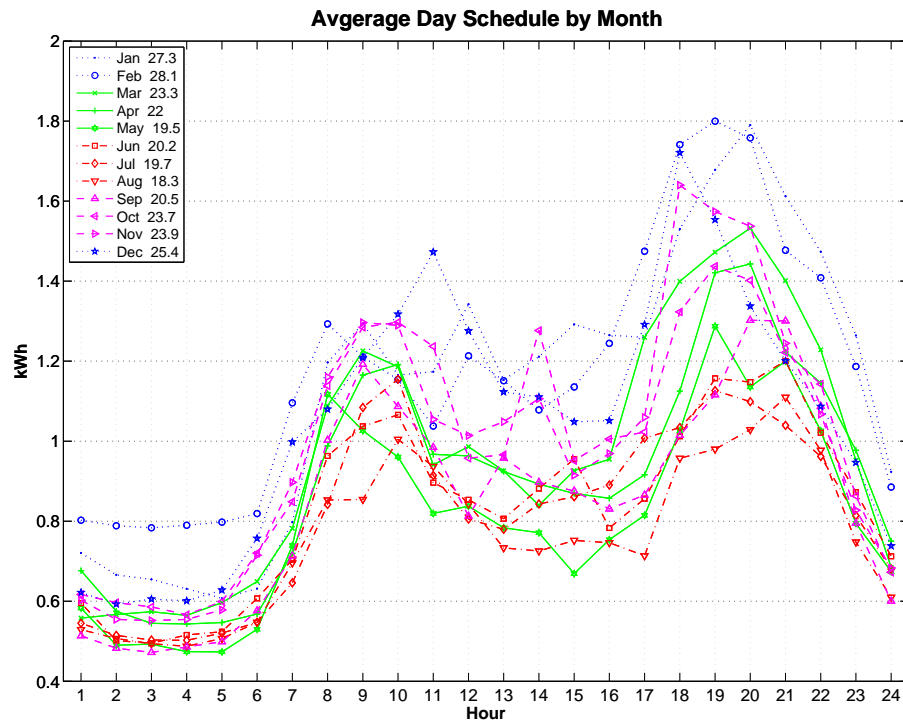


Figure 5.10: Average day schedule for all months in 2009 no AC

Chapter 6

Building Energy Model Calibration

It is clear from the case study that cooling energy can account for a significant portion of summer peak energy loads. Thus, a control enabling thermostat is one device that should certainly be implemented in a peak energy reduction strategy for any home with an air conditioning.

To evaluate energy savings from a variety of set point control strategies, a physics based building energy model is needed to account for the effects of construction features, building thermal interactions, and weather variables on the temperature in the home. Yet, before using a model to simulate control strategies, it is necessary to match the simulated output from the building model to actual metered data to ensure the model represents the true performance of the building.

Typically, the process of calibrating a building energy model is completed for residential homes only using monthly meter data from the utility. However, monthly data will not allow for accurate calibration of control strategies implemented at the hourly level. For this research project, a building energy model must be calibrated to the hourly load profile of the home.

For this case study, a building energy model was created in EnergyPlus [46], a software program that allows for hourly simulation of building energy consumption. The building energy model was first calibrated for the October-November period of measurement in the case study. Furnace fan energy and inside temperature measurements were available for this period to guide the calibration of the building construction and end use profiles. The building model and schedules were ultimately calibrated to fit the average daily energy consumption profile for July, a month with higher peak reduction potential, to be used in evaluating automated control strategies.

6.1 Weather Pre-processing

EnergyPlus uses an .epw weather file which contains a variety of weather variables such as temperature, humidity, sky cover, snow accumulation and many more. The values in this file are considered to be the 'typical meteorological year' (TMY), however, for accurate simulation of a specific historical period, the real weather data for that period is needed. To obtain this, a MATLAB script was created to download historical weather data from the closest available weather station to the home and replace the .epw fields with this data for the period of simulation.

Unfortunately, not all of the variables contained in the .epw file are available from the weather station. Most notably, the solar radiation for this location was not available. Thus, the TMY solar data, in the .epw file was used. The available solar radiation can have a significant effect on the building load in the form of solar heat gains through windows. Calibrating the building model to hourly consumption values with no knowledge of the actual solar heat gains for the time period will undoubtedly induce error in the model calibration.

Code developed by Chad Corbin was utilized for the process of updating the .epw weather file with historical weather data. The difference between the outdoor dry bulb temperatures from the .epw file and the obtained historical temperatures are plotted in Figure 6.1. A plot of the average daily profile is shown in Figure 6.2. These plots reveal that the TMY and actual historical weather temperatures vary by up to 14.5°F during this period and show a significant difference in the average daily profile as well. This demonstrates the importance of using real, local weather data to ensure simulation accuracy.

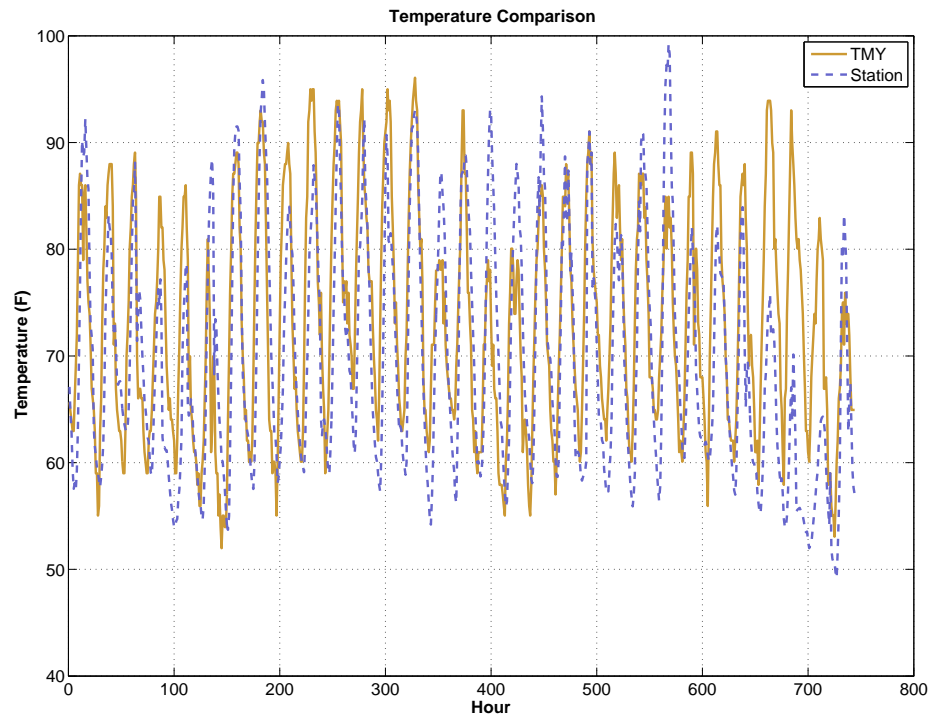


Figure 6.1: Outdoor Drybulb temperature comparison for July

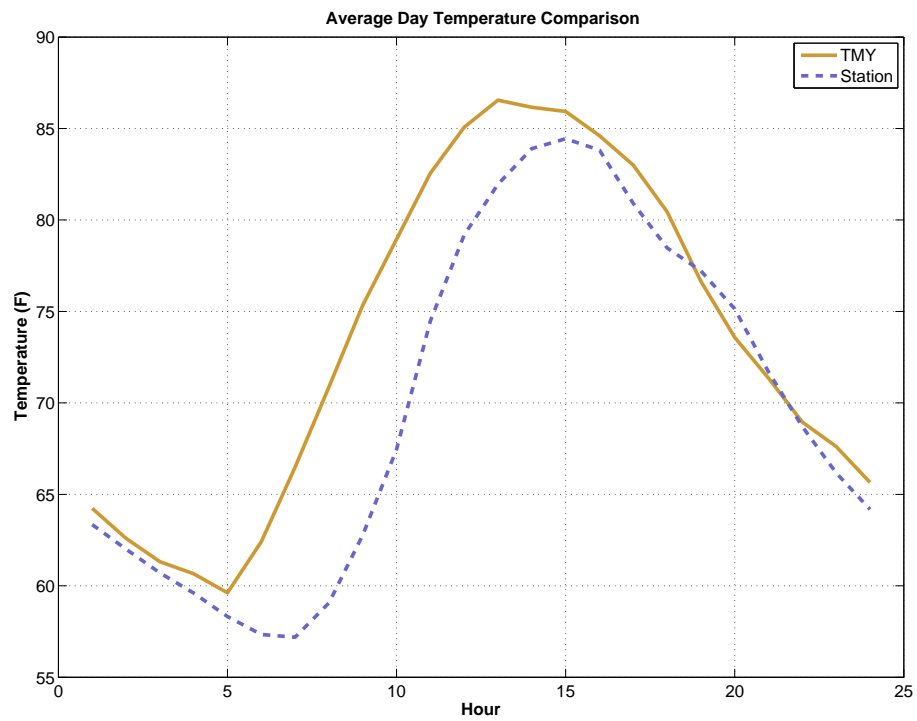


Figure 6.2: Average day temperature comparison for July

6.2 Schedules and Model Manipulation

The appliance schedules as measured for the simulation period were applied to the model. Also, a set point schedule was created that fit within the bounds of the indoor temperatures measured with the Hobo as shown in Figure 6.3. The occupants have a programable thermostat, but from the measurements and occupant interviews it is known that the temperature is often allowed to float during the day and controlled manually in the evenings.

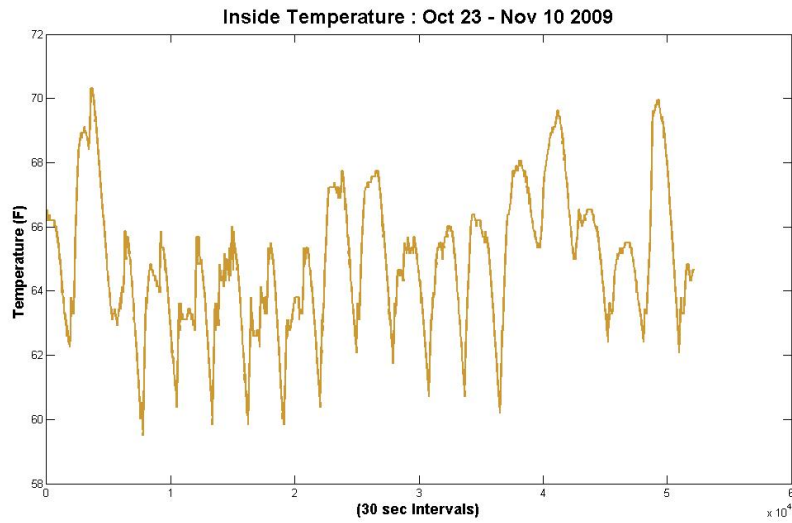


Figure 6.3: Measured internal temperatures for Oct 23 - Nov 10

The set point schedule was adjusted to meet the fan energy load as shown in Figure 6.5. In addition to the measured circuit data and the calibrated set point schedule, a lighting schedule from the Building America Benchmark[19] (BAB) was initially used as the lighting schedule for this period. Figure 6.4 shows the normalized BAB lighting schedules for each month of the year. The November lighting schedule was used for the initial calibration.

The initial calibration attempt is shown below in Figure 6.5. Also, this chart includes the measured appliance schedules. This, however, does not include the washing machine, extra fridge, and many miscellaneous plug loads throughout the house. It is clear from the known data that the Building America Benchmark lighting schedules do not accurately represent this specific house, especially in the evening hours.

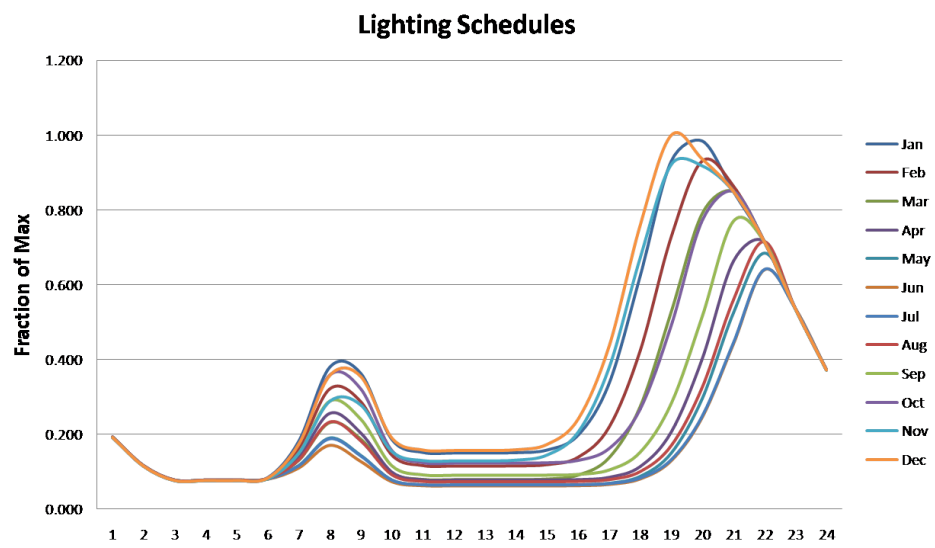


Figure 6.4: Building America Benchmark Lighting Schedules

Many iterations were performed tweaking building construction elements, appliance thermal loads, fan efficiency, and other factors until a reasonable building energy model with accurate heating energy consumption was produced. Meters which measure energy consumption for any end use in the home as well as variables that measure heat gain, temperatures, on/off fields, etc. can be obtained from the model results. As a learning exercise, and to verify that the building was performing properly, over 250 output meters and variables were examined.

The set point schedule was tweaked until the simulated fan energy matched the measured fan energy. The appliance loads were applied to the model as measured. The BAB lighting load was adjusted to not be quite as aggressive in the evening. Miscellaneous loads were applied to the model so that the simulated energy profile, matched real meter data. The building construction features, thermostat set point, and miscellaneous plug loads and lighting profile used for the calibrated October-November model are all based on sound engineering judgement. The final calibrated model for the measurement period is shown in Figure 6.6.

Next, the pool pump energy profile was added to the building energy model and an attempt was made to calibrate the model to the measured consumption profile in July. Removing the miscellaneous plug loads and applying the pool pump causes the simulated model output fit nicely under the July consumption profile. The BAB lighting schedule for July was then added, and, as expected, was a bit too aggressive in the evening as shown in Figure 6.7. This home has a high lighting power density, but based on occupant surveys, many of the lights are rarely used. Thus, it is reasonable to reduce the lighting load slightly.

The two unknowns in this model are miscellaneous plug loads and the cooling load. Unfortunately, there is no measured set point data from this home for July. Therefore the July temperature set point schedule is based on occupant interviews. The set point schedule has been set such that the cooling load matches the profile observed for the summer months in the interval meter data. Miscellaneous plug loads have been applied with engineering judgement so that the simulated consumption profile in July matches the actual measured consumption profile with less than 5% error for all hours of the day. The final calibrated model for July is shown in Figure 6.8

This calibrated model, including schedules, will be used in the Tendril Control Analytic Tool simula-

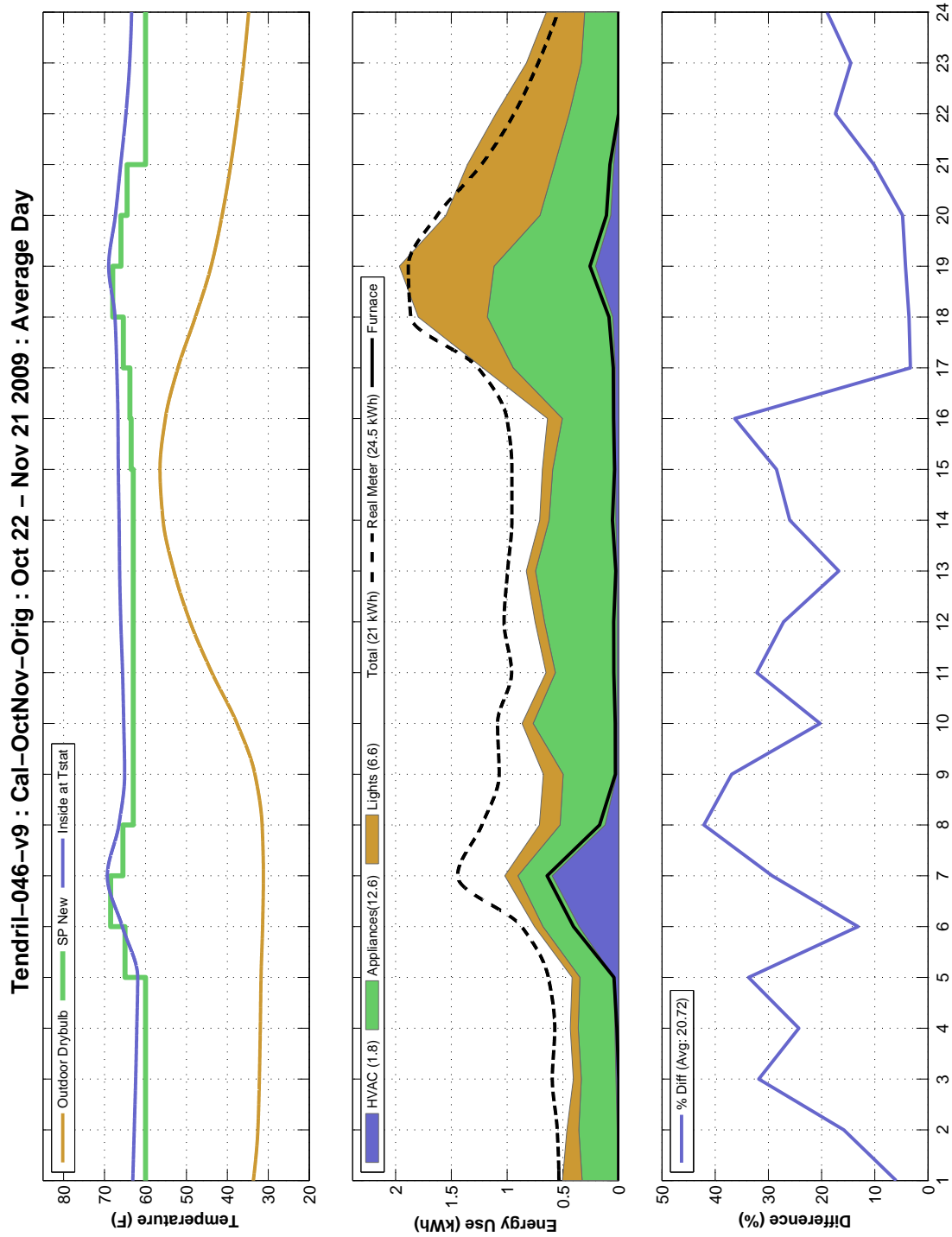


Figure 6.5: Initial calibration attempt for measurement period

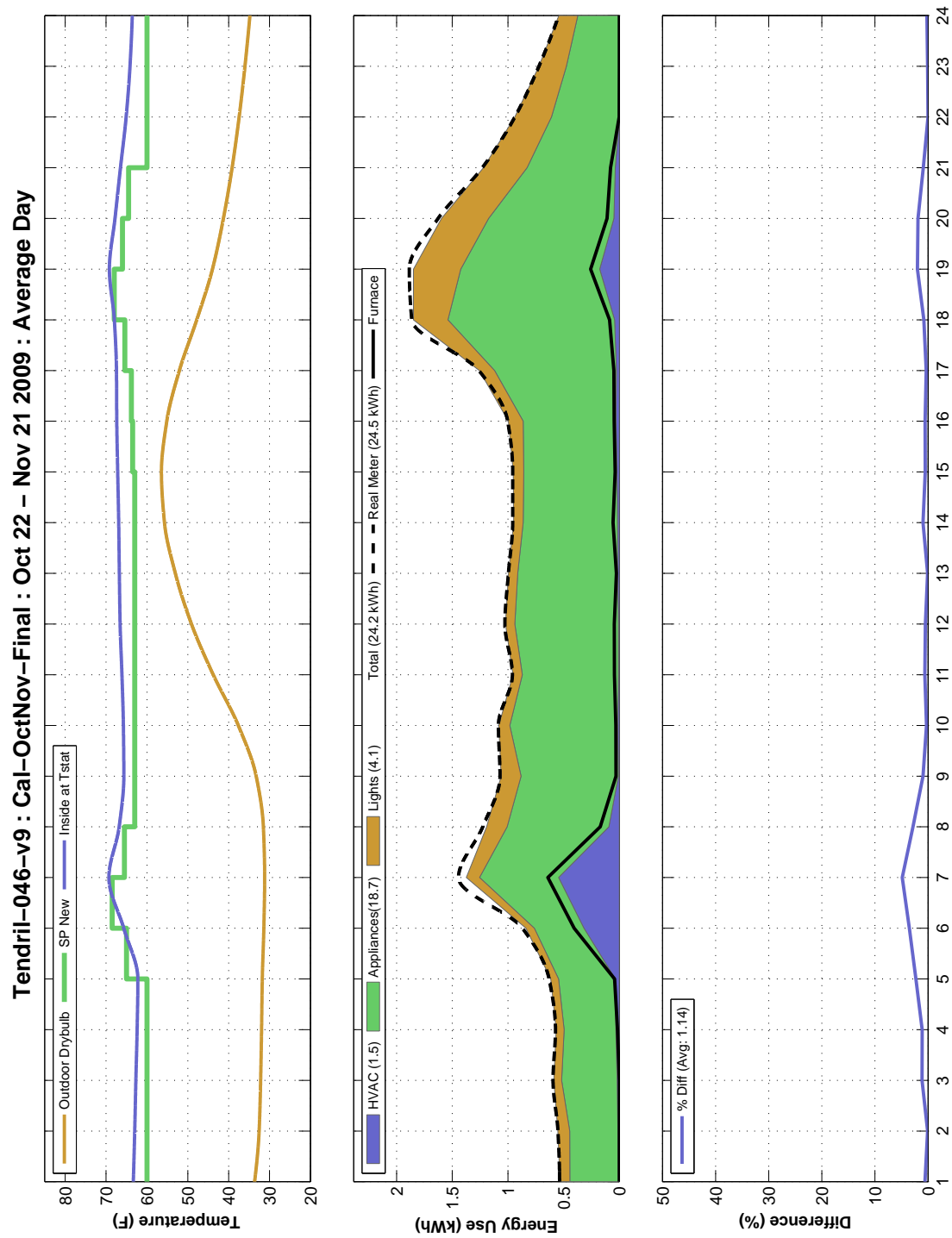


Figure 6.6: Calibrated model for measurement period

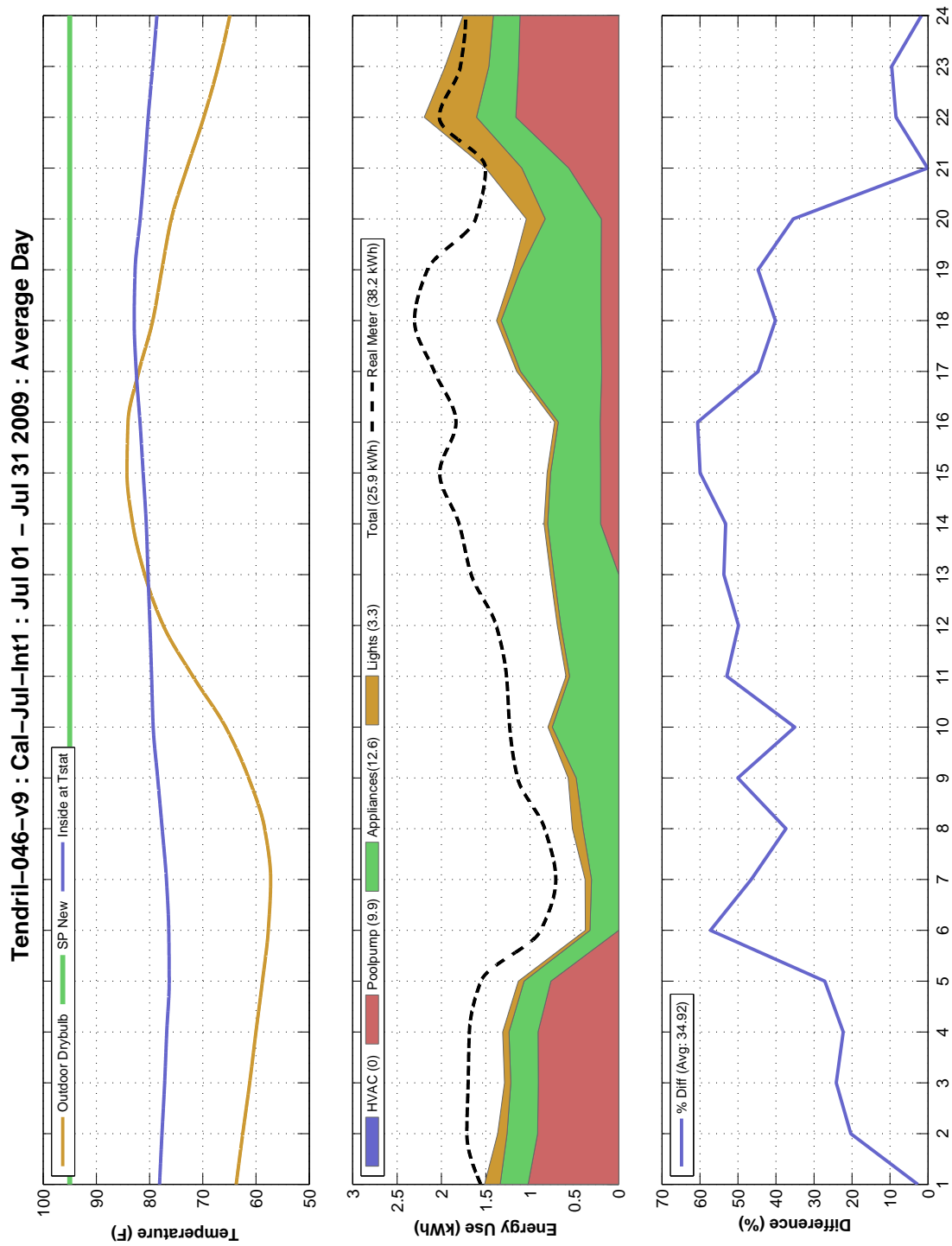


Figure 6.7: Initial calibration attempt for July

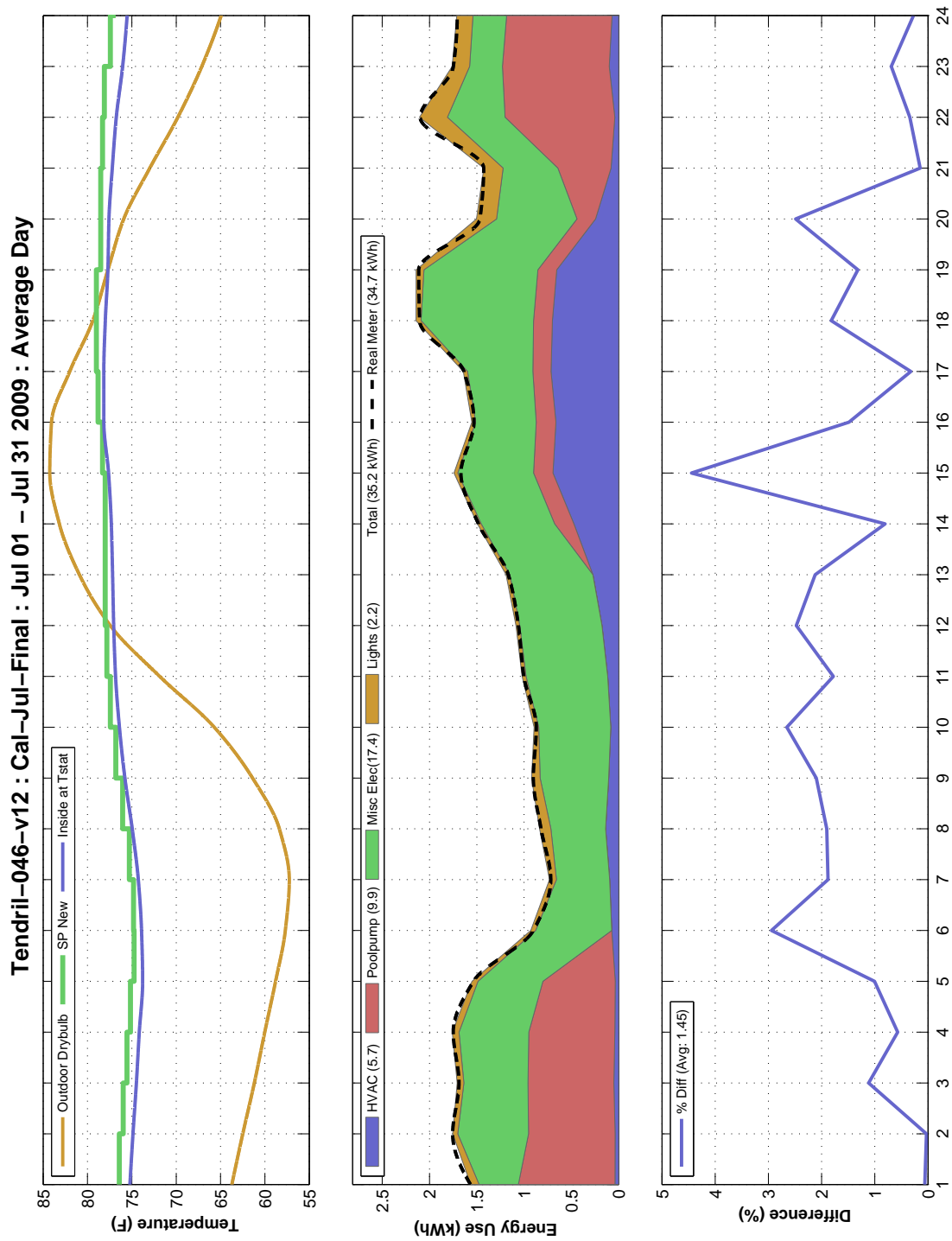


Figure 6.8: Calibrated model for July

tions to evaluate the effectiveness of automated control strategies for a variety of end uses.

Chapter 7

Development of a Control Analytic Tool

This chapter describes the simulation environment developed and the software tools used to develop and execute the control simulations. Also, the simulation process is outlined and the reasoning for design decisions are presented.

7.1 Introduction to TCAT

The Tendril Control Analytic Tool (TCAT) is designed to provide customers and utilities with the ability to calculate energy reduction and shift as well as cost differences resulting from peak energy use reducing control strategies. The capabilities and applications of this tool were developed and updated in constant collaboration with Tendril's engineers and product management teams, making it relevant to the real needs of Tendril and their customers.

TCAT simulates hourly energy consumption for a home based on its construction, the real device consumption and set point schedules of the owner, real local weather information, and most importantly, control rules applied to individual devices based on real time-of-use energy rates. Based on a set of control rules, it can analyze the impact on the energy consumption schedule and associated energy cost. The tool utilizes a MATLAB - EnergyPlus (MEP) environment developed in collaboration with the Building Energy Research Group at the University of Colorado to seamlessly run building energy simulations that account for the effects of building thermal interactions.

7.2 Software Selection

This control analytic tool utilizes two powerful software programs for gathering the necessary data, executing control algorithms, simulating a building energy model, calculating the results of the base and control simulations, and displaying this information in a clear and manageable format.

EnergyPlus [46, ?] is a free building energy simulation software tool provided by the Department of Energy's Building Technologies Program. EnergyPlus software is continually updated with new features and modeling capabilities including new systems and control capabilities making it preferable to other non-updated simulation software. Yet the most compelling case is the ability to utilize existing code developed by BERG for writing and saving input files via MATLAB. EnergyPlus reads a text file for input and also writes output as text files. Code developed by, and in some cases with, Chad Corbin, as part of BERG's MEP simulation environment, is used for the process of controlling EnergyPlus via MATLAB.

MATLAB [26] is a numerical computing environment developed by MathWorks[26] that allows matrix manipulations, plotting of functions and data, implementation of user created algorithms, and interaction with programs written in other languages. These features make it ideal for automating the process of data collection, schedule control, model simulation, and reporting. It is used in this research project as the driving engine to run the algorithms, pull in data from different locations, and automatically write the EnergyPlus .idf input files for the building energy simulations. It is also used to run EnergyPlus automatically from the windows command prompt, upload the meter and variable output files, calculates control results, and display the results in a series of charts.

7.3 TCAT Simulation Procedure

To offer a high level view of the processes involved in running a simulation with TCAT, a flow diagram is presented in Figure 7.1. This tool will calculate energy savings and shifting as well as cost reduction during the simulation period for a given set of control strategies and display this information in a series of automatically generated charts for the home owner or utility operator.

Simulation inputs include: 1) the name of the building energy model to be used, 2) the name of the

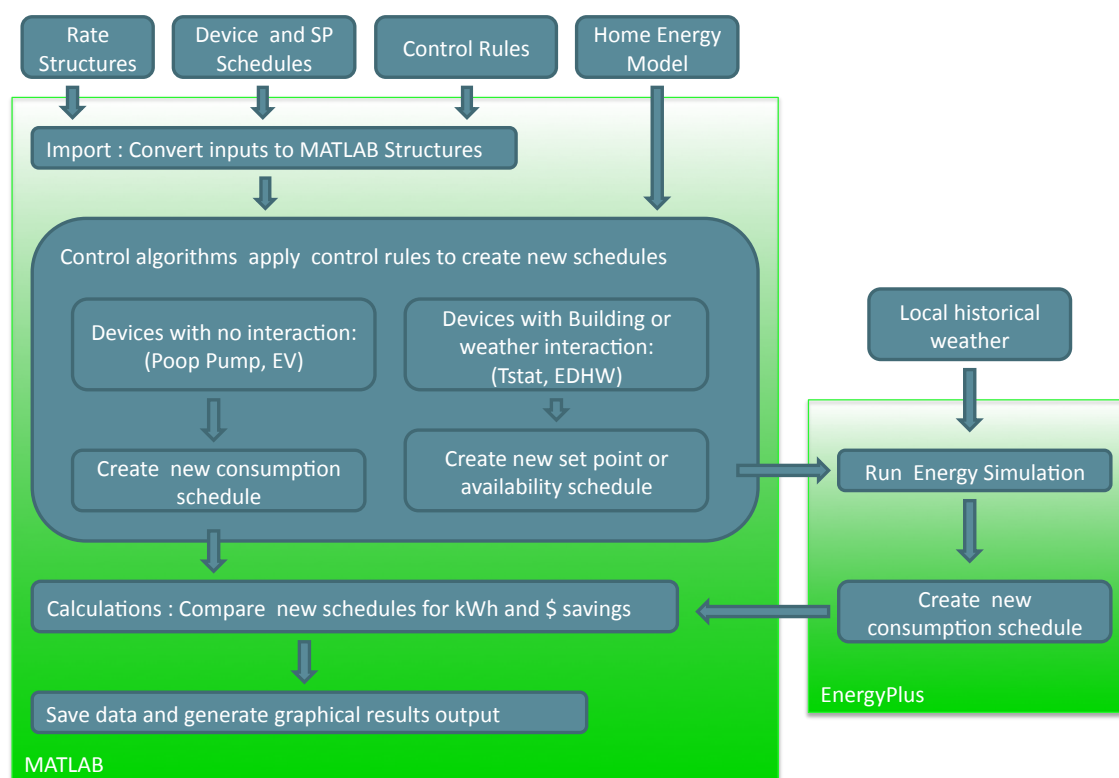


Figure 7.1: Flow Diagram of TCAT Processes

file with the stored customer rate information, 3) the name of the file with the stored wholesale utility rate information, 4) the name of the simulation case to be used for naming files and figures, 5) the name of the file with the stored device consumption schedules, 6) the name of the .epw weather file to be used, 7) and the dates to begin and end the simulation period. The following processes then take place:

- (1) All device and rate schedules are loaded.
- (2) Schedules to be use in the building energy simulation are written into a text string that can be read by the EnergyPlus software.
- (3) The EnergyPlus .idf input text file template is loaded into MATLAB where the schedule and date strings are placed into the locations preallocated by tokens (specific text strings that are found and replaced with the associated schedule or date string).
- (4) EnergyPlus software is run using the command prompt.
- (5) The .csv output files created by EnergyPlus are loaded into MATLAB and data is stored into structures using EnergyPlus naming conventions as field identifiers.
- (6) The base case calculations are completed.
- (7) New device consumption and set point schedules are created based on the control algorithms.
- (8) The EnergyPlus simulation process described in steps 2-6 is repeated for the control case
- (9) Control case calculations are completed as well as comparison calculations between the base and control case
- (10) Charts are created and saved showing the effect of the controls with new energy consumption and cost schedules shown in relation to the base case simulation schedules.

It is important to note that the process of converting schedules into EnergyPlus inputs and running this software adds significant time and complexity to the model that is not necessary for all devices. This functionality has been developed due to the need for analyzing important control strategies, such as thermostat set points, in a way that accounts for all the building thermal and weather interactions necessary

to accurately calculate actual hourly energy effects. This process is not necessary for all devices and so a distinction is made between devices with and without building interactions. For example, a pool pump or electric vehicle can be modeled simply as an electrical load and does not need to be processed in the EnergyPlus software.

Once the base case is simulated it is possible to run different control algorithms and simulate any number of control scenarios without needing to rerun the base case simulation. The results of each control case and its comparisons to the base case are computed and stored as unique entities identified by the building model, rate, case name and simulation period chosen by the user and can be accessed later if needed.

7.4 Control Simulation Design

This tool has been developed with two major objectives: 1) to improve the understanding and knowledge of an energy customer by allowing for the simulation of practical control scenarios that reveal what would happen in regards to energy consumption and cost if devices and appliances were operated differently, and 2) to guide utilities in implementing incentives for energy reduction that are beneficial to both them and the individual needs of their customers.

This tool and its control possibilities have been designed to represent the capabilities of Tendril's devices and control options. It's functionality takes into effect Tendril's current capabilities and their potential capabilities concerning data management and control implementation. Control simulations demonstrating this functionality can be executed now with any data that is made available or obtained by Tendril to gain insight into the application of different control strategies utilizing their technology even without automated data streams for obtaining data being implemented.

There are three notable control cases: 1) loads turned off (pool pump), 2) loads shifted without energy change (dryer, dishwasher), and 3) loads shifted with energy reduction (thermostat).

It is possible to simulate control strategies to answer many customer and utility questions such as:

Customer Questions:

- Would it save energy if I pre-cooled MY home in the morning to reduce energy consumption and

cost in the evening?,

- How much money could I save if I limited the operation of MY pool pump during the times with higher energy rates?
- How would a change in rate structure effect the results of MY control strategies?
- How much more energy and money will I save if I set MY temperature setpoint to 79° instead of 76°F during the peak periods?

Utility Questions:

- How does a flat rate of \$0.10/kWh compare to our wholesale rate for this customer during the month of July?
- What flat rate is needed to equal the wholesale equivalent cost of energy for this period?
- What time-of-use rates could be used to incentivize peak energy reduction without raising the overall cost of energy for the consumer if controls are not implemented?
- How much money will I save and how much money will the customers save with this time-of-use rate and using these specific control strategies to reduce peak energy use?

Based on the results of the case study, devices with little peak energy reduction potential are not controlled in these simulations. The focus for the controls implemented are to evaluate significant energy and cost savings potential, and thus only the appliances that can achieve this are modeled at this time. The output charts are split into two categories, customer and utility, with a chart generated with hourly data for the entire simulation period and a chart generated of the average day schedules over the simulation period. This allows the user to easily see aggregate effect of a control for the entire simulation period but also to analyze the variability in control effectiveness based on weather and schedule differences on individual days. The same four charts are generated for the control case but with emphasis on the total change in energy use due to the controls implemented.

Chapter 8

Simulation Results and Discussion

This chapter presents TCAT control simulation outputs accompanied with discussions of the specific case results. The first section focuses on a description of the chart types generated for graphical comparison of control strategy effectiveness at reducing peak energy use and energy cost. The controls used to generate the simulation results and the most interesting results for the control scenario are also discussed. The second section presents the results of specific control cases demonstrating TCAT's ability to answer control questions for customers and utilities concerning energy consumption and cost.

8.1 Simulation Results Output

For all results generated and displayed in this chapter, the calibrated building energy model of the case study home is used with the calibrated July schedules, except where otherwise noted. Different customer rate schedules are used as necessary. The utility wholesale rate used is a real, variable price schedule downloaded from the Independent Electricity System Operator website[21]. This schedule represents real hourly fluctuations in energy price for a utility in Ontario, Canada. This schedule is not meant to accurately represent the territory in which this home is located, but to provide a demonstration for simulations from the utility perspective.

Controls are implemented in MATLAB to change the schedules based on the price of energy in a particular hour. For the set point schedule if the price of energy is above a given value than the set point for that hour is changed. In the case demonstrated below the original set point schedule was varied from 72°F to 75°F during different periods of the day. The control algorithm used raises the set point to 78°F

during peak hours as signified by the customer energy rate. When the control period ends, the original set point schedule is left unchanged with no compensation made for previous temperature setbacks. The pool pump is simply turned off during peak hours with no additional runtime being added in off-peak hours as it is not a critical load. The electric vehicle schedule is based on data provided by Dr. Michael Kintner-Meyer of the Pacific Northwest National Laboratory[47] and represents a vehicle charging only at home at a charge rate of 240V/30A. This load profile was determined using the 2001 Department of Transportation National Household Survey Data Set which identifies 35,000 individual trips with a personal vehicle. This schedule is used to show the potential for an electric vehicle to exacerbate peak energy consumption and cost, though no conclusions on the variability across individual days can be made at this point. The control for this vehicle is designed to emulate a max charge limit during peak hours. It is assumed in this control case that the car is only allowed to charge up to 50% during on-peak hours. Hourly battery charge data is not available so the current charge is simply limited to 50% of its hourly consumption value. All consumption reduced during peak hours is applied during the off peak hours a rate of 25% of the full charge capacity until all energy consumption has been replaced. Tendril is developing electric vehicle control capabilities at the moment and so this control algorithm serves as a preliminary analysis to make certain conclusions. More in depth conclusions can be made when a real hourly charge schedule and charge status are available for a specific homeowner vehicle.

The chart titles provide information on the specific simulation, given in the following order: 1) the name of the home energy model, 2) the name associated with the customer rate structure, 3) the case name, and 4) the simulation period. The legend is used to distinguish the lines and area plots as well as to provide numerical energy consumption and cost information for the specific energy end-uses and rates.

8.1.1 Customer Charts

Figures 8.1 through 8.4 show the charts generated to understand control results from the customer perspective. The customer chart contains three plots including temperature, energy consumption, and price. The temperature plot displays the outdoor dry bulb temperature, the thermostat set point, and the actual indoor average temperature for the zone containing the thermostat. This allows the customer to make

inferences about the weather and its effect on the inside temperature and energy use as well as understand the variability in energy consumption and cost associated with the cooling or heating systems. The energy use plot displays a stacked area plot of energy consumption for major home energy end-uses and each individual device that is equipped with control capabilities. The total energy use for each of these end-uses is displayed in the legend for either the simulation period or average day along with the total consumption. The price chart combines the rate with the actual price of energy to show the peak periods defined by the customer rate structure as well as the actual price of energy calculated by multiplying the rate and the total energy use. The total cost of energy for the simulation period and average day is given in the legend.

The charts generated for the control scenario provide the same information as the base case but with an additional fields to represent the previous set point schedule, previous total energy consumption schedule, and previous energy cost schedule for comparison. Also, they provide information on energy consumption reductions for each end-use and total cost reduction.

The average day charts provide a clean and simple view of the aggregate effect of energy consumption and control effects for the simulation period. From this chart it is easy to identify the weather trends, typical energy consumption schedules, and peak energy pricing periods. The chart of the simulation period allows for and understanding of schedule variability for different days and how this determines the effectiveness of a control strategy on an individual day.

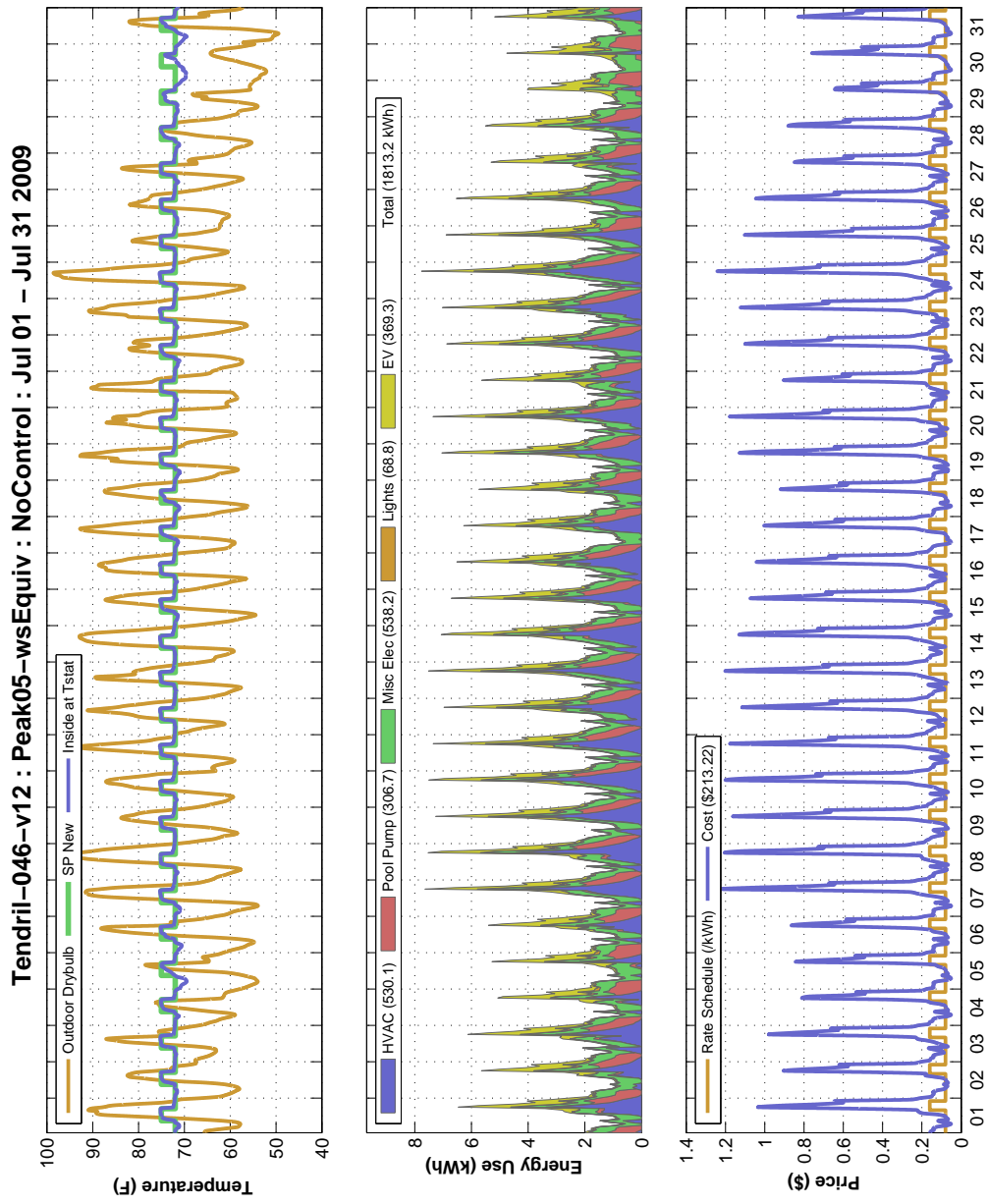


Figure 8.1: Results for customer of full base case simulation with no control

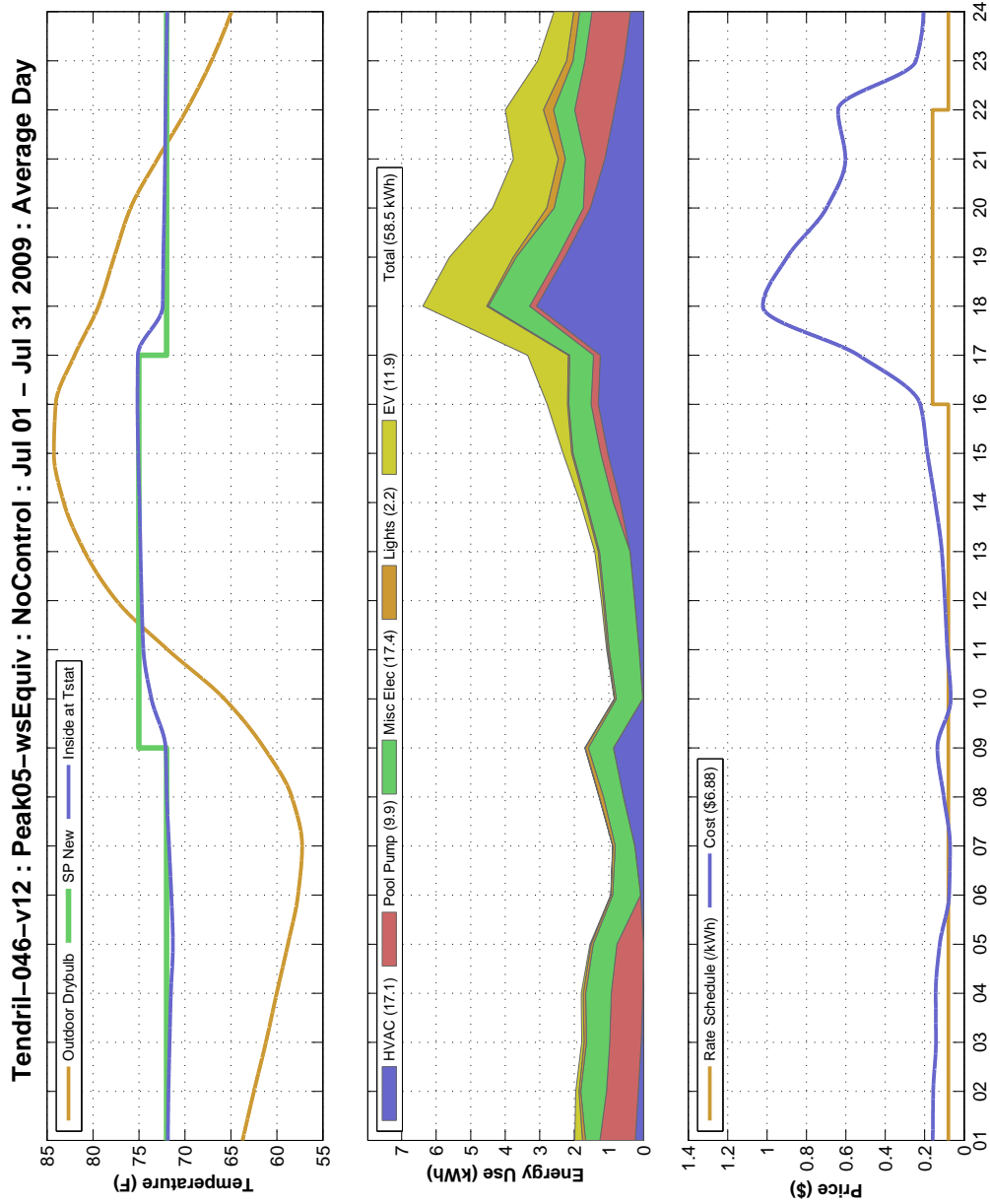


Figure 8.2: Results for customer showing the average day for base case with no control

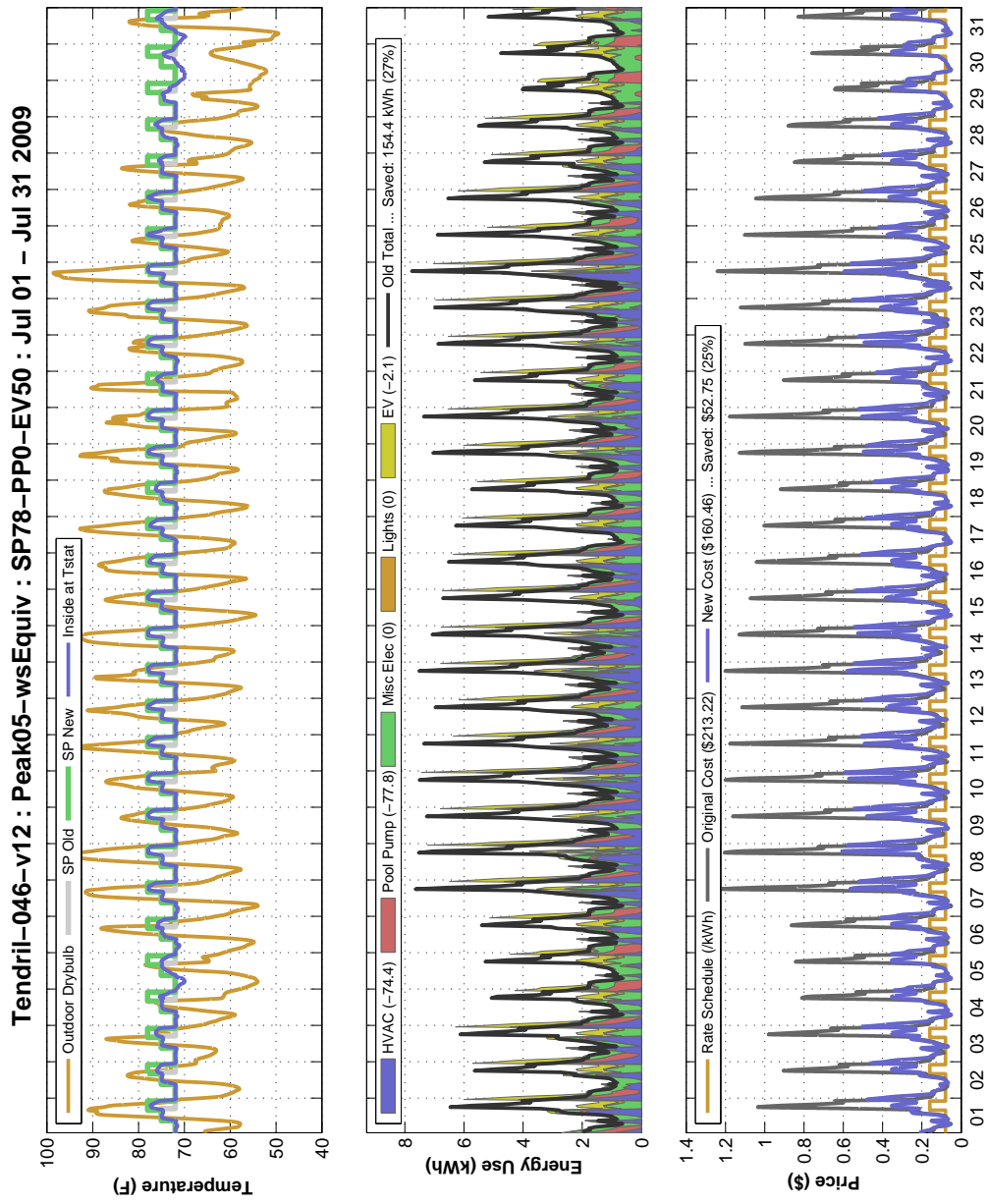


Figure 8.3: Results for customer of full control case simulation with no control

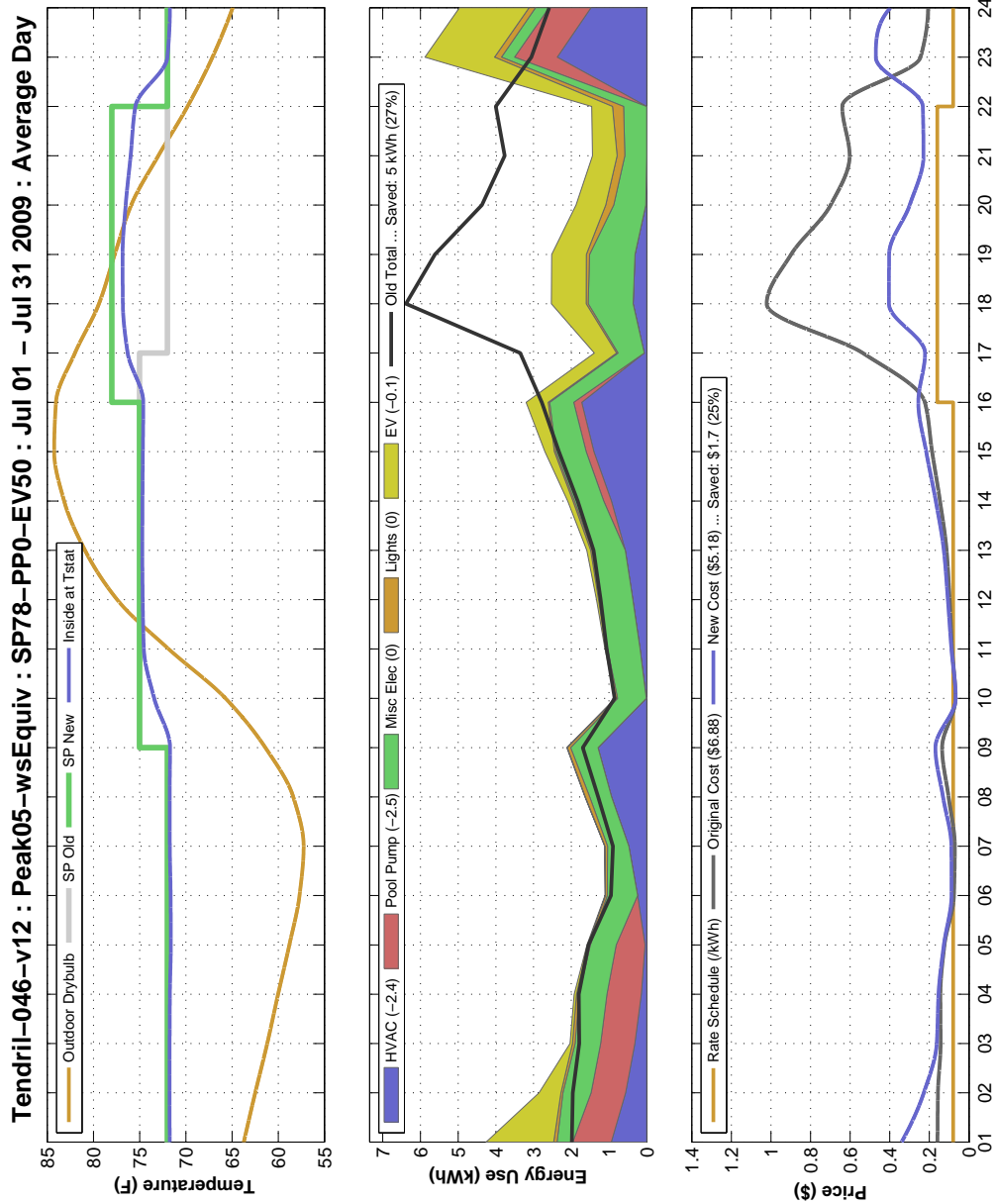


Figure 8.4: Results for customer showing the average day for control case with no control

8.1.2 Utility Charts

Figures 8.5 through 8.8 show the charts generated to understand control results from the utility perspective. The utility chart contains three plots including energy consumption, energy rates, and price. The energy consumption chart is provided so the utility can understand the energy consumption profile for a particular customer and how this contributes to the cost fluctuations. It also allows the utility to analyze the effectiveness of specific customer controls or demand response load control events to be used in evaluating possible incentives. The rate chart allows the utility to see the difference between the rate customers are being charged and the actual wholesale price of energy they are paying. The price charts shows the discrepancies between customer and utility cost for energy throughout the day. These outputs allow a utility to see consumption peak periods, identify energy cost discrepancies, design incentive programs for reducing peak energy use, and to create time-of-use rate structures.

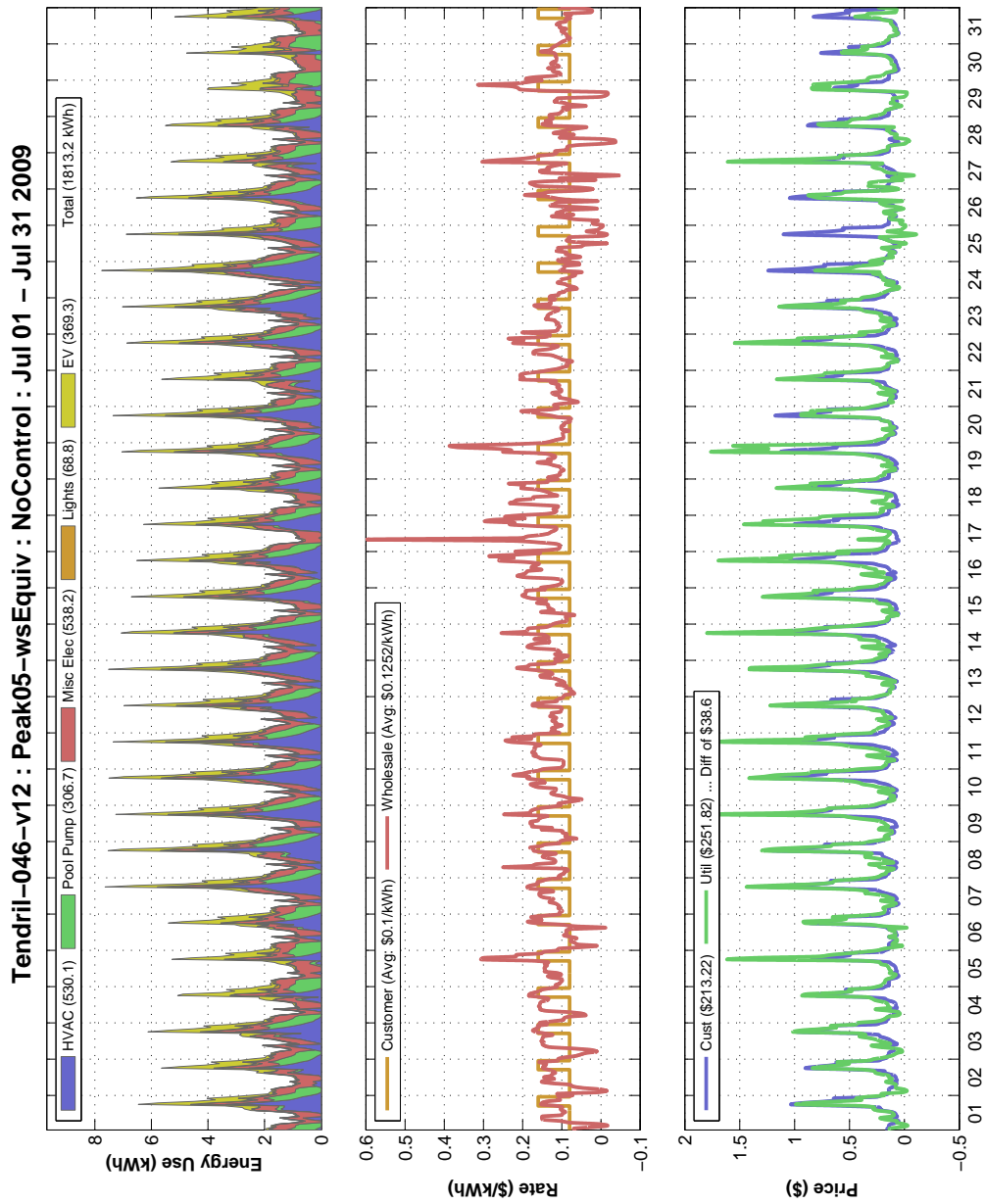


Figure 8.5: Results for utility of full base case simulation with no control

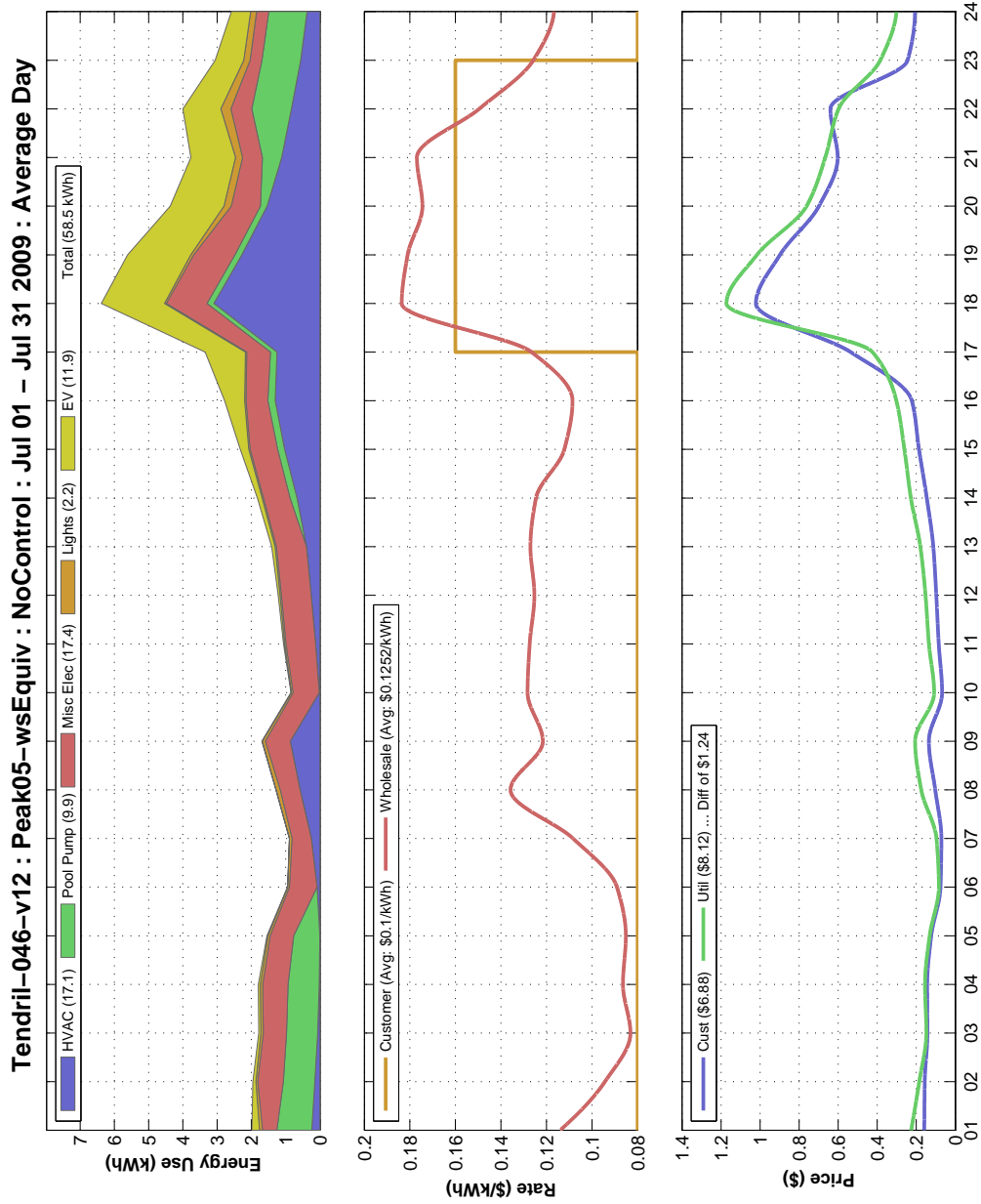


Figure 8.6: Results for utility showing the average day for base case with no control

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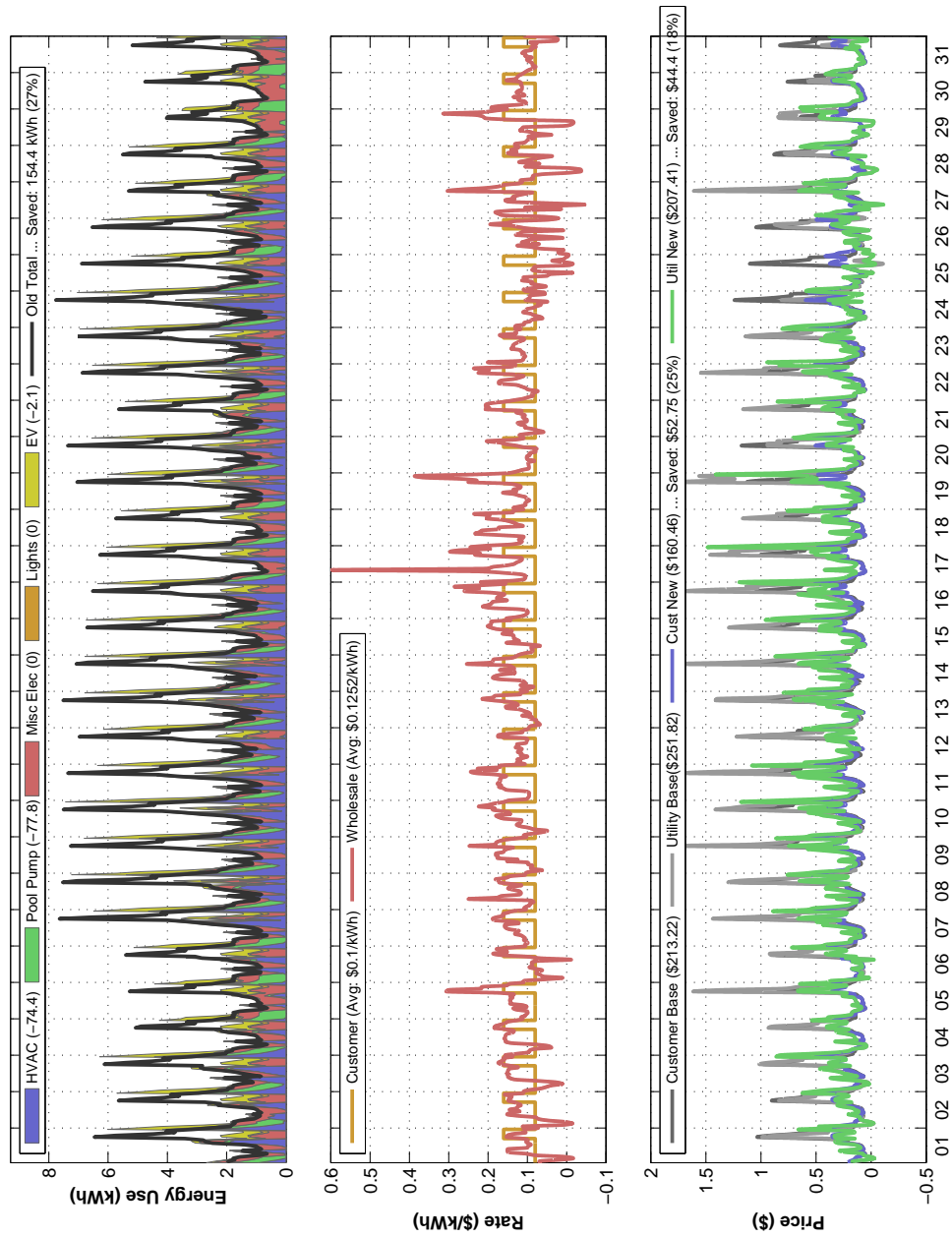


Figure 8.7: Results for utility of full control case simulation with no control

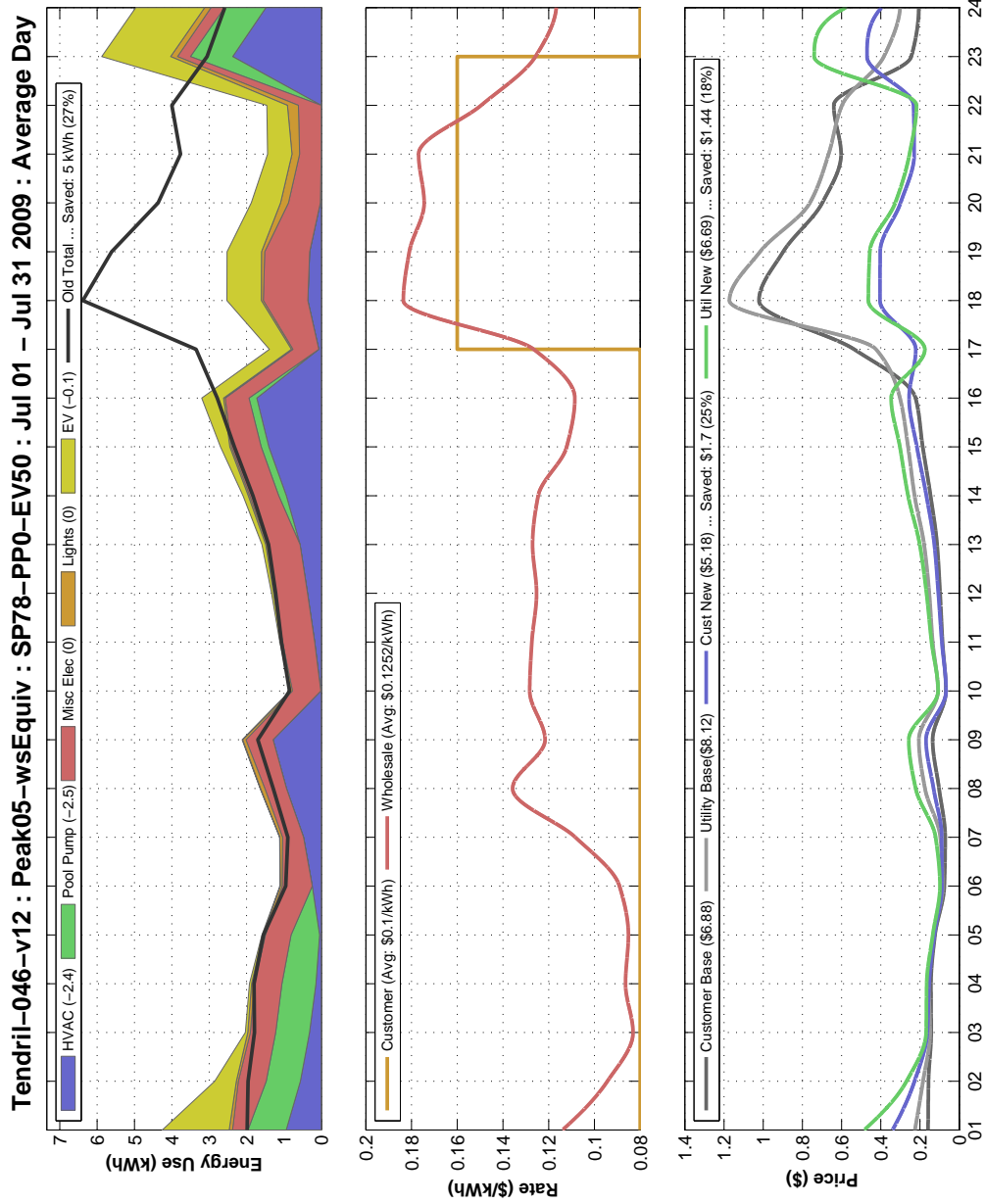


Figure 8.8: Results for utility showing the average day for control case with no control

There are a few noteworthy points to be made about the results of this particular simulation. First is should be pointed out that the majority of peak energy reduction potential comes from the air conditioning and the electric vehicle. These simulations are conducted with a calibrated building model and schedules which suggest that introducing just a couple control enabled devices can provide most of the potential peak energy reduction and cost savings for some homes.

There is a large spike in HVAC consumption during peak hours due mostly to the temperature set point change that occurs to cool the house before occupant arrival. This suggest that simple information of energy consumption schedules such as these can be highly informative to a homeowner wishing to reduce energy use and save money on electricity bills. This tool could be used by a homeowner to simulate and compare a variety of different set point control schedules, including off-peak pre-cooling strategies, to potentially lower peak energy consumption and cost.

The control simulation for this scenario reveals an interesting effect due to the delayed temperature setback. Despite the larger temperature change at the end of the peak period the HVAC energy spike is much lower than would be expected given the larger set point change. This simulation demonstrates the increase in air conditioning efficiency when the outdoor temperature is lower. This is another example of how informative this tool can be to a homeowner.

It is clear that the majority of energy cost is associated with the peak period due to the combined effect of higher energy consumption and a higher customer rate. Yet there is a significant opportunity for cost reduction as in this scenario a 25% reduction, equivalent to \$52.75, is achieved. This is partly due to the fact that HVAC and pool pump energy consumption are not just shifted but reduced overall. However, it is also important to note that given this particular assumed rate structure the customer has a larger average on/off peak rate differential then the utility. Thus the utility is essentially paying the customer more for their reductions than they are saving which is not ideal.

8.2 Customer Questions

This section demonstrates the use of TCAT to answer important customer focused questions around control enabling technology.

8.2.1 Would it save energy if I pre-cooled my home in the morning to reduce energy consumption and cost in the evening?

Figure 8.9 shows the result of an attempt to pre-cool the house in the early morning hours, when the outside temperature is typically cooler, to avoid cooling energy required during peak periods. It can be seen that afternoon and evening cooling requirements are reduced, however the temperature in the home rises over the course of the day and reaches the original setback temperature of 75°F just before the evening temperature change. This results in a cooling energy spike only slightly less than the spike caused by the set point schedule without pre-cooling. As a result this pre-cooling schedule adds a significant amount of energy use in the morning yet does not save enough energy or money in the evening to be effective. This is not to say that a different pre-cooling schedule could not be effective, but this one certainly is not.

Figure 8.10 reveals another unsuccessful attempt to pre-cool this home by setting the pre-cool temperature lower and removing the set back during the day. This creates less energy use in the evening but much more in the morning and again the customer loses on both energy consumption and cost. These results are to be expected as it is not typical for residential buildings to have enough mass to make pre-cooling strategies effective. However, there may be some homes in which a specific pre-cooling strategy may work and this tool would certainly be able help find that particular strategy.

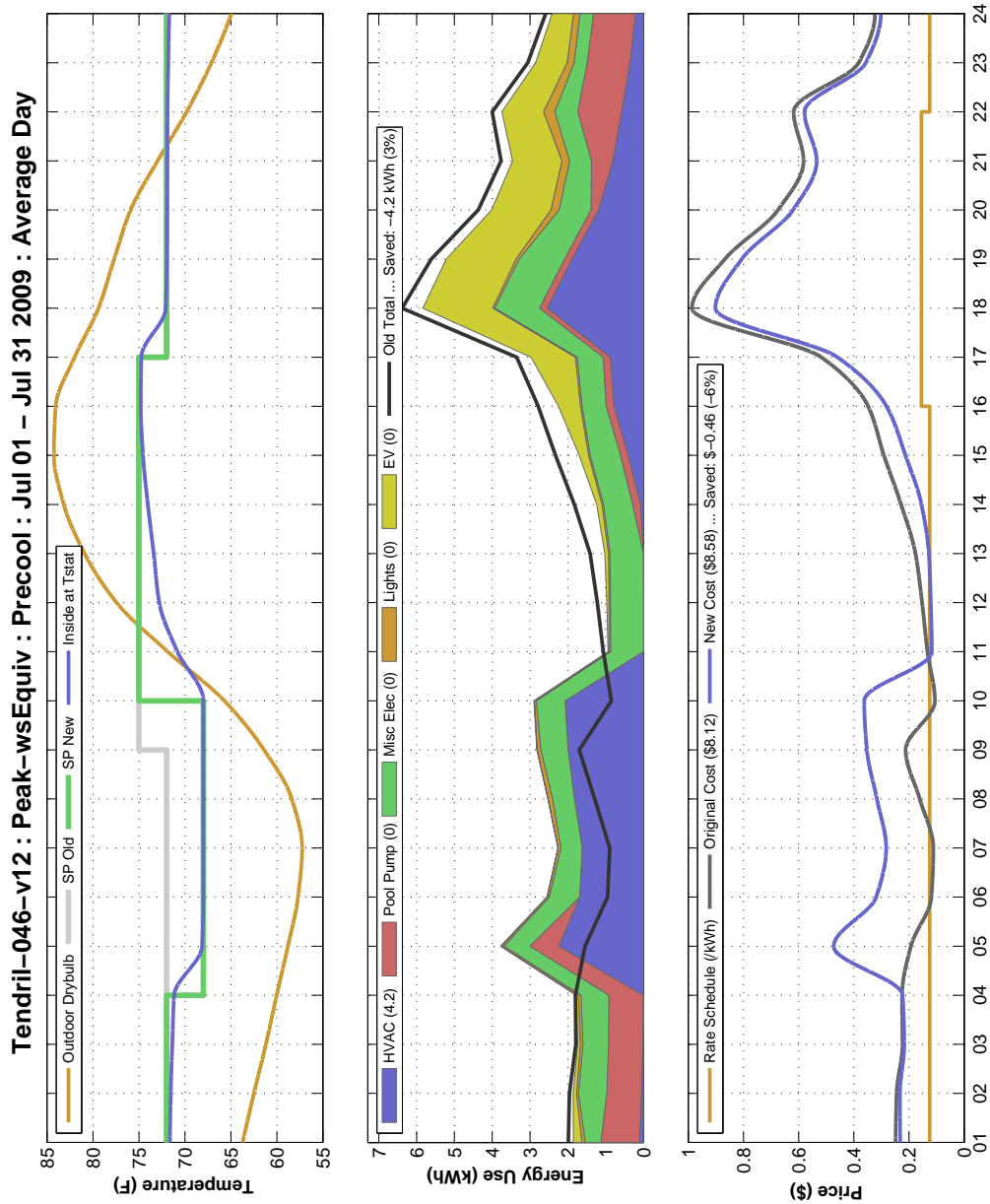


Figure 8.9: Results for a pre-cooling control scenario

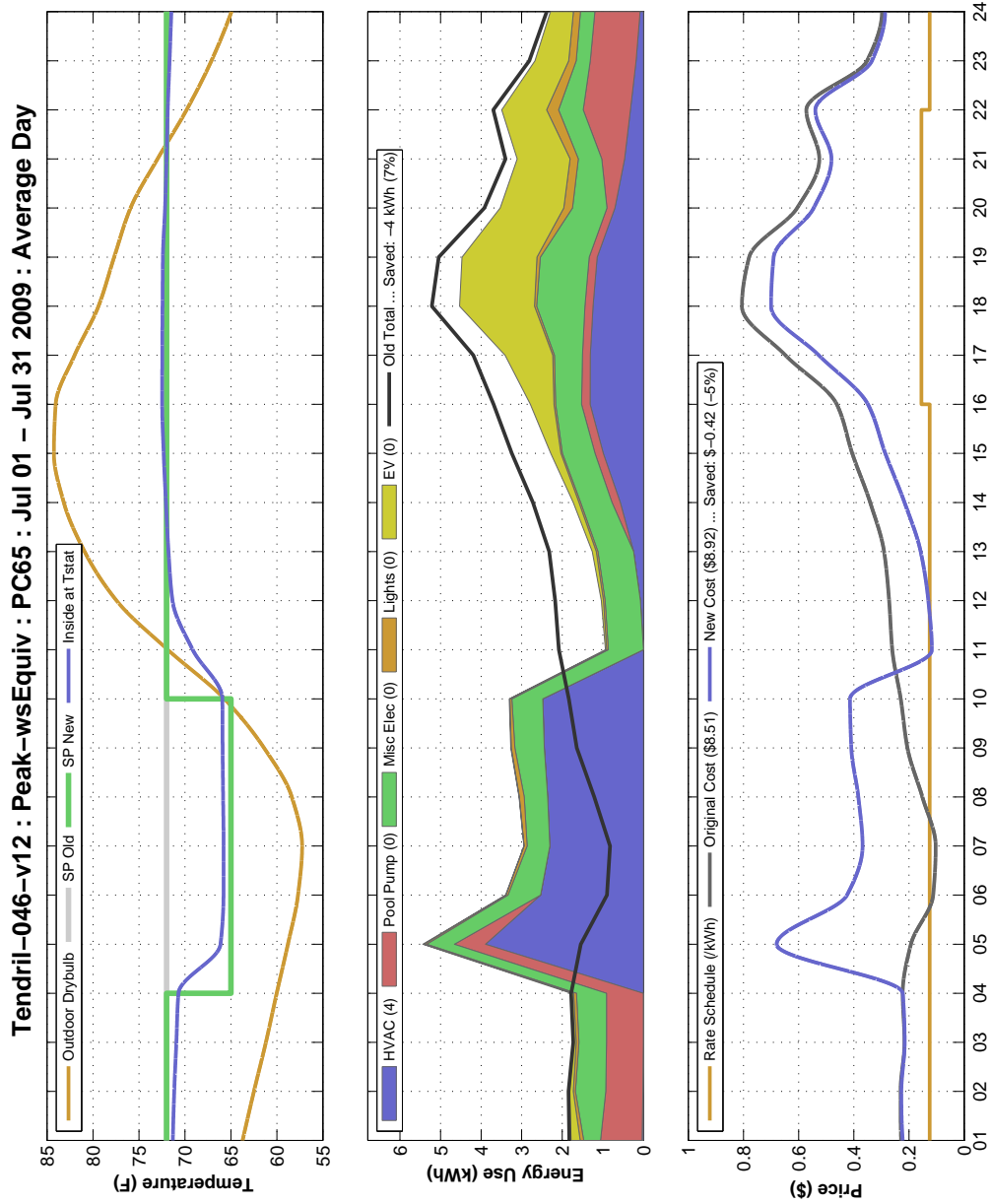


Figure 8.10: Results for another pre-cooling control scenario

8.2.2 How much money could I save if I just turned off my pool pump during the times with higher energy rates?

The answer is \$0.39/day as demonstrated in Figure 8.11 which also equals \$12.09/month. A similar simulation is shown for the electric vehicle in Figure 8.12. Because the vehicle still needs to be charged when the control event is over, the cost savings is dependent on the difference between on and off-peak rates. With the rate used in this scenario having a small difference of \$0.03/kWh, savings only amount to \$0.29/day, less than the pool pump.

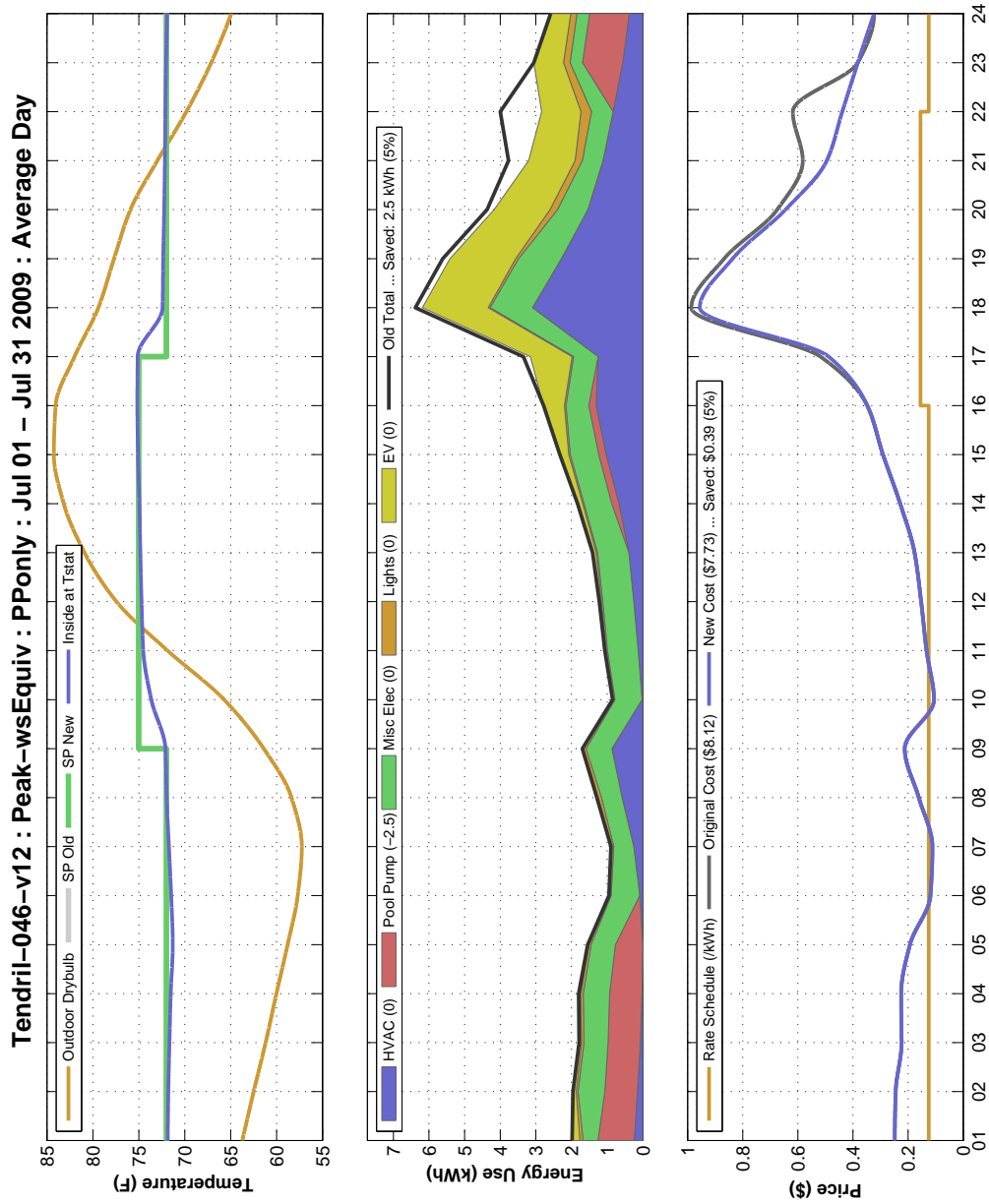


Figure 8.11: Results for complete pool pump reduction during peak

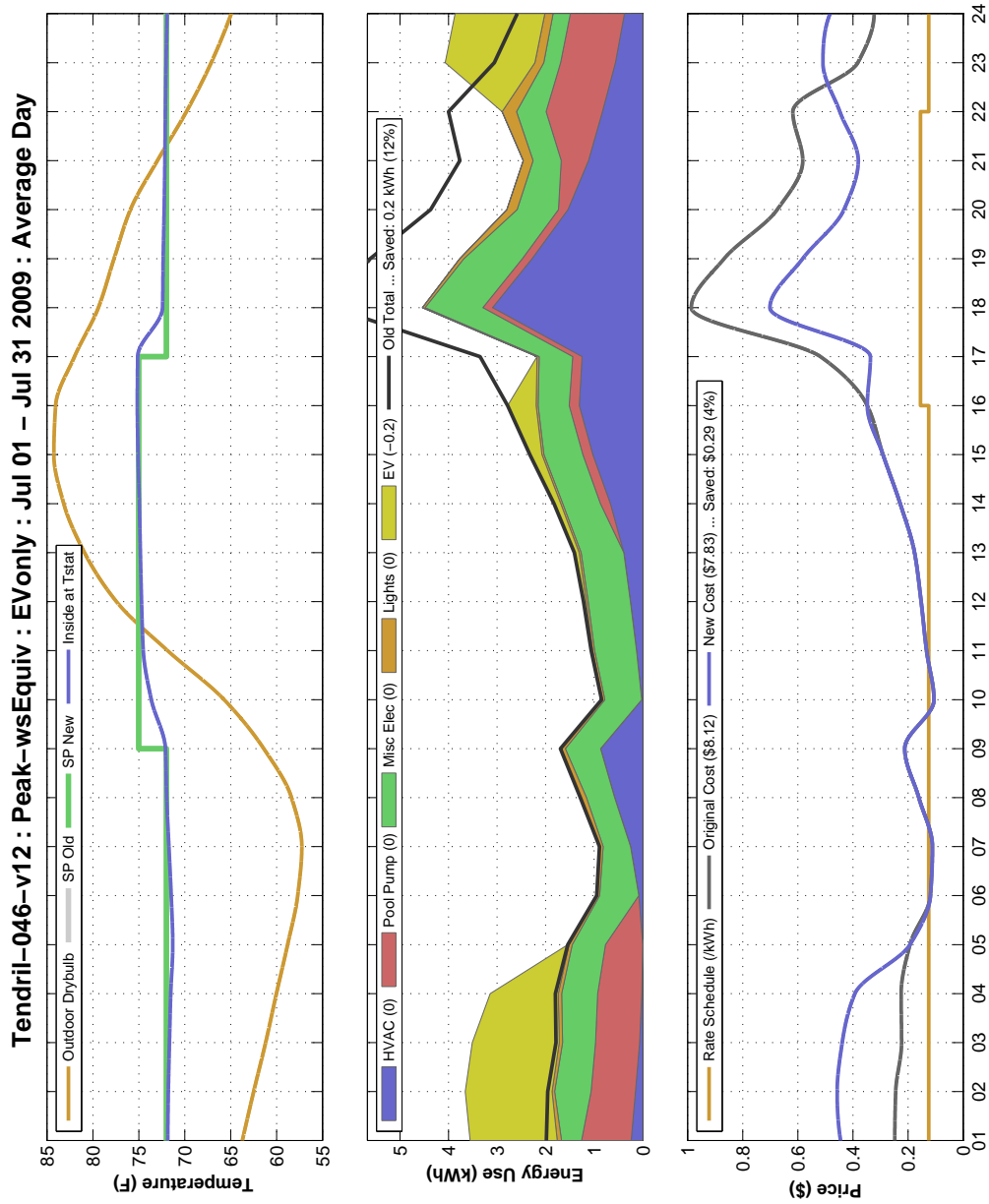


Figure 8.12: Results for complete EV reduction during peak

8.2.3 How would a change in rate structure effect the results of my control strategies?

The exact same electric vehicle schedule as used in the last scenario is used here, but this time with a more dramatic peak rate difference. In this scenario it is possible to save \$35/day, nearly four times as much. The simulation results are shown in Figure in 8.13.

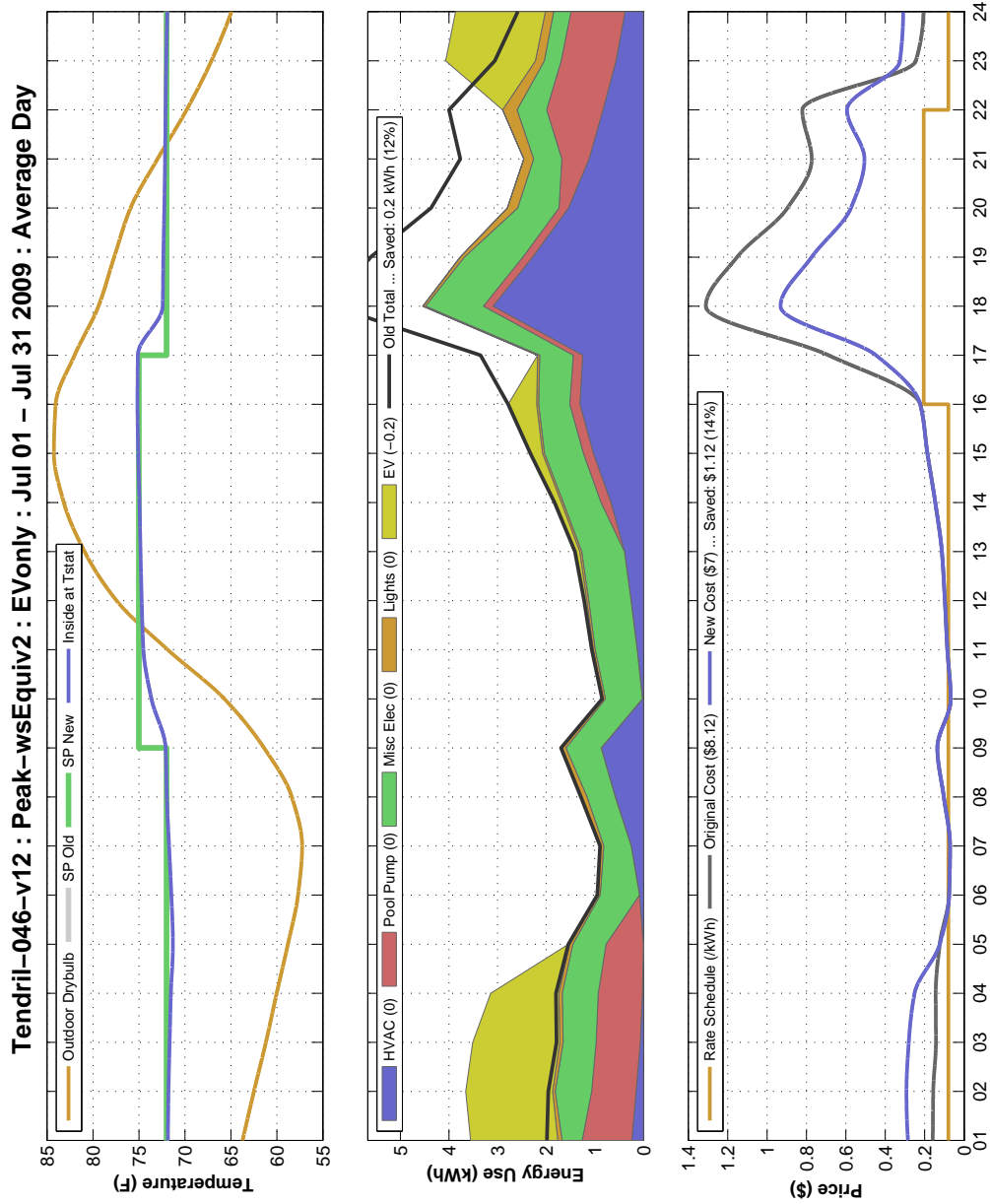


Figure 8.13: Results for complete EV reduction during peak with a higher peak rate

8.2.4 How much more energy and money will I save if I set my temperature to 79°F instead of 76°F during the peak periods?

Figures 8.14 and 8.15 reveal the results of these two control scenarios. Changing the set point to 76°F from the original 72-75°F set point schedule for this month creates an energy reduction of 1.4 kWh/day and cost reduction of \$0.97/day. Changing the set point to 79°F creates an energy reduction of 2.7 kWh/day and cost reduction of \$1.45/day. Interestingly, that is 48% more energy reduction and 33% more cost reduction.

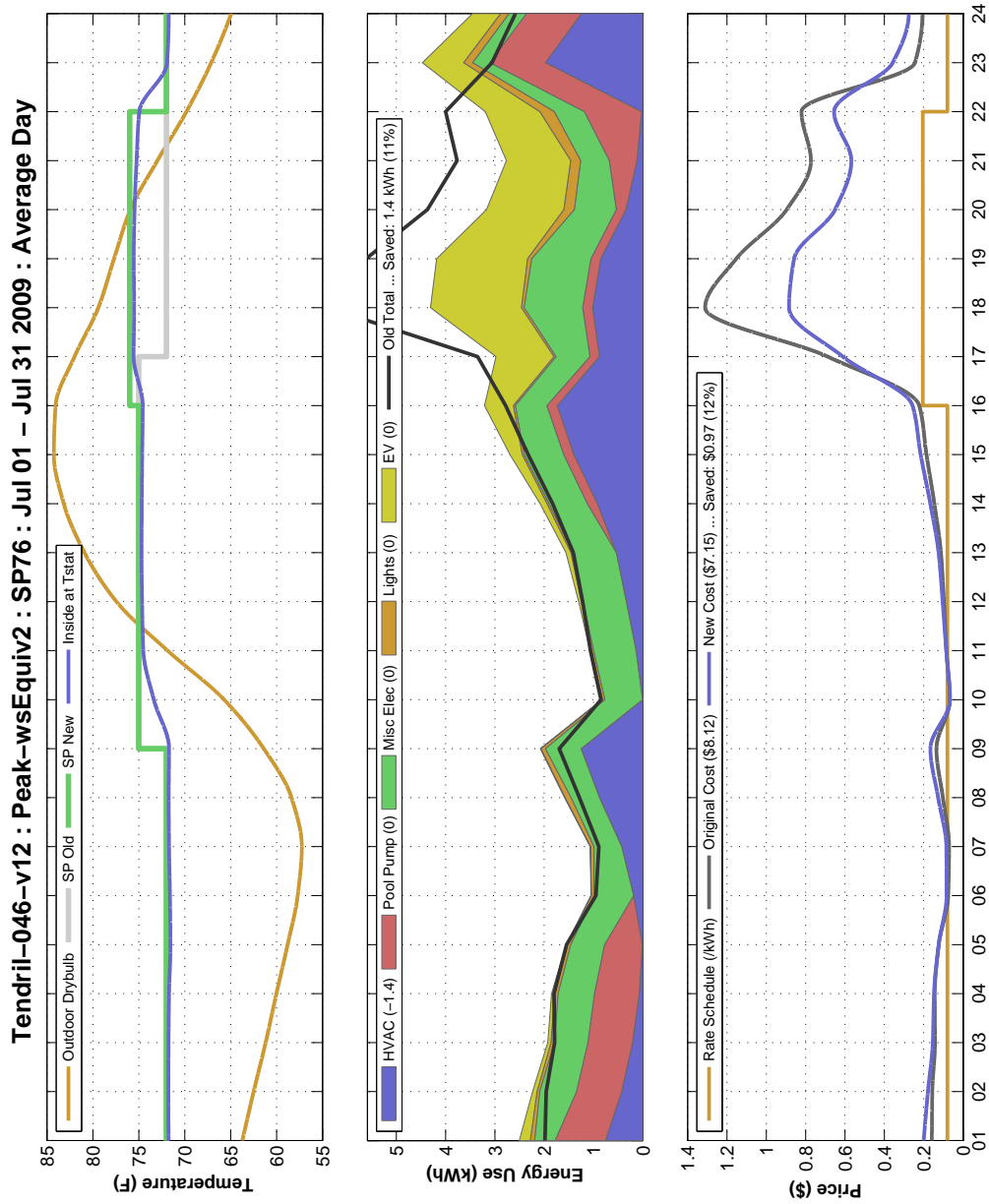


Figure 8.14: Results for a 76°F setpoint during peak

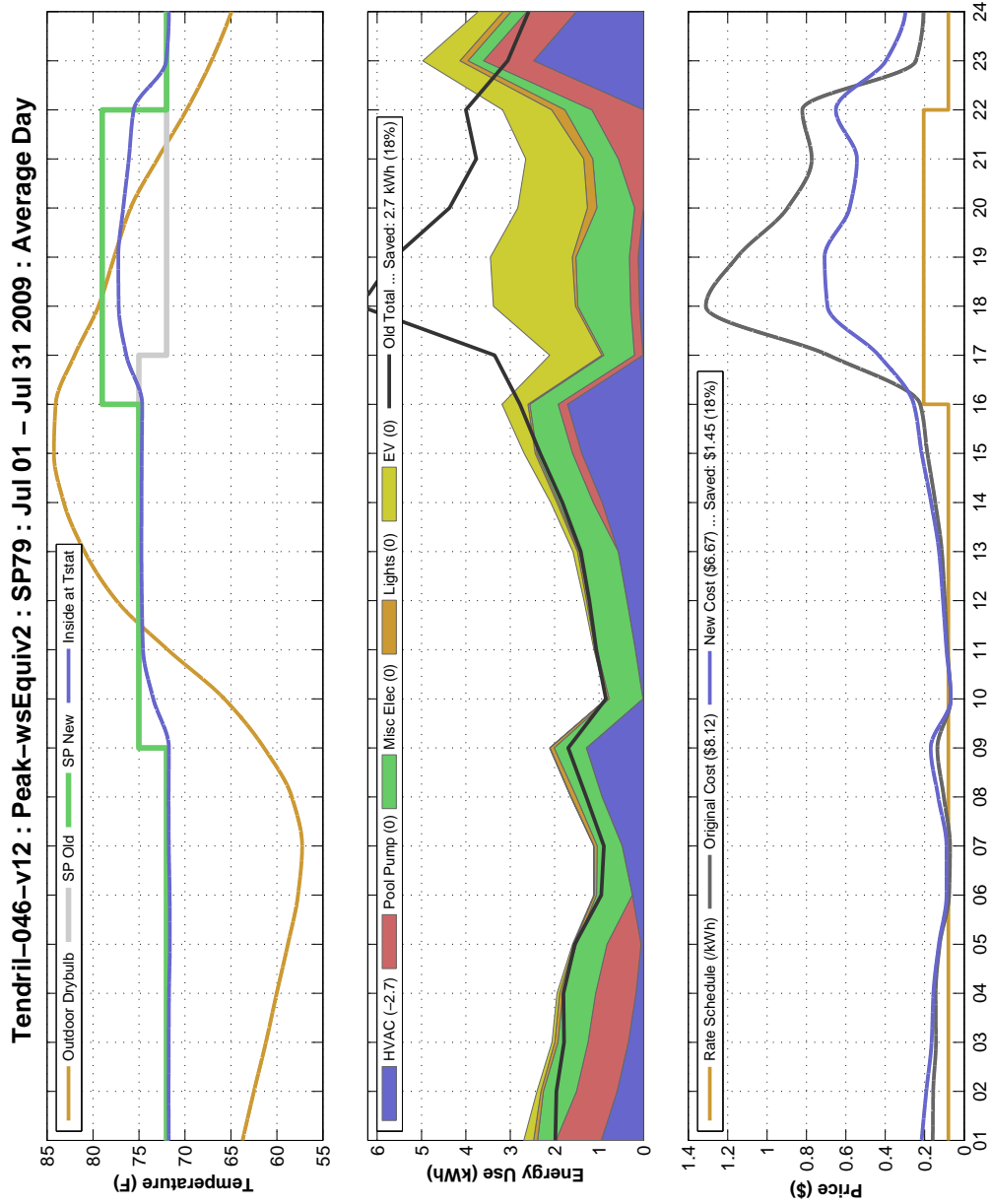


Figure 8.15: Results for a 79°F setpoint during peak

One more simulation is provided to conclude the customer portion of the results. Figure 8.16 shows the results of changing the set point temperature by one more degree to 80°F during the peak period. This results in energy reduction of 2.9 kWh/day and cost reduction of \$1.5/day, which is only 0.07% more energy reduction and 0.03% more cost reduction than the 79°F. This demonstrates the diminishing ability for setpoint controls to save energy and cost. As the temperature setpoint increases less energy is used for cooling during the peak period and ultimately the maximum potential for energy and cost savings is reached as shown in this simulation scenario. The set point at which this situation occurs will likely vary for different months, building characteristics, and occupant behavior in the home.

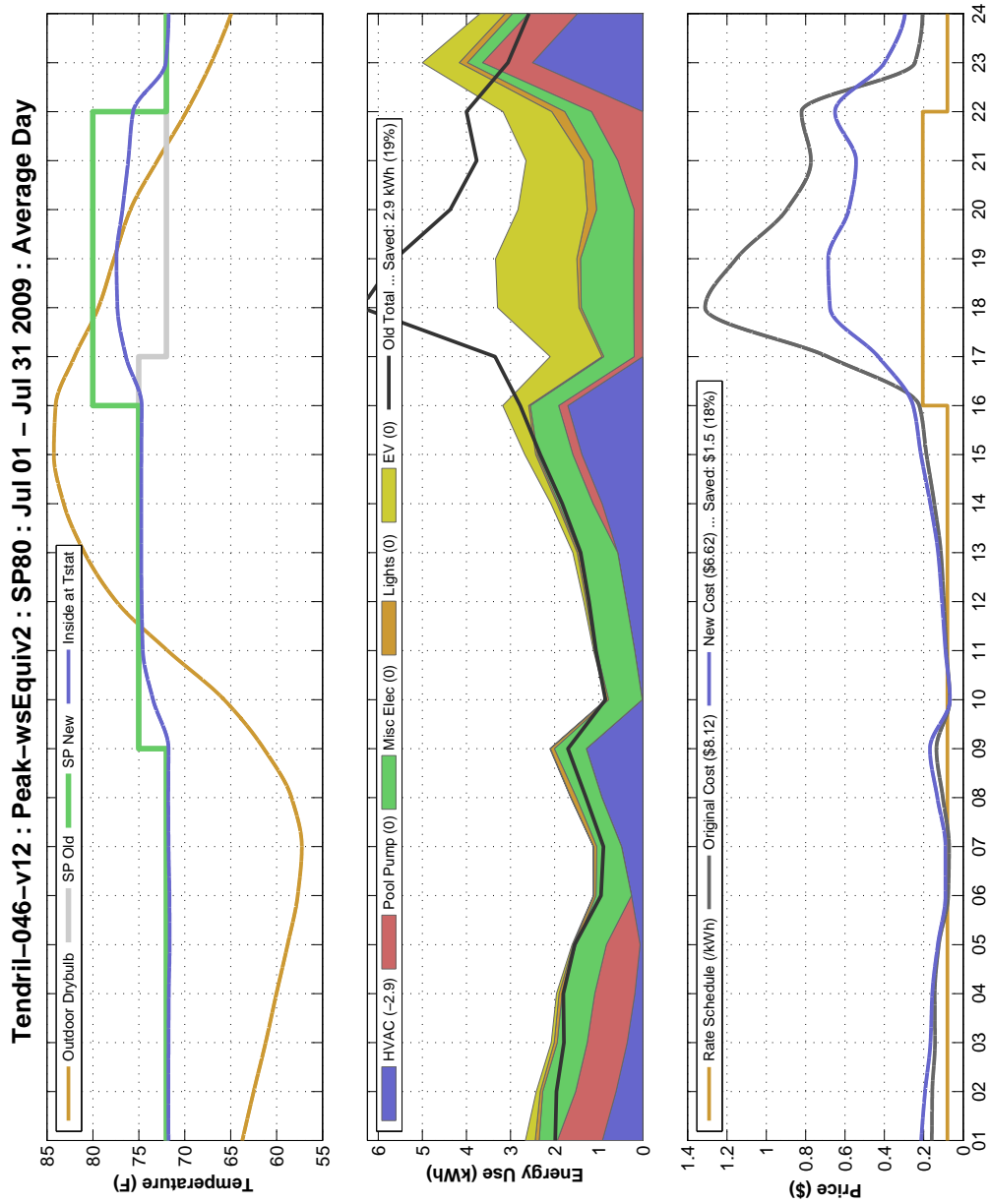


Figure 8.16: Results for a 80°F setpoint during peak

8.3 Utility Questions

8.3.1 How does a flat rate of \$0.10/kWh compare to our wholesale rate for this customer during the month of July?

The initial simulation results shown in Figure 8.17 and Figure 8.18, show the resulting energy cost based on home energy consumption and corresponding customer and utility energy rates for the entire simulation period and in terms of the average day schedule. These charts reveal a clear six hour peak period between the hours ending at 17 and 22 o'clock. This period has the highest energy demand and thus the wholesale energy price is also higher for the utility due to transmission grid and power plant capacity concerns. This higher energy price is not due to the energy use of this one specific home, but to the aggregate effect of all homes and buildings on the grid using more energy during this period of the day. The combined effect of higher energy use and higher prices creates an incongruous cost schedule with the utility 'losing' the most during this peak period. It is this period that drives up the overall utility cost. In this example, the utility is paying \$2.27 more per day than the customer to provide energy to this home. Under this circumstance a rate increase will be required.

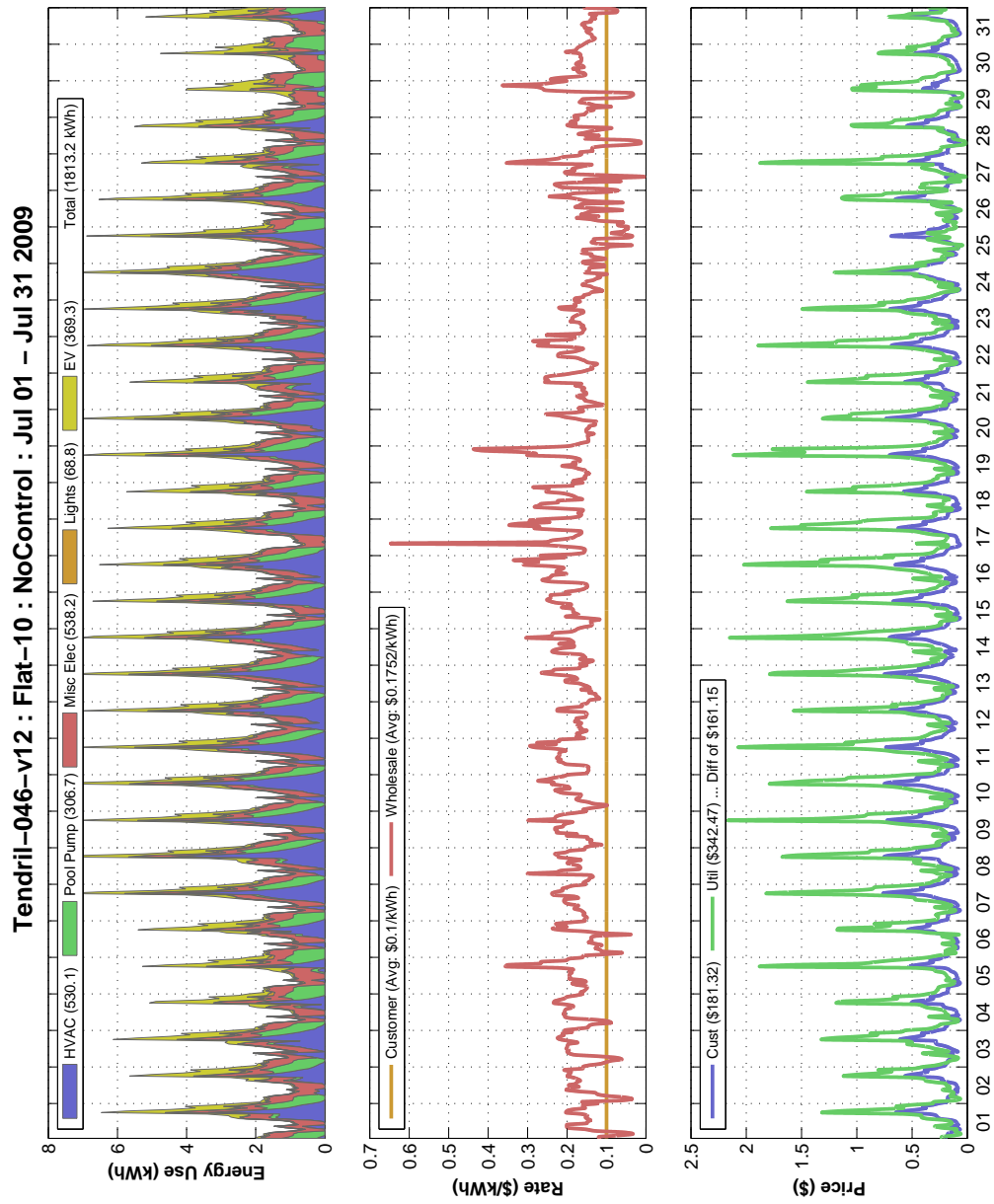


Figure 8.17: Results for a \$0.10/kWh flat rate comparison

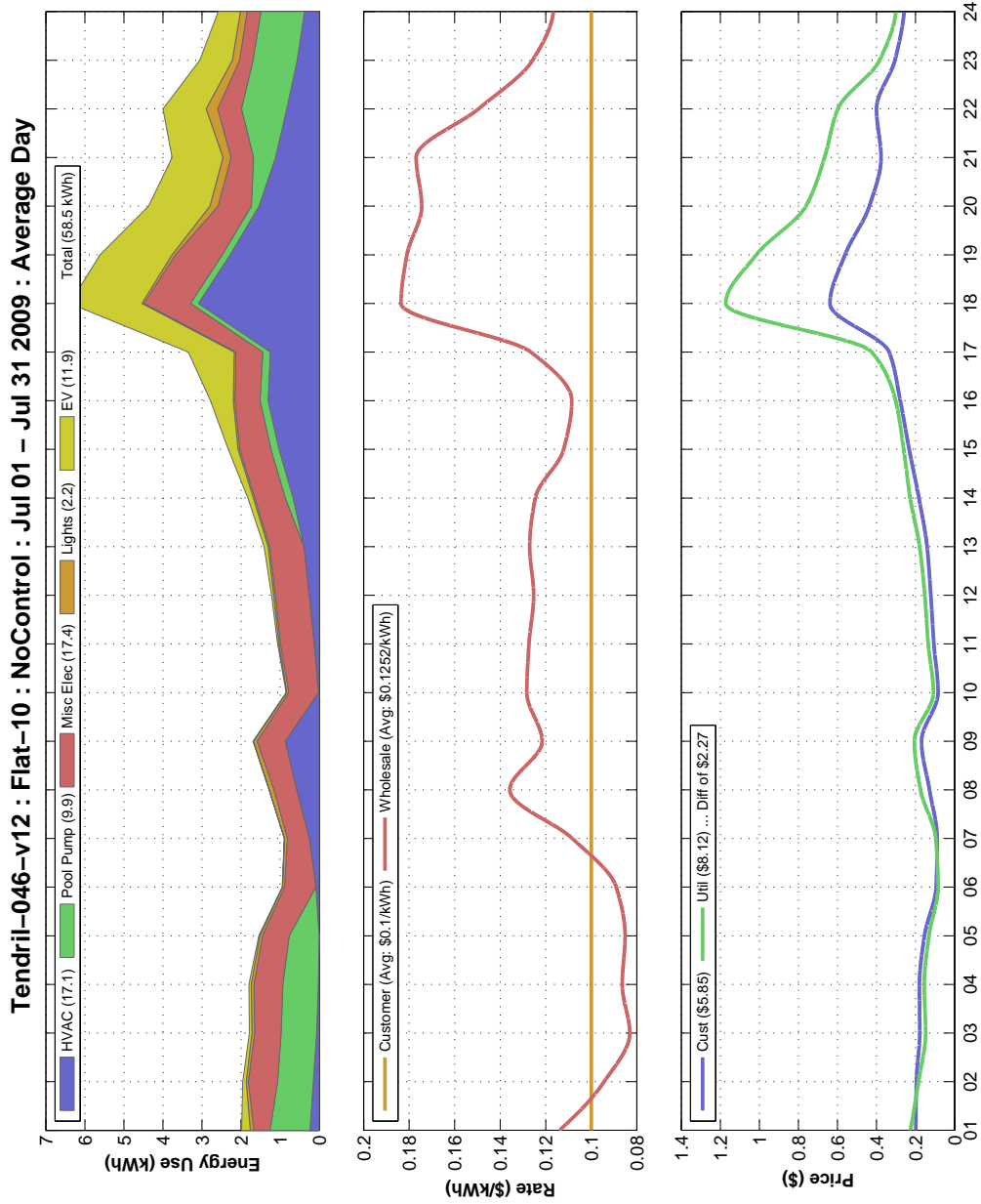


Figure 8.18: Results for a \$0.10/kWh flat rate comparison for the average day

8.3.2 What flat rate is needed to equal the wholesale equivalent cost of energy for this period?

To adequately transfer utility cost to the customer a flat rate of \$.1389/kWh would be required. At this rate both the customer and utility pay the same amount for the energy required for this simulation period, \$8.12/day, as shown in Figure 8.19. Rate increases of this sort occur with regular frequency as peak demand rises and with it, the cost of providing peak energy. This also creates a need for utilities to build more infrastructure and plants. However, simply increasing the flat energy rate does not help to solve the problem of the incongruous peak energy cost which is driving the cost difference between utility and customer and ultimately leading to higher rates yet with no mitigation of peak energy use. This also fails to provide the consumer with an incentive to reduce peak energy use. An alternative solution is to apply a time-of use rate that more accurately reflects the time varying price of energy for the utility. With smart meters measuring hourly energy consumption data, it is possible for utilities to accurately measure and charge customers for their energy use during different times of the day.

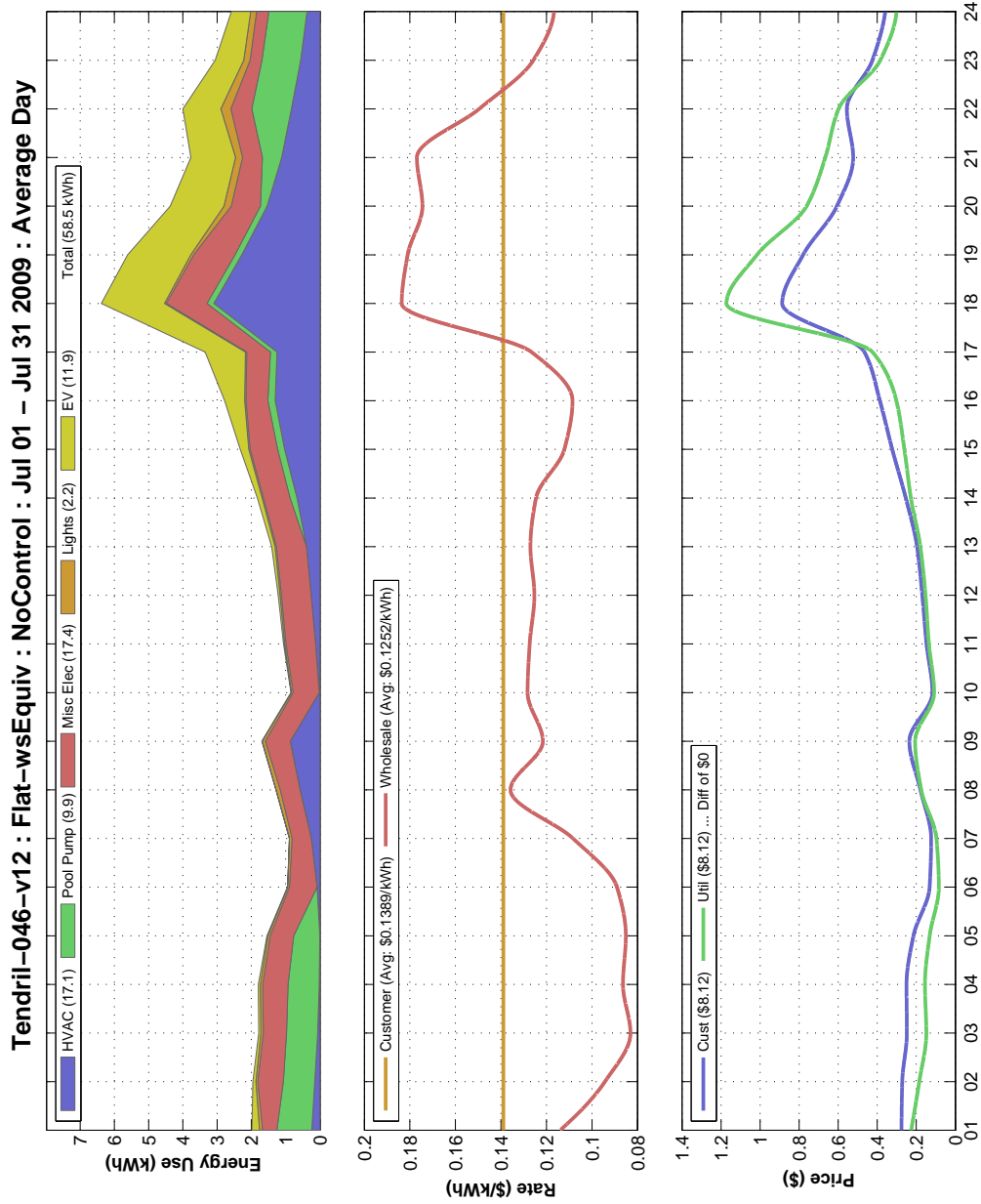


Figure 8.19: Results for a wholesale equivalent rate comparison

8.3.3 What time-of-use rates could be used to incentivize peak energy reduction without raising the overall cost of energy for the consumer if controls are not implemented?

A concern for utilities is causing customer dissatisfaction by creating a time-of-use rate that significantly increases the customers overall energy bill. It is important to create a time-of-use rate that is equivalent to the existing flat energy rate or wholesale equivalent flat energy rate. Using the energy consumption schedules and energy rate schedules on and off-peak energy rates can be computed to through substitution to equal a given flat rate for the specific energy consumption profile over the simulation period. The rates will vary lineally from small differences right around the original rate to large difference that always equal the previous total energy cost for the customer. Figure 8.20 shows the results of this computation for a range of flat rate cost-equivalent on/off-peak rates between the previous flat rate of \$.10/kWh and wholesale cost equivalent rate of \$.1389/kWh. The slope of the curve depends on the amount of energy that is used during the peak and off-peak periods. In this example, 852 kWh is used during the 6 hour peak period from 16 to 22 o'clock, and 961 kWh is used during the off-peak period. 12% more energy is consumed during off-peak hours and this dictates the slope of the line. Increasing the equivalent flat rate causes a linear shift in the rate possibilities. For this demonstration the wholesale equivalent rate curve is used to choose an on and off-peak rate pair that will incentivize the home owner to reduce peak energy use, but not increase their overall energy cost if they do not.

For this particular historical wholesale rate schedule the average rate during the identified on-peak period is \$.1690/kWh and the average rate during the off-peak period is \$.1122/kWh. Of course it depends on the exact hour of energy reduction and the percentage of the reduction that is shifted, but on average, energy that is moved by the customer from the on-peak period to the off-peak period will save the utility \$.0568/kWh. Using this information the utility can decide on an on/off-peak rate pair that attempts to split the energy savings with the customer. Choosing an on/off-peak rate pair of \$.1545/kWh and \$.1250/kWh respectively as shown in Figure 8.21 reveals that, as planned, the total energy cost for the customer has not raised beyond the wholesale equivalent flat rate shown previously.

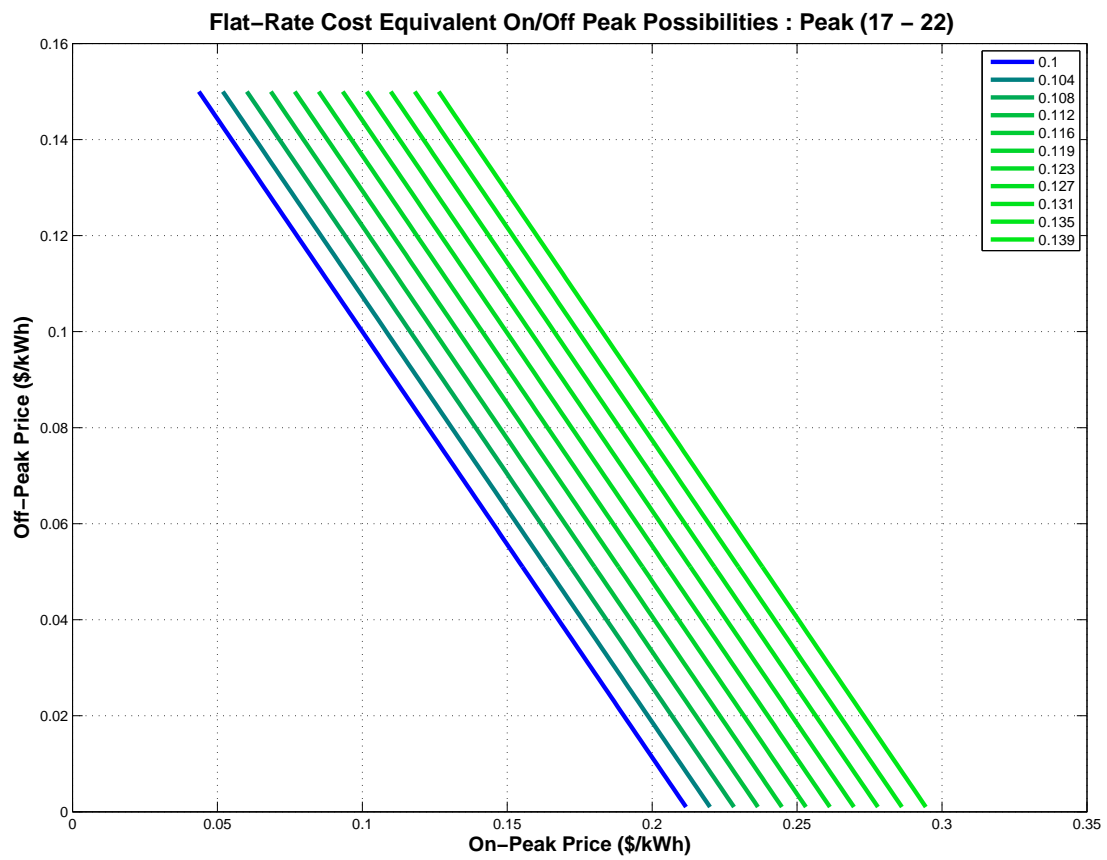


Figure 8.20: Rate comparison chart

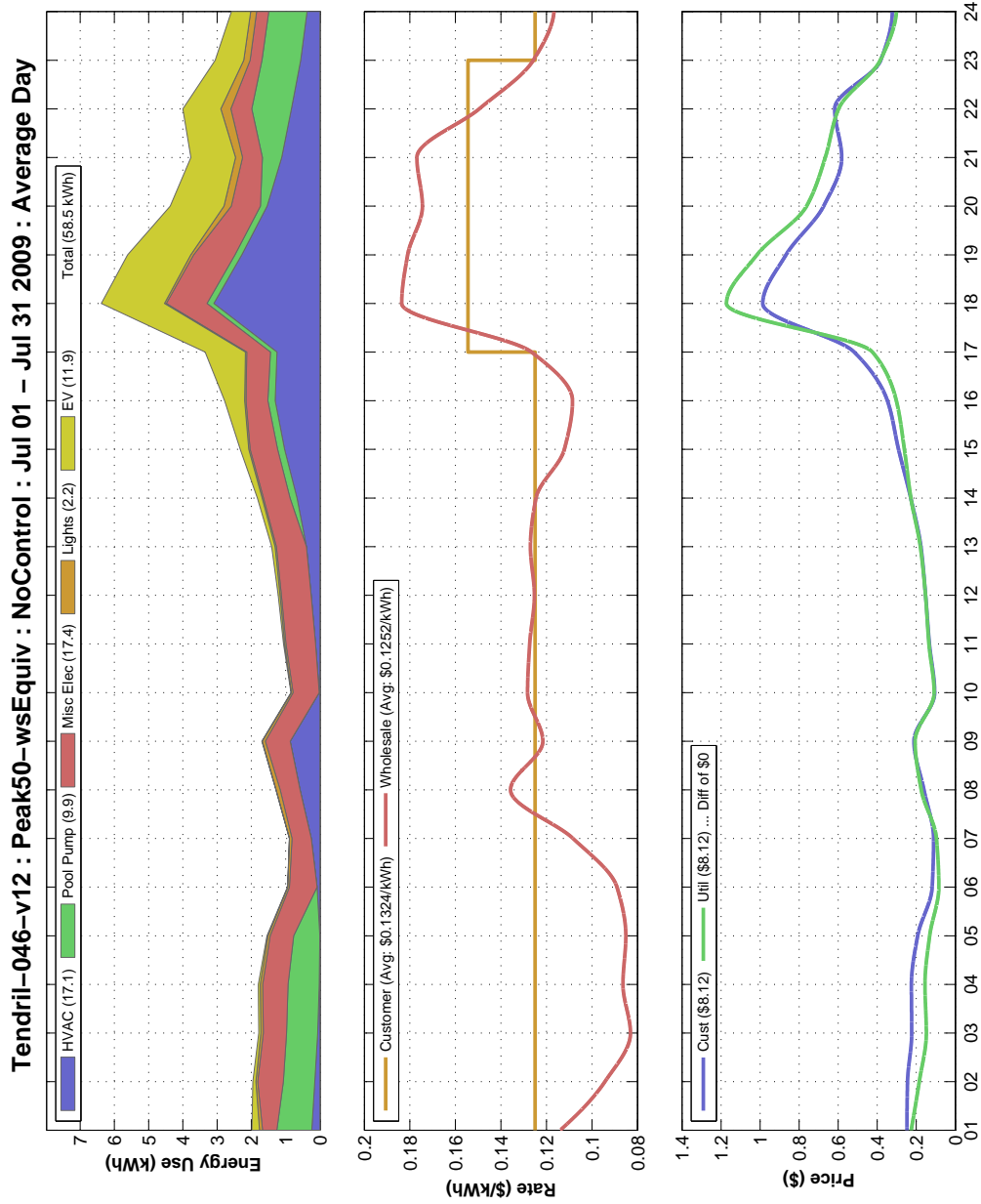


Figure 8.21: Results for a cost equivalent rate case test

8.3.4 **How much money will we save and how much money will the customers save if controls are implemented with this time-of-use rate?**

Given a set control scenario TCAT can test to see the actual cost savings for the customer and the utility based on energy shifting and reduction. The rate used in this control scenario is designed to have 1/2 of the on/off peak rate difference compared to the difference between the utility's average on and off peak wholesale energy rates. Fundamentally, this would lead to half of the utility's cost saving from peak energy reduction being transferred to the customer if all energy reduction in peak hours were shifted into off-peak hours. Figure 8.22 reveals that this is far from true. In this control scenario the utility saves \$1.5/day, and the customer saves \$1.15/day, meaning that in actuality, 75% of the utilities cost savings from peak energy reduction associated with the wholesale rate are transferred to the customer. This effect is likely due to the fact that the pool pump energy reduced during peak is not transfer to off-peak hours. Also the HVAC energy use is reduced overall as a result of this temperature setback. This means that the peak energy reduction cost analysis is skewed by the on peak rates which are \$0.1545/kWh for the customer and \$0.1690/kWh for the utility leading to 91% of peak energy reduction savings being transferred to the customer. Thus the actual savings transmitted to the customer for peak energy reduction depends on energy shifting vs. savings. Control simulations such as these can help utilities to develop a rate case for specific customers, regions, or even devices to incentivize peak energy reduction controls.

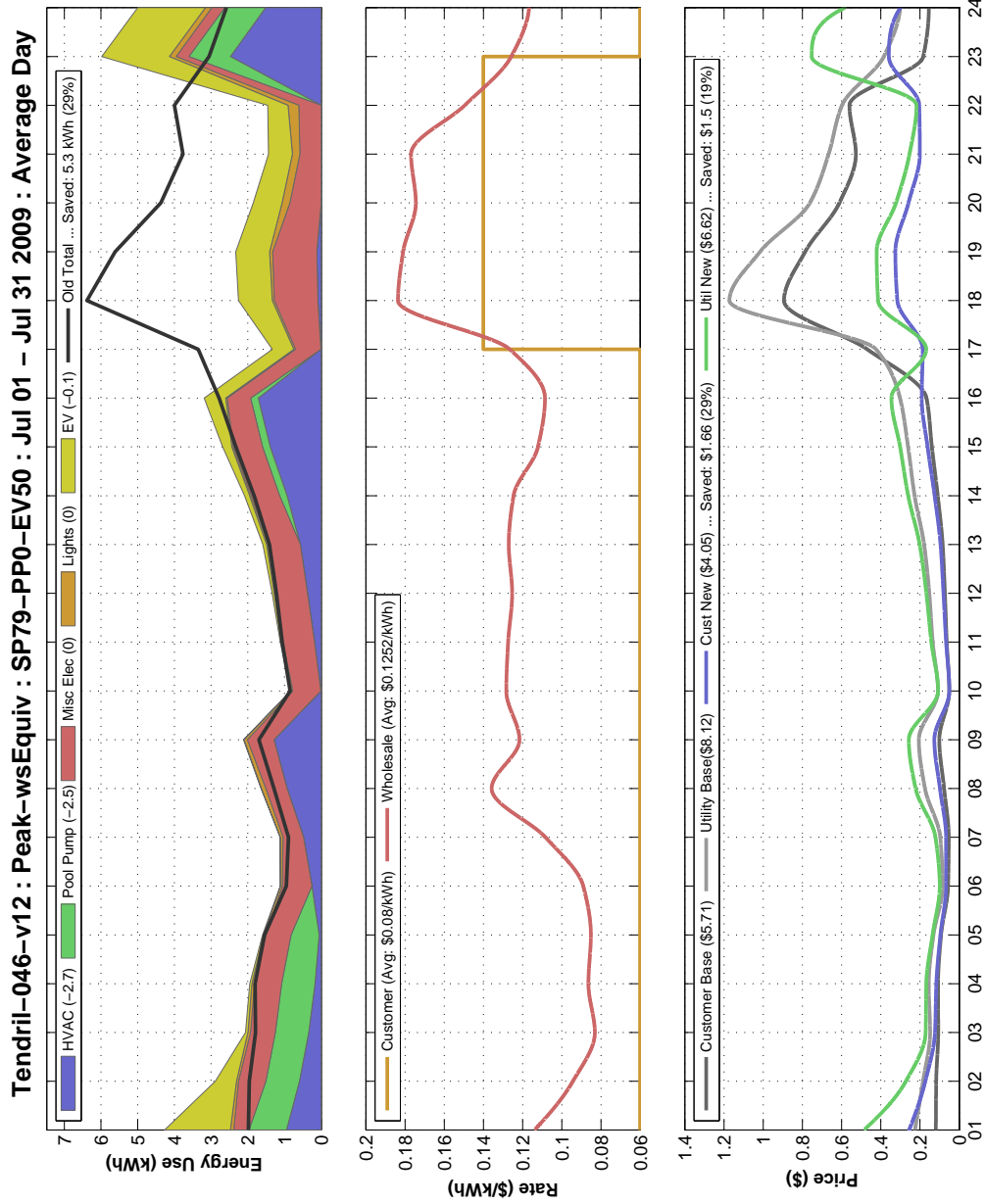


Figure 8.22: Results for a rate case test with controls

Chapter 9

Development of a Regional Benchmark Study

9.1 Objective

In order to use TCAT more broadly to gain market insight, a study was designed to evaluate the benefit of a controlled set point offset in typical homes with benchmark schedules in four different climate regions. This study examines the energy reduction, as well as avoided cost from using an automatic thermostat set point control strategy that responds to the price variation in a time-of-use rate plan. In this study the length of the peak period, rate ratio (the ratio of peak to off-peak price), and set point offset are systematically varied. All time-of-use rate plans are designed to be cost neutral when no changes are made to the home's energy consumption profile. These control scenario variations are applied to three different homes sizes in four different climate regions. Historical real time summer prices for 2008 are used to design the time-of-use rate in each region and to calculate the avoided cost from load reduction during peak periods. Each home's construction features conform to the typical design practices of the region.

9.2 Location Selection

Houston, Los Angeles, Chicago, and New York City (hereafter referred to as New York) were chosen for this study. Each city is in a unique energy market and climate zone. Real time price data is available for these cities from the Regional Transmission Organizations (RTO). Figure 9.1 shows a map of the RTOs. Houston is in the region operated by the Energy Reliability Council of Texas (ERCOT) [12]. Los Angeles is in the region operated by the California Independent System Operator (CAISO) [3]. Chicago is in the region

operated by PJM [37]. New York is the region operated by New York ISO (NYISO) [30]. These markets are governed by the Federal Energy Regulatory Commission [13].

Real time price data files were downloaded from each RTO website. Custom scripts created in MATLAB were used to pull the desired node data (price and timestamp) out of each unique RTO file. These scripts were modified from the loadCSV.m file created by Chad Corbin for prior work in the MATLAB - EnergyPlus environment. The source code is provided in Appendix D

The ASHRAE climate zones are shown in Figure 9.2 below [10]. The cities chosen represent ASHRAE climate zones 2, 3, 4, and 5.

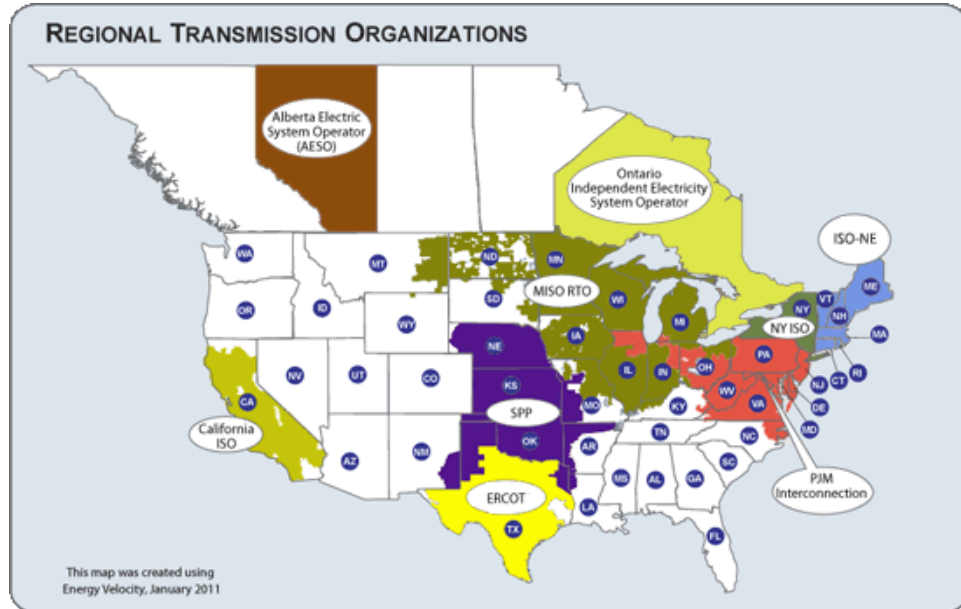


Figure 9.1: Regional Transmission Organizations [13]

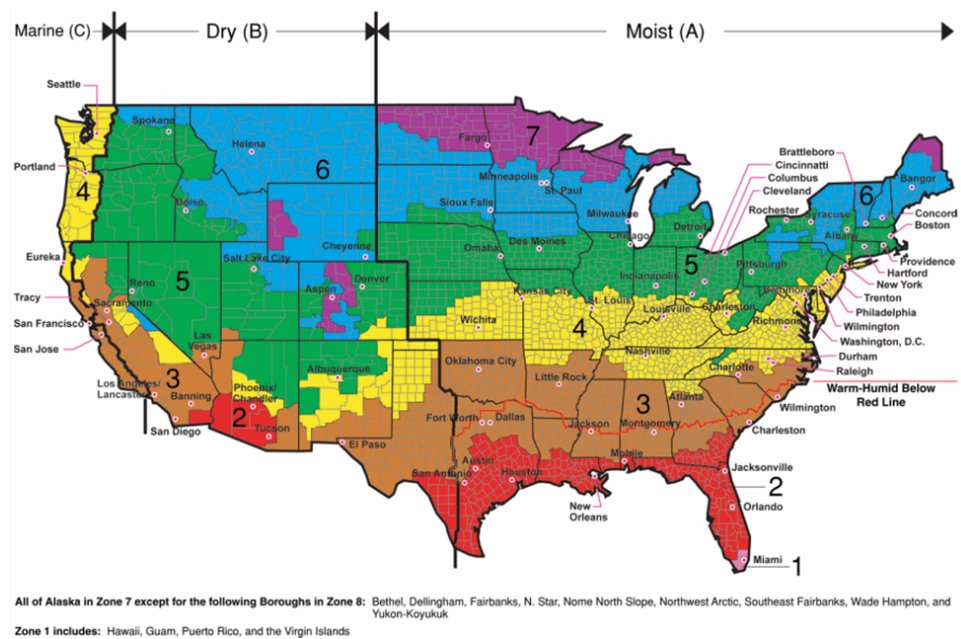


Figure 9.2: Climate Zones for U.S. locations from Figure B-1 of ASHRAE 90.1-2004

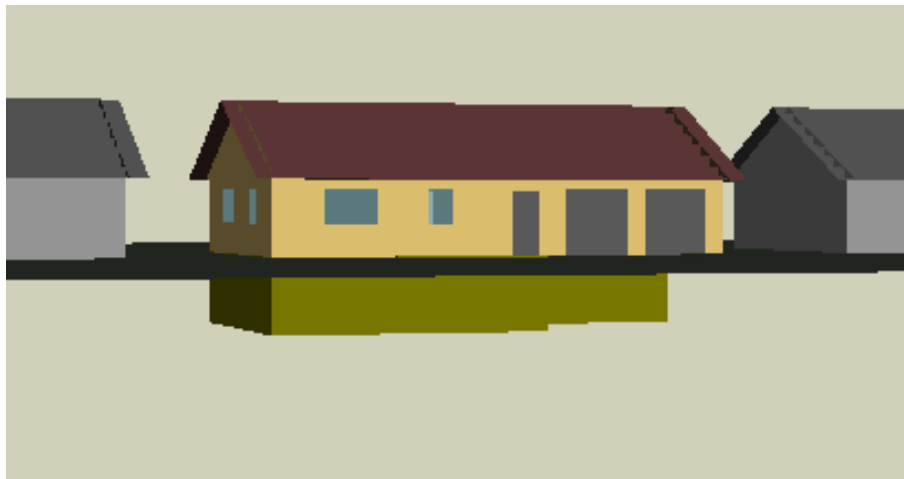
9.3 Building Model Creation

BEOpt [4] [5] was used to generate the benchmark home models. BEOpt is a software program designed by building energy scientists at the National Renewable Energy Laboratory in Golden, Colorado, which provides a quick and intuitive process for generating benchmark home models. Three homes sizes were created, 1,200 sqft, 2,700 sqft, and 5,030 sqft, in each of the four locations (Los Angeles, Houston, Chicago, and New York). The Residential Energy Consumption Survey (RECS) [51] conducted by the Energy Information Administration was used to adapt the home models to each specific region. The construction features that are the most common to each region, as specified in the RECS data, were applied to the home models in each location. Figure 9.4 shows a map of the RECS regions. Table 9.1 lists the input values used in BEOpt (as presented in the program interface) which differ from the default values. The full list of default inputs, as well as the range of options for each input category, is provided in Appendix B. Renderings of the three home sizes (for New York) are shown in Figure 9.3 below.

Table 9.1: Non-Default Inputs to BEOpt

Region	NorthEast	Midwest	South	West
SubRegion	Middle Atlantic	East North Central	West South Central	Pacific
City	New York	Chicago	Houston	Los Angeles
Foundation	Unfinished Basement	Unfinished Basement	Slab	Slab
Garage Type	Attached	Attached	Attached	Attached
Garage Size	2 car	2 car	2 car	2 car
Neighbors	15ft	15ft	15ft	15ft
Wood Stud	R11 Batts, 2X4, 16" o.c.	R11 Batts, 2X4, 16" o.c.	R11 Batts, 2X4, 16" o.c.	R11 Batts, 2X4, 16" o.c.
Exterior Finish	Gray Vinyl Siding	Gray Vinyl Siding	Red Brick	Stucco
Unfinished Attic	Ceiling R19 Cellulose, Blown-In, Vented	Ceiling R19 Cellulose, Blown-In, Vented	Ceiling R19 Cellulose, Blown-In, Vented	Ceiling R19 Cellulose, Blown-In, Vented
Infiltration	Typical	Typical	Typical	Typical
Window Type	Double Clear	Double Clear	Single	Single
Cooking Range	Gas, Conventional	Electric, Conventional	Electric, Conventional	Electric, Conventional
Lighting	20% florescent, Hardwired	20% florescent, Hardwired	20% florescent, Hardwired	20% florescent, Hardwired
Air Conditioner	SEER 13	SEER 13	SEER 13	SEER 13
Furnace	Gas, AFUE 78%	Gas, AFUE 78%	Gas, AFUE 78%	Gas, AFUE 78%
Water Heater	Gas Standard	Gas Standard	Gas Standard	Gas Standard

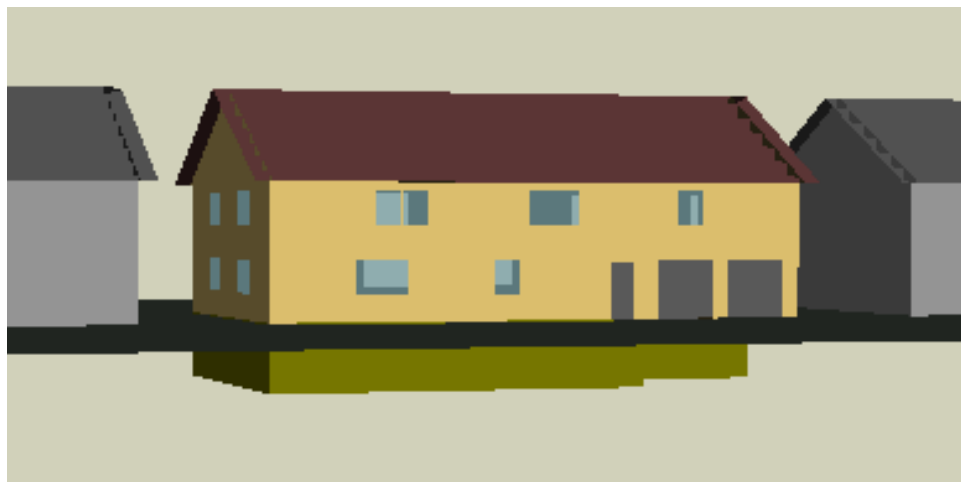
New York and Chicago homes were built above an unfinished basement while Houston and Los Angeles homes are on slabs as defined in the RECS data. The basement, when applied, is uninsulated and unconditioned. Neighbors were set at 15ft in all cases to represent the majority of the population being in or near cities. Exterior finishes vary by region with gray vinyl siding in New York and Chicago, brick (red) in



(a) 1200 sqft Home (NY)



(b) 2700 sqft Home (NY)



(c) 5030 sqft Home (NY)

Figure 9.3: Home Model Renderings

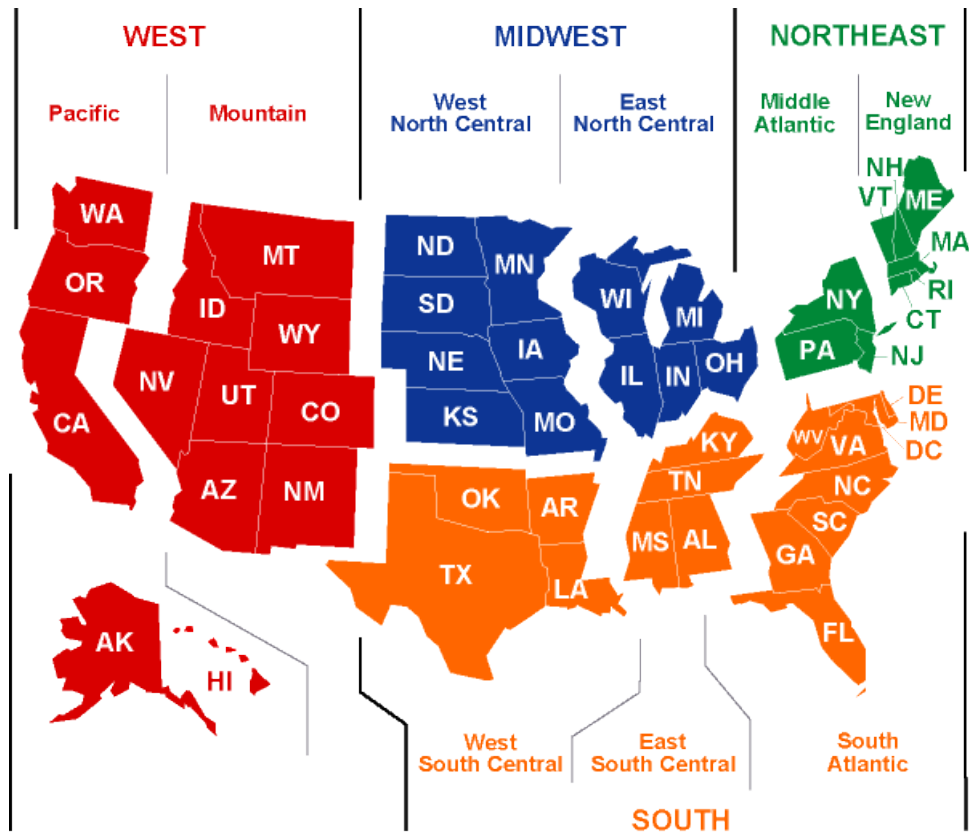


Figure 9.4: RECS Regions [51]

Houston, and stucco in Los Angeles. R11-batt insulation in 2x4 wood stud walls and R-19 blown-in cellulose in the attic were chosen to represent ‘adequate insulation’ described in the RECS data. Infiltration was set to ‘typical’ in BEopt for all locations per the RECS data describing the homes in these regions as never being drafty. It is not common to have energy efficient bulbs in any region according to the RECS data so the minimum option of ‘20% florescent’ was chosen in BEopt for all homes.

Air conditioning efficiency is not listed in the RECS data. SEER 13 Air conditioners were used in all homes. It is worth noting that in the Northeast (New York) window units are more common than central units, however New York homes were given SEER 13 central units for this study as window units are not an option in BEopt. The Building America Benchmark [19] set points and schedules were used in BEopt: the heating set point is set to 71 and the cooling set point is set to 76. In all regions a non-programmable thermostat is typical, yet this study is based on the assumption that control enabling thermostats are provided by the utility or purchased by the homeowner to engage in the time-of-use rate plan.

9.4 Simulation Procedure

Each building model was turned into a template by replacing the necessary fields and schedules with tokens. The desired output variables were also placed in each of the .idf templates. The edits made to the .idf files to create the model templates are provided in Appendix D. An .epw weather file for each city was chosen and used for all simulations in that location along with the downloaded price data for each region. The full list of simulation permutations is provided in Table 9.2. There are 4 locations, each with three home sizes for a total of 12 unique building models. Each model was simulated with three different peak period lengths, two rate ratios, and two set point temperature offsets for a total of 12 unique control scenarios. Thus, a total of 144 model permutations were simulated for this study.

Table 9.2: Simulation Permutations

location	sqft	peakHrs	peakRatio	spOffset
New York	1200	4	1.5	3
Chicago	2700	6	2	6
Houston	5030	8		
Los Angeles				

In all cases the peak period is centered on the hour with the highest average wholesale price. After the

base case is simulated the flat rate price is calculated so that the cost to the utility and homeowner are equal based on the baseline energy profile. In the control scenario, the length of the peak period is chosen and the peak period price is set to either 1.5 or 2 times the flat rate. The off-peak rate is then calculated so that the cost to the homeowner is equivalent to the previous cost with the flat rate. This prevents the time-of-use rate from penalizing the homeowner if no change is made to the baseline energy profile. The temperature offset is applied to the set point schedule for all peak hours and then the unique control scenario is simulated. An output chart of price, temperature, energy consumption, and cost is created for each simulation. The hourly average peak energy savings, daily average energy savings, total utility cost savings, and total homeowner cost savings are calculated and stored in a table.

Chapter 10

Real Time Price Analysis

The average hourly real time prices for each city for the period June 1 through September 30, 2008 are shown in Figure 10.1. For New York, the New York City zonal LBPM was used (Zone PTID 61761). This price is published in 5 minute intervals. For Chicago, the total local marginal price for the Chicago Hub (PnodeId 33092313) was used, published as hourly intervals. For Los Angeles, the hourly average energy price for CNGS_Zone LA1 was used. For Houston, the market clearing price for load was used from the Houston zone (MCPEL-H08), published in 15 minute intervals. New York and Houston have the most extreme price spikes, which occur mostly in the first three months.

The price density in each region is shown in Figure 10.2. Chicago has far more hours with lower prices than the other locations, and a left tail that extends into the negative price range more than the other locations. New York and, especially, Houston have a significant hump on the right tail. This may be the affect of congestion driving up the price of electricity. Every location has this hump to some degree on the right tail, yet no location has a hump on the left tail. This chart is cut off at \$500/MWh, but it is worth noting that New York and Houston both have price spikes that extend far beyond the right most boundary of this graph. Houston reaches nearly \$2000/MWh on one occasion as shown in Figure 10.1.

A box plot of each location's daily price profile is shown in Figure 10.3(a) and Figure 10.3(b) (zoomed in for detail). The whiskers on this plot represent the maximum and minimum price occurrence for that hour of the day. The high price spikes in New York occur between hours 14 and 22, while the high price spikes in Houston occur between hours 12 and 21 and in hour 23. The high price spikes in Los Angeles are much more mild, but occur on almost all hours of the day and tend to follow the general price profile throughout the

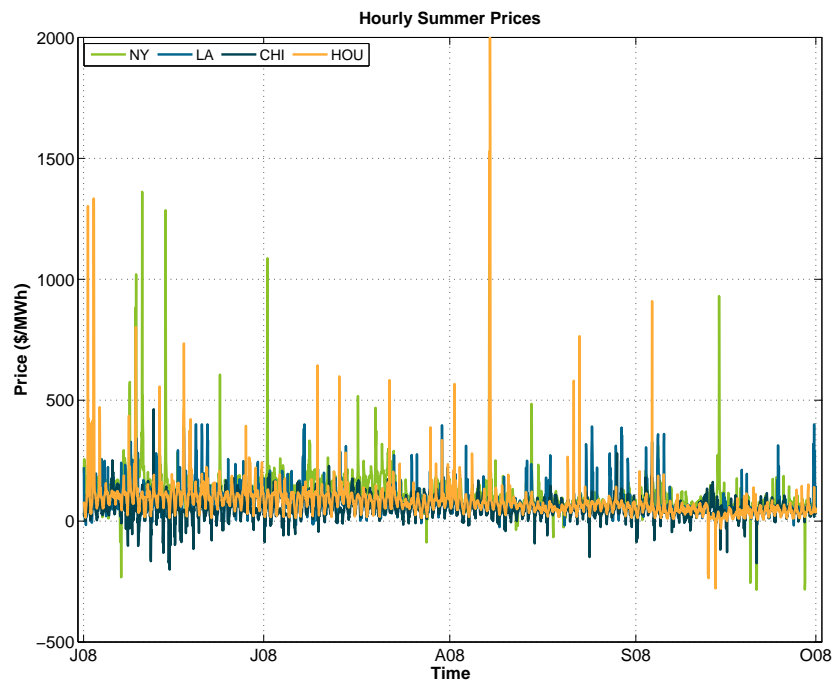


Figure 10.1: Hourly Prices : June - Sept 2008

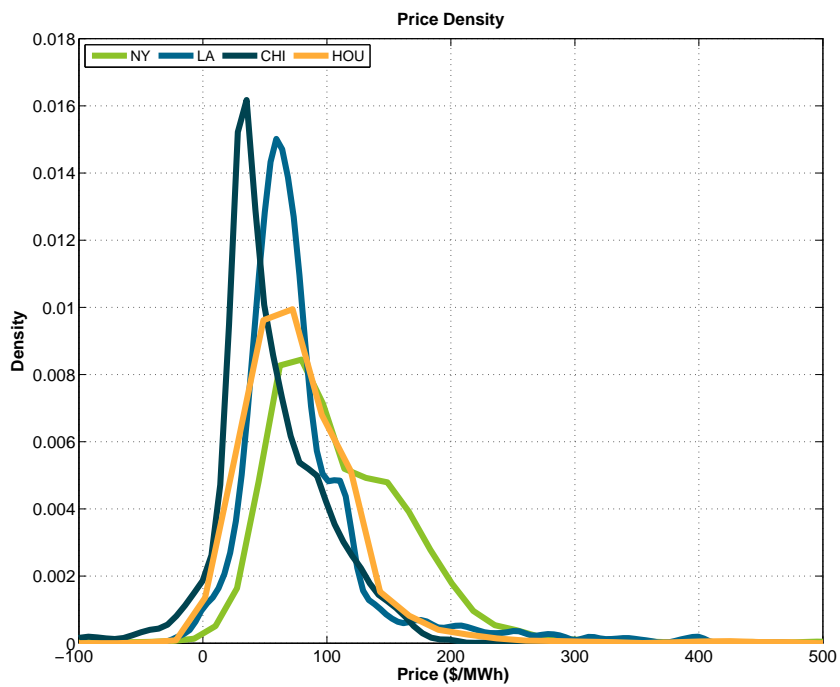
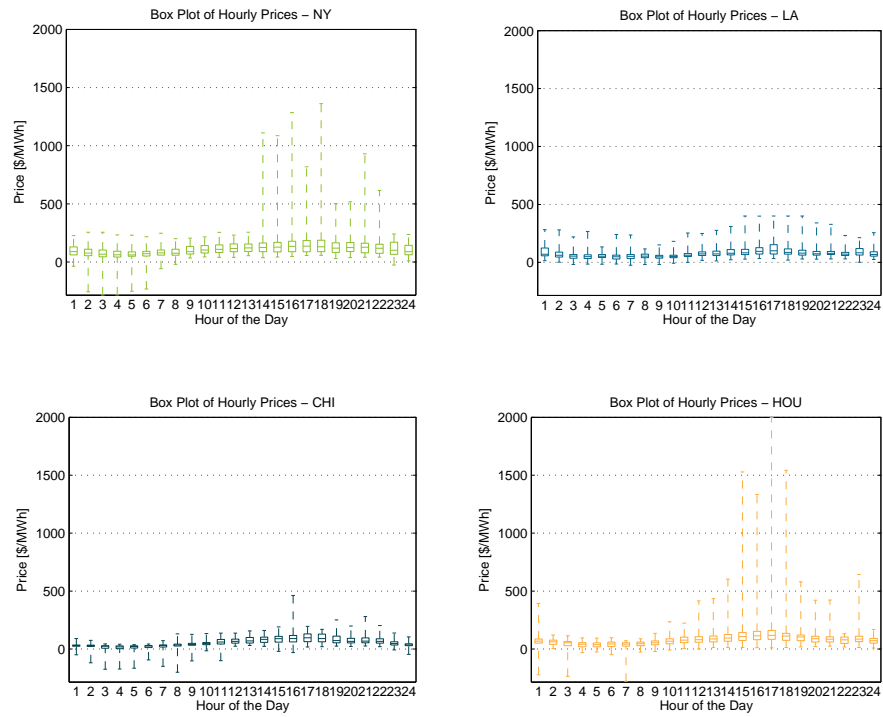


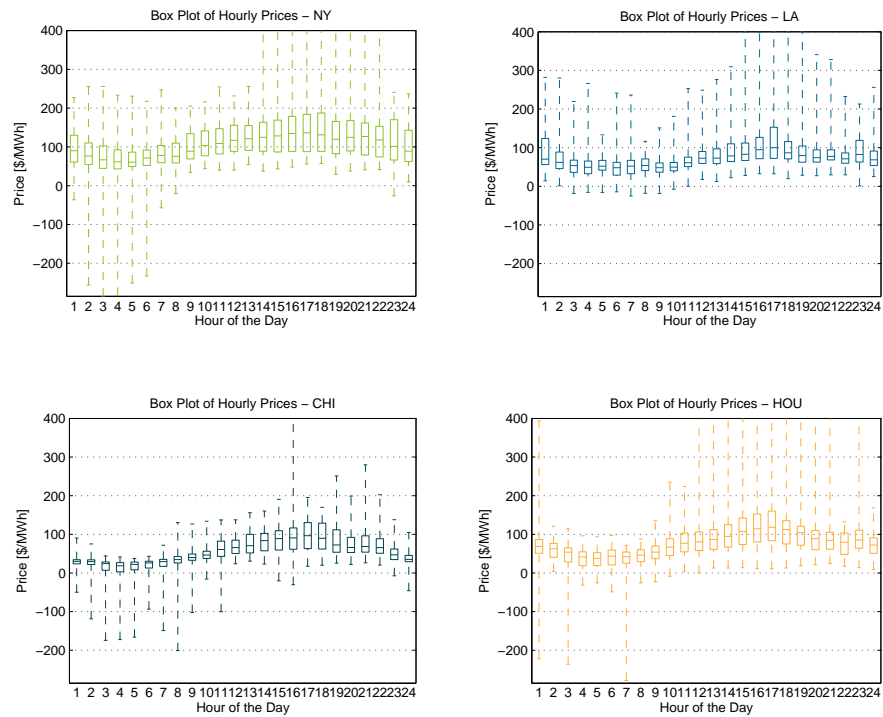
Figure 10.2: Price Density : June - Sept 2008

day. Prices in Chicago during the early hours of the day are very low, comparatively, to the other locations. Both Chicago and New York have early morning low price spikes that fall well into the negative range. New York even reaches negative prices below $-\$200/\text{MWh}$.

Figure 10.4 shows the average daily price profile for each location. New York has the highest average daily price profile for most of the day. Houston has the highest peak in the average daily price profile. Los Angeles and Houston have a very sharp average daily price profile, peaking at hour 17. Chicago has the lowest average daily price profile throughout the day, yet there is still a significant difference between the highest and lowest hours because of the very low prices in the early morning hours. All locations have an average daily price profile that peaks in hour 17.



(a) Full Scale



(b) Zoomed In

Figure 10.3: Box Plots of Hourly Price Variability : June - Sept 2008

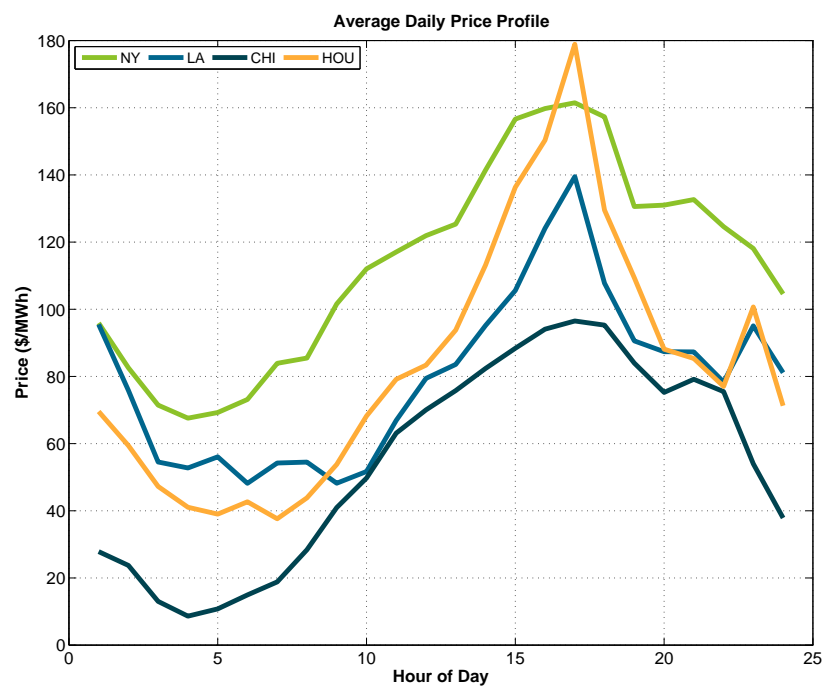


Figure 10.4: Average Daily Price Profile : June - Sept 2008

Chapter 11

Regional Benchmark Study Results

11.1 Overview

In this chapter the outputs from the simulation tool for the regional benchmark study are explained in detail. The affect of each simulation permutation is examined in isolation and the high and low savings cases for each energy and cost savings metric are presented. Finally, insights into the design of an effective time-of-use rate program is discussed.

11.2 Location Comparison

For each control scenario a chart like the one shown in Figure 11.1(a) is created. This chart shows the average profiles for the period of study in the following order: 1) the prices involved for both the utility and homeowner, 2) the temperatures outside and inside including set point, 3) the energy consumption, which is split by cooling and non-cooling end use, and 4) the associated cost to the utility and homeowner.

The first graph shows: 1) the average hourly wholesale price of energy, 2) the flat rate required to create an equal cost for the utility and homeowner, 3) the time of use rate where the peak rate is a factor of 1.5 or 2 greater than the flat rate and the off-peak rate is calculated to be cost neutral with the flat rate.

The second graph shows: 1) the outdoor dry bulb temperature, 2) the set point without control, 3) the set point temperature with control, and 4) the inside temperature at the thermostat in the control scenario.

The third graph shows 1) the baseline consumption profile, 2) the controlled consumption profile with the set point offset applied, and 3) the consumption profile not related to cooling.

The fourth graph shows 1) the energy cost for the utility for the base case, 2) the energy cost for the utility for the control case, 3) the energy cost for the homeowner for the base case, and 4) the energy cost for the homeowner for the control case.

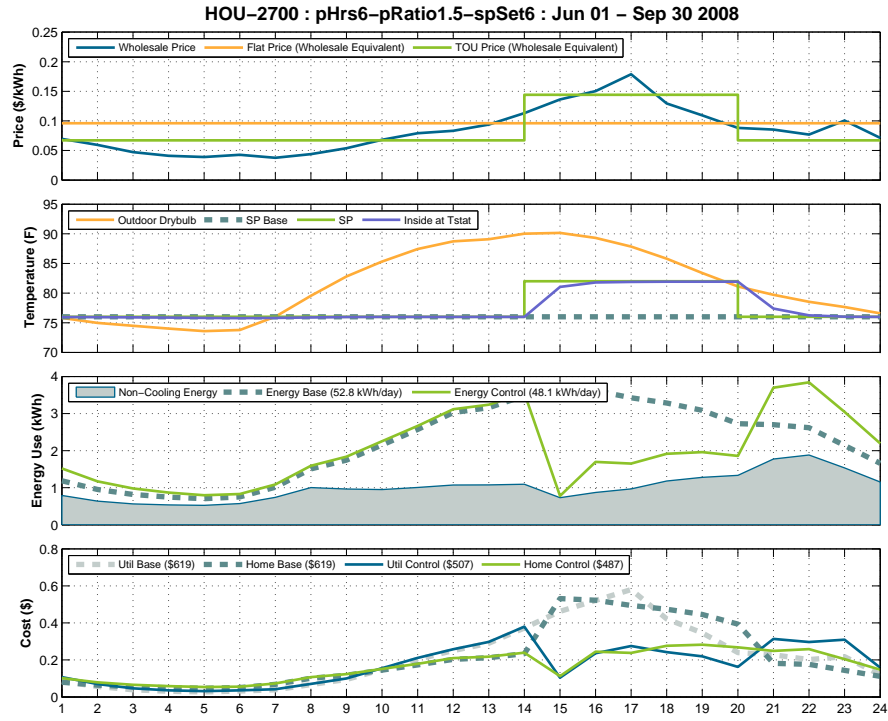
The output chart for each control scenario in this study is provided in Appendix C. The chart title reveals the details of the simulation variables. In this example the simulation is for Houston, the 2700 sqft home, a peak period of 6 hours, a peak price 1.5 times that of the flat rate, a set point offset of 6 °F, from June 1, 2008 through September 30, 2008.

In the third graph, energy consumption is plotted as a line graph with the data point at each hour being the total energy consumption for the hour. This is, in essence, kWh/h and thus can also be interpreted as the average demand (kW) over the hour. However, as this chart is an average profile from four months of data, the actual demand on any given day could vary greatly.

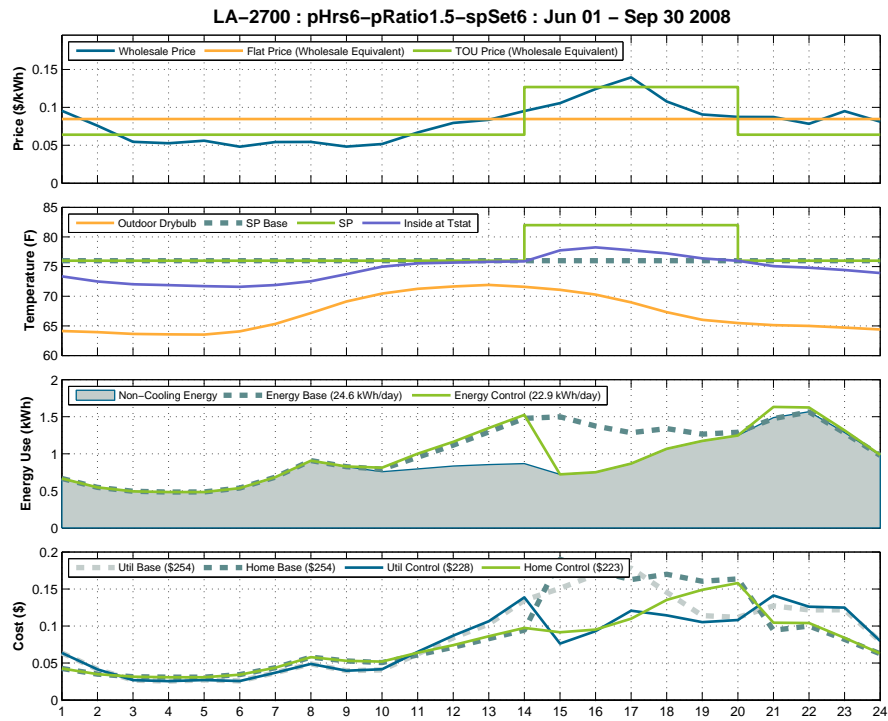
After each simulation the hourly average peak energy, daily average energy, total utility energy cost, and total homeowner energy cost are calculated. These values and the calculated savings are stored in an output table. The simulation parameters have been condensed into one field which can be read as follows: City - Home Size (sqft) - Peak Hours - Rate Ratio - Set Point Offset. Table 10.1 provides the results for a single home and control scenario in the four different locations. This is the same home and control scenario shown in Figure 11.4 for the locations of Houston and Los Angeles.

From these results it is clear that each city's unique climate and energy market affects the results of the control strategy tremendously. The home in Houston reduced its peak energy consumption by over 50% while the reduction in Los Angeles was less than 30%. Moreover, the average kWh saved per hour in Houston is 4.7 times greater than in Los Angeles. It is clear from the charts in Figure 11.4 that the greater energy reduction potential in Houston is due to the hot climate and, accordingly, the higher base consumption profile. The base consumption for both the average hourly peak and average daily energy is twice as large in Houston. In all regions, the percentage for cost savings exceed that of daily average energy savings.

A snapshot of the temperature profile for each city is provided in Figure 11.2 below. In Los Angeles the average temperature profile at its peak is still a few degrees below the benchmark set point of 76 °F.



(a) Houston



(b) Los Angeles

Figure 11.1: Output for Houston and Los Angeles

Table 11.1: Savings Comparison By City

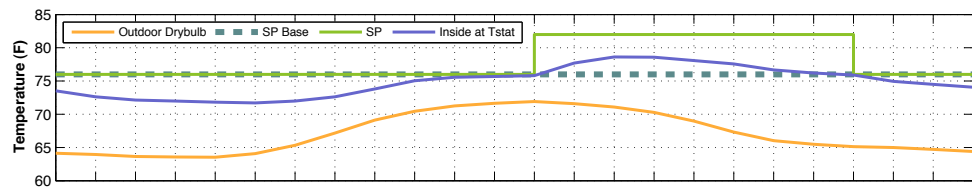
Hourly Average Peak Energy				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
LA-2700-6-1.5-6	1.34	0.97	0.37	27.6
HOU-2700-6-1.5-6	3.43	1.7	1.73	50.3
CHI-2700-6-1.5-6	1.68	1.01	0.67	39.8
NY-2700-6-1.5-6	1.67	0.91	0.76	45.3

Daily Average Energy				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
LA-2700-6-1.5-6	24.61	22.86	1.76	7.1
HOU-2700-6-1.5-6	52.75	47.98	4.77	9
CHI-2700-6-1.5-6	28.7	26.27	2.43	8.5
NY-2700-6-1.5-6	29.91	27.68	2.23	7.5

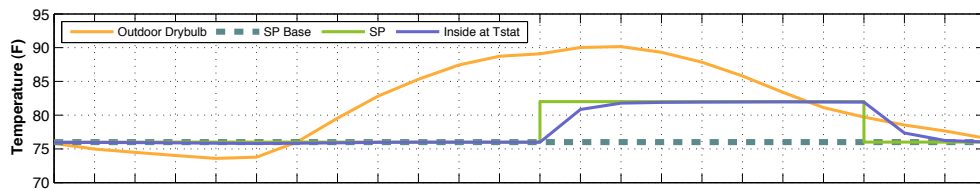
Total Utility Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
LA-2700-6-1.5-6	254	228	26	10
HOU-2700-6-1.5-6	628	500	128	20
CHI-2700-6-1.5-6	232	199	32	14
NY-2700-6-1.5-6	455	404	51	11

Total Homeowner Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
LA-2700-6-1.5-6	254	223	31	12
HOU-2700-6-1.5-6	628	488	140	22
CHI-2700-6-1.5-6	232	192	39	17
NY-2700-6-1.5-6	455	378	77	17

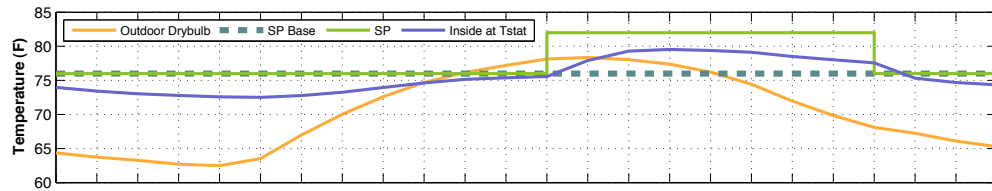
However, in Houston, the average temperature peaks at 90 °F and is above the set point for 17 hours, from hour 7 to 24. Comparing Houston to the other three cities, it stands out in that within the first two hours of the peak period, even with at 6 °F offset, the new set point is reached nearly every day. While this home still continues to create peak energy savings, the air conditioning unit will be cycling on and off and, unless this process is coordinated with controls, continued demand savings is not guaranteed at any moment.



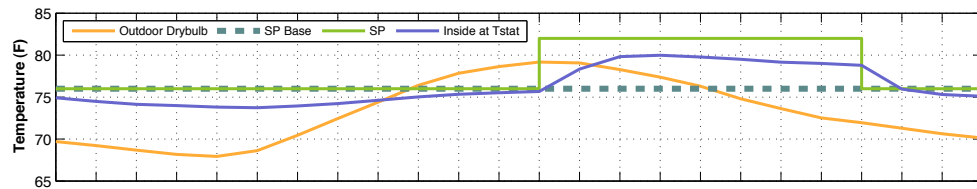
(a) Los Angeles



(b) Houston



(c) Chicago



(d) New York

Figure 11.2: Temperature Snapshot

11.3 Peak Period Length Comparison

To compare the effect of the peak period length on energy and cost savings the 2700 sqft home in New York is presented in Table 10.2 and the control scenario with a peak period of 6 hours is shown in Figure 11.3. The average hourly peak energy savings decreases as the peak period is lengthened because the potential for cooling load reduction diminishes as the evening approaches. This is a very different scenario than in Houston where the control set point is reached within a couple hours on all days. The average daily energy savings, naturally, increases with the length of the peak period. In this case doubling the length of the peak period more than doubles the daily average energy savings and the cost savings for both the utility and homeowner. This is likely due to the reduced snapback effect for a set point change later in the evening, when it is cooler.

Table 11.2: Savings Comparison By Peak Period Length

Hourly Average Peak Energy				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
NY-2700-4-1.5-6	1.64	0.86	0.78	47.7
NY-2700-6-1.5-6	1.67	0.91	0.76	45.3
NY-2700-8-1.5-6	1.7	0.99	0.71	41.7

Daily Average Energy				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
NY-2700-4-1.5-6	29.91	28.59	1.32	4.4
NY-2700-6-1.5-6	29.91	27.68	2.23	7.5
NY-2700-8-1.5-6	29.91	26.77	3.15	10.5

Total Utility Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-2700-4-1.5-6	455	423	32	7
NY-2700-6-1.5-6	455	404	51	11
NY-2700-8-1.5-6	455	385	70	15

Total Homeowner Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-2700-4-1.5-6	455	407	48	11
NY-2700-6-1.5-6	455	378	77	17
NY-2700-8-1.5-6	455	348	107	23

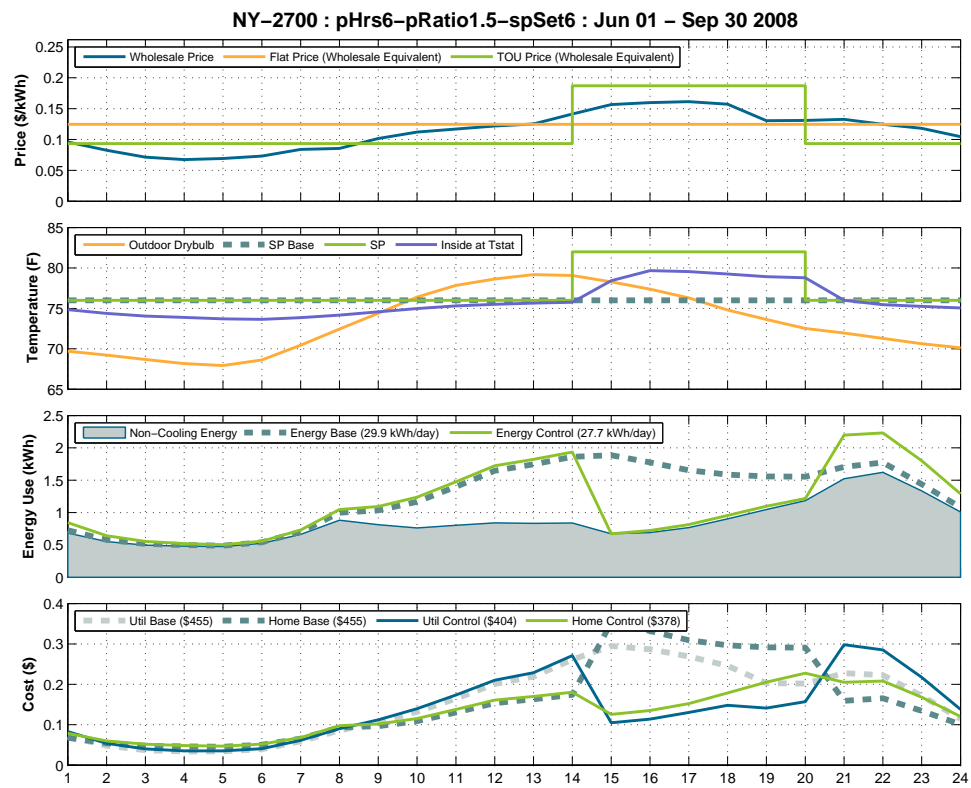


Figure 11.3: Output for New York

11.4 Home Size Comparison

As expected the energy and cost savings increase with home size, though the percent savings are equal for the mid-size and large home. The small home has a smaller percent savings which may raise concerns of disadvantaging lower income customers, though it should be noted that in this study the small home has all of the same appliances, which will obviously create a higher proportional energy consumption. Still, it is easy to see that when savings are measured as \$/sqft the small homes fairs far better than the large home.

Table 11.3: Savings Comparison By Home Size

Hourly Average Peak Energy				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
NY-1200-6-1.5-6	1.19	0.76	0.42	35.7
NY-2700-6-1.5-6	1.67	0.91	0.76	45.3
NY-5030-6-1.5-6	2.15	1.12	1.03	47.7

Daily Average Energy				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
NY-1200-6-1.5-6	21.56	20.14	1.42	6.6
NY-2700-6-1.5-6	29.91	27.68	2.23	7.5
NY-5030-6-1.5-6	38.78	35.92	2.86	7.4

Total Utility Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-1200-6-1.5-6	325	294	31	9
NY-2700-6-1.5-6	455	404	51	11
NY-5030-6-1.5-6	587	522	65	11

Total Homeowner Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-1200-6-1.5-6	325	280	45	14
NY-2700-6-1.5-6	455	378	77	17
NY-5030-6-1.5-6	587	485	102	17

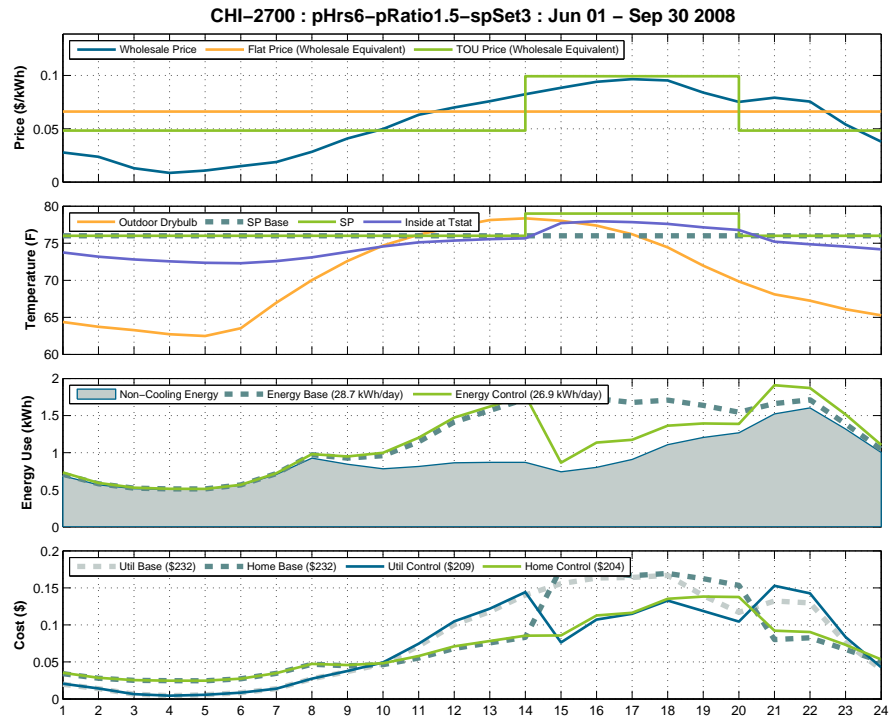
11.5 Set Point Offset Comparison

Increasing the set point during the peak period is only effective to a certain degree. The point at which the reduction begins to diminish depends largely on the climate and the characteristics of the home. For the benchmark home (2700 sqft) in Chicago, the 6 °F offset reaches the maximum potential for energy and demand savings with a 6 hour peak period. The air conditioning is off the entire time on all but a few of the hottest days. This is also the case in New York and Los Angeles as shown in the previous charts. In Los Angeles the air conditioning does not run during the peak period on any day with the 6 °F offset control strategy . In Houston, however, the 6 °F offset is effective for only the first hour as shown in Figure 11.1(a). This location would benefit from higher set point offsets. A snapshot of the consumption profile for each

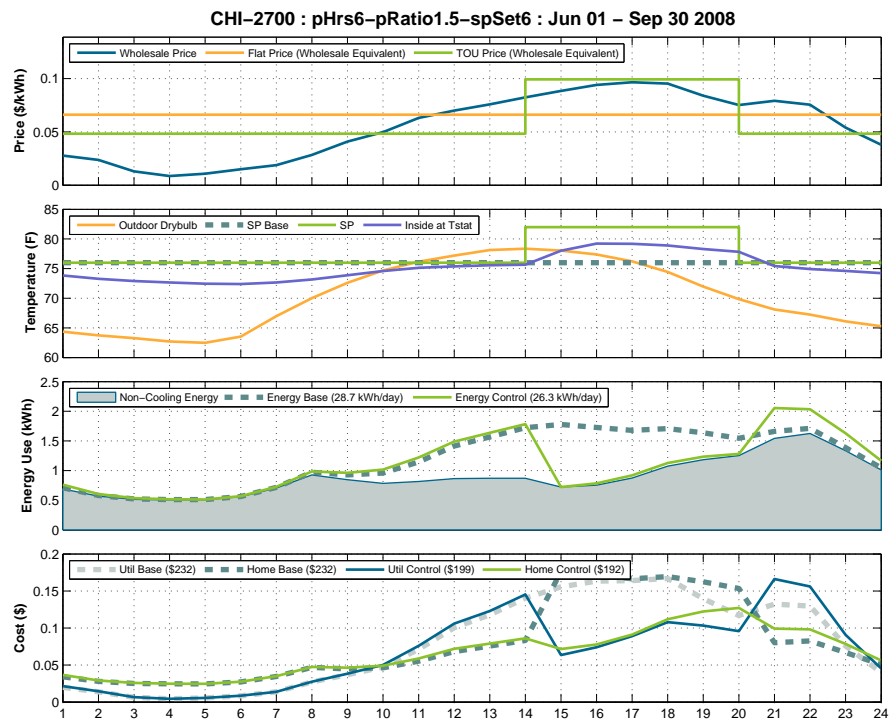
city is provided in Figure 11.5 below.

Table 11.4: Savings Comparison By Set Point Offset

Hourly Average Peak Energy				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
CHI-2700-6-1.5-3	1.68	1.22	0.46	27.4
CHI-2700-6-1.5-6	1.68	1.01	0.67	39.8
Daily Average Energy				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
CHI-2700-6-1.5-3	28.7	26.87	1.83	6.4
CHI-2700-6-1.5-6	28.7	26.27	2.43	8.5
Total Utility Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
CHI-2700-6-1.5-3	232	209	23	10
CHI-2700-6-1.5-6	232	199	32	14
Total Homeowner Cost				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
CHI-2700-6-1.5-3	232	204	28	12
CHI-2700-6-1.5-6	232	192	39	17

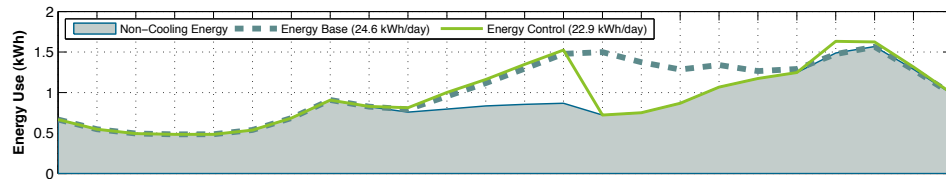


(a) 3 degree off set

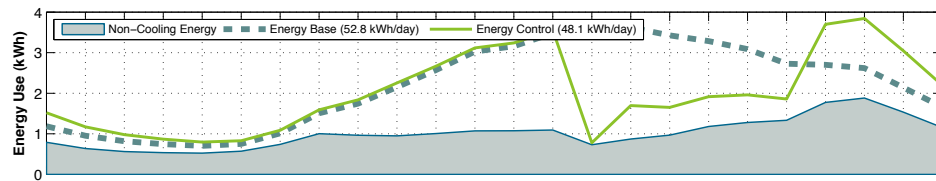


(b) 6 degree off set

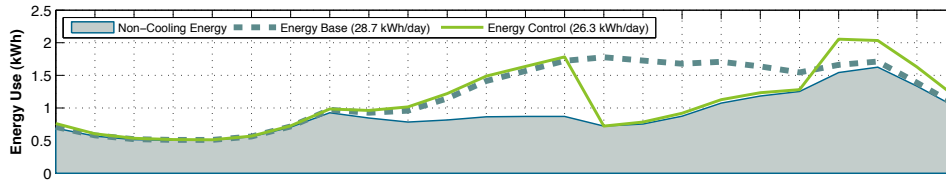
Figure 11.4: Output for Chicago



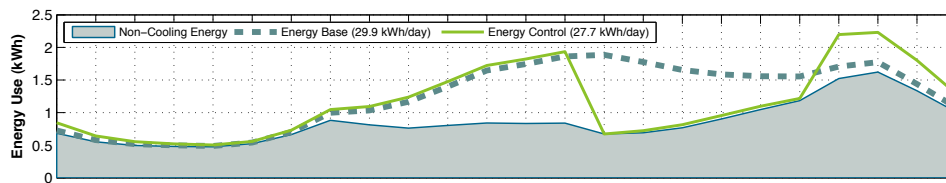
(a) Los Angeles



(b) Houston



(c) Chicago



(d) New York

Figure 11.5: Load Reduction Snapshot

11.6 Savings Comparison

In the following tables the six highest and six lowest results for each metric are presented.

11.6.1 Hourly Average Peak Energy Savings

Table 10.5 contains the homes with the highest and lowest hourly average peak energy savings from this benchmark study. The highest load reduction occurs in Houston, in the larger homes, with shorter peak periods. This make perfect sense. Long control periods for cooling load reduction tend to lose effectiveness from either diminished cooling load or reaching the control set point.

The lowest peak reduction occurs in Los Angeles and Chicago, in the smaller homes, with the longer peak periods. These results coincide well with the price variation discussed previously in that Los Angeles and Chicago suffer the least from peak period price spikes while Houston and New York suffer the most.

Table 11.5: Savings Comparison By Hourly Average Peak Energy Reduction

Highest Savings				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
HOU-5030-4-1.5-6	4.88	1.68	3.2	65.5
HOU-5030-4-2-6	4.88	1.68	3.2	65.5
HOU-5030-6-1.5-6	4.77	1.97	2.8	58.7
HOU-5030-6-2-6	4.77	1.97	2.8	58.7
HOU-2700-4-1.5-6	3.5	1.5	2.01	57.2
HOU-2700-4-2-6	3.5	1.5	2.01	57.2

Lowest Savings				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
LA-1200-6-1.5-3	1.08	0.87	0.21	19.2
LA-1200-6-2-3	1.08	0.87	0.21	19.2
CHI-1200-8-1.5-3	1.21	1	0.21	17.4
CHI-1200-8-2-3	1.21	1	0.21	17.4
LA-1200-8-1.5-3	1.08	0.89	0.19	17.7
LA-1200-8-2-3	1.08	0.89	0.19	17.7

11.6.2 Daily Average Energy Savings

Observing the daily average energy savings shown in Table 10.6, two distinct situations stand out. First, the mid-size home in Houston saved more than any of the large homes with the longest peak period. This is due to Houston's extremely hot temperatures which make cooling loads a large contributor to the peak energy load. Secondly, it is interesting that even a 6 °F offset in Los Angeles saved less than the 3 °F offsets in Houston and New York.

Table 11.6: Savings Comparison By Daily Average Energy Reduction

Highest Savings				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/day)	Saved (%)
HOU-5030-8-1.5-6	72.8	63.55	9.26	12.7
HOU-5030-8-2-6	72.8	63.55	9.26	12.7
HOU-5030-6-1.5-6	72.8	65.54	7.26	10
HOU-5030-6-2-6	72.8	65.54	7.26	10
HOU-2700-8-1.5-6	52.75	46.67	6.09	11.5
HOU-2700-8-2-6	52.75	46.67	6.09	11.5

Lowest Savings				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/day)	Saved (%)
CHI-1200-4-1.5-3	21.11	20.41	0.69	3.3
CHI-1200-4-2-3	21.11	20.41	0.69	3.3
LA-1200-4-1.5-6	19.46	18.76	0.69	3.6
LA-1200-4-2-6	19.46	18.76	0.69	3.6
LA-1200-4-1.5-3	19.46	18.83	0.63	3.2
LA-1200-4-2-3	19.46	18.83	0.63	3.2

11.6.3 Cost Savings

The large Houston home, with the 6 °F offset, has a monopoly on the utility cost savings as shown in Table 10.7. The results are roughly the same for the homeowner cost savings in that the large Houston home tops the charts and the small Los Angeles and Chicago home is at the bottom. Although, an important detail revealed in these two tables, is the fact that the homeowner saved more than the utility. In these two tables, especially in the homes with the higher cost savings, the homeowner saved far more than the utility, meaning the utility is losing revenue on the time-of-use program. In other words this is a poorly designed time-of-use rate plan. The following section provides insight into this situation and how the time-of-use program can be protected from this situation.

Table 11.7: Savings Comparison By Total Utility Cost Reduction

Highest Savings				
simulation	Base (\$)	Control(\$)	Saved (\$)	Saved (%)
HOU-5030-8-1.5-6	867	642	225	26
HOU-5030-8-2-6	867	642	225	26
HOU-5030-6-1.5-6	867	665	201	23
HOU-5030-6-2-6	867	665	201	23
HOU-5030-4-1.5-6	867	710	157	18
HOU-5030-4-2-6	867	710	157	18

Lowest Savings				
simulation	Base (\$)	Control(\$)	Saved (\$)	Saved (%)
LA-1200-4-1.5-6	201	189	12	6
LA-1200-4-2-6	201	189	12	6
LA-1200-4-1.5-3	201	190	11	5
LA-1200-4-2-3	201	190	11	5
CHI-1200-4-1.5-3	168	159	9	5
CHI-1200-4-2-3	168	159	9	5

Table 11.8: Savings Comparison By Total Homeowner Cost Reduction

Highest Savings				
simulation	Base (\$)	Control(\$)	Saved (\$)	Saved (%)
HOU-5030-8-2-6	867	397	469	54
HOU-5030-6-2-6	867	507	360	41
HOU-5030-8-1.5-6	867	577	290	33
HOU-2700-8-2-6	628	341	287	46
HOU-5030-8-2-3	867	600	267	31
HOU-5030-4-2-6	867	621	245	28

Lowest Savings				
simulation	Base (\$)	Control(\$)	Saved (\$)	Saved (%)
CHI-1200-4-2-3	168	153	15	9
CHI-1200-4-1.5-6	168	154	14	8
CHI-1200-6-1.5-3	168	153	14	9
LA-1200-4-1.5-6	201	188	13	6
LA-1200-4-1.5-3	201	190	11	6
CHI-1200-4-1.5-3	168	158	10	6

11.6.4 Utility to Homeowner Savings Ratio

There are only six cases in all of the 144 simulations in which the utility saves more than the homeowner. Table 10.9 shows the six highest and lowest utility to homeowner savings ratios. The savings ratio for all simulations is split almost perfectly with the rate ratio variable. A ratio of two (times the flat rate) creates the worst cases for the utility.

The root of this problem is the low off-peak price used to achieve rate neutrality. The off-peak price was calculated in order to make the time-of-use rate program to be cost neutral with the existing flat rate if no control is applied. When the difference between peak and off-peak prices in the time-of-use rate is greater than the general swing in wholesale price for the utility, then the homeowner has a higher potential to save energy cost by reducing or shifting load. This effect is shown graphically for a New York case in Figure 11.6.

Table 11.9: Savings Comparison By Utility/Homeowner Savings Ratio

Highest Savings Ratio			
simulation	Utility Saved (\$)	Homeowner Saved(\$)	Utility/Homeowner Ratio
HOU-1200-4-1.5-3	36	33	1.09
HOU-5030-4-1.5-3	98	93	1.05
HOU-1200-4-1.5-6	61	58	1.05
HOU-2700-4-1.5-3	61	58	1.05
HOU-5030-4-1.5-6	157	152	1.03
HOU-2700-4-1.5-6	100	97	1.03
Lowest Savings Ratio			
simulation	Utility Saved (\$)	Homeowner Saved(\$)	Utility/Homeowner Ratio
NY-2700-8-2-6	70	166	0.42
NY-2700-6-2-6	51	121	0.42
NY-2700-4-2-6	32	76	0.42
NY-5030-4-2-6	42	100	0.42
NY-5030-6-2-6	65	161	0.40
NY-5030-8-2-6	92	228	0.40

The same affect is demonstrated in Figure 11.7 which shows the kernel smoothed density functions of the utility price for all hours in the simulation period. The homeowner price is plotted as a vertical line. In the top graph all hours are plotted with the cost neutral flat rate. In the bottom graph the time-of-use program splits the hours into peak and off-peak hours. In both the New York and Houston case the peak period price for the homeowner is greater than the wholesale price for the utility during the majority of the peak hours. However, in the New York case, the off-peak price is significantly lower than the wholesale price for almost all off-peak hours. This off-peak rate was necessary to balance the high peak price, to make the program cost neutral. However, in this scenario, any load reduction or shift from peak hours creates cost

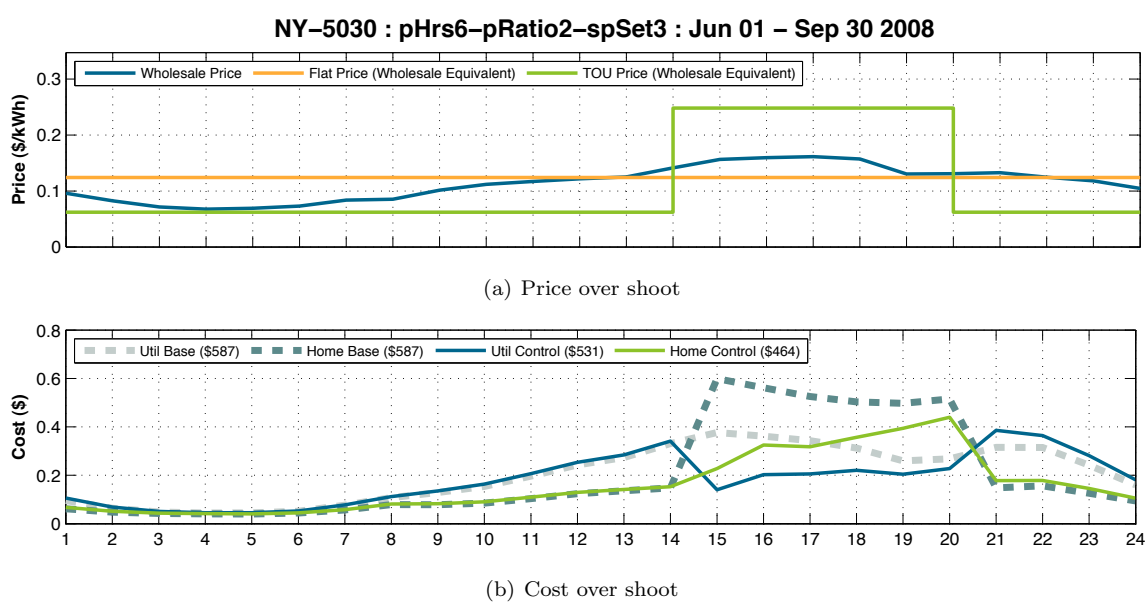
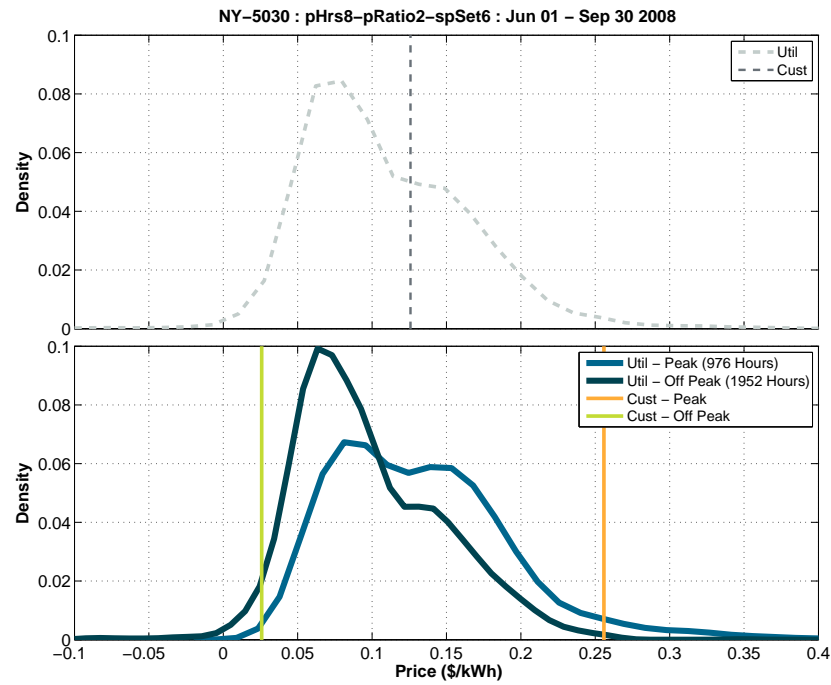
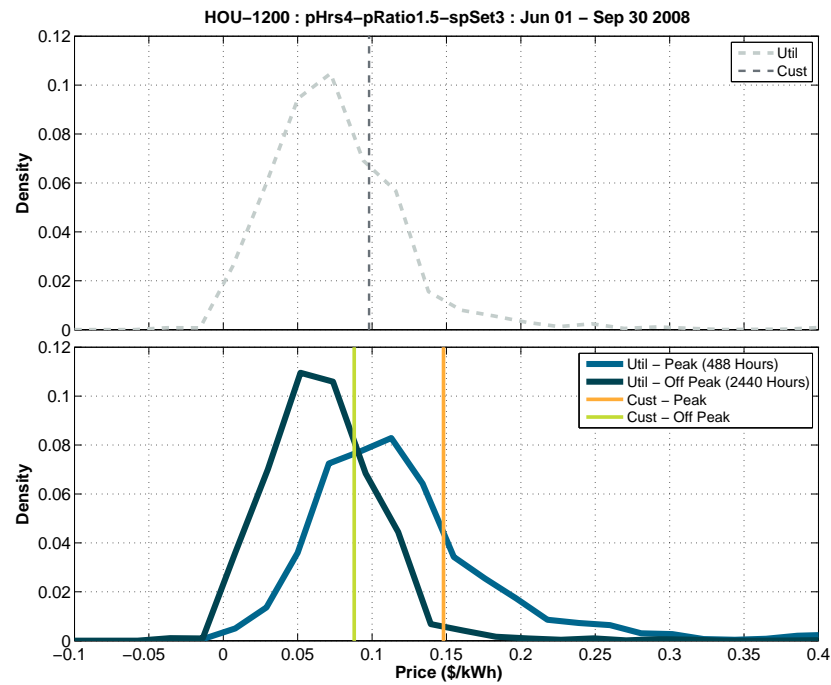


Figure 11.6: Time-of-use Price Overshoot

savings largely in favor of the homeowner due to the greater price differential. The Houston case shows a more ideal scenario where the difference between the peak and off-peak price is far less dramatic. Nor is the off-peak price for the homeowner below the wholesale price for the majority of off-peak hours. In this situation the utility has a higher cost savings than the homeowner, yet the majority of the cost savings that the utility receives are passed to the customer because the savings ratio is only 1.09. A ratio of two is ideal, as this splits savings evenly between the utility and homeowner.



(a) NY - Worst Price Ratio



(b) Houston - Best Case

Figure 11.7: Wholesale versus Time-of-use Price Density

Chapter 12

Conclusions and Future Work

This research project, completed through collaboration between Tendril and the Building Energy Research Group (BERG) at the University of Colorado at Boulder, focused on designing a control analytic tool for evaluating the effectiveness of different energy control strategies to shift/reduce energy consumption during peak pricing periods and lower energy cost for homeowners and utilities. This simulation tool was used to evaluate control strategies with building and weather interactions and provide insight into the most effect approaches for saving peak energy consumption and overall cost for both home owners and utilities. Conclusions related to TCAT's application in evaluating control strategies for utilities and homeowners are presented in this chapter. A summary of completed work is provided as well as a summary of the benefits of this work. Following, a brief discussion of future research direction concludes this masters thesis.

12.1 Conslusions from Benchmark Study

Based on the price variations and simulation results Houston and New York are best suited for thermostat set point control strategies to reduce peak energy consumption. Houston has the greatest potential for a thermostat set point offset to reduce peak energy consumption. LA would benefit more from a mix of technology to apply control strategies to both the thermostat and other appliances and devices in the home. LA and Chicago do not suffer from extreme price spikes as much as Houston and New York. In both Houston and New York a demand response or critical peak pricing program would also be appropriate.

To balance the savings potential of the utility and homeowner, the time-of-use rate must be designed to vary less than the wholesale energy price. Yet, if the peak to off-peak ratio is too small, than there is little

incentive for the homeowners to reduce or shift energy. A variety of options exist. The utility can design a rate that is not cost neutral with the existing flat rate. This would require careful analysis of potential energy savings through simulation with the savings goal for homeowners considered. A utility may also use shorter peak periods with a mild price increase, or design a demand response or critical peak pricing program that focuses only on a handful of days that have the highest wholesale energy prices. In any of these cases, the results will vary by region and home type. Using the insight gained from simulations of control scenarios is an effective way to evaluate the costs and benefits associated with a variety of peak load reducing programs.

12.2 Summary of Completed Work

This thesis explored the results of demonstration projects focused on reducing residential energy consumption and shifting demand loads. An investigation of the potential for residential energy load shifting and peak reduction focusing on large home appliances and devices as well as the integration of electric vehicles into control strategies was completed. A description of Tendril’s own device and platform capabilities was provided.

A case study on a home with Tendril’s smart grid enabling technology was conducted. A calibrated building energy model was created for this home using local weather data and used to evaluate a variety of control strategies for practical end uses with potential for reducing peak energy load.

The simulation environment in which the Tendril Control Analytic Tool was designed and the data flow for control strategy evaluation was discussed.

TCAT was modified to systematically evaluated a variety of control scenarios applied to benchmark homes in varying climate regions around the United States. The results of this study informs utilities on the benefits and risks involved in designing effective programs for reducing peak energy consumption and overall energy costs.

12.3 The Value of TCAT to Tendril and Utilities

TCAT allows Tendril to test a variety of control scenarios to understand the effectiveness of a program utilizing Tendril’s platform and devices to reduce peak energy consumption and save money for utilities and

homeowners. This tool can be used to guide utilities in implementing incentives for energy reduction that are beneficial to both the utility and their customers. TCAT can be used by Tendril's engineers to evaluate the practicality and potential of control capabilities enabled by their device and software technology as it is being developed.

12.4 Future Work

There are two natural directions for future work. Tendril is currently involved in pursuing both of these directions. First, faster and lighter weight modeling capabilities that integrate with Tendril's platform and software products would be highly valuable. Eliminating the need for third party applications to create and simulate building energy use is an important step in productizing a tool with capabilities, such as those applied in this thesis, for further smart grid applications. Second, work is needed in building an appropriate cost benefit analysis for each region based on the unique grid elements that effect the real time prices. Results such as those obtained in this thesis can be used to inform development of smart grid programs that cater to each regions unique balance of costs and benefits.

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Appendix A

Case Study Appliance Profiles

The following charts in this appendix provide insight into the occupant behaviors and schedules in the case study home. These profiles were used in the calibration of a building energy model used to evaluate automated smart grid control strategies.

The dishwasher is run much more frequently than the dryer. It appears from the recording data that is usually run at least everyday. When the heating element is on the dishwasher consumes just over 1 kW. This never occurs at the same time as the wash cycle. The wash cycle has two distinct loads at about .1 and .2 kW.

It is obvious from the consumption and operation schedule that the dishwasher is run immediately after being fully loaded. Every spike occurs just after a meal time, with the largest being in the evening, after dinner. There is also a distinct spike after breakfast, lunch, and other probably meal or snack times. The dishwasher is run nearly everyday but its peak average consumption only accounts for just over .12 kW on either the average weekend or weekday.

The refrigerator cycles on and off at intervals less than one hour. The compressor uses the most energy when it first turns on and then reduces slightly during the run period. Yet, as apparent in the histogram there is only one operating mode. The refrigerator typically consumes .14 kW when on. The maximum consumption on the average day chart is around .09 kW. The refrigerator is typically considered to be one of the largest energy consuming appliances in many homes. However, this is a result of its frequent operation, but does not necessarily make it a good option for peak reduction. The consumption and runtime charts match almost exactly as expected for an appliance with such a small power consumption variance as

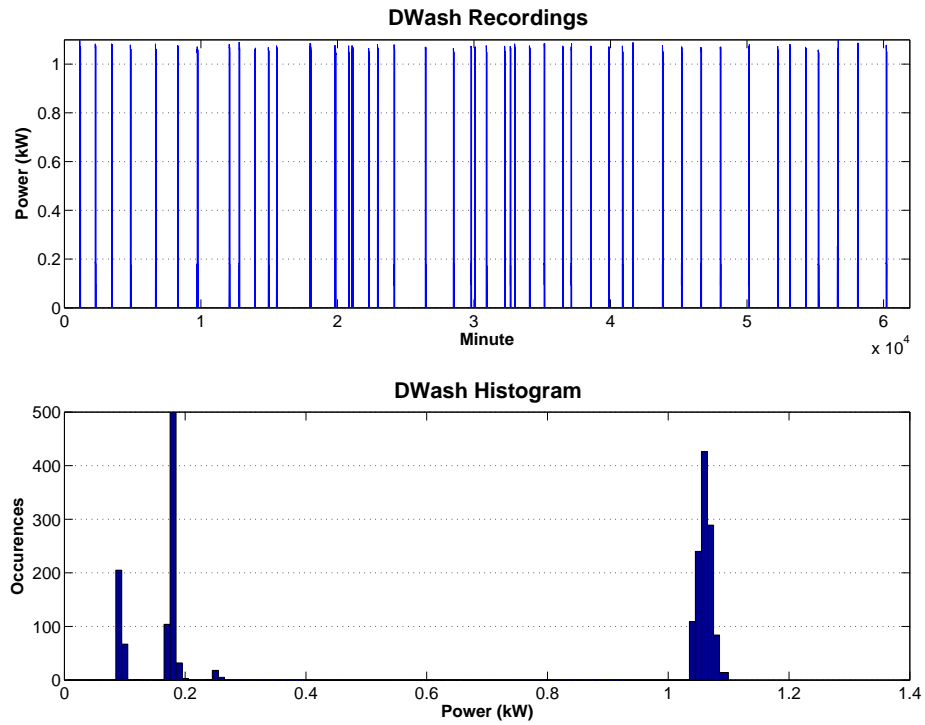


Figure A.1: Dishwasher recorded data

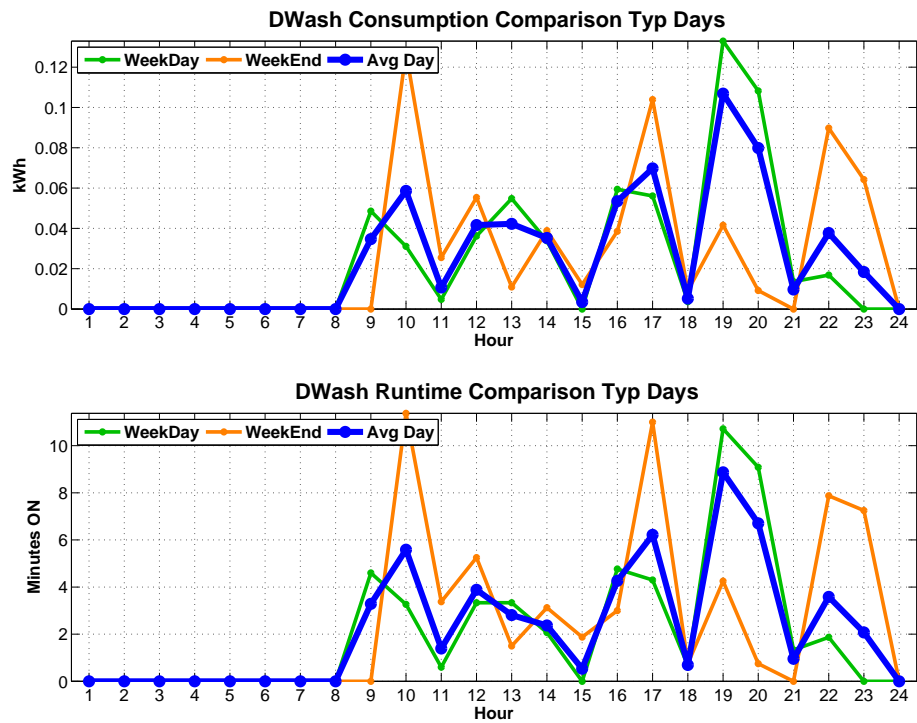


Figure A.2: Dishwasher average schedules

shown in the histogram.

The oven is the largest load in the home when on. It can consume up to 3.8 kW. There are 3 distinct heating power modes all between 2.5 and 4 kW, though it typically operates at 2.7 or 3 kW. It is used fairly frequently by the family and most often in the evenings. This appliance accounts for a large portion of evening loads on both weekends and weekdays with the weekend average load of .8kW at 18 o'clock. Unfortunately, this is not a good qualifier for peak energy reductions due to inconvenience.

The pool pump is also a significant load when on. It normally consumes around 1 kW, but also may consume between 2.5 and 3 kW on certain occasions. On weekdays the pool pump is scheduled to run between 9 PM and 5 AM, though it appears to have run on one afternoon during the weekday. On the weekends the pool pump may run through out the day and always runs between 9 and 15 o'clock. Though the pump runs constantly during certain hours of the day, it does have slightly different consumption throughout its runtime period because the power consumption slowly decreases the longer it operates.

The study room circuit includes many different pieces of office equipment as well as a few lights and miscellaneous loads such a fan and random plug loads. It is clear from the recorded data that there are constant standby loads from the office equipment. The histogram varies consumption from .1 to .6 kW, not including the standby load of .5 kW which has been removed for clarity. The schedule reveals, as expected, larger consumption during the daytime hours. On weekdays, there is a very smooth curve peaking around noon and then dropping of completely between 3 and 4 PM, likely when the kids are picked up from school, and then spiking again after. On the weekend the office is used much less and spikes just before noon and again in the early afternoon. Even without the stand by loads, something appears to run regularly in the even hours, possible an automatically scheduled data backup system.

The family room has a very large standby load of .1 kW and wide variety of consumption levels depending on which entertainment devices are being used. This equipment is used predominantly in the evening after work, but on occasion in the mornings, and it is used more on the weekends. There are obviously some standby load reduction potential, but little should be expected in the way of automatic controls for this entertainment equipment.

These recording were taken during a period when the thermostat was set to heating mode and the

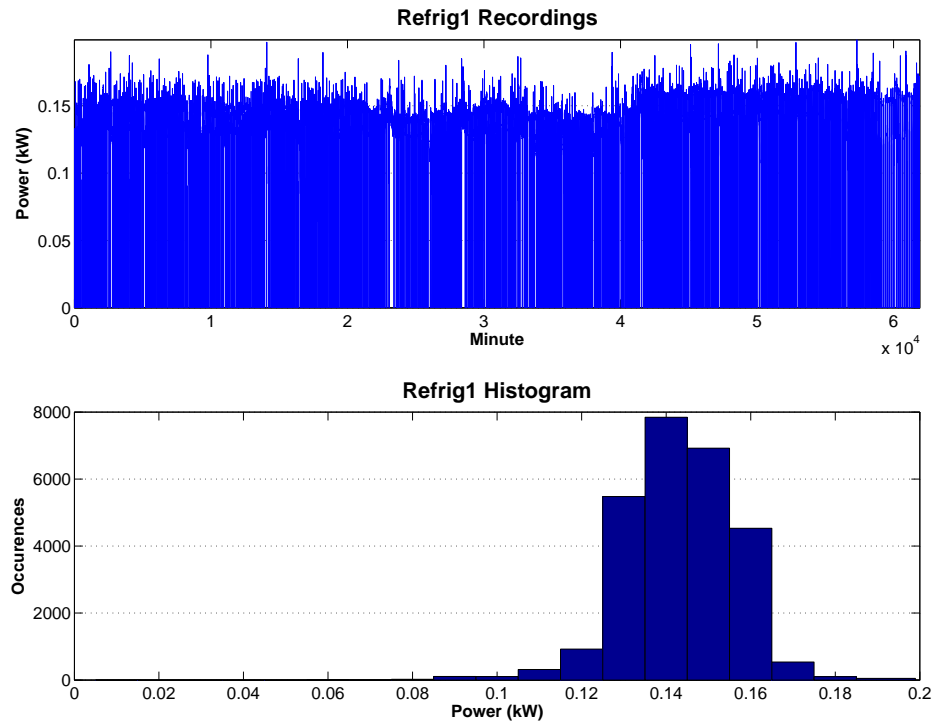


Figure A.3: Refrigerator recorded data

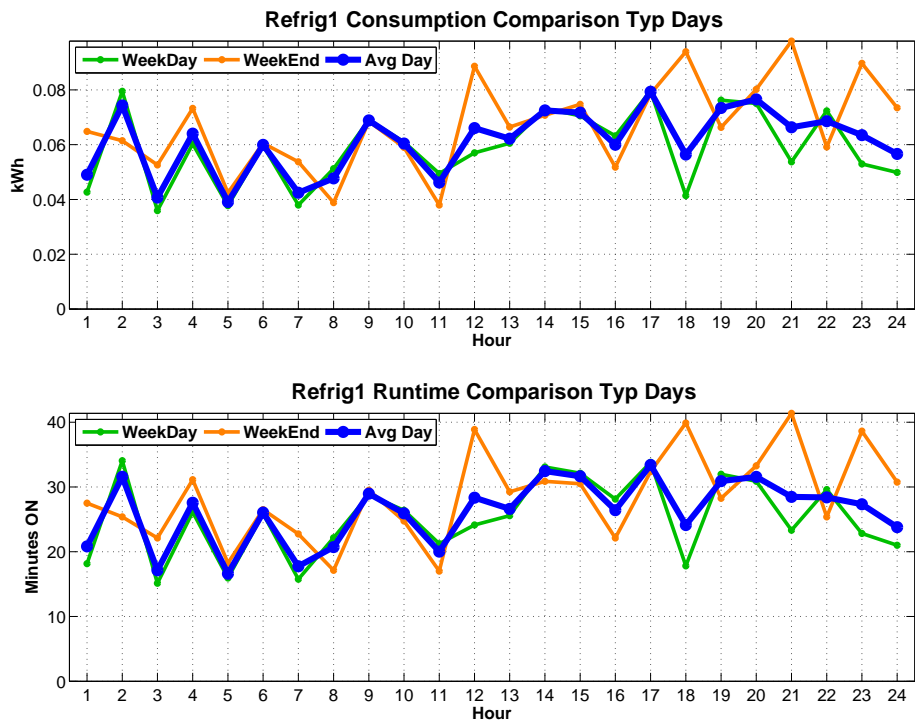


Figure A.4: Refrigerator average schedules

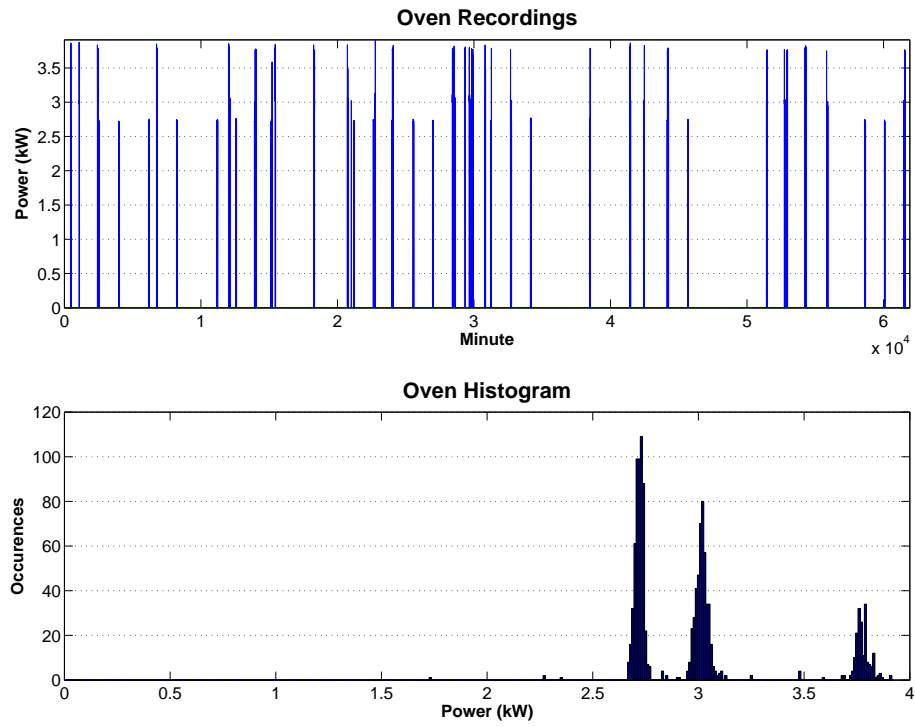


Figure A.5: Oven recorded data

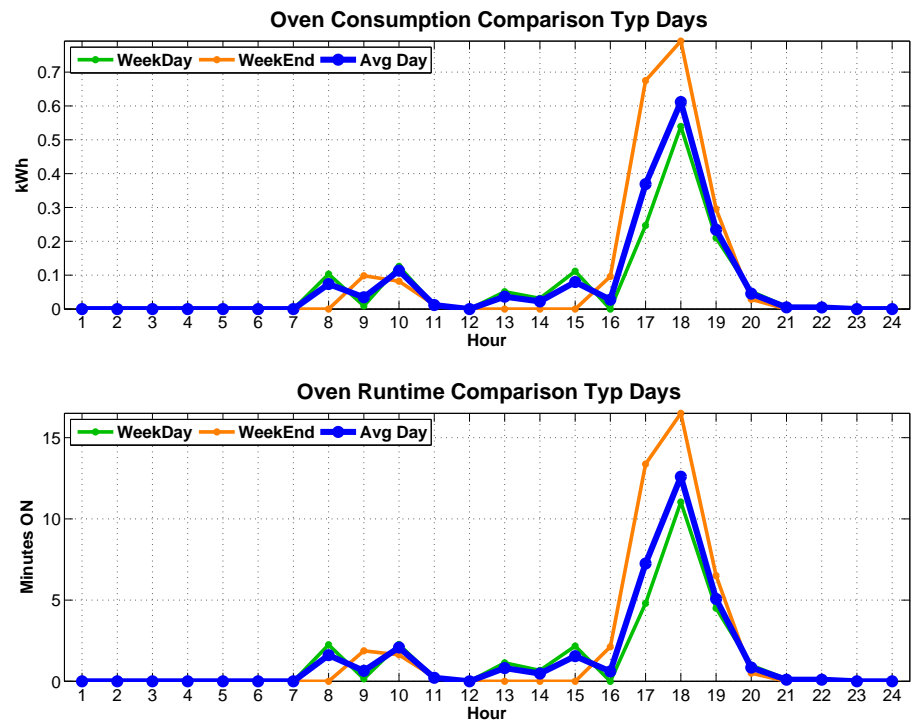


Figure A.6: Oven average schedules

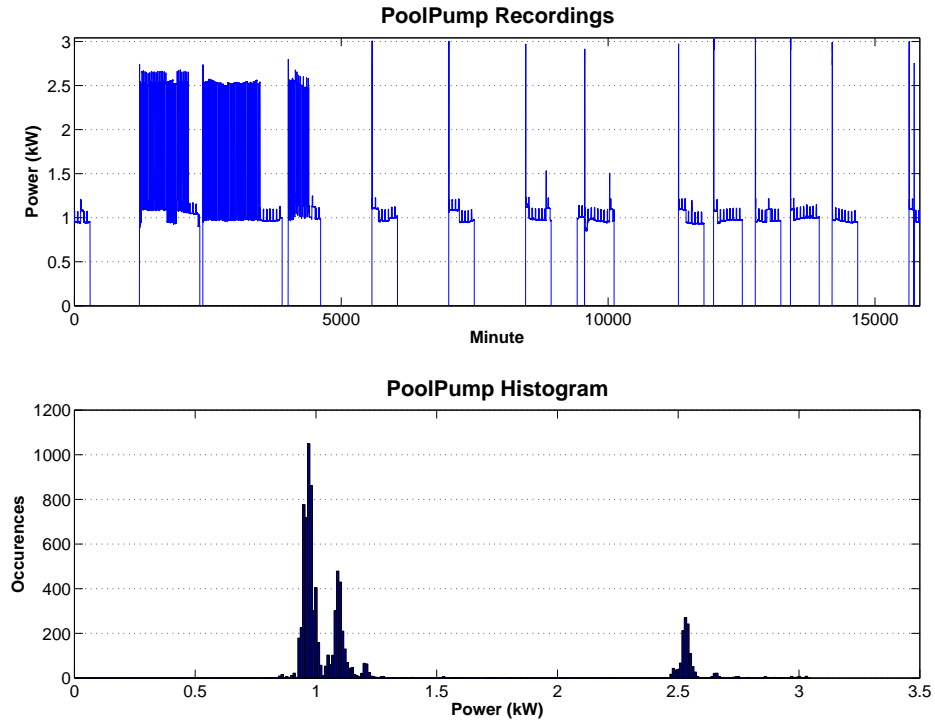


Figure A.7: Pool pump recorded data

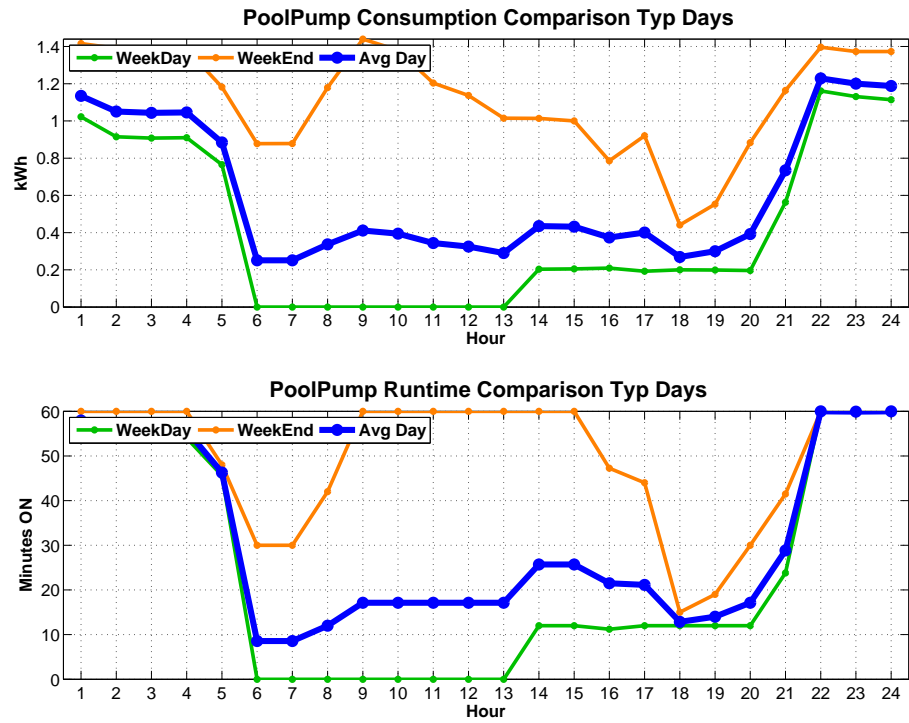


Figure A.8: Pool pump average schedules

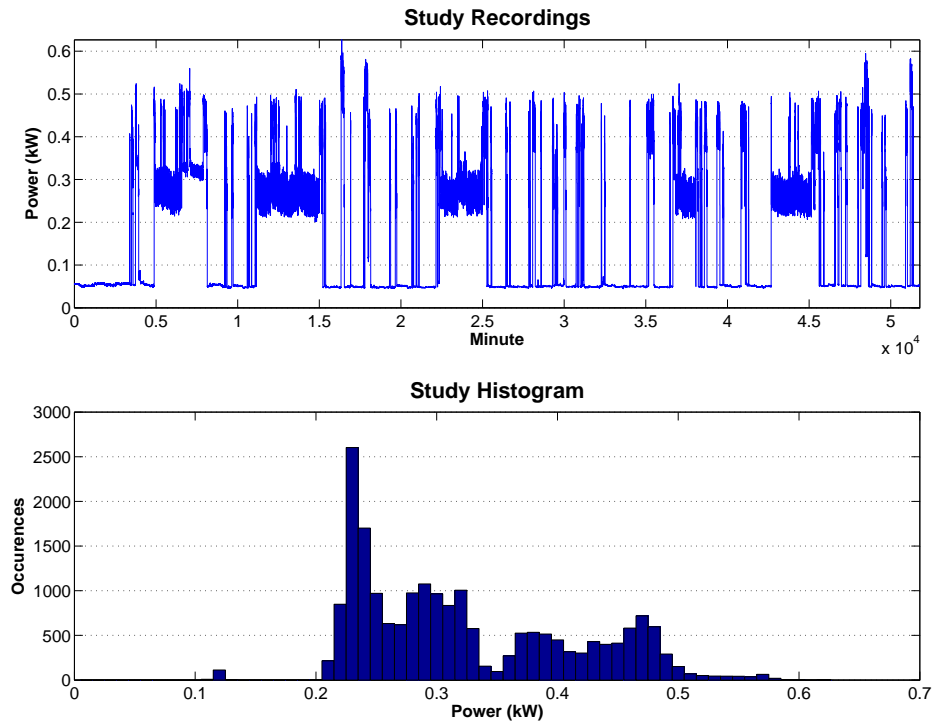


Figure A.9: Office Room recorded data

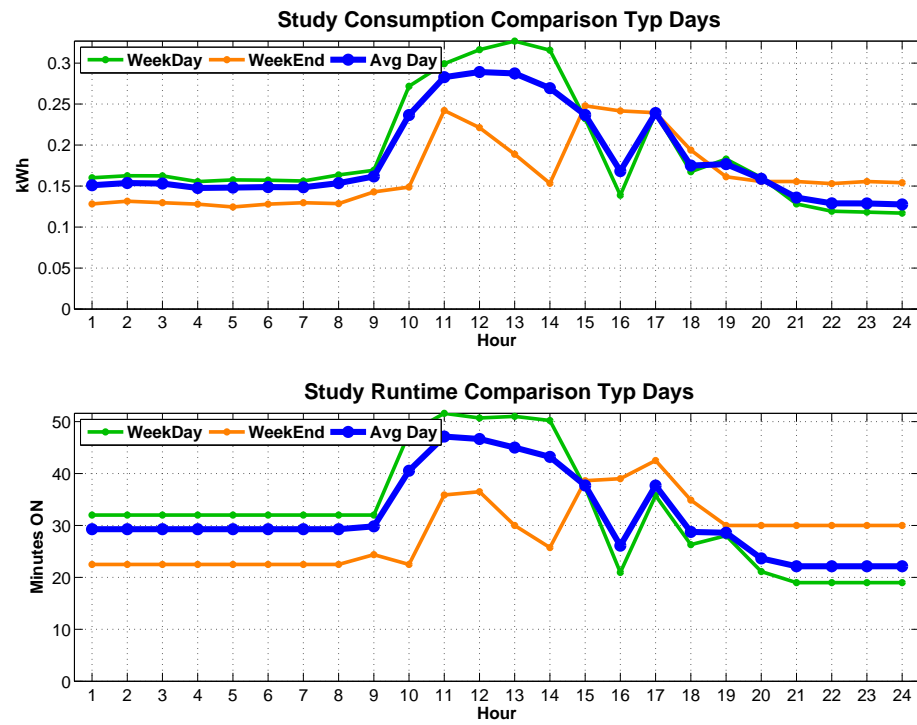


Figure A.10: Office Room average schedules

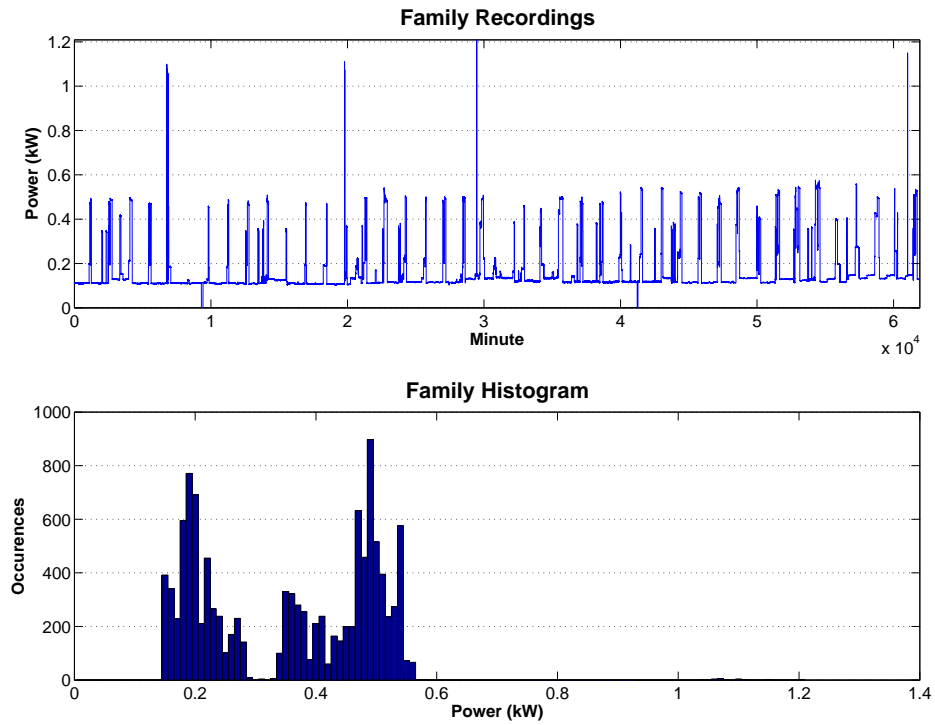


Figure A.11: Family Room recorded data

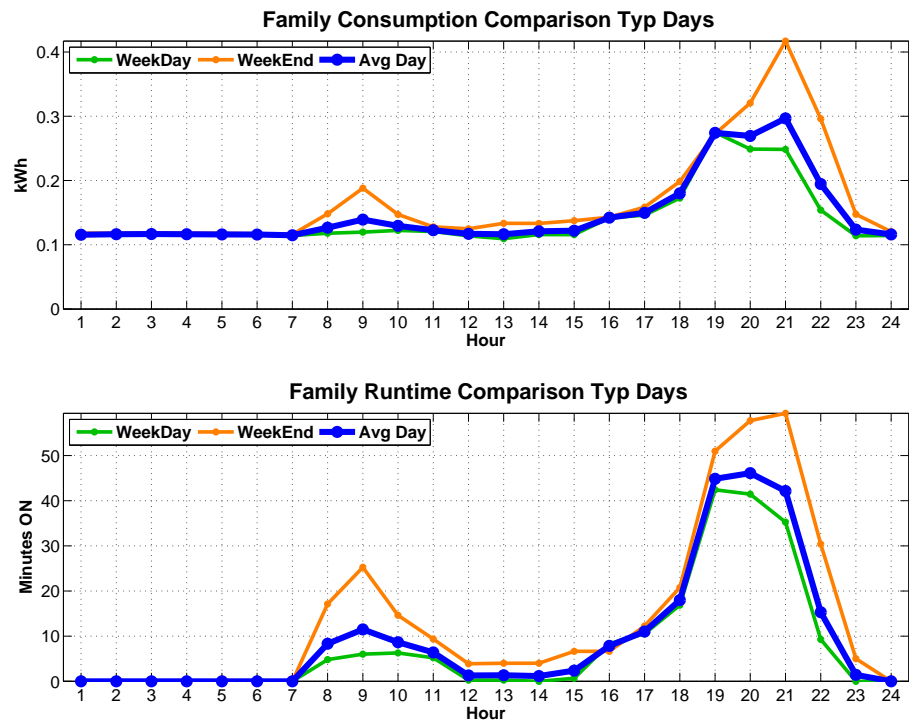


Figure A.12: Family Room average schedules

furnace was in operation. The furnace consumption is dependent on external weather conditions, so this particular data set should not be considered to be typical for all months. The furnace uses gas for heating, thus power consumption measured here is strictly for fan energy use. Yet, the furnace data does reveal insight into the occupants behavior in terms of scheduling as can be seen by the large spike in fan energy use in the early morning, with fairly constant heating through out they day (on average), and another spike in the evening.

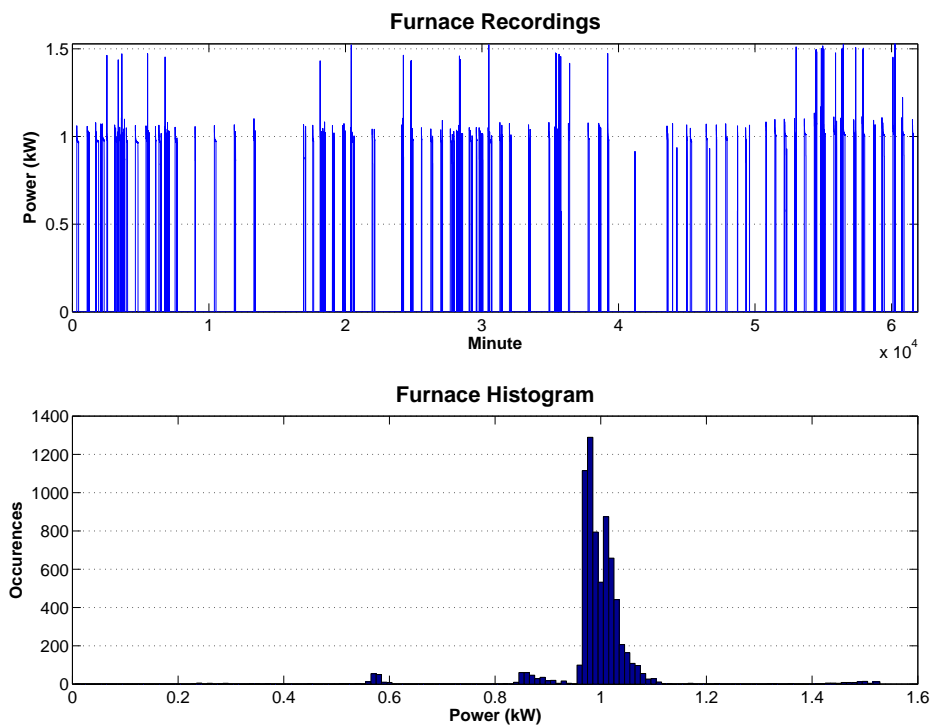


Figure A.13: Furnace recorded data

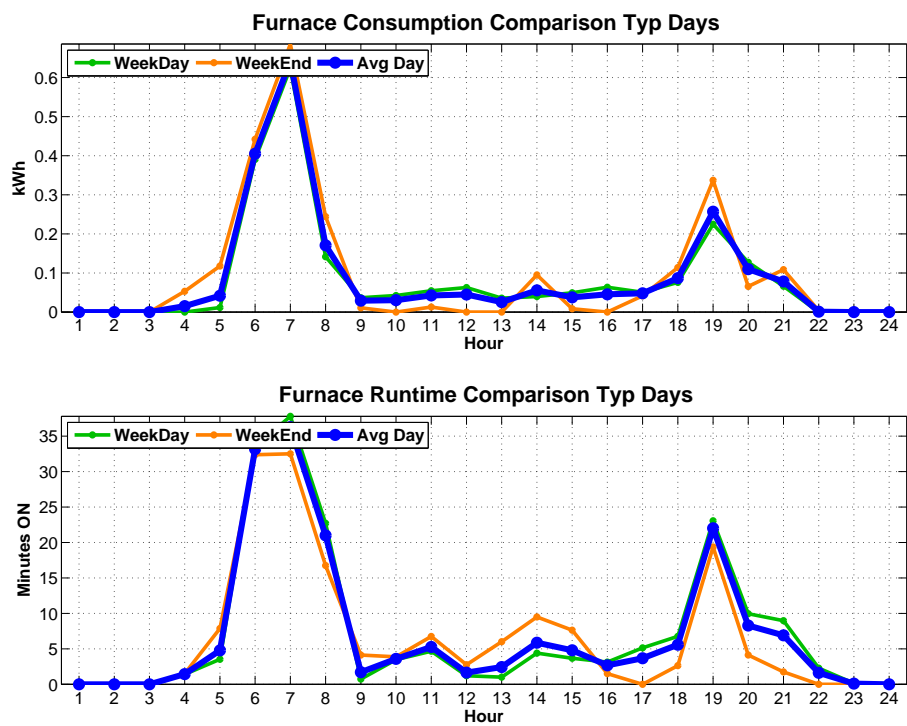


Figure A.14: Furnace average schedules

Appendix B

Additional Tables

Table B.1: BEopt Default Inputs and Options

OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
Building			
	Orientation		
		1	North
			NNE
			Northeast
			ENE
			East
			ESE
			Southeast
			SSE
			South
			SSW
			Southwest
			WSW
			West
			WNW
			Northwest
			NNW
	Neighbors		
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
		1	None
			at 20ft
			at 15ft
			at 10ft
Operation			
	Heating Set Point		
			68 F
			69 F
			70 F
		1	71 F
			72 F
			73 F
			74 F
			75 F
			71 F w/ setback 65 F
			71 F w/ setback 65 F (wkdy)
	Cooling Set Point		
			73 F
			74 F
			75 F
		1	76 F
			77 F
			78 F
			79 F
			80 F
			76 F w/ setup 85 F
			76 F w/ setup 81 F
	Humidity Set Point		
			60% RH
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
		1	55% RH
			50% RH
	Misc Electric Loads		
			4
			2
			1.5
		1	1
			0.75
			0.5
			0.25
	Misc Gas Loads		
			2
		1	1
			0.5
			0
	Misc Hot Water Loads		
		1	Benchmark
			Sink Aerators
			Low-Flow Showers
			Low-Flow Showers & Sinks
	Natural Ventilation		
			None
		1	Benchmark
			Seasonal
Walls			
	Wood Stud		
			None
			Uninsulated, 2x4, 16" o.c.
			R7 batts, 2x4, 16" o.c.
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			R11 batts, 2x4, 16" o.c.
		1	R13 batts, 2x4, 16" o.c.
			R13 loose-fill, 2x4, 16" o.c.
			R15 batts, 2x4, 16" o.c.
			R19 batts, 2x6, 24" o.c.
			R11 batts, 2x4, 16" o.c. + 1" foam
			R21 batts, 2x6, 24" o.c.
			R13 batts, 2x4, 16" o.c. + 1" foam
			R19 batts, 2x6, 24" o.c. + 1" foam
			R21 batts, 2x6, 24" o.c. + 1" foam
			R19 batts, 2x6, 24" o.c. + 2" foam
	Double Stud		
		1	None
			R33 batts, 2x4 Centered, 24" o.c
			R33 batts, 2x4 Staggered, 24" o.c
			R39 batts, 2x4 Centered, 24" o.c
			R39 batts, 2x4 Staggered, 24" o.c
			R45 batts, 2x4 Centered, 24" o.c
			R45 batts 2x4 Staggered, 24" o.c
	CMU		
		1	None
			6" concrete filled
			6" hollow
			8" hollow
			12" hollow
			6" perlite filled
			6" hollow + 2" foam
			8" hollow + 2" foam
			12" hollow + 2" foam
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
	SIP		
		1	None
			3.6" EPS Core, both sides OSB
			5.6" EPS Core, both sides OSB
			7.4" EPS Core, both sides OSB
			9.4" EPS Core, both sides OSB
			3.6" EPS Core, OSB ext., gypsum int.
			5.6" EPS Core, OSB ext., gypsum int.
			7.4" EPS Core, OSB ext., gypsum int.
			9.4" EPS Core, OSB ext., gypsum int.
	ICF		
		1	None
			2" EPS, 4" concrete, 2" EPS
			2" EPS, 8" concrete, 2" EPS
			2" EPS, 12" concrete, 2" EPS
	Other		
		1	None
			T-Mass wall w/ metal ties (ORNL)
			T-Mass wall w/ plastic ties (ORNL)
			10" grid ICF (ORNL)
	Exterior Finish		
		1	Stucco
			Red Brick
			White Brick
			Gray Wood Siding
			White Wood Siding
			Gray Metal Siding
			White Metal Siding
			Gray Vinyl Siding
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			White Vinyl Siding
			Gray Fiber-Cement Siding
			White Fiber-Cement Siding
	Interzonal Walls		
			Uninsulated, 2x4, 16" o.c.
		1	R-11 Batts, 2x4, 16" o.c.
			R-13 Batts, 2x4, 16" o.c.
			R-13 Loose-fill, 2x4, 16" o.c.
			R-15 Batts, 2x4, 16" o.c.
			R-19 Batts, 2x6, 24" o.c.
Ceilings/Roofs			
	Unfinished Attic		
			Uninsulated, Vented
			Ceiling R11 Cellulose Blown-In, Vented
			Ceiling R19 Cellulose Blown-In, Vented
		1	Ceiling R30 Cellulose Blown-In, Vented
			Ceiling R38 Cellulose Blown-In, Vented
			Ceiling R49 Cellulose Blown-In, Vented
			Ceiling R60 Cellulose Blown-In, Vented
			Ceiling R11 Fiberglass Blown-In, Vented
			Ceiling R19 Fiberglass Blown-In, Vented
			Ceiling R30 Fiberglass Blown-In, Vented
			Ceiling R38 Fiberglass Blown-In, Vented
			Ceiling R49 Fiberglass Blown-In, Vented
			Ceiling R60 Fiberglass Blown-In, Vented
			Ceiling R30 Fiberglass Batts, Vented
			Ceiling R38 Fiberglass Batts, Vented
			Ceiling R49 Fiberglass Batts (R19 + R30), Vented
			Roof R19 Fiberglass Batts
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			Roof R30 Fiberglass Batts
			Roof R38 Fiberglass Batts
			Roof R38 Fiberglass + 3.5" Rigid Ins
			Roof R27.5 SIPs
			Roof R37.5 SIPs
			Roof R47.5 SIPs
	Finished Roof		
			Uninsulated
		1	R19 Fiberglass
			R30 Fiberglass
			R38 Fiberglass
			R38 Fiberglass + 3.5" Rigid Ins
			R27.5 SIPs
			R37.5 SIPs
			R47.5 SIPs
	Roofing Material		
		1	Asphalt Shingles, Dark
			Asphalt Shingles, Medium
			Asphalt Shingles, Light
			Asphalt Shingles, White or cool colors
			Tile, Dark
			Tile, Medium (mottled, terra cotta, buff)
			Tile, Light
			Tile, White
			Metal, Dark
			Metal, Medium
			Metal, Light
			Metal, White
			Galvanized Steel
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
	Radiant Barrier		
		1	None
			Radiant Barrier
Foundation/Floors			
	Slab		
		1	Uninsulated
			2ft R5 Perimeter, R5 Gap
			4ft R5 Perimeter, R5 Gap
			2ft R10 Perimeter, R5 Gap
			4ft R10 Perimeter, R5 Gap
			Whole Slab R10, R5 Gap
			2ft R5 Exterior
			4ft R5 Exterior
			2ft R10 Exterior
			4ft R10 Exterior
			4ft R15 Exterior
			4ft R20 Exterior
	Finished Basement		
		1	Uninsulated
			4ft R5 Rigid
			4ft R10 Rigid
			8ft R5 Rigid
			8ft R10 Rigid
			8ft R15 Rigid
			8ft R20 Rigid
			8ft R13 batts, 2x4, 24 o.c.
	Unfinished Basement		
		1	Uninsulated
			Wall 4ft R5 Rigid
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			Wall 4ft R10 Rigid
			Wall 8ft R5 Rigid
			Wall 8ft R10 Rigid
			Wall 8ft R15 Rigid
			Wall 8ft R20 Rigid
			Wall 8ft R13 batts, 2x4, 24 o.c.
			Ceiling R13
			Ceiling R19
			Ceiling R30
			Ceiling R38
	Crawlspace 2'		
		1	Uninsulated, Vented
			Ceiling R13, Vented
			Ceiling R19, Vented
			Ceiling R30, Vented
			Ceiling R38, Vented
			Wall R5 Rigid
			Wall R10 Rigid
			Wall R15 Rigid
			Wall R20 Rigid
	Crawlspace 4'		
		1	Uninsulated, Vented
			Ceiling R13, Vented
			Ceiling R19, Vented
			Ceiling R30, Vented
			Ceiling R38, Vented
			Wall R5 Rigid
			Wall R10 Rigid
			Wall R15 Rigid
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			Wall R20 Rigid
	Interzonal Floor		
			Uninsulated
		1	R13 Fiberglass
			R19 Fiberglass
			R30 Fiberglass
			R38 Fiberglass
	Exposed Floor		
			None
		1	20% Exposed
			40% Exposed
			60% Exposed
			80% Exposed
			100% Exposed
Thermal Mass			
	Floor Mass		
		1	Wood Surface
			2" Gypsum Concrete
	Ext Wall Mass		
		1	1/2" Drywall
			5/8" Drywall
			2 x 1/2" Drywall
			2 x 5/8" Drywall
	Partition Wall Mass		
		1	1/2" Drywall
			5/8" Drywall
			2 x 1/2" Drywall
			2 x 5/8" Drywall
	Ceiling Mass		
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
		1	1/2" Ceiling Drywall
			5/8" Ceiling Drywall
			2 x 1/2" Ceiling Drywall
			2 x 5/8" Ceiling Drywall
	Furniture Mass		
		1	Light-Weight
			Heavy-Weight
Windows & Shading			
	Window Areas		
			18.0% F25 B25 L25 R25
			18.0% F20 B40 L20 R20
			15.0% F25 B25 L25 R25
		1	15.0% F20 B40 L20 R20
			12.0% F25 B25 L25 R25
			12.0% F20 B40 L20 R20
	Window Type		
			Single Pane
		1	Double Clear
			Low-e low SHGC arg
			Low-e std SHGC arg
			Low-e high SHGC arg
			Low-e v. high SHGC arg
			Low-e, low SHGC
			Low-e std. SHGC
			Low-e high SHGC
			Low-e v. high SHGC
			3 pane, 1 HM
			4 pane, 2 HM Kr
	Interior Shading		
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
		1	Benchmark
			Summer = 0.6
			Summer = 0.5
			Winter = 0.95
			Summer = 0.5, Winter = 0.95
	Eaves		
			None
			1 ft
		1	2 ft
			3 ft
	Overhangs		
		1	None
			1 ft
			1.5 ft
			2 ft
			Autosized Full Shade at Solar Noon, Sept. 1
Airflow			
	Infiltration		
			Very Leaky
			Leaky
			Typical
		1	Tight
			Tighter
			Tightest
			Constant 0.1 ACH
	Mechanical Ventilation		
			None
			Spot Vent Only
			Exhaust, 50% of A-62.2
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
		1	Exhaust, 100% of A-62.2
			Supply, 50% of A-62.2
			Supply, 100% of A-62.2
			ERV, 50% of A-62.2
			ERV, 100% of A-62.2
Major Appliances			
	Refrigerator		
			None
			Old, Top Mount Freezer
			Old, Bottom Mount Freezer
			Old, Side-by-Side Freezer
		1	Standard, Top Mount Freezer
			Standard, Bottom Mount Freezer
			Standard, Side-by-Side Freezer
			EnergyStar, Top Mount Freezer
			EnergyStar, Bottom Mount Freezer
			EnergyStar, Side-by-Side Freezer
			Standard, Top Mount Freezer, at wear out
	Cooking Range		
			None
		1	Electric, Conventional
			Electric, Induction
			Gas, Conventional
	Dishwasher		
			None
		1	Standard
			EnergyStar
	Clothes Washer		
			None
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
		1	Standard
			EnergyStar
			Standard - Cold Only
			EnergyStar - Cold Only
	Clothes Dryer		
			None (Clothes Line)
		1	Electric
			Gas
Lighting			
	Lighting		
		1	20% Fluorescent, Hardwired
			40% Fluorescent, Hardwired
			60% Fluorescent, Hardwired
			80% Fluorescent, Hardwired
			100% Fluorescent, Hardwired
			20% Fluorescent, Hardwired & Plugin
			40% Fluorescent, Hardwired & Plugin
			60% Fluorescent, Hardwired & Plugin
			80% Fluorescent, Hardwired & Plugin
			100% Fluorescent, Hardwired & Plugin
			50% Fluorescent, 10% LED, Hardwired & Plugin
			1300 kWh
Space Conditioning			
	Air Conditioner		
			None
			SEER 10
		1	SEER 13
			SEER 14
			SEER 15
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			SEER 16
			SEER 17
			SEER 18
			SEER 13, at wear out
	Furnace		
			None
		1	Gas, AFUE 78%
			Gas, AFUE 92.5%
			Fuel Oil, AFUE 78%
			Fuel Oil, AFUE 95%
			Propane, AFUE 78%
			Propane, AFUE 94%
			Electric
	Hydronic Heating		
		1	None
			Gas, 80% AFUE Boiler
			Gas, 85% AFUE Boiler
			Gas, 95% AFUE Boiler
			Fuel Oil, 80% AFUE Boiler
			Fuel Oil, 85% AFUE Boiler
			Fuel Oil, 90% AFUE Boiler
	Heat Pump		
		1	None
			SEER 10. HSPF 7.2
			SEER 13. HSPF 8.1
			SEER 14. HSPF 8.6
			SEER 15. HSPF 8.8
			SEER 16. HSPF 8.4
			SEER 17. HSPF 8.6
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			SEER 18. HSPF 9.2
	Ground Source HP		
		1	None
			200ft x 20ft Vertical Bore Hole Line-Of-2
			200ft x 20ft Vertical Bore Hole Line-Of-3
			200ft x 20ft Vertical Bore Hole Line-Of-4
			200ft x 20ft Vertical Bore Hole L-Config-2x2
			200ft x 20ft Vertical Bore Hole Rectangle-2x2
	Ducts		
			None
			Leaky, Uninsulated
			Leaky, R6 Insulation
			Leaky, R8 Insulation
			Typical, Uninsulated
		1	Typical, R6 Insulation
			Typical, R8 Insulation
			Tight, Uninsulated
			Tight, R6 Insulation
			Tight, R8 Insulation
			In Finished Space
	Ceiling Fans		
		1	Benchmark
			None
			1 Fan, Std, Typical, 0 F
			2 Fans, Std, Typical, 0 F
			3 Fans, Std, Typical, 0 F
			4 Fans, Std, Typical, 0 F
			5 Fans, Std, Typical, 0 F
			50% Coverage, Std, Typical, 0 F
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			50% Coverage, Eff, Smart, 0 F
			100% Coverage, Std, Smart, 4 F
			100% Coverage, Eff, Smart, 4 F
	Dehumidifier		
		1	None
			65 pints/day Std Eff
			65 pints/day High Eff
			90 pints/day Std Eff
			90 pints/day High Eff
			110 pints/day Std Eff
			110 pints/day High Eff
			150 pints/day Std Eff
			150 pints/day High Eff
Water Heating			
	Water Heater		
			Electric Standard
			Electric Premium
			Gas Standard
		1	Gas Premium
			Gas Tankless
			Gas Tankless, Condensing
			Fuel Oil Standard
			Fuel Oil Premium
			Propane Standard
			Propane Premium
	Distribution		
		1	R-0, TrunkBranch, Copper
			R-0, TrunkBranch, PEX
			R-0, HomeRun, PEX
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			R-2, TrunkBranch, Copper
			R-2, TrunkBranch, PEX
			R-2, HomeRun, PEX
			R-2, TrunkBranch, Copper, Timer
			R-2, TrunkBranch, PEX, Timer
			R-2, TrunkBranch, Copper, Demand
			R-2, TrunkBranch, PEX, Demand
			R-5, TrunkBranch, Copper, Timer
			R-5, TrunkBranch, PEX, Timer
	Solar DHW		
		1	None
			32 sq ft ICS
			40 sq ft closed loop
			64 sq ft closed loop
	SDHW Azimuth		
		1	Back Roof
			Front Roof
			Left Roof
			Right Roof
			West
			Southwest
			South
			Southeast
			East
	SDHW Tilt		
		1	Roof Pitch
			0
			10
			20
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
			30
			40
			50
			60
			70
			80
			90
			Latitude - 15
			Latitude
			Latitude + 15
Power Generation			
	PV System		
		1	0 kW
			0.5 kW
			1.0 kW
			1.5 kW
			2.0 kW
			2.5 kW
			3.0 kW
			3.5 kW
			4.0 kW
			4.5 kW
			5.0 kW
			5.5 kW
			6.0 kW
			6.5 kW
			7.0 kW
			7.5 kW
			8.0 kW
Continued ...			

Continued ...			
OPTIONS SCREEN	CATEGORY	SELECTED	OPTION NAME
	PV Azimuth		
		1	Back Roof
			Front Roof
			Left Roof
			Right Roof
			West
			Southwest
			South
			Southeast
			East
	PV Tilt		
		1	Roof Pitch
			0
			10
			20
			30
			40
			50
			60
			70
			80
			90
			Latitude - 15
			Latitude
			Latitude + 15

Table B.2: Average Hourly Peak Energy Savings - All

simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
NY-1200-4-1.5-3	1.18	0.87	0.31	26.3
Continued ...				

Continued ...				
Average Hourly Peak Energy Savings - All				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
NY-1200-4-1.5-6	1.18	0.73	0.45	38.2
NY-1200-4-2-3	1.18	0.87	0.31	26.3
NY-1200-4-2-6	1.18	0.73	0.45	38.2
NY-1200-6-1.5-3	1.19	0.91	0.27	23.1
NY-1200-6-1.5-6	1.19	0.76	0.42	35.7
NY-1200-6-2-3	1.19	0.91	0.27	23.1
NY-1200-6-2-6	1.19	0.76	0.42	35.7
NY-1200-8-1.5-3	1.2	0.95	0.24	20.4
NY-1200-8-1.5-6	1.2	0.81	0.39	32.7
NY-1200-8-2-3	1.2	0.95	0.24	20.4
NY-1200-8-2-6	1.2	0.81	0.39	32.7
NY-2700-4-1.5-3	1.64	1.06	0.59	35.6
NY-2700-4-1.5-6	1.64	0.86	0.78	47.7
NY-2700-4-2-3	1.64	1.06	0.59	35.6
NY-2700-4-2-6	1.64	0.86	0.78	47.7
NY-2700-6-1.5-3	1.67	1.16	0.51	30.8
NY-2700-6-1.5-6	1.67	0.91	0.76	45.3
NY-2700-6-2-3	1.67	1.16	0.51	30.8
NY-2700-6-2-6	1.67	0.91	0.76	45.3
NY-2700-8-1.5-3	1.7	1.25	0.45	26.6
NY-2700-8-1.5-6	1.7	0.99	0.71	41.7
NY-2700-8-2-3	1.7	1.25	0.45	26.6
NY-2700-8-2-6	1.7	0.99	0.71	41.7
NY-5030-4-1.5-3	2.1	1.25	0.86	40.7
NY-5030-4-1.5-6	2.1	1.06	1.04	49.4
NY-5030-4-2-3	2.1	1.25	0.86	40.7
NY-5030-4-2-6	2.1	1.06	1.04	49.4
NY-5030-6-1.5-3	2.15	1.38	0.77	35.6
Continued ...				

Continued ...				
Average Hourly Peak Energy Savings - All				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
NY-5030-6-1.5-6	2.15	1.12	1.03	47.7
NY-5030-6-2-3	2.15	1.38	0.77	35.6
NY-5030-6-2-6	2.15	1.12	1.03	47.7
NY-5030-8-1.5-3	2.21	1.53	0.68	30.8
NY-5030-8-1.5-6	2.21	1.23	0.98	44.4
NY-5030-8-2-3	2.21	1.53	0.68	30.8
NY-5030-8-2-6	2.21	1.23	0.98	44.4
CHI-1200-4-1.5-3	1.23	0.96	0.27	22.1
CHI-1200-4-1.5-6	1.23	0.84	0.39	31.5
CHI-1200-4-2-3	1.23	0.96	0.27	22.1
CHI-1200-4-2-6	1.23	0.84	0.39	31.5
CHI-1200-6-1.5-3	1.21	0.98	0.24	19.6
CHI-1200-6-1.5-6	1.21	0.85	0.36	29.6
CHI-1200-6-2-3	1.21	0.98	0.24	19.6
CHI-1200-6-2-6	1.21	0.85	0.36	29.6
CHI-1200-8-1.5-3	1.21	1	0.21	17.4
CHI-1200-8-1.5-6	1.21	0.88	0.33	27.2
CHI-1200-8-2-3	1.21	1	0.21	17.4
CHI-1200-8-2-6	1.21	0.88	0.33	27.2
CHI-2700-4-1.5-3	1.69	1.16	0.53	31.2
CHI-2700-4-1.5-6	1.69	0.98	0.71	41.8
CHI-2700-4-2-3	1.69	1.16	0.53	31.2
CHI-2700-4-2-6	1.69	0.98	0.71	41.8
CHI-2700-6-1.5-3	1.68	1.22	0.46	27.4
CHI-2700-6-1.5-6	1.68	1.01	0.67	39.8
CHI-2700-6-2-3	1.68	1.22	0.46	27.4
CHI-2700-6-2-6	1.68	1.01	0.67	39.8
CHI-2700-8-1.5-3	1.68	1.28	0.4	23.9
Continued ...				

Continued ...				
Average Hourly Peak Energy Savings - All				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
CHI-2700-8-1.5-6	1.68	1.07	0.61	36.5
CHI-2700-8-2-3	1.68	1.28	0.4	23.9
CHI-2700-8-2-6	1.68	1.07	0.61	36.5
CHI-5030-4-1.5-3	2.09	1.36	0.73	35.1
CHI-5030-4-1.5-6	2.09	1.19	0.9	43.1
CHI-5030-4-2-3	2.09	1.36	0.73	35.1
CHI-5030-4-2-6	2.09	1.19	0.9	43.1
CHI-5030-6-1.5-3	2.09	1.45	0.65	30.9
CHI-5030-6-1.5-6	2.09	1.23	0.86	41.2
CHI-5030-6-2-3	2.09	1.45	0.65	30.9
CHI-5030-6-2-6	2.09	1.23	0.86	41.2
CHI-5030-8-1.5-3	2.12	1.55	0.57	26.7
CHI-5030-8-1.5-6	2.12	1.31	0.81	38.1
CHI-5030-8-2-3	2.12	1.55	0.57	26.7
CHI-5030-8-2-6	2.12	1.31	0.81	38.1
HOU-1200-4-1.5-3	2.34	1.71	0.63	27.1
HOU-1200-4-1.5-6	2.34	1.22	1.12	48
HOU-1200-4-2-3	2.34	1.71	0.63	27.1
HOU-1200-4-2-6	2.34	1.22	1.12	48
HOU-1200-6-1.5-3	2.31	1.76	0.55	24
HOU-1200-6-1.5-6	2.31	1.32	0.99	42.8
HOU-1200-6-2-3	2.31	1.76	0.55	24
HOU-1200-6-2-6	2.31	1.32	0.99	42.8
HOU-1200-8-1.5-3	2.24	1.76	0.49	21.7
HOU-1200-8-1.5-6	2.24	1.37	0.87	38.9
HOU-1200-8-2-3	2.24	1.76	0.49	21.7
HOU-1200-8-2-6	2.24	1.37	0.87	38.9
HOU-2700-4-1.5-3	3.5	2.34	1.16	33.1
Continued ...				

Continued . . .				
Average Hourly Peak Energy Savings - All				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
HOU-2700-4-1.5-6	3.5	1.5	2.01	57.2
HOU-2700-4-2-3	3.5	2.34	1.16	33.1
HOU-2700-4-2-6	3.5	1.5	2.01	57.2
HOU-2700-6-1.5-3	3.43	2.45	0.98	28.7
HOU-2700-6-1.5-6	3.43	1.7	1.73	50.3
HOU-2700-6-2-3	3.43	2.45	0.98	28.7
HOU-2700-6-2-6	3.43	1.7	1.73	50.3
HOU-2700-8-1.5-3	3.31	2.46	0.84	25.5
HOU-2700-8-1.5-6	3.31	1.81	1.5	45.4
HOU-2700-8-2-3	3.31	2.46	0.84	25.5
HOU-2700-8-2-6	3.31	1.81	1.5	45.4
HOU-5030-4-1.5-3	4.88	2.96	1.92	39.3
HOU-5030-4-1.5-6	4.88	1.68	3.2	65.5
HOU-5030-4-2-3	4.88	2.96	1.92	39.3
HOU-5030-4-2-6	4.88	1.68	3.2	65.5
HOU-5030-6-1.5-3	4.77	3.14	1.62	34
HOU-5030-6-1.5-6	4.77	1.97	2.8	58.7
HOU-5030-6-2-3	4.77	3.14	1.62	34
HOU-5030-6-2-6	4.77	1.97	2.8	58.7
HOU-5030-8-1.5-3	4.6	3.21	1.39	30.3
HOU-5030-8-1.5-6	4.6	2.15	2.45	53.3
HOU-5030-8-2-3	4.6	3.21	1.39	30.3
HOU-5030-8-2-6	4.6	2.15	2.45	53.3
LA-1200-4-1.5-3	1.08	0.86	0.22	20.1
LA-1200-4-1.5-6	1.08	0.82	0.25	23.4
LA-1200-4-2-3	1.08	0.86	0.22	20.1
LA-1200-4-2-6	1.08	0.82	0.25	23.4
LA-1200-6-1.5-3	1.08	0.87	0.21	19.2
Continued . . .				

Continued . . .				
Average Hourly Peak Energy Savings - All				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
LA-1200-6-1.5-6	1.08	0.82	0.26	24.2
LA-1200-6-2-3	1.08	0.87	0.21	19.2
LA-1200-6-2-6	1.08	0.82	0.26	24.2
LA-1200-8-1.5-3	1.08	0.89	0.19	17.7
LA-1200-8-1.5-6	1.08	0.83	0.25	23.5
LA-1200-8-2-3	1.08	0.89	0.19	17.7
LA-1200-8-2-6	1.08	0.83	0.25	23.5
LA-2700-4-1.5-3	1.32	0.98	0.33	25.3
LA-2700-4-1.5-6	1.32	0.96	0.35	26.7
LA-2700-4-2-3	1.32	0.98	0.33	25.3
LA-2700-4-2-6	1.32	0.96	0.35	26.7
LA-2700-6-1.5-3	1.34	1.02	0.32	24.1
LA-2700-6-1.5-6	1.34	0.97	0.37	27.6
LA-2700-6-2-3	1.34	1.02	0.32	24.1
LA-2700-6-2-6	1.34	0.97	0.37	27.6
LA-2700-8-1.5-3	1.38	1.08	0.3	21.7
LA-2700-8-1.5-6	1.38	1	0.37	27.1
LA-2700-8-2-3	1.38	1.08	0.3	21.7
LA-2700-8-2-6	1.38	1	0.37	27.1
LA-5030-4-1.5-3	1.57	1.19	0.39	24.6
LA-5030-4-1.5-6	1.57	1.18	0.39	24.9
LA-5030-4-2-3	1.57	1.19	0.39	24.6
LA-5030-4-2-6	1.57	1.18	0.39	24.9
LA-5030-6-1.5-3	1.63	1.23	0.4	24.4
LA-5030-6-1.5-6	1.63	1.21	0.41	25.4
LA-5030-6-2-3	1.63	1.23	0.4	24.4
LA-5030-6-2-6	1.63	1.21	0.41	25.4
LA-5030-8-1.5-3	1.69	1.31	0.38	22.5
Continued . . .				

Continued ...				
Average Hourly Peak Energy Savings - All				
simulation	Base (kWh/hr)	Control(kWh/hr)	Saved (kWh/hr)	Saved (%)
LA-5030-8-1.5-6	1.69	1.27	0.42	24.7
LA-5030-8-2-3	1.69	1.31	0.38	22.5
LA-5030-8-2-6	1.69	1.27	0.42	24.7

Table B.3: Daily Average Energy Savings - All

simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
NY-1200-4-1.5-3	21.56	20.87	0.7	3.2
NY-1200-4-1.5-6	21.56	20.65	0.91	4.2
NY-1200-4-2-3	21.56	20.87	0.7	3.2
NY-1200-4-2-6	21.56	20.65	0.91	4.2
NY-1200-6-1.5-3	21.56	20.54	1.03	4.8
NY-1200-6-1.5-6	21.56	20.14	1.42	6.6
NY-1200-6-2-3	21.56	20.54	1.03	4.8
NY-1200-6-2-6	21.56	20.14	1.42	6.6
NY-1200-8-1.5-3	21.56	20.25	1.32	6.1
NY-1200-8-1.5-6	21.56	19.64	1.93	8.9
NY-1200-8-2-3	21.56	20.25	1.32	6.1
NY-1200-8-2-6	21.56	19.64	1.93	8.9
NY-2700-4-1.5-3	29.91	28.74	1.18	3.9
NY-2700-4-1.5-6	29.91	28.59	1.32	4.4
NY-2700-4-2-3	29.91	28.74	1.18	3.9
NY-2700-4-2-6	29.91	28.59	1.32	4.4
NY-2700-6-1.5-3	29.91	28.19	1.73	5.8
NY-2700-6-1.5-6	29.91	27.68	2.23	7.5
NY-2700-6-2-3	29.91	28.19	1.73	5.8
NY-2700-6-2-6	29.91	27.68	2.23	7.5
NY-2700-8-1.5-3	29.91	27.69	2.23	7.4
NY-2700-8-1.5-6	29.91	26.77	3.15	10.5
Continued ...				

Continued ...				
Daily Average Energy Savings - All				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
NY-2700-8-2-3	29.91	27.69	2.23	7.4
NY-2700-8-2-6	29.91	26.77	3.15	10.5
NY-5030-4-1.5-3	38.78	37.14	1.64	4.2
NY-5030-4-1.5-6	38.78	36.95	1.82	4.7
NY-5030-4-2-3	38.78	37.14	1.64	4.2
NY-5030-4-2-6	38.78	36.95	1.82	4.7
NY-5030-6-1.5-3	38.78	36.32	2.46	6.3
NY-5030-6-1.5-6	38.78	35.92	2.86	7.4
NY-5030-6-2-3	38.78	36.32	2.46	6.3
NY-5030-6-2-6	38.78	35.92	2.86	7.4
NY-5030-8-1.5-3	38.78	35.57	3.21	8.3
NY-5030-8-1.5-6	38.78	34.66	4.12	10.6
NY-5030-8-2-3	38.78	35.57	3.21	8.3
NY-5030-8-2-6	38.78	34.66	4.12	10.6
CHI-1200-4-1.5-3	21.11	20.41	0.69	3.3
CHI-1200-4-1.5-6	21.11	20.21	0.9	4.3
CHI-1200-4-2-3	21.11	20.41	0.69	3.3
CHI-1200-4-2-6	21.11	20.21	0.9	4.3
CHI-1200-6-1.5-3	21.11	20.12	0.98	4.7
CHI-1200-6-1.5-6	21.11	19.75	1.36	6.4
CHI-1200-6-2-3	21.11	20.12	0.98	4.7
CHI-1200-6-2-6	21.11	19.75	1.36	6.4
CHI-1200-8-1.5-3	21.11	19.86	1.25	5.9
CHI-1200-8-1.5-6	21.11	19.29	1.82	8.6
CHI-1200-8-2-3	21.11	19.86	1.25	5.9
CHI-1200-8-2-6	21.11	19.29	1.82	8.6
CHI-2700-4-1.5-3	28.7	27.44	1.26	4.4
CHI-2700-4-1.5-6	28.7	27.13	1.57	5.5
Continued ...				

Continued ...				
Daily Average Energy Savings - All				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
CHI-2700-4-2-3	28.7	27.44	1.26	4.4
CHI-2700-4-2-6	28.7	27.13	1.57	5.5
CHI-2700-6-1.5-3	28.7	26.87	1.83	6.4
CHI-2700-6-1.5-6	28.7	26.27	2.43	8.5
CHI-2700-6-2-3	28.7	26.87	1.83	6.4
CHI-2700-6-2-6	28.7	26.27	2.43	8.5
CHI-2700-8-1.5-3	28.7	26.37	2.33	8.1
CHI-2700-8-1.5-6	28.7	25.45	3.25	11.3
CHI-2700-8-2-3	28.7	26.37	2.33	8.1
CHI-2700-8-2-6	28.7	25.45	3.25	11.3
CHI-5030-4-1.5-3	36.5	34.77	1.72	4.7
CHI-5030-4-1.5-6	36.5	34.55	1.95	5.3
CHI-5030-4-2-3	36.5	34.77	1.72	4.7
CHI-5030-4-2-6	36.5	34.55	1.95	5.3
CHI-5030-6-1.5-3	36.5	33.97	2.53	6.9
CHI-5030-6-1.5-6	36.5	33.42	3.08	8.4
CHI-5030-6-2-3	36.5	33.97	2.53	6.9
CHI-5030-6-2-6	36.5	33.42	3.08	8.4
CHI-5030-8-1.5-3	36.5	33.3	3.19	8.7
CHI-5030-8-1.5-6	36.5	32.31	4.18	11.5
CHI-5030-8-2-3	36.5	33.3	3.19	8.7
CHI-5030-8-2-6	36.5	32.31	4.18	11.5
HOU-1200-4-1.5-3	37.19	35.85	1.34	3.6
HOU-1200-4-1.5-6	37.19	34.91	2.28	6.1
HOU-1200-4-2-3	37.19	35.85	1.34	3.6
HOU-1200-4-2-6	37.19	34.91	2.28	6.1
HOU-1200-6-1.5-3	37.19	35.28	1.91	5.1
HOU-1200-6-1.5-6	37.19	33.92	3.28	8.8
Continued ...				

Continued . . .				
Daily Average Energy Savings - All				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
HOU-1200-6-2-3	37.19	35.28	1.91	5.1
HOU-1200-6-2-6	37.19	33.92	3.28	8.8
HOU-1200-8-1.5-3	37.19	34.81	2.38	6.4
HOU-1200-8-1.5-6	37.19	33.1	4.09	11
HOU-1200-8-2-3	37.19	34.81	2.38	6.4
HOU-1200-8-2-6	37.19	33.1	4.09	11
HOU-2700-4-1.5-3	52.75	50.69	2.06	3.9
HOU-2700-4-1.5-6	52.75	49.51	3.24	6.1
HOU-2700-4-2-3	52.75	50.69	2.06	3.9
HOU-2700-4-2-6	52.75	49.51	3.24	6.1
HOU-2700-6-1.5-3	52.75	49.79	2.97	5.6
HOU-2700-6-1.5-6	52.75	47.98	4.77	9
HOU-2700-6-2-3	52.75	49.79	2.97	5.6
HOU-2700-6-2-6	52.75	47.98	4.77	9
HOU-2700-8-1.5-3	52.75	49.07	3.69	7
HOU-2700-8-1.5-6	52.75	46.67	6.09	11.5
HOU-2700-8-2-3	52.75	49.07	3.69	7
HOU-2700-8-2-6	52.75	46.67	6.09	11.5
HOU-5030-4-1.5-3	72.8	69.63	3.17	4.4
HOU-5030-4-1.5-6	72.8	67.81	4.99	6.9
HOU-5030-4-2-3	72.8	69.63	3.17	4.4
HOU-5030-4-2-6	72.8	67.81	4.99	6.9
HOU-5030-6-1.5-3	72.8	68.27	4.53	6.2
HOU-5030-6-1.5-6	72.8	65.54	7.26	10
HOU-5030-6-2-3	72.8	68.27	4.53	6.2
HOU-5030-6-2-6	72.8	65.54	7.26	10
HOU-5030-8-1.5-3	72.8	67.16	5.64	7.7
HOU-5030-8-1.5-6	72.8	63.55	9.26	12.7
Continued . . .				

Continued ...				
Daily Average Energy Savings - All				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
HOU-5030-8-2-3	72.8	67.16	5.64	7.7
HOU-5030-8-2-6	72.8	63.55	9.26	12.7
LA-1200-4-1.5-3	19.46	18.83	0.63	3.2
LA-1200-4-1.5-6	19.46	18.76	0.69	3.6
LA-1200-4-2-3	19.46	18.83	0.63	3.2
LA-1200-4-2-6	19.46	18.76	0.69	3.6
LA-1200-6-1.5-3	19.46	18.5	0.96	4.9
LA-1200-6-1.5-6	19.46	18.29	1.16	6
LA-1200-6-2-3	19.46	18.5	0.96	4.9
LA-1200-6-2-6	19.46	18.29	1.16	6
LA-1200-8-1.5-3	19.46	18.18	1.27	6.5
LA-1200-8-1.5-6	19.46	17.82	1.63	8.4
LA-1200-8-2-3	19.46	18.18	1.27	6.5
LA-1200-8-2-6	19.46	17.82	1.63	8.4
LA-2700-4-1.5-3	24.61	23.61	1	4.1
LA-2700-4-1.5-6	24.61	23.59	1.02	4.2
LA-2700-4-2-3	24.61	23.61	1	4.1
LA-2700-4-2-6	24.61	23.59	1.02	4.2
LA-2700-6-1.5-3	24.61	23.04	1.57	6.4
LA-2700-6-1.5-6	24.61	22.86	1.76	7.1
LA-2700-6-2-3	24.61	23.04	1.57	6.4
LA-2700-6-2-6	24.61	22.86	1.76	7.1
LA-2700-8-1.5-3	24.61	22.55	2.06	8.4
LA-2700-8-1.5-6	24.61	22.1	2.51	10.2
LA-2700-8-2-3	24.61	22.55	2.06	8.4
LA-2700-8-2-6	24.61	22.1	2.51	10.2
LA-5030-4-1.5-3	31.08	29.92	1.16	3.7
LA-5030-4-1.5-6	31.08	29.91	1.16	3.7
Continued ...				

Continued ...				
Daily Average Energy Savings - All				
simulation	Base (kWh/day)	Control(kWh/day)	Saved (kWh/Day)	Saved (%)
LA-5030-4-2-3	31.08	29.92	1.16	3.7
LA-5030-4-2-6	31.08	29.91	1.16	3.7
LA-5030-6-1.5-3	31.08	29.16	1.92	6.2
LA-5030-6-1.5-6	31.08	29.1	1.98	6.4
LA-5030-6-2-3	31.08	29.16	1.92	6.2
LA-5030-6-2-6	31.08	29.1	1.98	6.4
LA-5030-8-1.5-3	31.08	28.46	2.62	8.4
LA-5030-8-1.5-6	31.08	28.24	2.84	9.1
LA-5030-8-2-3	31.08	28.46	2.62	8.4
LA-5030-8-2-6	31.08	28.24	2.84	9.1

Table B.4: Total Utility Cost Savings - All

simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-1200-4-1.5-3	325	309	15	5
NY-1200-4-1.5-6	325	304	20	6
NY-1200-4-2-3	325	309	15	5
NY-1200-4-2-6	325	304	20	6
NY-1200-6-1.5-3	325	303	22	7
NY-1200-6-1.5-6	325	294	31	9
NY-1200-6-2-3	325	303	22	7
NY-1200-6-2-6	325	294	31	9
NY-1200-8-1.5-3	325	298	27	8
NY-1200-8-1.5-6	325	284	40	12
NY-1200-8-2-3	325	298	27	8
NY-1200-8-2-6	325	284	40	12
NY-2700-4-1.5-3	455	428	27	6
NY-2700-4-1.5-6	455	423	32	7
NY-2700-4-2-3	455	428	27	6
Continued ...				

Continued . . .				
Total Utility Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-2700-4-2-6	455	423	32	7
NY-2700-6-1.5-3	455	416	39	9
NY-2700-6-1.5-6	455	404	51	11
NY-2700-6-2-3	455	416	39	9
NY-2700-6-2-6	455	404	51	11
NY-2700-8-1.5-3	455	407	48	11
NY-2700-8-1.5-6	455	385	70	15
NY-2700-8-2-3	455	407	48	11
NY-2700-8-2-6	455	385	70	15
NY-5030-4-1.5-3	587	549	38	6
NY-5030-4-1.5-6	587	545	42	7
NY-5030-4-2-3	587	549	38	6
NY-5030-4-2-6	587	545	42	7
NY-5030-6-1.5-3	587	531	55	9
NY-5030-6-1.5-6	587	522	65	11
NY-5030-6-2-3	587	531	55	9
NY-5030-6-2-6	587	522	65	11
NY-5030-8-1.5-3	587	517	70	12
NY-5030-8-1.5-6	587	495	92	16
NY-5030-8-2-3	587	517	70	12
NY-5030-8-2-6	587	495	92	16
CHI-1200-4-1.5-3	168	159	9	5
CHI-1200-4-1.5-6	168	155	12	7
CHI-1200-4-2-3	168	159	9	5
CHI-1200-4-2-6	168	155	12	7
CHI-1200-6-1.5-3	168	156	12	7
CHI-1200-6-1.5-6	168	150	17	10
CHI-1200-6-2-3	168	156	12	7
Continued . . .				

Continued . . .				
Total Utility Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
CHI-1200-6-2-6	168	150	17	10
CHI-1200-8-1.5-3	168	153	15	9
CHI-1200-8-1.5-6	168	145	23	14
CHI-1200-8-2-3	168	153	15	9
CHI-1200-8-2-6	168	145	23	14
CHI-2700-4-1.5-3	232	215	17	7
CHI-2700-4-1.5-6	232	209	22	10
CHI-2700-4-2-3	232	215	17	7
CHI-2700-4-2-6	232	209	22	10
CHI-2700-6-1.5-3	232	209	23	10
CHI-2700-6-1.5-6	232	199	32	14
CHI-2700-6-2-3	232	209	23	10
CHI-2700-6-2-6	232	199	32	14
CHI-2700-8-1.5-3	232	203	28	12
CHI-2700-8-1.5-6	232	190	42	18
CHI-2700-8-2-3	232	203	28	12
CHI-2700-8-2-6	232	190	42	18
CHI-5030-4-1.5-3	292	269	23	8
CHI-5030-4-1.5-6	292	264	28	10
CHI-5030-4-2-3	292	269	23	8
CHI-5030-4-2-6	292	264	28	10
CHI-5030-6-1.5-3	292	260	32	11
CHI-5030-6-1.5-6	292	251	41	14
CHI-5030-6-2-3	292	260	32	11
CHI-5030-6-2-6	292	251	41	14
CHI-5030-8-1.5-3	292	253	39	13
CHI-5030-8-1.5-6	292	237	55	19
CHI-5030-8-2-3	292	253	39	13
Continued . . .				

Continued . . .				
Total Utility Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
CHI-5030-8-2-6	292	237	55	19
HOU-1200-4-1.5-3	436	401	36	8
HOU-1200-4-1.5-6	436	375	61	14
HOU-1200-4-2-3	436	401	36	8
HOU-1200-4-2-6	436	375	61	14
HOU-1200-6-1.5-3	436	391	45	10
HOU-1200-6-1.5-6	436	358	78	18
HOU-1200-6-2-3	436	391	45	10
HOU-1200-6-2-6	436	358	78	18
HOU-1200-8-1.5-3	436	387	49	11
HOU-1200-8-1.5-6	436	350	86	20
HOU-1200-8-2-3	436	387	49	11
HOU-1200-8-2-6	436	350	86	20
HOU-2700-4-1.5-3	628	567	61	10
HOU-2700-4-1.5-6	628	528	100	16
HOU-2700-4-2-3	628	567	61	10
HOU-2700-4-2-6	628	528	100	16
HOU-2700-6-1.5-3	628	552	75	12
HOU-2700-6-1.5-6	628	500	128	20
HOU-2700-6-2-3	628	552	75	12
HOU-2700-6-2-6	628	500	128	20
HOU-2700-8-1.5-3	628	546	82	13
HOU-2700-8-1.5-6	628	486	141	23
HOU-2700-8-2-3	628	546	82	13
HOU-2700-8-2-6	628	486	141	23
HOU-5030-4-1.5-3	867	768	98	11
HOU-5030-4-1.5-6	867	710	157	18
HOU-5030-4-2-3	867	768	98	11
Continued . . .				

Continued ...				
Total Utility Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
HOU-5030-4-2-6	867	710	157	18
HOU-5030-6-1.5-3	867	745	121	14
HOU-5030-6-1.5-6	867	665	201	23
HOU-5030-6-2-3	867	745	121	14
HOU-5030-6-2-6	867	665	201	23
HOU-5030-8-1.5-3	867	735	131	15
HOU-5030-8-1.5-6	867	642	225	26
HOU-5030-8-2-3	867	735	131	15
HOU-5030-8-2-6	867	642	225	26
LA-1200-4-1.5-3	201	190	11	5
LA-1200-4-1.5-6	201	189	12	6
LA-1200-4-2-3	201	190	11	5
LA-1200-4-2-6	201	189	12	6
LA-1200-6-1.5-3	201	186	14	7
LA-1200-6-1.5-6	201	183	18	9
LA-1200-6-2-3	201	186	14	7
LA-1200-6-2-6	201	183	18	9
LA-1200-8-1.5-3	201	183	18	9
LA-1200-8-1.5-6	201	177	23	12
LA-1200-8-2-3	201	183	18	9
LA-1200-8-2-6	201	177	23	12
LA-2700-4-1.5-3	254	237	17	7
LA-2700-4-1.5-6	254	236	18	7
LA-2700-4-2-3	254	237	17	7
LA-2700-4-2-6	254	236	18	7
LA-2700-6-1.5-3	254	231	23	9
LA-2700-6-1.5-6	254	228	26	10
LA-2700-6-2-3	254	231	23	9
Continued ...				

Continued ...				
Total Utility Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
LA-2700-6-2-6	254	228	26	10
LA-2700-8-1.5-3	254	226	28	11
LA-2700-8-1.5-6	254	219	35	14
LA-2700-8-2-3	254	226	28	11
LA-2700-8-2-6	254	219	35	14
LA-5030-4-1.5-3	318	299	20	6
LA-5030-4-1.5-6	318	299	20	6
LA-5030-4-2-3	318	299	20	6
LA-5030-4-2-6	318	299	20	6
LA-5030-6-1.5-3	318	290	28	9
LA-5030-6-1.5-6	318	289	29	9
LA-5030-6-2-3	318	290	28	9
LA-5030-6-2-6	318	289	29	9
LA-5030-8-1.5-3	318	282	36	11
LA-5030-8-1.5-6	318	279	39	12
LA-5030-8-2-3	318	282	36	11
LA-5030-8-2-6	318	279	39	12

Table B.5: Total Homeowner Cost Savings - All

simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-1200-4-1.5-3	325	304	21	6
NY-1200-4-1.5-6	325	296	29	9
NY-1200-4-2-3	325	293	32	10
NY-1200-4-2-6	325	280	45	14
NY-1200-6-1.5-3	325	295	30	9
NY-1200-6-1.5-6	325	280	45	14
NY-1200-6-2-3	325	280	45	14
NY-1200-6-2-6	325	257	68	21
Continued ...				

Continued ...				
Total Homeowner Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
NY-1200-8-1.5-3	325	286	38	12
NY-1200-8-1.5-6	325	265	60	18
NY-1200-8-2-3	325	268	57	17
NY-1200-8-2-6	325	234	90	28
NY-2700-4-1.5-3	455	417	38	8
NY-2700-4-1.5-6	455	407	48	11
NY-2700-4-2-3	455	397	58	13
NY-2700-4-2-6	455	379	76	17
NY-2700-6-1.5-3	455	400	55	12
NY-2700-6-1.5-6	455	378	77	17
NY-2700-6-2-3	455	372	84	18
NY-2700-6-2-6	455	334	121	27
NY-2700-8-1.5-3	455	385	70	15
NY-2700-8-1.5-6	455	348	107	23
NY-2700-8-2-3	455	349	106	23
NY-2700-8-2-6	455	289	166	36
NY-5030-4-1.5-3	587	532	54	9
NY-5030-4-1.5-6	587	523	64	11
NY-5030-4-2-3	587	503	84	14
NY-5030-4-2-6	587	487	100	17
NY-5030-6-1.5-3	587	507	80	14
NY-5030-6-1.5-6	587	485	102	17
NY-5030-6-2-3	587	464	123	21
NY-5030-6-2-6	587	426	161	27
NY-5030-8-1.5-3	587	483	104	18
NY-5030-8-1.5-6	587	442	145	25
NY-5030-8-2-3	587	428	159	27
NY-5030-8-2-6	587	359	228	39
Continued ...				

Continued . . .				
Total Homeowner Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
CHI-1200-4-1.5-3	168	158	10	6
CHI-1200-4-1.5-6	168	154	14	8
CHI-1200-4-2-3	168	153	15	9
CHI-1200-4-2-6	168	147	21	13
CHI-1200-6-1.5-3	168	153	14	9
CHI-1200-6-1.5-6	168	147	21	13
CHI-1200-6-2-3	168	147	21	13
CHI-1200-6-2-6	168	137	31	19
CHI-1200-8-1.5-3	168	150	18	11
CHI-1200-8-1.5-6	168	140	28	16
CHI-1200-8-2-3	168	142	26	16
CHI-1200-8-2-6	168	127	41	24
CHI-2700-4-1.5-3	232	212	20	9
CHI-2700-4-1.5-6	232	206	26	11
CHI-2700-4-2-3	232	202	29	13
CHI-2700-4-2-6	232	193	39	17
CHI-2700-6-1.5-3	232	204	28	12
CHI-2700-6-1.5-6	232	192	39	17
CHI-2700-6-2-3	232	191	41	18
CHI-2700-6-2-6	232	173	59	25
CHI-2700-8-1.5-3	232	197	35	15
CHI-2700-8-1.5-6	232	180	52	22
CHI-2700-8-2-3	232	180	51	22
CHI-2700-8-2-6	232	154	78	34
CHI-5030-4-1.5-3	292	265	27	9
CHI-5030-4-1.5-6	292	260	32	11
CHI-5030-4-2-3	292	252	40	14
CHI-5030-4-2-6	292	244	48	17
Continued . . .				

Continued . . .				
Total Homeowner Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
CHI-5030-6-1.5-3	292	254	39	13
CHI-5030-6-1.5-6	292	242	50	17
CHI-5030-6-2-3	292	235	57	20
CHI-5030-6-2-6	292	217	75	26
CHI-5030-8-1.5-3	292	244	48	17
CHI-5030-8-1.5-6	292	225	67	23
CHI-5030-8-2-3	292	221	71	24
CHI-5030-8-2-6	292	191	101	34
HOU-1200-4-1.5-3	436	403	33	8
HOU-1200-4-1.5-6	436	379	58	13
HOU-1200-4-2-3	436	386	50	11
HOU-1200-4-2-6	436	348	88	20
HOU-1200-6-1.5-3	436	389	47	11
HOU-1200-6-1.5-6	436	354	83	19
HOU-1200-6-2-3	436	365	71	16
HOU-1200-6-2-6	436	310	127	29
HOU-1200-8-1.5-3	436	377	59	14
HOU-1200-8-1.5-6	436	332	105	24
HOU-1200-8-2-3	436	346	90	21
HOU-1200-8-2-6	436	275	161	37
HOU-2700-4-1.5-3	628	570	58	9
HOU-2700-4-1.5-6	628	531	97	15
HOU-2700-4-2-3	628	537	91	14
HOU-2700-4-2-6	628	473	155	25
HOU-2700-6-1.5-3	628	546	82	13
HOU-2700-6-1.5-6	628	488	140	22
HOU-2700-6-2-3	628	500	128	20
HOU-2700-6-2-6	628	405	223	35
Continued . . .				

Continued ...				
Total Homeowner Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
HOU-2700-8-1.5-3	628	525	102	16
HOU-2700-8-1.5-6	628	448	180	29
HOU-2700-8-2-3	628	467	161	26
HOU-2700-8-2-6	628	341	287	46
HOU-5030-4-1.5-3	867	773	93	11
HOU-5030-4-1.5-6	867	714	152	18
HOU-5030-4-2-3	867	718	149	17
HOU-5030-4-2-6	867	621	245	28
HOU-5030-6-1.5-3	867	735	132	15
HOU-5030-6-1.5-6	867	644	223	26
HOU-5030-6-2-3	867	657	210	24
HOU-5030-6-2-6	867	507	360	41
HOU-5030-8-1.5-3	867	700	167	19
HOU-5030-8-1.5-6	867	577	290	33
HOU-5030-8-2-3	867	600	267	31
HOU-5030-8-2-6	867	397	469	54
LA-1200-4-1.5-3	201	190	11	6
LA-1200-4-1.5-6	201	188	13	6
LA-1200-4-2-3	201	185	16	8
LA-1200-4-2-6	201	182	18	9
LA-1200-6-1.5-3	201	184	17	8
LA-1200-6-1.5-6	201	180	21	11
LA-1200-6-2-3	201	177	24	12
LA-1200-6-2-6	201	171	30	15
LA-1200-8-1.5-3	201	179	22	11
LA-1200-8-1.5-6	201	172	29	14
LA-1200-8-2-3	201	170	31	16
LA-1200-8-2-6	201	160	41	21
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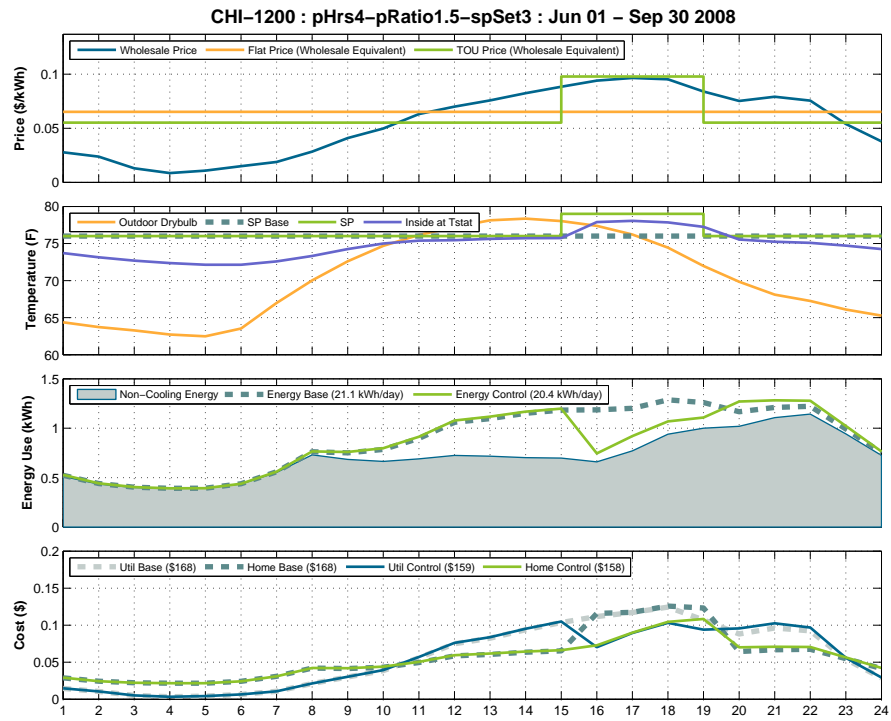
Continued . . .				
Total Homeowner Cost Savings - All				
simulation	Base (\$)	Control (\$)	Saved (\$)	Saved (%)
LA-2700-4-1.5-3	254	236	18	7
LA-2700-4-1.5-6	254	236	18	7
LA-2700-4-2-3	254	229	25	10
LA-2700-4-2-6	254	228	26	10
LA-2700-6-1.5-3	254	227	27	11
LA-2700-6-1.5-6	254	223	31	12
LA-2700-6-2-3	254	216	38	15
LA-2700-6-2-6	254	210	43	17
LA-2700-8-1.5-3	254	219	35	14
LA-2700-8-1.5-6	254	211	43	17
LA-2700-8-2-3	254	205	49	19
LA-2700-8-2-6	254	193	61	24
LA-5030-4-1.5-3	318	298	20	6
LA-5030-4-1.5-6	318	298	20	6
LA-5030-4-2-3	318	290	29	9
LA-5030-4-2-6	318	289	29	9
LA-5030-6-1.5-3	318	285	33	10
LA-5030-6-1.5-6	318	284	34	11
LA-5030-6-2-3	318	272	46	15
LA-5030-6-2-6	318	270	48	15
LA-5030-8-1.5-3	318	274	44	14
LA-5030-8-1.5-6	318	270	48	15
LA-5030-8-2-3	318	257	61	19
LA-5030-8-2-6	318	251	67	21

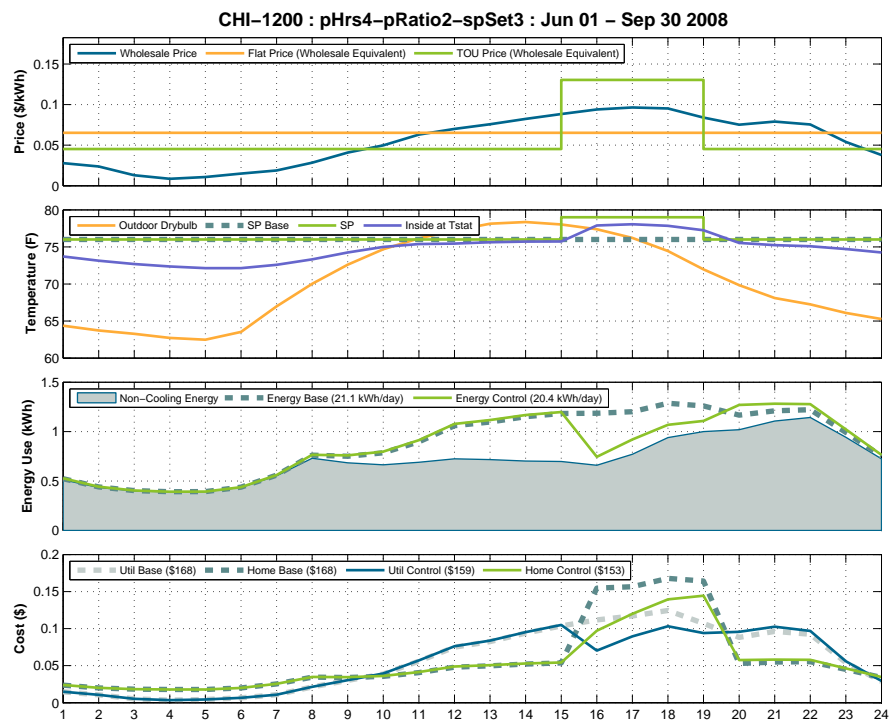
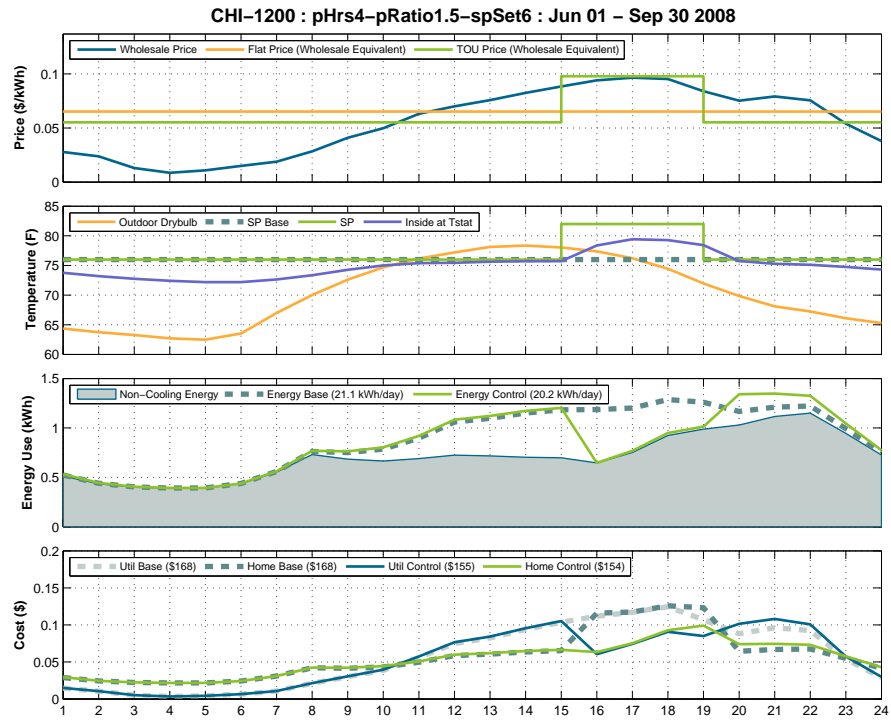
Appendix C

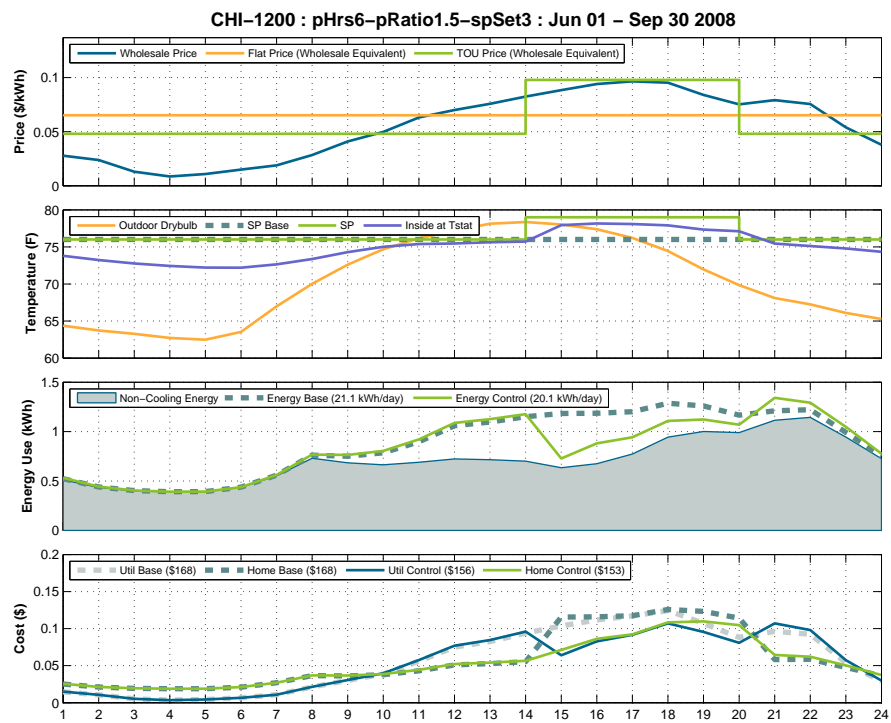
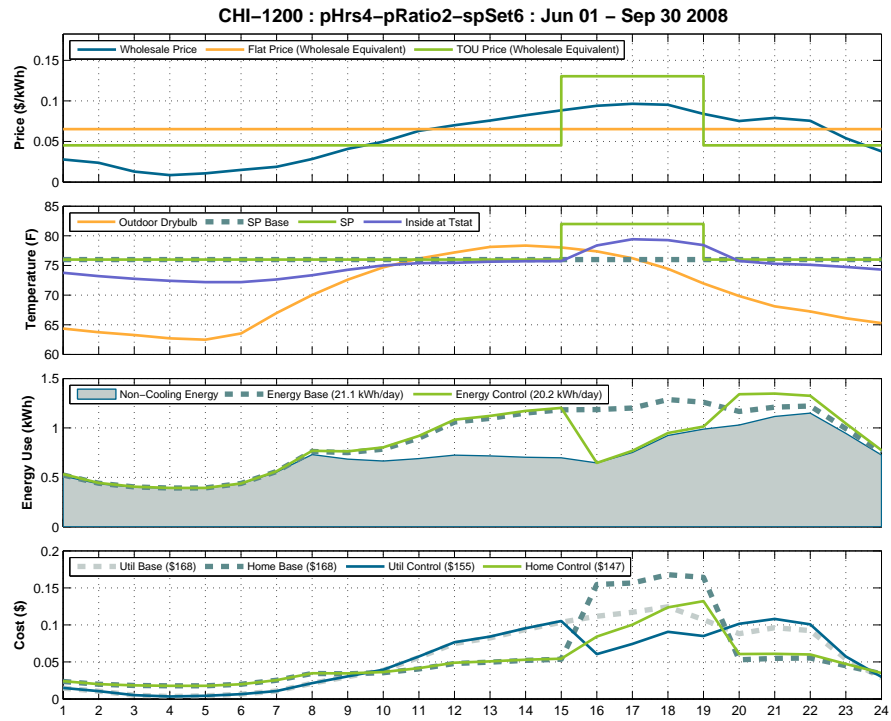
Additional Charts

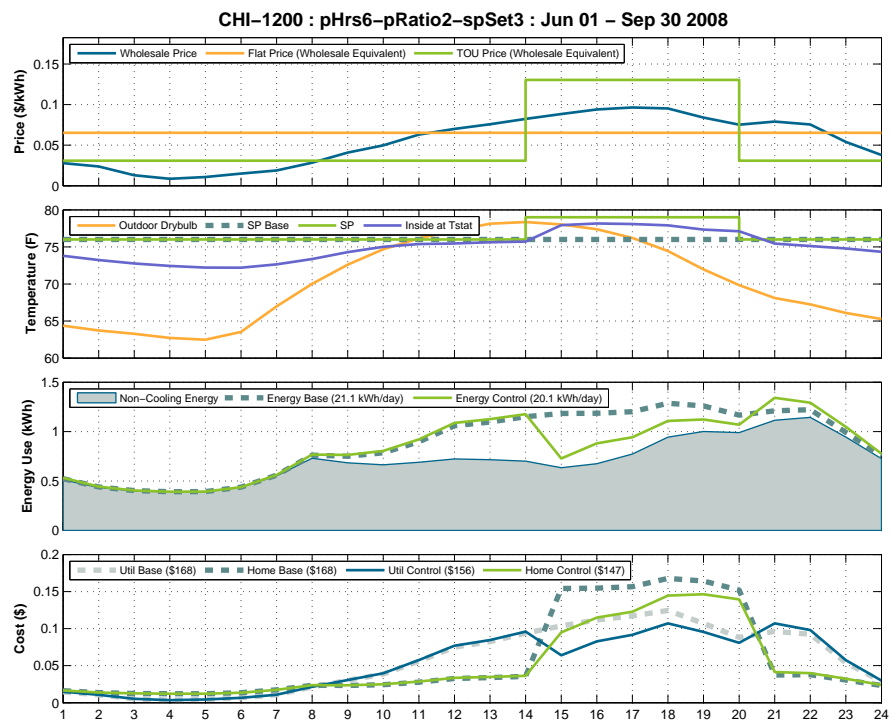
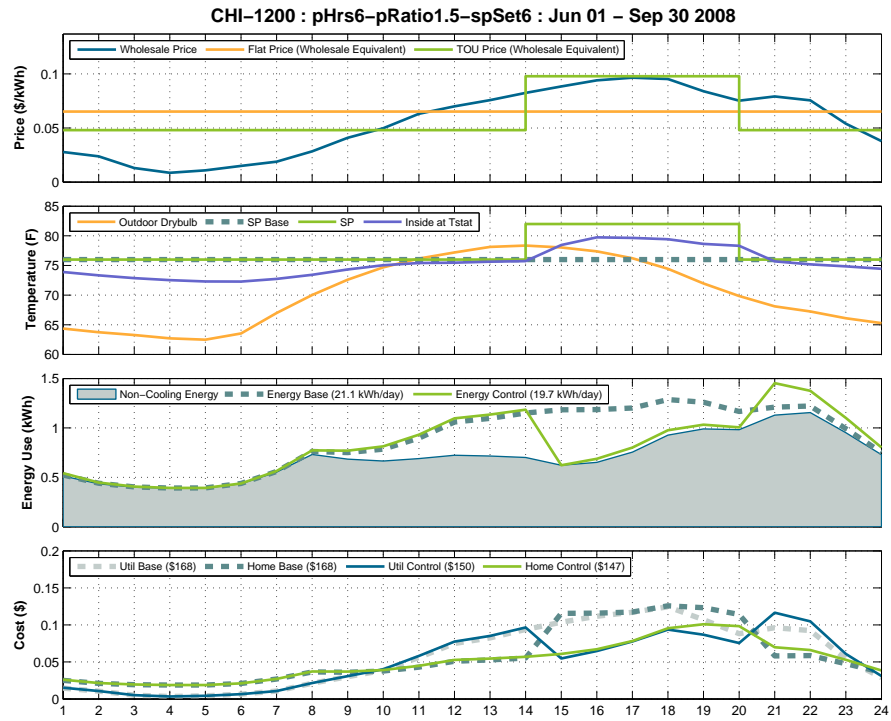
C.1 Chicago

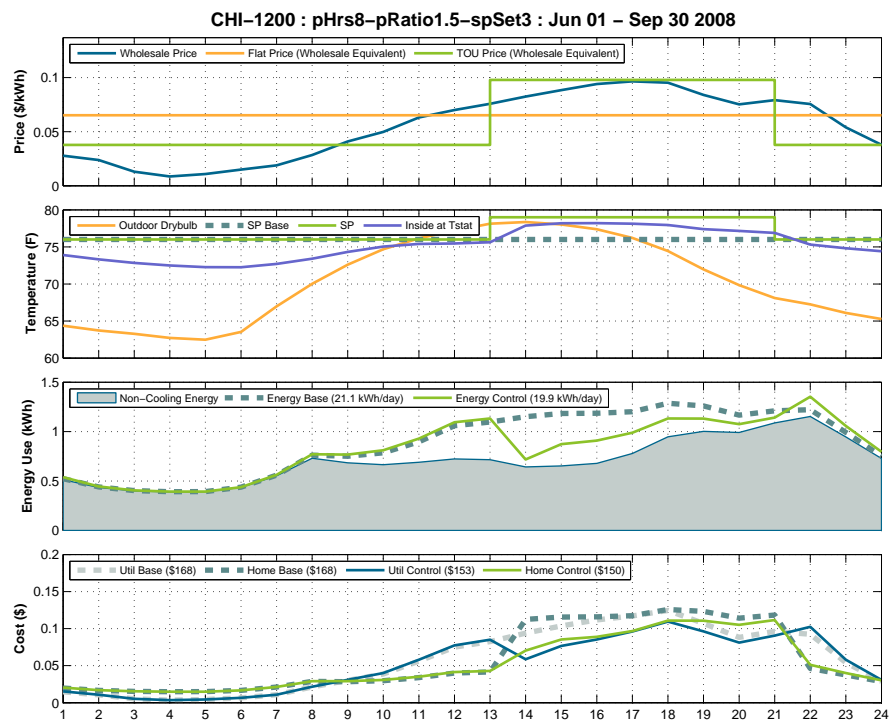
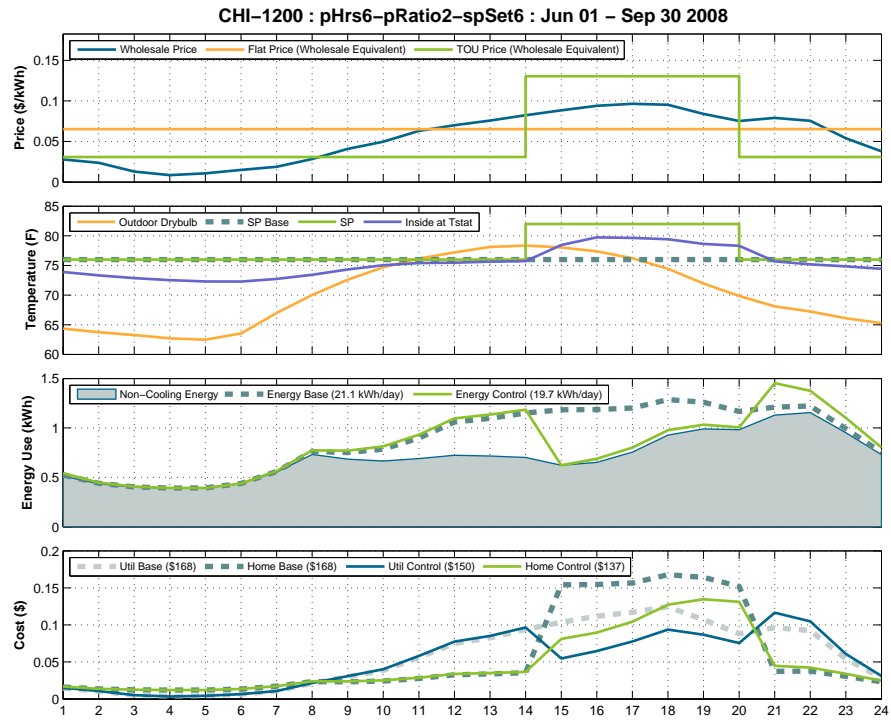
C.1.1 1200

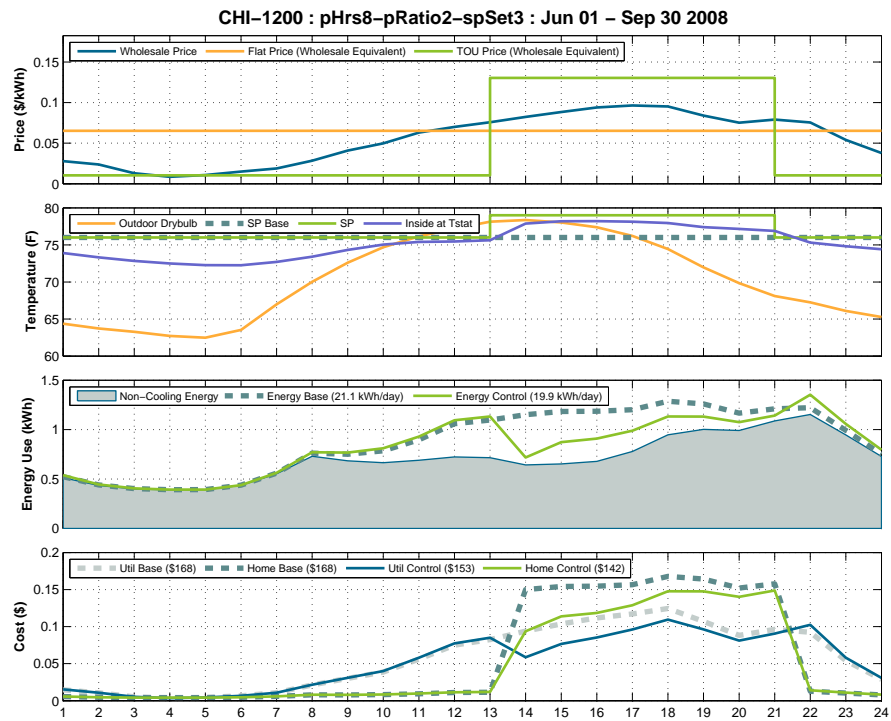
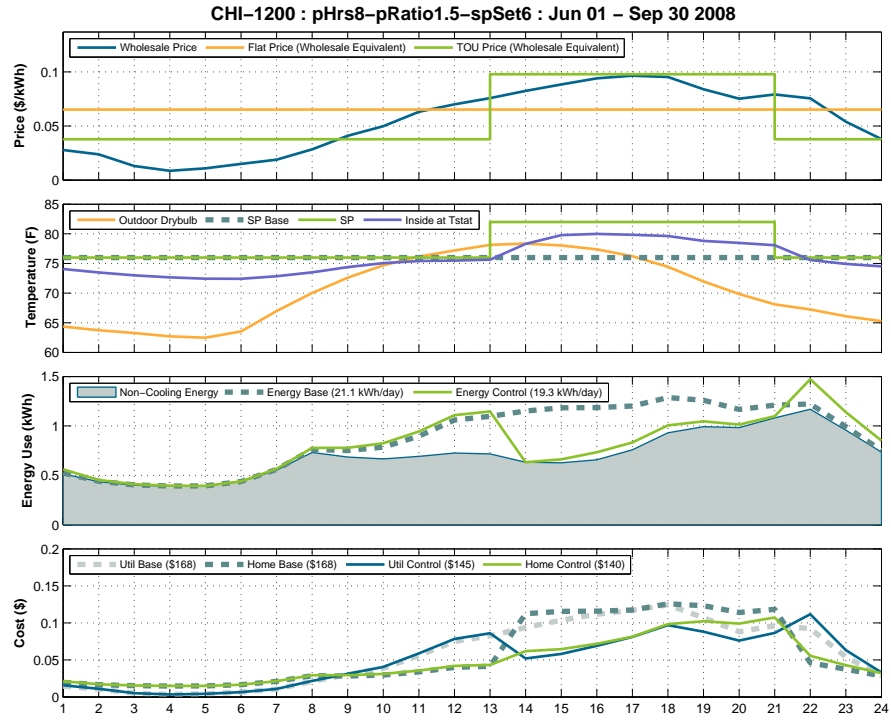


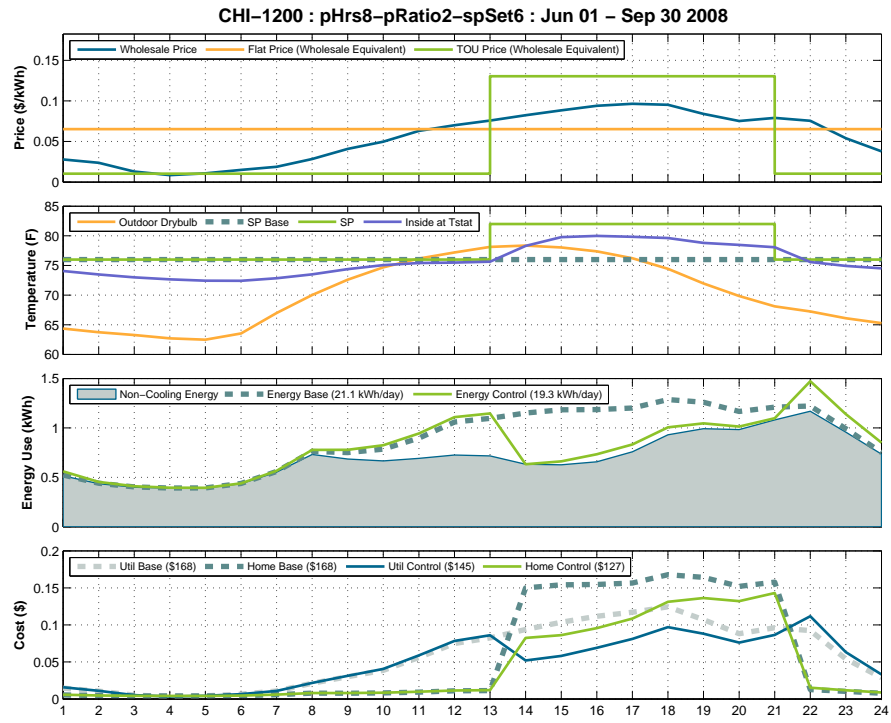




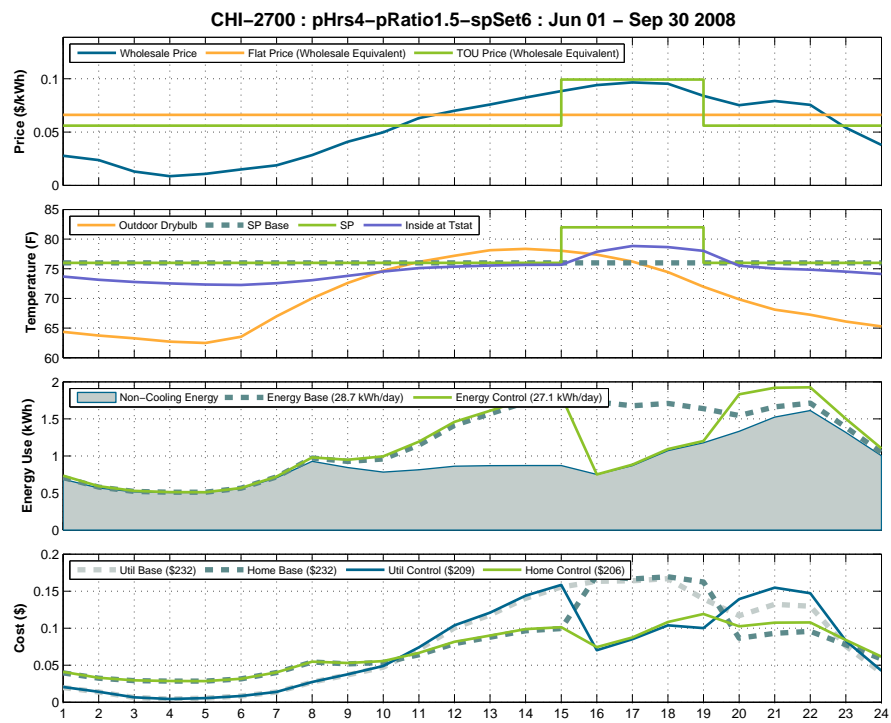
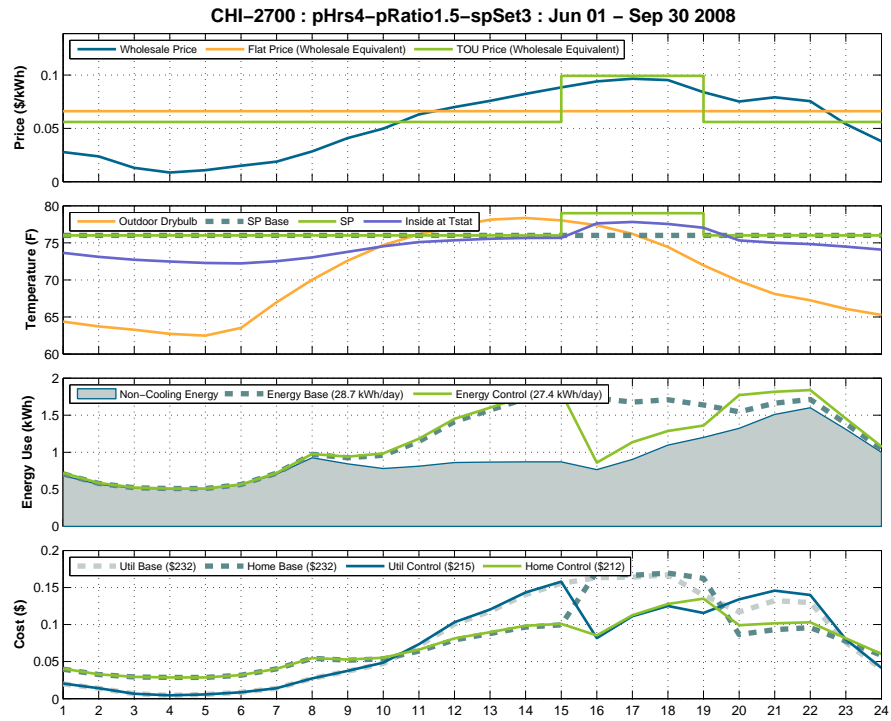


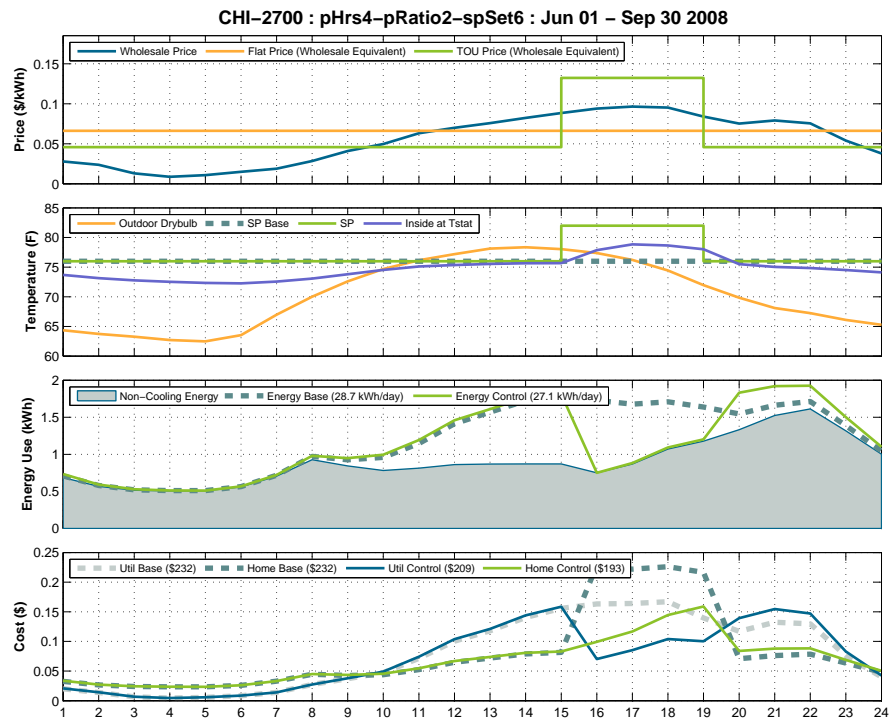
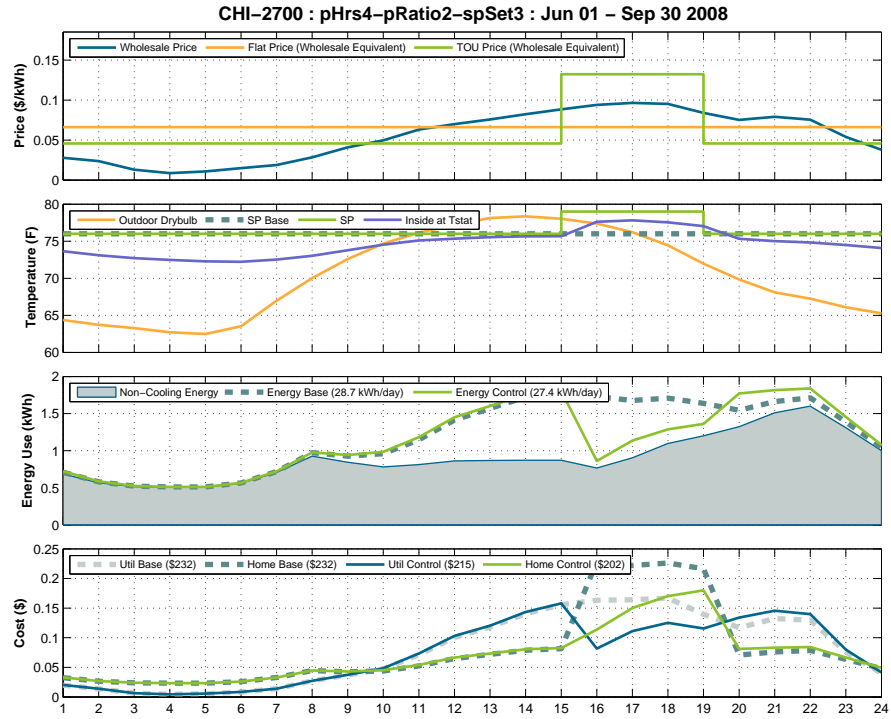




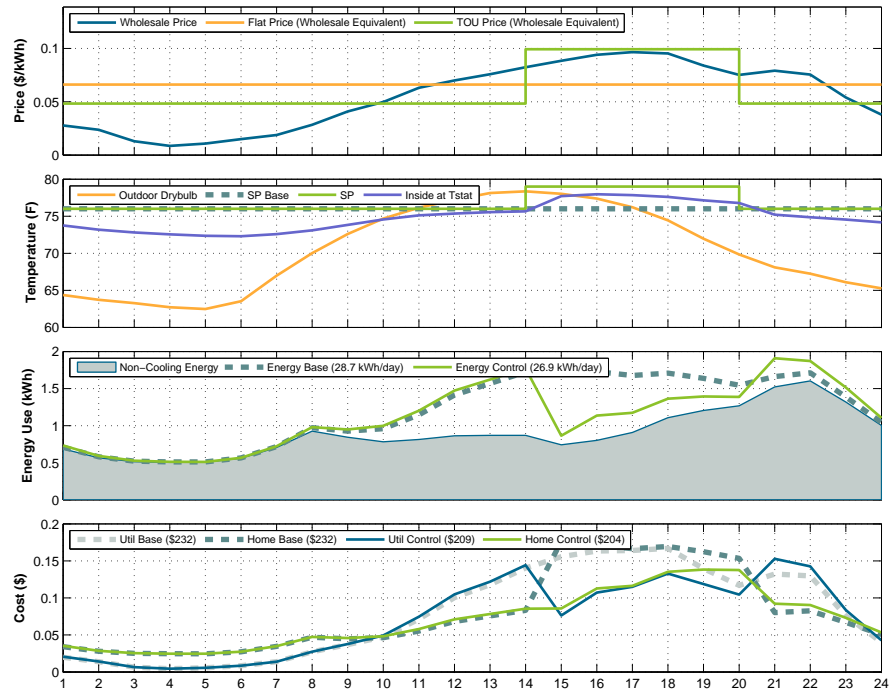


C.1.2 2700

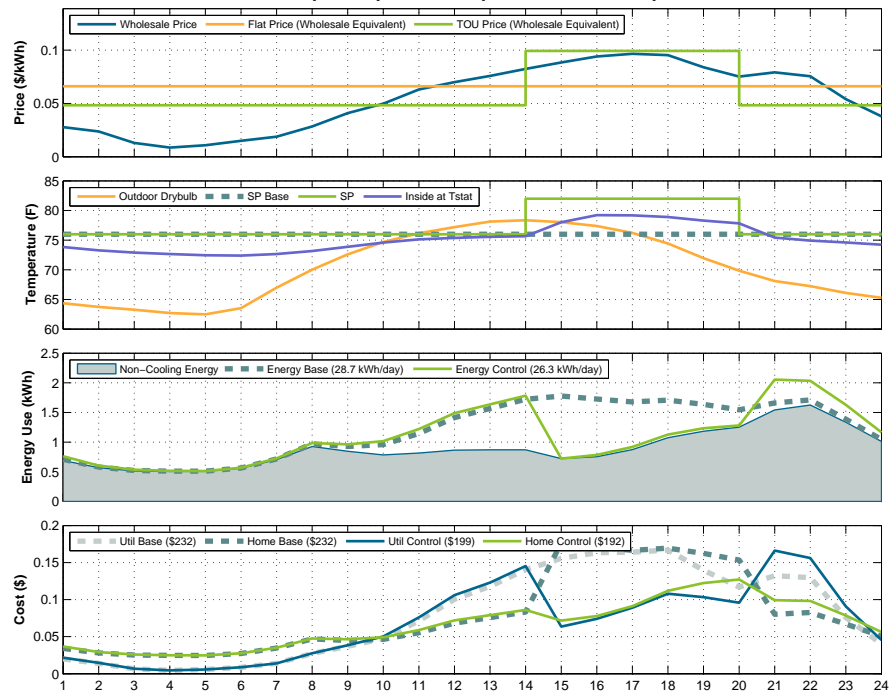


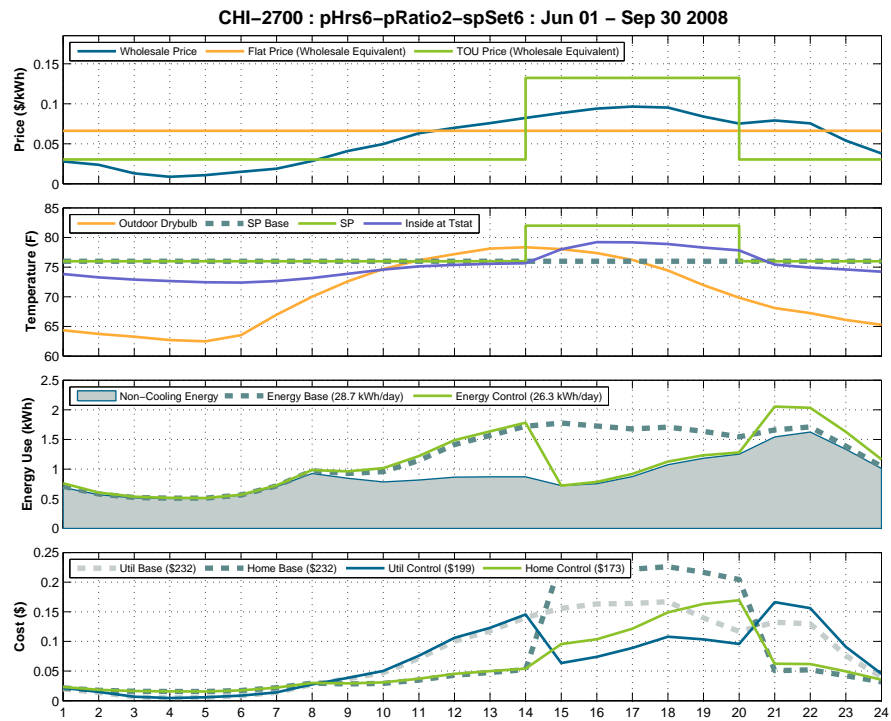
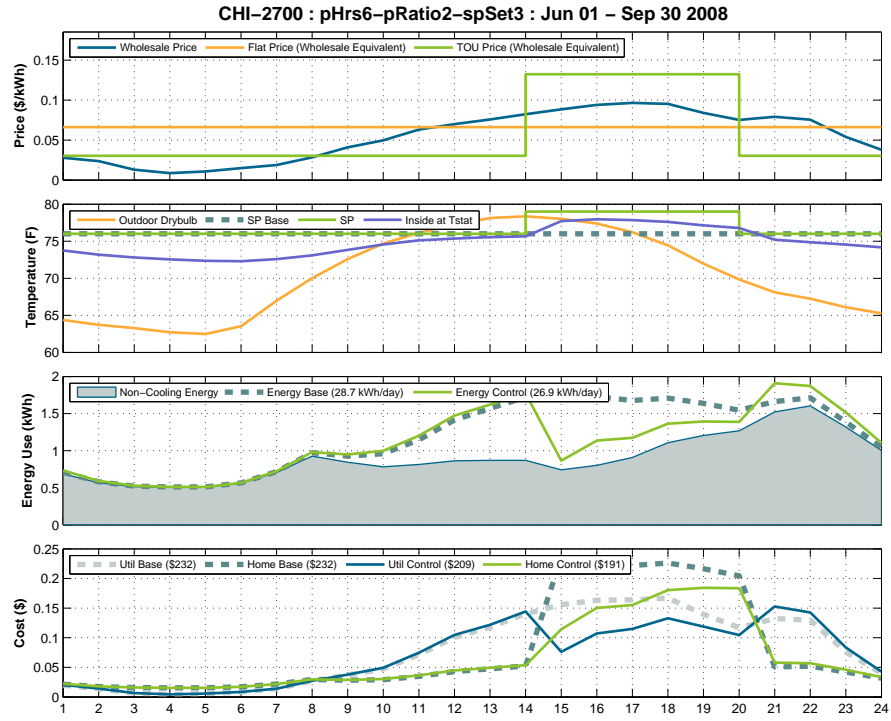


CHI-2700 : pHrs6-pRatio1.5-spSet3 : Jun 01 – Sep 30 2008

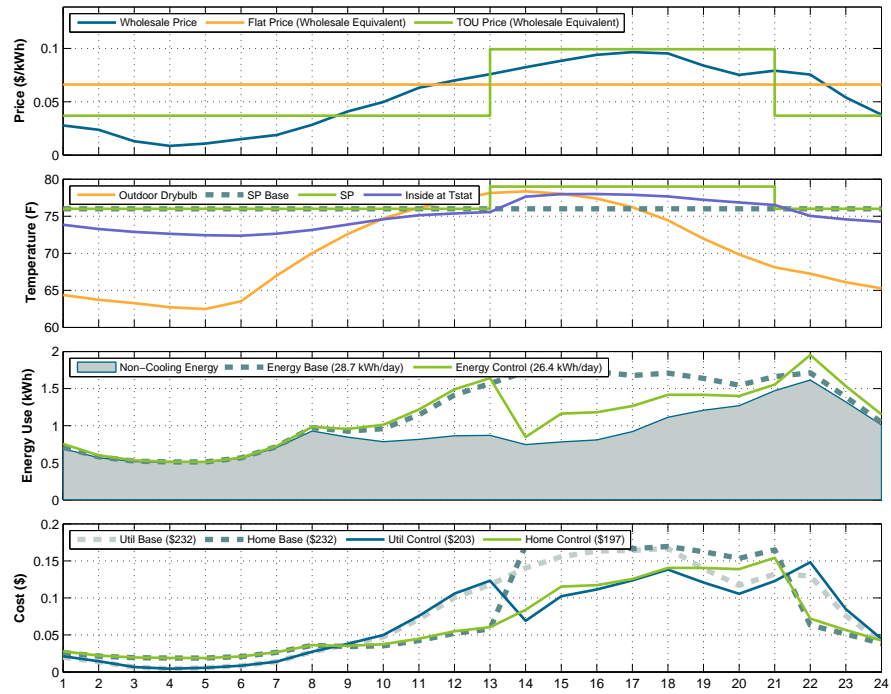


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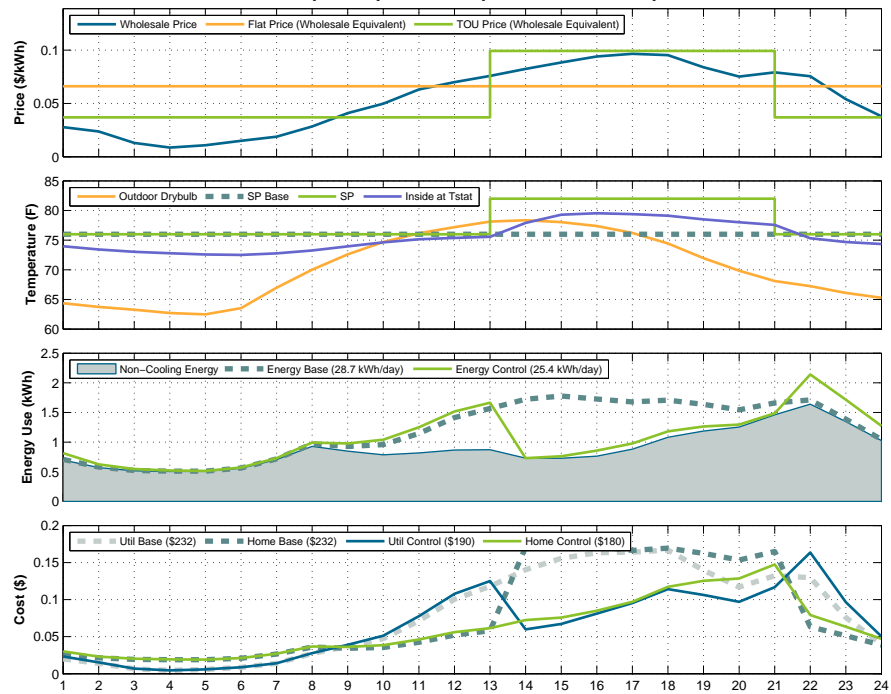


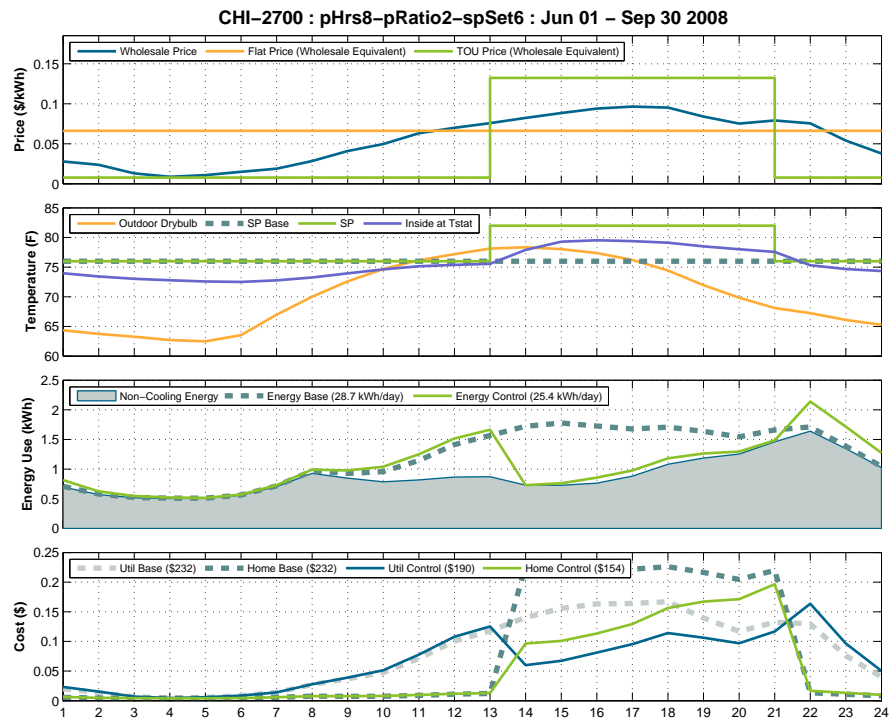
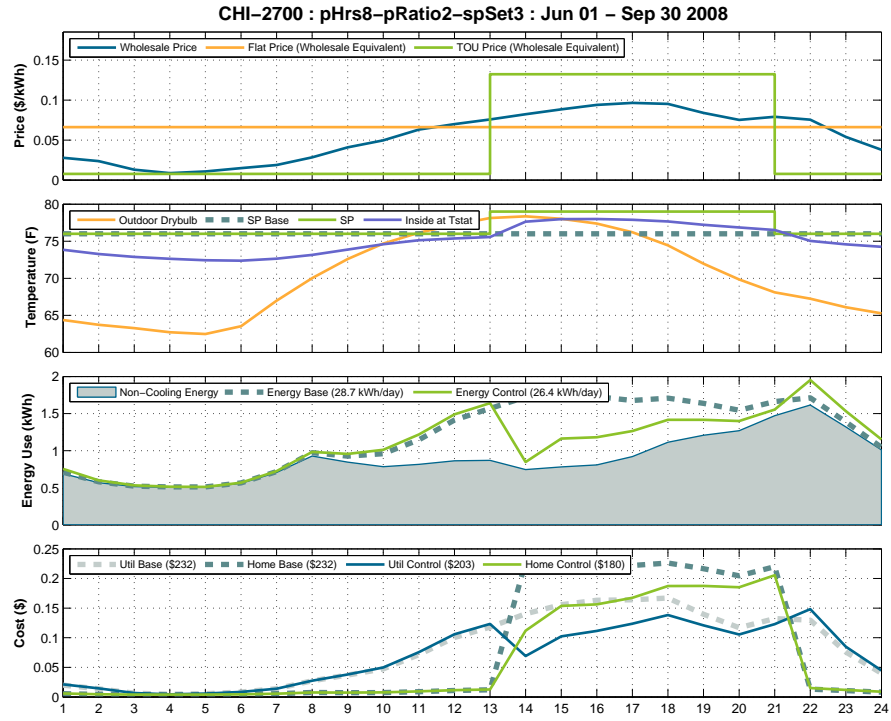


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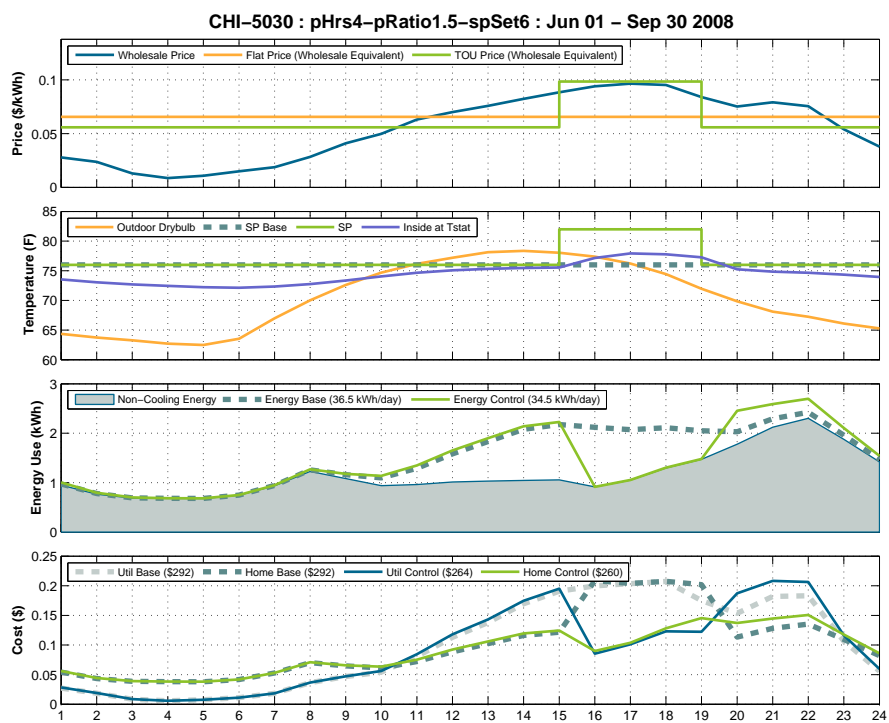
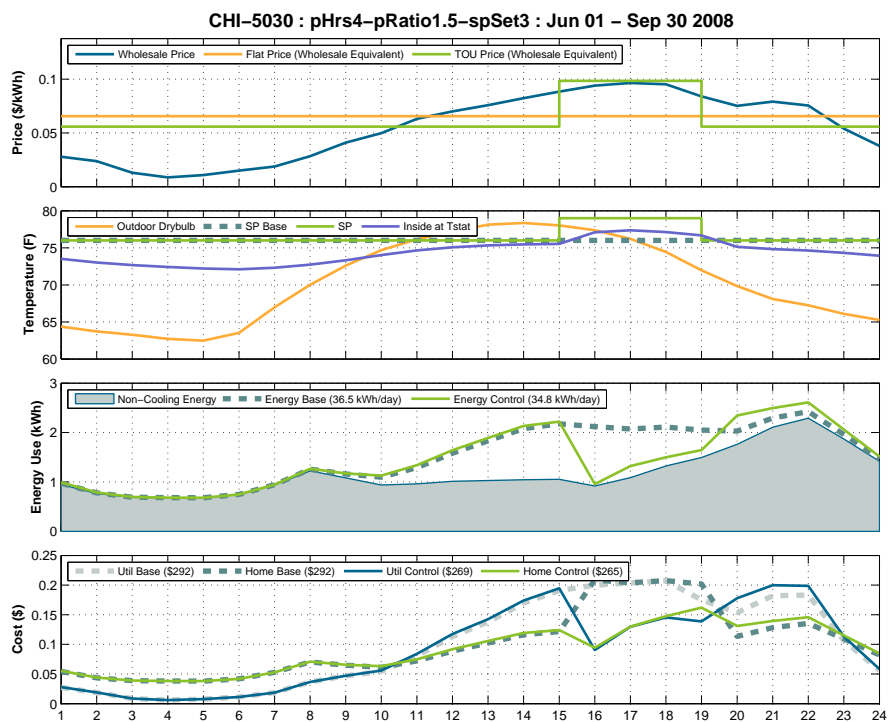


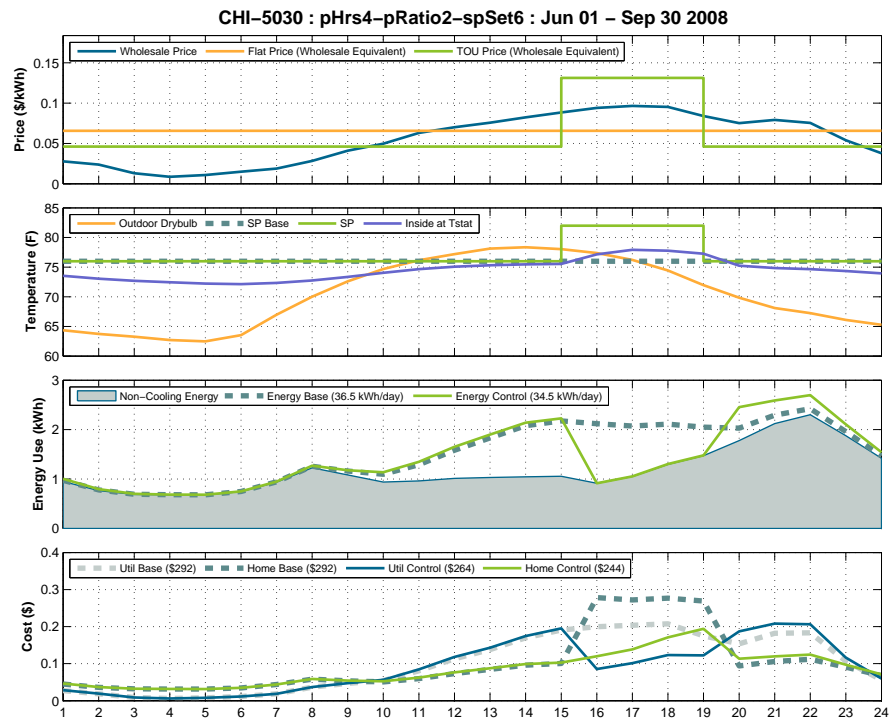
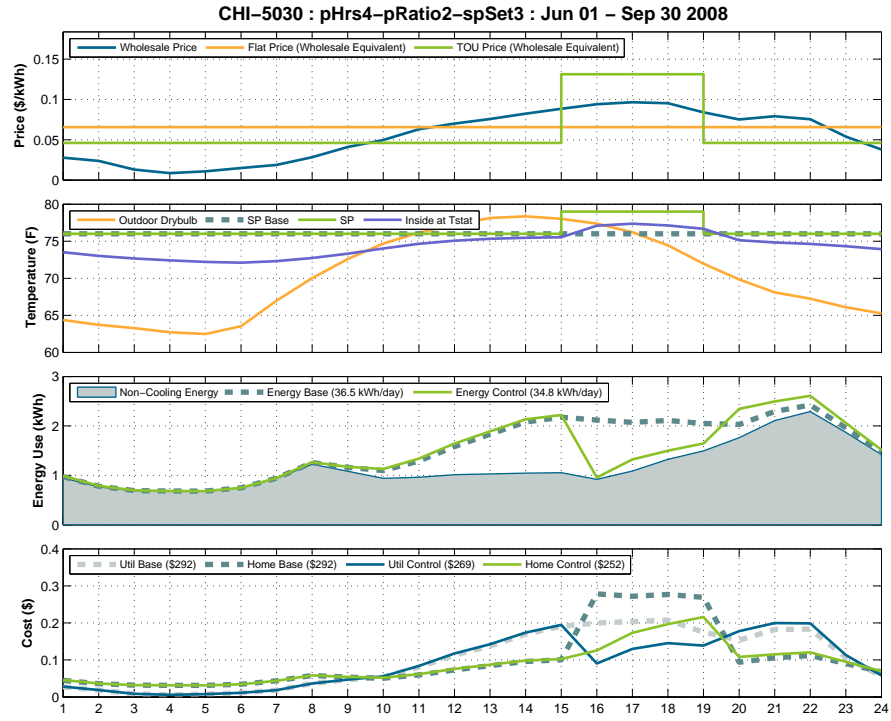
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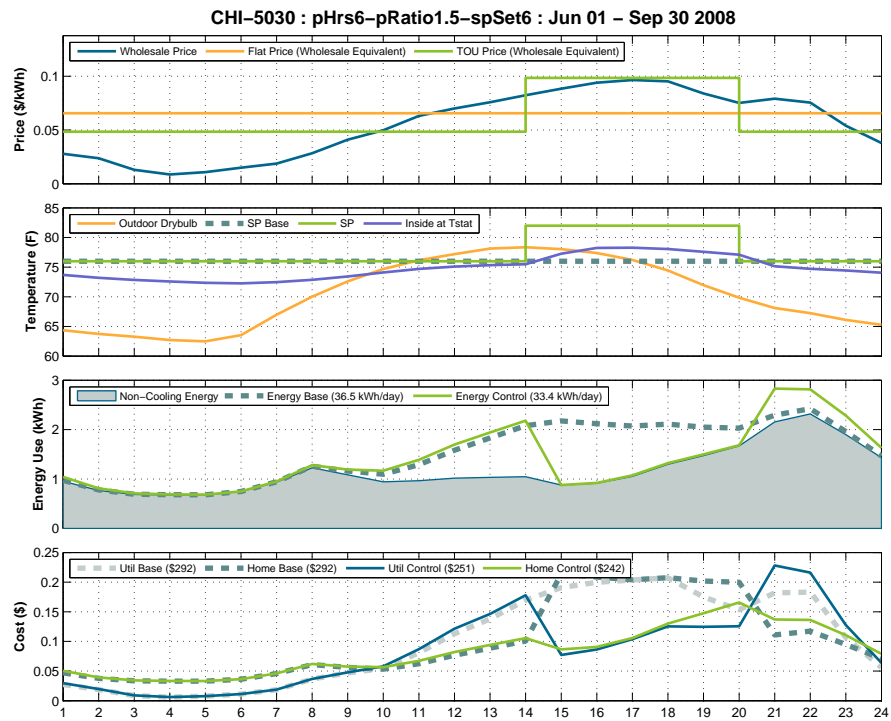
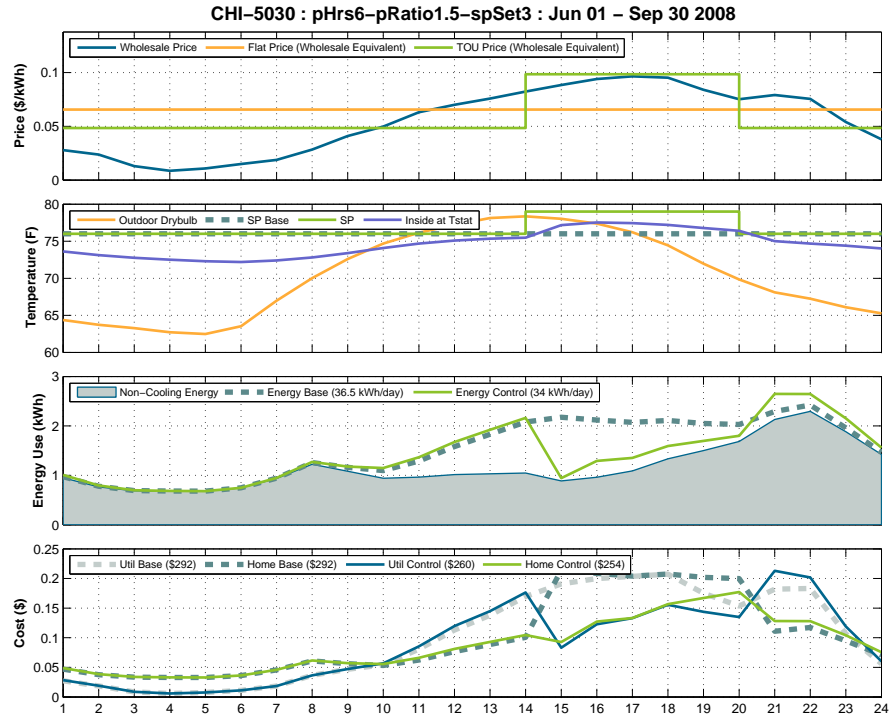


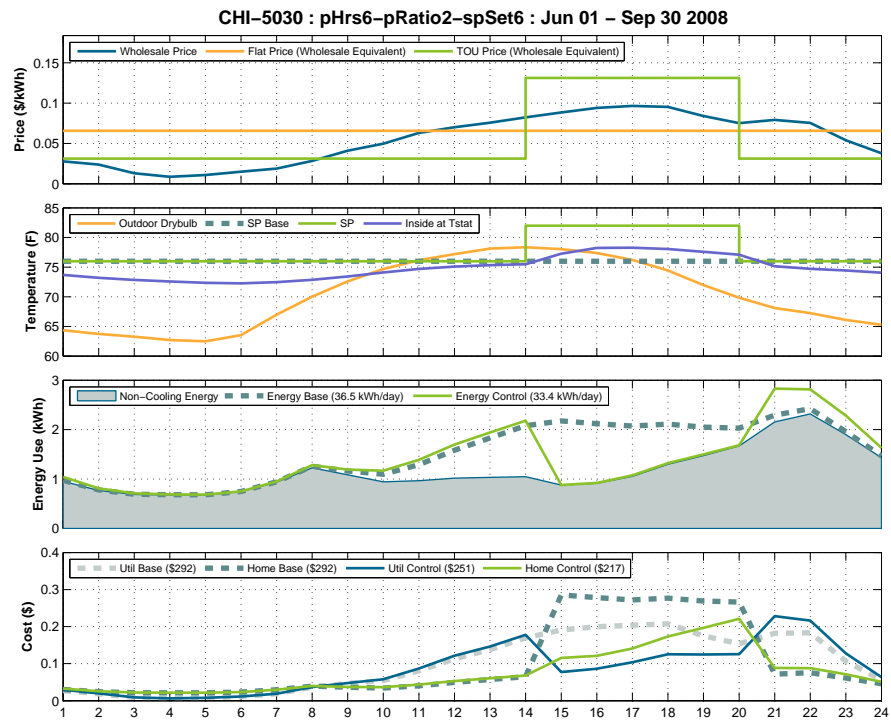
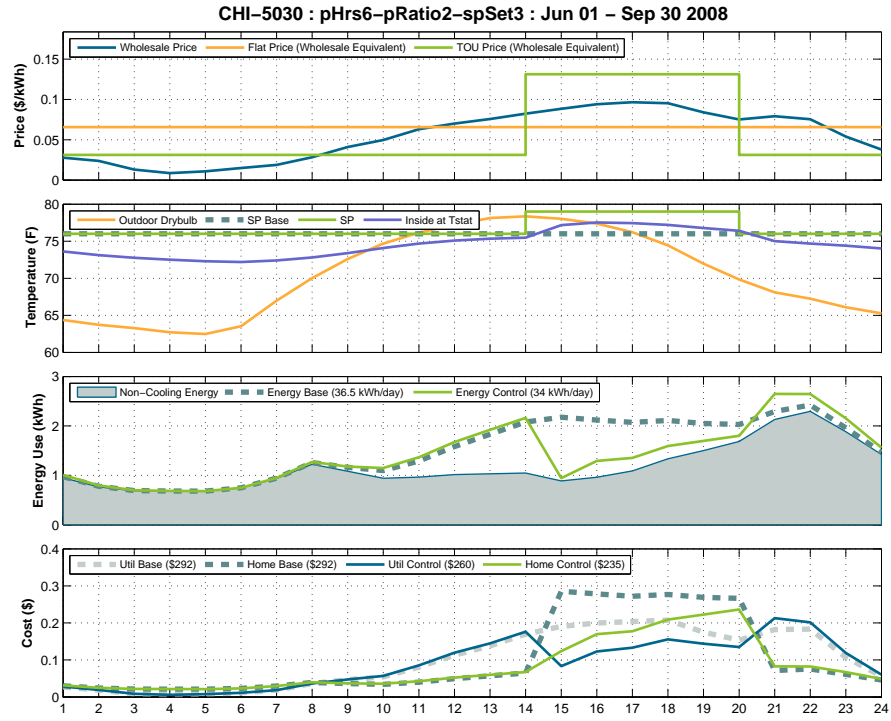


C.1.3 5030

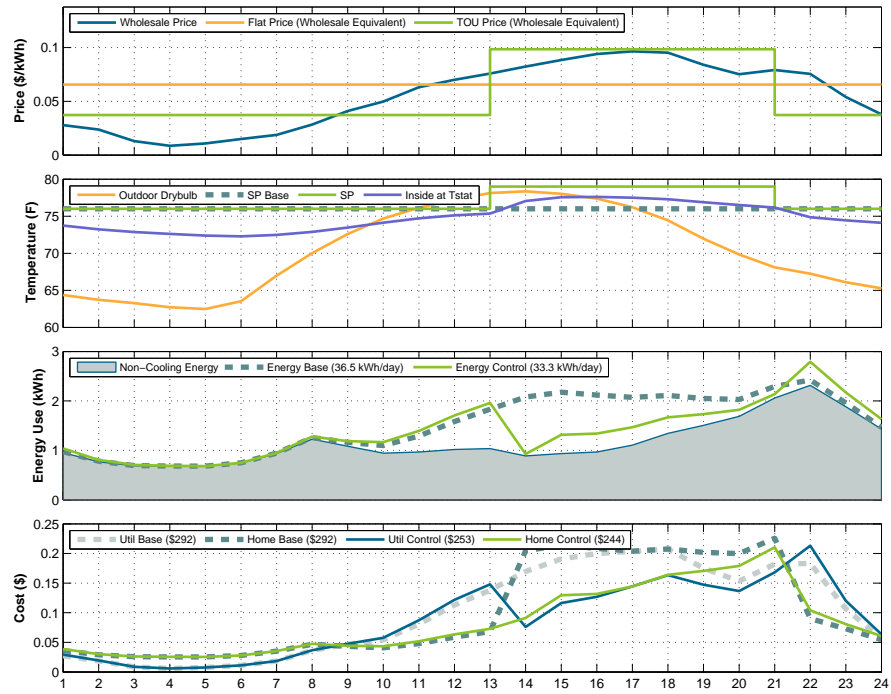




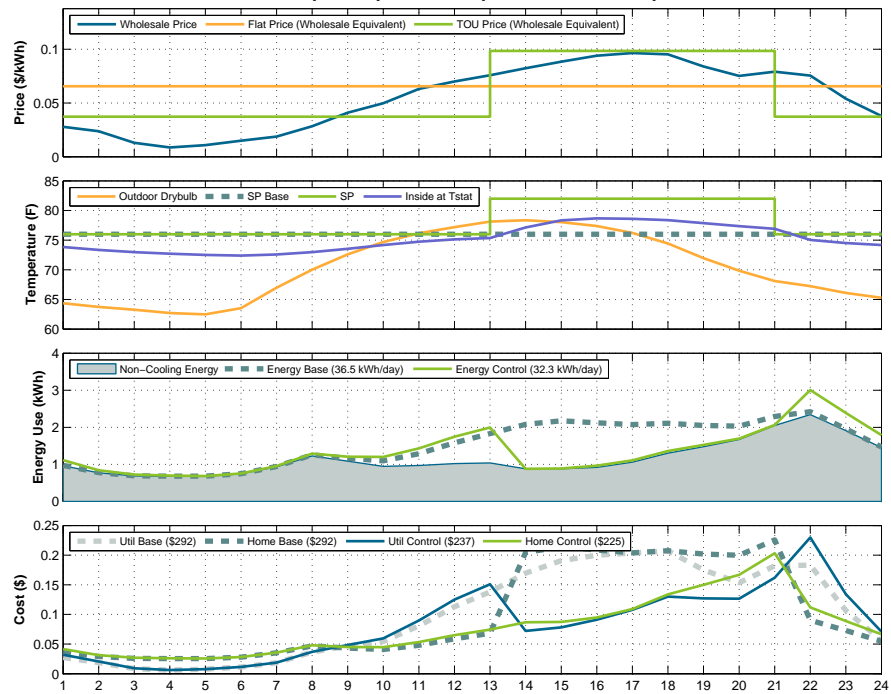


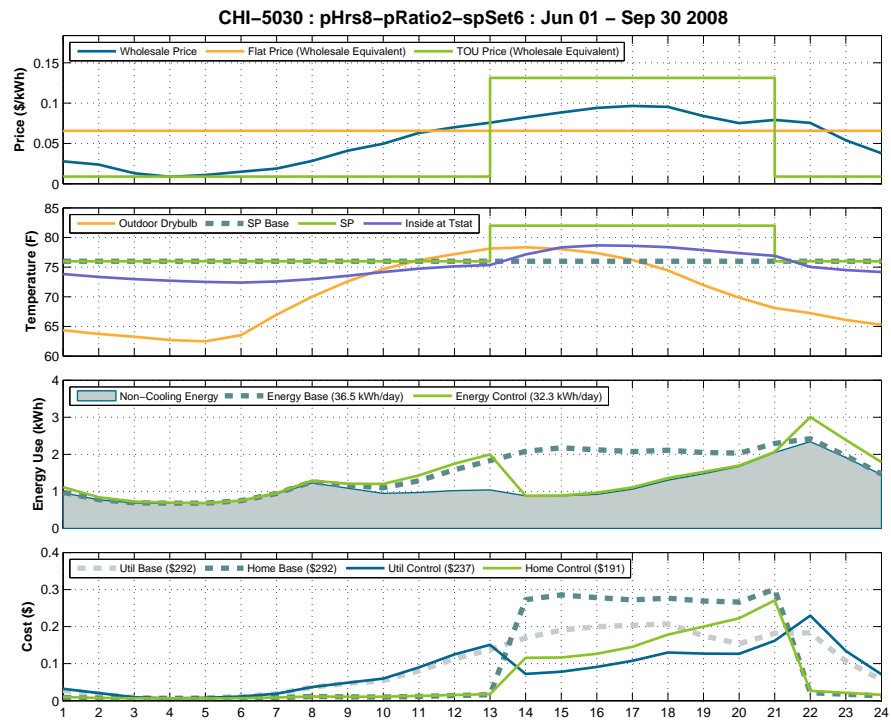
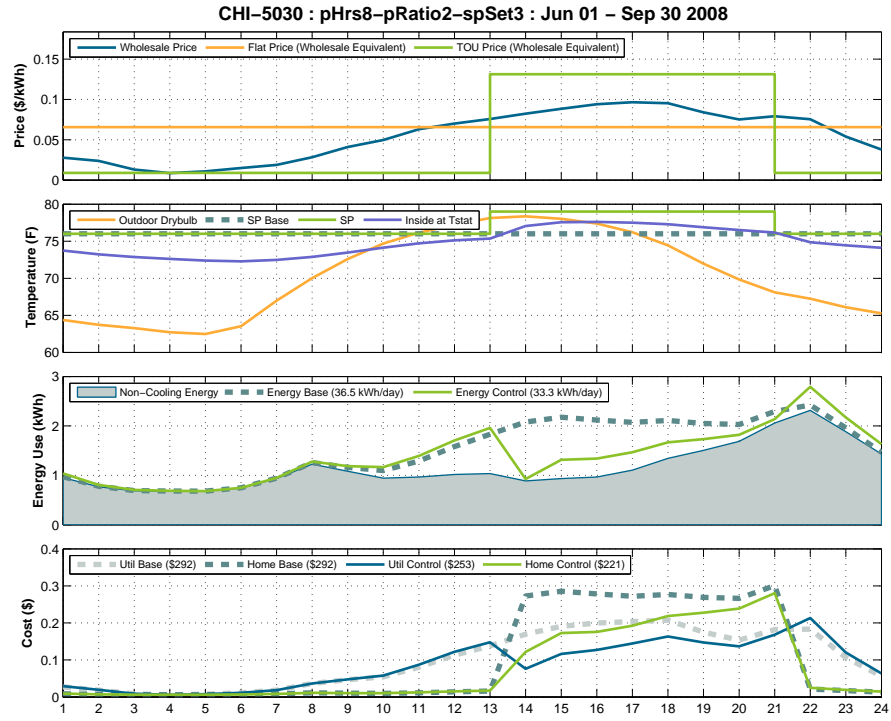


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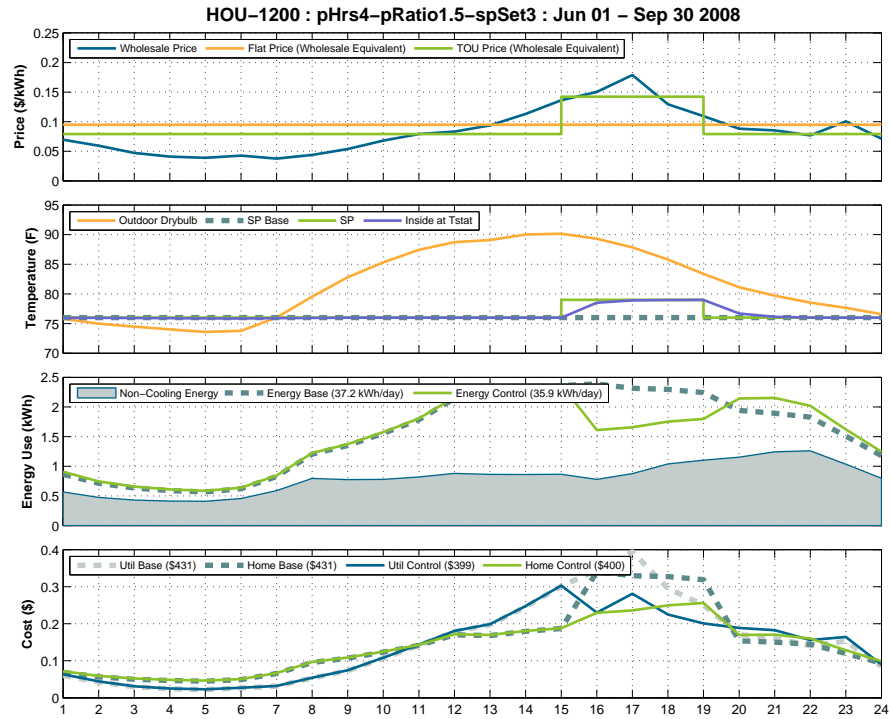
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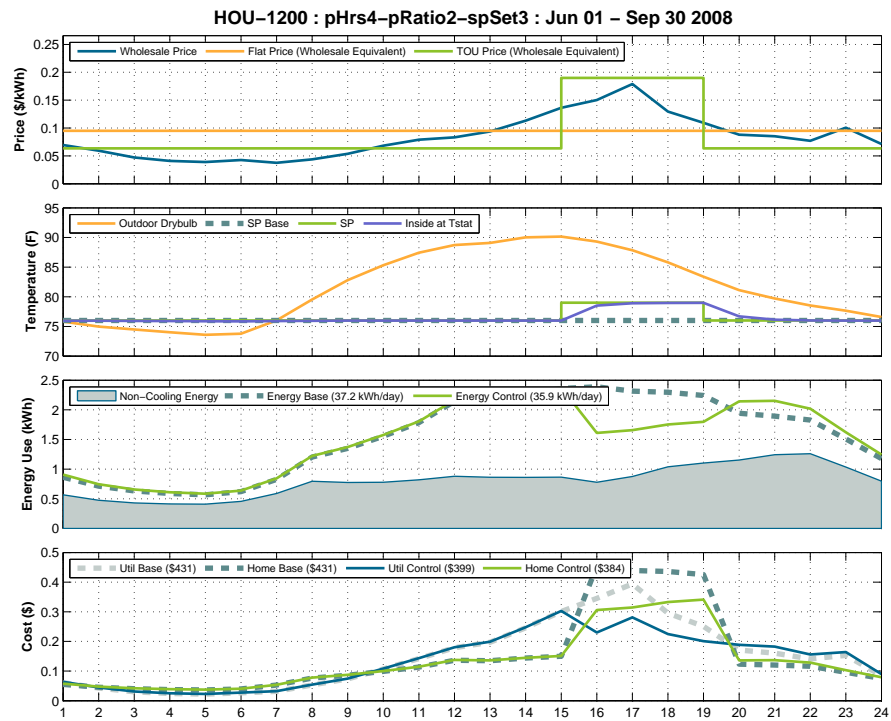
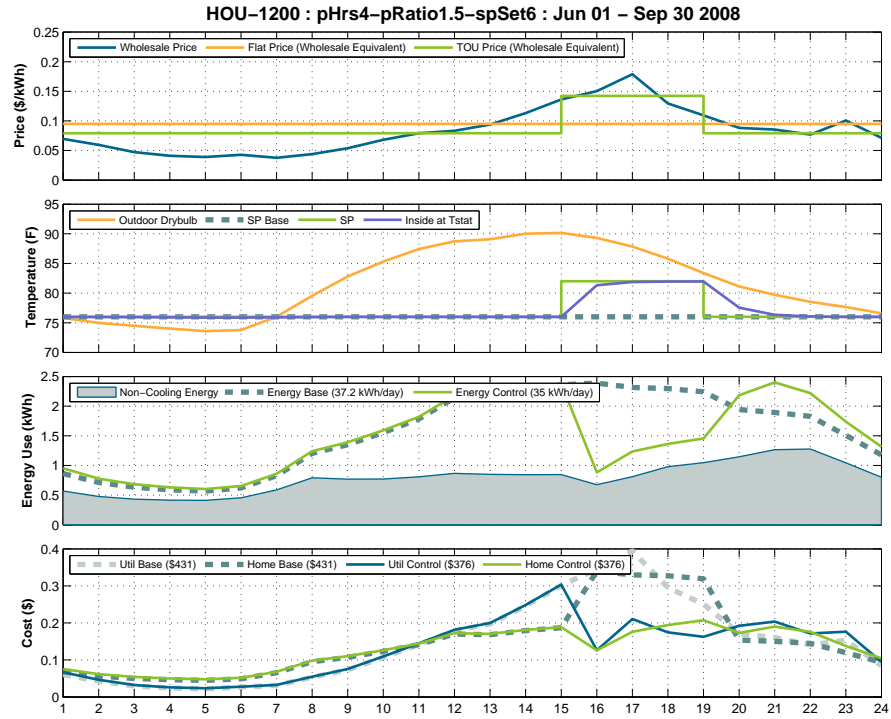


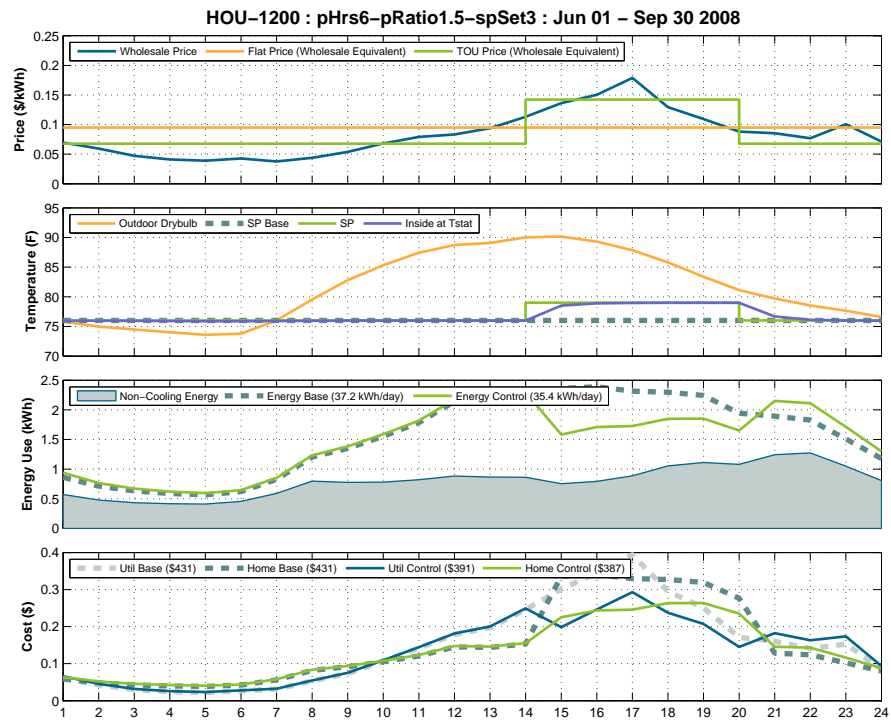
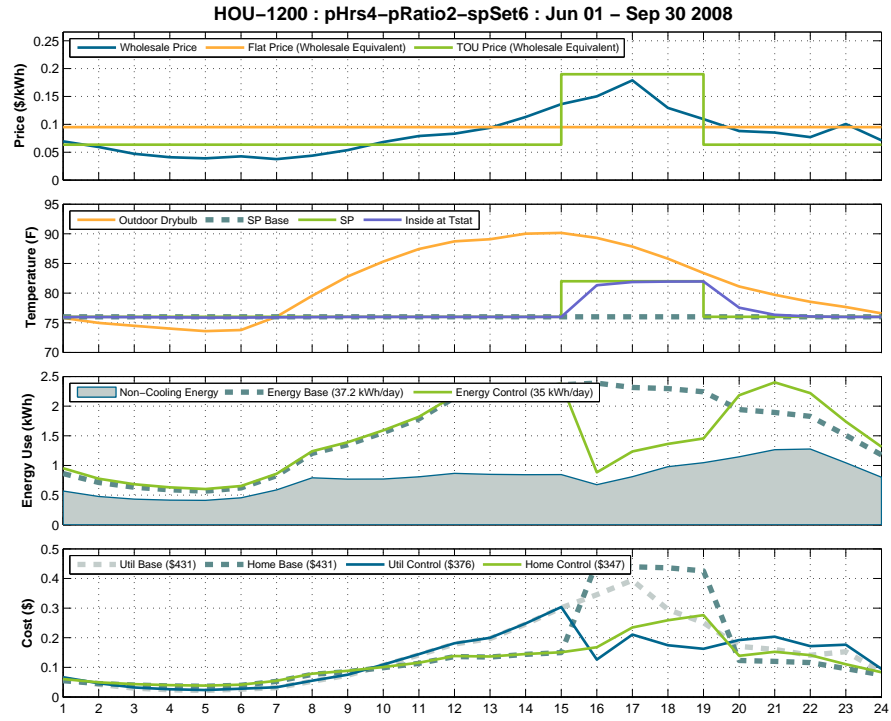


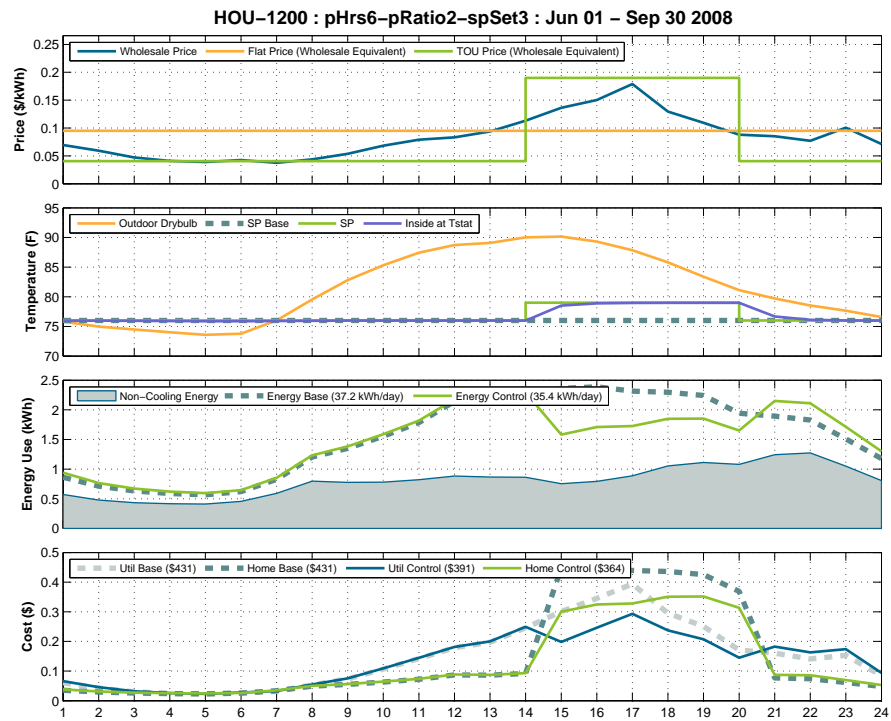
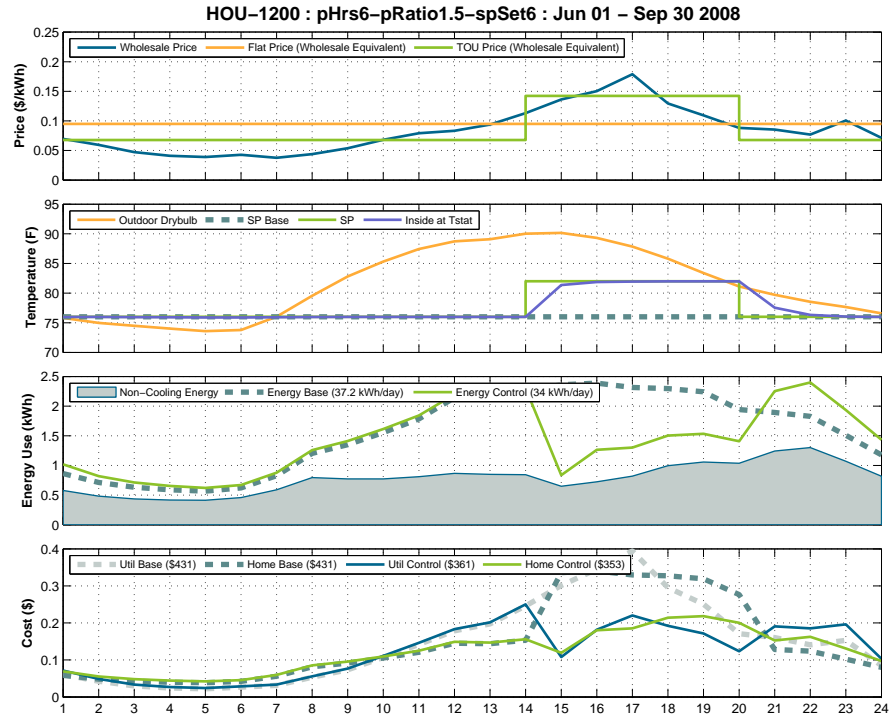
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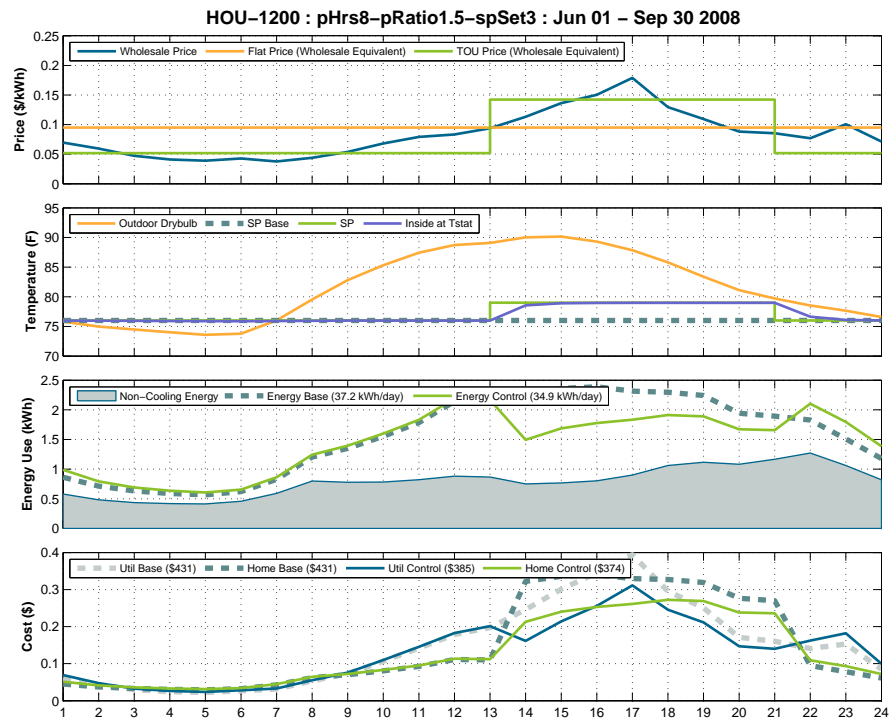
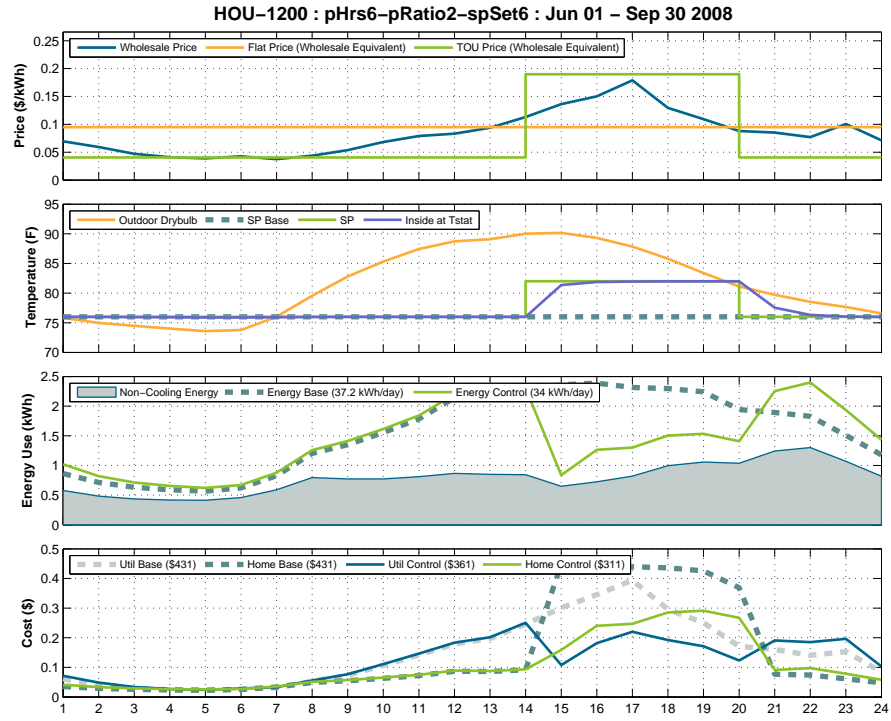
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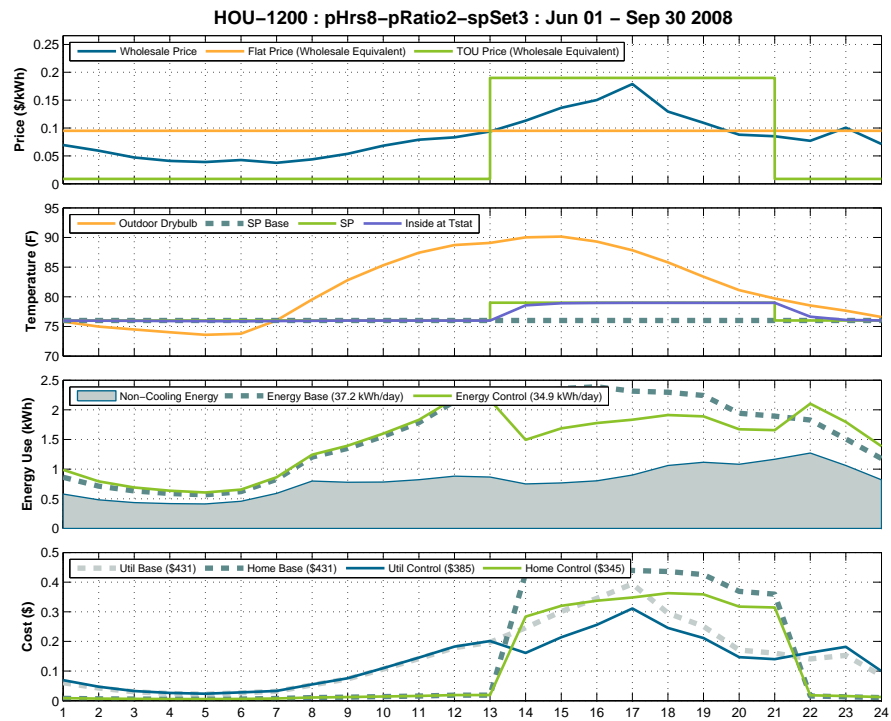
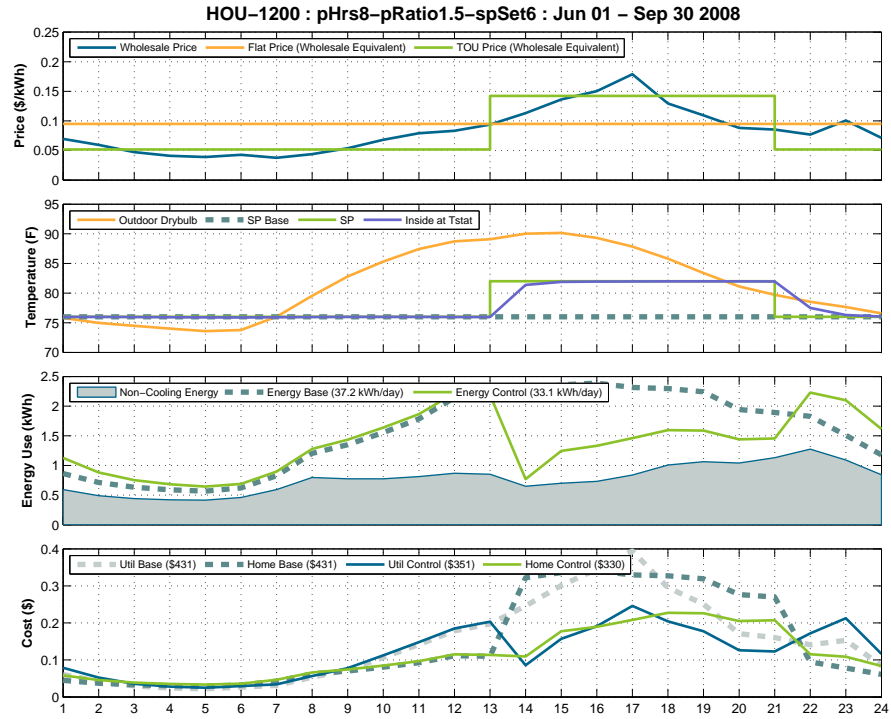


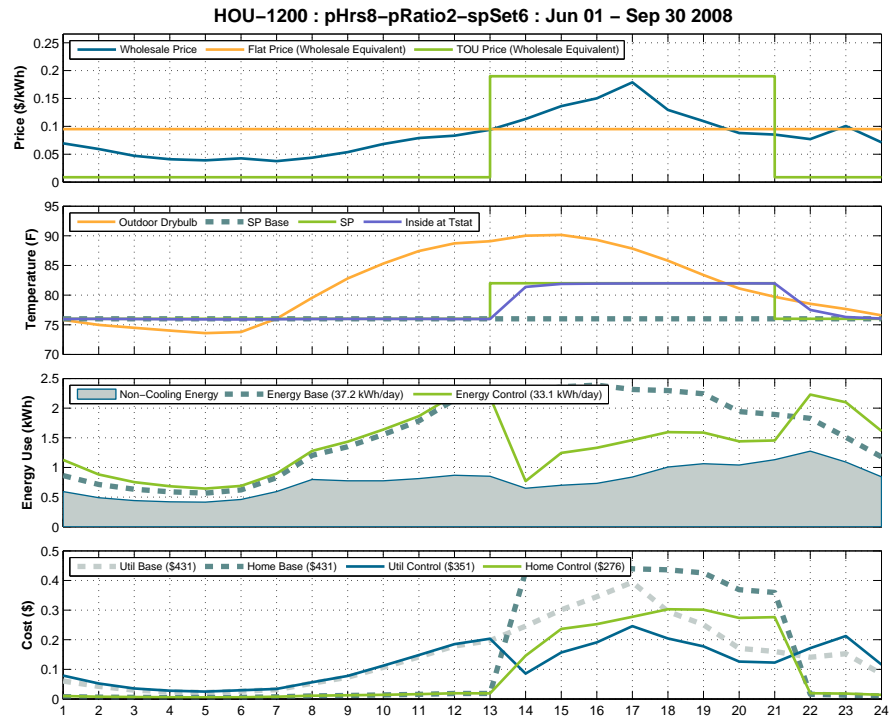




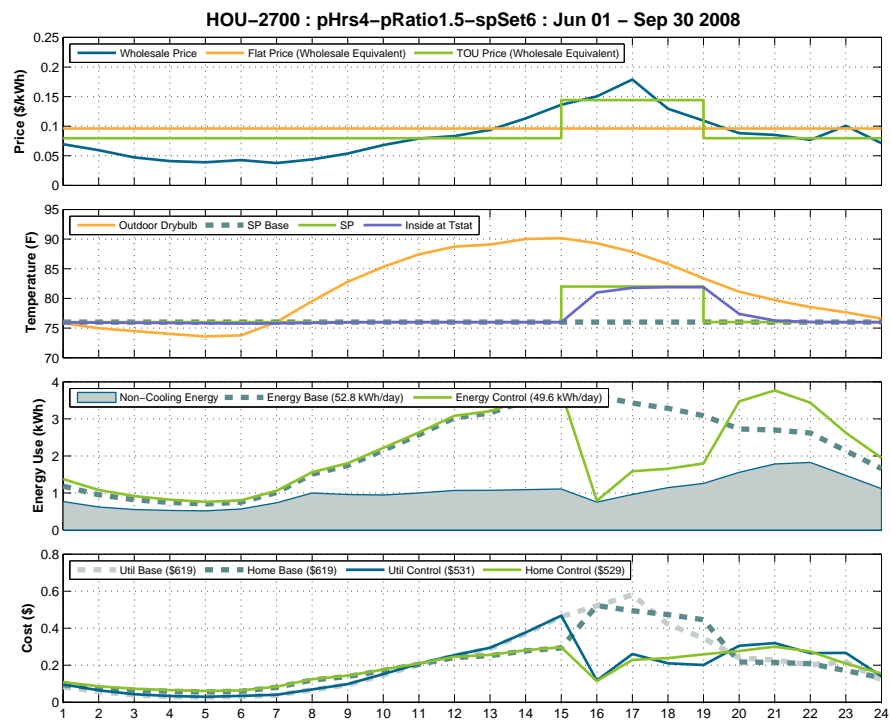
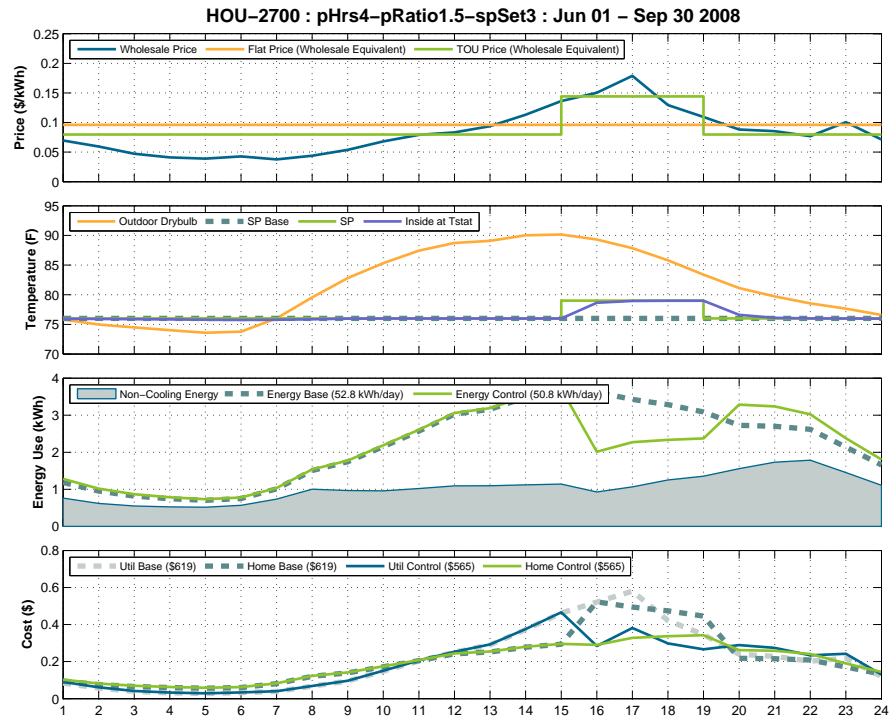


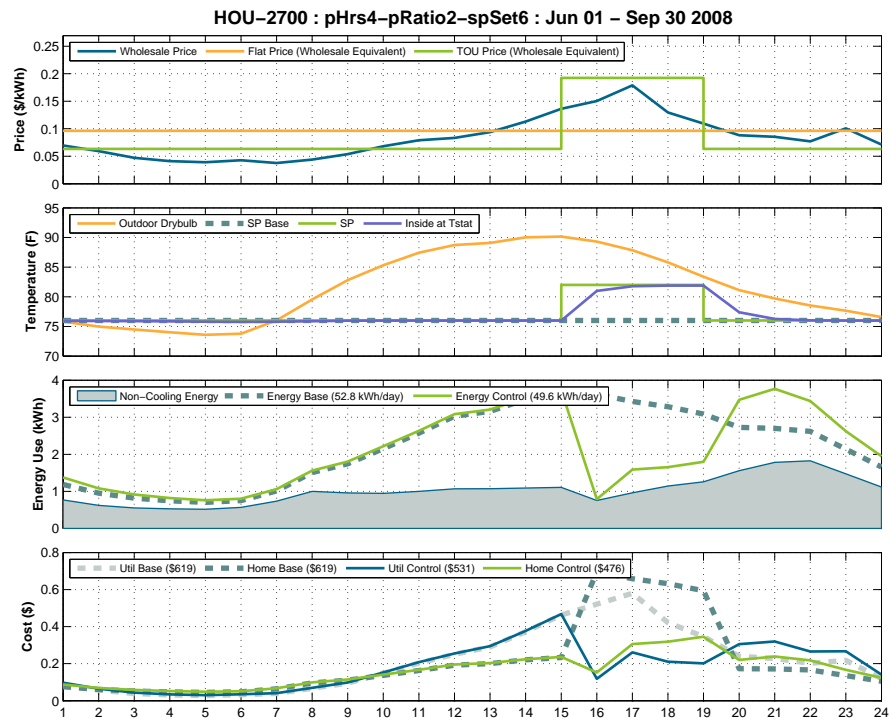
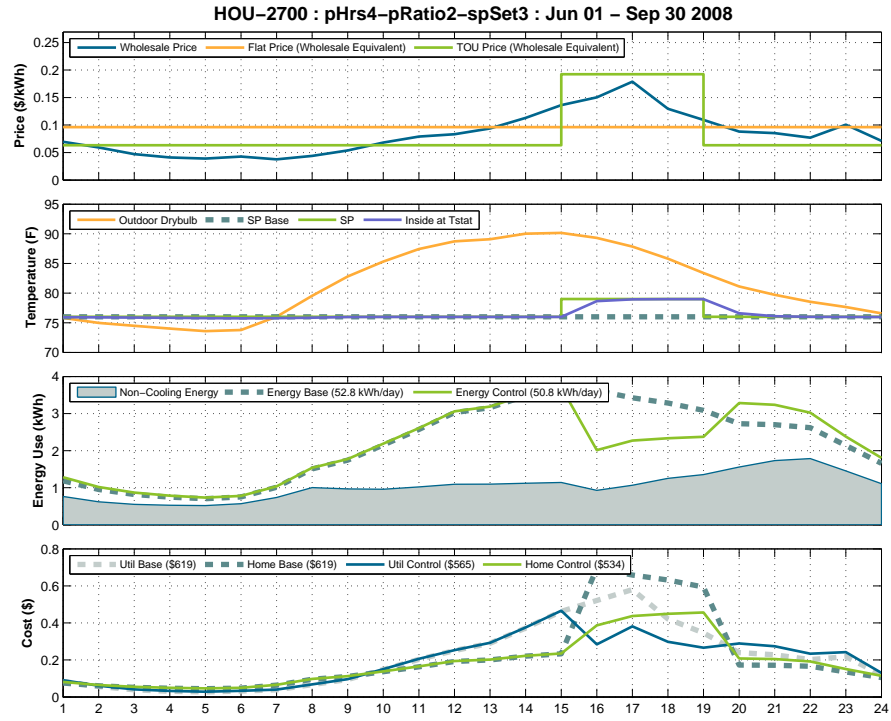


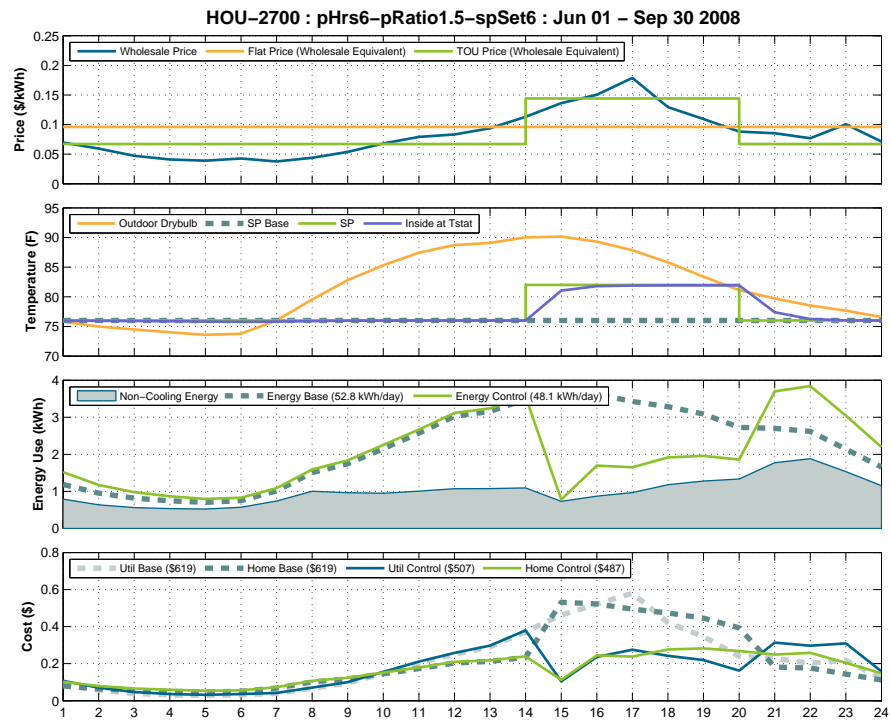
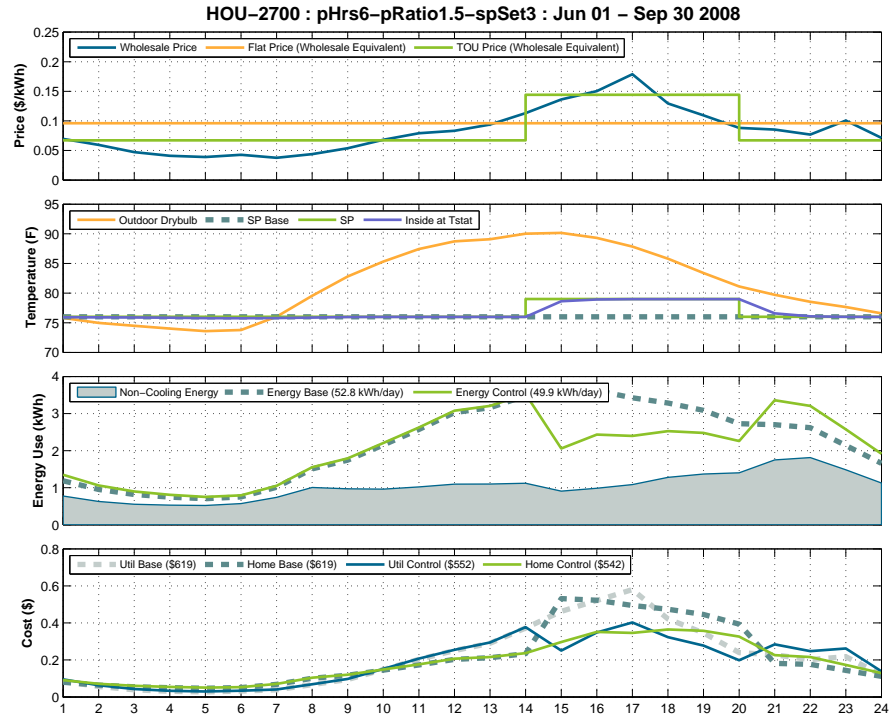


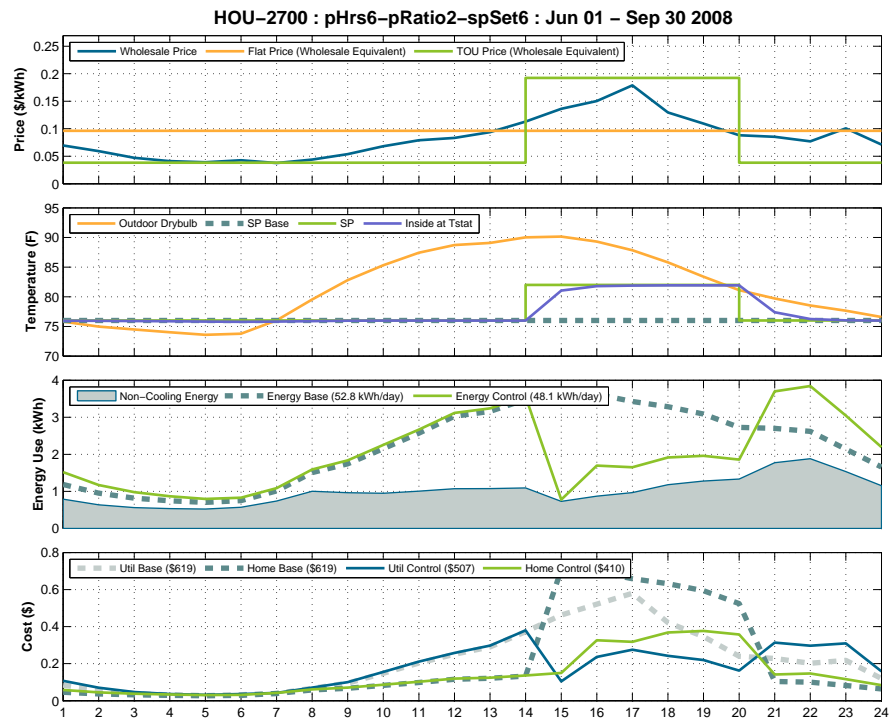
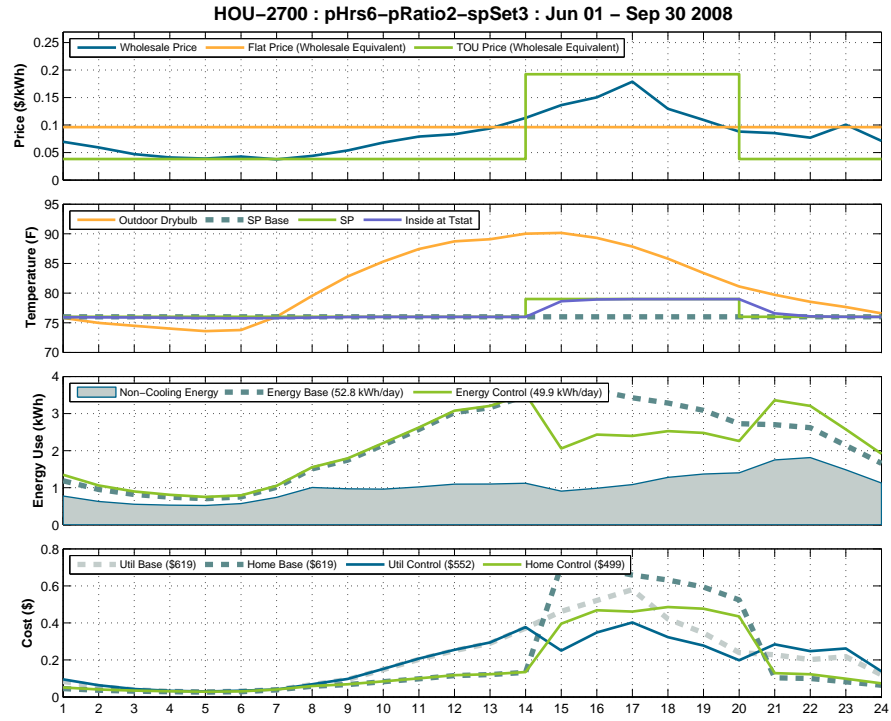


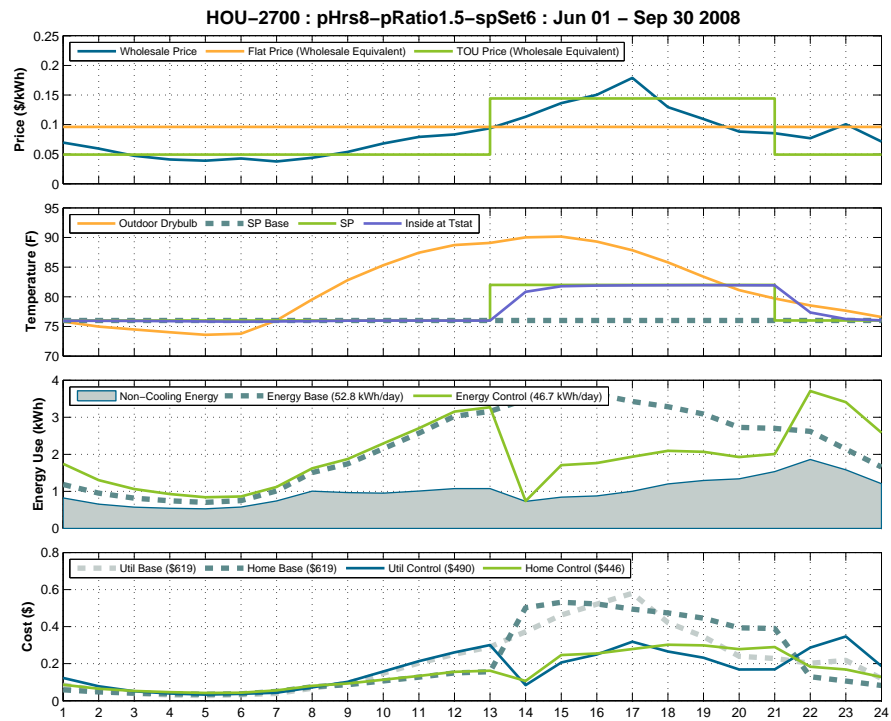
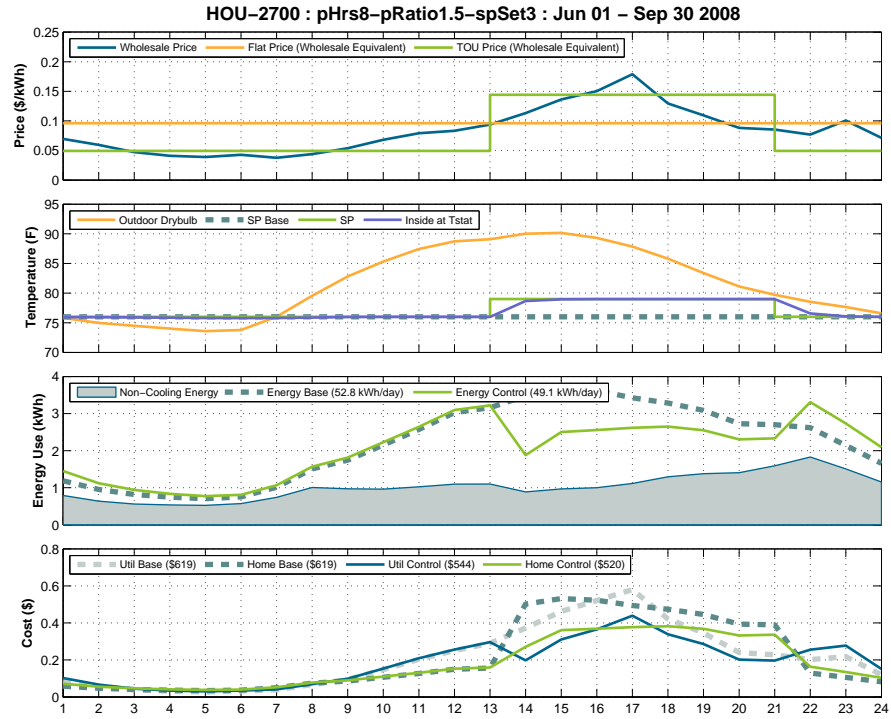
C.2.2 2700

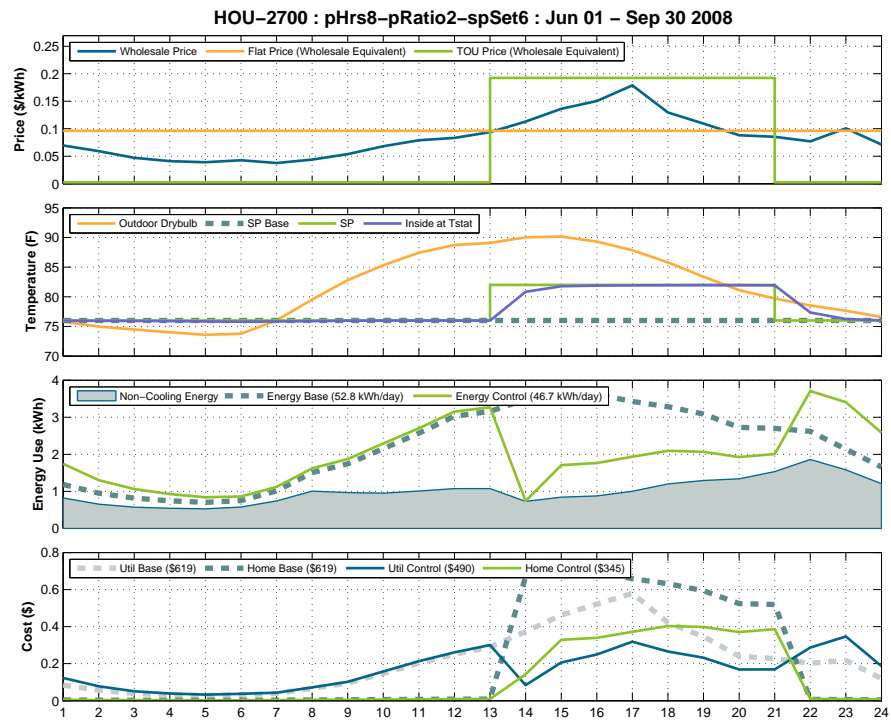
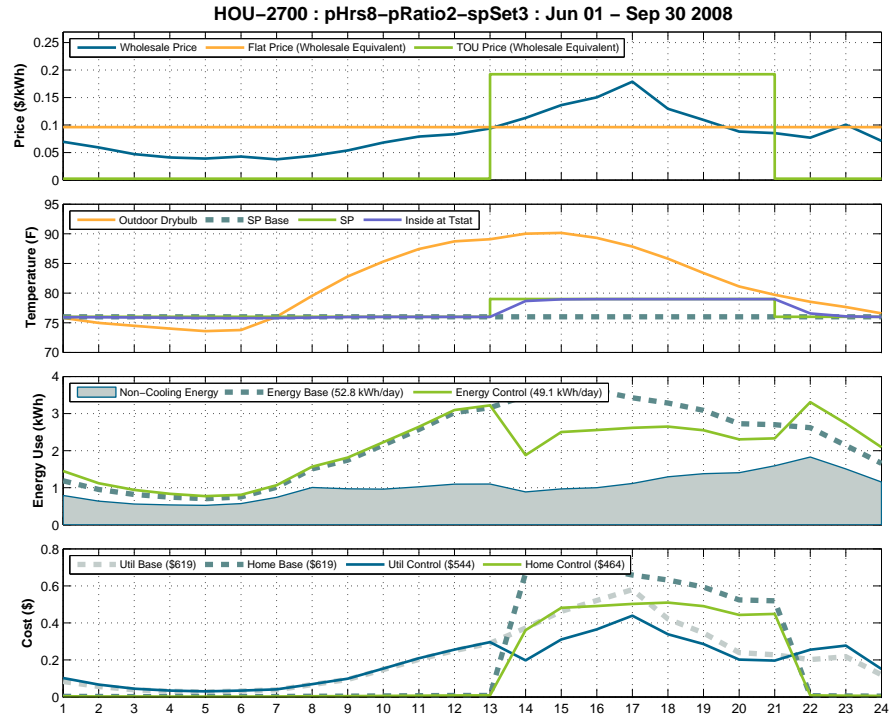




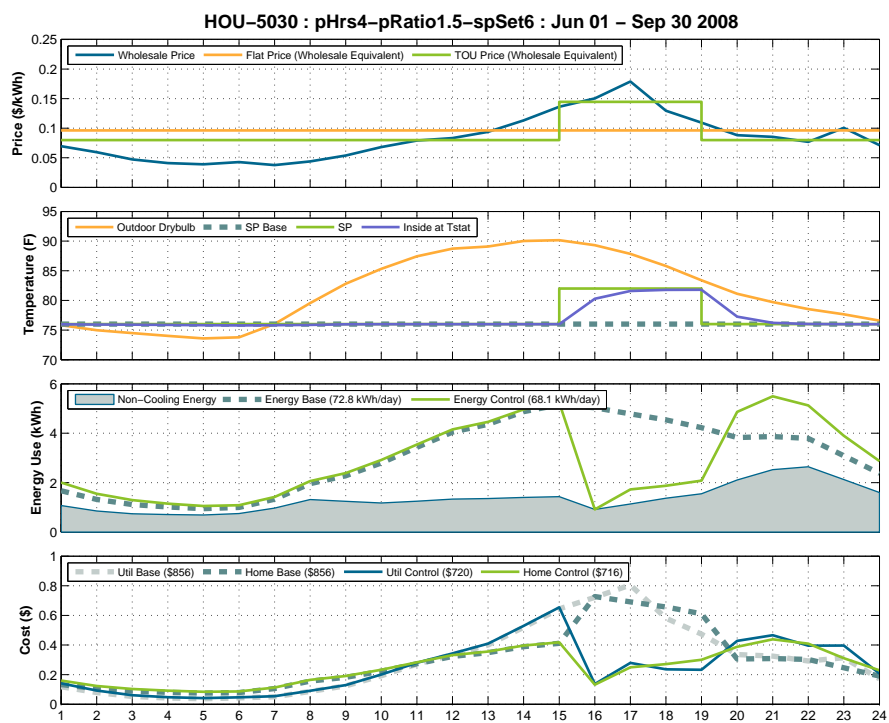
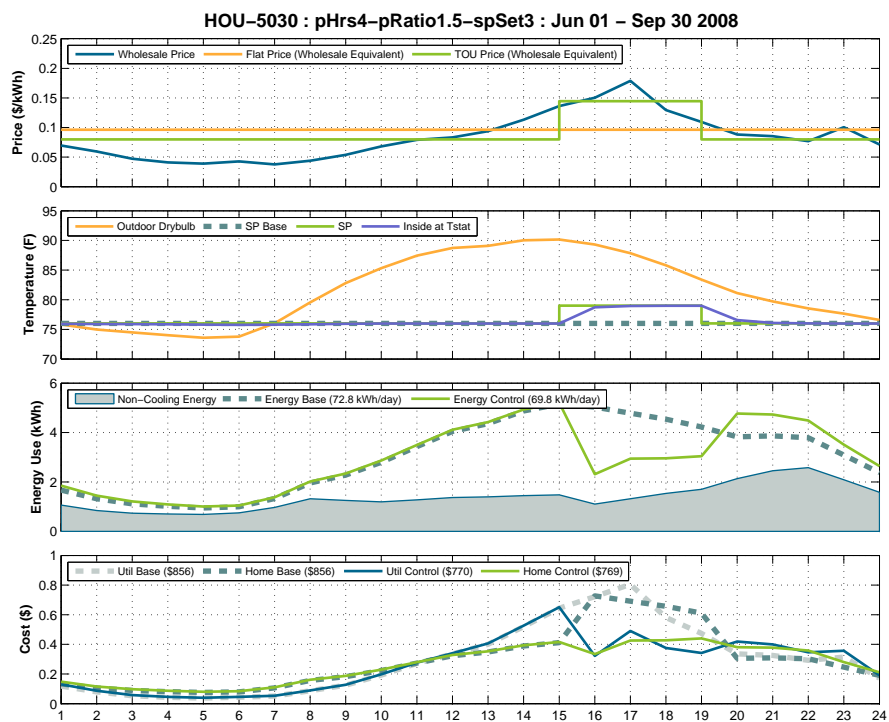




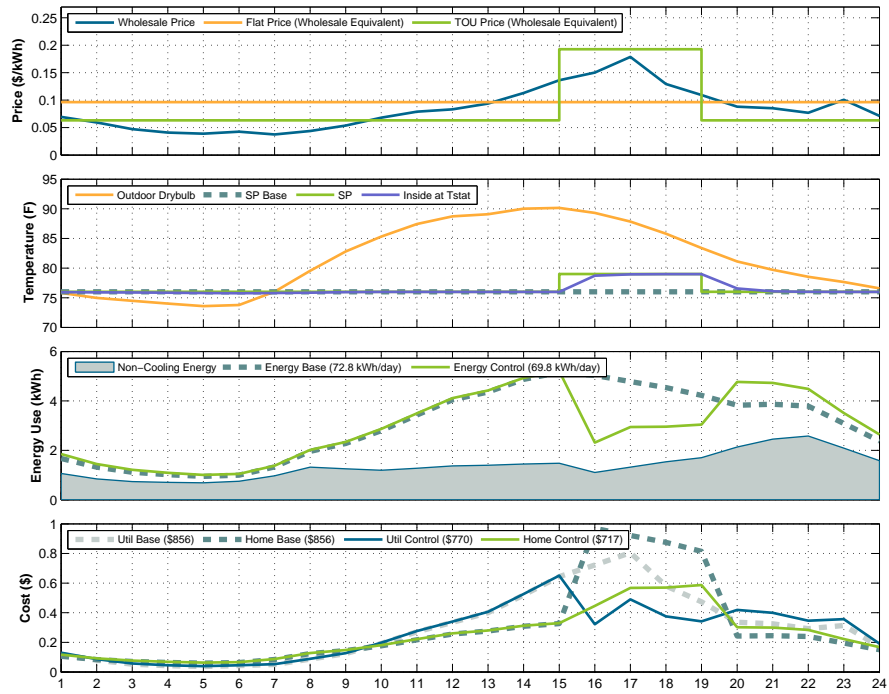




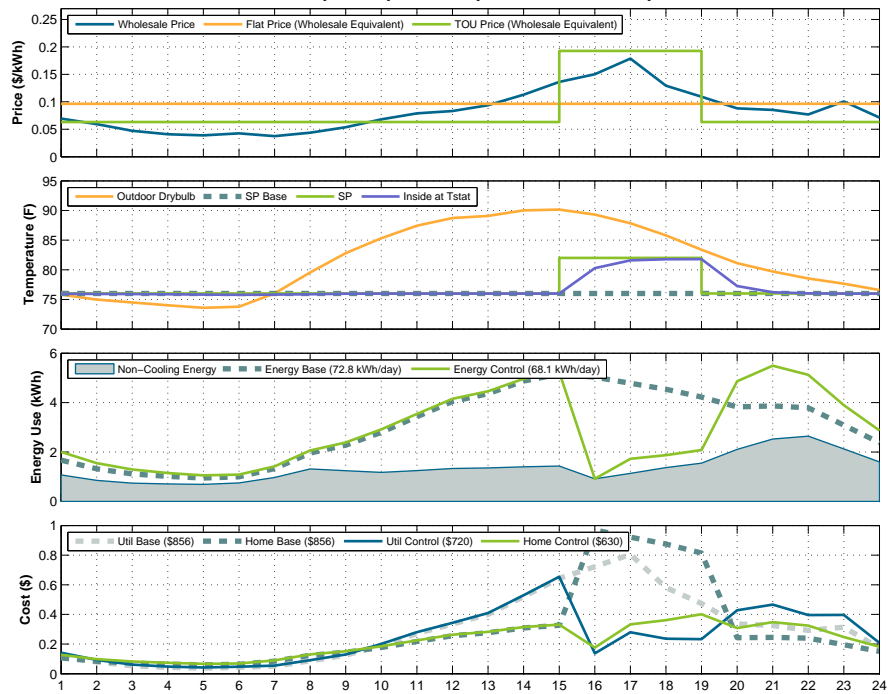
C.2.3 5030

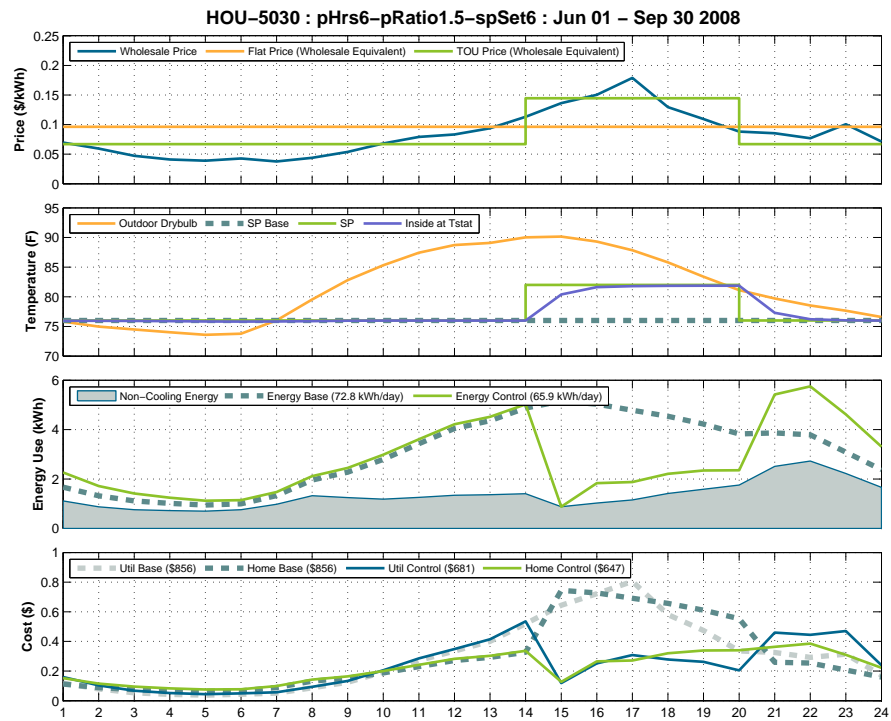
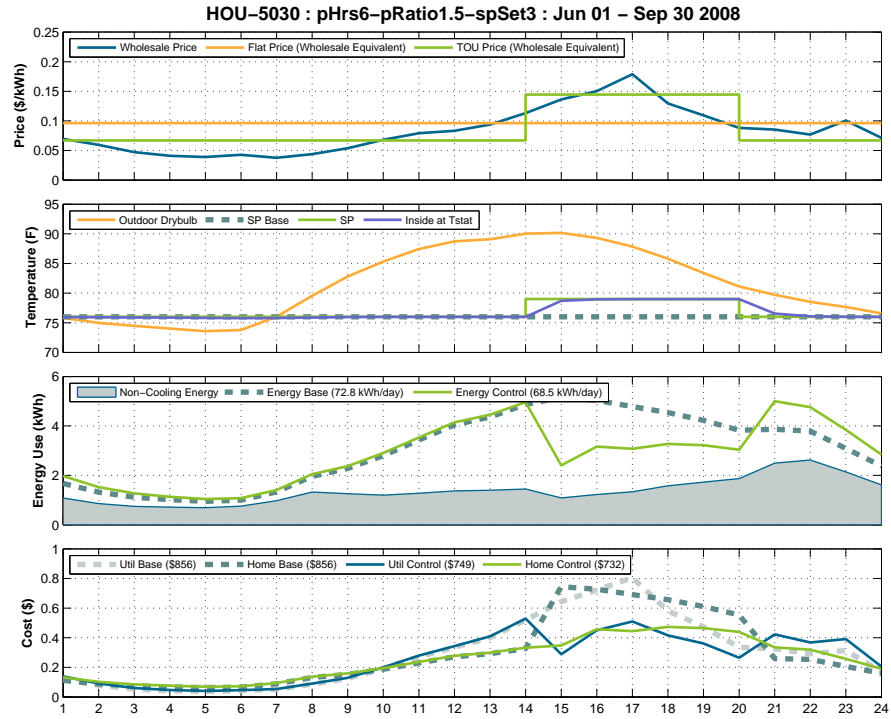


HOU-5030 : pHrs4-pRatio2-spSet3 : Jun 01 – Sep 30 2008

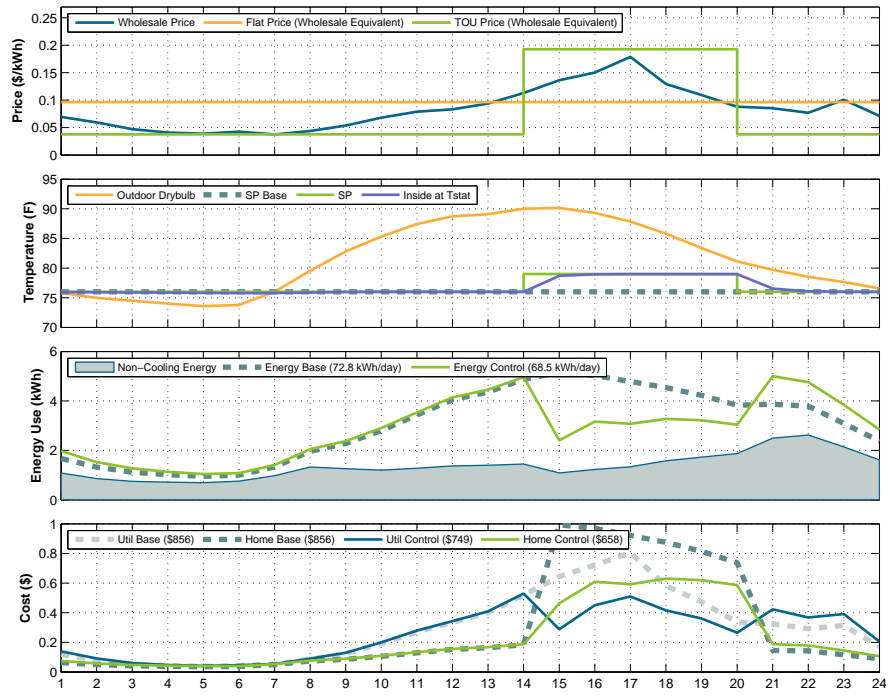


HOU-5030 : pHrs4-pRatio2-spSet6 : Jun 01 – Sep 30 2008

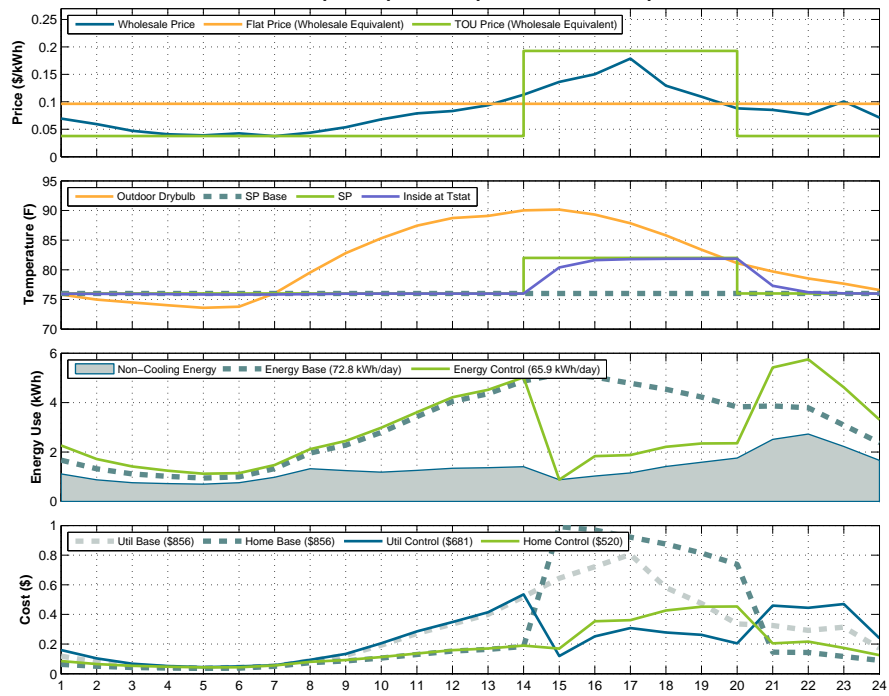


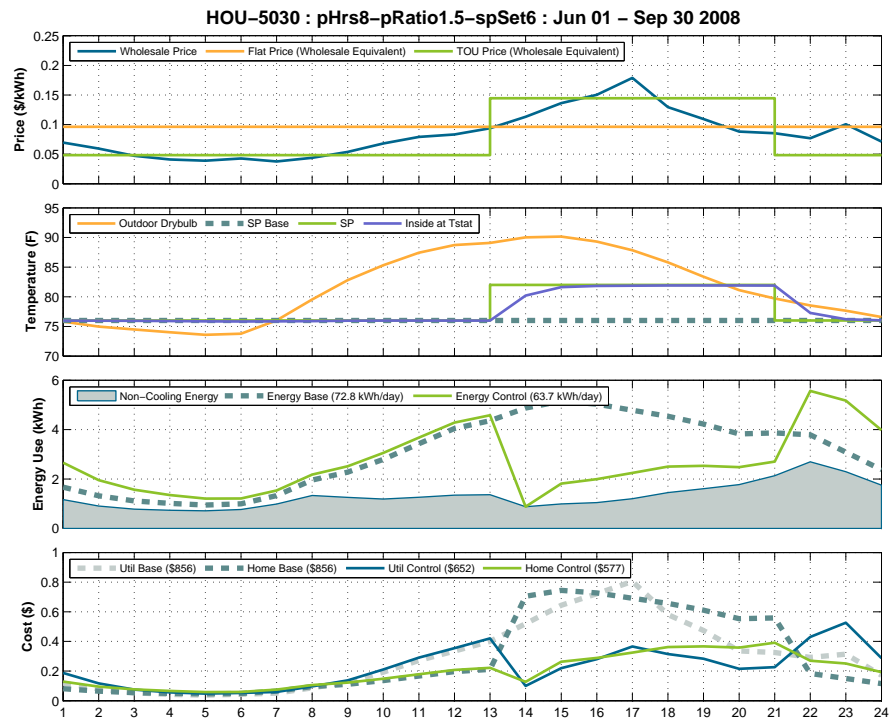
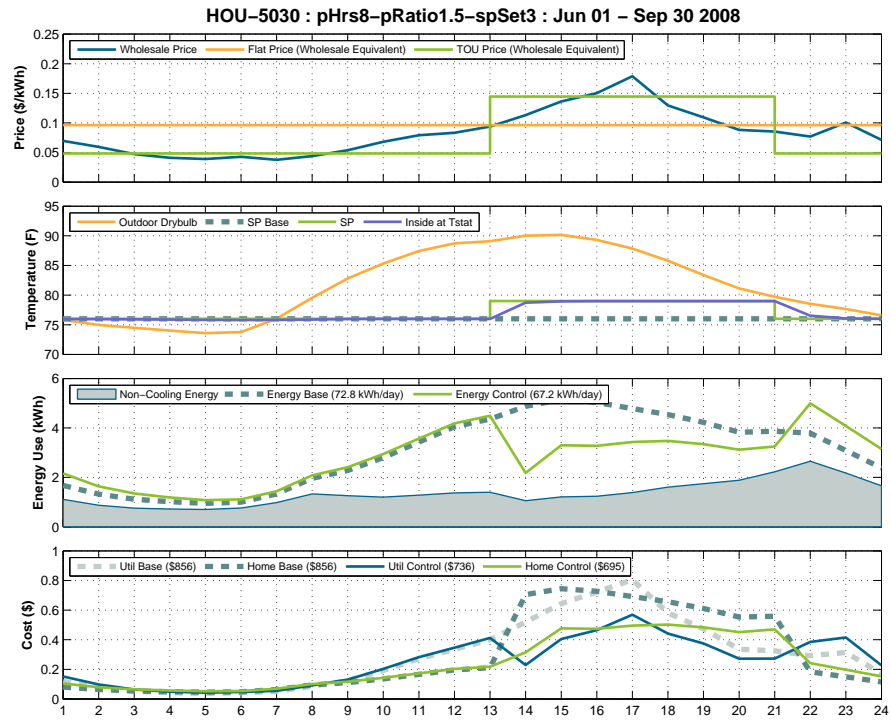


HOU-5030 : pHrs6-pRatio2-spSet3 : Jun 01 – Sep 30 2008

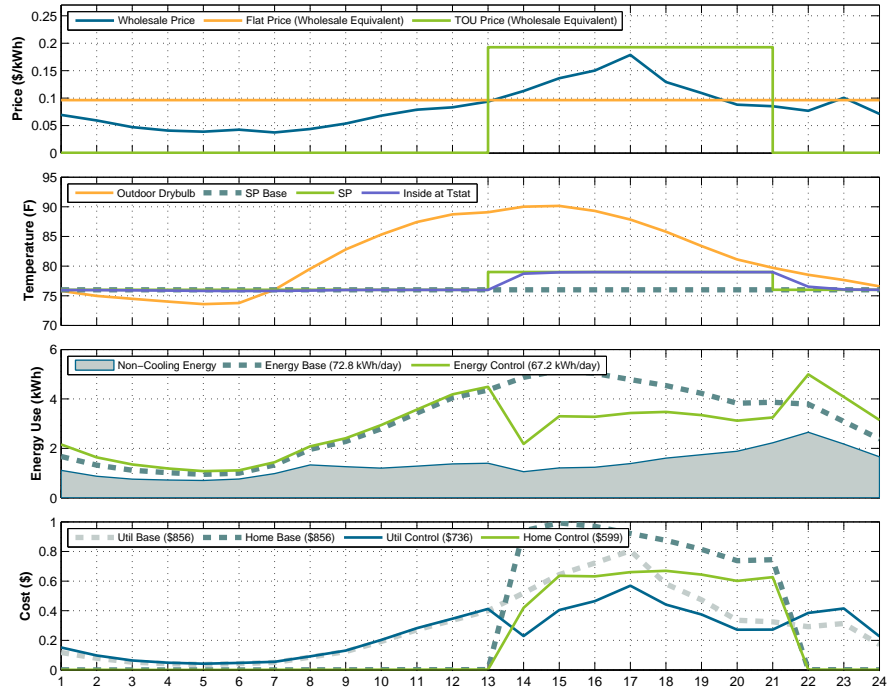


HOU-5030 : pHrs6-pRatio2-spSet6 : Jun 01 – Sep 30 2008

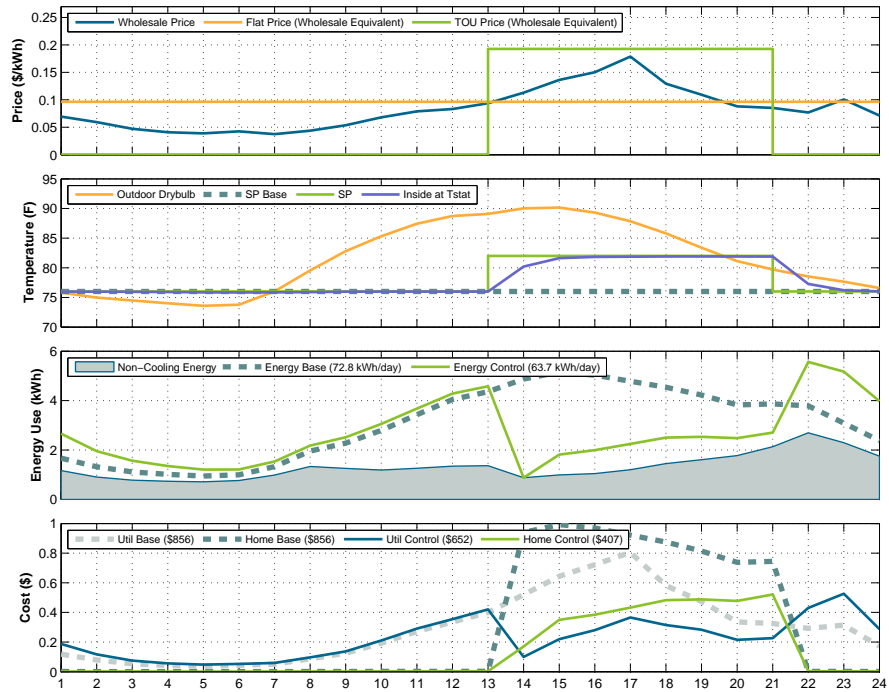




HOU-5030 : pHrs8-pRatio2-spSet3 : Jun 01 – Sep 30 2008

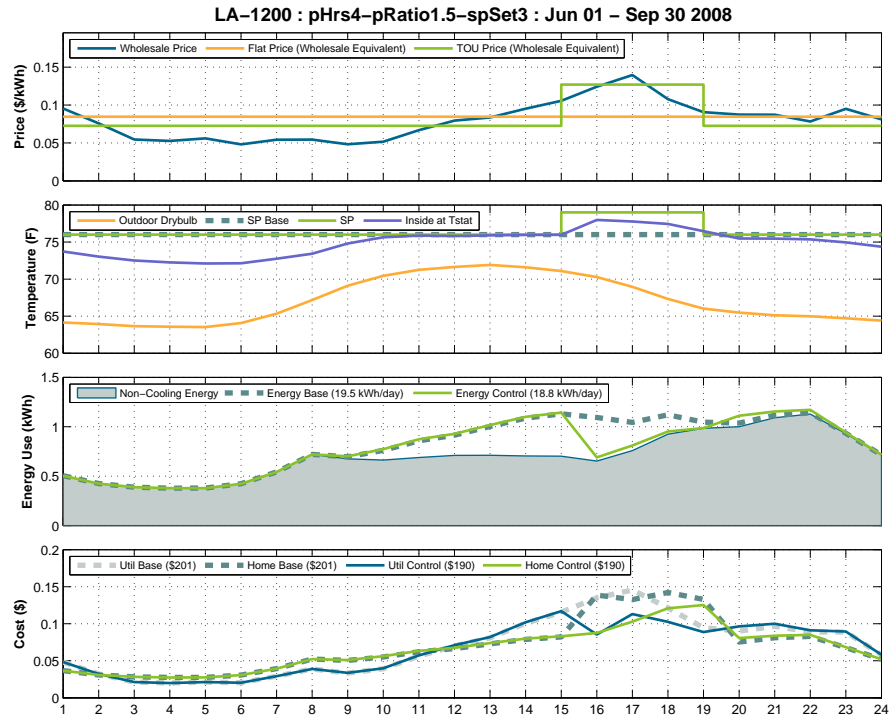


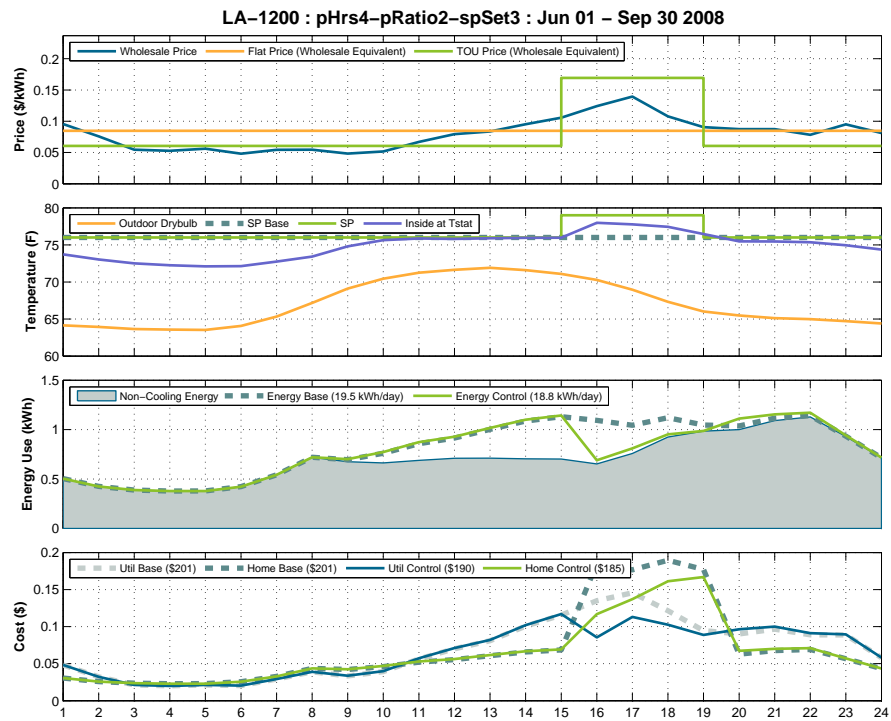
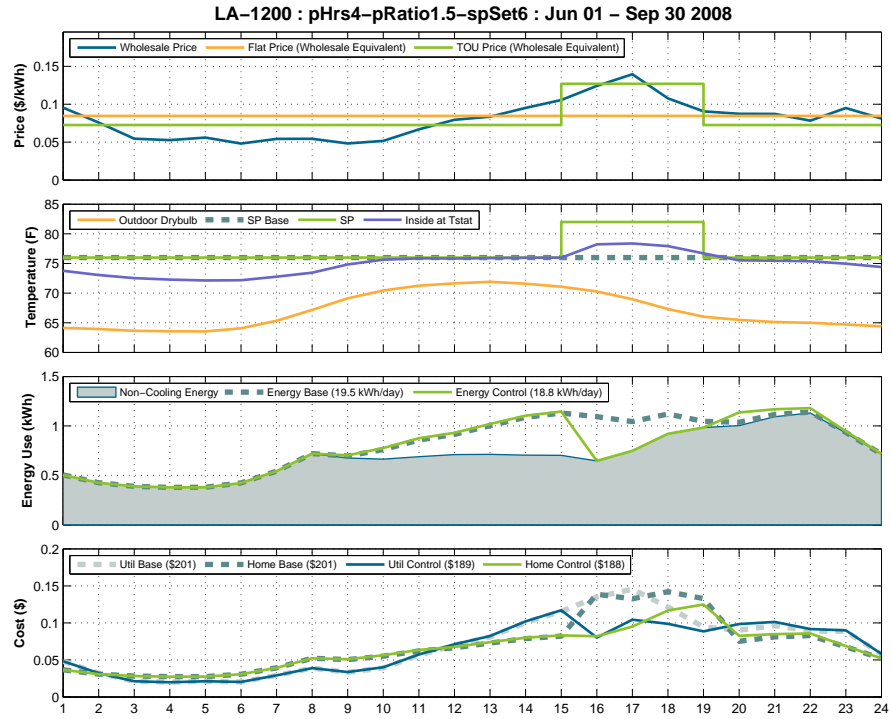
HOU-5030 : pHrs8-pRatio2-spSet6 : Jun 01 – Sep 30 2008

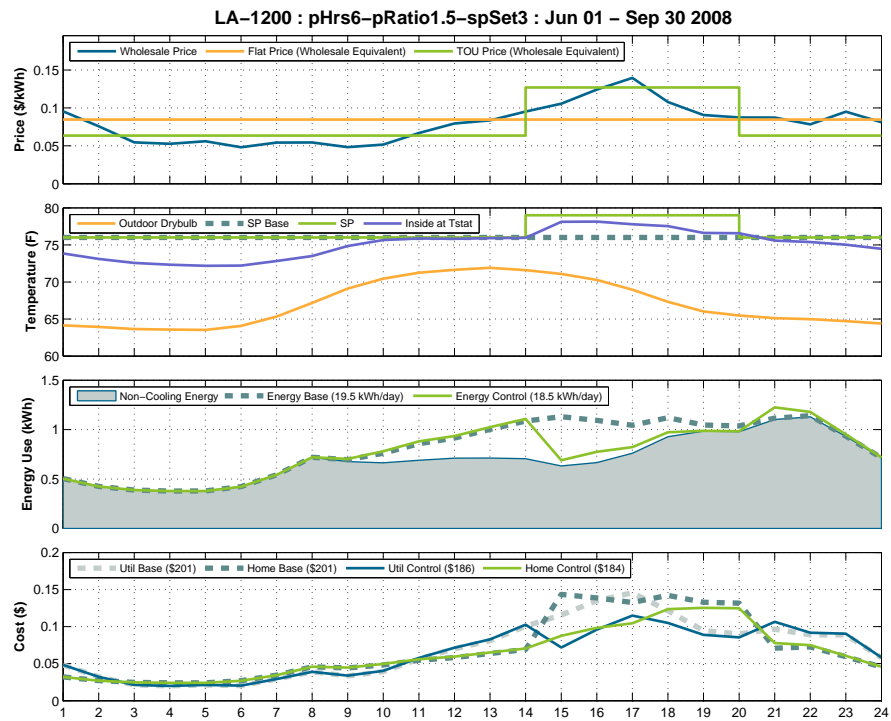
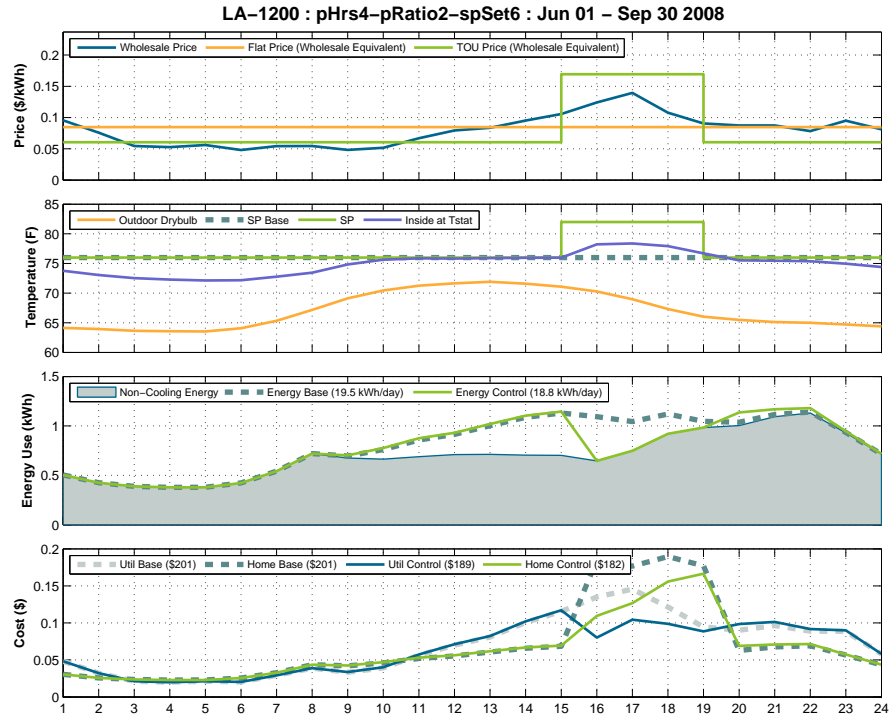


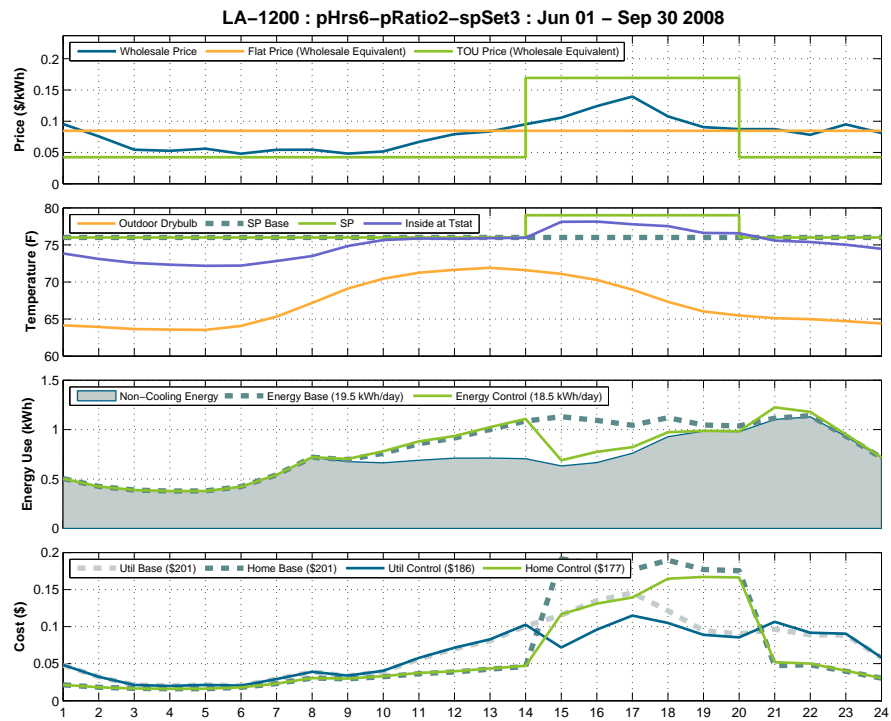
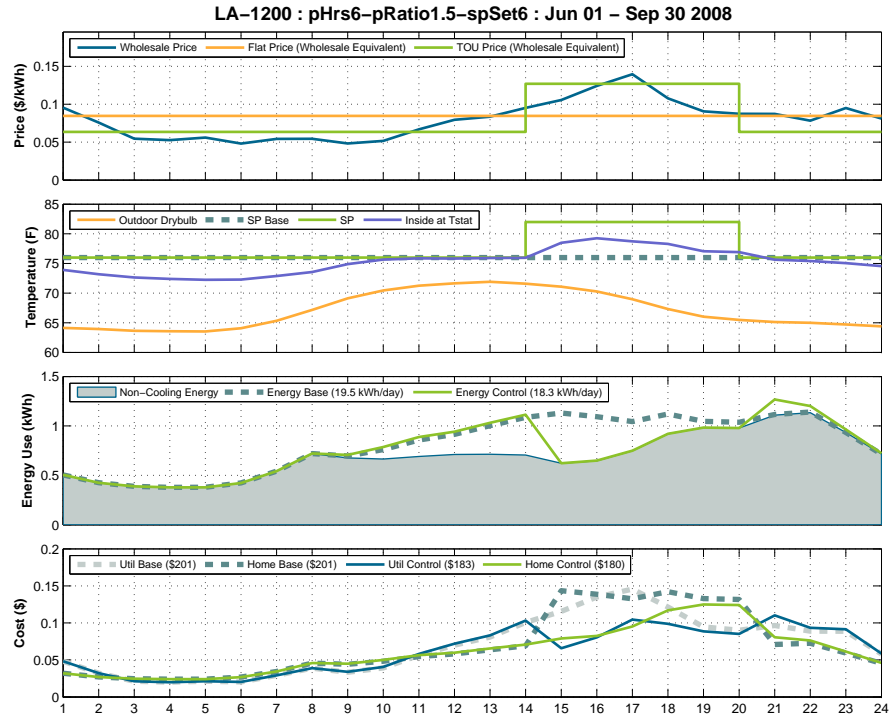
C.3 Los Angeles

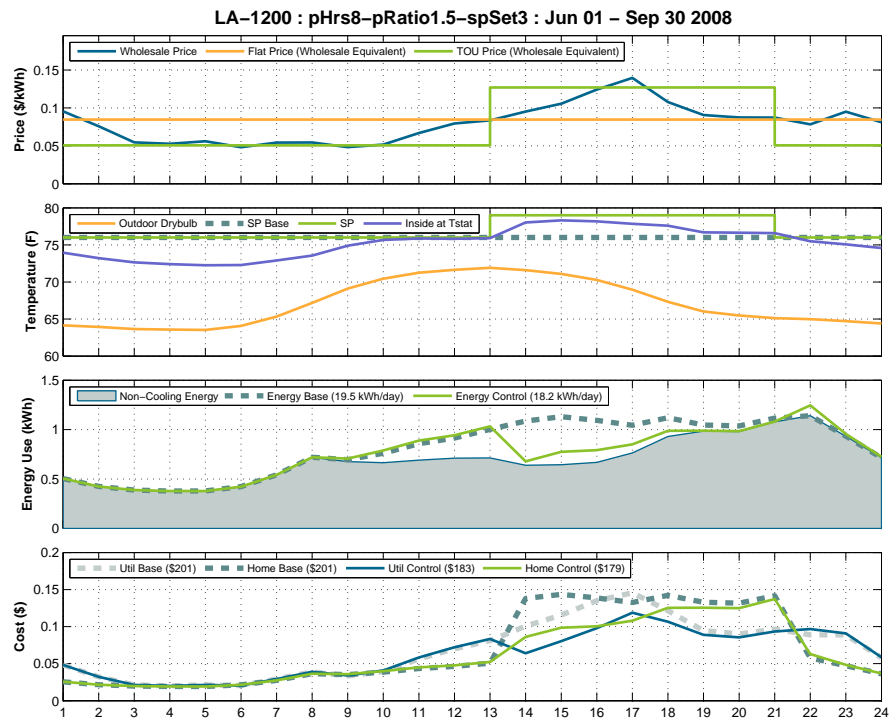
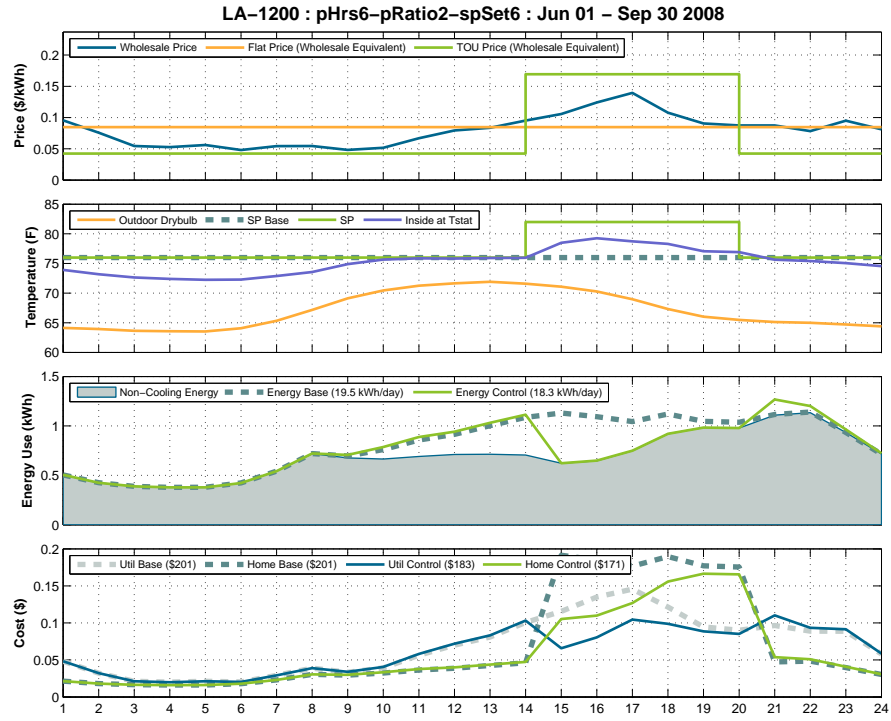
C.3.1 1200

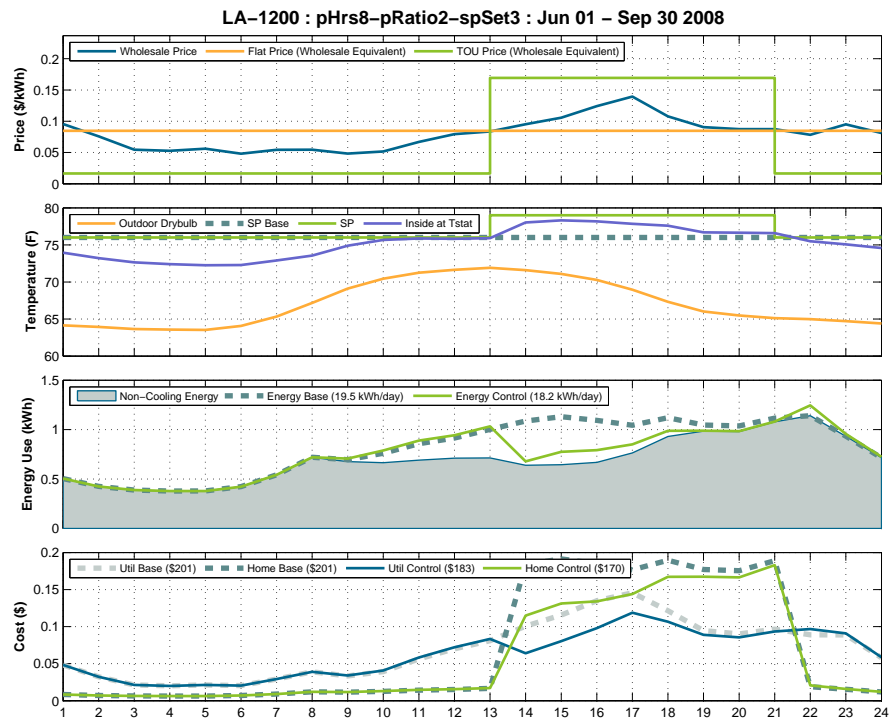
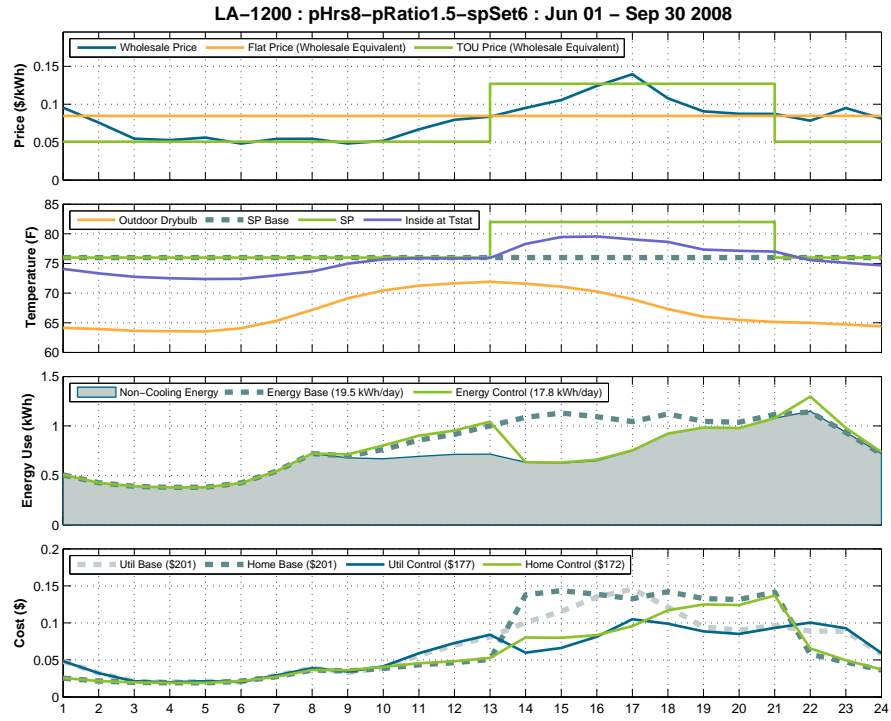


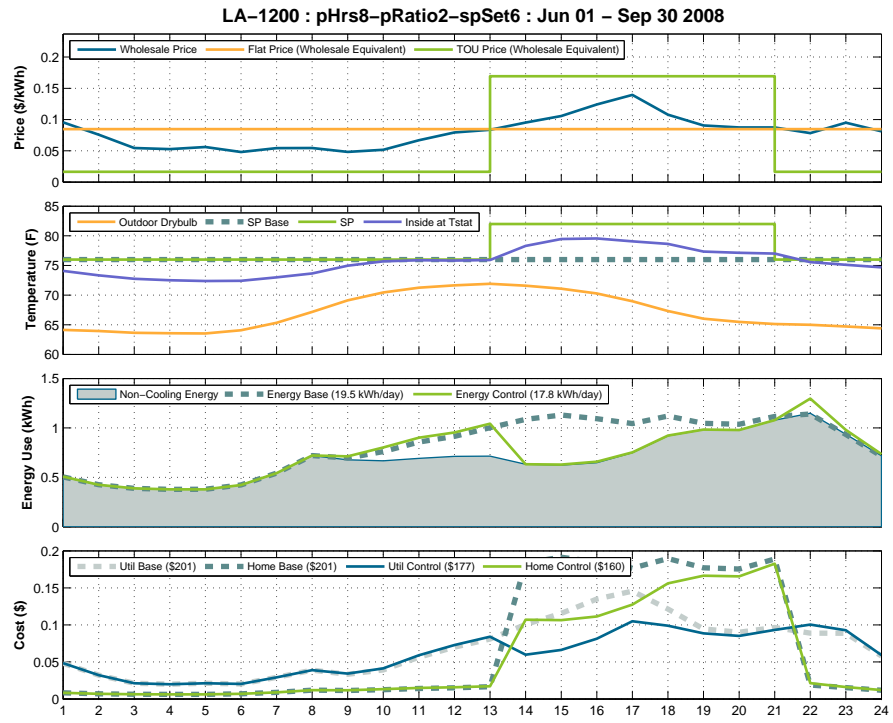




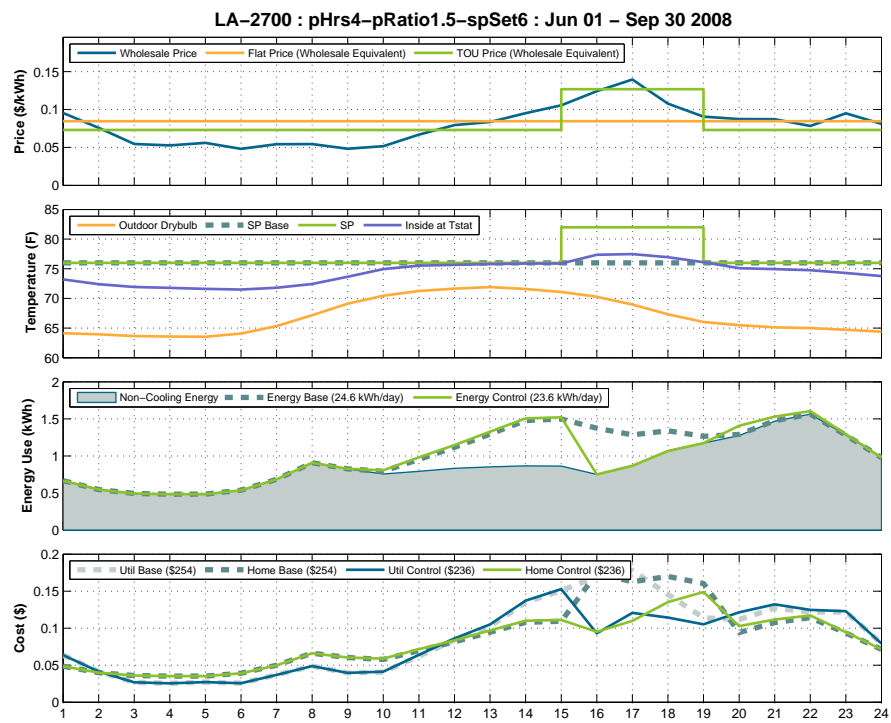
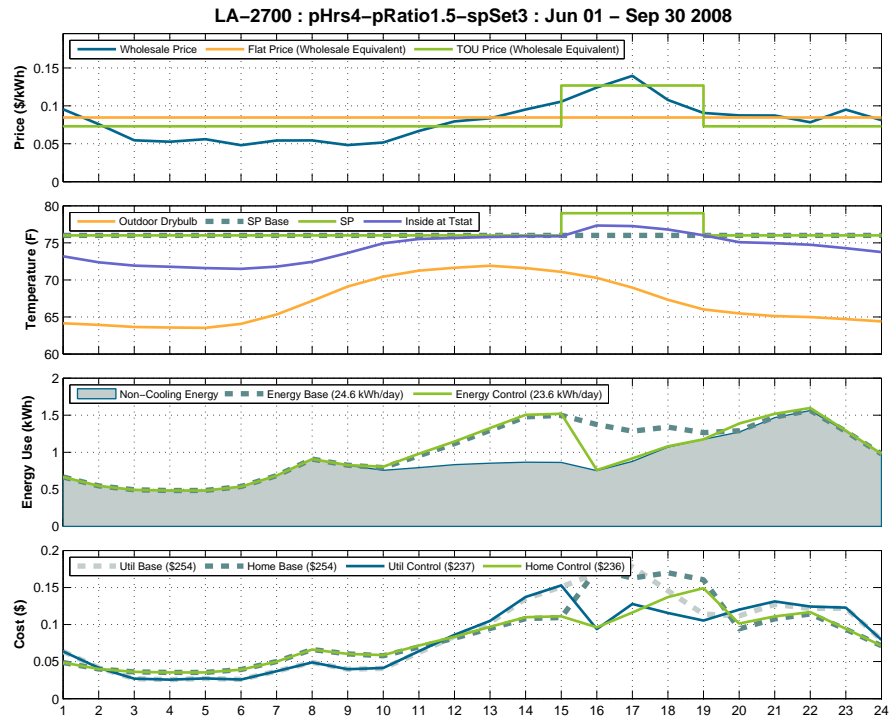


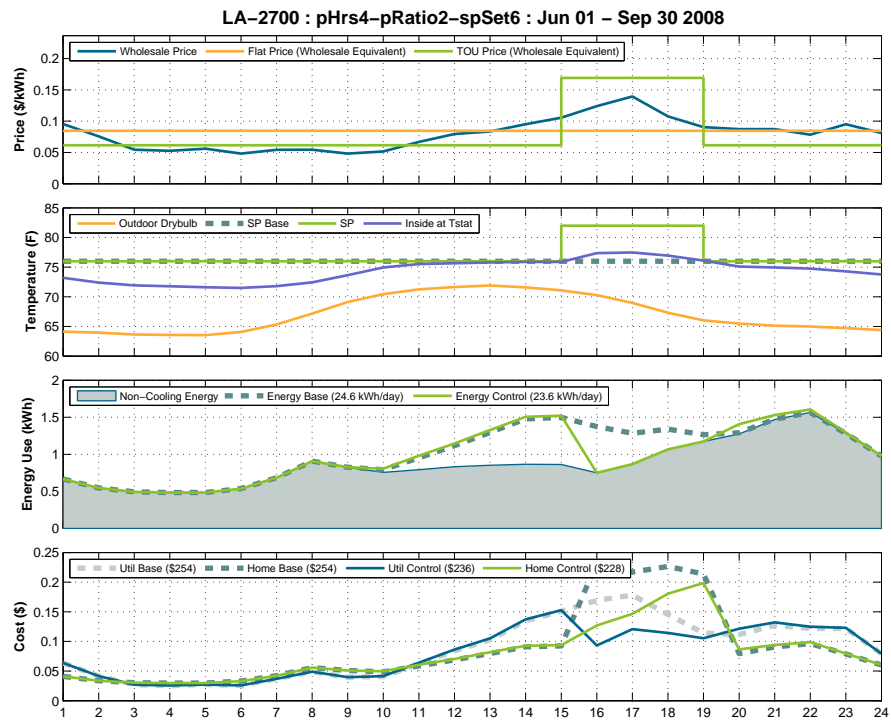
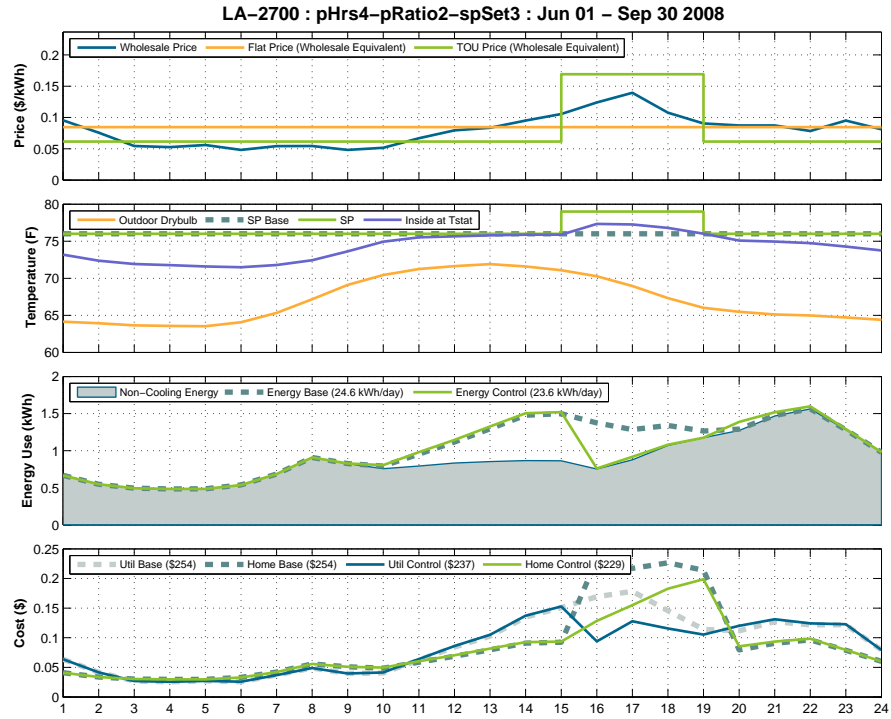




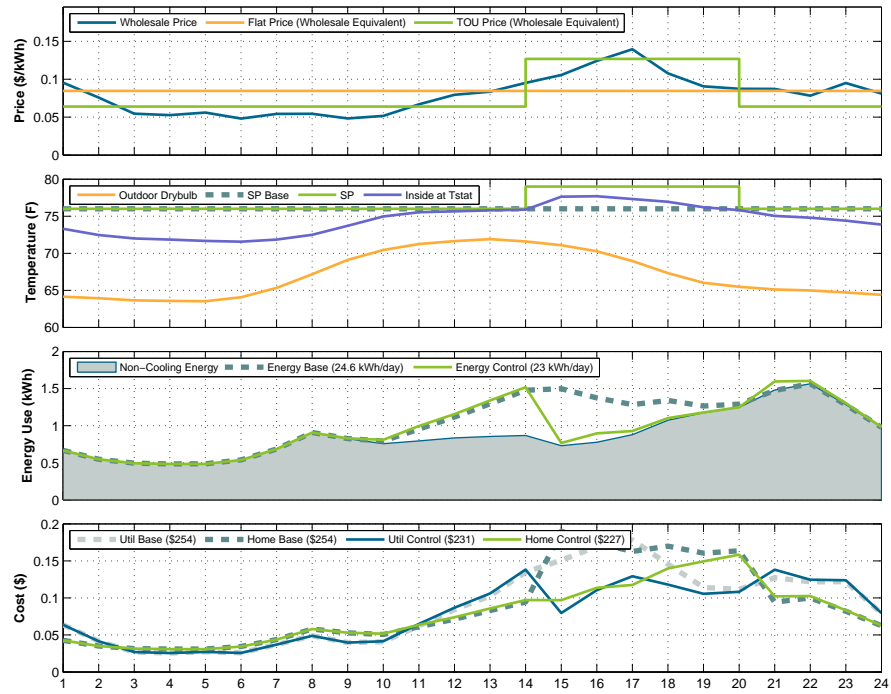


C.3.2 2700

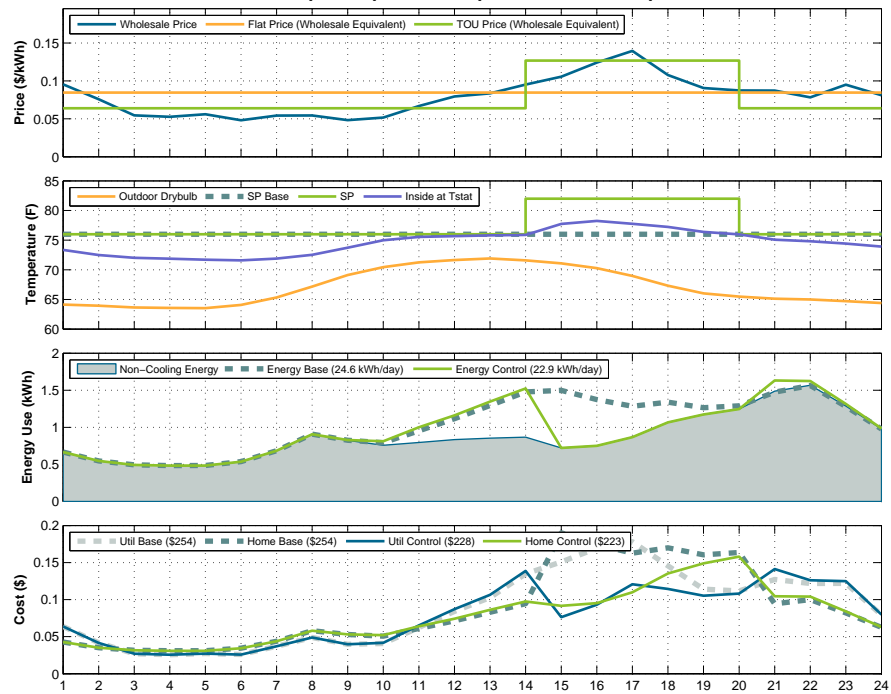


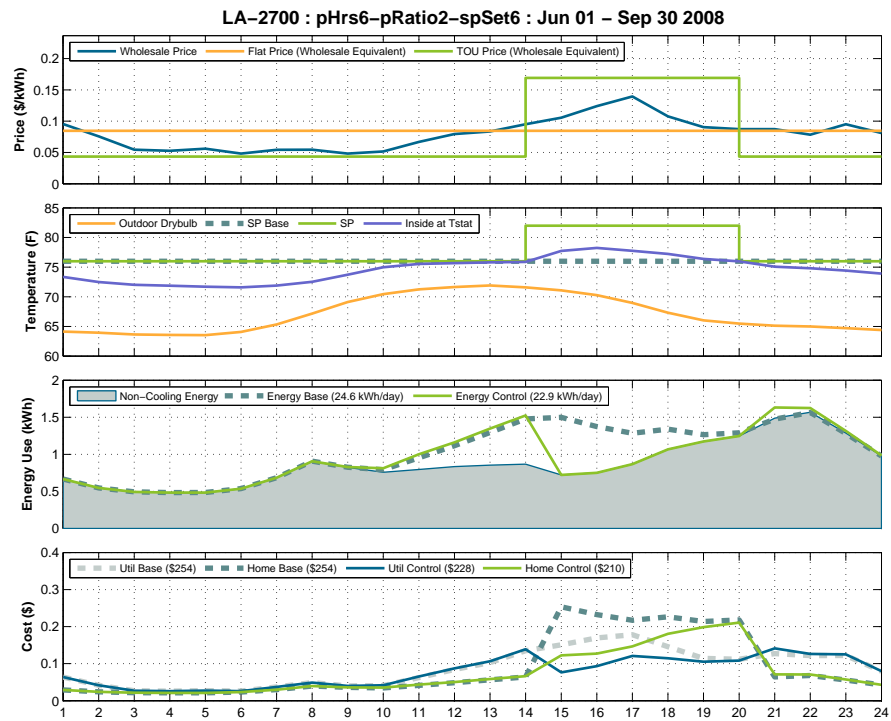
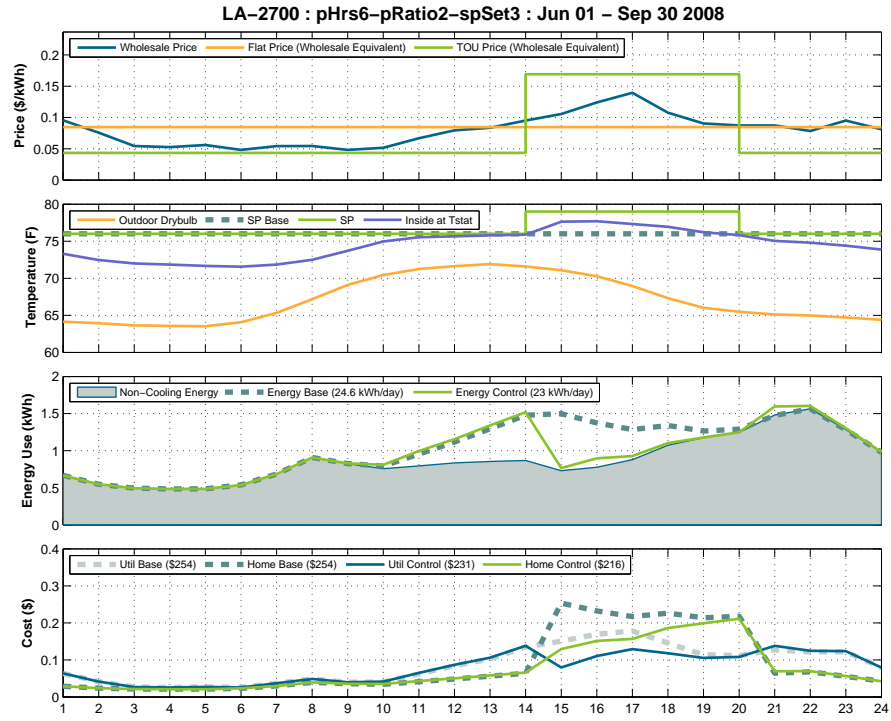


LA-2700 : pHrs6-pRatio1.5-spSet3 : Jun 01 – Sep 30 2008

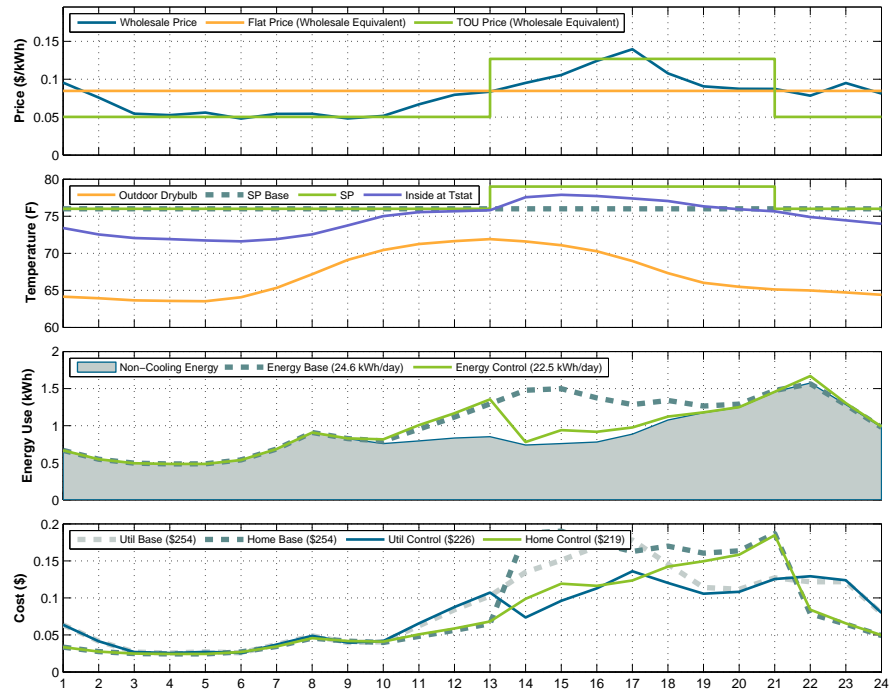


LA-2700 : pHrs6-pRatio1.5-spSet6 : Jun 01 – Sep 30 2008

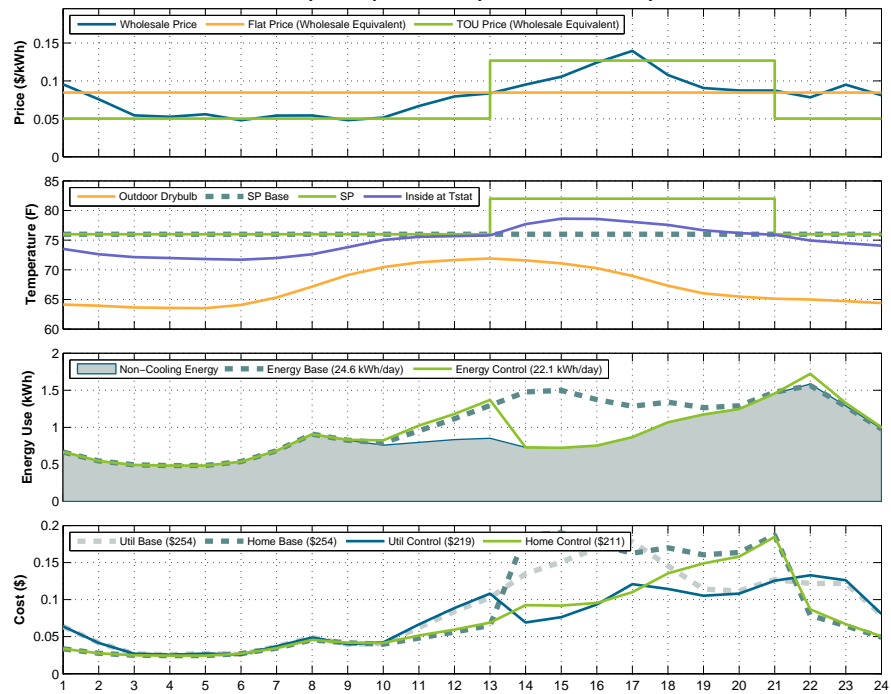


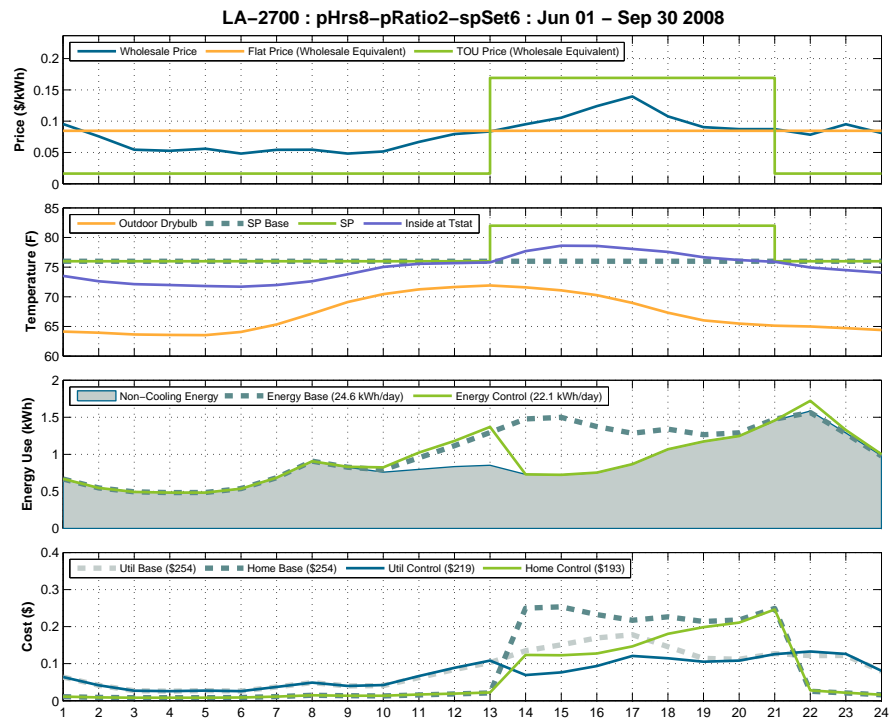
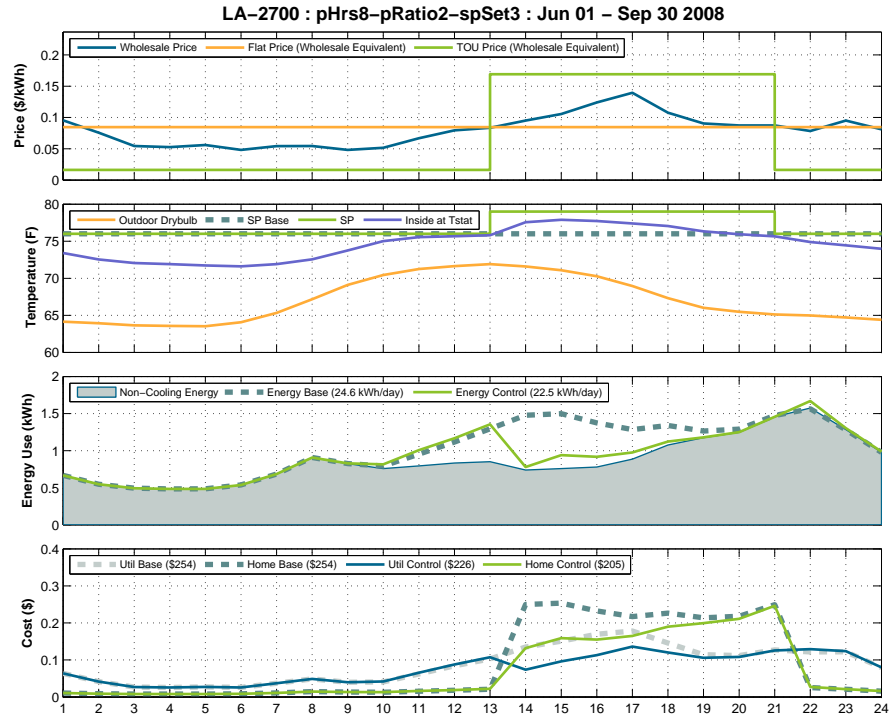


LA-2700 : pHrs8-pRatio1.5-spSet3 : Jun 01 – Sep 30 2008

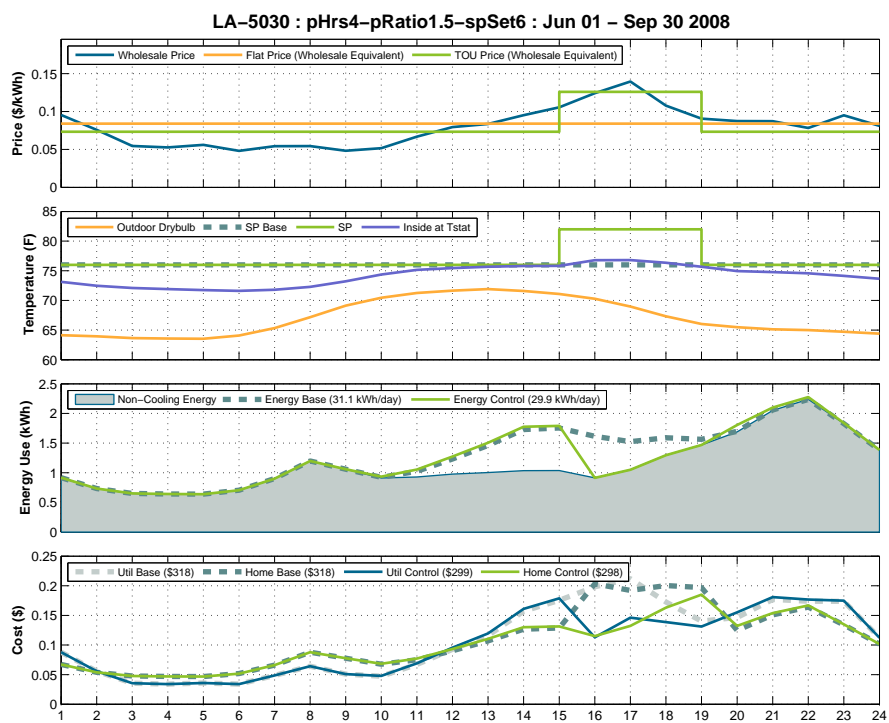
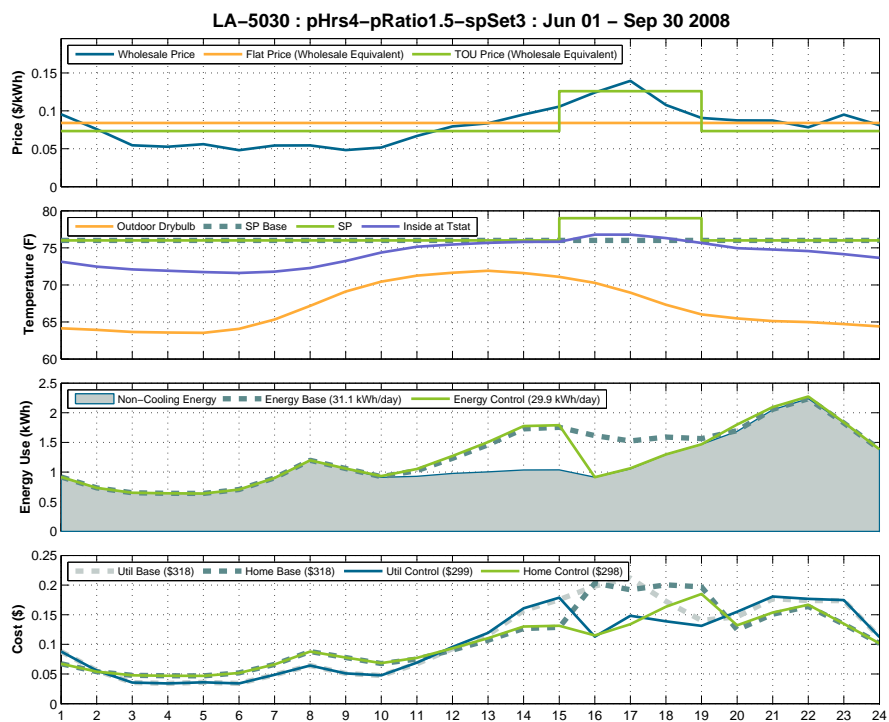


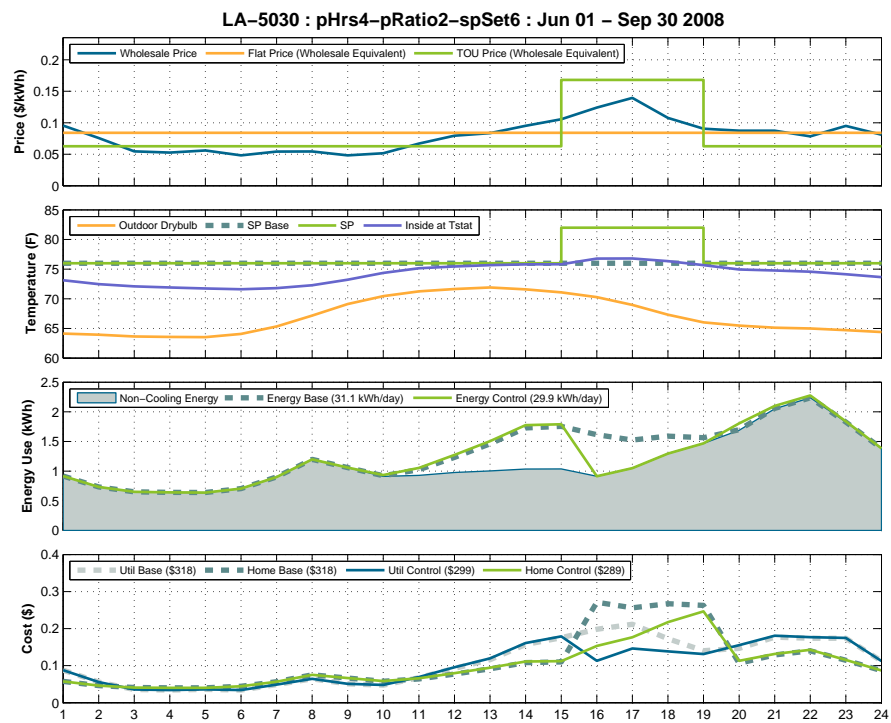
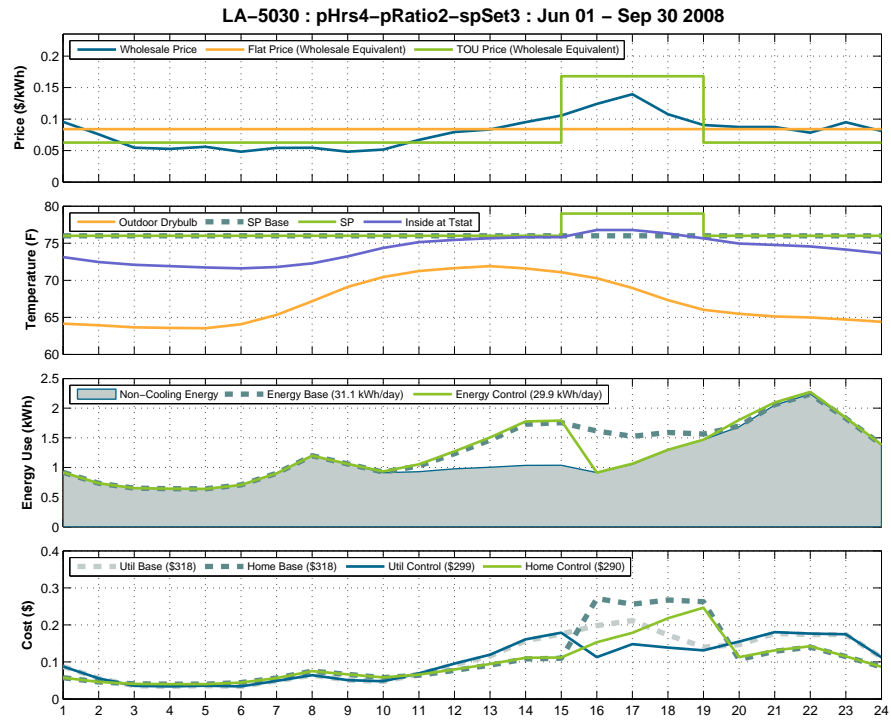
LA-2700 : pHrs8-pRatio1.5-spSet6 : Jun 01 – Sep 30 2008

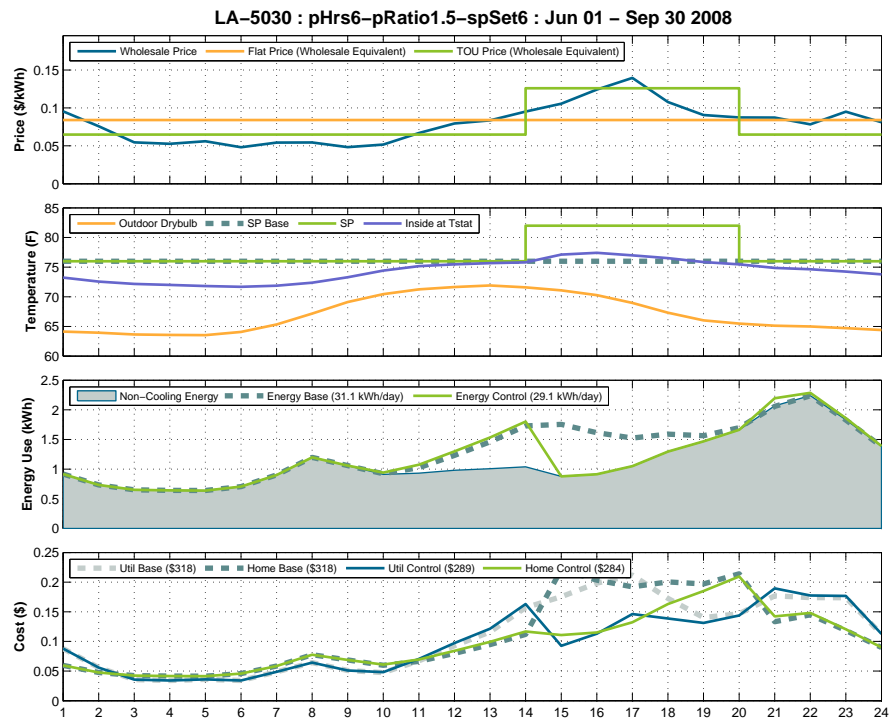
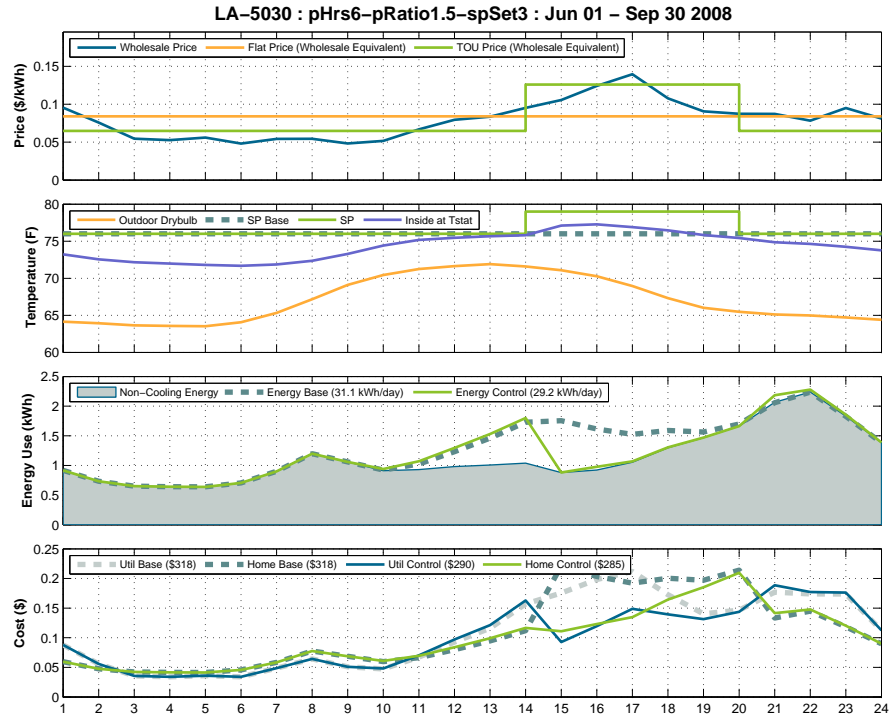


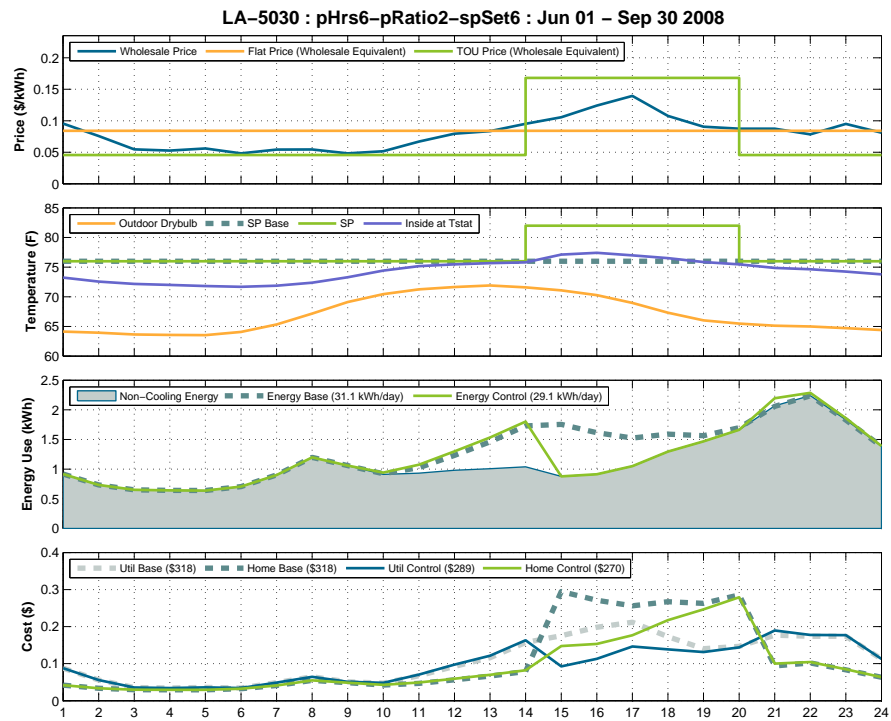
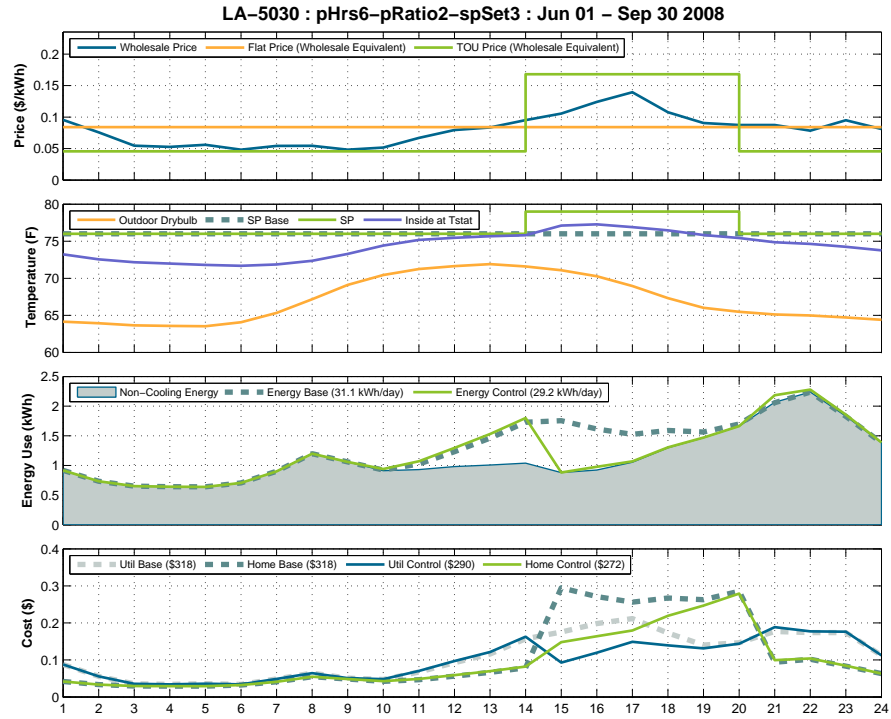


C.3.3 5030

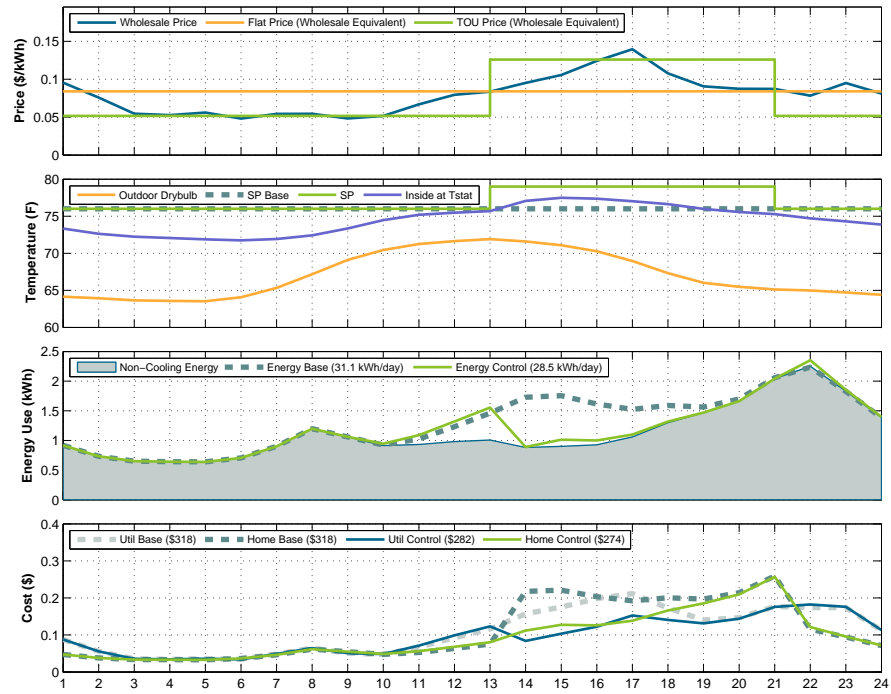




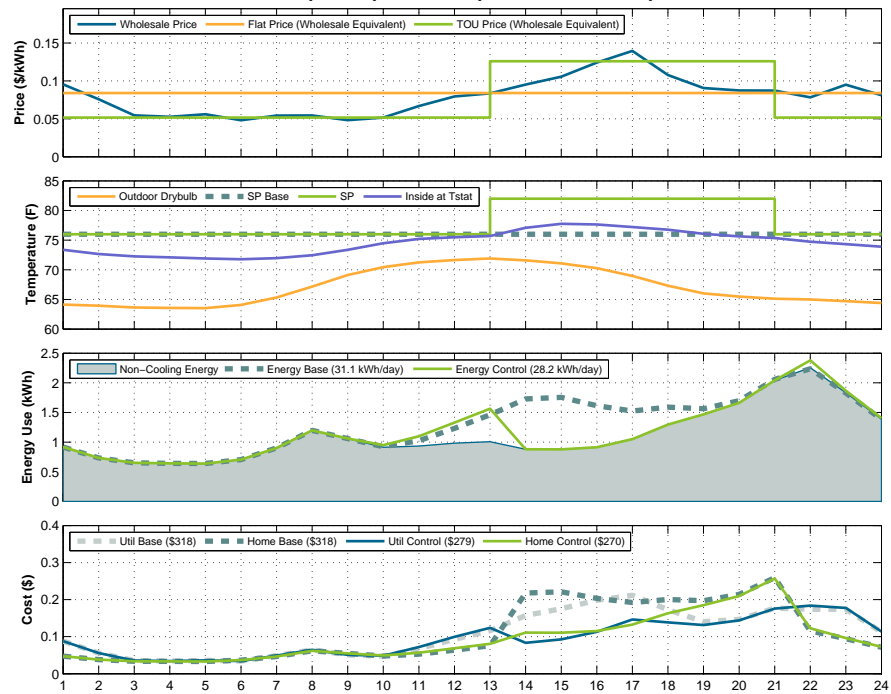


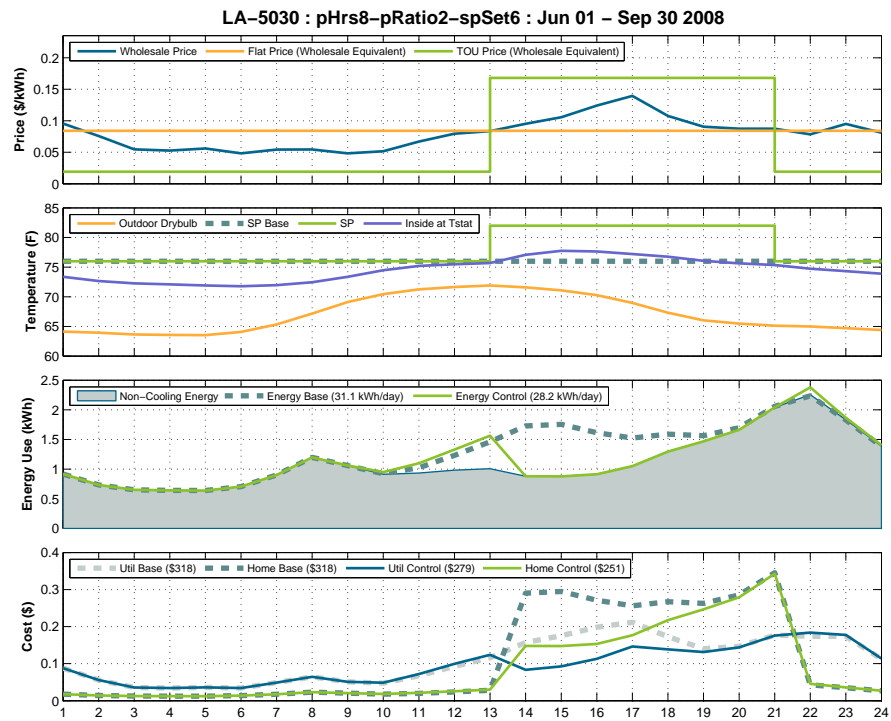
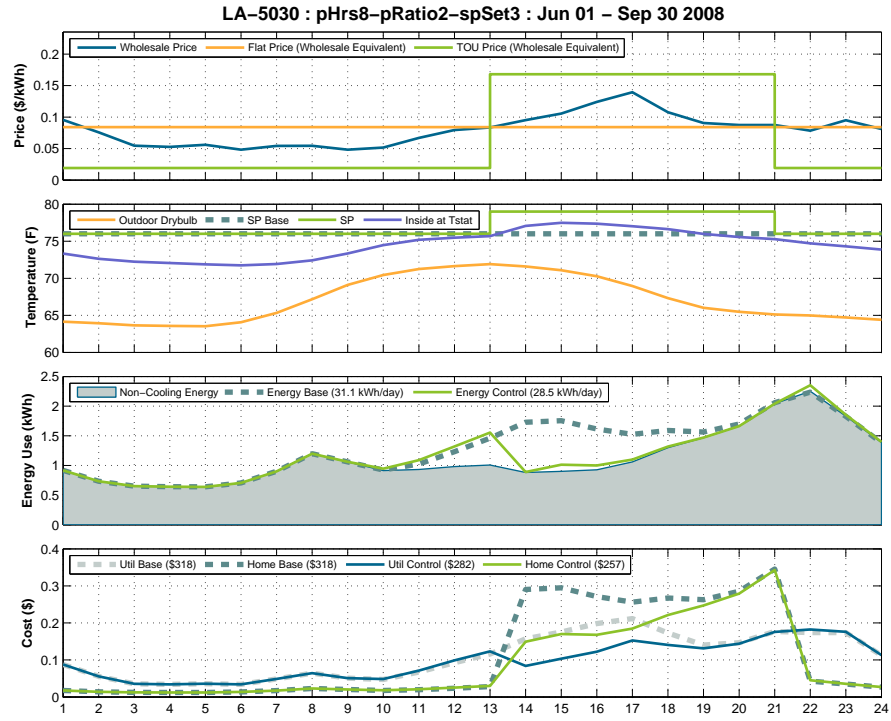


LA-5030 : pHrs8-pRatio1.5-spSet3 : Jun 01 – Sep 30 2008



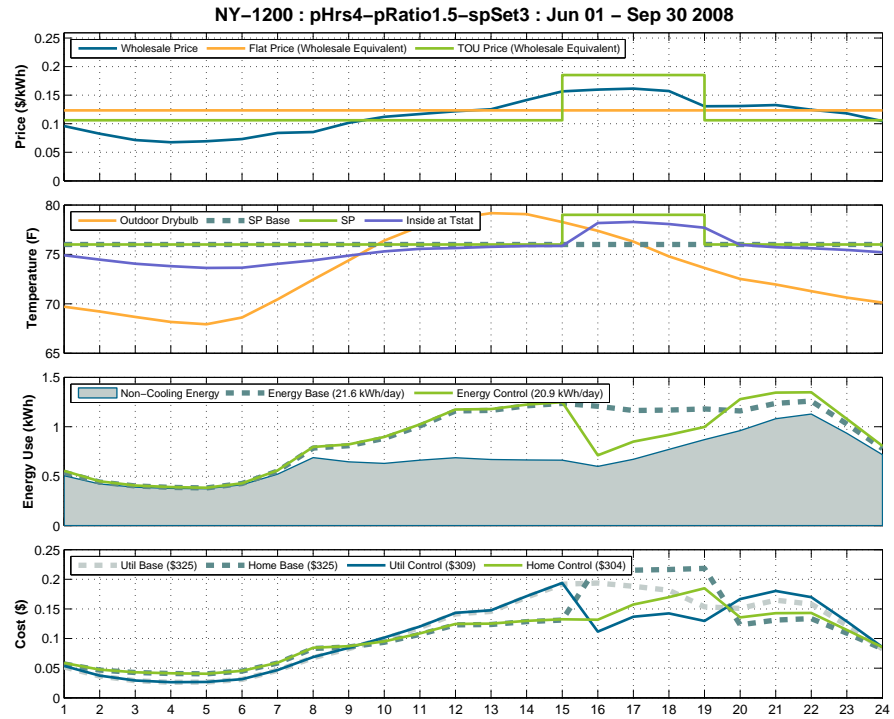
LA-5030 : pHrs8-pRatio1.5-spSet6 : Jun 01 – Sep 30 2008

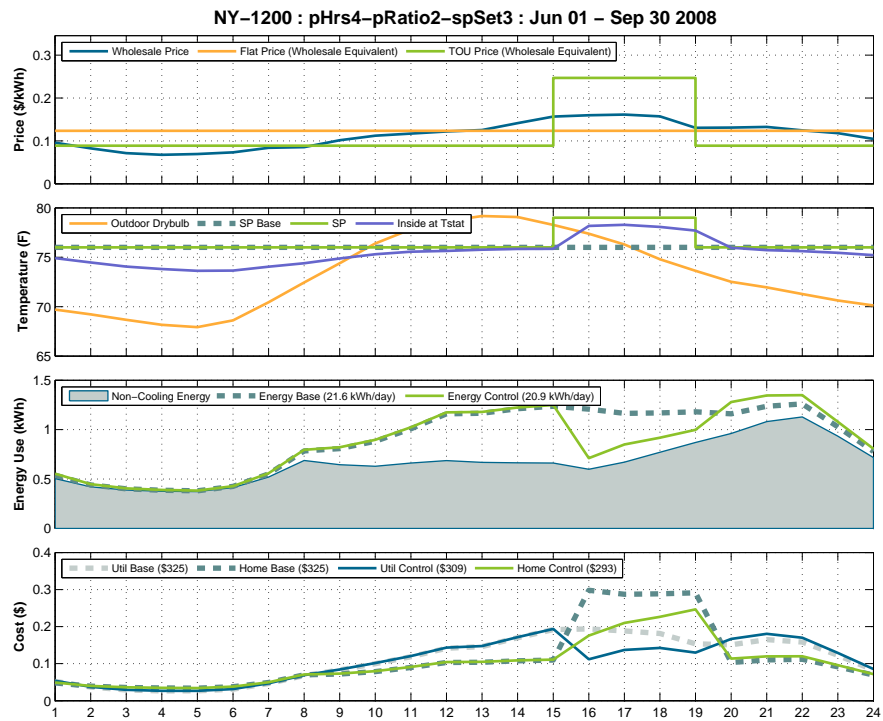
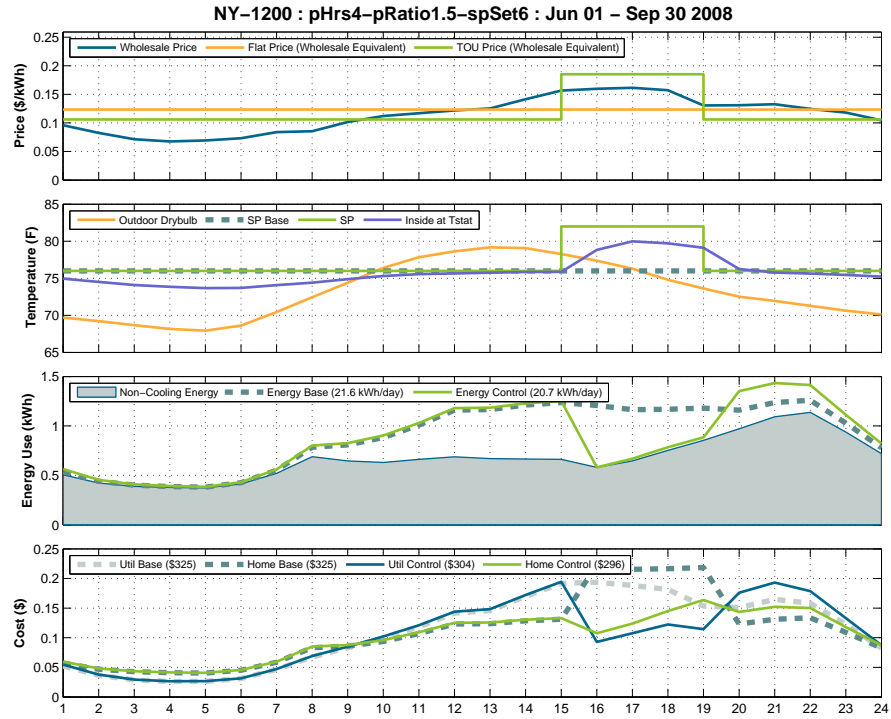




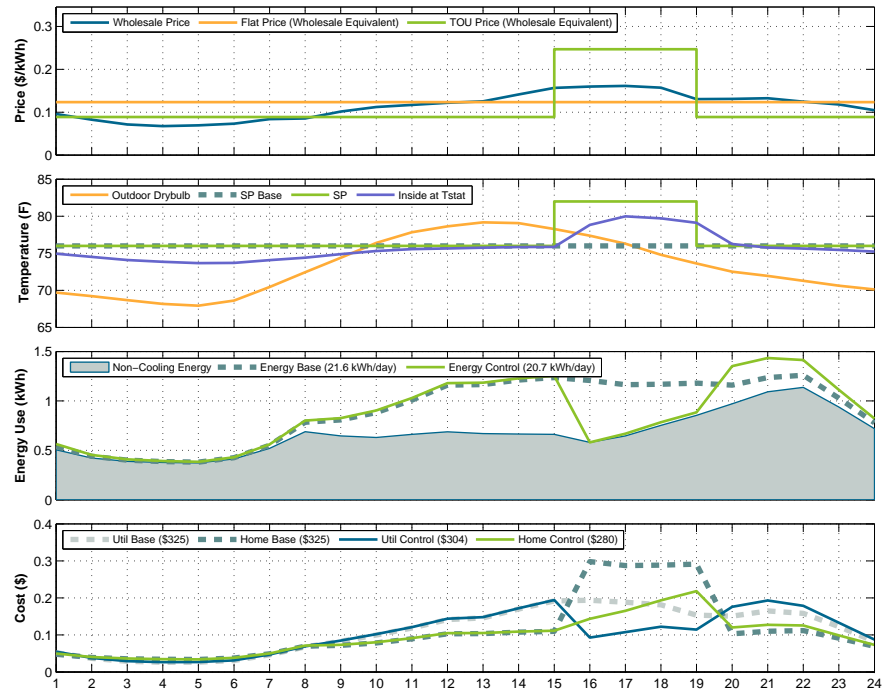
C.4 New York

C.4.1 1200

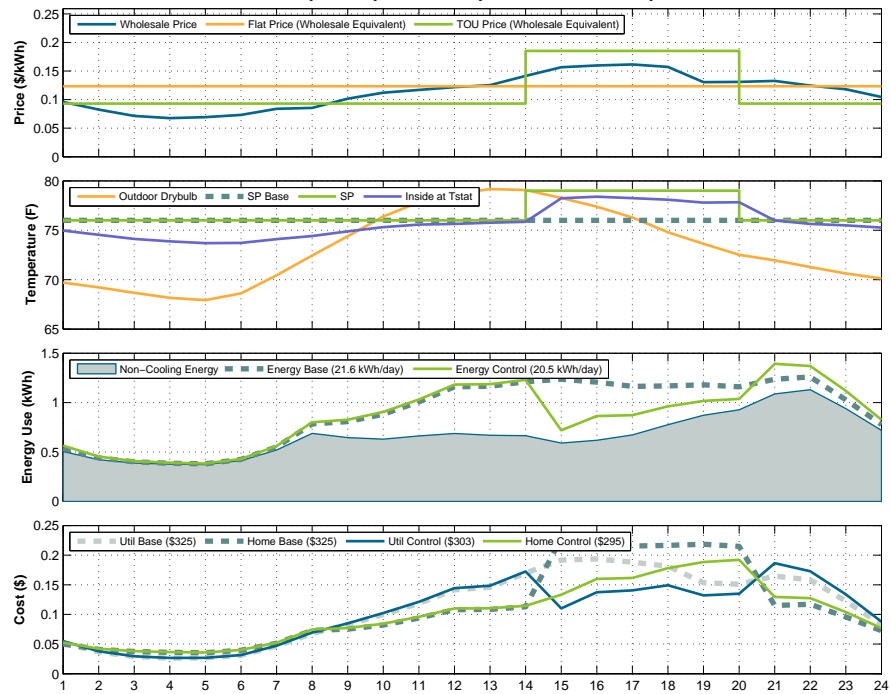




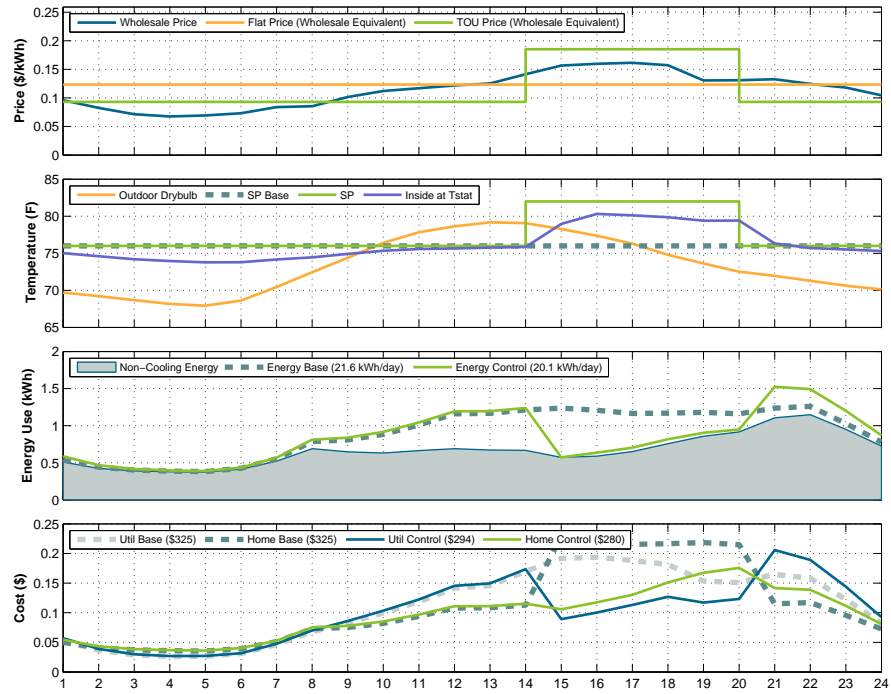
NY-1200 : pHrs4-pRatio2-spSet6 : Jun 01 – Sep 30 2008



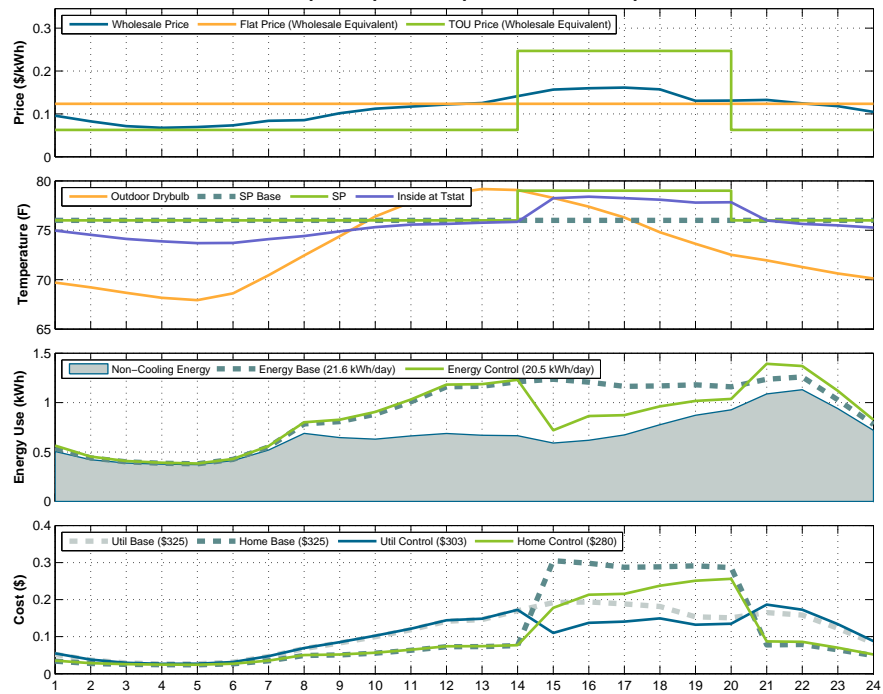
NY-1200 : pHrs6-pRatio1.5-spSet3 : Jun 01 – Sep 30 2008



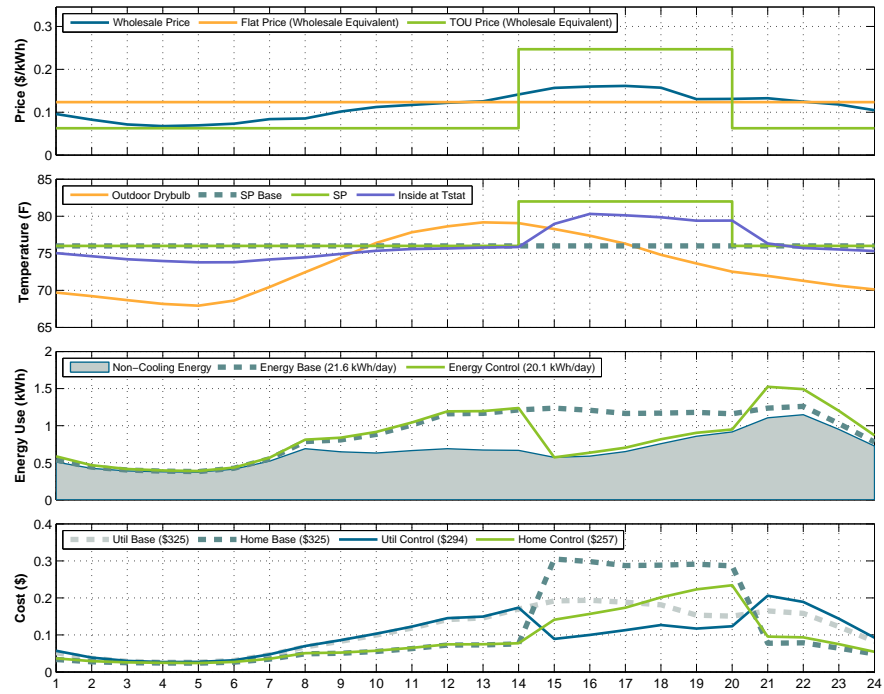
NY-1200 : pHrs6-pRatio1.5-spSet6 : Jun 01 – Sep 30 2008



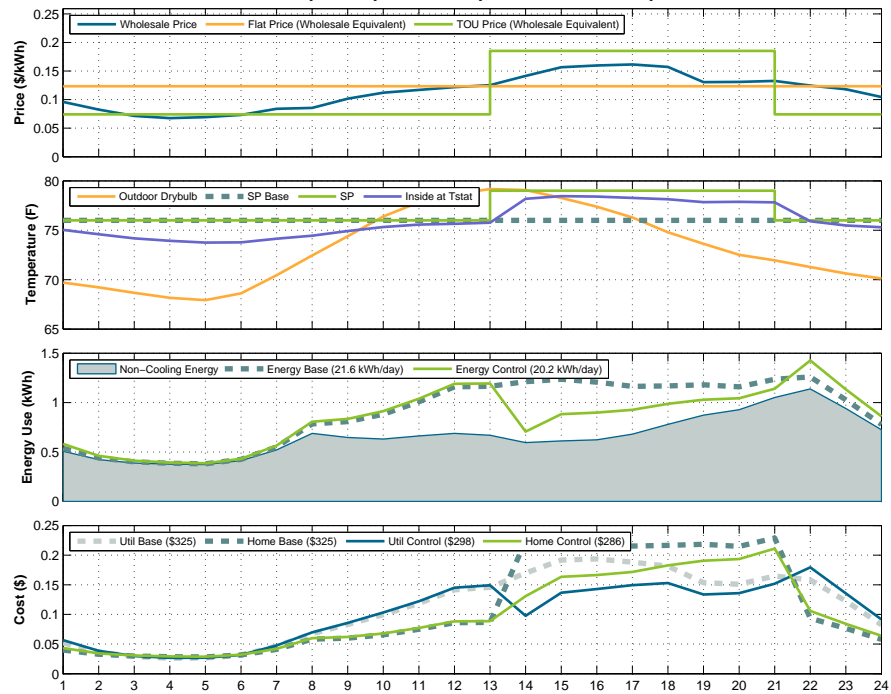
NY-1200 : pHrs6-pRatio2-spSet3 : Jun 01 – Sep 30 2008



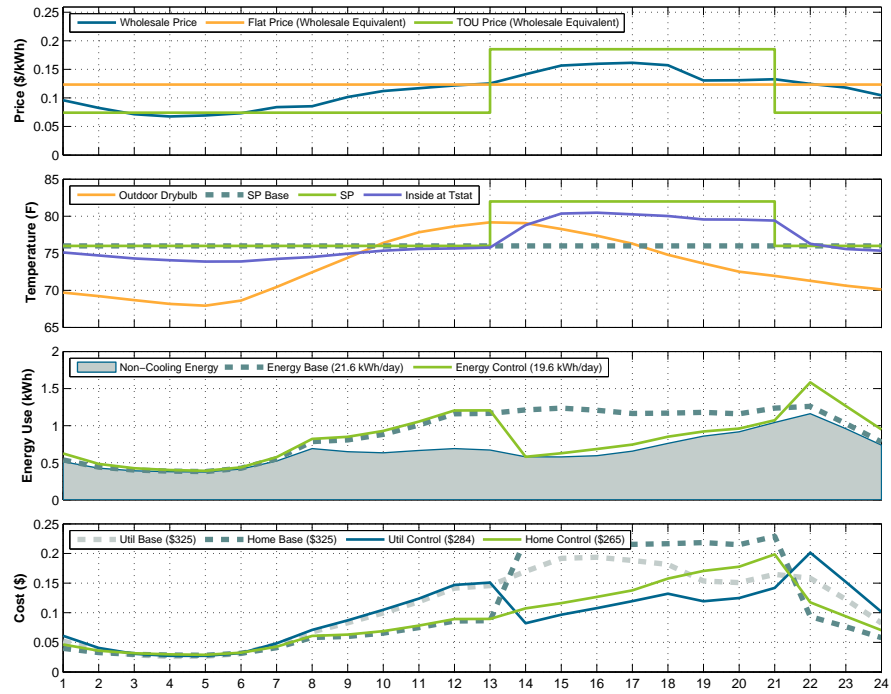
NY-1200 : pHrs6-pRatio2-spSet6 : Jun 01 – Sep 30 2008



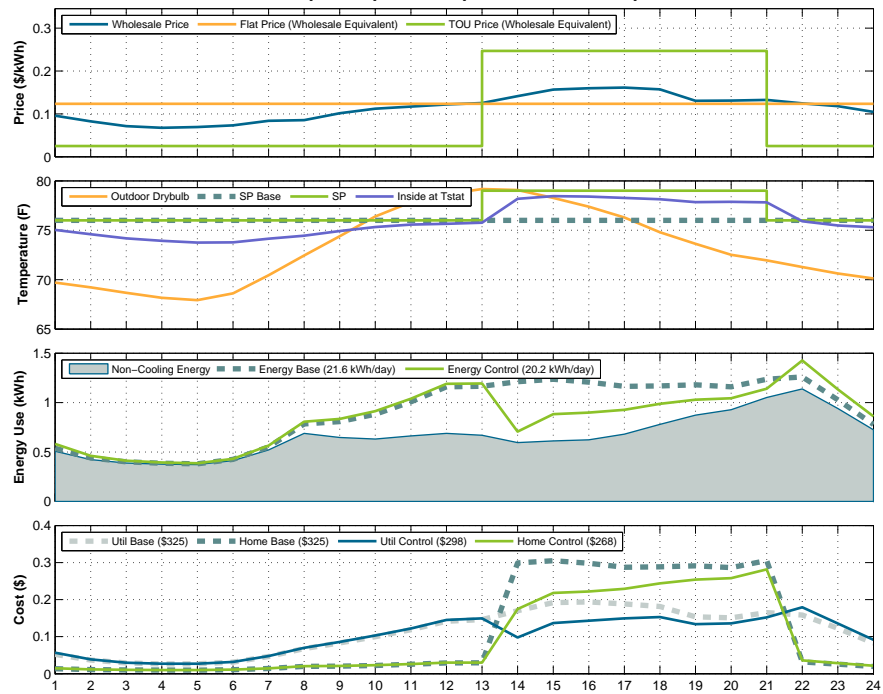
NY-1200 : pHrs8-pRatio1.5-spSet3 : Jun 01 – Sep 30 2008

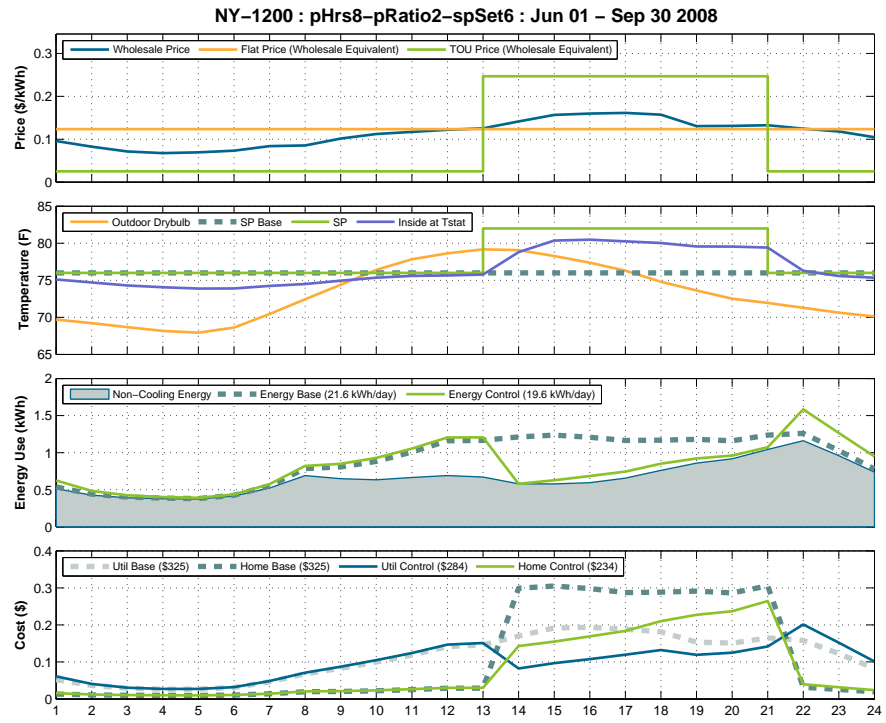


NY-1200 : pHrs8-pRatio1.5-spSet6 : Jun 01 – Sep 30 2008

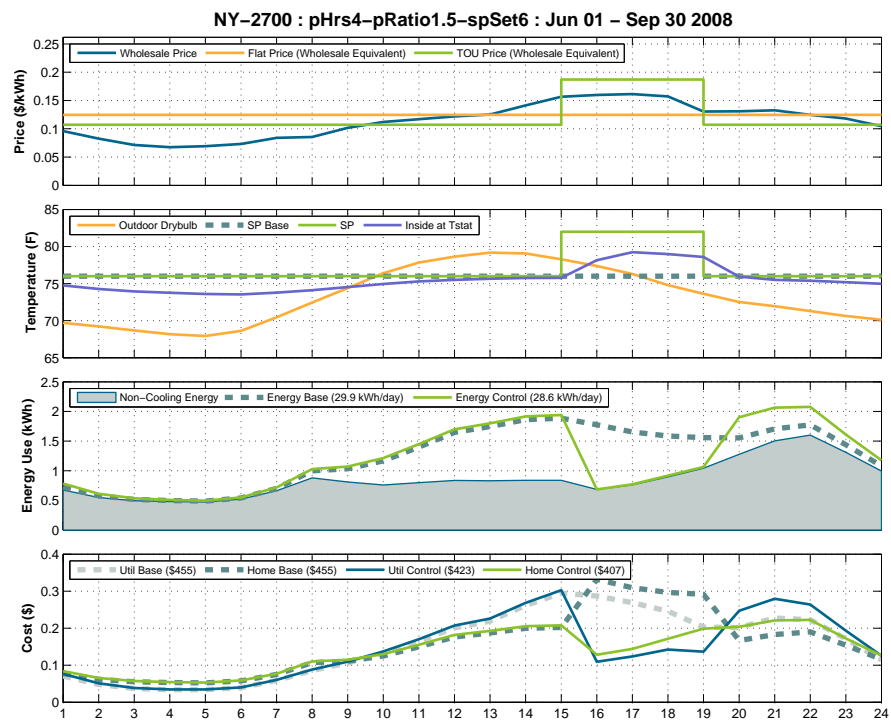
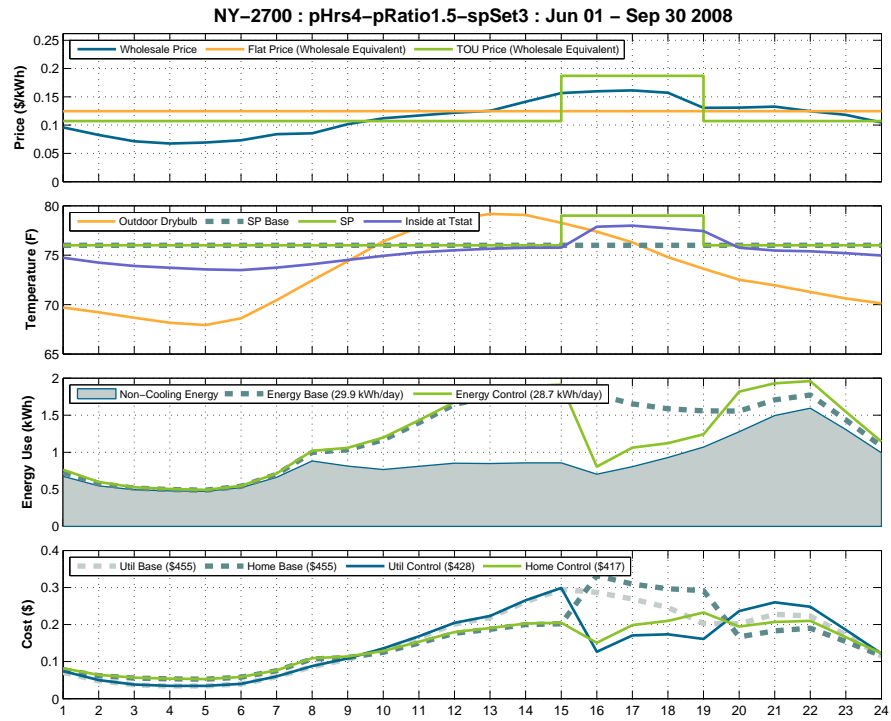


NY-1200 : pHrs8-pRatio2-spSet3 : Jun 01 – Sep 30 2008

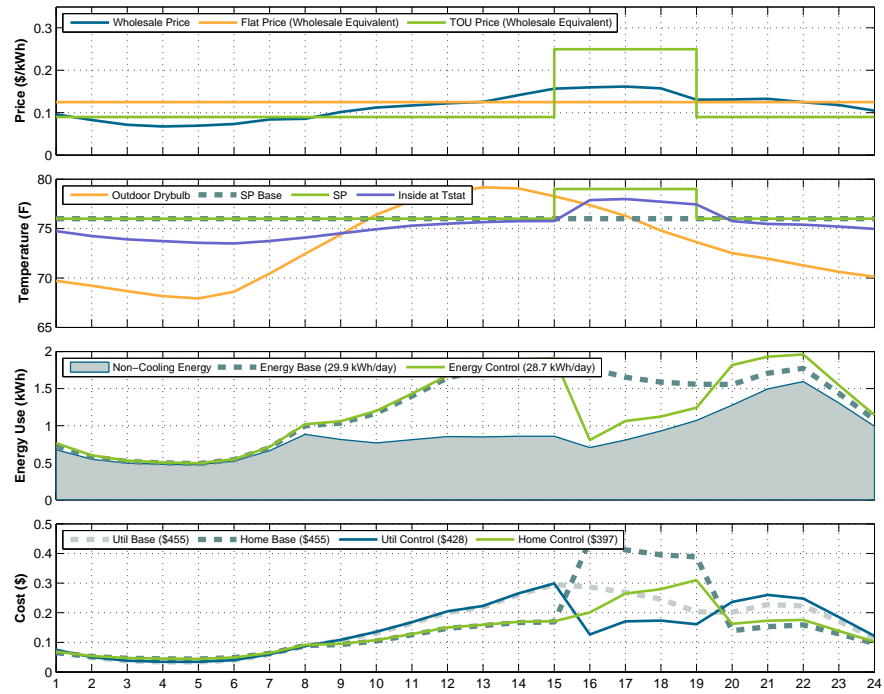




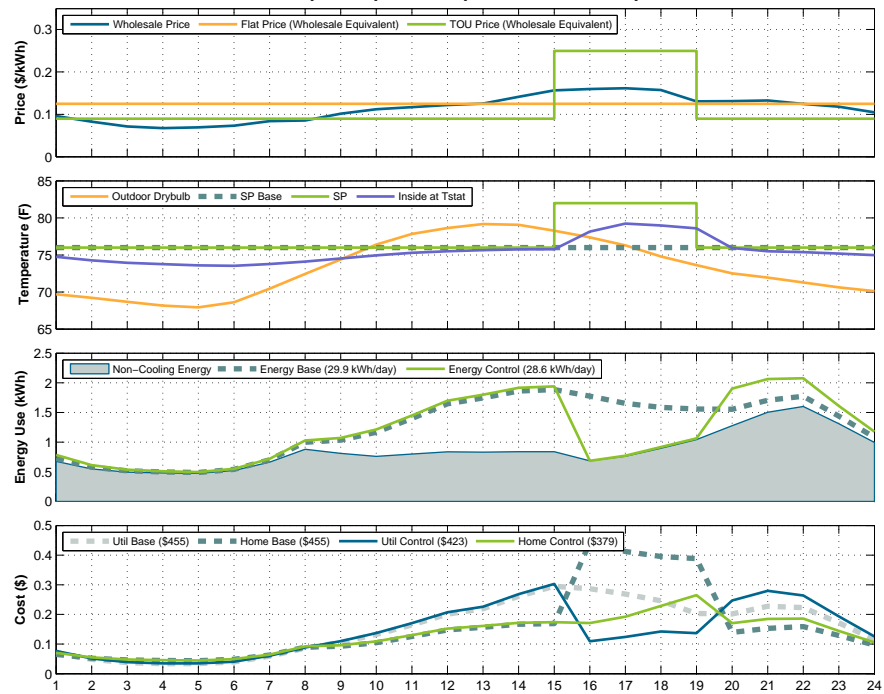
C.4.2 2700

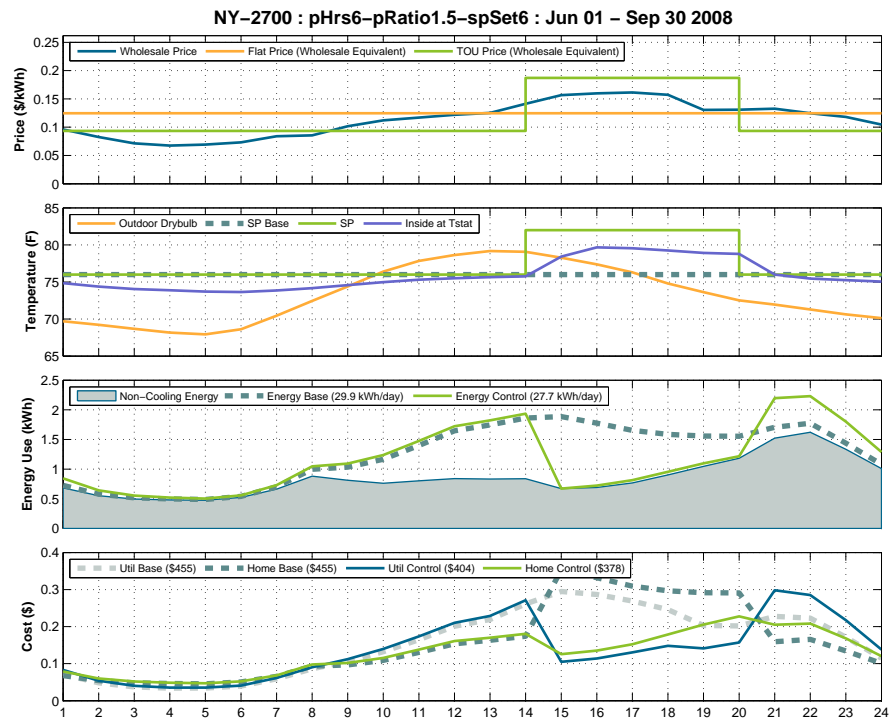
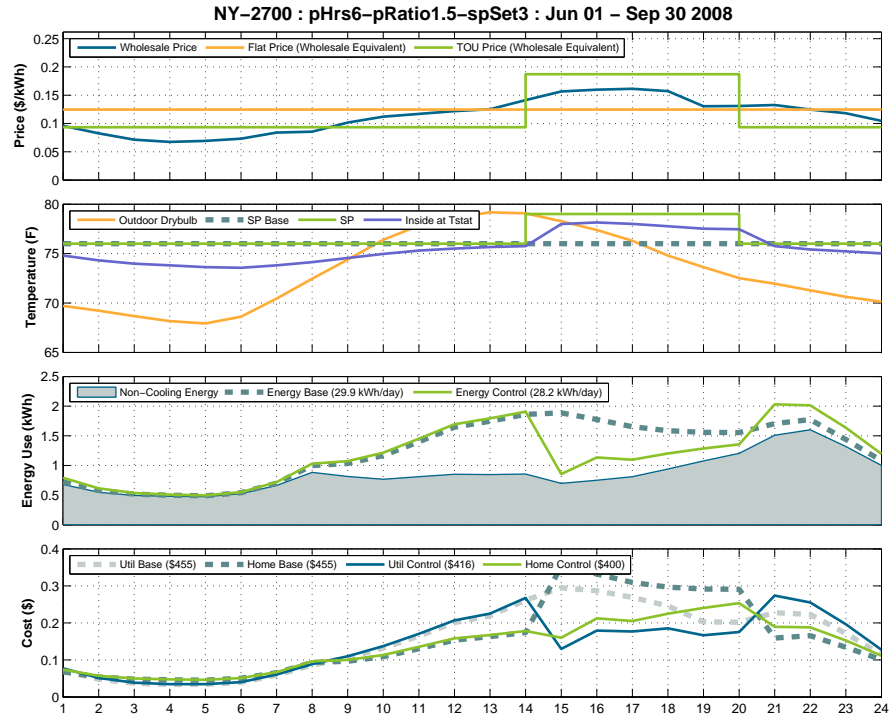


NY-2700 : pHrs4-pRatio2-spSet3 : Jun 01 – Sep 30 2008

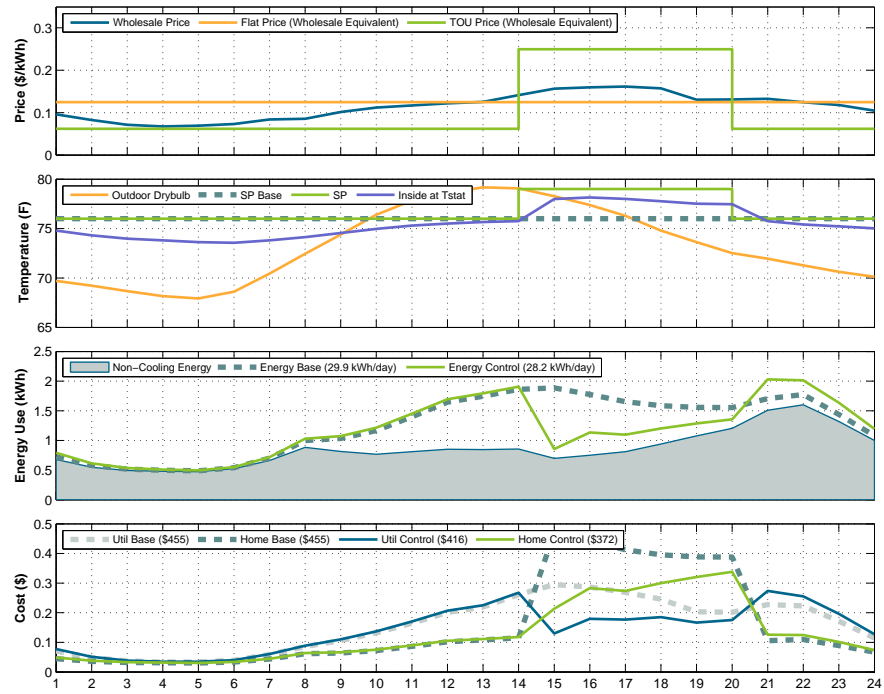


NY-2700 : pHrs4-pRatio2-spSet6 : Jun 01 – Sep 30 2008

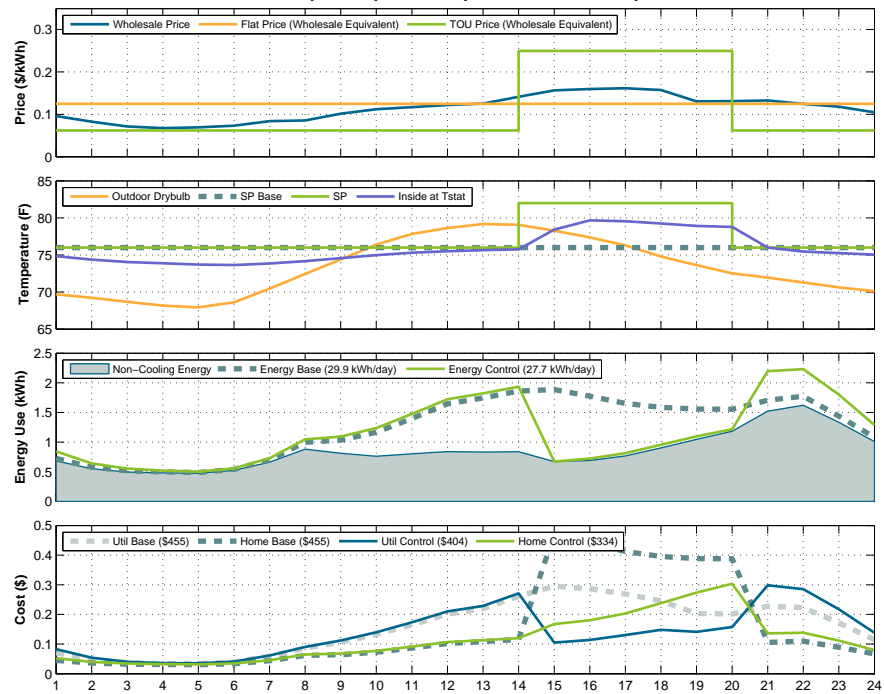


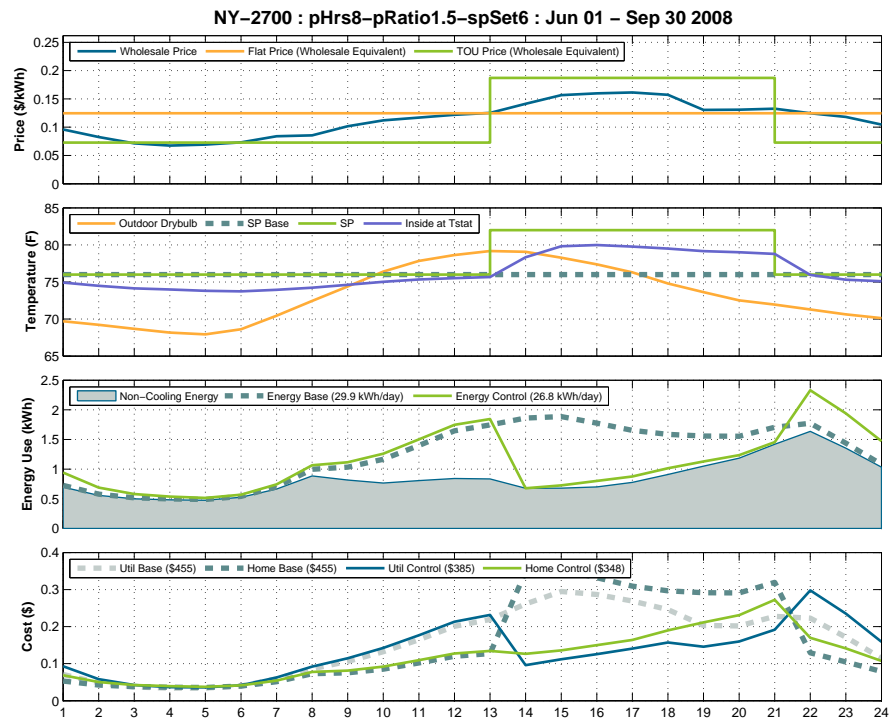
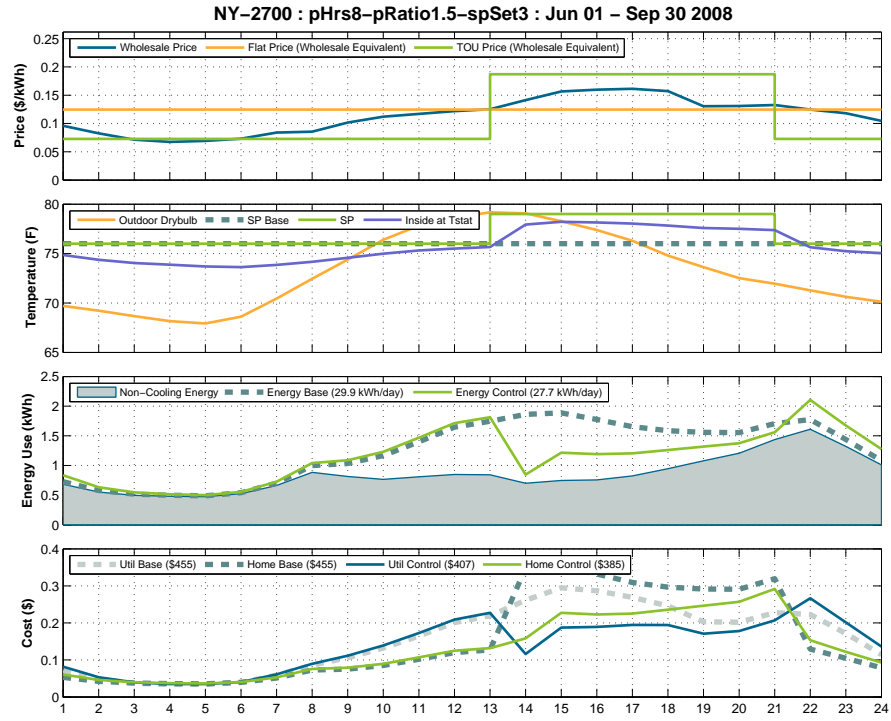


NY-2700 : pHrs6-pRatio2-spSet3 : Jun 01 – Sep 30 2008

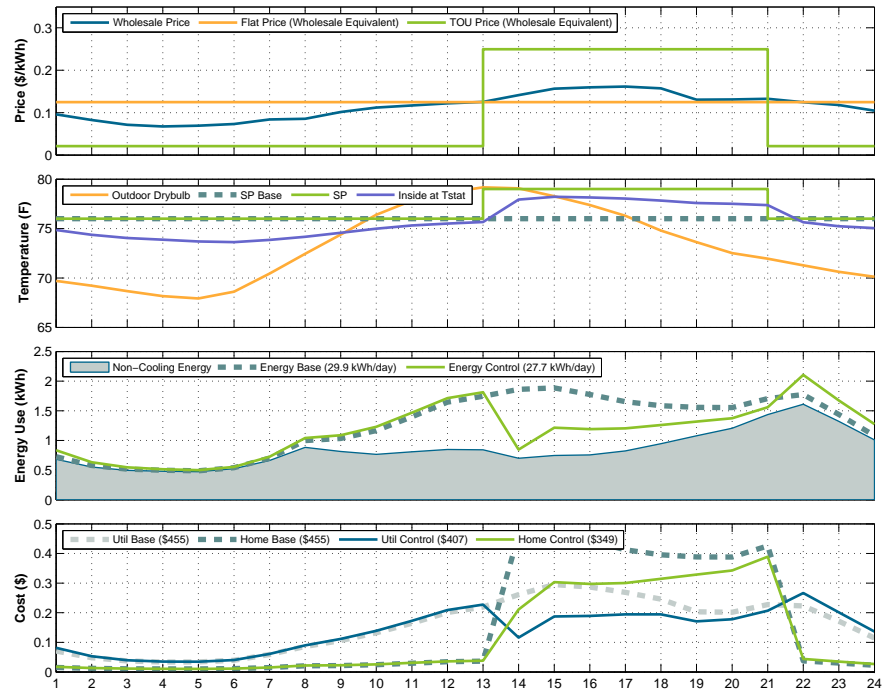


NY-2700 : pHrs6-pRatio2-spSet6 : Jun 01 – Sep 30 2008

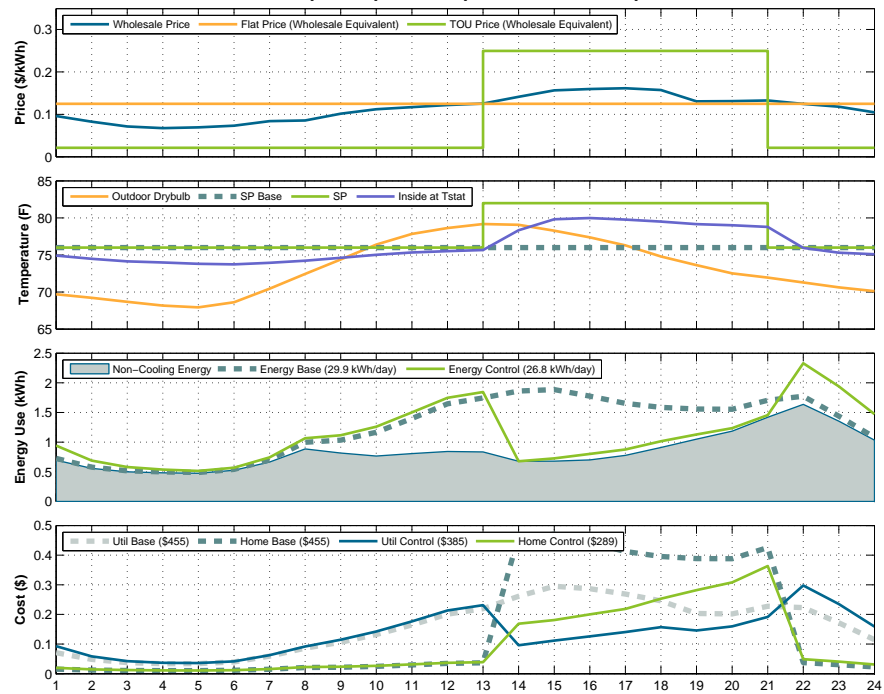




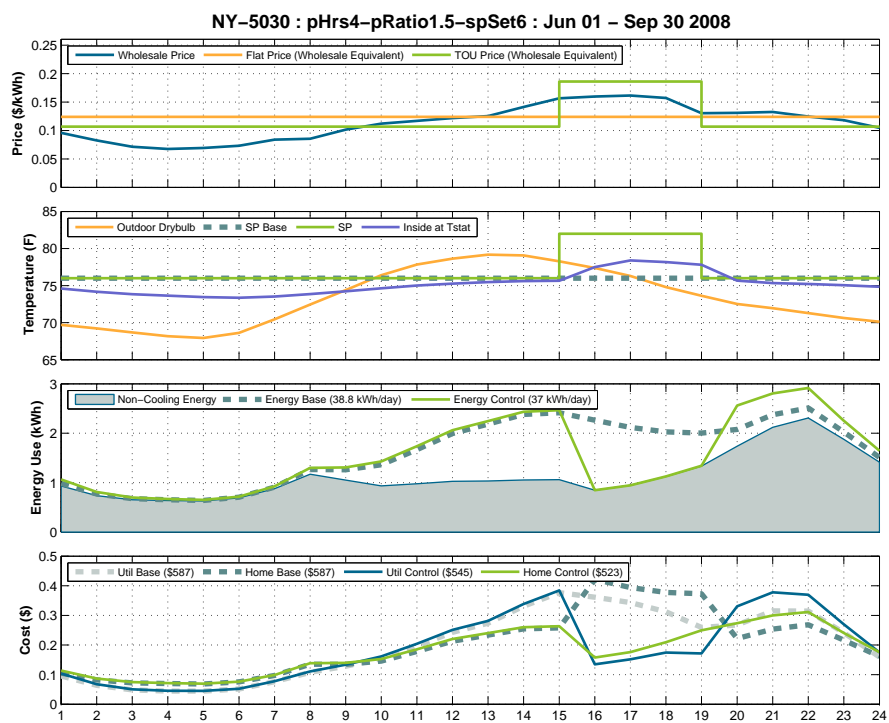
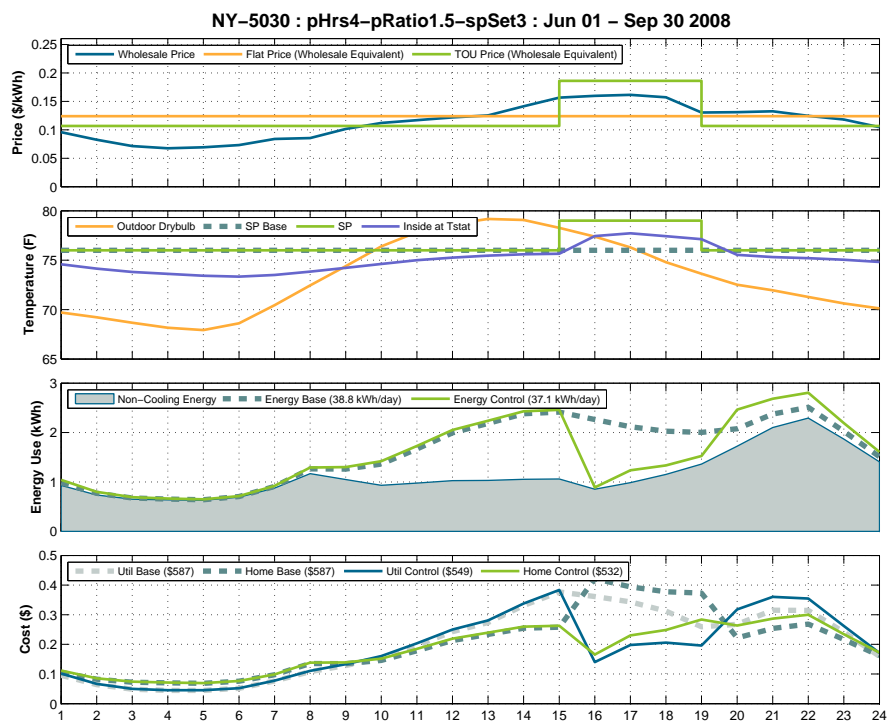
NY-2700 : pHrs8-pRatio2-spSet3 : Jun 01 – Sep 30 2008

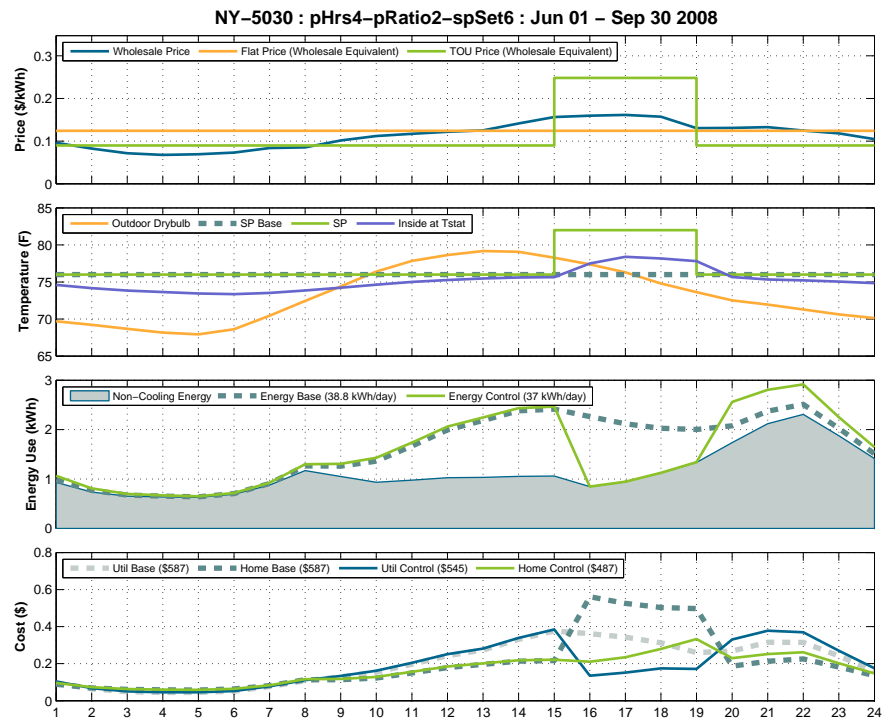
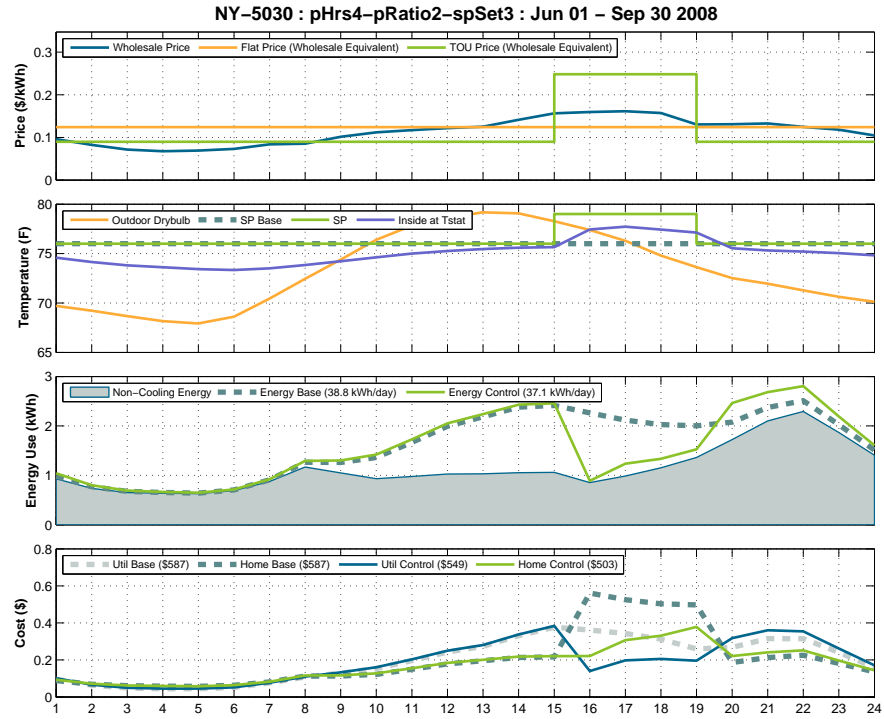


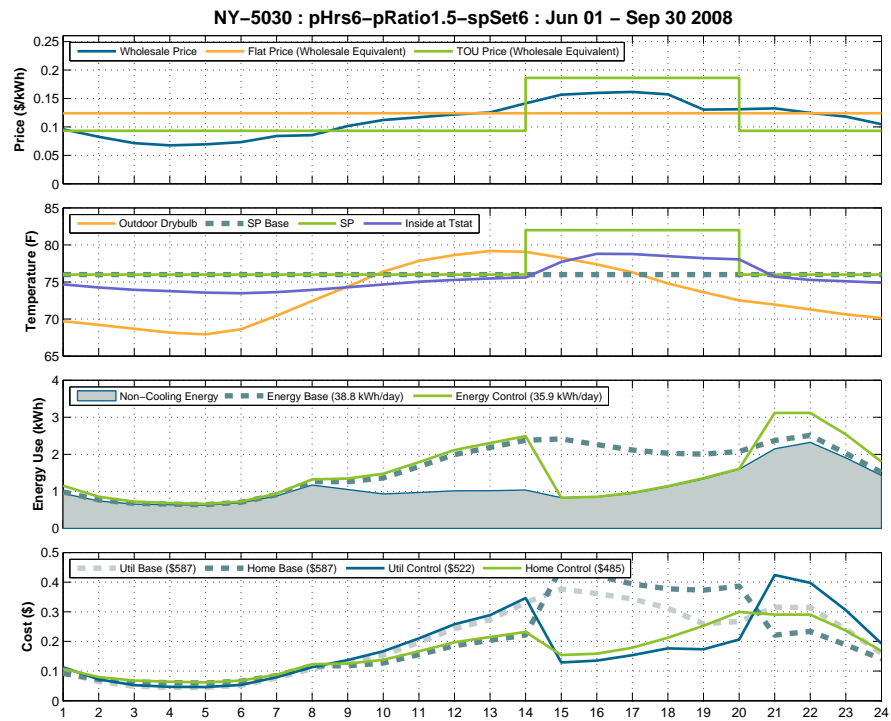
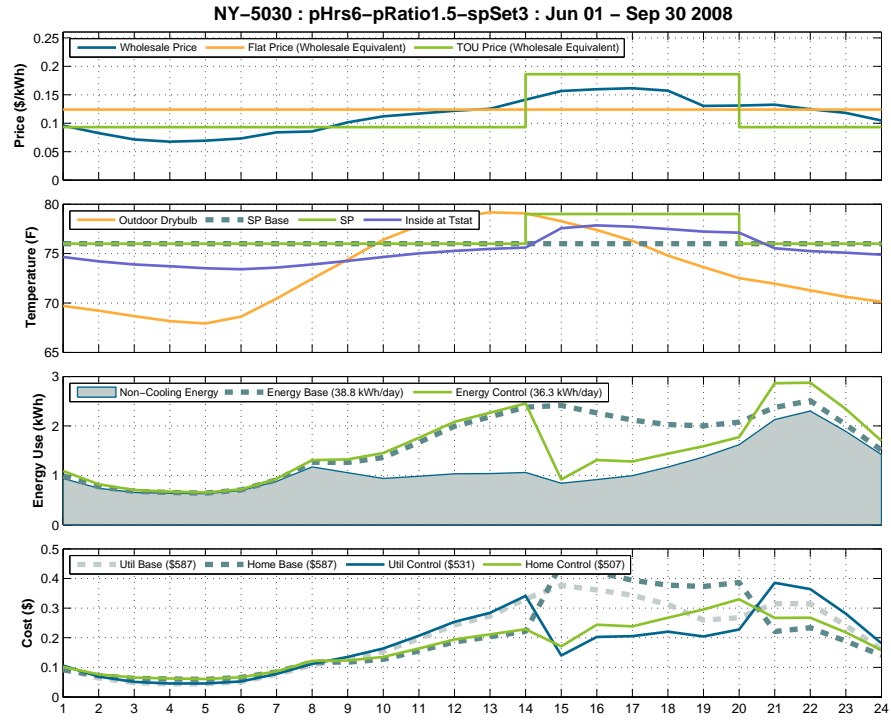
NY-2700 : pHrs8-pRatio2-spSet6 : Jun 01 – Sep 30 2008

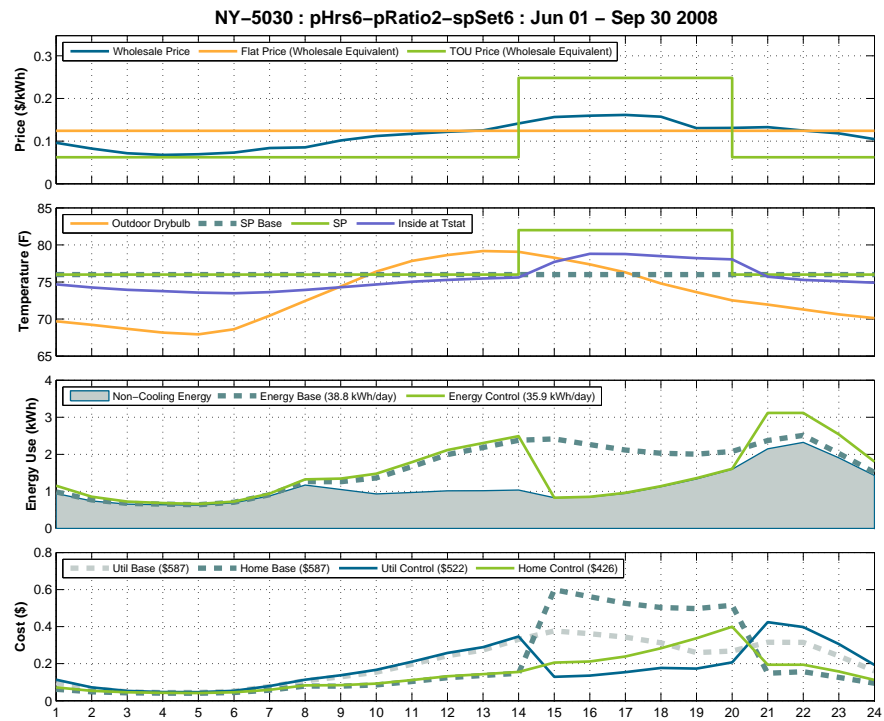
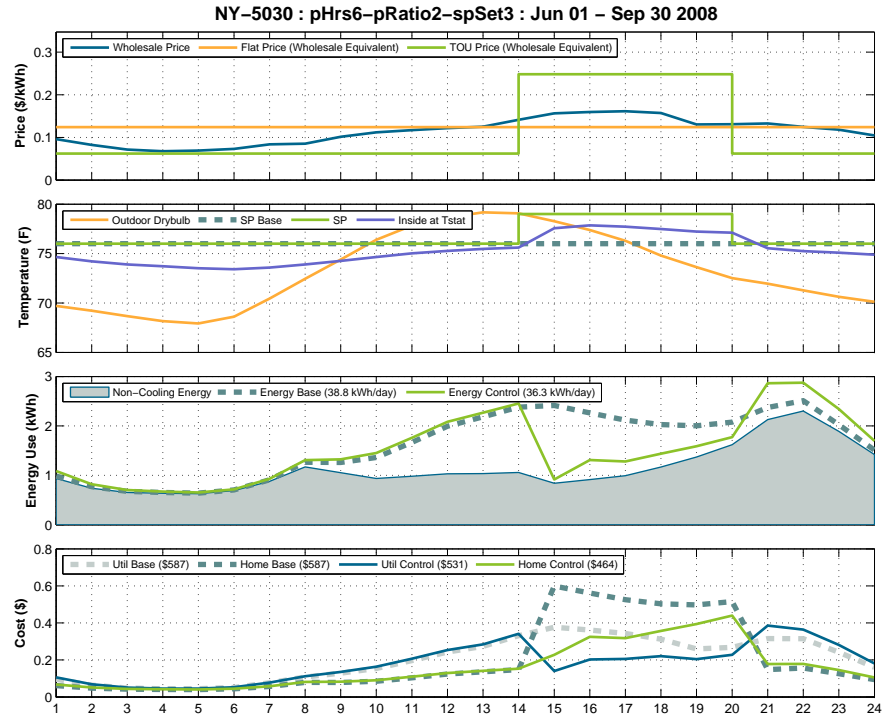


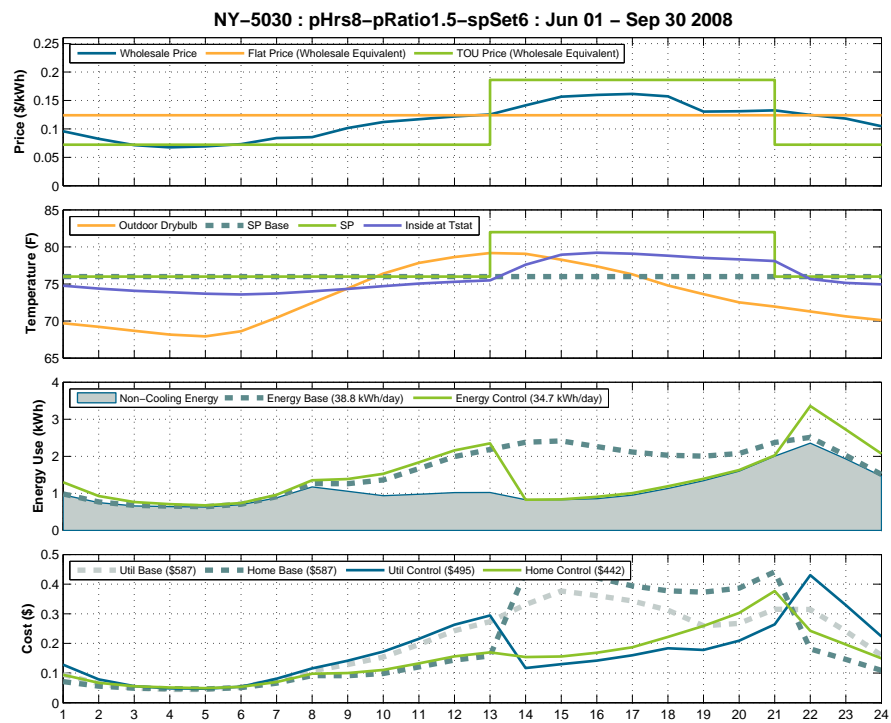
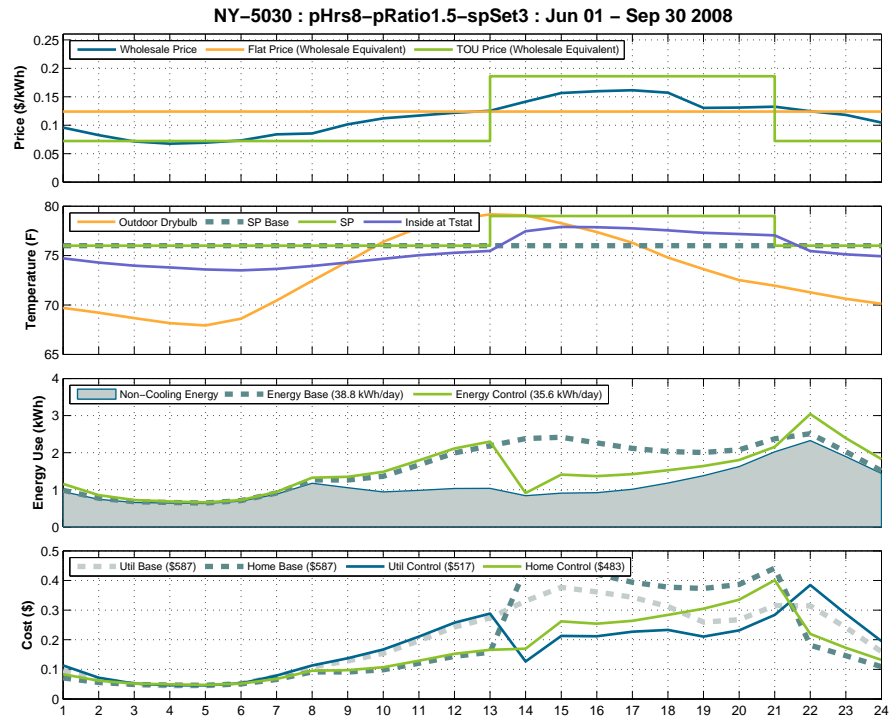
C.4.3 5030



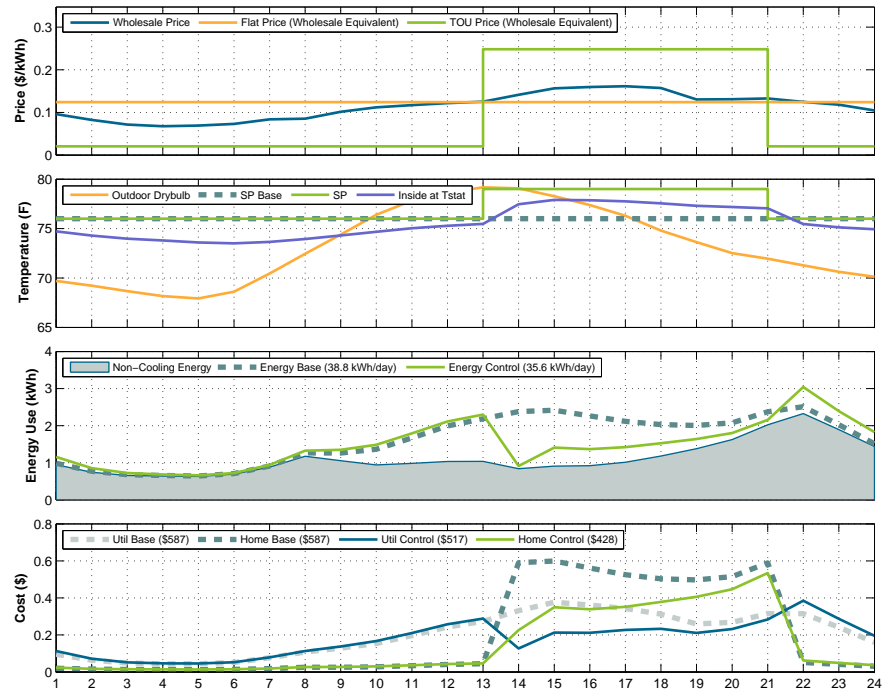




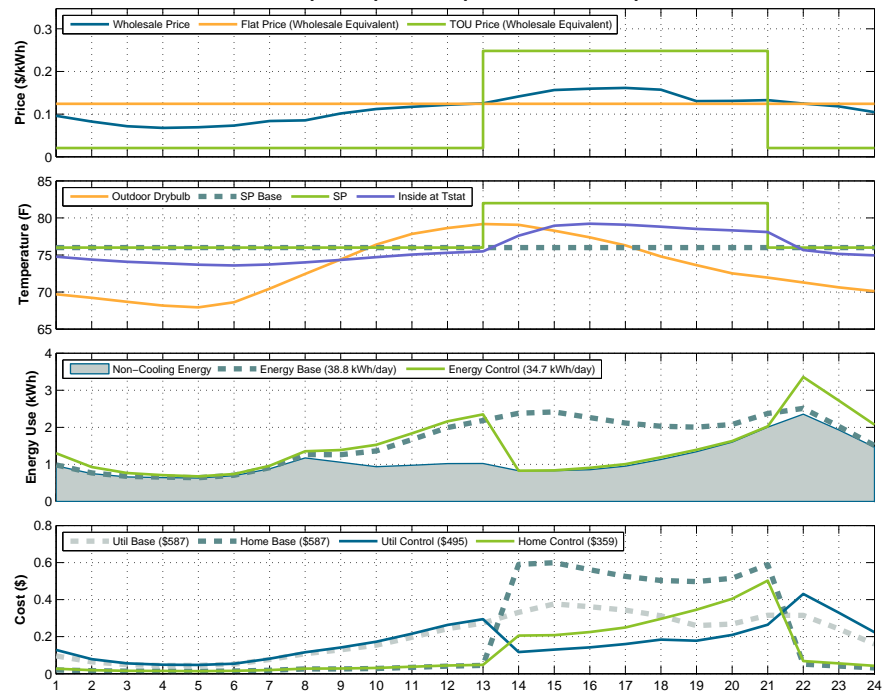




NY-5030 : pHrs8-pRatio2-spSet3 : Jun 01 – Sep 30 2008



NY-5030 : pHrs8-pRatio2-spSet6 : Jun 01 – Sep 30 2008



Appendix D

Source Code

Edits made to .idf file to create model template

```
1  RunPeriod,
2      New York J F Kennedy IntL Ar NY 1200 ft?,
3      %startmonth%,
4      %startday%,
5      %endmonth%,
6      %endday%,
7      %weekday%,
8      No,
9      Yes,
10     No,
11     Yes,
12     Yes;
13
14  Schedule:Compact,
15      CoolingSetPoint,  !- Name
16      Temperature,      !- Schedule Type Limits Name
17      %string.setpointcool%;
18
19  !-  =====  ALL OBJECTS IN CLASS: OUTPUT:VARIABLE  =====
20  Output:Variable,
21      *,                  !- Key Value
```

```

22     Outdoor Dry Bulb,           !- Variable Name
23     hourly;                     !- Reporting Frequency
24 Output:Variable,
25     *,                           !- Key Value
26     Zone Mean Air Temperature,  !- Variable Name
27     hourly;                     !- Reporting Frequency
28 Output:Variable,
29     *,                           !- Key Value
30     Zone/Sys Thermostat Cooling Setpoint, !- Variable Name
31     hourly;                     !- Reporting Frequency
32 Output:Variable,
33     *,                           !- Key Value
34     Zone/Sys Thermostat Heating Setpoint, !- Variable Name
35     hourly;                     !- Reporting Frequency
36 Output:Variable,
37     *,                           !- Key Value
38     Zone/Sys Air Temperature at Thermostat, !- Variable Name
39     hourly;
40 Output:Variable,
41     *,                           !- Key Value
42     System Node Setpoint Temp,  !- Variable Name
43     hourly;                     !- Reporting Frequency
44 Output:Variable,
45     *,                           !- Key Value
46     Time Cooling Setpoint Not Met [hr], !- Variable Name
47     hourly;                     !- Reporting Frequency
48 !- ===== ALL OBJECTS IN CLASS: OUTPUT:METER:METERFILEONLY =====
49 Output:Meter:MeterFileOnly,
50     Electricity:Facility,       !- Name
51     Hourly;                     !- Reporting Frequency
52 Output:Meter:MeterFileOnly,
53     InteriorLights:Electricity, !- Name
54     Hourly;                     !- Reporting Frequency

```

```

55 Output:Meter:MeterFileOnly,
56     ExteriorLights:Electricity,  !- Name
57     Hourly;                      !- Reporting Frequency
58 Output:Meter:MeterFileOnly,
59     InteriorEquipment:Electricity,  !- Name
60     Hourly;                      !- Reporting Frequency
61 Output:Meter:MeterFileOnly,
62     PoopPump:ExteriorEquipment:Electricity,  !- Name
63     Hourly;                      !- Reporting Frequency
64 Output:Meter:MeterFileOnly,
65     Electricity:HVAC,            !- Name
66     Hourly;                      !- Reporting Frequency
67 Output:Meter:MeterFileOnly,
68     Cooling:Electricity ,       !- Name
69     Hourly;                      !- Reporting Frequency
70 !- ===== ALL OBJECTS IN CLASS: OUTPUT:DEBUGGINGDATA =====
71 Output:DebuggingData,
72     0,                          !- Report Debugging Data
73     0;                          !- Report During Warmup

```

```

1  function struct = loadCSV(fileName)
2
3  fid = fopen(fileName);
4
5  % read file
6  tmp = textscan(fid, '%s', 'MultipleDelimsAsOne', 1, 'Delimiter', '\r',...
7      'BufSize',4095*16);
8  array = tmp{1};
9
10 % read first line (header)
11 tmp = textscan(array{1}, '%s', 'Delimiter', ',');
12 name = regexp(tmp{1}, ' ', '');

```



```

13
14 leni = length(array);
15 lenj = length(name);
16
17 for i = 2:leni
18
19     % read row
20     tmp = textscan(array{i}, '%s', 'Delimiter', ',', '');
21     row = tmp{1};
22
23     for j = 1:lenj
24
25         if j > length(row) || isempty(row{j}) % empty
26
27             struct.(name{j}){i-1} = '';
28
29         elseif ~isempty(str2num(row{j})) % integer
30
31             struct.(name{j})(i-1) = str2num(row{j});
32
33         else % string
34
35             struct.(name{j}){i-1} = row{j};
36
37         end
38
39     end
40
41 end
42
43 fclose(fid);
44
45 end % function

```

```

1  function struct = loadNyisoCSV(fileName)
2
3  fid = fopen(fileName);
4
5  % read file
6  tmp = textscan(fid, '%s', 'MultipleDelimsAsOne', 1, 'Delimiter', '\r');
7  array = tmp{1};
8
9  % read first line (header)
10 tmp = textscan(array{1}, '%s', 'Delimiter', ' ');
11 name = regexp(tmp{1}, ' ', '');
12
13 leni = length(array);
14 lenj = length(name);
15
16 for i = 2:leni
17
18     % read row
19     tmp = textscan(array{i}, '%s', 'Delimiter', ' ');
20     row = tmp{1};
21
22     for j = [1,4]
23
24         if j > length(row) || isempty(row{j}) % empty
25
26             struct.(name{j})(i-1) = '';
27
28         elseif strcmp(name{j}, 'RTDEndTimeStamp')
29
30             struct.(name{j})(i-1) = datenum(row{j});
31
32         elseif ~isempty(str2num(row{j})) % integer
33

```

```

34         struct.(name{j})(i-1) = str2num(row{j});
35
36         else % string
37
38         struct.(name{j}){i-1} = row{j};
39
40         end
41
42     end
43
44 end
45
46 fclose(fid);
47
48 end % function

```

```

1  function struct = loadErcotCSV(fileName)
2
3  fid = fopen(fileName);
4
5  % read file
6  tmp = textscan(fid, '%s', 'MultipleDelimsAsOne', 1, 'Delimiter', '\r',...
7      'BufSize',4095*16);
8  array = tmp{1};
9
10 % read first line (header)
11 tmp = textscan(array{1}, '%s', 'Delimiter', ' ');
12 name = regexp(tmp{1}, ' ', '');
13
14 leni = length(array);
15 lenj = length(name);
16

```

```

17 for i = 2:leni
18
19     % read row
20     tmp = textscan(array{i}, '%s', 'Delimiter', ',', '');
21     row = tmp{1};
22
23     for j = 1:lenj
24
25         if j > length(row) || isempty(row{j}) % empty
26
27             struct.(name{j})(i-1) = nan;
28
29         elseif strcmp(name{j}, 'StartTime')
30
31             struct.(name{j})(i-1) = datenum(row{j});
32
33         elseif ~isempty(str2num(row{j})) % integer
34
35             struct.(name{j})(i-1) = str2num(row{j});
36
37         else % string
38
39             struct.(name{j})(i-1) = row{j};
40
41         end
42
43     end
44
45 end
46
47 fclose(fid);
48
49 end % function

```

```

1  function struct = loadPjmCSV(fileName,node)
2
3  fid = fopen(fileName);
4
5  % read file
6  tmp = textscan(fid, '%s', 'MultipleDelimsAsOne', 1, 'Delimiter', '\r',...
7      'BufSize',4095*16);
8  array = tmp{1};
9
10 header = find(strcmp(regexprep(...
11     array,'Start of LMP Data.*','YEP'),'YEP'))+ 1;
12
13 if isempty(header)
14
15     header = find(strcmp(regexprep(...
16         array,'Start of Real Time LMP Data.*','YEP'),'YEP'))+ 1;
17
18 end
19
20
21 % read first line (header)
22 tmp = textscan(array{header},'%s','Delimiter', ' ');
23 name = regexprep(tmp{1}, ' ','');
24
25 leni = length(array)-1;
26 lenj = length(name);
27
28 indi = find(strcmp(regexprep(array,['.*',node,'.*'],'YEP'),'YEP'));
29 indj = [1;3;find(strcmp(name,'TotalLMP'))];
30
31 name2 = name(indj);
32
33 for i = 1:length(indi)

```

```

34
35     % read row
36     tmp = textscan(array{indi(i)}, '%s', 'Delimiter', ',', '');
37     row = tmp{1};
38
39     for j = 1:length(indj)
40
41         jj = indj(j);
42
43         if strcmp(name2(j), 'TotalLMP')
44
45             fld = [name2{j}, num2str(j-2)];
46
47         else
48
49             fld = [name2{j}];
50
51         end
52
53
54         if j > length(row) || isempty(row{jj}) % empty
55
56             struct.(fld){i} = '';
57
58         elseif strcmp(fld, 'Date')
59
60             struct.(fld)(i) = datenum(row{jj}, 'yyyymmdd');
61
62         elseif ~isempty(str2num(row{jj})) % integer
63
64             struct.(fld)(i) = str2num(row{jj});
65
66         else % string

```

```

67
68         struct.(fld){i} = row{jj};
69
70     end
71
72 end
73
74 end
75
76 fclose(fid);
77
78 end % function

```

```

1  %% Load Price Data
2  clear all, clc,
3
4  %% CAISO
5
6  priceFiles = {'20080601_20080630_RTM_HRLY_ENGY_PRC_N_N.csv',...
7               '20080701_20080731_RTM_HRLY_ENGY_PRC_N_N.csv',...
8               '20080801_20080831_RTM_HRLY_ENGY_PRC_N_N.csv',...
9               '20080901_20080930_RTM_HRLY_ENGY_PRC_N_N.csv'};
10 node = 'LA1';
11
12 count = 0;
13
14 for p = 1:length(priceFiles)
15
16     % load price csv
17     fileName = priceFiles{p};
18     disp(['Loading : ',priceFiles{p}]);
19     tmp = loadCSV(fileName);

```

```

20
21     % get date for node
22     bool = strcmp(tmp.CNGS_ZONE,node);
23     fldsPrice = fields(tmp);
24
25     for i = 1:length(fldsPrice)
26
27         tmp2.(fldsPrice{i}) = tmp.(fldsPrice{i})(bool);
28
29     end
30
31     % find days in file
32     startDate = datenum(priceFiles{p}(1:8),'yyyymmdd');
33     endDate = datenum(priceFiles{p}(10:17),'yyyymmdd');
34     day = startDate:endDate;
35
36     % build price structure
37     disp(['Creating Price Structure : ',...
38         datestr(startDate),' to ',datestr(endDate)]);
39     for i = 1:length(day)
40
41         for j = 1:24
42
43             count = count +1;
44
45             Price.hourEnd(count) = day(i) + j/24;
46             Price.rtp(count) = tmp2.(fldsPrice{j+3})(i);
47
48         end
49
50     end
51
52 end

```



```

53
54 save(['./matFiles/PriceCAISO'],'Price')
55 disp(['Done']);
56
57 %% NYISO
58
59 priceFiles = {'2008_06-OASIS-Real-Time-Dispatch-Zonal-LBMP.csv',...
60     '2008_07-OASIS-Real-Time-Dispatch-Zonal-LBMP.csv',...
61     '2008_08-OASIS-Real-Time-Dispatch-Zonal-LBMP.csv',...
62     '2008_09-OASIS-Real-Time-Dispatch-Zonal-LBMP.csv'};
63
64 count = 0;
65
66 for p = 1:length(priceFiles)
67
68     % load price csv
69     fileName = priceFiles{p};
70     disp(['Loading : ',priceFiles{p}]);
71     tmp = loadNyisoCSV(fileName);
72
73     % find days in file
74     fldsPrice = fields(tmp);
75     startDate = datenum(datestr(tmp.(fldsPrice{1})(1),'yyyy-mm-dd'));
76     endDate = datenum(datestr(tmp.(fldsPrice{1})(end),'yyyy-mm-dd'));
77     day = startDate:endDate-1;
78
79     % build price structure
80     disp(['Creating Price Structure : ',...
81         datestr(startDate),' to ',datestr(endDate)]);
82
83     for i = 1:length(day)
84
85         for j = 1:24

```

```

86
87         count = count +1;
88         hourStart = day(i) + j/24 - 1/24;
89
90         Price.hourEnd(count) = day(i) + j/24;
91
92         bool = tmp.(fldsPrice{1}) > hourStart &...
93             tmp.(fldsPrice{1}) ≤ Price.hourEnd(count);
94
95         Price.rtp(count) = mean(tmp.(fldsPrice{2})(bool));
96
97     end
98
99 end
100
101 end
102
103 save(['./matFiles/PriceNYISO'],'Price')
104 disp(['Done']);
105
106 %% PJM
107
108 priceFiles = {'200806-rt.csv',...
109     '200807-rt.csv',...
110     '200808-rt.csv',...
111     '200809-rt.csv'};
112 node = 'CHICAGO HUB';
113 count = 0;
114
115 for p = 1:length(priceFiles)
116
117     % load price csv
118     fileName = priceFiles{p};

```

```

119     disp(['Loading : ',priceFiles{p}]);
120     tmp = loadPjmCSV(fileName, node);
121
122     % find days in file
123     fldsPrice = fields(tmp);
124     startDate = datenum(datestr(tmp.(fldsPrice{1})(1),'yyyy-mm-dd'));
125     endDate = datenum(datestr(tmp.(fldsPrice{1})(end),'yyyy-mm-dd'));
126     day = startDate:endDate;
127
128     % build price structure
129     disp(['Creating Price Structure : ',...
130         datestr(startDate),' to ',datestr(endDate)]);
131
132     for i = 1:length(day)
133
134         for j = 1:24
135
136             count = count +1;
137
138             Price.hourEnd(count) = day(i) + j/24;
139             Price.rtp(count) = tmp.(fldsPrice{j+2})(i);
140
141         end
142
143     end
144
145 end
146
147 save(['./matFiles/PricePJM'],'Price')
148 disp(['Done Loading Prices']);
149
150 %% ERCOT
151

```

[illegible]

```
185         tmp2.(['Int',num2str(j-1)])(i),...
186         tmp2.(['Int',num2str(j)])(i));
187
188     end
189
190 end
191
192 end
193
194 save(['./matFiles/PriceErcot2'],'Price')
195 disp(['Done']);
```