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California DREAMing: the design of residential demand responsive technology with people in mind

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California DREAMing:
the Design of Residential Demand Responsive Technology
with People in Mind

by

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Committee in charge:

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Professor David Auslander
Professor Galen Cranz

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Abstract

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Electrical utilities worldwide are exploring “demand response” programs to reduce electricity consumption during peak periods. Californian electrical utilities would like to pass the higher cost of peak demand to customers to offset costs, increase reliability, and reduce peak consumption. Variable pricing strategies require technology to communicate a dynamic price to customers and respond to that price. However, evidence from thermostat and energy display studies as well as research regarding energy-saving behaviors suggests that devices cannot effect residential demand response without the sanction and participation of people.

This study developed several technologies to promote or enable residential demand response. First, along with a team of students and professors, I designed and tested the Demand Response Electrical Appliance Manager (DREAM). This wireless network of sensors, actuators, and controller with a user interface provides information to intelligently

control a residential heating and cooling system and to inform people of their energy usage. We tested the system with computer simulation and in the laboratory and field. Secondly, as part of my contribution to the team, I evaluated machine-learning to predict a person's seasonal temperature preferences by analyzing existing data from office workers. The third part of the research involved developing an algorithm that generated temperature setpoints based on outdoor temperature. My study compared the simulated energy use using these setpoints to that using the setpoints of a programmable thermostat. Finally, I developed and tested a user interface for a thermostat and in-home energy display. This research tested the effects of both energy versus price information and the context of sponsorship on the behavior of subjects. I also surveyed subjects on the usefulness of various displays.

The wireless network succeeded in providing detailed data to enable an intelligent controller and provide feedback to the users. The learning algorithm showed mixed results. The adaptive temperature setpoints saved energy in both annual and summertime simulations. The context in which I introduced the DREAM interface affected behavior, but the type of information displayed did not. The subjects responded that appliance-level feedback and tools that provided choices would be useful in a dynamic tariff environment.

for Mom

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1 Introduction

1.1 Introduction to and statement of the problem

Matching electrical supply to demand, especially during times of high demand, presents a problem found worldwide. In California, peak electricity demand has social, political, economic, and environmental consequences. Typically during hot summer afternoons, Californian electrical utilities must provide 25% more power to provide air conditioning to homes and offices. The power could be imported at a high cost or met by bringing online “peaking” power plants that tend to be older and create more air pollution. The California Public Utility Commission (CPUC)[1] is working with the utilities to create the policy and the technical infrastructure to match wholesale costs of electricity to customers’ bills. But how will customers, especially residential customers unused to this new paradigm, accept this policy and technology? Such a multifaceted problem requires an equally multifaceted solution not provided by technology or policy alone, but a combination of understanding human behavior, the appropriate use of technology, and the careful design of policy to protect individual and collective interests.

The state of California provides a prime example of the complex nature of energy supply and demand mitigated by the built environment, technology, and social and cultural factors. California is the most populous state in the union and ranks second in total energy consumption.[2] However, state government energy policies over the past 30 years (plus a mild climate) contribute to the low per-capita energy consumption of

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[1] Please note that a list of definition of terms and abbreviations may be found on page 12.
[2] The Energy Information Administration website lists the total end use of energy by sector: 40% consumed by the transportation sector, 23% by the industrial sector, 19% by the commercial sector, and 18% by the residential sector (Energy Information Administration (EIA), 2006a).

California, which ranks 48 out of 50 states in this regard. Part of California building code contains several components to reduce energy consumption in buildings. In addition, the state's major utility companies provide many programs to encourage energy efficiency and conservation.

The 2000-2001 electricity crisis that resulted in blackouts affecting millions of customers in California prompted the drive for reducing market volatility and increasing the reliability of the electricity grid.[3] (A megawatt-hour[4] of electricity typically costs $20-$50 wholesale, but during the crisis the price rose to $200-$1000). The price of electricity is especially unpredictable during periods of peak electricity consumption. In addition, the customer currently pays a flat rate for electricity. Since the wholesale cost to the electrical utilities far exceeds this rate during peak periods, the electrical utilities lose money supplying peak power.

Energy policy recently imposed at both the federal and state levels requires electrical utilities to utilize demand response as part of a plan to increase grid reliability and reduce costs. Demand response[5] describes the mechanism of managing electricity load or demand. Electrical utilities can implement a variable price tariff that reflects the actual cost of electricity to the utility, thus matching actual wholesale cost to customers' bills. Another method, direct load control, allows the electrical utility to turn off an

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[3] The electricity grid refers to the interconnected network of electrical generation, transmission, and distribution to customers.

[4] Utility companies typically bill customers in kilowatt-hours (a light bulb that requires 25 watts of power that is turned on for one hour consumes 25 watt-hours, consumes 100 watt-hours if on for four hours, if on for four hours each day for 10 days consumes 1000 watt-hours or 1 kilowatt-hour of energy); however, larger amounts of electricity, such as that purchased by the utility, is typically metered in megawatt-hours, which is one thousand kilowatt-hours.

[5] The U.S. Department of Energy's definition: demand response is a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time.

appliance temporarily, such as an air conditioner compressor or water heater, in order to reduce electrical load when overall demand is high.

A successful state-wide endeavor to include demand response requires three elements: 1) carefully crafted policy and tariff design, 2) technology that enables or facilitates this policy for both the electrical grid and at the customer site, and 3) adoption of both the policy and technology by the customer. The policy development and the deployment of enabling technology in the electrical grid are currently in progress. In 2003, the California Public Utility Commission (CPUC) ordered the three Investor Owned Utilities (IOUs), Pacific Gas & Electric, Southern California Edison, and San Diego Gas & Electric, to provide all electric customers with advanced or smart meters[6] to permit dynamic pricing. These Advanced Meter Infrastructure (AMI) deployments plans are expected to be complete by 2012. Regarding policy development, on July 31, 2008, the CPUC signed a ruling that will make dynamic pricing the default pricing scheme within a few years.

Ensuring customer adoption and providing “the last yard” of enabling technology between the customer and the grid is still under development. Since residential[7] air conditioning constitutes the single largest contributor to peak electrical demand in California (Brown & Koomey, 2002), one proposed technology to enable residential

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[5] An advanced or smart meter refers to an electrical watt-hour meter that can communicate interval (i.e., every 15-60 minutes) electrical use back to the electrical utility.

[7] Overall, the residential sector consumes approximately 30% of the electrical energy in California (35% of peak electrical energy), while the commercial sector consumes 36% (38% of peak electricity), the industrial sector consumes 21% (17% of peak electricity), agriculture consumes 7% (5% of peak) and other consumes 6% (Energy Information Administration (EIA), 2006a). However, during peak periods, residential air conditioning constitutes 15% of the total, followed closely by commercial air conditioning at 14% and commercial lighting and industrial assembly functions each consuming 11% of the total (Brown & Koomey, 2002).

demand response[8] is a Programmable Communicating Thermostat (PCT). A PCT can receive price or emergency signals and change the setpoint—the temperature at which the air conditioning turns on—based on these communications. However, in January 2008, the proposal by the California Energy Commission (CEC) to include PCTs as part of California's energy code failed.

Although the CEC still supports the potential of PCTs, it removed PCTs from the proposed building standards largely because of public comments regarding the control of PCTs by the electrical utilities during emergency events. During normal operation, the PCT would raise the temperature 4 degrees Fahrenheit (4ºF or 2.2ºC) which the resident could then change or override. However, during an emergency event, the resident could not override the setpoint chosen by the electrical utility. Although this control would be utilized in order to prevent blackouts, news articles and blogs across the country denounced the "Big Brother" feel of this feature. Many objected to a device—placed mandatorily in homes—that allowed the utility to control temperatures in one's home, even in the rare case of an emergency.

This incident showcases the "stick or carrot" dilemma of policy, that is, the effectiveness of requirements versus incentives. Currently, the majority of existing residential demand response programs in the U.S. include utility control. A review of these programs across the country shows that the vast majority utilize direct load control of air conditioning systems, whereby electrical utilities can temporarily turn off compressors to reduce load during peak periods (Rosenstock, 2005). However, all of these are voluntary and include a financial incentive. People voluntarily give up control

[8] Arguably the only enabling technology required is price notification and interval meters, but a pilot program indicated an increase in response with communicating thermostats.

when given an incentive, but do not like the perception that control might be taken away from them in their homes. While policy regarding the PCT during emergencies may be rewritten for inclusion in the next energy code, the recent 2008 CPUC ruling has introduced a new paradigm for residential electricity pricing. By 2012, a dynamic pricing tariff will be established as the default without a guarantee of bill reduction for the customer.[9] Incentives as well as marketing the societal benefits and grid reliability promised by demand response will need to play a role in encouraging acceptance of the policy by customers.

A PCT adds greater functionality—the communication of price signals—to a problematic precedent, the existing Programmable Thermostat (PT). The PT has not seen wide adoption beyond code requirement in California, nor have PTs proven to save energy. Recently, the Environmental Protection Agency (EPA) examined the energy-saving benefits of programmable thermostats as part of the review of the EnergyStar[10] specification. After reviewing several studies, the EPA concluded that "the energy savings of programmable thermostats depends on behavior, and the units themselves cause no significant behavior change" (Harris, 2008, ¶3). Thus, the automation features of the programmable thermostat are not realized, which does not bode well for the PCT.

At least one utility, Southern California Edison (SCE), includes providing energy use information (as well as providing a choice of tariffs and smart appliances) as evidence that residential demand response can "empower customer choice" (Oliva, 2008).

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[9] While many customers' bills are expected to decrease under a dynamic pricing scheme, those customers whose loads remain "peaky" (who ostensibly are currently subsidized by those with flatter load shapes) will most likely pay more.
[10] The EnergyStar label is a program of the Environmental Protection Agency that demands certain quality and energy usage standards of various appliances.

Several “dashboard” technologies in the form of in-home energy displays are entering the market in anticipation of providing feedback with smart metering. A review of numerous studies over two decades found that customers reduce energy consumption 4-15% in response to direct feedback from in-home energy consumption displays (L. F. Stein, 2004). A recent study, however, revealed that some customers increased their energy consumption even with these energy displays, suggesting that motivation, not technology, may play a greater role in energy conservation (Parker 2008). In addition, although certainly choice and information are key, little is known about what type of information people need to make decisions regarding their energy consumption in a dynamic tariff environment.

With dynamic pricing, a high electricity price is expected to be the primary motivator [11] to reduce peak consumption, yet price may not be the most effective motivator nor be persistent over time. While the recent California Statewide Pricing Pilot (SPP) showed positive results using price to reduce peak electrical demand, an older variable rate pilot program showed that sometimes even high energy prices were readily accepted by consumers (Lutzenhiser, 1993). Price elasticity has its limits; the SPP showed no significant difference in energy use curtailment between a $0.50 and a $0.68 critical peak price (Herter, 2006). Other means of motivation, such as education, feedback, and social norms, may prove to be more effective than financial incentives alone.

In summary, the CPUC has introduced a new policy on electricity pricing that represents a completely new paradigm for residential customers. A dynamic price tariff

[11] As noted previously, societal benefits (such as environmental issues), improving grid reliability, and financial incentives also play a role in motivating peak energy reduction.

requires some means of dispersing price information to the customer. The initial policy surrounding the PCT suggests that people want to retain control of their household thermostat. Many studies indicate the benefit of feedback on reducing energy use—and interval metering can provide real-time electrical consumption data. However, little is known about what type and how much information to provide to help people make better decisions about their energy consumption when the price of electricity changes based on the time of day. Evidence from studies on PTs indicate that PCTs must improve upon the existing technology of PTs to ensure customer adoption; at minimum, PCTs will require a better user interface and control strategies for different prices. While dynamic pricing better matches the actual cost of electricity, for those residential customers with air conditioning, comfort will become a lot more expensive. Dynamic pricing assumes that the high cost of electricity will reduce demand, yet additional means of motivation may improve the effectiveness as well as increase persistence of behavior.

1.2 Purpose of the study

The purpose of this study is two-fold: 1) design and test control and information technology that facilitates residential demand response in order to improve customer adoption of the technology and responsive behavior, and 2) test the effect of context and type of information as motivators for energy saving behavior. Figure 1 below shows the framework for the study. Residential demand response is influenced by several factors. The built environment includes climate, house construction, and heating, ventilation, and air conditioning (HVAC) systems. As defined by this study, social and cultural factors stem from personal (such as the psychological and physiological issues of thermal comfort, personal control, and motivation), lifestyle and family, to economics, policy, and institutions. The technology appropriate to this study includes control of HVAC equipment and other appliances, user interfaces, intelligence and machine learning, and display of information.

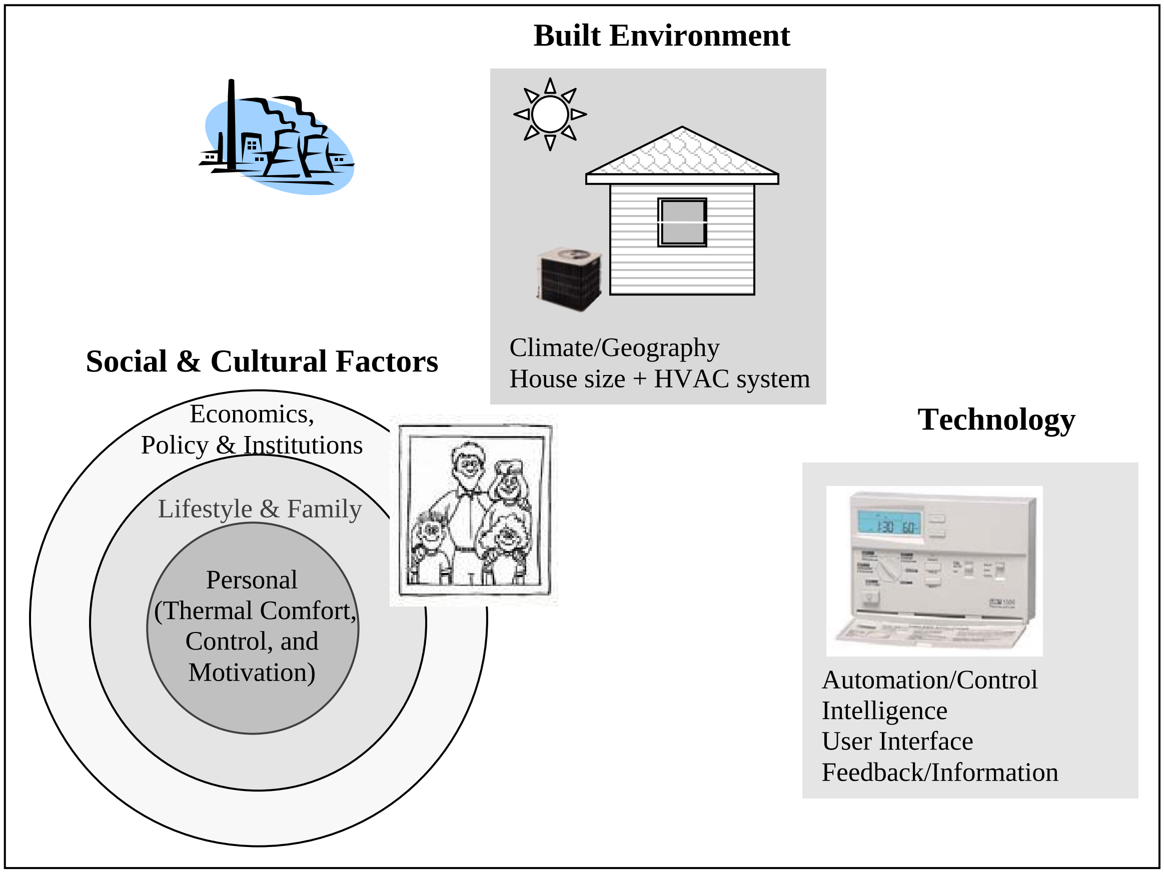

Figure 1: The built environment, social & cultural factors, and technology all affect residential demand response.

A key issue is control: not only who is in control, but the appropriate use of automation and machine-learning balanced with control by humans and human learning. Successful demand response requires behavior change to reduce household energy consumption during peak demand periods. A critical question asks, to what degree can behavior change occur as a result of social factors, such as context and price incentives, compared to and/or in conjunction with technology that provides automatic control and/or energy consumption feedback? Technological devices will not by themselves produce residential demand response without the sanction and participation of the residents.

The next chapter entitled Background covers the history of policy, the character of the housing stock in California, human behavior with regard to thermal comfort and energy, appropriate technologies as precedents, and the interactions among them. Socially-derived policy affects both technology as well as the built environment, personal factors influence thermostat settings and energy consumption, and technology shapes both personal interaction and energy consumption. The Objectives chapter outlines the contribution of this study to present knowledge and describes the goals of the study. The Research Designs chapter describes the six major hypotheses and the research designs to study each.

The Research Methods chapter illustrates the instruments designed to collect and study data. The study covered a broad scope and was multifaceted including vetting wireless technology, finding an appropriate balance of autonomous control and real-time feedback to enable appropriate personal control, and testing a new user interface. One goal was to test the viability of wireless technology as the infrastructure to enable residential demand response; this test included work by a team of undergraduate students, graduate students, and two professors. Another goal was to design and test appropriate control algorithms. While mechanical engineering graduate students Jaehwi Jang and Xue Chen developed algorithms on learning the thermal house parameters (Jang, 2008) and optimizing cost and comfort (Chen, 2008), I developed algorithms for learning occupant temperature preferences and adaptive temperature setpoints. A third goal was the design and testing of a user-friendly and information-appropriate user interface. The initial user interface was designed and tested in a UC Berkeley School of Information Management Systems course with Alex Do, Ken Langford, and Colleen Whitney (Peffer, Do, Whitney, & Langford, 2005). I then implemented the interface in Java computer software, and further developed it. Finally, I tested the context of the interface and different graphic displays in the Haas Business School's Experimental Social Science Laboratory (Xlab) at UC Berkeley. The Results chapter describes and discusses the outcome of these tests.

1.3 Significance of the study

The example of programmable thermostats indicates that technologies are often required by policies that fail to account for people's motivation to accept and use them. This study tests the potential of wireless technology, smart algorithms, and appropriate information display and context as a motivator in facilitating residential demand response. Since wired sensors are cost-prohibitive in existing construction, wireless technology can provide an inexpensive source of information for both controller and user. Understanding people's behavior and information they find useful for demand response can help shape education programs and interface design, as well as develop more sophisticated control strategies. This study concludes by suggesting other areas of research still needed in order to enable residential demand response in the near future.

1.4 Research questions

This study addresses the following research questions:

1) Is wireless technology an appropriate platform to provide information on price and household energy usage to enable demand response for a low installation cost?

2) Can computer learning adequately predict occupant temperature preferences and schedule in order to provide acceptable thermal comfort and eliminate the need for programming by homeowners?

3) Would temperature setpoints based on the Adaptive Comfort Standard save energy compared to the default settings provided by an EnergyStar labeled programmable thermostat?

4) Is energy consumption feedback and demand information as effective in motivating peak energy reduction as cost and price information in a variable electricity tariff environment?

5) Does the (apparent) sponsor of a demand response enabling technology (whether a community-based nonprofit organization or an electrical utility/governmental agency) affect people's behavior regarding peak energy reduction?

6) What type of information, graphics, advice, or tools would people find useful in making decisions about their electrical energy consumption in a dynamic electricity pricing paradigm?

1.5 Scope and limitations

This study had a broad scope and intended to design and test technology that would enable demand response behavior in houses. As such, the material covers a broad range of subjects. The wireless technology tested was not the typical ZigBee[12] or powerline[13] technology found in most home area networks, which both posed minor problems and provided a malleable infrastructure. While wireless technology and touch-

[12] ZigBee is the name of a standard for communication among small low-power digital radios based on IEEE 802.15.4-2006 standard for Wireless Personal Area Networks.
[13] "Powerline" refers to communication via the existing electrical wires in a house.

screen displays are expected to decrease in cost, especially in high volume, the costs at the time of the research were high. Thus, tests relied on simulations and laboratory studies, with three field case studies. To answer the first question required evaluating the reliability and accuracy of wireless data transfer for maximum information with the minimum number of sensors; in this case, a few field tests are sufficient. Machine learning was assessed in analysis, adaptive setpoints were evaluated through simulation. The effect of the type of information displayed and sponsorship was evaluated in a laboratory setting, as was the survey of types of information, advice, and tools to enable demand response. These methods of testing offer initial answers to the research questions and provide a necessary step before extensive field testing.

1.6 Definition of terms

AC, Air Conditioning: typically refers to the cooling of air to provide comfort, but can include the control of humidity as well.

AMI, Advanced Metering Infrastructure: part of the electricity grid that includes advanced or interval electric watt-hour meters that can communicate to the electric utility.

advanced meter: see interval meter.

ASHRAE: American Society of Heating, Refrigerating, and Air-conditioning Engineers. Standards developed by ASHRAE for heating, cooling, and ventilating buildings have been adopted by many jurisdictions in the U.S.

CEC: California Energy Commission

CPUC: California Public Utilities Commission

DR, Demand Response: a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time.

EnergyStar: a program of the Environmental Protection Agency that demands certain quality and energy usage standards of various appliances.

grid: the interconnected network of electrical generation, transmission, and distribution to customers.

HVAC: Heating, Ventilating, and Air-Conditioning

In-Home Energy Display: a device that displays the energy consumption in a house.

IOU: Investor Owned Utility

interval meter: an electrical watt-hour meter that can communicate interval (i.e., every 15-60 minutes) electrical use back to the electrical utility. Also called advanced or smart meter.

kilowatt: a unit of electrical power equivalent to 1000 watts.

kilowatt-hour: a unit of electrical energy equivalent to 1000 watts used for one hour, commonly used by electrical utilities in billing residential customers.

MW, megawatt: a unit of electrical power equivalent to one million watts or 1000 kilowatts.

megawatt-hour: a unit of electrical energy equivalent to one million watts (1000 kilowatts) used for one hour.

mote: a small low-power microprocessor with a radio transceiver and multiple analog or digital input/output channels for sensing and actuation.

MZEST, MultiZone Energy Simulation Tool: a simulation tool built on the California Non-Residential Engine (CNE) found at the heart of many of the simulation tools currently approved for establishing performance compliance with California Title 24 energy code. The tool was modified to run on a five minute time-step.

offset: for the purposes of this study, a temperature offset refers to a change of the thermostat setpoint in response to a change in price or demand.

PCT, Programmable Communicating Thermostat: a device that can control the Heating, Ventilating, and Air Conditioning (HVAC) system of a building. While "communication" can mean that the device communicates with a house network (such as with the security system), for the purpose of this study "communication" refers to receiving price signals from the electrical utility.

PMV, Predicted Mean Vote: a standard developed by Fanger through laboratory studies to indicate thermal comfort given environmental conditions such as air temperature, relative humidity, air speed, and mean radiant temperature.

PT, Programmable Thermostat: a thermostat that can be programmed to automatically setup or setback the temperature setpoint for nighttime or periods when the occupants are away.

PTEM, Physical-Technical-Economic Model: a model to predict energy consumption that includes physical, technical and economic factors.

SCE: Southern California Edison, an investor owned utility company.

SIMS: School of Information Management Systems at UC Berkeley.

setback: to reduce the temperature setpoint for heating especially for nighttime or periods when the occupants are away.

setup: to increase the temperature setpoint for cooling especially for nighttime or periods when the occupants are away.

SPP: Statewide Pricing Pilot in California, a statewide pilot demand response program involving the major electrical utilities.

Temperature Setpoint: the temperature that a heating or cooling system attempts to attain via a thermostatic control system. For example, a heating temperature setpoint of 68ºF would cause the heating system to turn on when the interior air temperature drops below this point; a cooling temperature setpoint of 78ºF would cause the air conditioner to turn on when the air temperature rose above this point.

Title 24: typically refers to California's energy efficiency standards for residential and non-residential buildings, which is part 6 of the Title 24 California Code of Regulations regarding building construction.

Thermal comfort: a state or condition of *mind* "that expresses satisfaction with the thermal environment" (American Society for Heating Refrigerating and Air-Conditioning Engineers (ASHRAE), 2004).

Xlab: The Haas Business School's Experimental Social Science Laboratory at UC Berkeley.

2 Background

The following four sections describe policy, the built environment, human behavior, and technology in regard to energy consumption and demand response.

2.1 History of electricity generation, policy, and institutions

While by no means exhaustive and comprehensive, this section outlines the role of policy, especially regarding energy use in buildings. This background illustrates the evolution of electricity generation, policy, and institutions in California leading to the current focus on demand response.

2.1.1 Role of policy

The resources of our world are not infinite, thus some sort of regulation is necessary to protect the common interests. Ideally, policy and standards should justifiably maximize societal goods and services for the cost of implementation. For example, policies aimed at technology, such as appliance standards, basically remove inefficient models from the market. Any additional cost incurred by changes in design is shared by consumers and is justified by the consumer benefits in lower operational energy costs. Policies that rely on marketing, such as demand-side management, however, face the additional challenge of human behavior, which is not often economically rational (Sanstad & Howarth, 1994). These types of policy present a challenge to traditional cost-benefit analysis.

One role of energy efficient policy is to "bridge the gap" between the public good (i.e. technological and economic potential) and market behavior in adopting energy conservation measures (Wilson & Dowlatabadi, 2007). Measures to reduce transaction costs[14], such as EnergyStar labels on appliances, help consumers include the intrinsic value of energy efficiency into their decision-making. Providing rebates, "feebates", or other incentives can help overcome financial constraints of consumers.

Incentives and other measures are useful in increasing the adoption of energy efficient technology. In 1962, Everett Rogers published a theory to evaluate why some people adopt innovative technology and others do not, and why "seemingly advantageous innovations" take some time to diffuse in a social system (Wikipedia, 2008b, ¶4). Rogers' Adoption/Innovation Curve shown below shows the adoption of technology by different sectors of the population. Rogers defined each sector of the population with a willingness and ability to adopt new technology based on several attributes, such as awareness, interest, evaluation, and trial (Rogers, 2003). Creating a "tipping point" with policy, such as providing rebates for solar systems, can bridge the gap in technology diffusion.

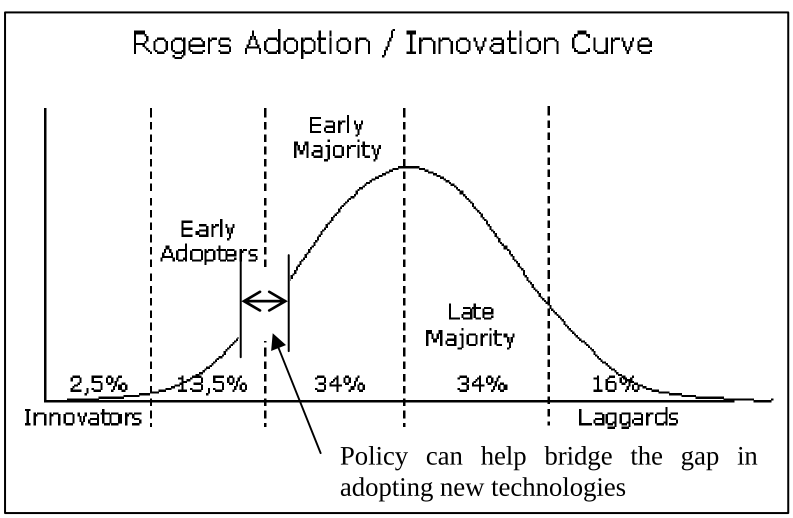

Figure 2: Rogers' technology adoption curve (Rogers, 2006).

[14] A transaction cost—the total time/energy/financial cost of a purchase—refers to not only the price of merchandise, but also the time and energy it takes to make the decision and purchase the product.

An historical view of policy with respect to energy implications in buildings reveals its socially-driven nature, affected primarily by politics and economics. Early standards of ventilation requirements for buildings were based on the smell of the working class and of school children (Cooper, 1998). Recommended levels of heating and lighting have changed dramatically over the past 100 years. Driven by the electric companies, the recommended light level in 1945 was 20 footcandles for regular office work, 100 footcandles in 1971, and then after the energy crisis back down to 50 footcandles in 1992 (B. Stein & Reynolds, 1992).

Standards for indoor temperature have evolved as well. In 1914, the specification for thermal comfort in office buildings was 68ºF (20ºC) dry bulb temperature (at 40% relative humidity); in 1941, 74ºF (23.3ºC); in 1965, 78ºF (25.6ºC); and in 1975, 72ºF (22.2ºC) in winter and 78ºF (25.6ºC) in summer (B. Stein & Reynolds, 1992). For many years, the accepted standard for thermal comfort in the U.S., ASHRAE Standard 55, included a comfort zone prescribed for office buildings: one for summer and one for winter to account for clothing differences (American Society for Heating Refrigerating and Air-Conditioning Engineers (ASHRAE), 2004). (No standard exists for residences.) This standard is primarily based on laboratory and chamber studies from the late 1960s. But recent research conducted in field studies led to the development of the Adaptive Comfort Standard for naturally ventilated buildings, which was recently adopted in the ASHRAE Standard 55-2004 (de Dear & Brager, 1998).

2.1.2 History of electricity generation, policy and institutions

The history of electricity generation spans a little over 100 years and profoundly influenced culture, politics, and the natural environment. Electrical utilities were created at the turn of the century, and by 1930, 7 out of 10 houses in the U.S. had electricity (Hirsh, 1999). The boom economy after World War II saw further increases in power usage as electricity was promised “too cheap to meter”. The supply of coal did not keep up with demand, and utilities started using more oil. The country imported increasing amounts of oil, especially from Middle Eastern nations that belonged to the Organization of Petroleum Exporting Countries (OPEC). Supply did not always keep up with demand. By 1966, the nation was already experiencing blackouts due to air conditioning use in the summer (Cooper, 1998) and customers were asked to curtail use. Severe winters in the early 1970s caused natural gas and fuel oil shortages. In 1973, OPEC imposed a five month embargo against the U.S., in retaliation for military aid given Israel after the Egyptian attack, and after the embargo, raised the price of oil to nearly $12 per barrel (Hirsh, 1999).

The energy crisis marked a pivotal point in both energy use and policy development in the U.S. One important social movement that affected energy use in the early 1970s was the environmental movement. The National Environmental Policy Act in 1970 created the Environmental Protection Agency which enforced laws such as the Clean Air Act and created EnergyStar labels for efficient equipment. Earth Day was celebrated for the first time in 1970. Protests prevented the construction of many nuclear power plants.

Political leadership paved the path for energy saving policies, the effects of which are still seen today. President Carter encouraged energy conservation[15], but also introduced legislation, such as the Public Utility Regulatory Policies Act (PURPA) which encouraged more efficient use of power and opened the electricity generation market to independent power sources. When Jerry Brown became governor of California in 1975, he influenced state energy policy by appointing influential leaders to the California Energy Committee (CEC) and the California Public Utilities Commission (CPUC). In 1978, the first energy efficiency standards for residential and non-residential buildings became part 6 of the Title 24 California Code of Regulations regarding building construction, generally (albeit incorrectly) referred solely as Title 24. The energy code required new building construction in California to comply with certain standards, including building envelope insulation levels, windows, and efficiency standards for lighting, water heating, and space heating and cooling equipment.

The history of Demand Side Management shows social forces at work in reducing energy consumption. Demand Side Management (DSM) describes the influence of the demand-side or customer use of energy to produce the desired changes in the utility's load shape. In the vernacular, DSM is another term for energy efficiency[16], although when first introduced, it included load management (shaving peaks and shifting load) though direct load control[17], such as water heater and air conditioning cycling (Hirsh, 1999). In the late 1970s, regulators at the state level encouraged utilities to promote

[15] Energy conservation refers to reducing energy consumption rather than building new electrical generators and distribution lines. Energy conservation to many still connotes the idea of doing without or suffering, as in wearing a sweater and turning down the thermostat in winter to save energy

[16] Energy efficiency refers to providing the same service with less energy.

[17] Typical direct load control uses a radio-controlled switch directly on the water heater or air conditioner compressor that the electrical utility can use to turn off these devices for a period of time when the electrical demand is high.

energy-efficiency from their customers (Hirsh, 1999). But utilities had little incentive to push conservation, because they lost revenue; moreover, regulators wanted to see effort, but not necessarily results. Early programs were based on little consumer research or cost benefit analysis; the utilities portrayed energy conservation as cutting back and depriving oneself, and saw lukewarm response (Hirsh, 1999).

By the late 1980s, several forces led to high supply: the Diablo Canyon nuclear power plant in central California was initiated and a recession especially in the Pacific Northwest created less demand, which increased the available supply. The regulators again changed the incentives for the investor-owned utilities (IOUs) such as Pacific Gas & Electric (PG&E) and Southern California Edison (SCE), so they could make a profit from energy efficiency. The utilities were rewarded to spend money, but were not held accountable for the programs saving energy (Hirsh, 1999). In 1989, Amory Lovins introduced negawatts [18] and encouraged utilities to provide rebates for efficient appliances (Lovins, 1989). By early 1990s, utilities were spending $2 billion per year on DSM up from zero in the 1970s (Geller & Walmet, 1992).

Several factors led to the energy crisis in California in 2000-2001. In 1996 California passed an energy deregulation law, promoted to increase market competition. The large IOU's sold a large portion of their power generation to private companies, which then sold electricity wholesale to the utilities. The California Independent System Operator (ISO) emerged in 1998 as a not-for-profit public benefit corporation to manage the transmission of electrical power and to operate competitive markets for electrical power (California Independent System Operator, 2007). However, lack of oversight led

[18] For example, a compact fluorescent bulb produces light for 18 watts and replaces a 75 watt incandescent bulb for 57 negawatt savings.

to the manipulation of prices in the electricity market by Enron and others.[19] In addition, deregulation reduced incentive to maintain infrastructure of the electricity grid. By 2000, the capacity margin was less than 10%, whereas before 1990, there was a 15-20% margin (Fleay, 2001). In addition, the transmission network grew by less than 15% between 1988 and 1998; the generating capacity grew by only 0.1% during the dot-com era (roughly 1995-2001) (Electric Power Research Institute (EPRI), 2001).

2.1.3 Current problem in California and plans for demand response

As a result of the crisis, regulators and the CEC took a new look at policy to achieve better grid reliability as well as provide more equitable pricing. In a typical year, California utilities have to come up with 10 gigawatts[20] of extra electrical power for peak summertime use, and usually import 25% of this, but during the 2000-2001 crisis ended up 5 gigawatts short. Figure 3 below illustrates the problem of peak electricity demand: for only about 1% of the hours of the year, California utilities must generate the power equivalent to eight small (500 megawatt (MW)) power plants. The power could be imported at a high cost[21] or met by bringing online "peaking" power plants that tend to be older and create more pollution. Another way of looking at this is that one megawatt of power can serve 1200 California households on average or 600 households at peak (Brown & Koomey, 2002).

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[19] Wikipedia describes "gaming the market" as withholding electricity generation, then simultaneously buying and selling internally generated and imported electricity to create artificial constraints on transmission (Wikipedia, 2009).
[20] One gigawatt is one billion watts or 1000 megawatts of electrical power.
[21] During June 2000, the wholesale price of electricity ranged from $0.064 to $0.925 per kilowatt-hour (Borenstein, Jaske, & Rosenfeld, 2002).

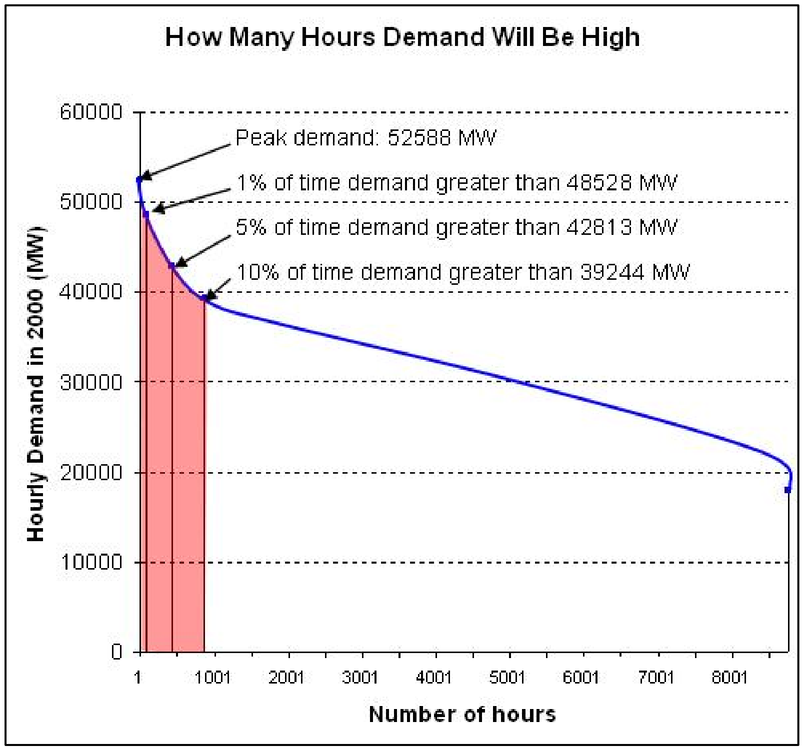

Figure 3: Electricity demand in megawatts (MW) for one year in California (reproduced from Figure II-1-12 from (California Energy Commission (CEC), 2002)).

Whether the wholesale price of electricity is $0.05 or $5 per kilowatt-hour during peak demand periods, currently the customer pays the same rate. According to (Svoboda, 2004), residential electricity billing has not changed much since its inception. The utility company periodically reads a mechanical watt-hour meter at the resident's house. The bill is calculated for most residential customers using an inverted tier rate; a flat rate is charged for the first set number of kilowatt-hours, then a higher rate applies.

New smart or interval meters will provide a means of determining not just *how much* electricity is used, but *when*. The CPUC and CEC created the first Energy Action Plan in 2003, which emphasized demand response as well as energy efficiency in improving grid reliability. The three Investor Owned Utilities (IOUs), Pacific Gas & Electric, Southern California Edison, and San Diego Gas & Electric were required to provide all their electric customers (representing 68% of total consumption) with kilowatt-hour meters that could record electrical usage at set intervals (15 minutes or an hour). Instead of meter readers coming around to each home to physically read and record electrical consumption per month, this data could be transmitted to the utility automatically. This technology would also enable utilities to obtain more information about electrical consumption over the time of day. The plans to install interval meters—the Advanced Meter Infrastructure (AMI) deployment plans—are expected to be complete by 2012.

On July 31, 2008, the CPUC signed a ruling that will make dynamic pricing the default pricing scheme within a few years. With the recent CPUC ruling, the plans—for both policy and technology—are in place to enable residential demand response across the state of California.

2.2 California household energy consumption

Developing residential demand response strategies for California requires understanding the characteristics of the built environment in California. Both load shifting and load shedding are strategies that reduce the electrical energy consumption during hours of peak demand or high price. Load shifting includes precooling or preheating a home before the price increases, or scheduling certain appliances such as water heaters and pool equipment to turn on before or after the high price period. Load shedding includes raising the temperature setpoint so the air conditioner cycles less frequently during the high price period or shutting off certain appliances or dimming lights. Different climates, type of building construction and amount of insulation, and the number and use of electrical appliances all affect the electrical load profile of a residential building. This section describes the diverse climates, building envelope, and electrical loads found in California.

2.2.1 Trends and climate zones

The likely users of demand responsive control systems in California are considered to be those with individual interval meters. Most owned housing units (88%) are single family dwellings, both attached and detached. This represents about two-thirds, or 64% of the 12.2 million housing units (11.5 million occupied) in California (U.S. Census Bureau, 2000).

Air conditioning, both for commercial and residential buildings, accounts for about 30% of peak load (Brown & Koomey, 2002). The current trends in California exacerbate the problem: houses built in California in the past 10 years are 42% larger than the average existing stock and have central air conditioning installed at double the rate of existing dwellings (California Energy Commission (CEC), 2004). While these newer houses are more energy efficient with respect to insulation and HVAC equipment, they still use 20% more air conditioning than older dwellings. This increase in air conditioning use is partly driven by the trend towards population growth in California's hot and dry central valley, and partly due to the current trend in the U.S. towards greater comfort, convenience, and consumption (Chappells & Shove, 2004; Corrigan, 1997).

The CEC projects about 2 million new single family homes will be constructed in California by 2013, which will increase the electrical demand by 25-30% (Lutzenhiser, 1995). This new growth is expected to occur mostly in the interior regions of the state, where the temperatures are warmer during the day and colder at night, and will thus require more energy for space conditioning than the coastal areas.

Insulation requirements and air conditioning needs vary depending upon the climate. California's diverse geography includes a west coast bordered by the Pacific Ocean, coastal hills, desert plains, and mountain region with 14,000 foot peaks. The Title 24 energy code defines 16 climate zones for California (see Figure 4 below).

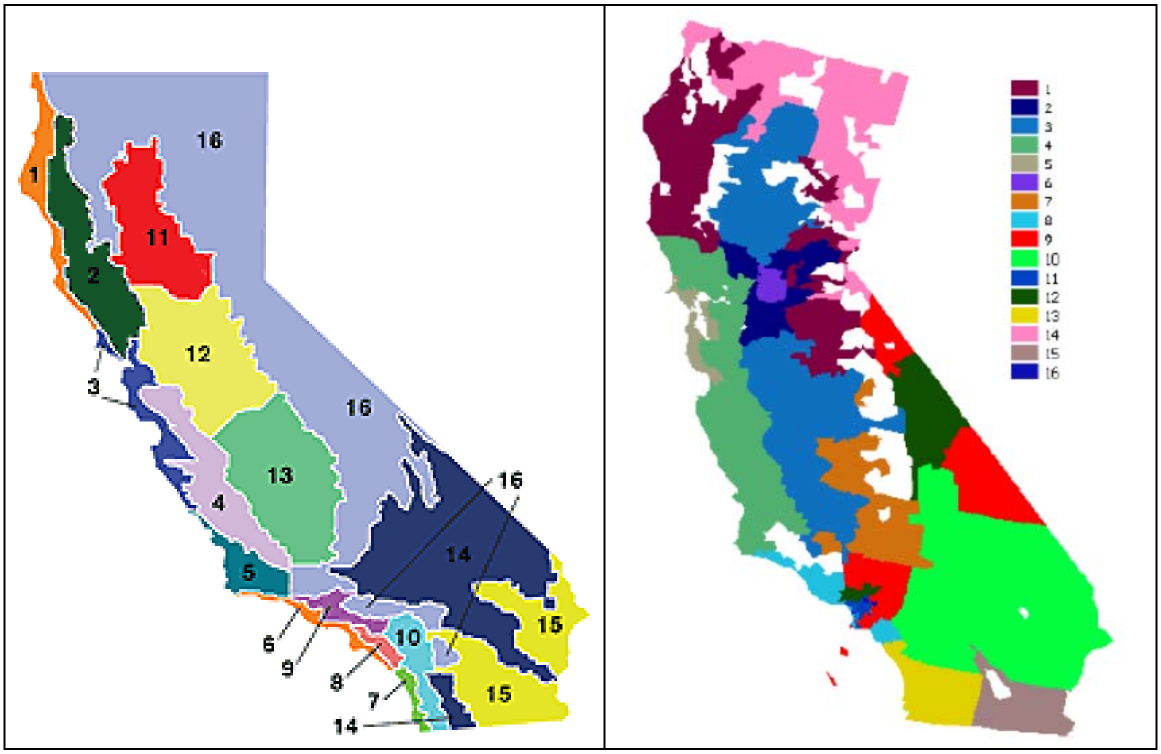

Figure 4: Left: California climate zones used for Title 24 energy code. Right: CEC forecast climate zones.

About half the households in California have air conditioning (56% reported by (CEC, 2004), 49% reported by (Energy Information Administration (EIA), 2001)). Most of the air conditioning units can be found in houses in the Central Valley from Redding (Title 24 zone 11), to Sacramento (Title 24 zone 12), to Fresno/Bakersfield (Title 24 zone 13), and the Imperial Valley (Title 24 zone 15) and Mojave Desert regions (Title 24 zone 14) (CEC, 2004). These correspond to Energy Commission forecast climate zones 2, 3, 7, 10, and 12, which show about 90% saturation of air conditioning.

One method of predicting the cooling needs of a building is using cooling degree days (CDD), a unit related to the average daily outdoor air temperature of a region. For example, to calculate CDD-65 (cooling degree days based on 65ºF (18.3ºC)), the number of degrees a day's average outside temperature is above 65ºF is summed over the course of a year. Table 1 below shows the cooling degree days for different climate zones in California.

CDD by Climate Zone for Years 2002-2004

T24	CEUS	cdd65 2002	cdd65 2003	cdd65 2004	cdd65 Normalized
15	15	4,487	4,538	4,327	4,407
14	14	3,116	3,450	3,193	2,985
13	13	2,363	2,316	2,151	1,945
11	11	2,225	2,004	1,876	1,695
10	102	1,558	1,880	1,533	1,479
9	9	1,152	1,581	1,352	1,249
12	12	1,302	1,384	1,243	1,089
9,16	162	1,255	1,300	949	986
8,10	8	725	1,017	1,103	930
10	101	537	868	800	680
4	4	601	637	622	552
7	7	384	622	890	523
16	161	539	602	402	361
6	6	380	575	651	483
2	2	392	409	444	352
3	32	140	228	162	130
3	31	159	225	232	90
3	33	28	98	84	17
5	5	43	85	99	32
1	1	0	11	3	0

Table 1: Cooling Degree Days in California's climate zones (Table 5 from (KEMA & Tobiasson, 2006)).

2.2.2 Building envelope

For its relatively short history, residential construction in California shows a wide diversity of size, thermal mass, insulation values, and HVAC equipment efficiency, which all contribute to energy consumption. Most house construction is wood-framed on concrete slab-on-grade or over crawl space on a perimeter foundation. The median year that single family homes were built is 1971, and median size is 1800 square feet (U.S. Census Bureau, 2000).

Two-thirds (66%) of the existing occupied housing stock was constructed before the first Title 24 energy standards took place in 1978, and these houses are assumed to have an insulated roof, uninsulated walls over an uninsulated crawl space or slab, single-pane windows, and a gas furnace (0.75 AFUE[22]) (Table R3-7 (CEC, 2001)). Only about 29% of all housing units constructed at this time (before 1975) had central air conditioning and another 17% had room air conditioners or evaporative units (CEC, 2004). The average size of approximately half of these houses is 1100 square feet (sf).

Approximately one fifth of the housing stock (20%) was constructed between 1979 and 1992. These houses have insulated roofs and walls, and a gas furnace (0.78 AFUE) (Table R3-7 (CEC, 2001)). In 1983, the energy standards changed to require double paned windows in houses, so about half of these houses most likely have single-pane windows, and the other half double-pane windows (personal correspondence from Nittler, Lawrence Berkeley National Laboratory). Approximately 60% of these homes have central air conditioning, with about 9% with room air conditioners or evaporative units (CEC, 2004).

About 14% of the housing stock has been constructed from 1992 to 2005. These houses are assumed to have insulated roofs, walls, crawl spaces, double-pane windows and a gas furnace (0.78 AFUE) (Table R3-7 (CEC, 2001)). (Half or more of these houses have slab-on-grade construction; this type of construction increased from 50% in 1992 to

[22] AFUE is the Annual Fuel Utilization Efficiency, a rating of furnace efficiency over a season. Beginning in 1992, the U.S. Department of Energy required all furnaces sold have a minimum AFUE of 78%.

63% in 2005.) About 76% of these homes have air conditioning, with only 1% with room air conditioners or evaporative units (CEC, 2004). The average dwelling size (post-1996)[23] is 2039 square feet with an average of 3.14 residents; 85%[24] of these houses report having Programmable Thermostats (KEMA & Tobiasson, 2006).

Since the age of construction influences the efficiency of HVAC systems, I combined U.S. Census Bureau data and CEC data on air conditioning saturation to create Figure 5 below. Note that nearly half of the houses that currently have central air conditioning were constructed before 1978. A certain percentage of these homes have certainly been renovated (i.e., roof insulation, windows replaced). The 2003 Residential Appliance Saturation Survey (RASS) states that on average one in ten dwellings in California was remodeled in the previous 12 months: 5% of which added HVAC equipment, 10% added square footage, and approximately 25% had heating and/or cooling system maintenance performed (CEC, 2004). While I was unable to determine how many houses with air conditioning are currently poorly insulated, most likely not all of the houses built prior to 1978 have undergone such renovations. Those that have been renovated most likely did not insulate walls, but instead performed easier fixes such as weatherproofing, insulating the roof, and replacing windows.

[23] The average dwelling size of pre-1996 houses is 1434 square feet with 2.93 residents with only 47% with Programmable Thermostats (KEMA & Tobiasson, 2006).

[24] Since all new housing construction since the early 80s in California was required by energy code to have at least a setback thermostat, this number was expected to be 100% instead of 85%. This may represent a lack of knowledge of the survey taker of what he/she actually has in his/her home.

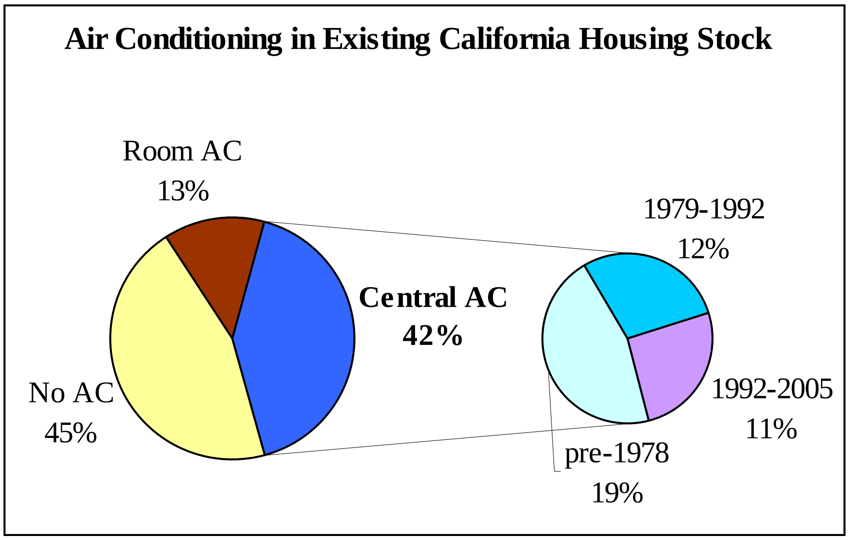

Figure 5: Percent of California houses with air conditioning, showing the year of construction of houses with central air conditioning.

2.2.3 Electrical appliances and load profile

Residences use approximately one-third of the electricity in California. Since most space heating and water heating[25] use gas, most of the residential electrical energy is consumed by lights, refrigeration, air conditioning, and appliances (CEC, 2004).

[25] Only 11% of water heaters in California use electricity, typically in areas where gas is scarce such as northwest California

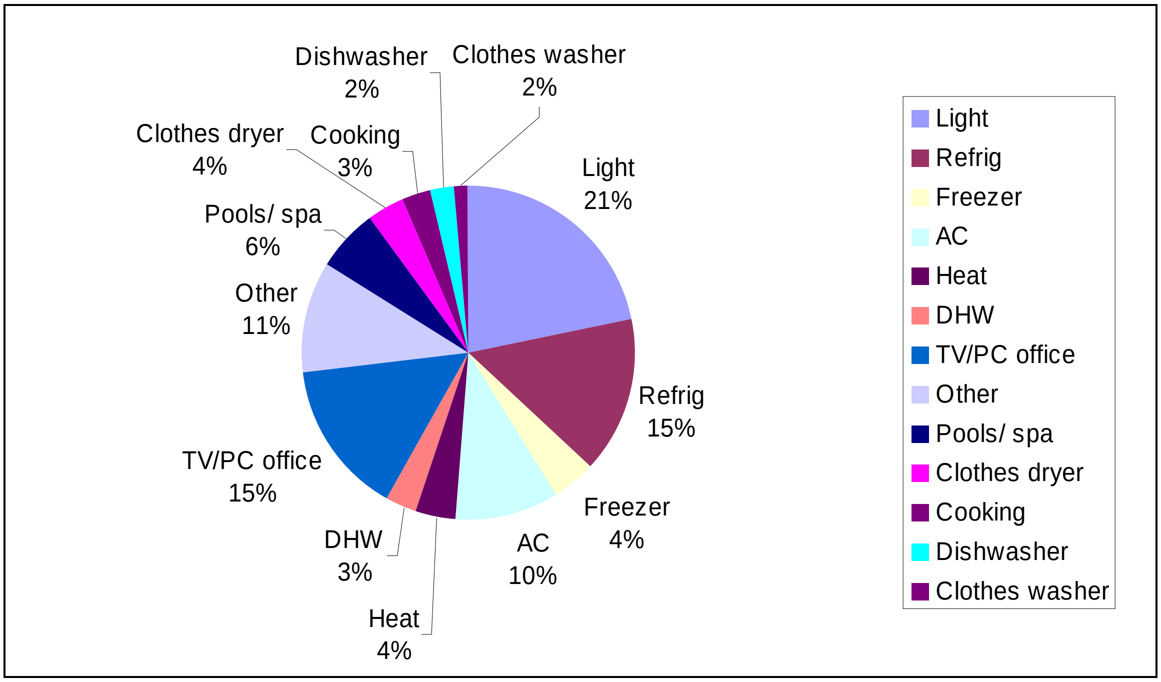

Figure 6: California residential electrical energy end use per household (CEC, 2004).

Of the appliances, the major power consumers are: pool pumps (found in 14% of single family dwellings), second refrigerators (found in 25% of single family homes, and tend to consume more energy than first refrigerators), and electric clothes dryers (found in 34% of single family dwellings) (CEC, 2004). Of the houses that have clothes dryers in California, approximately 47% use electricity instead of gas (Table HC15.9 from (EIA, 2005)).

Since the purpose of demand response is to reduce peak electricity consumption, the peak or coincident loads are more important to demand response than the total annual energy use. Figure 7 shows several appliances listed by their coincident power consumption in gigawatts compared to their annual energy consumption in terawatt-hours. Air conditioning is by far the most prominent peak load, which can possibly be mitigated through people cooling their houses before peak periods to shift the load or by raising the thermostat setpoint so the air conditioner does not cycle as much. The next three highest loads, lighting, refrigeration and miscellaneous, might be reduced through better efficiency. Other loads such as cooking, clothes drying and washing, and dishwashing are more discretionary and might be shifted to off-peak times.

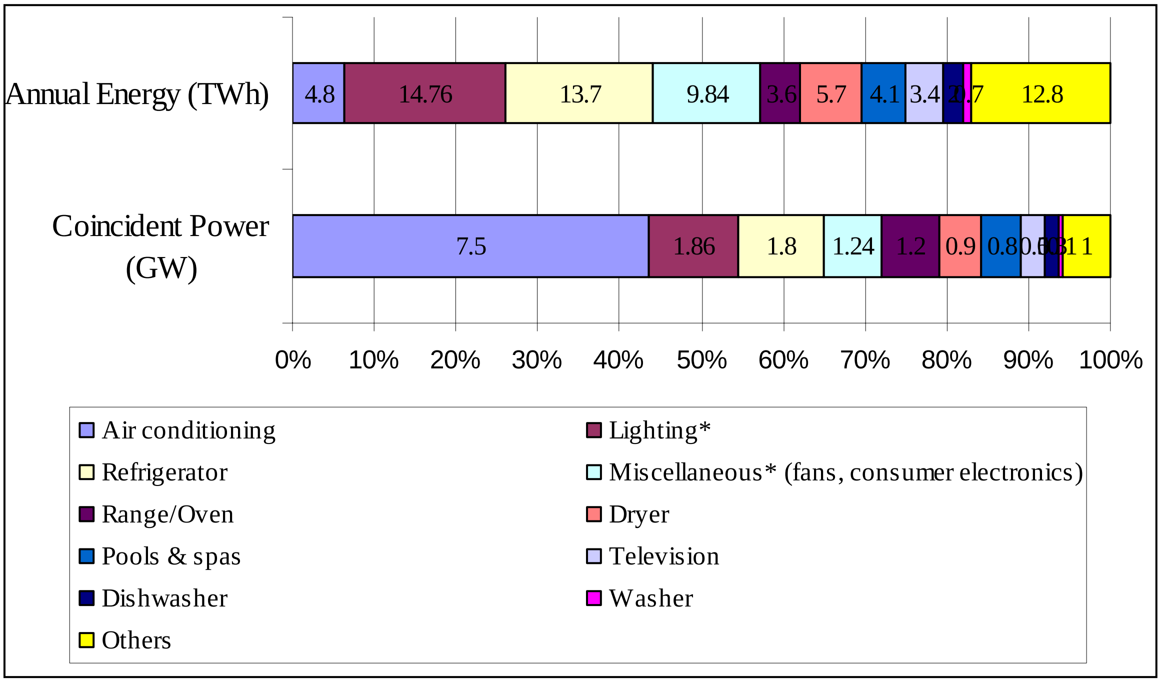

Figure 7: Residential annual energy consumption compared to coincident power (Brown & Koomey, 2002), (CEC, 2004).[26]

This subsection described the influence of climate, building construction, and electrical appliances on residential electrical energy consumption in California. This background sets the stage for the design of demand response strategies whether policy (i.e., efficiency of appliances), program (i.e., aimed at insulating older homes with air conditioning), or technological (i.e., to enable different air conditioning control during

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[26] For purposes of comparison, Lighting was separated from Miscellaneous loads; according to CEC's Residential Appliance Saturation Survey (RASS), lighting is estimated to make up approximately 60% of the miscellaneous load.

high demand periods and/or encourage use of discretionary appliances before or after peak periods).

2.3 Human dimension of energy consumption

This section describes social and cultural factors of energy consumption. First described is the physiology and psychology of thermal comfort, including the discussion of the relatively new adaptive model. Finally, I discuss the influence of behavior on energy consumption.

2.3.1 Thermal comfort

The study of thermal experience and perception spans centuries, but the last 30 years have seen a great interest in the influence of social and behavioral factors. Earlier studies in this century were static, steady-state laboratory studies, mostly focused on the physics and physiology of thermal sensation and comfort. Early models of thermal comfort used such environmental or physical variables as temperature, humidity, and wind speed to generate rational indices of comfort (such as Effective Temperature (ET)).

About 40 years ago, comfort studies consisted primarily of human subjects in the laboratory: Nevins et al at Kansas State University, Gagge et al at the John B Pierce Laboratory at Yale, and Fanger at Danish Technical University. These researchers studied the six variables that contribute to the prediction of comfort: air temperature, radiant temperature, air speed, humidity, and a person's clothing and activity level. Subjective discomfort stemmed from the human physiological response to the physical surrounds (Brager & de Dear, 1998). Fanger quantified the heat balance between the human body (heat gain through metabolic rate, heat loss through skin temperature, and rate of sweat secretion) and the environment. Through laboratory studies he developed a statistical fit of his human body heat balance equation to develop the Predicted Mean Vote (PMV) of comfort for a large group of persons. This was developed into standards and used worldwide.

In the 1970s and 80s as researchers began to conduct detailed comfort studies in the field, they noticed that the results differed from those found in laboratory tests and expressed in the standard. For example, both air speed (drafts) and temperature swings have been found by subjects in the field to be far more tolerable than that found in the laboratory (Arens et al., 1998; Brager, Paliaga, & de Dear, 2004; de Dear & Brager, 1998; Markus & Morris, 1980). Some surmise that laboratory tests raises people's sensitivity and attention to environmental effects compared to actual working conditions.

Researchers also found discrepancies in actual comfort temperatures and the temperature predicted by Fanger's PMV model (Humphreys & Nicol, 1998). Static models of comfort, such as Fanger's PMV and PPD[27] models which seemed to hold true for uniform environments, light clothing and sedentary activity, did not often reflect field conditions. One thrust of research began to look at dynamic, transient, and asymmetric environments.

Much is known about the physiology of thermal sensation.[28] For example, we know that humans have many more cold receptors than warm, and they are closer to the surface of the skin. We know the distribution of sensors throughout the body and that these sensors are more stimulated by change than steady-state environments. The human adapts to thermal environments, more quickly to cooling than warming, and more

[27] PPD is the Predicted Percentage Dissatisfied in Fanger's comfort model
[28] An excellent review of human thermal sensation is (Arens & Zhang, 2006).

strongly to changes in the environment than static conditions. Four parameters influence the magnitude of experiencing thermal sensation: skin temperature, the change in skin temperature, the rate of change of skin temperature, and the size of skin area that experiences temperature change. However, thermal experience and comfort is not correlated with thermal sensation uniformly across the human body; the thermal sensation of individual body parts can predict overall thermal comfort (Zhang, 2003). In transient environments where people traveled from hot to cold or cold to hot chambers, research piloted by de Dear discovered that humans are more sensitive to cold transitions versus warm; the human is a tropical animal, more effectively alarmed by cold than heat (de Dear, Ring, & Fanger, 1993).

Social factors have played a role in the semantic scales used to determine thermal experience. The semantic artefact hypothesis suggests that “the preferred temperature in cold climates may, in fact, be described as ‘slightly warm’, whereas the residents of hot climates may use words like ‘slightly cool’ to describe their preferred thermal state” (de Dear & Brager, 1998, pp.5-6). The neutral temperature describes the temperature at which mean thermal sensation is neutral, determined from measured data or PMV. Yet, de Dear and Brager (1998) found that thermal neutrality did not coincide with thermal preference. Occupants in office studies are often asked their current thermal sensation, thermal acceptability, and thermal preference; however, the term satisfaction is used to refer to thermal comfort. As noted by Brager et al (2004), these terms are rather vague and may not have the same meaning for the subject as the researcher, much less universally among researchers.

2.3.1.1 Adaptive Comfort Standard

In field studies all around the world, people seemed to “accept a much more diverse set of thermal environments than the laboratory-based indices lead us to expect” (Humphreys & Nicol, 1998). For example, Humphreys et al (1998) notes people reporting to be comfortable at 64ºF (17.5ºC) for elderly at home in the winter in the U.K. to 90ºF (32ºC) for office workers in the summer in Iraq. This led to the understanding of thermal comfort as human adaptation, known as the adaptive model of comfort.

This adaptive model includes not only the physics of the environment and physiology of the body, but also cultural expectations, social settings, and conditioning. Humphreys et al (1998) describes circumstances that lead to restrictions placed on adaptive actions: climate (i.e., may affect diurnal patterns and clothing and may determine the range of comfort temperatures), affluence (i.e., may affect services and expectations—rich nations tend to have comfort temperatures different from poor nations), culture (i.e., may affect clothing and behavior), working conditions and social context (i.e., may constrain activity and clothing level), thermal control operated by another, conflicting requirements (i.e., open window and noise), personality, fashion, and gender (i.e., women tend to dress differently from men—for example, exposed legs—which can affect comfort), and finally health. Three categories of adaptation are described by de Dear and Brager (1998) as physiological adaptation, psychological adaptation, and behavioral adjustments.

Physiological adaptation refers to “changes in the physiological responses that result from exposure to thermal environmental factors, and which lead to a gradual diminution in the strain caused by such exposure” (de Dear & Brager, 1998, p.2).

Physiological adaptation can be genetic adaptation over generations or acclimatization within the individual’s lifetime (Ibid.). For example, a person acclimatized to a hot dry climate has an “increased sweating capacity for a given heat load….better distribution of sweat over the skin….reduced heart rate and an increased blood volume and peripheral blood flow compared to their unacclimatized counterpart” (Brager & de Dear, 1998, p.86). Heat acclimatization can occur in as few as four days, or take longer with more sedentary activity (Ibid.).

Psychological adaptation or habituation or expectation “refers to an altered perception of, and reaction to, sensory information due to past experience and expectations” (de Dear & Brager, 1998, p.2). One example is perceived comfort by association: one expects a stone church to be cold inside, just as the heat and humidity of a sauna is wonderful, but the same conditions in the workplace would be intolerable. Heschong describes several examples of the poetics of warmth and coolth (Heschong, 1979). Moving air, mint, and a cold lemonade can all be cooling and refreshing experiences. A hanging lantern can accentuate the sensation of a breeze. An inglenook or hearth can be warm and cozy (Heschong, 1979). Lovins recounts the story of researchers using a climate chamber. They needed a second chamber, and converted a used meat locker for this purpose. Subjects consistently perceived the temperature to be cooler than the first chamber, although the temperatures were the same. Only after the researchers masked the interior with paneling, carpet, and ceiling tile did the difference in perceived temperatures disappear (Lovins, 1992).

Of the three types of adaptation (including behavioral and physiological), psychological is the least studied (de Dear & Brager, 1998). Thermal variability might be introduced into workplaces to increase arousal and to use associations to augment sensations (i.e., smell of mint, sound of water, sight of moving leaves to increase sensation of coolth). Introducing changes in the environment allows for a richer experience. In climate chamber research, Zhang (2003) found that subjects only voted “very comfortable” when transitioning from a somewhat uncomfortably warm or cool situation to a comfortable one.

Behavioral adjustments include conscious or unconscious ways a person might act to achieve comfort. A personal adjustment might involve putting on or removing clothing. An example of a cultural response in hot climates is taking a siesta in the middle of the day or slowing down one’s metabolism to feel cooler (de Dear & Brager, 1998). Humphreys and Nicol add drinking a warm or cold beverage, moving to a warm or cooler location, or going for a swim (Humphreys & Nicol, 1998).

Behavioral adjustments include the use of technology: opening a window or turning on a fan. A recent field study showed that easy access to a swimming pool affected thermostat settings in homes; people tended not to turn down the thermostat if one could cool down by jumping into the pool (Hackett & McBride, 2001). The need for cooling may change depending on the social setting; in study conducted in Davis, California, residents often turned down the thermostat when having guests over (Ibid.).

Currently, two standards that govern indoor thermal comfort conditions consider the adaptive method. ASHRAE Standard 55-2004 has adopted the Adaptive Comfort Standard to guide indoor temperature conditions for naturally ventilated commercial buildings in the U.S. (ASHRAE, 2004). The ACS was developed using data from buildings around the world (de Dear & Brager, 1998). This method uses the mean monthly outdoor temperature to determine indoor temperature settings for 80% and 90% acceptance. Europe has adopted a related standard for indoor environmental quality, entitled EN 15251, Annex A.2 of which addresses buildings in "free-running"[29] mode (Comité Europeén de Normalisation (CEN), 2007). Annex A.2 was developed using the Smart Controls and Thermal Comfort project, which implemented an adaptive algorithm in buildings across Europe (Nicol & Humphreys, 2009a). This method uses a weighted running mean of outdoor temperature and defines three categories of buildings (I for sensitive persons, II for new buildings/renovations, and III for existing buildings) in guiding the range of acceptable temperatures (Ibid.).

2.3.2 Social factors of energy consumption

The field of human behavior regarding energy consumption includes the research from many fields, such as psychology, sociology, anthropology, and economics—including the fairly recent introduction of behavioral economics. The fields of psychology and economics tend to favor an individual model for decision-making compared to sociology which emphasizes the social and technical construction of behavior (Wilson & Dowlatabadi, 2007). The determinants of these decisions are primarily psychological (i.e., attitude, values, personal norms) and contextual (i.e., available choices, economic incentives, social norms, technology, and infrastructures) (Ibid.). This section discusses the variability in residential energy consumption, behavior and attitudes, motivating energy conservation with information and incentives, framing and context, and finally group influences on energy consumption.

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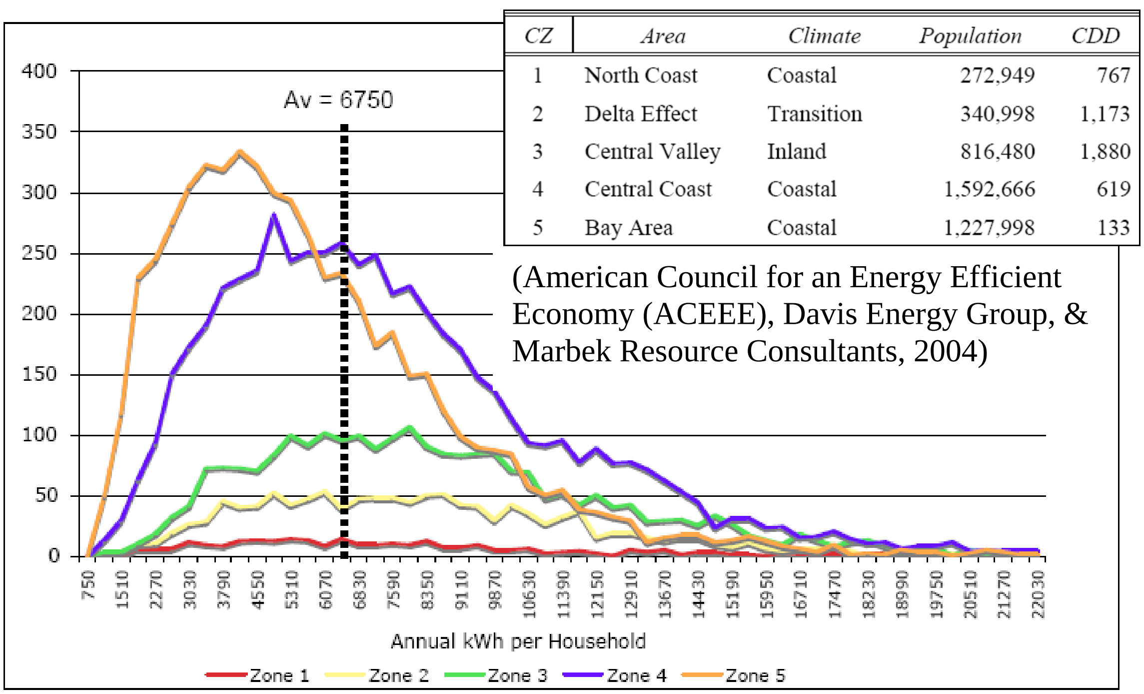
[29] A "free-running" building is not using mechanical cooling or heating to condition the interior space.

2.3.2.1 Variability in consumption

While climate has an impact on energy consumption, the many different climates in California do not account for all of the variation of energy consumption among households. Figure 8 below shows the distributions of annual electricity consumption for households in just five CEC climate zones (see map in Figure 4). Zone 5 represents households in the San Francisco Bay Area; the mild climate (note cooling degree days (CDD) of 133) contributes to a slightly lower than average energy usage. Zone 4, representing the central coast (CDD of 619), has a distribution of annual consumption centered on the average. Note the wide distribution of energy consumption within each climate zone, from 1000 kilowatt-hours to over 20,000 kilowatt-hours annual electricity usage. The long tails are significant: in California, one quarter of the households consume nearly one half of the electrical energy (Lutzenhiser & Lutzenhiser, 2006).



CZ	*Area*	*Climate*	*Population*	*CDD*
1	North Coast	Coastal	272,949	767
2	Delta Effect	Transition	340,998	1,173
3	Central Valley	Inland	816,480	1,880
4	Central Coast	Coastal	1,592,666	619
5	Bay Area	Coastal	1,227,998	133

Figure 8: Distributions of annual electricity consumption in households in five CEC forecast climate zones (Lutzenhiser & Bender, 2008).

Physical parameters, such as house size and age, factor into this wide variability, but is now thought to contribute less than social parameters. A recent study found that of the contributors to the variation in energy consumption in California households, 39% were social variables, building characteristics explained 9%, and the environment attributed 17%; the rest (39%) was the result of the joint effect of all three (Lutzenhiser & Bender, 2008).

Research over the past 20 years has found some important social indicators of this variability in energy usage. Studies with identical units with similar household composition report a 200-300% variation in energy use (Lutzenhiser, 1993). One recent study included “income, education, family size, number of people living in the home, number of hours that a home is occupied, size and type of dwelling, and stage of lifecycle (e.g., young singles, young families, families with teenagers, empty-nesters, and retired households)” as influential in energy usage (Lutzenhiser & Lutzenhiser, 2006, p.167). This wide spectrum of energy consumption stems from variability at the end-use of appliances as well as energy use patterns, both in average consumption and in daily load shapes. Figure 9 below shows load shapes from 70 houses in the Sacramento, California area on a hot day. While the early morning hours show a fairly tight range (from 200 watts to 5000 watts of power), usage during the peak period ranges from 200 to nearly 18,000 watts.

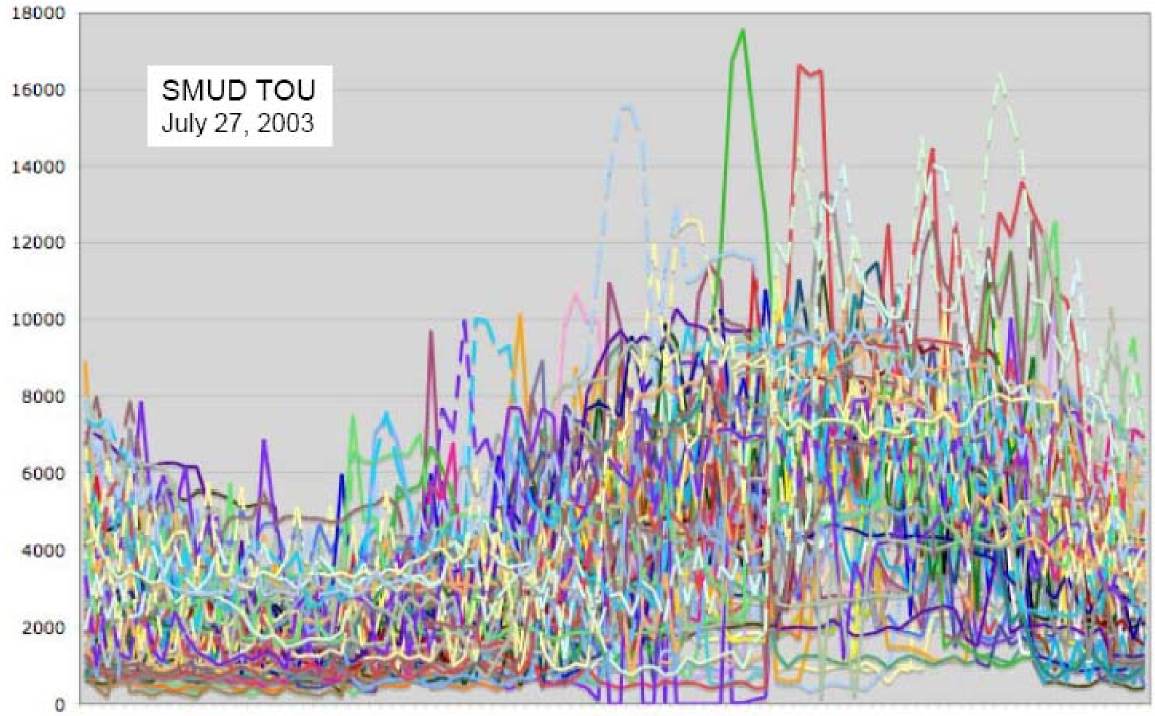


Figure 9: 24-hour load shapes from 70 households (Lutzenhiser, 2008).

Currently this variability is not widely understood. Certainly there are trends such as increased air conditioning systems in homes, a greater number and wider range of appliances, and increased hot water use per capita. The "miscellaneous" sector of residential energy consumption, which includes consumer electronics, is currently the fastest growing sector. More research is needed to uncover lifestyle choices and values that affect household energy use in order to effectively target energy efficient policy and programs, especially regarding demand response.

2.3.2.2 Behavior and attitudes

Why some people choose energy saving technology and behaviors and others do not is the subject of much debate. Some common reasons listed are: "lack of relevant information on available technologies, limited access to capital, misaligned incentives [i.e., landlords paying for energy-efficient measures and tenants reaping the benefits], imperfect markets for energy efficiency, and organizational barriers" (Wilson & Dowlatabadi, 2007, p.172). With respect to human behavior, factors include "(*a*) aversion to risk, uncertainty, and irreversibility; (*b*) use of high short-term discount rates[30]; (*c*) heterogeneity of preferences within a population; (*d*) transaction costs of searching for and processing information; (*e*) sensitivity to changes in the attributes of energy services; and (*f*) the relative unimportance of energy costs as a proportion of total expenditure" (Ibid.).

The relationship between attitudes and behavior is the subject of much research, but is not conclusive. Technology diffusion theory focuses on the attitude formed around innovations through social communication (Wilson & Dowlatabadi, 2007). However, technologies and behavior are not always adopted based on favorable attitude: people may profess concern about the environment, but are not willing to make sacrifices if it concerns their health or comfort (Bell, Greene, Fisher, & Baum, 1996). Environmental psychologist Nickerson asserts that addressing behavioral change rather than attitude change is more cost-effective (Nickerson, 2002). However, Gardner and Stern report that education as a means of attitude change is effective. Focus on changes in upstream behavior (such as encouraging the adoption of energy efficiency measures) is more effective than changes in downstream behavior (such as limiting or curtailing energy use) (Gardner & Stern, 2002). Since studies seeking a relationship between attitude and behavior have had varied results, Lutzenhiser suggests a multi-dimensional research

[30] "Discount rates measure an individual's willingness to exchange present consumption for future consumption, for example, by spending more up front on an appliance with lower operating (energy) costs" (Wilson & Dowlatabadi, 2007).

approach including beliefs, events, institutions, and other variables such as income, education, family size, and so on to tease out potential correlations to conservation behavior. Some research looks at values rather than attitude as determinants of behavior: conservers have a sense of obligation and an ideology of conservation; nonconservers value comfort as more important than conservation (Lutzenhiser, 1993).

Public opinion polls are a typical source of attitudes and beliefs. In 1977, according to a Gallup poll, 51% of Americans felt that the energy crisis was only fairly or not at all serious, and preferred to believe in a conspiracy theory that greedy oil companies were withholding supply (Hirsh, 1999). Lutzenhiser reports that 84% people in 1991 believed that energy was a serious problem. Currently, polls show good public support for renewables and energy efficiency, with evidence that growing environmentalism is linked to an interest in energy.

2.3.2.3 Motivation, information, and incentives

Another major topic is what motivates people to conserve energy. Nickerson discusses intrinsic motivation (behavior valued in and of itself) versus extrinsic motivation (behavior resulting from incentives). He cautions that strong incentives may undermine intrinsic motivation, which he deems as more effective than extrinsic motivation (Nickerson, 2002). A recent survey of energy conservation listed motivations given by residents: to do the right thing, set good examples for their children, and have comfortable homes—both altruistic and egoistic motives (McMakin, Malone, & Lundgren, 2002).

In designing research experiments as well as conservation programs, understanding what consumers know and what governs their choices is vital. When answering surveys, people cannot accurately estimate the duration or amount of energy used and in general don't know the size of their house, degree of insulation, or fuels used, yet this information is commonly used and thought to be accurate (Lutzenhiser, 1993). Unconscious habits such as turning on lights or opening the refrigerator play a large role in everyday energy use; asking people to keep diaries is more accurate than asking them to list normal behavior (Ibid.). Samples of people undertaking energy conservation measures show a lack of knowledge of the economic advantage or savings, but rather "conservation measures were chosen on the basis of visibility to neighbors and visitors" and sometimes the least effective measures were chosen (Lutzenhiser, 1993, p. 260). Lights, for example, are the most visible elements of energy use, and are often thought to consume the most energy in a home. Kempton and Krabacher (1987) found a number of people reporting lower than actual temperature settings even when they knew the temperature setpoint was recorded. In a study of air conditioner use in an apartment building, Lutzenhiser (1992) noted the effect of cultural and ethnic background, including unfamiliarity with air conditioning and different climate expectation, on conservation behavior among the tenants.

Luzenhiser describes the effectiveness of information and incentives on residential customer behavior. Consumer energy use guide labels on appliances have been around since 1970s, but it is unclear whether they are effective. Labels used in public settings asking people to turn off lights are largely ignored; however, media campaigns and utility efforts to reduce thermostat settings are effective (Lutzenhiser, 1993).

Other factors in conservation behavior include types of metering. Lutzenhiser concluded that “consumer response to price is both highly variable and dependent upon the social structuring of economic choices” (Lutzenhiser, 1993, p. 256). With no feedback, for example, apartment dwellers who pay utilities as part of the rent consume about 35% more energy than individual metered sites (Ibid.).

Direct information given before the subject action (antecedent strategy) is not as effective as feedback information (consequent strategy) (Bell et al., 1996). Even more effective is when feedback is delivered not as written information, but “humanized” info provided by video image, role model, or personal contact. Coltrane et al (as reported in (Lutzenhiser, 1993, p. 253)) suggests that for energy conservation program design, both “providing vivid and personalized information to consumers” and having a “socially significant conservation role model” is important.

Energy consumption feedback has received a great deal of attention in recent years. Darby reviewed the effectiveness of three types of feedback on energy consumption: direct feedback in the home, indirect feedback by way of electric bills, and “inadvertent” feedback (“a by-product of technical, household, or social changes”) (Darby, 2000, p.1). The best results indicate direct feedback aided with some form of advice is effective. Wood et al have shown that direct feedback via smart meters and displays can reduce energy consumption in cooking appliances 15% compared to 3% savings with information only (G. Wood & Newborough, 2003). Egan et al reports that while some innovative billing information studies have achieved savings up to 13%, other studies have shown little or no savings due to a lack of understanding of what the consumer wants to see and can understand easily (Egan, Kempton, Eide, Lord, & Payne, 1996). In Allen and Janda's review of feedback studies, they assert that the primary benefit of real-time feedback is affecting awareness (Allen & Janda, 2006).

The use of commitment, modeling, and prompts has been successfully implemented as an antecedent to encourage residential energy conservation (Bell et al., 1996). Withdrawal of feedback and incentive can result in return of energy use to previous levels, but sometimes information-only conservation persists (Lutzenhiser, 1993). Social psychologist Cialdini (1993) postulates that humans have an unconscious desire to appear consistent with previous behavior and to commitments. In one experiment, Iowa residents were promised that their names would appear in the paper if they conserved energy. When the offer was later rescinded, the residents continued to conserve even more energy than before.

Financial incentives have shown mixed results; consumer behavior is not always driven by price. On the one hand, a greater number of retrofits are achieved with direct grants and rebates than loans (Lutzenhiser, 1993). But on the other hand, in a pilot program using time of day rates to discourage energy use during peak periods, sometimes even high changes in energy price were readily accepted by consumers (Ibid.). Time-differentiated rate pilot programs in California and Wisconsin showed that residents reduced peak consumption primarily by shifting load and liked the rates (Lutzenhiser, 1993; Momentum Market Intelligence, 2003). Once familiar with the rate structure, an attitude study showed that people felt a social obligation to continue shifting load away from peak (Lutzenhiser, 1993). This corroborates Cialdini's principle of commitment (Cialdini, 1993) and explains how education and behavior changes can affect attitude.

2.3.2.4 Context and framing

In the energy conservation literature are a few examples of how context can affect the adoption of energy conserving measures. A trusted and credible promoter of the desired measure elicits the best results (McClelland & Canter, 1981). Trust in electrical utilities has historically been low. Many people have an inherent distrust of certain social institutions and think that business and industry priorities and government decisions run counter to energy efficiency (Lutzenhiser, 1993). In one study, a letter soliciting a energy conservation program used three different letterheads; the one that did not list affiliation with the utility received a significantly better response (Miller & Ford, 1985). In examining conservation programs, the use of community-based, nonprofit contractors was effective (Cialdini, 2005; Lutzenhiser, 1993; Stern, Aronson, Darley, Hill, & Hirst, 1986). Recently, the rejection of proposed Title 24 code requiring a PCT provides another example; a brief survey of online news commentary shows that many believed the utility company would have full control over one's thermostat and objected to the code based on this misinformation.

Framing decisions can affect the outcome. One principle of persuasion Cialdini mentions is the scarcity principle: people are often more motivated by the thought of losing something rather than gaining something. Cialdini reports that "homeowners told how much money they could lose from inadequate insulation are more likely to insulate their home than those told how much money they could save" (Cialdini, 1993). The scarcity principle may explain the negative connotation of energy "conservation" from the 1970s. Lutzenhiser states, "energy prices increases and regulations adopted during the 1970s did not, in fact, induce conservation in all households, and some observers even suggested that appeals for efficiency might have had the perverse effect of increasing the desire for consumption and stiffening opposition to conservation" (Lutzenhiser, 1993, p. 252). While energy conservation became popular among some, it was considered counterculture by many. Americans in general adapted to the higher prices of gasoline, and continued the same pattern of consumption (Hirsh, 1999).

2.3.2.5 Group effects rather than individual

Lutzenhiser suggests "adequate models of energy and behavior must be more directly concerned with the social contexts of individual action" (Lutzenhiser, 1993, p. 262). Existing models of the behavioral, cognitive and social processes involved in energy conservation, such as attitude change, economic rationality, social networks, and technological diffusion in and of themselves are overly simplistic.

More complex models include the study of families and group effects. For example, the transmission of energy attitudes and values to children is strongly correlated with the mother in case of ecological and social responsibility (Cramer et al., 1985; Lutzenhiser, 1993). Lower income families cut back when faced with higher energy bills while higher income families maintained consumption but also invested in building or appliance energy efficiency measures (Cramer et al., 1985; Lutzenhiser, 1993). Cialdini (1993) has reported the importance of social proof in human decision making: people tend to imitate other's behavior. Thus, role modeling through social networks in "instrumental in expanding the basis of support for new technologies" (Lutzenhiser, 1993, p. 264). For example, Rogers' diffusion of innovation model provided a good model for the spread of solar energy technology (Lutzenhiser, 1993; Rogers, 2006).

Comparing one's consumption with that of the neighborhood is effective to reduce energy consumption (Lutzenhiser, 1993) and customers appreciate the feedback (Egan et al., 1996). A study with California residents demonstrated that seeing the comparison of one's energy consumption with one's neighbors was effective in reducing consumption (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). One study showed that the effect of peers is more effective than incentives such as saving money, conserving resources, or being socially conscious (Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008).

Although between-household energy consumption is highly variable, studies show that within-household behavior and end-use energy consumption is highly patterned. Bernard et al describes three types of household energy use: structural consumption when building is unoccupied, habitual from routine conscious and unconscious behavior, and daily variation consumption from events like holidays, vacations, sick child, visitor; the non-routine events showed a significant impact on overall consumption (Bernard, McBride, Desmond, & Collings, 1988).

Although thermostat control shows seasonal variation (winter is predictable, but fall and spring more erratic) (Kempton & Krabacher, 1987), Lutz et al reported that half of those people who control their heating system manually produce load shapes that are so regular that they are indistinguishable from those produced by automatic operation (Lutz & Wilcox, 1990). Weihl & Gladhart proposed six distinct patterns of thermostat control: night setback, flat, erratic, morning setup, day setback, dual setback and found that once a pattern is set, it remains remarkably stable (Weihl & Gladhart, 1990). This suggests that learning algorithms might effectively learn occupancy preferences for thermostat settings, which may alleviate some of the problems with the complexity of programming.

Defining lifestyle choices may be a way of effectively targeting conservation programs. Marketing researchers have identified five consumption styles in predicting purchases: concern with appearance, avoidance of hassles, concern for safety, resistance to electric company control, and high-tech orientation (Lutzenhiser, 1993). In the 1980s, the Electric Power Research Institute (EPRI) proposed five basic consumer types: comfort seekers, strivers, indifferent consumers, control seekers, nonconformists in 1980s; later this changed to lifestyle groups: pleasure seekers, appearance conscious, lifestyle simplifiers, conservers, hassle avoiders, value seekers (Ibid.). Still other consumer types include: warmth seekers, self-doubters, entertainers, budgeters, survivors, emulator, nature oriented, religious, convivial, fashionable, entrepreneurial, homebodies, muppies (mature urban professional)-empty nest, and muppies-full nest (Ibid.).

Lifestyle analysis has been successfully used to correlate socioeconomics and demographics with energy consumption (Wilson & Dowlatabadi, 2007). Developing “energy communities” in California (by combining climate, income, house size and age, ethnicity, renter versus owner, heat with electricity, non college educated adults, work at home, children at home) has elicited some corollaries to energy consumption as well (Hanson & Bernstein, 2007).

Several electrical utilities are using psychographic segmentation to improve programs. BC Hydro, for example, recently surveyed over 4000 residential customers and combined energy consumption with attitude and self-reported behavior to arrive at the following six segments: Tuned-Out and Carefree (highest consumption), Stumbling

Proponents, Comfort Seekers, Entrenched Libertarians, Cost-Conscious Practitioners, and Devoted Conservationists (Pedersen, 2008). In a recent presentation, Southern California Edison revealed three persona-based plans to engage customers: an Easy Savings program targeted to Proactive Savers, Conservers and Uncertain Savers; an Empowerment message for Proactive Savers and Conservers Set In Their Ways; and an Environmental message for Conservationists (Southern California Edison, 2008). The Sacramento Municipal Utility District also has plans for psychographic segmentation to "Develop products/services that are most appropriate for different segments, understand how best to reach customers in each segment, and tailor appropriate messaging to customers" (V. Wood & Furlong, 2008).

Other macro-social dimensions include the potential role of intermediaries between consumer and manufacturer: builders, code officials, heating contractors, automobile dealers, utility company representative, architects, and appliance salesmen. Currently, these intermediaries have no incentive to encourage energy efficiency, in fact, are discouraged due to desire to avoid problems and reduce risk (Lutzenhiser, 1993). Blumstein et al (Blumstein, Krieg, Schipper, & York, 1980) and others have looked at social and institutional barriers to energy efficiency including technology adoption by builders, appliance selection by contractor and architect, conservation motivation of multifamily property owners, and the builder-installer barrier to non-compressor air conditioning (Lutzenhiser, 1993).

Residential energy consumption presents a complex subject due to its extreme variability. Yet, understanding the human factor in energy consumption is vital towards developing engaging and effective technologies and policies towards reducing consumption. Figure 10 below captures the many elements thought to factor into desired behaviors and decision-making, including psychological elements such as attitudes and values as well as contextual elements such as income and social norms.

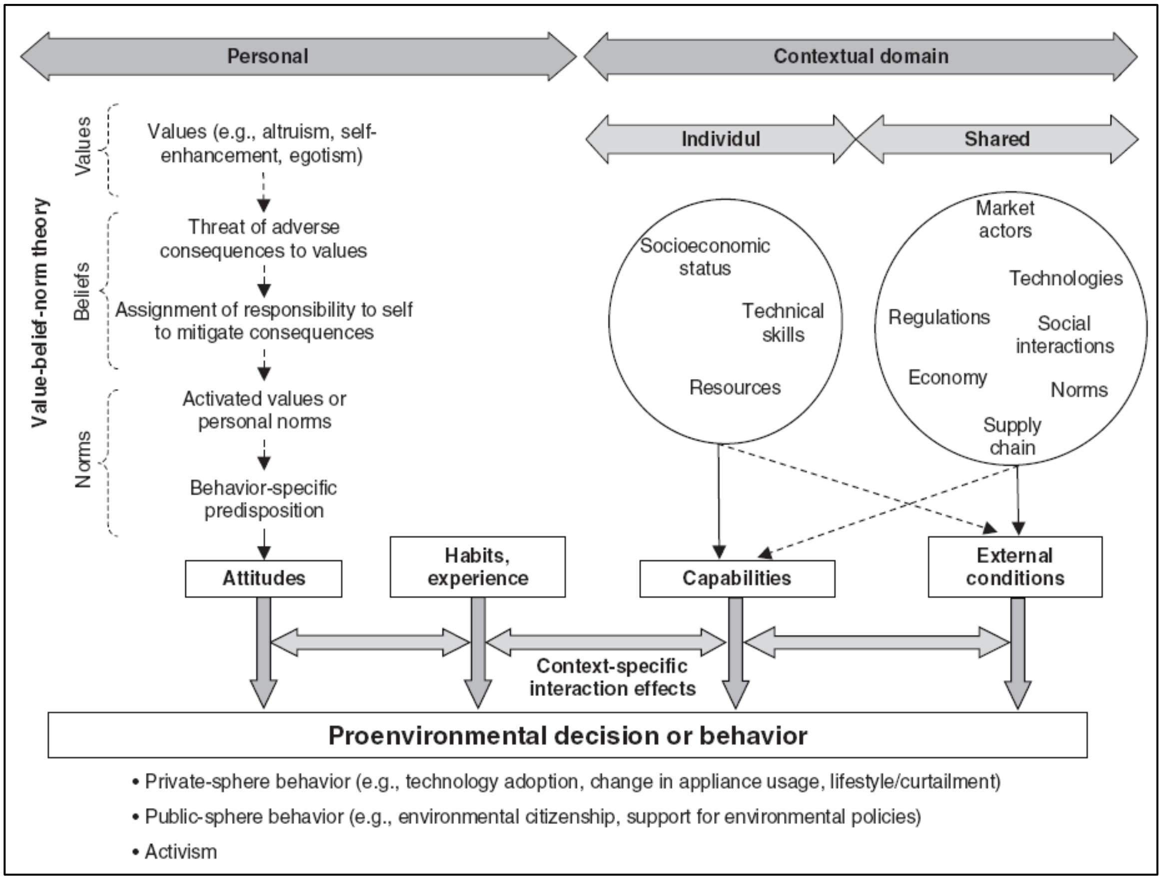


Figure 10: An integrated model of behavior (Wilson & Dowlatabadi, 2007).

2.4 Technology

This section describes control design (through the example of an air conditioner controller) and artificial intelligence or machine-learning. The section also includes a brief description of thermostat history and current trends in thermostats and in-home energy displays.

2.4.1 Control design

Many types of control systems exist, from simple actuators to feedback control, whether linear or proportional, and "fuzzy logic" as a means of controlling continuously varying systems. This section will focus on simple feedback control, through the example of an air conditioner controller. Basic control design includes a desired output or goal, a reference, measurements, feedback, and a means of manipulating the system to achieve the desired goal given the feedback (Figure 11 below). "Control" can include sequencing, operator interface, safety, diagnostics, and signal processing (Auslander, Ridgely, & Ringgenberg, 2002). An air conditioner controller will provide the framework for discussing the measurements, safety, hierarchical structure of control code, and task and state diagrams.

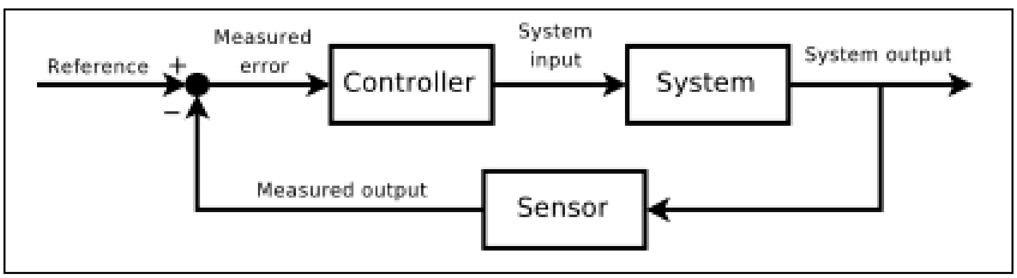


Figure 11: Feedback control of a system with dynamic behavior (Wikipedia, 2008a).

2.4.1.1 Brief history of air conditioners

When the term "air conditioning" was first coined in the early 1900s, the term referred to the control of humidity by conditioning or changing the air (as opposed to water conditioning) for textile mills (Cooper, 1998). In everyday vernacular, however, air conditioning or AC is associated with the cooling of air; most residential air conditioning units do not sense or control for humidity. (However, the process of air conditioning does dry the air.) While there are several types of air conditioning units in residences, the majority use refrigerant-based compressor cooling, although “swamp” or evaporative cooling via direct humidification of the air saw popularity briefly in desert climates. The first widespread introduction of AC in dwellings came in the form of window or wall appliances for room air conditioning in the 1950s (Cooper, 1998).

The majority of systems installed today in single family homes are central air conditioning systems, which have a main AC unit that distributes cool air to most rooms in the house via ducts, often shared with a forced air heating system. In California, typically these are “split” systems. The evaporator coils and expansion valve are located inside the house, often sharing the air handling unit with the furnace to distribute conditioned air throughout the house via ducts. The condensing unit, with condenser coils, fan, and compressor, sits outside to keep the hot air and noise outside the building (Brain, 2000). Single packaged systems are also often used; more rarely are heat pump systems installed. As the trend towards finer grained control grows, we may see the prevalence of new technologies such as mini split ductless (water) systems, with multiple indoor evaporators panels tied to a single outdoor unit, allowing for multi-zone cooling.

2.4.1.2 Components of air conditioning control

The controlled components of a typical residential refrigerant-based compressor cooling system are the compressor and the fans, which can be coordinated for increased energy efficiency. The operator interface (thermostat) allows input via two switches (COOL-OFF for the air conditioner and AUTO-ON for the Fan) as well as schedule and temperature setpoint input, temporary override, and permanent override called HOLD mode. When the system is in COOL mode, the control input is a feedback signal from the interior temperature sensor to cool down to a temperature setpoint. The system has hysteresis, meaning that in order to maintain a desired temperature of, say 78ºF (25.6ºC), the signal might turn on the compressor at 79ºF (26.1ºC) and off at 77ºF (25ºC). The system in ON mode represents a call to turn on the blower fan continuously in the house; AUTO mode means that the fan is controlled along with the air compressor. In addition, most air conditioner manufacturers suggest a minimum off period for the compressor after it has been running. Thus, the control input to the compressor is a call for cooling mitigated by whether it has been running in the previous 5 minutes. The control input to the fan is whether the compressor is on or an independent call to turn on from the user.

The simplest system measures indoor temperature, time, and the state of the compressor. Many other measurements could be added to improve system performance and energy efficiency: outside temperature, failure detection of airflow through air filter (to alert user to replace when needed), at return and supply grilles and outside compressor unit (to ensure no blockage), level of condensate water (so it drains properly and does not cause leaks), failure detection of compressor, and pressure in refrigerant (to ensure proper function and maintenance).

Additional components may be added to increase the energy efficiency of these units to comply with the new SEER (Seasonal Energy Efficiency Ratio) of 13 set by the U.S. Department of Energy in late January 2006. To achieve a high SEER, air conditioners may have a number of components: large coils for better heat transfer, variable speed blower and fan motors to reduce electrical consumption, two compressors for a multistage system, fan delay relay, and an indicator for filter replacement (Vandervort, 2006). The proper changing of the refrigerant can also significantly improve air conditioner performance (CEC, 2005). Heat recovery systems may also reduce energy consumption.

Some safety issues are covered by code, such as fire and electrical codes that require a separate electrical breaker or disconnect for the air conditioner and the proper sizing and insulation of wires. Other safety issues are listed in the installation and owner's manual for the device, such as ensuring free air flow, replacing filters, and the catchment and disposal of condensate water. A few safety issues can be addressed by the control code such as checking the cycle time of the compressor and having a safety switch on the panel of the equipment so that it turns off power when unit is opened up (similar to a door on a washing machine).

2.4.1.3 Objective of control system

The objective of the following control system is to provide a means of turning on and off the air conditioner and the fan as well as providing a means of having the air conditioner turn on when the indoor air temperature rises above a scheduled setpoint. One objective of the control system is simply to turn the system on or off. A second objective is to provide feedback control through a temperature setpoint and measurement of current temperature according to a daily and weekly schedule provided by the user. Another objective is to turn the fan in the house on by itself. Many other control issues are worthy of discussion but are not addressed here. Cool anticipation (eliminating overshoot) exists in a few air conditioning control systems but is not addressed. Pre-comfort recovery (turning on air conditioning before the scheduled time in order to achieve the setpoint at the scheduled time) is not universally liked by occupants and is not discussed (personal communication, Mark Martinez, SCE). More complex functions such as filter notification, heat recovery, multi-zoning, and coordinating with a whole house fan, dehumidifier or humidifier, two stage compressors, or variable speed fans are also not addressed.

2.4.1.4 Task and state diagrams

In programming digital thermostatic control, clearly outlining their sequences in task and state transition diagrams can aid in generating computer code, especially object-oriented code such as Java. The resulting application becomes a series of Finite State Machines (FSMs), where each state refers to a unique configuration of parameters that describe a condition (i.e., open door, closed door). Auslander defines tasks as “units of work; they are the functional subunits of the job” (Auslander et al., 2002). Several tasks can operate at the same time. Information for each task includes “task parameters such as priority, sample time….and transient information such as present state and status” (Ibid). Tasks can be continuous or intermittent and can communicate with other tasks.

One framework of organizing the communication among the tasks is an eight-layer model developed by Auslander. This model provides a modular hierarchy and limits information flow between layers. This layered model is similar to other layered models that such as the OSI 7-layer reference model (Jain & Agrawala, 1993; Wikipedia, 2006). For this simple application, two of the layers—Goal Seeking and Coordinator—are not used.

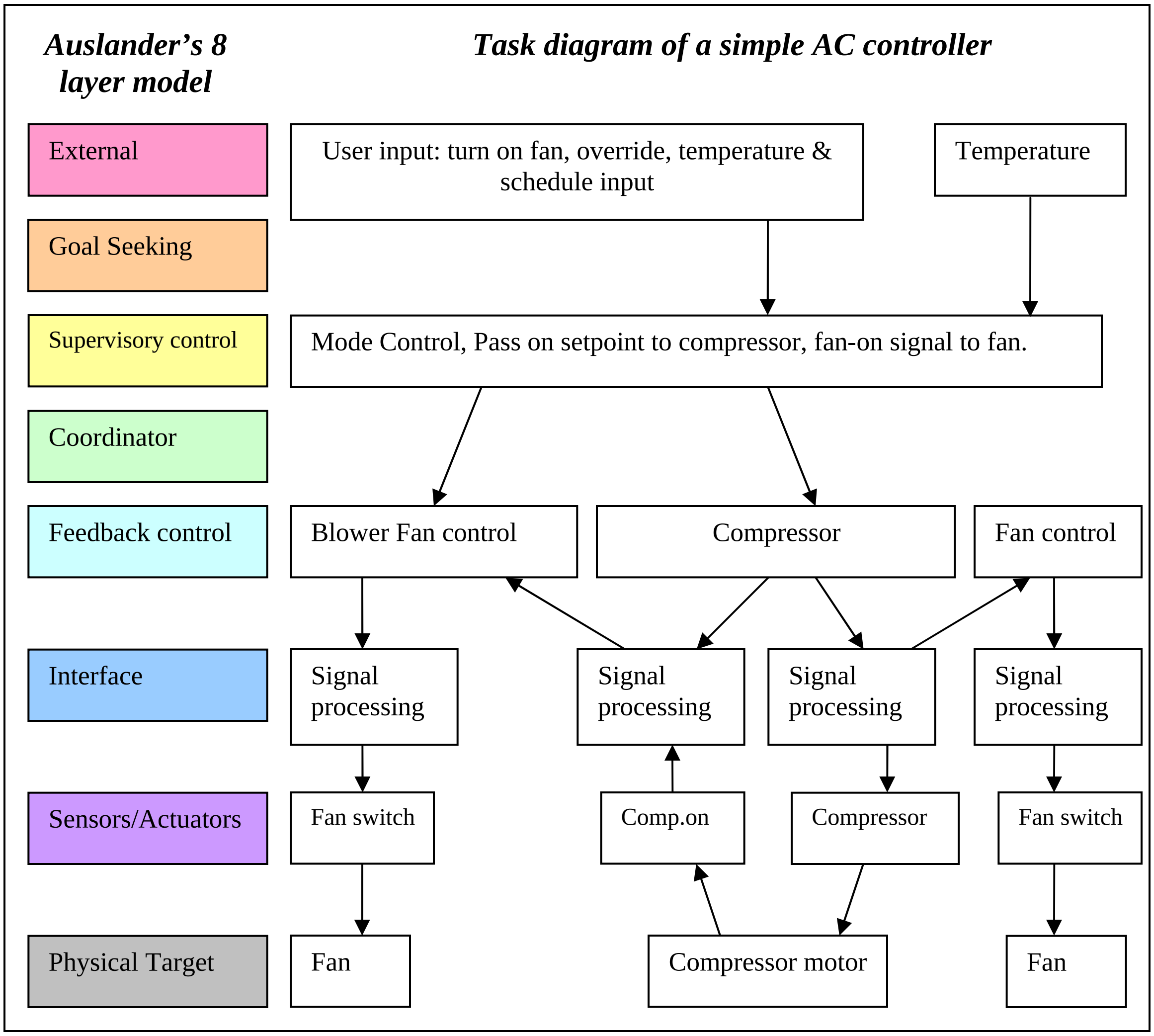


Figure 12: Layered task diagram for an air conditioner controller.

The sequential order of a process is developed by states. Only one state can be active at a time, and "the active state controls the current activity of a given task (Auslander et al., 2002). Each state typically has the following functions defined: Entry (executed once on entry to the state, which sets the initial conditions of the state and dictates the amount of time spent in this state), Action (executed on every scan of the state), and Transition or exit test (executed after the action function on every scan of the state, which would determine which state would be entered next) (Ibid.).

Each task has its own set of state diagrams. A few of the tasks are shown here. At the lowest level of the sensor and actuator tasks, the state of the sensor or actuator task is Idle until an event is detected (i.e., received signal to turn on fan or compressor, sensed that fan or compressor was on). Then the state becomes Active, in which the data or signal is received and sent to the appropriate level. After the signal is sent, the state of the task returns to Idle.

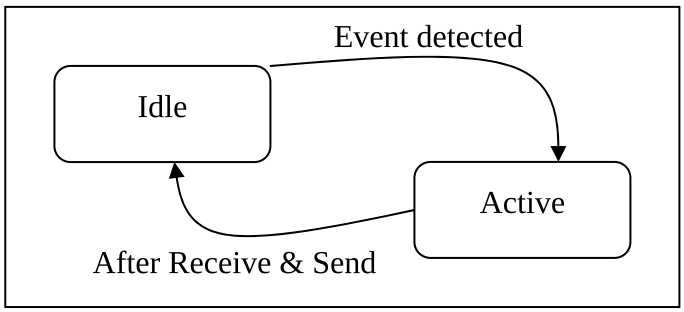


Figure 13: State diagram for sensor/actuator task.

The state diagram of the Blower Fan Control Task is slightly more complicated since there are two sources of control: the user and the compressor. The state of the fan is Idle until it receives an ON signal from the user interface or a signal from the compressor sensor that it has been on for one minute. Then the fan starts up and is in the Running state until it receives an OFF signal from the user interface or a signal from the compressor sensor that it has been off for one minute.

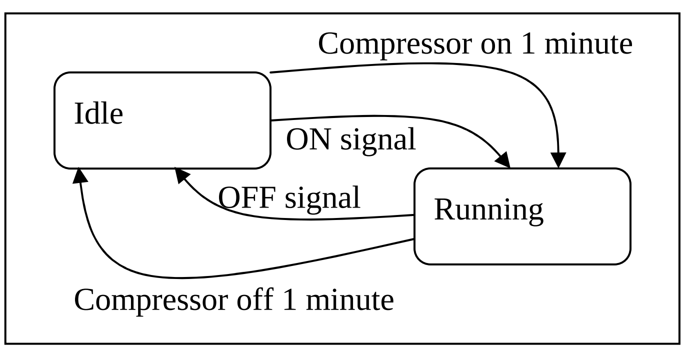


Figure 14: State diagram for a blower fan.

Finally, the state diagram of the Compressor Feedback Control Task is the most complex. The compressor is in the Ready state until it receives a signal that the temperature is above the setpoint. Then it moves into the Running state. When the signal is received that the temperature is below the setpoint, then the compressor turns off and is in the Standby state. The compressor remains in the Standby state for 5 minutes to allow the pressures in the system to equalize so the compressor is not starting in a loaded condition. After 5 minutes, the compressor moves back to the Ready state.

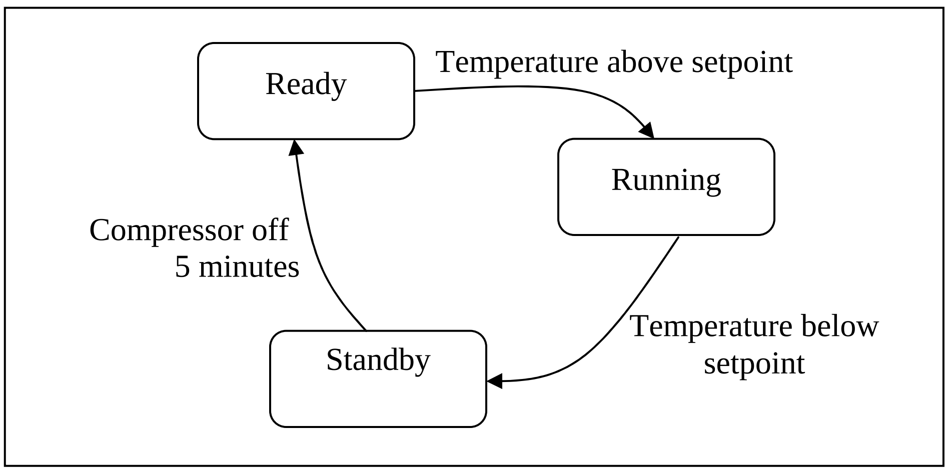


Figure 15: State diagram of a compressor.

This section described a control design for an air conditioner. Designing a controller involves knowing how the equipment operates, managing data and communication flow, and understanding the sequence of the process. The modular organization of task and state diagrams enables controller development and allows multiple parties to work on different aspects of the controller. This organization also allows easy addition and modification of existing tasks and states.

2.4.2 Intelligence

Intelligence in buildings can take many forms. Early exploration of non-human or *artificial* intelligence (AI) focused on knowledge acquisition and acting based on that knowledge: artificial neural networks, expert systems, and fuzzy logic. Culp et al describe the different forms: “Expert systems are computer programs that mimic a human expert. Neural networks are computer programs that are designed to operate the way neurons operate in humans. Fuzzy logic is useful when the correct response in somewhere between a yes or a no because it can represent concepts such as almost, all, most and others” (Culp, Haberl, Norford, Brothers, & Hall, 1995). Expert systems require transferring the knowledge of persons knowledgeable about a subject into if-then type statements that a computer can run. Artificial neural networks are useful for multiple inputs. Just like neurons in the brain develop connections to other neurons, certain associations or links are made between nodes; each link is associated with a weight which determines the strength and direction of the connection (Russell & Norvig, 2003). The neural network is trained with data and learns patterns; this information is then used to develop predictions. Fuzzy logic based controllers are useful in applications that have “small rule bases, no chaining of inferences, and tunable parameters that can be adjusted to improve the system’s performance” (Ibid.).

Much of the current AI focus is on learning algorithms, which include neural networks and can incorporate expert systems. The idea behind learning is not only to gain knowledge for immediate action, but also improve the ability to act in the future. Learning can occur from observations (inductive and reinforcement learning) and based on prior knowledge, with probability and statistical models used to help learning (Ibid.).

A learning algorithm is computer code that takes as its input certain observable attributes, and based on multiple sets of the value of these attributes, makes a prediction about the value of one parameter given the others.

A learning algorithm may be structured in a number of ways: a simply supervised learning problem appropriate for decision tree learning, a support vector machine, or a neural network (Ibid.). Supervised learning requires learning a function from examples of inputs and outputs. A decision tree takes in a set of attributes that describe a situation and returns an output that is the predicted value for the input. This output is reached based on a series of tests that form nodes in the tree, with each branch representing a test of one of the values. Support vector machines, also known as kernel machines, use complex nonlinear functions (Ibid.). For simple applications (single user, consistent schedule), reinforcement learning might be added, where a utility function is introduced. This introduces a "reward" for choosing an appropriate temperature setpoint and "punishment" for an inappropriate setpoint.

2.4.3 Thermostats

This section describes a brief history of thermostats, typical control and interfaces. A detailed description of thermostats and their relationship to demand response can be found in a literature review conducted recently by Iain Walker and Alan Meier (Walker & Meier, 2007).[31]

The residential thermostat has its precedent in electro-mechanical thermostats invented in the U.S. in the 1880s; the first modern thermostat is the ubiquitous Honeywell Round which emerged in 1953 (Figure 16, left). By 1960, thermostats had typical heating

[31] Another source of thermostat history may be found at http://www.prothermostats.com/history.php.

or cooling control (COOL-OFF-HEAT) as well as fan control (AUTO-ON). While the first clock or setback thermostats were available 100 years ago, they were more readily available by the late 1970s when the first energy code in California required them for new houses (Figure 16, right). Setback or programmable thermostats (PTs) can be "programmed" or set on a timed schedule to "set back" or lower the temperature "setpoint" at which the heating system turns on (or conversely, "set up", that is, raise the temperature setpoint at which the air conditioning system turns on) at night or when the building is unoccupied. The current California energy code requires the ability to set temperature preferences for at least two different time periods for each day. These changes in temperature setpoints are meant to reduce the on-time or cycle time of the heating and cooling equipment.

Figure 16: Left: The well-known Honeywell Round thermostat. Right: A typical clock or setback thermostat.

By the mid-1980s, the "modern" look for thermostats was a plastic rectangular box with digital display and push buttons for programming. The analog display that provides a visible scale of temperatures was replaced with digital numbers. In complying with the Americans with Disabilities Act (ADA) disability guidelines that prohibit devices which require the twisting of one's wrist, push button and simple slider bars replaced the more haptic and intuitive Honeywell Round interface. Throughout the 1990s programming grew more complex, with seven day programming, override and hold functions. Figure 17 below shows the Consumer Reports' highly rated LUX1500 programmable thermostat.

Figure 17: A typical programmable thermostat.

In the 1990s, the EnergyStar label was introduced to help consumers purchase energy efficient equipment. In order to place an EnergyStar label on an appliance, the appliance must comply with EnergyStar eligibility requirements. For programmable thermostats, these requirements include certain features: default energy-saving and comfort setpoint temperatures, cycle rate setting, recovery systems, and hold or override option (Environmental Protection Agency (EPA), 2009). Figure 18 below lists the default temperature setpoints and times.

Table 2: Acceptable Setpoint Times and Temperature Settings			
Setting	**Time**	**Setpoint Temperature (Heat)**	**Setpoint Temperature (Cool)**
Wake	6 a.m.	70°F	78°F
Day	8 a.m.	62°F	85°F
Evening	6 p.m.	70°F	78°F
Sleep	10 p.m.	62°F	82°F

Figure 18: Acceptable setpoints for PTs (EPA, 2009).

In the last few years, manufacturers have responded to problems of programming in several ways. Carrier brought in the design expertise of IDEO—the design firm that developed the first Apple computer mouse—to create the Infinity thermostat for their top-of-the-line residential HVAC systems (Figure 19). The NightBreeze thermostat (Figure 19) was another attempt to improve on aesthetics while adding night ventilation control. A few thermostat manufacturers feature voice-controlled thermostats for easier programming. In general, the newer models of thermostats boast larger Liquid Crystal Display (LCD) screens; White-Rodgers offers simple colors on their touch-screen display 90 series™ Blue thermostat.

Figure 19: Left: IDEO-designed Infinity thermostat by Carrier. Right: NightBreeze thermostat by Davis Energy Group.

New features include zonal control, where heating, cooling, ventilation, and/or humidity levels can be controlled separately in different rooms or areas in a house. Outdoor temperature display with a wireless sensor is available on the White Rodgers Blue thermostats. Remote control of the thermostat via the telephone or internet is a relatively new feature as well. Perhaps a preview of what is to come is the AMX ViewStat communicating thermostat with full color display and paintable surface.

Figure 20: Left: White-Rodgers Blue thermostat, Right: ViewStat communicating thermostat.

Regarding the programmable communicating thermostat, one reference design suggests that a PCT has the capability of communicating with a default one-way statewide demand response communication system that utilities will use to notify customers of price events and emergency events (Gunther, 2007). Typical programmable features are also required, such as the capability of programming heating or cooling setpoints for at least four time periods per day (two more than the current energy code requirements for PTs). In addition the customer can set an offset for heating and one for cooling during price events; the defaults are set for +4ºF for cooling and -4ºF for heating. The original proposed policy stipulated that the customer would be allowed to override the offset for price events, but not allowed to override the utility-specified temperature setpoint or offset during an emergency event (Ibid.). This verbiage is expected to change in future versions for Title 24 adoption.

2.4.4 In-home energy displays

This section briefly describes common and innovative in-home energy displays. A more thorough review was recently completed by Stein and Enbar (L. F. Stein & Enbar, 2006).

With the advent of interval metering deployment in California and current installation in Europe, many manufacturers are producing in-home energy displays.[32] Several are providing web-based energy displays, such as GreenBox Technology, Tendril Network's TREE system, and Lucid Design Group's Building Dashboard.[33]

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[32] While California should have some 12 million meters installed by 2012, it is estimated that Europe will have 80 billion installed by 2013 (Olsen, 2008).

[33] Websites are: http://www.getgreenbox.com/, http://www.tendrilinc.com/, and http://www.luciddesigngroup.com/ respectively.

Both a Whirlpool study (Ibid.) and recent studies in Europe (Van Elburg, 2008) indicate that most people prefer a dedicated display device rather than a web page on their computer. The 2003/2004 pilot study by Whirlpool only included six homes, but found that people didn't want to go to their computers to look at energy consumption, but wanted a dedicated screen on the wall. The 2007 TNS/Future Foundation study in (Van Elburg, 2008) reported the preferred communication technology for smart feedback information in 10 countries in Europe. The study found that on average 55% preferred a dedicated display compared to 30% who wanted to view energy feedback on a website.

Appendix A compares the type of display of 15 different devices. Some are quite simple and display price per kilowatt and total kilowatt-hours of energy use. The PowerCost Monitor by Blue Line Innovations is a nice example of a simple aesthetic display with minor graphics (Figure 21). The Energy Detective has slightly more complex functionality, including both monthly and daily energy and cost information, as well as a projected energy bill.

Figure 21: Left: Blue Line Monitor, Right: The Energy Detective.

A few displays are geared towards demand response price alerts by displaying different colors, such as The Energy Joule by Consumer Powerline and the In-Home Display by Az-Tech. Only a few have bar graph displays instead of numbers (such as the EMS-2020 and the EcoMeter). A new display called the PowerPlayer provides a simple aesthetic display, with the ability to set a goal, such as a monthly budget, and shows progress towards that projected goal.

Figure 22: Above: The Energy Joule. Bottom Left to Right: PowerPlayer, EMS-2020, EcoMeter.

Some displays do not include numbers at all but rely on colors, movement, or animation to convey energy consumption, reward conservation, or alert a person to price changes. Stein includes mention of a few innovative displays, such as changing wallpaper or an animated bunny (L. F. Stein & Enbar, 2006). The TellEmotion Green Lite system uses an animated polar bear on an iceberg that reacts to real-time energy usage to encourage and reward conservation (Loeb, 2009). In general the trend seems to be towards more aesthetic design, following popular consumer electronics. As displays become cheaper, we see larger displays, graphics, and color.

I have used this background on electricity policy, the built environment, thermal comfort and behavior, and current technology to guide the design of demand response enabling technology for residences to encourage adoption of this technology. The next chapter provides the initial analysis and formulation of the hypotheses.

3 Objectives

3.1 Contribution of research to present knowledge

This section presents the initial analysis of the challenges facing residential demand response and outlines the research questions of this study. While utilities are installing interval meters and dynamic pricing has been ruled the future default for an electricity tariff, ensuring customer adoption remains a major issue. Residential energy use is influenced by policy, climate and the built environment, and human behavior. The design of new technology to enable demand response, whether a programmable communicating thermostat or in-home energy display, must take all these factors into account.

On the one hand, we see that energy conservation policy and technologies have been effective. Electricity demand is currently only increasing by 3% per year (EIA, 2006b). On the other hand, Lutzenhiser estimates that most of the reduction in energy consumption in 2001 in California was due to changes in behavior, not technology (Lutzenhiser, 2003).

Technology in turn has affected behavior. Air conditioning has a homogenizing effect on social behavior: families with air conditioned homes tended to stay at home more instead of cooling off with a picnic at the park or going to the beach (Cooper, 1998). The definition of comfort has changed, affecting both thermal comfort and energy use (Chappells & Shove, 2004). Air conditioning is becoming the norm even in areas such as San Jose, California, where cooling is typically needed for only a handful of days out of the year. People who have air conditioning at work tend to use it at home (Ubbelohde, Loisos, & McBride, 2003). Part of the problem with air conditioning is that the occupants of air conditioned buildings tend to expect a smaller range of temperatures and become less tolerant of temperatures that deviate from the optimal temperature (de Dear & Brager, 1998).

The following sections describe a new model for energy policy, a framework for analyzing the acceptability of technology, and a proposal for residential thermal comfort. The first section describes the need for a new policy model that includes actual consumer behavior. The next section presents a model for technology adoption using the programmable thermostat as an example, including issues of usability, balance of automation and personal control, and motivation. The third section proposes a new standard for residential thermal comfort. The final section describes the objectives of this study with respect to current knowledge.

3.1.1 New policy model

To date, an economic-engineering model has dominated energy policy (Wilson & Dowlatabadi, 2007). Whether seen as a top-down economic model or a bottom-up technology model, Lutzenhiser refers to this model as the Physical-Technical-Economic Model or PTEM (Lutzenhiser, 1993). The implication is that this model is primarily linear, whether economics is driving policy-making and in turn technological innovation, or technology is informing policy or changing attitudes, as depicted in Figure 23.

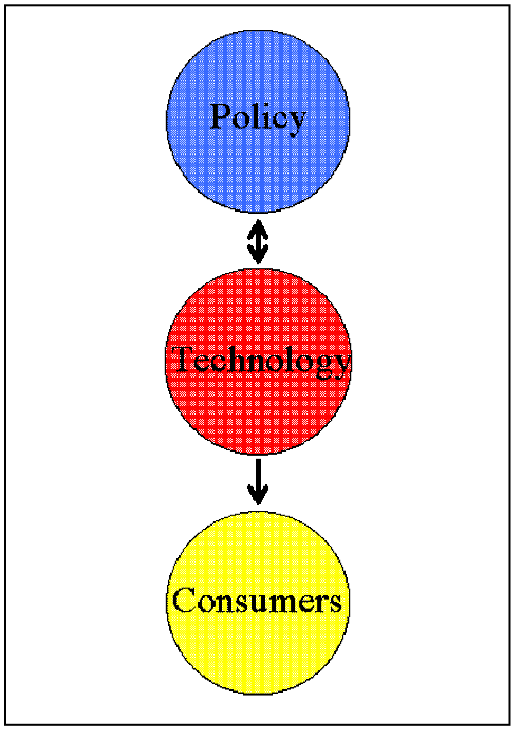

Figure 23: Linear model of achieving energy efficiency goals.

The PTEM has had a profound influence on energy forecasting and policy. The physical-technical part of PTEM looks primarily at building energy efficiency and appliance standards as a means of reducing energy consumption. When Amory Lovins introduced the Soft Energy Path approach to the U.S. energy future in 1976, he included energy efficiency as well as small-scale generation, especially from renewable resources, to steadily replace a centralized energy system based on nuclear and fossil fuels (Hirsh, 1999). The founder of the Center for Building Science at Lawrence Berkeley National Laboratory, Art Rosenfeld, pushed for more efficient appliances, and introduced the concept of a supply curve of conserved energy, to look at future conservation savings as a source of supply (Ibid.). The minimum efficiency standards required for appliances have been successful in reducing energy consumption over the past 30 years. The U.S. currently has efficiency standards on refrigerators and freezers, room and central air conditioners, heat pumps, boilers, space heaters, ballasts and lamps, motors, water heaters, dishwashers, and clothes washers and dryers (Nadel, 2002). In 2000, the U.S. federal efficiency standards reduced national electrical use by 88 terawatt-hours; utility demand side management programs saved 51 terawatt-hours nationwide in 1999 (Ibid.).

The economic part of the PTEM includes the Least Cost Approach or Integrated Resource Planning, which focuses on multiple solutions towards the demand or end result desired (Hirsh, 1999). Least cost planning is “an approach to resource planning that considers demand management solutions equally with strategies to increase capacity, considers all significant impacts (cost and benefits), including non-market impacts, [and] involves the public in developing and evaluating alternatives” (Victoria Transport Policy Institute, 2006, ¶1).

Lutzenhiser asserts that a PTEM does not fully explain energy conservation. From the early 1970s to early 1990s, total residential sector energy decreased by 15%; a U.S. Department of Energy study of changes in household energy use suggests that social and behavioral factors played a role in efficiency gains in that time period (Lutzenhiser, 1993).

The PTEM assumes rational behavior by consumers. In other words, PTEM assumes that a consumer will use energy in relationship with his income, weighted by his priorities of services, convenience, comfort, and time (Ibid.). By contrast, a behavioral model looks at the driver of what people actually do with respect to behavioral modifications, such as turning down the thermostat or the decision to weatherize the house.

A physical-technological-economic model of consumption is indeed lacking; one need only look at the technologies that do not “work”, whether by design (i.e., low-flush toilets) or by lack of understanding of consumer behavior (i.e., programmable thermostats). Sanstad, Lutzenhiser and more recently Wilson and Dowlatabadi have argued for more integrated approaches to the study of social and behavior components of energy use, and to some extent that has happened. The once polar views of economists who look for rational behavior and social scientists who argue for understanding consumer's real-world decisions (Sanstad & Howarth, 1994) have been united in the field of behavioral economics. Kempton (2004) suggests that rather than looking at end user behavior, one should look at the broader picture of the cause and construction of demand. Recently, Ehrhardt-Martinez and Laitner call on utilities and policy-makers to look at socially-rational rather than economically-rational behavior with respect to residential energy consumption (Ehrhardt-Martinez & Laitner, 2008).

What is needed is a model that neither favors technological determinism (which ignores social and behavioral constructs) nor social constructivism (which ignores nonhuman elements) (Akrich, 1992), but rather an integrated approach. A new model is necessary to understand the relationship among policy, technology, and people in achieving energy efficiency goals. A proposed model is described below in Figure 24. In this model, the relationship between policy and technology is no longer top-down or bottom-up, but mutually informative. Economics still informs policy, policy can drive technological innovation and the diffusion of technology, and technology can in turn inform policy.

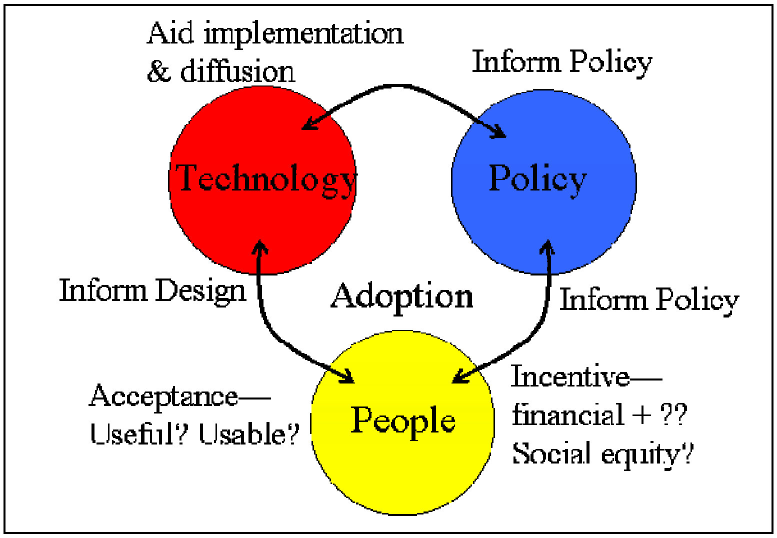

Figure 24: Proposed model for achieving energy efficiency goals through adoption of technology.

This model proposes a direct relationship between policy and people. Education and direct incentives can effect behavioral change towards achieving energy efficiency, but has been underutilized to date. Individual consumer behavior as well as networks of players (i.e., architects, developers, building inspectors, manufacturers) must be understood in order to create effective policy. The goal of technology development is not only to achieve policy goals but ensure adoption and use by consumers in attaining these goals.

3.1.2 Issues of technology adoption: the programmable thermostat

When the use of a new technology may be mandated for millions of people, understanding the acceptance and usability of that technology in order to ease the transition is vital. Adding to the complexity of a new device, such as the PCT thermostat, is the new supply and demand paradigm of time-dependent or dynamic pricing of electrical energy. The following briefly describes the thermostat and usability in general, and then discusses usability and acceptance issues.

The purpose of the policy requiring setback thermostats was to save energy compared to the traditional manual thermostats, which maintained static temperature setpoints unless the occupant changed them. One assumption of the policy is that for people that have a regular schedule of work away from home during the day, a properly programmed PT would ensure the house is not heated or cooled when unoccupied, in case the occupant forget to turn off the heating or cooling equipment before he or she left. The policy also assumes that the automation provided by a PT represents convenience to the consumer compared to a manual thermostat without reduction in thermal comfort.

One role of energy efficiency policy is to speed the adoption of cost-effective technology through incentives or other measures. However, while the setback and now Programmable Thermostat (PT) has been available for over 30 years, it has not been widely adopted beyond the code requirement (CEC, 2004; U.S. Census Bureau, 2000), programming features are used by perhaps only half to two-thirds of the users (Archacki, 2003), and the thermostat doesn't necessarily save energy (Shiller, 2006). The 2003 Residence Appliance Saturation Survey (RASS) found that about half (54%) of all California dwellings have programmable setback thermostats (CEC, 2004). This suggests that only about a third of pre-1978 housing units (which represents two-thirds of the housing stock) have programmable thermostats, and a proportion of these would have been required as part of renovations. A study by Carrier indicated that about 35% of the thermostats in houses in the jurisdiction of two California utilities were in "hold" mode. This overrides the programming features and turns the thermostat into a manual thermostat (Archacki, 2003). Several studies have suggested a programmable thermostat does not save energy, but behavior is a better indicator of energy savings (Haiad, Peterson, Reeves, & Hirsch, 2004; Shiller, 2006).

Many hypotheses exist as to why the PT has not been adopted nor used in the manner it was designed. A useful model for studying the acceptance of technology (Figure 25) was developed by Nielsen to evaluate website design, and will frame the following discussion.

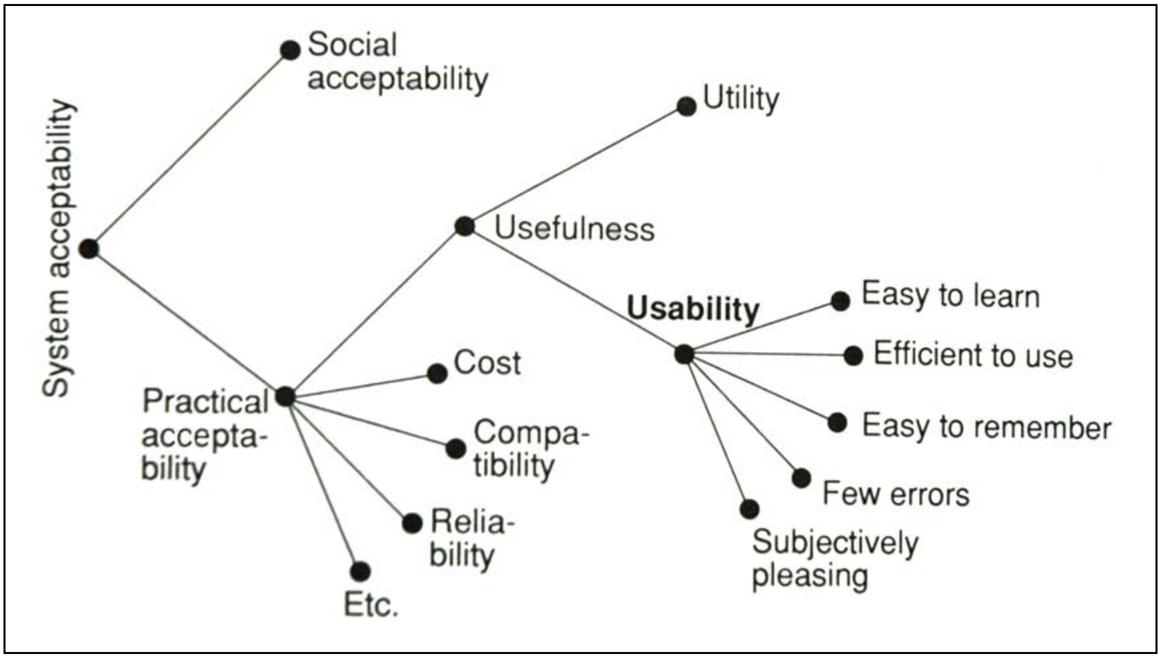

Figure 25: Model for system acceptability (Nielsen, 1993).

One issue often quoted by installers is *usability*. Some programmable thermostats come with 100+ page manuals, and are not easy to learn or remember how to program. Some people do not understand how their thermostats work. One myth about thermostats is that it works like a valve—the lower the setpoint the faster the air conditioner will cool down the house. Another myth is if one offsets the thermostat during the day when the house is unoccupied, more energy will be required to heat or cool the house when the occupant arrives home than the energy that was saved by the offset (Norman, 2002). [34]

Kempton refers to the lack of visibility of some energy conservation features as a problem with the lack of understanding. In the 2003 RASS, some of the survey questions illustrate this very point. For example, the question regarding what energy efficient measures their house had in place should have shown 100% saturation for insulation, double-pane windows, and programmable thermostats for newer homes because of the energy code. Instead, about 90% of occupants of new homes thought their attics and exterior walls were insulated, and only about 80% thought their windows were double pane (CEC, 2004). Regarding programmable thermostats, only 82% or 85% respectively thought they had a programmable heating thermostat or programmable cooling thermostat.

In addition, PTs may not be subjectively pleasing to use; the typical colorless digital LCD in a white plastic box is not very attractive. In a recent study of a similar device, an in-home energy display, one participant considered the device “an eyesore” (Parker, Hoak, & Cummings, 2008).

Utility relates to functionality—does it do what its users need? One potential *utility* issue is the fixed schedule provided by the PT. The typical PT does not allow much flexibility in scheduling: only two time periods and two temperature choices per day. Many studies describe patterns of thermostat use, which indicate that a fixed schedule may work for some, but certainly not all people.

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[34] Some recent evidence suggests that for some houses with poor insulation and undersized HVAC systems, this is not a myth, but true.

Another issue of *utility* is seasonal thermal comfort: static temperature settings provided by a PT may not provide comfort year-round. All PTs with the EnergyStar[35] label have static default temperature settings for heating (70ºF (21.1ºC) and 62ºF (16.7ºC) for away and night setback) and cooling (78ºF (25.6ºC) and 85ºF (29.4ºC) for away setup, 82ºF (27.8ºC) for night setup) (Environmental Protection Agency (EPA), 2009). Yet in two studies, one with manual thermostat control and the other with a programmable thermostat, people changed the thermostat settings seasonally (Kempton & Krabacher, 1987; Woods, 2006). Of seven houses monitored for a year, "all houses show a similar pattern of more modest winter adjustments and more extreme and more irregular changes during the fall and spring….people frequently adjust the thermostat according to outside conditions rather than letting it operate automatically" (Kempton & Krabacher, 1987, p.248). One study revealed that even among a similar population, a wide range of temperatures was considered comfortable (Hackett & McBride, 2001). See figure below.

[35] The EPA is considering withdrawing EnergyStar labels from PTs since they have not proven to save energy.

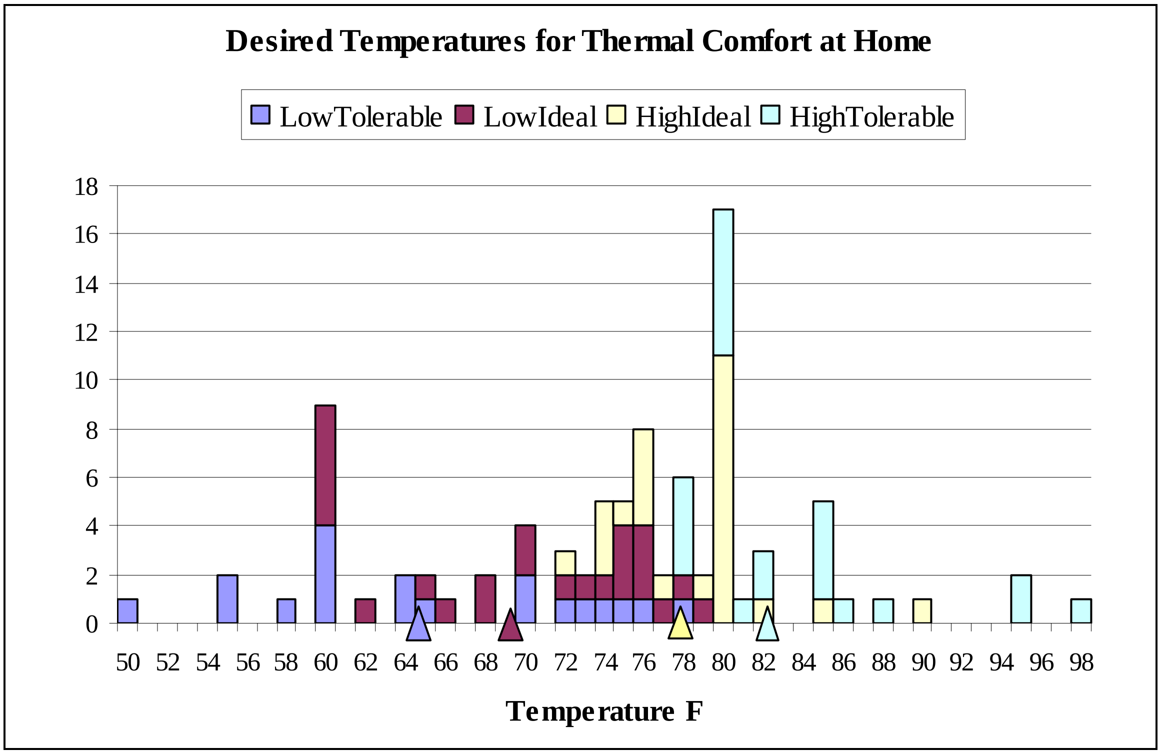

Figure 26: Wide variation in comfortable temperatures (generated from data in Hackett & McBride, 2001a).

From commercial sector studies, people in naturally ventilated offices tolerate a wider temperature range than those in air conditioned offices (de Dear & Brager, 1998). Since houses are by law naturally ventilated, the Adaptive Comfort Standard (ACS), described in ASHRAE Standard 55-2004 for naturally ventilated buildings, may be most appropriate for defining comfort in residential buildings (Lovins, 1992; Ubbelohde et al., 2003).[36] This standard allows the indoor temperature to change seasonally, allowing warmer temperatures in summer and cooler ones in winter. However, people who are used to air conditioning at home and at work may prefer a more narrow temperature range (Cooper, 1998; Ubbelohde et al., 2003).

[36] Uniform Building Code 1203.3 requires all habitable rooms have operable windows equal to 5% floor area.

A related issue of *utility* is daily thermal comfort and expected energy savings. The default temperature setpoints mentioned previously do not necessarily reflect how people actually set their thermostat. The RASS found that about 54% of all households kept the AC at a constant temperature (57% have programmable thermostats). Only 28% setup the AC during the day (58% of which have programmable thermostats) and 10% keep the AC off (50% have PTs), 8% report that daytime is the highest setting (45% have PTs) (Figure 23, CEC, 2004). The general tendency is to keep the thermostat off at night; the average temperature setting is 79.4ºF (26.3ºC) in the mornings, 77.4ºF (25.2ºC) during the day, 76.6ºF (24.8ºC) in the evenings and 79.6ºF (26.4ºC) at night (CEC, 2004).

A study in California found that setpoints found in Title 24 energy code compliance software (similar to those required for EnergyStar eligibility) overestimate the cooling setpoint and underestimate the heating setpoint (Woods, 2006). Similarly, the nighttime setup/setback default from EnergyStar does not reflect comfortable temperatures found in lab studies (Muzer, Libert, & Candas, 1984; Schmidt-Kessen & Kendel, 1973; Tsuzuki, Okamoto-Mizuno, Mizuno, & Iwaki, 2005). Yet these default temperatures found in programmable thermostats are used to determine energy savings in Title 24 compliance software programs (Woods, 2006). One reason PTs do not necessarily save energy might be because the default “energy-saving” settings do not provide comfortable temperatures.

Nielsen’s diagram links *utility* with *usability* to describe *usefulness*. Professor Michael Mozer, one of Donald Norman’s students, claims that while smart technology and automation have been touted for decades, it has failed to become mainstream because for one, people are satisfied with traditional home controls and secondly, the resistance to learning a new interface is high.[37] Mozer states, “Technology will be adopted only if the perceived return outweighs the effort required to understand the new technology” (Mozer, 2005). While some widely adopted technologies such as cell phones also have an initial learning curve, apparently for many the benefits of the PT do not outweigh the time and energy to learn how to use it.

3.1.2.1 Balance of automatic and personal control

Automation and intelligence are increasingly part of control systems, and warrant careful consideration. Automation brings up the question of control, as in *who* is in control. While there are benefits to automatic control (garage door openers, for example), other forms of automation may be doing people a disservice. Norman suggests that “too much automation takes the human out the control loop, it deskills them, and it lowers morale” (Norman, 1990).

Utilities have been implementing residential demand response programs across the U.S. for the past 20 years. The programs are mostly voluntary and have not grown substantially over time. A review of residential demand response programs in late 2005 revealed that 80% employ direct load control for air conditioning cycling[38] (Rosenstock, 2005). See figure below.

One reason that these programs haven’t seen wider acceptance relates to control, arguably a *social acceptability* issue.[39] Residents tend to prefer voluntary to restrictive

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[37] Donald Norman, cognitive psychologist, has been an advocate of human-centered industrial design since his book *The Design of Everyday Things* was published in the late 1980s.
[38] The utility has a radio-controlled device on the customer’s air conditioner compressor to turn it off during peak demand periods.
[39] *Social acceptance* in Nielsen’s model includes both personal (psychological) and social (sociological) issues.

programs (Blanc, 2006; Haiad, 2006). Even when the customer volunteers for the program, they often opt out or override the system. “Every time an event occurs, we get 10,000 calls from 150,000 customers wanting to get out of the program” (Haiad, 2006).

			Devices Controlled				
Company Name	*Program Name*	*States*	*AC*	*DHW*	*Heat*	*Pool Pump*	*Other*
Commonwealth Edison (Exelon)	Nature First	Il, PA	x				
Consolidated Edison	Cool Program	NY	x				
DTE Energy	Interruptible AC	MI	x				
Georgia Power Company	Power Credit	GA	x				
Indianapolis Power & Light (IPALCO Enterprises)	CoolCents	IN	x				
Kentucky Utilities	Demand Conservation	KY	x				
MidAmercian Energy	Energy Advantage SummerSaver	Il, IA, SD	x				
Nevada Power	Cool Credit	NV	x				
Northern States Power (Xcel energy)	Saver's Switch	MI, MN, ND, SD, WI	x				
Xcel energy	Saver's Switch	CO, MN, ND, SD, WI	x				
Pacificorp	Cool Keeper	UT	x				
Savannah Electric	Power Credit	GA	x				
Southern California Edison	Summer Discount Plan	CA	x				
Alaska Electric Light & Power	The Great Rebate	AK		x			
Otter Tail Power	Residential Demand Control	MN, ND, SD		x	x		
Florida Power Corp (Progress Energy)	Residential EM	FL		x	x		
Hampshire	HEATSMART	NH	hp only	x	x		
Florida Power & Light	Residential On Call	FL	x	x		x	
LG&E Energy	Demand Conservation	KY	x	x		x	
Alliant Energy	Residential Appliance Cycling	IA, IL, MN, WI	x	x	x	x	
Gulf Power	GoodCents Select	FL	x	x	x	x	
Nevada Power	GoodWatts EMS	NV	x	x	x		spa, dryer
Black Hills Power	Residential Demand Controller	MT, SD, WY	x	x	x		dryer
			19	**10**	**7**	**4**	**3**

Figure 27: Residential DR programs in 2005 (created from (Rosenstock, 2005)).

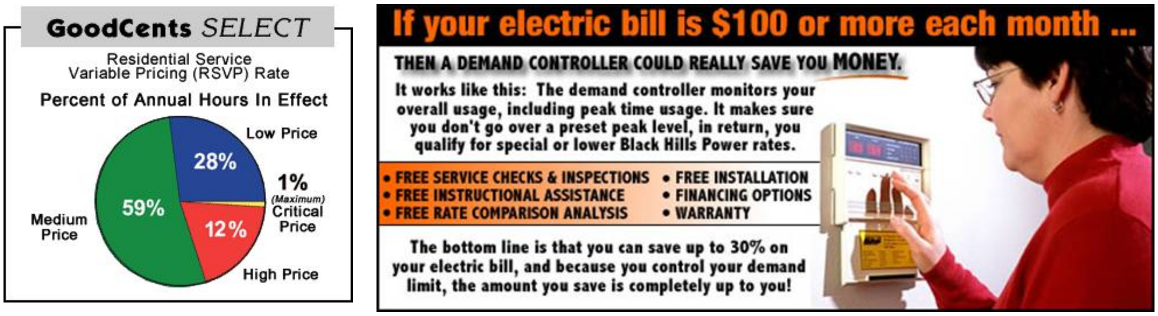

Figure 28: Two demand response programs that include customer choice; Left: Gulf Power's PCT, right: Black Hills Power's multi-use interface.

Several studies have shown that personal control or perceived control over one's environment in the office contributes to health, productivity, and comfort (Bauman, Carter, Baughman, & Arens, 1998; Bordass, Leaman, & Willis, 1994; Brager et al., 2004; Ubbelohde et al., 2003; Wyon, 1997). In an office study, people with a higher degree of control (proximity to window) were comfortable at warmer temperatures than people with less control (Brager et al., 2004). In another field study of office workers, those using a task ambient conditioning system reported the highest increase in satisfaction with thermal, acoustic, and air quality (Bauman et al., 1998). In addition, a study conducted by Wyon et al as reported in (Markus & Morris, 1980) showed that subjects that were free to adjust temperature swings accepted much greater swings than that acceptable by ASHRAE Standard 55.[40]

If personal control leads to better comfort for less energy, then what role does automation and intelligence play in building controls? Humphreys suggests sophisticated controls can be fine as long as the user has the ultimate control—the manual override—

40 The current version of ASHRAE Standard 55-2004 includes the adaptive comfort model which incorporates behavioral adaptation, such as technological adjustments, such as personal control: opening a window, turning on a fan, or turning up the thermostat.

and understands the control, such as how closing a window on a hot day can contribute to comfort (Humphreys & Nicol, 1998). David Wyon uses the *Three-I*'s principle of user empowerment as a means of providing better satisfaction. Occupants must be allowed *Insight* into how their house works and the consequences of their actions. They must be given *Information* (feedback) so they can appropriately use the control delegated to them. Armed with *Insight* and *Information*, they must be provided with *Influence* or a means of control of the various systems around them (Wyon, 1997).

The policy requiring programmable thermostats was intended to save energy. However, several studies show that conserving-type people will conserve energy whether or not they have a programmable thermostat (Nevius & Pigg, 2000). Recently the EPA reviewed several studies conducted between 1996 and 2004 and concluded that behavior was the best indicator of energy savings, not the technology. The findings: "1. Programmable thermostats were being used much in the same way as manual thermostats, 2. Programming difficulties inhibited users and 3. There was little understanding or awareness of key terms such as default, set point, and programmable. Overall there was a lack of knowledge, confidence, and motivation to face programming challenges" (Harris, 2008, ¶7).

Another example of a barrier to *social acceptability* is custom: the inertia to overcome long-held habits, "what we've always done." Perhaps the lack of control over the thermal environment at the office makes the control at home especially important. Some people may not wish to relinquish their control over their thermal environment, or perhaps it is not the right kind of control. Kempton et al found that 75% of residents in a multi-family building did not use their thermostats but controlled cooling manually

(Kempton, Feuermann, & McGarity, 1992). In designing a new control interface, Kempton contemplated adding a timer feature, since some people tended to want the air conditioner on for a certain length of time, not to control to a certain temperature. A study of 279 apartment residents in Davis, California, 58% reported controlling the air conditioner manually and 13% used a combination of manual and automatic (thermostat) strategies (Lutzenhiser, 1992). An Emerson survey found that 20% of homeowners adjust their thermostat setting two or more times per day (Emerson Climate Technologies, 2004). A PG&E survey found that up to two-thirds of homeowners "continuously adjust and reset their systems in reaction to real or perceived climate changes and building performance" (Hackett & McBride, 2001).

Hackett suggests that the reason so few people use programmable thermostats is they misunderstand how they work (such as thinking of the thermostat as a valve), but also likely that it is in the act of making one's self comfortable that is important (Ibid.). Perhaps it is not only a control issue, but lack of appropriate information provided to the occupant; Norman suggests that it is not automation or over-automation that is the problem, but poor design and lack of feedback (Norman, 1990).

3.1.2.2 Motivation and feedback

Incentives encourage both *social* and *practical acceptability* of a technology and policy. With the PCT, a high electricity price is the primary motivator to reduce peak consumption—the California Statewide Pricing Pilot (SPP) showed positive results using price to reduce peak electrical demand. Yet price may not be the most effective motivator nor be persistent over time. Price elasticity has its limits. However, incentives to increase participation in demand response programs have been effective. After the first year of the

SPP, when asked if they would continue with the program, 77% of the participants responded that they would, but when the initial incentive was removed, only 50% actually continued (Herter, 2006). A GoodWatts program survey showed similar results: 20% would definitely continue if they had to pay $5 per month, but 52% would continue if the program were free (Boice, 2005).

Other means of motivation, such as education, feedback, and social norms, may prove to be more effective than financial incentives alone. With the PT, education has been shown to increase energy savings (Jennings, Pasqualetti, Harrigan, & Boscamp, 1995) and shows promise for the PCT as well (Momentum Market Intelligence, 2003). A comprehensive review of in-home energy displays found that customers reduce energy consumption 4-15% in response to direct energy feedback (L. F. Stein, 2004). A recent study, however, showed that some people increased their energy consumption with these displays, suggesting that feedback alone may not suffice (Parker et al., 2008).

3.1.3 Going beyond the Adaptive Comfort Standard

ASHRAE Standard 55 is generally applied to commercial buildings across the country, but no standard exists for residential buildings. Ubbelohde et al (2003) suggest that for several reasons, the adaptive model is applicable to houses, whereas the old ASHRAE Standard 55-1992 was not. The reasons listed are: 1) the unpredictable and changing activities in time, place, and between individuals; 2) the greater temperature variation in an externally loaded house compared to an internally loaded office, and 3) the role of choice and flexibility is maximized.[41] The report asserts that "people in their

[41] An externally loaded building refers to a building that has a relatively small volume for the amount of surface area; the energy consumption is dominated by heat loss and gain from outside temperature and

own homes have a wide latitude in choice of clothing, activity, and location in order to make the adjustments necessary to be comfortable" (Ibid.). In addition, in general people pay for the energy to heat and cool their homes, and thus tolerate more discomfort at home than in the office. In an older study on residential thermal comfort during the heating season, the author asserts that in the winter people tolerated lower temperatures at home than in the office since they paid for their fuel at home (Fishman & Pimbert, 1981).

While the Adaptive Comfort Standard seems the most appropriate to use for residences, it has some drawbacks. The standard was developed from votes of people in commercial buildings during the day, and mostly used to look at cooling issues, not heating. In addition, the adaptive comfort standard does not include the comfort effects of relative humidity, air movement, or daily temperature trends, yet including these factors in a control algorithm could improve comfort and/or save energy especially during peak demand periods.[42] For example, using ceiling fans to increase air flow can provide a comfortable environment at a fraction of the cost of air conditioning.

Currently, the adaptive comfort standard changes with seasons, although Humphreys suggests the adaptive model might also apply to daily temperature swings (Humphreys & Nicol, 1998). Using daily drifts in temperature control is not a new idea. Back in 1907, Wittenmeier stated that inside temperatures should be set in relation to the outside temperature (Cooper, 1998). In the early 1950s, Carrier used a 7ºF drift from morning to evening to represent the ideal comfort in houses (Cooper, 1998). Humphreys

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solar gain through this surface area. By contrast, an internally loaded building has a relatively large volume to surface area ratio; energy consumption is dominated by internal factors, such as the heat gains due to people, lights, and equipment.

[42] A recent article outlines the inclusion of air movement in the European adaptive comfort standards, Annex 2 of EN15251; the authors note that the effect of relative humidity on comfort in European climates is minimal (Nicol & Humphreys, 2009a).

had reported back in 1975 that people's judgments of optimal temperature tends to shift in the same direction as the general thermal experience, whether that is made up of the outdoor, home or work environment. He noted a positive correlation of thermal sensation and monthly outdoor air temperature in 1976 (Markus & Morris, 1980). Fanger had reported no significant effect in comfort requirements with diurnal temperatures swings, but those studies were conducted in the laboratory. Auliciems (1984) suggests controlling a thermostat according to the outside temperature—a "thermobile" instead of a thermostat.

A few field studies have found different votes for the same temperatures depending on the time of day. Figure 29 shows the results of a study in an office building in Germany in the summer. On average people found 25ºC (77ºF) "just right" in the afternoon, but 25ºC in the morning was "slightly warm"; the temperatures of the same votes were about 1.3ºC (2.3ºF) higher in the afternoons (Wagner, Moosmann, Gropp, & Gossauer, 2007). In the months of summer heat in the central valley (where temperatures reach 85-105ºF (29.4-40.6ºC) during the day), morning temperatures below the ASHRAE Standard-55 prescribed minimum of 73.4ºF (23ºC) as low as 60ºF (15.6ºC) were described as "a luxury attained for free, an inexpensive excess of pleasant experience beyond thermal neutrality" (Ubbelohde et al., 2003).

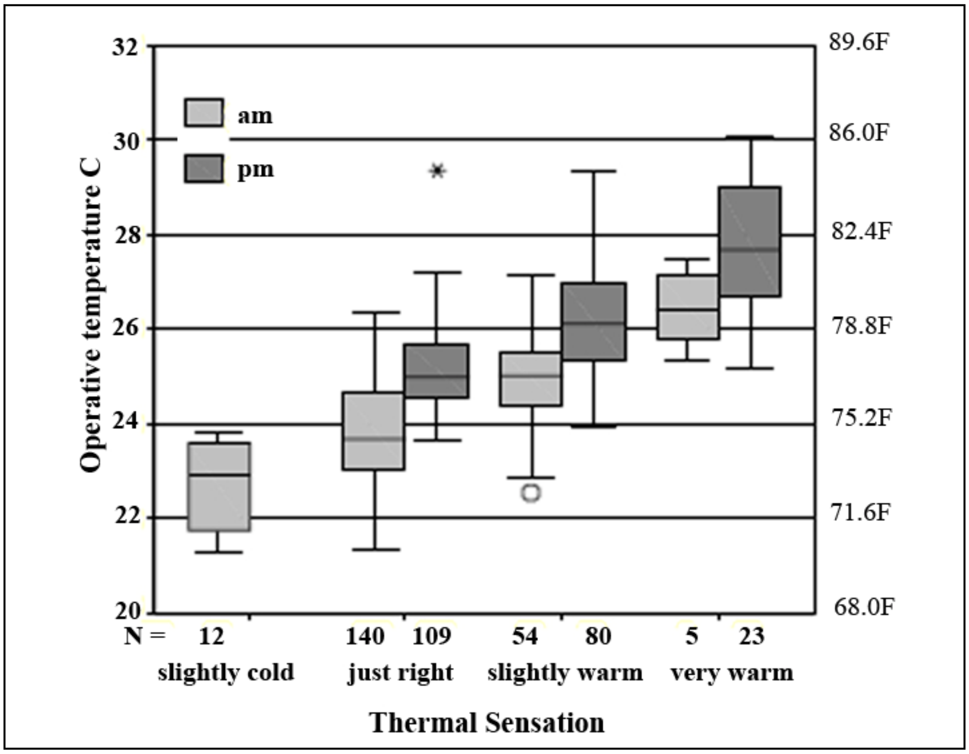

Figure 29: Box plot of votes of thermal sensation vs. temperature for morning and afternoon (Wagner et al., 2007).

While this diurnal shift is not part of the Adaptive Comfort Standard, the adaptation mechanism may be similar to the seasonal shift, in that it has psychological, behavioral (i.e., change clothing), and physiological bases. What is known about the physiological basis is that a person's core temperature rises approximately 0.4ºC (0.7ºC) over the course of the day (Zhang, 2003). It is lowest in the very early morning (midnight to 4 am) and peaks in the afternoon (2 to 6 pm).

Dynamic temperature setpoints may save energy compared to static temperature setpoints while still providing comfort. For example, a typical programmable thermostat has a built-in default setback and setup temperature setpoint schedule for an occupied house: from 6am–10pm: 70ºF (21ºC) heat, 78ºF (25.6ºC) cool and at night, from 10pm-6am: 62ºF (16.7ºC) heat, 82ºF (27.8ºC) cool. These static temperature setpoints may overheat or overcool for some months and would therefore consume more energy. But dynamic setpoints could save energy by not overcooling or heating. In addition, dynamic temperature setpoints may better model actual human behavior than do year-round static temperature setpoints.

More importantly for demand response, however, dynamic temperature setpoints may expand the comfort zone for people compared to typical thermostat control. People who spent a lot of time in air conditioned environments tend to grow accustomed to a more narrow comfortable temperature range (Cooper, 1998; de Dear & Brager, 1998; Ubbelohde et al., 2003). Yet, people who are in naturally ventilated offices, especially who have perceived control of their environment (i.e., windows, thermostats), are more comfortable at higher temperatures (Brager et al., 2004). A recent article by Nicol and Humphreys suggests new standards based on the adaptive approach that include indoor temperature drifts up to ±2K (±2ºC or ±3.6ºF) during a day and up to ±1K (±1ºC or ±1.8ºF) variation allowed between daily mean temperatures, limited to ±3K (±3ºC or ±5.4ºF) over the course of a week (Nicol & Humphreys, 2009b).[43]

A thermostat that provided changing temperature setpoints based on outdoor temperature would provide a wider temperature range than a typical thermostat. If people could adapt to a wider temperature range, then the higher temperatures expected to help reduce air conditioning loads during peak periods may be perceived as less uncomfortable than if people were accustomed to a more narrow range.

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[43] For comparison, Table 7 of ASHRAE Standard 55 suggests 3.3C (6.0F) as a maximum temperature change allowed within a four hour period (American Society for Heating Refrigerating and Air-Conditioning Engineers (ASHRAE), 2004).

3.2 Questions for this study

By 2012, people across California will experience a new paradigm in electricity pricing. Technological infrastructure, customer marketing and education programs are currently undergoing design. A new model that examines the relationships among policy, technology, and people can inform the future technology of the programmable communicating thermostat and policy design of demand response relating to this new technology. Analyzing the programmable thermostat suggests several areas to improve the programmable communicating thermostat and reduce peak electricity demand: provide more feedback and information, accommodate desire for personal control, create a more usable and aesthetic interface, and develop more flexibility in schedule and temperature setpoints. Other issues such as the need or utility of demand response[44] and overcoming consumer inertia will have to be addressed through marketing and education programs.

The objectives of this study are to answer the following research questions:

1) Is wireless technology an appropriate platform to provide information on price and household energy usage to enable demand response for a low installation cost?

2) Can computer learning adequately predict occupant temperature preferences and schedule to provide acceptable thermal comfort and eliminate the need for programming by homeowners?

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[44] A customer may well ask why this system is even needed: why don't the electrical utilities just make more electricity or find other ways of balancing load? Utilities will need to make a case for the benefit of demand response to the customer, whether through financial incentives to participate, better grid reliability/fewer blackouts, or societal/environmental benefits.

3) Would temperature setpoints based on the Adaptive Comfort Standard save energy compared to the default settings provided by an EnergyStar labeled programmable thermostat?

4) Is energy consumption feedback as effective in motivating peak energy reduction as cost and price information in a variable electricity tariff environment?

5) Does the (apparent) sponsor of a demand response enabling technology (whether a community-based nonprofit organization or an electrical utility/governmental agency) affect people's behavior regarding peak energy reduction?

6) What type of information, graphics, advice, or tools would people find useful in making decisions with dynamic electricity pricing?

3.3 Summary

This study explores several issues of technology design to allow residents to respond to peak electrical demand. The built environment and the social influences of policies, institutions, families, and personal sense of comfort and behavior affect technological design. The next chapter describes the research design chosen to explore each research question described above.

4 Research Designs

This study proposes to improve upon the basic technology that allows residents to respond to a time-differentiated electricity tariff. The background study and initial analysis indicate: 1) both feedback in the form of detailed energy usage information and providing choices can engage and motivate the resident to reduce peak electricity consumption, and 2) more sophisticated control can reduce peak electricity consumption in a manner acceptable by people.

The goal is to develop a new enabling technology for residential demand response. The proposed technology is a combination of thermostat and in-home energy display, plus the option of controlling other appliances. Since control seems highly influential in personal satisfaction, we felt that keeping control of the household appliances and thermostat within the household instead of by the electrical utility would lead towards greater adoption of the device. We disaggregated the typical thermostat into its separate components of user interface, sensors, and control system in order to better model and study new approaches. We envisioned an enabling technology that:

1) can control several appliances,
2) can display and respond to price signals,
3) represents low cost to install,
4) provides autonomous control upon installation (that is, the device should work well right out-of-the box with no user input),
5) provides feedback to encourage the occupant to reduce electricity consumption during peak periods,

6) learns the behavior of the house, its HVAC system and climate, and its occupants' schedule and temperature preferences, and
7) optimizes the cost of energy with people's thermal comfort.

Each research question requires a different research design, whether case study, analysis of data, survey or experiment, with each having its own measure of success. The research designs to test the following five hypotheses are discussed below.

Hypothesis #1: A wireless system using microcomputer "motes[45]" provides an information-rich, low-cost framework for technology that enables residential demand response. The proposed technology to enable residential demand response is a PCT. However, the consequent strategy of direct feedback with some form of advice has been shown to be effective in reducing energy consumption (Darby, 2000, Lutzenhiser, 1993). In addition, providing information in order to help the user develop insight leads to better comfort and satisfaction (Wyon, 1997). A distributed network of wireless sensors and actuators in a house may provide a cost-effective means of providing information as well as distributed control.

To test this hypothesis, I worked with a team of undergraduate and graduate students and professors to develop an exploratory qualitative case study.[46] We had several goals: 1) to alert the consumer to price changes, 2) to replicate thermostatic control functions and add additional control functions appropriate to demand response,

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[45] A mote is a small low-power microprocessor with a radio transceiver and multiple analog or digital input/output channels for sensing and actuation.
[46] "Exploratory" because we were using a new technology and didn't know what to expect; "qualitative" because our measure of success was qualitative: widespread system adoption; a "case study" because at the time of this test, the high cost of wireless technology permitted just 2-3 field tests as opposed to a sizable representative sample.

and 3) to provide information, advice, and tools to help the consumer manage electrical energy usage. We defined our measure of success as reliable and timely data transfer, efficient use of sensors, ease-of-installation of the system, and appropriate demand responsive control strategies.

Our plan to implement the case study is as follows. First, we would choose an available open platform of wireless technology that would allow us to design our own sensors and actuators and control the communication among them. Then we would choose what to measure, how many sensors to use and where to locate them, and how often to sample and send data. We would develop control algorithms that used these data. We would test this system through simulation, in the laboratories on campus, and in a few houses. We anticipate many rounds of testing as we seek to continually improve and optimize the system.

Hypothesis #2: Computer algorithms can adequately "learn" occupant temperature preferences and schedule to provide acceptable thermal comfort and eliminate the need for thermostat programming by homeowners. The balance of automation versus personal control has proven integral to customer adoption. Using intelligence offers convenience for the user compared to the tedium of programming the thermostat, which is often given as one of the reasons programmable thermostats are not used properly. However, learning algorithms must have near-perfect accuracy in prediction in order to be acceptable to people; mistakes in providing something as personal as thermal comfort are not well tolerated. The research design required to test this hypothesis is two-part: to use a quantitative analysis of existing data to determine the predictability of temperature preferences, and to implement both a survey and field observation to evaluate the predictability of people's schedules.

The first part would require a data set of environmental conditions and temperature preferences of several people. For this feasibility study, finding ready and accessible data was more important than assuring a representative sample of the population. I could analyze this data with an available learning algorithm or create one. The measure of success is the accuracy of predicting whether a given temperature is comfortable based on a person's previous comfort vote.

The second part invoked the use of surveys and field observation to determine the variability of people's daily schedule. The survey would ask people to describe the nature of their schedule. The field study would provide an opportunity to observe the pattern of schedule of several households over several weeks, whether through occupant sensors or self-reporting of the subjects. Again the measure of success is the accuracy of predicting a person's schedule pattern given the past schedule.

Hypothesis #3: Temperature setpoints based on the Adaptive Comfort Standard save energy while still providing comfort compared with the default settings provided by an EnergyStar labeled programmable thermostat. Currently, residential thermostat setpoints are based on the same static temperature setpoints seen in office buildings. Although no thermal comfort standard covers residences, several studies indicate that the Adaptive Comfort Standard (ACS) is appropriate. An adaptive control algorithm has been developed and tested in office buildings in Europe (McCartney & Nicol, 2002), but not in residences. In addition, setpoints based on the ACS as well as other comfort parameters such as relative humidity may save energy compared to traditional setpoints.

Testing this hypothesis would require a comparative analysis of data. Two algorithms are needed: one that supplies the annual heating and cooling temperature setpoints of an EnergyStar programmable thermostat and another that generates temperature setpoints based on the outdoor temperature, relative humidity, and diurnal temperature. I would test these algorithms in a simulation tool that models the annual energy of a house in a given climate. The measure of comparative success is the comparison of the number of hours of heating and cooling required in each case.

Hypothesis #4: Energy consumption feedback is at least as effective in motivating peak energy reduction as cost and price information in a variable electricity tariff environment.

Hypothesis #5: The messenger influences acceptance of the message: a community-based, nonprofit contractor promoting a device will result in more energy-saving behavior than if an electrical utility or governmental agency promotes it.

These two hypotheses assert different motivators to reduce peak energy: the type of information (price versus energy usage) and the context of who promotes the technology. Many recognize that dynamic pricing deserves better than a one-size-fits-all solution with respect to educating and motivating residential customers. While high priced electricity is expected to reduce consumption during peak periods, feedback in the form of real-time electrical energy consumption has also been found to reduce consumption. In addition, a few studies indicate that people do not trust their electrical utilities with respect to promoting energy efficiency programs. The response to a new technology may differ depending on whether the recipient perceives that the device was sponsored by an electrical utility compared to a nonprofit organization.

Since the variables of these hypotheses were thought independent, these two hypotheses shared the same research design. I chose to study these hypotheses with a laboratory experiment as it would be more cost-effective for this preliminary test than a field experiment in people's homes with actual changing prices. The Experimental Social Science Laboratory (Xlab) at UC Berkeley's Business School has a computer laboratory used for similar decision-making tests. The Xlab provides a random sample of subjects from their pool of staff and student volunteers, and takes care of soliciting and compensating the subjects for their participation.

A two-by-two parameter test would divide subjects into four groups, as shown in Table 2 below. I would develop a user interface that could display either energy usage or price information; half the subjects would see one, half would see the other. Half the subjects would see an introduction as if the interface were sponsored by a fictitious electrical utility, the other half as if it were sponsored by a fictitious nonprofit. I would ask subjects to make some sort of intervention with the interface, for example, ask them to choose a temperature setting for a high price period. This intervention is the dependent variable that would be analyzed for differences between the groups.

	Utility sponsored	*Nonprofit sponsored*
Price information		
Energy consumption information		

Table 2: Two-by-two parameter test scheme.

One of the drawbacks of using a laboratory test for this experiment is that people might behave differently in a lab than they would in their homes. One means of addressing this problem is to screen the participants: only those who pay an electrical bill and those who have experience living with air conditioning could take the test. Another idea is to animate the user interface so that temperature, price, and energy usage change with time. While the subject would not be personally experiencing the changes shown, animation would engage the subject in imagining one's own daily rhythm more so than a static display.

Hypothesis #6: People will find detailed information more useful than general information, and some advice/tools useful and others not useful in making decisions regarding energy consumption. Testing this hypothesis requires a survey of people's opinions on several different user interface displays. This test is ideally suited for the Xlab. The goal of this test is to develop several types of displays and tools and ask subjects to rate the usefulness of each.

5 Research Methods

This chapter describes the actual process of the research methods in collecting data as it evolved from research design.

5.1 Wireless network[47]

We tested the feasibility of a wireless platform to enable residential demand response. Data communication through radio signals was less expensive than wired components, especially for existing homes. In addition, a wireless platform allowed the development and testing of multiple sensors and multiple types of sensors for an information-rich system. Moreover, we could split the control system into its components of actuator (relay) and control algorithms implemented in software. This provided a means of developing and testing different algorithms and optimization strategies. In the same way, the user interface could be designed and tested in conjunction as well as separately from the other components. This section describes the development of hardware and software of the wireless network; this system was tested through computer simulation tools, small scale laboratory testing, and three field trials.

The figure below shows the vision of the thermostat/in-home energy display device that we dubbed the Demand Response Electrical Appliance Manager (DREAM):

- Price information from the utility is transmitted to a household;

[47] This section describes the group effort (which I helped lead) of the Thermostat Control Group of the Demand Response Enabling Technology Development PIER contract from August 2003 through December 2007. Members of this group include Professors Ed Arens and Dave Auslander, Research specialists Charlie Huizenga and Cliff Federspiel, graduate students Xue Chen, Jaehwi Jang, Anna LaRue, Carrie Brown, Florian Jourda, Kyle Konis, Stet Sanborn, and William Watts, and undergraduate students Jonathan Ellithorpe, Sun Chen, Reman Child, Po-kai Chen, Yi Yuan, Marc Ramirez, and Randy Chen.

- The controller receives data from multiple wireless temperature, motion, and electrical current sensors, as well as price information;
- The controller automatically controls the HVAC system via wireless actuators in response to price with built-in defaults;
- Control is adapted over time as the system "learns" house/climate behavior and the schedule and preferences of its occupants;
- Control is optimized based on an occupant cost-comfort index selection and house/climate behavior;
- The controller sends price information to "traffic light" type indicators at various appliances (i.e., clothes washers, dryers, dishwashers).
- An interface receives user input and displays price and usage information.
- Electrical interval consumption data is relayed back to the utility.

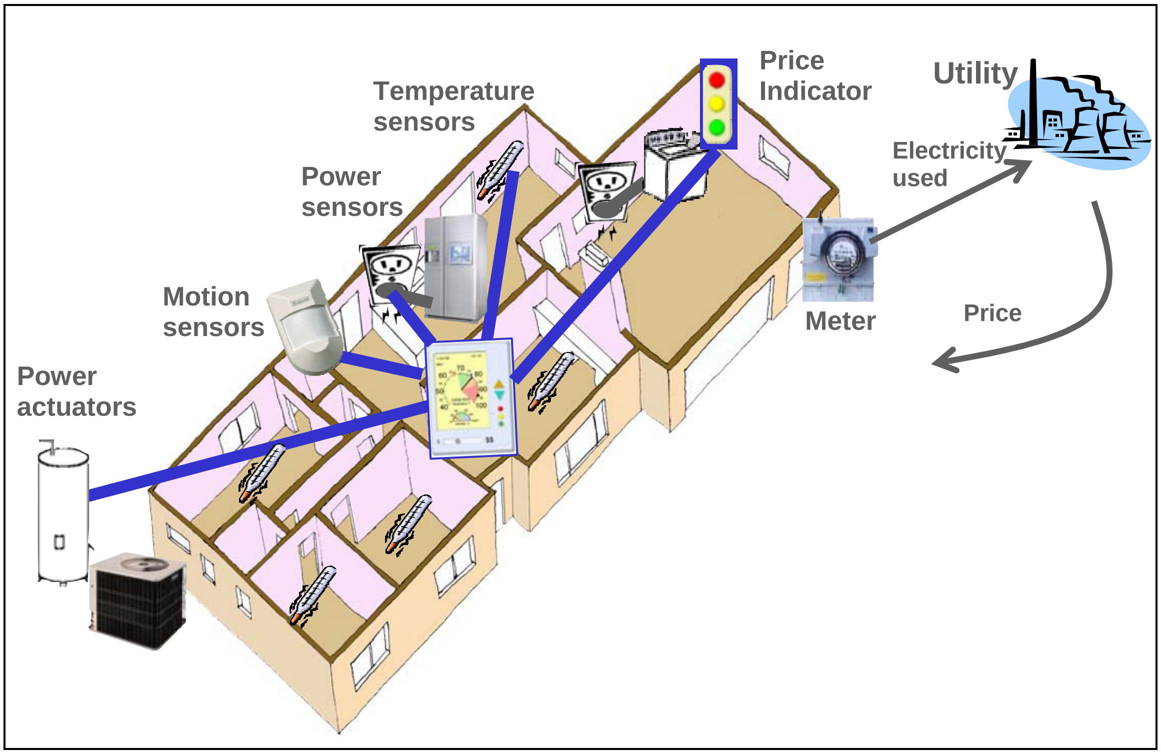


Figure 30: The Demand Response Electrical Appliance Manager (DREAM).

The DREAM is composed of communication, hardware, and software. Communication consists of the network communication between the motes and the base mote on the controller, communication to a local database on the computer, and communication to a remote database on a server via the internet. More detailed information about communication may be found in the Phase I report (Arens et al., 2006) and the Phase II report (Arens, Auslander, & Huizenga, 2008).

5.1.1 Hardware

The hardware consists of so-called "motes", which are small low-power microprocessors with radio transceivers and multiple analog or digital input/output channels for sensing and actuation. Over the course of the project, we used several types[48] of motes (mica and mica2dot from Crossbow; Telos and TmoteSky from Moteiv). The TmoteSky, shown below, is powered by two AA batteries and has a high data transfer rate.

Figure 31: Tmote Sky from Moteiv[49] (plastic enclosure by Alex Do).

[48] We were working with three other groups on campus who preferred the open source platform of these motes compared to those commercially available from Ember, Dust, or other companies.
[49] Moteiv changed its company name to Sentilla in 2007.

While the motes we used were capable of "mesh" networking (where each mote can communicate with each other), we found a "star" network sufficient for our purposes (each mote communicates with a central point, in our case the controller). The sensor and actuator development for the first field test is detailed in the Phase I report (Arens et al., 2006) and for the second field tests in the Phase II report (Arens et al., 2008).

A "generic" sensor mote design formed the basis of most of the motes. The table below shows the types of sensors built for each round of field testing. A circuit board and several monojacks allowed temperature sensors and/or infrared motion sensors to plug into these motes. A weather station mote received data from global and diffuse solar radiation sensors, and wind direction and wind speed sensors. We developed two methods to measure household current and voltage. One entailed the use of a Veris smart current transducer (CT) and developing the interface to a mote.[50] The other used simple clamp-on current transducers to interface to the mote, and required separate calibration. Actuation hardware included an HVAC relay mote, which replaced the actuation functions of a thermostat by using mote-controlled relays for the compressor, fan, and furnace. We developed a thermostat switch to allow the occupant to switch from their thermostat to the DREAM system. Finally, we developed a signal mote with Light Emitting Diodes (LEDs) to indicate price information. Appendix B describes initial sensor and actuator mote development.

[50] This work was conducted by electrical engineering undergraduate Xin Yang and is described in detail in the Phase I report.

Initial Field Test: Summer/Fall 2005	***Final Field Tests: Summer 2007***
Sensors	
Battery voltage	Battery voltage
Air temperature (shielded from radiation) and globe temperature (available to radiative effects)	Air temperature (shielded from radiation)
Relative Humidity (sensor integrated on the mote circuit board)	Relative Humidity (sensor integrated on the mote circuit board)
Motion (passive infrared sensor used for occupancy sensing and to reduce power consumption on price indicator)	Motion (passive infrared sensor used for occupancy sensing and to reduce power consumption on price indicator)
Outside weather (air temperature, relative humidity, global and diffuse solar radiation, wind direction and speed)	Outside weather (air temperature, relative humidity, global solar radiation)
Power (whole house consumption at the main circuit breaker panel)	Power (whole house and breaker level consumption at the main circuit breaker panel, air conditioner compressor, miscellaneous individual appliance)
Repeater (relay data from most remote mote to the controller)	Repeater (relay data from most remote mote to the controller)
	Occupancy switch (manual switch used by occupant when leaving or arriving home)
Actuators	
HVAC relay (replaced household thermostat control with relays for air compressor, blower fan, and furnace)	HVAC relay (replaced household thermostat control with relays for air compressor, blower fan, and furnace)
Price indicator (indicates high, medium or low price by use of LED lights)	Price indicator (indicates high, medium or low price by use of LED lights and sound)

Table 3: Wireless sensors and actuators developed.

We made several changes to the communication and hardware as a result of the first field test. We rewrote the software for the mote communication to improve reliability, since we had many power management-caused network failures in the first field test. The communication to the remote server was also problematic and was completely revised.

We also upgraded the hardware. The temperature sensors needed more precise calibration, requiring the use of a precision resistor on the mote. We also decided that for the purposes of our research, only the air temperature would be used, not the globe temperature which can be used to estimate radiant temperature from surfaces. While the motion sensors worked, we decided we needed a more direct manner of communicating occupancy to the controller and developed an occupancy switch. This occupancy switch was placed near the main entryway of the house and used for times of departure and arrival. The occupant pressed the button upon leaving and arriving; an LED indicated occupancy (i.e., red = unoccupied, green = occupied).

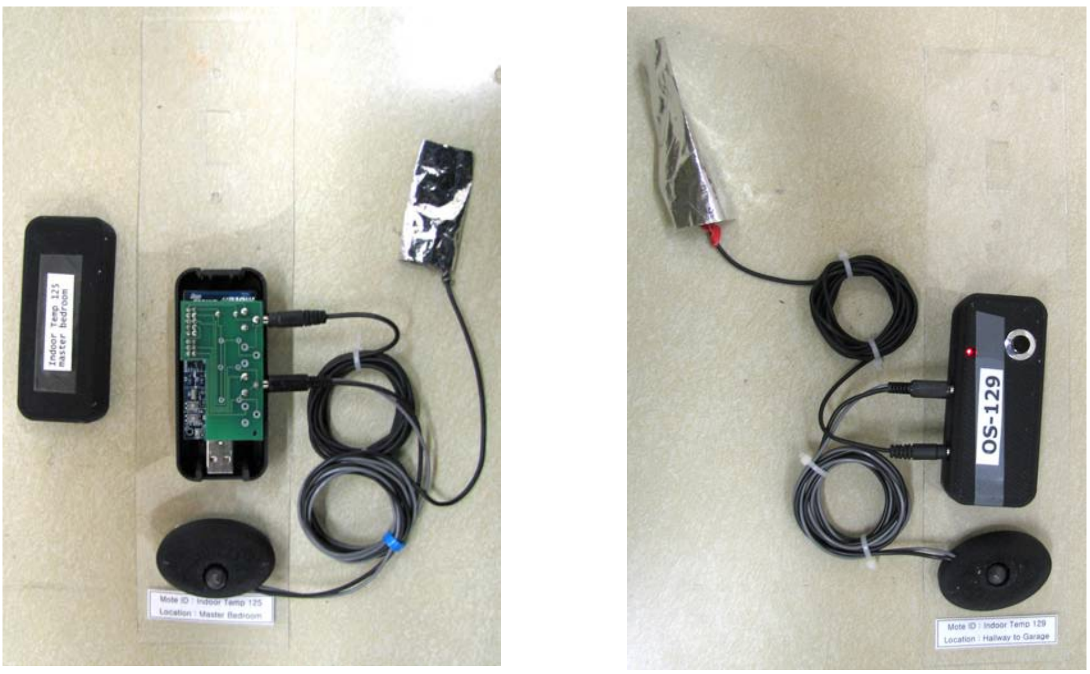


Figure 32: Left: Temperature and motion-sensing mote mounted to a plastic sheet for attachment to a light switch plate. Right: Occupant switch mote.[51]

While the weather station provided interesting data, we also decided to minimize effort and equipment in this area and only collect outdoor temperature, relative humidity, and global solar radiation data. The Veris smart meter was expensive, and we decided we didn't need precise power measurements, so we decided to use the clamp-on current

[51] Undergraduate electrical engineering student Jonathan Ellithorpe made the occupant switch.

transducers. One mote had six CTs to measure whole house and individual loads at the circuit breaker panel. The other two motes each had a single CT to measure special loads such as the air compressor of the air conditioner. The photos below show both types.

Figure 33: Current sensors for the circuit breaker panel (left) and for an individual appliance cord (right). [52]

5.1.2 Software

The software included both control software and the user interface, both written in Java. We implemented a typical thermostat control system; in addition, we wrote several modules to provide an intelligent, adaptive and optimized demand-responsive controller. I designed the user interface to display temperature, price, cost, energy consumption, and advice in an easy-to-use format.

Jaehwi Jang designed the control software in a layered format from the complex goal-seeking functional layer to the simple sensing and actuating layer (see figure below). The layered design allowed us to separate and organize functions and maintain a modular structure. The controller interfaced with an external realm as well, including price

[52] Undergraduate electrical engineering student Sun Chen made the current sensor motes.

information and the user interface, which allows user input and graphic display of information to the users.

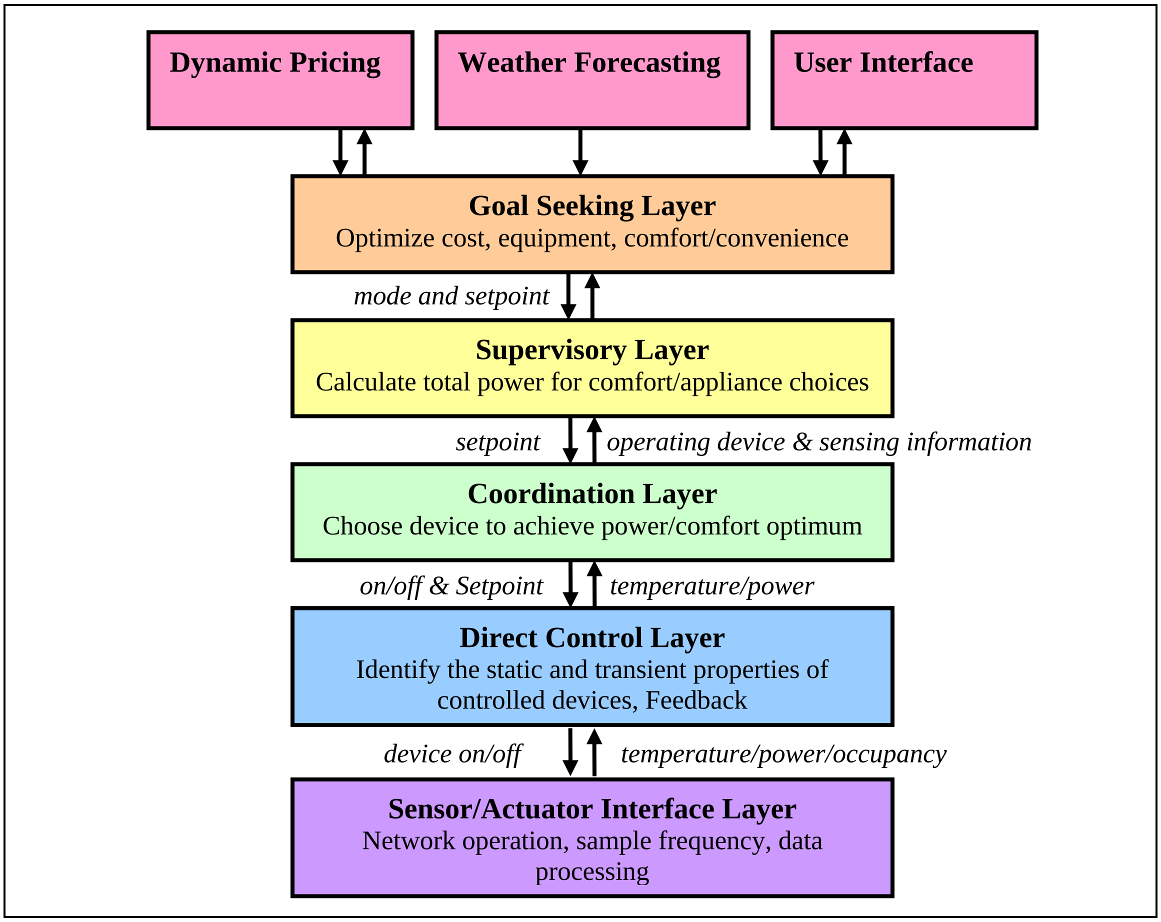


Figure 34: Control code hierarchy.

Initially, we implemented the base functions of typical thermostats: control of air compressor, fan, and furnace, with hysteresis; then we developed demand response functions. We developed simple temperature offsets for each price category on a schedule-basis, assuming there would be a low or off-peak period, middle or shoulder period, high or peak period, and critical for emergencies. Xue Chen developed a price generator that developed price levels based on weather and random events (Arens et al., 2006). Jaehwi Jang developed a precooling algorithm to turn on the air conditioner before the high price period for better comfort at a lower cost.

For the second field test, we developed learning and optimization algorithms to make the thermostat autonomous—able to work out-of-the-box and adapt to its environment. The goal of the DREAM thermostat was to learn about the house's HVAC system, climate, occupant's schedule and temperature preference, and then given electricity price data, optimize the performance of the HVAC system to minimize cost and maximize comfort.

5.1.3 Testing

The choice of Java for portability and the hierarchical structure of the control software enabled seamless testing of the DREAM via simulation, and both laboratory and field testing. See Figure 35 below. We tested the functions and hardware-communication-software infrastructure of the DREAM system via a simulation tool, in a controlled setting at the university and a researcher's home, and finally in a few occupied houses.

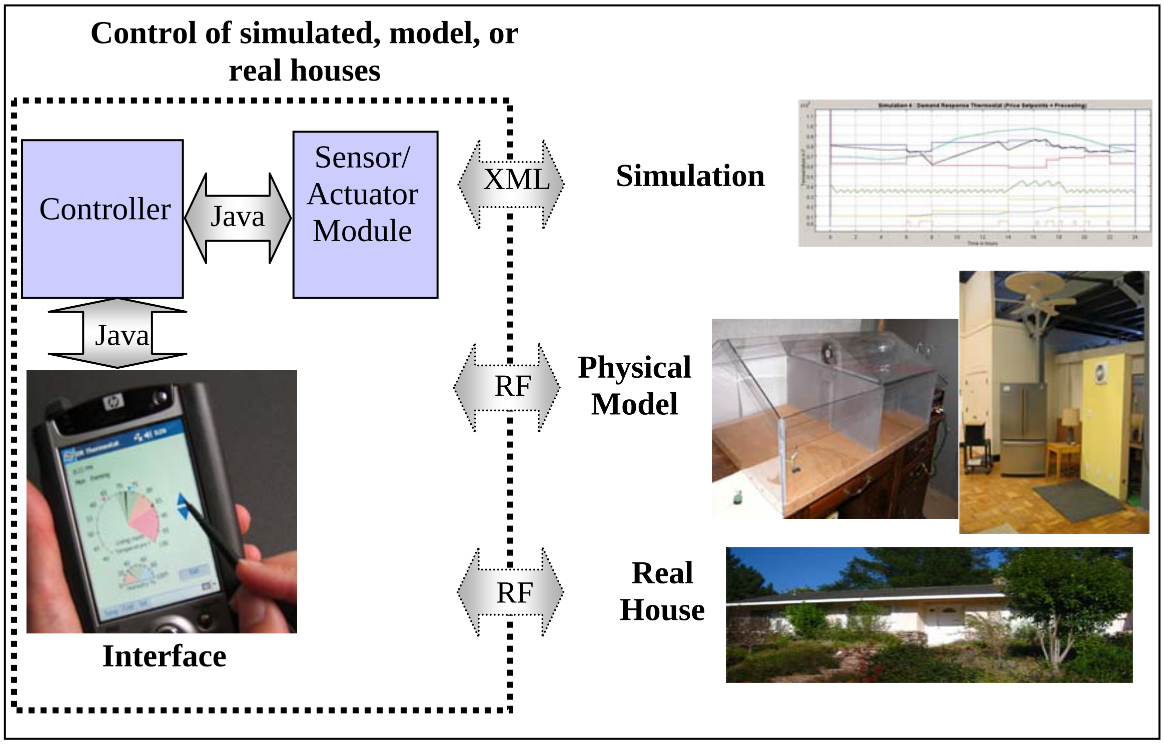


Figure 35: Java controller interfaces with simulation tools and actual sensors/actuators.

5.1.3.1 Simulation testing

Computer simulation allowed us to easily change different aspects of the system in evaluating the performance of control strategies. We developed a simulation tool built on the California Non-Residential Engine (CNE) found at the heart of many of the simulation tools currently approved for establishing performance compliance with California Title 24 energy code. The tool was modified to run on a five minute time-step and was named the MultiZone Energy Simulation Tool (MZEST) (Arens et al., 2006). Initially, Architecture Masters student Anna LaRue developed a house model in MZEST based on the first test house. She used a separate set of sensors to collect temperature and electric lighting data, and then modified the MZEST model until it generated the same indoor temperature readings as the occupied house (LaRue, 2006).

We developed four different house models to represent the spectrum of California houses; we used these models to understand the effect of different control strategies. After my initial analysis, Anna LaRue developed these models in MZEST; they were later modified by Kyle Konis, Architecture Doctoral student. A model was developed from the original validated house model to represent characteristics typical of a house built before the Title 24 energy efficiency standards. This house is assumed to be poorly insulated, with single-pane windows and equipment efficiencies typical of the 1970s. To represent the opposite extreme, a post-1992 model was developed representing a house with double-pane windows, insulated walls, floor and roof, and equipment efficiency meeting the minimum for Title-24 compliance for 1992. Further, because of the role that thermal mass plays in attenuating heating and cooling loads, both a crawl-space model and a slab-on-grade version were created for each category (see figure 36).

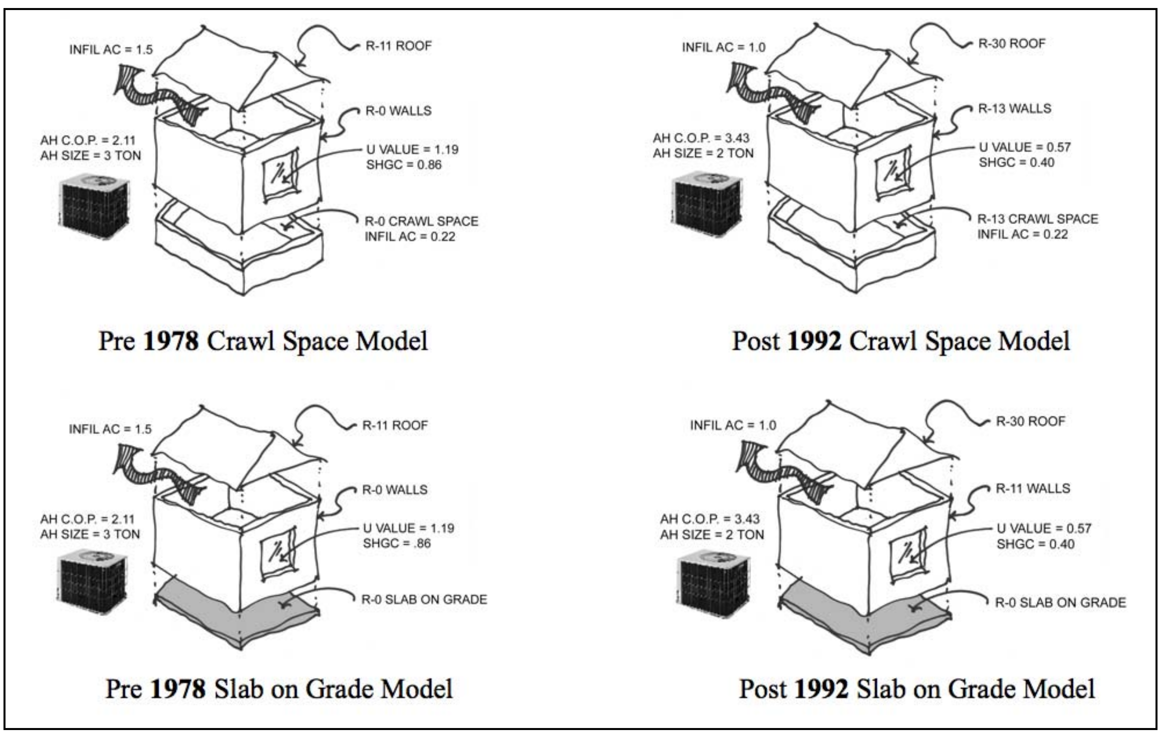


Figure 36: Four MZEST models to represent the spectrum of California houses (drawings by Kyle Konis).

5.1.3.2 Laboratory testing

The initial physical test of the hardware, software, and communication occurred in a controlled laboratory environment. First, we tested the network in the laboratory with a plastic "dollhouse" which had a thermoelectric cooler and separate fan. We placed temperature sensors inside the house, occasionally using a heat lamp to raise temperatures in the house to trigger the cooling system. We also developed a full-scale wall section[53], which had electrical outlets, wall fan, circuit breaker panel, and electrical meter. We demonstrated a closed-circuit control loop using motes to sense temperature, relative humidity, electric current and motion, and to control lights, a cooler, a ceiling fan, and appliance outlets. Photographs of these test beds are shown in Appendix C.

Between the field tests, we tested the motes again in the laboratory. The functions of all motes were verified. We monitored battery life to determine the length of the field test. We calibrated the new temperature sensors and discovered that the sensors have constant bias if using the same calibration formula. In order to get better resolution of temperature, the sensors were calibrated individually. Once we determined temperature resolution, we used an increment of 0.5ºF for the controller.

5.1.3.3 Field tests

In the first field test, we deployed a sensor network of 13 motes in an occupied house from August through December 2005. The three bedrooms had temperature and motion sensor motes; the hallway mote added a relative humidity sensor. The living room, dining room, and family room also had temperature and motion sensor motes. Two motes

[53] Architecture Masters student Stet Sanborn constructed this wall section; a licensed electrician installed the outlets, circuit breaker panel, and electrical watt-hour meter.

outdoors measured temperature, relative humidity, wind speed and direction, and solar radiation data. Another mote at the whole house circuit breaker panel in the garage measured current and voltage. Since the outdoor motes were on the opposite end of the house from the base mote, a repeater mote relayed data from the family room. A tablet personal computer located in the closet of the master bedroom received data via the base mote and relayed data to our server at UC Berkeley via the internet.

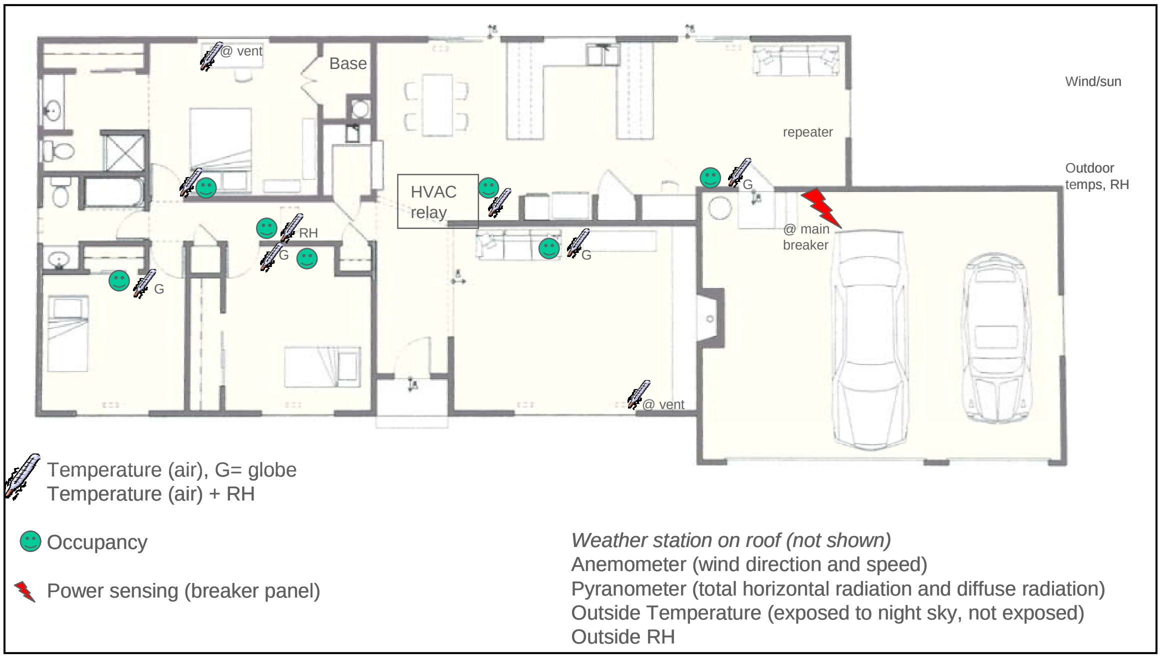


Figure 37: Floor plan of first field test house in 2005, showing type and location of motes.

The second field test took place in July through September 2007. We tested the DREAM system in two occupied houses to test the functions of the system, to verify simulation results, and to get feedback from participants. We were looking for single family detached houses not far from UC Berkeley, in which the occupants use their air conditioning during the summer months. By chance our two volunteer houses were located about 10 miles apart about 40 miles northeast of Berkeley. The two houses were exposed to similar outdoor conditions, but the house structure, HVAC system and residents' schedules were different. This diversity offered the opportunity to test the system under different conditions. We developed a detailed test plan, and adjusted this plan during the actual tests. The participants were interviewed before and after the tests to collect information about their energy use habits and to get feedback on the system.

5.1.3.3.1 Summer 2007: House 1

House 1 was a 1700 square foot two-story stucco house built in 1991. The living room had a cathedral ceiling that was open to the stairs and upstairs hallway that led to four bedrooms upstairs. Most of the windows faced east or west. Three ceiling fans were controlled manually in the living room, kitchen and master bedroom. The HVAC system was a Carrier split-system air conditioner/furnace, with supply grilles in the floor throughout the house. The owner replaced the original setback thermostat with a White Rodgers programmable thermostat.

Figure 38: House 1 of the Summer 2007 field test.

An adult male and teenage female occupied the house; he worked at home and left for business irregularly during the day and she was in the house some of the time. A black Labrador was inside most of the time. The owner reported that he normally kept the thermostat set to 74ºF (23.3ºC) during day and night; when he left and remembered to offset the temperature, he set the thermostat to 79ºF (26.1ºC). The owner opened up the upstairs windows at night and closed them during the day. The main electrical appliances were the clothes washer and dryer.

We installed fourteen motes in House 1. We designed a plastic sheet to hold many of the motes which attached to light switch plates as shown below. This allowed the temperature sensors to read at approximately the same height. We placed temperature sensors in the master bedroom, upstairs hallway, kitchen, and living room, where the thermostat was located. We located one temperature sensor directly in the supply grille in the floor of the master bedroom. The living room mote collected relative humidity data. We placed the occupancy switch at the entrance to the garage, the most common entry to the house. A mote outside under the southeast eave of the roof measured temperature, relative humidity, and solar radiation on top of the roof. Another mote measured current at the circuit breaker for the air conditioning compressor outside. A mote at the main circuit breaker panel measured current from the blower fan, clothes washer, clothes dryer, the kitchen, and on both main branches of the panel. The third current sensing mote measured current at the main computer in the house. We placed the motes for the HVAC relay, thermostat switch, price indicator, and base mote attached to the computer/user interface in the family room, since the participant indicated this room was typically occupied.

Figure 39: Example of generic mote installation.

We used an ultra mobile PC—the Samsung Q1—to host both the controller and the interface. The size of the computer was slightly larger than a programmable thermostat, and the touch-screen made it ideal for user input.

5.1.3.3.2 Summer 2007: House 2

House 2 was a 1500 square foot one-story house built in 1984. One ceiling fan continuously ran in the family room. The HVAC system was a General Electric split system air conditioner/furnace, with supply grilles in the ceiling. The thermostat was the original manual setback Honeywell Chronotherm. The house had two skylights in the roof and an attic fan.

Figure 40: House 2 of the Summer 2007 test.

Two people lived in this house, one male and one female who were normally out of the house during the day, but during a portion of the test were at home taking care of newborn puppies. The participants looked at the weather forecast for the day to decide to use the air conditioning. Usually the setpoint during the day was 70ºF (21.1ºC), and lowered in the evening, and turned off at night. If the weather was hot, the setpoint was 68ºF (20ºC) and 70ºF (21.1ºC) at night. The participants opened up the windows at night; two windows were left open during the day as well.

We installed fifteen motes in House 2. We located the occupancy switch mote near the front door. We placed temperature sensing motes in the master bedroom, bedroom, office, and living room; in addition we placed a temperature sensor in the supply grille in the ceiling of the living room. We located the outdoor mote under the southeast eave of the roof; in this house, the repeater mote was necessary to relay the data from the outside mote to the base mote. The mote in the bedroom had a relative humidity sensor. One mote outside measured the current at the air conditioner circuit breaker panel.

The mote at the main circuit breaker panel measured the current from the blower fan, dishwasher, the workshop 240V circuit, and workshop outlets, and two main branches of the panel. The third current sensing mote measured current from the clothes washer. We located the price indicator mote in the laundry room. We placed the HVAC relay mote, thermostat switch mote, and base mote attached to the computer near the existing thermostat in the family room.

5.1.3.3.3 Summer 2007: test plans and implementation

The total time for testing was approximately six weeks. The test for House 1 began two weeks earlier than the other. The test was divided into three phases as described below; however, the reliability of system communication was continuously monitored during the whole test.

System check-out period. For the first week, the DREAM system was installed in the house and was connected with the HVAC system, but did not control it. The AC was still controlled by the original thermostat, while the DREAM system monitored the temperature, occupancy status, electrical appliance use, and HVAC system status. The DREAM system evaluated the default internal model and AC efficiency with these data.

Mimicking period. This was a two-day period where the DREAM system controlled the HVAC system in order to reproduce the operation of original thermostat. This time was used to test the actuation functions and to train the occupants to use the DREAM interface.

Testing period. The testing focused on the main functions of the DREAM system: optimization, precooling and house energy prediction model. These strategies controlled the house temperature and we evaluated control behavior. One of the parameters was a simulated price. The participants could see a change in price on the user interface, but no actual change to their utility bill took place.

We visited each house several times during the tests. On the first and last visits we installed and removed the system; we made other trips to change batteries, change hardware settings and solve problems. We recorded test events, our activities and participants' activities. We adjusted test plans to respond to occupancy and climate changes. The next chapter discusses the findings of these tests.

5.2 Learning people's temperature preference and schedule

Since studies have found that many people find programming thermostats difficult, this next section explores the potential of an algorithm that can "learn" over time and thus anticipate the occupant's preferred temperature. The thermostat would have an initial schedule and default setpoints. An occupant would either increase or decrease the temperature setpoint at various times of day, indicating that he or she would like to be warmer or cooler.

Based on the thermal comfort literature, input indices to the learning algorithm include the concurrent and past interior and exterior temperatures and setpoints, the time of day, season, and occupancy, and initially, the occupant's preferences. The output from the learning algorithm is the predicted heating and cooling temperature setpoints for a given time, day, occupancy, and interior temperature that will provide a comfortable temperature for the occupant. The goal is that over time, the algorithm will choose an appropriate temperature setpoint predicting the occupant's desires. That is, the occupant will interact with the thermostat less over time.

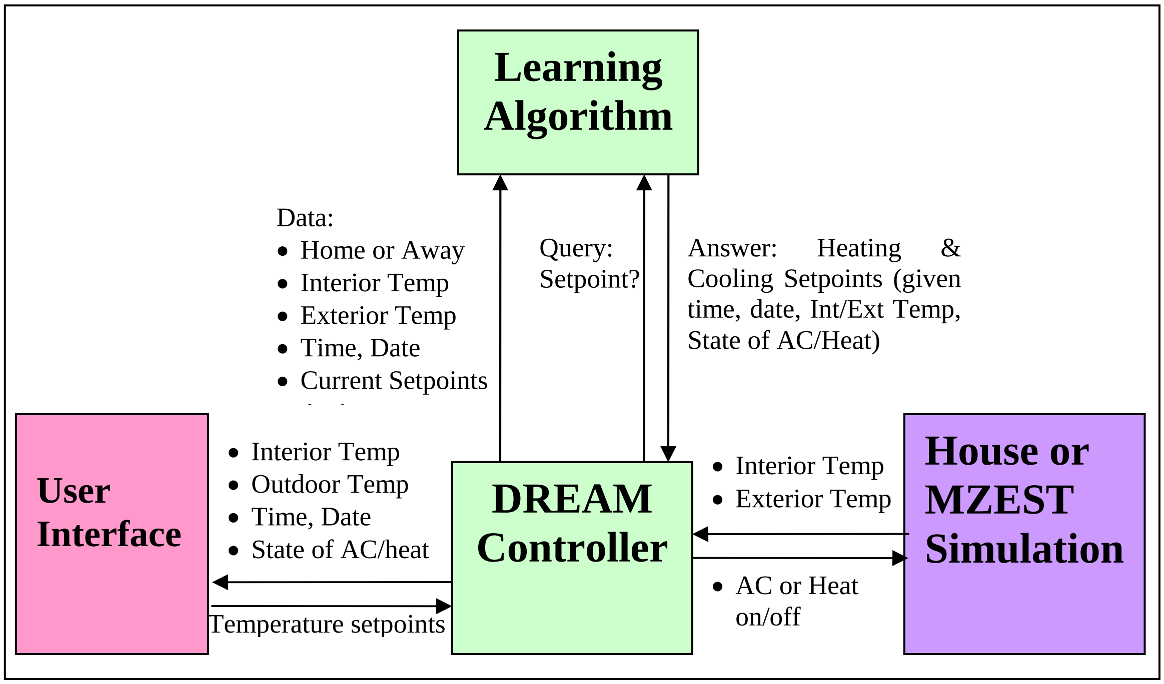


Figure 41: Learning algorithm input and output, within DREAM system.

Learning a discrete value is referred to as classification learning; learning a continuous function is termed regression learning. Thermostats generally have two setpoints: one for heating, below which the heater turns on, and one for cooling, above which the air conditioner turns on. The difference between the two setpoints is considered the comfort zone. In this case, learning will include two probability distributions, one for the heating setpoint and one for the cooling setpoint.

Thus choice *a* is the setpoint. The state of the world is *x*. This state has a probability distribution of P(*x*|*a*). Data will be recorded for every state, such that over time, the choice can be predicted given the state. A future development might consider a utility function U(*x*,*a*) which specifies the value of achieving the best choice *a* given the state *x*. The task would then be to select the action that maximizes the expected utility.

An important question to consider is whether a person's thermal preference is consistent or predictable with the information collected. That is to say, is a person's thermal preference consistent enough to be predicted, given the data available—is it in fact, learnable? The background chapter indicates many factors that lead to the state of mind that defines thermal comfort, including hard-to-measure personal traits such as clothing, metabolic rate, and adaptive mechanisms.

To answer this question, I looked at data from Berkeley Civic Center office workers collected in ASHRAE-sponsored research by UC Berkeley in 2002-2003. In this study, office workers were asked to take a short online survey several times per day regarding their thermal satisfaction and preference. They were asked to take the survey only if they had been at their desk for 30 minutes, to remove the effect of transient conditions with respect to thermal comfort. The study took place over a two week period in summer and two week period in winter. Thirty-eight people participated; each had a indoor comfort monitor on his/her desk that measured temperature, relative humidity, and air speed (Paliaga, 2004). The data from the survey and temperature measurements were combined to obtain a temperature reading and time and date stamp for each temperature preference vote for each person. Although 38 subjects were involved in the test, some subjects took the survey often (a few times per day) and others infrequently (a few times during the two week period).

These data were analyzed with an available simple decision tree algorithm, the Decision Tree Learning Applet 4.0.1 (Coelho et al., 2005; Poole, Mackworth, & Goebel, 1998). The applet loads data files of several examples; each example contains data from a point in time: initially, just interior temperature (in Celsius) and the thermal preference vote (-1: Want to be warmer, 0: Acceptable, or +1: Want to be cooler). The applet randomly splits data into training and testing pools, and based on the attribute splitting parameter (or decision tree node), attempts to predict the result of the testing pool given the data in the training pool.

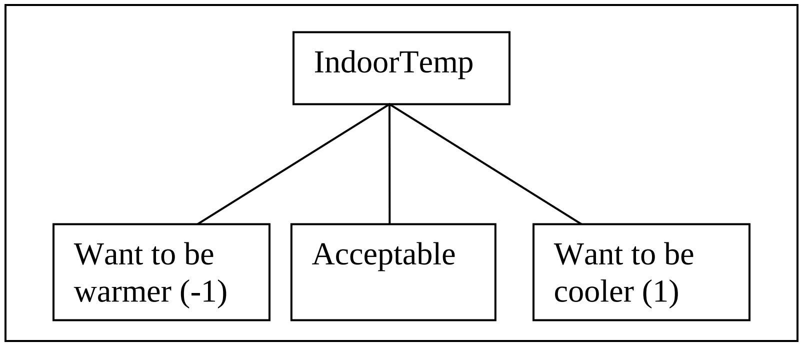
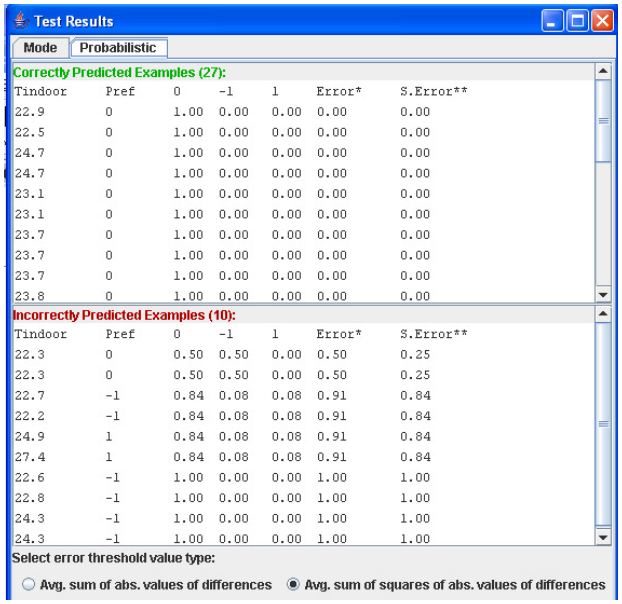


Figure 42: Initial decision tree learning diagram, using inside temperature as a node.

Initially, I ran the learning algorithm several times using the data from just two subjects. First, the only “node” on the decision tree was indoor temperature. Thus, based on half the examples of indoor temperature and comfort vote, the algorithm predicts what the comfort vote will be on the remaining indoor temperature points. Next, I added other nodes: time (whether it was morning or afternoon), and season (summer or winter). The following describes the process of choosing these parameters.

With just indoor temperature as a node, the learning algorithm correctly predicted 27 examples, and incorrectly predicted 10 examples in the first test of subject JS. The results are shown below. I ran the learning algorithm several times. The best prediction was 29 correct and 8 incorrect.



Test Results

Mode | Probabilistic

Correctly Predicted Examples (27):

Tindoor	Pref	0	-1	1	Error*	S.Error**
22.9	0	1.00	0.00	0.00	0.00	0.00
22.5	0	1.00	0.00	0.00	0.00	0.00
24.7	0	1.00	0.00	0.00	0.00	0.00
24.7	0	1.00	0.00	0.00	0.00	0.00
23.1	0	1.00	0.00	0.00	0.00	0.00
23.1	0	1.00	0.00	0.00	0.00	0.00
23.7	0	1.00	0.00	0.00	0.00	0.00
23.7	0	1.00	0.00	0.00	0.00	0.00
23.7	0	1.00	0.00	0.00	0.00	0.00
23.8	0	1.00	0.00	0.00	0.00	0.00

Incorrectly Predicted Examples (10):

Tindoor	Pref	0	-1	1	Error*	S.Error**
22.3	0	0.50	0.50	0.00	0.50	0.25
22.3	0	0.50	0.50	0.00	0.50	0.25
22.7	-1	0.84	0.08	0.08	0.91	0.84
22.2	-1	0.84	0.08	0.08	0.91	0.84
24.9	1	0.84	0.08	0.08	0.91	0.84
27.4	1	0.84	0.08	0.08	0.91	0.84
22.6	-1	1.00	0.00	0.00	1.00	1.00
22.8	-1	1.00	0.00	0.00	1.00	1.00
24.3	-1	1.00	0.00	0.00	1.00	1.00
24.3	-1	1.00	0.00	0.00	1.00	1.00

Select error threshold value type:

Avg. sum of abs. values of differences | Avg. sum of squares of abs. values of differences

Figure 43: Initial test results for subject JS, with just indoor temperature information.

Below is the decision tree showing how the probability was developed for each temperature value.

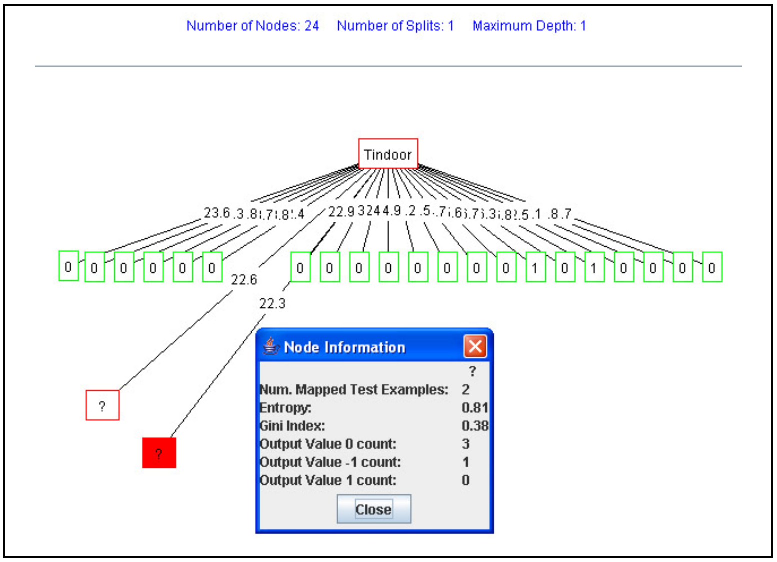


Figure 44: Simple decision tree for JS.

To check the learning algorithm, I decided to test it against an expert system, using myself as an expert. I wanted to see how well I would do in predicting temperature acceptability with the same data. After my analysis, I determined that this person would want to be warmer below 23ºC (73.4ºF) and cooler above 25ºC (77ºF) unless the time was morning (then warmer below 22ºC (71.6ºF)). See graph below. Using this rule, I predicted 62 correctly, and incorrectly predicted 12 examples out of 74.

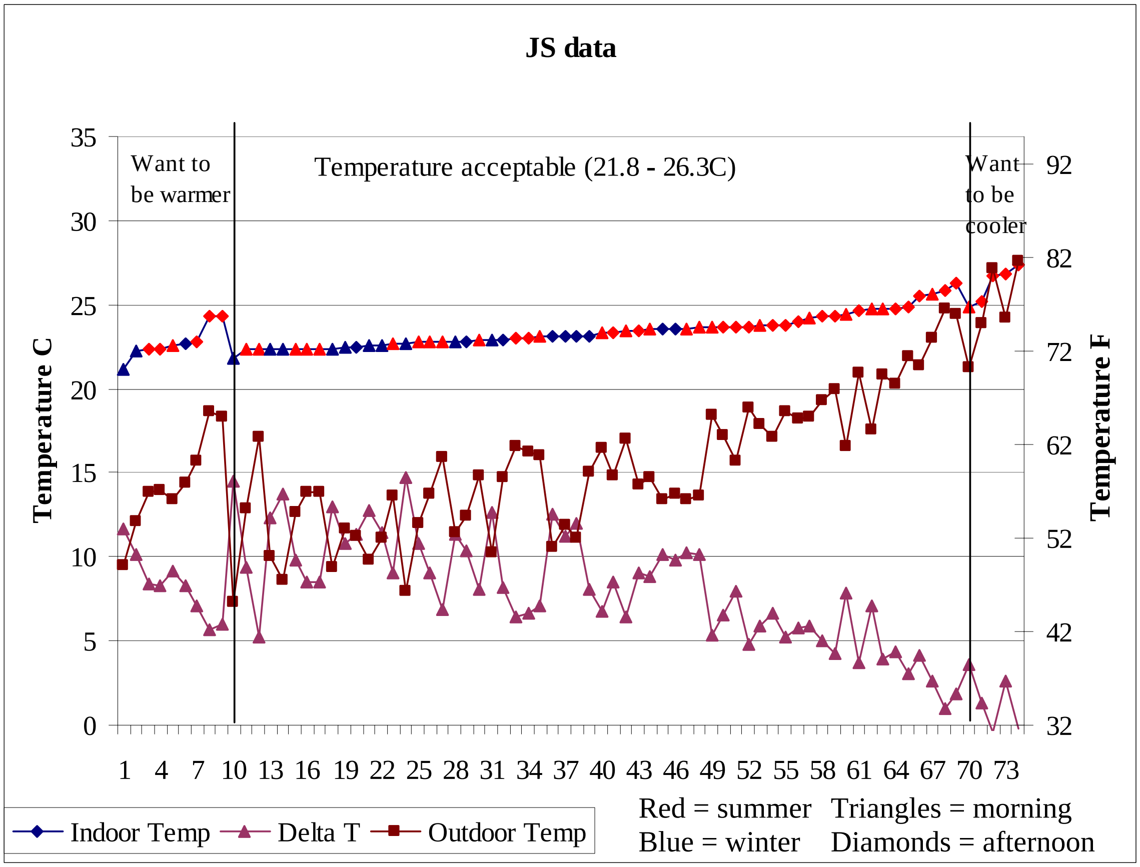


Figure 45: Graph of survey events for JS ordered first by comfort vote, then by indoor temperature.

I added time and outdoor temperature information to the decision tree algorithm and explored the different ways the applet had of building the tree. The applet allowed the choice of the attribute on which to split to be determined in several ways: randomly, by maximum information gain, by the maximum gain ratio, or highest GINI value (which measures impurity of data, and was identical to gain ratio).

I evaluated the different methods of choosing the first decision tree node. With the index of time added to the decision tree, the performance improved to 31 correct and 6 incorrect, using a randomly chosen attribute on which to split first. See results below. I ran the test several times to get the following ratios of correct to incorrect predictions: GINI (split on IndoorTemp): 30:7; InfoGain (split on OutsideTemp) 29:8, GainRatio (split on IndoorTemp) 30:7. For this subject, indoor temperature alone was a fairly good predictor of his/her comfort vote. Adding time information did not significantly increase the prediction rate.

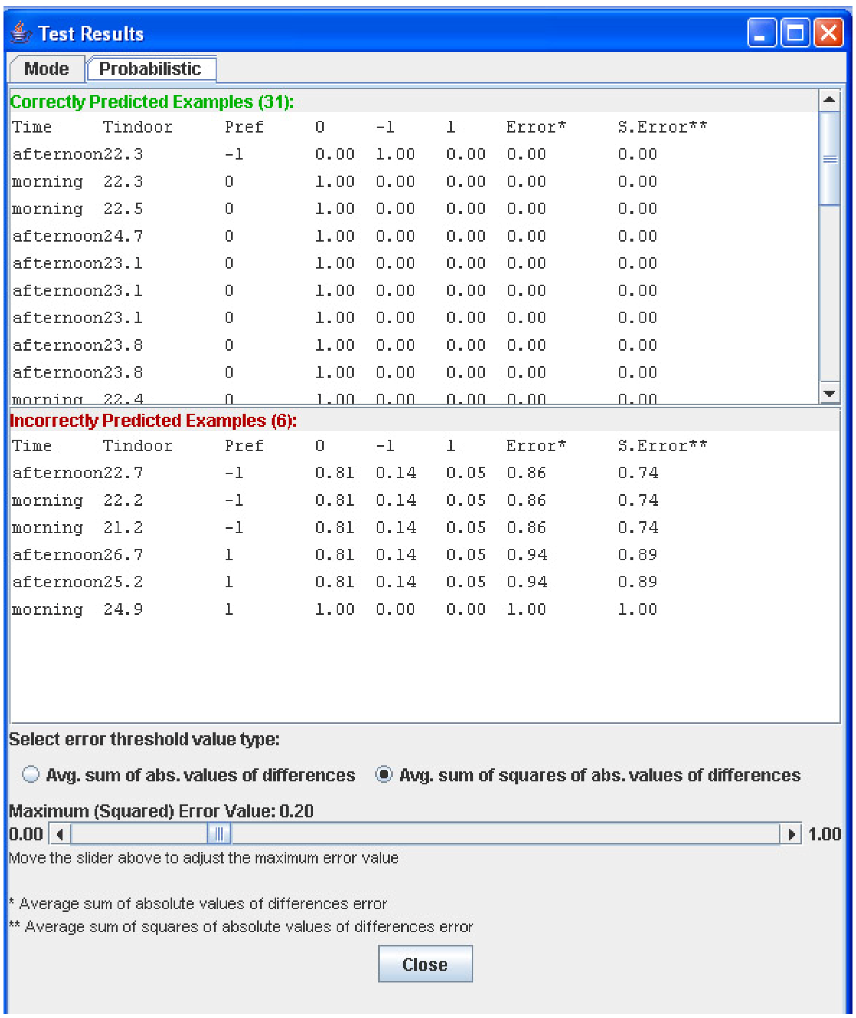


Figure 46: Best results for JS using time and indoor temperature to predict temperature preference.

The next step was to test other individuals, choosing subjects with the largest number of data points. The next test was with data from subject DK. Based on the simplest test of just indoor temperature, the results were: 10 correct: 31 incorrect. I again reviewed the raw data to see if I could detect any issues. This subject's comfort votes were influenced by season.

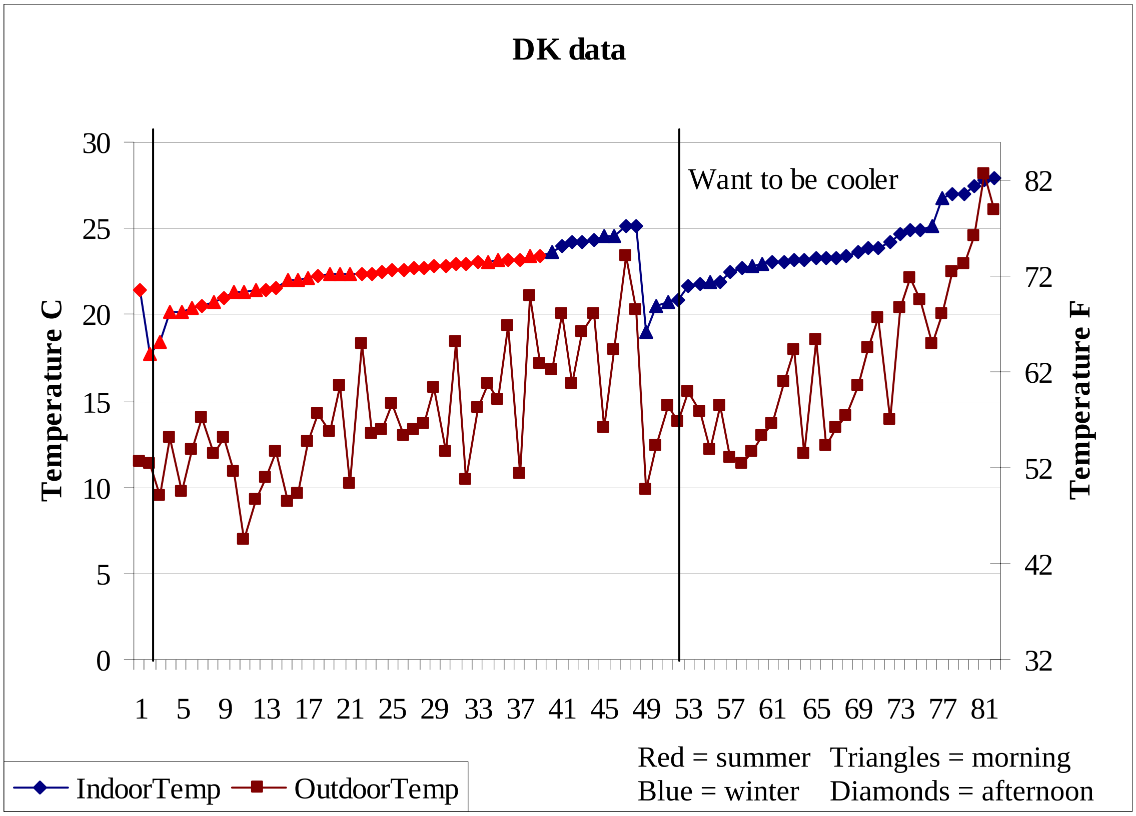


Figure 47: Survey results for DK showing a seasonal split.

The next step was to add more attributes to the decision tree to see if this improved the performance. I added season, time, and outdoor temperature. Using the random split option, the decision tree split on season and correctly predicted 34, with 7 incorrect examples the first time. (I ran the algorithm a few more times and saw 35: 6 as the highest correct prediction ratio). Selecting the gain ratio, the split was on season, and then time, and the result was 35 correct to 6 incorrect. With information gain, the split occurred on outside temperature and the result was 21 to 20. Using GINI, again the split was on season, then outside temperature with a result of 35:6. For this subject, the comfort vote was highly dependent on season (perhaps the expectation of being cooler in winter) rather than the actual indoor temperature. Possibly this is due to a higher clo value (i.e., more layers of clothing) in the wintertime.

After I had developed and tested the initial methodology, I used the learning algorithm to test the data of several more subjects. I selected subjects based on the amount of data collected, both in number of data points and a fairly even distribution among summer and winter data points. I used indoor temperature, time, and season as the nodes in the decision tree. The results of these tests are discussed in the next chapter.

5.3 Adaptive temperature setpoints

This section outlines the development of dynamic temperature setpoints suitable for residential thermal comfort, building on the Adaptive Comfort Standard by adding the effects of diurnal temperature changes, relative humidity, air movement, and suggesting setpoints for nighttime comfort. The purposes of developing a thermostat that adapts the temperature setpoints based on outside air temperature, relative humidity, and air movement are two-fold: to save energy and provide better comfort during high price periods.

5.3.1 Developing the algorithm

The objective was to use what is known about thermal comfort in residences to develop an algorithm that provides comfort, saves energy, and engages the person, not only in his/her comfort but also understanding its implications on energy use. The method described to develop the algorithm began by using the outdoor temperature, similar to the Adaptive Comfort Standard. The next step was to modify the setpoint based on time of day. Next, I modified the setpoint using relative humidity in developing a setpoint that reflects a “feels like” temperature, similar to wind chill. The final step in modifying the temperature setpoint was based on price and comfort. An additional step was to develop advice based on what the person can do to feel more comfortable, regarding opening windows and using fans to increase comfort for less cost.

This section describes these five steps in detail.

1) Develop a seasonal change in setpoints by using a running weekly weighted average outdoor dry bulb temperature as input to the Adaptive Comfort Standard to predict an indoor comfortable temperature range during waking hours.[54]

2) Develop a diurnal change in setpoint for winter mornings and summer afternoons. In the cooling months, allow the temperature to drift from the center of the comfort range to the upper limit. In the heating months, allow the temperature to drift from the lower limit of the range to the center of the range.

3) Modify the cooling setpoint based on relative humidity, since a high relative humidity reduces thermal comfort.

4) Modify the final setpoint based on price (low, medium, high or critical).

5) Develop advice generated from the added effect of adding air movement, especially to achieve comfort in high price periods. In addition, develop advice for opening and closing windows based on outdoor temperature and indoor temperature.

[54] Temperatures for nighttime came from laboratory sleep studies.

5.3.1.1 Develop a seasonal change in setpoint

The Adaptive Comfort Standard provides a means for establishing a comfortable indoor temperature range for naturally ventilated buildings based on the mean monthly outdoor air temperature. As seen in the figure below, one enters a mean monthly air temperature on the horizontal axis to determine a temperature range found acceptable by 90% of the population and a range found acceptable by 80% of the population. This standard was developed using comfort votes from commercial buildings, and therefore is meant to give comfort criterion during the daytime hours. A given mean monthly outdoor temperature provides a range of operative temperatures, which could define a heating and cooling setpoint. For air velocities less than 80 fpm (0.41 m/s) and mean radiant temperatures less than 120ºF (48.9ºC), the operative temperature is approximately equal to the adjusted dry-bulb temperature, which is the average of the air and mean radiant temperatures. Thus, we will assume the operative temperature is equivalent to dry bulb temperature setpoint for the HVAC equipment.

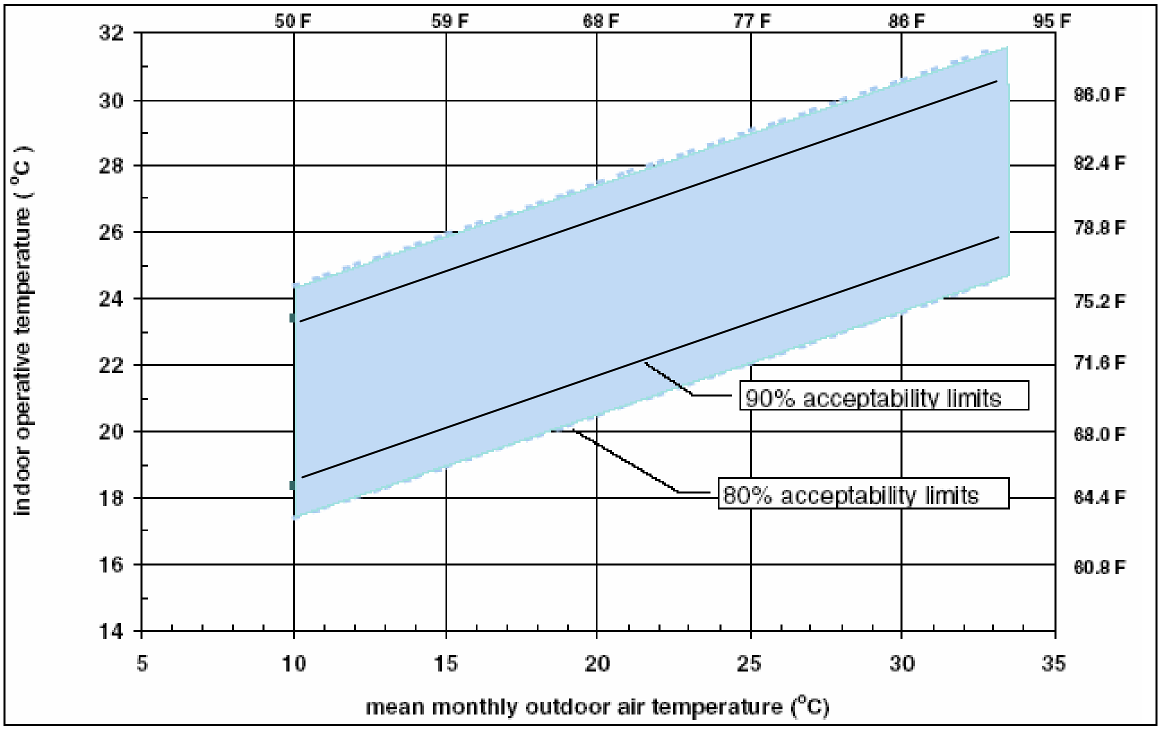


Figure 48: The Adaptive Comfort Standard from ASHRAE 55-2004 for naturally ventilated buildings (American Society for Heating Refrigerating and Air-Conditioning Engineers (ASHRAE), 2004).

The figure below shows an example of generating heating and cooling setpoints based on the monthly outdoor temperature, using the mean monthly outside temperature from Sacramento, California. The default setpoints suggested for EnergyStar thermostats (for houses occupied during the daytime) are shown for comparison: 70ºF (21ºC) heat, 78ºF (25.6ºC) cool. The cooling setpoints for the adaptive strategy are higher than the static cooling setpoint (and the reverse for the heating setpoints). For example, in July and August when the outside temperature reaches 100ºF (37.8ºC), the adaptive thermostat temperature setpoint might drift to 82ºF (27.8ºC), which is higher than the programmable thermostat setpoint of 78ºF (25.6ºC). This represents energy savings, since the heating and cooling equipment would not cycle as often.

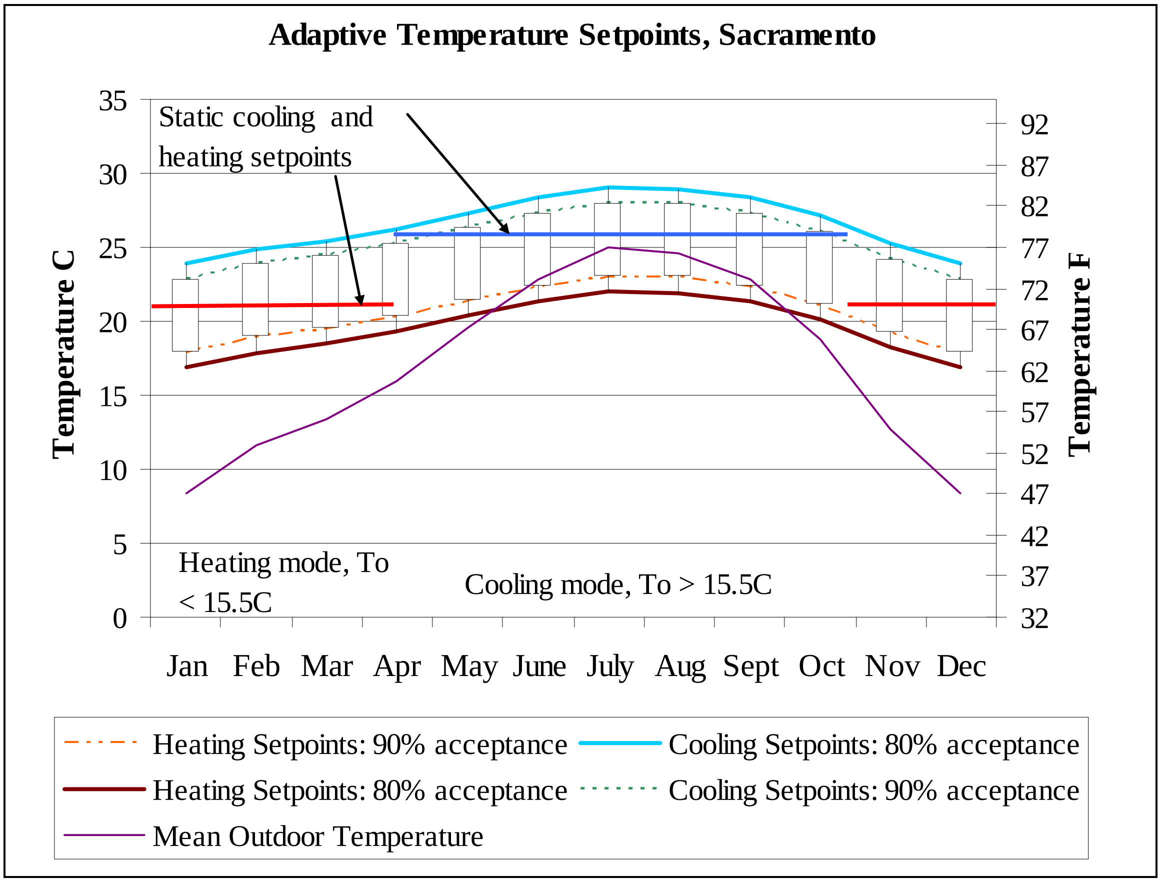


Figure 49: Adaptive temperature setpoints for a house in Sacramento, CA.

Humphreys has suggested that instead of using a monthly outdoor temperature mean, that the previous two weeks or even a week can be indicative of the adaptive effect (Humphreys & Nicol, 1998). For this algorithm, I used the weighted running average of the previous seven days.[55] The weighted average comes from Morgan & de Dear (2003), who developed a formula for the exponential decay of the effect of outdoor temperature on indoor clothing decisions.

> "These weighting coefficients can be used to calculate the appropriate mean outdoor temperature (*T*mot) for subsequent input to an adaptive indoor temperature algorithm: *T*mot = 0.34*T*Dayx-1 + 0.23*T*Dayx-2 + 0.16*T*Dayx-3 +

[55] The European adaptive comfort standard, Annex A.2 of EN15251, uses an exponentially-weighted running mean outdoor temperature and is well described in (Nicol & Humphreys, 2009a).

> $0.11T$Dayx-4 + $0.08T$Dayx-5 + $0.05T$Dayx-6 + $0.03T$Dayx-7 and then the adaptive algorithm for indoor comfort temperatures in a naturally ventilated or free running building (de Dear & Brager 2002) can be written as comfort temperature (°C) = $0.31T$mot + 17.8 (4) and the *acceptable range* of temperatures is defined as the optimal comfort temperature (Eq. 4) ± 2.5°C for 90% acceptability, or ±3.5°C for 80% acceptability (ASHRAE 2002)" (Morgan & de Dear, 2003).

Figure 50 below shows the upper and lower limits for comfort temperature in free-running buildings (without mechanical cooling systems in use) using the exponentially-weighted running mean of the outdoor temperature from EN15251. Of the three types of buildings, Type III is most appropriate for residences (existing buildings, as opposed to new (II) or those for sensitive persons (I). The model I have developed uses the 90% acceptance range as the default (low price period). This is then modified based on time of day, relative humidity, and the price of electricity.

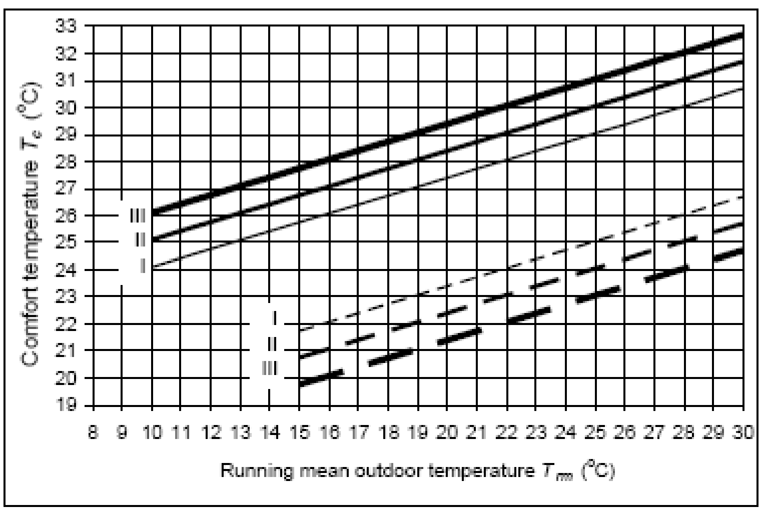


Figure 50: Design values for the upper (continuous) and lower (dashed) limits for limits for operative temperature in free-running buildings for different categories of building (Figure 1 from (Nicol & Humphreys, 2009a)).

5.3.1.2 Developing diurnal drift

In addition to adaptive temperature setpoints that change with outside temperature over the seasons, a few studies indicate that comfortable temperatures can drift with the outdoor diurnal temperature shift. People are comfortable at cooler temperatures in the morning and at higher temperatures in the afternoon. A diurnal drift may save energy as well, especially winter mornings and summer afternoons. The figure below reflects adjusting the heating and cooling setpoints to accommodate a daily diurnal temperature shift for the waking hours. The EnergyStar temperature setpoints are compared with the Adaptive setpoints for July and January. The shaded area indicates potential energy savings from the change in setpoint.

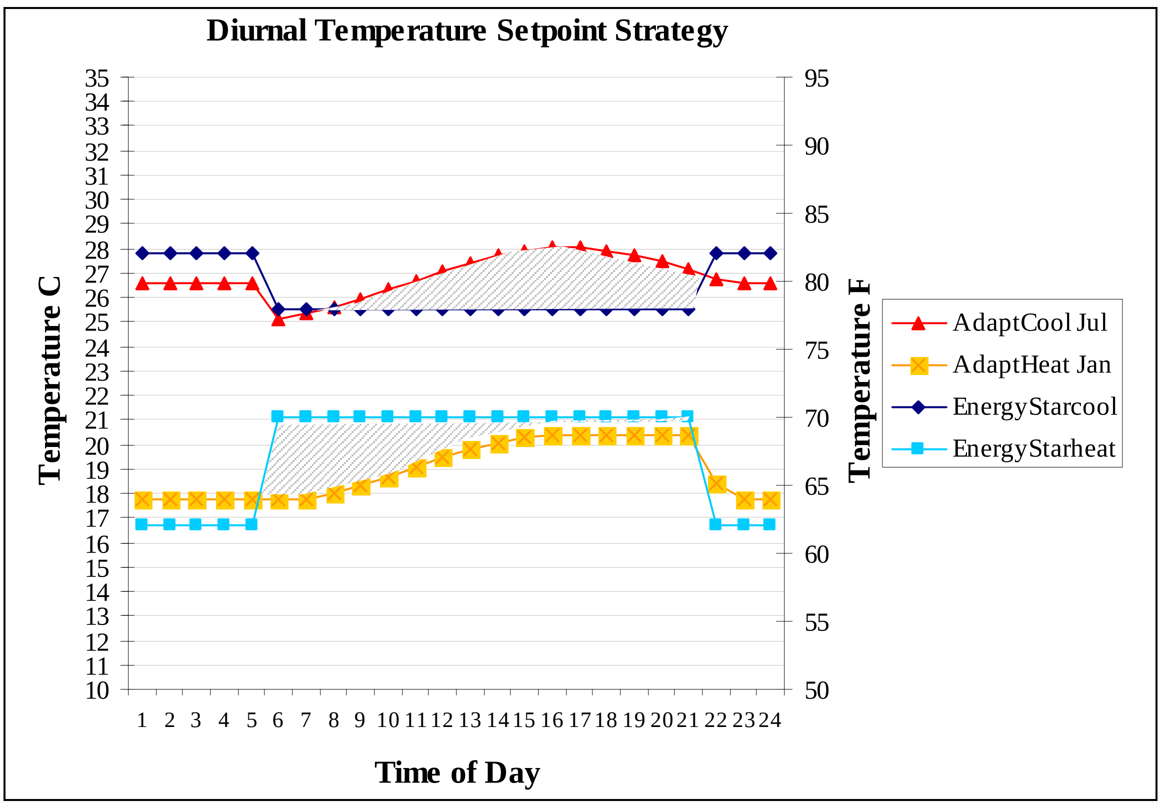


Figure 51: Changing the adaptive temperature setpoints over the course of a day.

For cooling during waking hours, the lowest temperature setpoint is based on the center of the Adaptive Comfort Standard for that month, then gradually rising +2.5ºC to peak at the maximum 90% acceptability temperature allowed by the ACS. The temperature setpoint during the day follows the outdoor temperature.

For heating during waking hours, the temperature setpoint starts at the minimum 90% acceptability temperature and rises to peak at the center of the Adaptive Comfort Standard in the afternoon. During cold weather, the temperature setpoint is lower in the morning, and then remains at the peak until the person goes to sleep.

The temperature setpoints were modified at night for energy savings, just like the default settings for programmable thermostats. Physiological evidence supports a nighttime winter setback for heating, but not a nighttime summer setup for cooling. Of the six factors that influence thermal comfort (air temperature, humidity, air speed, radiation, metabolic rate (Met), and clothing value (Clo)), the two personal elements of thermal comfort, Met and Clo, are conducive to winter nighttime temperature setback. Not only do people tend to have a higher insulation value (blankets, comforters) at night, but physiologically, a person’s core temperature changes approximately 0.4ºC (0.7ºF) over the course of the day, peaking in the late afternoon and at its lowest point at night (Zhang, 2003). Several studies concur with thermoneutrality of 86ºF (30ºC) inside the bed, and increased wakefulness if this temperature drops below 78.8ºF (26ºC) with ambient temperature of 55.4ºF (13ºC). Preferred nighttime room temperature was found to be 66.2ºF (19ºC) (Muzer et al., 1984). A survey of 100 houses showed average winter temperatures set at 65.3-66.6ºF (Woods, 2006). The EnergyStar default for nighttime setback is 62ºF; I used a static 64ºF (17.8ºC) nighttime setback from 10 pm to 6 am.

But what about the summer nighttime temperature setup? On one hand, nighttime outdoor temperatures tend to drop within a comfortable temperature range for most climates in California, and the indoor temperatures tend to follow the outdoor temperatures with some time lag. Also, when a person is asleep, he or she is less aware of the temperature (personal correspondence, Zhang). But on the other hand, some climates do not cool down at night. Several studies have been conducted to determine the effect of temperature on sleep, with mixed results. Tsuzuki et al (2005) suggested if the air temperature was above 26ºC (78.8ºF) or the relative humidity was high, or person was clothed, then the person may be uncomfortable and unable to fall asleep unless adequate air flow was provided (Tsuzuki et al., 2005). Several studies show better sleep at 26-27ºC (78.8-80.6ºF) compared to 31 or 36ºC (87.8 or 96.8ºF) (Schmidt-Kessen & Kendel, 1973). The Residential Appliance Saturation Survey (RASS) shows an average of 79.6ºF (26.4ºC) at night (CEC, 2004) and Woods reports 77.4 – 78.4ºF at night (Woods, 2006). The EnergyStar setup for night is 82ºF (27.8ºC). Based on these studies, I chose 26.6ºC (80ºF) as a static nighttime setup from 10 pm to 6 am.

In summary, the algorithm generated temperature setpoints that adapted to the outside temperature during the day, but were static at night. In addition, for cooling, the minimum setpoint allowed was 77ºF (25ºC); for heating, the maximum was 68ºF (20ºC). The nighttime setup was 80ºF (26.6ºC) for the cooling season and the setback was 64ºF (17.8ºC) for the heating season. For the programmable thermostat, the EnergyStar default for the cooling setpoint was 78ºF (25.5ºC) during the day and 82ºF (27.8ºC) at night, and for the heating setpoint was 70ºF (21.1ºC) during the day and 62ºF (16.7ºC) at night.

5.3.1.3 Modifying setpoint for high relative humidity

The next step involves adding the effect of relative humidity on the daytime comfort setpoint using effective temperature (ET*) and discomfort index (DISC). ET*, the effective temperature, is the temperature at 50% relative humidity that yields the same total heat loss from the skin as for the actual environment (ASHRAE, 2005). It can be thought of as a "feels like" temperature; high relative humidity causes the temperature to "feel" warmer, similar to the effect of wind chill causing the temperature to feel cooler. DISC provides a scale for discomfort from -4 (Intolerably cold) to +4 (Intolerably hot) as follows:

4-Intolerable
3-Very uncomfortable
2-Uncomfortable
1-Slightly uncomfortable
0-Comfortable

I used the two-node comfort model software tool, Comfort 1.07 (Fountain & Huizenga, 1996; Huizenga & Fountain, 1997), to generate the effective temperature curve for a given temperature at various relative humidities. The effect of relative humidity on the temperature can be seen in the following figure, which plots the effective temperature and discomfort index. According to this figure, humidity level does not seem to affect comfort at low temperatures, but has an increasing effect on temperatures greater than 25ºC (77ºF). For example, 77ºF (25ºC) feels slightly warmer (77.7ºF (25.4ºC)) at 80% relative humidity, but 80.6ºF (27ºC) feels even warmer (82.2ºF (27.9ºC)) at 80% relative humidity and slightly cooler 79.9ºF (26.6ºC) at 20% relative humidity. The figure below indicates that indoor temperature setpoints greater than 79ºF (26.1ºC) should be reduced if the relative humidity is greater than 70%.

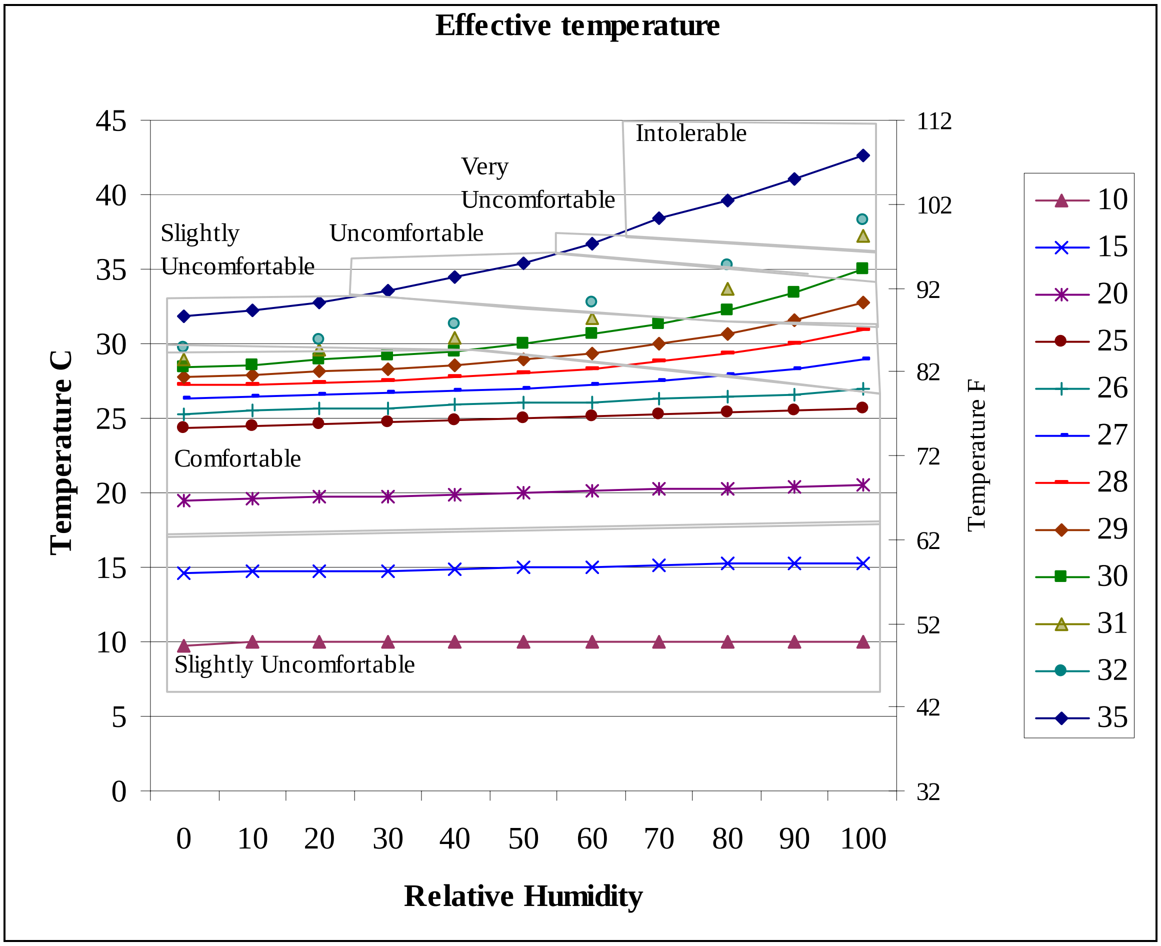


Figure 52: Effect of relative humidity on comfort.

5.3.2 Developing a comfort index for price setpoints

To develop setpoints for different price levels, we attempted to create a cost-comfort index. Since the Adaptive Comfort Standard doesn't have a comfort index, I developed one based on a seven-point comfort scale similar to the Bedford psycho-physical voting scale:

-1 to 1 is comfortable (ACS center ± 2.5ºC: 90% acceptance)
-2 to -1 & 1 to 2 is comfortably cool/warm (ACS center ± 3.5ºC: 80% acceptance)
-3 to -2 & 2 to 3 is uncomfortably cool or warm (ACS center ± 4.5ºC)
less than -3 & greater than 3 is very uncomfortably cool or warm (beyond ACS center ± 4.5ºC)

The graphic below shows how the comfort index was developed from the Adaptive Comfort Standard.

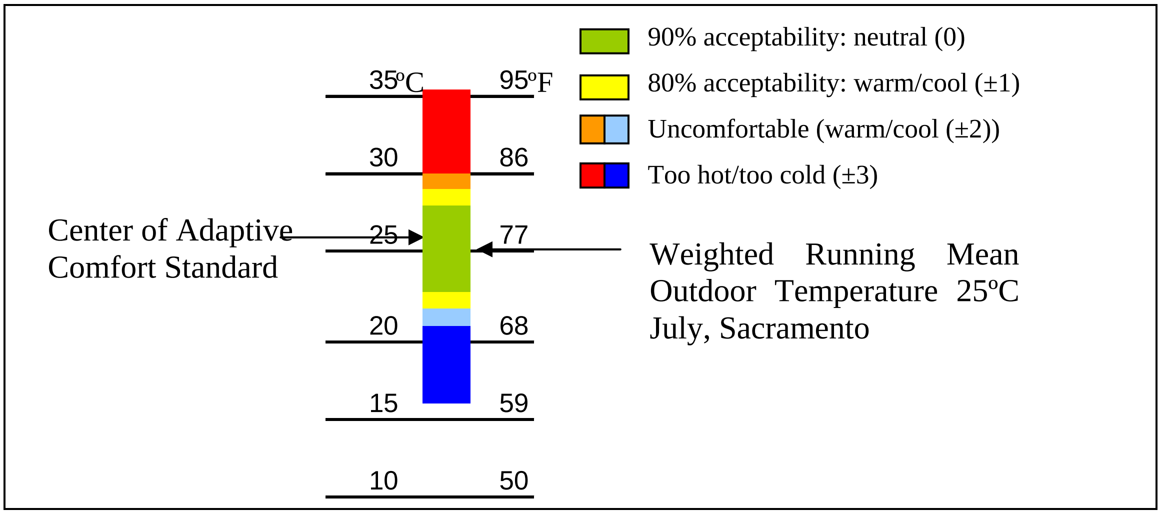


Figure 53: Comfort index.

This index was then combined with a cost index for use in the cost-comfort optimization algorithm developed and tested by Xue Chen (Chen, 2008).

The figure below shows a graphic summary of developing temperature setpoints. First, choose the comfort temperature predicted from the Adaptive Comfort Standard using a weighted running mean of outdoor temperature. Second, choose a comfort range, based on occupant preference and electricity price. Then adjust the setpoint based on the time of day. Finally adjust the cooling setpoint based on the relative humidity.

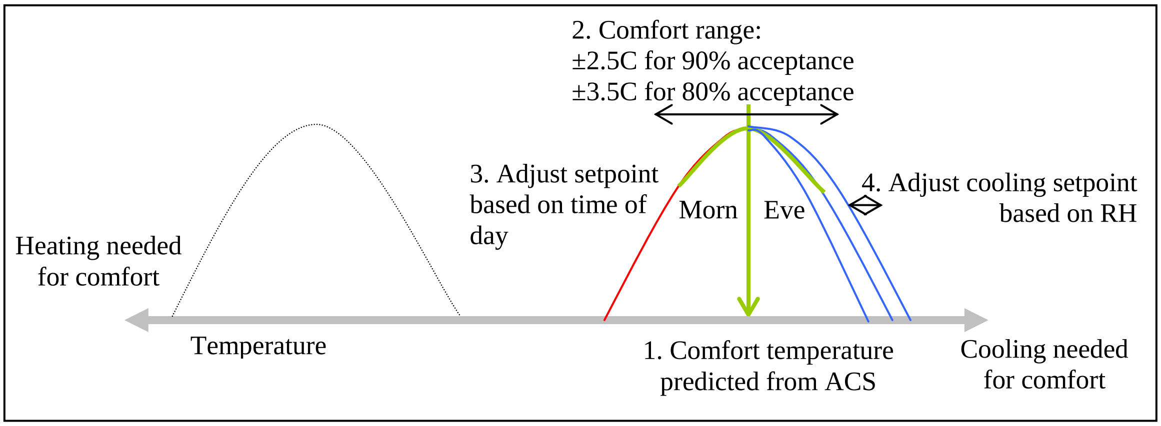


Figure 54: Summary of adaptive setpoints.

5.3.3 Advice generation to engage energy saving behavior

Many behaviors can help save energy and reduce costs during high peak periods. While some people already open and close windows appropriately to save energy, others may need prompting and information to do so. Similarly, air movement with fans will provide comfort at higher temperatures. Yet some people may not know how much money can be saved by using ceiling fans instead of air conditioning.

One rule of thumb used for natural ventilation of buildings is that if the outdoor temperature is at least 3ºF (1.6ºC) cooler than the inside, opening windows can cool the building (B. Stein & Reynolds, 1992). Initially, a prompt to open the windows and/or turn on the whole house fan can be provided through the user interface; perhaps future control systems will handle the control of an economizer or whole house fan. In a similar vein, in the winter, if people are too hot, they are likely to open a window if the outdoor temperature is lower than indoor, especially if they have information about the outdoor temperature. Also, one might assume the reverse is true, that if the outdoor temperature is higher than indoor and people are too cold, they will open up a window.

Another source of comfort is moving air. One study found that a person can achieve comfort at 31ºC (87.8ºF) by adding 1 m/s (197 fpm) air speed (Arens et al., 1998). Another study developed curves of effective cooling from a study in Thailand, showing 5-12 degrees F (2.5-6.7ºC) effective cooling with air speeds from 40 to 300 fpm (0.2 to 1.5 m/s) (Aynsley, 2006). A recent revision of ASHRAE Standard-55 allows higher air speeds to offset increased air temperature (see figure below), based on the Standard Effective Temperature or SET[56] (Arens, Turner, Zhang, & Paliaga, 2009). Air movement from fans or ceiling fans can make uncomfortable indoor temperatures comfortable. The user interface can provide information about comfort for less cost under these conditions.

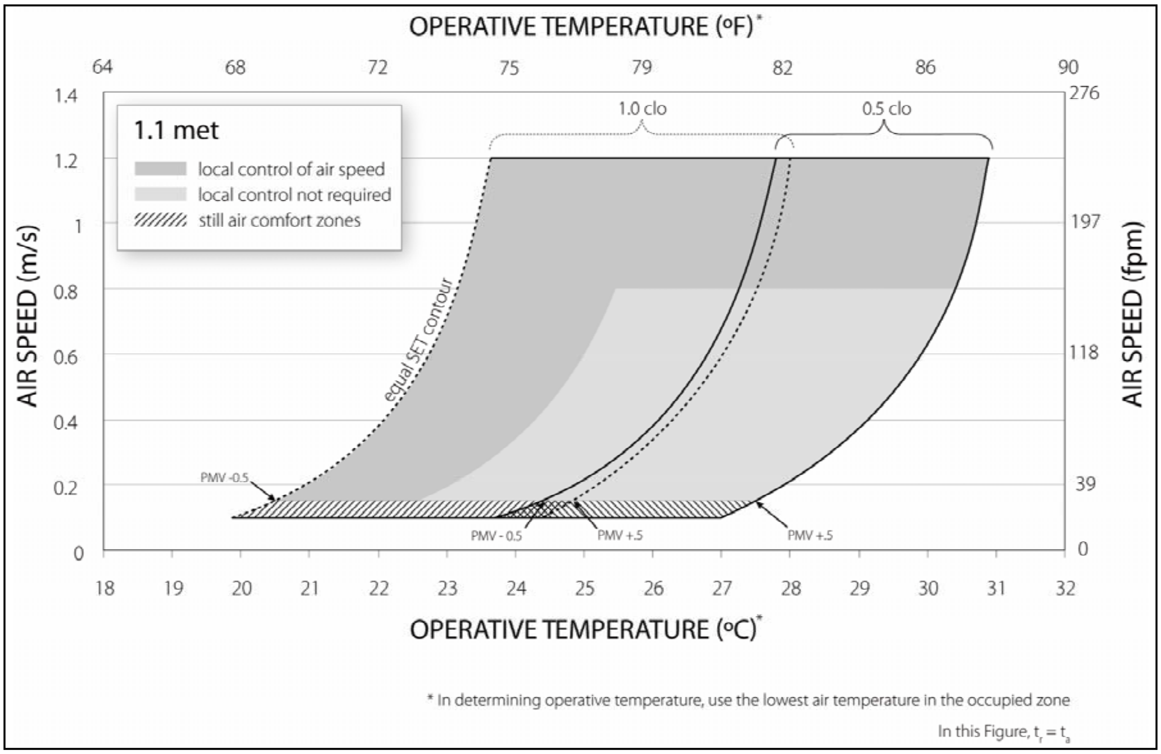
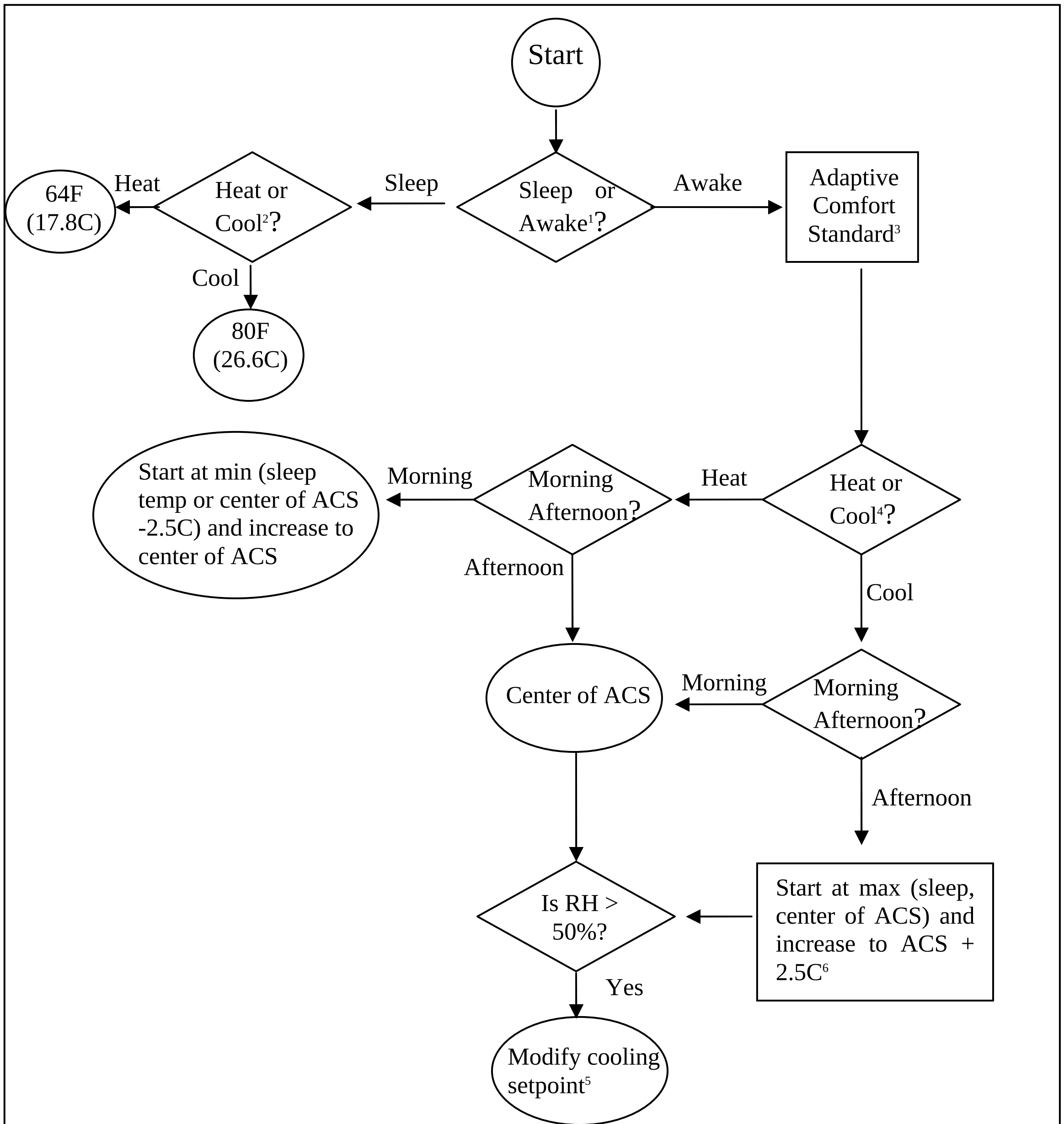


Figure 55: Allowable higher indoor air temperatures with elevated air speed (Arens et al., 2009).

[56] SET refers to "the temperature of an imaginary environment at 50% RH, <0.1 m/s air speed, and with mean radiant temperature equal to air temperature, in which the total heat loss from the skin of an imaginary occupant with an activity level of 1.0 met and a clothing level of 0.6 clo is the same as that from a person in the actual environment, with actual clothing and activity level" (Arens et al., 2009).

5.3.4 Testing

The code to implement this algorithm was written in Java as part of the Demand Response Electrical Appliance Manager (DREAM). The figure below outlines the algorithm. This algorithm was tested with a simulation tool (the MultiZone Energy Simulation Tool (MZEST). I ran several simulations for a house in Sacramento with EnergyStar temperature setpoints versus one with the adaptive temperature setpoints. I compared the total energy use for heating and cooling as well as expected comfort in an annual simulation and summertime simulation. The results are in the next chapter.



1 Sleep (night) and Awake (day) based on time (default: 10pm to 6am sleep, 6am to 10 pm awake. May be changed by occupant).
2 Heating or cooling mode based on running average outdoor temperature of day 8 through day 2 prior to current day, using a threshold temperature of 60F (15.6C).
3 The input for the ACS is a weighted running average of outdoor temperature. The lower limit for the mean outdoor temperature is 50F (10C) and the upper limit is 92F (33.5).
4 A diurnal drift can save energy during winter mornings and summer afternoons.
5 The equation is approximate to subtracting 0.5C per 10% increase in relative humidity above 50%.
6 For medium price, go to ACS + 3.5C and for high price go to ACS + 4.7C

Figure 56: Outline of adaptive temperature setpoints algorithm.

5.4 User interface

I developed the user interface as part of the Demand Response Electrical Appliance Manager (DREAM). The objectives were to develop an easy-to-use interface that enabled demand response by informing the occupant of price changes and electrical energy consumption. Since DREAM includes thermostat control, I looked at user-adoption issues with programmable thermostats to inform my design of the user interface. This section describes early prototyping, the process of design development in a School of Information Management Systems graduate course at UC Berkeley, Java development, and final field and laboratory testing.

5.4.1 Early prototyping

The initial design grew out of an informal questionnaire and anecdotal evidence from my own experience as an architect as well as experience as a volunteer for the Energy Team[57] of Rebuilding Together.

5.4.1.1 Analog display

Since information display would play a leading role in the design of the interface, I considered both what to display so as not to overload people with information and how to display it. An initial question was the use of analog display versus digital display. For example, all programmable thermostats use a numerical display of temperature; the Honeywell Round thermostat displays the temperature in an analog format, using a needle against an array of numbers. A digital display tells what a single value is. An

[57] Lisa Gartland of PositivEnergy developed the Energy Teams for the San Francisco branch of the national Christmas in April day, renamed Rebuilding Together. On two separate occasions, I worked on a team providing energy savings measures to homes of disadvantaged persons (typically poor or elderly). This included installing programmable thermostats.

analog display indicates where a value is within certain parameters, and provides a context for that value. In that sense, an analog display offers a status indicator: too hot, too cold, just right (Tufte, 2004). In addition, analog display allows the brain to associate a shape with the status.

One example is thermometers to measure fever. Analog thermometers typically have a mark at 98.6ºF (37ºC), the normal core body temperature of a resting adult. After taking one's temperature, one can see at a glance whether one has a temperature above or below what is considered normal and how far above or below normal. In contrast, most digital thermometers offer just the numeric value of temperature, with no indication of whether and how much it might be different from normal.

Another issue of measurement is precision: a numeric display can provide greater precision than an analog display, especially upon a quick glance. However, while temperature sensors can provide a precise number, the human sensation of temperature is not precise. Physiologically, people are more sensitive to changes in temperature (within a wide range) rather than an absolute temperature (de Dear et al., 1993). Even small changes in temperature over time are undetected by people (ASHRAE, 2004). As outlined in the background chapter, thermal sensation is affected by many factors, physical, physiological, psychological, and behavioral. A recent study indicated that many people have difficulty mapping a numeric temperature to their thermal comfort (Steinberg & Hublou, 2008).

Since people are profoundly affected by change in temperature, thermostat control should provide a means for a person who wants to be warmer or cooler to achieve that goal. Thermal comfort studies indicate a range of temperatures found comfortable—a wider range at home than in the office. Thus, an analog display better matches the concept of "comfort zone" rather than a single precise numeric temperature at which one might be comfortable.

In a similar vein, energy consumption data can be represented in graphic or numeric display. The goal of reducing energy consumption indicates a relative, not absolute metric (i.e., I've reduced energy consumption during peak periods or high priced periods compared to my consumption during low demand periods or compared to how I consumed without any feedback). The literature on feedback displays indicate that humanized, graphic, and specific feedback is effective at engaging people (Darby, 2000; Lutzenhiser, 1993). Arvola et al in (G. Wood & Newborough, 2007a) found that people paid more attention to pie charts and bar charts than numeric kilowatt-hour energy consumption information.

5.4.1.2 Initial prototyping

From 2003-2004, I developed the initial prototype first in sketches, then modeled in Adobe Photoshop, and finally written with a form of Java Swing for a Personal Digital Assistant (PDA). The DREAM system used the PDA as both a controller and user interface in early laboratory tests and demonstrations. I used an analog format to display both temperature and relative humidity data from the wireless sensors.

The PDA displayed power, cost and energy information in graphic as well as numeric form. Initially, I simulated these data, using several sources of information regarding power consumption and typical load profiles for residences. The air conditioner power information, although scaled in number to reflect an actual house, would display when the proxy air conditioner on the doll house or wall section turned on. Two screens of the interface are shown below.

Figure 57: The early DREAM user interface showing temperature (left) and energy, cost, and power information (right).

5.4.2 SIMS prototyping, development and testing

In Spring 2005, I took a graduate course with Professor Marty Hearst in the School of Information Management Systems (SIMS) on user interface design and development. Together with Alex Do from Mechanical Engineering, and Ken Langford and Colleen Whitney, both from SIMS, we developed initial concepts, paper prototypes, personas, and flow diagrams, and performed several rounds of user testing of the interface. In addition, another team within the class performed a heuristic evaluation on the interface. The process is outlined on a website (Peffer et al., 2005), and the highlights summarized in this section.

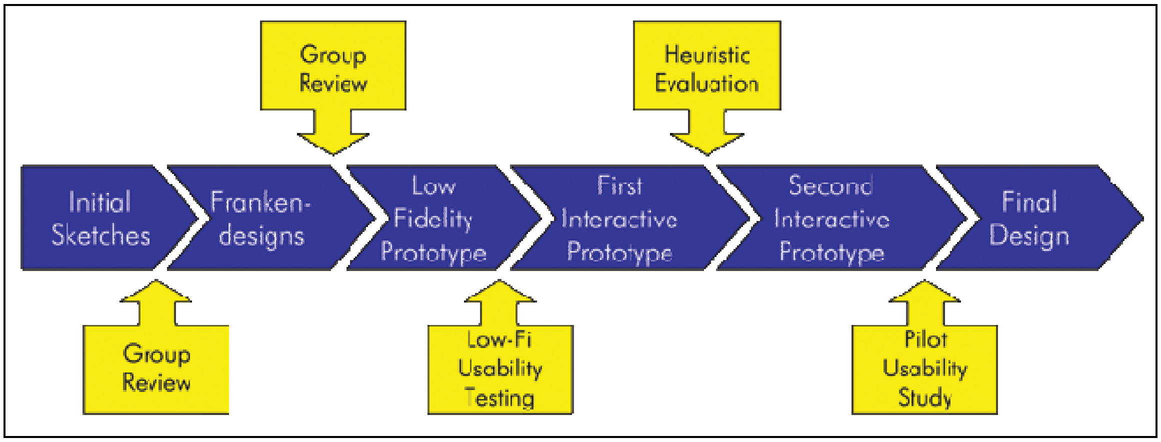


Figure 58: Design flow (created by Alex Do).

The first step was to develop personas, which are fictitious characters who are representative of actual users of the proposed thermostat/in-home energy display device. We started by interviewing 10 people regarding their current use of thermostats and appliances, and what they would need in a dynamic electricity tariff environment. Although the interviewees represented a wide range of income levels and household types (single, couple, families, elderly, middle age, young), they tended to be mostly white and college-educated and not representative of the wide diversity found in California households.

We developed five personas: Mabel, an elderly African American woman living on a fixed income; Alison and James, a young family with two children and parents that both work (one part-time); Tim, a working class single parent; Sue and Tom, a double-income-no-kids household in an upper-class neighborhood, and Brad, a young single male a few years out of college. From this we developed goals and priorities for each household regarding temperature control, pricing and billing information, and appliance use and energy consumption feedback. We then developed detailed scenarios for each household regarding how they might interact with and use the device.

We performed a comparative analysis of available technology, looking at existing thermostat interfaces, in-home energy displays, and related devices such as sprinkler system programming interfaces, web interfaces, and a glowing orb that could display price information. Sixteen different devices were analyzed with respect to strengths and weaknesses regarding goals of the project, including usability and aesthetics.

Then, each member of the team developed an initial design and interaction design flows for the use of the designed device.

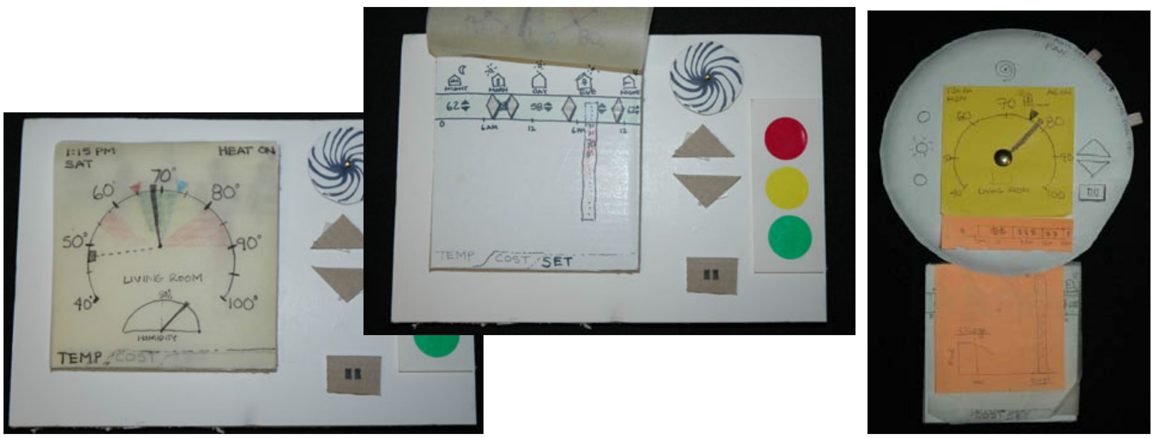


Figure 59: Early paper prototyping by the author.

We took the designs and flow diagrams, and decided on the most usable functions of each to create a new combined prototype and flow diagram.

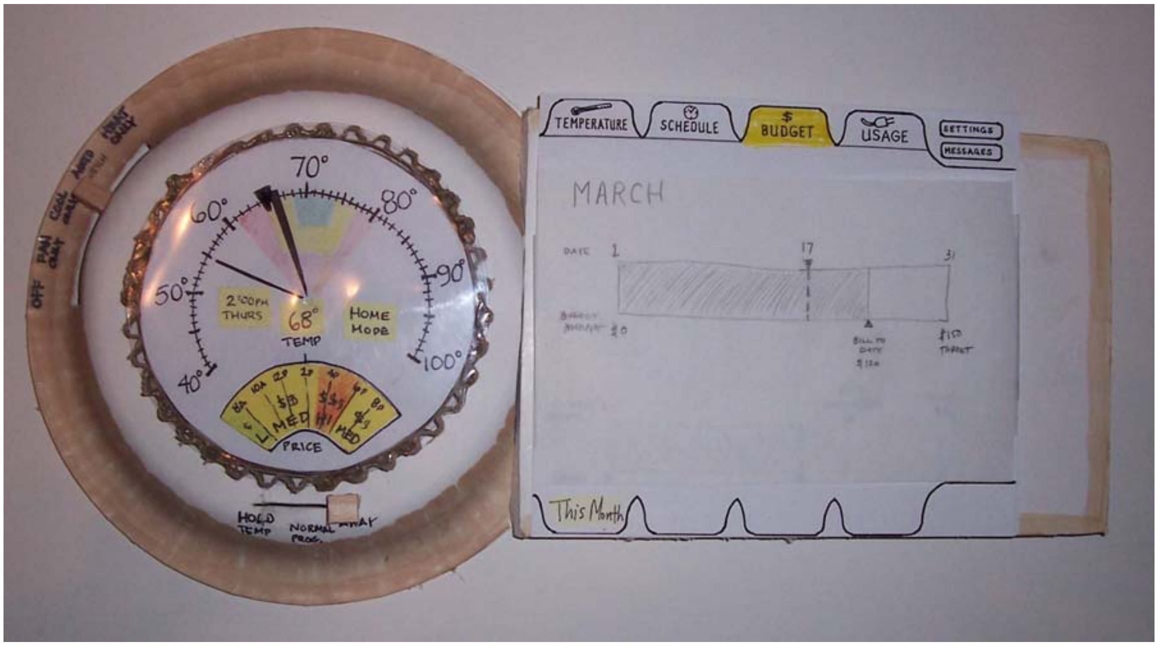


Figure 60: Combined paper prototype showing the Budget screen.

We then performed initial user testing of the device. First, we defined a number of tasks to test the usability of our device, ranging from simple (i.e., what is the current temperature, how would you increase temperature) to complex (i.e., what are the highest consuming appliances, when would be the best time to run the dishwasher). We found three subjects who closely resembled our personas. We explained 12 different scenarios and asked them to perform these tasks while “thinking” aloud. One team member led the subject through the tasks while the others observed and took notes. We looked at the time it took to perform the tasks, the ease or difficulty in performing the task, and noted problems.

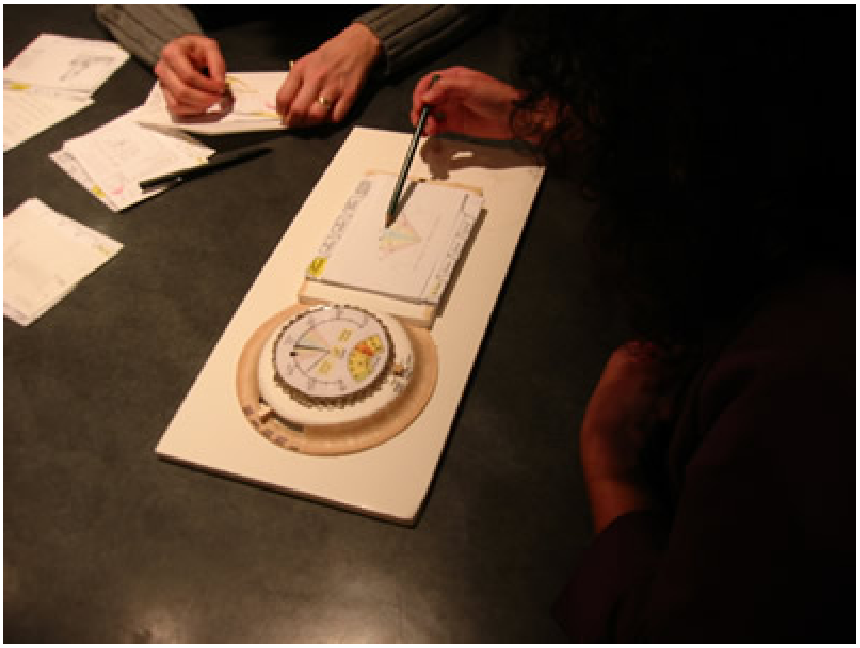


Figure 61: Subject performing task in paper prototyping test.

We made several changes to the design as a result of the first set of tests. We then developed an interactive prototype using a Java applet (see figure below).

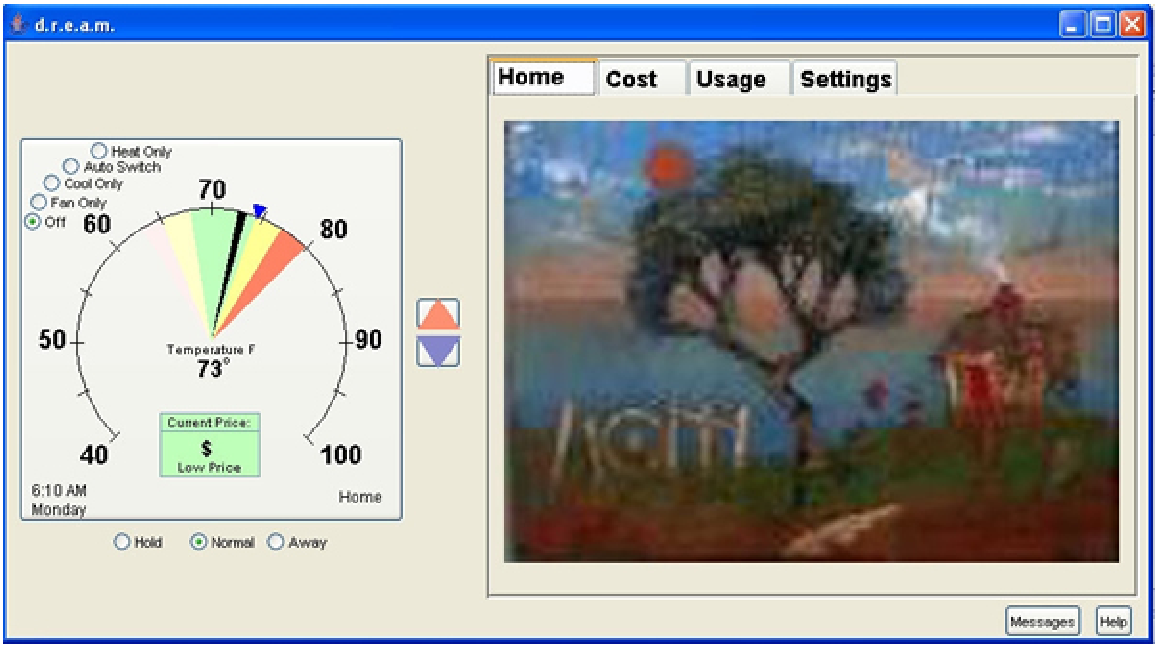


Figure 62: Initial interactive prototype in Java.

Then another team in the class performed a heuristic evaluation of the interface. Heuristic evaluations are intended to identify many problems compared to other methods of usability testing (Jeffries, Miller, Wharton, & Uyeda, 1991). This method employs a handful of experts, not users, and asks them to conduct an in-depth systematic evaluation of the prototype, which is a functional model of the device. Nielsen identifies ten general principles for user interface design, called heuristics because they are general rules of thumb rather than specific guidelines. The ten principles are described below.

Visibility of system status

The system should always keep users informed about what is going on, through appropriate feedback within reasonable time.

Match between system and the real world

The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order.

User control and freedom

Users often choose system functions by mistake and will need a clearly marked "emergency exit" to leave the unwanted state without having to go through an extended dialogue. Support undo and redo.

Consistency and standards

Users should not have to wonder whether different words, situations, or actions mean the same thing. Follow platform conventions.

Error prevention

Even better than good error messages is a careful design which prevents a problem from occurring in the first place. Either eliminate error-prone conditions or check for them and present users with a confirmation option before they commit to the action.

Recognition rather than recall

Minimize the user's memory load by making objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. Instructions for use of the system should be visible or easily retrievable whenever appropriate.

Flexibility and efficiency of use

Accelerators—unseen by the novice user—may often speed up the interaction for the expert user such that the system can cater to both inexperienced and experienced users. Allow users to tailor frequent actions.

Aesthetic and minimalist design

Dialogues should not contain information which is irrelevant or rarely needed. Every extra unit of information in a dialogue competes with the relevant units of information and diminishes their relative visibility.

Help users recognize, diagnose, and recover from errors

Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution.

Help and documentation

Even though it is better if the system can be used without documentation, it may be necessary to provide help and documentation. Any such information should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large. (Nielsen, 1994b)

Each problem that the team encountered they reported as violating one of the ten heuristics listed above, and rated according to the following severity rating:

0 not the best choice,
1 annoying, cosmetic problem
2 confusing, minor usability problem
3 frustrating/took time to figure out, major usability problem
4 took a wild stab to get past, usability catastrophe

The heuristic evaluation provided 14 points to consider, two of which were of severity level 4. We made additional changes to the interface based on this evaluation. Since Java programming proved to be cumbersome for quick changes, we transitioned the interactive prototype to a combination of HTML and Javascript.

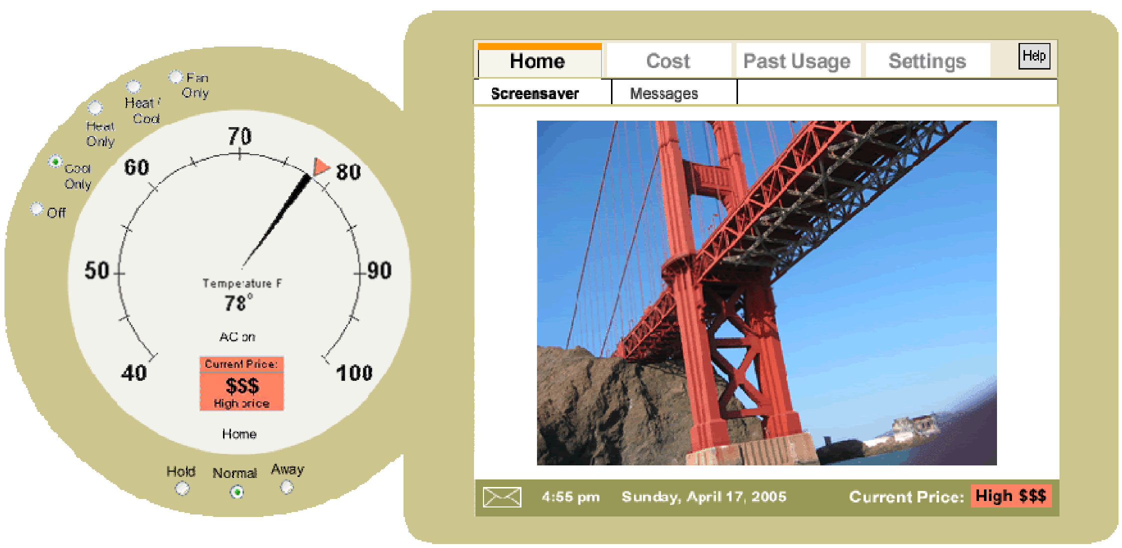


Figure 63: Final interactive prototype using HTML and Javascript.

We tested the interface again with three subjects with scenarios as we did before. In general, temperature information, price forecast, budget, and usage graphs were easily understood. The biggest problem was the navigation of the cost and usage screens; for example, both budget and price forecast screens were difficult for the subjects to locate.

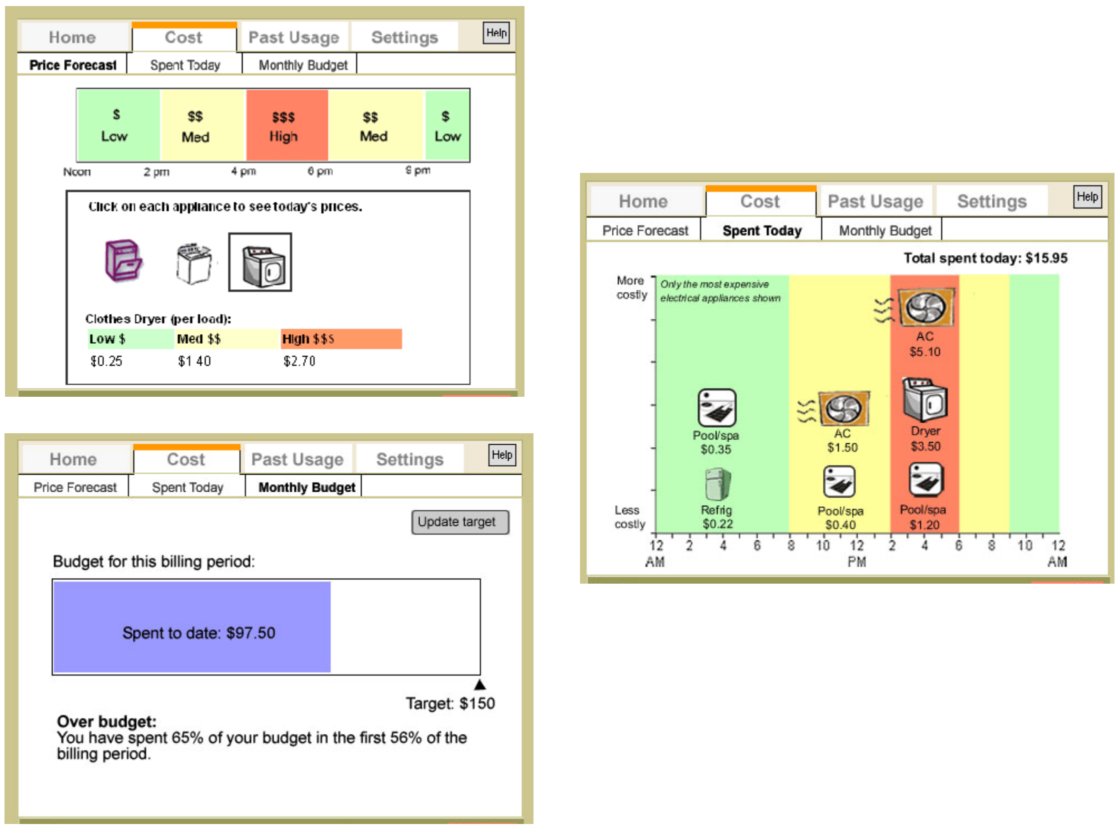


Figure 64: Screens under the Cost tab.

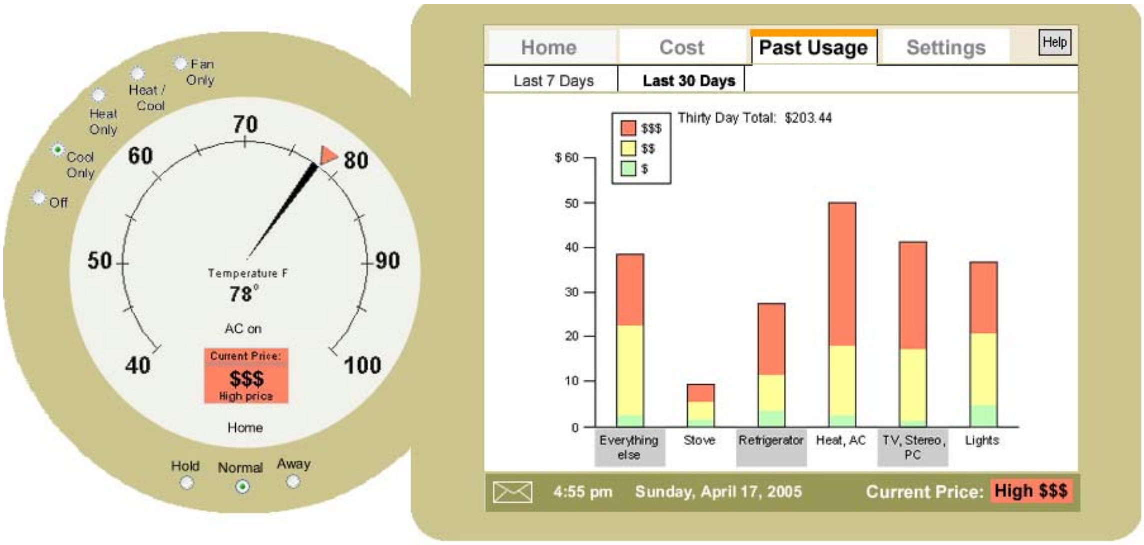


Figure 65: Screen showing a bar graph display of electrical energy consumption.

We also implemented a wizard to help users set up temperature preferences and schedules, and introduced a video to show how to perform these tasks.

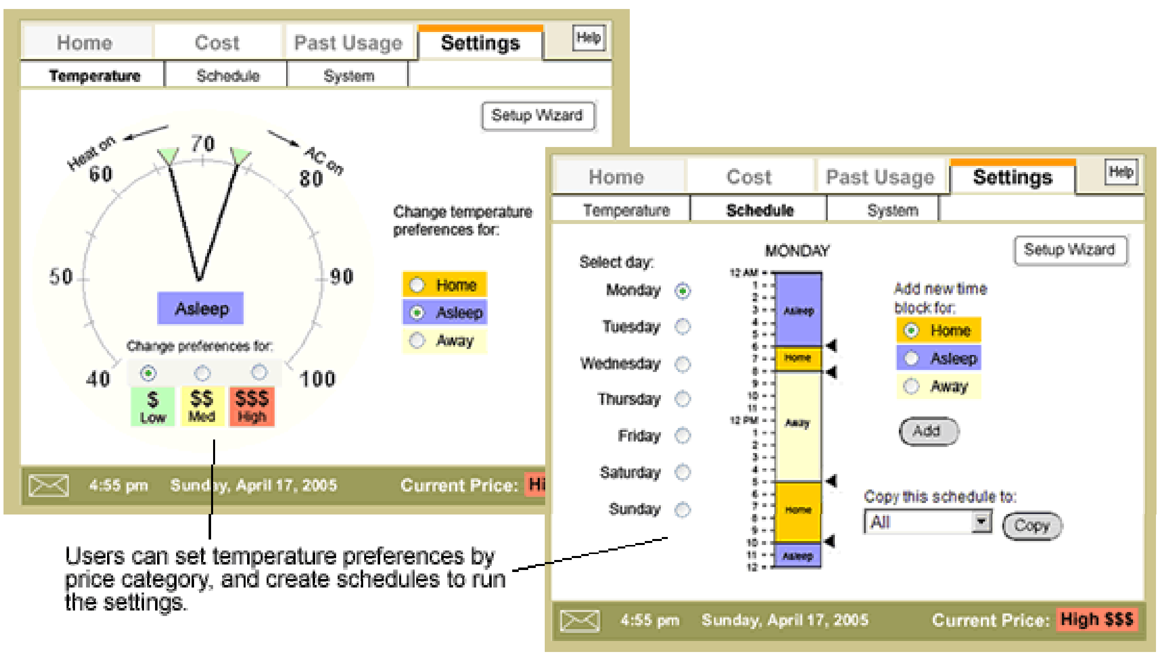


Figure 66: Screens under the Settings tab.

Since we found that navigation and semantics were the main problems, we undertook a card-sorting exercise. We wanted to know how to group the functions under the cost and past usage categories, and choose labels to describe these functions. This test asked subjects to sort various cards into categories. We asked four people to sort four descriptions of screen functionality with screenshots, and another four to sort the descriptions with no screenshots. The results indicated that usage was fairly easily sorted, but both Budget and Price Forecast were not necessarily associated with cost. A larger sample size would be useful to make a determination.

The final flow diagram is shown in the figure below.

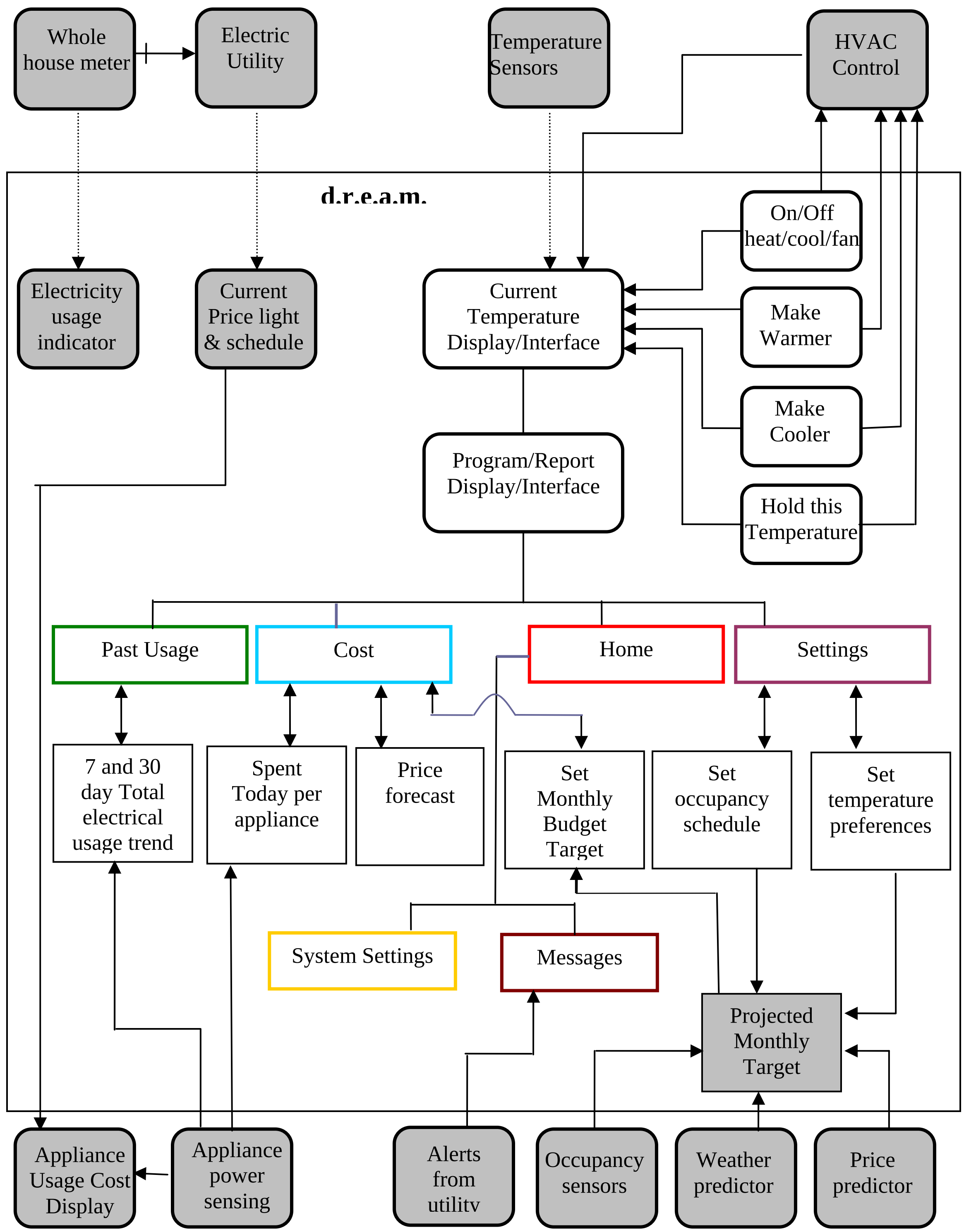


Figure 67: Interaction flow diagram.

5.4.3 Java development and testing

After the course ended, I implemented the prototype in Java within the DREAM controller. I then connected the interface to a simulation tool for testing and to the controller for the field tests. After the field tests, I further refined the interface and developed an internal simulation to create a stand-alone animation. I then tested this animation with multiple subjects in the Experimental Social Science Laboratory (Xlab) at UC Berkeley's Business School.

5.4.3.1 Development for field testing

The main objective in implementing the prototype in Java was to test the demand response functions. Toward that end, I eliminated the Settings tab, and did not develop the temperature setting and schedule setting functions further. In addition, I did not develop the budget screen. Initially, we developed a Home tab so that people could use the device as a digital photo frame or perhaps message board. The next iteration included a message screen that could provide advice to the homeowner (see figure below) or display a message from the electrical utility.

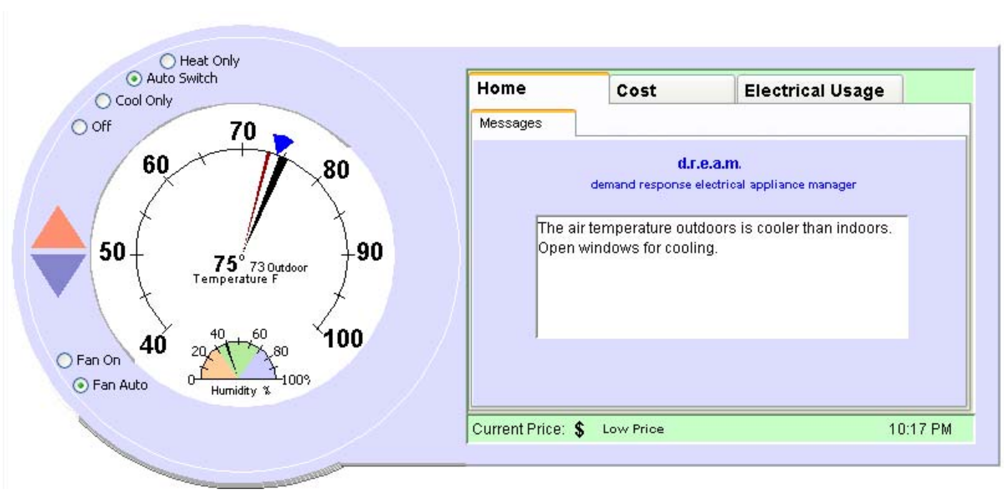


Figure 68: Java implementation of DREAM interface.

For the purposes of the field experiment, only Home, Cost, and Electrical Usage tabs remained. Under the Cost folder, one found information such as the current and forecasted price of electricity, the cost of electricity, and a cost-comfort index the occupant could use to get some feedback on how the temperature setpoint affects both comfort and cost. See Figure 69 below.

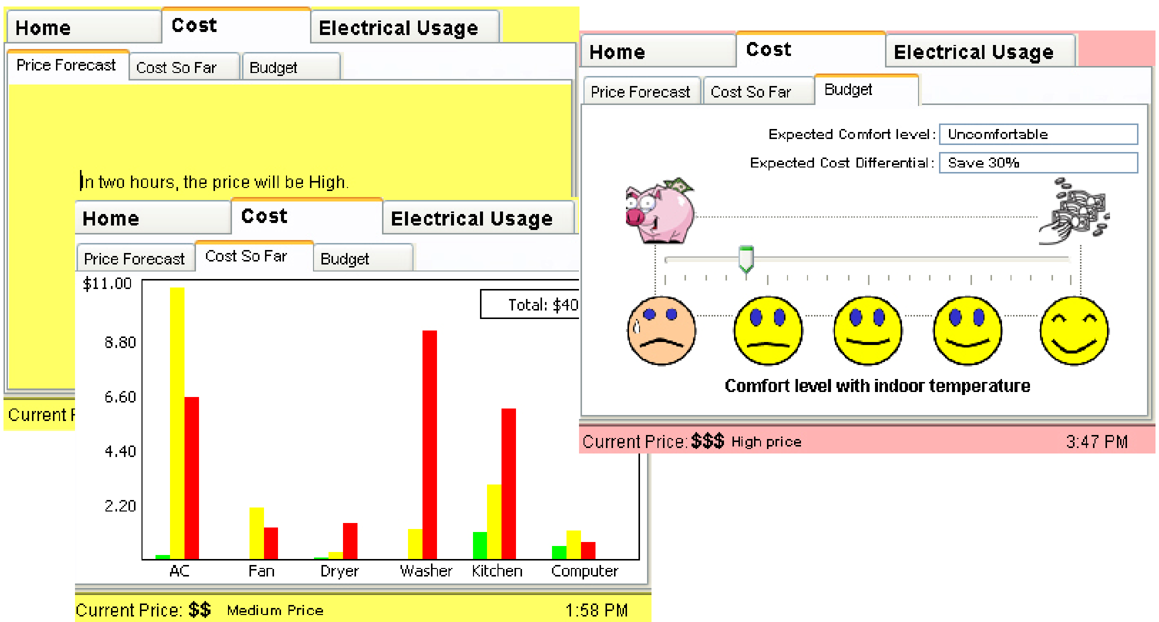


Figure 69: Cost folder screens.

One could find current instantaneous power consumption, energy used today, and energy used so far this billing period under Electrical Usage (see Figure 70 below). The electrical usage is broken down by major appliance, such as air conditioning, clothes dryer, clothes washer, and kitchen appliances. For House 1 of the Summer 2007 field tests, the interface displayed the air conditioner, blower fan, clothes dryer and washer, kitchen outlets (from the circuit breaker panel), and computer (on all the time) loads as shown below. For House 2, the interface displayed the dishwasher and machine shop outlets instead of the clothes dryer, kitchen outlets, and computer. For both houses, the total power and energy shown came from the total circuit breaker load plus the air conditioner compressor (which was on a separate circuit breaker).

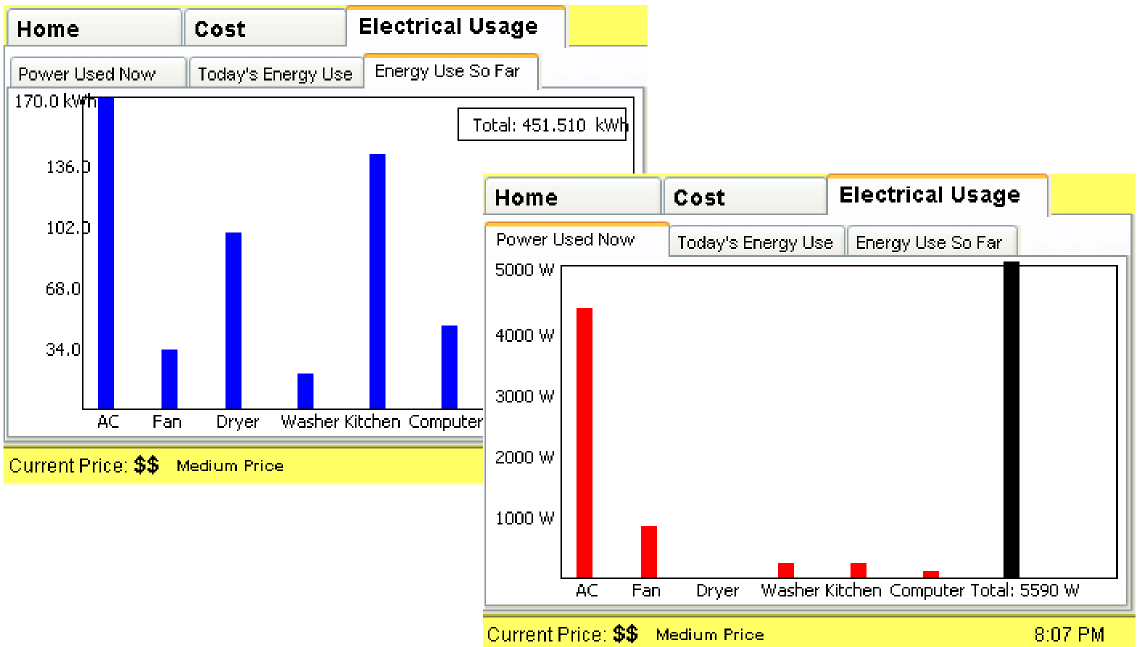


Figure 70: Electrical Usage screen examples.

The ultra-mobile touch-screen computer used in the field tests is shown below. For the field test, the computer interface displayed outdoor and indoor temperature, and indoor relative humidity as well as the various appliance loads. Price information came from the price generator, and affected the display, but no actual dynamic pricing tariff was involved. Other information displayed was the temperature setpoint and the on-off status of the air conditioner and/or fan. During the first test, we added the display of whether the house was occupied according to the occupancy switch.

Figure 71: The DREAM controller and interface.

5.4.3.2 The Xlab test

The next step was to test the interface in the Haas Business School's Experimental Social Science Laboratory (Xlab). I had several goals in mind for this test. One hypothesis was that energy and demand information are at least as effective in motivating peak energy reduction as cost and price information in a variable electricity tariff environment. Another hypothesis was that the messenger influences acceptance of the message: a community-based, nonprofit contractor promoting a device will result in higher adoption and use of the technology than if an electrical utility or governmental agency promotes it. The third hypothesis was that people will find detailed information more useful than general information, and some advice/tools useful and others not useful in making decisions regarding energy consumption.

I had several minor objectives as well. Since studies linking attitude/values with behavior have had mixed results, I wanted to see if I could measure people's attitude through the List of Values (LOV) (Kahle, Beatty, & Homer, 1986) and Connection to Nature Scale (CNS) (Mayer & Frantz, 2004) tools and see if this affected their behavior regarding the interface. Also, I wanted to find out more about how people used their current thermostat.

Toward these ends, the goals of the animated interface for the Xlab were:

1) to detect differences in the degree to which subjects are willing to reduce energy consumption when presented cost information versus energy consumption information,

2) to discern differences in the degree to which subjects are willing to reduce energy consumption if it were promoted by an electrical utility company versus a nonprofit organization.

3) to get feedback on what information/tools/advice people would like to see in order to make decisions on energy consumption in a variable electricity rate paradigm,

4) to get feedback from subjects on a prototype residential thermostat and in-home energy display user interface,

5) to test the LOV and CNS with respect to behavior, and

6) to understand how people think of and use their current thermostats.

The next section describes the preparation of the interface, and the following section outlines the test flow and survey.

5.4.3.2.1 Developing the interface

Feedback from the participants of the field tests informed further changes to the interface in preparation for testing in the Experimental Social Science Laboratory (Xlab). One participant found the different colors of the Cost-so-far tab confusing and suggested using pie charts. He also commented on the redundancy between cost and energy information. In addition, the colors for display of the appliance energy and cost were neither interesting nor aesthetic. I replaced the red and blue displays with Brewer[58] colors for qualitative comparison (Brewer, 2008). The cost-comfort index was colorful, but confusing. The feedback from the index did not have enough detail to be useful. One issue from the SIMS course user tests that led to confusion and misunderstandings was that time was static: the time did not change, which affects the price, outdoor and indoor temperature, temperature settings, and energy consumption of all appliances. Thus, I developed an internal model for simulation to create an animated interactive interface.

The internal model was part of the DREAM controller code which included the interface. The internal model consisted of a series of simple equations to model the heat transfer in a house via solar radiation, conduction through the building envelope, infiltration given outdoor temperature, a source of cooling via an air conditioner, and internal gains through people, lights, and equipment. The outdoor temperature came from TMY2 (Typical Meteorological Year) data for Sacramento. I decided to run the simulation for three days and chose three hot days in August. The animation showed a clock with date and time, changing outdoor temperature and relative humidity, and indoor temperature depending on the temperature setpoint. This model is described in more detail in Appendix D.

The energy consumption from various appliances also changed as these appliances were used over the course of the day. To simplify the simulation, the

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[58] Cynthia Brewer, Professor of Geography at Pennsylvania State University, developed several sets of colors for use in graphs, depending on the number of items to be displayed and whether the information to be displayed is sequential, diverging, or qualitative.

appliances used the same energy during the same time each day. I chose the top energy consuming appliances over which a person has some discretion: air conditioning, cooking appliances (range, oven, and microwave), clothes washer and dryer, dishwasher, television and personal computer, and lights. Steady loads, such as from standby loads in consumer electronics and (for purposes of the simulation) the refrigerator, were included in the total. The simulated load profile is shown below and a full description of how I developed it is outlined in Appendix E.

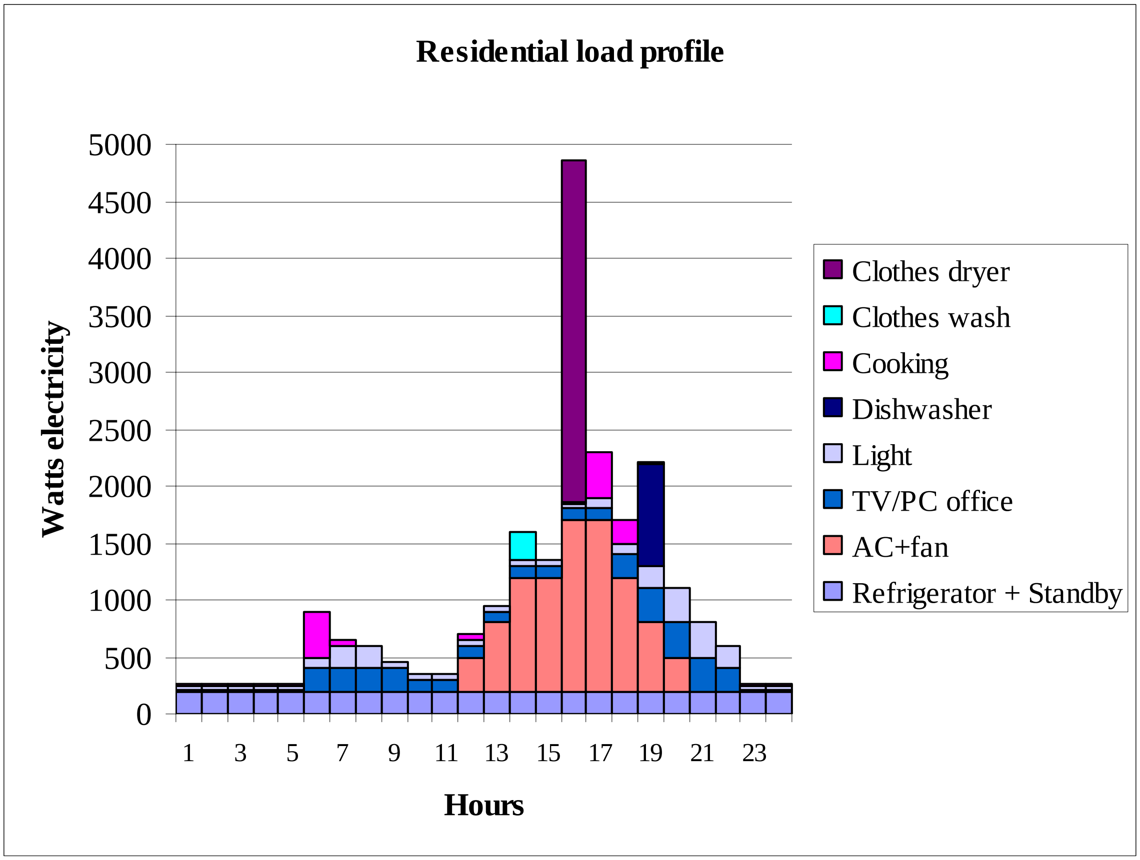

Figure 72: Electrical consumption of various appliances over a 24 hour period.

The test of whether energy or cost information would affect behavior required two separate simulations: one depicting demand levels and energy usage by various appliances and one to display price levels and the associated cost to run these appliances in a variable price electricity tariff. For the purposes of the experiment, the demand changed based on a time schedule: low period from 10 pm to 6 am, high period from 2 pm to 6 pm, and the medium or shoulder periods from 6 am to 2 pm and 6 pm to 10 pm. One part of the display showed the level of the current price or demand and a color associated with that period: green for low, yellow for medium, and red for high. Thus one simulation showed energy usage and demand information and the other showed cost of energy plus price information. I added a pie chart to show the contribution of each appliance's energy consumption during that price period, whether low, medium, or high demand. Two screenshots of the two animations are shown below.

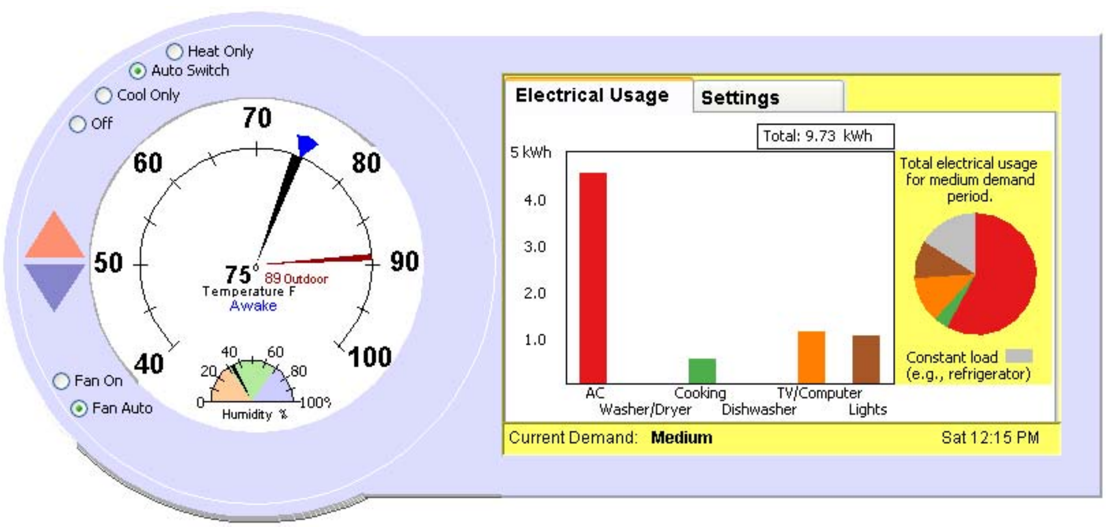

Figure 73: DREAM interface simulation showing energy and demand information.

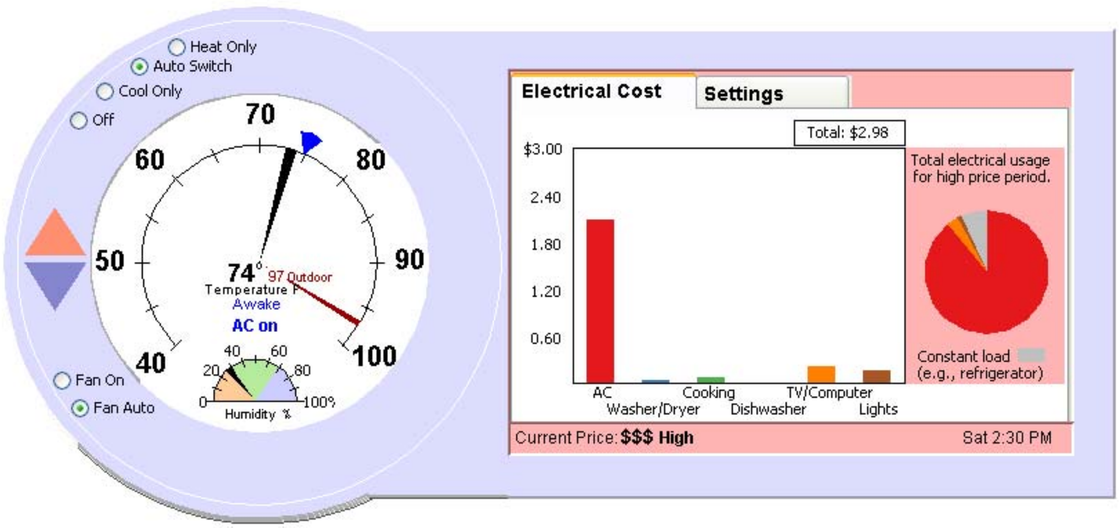

Figure 74: DREAM interface simulation showing cost of appliance energy use and price level.

I modified the cost-comfort index to provide detailed feedback on specific temperature setpoints. This allowed the user to set the device to automatically offset the temperature when demand or price was high. The default of the slider bar was 75ºF (23.9ºC) and could be adjusted 12 degrees F to 87ºF (30.6ºC). To develop the feedback, I used the internal model to run simulations for the month of August at several setpoints to create feedback at each degree offset.[59] For example, if one set the offset to 4 degrees, the temperature setpoint during high demand period would be raised to 75ºF+4ºF = 79ºF; the temperature setpoint during the medium period would be raised to half of 4 or 77ºF. The user saw a statement regarding approximate savings in energy or cost as well as peak savings if extrapolated for that month.[60] I developed feedback for energy, cost, and

[59] The simulation tool was fairly simple, and thus the feedback is linear. The efficiency of an actual air conditioner would mostly likely not reflect a linear relationship between outdoor air temperature and electricity consumption.

[60] My intention is that this feedback in an actual thermostat could be learned over time.

carbon emissions diverted, but only used the energy and cost feedback. The screens below show the cost-comfort index for energy and cost.

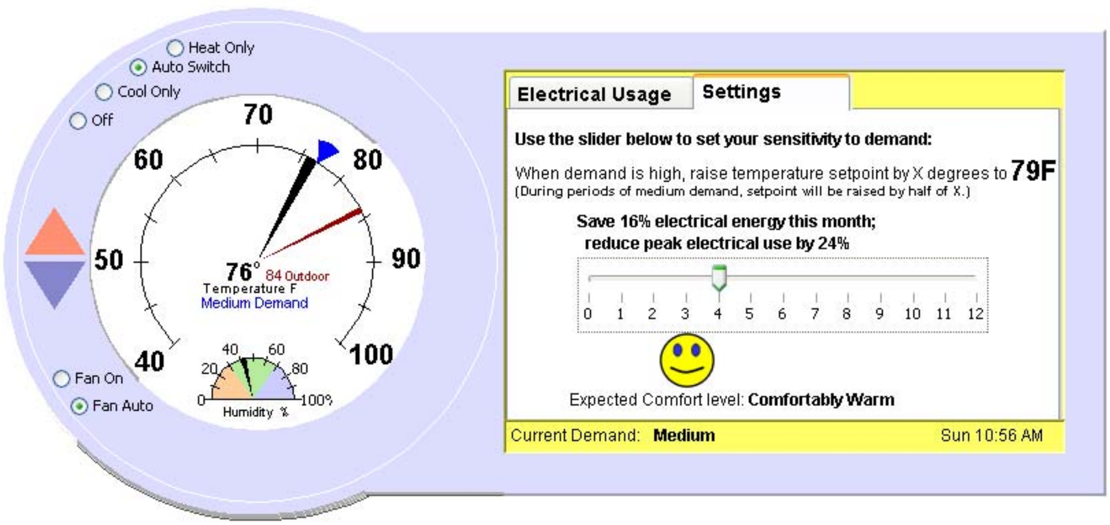

Figure 75: DREAM interface simulation showing the cost-comfort index with energy feedback.

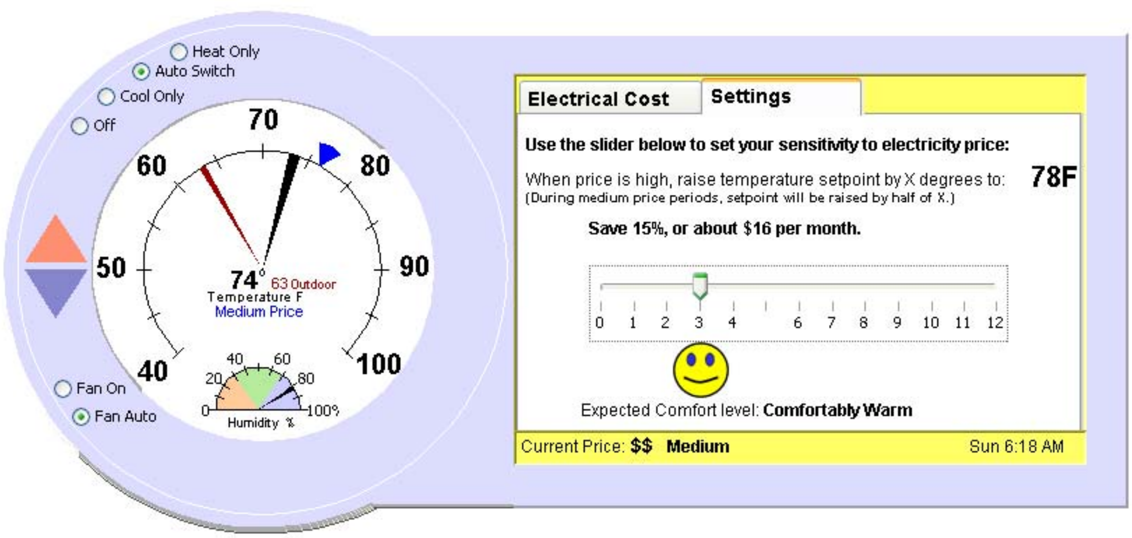

Figure 76: DREAM interface with the cost-comfort index providing cost feedback.

The comfort "smiley faces" were based on the Comfort 1.07 program (Fountain & Huizenga, 1996; Huizenga & Fountain, 1997). Below 78ºF (25.6ºC) was considered Comfortable and between 78ºF (25.6ºC) and 80ºF (26.7ºC) was Comfortably Warm.

Between 80ºF (26.7ºC) and 83ºF (28.3ºC) was considered Slightly Uncomfortable, and between 83ºF (28.3ºC) and 87ºF (30.6ºC) Uncomfortable. From 87ºF (30.6ºC) and above was considered Very Uncomfortable.

Other information displayed that changed during the animation was the setpoint type. Two main categories of setpoint type were used: Awake versus Sleep, and Medium versus High price/demand.

During the Xlab test, I asked the subjects to view the simulation as if they were at home. I established a default setpoint of 75ºF (23.9ºC) for the air conditioner during the day or Awake period and 80ºF (26.7ºC) during the night or Sleep period. If the subject changed the slider bar to change the setpoint during high price or demand periods, the text changed during the medium or high periods to reflect this change. (Note that Figure 76 above shows the text "Medium Price" in the left side of the display).

Creating the Java applet to run the simulation on the Xlab computers turned out to be no trivial matter. In order to record how the subjects interacted with the animation, I wrote code to create a text file with the subject number (a unique number that the subjects entered) and type of display (i.e., showing energy or price information). This text file also recorded the date and time in the simulation, the offset from the slider bar input, any manual manipulation of the up and down arrows, the state of the air conditioner (whether on or off) and the indoor temperature. Writing a file to the host computer required dealing with security issues. The final result was the application packaged in JNLP (Java Network Launch Protocol) and using Java Web Start to run the interface animation.

5.4.3.2.2 Development of the Xlab test

I designed the entire study to take place in the Xlab using the computers. Subjects answered a brief online survey, read a short introduction, observed a simulation of the thermostat interface, were asked to make an intervention with the interface, observed the results of their intervention, and answered another online survey.

Subjects were divided into four groups: half read an introduction as if an electrical utility promoted the interface technology, half read an introduction from the point of view of a fictitious nonprofit organization. Half of each group viewed a simulation where price information and cost to run appliances was displayed; the other half observed demand and energy consumption information.

The Xlab recruited the subjects from their pool of staff and student volunteers. The subjects were screened for those who pay an electricity bill and had experience living with air conditioning in his or her house/apartment. Dorm residents and others whose electrical bill is included in the rent were thus excluded from this study. If the subject currently had air conditioning or had lived with air conditioning in the past, the subject was allowed to take the test.

The survey was developed using Qualtrics.com, a free survey tool available through internet access. The initial questions included age, gender, attitude towards household bill and energy use. Two questions addressed values and attitude: the List of Values (LOV), which asks people to rate what values are important to them, and Connectedness to Nature Scale (CNS), which determines general environmental attitude. One question asked subjects to order the energy consumption of various appliances.

Next, the subjects were asked to launch the interface simulation. Initially, they were asked to observe it without making any changes. Then, the subjects were asked to view the simulation again, but go to the Settings tab and change the slider bar to whatever they wished, keeping in mind their comfort level. Although the comfort or pocketbook of each was not at stake, all the participants were subject to the same conditions. Any differences among where each set the slider bar might be influenced by the context or sponsorship of the display and/or the type of information displayed. The metric to analyze is how much the subjects changed the temperature setpoint from the default (75ºF) to reduce the air conditioning load in a simulation.

In designing this test, I knew that the simulation posed would not provide people the thermal feedback to set the thermostat the way they would in a house. Plus, this study requires people to focus attention on the thermostat interface, which is different than the distracted way people manage thermostats in their homes. In addition, one's personal attitude regarding the environment and energy conservation may override the context and information variables. However, the survey has questions regarding attitude towards energy and the environment, so this potential issue can be looked at.

After viewing the simulation, the subjects were asked several questions. First, they were asked a number of open-ended questions. Next, a set of questions asked their feedback on several types of graphic displays, such as the ability to set goals or see the cost of running an appliance at various price levels. Several questions asked about what type of information they would find useful in a dynamic electricity tariff environment. Several questions addressed thermostat use, specific to a type of thermostat and general likes and dislikes.

This chapter described the methods of data collection and instrumentation of several different tests: a field test of a distributed wireless sensor and actuator network, the software test of a learning algorithm with field data, the simulation test of residential adaptive comfort temperature setpoints, and the development and use of an animated interface and online survey to obtain feedback on demand response technology. The next chapter describes the results of these tests.

6 Results, Findings and Discussion

The previous chapter outlined the methods and instrumentation developed to test each of the six hypotheses, whether computer simulation or testing with subjects. This chapter describes the results of the final tests. The first section discusses the findings of the final field test of the DREAM wireless network. The next section describes the results of using a learning algorithm to “predict” people’s temperature sensation. The third section details the results of the simulations testing the residential adaptive comfort temperature setpoint algorithm. The final section describes the results of the Xlab testing of the DREAM user interface.

6.1 Wireless network

Our objective in developing and testing the wireless network of sensors and actuators was to prove the effectiveness of the technology in the field for enabling residential demand response. Toward that end, we successfully replaced the thermostats of two houses for six weeks, displayed energy consumption for several devices, and tested precooling, house and HVAC system learning, and optimization of cost and comfort algorithms. This section discusses the overall results of the field test, and emphasizes what was learned regarding human behavior. Details on learning the house parameters may be found in Jaehwi Jang’s dissertation (Jang, 2008) and details on optimization testing may be found in Xue Chen’s dissertation (Chen, 2008).

We captured the behavior of the house plus HVAC for warm days and very hot days; over the course of the tests, the outdoor daily high temperature ranged from 27 to 41ºC (80.6 to 105.8ºF). House 1 performed reasonably well under hot conditions, and responded well to precooling scenarios. Figure 77 shows the inside (Ti), outside (To) and AC supply temperature (Tac) for house 1 for three days. The air conditioner cycled all three days to cool the house, but struggled on the hottest day.

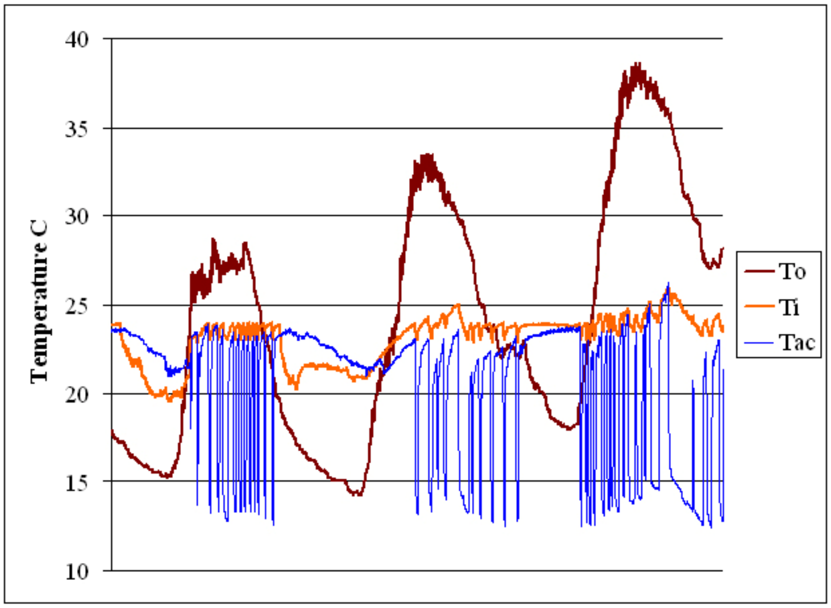

Figure 77: House 1 temperature, 26-28 August 2007.

House 2 however appeared to have an undersized HVAC unit, which could barely keep up on hot days, and was completely underpowered for very hot days. Precooling was not an option for this house. Figure 78 shows the same three days in August. The air conditioner was cycling the first two days (albeit on a lot of the time), but on the hottest day, was on constantly, and still allowed the temperature to rise.

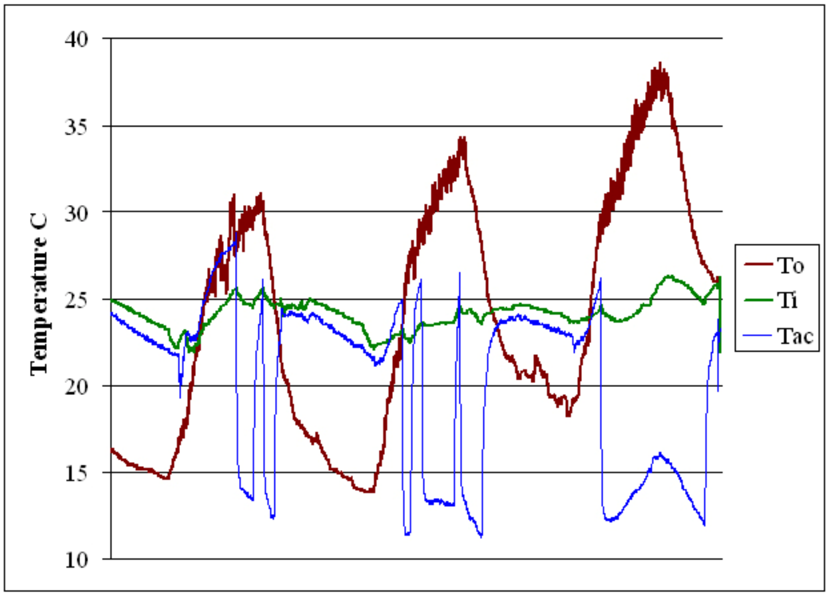

Figure 78: House 2 temperature, 26-28 Aug 2007.

6.1.1 Control test results

The results from testing indicate that learning about house parameters is promising. In fact, the algorithms were further developed in field testing of EcoFactor's remote thermostat service in December through June 2008 (personal correspondence, (Steinberg & Hublou, 2008). The ability to predict a house's internal temperature, given weather forecast and learned parameters, enabled energy savings from a more efficient controller. This shows promise for precooling in demand response scenarios as well.

Other elements of testing showed mixed results. While learning about the house and system was successful, learning the occupant's schedules was not. Both houses had fairly erratic schedules, which makes learning difficult. However, the test of the cost-comfort index indicated that the cost-comfort optimization successfully generated appropriate temperatures for the cost-comfort level selected. Another test, precooling, was only successful in the house that had an appropriately sized HVAC system. While undersized systems are more rare than oversized systems, one might expect similar results for a house with leaky ducts or poor insulation. Given that half of the houses in California with central air conditioning were built before the energy codes, one would suspect that many other houses would have a similar problem with precooling.

6.1.2 Hardware and network problems

In general, the main concern in developing a new system is reliability and stability of the software, hardware and communication. Despite our extensive lab testing, we encountered a few problems in the control code, hardware, and network during the field tests.

We experienced system failures in both tests, in which the controller on the computer froze. Usually the system failed while the air conditioner was off, so the temperature in the house grew uncomfortable. In many cases, we were able to restart the computer remotely to resolve the problem. On some occasions, the computer had to be restarted manually. We think the problem was in the connection to the internet. In house 1, the computer was connected via wireless to the internet. When we used a wired network connection instead, network stability definitely improved, but the same system freezes occurred in the second house test. We discovered that the system can freeze when the network connection is destabilized when data was transferred from our computers to the house computer, which occurred a few times per week when we changed the controller software for the next test.

Another issue was the length of time the batteries would last. Many efforts were made to maximize the battery life within the mote communication code. However, in the first house test, the compressor froze due to the exhausted batteries in the HVAC relay after five weeks. The batteries were also replaced in house 2 at five weeks because the outdoor mote's battery was depleted.

Other issues were not immediately resolved. For example, the price indicator mote ran out of batteries after about a week probably due to high drainage from the LEDs. This was not a crucial part of the test, so we did nothing. Another issue was the calibration of the current sensor motes. The fan current, for example, read 10 amps in house 2, but was actually approximately 7 amps. Better resolution and filtering of the appliance current sensors would improve validity of the data.

We also discovered that the sensors could be used for fault detection. In house 1, a relatively high (mid-60sºF (18ºC)) supply temperature taken at the supply grille indicated a problem. A contractor found that the refrigerant in the compressor needed recharging. After he performed the required maintenance, the supply temperature was back in the mid-50sºF (13ºC).

6.1.3 Human behavior

The two households demonstrated different ranges of thermally comfortable temperatures. The occupant in house 1 seemed to have a fairly narrow comfort range, from 22 to 26ºC (71.6 to 78.8ºF); the high temperature seemed only acceptable for the hottest day. Otherwise the high comfort temperature was about 24.5ºC (76.1ºF). However, occupants of house 2 had a wider comfort range, from 21 to 28ºC (69.8 to 82.4ºF).

After the test, the participants were asked a number of questions about the thermostat and demand response. In general, the participants were able to easily read the indoor and outdoor temperature and relative humidity. They appreciated having information about their electrical consumption—the bar graphs were helpful, especially at the appliance level. One participant suggested using a pie chart instead to easily see what percentage of energy use goes towards which device. He also suggested that cost is really the main issue, not energy consumption, and would be better to focus on those graphs. The other participant found all the graphs a bit overwhelming; he didn't want to explore the user interface too much for fear of interfering with the test. (He also made comments indicating a lack of trust of utilities, suggesting he would go offgrid to avoid "offensive" rates).

6.1.4 Discussion

We successfully deployed a wireless network of sensors and actuators in two houses to replace the existing thermostat and control air conditioning over a six week period. In general, we experienced few problems with the hardware. In the first field test in 2005, we had numerous problems with the motes freezing, but in this later field test, the only problem with the motes was limited battery life. We had some difficulty with the software system freezing due to the internet connection, but we were also uploading new test code to the field computer through a remote link every few days. We performed a number of tests in each house to explore the dynamics of the HVAC+building system. We tested the optimization algorithm, the default house internal model and looked at the potential for computer learning for the occupant schedule and house parameters. The participants used the user interface to control the HVAC system. The DREAM interface also successfully displayed temperature, humidity, and total electrical energy consumption as well as display of energy and power of major appliances. In short, we demonstrated the potential of a smart, adapting, demand responsive, disaggregated thermostat that uses wireless technology.

We learned a great deal, especially from the field test, and would recommend the following improvements. For one, find a better method for uploading new code to the computer remotely without causing a system freeze. The current sensors should be more accurate. Fault diagnostics should be added to the system as well. For example, if the blower fan should fail to turn on, the air compressor should be turned off. Having an alert message when the battery voltage drew low would have been helpful. In general, diagnostics would be fairly simple to implement in this information-rich system, and would be a useful feature in detecting abnormal behavior in indoor temperature or the HVAC system.

We learned about human behavior and HVAC system plus house behavior through these tests. The thermal tolerance of each participant was different: the participant who worked at home and had grown up in a closed-house environment preferred a tight temperature range (74-75ºF) during the day. (Although we note that he was quite tolerant when our system accidentally created an uncomfortable environment.) The other household had an undersized air conditioner; they set the thermostat to 70ºF in the morning in order for the house to reach 78ºF in the afternoon—a manual “precooling” of sorts. They were tolerant of much higher temperatures. (Note that this supports the Adaptive Comfort Standard: people who are used to air conditioning have a more narrow temperature range). Both households opened up the house at night to take advantage of the breeze and appreciated outdoor temperature information, although one household kept a few windows open all the time. One participant welcomed smart technology; the other seemed a bit more wary of it. One participant used the setback feature of the thermostat when he remembered to set it when he left. The other participant indicated that a setback feature would be useful, not knowing that their thermostat already had a setback mechanism.

The current design for PCTs is an automatic 4ºF change in response to a price increase, but our tests indicate that a setpoint is meaningless without the context of the house, the HVAC equipment, and its occupants. What if the air conditioner is undersized or oversized? What if the house has a great amount of thermal mass or just a little mass? What if it is well insulated or poorly insulated? How will this affect people that work at home or have animals or those gone during the day?

This work leaves some interesting questions unanswered. The house internal model could benefit by testing in more houses. The precooling algorithm should consider price as well as the dynamics of the house+air conditioning system. The occupancy learning module might first determine whether there is a pattern to be learned. Learning algorithms of the house, HVAC system, and occupants' behaviors should be tested in different homes. Testing with a real price incentive would be useful as well.

6.2 Learning people's temperature preference

This section describes the result of using an available decision tree algorithm (Decision Tree Learning Applet 4.0.1) on office workers' temperature sensation votes. The purpose was to see how consistent people were in their temperature votes (too cool, just right, too warm), given available metrics. After experimenting with the applet, I manually observed the data to establish useful parameters, which were the time of day, season, and indoor and outdoor temperature. I tested eight subject data in all; this was based on subjects having enough data from both seasons.

The applet provided three methods of choosing the attribute on which to split the data first. This basically forms the "shape" of the decision tree. Of the eight subjects, three showed the best results when the first node of the decision tree was Season. Outdoor temperature (related to Season) was also a good node on which to split. The data of two subjects were best split with Indoor temperature, and one best split with Time. The data of one subject showed poor results with the learning applet; no single attribute seemed particularly helpful in predicting temperature preference.

Since the data were randomly split in half (half to "learn" the pattern by creating a decision tree and the other half to test), several different trees might be developed for each subject. Each tree would have different success in predicting thermal preference.

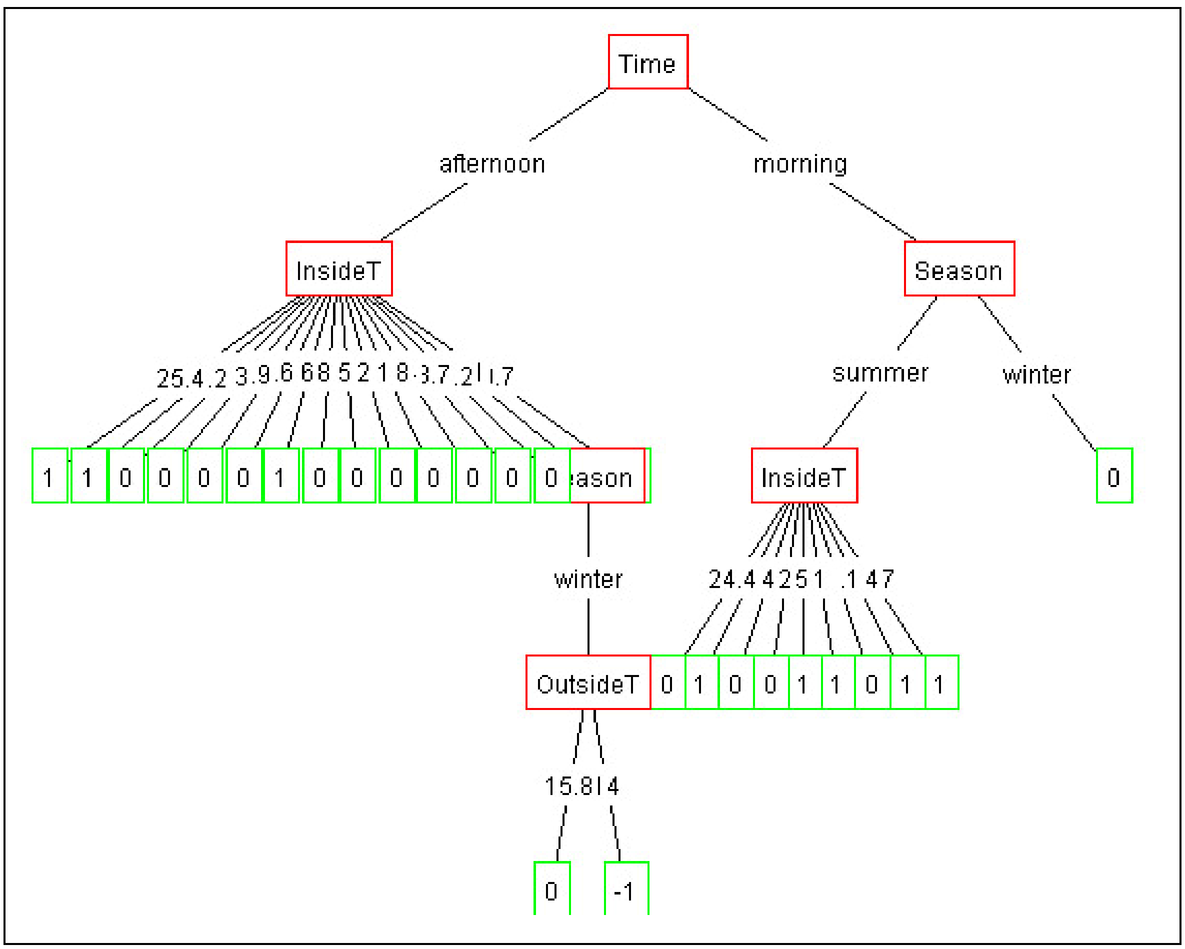

Figure 79: Decision tree for WB, split first on time.

The following table shows the results for all eight subjects, using the three different methods provided by the applet. The decision tree algorithm successfully predicted examples approximately 69% of the time; this average increased to 75% if the score from the lowest subject was removed. With the four subjects whose data were predicted at a better than 80% rate, three were split on Season. The data of one subject (WT) were not able to be "learned" better than a guess.

Person	*Gain Ratio*	*% Correct*	*Information Gain*	*% Correct*	*Random*	*% Correct*	*Best Split*
JS	30:7	81%	29:8	78%	31:6	84%	IndoorTemp
DK	35:6	85%	21:20	51%	34:7	83%	Season
PK	33:7	83%	33:7	83%	33:7	83%	OutdoorTemp or Season
WT	4:26	13%	5:25	17%	14:16	47%	
EB	26:13	67%	27:12	69%	27:12	69%	IndoorTemp or OutdoorTemp
WB	29:13 (S)	69%	28:14 (To)	67%	30:12	71%	Time
CM	12:12 (S)	50%	17:7 (Ti)	71%	18:6	75%	OutdoorTemp
TM	21:3	88%	19:5 (Ti)	79%	21:3	88%	Season

S = Season, To = Outdoor Temperature, Ti = Indoor Temperature

Table 4: Decision tree prediction with different strategies of choosing the first node.

I looked at the differences between the methods and the effect of the amount of data on the prediction. The following table lists the results from the three strategies, the averages, and the standard deviations. For five subjects, the three strategies of choosing the initial decision tree node split were close: the standard deviations are low. While I thought the amount of data would influence the prediction, I found no correlation (r=0.197). The table below shows that one of the highest prediction scores of 85% came from a person (TM) with the lowest number of data points (only 24).

Person	*# votes*	*Gain Ratio*	*Info Gain*	*Random*	*Std. dev.*	*Avg.*
CM	24	50%	71%	75%	0.13	65%
TM	24	88%	79%	88%	0.05	85%
WT	30	13%	17%	47%	0.19	26%
JS	37	81%	78%	84%	0.03	81%
EB	39	67%	69%	69%	0.01	68%
PK	40	83%	83%	83%	0.00	83%
DK	41	85%	51%	83%	0.19	73%
WB	42	69%	67%	71%	0.02	69%

Table 5: Summary of number of votes, mean scores, and standard deviation.

6.2.1 Discussion

What do the results tell us about the applicability of learning people's temperature preference? On the one hand, an office environment is quite different from a residence. The office workers were asked to only answer the questionnaire when they had been in their office space for 30 minutes; the conditions were sedentary and static as opposed to a home, where the occupants might be sedentary or active, coming home after a vigorous run or waking up after a nap. In an office, people may expect less comfort than at home where they have (presumably) more control. In addition, a thermal preference vote is not the same as turning up or down the thermostat.

Arguably, this test reflected the extent to which a person's temperature preference, given parameters we can measure, is consistent. The results suggest that either I did not use or did not have access to the parameters that would show a consistent pattern in thermal preference. Perhaps other data, such as the temperature slope before the vote would improve performance. However, clothing, warm or cool drinks, and metabolic rate all play a role in thermal comfort, and are difficult to measure. Yet if a pattern of thermal preference is not consistent, it cannot be "learned" with the success necessary for adoption. Evidence from other embedded intelligent devices suggests that a person's tolerance for error is expected to be quite low. A mistake by TiVo[61] is permissible, but by a smart thermostat is not. The results suggest that the application of a learning algorithm may not work for all people, and is best suited for occupants with consistent schedules and preferences. Multiple occupants will also add a level of complexity.

6.3 Adaptive temperature setpoints

I ran two different types of simulations using our validated house model with MZEST to test the residential adaptive comfort temperature setpoints. The first set of simulations compared the heating and cooling energy used for a house using the adaptive temperature setpoints and one using EnergyStar default setpoints for a programmable thermostat for an entire year. The second set of simulations compared the same adaptive method to both a programmable communicating thermostat and a manual thermostat during two summer months. Both used Sacramento, California temperature data.

6.3.1 Annual simulation

The first step was to compare an annual simulation of the adaptive temperature setpoints to energy-saving default setpoints from an EnergyStar programmable thermostat. The adaptive temperature setpoints for heating and cooling were based on the method outlined in the last chapter for 90% acceptability.

The following graph shows the indoor temperature for both simulations as well as the running weighted average outdoor temperature for an entire year. Note the increase in setpoint in the summer months for the adaptive setpoints compared to the static setpoints.

[61] TiVo is a service that digitally records television programming and can "learn" one's viewing preferences.

The peak indoor temperature is 29ºC (84.2ºF) when the weighted average outdoor temperature reaches 25ºC (77ºF).

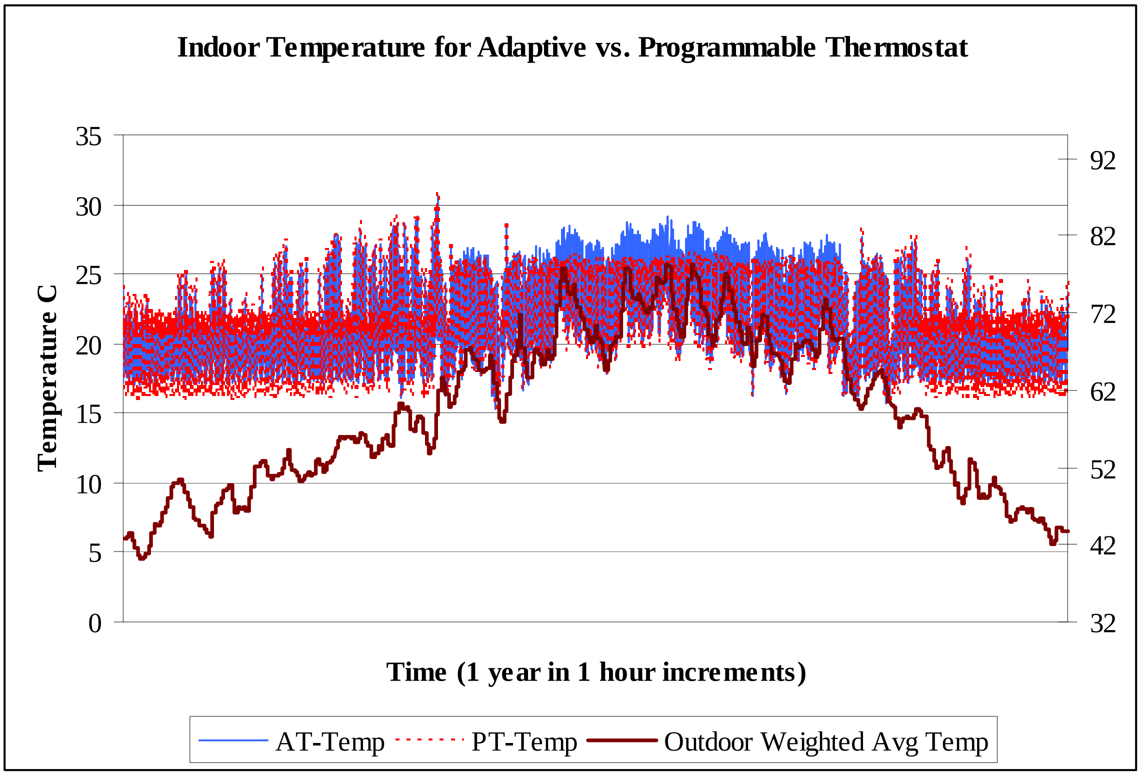

Figure 80: Annual simulation indoor temperatures.

An initial look at the data suggested a few problems. For one, the diurnal change of the adaptive setpoints caused the air conditioner to run more often in the evening. In addition, sometimes the air conditioning was on in the fall and spring afternoons when the outdoor temp was lower than the indoor temperature. According to several studies, air conditioner use in these circumstances does not reflect real world conditions.

A review of the comfort votes revealed quite a number of issues. For example, of the hours that the index indicated too hot, 96% of the time the outdoor temperature was at least 3ºF (1.6ºC) cooler than the inside. Figure 80 above shows high indoor temperatures especially in the spring months, possibly a combination of the heating system and the area of west facing windows in this particular house model picking up heat gain from the low springtime sun angle. People would most likely open up windows to increase comfort for these times rather than turn on the air conditioning. Providing advice to encourage the opening of windows and outdoor temperature information would be helpful to save energy.

Of the hours where the index indicated “too cold”, 93% of the time this occurred in the cooling months! Nearly a third of the time the outdoor temperature was warmer than the indoor temperature, and thus again, advice to encourage opening up the house could save energy. Two-thirds of the time, the indoor temperature was at least 64.4ºF (18ºC).

The diurnal drift seemed to save energy for heating, but had less effect on summer cooling savings. Most likely the setpoint drift paralleled the indoor temperature increase due to the outdoor temperature. The effect of the drift for comfort for the cooling season is still a viable concept, but should be further tested with field research rather than simulations.

The decision to switch from heating to cooling mode was based on a simple average of the previous week’s outdoor temperature, based on the Alternative Calculation Method for developing Title-24-based compliance software (CEC, 2001). However, the above temperature graphs indicate some problems with this approach, especially during the swing months of spring and fall. In general, a better understanding of behavior during the swing months would improve the performance. For example, one study by Kempton showed that people tended to withstand a greater temperature swing in the fall and spring seasons (Kempton & Krabacher, 1987). Rather than switching from heating to cooling (or the reverse) in a single day, people may delay turning on the air conditioner or heater until the season develops a pattern.

Although the Adaptive Comfort Standard suggests a range of comfort, the low limit for cooling seems to be too high. Some evidence indicates that during the cooling season, people do not mind being “too cold”. For example, the outdoor temperature may reach 92ºF (35ºC) in Sacramento during the day and down to 58ºF (14ºC) at night. While 68ºF (20ºC) might be found too cool according to the model, Hackett’s interviews with Davis residents found that temperatures in the 60sºF were comfortable, even refreshing especially if they expected the day to get quite warm (Hackett & McBride, 2001).

Given that the low limit for the Adaptive Comfort Standard for cooling may be too high especially during the swing or transition months, I then modified the comfort index slightly. For example, for days when the weather was expected to be hot, cool temperatures in the morning (i.e., > 68ºF (20ºC)) were considered comfortable on a summer morning. This was also based on the assumption that people will dress warmly for cool mornings; according to Comfort 1.07, a person with a Clo value of 1.2 is comfortable at 68ºF (20ºC). Morning temperatures between 66.2ºF (19ºC) and 68ºF (20ºC) were considered slightly cool, and below 64.4ºF (18ºC) uncomfortably cool.

Trying to adapt the simulation tool to reflect passive cooling and heating through increased infiltration proved to be a daunting task and was abandoned. Instead the algorithm was modified to not allow cooling when outdoor air was cooler than indoor air.

The results indicate the viability of passive cooling and heating, as well as adaptive setpoints for saving energy. The adaptive setpoints used 34% fewer hours of air conditioning and 17% fewer hours of heating than did the conventional setpoints for the annual simulation, as shown in the figure below.

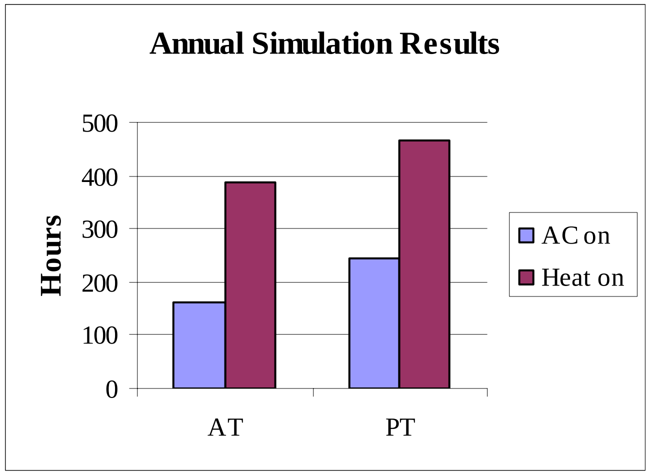

Figure 81: Annual simulation results on HVAC systems.

6.3.2 Summer simulation

I ran three simulations using July and August Sacramento climate data. The simulations used three different temperature setpoints profiles: PT = Programmable thermostat that has a set schedule based on time of day, PCT = Programmable Communicating Thermostat that has a set schedule and is modified by price, and AT = Adaptive Thermostat which adapts the temperature setpoints based on time of day, price, and outside air temperature. In this test, the PCT had the following offset for each price period: +2ºF (1.1ºC) for medium periods and +4ºF (2.2ºC) for high price periods. I changed the Adaptive setpoints to ignore diurnal changes. Then I created price setpoints for the adaptive strategy: +1ºC (1.8ºF) for medium price (same as 80% acceptability) and +2ºC (3.6ºF) for high price periods. The figure below shows the comparison of the four setpoint strategies for four days in July. Note that the AT setpoints drift up with outside temperature: on the hottest day during the period of high price, the temperature setpoint reaches nearly 30ºC (86ºF).

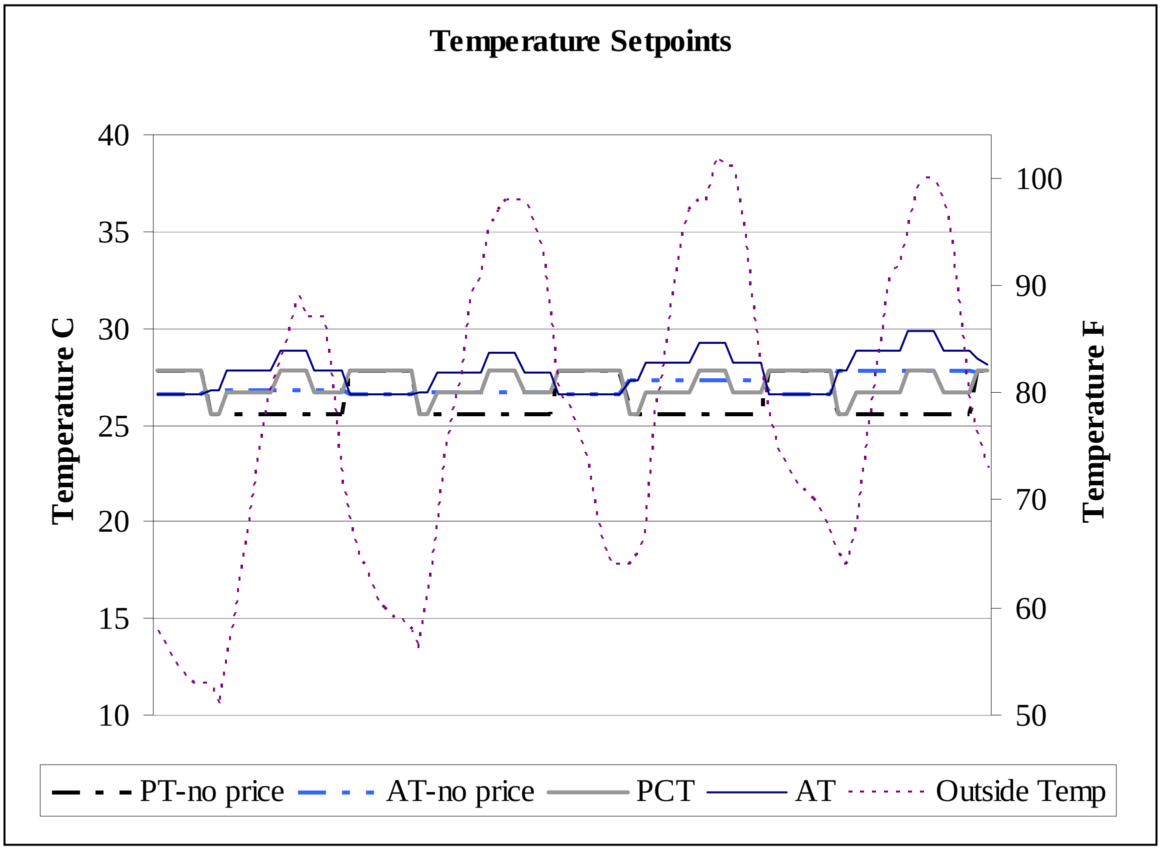

Figure 82: Temperature setpoints for four setpoint strategies.

The following figure shows the number of hours that the air conditioner is on for each of the temperature setpoint strategies. The PT-strategy consumes the most energy during the high price period, and AT-strategy with price offset consumed the least. Compared to the PT, the adaptive setpoints that did not change with price resulted in 60% fewer hours of AC use, while the PCT achieved 69% fewer hours during the high price period. During the medium period, the adaptive strategy showed 32% fewer hours and the PCT resulted in 15% fewer hours than the PT. Note that the adaptive setpoints assume a 90% acceptance rate for comfort; modifying these setpoints for price reduced the need for cooling (91% fewer hours during peak periods than a programmable thermostat and 70% fewer than a PCT), but at a cost to comfort.

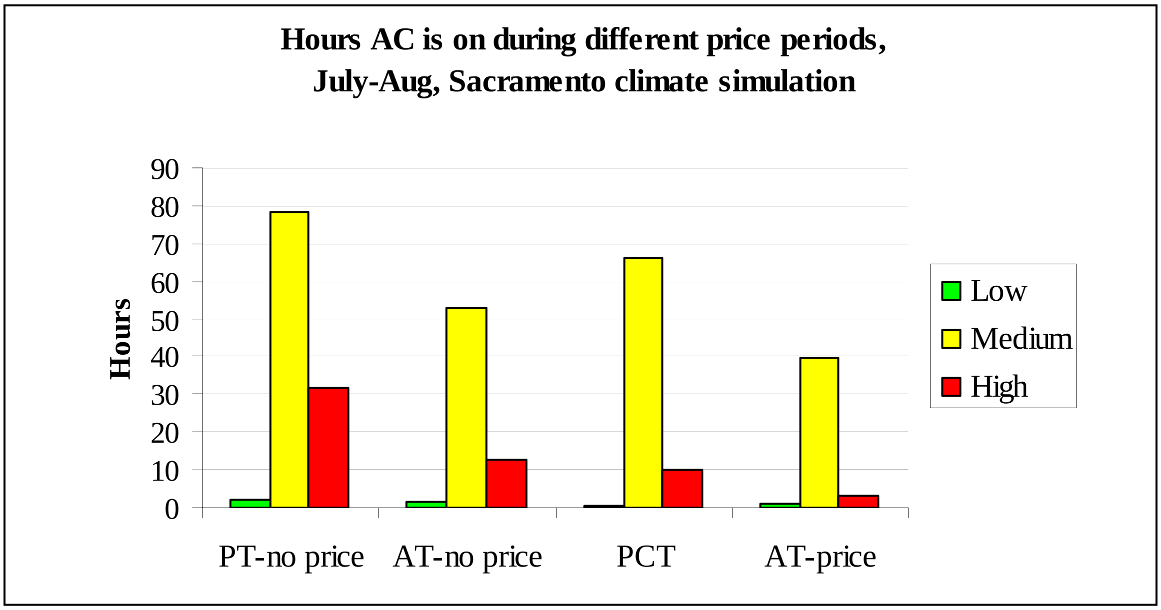

Figure 83: Hours of AC usage for different setpoint strategies for demand response.

The results show promise for the residential adaptive comfort temperature setpoints in saving energy and providing comfort. More simulations in different climates might bear other issues. For example, the climate I chose for simulations did not need any adjustment in temperature setpoint due to relative humidity; however, other climate simulations may show the benefit of this part of the algorithm. Many aspects of the study require field study to evaluate success with respect to energy savings and increased comfort, whether in the existing flat rate electricity tariff or a dynamic price tariff. A diurnal drift of temperature may be effective with demand response scenarios, especially if the ramp rate is not detectable. The advice generated to improve comfort also warrants field testing. In addition, the comfort index that was developed could be improved with field trials.

6.4 User interface testing

This section describes the results of the test in UC Berkeley's Experimental Social Science Laboratory (Xlab). The animated interface part of the test evaluated the influence of the context (sponsorship) of the device and the type of information displayed on the amount subjects offset temperature in high demand periods. The survey section had many objectives: it sought feedback on the interface as well as other types of information and tools useful to making decisions with a variable electricity tariff. The survey contained two tools to assess correlation between certain values and behavior. The survey also included simple demographics and current behavior regarding household electricity use, thermostat use, and energy conservation.

The experiment ran two times on June 10, 2008, once at 10:30am and the second at 12:00pm. I gave the subjects a short introduction before the test began; they signed consent forms at this time. Following the test, I provided a short debriefing, where the subjects were informed that they had been deceived: the thermostat/in-home energy display device was developed on campus and not sponsored by an electrical utility or a nonprofit organization. Then, they signed a debriefing form to acknowledge the debriefing and allow use of their data.

Most (46) of the 53 subjects were between 15-24 years old, 6 were between 25-34 years old, 1 was between 35-44 years old.[62] The majority of the subjects were female (36 or 68%); there were 17 males. Appendix F has the full text of the survey along with the results.

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[62] I did not ask whether the subjects were students or staff, but the Xlab staff indicated that most of the subjects were students.

6.4.1 Influence of context and information

The study involves two variables: context (introduction of technology) and information (whether price or energy information was displayed). I analyzed how much the subjects changed the temperature setpoint to reduce the air conditioning load on a simulated thermostat user interface. My hypotheses were 1) that the subjects who saw price would not offset differently than those who saw energy demand information, and 2) those subjects who saw the nonprofit introduction would be more likely to select a higher offset than those who saw the introduction from the utility company.

The computers were numbered 1-32. Half the computers had the simulation that showed price information and half had the simulation that showed energy information. The survey asked subjects to enter the number on their computer to further split the groups into two to determine which introduction they would see. This resulted in the four groups as described in the table below.

	Utility company sponsored	*Nonprofit sponsored*
DREAM1: price information	#1-8	#17-24
DREAM2: energy consumption information	#9-16	#25-32

Table 6: Developing four groups of subjects.

The morning test had 29 subjects. The text file for the simulation from computer #20 could not be found. While an hour was allowed for the test, some people completed it rather quickly (under 20 minutes) and others took over 35 minutes to complete. A few subjects asked if they were taking the test over again since they recognized some of the same questions after the simulation as before. The afternoon test had 24 subjects. The test was started a few minutes late and lasted approximately 35 minutes. The subjects for each test remained in the computer lab until the debriefing after each. The Xlab staff handled the compensation of $15 per subject at the end of the tests.

The final result was that the four groups were not equal in number, since not all computers were used. Slightly more than half of the subjects (29) saw an introduction as if a utility company was sponsoring the technology and slightly less than half (24) saw the introduction as if a nonprofit was the sponsor. The information display groups were split roughly in half (27 versus 26). However, gender was not equally distributed among the four groups. The actual numbers are shown in the table below.

	Utility company sponsored	*Nonprofit sponsored*	
DREAM1: price information	7 morning 7 afternoon **14 total (13 female, 1 male)**	8 morning 5 afternoon **13 total (5 female, 8 male)**	**27**
DREAM2: energy consumption information	8 morning 7 afternoon **15 total (11 female, 4 male)**	6 morning 5 afternoon **11 total (7 female, 4 male)**	**26**
	29	**24**	**53**

Table 7: Breakdown of subjects and gender per group.

6.4.1.1 Analysis of the data

Question 10 of the survey (Appendix F) contained the text that introduced the interface and the subsequent questions provided the instructions that the subjects saw. The subjects were asked to look at the simulation once without changing anything and then asked to view simulation a second time changing the slider bar if they chose to. They were not instructed to make any other changes.

I reviewed each text file produced by the simulations. Of the 53 subjects, 47 responses were recorded. Of the six subjects for which no responses were recorded, one text file was not found; since the subject responded he disliked the simulation's length, I assumed that the text file was somehow lost (although he was the first person to answer the first question after the simulations). Since not all actions were recorded, I do not know what happened to the other five. Two only ran the simulation once, and one stopped at the beginning of the second simulation. Although subjects were asked to only use the slider bar to change settings, one turned the air conditioning off and another used the up/down arrows to control temperature instead of the slider bar.

Approximately a third of the subjects did not follow directions. For example, ten only ran the simulation once. Others used other methods of controlling temperature. Eight used the up/down arrows, and four turned off the air conditioning. Three subjects used all three means of controlling the temperature: up/down arrows, off button, and slider bar.

Many subjects changed the slider bar continually throughout the simulation, but a few changed it early on in the simulation and left it there. Two subjects appeared to change the slider bar continuously according to the price/demand shown (low, medium, or high). I decided to use the final setting—where each subject left the slider bar at the end—as their final decision. The following graphs show the amount of offset that each subject chose, categorized by the four groups. The first set of graphs show the histograms for each group:

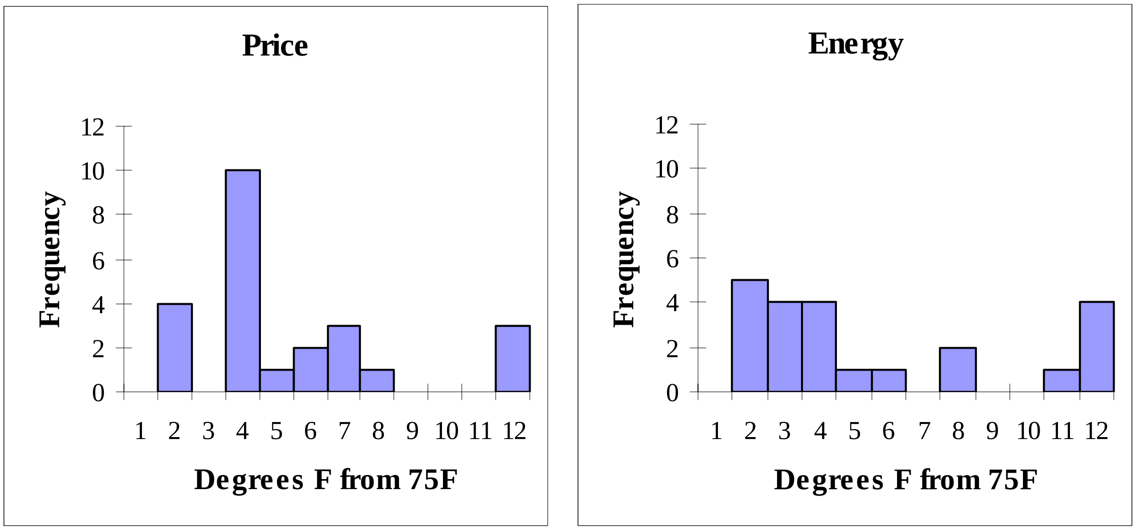

Figure 84: Histograms from the Price versus Energy information display groups.

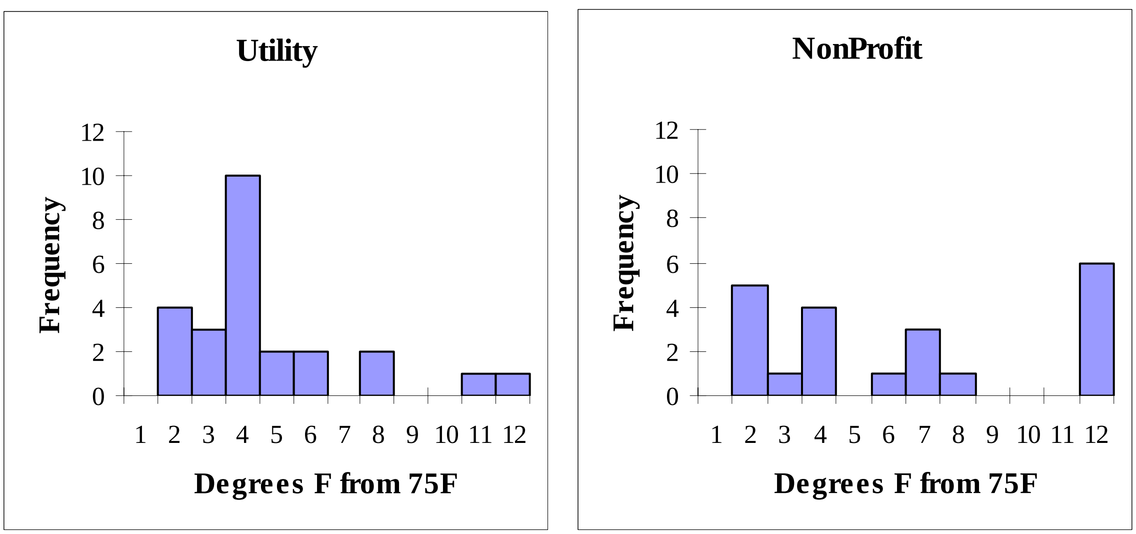

Figure 85: Histograms from the Utility versus NonProfit sponsorship groups.

While the histograms were not perfectly normal, for the number of subjects they were considered to have adequate spread and uniformity to perform two-sample t-tests. The box and whisker plots below show quartiles and outliers of the four groups; the X marks the average of each group.

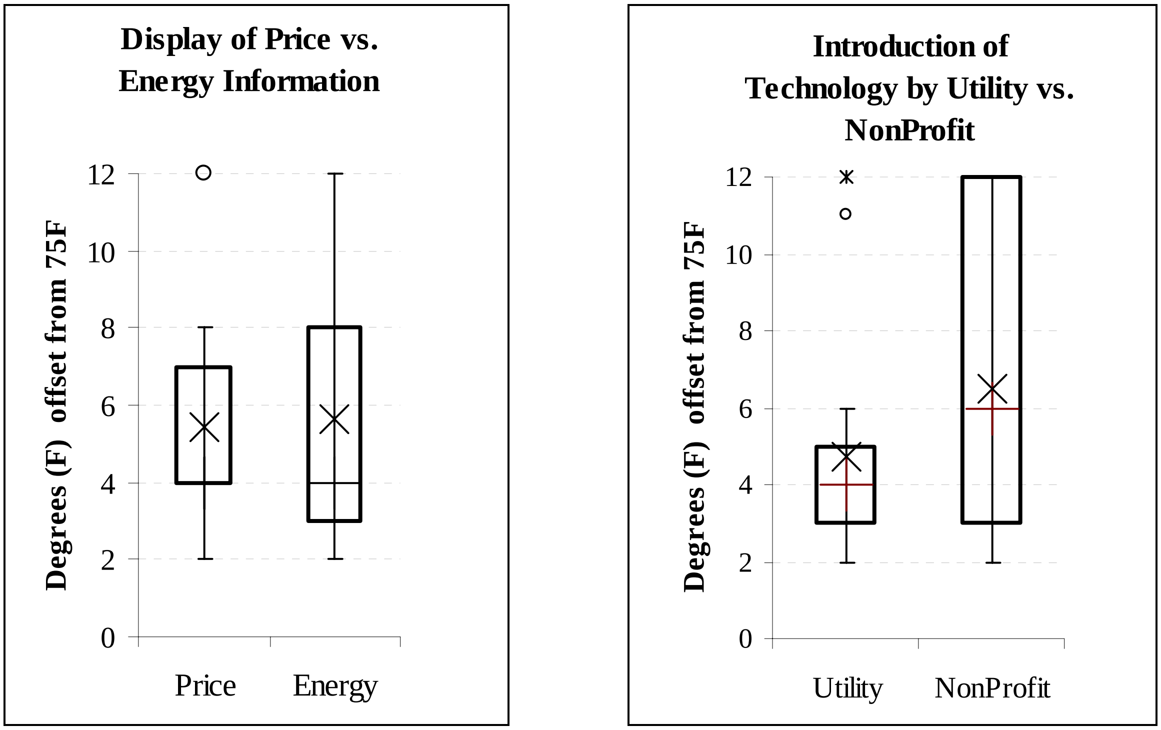

Figure 86: Box and whisker plots of the temperature offset in all four groups.

I used Microsoft Excel to run a two-sample t-test assuming unequal variance, using alpha = 0.10.[63] While the standard deviation in the group that saw energy information was greater than that of the price information display group (3.82 vs. 3.04), the average was not significantly different (5.64 vs. 5.42). Since I hypothesized no difference in behavior in subjects seeing price versus energy information, I used the two-tail result of P(T<=t) = 0.83. A typical test for significance is whether this value is less than 0.05 (De Veaux, Velleman, & Bock, 2006); thus, the result indicates that the difference between the groups is not significant. The difference in the offset between the utility and nonprofit groups, however, was significant; the average of the utility group was 4.72 compared to the average of the nonprofit group at 6.48. Since I hypothesized a

[63] I would like to acknowledge the help of graduate student Megan Goldman in UC Berkeley's Statistics Department consulting group, who advised on the type of analytical tests to run and the choosing the appropriate significance.

difference in behavior between these groups, I used the one-tail result of P(T<=t) = 0.047. This result is less than 0.05, and thus indicates a significant difference between the groups.

Plotting combination boxplots revealed the potential of interaction among the variables. The box and whisker plot below left indicates a very low distribution of offset for those that saw both the utility introduction and price information displayed. A plot of the mean offset in each group shows the interaction. If no interaction existed, the lines would be parallel. Since the lines cross, these variables were not necessarily independent (Goldman, 2008, personal communication).

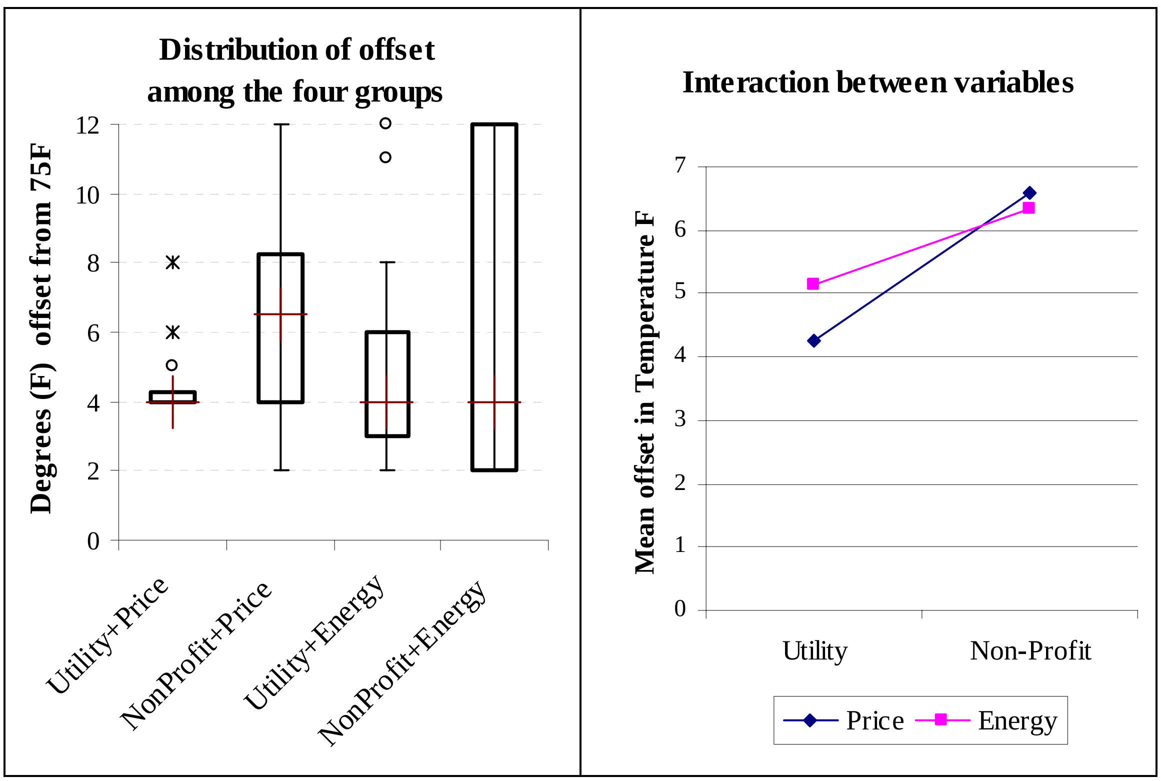

Figure 87: Left: Box and whisker plot of the four groups. Right: Interaction plot.

6.4.1.2 Influence of gender

Could gender have influenced the outcome of the offset test? Of the 11 subjects who only ran the simulation once (or not at all), five were male. I wanted to determine if gender made a difference so I plotted the results according to gender. I did not suspect gender would influence the results. However, the initial plot below indicates that both the average offset and standard deviation among males was greater than females (average of 6.00 for males compared to 5.06 for females; standard deviation of 3.88 versus 3.11).

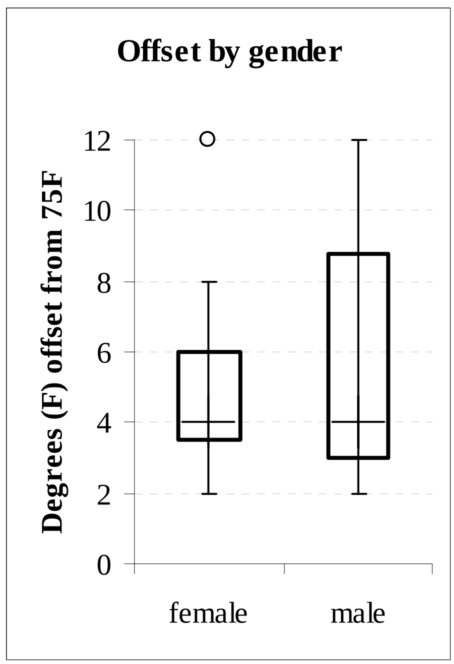

Figure 88: Gender difference in temperature offset.

I then plotted each variable by gender. The plot below indicates some differences between the genders in both price information display and the nonprofit sponsorship categories. The dark circles indicate the average within each group; the number in each group is indicated above each plot. Of those that saw the introduction by the nonprofit, the average offset of males is higher than the females (6.6 versus 5.3); both averages are above the averages for the utility group which were similar (4.6 versus 4.7). However, for those that saw price information, the average of the females was lower than that of the males (4.4 versus 6.5). The average offset of the females for price information was lower than for energy information (4.4 versus 5.6), but the average offset of the males for price information was higher than for energy information (6.5 versus 5.5).

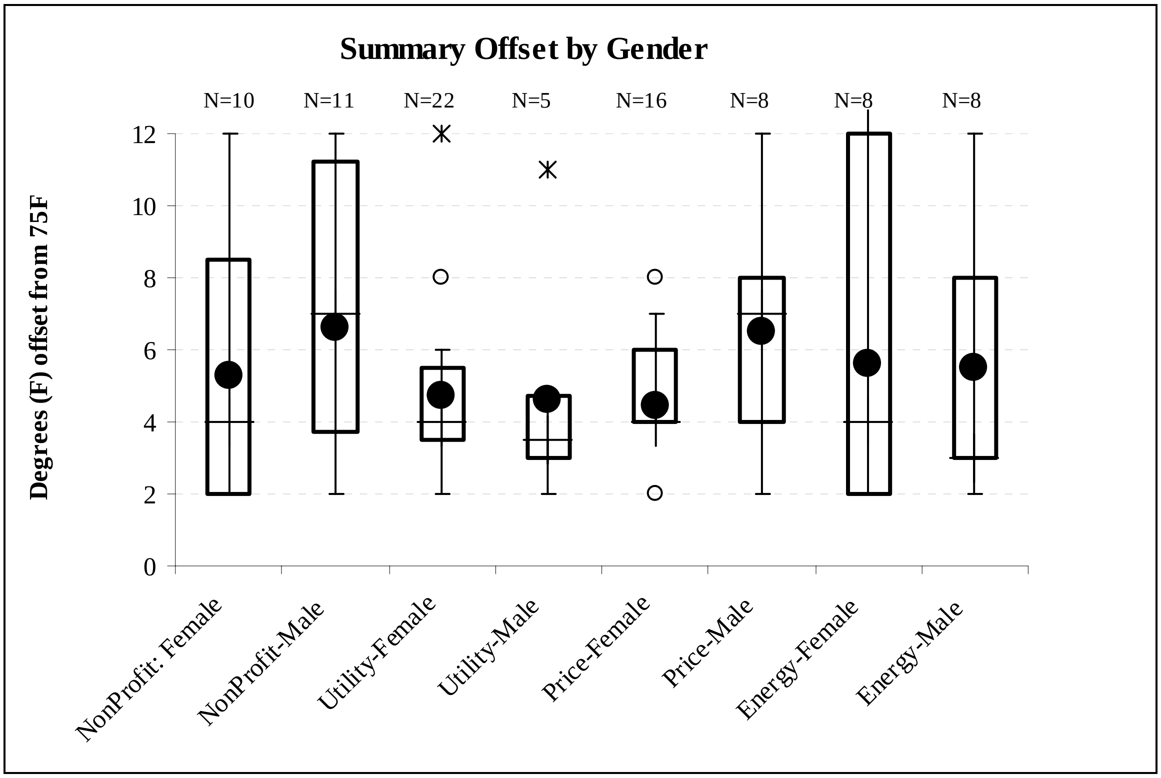

Figure 89: Box and whisker plot of gender differences among the four variables.

None of these gender differences, however, are significant. The table below lists several tests that I conducted. While males offset temperature more when they saw the technology introduced by a nonprofit organization than did females, the effect is not significant (two-tailed result of P(T<=t) = 0.45). Did males offset temperature more when they saw price information, and females offset more when they saw energy information? The test indicates some effect on seeing price information for females versus males

(P(T<=t) = 0.17), but is not significant. While analysis found no significant difference, this may be due to the small sample size and is worthy of further study with more subjects.

Difference between		*P(T<=t) One tailed*	*P(T<=t) Two tailed*	*Significant?*
Nonprofit-Female	Nonprofit-Male	0.22	**0.45**	No
Price-Female	Price-Male	0.09	**0.17**	No
Utility-Male	Nonprofit-Male	**0.17**	0.34	No
Price-Female	Energy-Female	0.16	**0.33**	No
Price-Male	Energy-Male	0.31	**0.62**	No

Table 8: Summary of two-sample t-tests of gender.

6.4.1.3 Conclusion of the parameter test

Overall the type of introduction of the technology (utility versus nonprofit) had a significant effect on the amount of offset. Those that saw the nonprofit introduction tended to offset more. The data show more offset from males than females, although difference is not considered significant. Overall the type of information did not significantly affect the amount of offset, but between the genders, males seeing price information tended to offset more than females. Males viewing price information offset more than males seeing energy information, and females that saw energy information offset more than those viewing price information. However, the sample size of genders within each group is small and the distributions are somewhat skewed, so this effect is not easily generalized without more data.

6.4.2 Impressions of the interface

Participants were asked to write their initial impressions of the interface simulation (question 18, Appendix F) and most (52 of 53) did so. The majority (75%) had positive comments; 12 offered suggestions. Several noted that it took time to understand. About a third (35%) remarked that the simulation was easy to use; 12 (23%) stated that it was hard or confusing. Interestingly, one person who saw energy information remarked that cost information would be more useful and one who saw cost information noted that energy information would be better.

Of those who found the simulation confusing, three only saw the simulation once and seven attempted to use thermostat functions that they were not instructed to use, which may have led to confusion. Ten used the up/down arrows and/or turned off the air conditioner—which may not have functioned as they expected.[64] Fan functionality was not recorded, but at least one of the comments indicated that the participant tried to turn the fan off, and the behavior of the simulation did not react as expected. Another point of confusion may have been usage. A couple of the subjects mentioned that the simulation did not reflect their usage; one wrote that she would not use the air conditioner as much and another remarked that using lights in the morning was wasteful.

In general the aesthetics of the interface were satisfactory. Most liked the colorful display and graphs especially the pie charts. One remarked that the interface was appealing in simulation, but might not be so appealing in real-time. Some liked the analog format of the temperature; some found it difficult to read and preferred a digital readout.

[64] For the purposes of the experiment, the up/down arrows did not change the temperature during the medium and high priced periods.

6.4.3 *Attitudes and behavior*

I analyzed the results of the List of Values (LOV) question for any correlation between importance of certain values and either temperature offset and/or attitude towards energy and the environment (question 52). The List of Values (LOV) question (question 3) asked subjects to rank the importance of nine values, such as self-respect and excitement. The highest ranks were for self-fulfillment, then a sense of accomplishment, then self-respect: all so-called internal qualities. The lowest ranks overall were for excitement, sense of belonging and security, which are considered external qualities. I found no correlation between LOV scores and amount of offset. The only finding is that none of those who highly valued excitement and sense of belonging chose the highest temperature offset of 12ºF.

The Connection with Nature Scale (CNS) (question 4) asked subjects the extent they agree or disagree with certain statements in order to evaluate their environmental attitude. I found no correlation with offset. However, I found a small correlation with concern for environment (r=0.53) as seen in the graph below.

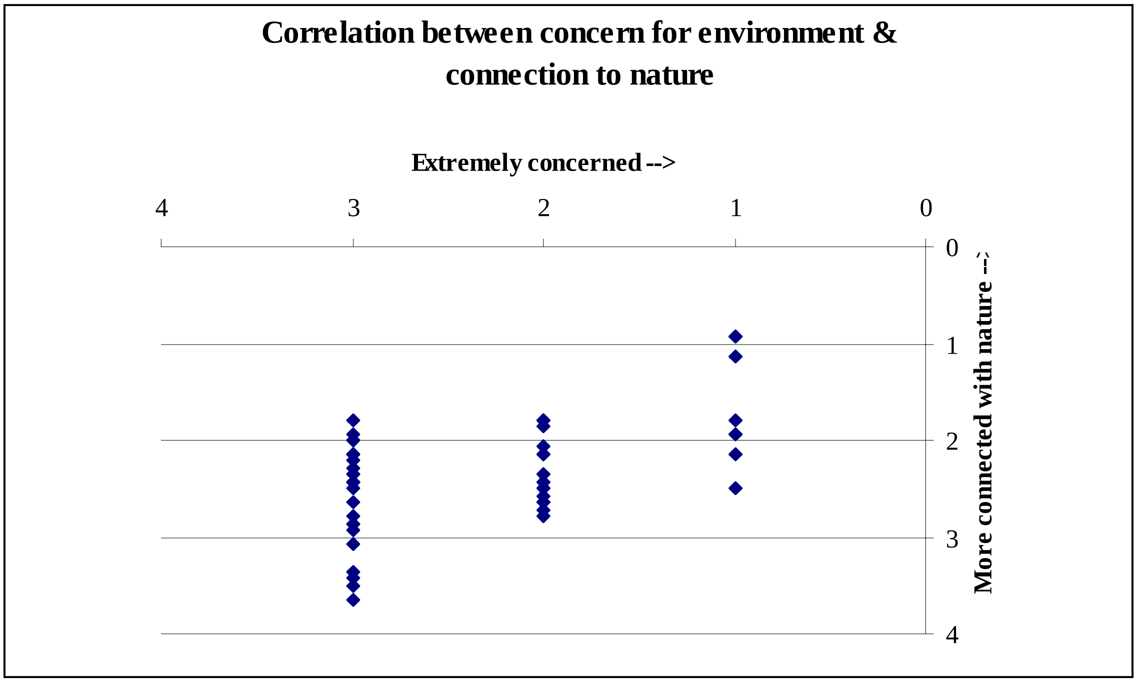

Figure 90: Correlation between connectedness to nature and concern for the environment.

Almost half of the subjects gave socially conscious as the reason for saving energy. The last question (question 54) asked which energy conserving behaviors participants had taken in the past five years. These subjects appear to be fairly conscientious: 60% listed energy saving behaviors.

6.4.4 Simulation as teaching tool

I used two questions before and after the simulation to discern whether subjects learned anything about energy consumption by watching the simulation. One question (questions 7 and 24) asked subjects to put 11 appliances in order of their electricity consumption in a 24 hour period on a hot summer day. Another question (questions 9 and 26) asked which behavior had a greater positive effect on the environment: turning off certain small appliances when not in use or running the clothes dryer in the mornings or late evenings on hot days. The objective was to determine if these results changed as a result of reading the introduction on peak electricity consumption and viewing the simulation.

The subjects were asked to put in order the following appliances:

- electric lights
- refrigerator/freezer
- plasma screen television on 3-4 hours
- air conditioning
- computer on 24/7
- one load of clothes in the washer
- one load of clothes in the dryer
- one load of dishes in the dishwasher
- microwave (10 minutes)
- cooktop (45 minutes)
- battery chargers (telephone, camera etc).

In reality, no exact “correct” answer exists, since many appliances have a range of power requirements. For example, a dishwasher might use 332 watts per load without water heating, but 1200-1500 watts with water heating built in (more typical with current market dishwashers). I used a combination of Table 7.2 of the Typical Appliance Usage Buildings Energy Databook (U.S. Department of Energy, 2004), the Residential Energy Consumption Survey (RECS) (EIA, 2005), and other online sources to determine an appropriate order for the appliances.

Before watching the simulation, only about half (51%) of the subjects thought the air conditioner would consume the most energy, 21% listed it as the second-most consuming appliance. A third of the participants thought the refrigerator/freezer was the most energy consuming load and another 31% put this in the number two spot. The standard deviation was 1.85 for the ranking of the refrigerator/freezer and 3.00 for the ranking of the air conditioner. This indicates that the subjects showed more variation with the ranking of air conditioning than with the refrigerator/freezer. In general, subjects overestimated the energy used by the clothes washer (put higher on the list than was warranted) and underestimated the energy consumed by both the clothes dryer and the stove cooktop (placed lower on the list than expected).

After watching the simulation, 92% thought that air conditioning consumed the most energy. The standard deviation for the ranking of the air conditioner dropped to 2.05; in general the standard deviation dropped for most appliances, especially the dishwasher and the cooktop. Of the three subjects that put air conditioning lower on the list after watching the simulation, all of them had air conditioning low on the list the first time they answered the question. Two subjects consistently thought refrigerators and lights consumed the most energy, the other felt her computer left on 24 hours a day consumed the most or at least was second most consuming. The answers provided on other questions by these three indicate that they personally don’t use the air conditioner much, and thus they answered the question accordingly.

Appliance	*Energy (Watt-hours)*	*Rank*		*Avg Rank Before*	*Avg Rank After*
Electric Light	2575 [1]	4		3	3
Refrigerator/Freezer	3287 [1]	2 or 3		**1**	2
Plasma screen TV (3-4 hours)	759 [3]	8		7	**6**
Air conditioner	13,500 [2]	1		**2**	1
Computer (24/7)	1675 [3]	5		6	**7**
Clothes Washer (one load)	375-500 [5]	9		**5**	**4**
Clothes Dryer (one load 45 min @3700-5000W)	2775-3750 [5]	3 or 2		**4**	**5**
Dishwasher (one load 1 h @1200-1500W)	1200-1500 [5]	7		8	8
Microwave (10 minutes)	250 [4]	10		10	10
Cooktop (45 minutes @2000W)	1500 [5]	6		**9**	**9**
Battery chargers (i.e., cell phone, camera etc)	86 [3]	11		11	11

1. RECS 2001

2. Assume 2 ton unit, on 4.5 hours

3. Energy Efficient Strategies 2006

4. DOE 2004

5. Face plate power from various sources

Figure 91: List of ranking of appliance energy consumption.

Another question asked which had a greater positive effect on the environment: shutting off lights, television, stereo, and computer when not in use or running the electric clothes dryer in the morning or evening. While in some sense the answer depends on the amount of electricity used with lights and so on, peak electricity in general has more impact because of the potential for bringing online older more polluting power plants—this was mentioned in the introduction. Before watching the simulation, 41 responded the former, 5 the latter, 1 said no difference, and 6 didn't know. After the simulation 33 responded the former, 15 the latter, 2 said no difference, and 3 didn't know.

Arguably this question is difficult. Nevertheless, while the majority still felt that turning off certain appliances had a more positive environmental effect, about a fifth of the subjects learned the environmental effect of the time of day that electricity is used.

6.4.5 Type of information useful for demand response

Several questions asked the subject to rate the types of information, advice, tools, and/or graphics that he or she would find useful in a dynamic electricity tariff environment, and how he/she might wish to receive this information. This section describes the results of these questions.

When asked how they would want to be notified if the utility were to charge a variable rate for electricity (question 27), the highest score was “mostly by email” (77%), followed by “through thermostat or other dedicated device” (58%), and “website” (51%). This response may well reflect the age of the subjects.

Another question (question 28) asked how useful would they find the following information: energy use from the highest consuming appliances, cost per load of appliance, current price and total household energy, advice/tips and total cost per billing period. The following figure shows the results of this question.

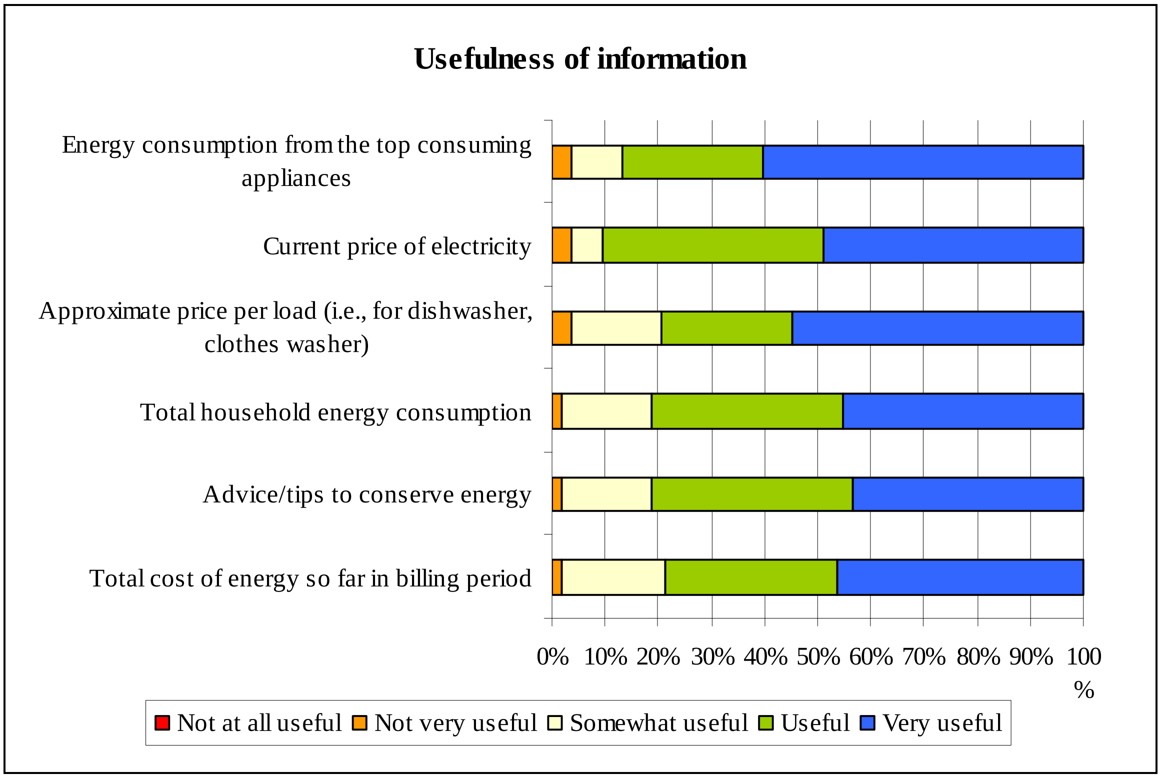

Figure 92: Usefulness of different types of information in a dynamic electricity tariff environment.

The next series of questions (questions 30-35) included graphics. Subjects saw six screenshots of a user interface and were asked to rank the usefulness of each with respect to making decisions about energy consumption in a dynamic electricity tariff. The following five point scale was used: Not at all useful-Not very useful-Somewhat useful-Useful-Very useful. Most of the participants felt all of the graphics were at least somewhat useful (mean of 3.0 or above on a 5 point scale).

The graphic with the highest rank (mean of 4.28 on a 5 point scale) was an iconographic display showing how much certain appliances will cost at different times/prices (Figure 93 below).

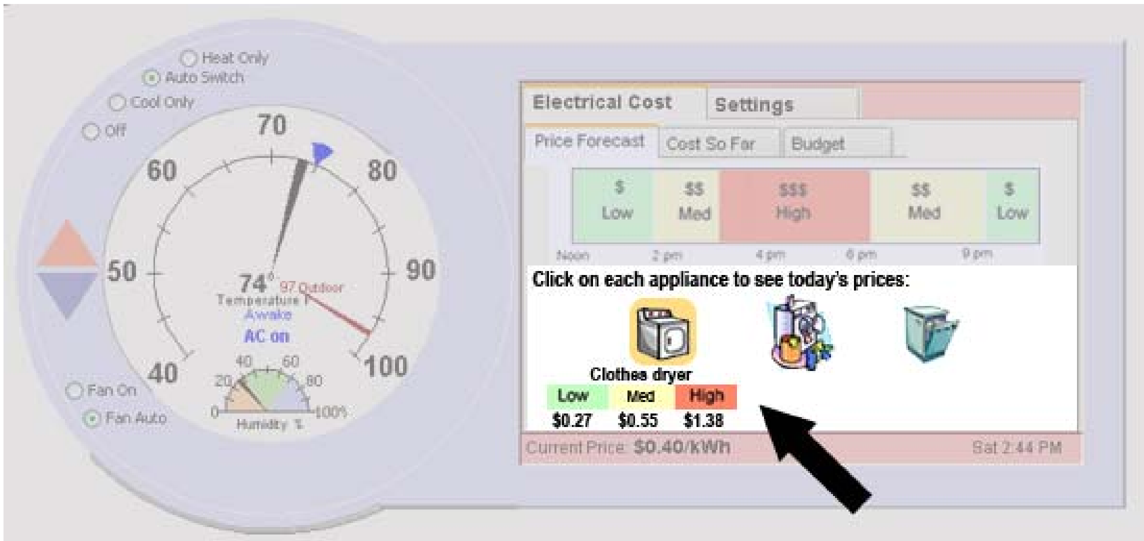

Figure 93: Graphic showing an iconographic display of appliances and how much each costs to run.

The second highest ranking (mean of 3.94) went to a display that had a barchart showing the time of price changes (Figure 94 below).

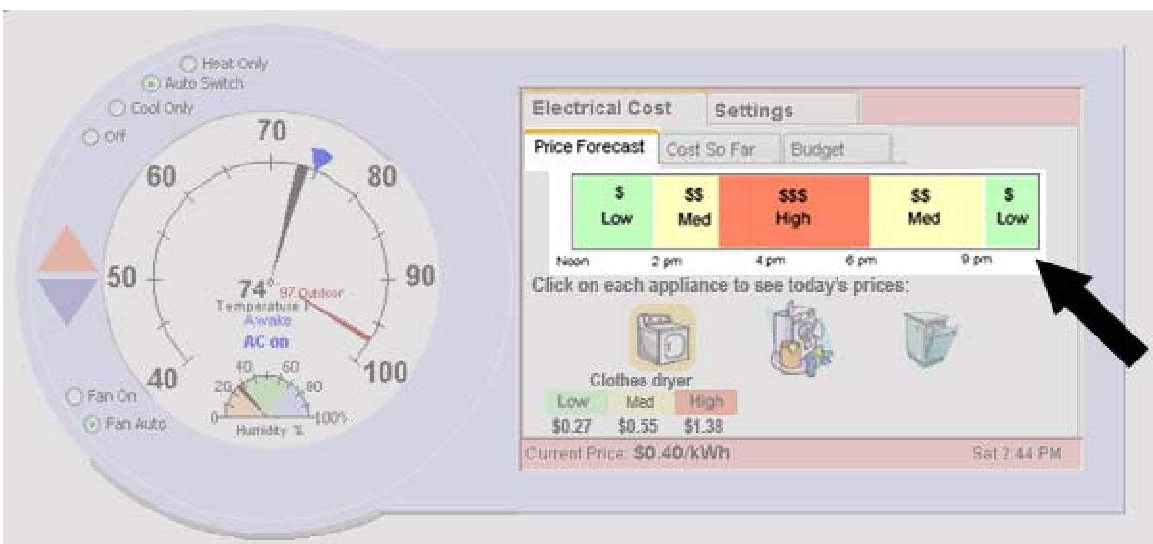

Figure 94: Display showing price forecast.

The slider bar graphic itself (Figure 95) was found useful (mean of 3.70), but the corresponding expected comfort level as a result of changing the temperature setpoint (Figure 96) was not as useful (mean of 3.15).

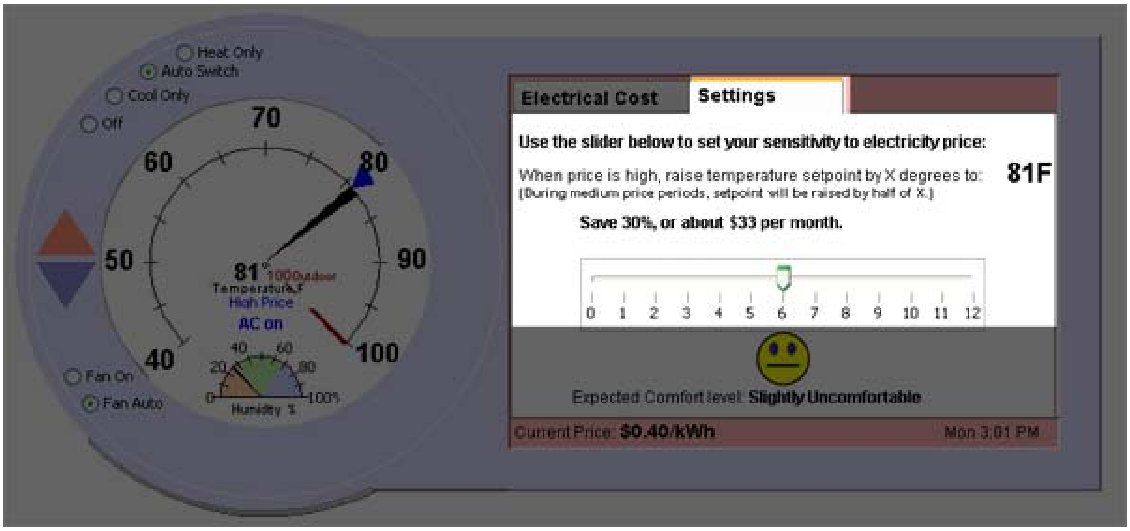

Figure 95: Slider bar to control the temperature during high price periods, with cost feedback.

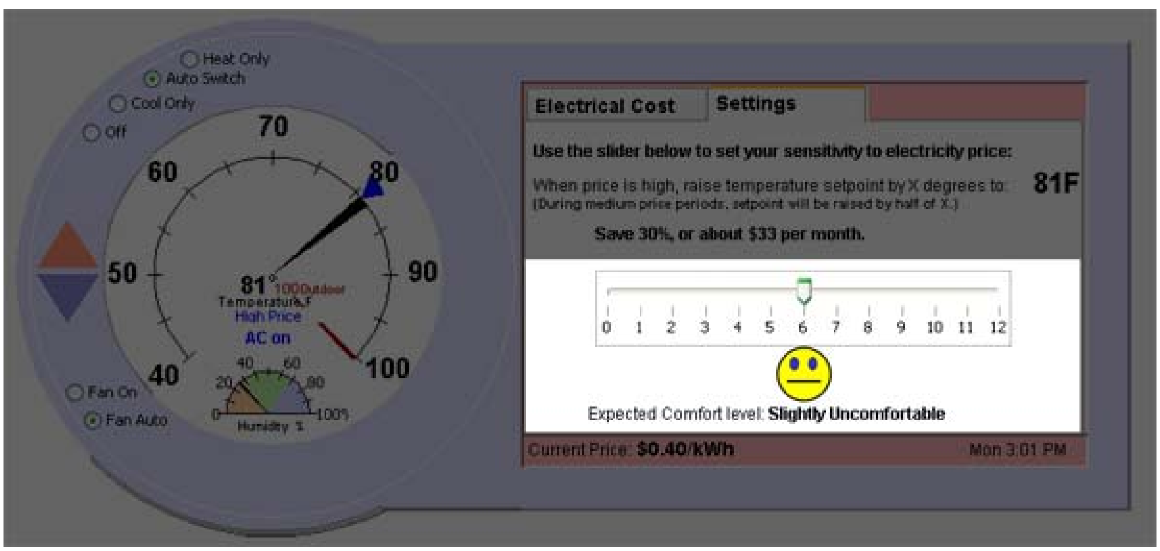

Figure 96: Corresponding expected comfort level as a result of changing the temperature setpoint.

Another tool that was found useful (mean of 3.69) was a tool that allowed one to set a monthly goal for energy consumption and see how current use compares to that goal (Figure 97).

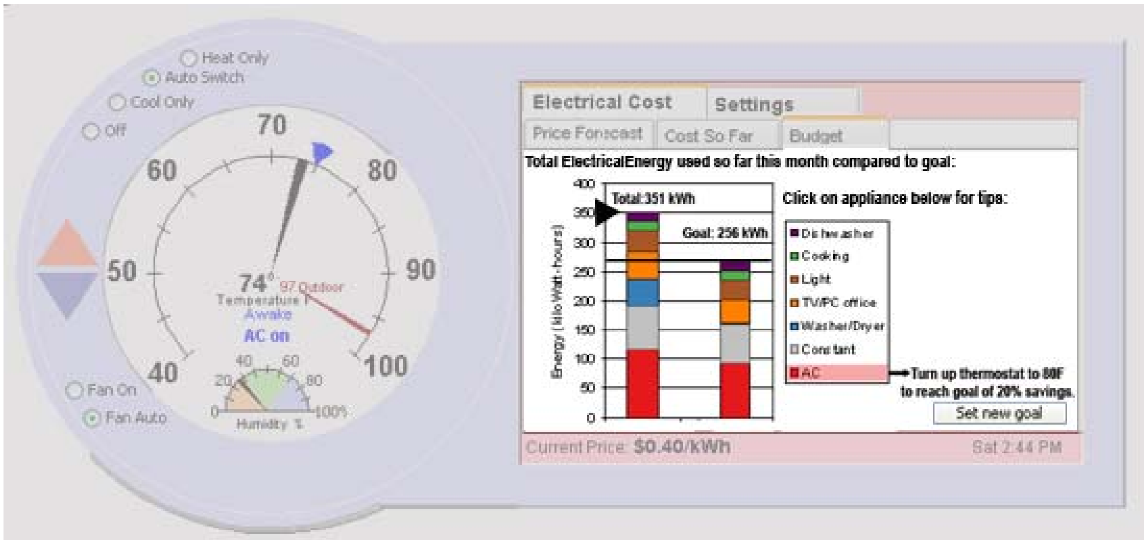

Figure 97: A goal setting and advice tool.

Finally, a colored display that showed the actual price of electricity (Figure 98) was also found useful (mean of 3.49).

Figure 98: Colored display showing the actual current price of electricity.

The following figure summarizes the subjects' feedback on the six graphic displays.

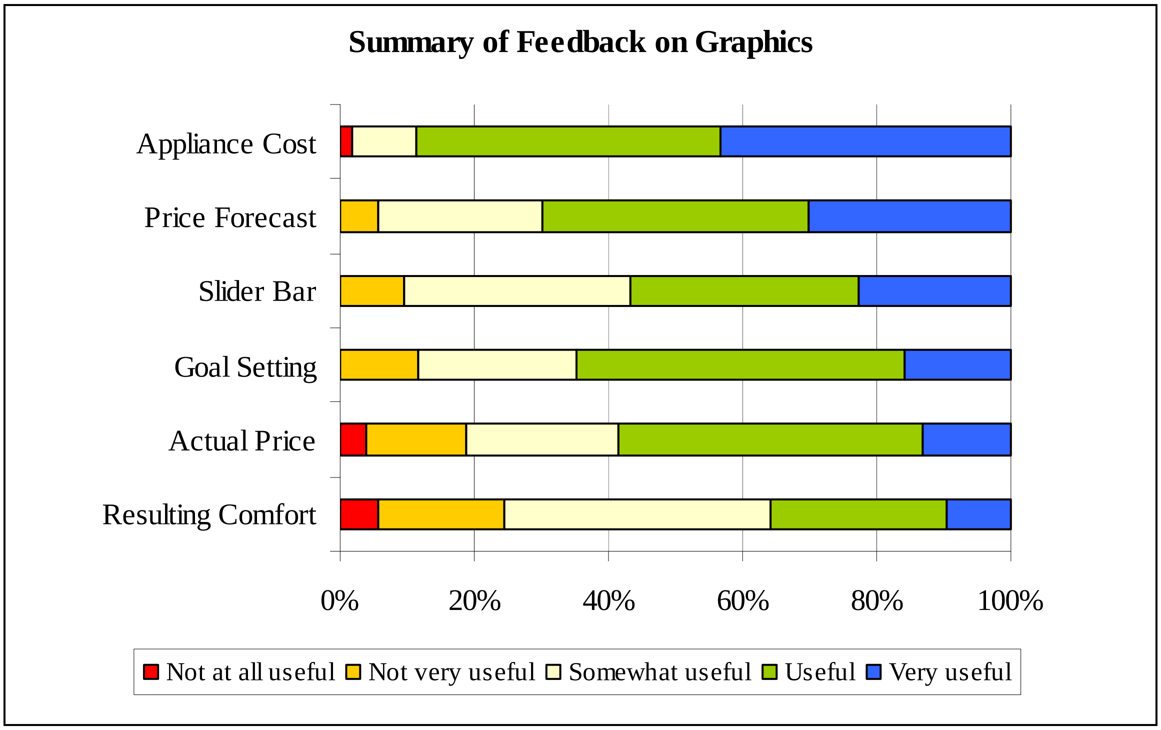

Figure 99: Summary of usefulness of graphic feedback.

A follow-up question (question 36) on setting goals found that 94% found energy information useful, 45% found carbon emissions reduction as a result of using less electricity would be useful, and 38% found energy consumption compared to one's neighbor's consumption would be useful for setting goals.

With respect to energy use feedback (question 37), most of the subjects (92%) felt verbal feedback on cost implications would be useful, such as "Save 30% or about $33 this month." A little more than half (58%) found the same verbiage but with energy savings was useful. Less than half (40%) found the following feedback on carbon dioxide emissions useful, "Prevent 62 pounds of CO_2 emissions, or the equivalent of about 15 trees absorbing this amount." However, these numbers do not tell the whole story. While a quarter selected only cost information, nearly a third wanted to see both energy and cost information, and another quarter wanted to see all three types of information.

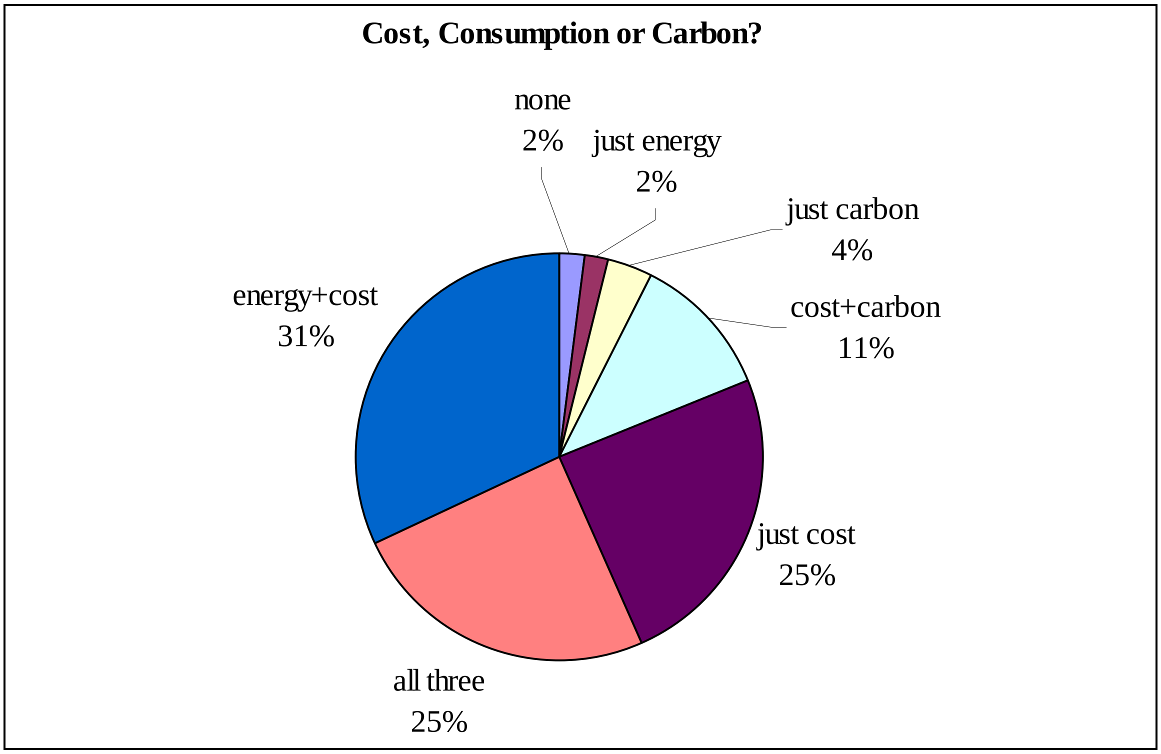

Figure 100: Desired feedback: cost, energy consumption, or carbon emissions averted.

Regarding other energy savings tips (question 38), using smart plugstrips[65] was found the most useful, followed by replacing incandescent light bulbs with compact fluorescent bulbs, not using power dry on the dishwasher, washing clothes in cold water, and the lowest rank went to using ceiling fans to increase comfort. This last rank is consistent with the vote on the usefulness of the smiley faces used to indicate comfort: about a quarter of the subjects found feedback on their presumed comfort not useful.

[65] A smart plugstrip is an electrical outlet power strip that turns off power when a device that is plugged into it is turned off. This eliminates standby power consumption, also known as a vampire or phantom load, which is the small electrical power consumed by appliances when they are not in use.

6.4.6 Thermostat use

The last section of the questionnaire addressed thermostat use. The subjects were supposed to be screened before the test; the requirements to participate in this test were that one should pay a separate electrical bill (as opposed to having the utilities as part of the rent) and have some experience with living with air conditioning whether currently or in the past. However, six responded that they had never lived with air conditioning. A third said there was no thermostat in their current dwelling, 23% had a manual thermostat and a third had either a setback thermostat (8%) or a programmable thermostat (26%). A third of the participants responded that the heating system was not used. Only two participants responded to the air conditioning questions, which may be an indication of test fatigue since these questions were very similar to those for heating.

The results from the question regarding schedule (question 50) showed a wide distribution. More than half of the subjects have a fairly regular schedule: a quarter describe their workday as the same day-to-day and week-to-week. However, 28% describe their schedule as different every day. Although the subjects were mostly students and are not representative of the population, this distribution reflects the response of other informal surveys. For half of the subjects, the schedule may be consistent enough to be learned and therefore predicted. But for the other half, their schedule is not conducive to learning in order to alleviate programming or optimize HVAC control strategies.

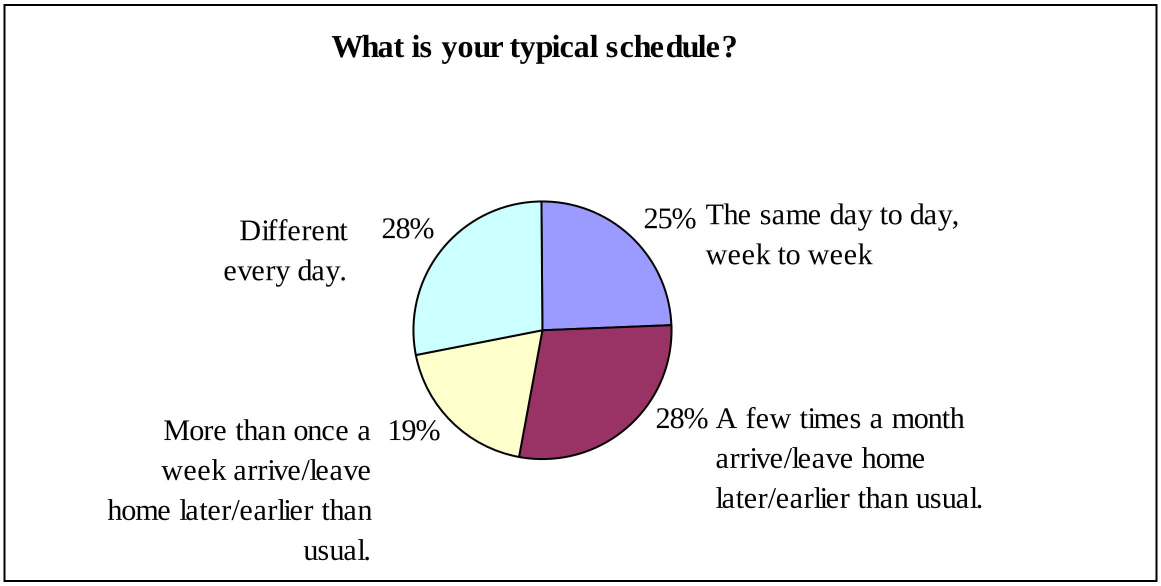

Figure 101: Regularity of schedule.

Several open-ended questions asked what features subjects use or would want on their thermostats. Several mentioned that they don't use the automatic features of the thermostat. A few stated that a timer would be useful to have, and outdoor temperature and radiation information would be useful.

In summary, the Xlab test of the user interface was successful in addressing two different motivators of peak energy reduction and in garnering people's opinions of different types of information, tools, and advice on energy consumption in a dynamic tariff environment. In addition, the results of the simulated Demand Response Electrical Appliance Manager (DREAM) interface indicate that animation and interaction successfully demonstrated the concept of providing information to enable residential demand response.

6.5 Discussion of results

I tested several aspects of the DREAM system. We successfully installed a wireless network of sensors in a house and recorded detailed data. The test to predict or learn temperature preferences of people, given physical metrics, showed mixed results. The survey of people's schedules also indicated that perhaps only half have consistent enough schedules to be conducive to learning. Using the residential adaptive comfort setpoints resulted in energy savings compared to traditional thermostats in an annual simulation and compared to a PCT in a summertime simulation. The Xlab test of the user interface indicated that the context of sponsorship affected behavior, but whether subjects saw price or energy information did not affect their behavior. The Xlab survey of graphics and tools revealed that the subjects preferred detailed appliance-level information and feedback tools for dynamic electricity pricing.

Two of the hypotheses I studied worked somewhat counter to each other. On the one hand, predicting temperature preference and schedule requires and perhaps rewards consistency in people. On the other hand, temperature setpoints that adapt to outdoor conditions celebrate the variety of sensations that come with seasonal changes. In addition, I am intrigued by the possibility of using adaptive setpoints to encourage a wider comfort range, and "wean" people from the constancy of air conditioning and provide a more thermally rich environment. Yet variable setpoints may incur frustration when the thermostat doesn't act as "expected", and would require education. Some automation provides desired convenience; learning the behavior of a particular house and its HVAC system in a particular climate seems promising for improving HVAC control systems, especially for demand response strategies such as precooling. However, I am less convinced of the benefit of learning people's behavior, especially given the connection between personal control and satisfaction. Since comfort is variable from day to day, hour to hour, and person to person, trying to predict comfort for all people may be futile. Perhaps some people may find this function convenient, however, so I will leave it for future field research.

The major question for residential demand response remains: how much personal control do people want rather than automation with respect to responding to a price signal? My guess is that a survey would reveal the spectrum of control, from the "set it and forget it" types to micromanagers, who want detailed information and to maintain full control. Just as in computer software, we might design demand response technology in layers, so that the simplest functions (i.e., setting temperature offset) are the most visible with the more complex functions (i.e., comparing today's energy use with yesterday's) requiring more involvement from the presumably interested and motivated user. Further research in psychographic segmentation may distinguish different people's values regarding control to improve demand responsive technology.

Successful residential demand response will require understanding behavior and influencing behavior change. As a result of the survey and field tests, I categorized three approaches to human behavior with respect to energy consumption and technology design. First of all, I came across existing behaviors that don't support energy conservation but most likely need to be accommodated in technology design, secondly I found behaviors that save energy and should be encouraged and reinforced, and finally, I saw behaviors that one might attempt to change.

Designers of thermostats may consider accommodating certain behaviors such as varying schedules and windows left open while the air conditioner is running. Some people may forget that a window is open, and through sensors, could be reminded or at least informed about the cost consequences. For some, the need for fresh air may take precedence over the energy wasted. This behavior could be accommodated by air-to-air exchangers to bring in fresh air instead of open windows. Schedules that vary from day to day might be accommodated by occupancy sensors or timers. A combination of motion, sound, and/or carbon dioxide sensors, or a signal from a home security system could provide occupancy information that could to control the house HVAC system. An off-timer would provide the ability to turn off the HVAC system momentarily while one leaves on a quick errand.

Energy saving behaviors that we might reinforce include opening windows appropriately for passive cooling (or heating), drawing or opening shades to block unwanted heat, and modifying the HVAC system when one is away or asleep, such as a setback or setup of temperature with the thermostat. The field test suggested that providing outdoor temperature information helps. Learning the house behavior offers the potential for providing advice to the consumer, and perhaps more importantly for supplying feedback to the consumer on the energy saved or wasted through these different behaviors.

Effecting behavior change is difficult; overcoming inertia will continue to present a major challenge to demand response. To encourage decreased use of appliances during peak times means creating behavior change—through education, marketing, feedback, and probably incentives as well. I have mentioned several possibilities. For example, increasing tolerance for warmer indoor temperature on hot days through dynamic setpoints that adapt to outdoor conditions might help. What about remembering to set the temperature up when one is away during a summer's day? Occupancy sensors might help here, and/or an intelligent controller that "knows" whether turning off the air conditioning will cause the system to cycle continuously later, thereby diminishing any energy savings or not. In addition, the need for personal control can be reinforced by offering choices and options to the customer. Detailed feedback on energy usage may effectively motivate people as well. I believe many means will be necessary for successful residential demand response, from economic incentives, marketing, feedback, and using social norms to change behavior.

7 Conclusion

In 2004, sociologist Dr. Loren Lutzenhiser, whose research in energy-related behaviors spans over two decades, stated, “We need to know considerably more about consumer behavior and decision-making in an energy system that increasingly depends upon intelligent consumer response—if we want to craft reasonable, fair and effective energy policies for managing that system.” I would add that for residential consumers we need to know more about their thermal comfort in conjunction with the houses and climates they live in to craft the technology to enable that intelligent response. Solving the problem of peak electricity requires the integration of policy, technology, and knowledge of human behavior in the context of the built environment.

7.1 Summary

7.1.1 Objective & achievements

This study tested six hypotheses regarding residential demand response. One suggested that a radio-based communication network of sensors could supply needed information for the control systems and feedback to enable and encourage demand response. The second looked at the potential of learning algorithms to predict a person’s schedule and temperature preferences in order to provide more intelligent control systems. The third postulated that temperature setpoints that adapt to outdoor climate can save energy compared to the traditional static setpoints. The fourth and fifth hypotheses suggested that the type of information displayed, whether price or energy, would not have a significant effect on reduction of peak energy, whereas the perceived sponsorship of that display would. The final hypothesis focused on feedback from potential users on a variety of graphics, tools, and advice that would help different people make better decisions about their electricity usage.

I worked with a team of graduate and undergraduate students and professors to develop and test a wireless network of sensors and actuators and control strategies to evaluate the applicability of a wireless network to enable residential demand response. We used simulation, small-scale laboratory testing, and field tests to evaluate the system we named the DREAM: Demand Response Electrical Appliance Manager.

To determine whether computer learning can adequately predict occupant temperature preferences and schedule, I implemented a quantitative analysis of existing data to determine the predictability of temperature preferences and conducted a survey to understand typical schedules. This study used an available data set of environmental conditions and temperature preferences of several office workers and an available learning applet to determine whether the temperature preferences could be predicted.

To test whether dynamic temperature setpoints would save energy compared to static setpoints, I employed a comparative analysis of data. For this study, I developed an algorithm that produced temperature setpoints based on outdoor temperature following the Adaptive Comfort Standard. I ran annual and summertime simulations of a house in the Sacramento, California climate. The analysis compared the number of hours of heating and cooling for the adaptive method versus a programmable thermostat for annual use and the number of hours of cooling for the adaptive method compared to a programmable communicating thermostat for summertime demand response scenarios.

I developed and tested a user interface with three other graduate students in a course at UC Berkeley and further refined it for testing in the Experimental Social

Science Laboratory (Xlab) at UC Berkeley. The user interface involved a combination thermostat and in-home energy display in order to test the effects of context and information display on behavior as well as to discover what types of information, tools, and advice people would find useful in a dynamic electricity pricing environment.

7.1.2 Contributions of this work

The case study of the wireless network indicates that wireless sensor networks can provide more detailed information than currently available for a low cost. We can use this information to improve control systems, so that a temperature setpoint offset for demand response, such as the 4ºF proposed for the Programmable Communicating Thermostat (PCT), includes the context of the house, its climate and HVAC system, and its occupants. Detailed appliance energy feedback can educate people about their energy use and encourage peak electricity reduction.

Learning people’s schedule and thermal preferences poses a more complex issue. Our wireless network field test and the results of my user interface survey indicate that as much as half the population may have variable schedules that preclude prediction. Learning temperature preferences in order to predict temperature setpoints presents a daunting task as well. The quantitative analysis of existing office worker temperature preferences provided an average of a 69% prediction rate. While the highest prediction rate was 88%, this still may not be acceptable.

Other machine learning seems quite promising, such as learning about a house, its climate, and HVAC system. An information-rich wireless network will be invaluable to learning algorithms (i.e., using sensors to indicate occupancy), providing advice, and providing the detailed appliance-level energy consumption data that seemed quite popular in the survey. In addition, this information could be used to diagnose problems and promote needed maintenance to save energy, such as alerting occupants to low refrigerant charge in the air conditioner.

The simulation results using the adaptive temperature setpoints indicate this strategy can save energy year-round, especially during peak periods in the summer, and still provide thermal comfort. I used a comparative analysis of data between several thermostat setpoint strategies in an annual simulation. Temperature setpoints that changed with outdoor temperature (adaptive setpoints) used 17% fewer hours of heating and 34% fewer hours of cooling compared to the traditional EnergyStar programmable thermostat setpoints. In addition, the adaptive setpoints performed nearly as well as the PCT with respect to peak electricity usage. The adaptive strategy used 60% fewer hours of air conditioning during peak periods than a programmable thermostat while the PCT used 69% fewer hours during a seven-week summer simulation using Sacramento climate data. When I added a temperature offset for price to the adaptive setpoints, the energy usage of the simulated house dropped below that using setpoints from a PCT: 91% fewer hours during peak periods than a programmable thermostat and 70% fewer than a PCT.

Developing and testing the DREAM user interface generated several results. The Xlab simulation testing of 53 subjects yielded no significant difference ($P(T \le t) = 0.83$) in the high-price temperature offset of subjects who saw price and cost information compared to demand and energy usage information. While the current emphasis in developing a dynamic electricity pricing scheme is the influence of price on behavior, the simulation results indicate that providing detailed energy usage information produced a similar behavioral response as did price information. Analysis showed a significant difference (P(T<=t) = 0.047) between the temperature offset of subjects who thought the thermostat was sponsored by an electrical utility versus a nonprofit organization. In general the group that saw an introduction by a nonprofit set the temperature higher for high price periods than those that saw an introduction by a utility (average of 6.48 compared to 4.72). Since the perceived sponsorship of this technology seemed to influence behavior, this indicates the importance of marketing and providing the appropriate context to introduce a technology. In addition, the results indicated the potential of a gender bias: males tended to offset more when they saw the introduction by a nonprofit organization or price information than females. However, analysis for significant difference did not suggest this difference, which may reflect the small sample size of the study.

The survey portion of the Xlab test indicated what types of information, tools, and advice people want with a dynamic electricity tariff. Most of the subjects found detailed information, especially the energy usage broken down by the top-consuming appliances or cost per load, useful or very useful. Most also found a price forecast display useful or very useful. Subjects found goal setting with advice on specific appliances slightly more useful than a slider bar to choose temperature offset during high price periods with feedback on the cost or energy ramifications. Only a quarter of the subjects wanted to see only cost information with respect to savings; nearly a third wanted to see both energy and cost information and a quarter of the subjects wanted to see energy, cost, and carbon emissions averted information.

7.2 Future work

This study introduces many areas for future research, which are outlined below.

Insulate and Recharge: Given that up to half the houses in California with central air conditioning may be poorly insulated, and many have leaky ducts or below optimum refrigerant charge, I suggest that policy-makers resolve to renew efforts to address these areas. Weatherization and commissioning[66], while not new or exciting concepts, would have a profound effect on reducing peak electricity, without the tariff design and enabling technology.

Sensor Streamlining: Information coming from a multi-sensor network is only as good as the sensor installation and granularity of data. Our field testing of the wireless sensor network indicated potential problems with locating sensors and the problem of filtering the data of extraneous “noise”. Reducing the number of sensors needed is key to an “idiot-proof” installation by the average do-it-yourself homeowner. One example is current work at Rensselaer Polytechnic Institute to “learn” the power signatures of different appliances through rapid measurements of the whole house current.

Learning Temperature Preference and Schedule: The results of this study are promising, but given the influence of personal control on comfort, I suggest that the next research step address whether consumers want this type of automation from their thermostat.

Residential Adaptive Comfort Setpoints: I recommend field testing to study the thermal comfort effect of adaptive setpoints, both year-round and especially with respect

[66] Building commissioning describes a process by which the functions of a building, such as heating, cooling, and lighting, are evaluated at various levels from construction design to occupancy to ensure proper operation.

to peak electricity demand. The effect of adapting a thermostat's setpoints based on relative humidity requires field testing in climates where they would have some effect, such as Minnesota's hot humid summers.

Advice on Improving Comfort and/or Energy Efficiency: While a thermostat could certainly provide advice on improving comfort by passive low-cost means (i.e., open windows, draw shades, turn on ceiling fan), the next step is to test this in the field. Are people interested in this advice, would they follow it, and would it be effective? In the same way, an in-home energy display could offer advice to save energy, whether during peak times or not, but field testing would provide answers to the relevance of this function.

Psychographic Segmentation: Understanding the range of energy-related behaviors, whether through attitude-, values-, or lifestyle-studies, could help planners develop policy, technology, or education programs targeted to different segments of the population. Research in this area needs to address how to reach different people and what are appropriate motivators to encourage energy conservation.

The study of what would encourage residents to reduce electricity usage during peak periods has drawn me to areas outside the field of architecture and building science. I have explored the whys of policy and institutions, the hows of technology, control and intelligence, and the mysteries of human behavior with respect to thermal comfort and energy. I hope that these fields continue to interweave and collaborate to design solutions, especially considering potential global and environmental consequences.

I welcome any comments or questions on this dissertation: therese.peffer@gmail.com.

Appendix A: In-home energy display comparison

		Information Displayed													
Name	Mfg	Temp	RH	GHG	$	$/hour	$/kWh	kW	daily kWh	Month to date kWh	daily $	Month to date $	projected bill	compare prev usage	Notes
Kill-a-watt	P3 International				x			x							
PowerCost Monitor	Blue Line Innovations	x				x	x	x							
Power Cost Display System	Energy Control Systems														
The Energy Detective	Energy Inc				x			x	x	x	x	x	x		
Whole House Energy Monitor (EUM2000)	Energy Monitoring Technologies				x			x	x	x	x	x	x		one rate
Cent-a-meter	Whitesands Ltd and Cenergies	x	x	x		x		x							
The Energy Joule*	Consumer Powerline	x			x		x		x						Colored background wrt price.
In-Home Display*	Az-Tech				x		x		x	x	x	x			Lights for on-mid-off peak.
Power Cost Display Monitor	ECSI				x			x							current/voltage displayed, cost projected for month
In-Home Energy Assistant	San Vision Energy Technology					x	x	x	x	x					
EMS-2020*#	USCL					x	x	x	x	x	x	x	x		
EcoMeter*	Ampy Email Metering			x	x			x							gas, water
PowerStat	DCSI				x	x	x				x	x			
Power Player#	Home Automation Europe							x							gas, water. Set goal & see projected info
Customer Interface Display	DENT Instruments								x	x	x	x			
DREAM*#		x	x	x	x		x		x	x	x	x		x	

*bar graph display #color

PowerCost Monitor
(Blue Line)

Power Cost Display
(Energy Control Systems)

The Energy Detective

Whole House Energy
Monitor

Cent-a-meter

EMS-2020

In-Home Energy Assistant

EcoMeter

In-Home Display

The Energy Joule

PowerPlayer

Appendix B: Wireless sensor and actuator development

We[67] developed sensors and actuators for the T-mote Sky wireless motes as well as a repeater mote for deployment in a house for our first field test in 2005. The motes have a microprocessor, small radio, and antenna powered by two AA batteries in series. Several analog/digital pins allow connection to various sensors and actuators. The code to operate the sensors is written in a C-subset language running under TinyOS on the mote itself. The motes communicate with a base mote attached to a laptop computer in a "star" type network. Control software written in Java administers messages from the sensor motes and to the actuator motes. Data from the motes are stored in a database locally on the laptop and sent via the internet to a remote database on a server at UC Berkeley.

Sensors

A generic sensor platform provided universal input jacks for up to four analog/digital sensors. These sensors included air and globe temperatures and an infrared motion sensor, along with an onboard relative humidity sensor. The air temperature sensor includes an RTD (resistance temperature detector) shielded from radiation effects with low-emissivity Mylar; the globe temperature sensor uses an RTD centered in a ping pong ball painted a flat grey to expose the sensor to the effects of radiation from all sides. We can use air and globe temperature and relative humidity to estimate thermal comfort.

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[67] Undergraduate electrical engineering students Po-kai Chen and Reman Child developed the motes and sensor/actuator interfaces, while Yi Yuan developed the server and the communication to the remote database and Vikas Bhargava developed the price indicator mote. Graduate mechanical engineering student Alex Do designed and made the packaging which mechanical engineering undergraduate William Watts developed communication code between the motes and helped develop the generic mote board. Fellow doctoral mechanical engineering students Xue Chen and Jaehwi Jang coordinated the communication between the motes and the controller.

The motion sensor indicates occupancy of rooms in the house. All motes recorded battery voltage since the radio required a minimum voltage to transmit and receive data.

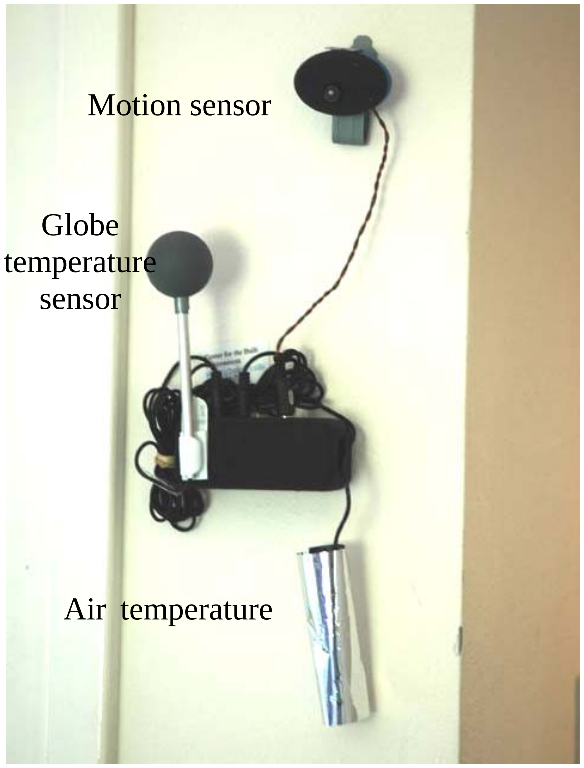


Figure 102: Mote in first field test with motion sensor and temperature sensors.

We obtained power consumption via two types of current sensing motes. One mote used the commercially available Veris transducers to measure current, voltage, and power at the main circuit breaker panel in the house. This sensor can provide power factor information as well. Another mote used current transducers to measure current at individual circuit breakers. This mote could also be used to measure current for single appliances at the outlet level.

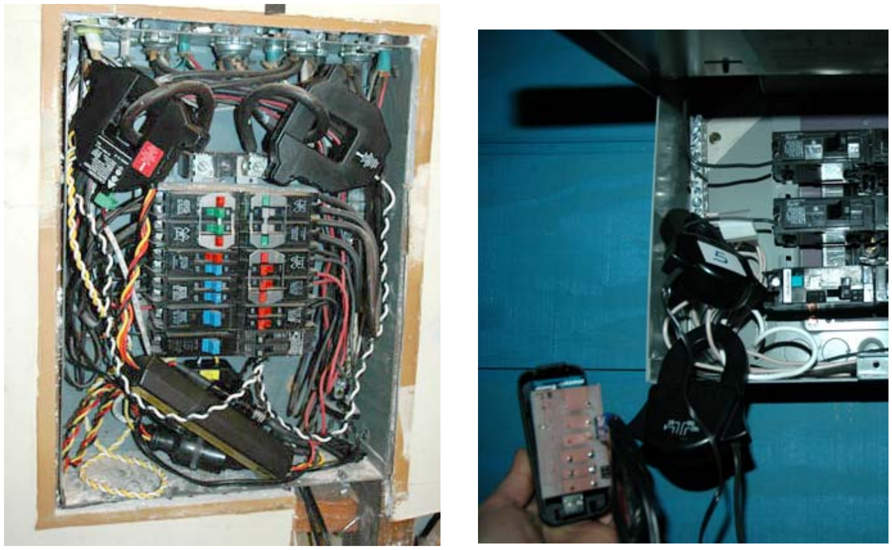


Figure 103: Left: Power sensing at mains level. Right: Current sensing at circuit breaker level.

We collected outdoor weather data and used them to calibrate the energy simulation model for the house. One mote had a relative humidity sensor on the main circuit board and two separate temperature sensors, one exposed to the sky and the other placed under the eave of the roof. Another mote collected solar radiation and wind data from the roof of the house. One pyranometer measured global solar radiation; another was shielded from direct solar radiation and thus measured diffuse radiation. An anemometer measured wind speed and indicated wind direction.

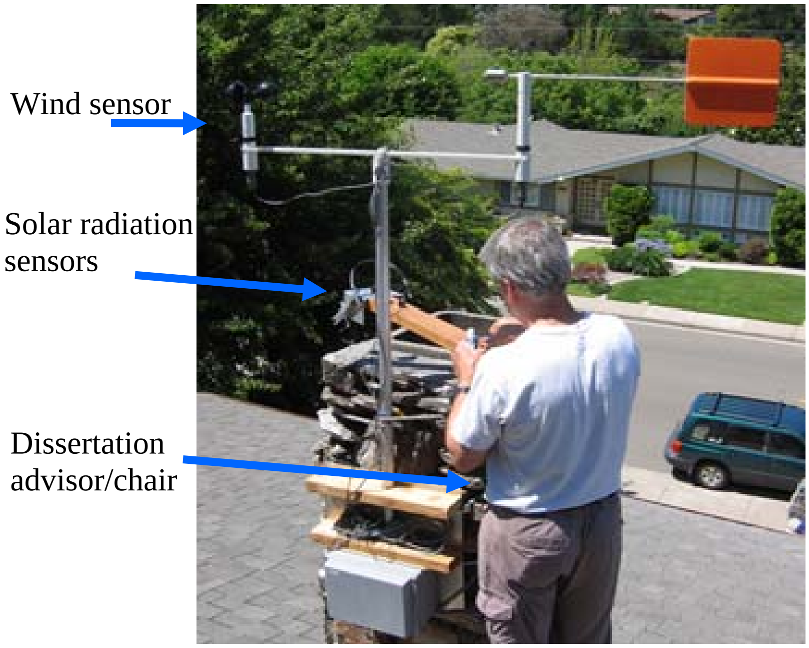


Figure 104: Weather station for first field test.

Since we located the base mote at one end of the house, we added a repeater mote to the network to relay the message from the motes farthest away from the base mote.

For safety purposes, we developed a switch mote to allow the user to switch control between the household thermostat and the wireless HVAC actuator.

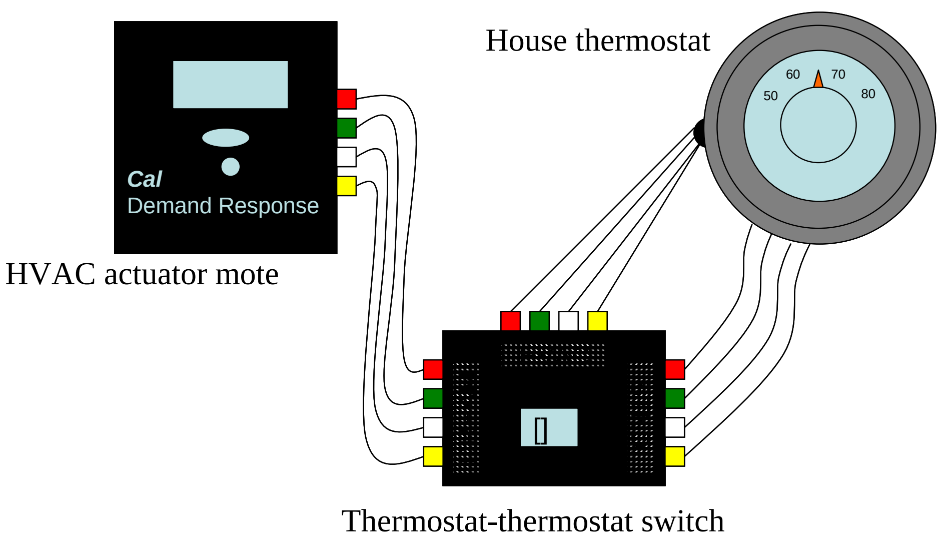


Figure 105: Schematic for thermostat-thermostat switch.

Actuators

In order to replace the thermostat in the house, we developed an HVAC actuator mote. This actuator mote contains three relays: one for the air conditioner compressor, one for the blower fan, and one for the furnace. These relays connect at the point of the existing thermostat and use the existing wiring. Since most people are accustomed to looking at the thermostat to find out temperature, we added an LCD screen and temperature sensor to this device to display current temperature. In addition, the current price level will be indicated by four LEDs: blue for critical price, red for high, yellow for medium, and green for low price.

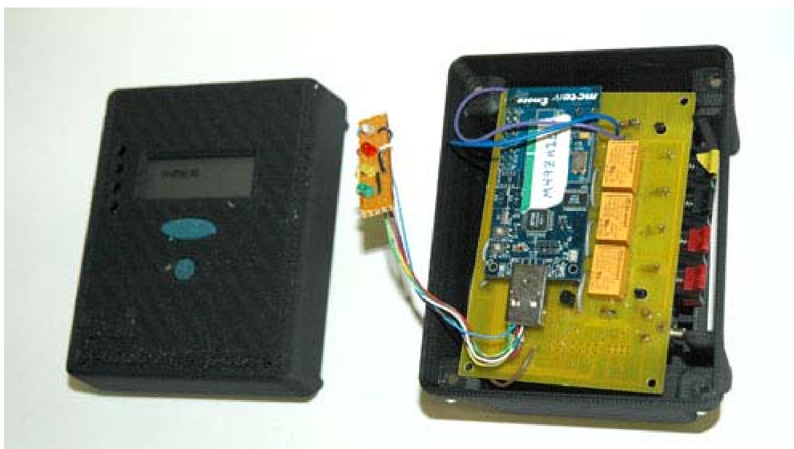


Figure 106: HVAC relay.

We developed a price indicator mote to place on high energy consuming appliances, such as clothes dryers, clothes washers, and dishwashers. This mote receives a price signal from the controller and displays the appropriate color light to indicate the current price. We also added sound to indicate the changes in price. In future models, this mote will have an LCD screen that will display cost information to the customer specific to the appliance in question, using past information from the current sensor mote on the appliance. To save energy, the display only lights up when the motion sensor indicates someone is nearby.

Figure 107: Price indicator with motion sensor.

Appendix C: Demonstration test beds

I designed and built the first plastic house to test and demonstrate a simple control feedback loop. The two bedroom 1 bathroom house had a “cooling” system supplied by a thermoelectric generator with a separate fan in the “attic”. Motes with temperature sensors placed inside the house relayed temperature data to the base station connected to a laptop computer. When the indoor temperature rose above the setpoint, the controller sent a signal to the mote-controlled power supply relay to turn on the cooling unit. In addition, the controller sent price information (low, medium, or high) to the price indicator mote, which lighted the appropriate colored LED (green, yellow, or red, respectively).

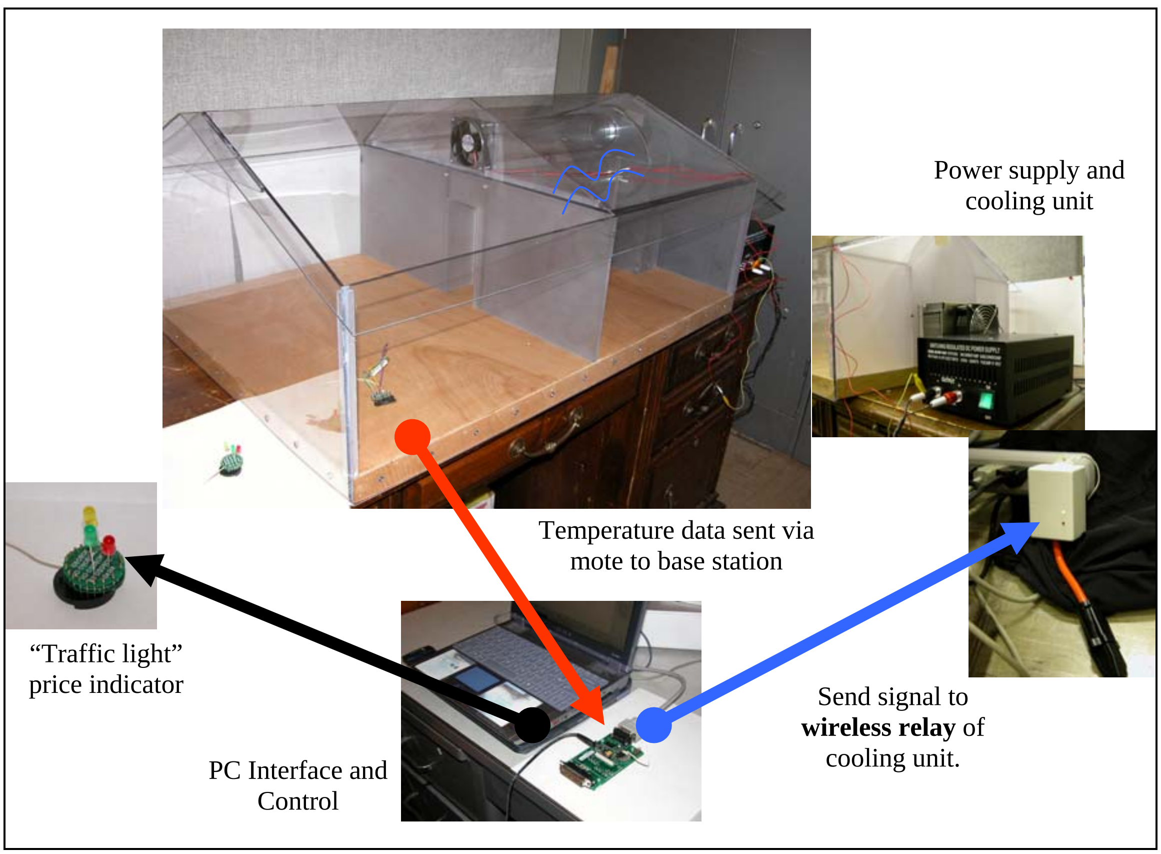


Figure 108: Plastic “dollhouse” test bed.

I designed the Wall, which was built by graduate student Stet Sanborn, to demonstrate functions of the wireless network and controller. An electrician installed the circuit breaker panel, watt-hour meter, and indoor and outdoor electrical outlets. The Wall had a built in wall fan as a proxy for a central air conditioner. While the Wall was designed to travel to demonstrate the functions of the wireless system, its permanent location included proximity to a ceiling fan, refrigerator and lamp. We demonstrated the flexibility of our control system using these appliances.

Figure 109: Left: “The Wall” demonstration test bed. Right: Watt-hour meter and breaker panel shown in mirror.

Appendix D: Developing the internal house thermal model

The control code was written in Java primarily by Jaehwi Jang, with portions written by Xue Chen and Therese Peffer. The code was designed in a modular structure, so it could be used in simulation mode or real-time with actual sensors and actuators. Several simulation modes were available: an internal simulation written as part of the code itself or interfacing with XML to a more robust and validated simulation program we named MZEST (MultiZone Energy Simulation Tool), based on the California Nonresidential Engine.

For the purposes of the Xlab experiment, I developed an internal model to match the internal temperature of an MZEST house model that had been validated.[68] The indoor temperature is determined by calculating the heat transfer from outdoors through conduction through the building envelope (floor, walls, windows, roof) and infiltration, solar radiation through the windows, internal heat gains from people, lights and equipment, and heat/coolth from the HVAC equipment. For each time step, the change in temperature is the net heat transfer divided by the volumetric heat capacity (VHC) of the house. I defined various parameters as defined below and then ran the simulation. I then modified certain parameters, such as the VHC and insulation value, until the output matched the validated MZEST model. These parameters and the equations used are described below. Radiation data was taken from the Solar Shading Analysis program for July in Sacramento (Huizenga, 2003). Outdoor temperature data was from August 5-7

[68] Graduate student Anna LaRue built and developed the simulation model in MZEST based on the dimensions and parameters of a real house. She measured temperature data from the real house, and validated the simulation model with these data.

and relative humidity data was adapted from August 16 from Sacramento TMY2 data (23232.TM2 from (Renewable Resource Data Center, 1990)).

Parameters:

VHC = 4000 BTU/ºF (Volumetric Heat Capacity) 3000 suggested by Charlie Huizenga for a 1200 sf house, modified to match output.[69]

cCond = 450 BTU/h-ºF (heat transfer by conduction through floors, walls, ceiling, and windows, calculated as 367 BTU/h-ºF for an insulated house and 900 BTU/hº-F for an uninsulated house, using typical wood framed construction and following methods found in Chapter 4 of (B. Stein & Reynolds, 1992).

cInf = 78 BTU/h-ºF heat transfer by air infiltration for a house with 0.4 ACH (Air Changes per Hour) in summer (B. Stein & Reynolds, 1992).

cRad = 120 sf of windows for solar radiation (used Uniform Building Code of minimum 10% of floor area for window area).

cInt = 1425 BTU/h for internal heat gains due to people, lights and equipment (B. Stein & Reynolds, 1992).

qHVAC = 24000 for a 2 ton air conditioning unit

Calculation of indoor temperature, updated every minute:

```
qCond = cCond * (outdoorTemp - indoorTemp1);

qInf = cInf * (outdoorTemp - indoorTemp1);

qRad = 0.25*cRad*temperatureSim.getRad(Time.getTimeInHour()); //Windows are
    distributed over four orientations (N-E-S-W), so total radiation is divided by 4

qInt = cInt; //BTU/h

qNet = qCond + qInf + qInt + qRad + qHVAC;

dTemp = qNet / VHC;  //current indoor delta T

indoorTemp1 = indoorTemp1 + dTemp * timeInterval;
```

[69] BTU is British Themal Unit, a unit of energy. BTU/h is BTU per hour, a common measure of heat flow or power.

Appendix E: Internal electrical load model

The first step in developing the electrical end use model was deciding what electrical loads to display. Since the DREAM interface was designed to enable residential demand response, I looked at the top appliances that contribute to peak or coincident load, according to Brown and Koomey, shown in the figure below. Air conditioning is the top contributor, followed by Miscellaneous, Refrigerator, Cooking, Dryer, Pools & Spas, and so on.

Table 3: 1999 California Electricity Consumption and Peak Demand by End Use

Sector & End-Use	Coincident Load		Annual Energy		Load	MWh/	kW/
	GW	% of Total	TWh	% of Total	Factor[b]	kW	MWh
Commercial Sector							
Air Conditioning	7.1	14%	13.8	5%	22%	1.9	0.51
Interior Lighting	5.4	11%	30.3	12%	64%	5.6	0.18
Other	3.1	6%	19.9	8%	73%	6.4	0.16
Ventilation	1.7	3%	9.1	4%	62%	5.5	0.18
Refrigeration	0.9	2%	6.5	3%	87%	7.7	0.13
Office Equipment	0.3	1%	1.6	1%	69%	6.1	0.16
Domestic Hot Water	0.1	0%	0.5	0%	53%	4.6	0.22
Exterior Lighting	0.1	0%	5.0	2%	606%	53.1	0.02
Cooking	0.1	0%	0.6	0%	77%	6.8	0.15
Space Heating	0.0	0%	2.1	1%	-	-	0.00
Total - Commercial	18.7	38%	89.5	36%	55%	4.8	0.21
Residential Sector							
Air Conditioning	7.5	15%	4.8	2%	7%	0.6	1.56
Miscellaneous	3.1	6%	24.6	10%	92%	8.1	0.12
Refrigerator	1.8	4%	13.7	5%	85%	7.5	0.13
Cooking	1.2	2%	3.6	1%	33%	2.9	0.34
Dryer	0.9	2%	5.7	2%	71%	6.2	0.16
Pools & Spas	0.8	2%	4.1	2%	60%	5.3	0.19
Domestic Hot Water	0.6	1%	4.2	2%	86%	7.5	0.13
Television	0.5	1%	3.4	1%	83%	7.3	0.14
Freezer	0.3	1%	2.5	1%	83%	7.3	0.14
Dishwasher	0.3	1%	2.0	1%	71%	6.2	0.16
Waterbed Heater	0.1	0%	2.1	1%	175%	15.3	0.07
Clothes Washer	0.1	0%	0.7	0%	75%	6.6	0.15
Space Heating	0.0	0%	4.0	2%	-	-	0.00
Total - Residential	17.2	35%	75.4	30%	50%	4.4	0.23
Industrial Sector							
Assembly	5.4	11%	33	13%	71%	6.2	0.16
Process	2.0	4%	14	6%	79%	6.9	0.14
Other	0.9	2%	6.1	2%	78%	6.8	0.15
Total - Industrial	8.3	17%	53.5	21%	73%	6.4	0.16
Agricultural Sector							
Total - Agricultural	2.3	5%	17.8	7%	88%	7.7	0.13
Transport & Street Lighting							
Total - Transport & St. Ltg.	2.9	6%	15.3	6%	60%	5.3	0.19
Statewide Total							
Total - Statewide[a]	49.6	100%	251.6	100%	58%	5.1	0.20

Source: CEC Demand Analysis Office (Tian, 2001).

[a] Statewide coincident load is estimated using utility-level coincidence factors from Table 5.

[b] Load Factor is the ratio of average annual load to coincident peak load. The load factors for commercial exterior lighting and residential waterbed heaters are very high because their consumption is mainly off-peak.

Figure 110: Electrical end uses (Brown & Koomey, 2002).

Another consideration was the appliance saturation; for example, Pools & spas and Domestic Hot Water contribute to peak loads (see Figure 110 above), but few houses have them (7-14% and 5% of the population respectively, according to Figure 111 below).

Table 1. Residential end uses in California single-family homes (RASS columns), sorted by their contribution to residential sector electricity use

End Use	UEC [kWh/yr]	Saturation [%]	UEC * Saturation	Percentage of Total (%)	1999 Residential Consumption[a] TWh	1999 Residential Consumption[a] Percentage of Residential Total (%)
Pool Pump	2,671	14	374	8	4.1[d]	5
Freezer	937	24	225	5	2.5	3
Outdoor Lighting	284	67	190	4	n.a.	
Water Heat	3,079	5	154	3	4.2	6
Spa (Electric Heat)	1,719	7	120	2	See Pool Pump	
Furnace Fan	162	68	110	2		
Aux. Elec. Heat	296	28	83	2		
Spa	467	13	61	1	See Pool Pump	
Conv. Electric Heat	1,494	4	60	1		
Dishwasher	84	70	59	1	2.0	3
Well Pump	862	5	43	1		
Evap. Cooling	688	5	34	1	(incl. above)	
Room A/C	227	15	34	1	(incl. above)	
Home Office	148	20	30	1		
Water Bed	840	2	17	0	2.1	3
HP Electric Heat	1,077	1	11	0		
Solar Water Heater	1,708	0	0	0		
Total			4948 kWh	100%	75.4 TWh	

Source: CEC 2004; Brown and Koomey (2003); authors' calculations

(a) Brown and Koomey (2003)
(b) This number is for all refrigeration, not just first refrigerators.
(c) Total for air conditioning, including types other than central air.
(d) Total for pools and spas.
(e) Included in the row for "Ranges/Ovens," for which we use Brown and Koomey (2003) total for the "Cooking" category.

Figure 111: Appliance saturation and energy use (Moezzi & Diamond, 2005, p.30).

I also considered the degree to which the appliances required human intervention, or automation of the device (G. Wood & Newborough, 2007b); that is, how discretionary is the use of the device. For example, while refrigerators and freezers contribute to peak load, these devices tend to cycle on and off automatically. Any energy reduction to be had during peak periods would best be achieved through automatic control. While there is talk of developing demand response timers for appliances, at the present time, dishwashers, clothes washers and dryers are controlled by people in the household, who have some discretion as to when they are used.

A large (and fast growing) contributor to peak electricity is the “miscellaneous” category, typically defined as including lighting, consumer electronics, and fans. The Residential Appliance Saturation Survey report estimates that electrical lighting consists of 60% of the miscellaneous load (CEC, 2004), and thus I separated lighting from miscellaneous energy usage in the display.

Total energy consumed included the refrigerator load (which was modeled as a steady load (as opposed to cycling 20 minutes of the hour)) and standby or phantom loads, such as that from clocks, and battery chargers for telephones, cameras, and other small consumer electronics. These loads were determined by the Unit Energy Consumption (UEC) of total refrigeration (CEC, 2004) and standby energy (U.S. Department of Energy, 2004). Total refrigeration UECs per household was approximately 1462 kilowatt-hours/year and standby energy was 500 kilowatt-hours/year; from these figures, the model included 200 watts per hour as a steady load.

I chose the following appliances to display:

- Air conditioner including the blower fan,
- Clothes washer and dryer combined,
- Cooking (combined range/oven and microwave),
- Dishwasher,
- Television and personal computers,
- Lights, and
- Total energy (including refrigerator and standby loads)

The next step was to develop a 24 hour load profile for each of these devices. The air conditioner and fan use was based on the thermal internal model, assuming a 1992 house with 2 ton unit with a SEER (Seasonal Energy Efficiency Ratio) of 10 (CEC, 2001). A 2 ton air compressor equates to 24,000 BTU/h of cooling, which equals (24,000 BTU/h x 1/3.413 BTU/h/watt =) 7031.94 watts of cooling. The COP (Coefficient of Performance, or the ratio of the change in heat to the supplied work) of an air conditioner with SEER of 10 is 2.64; therefore, the power drawn by this air compressor is (7031.94 watt/2.64 =) 2666.51 watts or approximately 12 amps at 220 volts. A typical blower fan consumes 1.3 horsepower (hp), which equates to 375 watts or approximately 3 amps at 120 volts. The load was considered steady at 3000 watts whenever the air conditioner was on; for the purposes of the simulation, I did not consider the variation in efficiency under different outdoor conditions.

Figure 6: California 1999 Summer Peak-day Residential Building End-use Load (GW). The end uses are ordered the same vertically in the graph and the legend. The miscellaneous end use includes lighting, pools, spas, waterbeds, and small appliances. This figure does not include the Residual ("Other" area) segment from Figure 5. Based on data from Tian (2001).

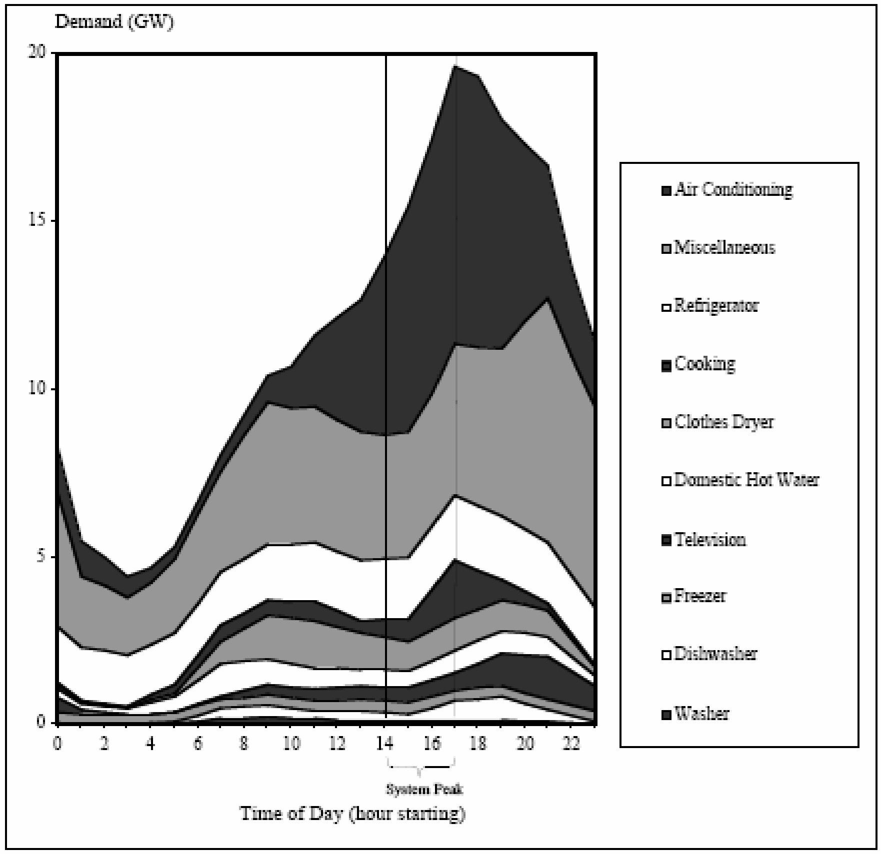


Figure 112: Residential load profile (Brown & Koomey, 2002, p.17).

I combined clothes washing with drying for two reasons: first, to try to eliminate clutter in the display, and because the loads are so dissimilar in power consumption, it is easy to distinguish the two. The loads were difficult to figure out because the UEC provides an estimate for a year, but does not assume that laundry is done every day. The UECs were 127 and 713 kilowatt-hours/year respectively for washing and drying (CEC, 2004). The Buildings Energy Databook (Figure 113 below) listed these as 110 and 1000 kilowatt-hours/year respectively, with 276 watts per cycle listed for a clothes washer (U.S. Department of Energy, 2004). The face plate values listed are 350-500 watts for a clothes washer and 1800-5000 watts for a clothes dryer (Energy Efficiency and Renewable Energy, 2005). The model used 250 watts (assumed 30 minutes of a 500 watt load) for washing at 2 pm, and 3000 watts for drying at 4 pm every day.

Buildings Energy Databook: ***7.2 Typical Appliance Usage*** *August 2004*

7.2.1 Residential Stock Electric Appliance and Building Equipment Usage

	Power Draw (W) (1) Operating	Power Draw (W) (1) Stand-by	Annual Usage (hours/year) Operating	Annual Usage (hours/year) Stand-by	Annual Consumption (kWh/year)	Annual Cost ($) (2)
Kitchen						
Coffee Maker	219	0	421	0	90	7
Dishwasher	(3) 0.332	0	(4) 365	0	120	10
Microwave Oven	1500	3	72	8688	140	11
Refrigerator-Freezer					940	76
Freezer					680	55
Lighting						
18-W Compact Fluorescent	18	0	1189	0	20	2
60-W Incandescent Lamp	60	0	672	0	40	3
100-W Incandescent Lamp	100	0	672	0	70	6
Torchiere Lamp-Halogen	300	0	1460	0	440	36
Bedroom and Bathroom						
Hair Dryer	710	0	50	0	40	3
Waterbed Heater	350	0	3051	0	1070	87
Laundry Room						
Clothes Dryer			(4) 359		1000	81
Clothes Washer	(3) 0.276	0	(4) 392	0	110	9
Home Electronics						
Cable Box	20	12	1456	7304	110	9
Computer (CPU & Monitor)	182/30	0	1337/632	0	260	21
Portable Stereo	7	2	526	5606	20	2
Compact Stereo		12	964	7796	110	9
Rack Stereo	53	12	1664	7096	150	12
Color Television	83	5	2810	5950	(5) 260	21
VCR	14	6	2424	6336	70	6
Heating and Cooling						
Dehumidifier	600	0	1620	0	970	79
Furnace Fan	295	0	1350	0	400	32
Window Fan	30	0	270	0	10	1
Water Heating						
Water Heater-Family of 4	4500	0	(6) 64	N.A.	4770	386
Water Heater-Family of 2	4500	0	(6) 32	N.A.	2340	190
Miscellaneous						
Clock/Radio	2	2	131	8629	20	2
Lawn Mower	1500	0	20	0	30	2
Pool Pump	1000	0	792	0	790	64
Well Pump	725	0	115	0	80	6
Total Standby	0	57	0	8760	500	41

Note(s): 1) Power draw will vary due to appliance components and modes of operation. 2) $0.080/kWh. 3) Excludes water heating. Units are in kWh/cycle. 4) Cycles/year. 5) Energy consumption is not multiplicative for multiple units. Electricity consumption increases approximately 40 kWh per unit. 6) Gallons/day.

Source(s): BTS/A.D. Little, Electricity Consumption by Small End Uses in Residential Buildings, August 1998, Exhibit 6-8, p. 6-10 for coffee maker, cable box, clothes washer, computer, dehumidifier, dishwasher, furnace fan, microwave oven, pool pump, torchiere lamp-halogen, waterbed heater, and well pump; LBNL, Energy Data Sourcebook for the U.S. Residential Sector, LBNL-40297, September 1997, p. 100-102 for clothes dryers, Table 10.2, p. 108 for lighting, and p. 62-67 for water heaters; LBNL, Miscellaneous Electricity Use in the U.S. Residential Sector, LBNL-40295, April 1998, Appendix D, p. D-1-D-9 for hair dryer, window fan, and lawn mower; EIA, Supplement to AEO 2000, Dec. 1999, Table 21 for refrigerator and freezer; BTS/LBNL, Energy Use of Home Audio Products in the U.S., Dec. 1999, Table 4-9, 28 and p. 31-35 for audio electronics; BTS/LBNL, Energy Use of Televisions and Videocassette Recorders in the U.S., Mar. 1999, Tables 3-6 - 3-8, p. 19-22, and Tables 4-6 - 4-8, p. 32-34; GAMA, Consumer's Directory of Certified Efficiency Ratings for Heating and Water Heating Equipment, April 2000 for water heater power draw; and LBNL for total standby.

Figure 113: Table from the Buildings Energy Databook (U.S. Department of Energy, 2004).

The cooking load consisted of the cooktop range/oven plus the microwave. The annual energy use for a typical microwave is estimated to be 140 kilowatt-hours/year (U.S. Department of Energy, 2004) and 301 kilowatt-hours/year for a range/oven (CEC, 2004). Typical faceplate values for microwave are 1000-1500 watts and for range/ovens 1300-2400 watts for burners and 2660 watts for the oven. Since many microwaves and cooktops have clocks, I used 5 watts/hour standby load. The load ranged during the day from 50 to 400 watts per hour for a few hours in the morning and in the evening.

The next load was the dishwasher. The UEC for dishwashers is 84 kilowatt-hours/year, which calculates to 230 watts per day (CEC, 2004). The Buildings Energy Databook lists 333 watts per cycle (U.S. Department of Energy, 2004). Yet another source listed the faceplate values from 1200-2400 watts (Energy Efficiency and Renewable Energy, 2005). A recent study compared the hot water energy used from dishwashers that ranged from 880-2000 watt-hours per cycle; in 1993 dishwashers averaged 2600 watt-hours per cycle, while the average in 2004 was 1800 watt-hours per cycle (Hoak, Parker, & Hermelink, 2008). The researchers assumed that the dishwasher runs approximately 215 cycles per year; each cycle ranges from 50 to 90 minutes (Ibid.). The dishwasher was run once a day at 7 pm, using 900 watts for one hour.

For Television and Personal Computers, I combined the UECs from RASS and then divided per day to achieve a total 2984 watt-hours per day. At night the consumption was 12 watt-hours per hour, assuming a small standby load. During the day, the load ranged from 100 to 300 watt-hours per hour, with most use occurring in the mornings and evenings.

For electrical lighting, I used the estimate from the 1993 RECS at 856 kilowatt-hours/year. In the model, lights consumed 40 watt-hours per hour at night; in the morning and evening, lights consumed from 100-300 watt-hours per hour. During the middle of the day, light consumption was 50 watt-hours per hour.

Assuming that air conditioning would only be used three months of the year and dishwashing, clothes washing and drying occurred every other day, this model would result in electricity consumption of approximately 5800 kilowatt-hours/year. This is just below the average of 5914 kilowatt-hours/year for all Californian households (CEC, 2004).

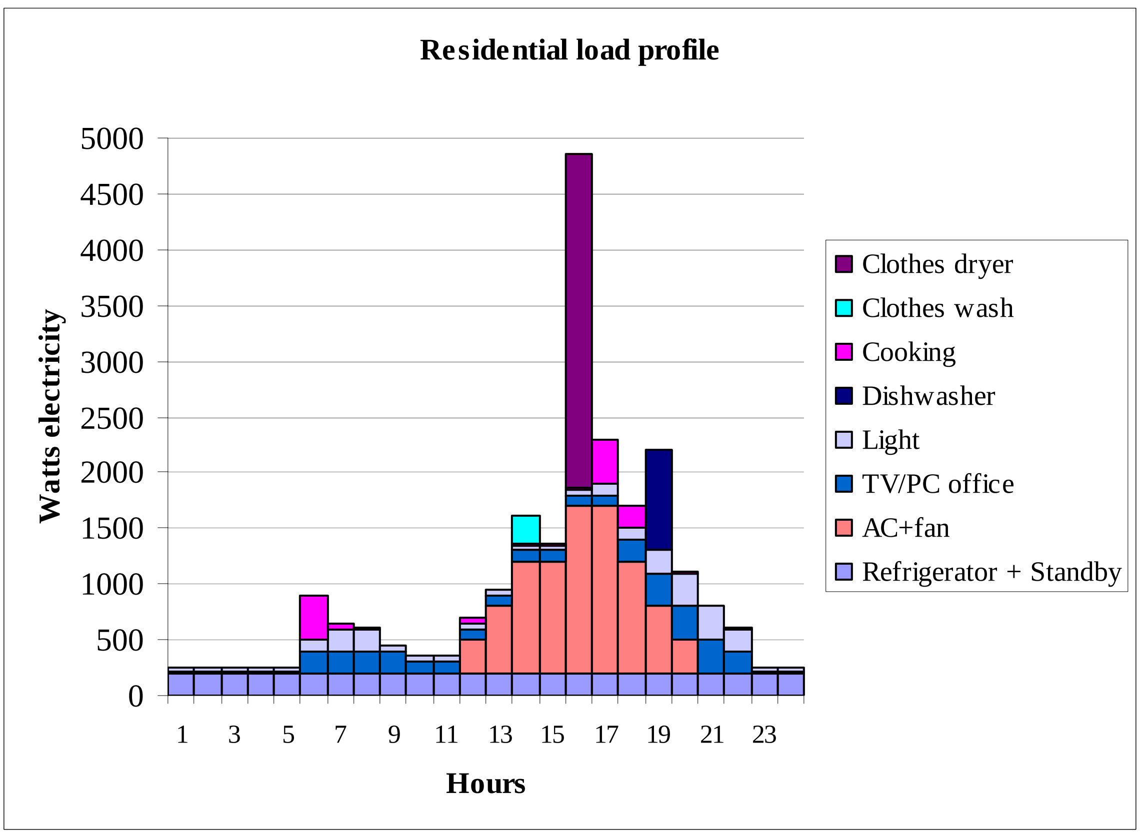


Figure 114: Combined loads for a single day load profile.

Appendix F: Text and results of the Xlab survey

1. What is your age?

#	Answer		Response	%
1	Under 15 years		0	0%
2	15 to 24 years		46	87%
3	25 to 34 years		6	11%
4	35 to 44 years		1	2%
5	45 to 54 years		0	0%
6	55 to 64 years		0	0%
7	65 to 74 years		0	0%
8	75 to 84 years		0	0%
9	85 years and over		0	0%
	Total		53	100%

2. What is your gender?

#	Answer		Response	%
1	Male		17	32%
2	Female		36	68%
3	Decline to state		0	0%
	Total		53	100%

3. People look for or want different goals out of life. Please study this list carefully and then rate each item in terms of how important it is to you in your daily life on the scale indicated.

#	Question	1Extremely Unimportant	2	3	4	5	6	7	8	9Extremely Important	Responses	Mean
1	Sense of belonging	0	0	2	1	4	5	18	15	8	53	7.13
2	Fun and enjoyment in life	0	0	0	0	1	7	12	24	9	53	7.62
3	Warm relationships with others	0	0	0	1	2	5	5	22	18	53	7.87
4	Self-fulfillment	0	0	0	0	1	2	6	21	23	53	8.19
5	Being well respected	0	1	0	0	2	4	9	23	14	53	7.72
6	Excitement	0	1	1	1	6	9	20	11	4	53	6.74
7	A sense of accomplishment	0	0	0	1	1	2	9	21	19	53	7.98
8	Security	0	0	0	1	3	8	14	17	10	53	7.38
9	Self-respect	0	0	1	0	2	3	9	17	21	53	7.91

Statistic	Sense of belonging	Fun and enjoyment in life	Warm relationships with others	Self-fulfillment	Being well respected	Excitement	A sense of accomplishment	Security	Self-respect
Mean	7.13	7.62	7.87	8.19	7.72	6.74	7.98	7.38	7.91
Variance	2.08	0.97	1.46	0.85	1.71	2.04	1.17	1.51	1.63
Standard Deviation	1.44	0.99	1.21	0.92	1.31	1.43	1.08	1.23	1.27
Total Responses	53	53	53	53	53	53	53	53	53

4. Using the following scale, please rate each statement as honestly and candidly as you can.

#	Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Response	Mean
1	I often feel a sense of oneness with the natural world around me.	1	6	20	20	6	53	2.55
2	I think of the natural world as a community to which I belong.	0	3	15	26	9	53	2.23
3	I recognize and appreciate the intelligence of other living organisms.	1	2	8	32	9	52	2.12
4	I often feel disconnected from nature.	8	23	14	8	0	53	3.58
5	When I think of my life, I imagine myself to be part of a larger cyclical process of living.	2	6	11	25	9	53	2.38
6	I often feel a kinship with animals and plants.	0	9	21	17	6	53	2.62
7	I feel as though I belong to the Earth as equally as it belongs to me.	1	7	22	20	3	53	2.68
8	I have a deep understanding of how my actions affect the natural world.	0	5	17	21	10	53	2.32
9	I often feel part of the web of life.	0	6	20	22	5	53	2.51
10	I feel that all inhabitants of Earth, human, and nonhuman, share a common 'life force'.	0	5	21	23	4	53	2.51
11	Like a tree can be part of a forest, I feel embedded within the broader natural world.	1	5	14	27	6	53	2.40
12	When I think of my place on Earth, I consider myself to be a top member of a hierarchy that exists in nature.	2	8	17	24	2	53	2.70
13	I often feel like I am only a small part of the natural world around me, and that I am no more important than the grass on the ground or the birds in the trees.	8	11	9	20	5	53	2.94
14	My personal welfare is independent of the welfare of the natural world.	4	17	18	11	3	53	3.15

Statistic	I often feel a sense of oneness with the natural world around me.	I think of the natural world as a community to which I belong.	I recognize and appreciate the intelligence of other living organisms.	I often feel disconnected from nature.	When I think of my life, I imagine myself to be part of a larger cyclical process of living.	I often feel a kinship with animals and plants.	I feel as though I belong to the Earth as equally as it belongs to me.	I have a deep understanding of how my actions affect the natural world.	I often feel part of the web of life.	I feel that all inhabitants of Earth, human, and non-human, share a common 'life force'.	Like a tree can be part of a forest, I feel embedded within the broader natural world.	When I think of my place on Earth, I consider myself to be a top member of a hierarchy that exists in nature.	I often feel like I am only a small part of the natural world around me, and that I am no more important than the grass on the ground or the birds in the trees.	My personal welfare is independent of the welfare of the natural world.
Mean	2.55	2.23	2.12	3.58	2.38	2.62	2.68	2.32	2.51	2.51	2.40	2.70	2.94	3.15
Variance	0.83	0.64	0.65	0.86	1.05	0.82	0.72	0.80	0.68	0.60	0.78	0.83	1.59	1.05
Std Dev	0.91	0.80	0.81	0.93	1.02	0.90	0.85	0.89	0.82	0.78	0.88	0.91	1.26	1.03
Total Responses	53	53	52	53	53	53	53	53	53	53	53	53	53	53

5. Please indicate the response that best represents your current thinking about your household electricity bill.

#	Question	1	2	3	4	5	Responses	Mean
1	Affordable:Expensive	8	12	15	14	4	53	2.89

Statistic	Affordable:Expensive
Mean	2.89
Variance	1.41
Standard Deviation	1.19
Total Responses	53

6. Please indicate the response that best represents your current thinking about your household electricity use.

#	Answer		Response	%
1	I don’t think much about it; it is what it is.		10	19%
2	It is a hassle/too hard to try to change my electricity consumption.		5	9%
3	I don’t know how to reduce my electricity consumption.		4	8%
4	The potential cost savings is not worth the effort.		1	2%
5	I am already taking measures to reduce my electricity consumption.		32	60%
6	Other (please specify):		1	2%
	Total		53	100%

Other (please specify):
i try a little to reduce it, but don't worry too much

7. Imagine you live in a three bedroom house in Sacramento, California. On a typical hot summer day, the following appliances are all in use. Please rank the appliances in order of what you think is their overall electricity usage over the 24 hour period (most electrical consumption at the top).

#	Answer	1	2	3	4	5	6	7	8	9	10	11	Responses
1	electric lights	6	6	7	11	5	1	3	4	5	3	2	53
2	refrigerator/freezer	17	18	6	4	5	0	1	1	1	0	0	53
3	plasma screen television (3-4 hours)	0	5	7	8	5	9	7	3	2	4	3	53
4	air conditioning	26	11	3	6	0	1	0	0	1	1	4	53
5	computer left on 24/7	2	4	10	5	9	2	7	6	5	3	0	53
6	clothes washer (1 normal load)	0	2	7	3	12	18	6	4	0	1	0	53
7	electric clothes dryer (1 normal load)	1	6	5	7	5	8	14	5	2	0	0	53
8	dishwasher (1 normal load)	1	0	3	2	5	5	7	14	7	9	0	53
9	microwave (10 minutes of use)	0	0	1	2	3	3	5	7	16	11	5	53
10	electric cooktop (45 minutes of use)	0	1	3	3	1	6	3	8	9	17	2	53
11	battery chargers (cell phone, camera, video, etc)	0	0	1	2	3	0	0	1	5	4	37	53
	Total	53	53	53	53	53	53	53	53	53	53	53	

Statistic	electric lights	Refrigerator /freezer	plasma screen television (3-4 hours)	air conditioning	computer left on 24/7	clothes washer (1 normal load)	electric clothes dryer (1 normal load)	dishwasher (1 normal load)	microwave (10 minutes of use)	electric cooktop (45 minutes of use)	battery chargers (cell phone, camera, video, etc)
Mean	4.98	2.57	5.77	2.83	5.45	5.45	5.38	7.30	8.38	7.96	9.92
Variance	8.94	3.40	6.79	9.03	6.56	2.71	4.43	4.71	3.82	5.58	4.65
Standard Deviation	2.99	1.85	2.61	3.00	2.56	1.65	2.11	2.17	1.95	2.36	2.16
Total Responses	53	53	53	53	53	53	53	53	53	53	53

8. Which of the following best expresses your thoughts about energy conservation?

#	Answer		Response	%
1	I don't try to conserve energy.		1	2%
2	I feel that better technology is the best solution to reduce energy use.		7	13%
3	I feel energy conservation is good for the environment.		20	38%
4	I feel it is my duty as a socially conscious person to conserve energy.		23	43%
5	My friends/neighbors conserve energy, so I do too.		1	2%
6	Other (please specify):		1	2%
	Total		53	100%

Other (please specify):
I try to conserve energy because it costs a lot of money.

Statistic	
Mean	3.36
Variance	0.77
Standard Deviation	0.88
Total Responses	53

9. Which action do you think has a greater positive impact on the environment:

#	Answer		Response	%
1	Turning off lights, television, stereo and computer when not in use.		41	77%
2	During hot summer days, running electric clothes dryer in the morning or evening.		5	9%
3	There is no difference.		1	2%
4	I don't know.		6	11%
	Total		53	100%

Half of the participants saw introduction 10-1, the other saw 10-2:

10-1. After the electricity crisis of 2000-2001 in California, the electric utility Sacramento Gas & Electric looked for ways to reduce peak electrical load as an alternative to building new power plants. Part of a recent report states, "For only 1% of the year, Californians need the additional electrical energy equivalent to that produced by eight power plants—at a time when there is less energy in neighboring states to import." Rather than start up existing older power plants that are expensive to run and more polluting than newer ones, one solution is to persuade residential customers to reduce their electrical consumption during peak periods.

Since the primary load during periods of high demand is air conditioning, one potential solution is to develop programmable communicating thermostats that can receive demand and emergency signals from the utility. SG&E sponsored research in this new area of development.

10-2. After the electricity crisis of 2000-2001 in California, the non-profit think tank Energy Watch began an investigation into the problem and explored potential solutions. One excerpt of their recent report states "The problem is not how much electrical energy Californians need, but when they use it. On hot summer afternoons, air conditioners in homes and offices create an enormous additional load. For only 1% of the year, Californians need the additional electrical energy equivalent to that produced by eight power plants—at a time when there is less energy in neighboring states to import. This is like having your own plane to make that one trip to grandma's every year—it represents expensive infrastructure for very little use. If we could reduce energy use during peak times, we could forestall building new power plants."

Since the primary load during periods of high demand is air conditioning, one potential solution is to develop programmable communicating thermostats that can receive demand and emergency signals from the utility. Energy Watch promoted research to develop a programmable communicating thermostat that receives messages from the electrical utilities to inform the occupant when demand is high.

Half of the participants saw description 11A, the other half saw 11B:

11A. One potential solution is to pass the higher cost of peak electricity to customers. This is similar to paying a higher price for talking on the telephone during the day versus evenings and weekends. The high price would discourage residential customers from using electricity during peak periods, such as hot summer afternoons. However, unlike the rates for telephone, the electricity rates would change day to day along with demand.

The proposed programmable communicating thermostat would receive price and emergency signals from the utility. This device also displays the current price of electricity and, with some additional simple sensors, the cost to run various appliances. The occupant can see the total accumulated cost of energy and which appliance costs the most during high periods.

11B. One potential solution is to inform customers when the demand is high, and ask them to reduce their electrical use during these peak periods, such as hot summer afternoons.

The proposed programmable communicating thermostat would receive demand and emergency signals from the utility. This device would display the current overall electricity demand. This device also displays how much electricity the customer is using, and with some additional simple sensors, the electrical energy used by various appliances. The occupant can see how much total accumulated energy they are using and which appliance uses the most during high demand periods.

The participants who saw introduction 10-1 saw this text:

12-1. Imagine that you live in a house in Sacramento, and it is now August. The days are hot and dry, with cool nights. Sacramento Gas & Electric has asked you to participate in a study that involves a new type of thermostat display that (they hope) will reduce electricity consumption during times of peak demand. You are at home looking at this new (and perhaps crude) display. You will see an accelerated simulation of the display that covers three days.

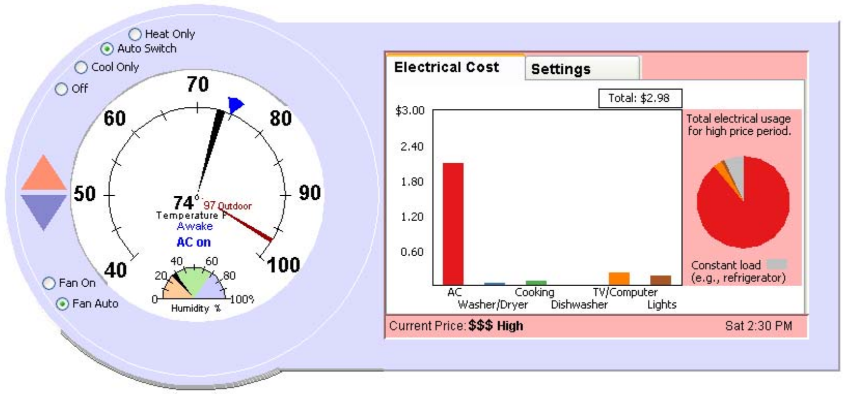
For the purposes of this experiment, please watch the simulation and feel free to explore the tabs, but please do not make any changes to the settings (you will be asked to do that in the next step). You will see the outdoor temperature and indoor temperature change as night fades into day and back into night again. The clock in the lower right part of the display will help you keep track of the time. You may watch the simulation as many times as you want.

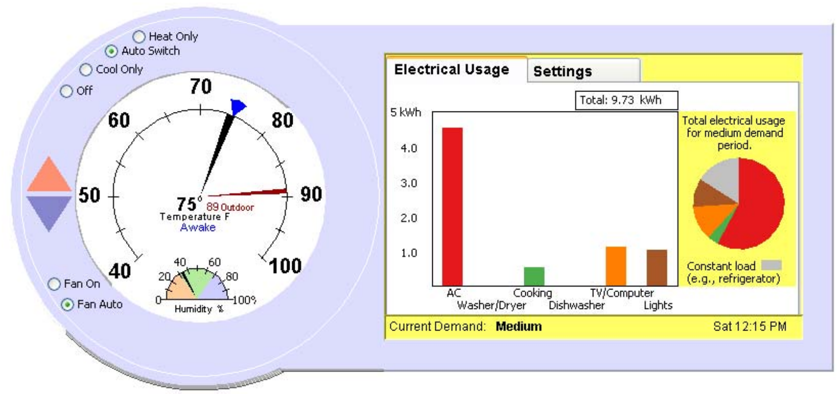
The participants who saw introduction 10-2 saw this text:

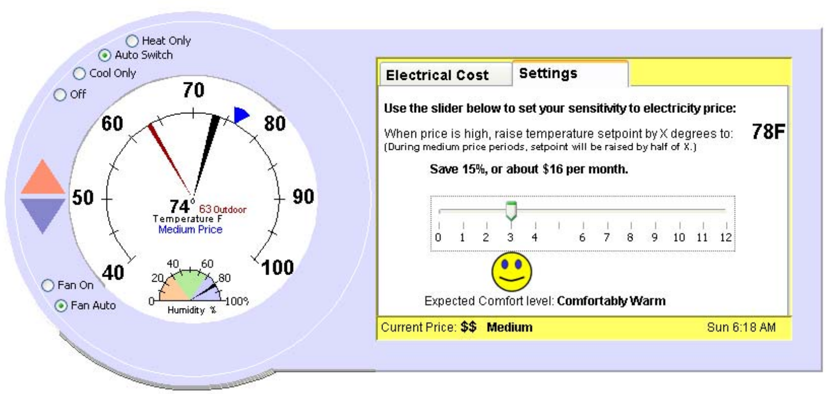
12-2. Imagine that you live in a house in Sacramento, and it is now August. The days are hot and dry, with cool nights. Energy Watch has asked you to participate in a study that involves a new type of thermostat display that (they hope) will reduce electricity consumption during times of peak demand. You are at home looking at this new (and perhaps crude) display. You will see an accelerated simulation of the display that covers three days.

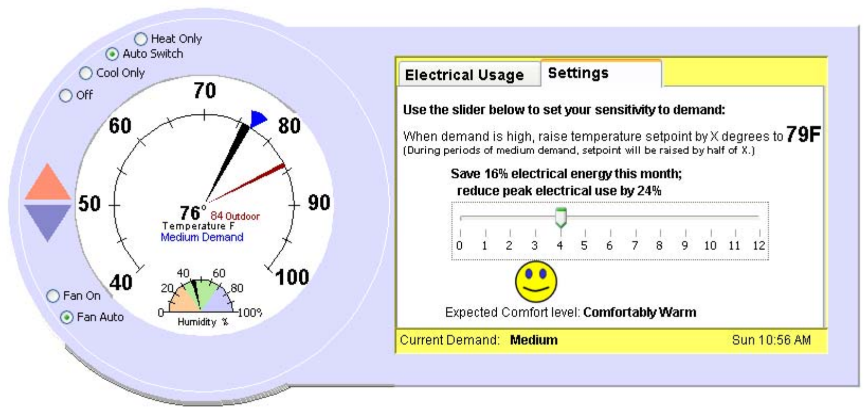
For the purposes of this experiment, please watch the simulation and feel free to explore the tabs, but please do not make any changes to the settings (you will be asked to do that in the next step). You will see the outdoor temperature and indoor temperature change as night fades into day and back into night again. The clock in the lower right part of the display will help you keep track of the time. You may watch the simulation as many times as you want.

The participants that saw 11A saw a simulation with price information and those that saw 11B saw a simulation with energy information. Below are "snapshots" of the changing simulations. The two on the left show price and cost of usage information and the two on the right show demand and energy usage information.









13. On the desktop of this computer, there is a shortcut icon entitled "launch" that looks like the icon below.
Please click on this icon on the desktop to start the simulation. It will take a few minutes to load. The simulation itself should take a few minutes.
When you are done, you may close the window. You may view the simulation again if you wish. After you are done, please return to the survey.

14. Now that you have seen the simulation in action, we would like you to make a change to the settings. On the right part of the thermostat interface, you will see a tab called Settings. Click on this and you will see a slider bar. You may use this slider bar to change the temperature at which the air conditioner turns on. Keeping in mind your theoretical comfort level, you are free to change this setpoint or not, and then watch the results of this change. When you are done, please close the simulation and return to the survey.

18. What are your initial impressions of the interface that you just saw (i.e., likes/dislikes, aesthetics, ability to read temperature or energy information, etc)?

Text Response
I dislike its length, it was aesthetically sound though. I was certainly able to read the information.
Pretty simple to understand, although it would be nice to have the ability to see at the end of the day the total amount of energy used per appliance.
fairly like it.
AC consumed too much energy.
It gives a good general idea on energy consumption based on the uses of common household appliances. However it may not be completely accurate because everyone has a different pattern of life. some people may not use one appliance as much as others, and some people like myself will not use the air conditioner and instead use fans to reduce energy consumption during the summer.
It's a bit confusing
I was a little confused with how the setting works as well as the temperature displayed on the right. I was also a bit confused with the dollar usage, it that what I would use or it is the avg. of what others used around that time period.
It's quite confusing. I have no idea what to do with it. But I can still obtain temperature and energy information from it.
I think it looks pretty cool and informative.
somewhat confusing. however, it is a good representation of energy use
I liked it. I think it provides a clear understanding of energy consumption in an average consumer household.
I found it a bit confusing and hard to read the outdoor temperature, electrical usage, and time initially. I think the graphs and the temperature gauge can also be improved in terms of aesthetics.
First view was confusing - it took me a while to figure out that the black line was indoor temperature and the red line was outdoor temperature. I understood the charts and usage slider right away. Once I figured everything out I found it easy to use, although I would have liked a chart of indoor & outdoor temperature over time. /
Hard to understand. It's easy to see that certain appliances take up more energy, but it's difficult to translate what that means. It would

be better if a digitized sum was indicated on each appliance, such as how many kwatts were accumulated over the course of the day. The bars don't tell me much, besides saying which appliance is CURRENTLY in high usage. I'd like to see what is consuming more overall. I also don't like how it doesn't indicate the cost of energy each appliance is consuming.
I liked the analog meter that showed the changes in temperature between the inside environment and the outside environment. I also liked knowing which appliances use up how much energy.
I liked that it showed indoor and outdoor temp on a dial, also the bar and circle graph were good visuals. The changing color for low/medium/high price was also a good reminder/indicator of how much it costs to run everything. overall I think it was really good
a bit confusing. the look is slightly displeasing because of its simplicity. setting part was good since you can tell how much energy you can save depending on what temperature you set the AC. the demand part was also useful. interface could use some improvement.
It's nice to have both a bar graph as well as pie graph to show the electrical uses of different appliances. The temperature interface is also easy to read, but I wish it was digital rather than analog.
There was definitely a lot going on, which might stress out a user. It would be helpful if you included more tabs so that the user could choose which information he or she wished to see.
I was confused at first about which line on the thermostat represented.
The temperature is somewhat difficult to keep a constant eye on, while also looking on the bar chart of the cost/use of electronics on the right. The use of a circular chart for the temperature is a little confusing, and I still am not sure exactly how it works. Overall, the information on the right is easier to read than the information on the left.
I like the ability to see where the energy goes to. I want to know how much energy is spent on what appliances. It allows me to control the usage. The functionality is a bit complicated. Not sure how to read it.
There seems to be too many information all being displayed at once, which makes it hard to read at times. But it is definitely useful to have charts showing the comparison of different usages of energy consumption.
I understand the display and it was okay to read. The thermostat was a little more difficult to read.
the graph doesn't seem to have the axis labeled? took a long time to figure out that the y-axis seemed to be cumulative use, not use at that point in time. a lot to take in at first. Also the blue arrow wasn't labeled either, is that supposed to be the thermostat setting? Things on the interface could be better labeled. Was there a clock on it somewhere? I couldn't see one, it made it hard to figure out what time of day it was. Why did the blue arrow move at night to 80 degrees? That was weird. This interface was initially somewhat confusing. Strengths were that it was colorful and not too cluttered, even though there was a lot of information on it. Could

differential the indoor and outdoor temperature arrows better.
I think it is not so easy to watch the information on the interface. I hope to see how much percentage has been increased in different time of using.
It's pretty clear and easy to use, but I would prefer if the slider was displayed within the same tab for easier access. I found the pie chart particularly useful.
There was one piece of information that was conspicuously missing, and that was the real units of electricity being consumed at any point in time (kilowatts or whatever). If that information were included, rather than relying on price alone (which is kw * some unknown and variable price per kw), then consumers could see what there electricity usage was in real-time and reduce consumption of kw for conservation's sake, as well as dollars. I think specific suggestions should also be communicated via the thermostat, like Why not dry your clothes on a clothesline instead of the electric dryer? (It's hot and dry out there, and free!) or, Try opening your windows now, as the air temperature outside is lower than inside. Information about phantom loads could be communicated as well.
Initially confusing to read but after about a minute it's pretty clear. I like it a lot! I also like the little pictures used for changing comfort-level in the turn-on temperature settings panel. I would very much appreciate having this system in place. Some people might prefer different layouts so maybe it's best to have a couple that can be switched between.
Pretty sophisticated simulation, user-friendly, good aesthetics.
I liked the interface. I enjoyed seeing the prices adjust with each time change. Also, I liked the ease with which I understood the energy consumption and use. I would have maybe liked an explanation of the different buttons on the left.
The information seemed a bit compacted and difficult to read and required that one pay close attention to the information given to fully understand its meaning.
It was kind of hard to keep track of everything at once (the proportion of usage, the current temperature, and the time, etc.). The thermostat was also a bit hard to interpret.
I think the interface is simple and easy to use and understand. However, it is not very appealing.
It can clearly show the drastic difference between usage of TV/computer, light versus AC. It helps me to realize AC is the most energy consuming appliance.
The interface was confusing. I couldn't quite figure out the effects of different decisions, i.e. turning the fan on or off, etc. The phrasing of the settings tab was also ambiguous.
The electrical usage of air conditioner is dramatically high. / Light usage in the morning, this is unnecessary. / the constant load is

pretty high too.
It is a little difficult to comprehend at first. I don't really know what the round meter and the various colored indicator means. / / I don't dislike it, but it is not the most user-friendly
Visuals like bright colors, graph, temperature points were helpful for me to understand the situation more clearly. But, it was a bit tedious just staring at the graph/$ change as time progresses. /
I liked how it showed how much energy was coming from each area of use while using a pie graph. It was very visual and easy to see how much air conditioning costs. / The only way such an interface would be acceptable is if it had an over-ride turn off switch so that it if did get extremely hot and I didn't care about money then I could have refreshing cold air.
I wasn't sure why the bar chart would be so low yet overall usage on the pie chart would be great i.e. for lights. Easy to change 'settings' and adjust as necessary.
It was very interesting and I liked it because it was easy to follow. After a while it was just the same trend over again but it got the message across.
The smiley face part was cute. It's nice to some kind of friendly feedback. I understood the slider part, but didn't quite see it's relation to the data under the energy usage tab. / / I liked the themostat that gave the reading for the outside and inside at the same time. I thought that would be useful, b/c if it's 95+ degrees outside maybe 85 degrees inside isn't so bad
The interface was easy to read and relatively user-friendly. I liked the bar graph at the right showing the electrical usage of various household appliances, as well as the indoor/outdoor temperature display. I enjoyed being able to read all of these data in sped-up time, however I'm not sure if it would be as appealing in real time.
There is a lot going on. I don't really understand what the pie graph shows; is it the relative usage of all the electrical products at any given moment? I think it makes more sense to see the bar graph of energy accumulate over only one day rather than three.
I think it was interesting to watch. The pie chart was particularly helpful to be able to see what proportion of energy consumption was related to which appliance/feature. It took me a while to figure out the setup (ie. when the air conditioning turned on, what the different colors represented, and how the pie chart was changing over time). I liked that it was easy to figure out, the colors were bold and easy to distinguish, and there were multiple pieces of information that I could piece together to get a better sense of what was going on.
We need to save energy
It was relatively easy to read and follow. I didn't realize that AC was such an electrical demand and used up that much power in

comparison to other household appliances.
If turns the AC on when the outside temperature is above 80F and turns it off at other times, it reduces the total KWh from 150 to 120 for the examining period, which is desirable in term of energy savings.
My initial impression is that I am intrigued by the cost of things during certain temperatures. However, I did find it difficult to focus my attention because things were always moving. I didnt know where I should really direct it. For example, there was the constant temperature changing, the costs increasing, the days/times changing and the costs. It was a bit difficult to keep track of what was affecting what.
At first i had a hard time figuring out how the prices worked for each appliance. However, after a new minutes I was able to see how time of day affected the price of electricity and how peak hours cause high prices and high usage. I liked the display, however, a digital read of the rice for each appliance rather than a bar graph would have been more helpful and possibly more convincing to reducing usage.
feel surprised to see how AC costs $$ and energy

Statistic	
Total Responses	52

19. How concerned are you about the environment?

#	Answer		Response	%
5	Not at all concerned		0	0%
4	Not very concerned		0	0%
3	Somewhat concerned		26	49%
2	Very concerned		19	36%
1	Extremely concerned		8	15%
	Total		53	100%

Statistic	
Mean	2.34
Variance	0.54
Standard Deviation	0.73
Total Responses	53

20. How concerned are you about energy?

#	Answer		Response	%
x5	Not at all concerned		0	0%
x4	Not very concerned		3	6%
x3	Somewhat concerned		22	43%
x2	Very concerned		21	41%
x1	Extremely concerned		5	10%
	Total		51	100%

21. Which of the following best represents your concern about energy?

#	Answer		Response	%
1	Concerned about the rising costs of energy		16	32%
2	Concerned about the dependence on foreign oil sources		5	10%
3	Concerned about the effect of production/consumption of energy on the environment		21	42%
4	Concerned about having enough energy, i.e., concerned about electrical “brownouts” or "blackouts"		5	10%
5	Other (please specify):		3	6%
	Total		50	100%

Other (please specify):
all of the above
all of the above

Concerned about how much it costs, especially with respect to foreign sources. Concerned about another energy crisis.

22. Please indicate the response that best represents your current thinking about your household electricity bill.

#	Question	1	2	3	4	5	Responses	Mean
1	Affordable:Expensive	9	12	11	18	2	52	2.85

Statistic	Affordable:Expensive
Mean	2.85
Variance	1.43
Standard Deviation	1.19
Total Responses	52

23. Please indicate the response that best represents your current thinking about your household electricity use.

#	Answer		Response	%
1	I don't think much about it; it is what it is.		7	13%
2	It is a hassle/too hard to try to change my electricity consumption.		7	13%
3	I don't know how to reduce my electricity consumption.		3	6%
4	The potential cost savings is not worth the effort.		1	2%
5	I am already taking measures to reduce my electricity consumption.		35	66%
6	Other (please specify):		0	0%
	Total		53	100%

24. Imagine you live in a three bedroom house in Sacramento, California. On a typical hot summer day, the following appliances are all in use. Please rank the appliances in order of what you think is their overall electricity usage over the 24 hour period (most electrical consumption at the top).

#	Answer	1	2	3	4	5	6	7	8	9	10	11	Responses
1	electric lights	3	11	10	6	8	0	3	2	4	3	3	53
2	refrigerator/freezer	4	21	7	8	6	2	2	2	1	0	0	53
3	plasma screen television (3-4 hours)	0	6	9	9	3	5	9	6	3	2	1	53
4	air conditioning	46	1	0	3	0	0	0	1	1	0	1	53
5	computer left on 24/7	0	3	5	11	13	4	2	3	8	4	0	53
6	clothes washer (1 normal load)	0	2	11	4	12	15	5	2	2	0	0	53
7	electric clothes dryer (1 normal load)	0	8	7	4	3	13	14	3	1	0	0	53
8	dishwasher (1 normal load)	0	0	2	4	2	6	8	24	2	4	1	53
9	microwave (10 minutes of use)	0	1	0	2	0	4	4	4	20	16	2	53
10	electric cooktop (45 minutes of use)	0	0	1	1	3	4	5	6	10	21	2	53
11	battery chargers (cell phone, camera, video, etc)	0	0	1	1	3	0	1	0	1	3	43	53
	Total	53	53	53	53	53	53	53	53	53	53	53	

Statistic	electric lights	refrigerator / freezer	plasma screen television (3-4 hours)	air conditioning	computer left on 24/7	clothes washer (1 normal load)	electric clothes dryer (1 normal load)	dishwasher (1 normal load)	microwave (10 minutes of use)	electric cooktop (45 minutes of use)	battery chargers (cell phone, camera, video, etc)
Mean	4.81	3.40	5.45	1.66	5.74	5.13	5.23	7.26	8.60	8.51	10.21
Variance	9.00	3.78	6.10	4.19	5.70	2.89	4.10	3.12	3.28	3.60	4.05
Standard Deviation	3.00	1.94	2.47	2.05	2.39	1.70	2.03	1.77	1.81	1.90	2.01
Total Responses	53	53	53	53	53	53	53	53	53	53	53

25. Which of the following best expresses your thoughts about energy conservation?

#	Answer		Response	%
1	I don’t try to conserve energy.		0	0%
2	I feel that better technology is the best solution to reduce energy use.		10	19%
3	I feel energy conservation is good for the environment.		18	34%
4	I feel it is my duty as a socially conscious person to conserve energy.		25	47%
5	My friends/neighbors conserve energy, so I do too.		0	0%
6	Other (please specify):		0	0%
	Total		53	100%

26. Which action do you think has a greater positive impact on the environment:

#	Answer		Response	%
1	Turning off lights, television, stereo and computer when not in use.		33	62%
2	During hot summer days, running electric clothes dryer in the morning or evening.		15	28%
3	There is no difference.		2	4%
4	I don’t know.		3	6%
	Total		53	100%

27. If the electrical utility were to charge a variable rate, how would you want to be notified (check all that apply)?

#	Answer		Response	%
1	Email		41	77%
2	Website		27	51%
3	Telephone call		8	15%
4	Text message		11	21%
5	Pager		0	0%
6	Through thermostat or other dedicated device		31	58%
7	I don’t know		2	4%
8	Other (please specify):		7	13%

Other (please specify):
tv/radio
Mail
Through mail
TV commerical and Newspaper
it could be a downloadable icon that sat in the corner of your computer's dock, start bar, or browser window, and displayed the price in a color that corresponded to the price level (red=high demand/expensive)
Snail Mail
regular mail

28. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following information?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
1	Total household energy consumption	0	1	9	19	24	53	4.25
2	Energy consumption from the top consuming appliances	0	2	5	14	32	53	4.43
3	Current price of electricity	0	2	3	22	26	53	4.36
4	Total cost of energy so far in billing period	0	1	10	17	24	52	4.23
5	Advice/tips to conserve energy	0	1	9	20	23	53	4.23
6	Approximate price per load (i.e., for dishwasher, clothes washer)	0	2	9	13	29	53	4.30
7	Other (please specify):	0	0	3	2	3	8	4.00

Other (please specify):
Daily consumption of energy
Peak usage times and days
programs to take away inefficient devices and give the consumer a rebate to buy a more energy efficient device
What the variable rate was dependent on - when it is least expensive to do things and when it is most expensive to do things. If the rate differs per appliance or duration.
Common number for charging appliance, light, tv...etc

Statistic	Total household energy consumption	Energy consumption from the top consuming appliances	Current price of electricity	Total cost of energy so far in billing period	Advice/tips to conserve energy	Approximate price per load (i.e., for dishwasher, clothes washer)	Other (please specify):
Mean	4.25	4.43	4.36	4.23	4.23	4.30	4.00
Variance	0.65	0.67	0.58	0.69	0.64	0.79	4.75
Standard Deviation	0.81	0.82	0.76	0.83	0.80	0.89	3.12
Total Responses	53	53	53	52	53	53	9

29. What time scale(s) would you like to see for the above (check all that apply)?

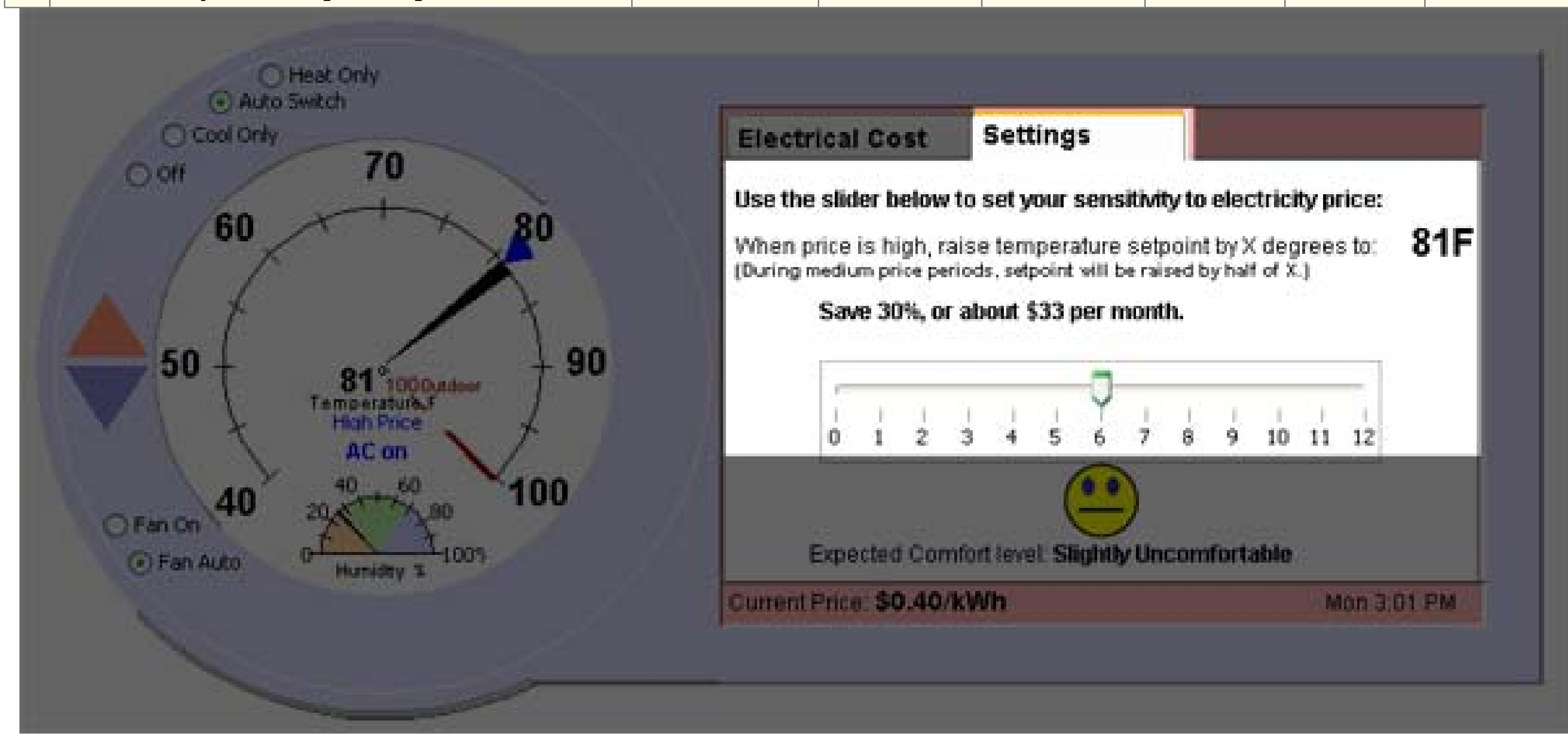
#	Answer		Response	%
1	Real-time/current data		40	75%
2	Current day		35	66%
3	Current week		22	42%
4	Current month		27	51%
5	Compare to last week		32	60%
6	Compare to this month last year		26	49%
7	Other (please specify):		2	4%

Other (please specify):
line graph depicting energy usage over the course of the calendar year
Compared to neighbors

Statistic	
Total Responses	53

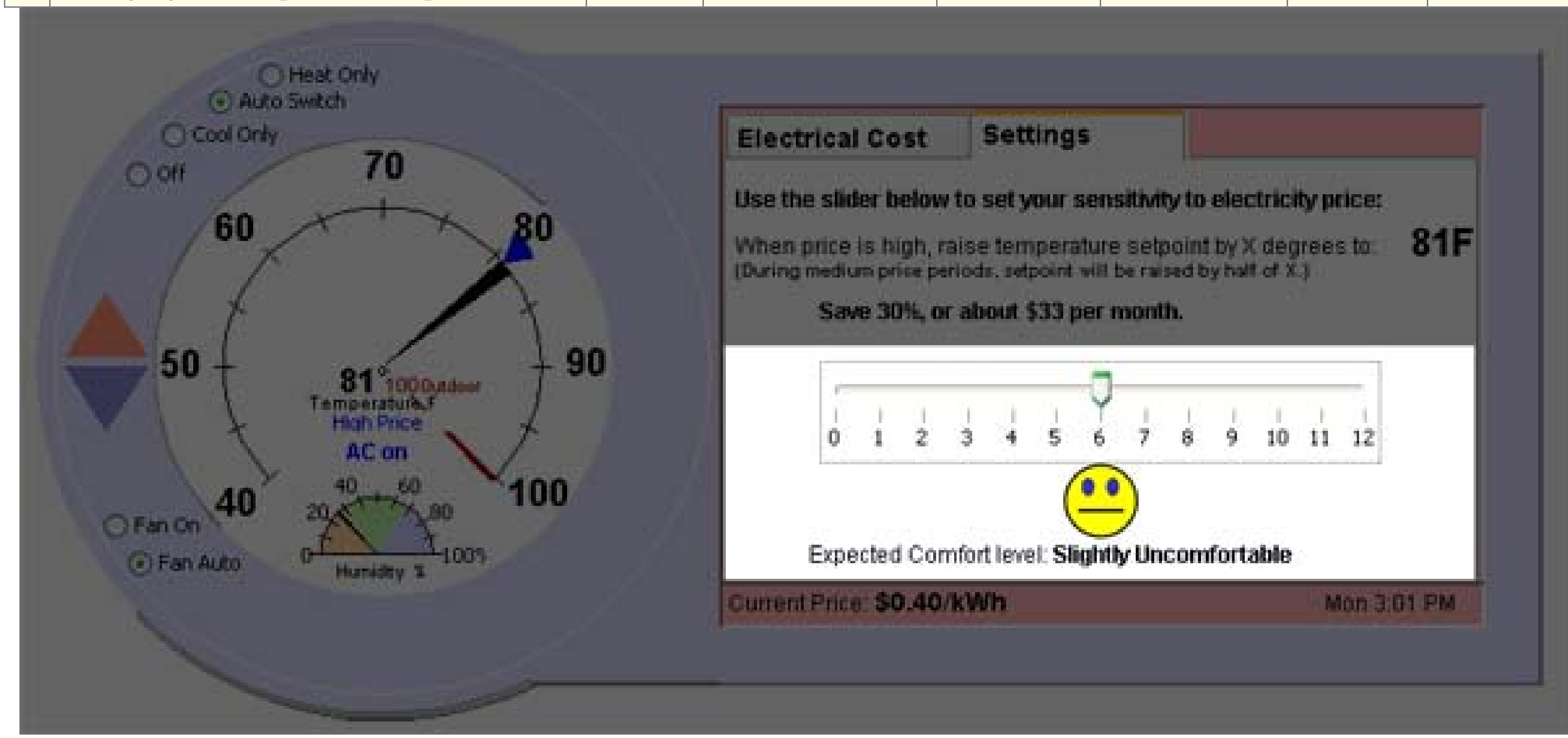
30. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following graphs/tools in helping you make decisions about energy use?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
1	Slider tool that allows user to select degree of reactivity with respect to price.	0	5	18	18	12	53	3.70



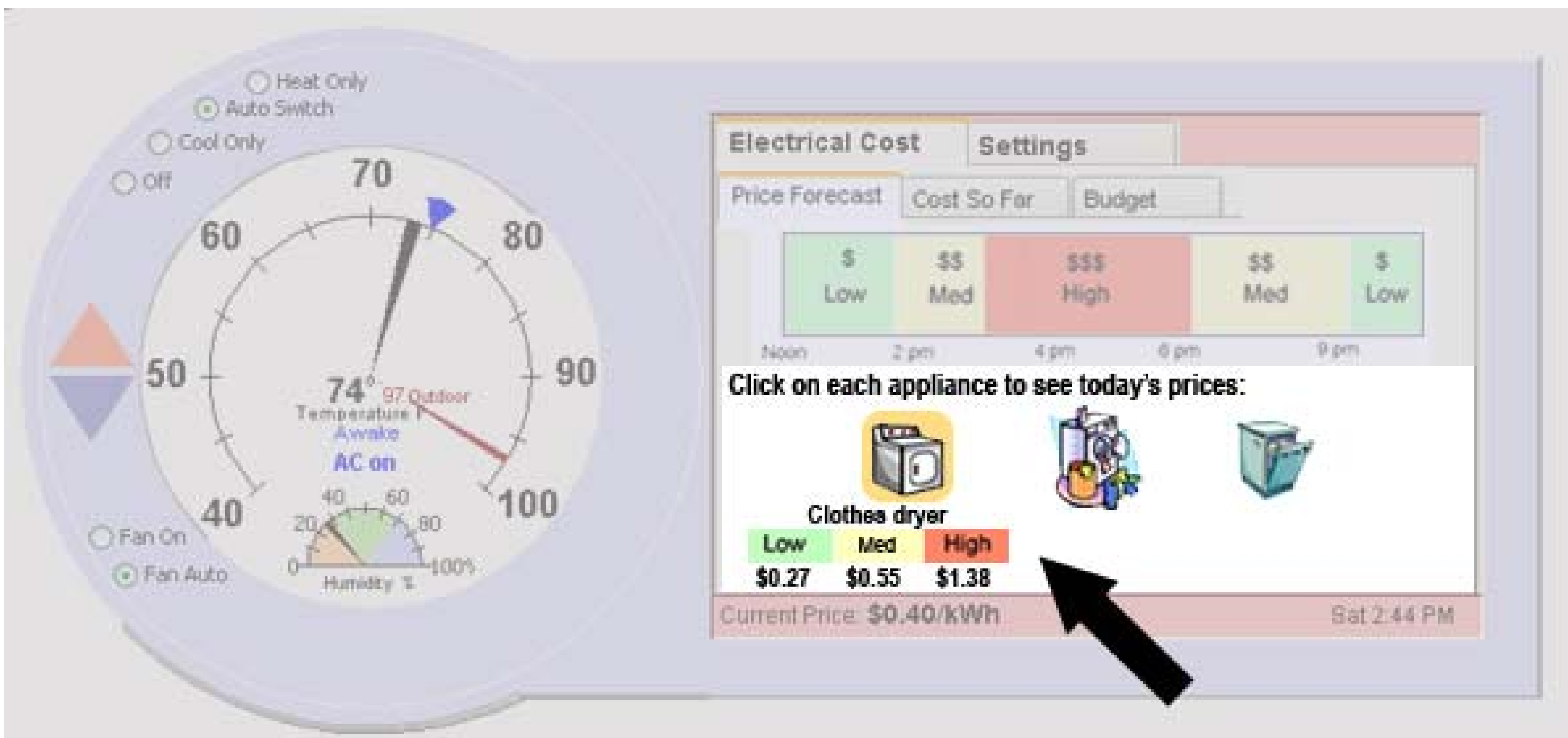
31. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following graphs/tools in helping you make decisions about energy use?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
1	The expected comfort as a result of changing the temperature setpoint.	3	10	21	14	5	53	3.15



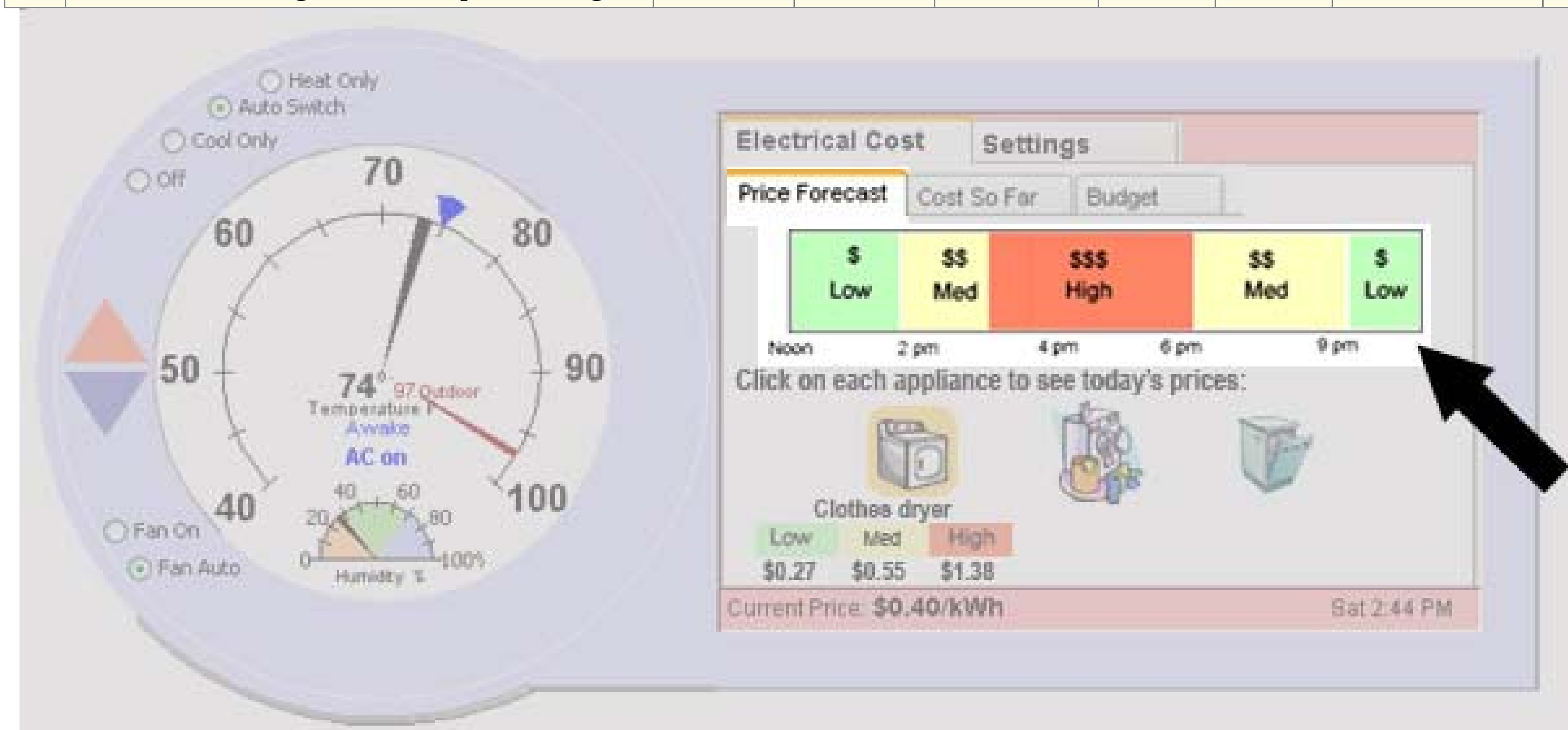
32. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following graphs/tools in helping you make decisions about energy use?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
11	Iconographic display showing how much certain appliances will cost at different times/prices.	1	0	5	24	23	53	4.28



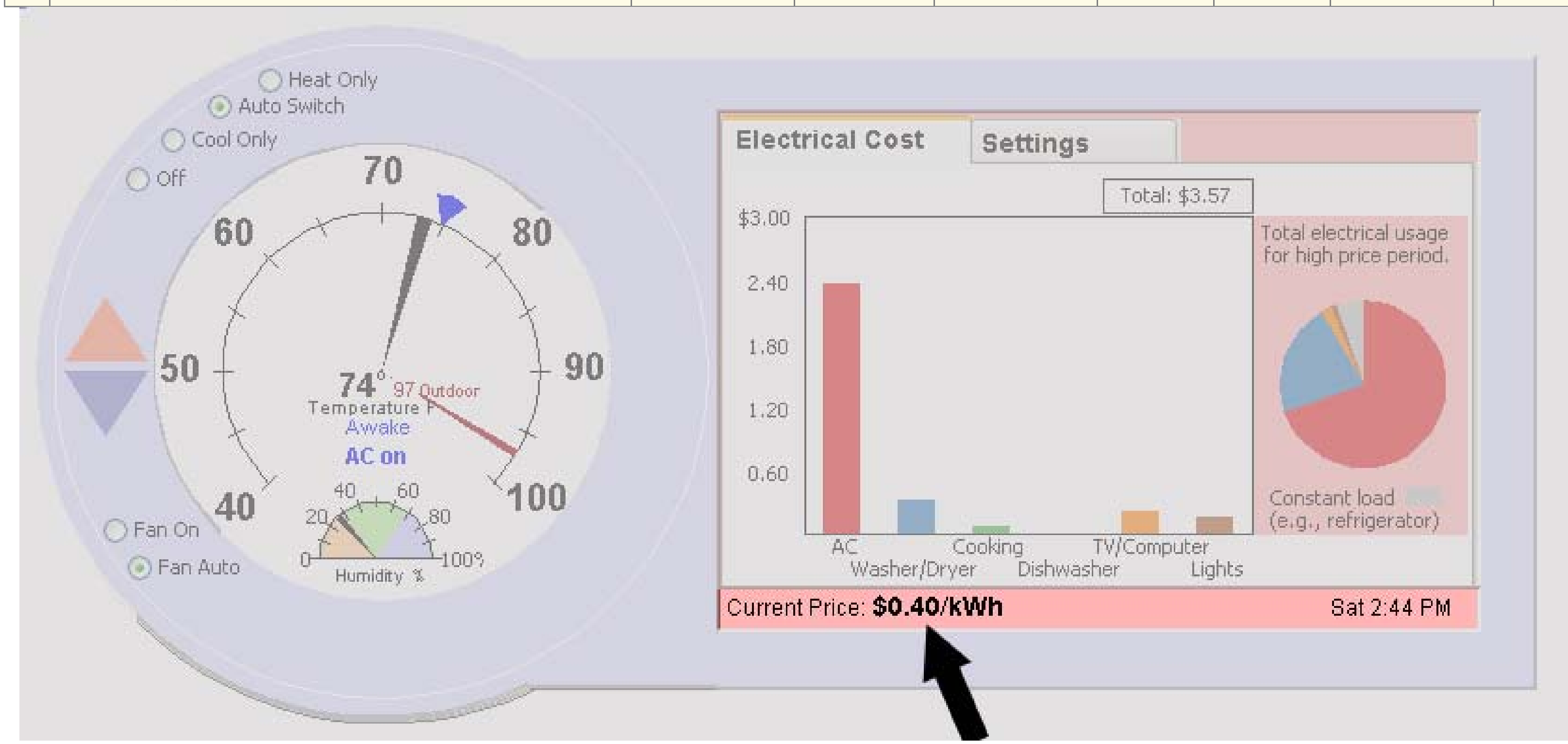
33. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following graphs/tools in helping you make decisions about energy use?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
12	Bar chart showing the time of price changes.	0	3	13	21	16	53	3.94



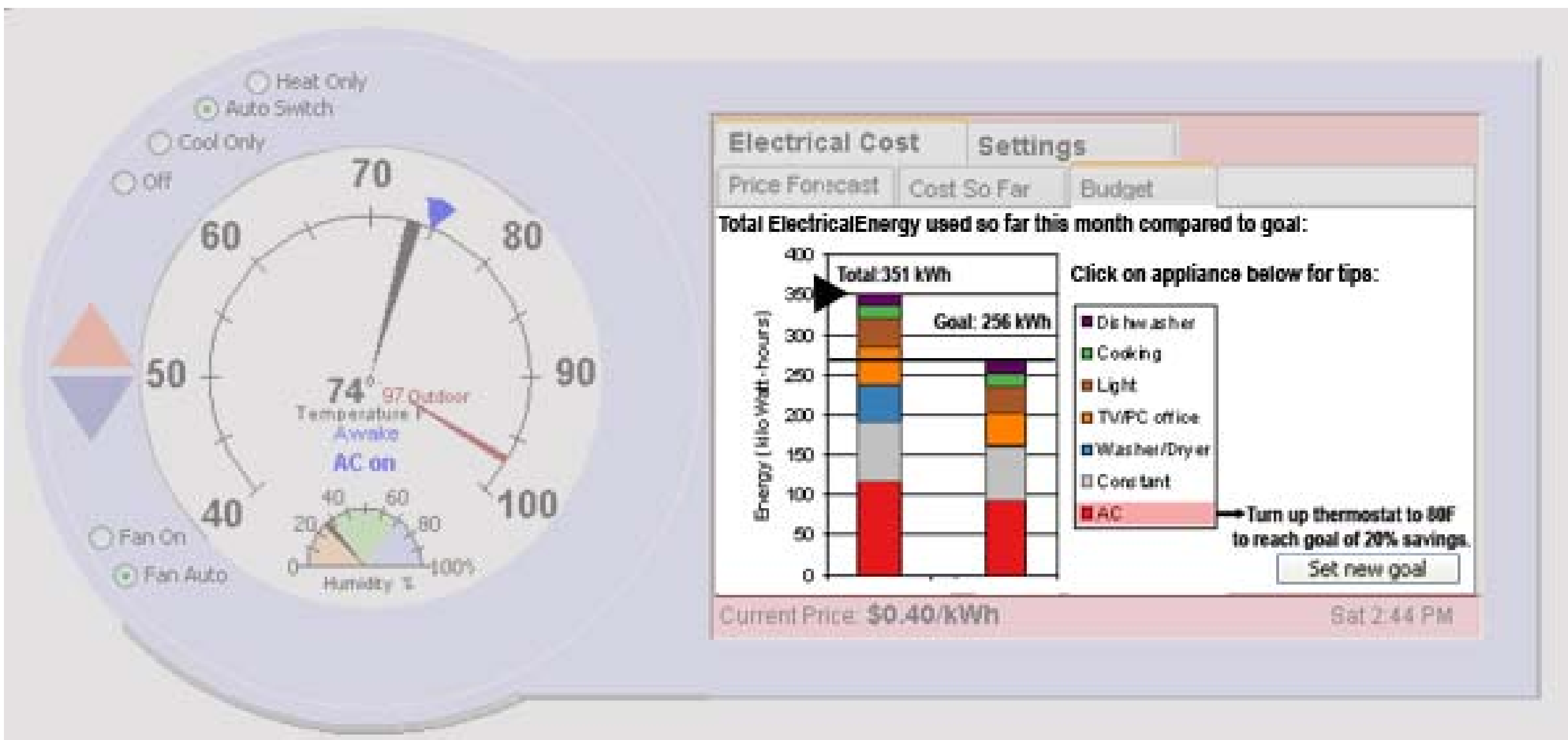
34. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following graphs/tools in helping you make decisions about energy use?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
1	Colored display showing the actual price of electricity (in cents per kiloWatt-hour).	2	8	12	24	7	53	3.49



35. Assuming the electrical utility charged a variable rate for electricity, how useful would you find the following graphs/tools in helping you make decisions about energy use?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
10	Set a monthly goal for energy consumption and see how current use compares to that goal.	0	6	12	25	8	51	3.69



36. Which of the following would you find useful with respect to setting a goal (check all that apply)?

#	Answer		Response	%
1	Energy consumption information.		50	94%
2	Water consumption information.		35	66%
3	Natural gas consumption information.		30	57%
4	Energy consumption compared to neighbors.		20	38%
5	Carbon emissions reduction as a result of using less energy.		24	45%
6	None of these/Goal setting not useful.		1	2%
7	Other (please specify):		0	0%

Statistic	
Total Responses	53

37. Please select which of the following would be useful with respect to helping you make decisions about energy use when you change the thermostat setting (check all that apply).

#	Answer		Response	%
1	Feedback on energy increase/savings: i.e., "Save 24% total electrical energy this month and reduce peak use by 36%."		31	58%
2	Feedback on cost increase/savings: i.e., "Save 30% or about $33 this month."		49	92%
3	Feedback on CO_2 emissions prevented: i.e., "Prevent 62 pounds of CO_2 emissions, or the equivalent of about 15 trees absorbing this amount."		21	40%
4	None of the above.		1	2%

38. How useful would you find the following advice or tips displayed on a thermostat/ in-home energy display (such as for the one you just saw the animation)?

#	Question	Not at all useful	Not very useful	Somewhat useful	Useful	Very useful	Responses	Mean
1	"Use fans or ceiling fans to increase comfort at this temperature."	4	8	16	17	6	51	3.25
2	"Put television, stereo, and computers on smart plugstrips to eliminate energy draw from these appliances when not in use. (Save xx% total energy.)"	1	4	9	23	16	53	3.92
3	"Replace lights with compact fluorescents to reduce energy use. (Save xx% total energy.)"	0	3	15	25	10	53	3.79
4	"Wash clothes in cold water to reduce energy use. (Save xx% total energy.)"	3	2	23	20	5	53	3.42
5	"Turn off power dry on dishwasher to reduce energy use. (Save xx% total energy.)"	1	6	18	21	6	52	3.48
7	Other (please specify):	0	0	1	1	2	4	4.25

Other (please specify):
use a clothesline instead of a dryer
install clothesline and dry your clothes in the sunshine (save xx% total energy/ $xx per load--it saves a lot!)

Statistic	"Use fans or ceiling fans to increase comfort at this temperature."	"Put television, stereo, and computers on smart plugstrips to eliminate energy draw from these appliances when not in use. (Save xx% total energy.)"	"Replace lights with compact fluorescents to reduce energy use. (Save xx% total energy.)"	"Wash clothes in cold water to reduce energy use. (Save xx% total energy.)"	"Turn off power dry on dishwasher to reduce energy use. (Save xx% total energy.)"	Other (please specify):
Mean	3.25	3.92	3.79	3.42	3.48	4.25
Variance	1.23	0.96	0.67	0.86	0.84	0.92
Standard Deviation	1.11	0.98	0.82	0.93	0.92	0.96
Total Responses	51	53	53	53	52	4

39. Describe your experience with air conditioning:

#	Answer		Response	%
1	I currently have air conditioning in the house/apartment that I live in.		10	19%
2	I don't currently have air conditioning in my house/apartment, but I have lived in a house/apartment with air conditioning.		36	68%
3	I have never lived in a house/apartment that had air conditioning.		6	11%
4	I don't know whether my current or past house/apartment has/had air conditioning.		1	2%
	Total		53	100%

40. What type of thermostat do you currently have in your house/apartment?

#	Answer		Response	%
1	Manual Thermostat (may or may not be similar to the one shown here): a thermostat that one sets the temperature by hand.		12	23%
2	Setback Thermostat (may or may not be similar to the one shown here): a thermostat that one can use a simple dial to set a lower temperature at night.		4	8%
3	Programmable Thermostat (may or may not be similar to the one shown here): a thermostat that one can set different temperatures at different times of day.		14	26%
4	There is no thermostat.		18	34%
5	I don't know.		5	9%
	Total		53	100%

Those that answered Setback or programmable thermostat in question 40 saw the following question:

41. How often is the automatic temperature offset function on the thermostat—to automatically turn down the heat at a specific time of day—used for night and/or periods you are away from your home during the heating seas...

#	Answer		Response	%
x1	The heating system is not used		6	26%
x2	Not at all		7	30%
x3	Occasionally		5	22%
x4	A few times per week		3	13%
x5	A few times per day		2	9%
	Total		23	100%

All participants that have a thermostat saw this question:

42. How often is the temperature setpoint manually changed to turn down the heat for night and/or periods you are away from your home during the heating season (days when heat is needed)?

#	Answer		Response	%
1	The heating system is not used		12	34%
2	Not at all		5	14%
3	Occasionally		11	31%
4	A few times per week		5	14%
5	A few times per day		2	6%
	Total		35	100%

Statistic	
Mean	2.43
Variance	1.61
Standard Deviation	1.27
Total Responses	35

43. How often is the temperature changed manually for comfort (i.e., not night or away periods) throughout a typical day where heating is needed?

#	Answer		Response	%
1	Never		11	31%
2	1-2 times		18	51%
3	3-4 times		5	14%
4	More than 4 times		1	3%
	Total		35	100%

Statistic	
Mean	1.89
Variance	0.57
Standard Deviation	0.76
Total Responses	35

44. Who uses the thermostat in the house you currently live in?

#	Answer		Response	%
1	No one (don't use a thermostat)		11	31%
2	I do		5	14%
3	Someone else does		8	23%
4	Both I do and someone else does		11	31%
	Total		35	100%

Those that answered manual thermostat and currently live with ac saw these two questions:

45. How often is the temperature setpoint manually changed to turn off the air conditioning for night and/or periods you are away from your home during the cooling season (days when cooling is needed)?

#	Answer		Response	%
1	The cooling system is not used		1	50%
2	Not at all		0	0%
3	Occasionally		0	0%
4	A few times per week		1	50%
5	A few times per day		0	0%
	Total		2	100%

46. How often is the temperature changed manually for comfort (i.e., not night or away periods) throughout a typical day where cooling is needed?

#	Answer		Response	%
1	Never		1	50%
2	1-2 times		0	0%
3	3-4 times		0	0%
4	More than 4 times		1	50%
	Total		2	100%

Those that answered live currently with ac AND have either a setback or programmable thermostat saw these questions:

47. How often is the automatic temperature offset function on the thermostat—to turn off the air conditioning at a specific time of day—used for night and/or periods you are away from your home during the cooling season (days when cooling is needed)?

#	Answer		Response	%
1	The cooling system is not used		0	0%
2	Not at all		0	0%
3	Occasionally		0	0%
4	A few times per week		0	0%
5	A few times per day		0	0%
	Total		0	0%

48. How often is the temperature setpoint manually changed (i.e, by hand, not automatically programmed) to turn off the air conditioning for night and/or periods you are away from your home during the cooling season (days when cooling is needed)?

#	Answer		Response	%
1	The cooling system is not used		0	0%
2	Not at all		0	0%
3	Occasionally		0	0%
4	A few times per week		0	0%
5	A few times per day		0	0%
	Total		0	0%

49. How often is the temperature changed manually (i.e, by hand, not automatically programmed) for comfort (i.e., not night or away periods) throughout a typical day where cooling is needed?

#	Answer		Response	%
1	Never		0	0%
2	1-2 times		0	0%
3	3-4 times		0	0%
4	More than 4 times		0	0%
	Total		0	0%

50. What best describes your weekday schedule (when you are at home) over the year?

#	Answer		Response	%
1	Pretty much the same day to day, week to week		13	25%
2	A few times a month I am home later/earlier than usual or leave later/earlier than usual		15	28%
3	More than once a week I am home later/earlier than usual or leave later/earlier than usual		10	19%
4	My schedule is pretty different every day.		15	28%
	Total		53	100%

51. What best describes your thoughts regarding your current thermostat?

#	Answer		Response	%
1	I don’t use it.		20	38%
2	It is easy to use		22	42%
3	I don't know how to use it		4	8%
4	Other (please specify):		7	13%
	Total		53	100%

Other (please specify):
don't have one
n/a
it is annoying, the cold air pools in the air conditioner so even though it is hot in the apartment the air conditioner won't turn on.
I am not supposed to mess with it.
I only use it for heat
Don't have one

52. If there are features on your current thermostat that you have but don’t use, what are they?

Text Response
I don't use my thermostat
Don't have one.
I don't have thermostat
I do not use the automatic setting to have the temperature be higher or lower at certain time of the day
I don't use thermostat
Nothing
I don't use a thermostat at this moment.
setting timed automatic temperature changes
N/A
n/a
I don't have a thermostat.
Automatic settings
I have never used my thermostat.
I use most of the the programmable features.
I don't use my current thermostat.
none
There isn't any features except for the temperature dial.
There are schedule settings that I don't know how to work. If I want to change the temperature I go over and press the button.
I don't currently have a thermostat.
n/a
I never really paid much attention...

I don't have a thermostat.
Adjustable temperature
None
I don't use my thermostat, my parents do, so I do not know.
none
NA (don't have one)
I don't have a thermostat in my current apartment. However, at my parent's house where I grew up I had one. I never really used it as I get cold very easily and prefer to be slightly warm than I do to be cold. I only turned the heat on when I was very uncomfortable and usually prefer to layer clothing. Air conditioning I only turned on when the temperature went above 85, otherwise I open doors and windows and try to create a cross breeze. There are pre-set controls on the thermostat but I don't use them because I don't want the air to turn on if I am not home or if the humidity has prevented me from being uncomfortable.
I do not use my thermostat much. I do however use it in the winter.
Sometimes no need to adjust the temperature or moisture
does not apply to me
N/A

Statistic	
Total Responses	32

53. What are features that you wish your thermostat had, if any?

Text Response
not applicable
Tell me the current price/kwh for the appliance.
N/A
Since mine is a setback thermostat it would be nice if i had a programmable one so it turns on automatically at a certain temperature.
A timer
I am not sure.
none
None
I don't use a thermostat at this moment.
reporting energy use, ideally with charts of usage over time
I wish it would tell me how much energy it was consuming to keep it on at a certain time of day.
n/a
I would like to have a better knowledge of the weather and the surrounding environment. For example, I'd like to know the humidity, and the UV rays outside. That way, I may better spend my day outside exercising or relaxing at a pool, rather than staying at home with the air conditioning on.
I wish it had a more understandable display and controls.
Tell me when I have peaked my usage.
Do not know what features my thermostat has, therefore not sure what else can be added to improve.
it would be nice if it had a nighttime setting so we wouldn't waste energy at night when we are asleep or during the day when we are gone. It is hard to do it manually, and it takes awhile to cool/heat up after returning home, so my boyfriend gets annoyed. if we could program it to turn on an hour before returning home/waking up, that would be very useful. and it would be nice if it were more accurate, it is a continuous dial with only the 70 degrees mark, so we never can tell exactly what temperature the house will end up at,

so we have to keep adjusting it a lot.
If it displayed total energy consumption and the source of the biggest energy use.
The ones we've been talking about; this is going to be cool and I hope it happens.
Everything that the simulation has! I've already gotten attached to it and I'll miss it very much when I go home.
I don't currently have a thermostat.
the ability to find out temperature outside the house as well
Some of the features mentioned before, such as reminders of peak usage or even little reminders of alternatives to using the thermostat.
Display everything digitally rather than in dial.
I don't have a thermostat.
Energy conservation info.
Understandable, easy to set, day versus night temperatures.
None
I wish it can have updates on how much my electricity bill is and things like that so I can keep track.
temperature outside, timer, predicted cost of heating at that particular temperature
NA (don't have one)
I wish it had a remote control so I could turn it on or off from farther away without having to walk right up to it. I wish it could give me an approximation of how much it will cost me for the energy I am using or the current status of my bill.
I can't think of any features I would want.
temperature adjustment, power, fan level
current cost, etc and total usage
Control for separate rooms, price of energy (how decision i am making on thermostat affect price and consumption.

Statistic	
Total Responses	36

54. Which of the following have you done in the past five years regarding energy consumption in your house/apartment (check all that apply)?

#	Answer		Response	%
1	I haven't made any changes		4	8%
2	Made improvements to my home's structure to make it more energy efficient (added insulation, added energy efficient windows, or other similar changes)		11	21%
3	Added a programmable thermostat to better regulate heating / cooling use		4	8%
4	Lowered/Raised thermostat setting on the heater/air conditioning to run less often		22	42%
5	Turned the air conditioning off more often/used it less		27	51%
6	Installed/use whole house fan and or ceiling fans in hot weather		11	21%
7	Replaced light bulbs with compact fluorescents or other low energy lighting / light bulbs		41	77%
8	Turn off lights when not using		48	91%
9	Used appliances and other household electronics less (e.g. turned off TV or computer when not using)		33	62%
10	Unplug or have television/stereo/computer on a plugstrip that is turned off when not in use.		20	38%
	Replaced old appliances with more energy efficient ones		13	25%
12	Open/close the drapes/blinds to let in sun in winter/block sun during hot weather		34	64%
	Wash most laundry using cold water		17	32%
14	Used the "air dry" or "energy saver" or "heat off" setting on the dishwasher		5	9%
	Line drying clothes more often rather than using the dryer		10	19%
16	Shifted the time for doing laundry to off-peak periods		14	26%
	Shifted the time for running the dishwasher to off-peak periods		3	6%
18	Shifted the timing for running pool and/or spa filters to off-peak periods		1	2%
	Turn off outdoor lights/other lights previously on all night		22	42%

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