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Demand response-enabled autonomous control for interior space conditioning in residential buildings.

Author
Chen, Xue

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Demand Response-enabled Autonomous Control for Interior Space Conditioning in Residential Buildings

by

Xue Chen

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Committee in charge:

Professor David M. Auslander, Chair

Professor Alice M. Agogino

Professor Edward Arens

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The dissertation of Xue Chen is approved:

Chair Date

Date

Date

University of California, Berkeley

Fall 2008

Demand Response-enabled Autonomous Control for Interior Space Conditioning in Residential Buildings

by

Xue Chen

To my parents and my husband,

for their love, support, and encouragement throughout my life

Abstract

Demand Response-enabled Autonomous Control for Interior Space Conditioning in Residential Buildings

by

Xue Chen

Doctor of Philosophy in Engineering - Mechanical Engineering

University of California, Berkeley

Professor David M. Auslander, Chair

Interior space conditioning means heating or cooling building interior space to provide comfort to occupants. In the modern world, the thermostat is a popular form utilized in residential and commercial buildings. Although the thermostat industry has recently matured, the development of new technology provides new opportunities to interior space conditioning. Motivated by the energy crisis, a demand response-enabled interior space conditioning system is designed for residential users. The feature of completely autonomous controls improves the acceptability and usability of the system.

Built on low-cost, low-power wireless technology, the system uses a disaggregated set of sensors and actuators. The software adopts a hierarchical layered structure, providing modularization of functions and semi-independent design. User interfaces provide easy and instructive interaction to users. The system interacts with the public utility, houses and their HVAC systems, users and outside climates. Robust adaptive control is used to address system uncertainties. Validation tools were developed to evaluate the system.

PhD Dissertation, Dept. of Engineering, University of California, Berkeley.

As the major contribution of this research to interior space conditioning, supervisory controls were developed to locate the optimal control settings. Adopting a hierarchical structure, supervisory controls determine control modes, control strategies/states, and control settings. To meet users' various requirements on utility cost and thermal comfort, four control strategies/states were designed: the normal strategy, the pre-cooling/pre-heating strategy, the pre-conditioning strategy and the overlapping strategy. The supervisory control strategies were realized by hybrid methods. Expert systems were utilized to choose control mode and control state. Model-based methods or performance-based methods were adopted in each state to seek optimal control settings. Results from computer simulations and field tests indicate that the system responds automatically to price signals with appropriate behavior of energy saving and load shifting. By identifying dynamic signatures of individual houses, the system is able to adapt its control strategies to a house and its HVAC systems as well as to the ever-changing outdoor conditions.

In conclusion, the thesis successfully demonstrates an intelligent, adaptive and autonomous interior space conditioning system under the context of demand response for residential buildings.

Professor David M. Auslander
Dissertation Committee Chair

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Chapter 1

Introduction

1.1 History of Interior Space Conditioning

Throughout history, one of the biggest challenges we have faced is to create comfortable living environments, keeping warm in winter and cooling down in summer. In ancient days, we approached this target by making fire, building shelters and storing ice. However, not only do those methods need heavy labor, they lack consistency in providing desirable living conditions. In the modern world, people have made significant progress in interior space conditioning with less and less labor.

The development of temperature controls began nearly 400 years ago. The first automated temperature control was invented by Cornelius van Drebbel. In the form of an electromechanical device, it was used to regulate the temperature of an oven or a boiler.[1] Thermostats, the modern form of interior space conditioning, was featured by a furnace regulator called "damper flapper", invented in 1885 by Albert Butz. It used a flap to control air entry (and thus heat output) to a furnace.[2] Almost at the same time, Warren S. Johnson, a professor at the State Normal School in Whitewater, Wisconsin, received a patent for the first electric room thermostat.[3] Both inventions launched the industry of interior space conditioning. They are the origins of two large companies in this business – Honeywell and Johnson Controls. In 1953 Honeywell produced the first device that usually is recognized as a modern residential thermostat – the "Round Thermostat". The iconic thermostat has been affecting the design and the use of residential thermostats for decades in North America.[4]

Starting as a heating regulator, the modern thermostat became more and more complex and sophisticated with various functionalities.[4] In 1906, Honeywell designed the first programmable thermostat with setback settings. The temperature is set down manually at night and set up automatically by a clock in the morning. The mechanical clock was substituted by an electric one in 1934. In 1924, the first heating anticipation thermostat was produced, turning off the heater slightly early to prevent the space temperature from greatly overshooting the thermostat setting. With the realization of temperature control, thermostat manufactures put more effort to combined functionalities. In 1995, an advanced thermostat was introduced with controls for humidification, dehumidification and ventilation, in addition to heating and cooling. It could also remind occupants to change filters.

Thermostats were first used by residential users. They later became popular in commercial buildings. Today, the thermostat in large commercial buildings has multiple responsibilities of controls and commissioning, usually monitored by professionals. It deals with large and complicated heating ventilating and air conditioning (HVAC) systems. The thermostat for residential or light commercial buildings performs controls on only basic heating and cooling systems autonomously. By interacting with its friendly and intuitive interface, persons with a little or no professional background are able to operate it properly.

Developments in technology have eroded some of the aspects of traditional thermostats. The fields of interest include remote controls, wireless devices, communicating with a central controller or public utilities, and intelligence to weather, buildings and occupants. Meanwhile, due to energy shortages, especially electricity blackouts, there have been additional demands placed on the interior space conditioning. In conclusion, the trend of interior space conditioning is towards customizing, adapting, intelligentizing and optimizing.

1.2 Motivation

Although the thermostat industry has become more mature recently, the development of technology and its applications provide new opportunities to the next generation of conditioning systems. There are two sources motivating the revolution of interior space conditioning. One is the energy crisis, which has become more severe. It requires optimal controls on HVAC systems to save energy and shift peak loads for electricity. The other comes from users that have additional requirements to basic heating and cooling. Personalized features are designed to meet the needs of individual users and houses. Adaption is necessary to accommodate control strategies to weather changes. All functions should be implemented automatically. Development in computer science and wireless communication offer new instruments to meet the challenges.

1.2.1 Demand Response

Due to the concerns of the energy crisis in recent years, namely, gas and electricity shortages, government and utility companies are pushing their effort to regulate the use of energy. It is important to note that unlike gas, water or other substance, electricity can not be stored massively in any form. It needs to be used just after it is generated and transmitted. Therefore, electricity shortages will occur when supply can not meet demand. This is usually caused by two reasons: 1) supply shortages: the failure of electricity generation or transmission systems, which are difficult to predict before their occurrences; and 2) critical peak demand of electricity, which is possible to avoid if offering more supply by constructing additional power generation systems or reducing the peak demand by managing the use of electricity. The construction of new power plants is considered inefficient because the critical peak demand occurs less than 1% of the time in a whole year [5], which means the new plants would only be needed for a few days per year. Therefore, reducing electricity demand during shortages is the main instrument to relieve the crisis.

Measures to reduce the demand at shortages are termed "demand response" (DR). They have the effect of adding elasticity to the electricity market. It has been estimated that a mere 2.5% reduction in demand in response to shortages can reduce the price spikes by 24%.[6]

What then are the main causes of electricity shortages? According to California energy demand report, the wide use of electricity-driven air conditioners and central air-conditioning system lead to most of the peaks of electricity consumption in the summer.[7] Demand response measures can be utilized to mitigate this problem, including variable price rates and control mechanisms of thermostats for utility users to respond to those rates. Variable or dynamic rates are those in which either time or price are specified in the rate. They are demand-driven, affected by weather conditions and human activity. For example, the electricity price on a hot summer afternoon would be much higher than that of a midnight during spring. Such a price schedule encourages customers to reduce their power use or shift use to off-peak periods during peak price events, which can result in an overall reduction to their bill.

The DR tariff presents challenging tasks on interior space conditioning. Under the traditional pricing policy, with a constant rate, thermostats should minimize the total energy usage. Under the context of DR, the total energy cost should be minimized, by trading the time when energy is used. Under particular conditions, it would be able to guide the users to maintain living comfort without consuming energy for a certain period.

1.2.2 Autonomous Controls

Before designing control systems for interior space conditioning, we must understand the problems with the existing technology. The main issue is adoption: if people do not accept the technology or use it as designed, then it will not achieve the objectives of energy savings and load shifting. Currently, this is the case for the households in California that have programmable thermostats. It is estimated that 35% of them do not use the programming features, but instead put the thermostat in hold mode and operate it manually [8]. To improve the acceptability and usability of thermostats, they should be capable of starting up automatically and operating autonomously with minimal input from the occupants.

First, the interior space conditioning system should perform reasonably well out-of-the-box with good default of control parameters. The built-in defaults come from the average thermal performance of common houses. Limited information will be queried upon installation, such as the location (zip code) and the year the house was built. From the very beginning that the system runs, it should adapt its control strategies to the specific house, HVAC systems and climate. It needs to learn how the specific house behaves in temperature based on historical data and detect any changes if they occur. Control parameters would be tuned adaptively with those learning results. Further, control strategies would be customized based on residents' preferences on comfort and economics. This enables the system to meet the needs of individuals better. The most important automation function is to respond the changes of electricity price automatically. Users do not wish to monitor the dynamic rates all the time as a “day-trader” of electricity. The control system will adopt strategies to shed load at high price without significantly sacrificing users’ comfort. It will also notify users of necessary accommodation to their activity, for example postponing doing laundry during high price periods. With all these user-oriented functions, the technology would be more acceptable and more effective.

1.3 Overview

Toward automated control under the context of demand response, an interior space conditioning system was designed and implemented. A wireless communication technique was adopted to construct a sensing and actuating network. An ad-hoc controller controlled interior space conditioning. It adapts control strategies to a specific house, HVAC systems, climate, various pricing and users. The system interacts with users through an intuitive user interface.

The research focuses on the control strategies design and its implementation for residential houses, while the same strategies could be applied to light commercial buildings. On one hand the HVAC equipment is relatively simple compared to those in large commercial and industrial buildings. On the other hand, the system should be more autonomous and robust without the operation of professionals. Due to the essence of demand response measures, the control system deals with only electricity-driven HVAC equipment. It is easy to modify the control strategies for gas heating systems without gas storage. However, the control system dealing with an HVAC system with energy storage is not within the scope of this thesis.

The body of the paper is divided into three parts. Chapter 2 is an overview of the interior space conditioning system. It discusses the working mechanism of the system, including how the system works and how it interacts with its surroundings.

The system adopted a disaggregated structure, which is completely different from the current thermostat concept. It is divided into three parts: hardware, controls and user interface. As other components involved in the system operation, public utility, houses and human beings are introduced as well. Several technology concepts and innovation ideas are described, which enable the implementation of control strategies.

Chapter 3 introduces the tools used to validate the design of an interior space conditioning system. Computer simulation programs mimic the DR variable electricity rates and the thermal behavior of actual houses. They provide quick, convenient and controllable approaches to evaluate the system. Field tests are another validation method in which the system runs in a real-life scenario. Test house characteristics and test conditions are described. The system infrastructure and control strategies are extensively tested through long-term tests, summer tests and large-scale tests.

The control strategies design and implementation are described in chapter 4. First, the interior space conditioning is formulated as an optimization problem. Supervisory control and local control are introduced to solve this problem. This paper focuses on the development of supervisory controls. Second, the technical background of supervisory control is described. Typical supervisory control methods are grouped into four categories. Their advantages and disadvantages compared to other methods are described. The detailed design of this particular problem, interior space conditioning, follows. Hierarchical control structure is adopted. Supervisory control determines control mode, control state and then temperature setpoint settings sequentially. To realize the control strategies, hybrid supervisory control methods introduced previously are applied. In details, a model-free method – expert system splits the big optimization problem into four problems. Model-based method and performance-based method are used to perform optimal HVAC control for each sub-problem. The performances are evaluated by both computer simulations and field tests. These results provide insights and reveal application constraints for control strategy design and control methodology.

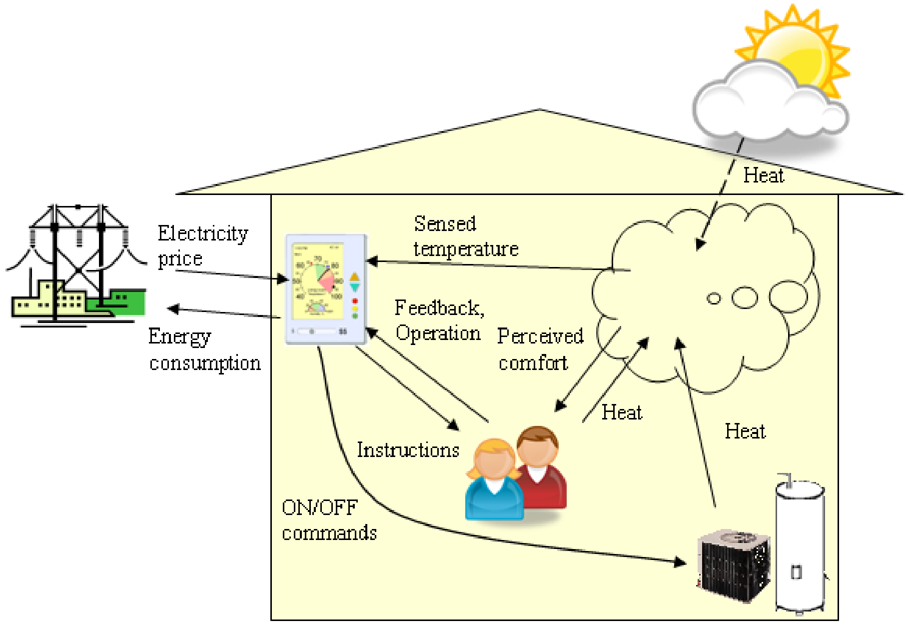
Chapter 5 summarizes the research work and the thesis contributions.

Chapter 2

System Working Mechanism

An interior space conditioning system for a residential house, the thermal control system, works under complex circumstances. It interacts with the following objects: the occupants, the house and its internal properties, its HVAC systems, the inside and outside surroundings, and the public utility (usually called "the utility"). Figure 2.1 shows their interactions. The occupants perceive thermal comfort from the house surroundings, and feedback their feelings by operating the control system. It is worth mentioning that a human's thermal comfort is determined by not only indoor surroundings, but also outside conditions and their activities. With comfort information provided by users and pricing information delivered from the utility, the control system adjusts temperature settings to operate HVAC systems. Meanwhile, the system may also guide users to take actions for the purpose of energy saving, such as opening or closing windows, although it is not sure whether or not the actions are taken. In other words, occupants could be "controlled" or "actuated" undirected and indefinitely. Finally, the interior space thermal conditions, especially temperature, are determined by a series of heat transfer processes. The thermal dynamics involve heat from the HVAC operations, the house and its internal properties, the occupants,

Figure 2.1: Working Mechanism of Interior Space Conditioning System



and the outdoor weather conditions. Additionally, data about energy consumption are collected by meters and then sent back to the utility.

In this chapter, all the components involved in the control processes are presented. First of all, I will introduce the disaggregated infrastructure of the interior space conditioning system. Taking advantage of wireless communication and internet services, the system is integrated by three sub systems: hardware, controller and user interface. Following that discussion, the other components in the control processes are described, including the public utility, houses and HVAC systems, and human factors. These components play significant roles in the design and the performance of control strategies. Their varieties require robust and adaptive controls.

2.1 Disaggregated Design for Interior Space Conditioning

The idea of disaggregation is to split a big problem into separate pieces. Therefore, it is easier to analyze the problem and allows for more flexibility in solving the problem piece by piece with fewer limitations. The concept of disaggregation has been applied to many fields: networking distribution, mobile communications[9], scientific computation, computer processor design, and even in some non-engineering fields such as management and politics. A similar concept could also be applied to the interior space conditioning system.

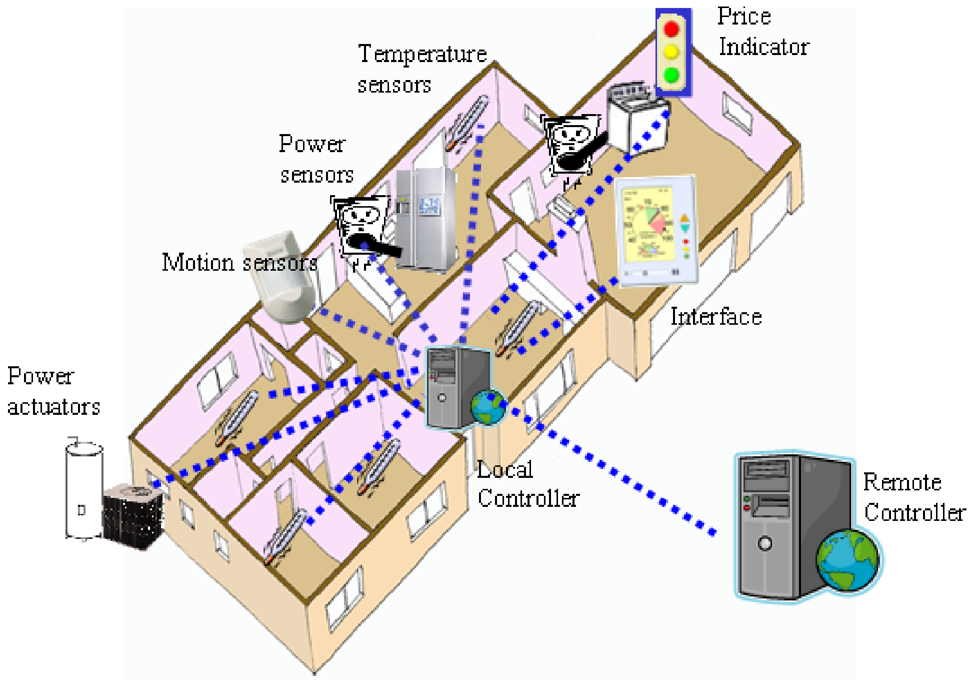
Instead of being a single device as a traditional thermostat, the interior space conditioning system could be in the form of a distributed system, formed by several subsystems:

- Hardware, including sensors and actuator relays, is designed as the physical interface of the system. Sensors collect data about the environment, the energy consumption, and the residents, providing necessary information to the controller. Receiving commands from the controller, the actuator relays operate HVAC systems and possbily other electric appliances.

- Controller, which responds to pricing signals, computes optimal control settings and sends commands to electrical appliances. To monitor the system and realize advanced control algorithms, a data management system is used as a part of the controller.

- User Interfaces, by which the system and users exchange information and interact with each other.

Figure 2.2: Schematic of the Disaggregated System



The traditional thermostat integrates all of these components in a single device and runs at one spot. With the idea of disaggregation, these components are spread inside and outside the house. Basic HVAC controls could be realized in different forms, and advanced control functions could benefit from the new infrastructure. Such design takes advantage of modern technologies like wireless communication and internet services, enabling convenience and flexibility to system installation and providing possibilities to improve control performance. Figure 2.2 presents the concept of disaggregated thermal controls.

Benefiting from the technology of wireless communication, all subsystems could be distributed separately, for the purpose of convenience and usefulness. For example, temperature sensors could be mounted beside a bed in the bedroom or behind a couch in the living room. On one hand, temperatures at such spots are closer to our living surroundings than locations where traditional thermostats are installed (e.g., on the wall of the kitchen, the living room or the hall way). A more precise evaluation of thermal comfort could be obtained. On the other hand, the system is able to collect data from multiple spots, which provides possibilities for advance control strategies. For instance, multiple sensing at the same location provides redundant information, enabling the function of fault detection. Data collected in different rooms enable multi-zone conditioning. So do HVAC actuators. They could be installed without the limitation of organizing cables to receive control signals. As the key component, the main controller could be running on a conventional chip or a home computer as a software program with a wireless receiver. Similarly, without the limitation of locations, user interfaces could be displayed in various forms: an LCD showing the major information, a lighting device showing electricity rates and even an alarm indicating a critical-peak-pricing event.

In addition, the internet provides new opportunities for the evolution of interior space conditioning. As mentioned above, the main controller could be located at a computer as a software program. With this, the software actually can be in the form of an online service running on a remote server. Sensing data and control settings would be transmitted through high speed internet. Without the limitation of conventional thermostat chips, powerful computation capability could be achieved at remote servers, enabling the implementation of advanced control algorithms. Moreover, large database systems could be supported, which are necessary to store historical information. Because it is not necessary that the controller be physically accessible to users, service providers would be able to upgrade or restart the control system software without going to residential homes. The design of user interface is very innovative, and it does not need to be physically located at a residence. Using an online service, it could be available through any type of device as long as there is an internet connection, such as computers, PDAs and cell phones. Users are able to monitor and modify system settings at any time and anywhere. Users can even customize the display with colors, font size and so on.

From the above description, we see how the concept of interior space conditioning system is expanded from conventional thermostats. Development of technologies promotes evolution of the interior space conditioning system, as well as the subsystems mentioned above.

2.1.1 Multiple Sensing and Actuating

A conventional thermostat merely senses temperature through a thermistor mounted on the thermostat circuit board. Such limited information restricts the functionalities and the performance of the control system. There is a need for much more information via multiple sensing.

First of all, human comfort is affected by various factors, in addition to temperature. Of the most significance are humidity, air movement, solar radiation, outdoor conditions and individual metabolic rate. (Details are in section 2.5.1.) In order to make a better evaluation of thermal comfort, measuring these conditions is important. Useful sensing metrics might include temperature, humidity and air speed throughout the house; outside weather conditions such as temperature and radiation; and occupants' motions and locations for the estimation of users' activity. The motion sensing could be utilized in multi-zone conditioning as well. Second, to monitor energy consumption and HVAC status, power sensing is required. As the feedback to the control system, these data could be used for fault detection as well. Moreover, analyzing these data enables the prediction of energy cost. Finally, to improve usability of the system, system information should be obtained via sensing and expressed to users. For example, in order to inform users to change sensor batteries, the battery voltages need be sensed. The system is thus far more information-rich than current thermostats and has extended command capability.

The sensing metrics accomplished are temperature, battery voltage, relative humidity, motion, outside weather, power usage, and On/Off status.

- Temperature – ubiquitous for the interior space conditioning. The actual sensor is normally of thermistor or resistance temperature detectors (RTD) type. Both air temperature (shielded from radiation) and globe temperature (available to radiative effects) are measured.

- Battery voltage – this is a quantity of internal interest. It provides information for the maintenance of sensors and actuators.

- Relative humidity – important for comfort estimation.

- Motion – used to determine occupancy of various spaces, for multi-zone controls and activity estimation. It uses a passive infrared motion sensor to detect changes in infrared radiation when there is movement by an object with a temperature different than the surroundings.

- Outside weather – Outside weather conditions are needed for comfort evaluation and temperature profile prediction, to determine optimal settings for advanced control strategies. We measure outdoor temperature, global and diffuse solar radiation, wind direction and wind speed.

- Power usage – measurements of power usage are done for the whole house and for individual subsystems or appliances. CT metering devices are used.

- ON/OFF status – check HVAC status as the feedback to the controls, for the purpose of system monitoring and fault detection.

There are two actuation modules in current use. One is the ON/OFF relay receiving commands from a central controller to actuate electrical appliances. Another is the signal light unit to let people know the current cost range for electricity so they can decide whether or not to run selected appliances such as washing machines. The signal light uses the traffic light pattern of red-yellow-green along with an extra light for critical–peak-pricing or emergency conditions. It is called a partial actuator because it requires cooperative action on the part of the occupants. For the same reason, it could also be considered as a form of user interface.

An important technology enabling the multiple sensing and actuating system is low-power, low-cost wireless communication. The node unit in this wireless system is called mote. It consists of a low-power microprocessor, a low-power radio transceiver, and multiple analog or digital input/output channels for sensing and actuation. "The system architecture uses a central controller and the wireless equivalent of a "star" network for connectivity to distributed motes."[10] A "base station" mote connects to the central controller and one repeater is strategically located elsewhere in the house to expend the communication ranges. The system has been built on several different platforms of motes, to which we have migrated as the technology improved, demonstrating portability of our sensing and control structure. Figure 2.3 shows the latest type of motes we used – a Moteiv telosb mote. For the details of hardware construction, please refer to the project reports [10, 11].

In order to achieve maximum demand response effectiveness, the hardware design envisions control or influence over many residential electrical subsystems. If in addition to the control of the HVAC system, as with current thermostats, this system can control electric hot water heaters, refrigerators, pool pumps, etc., then it will be able to do a much better job of shedding electrical load as needed for demand response without undue disturbance to the occupants. Some of these appliances, such

Figure 2.3: Moteiv T-mote

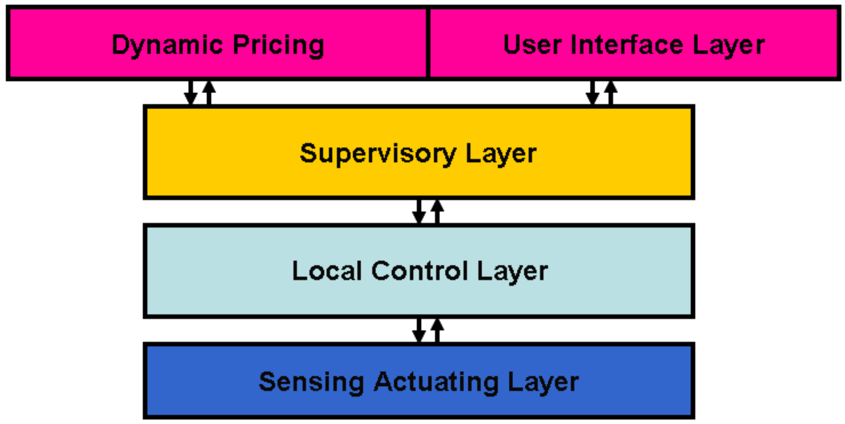
as pool pumps, could be controlled directly. For others, such as clothes washers and dryers, direct control is probably not practical. The actuation in this case would be occupant-assisted through signaling the occupant via signal lights that tell occupants when the time is propitious to run these appliances.

2.1.2 Controls

Demand responsive optimization in conjunction with autonomous functionality lead to a control system with considerable complexity. In order to handle that complexity, we have adopted a layered design for the control system software[12] (see Figure 2.4). In a layered design, each layer (in theory) interacts only with the layers above and below it. This provides for modularization of function and semi-independent design of each layer.

At both the top and the bottom of the hierarchy are communication modules. The highest layer connects the public utility and the user interfaces to the controller. The lowest layer, the Sensing/Actuating layer, maintains communication between the controller and the hardware sets. And in the middle are layers that determine control strategies, controller settings and therefore HVAC operations. The Supervisory Layer

Figure 2.4: Hierarchical Control Structure



is the most complex and critical layer. It receives price information and users' settings from above and must make decisions about how to best compromise comfort and cost. Then the compromise is realized by the Local Control Layer. Choices must be made as to how to manipulate the HVAC system for basic thermal control. As the most significant contribution of this research, the detailed algorithms in the Supervisory Layer are described in Chapter 4.

Parallel to the hierarchical structure, a data management system records the data flow for several purposes. First, the software development should be generic with respect to the hardware sets. To enable such independent design, the database stores hardware information such as mote IDs, calibration information, code versions, maintenance dates and so on. The controller downloads the information from database every time it restarts. Thus, it needs not be modified when we change a broken sensor or recalibrate a thermister. In addition, information about the specific house and its occupants are saved, including house locations, occupants' schedules and their economics preferences input by users. Based on these, the system is able to customize control strategies for an individual house. Control parameters of the system are saved as well. A set of default values are used as initial settings and control algorithms up-date those values when necessary. With control parameters recorded, even if the system is restarted, it can still track the latest controls. Those values are useful for research purposes as well. Finally, real sensing data during the control process need to be stored into the database for advanced functions (i.e., learning, fault diagnostics, commissioning). Due to these reasons, a reliable database service including uploading and downloading data is non-trivial. As mentioned earlier, the database could be run on a remote server.

2.1.3 User Interfaces

As a main component of interior space conditioning, the user interface works as a bridge between users and the control device. Although the goals of the user interface are to display information to users and allow input from users, there are responsibilities other than these to achieve the best acceptability for the system.

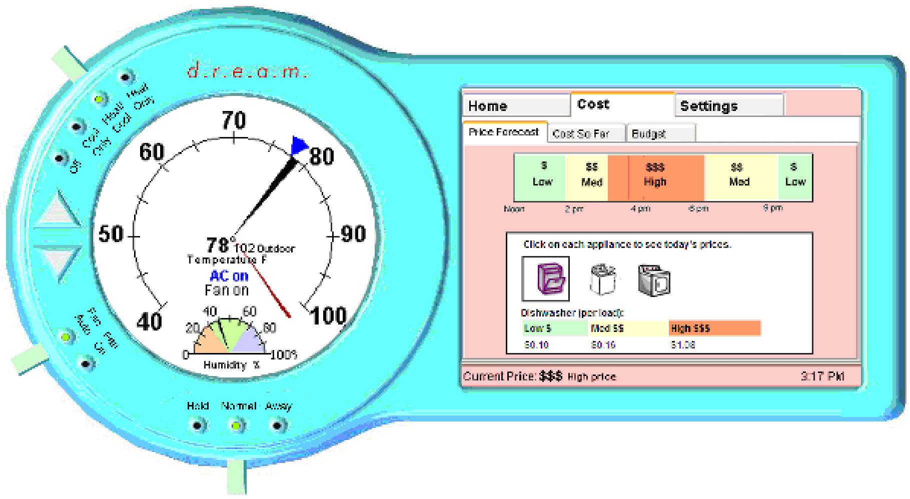
The basic display functions are similar to a conventional thermostat – showing actual indoor temperature, air conditioner/heater status, and electricity rate (in the context of DR), as well as controller settings such as temperature setpoints and control mode (cooling/heating/auto/OFF). Advanced thermostats may also display total energy consumption and scheduled setpoint (programmable thermostat). However, users are expected to be more informed, receiving real-time energy/cost information. Pilot programs showed that householders who monitor real-time energy usage can reduce total electricity consumption by as much as 10% to 15%[13]. The savings can be enlarged by reminding users to do maintenance such as change filters. Thus, systems with functions of fault detection and commissioning and display diagnostic information and the corresponding suggestions are desired. This avoids energy wasting and improves energy efficiency. The interface may also guide the user to take beneficial actions for the purpose of energy/cost saving, such as opening windows when the outside temperature is cooler than the inside temperature on summer nights.

As another end, the user interface allows users to input their preferred temperature schedules. In addition, users should be able to control HVAC systems manually through the user interface, although automatic control is dominant. Finally, with the emergence of DR techniques, the system would like to know users' economic preferences, or how people would like to balance cost and comfort. For users with a large budget, the system would make the best effort to achieve comfort even when the electricity rate is high. For users who have a limit budget, the system will apply strategies to meet their economics requirements. This is important information for the system to do optimization control. The user interface needs a tool to let users express their "sensitivity to price".

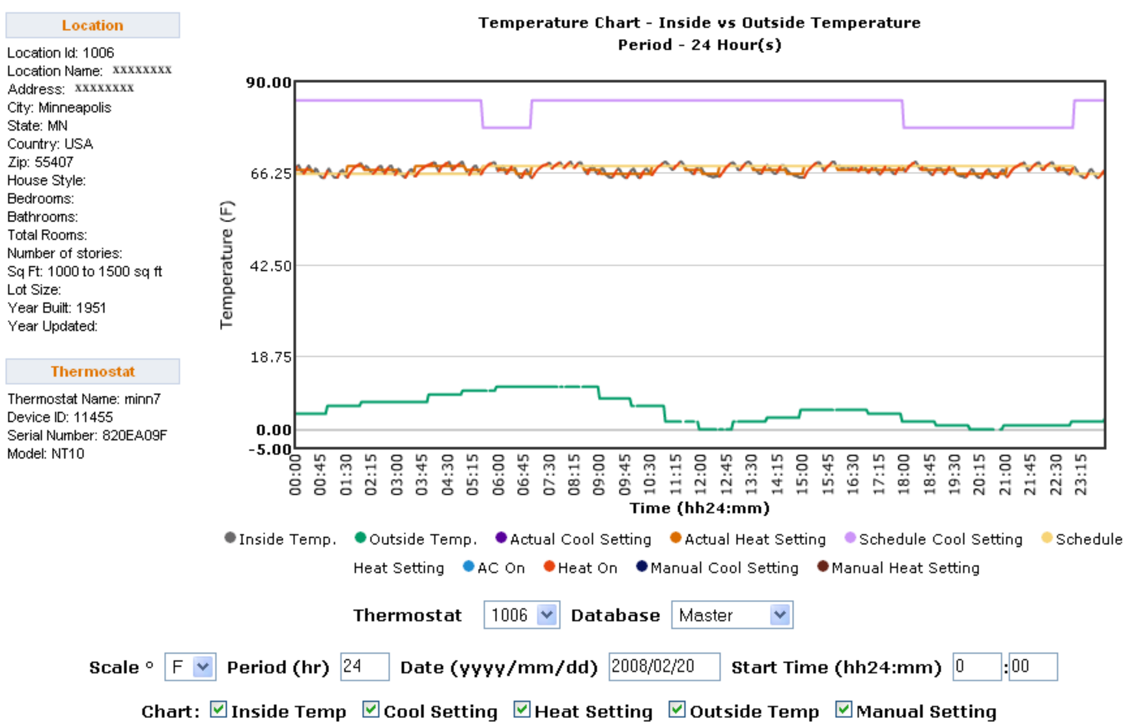
Besides all of these functionalities, the system should also educate users and make sure they understand how the system works. Based on our experience from field tests, using the thermostat properly is crucial for the system to achieve the optimized performance as designed. Failing to do that, users could not benefit from the new technology and energy is wasted. Here are some examples. Some users thought the AC and heaters work as valves – that setting a large difference between the actual value and reference would speed up the cooling/heating process. When they feel cold or hot, they modify the temperature setpoint by a big jump and change backward later, instead of directly setting setpoints to what they prefer. In actuality, the cooling/heating speed is determined by equipment capacity only, and the temperature difference between actual values and settings has no effect. Educating users about this fact would prevent them from changing settings back and potentially saving energy if they forget to do so. Another misperception some people have is that keeping the temperature low on summer afternoons when the house is not occupied saves energy because the house is cooled down again later in the afternoon when people come back. However, this is not accurate. The total energy consumption is larger if the average temperature is lower. Due to these observations, the system should detect questionable actions and inform users through user interfaces, so that users could make better decisions.

To achieve these goals, there are several forms of implementation for user interfaces at present. A user interface design was developed, prototyped by our research group, and tested in laboratory environment[14, 15]. See figure 2.5(a) below. It has most of the desired functions described above. Our research group tested it in several field tests. We also tested another innovation together with a startup company, Ecofactor, which provides online services and uses a website as user interface. It shows historical energy data and plots temperature curves so that users obtain information. (figure 2.5(b)) There are also different types of display devices on the market showing electricity rates, monitoring real-time energy consumptions[16].

Figure 2.5: User Interfaces



(a) User interface used in field tests



(b) User interface for online services

2.2 Other Issues Involved

During the processes of interior space conditioning, there are several issues involved. Policy is one of the key components that support the technology. Utility companies and state regulators offer necessary instruments to enable the implementation of residential thermostat controls under the background of DR. Houses, HVAC systems and users are other factors. Their wide range of varieties challenge the design of a generic controller. Robustness is required to deal with their uncertainties.

2.2.1 Policy issues

It takes a mix of technology and policy for demand response to meet its potential of load reducing and shifting. The first step into the domain is that the public utilities have to install smart meters, which support the billing applications dealing with dynamic rates. Then state regulators and energy marketers need to design dynamic rates that are beneficial to the utilities as well as to consumers.

Smart Meters

Smart meters are essential to perform demand response. Although it is a type of power sensing device, but it is very different from the one mentioned in section 2.1.1. As a gateway between interior space conditioning system and the public utility, it collects and delivers information about electric power usage. It allows users to be charged by not only the amount of electricity consumed but also when it is used.

Currently, there are two types of smart meters: automated meter reading (AMR) and advanced metering infrastructure (AMI). AMR performs data transition one way from customers to the utility, AMI enables two-way communication. "AMR implementations collect real-time customer usage data but do not provide the information to the utility in real time"[17]. Instead, AMR meters store the information locally in the meter itself, and periodically the information is retrieved and sent to utility billing systems. Such implementation is sufficient to support billing applications and yields the associated benefit of reducing meter reading costs. With two-way communication, AMI is able to deliver real-time information to the public utility and may control HVAC directly based on consumers' willingness to reduce electricity consumption or to have their service temporarily interrupted when demand overwhelms the supply. In other words, it combines the functionalities of a meter and a controller. In addition, its capabilities allow the utility to monitor real-time power outages and spikes and to deploy outage management strategies. Table 2.1 compares both types of smart meters with the current manual meters on their characteristics and applications.

Although there are still questions about legislative issue, cost of meters, data transmission techniques and manufacturing standards, smart meters are absolutely one of the necessary solutions to demand response, whatever form they take.

Utility Tariff

To spur activities that have benefits of energy savings and peak load shifting, energy marketers and government regulate the market by using an economy instrument – price. There are evidences showing that its effect is significant. Since 1980, the state of California maintained the same level of electricity consumption per capita with a growing economy, while most other states have increasing trends on the same index[18]. One of the main reasons is that the electricity is far more expensive in California than most other states. Therefore, it is reasonable to assert that dynamic rates would have an impact on the way people use electricity and perhaps even help to lessen the growing need for more electric power and power infrastructure.

In pilot programs around the country, a few forms of DR rates were used[19, 20].

Table 2.1: Comparison of Utility Meters

System Feature	Manual Meter	Automatic Meter Reading (AMR)	Advanced Metering Infrastructure (AMI)
Meters	Electromechanical analog	Hybrid digital	Hybrid or solid-state digital
Data recording	Total consumption	Total consumption or time-based	Time-based (usage each hour or more often)
Data collection	Manual, monthly	Drive-by, periodically (monthly)	Remote via communication network, daily or more often, even real-time
Primary applications	Total consumption billing	Pricing options billing	Pricing options, customer options, utility operations, emergency demand response
Key software interfaces	Billing and customer information system	Billing and customer information system	Billing and customer information system; Customer data display; Outage management; Emergency demand response
Additional devices enabled	None	Smart thermostats	Smart thermostats; In-home displays; Appliance controllers

The details are as follows.

- Time of use (TOU) rates. The rates are defined as off-peak, partial-peak (sometimes called mid-peak or shoulder-peak) and peak (on-peak), with a fixed schedule. Sometimes the rates are also called the low, medium and high price in this thesis. The schedules may be different based on weekday/weekends, holidays and seasons. It is important to note that TOU is not a type of dynamic rate because it is predetermined. However, it has the same effect of load shifting as dynamic rates. I include it here as a type of DR rate.

- Critical peak pricing (CPP). As a real-time price schedule, users are notified one day ahead. It is triggered primarily by peak demand and/or low generation reserves during summer weekdays. Usually the limit of maximum event number is pre-determined. Sometimes TOU rates are used as a base for CPP.

- Real-time pricing (RTP). The price of electricity varies as wholesale prices fluctuate over the course of the day. It changes hourly (or even more often) based on day-ahead forecasts of hourly energy costs. The rates have only been applied for commerce and industry. Users benefit if they are able to shift or reduce energy consumption during high-cost periods.

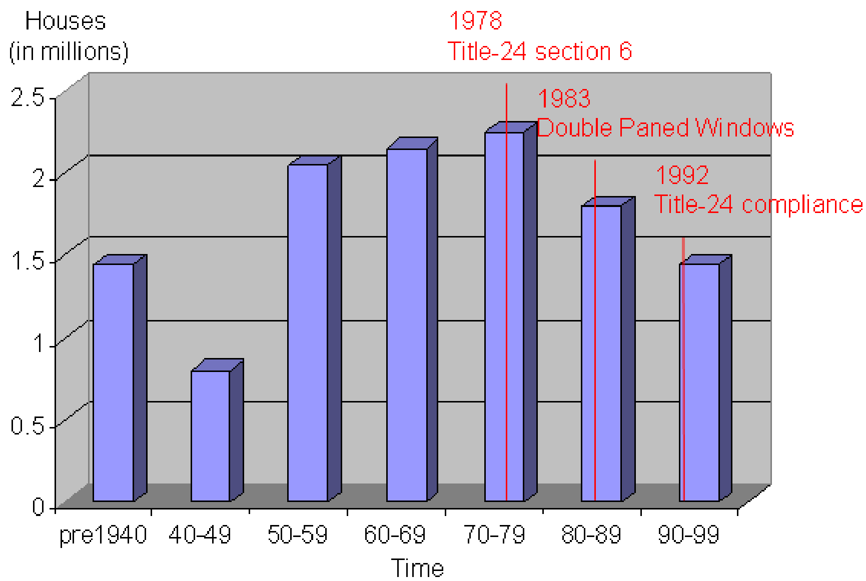
All above DR policies demonstrated non-trivial effects on energy saving and load shifting under certain conditions[21]. However, there is no particular work showing what the optimal tariff should be to maximize the benefit to both users and the public utility. Obviously, relatively high price for peak load hours will promote electricity management programs that shift loads to non-peak periods. However, a large peak-to-off-peak price ratio in conjunction with long peak durations might increase monthly bills or worsen users' living conditions. A project with more than 300,000 customer participants in Washington demonstrated that many customers under time-of-use rates actually paid more than their counterparts with traditional flat rates, although the total consumption decreased by 5% during peak hours[21]. Additionally, the impact differences when applying TOU, CPP and RTP are unclear currently, although all have potential for load reduction and peak load shifting.

However, this topic is not within the scope of this thesis, but the behavior and the performance of control strategies are highly related to the utility tariff, including the type of DR rates, the ratios of different price levels, their schedules and the time left for users to respond in the case of CPP and RTP. To deal with such undetermined issues, the optimal control strategies should be generic with respect to these variations. In this dissertation, a generic system is developed dealing with the tariff of TOU plus CPP, with notice one day ahead. Different price ratios are deployed to illustrate the control performance.

2.2.2 House and HVAC Systems

For interior space conditioning, the control object is the thermal conditions inside a house. Therefore, thermal characteristics of a house and its HVAC equipment play significant roles in the dynamics processes that determine the indoor conditions, specifically temperature. For instance, a large house has the capacity to store a great deal of heat, which is mathematically described by a large value of time constant in the house model so that indoor temperature is slowly affected by outdoor conditions. Thermal characteristics of a house consist of house structure (foundation, number of stories, etc.), orientation, size, construction material, internal mass, the year built and the corresponding construction code, and window style, number and directions. Factors of HVAC equipment include equipment type, capacity or size, years of use, and filter changing frequency.

Figure 2.6: California Residences Distribution



Source: Energy Information Administration, 2001[22]

The variance of these factors is widely distributed in California. Figure 2.6 shows the distribution of California residential houses based on decade of their construction. Roughly two-thirds of the occupied existing California housing stock was constructed before the first Title-24 energy standards took effect in 1978. And before 1983, double paned windows were not required in California. These houses are assumed to be poorly insulated, with single-pane windows and equipment efficiencies typical of the 1970s. On the other hand, the newly constructed houses have windows, insulation values and equipment efficiency meeting the minimum for Title-24 compliance. In other words, the thermal performance of the building envelope and HVAC equipments have improved over time, due to more efficient window technologies, equipment efficiencies, and insulation values mandated by code.

The variety in thermal characteristics causes uncertainties and leads to difficulties in the control strategy design. A strategy might work for some types of houses but not for others. For example, a house with large heat storage capacity is able to benefit from the long recovery time when we apply a pre-cooling strategy that cools the house before peak price time. Yet a house with relatively small mass has few benefits because the indoor temperature recovers quickly when the air conditioner is turned OFF. Even the same strategy deployed to the same house can perform differently under different circumstances. In the above example, higher outside temperature will lessen the benefit of pre-cooling since the recovery time is shorter. Similarly, as the actuation devices of thermostat controls, HVAC systems have non-trivial impacts on control performance. An air conditioner of small capacity, an undersized AC, can not cool the house under extreme weather conditions. That is, the control target cannot be achieved with an undersized AC on a hot summer afternoon. In this case, to keep a comfortable living environment, other strategies should be used, such as cooling the house before the outdoor temperature reaches its peak.

Due to these reasons, there is a need to customize interior space conditioning controllers for individual houses. Unlike commercial buildings where the thermal control programs are usually designed specifically for their complicated building structures and HVAC equipment, residential thermostats cannot be personalized due to the cost. Controllers are designed for general use and should work appropriately for all kinds of houses and HVAC systems automatically. Such autonomous function requires the controller to recognize thermal characteristics of a house and its HVAC systems, and also detect changes if they occur. Users are queried to input basic house information to initialize the identification process at the first installation. Then robust and adaptive control strategies are applied based on the identifications. Simulations and field tests also show the importance of recognizing these differences that exist in houses and HVAC systems (refer to chapter 4). The customized strategies enlarge energy and cost savings and improve users' satisfaction.

2.2.3 Human Factors

One important component in interior space conditioning is human beings, the occupants. First, the ultimate goal of the conditioning is to maintain comfortable living conditions so the performance of the system depends on perceived thermal comfort to a significant degree. Second, different economic sensitivity of users could affect the choice of optimal control settings significantly. Both of these points are expatiated in the following sections.

Additionally, human factors include users' impact on house thermal dynamics that determine indoor temperature. The number of occupants and their behavior would change internal heat or building envelope. More persons would generate more heat; building a fire and cooking will heat the house; house cleaning (washing floors) cools the house; and opening windows may either heat or cool a house depending on outdoor conditions. It is important to mention that users' behavior could have mixed effects. Some activity, for example cooking, could change a person's metabolic rate so that he or she feels comfortable in lower temperature. Meanwhile, the activity of cooking generates more heat and changes the thermal dynamics of interior space. Finally, occupancy schedules make a big difference in the interior space conditioning. Large energy savings could be achieved if the control system takes advantage of unoccupied periods.

All of these human factors pose challenges to the design of the interior space conditioning system and provide opportunities for energy savings and peak load shifting.

Thermal Comfort

Currently, the typical programmable thermostat on the market has two time periods and two temperature choices per day corresponding to occupied comfort setpoint and a setup/setback for unoccupied periods or night times. In this design, it is assumed that users perceive the same level of comfort at a fixed temperature at any time in the daytime or night under any weather conditions. This is similar to what is done in office buildings, for which a thermal comfort standard is established. However, this standard may not fit for residential sectors. One reason is that residential buildings are usually naturally ventilated while office buildings are mostly fully or partially closed. Also, people have more control over ventilating, such as opening windows. These make a big difference on perceived comfort, especially in summer. Further, it is more flexible for residential users to adapt themselves to surrounding temperature, such as by adding or reducing clothing. In other words, people in residential houses have more ability to adapt to indoor temperature based on the outdoor conditions. This, theoretically, provides a large potential for the control system to save energy by enlarging temperature ranges for thermal comfort.

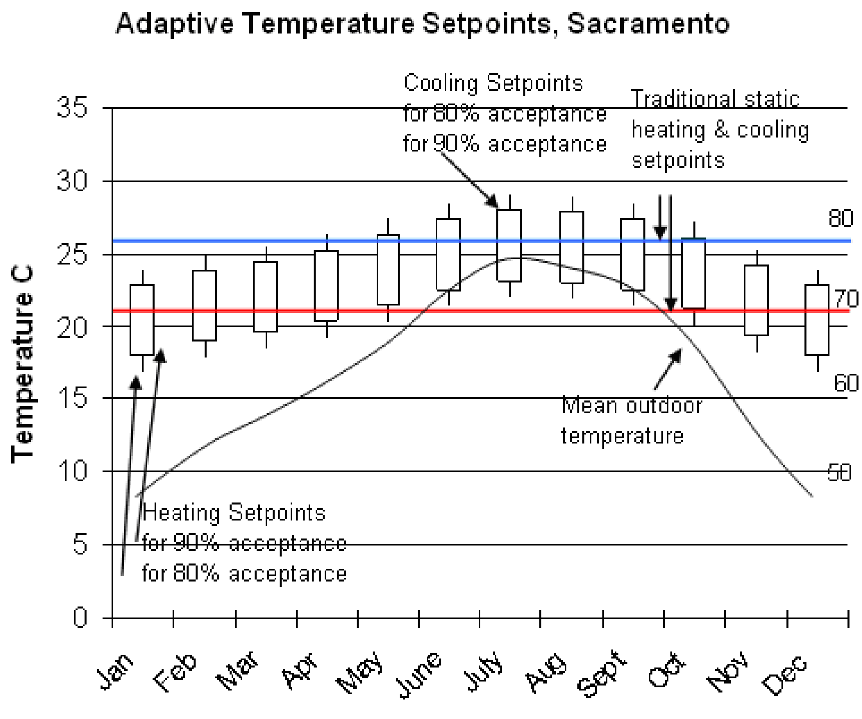
Another reason for establishing new standards is that thermal comfort varies among people. For instance, females often prefer higher room temperatures than males, and feel both uncomfortably cold and uncomfortably hot more often than males[23]. Since residential houses can be occupied by fewer people than commercial buildings, which consider the average thermal comfort, individual differences on thermal preference is not negligible for the controls. Due to these reasons, we adopt different standards to evaluate thermal comfort for residential buildings.

There are six factors that influence thermal comfort: air temperature, humidity, air speed, radiation, metabolic rate (Met), and clothing value (Clo)[24]. In a naturally ventilated building, we also consider outside conditions, namely temperature and humidity. However, limited sensing in the current system platform restricts the way to evaluate these factors. The new standard needs to be established based on available information, including sensed indoor temperature, possibly humidity, and outdoor conditions collected from a weather station.

At present, no thermal comfort standard exists for the residential sector. The Adaptive Comfort Standard (ACS) from ASHRAE 55-2004 has been suggested as most appropriate since it is based on buildings with natural ventilations[24, 25]. The ACS suggests that people adapt to indoor temperature based on the average outdoor temperature for the previous month. Two studies in residential buildings support this approach; one with manual thermostat control and the other with a programmable thermostat showing a seasonal variation in temperature[26, 27]. An example of ACS-based temperature setpoints for Sacramento, California's climate is shown in figure 2.7[11]. The default temperature setpoint for occupied homes with an EnergyStar programmable thermostat is 78F (25.5C); by contrast, in July and August when the outside temperature reaches 100F (37.8C), the adaptive thermostat temperature setpoint might drift to 82F (27.8C). Based on ACS, this temperature is expected to be within the range of comfortable temperatures or comfort zone of most people, and it also represents a savings in energy.

The ASC only involves users' thermal adaption to outdoor conditions without considering the individual thermal preference. Ideally, an intelligent thermal control system is capable of learning this by observing setpoint changes made by users. With the learning results, it could adjust the setpoint or reset it based on time of day and day of the week. For example, if a user lowers temperature setpoints around 6 p.m. occasionally, the thermostat should remember this and adjust the setpoint automatically everyday at 6 p.m. There are several learning methodologies that might be applied to this problem. But this is not within the scope of this thesis.

Figure 2.7: ACS-based Temperature Setpoints



Source: DR phase II project report [11]

Combining ASC and the functionality of thermal comfort preference learning, a reasonable standard could be established to evaluate thermal comfort numerically. This is crucial for the control system to make trade-offs between energy cost and thermal comfort.

In addition to the six factors mentioned above that influence thermal comfort, people are sensitive to the rate at which temperature shifts. People detect quick temperature changes, but may not detect small fluctuation of temperature over a long period. This interesting phenomenon provides opportunities for control systems to make energy savings. An algorithm called "straw curve" was designed and tested[28]. And it makes appropriate energy savings by slightly modifying setpoint periodically.

Economic Sensitivity

Another human factor is the way people think about money and comfort. In the context of DR, users' sensitivity to electricity price would affect the control decisions dramatically.

Here is how people make different decisions when responding to price changes. In a summer afternoon, when price goes up from 20 cents to 50 cents, some families may turn up the setpoint by 1F or 2F in order to have some cost savings. Some do not care to pay more to keep the same temperature unless the price is much higher, say 70 cents. Some would like to maintain the maximum comfort regardless of the price. Instead of modifying setpoints manually every time the price changes, users need the interior space conditioning system to respond to price signals automatically based on their own economic preferences. Besides mimicking the operations of human being, the control system could do an even better job than human beings by calculating the optimal control settings to minimize cost as well as maximize comfort, through a complex process of decision making.

To customize the trade-off between cost and comfort, the first step is to get a user's economic sensitivity. There are several ways to obtain the information from users. One possibility is to query the total electricity budget for a month. One month's cost is easily understood by users, but it is hard for a controller to explain this information and extract users' sensitivity to prices. Another way is to query users their preferred temperature corresponding to an electricity price or a range of price directly. One shortcoming of the method is that users might not know the consequences of their choices: the monthly bill may be different from their expectation. A controller could compensate for this by making a rough estimation of a monthly bill, although this is not an easy task. Another drawback is that it needs a certain amount of inputs from users.

In the current work, we propose to use one variable, the "economics index," as the index of economic sense. It is a user-specified term used in the controller optimization. Ranging from 0 to 1, it equals 1 when users would like to maintain 100% comfort without considering price. It is 0 when only minimum comfort is maintained, and the users would like to keep the cost to no more than they would have spent if there were no increase in price. The default value 0.5 indicates a common case under TOU tariff: users are sensitive to price when price changes from medium level to high level so that setpoints are adjusted moderately. To help users understand the use of the economics index, the corresponding comfort level and cost changes are shown. Users' acceptance of this method is still under investigation. A detailed algorithm of optimization using economics index is in Chapter 4.

Chapter 3

Validation Tools

To validate the hypothesis made in the control strategy design and evaluate the performance of the interior space conditioning system, including infrastructure, hardware and control strategies, several tools are used including computer simulations and real-time tests.

Computer programs are able to simulate the whole process of demand-responsive interior space conditioning, including thermal dynamics of houses and HVAC systems, behavior of human beings and dynamic rates. Simulations are chosen as validation methods because field testing in a range of real California houses is costly, considering the expenses to instrument the houses and log data, the long periods of time required to run the tests, and the variability of weather conditions. Further, because we are concerned with the load reducing and shifting performances of control strategies during peak load periods, simulations also provide opportunities to repeat tests using different controls over the same weather data. In other words, as quick and convenient instruments, computer simulations provide comparable and controllable results for system strategy validation and evaluation.

In addition to computer environments, the system was tested in real residential houses as well. In the field tests, the system interacted with real life scenes for weeks. Stability and consistency of the system were examined. Effectiveness and efficiency of the control strategies are evaluated. Interesting concerns were raised about the system design. Furthermore, feedback from volunteer users provided valuable insight to improve the technology.

3.1 Price Generator

3.1.1 Introduction

As stated in section 2.2.1, the key to promote Demand Response technology to thousands of residential customers is the dynamic electricity price. High price has the effect of regulating electricity demand and avoiding shortages of electrical energy. Instead of getting actual price signals from the public utility, such as PG&E and South California Edison, I developed a simulation tool – a price generator to simulate the dynamic electricity rates. Two types of price signals are generated: time-of-use rate with critical-peak price, and dynamic four-level rates. In addition, it is convenient to modify the price generator to simulate other forms of dynamic rates. Combined with other simulation instruments, we are able to observe the controller's responses to the DR tariff.

Here are the definitions of two types of rates generated by the price generator.

- Static Time-of-Use Rate with Dynamic Critical-Peak-Price (TOU with CPP): As the basis of the rates, TOU rates are in fixed schedules, which are reset seasonally. Added to the base rates, critical peak price (CPP) is dispatched during medium and high price periods for a maximum of 50 hours per year, with a non-fixed schedule. CPP signals are delivered in advance by several hours.

- Dynamic Four-Level Rate: Dynamic schedules of low, medium, high and critical peak price are delivered in advance by several hours.

3.1.2 Method

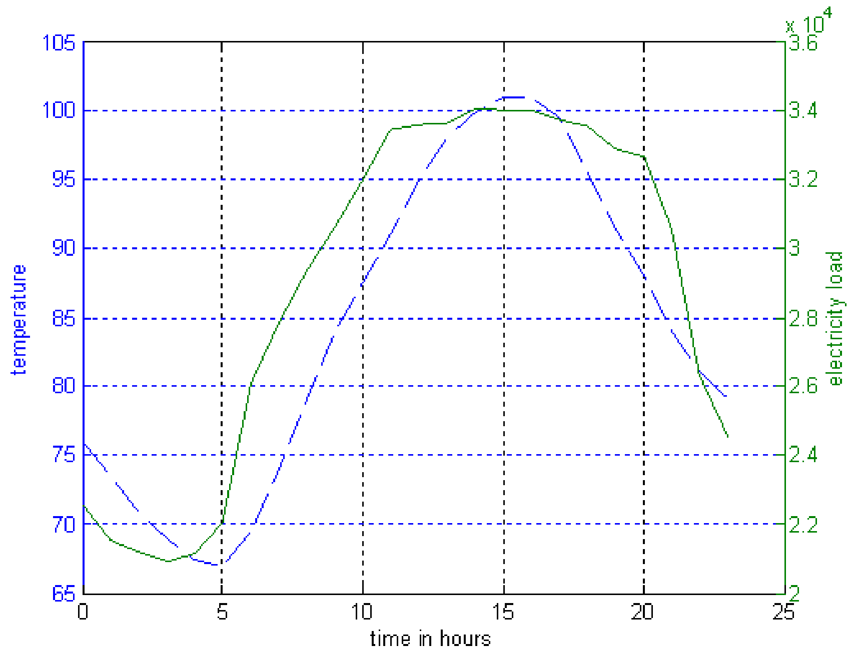
To simulate price signals, a model of electricity rates is developed based on meteorology, in particular, temperature, and some randomly-generated events that simulate the malfunctions or maintenance of electricity generation or transmission systems. It is important to note that I am not attempting to replicate the pricing procedures used by public utility companies. The actual procedures of utility pricing are much more complex. Our goal here is to use a simple model to simulate the complex procedures and to produce a reasonable-looking price pattern to evaluate interior space conditioning strategies.

Here is the basic idea of price generator. By analyzing hourly data of outside temperature and electricity usage using statistical methods, a correlation is observed. There is an inevitable relationship between electricity usage and electricity retail price in the context of DR. Based on these observations, models are developed to simulate these relationships. Randomly-generated events are added into the simulation to mimic the emergency cases of short-of-energy, such as equipment failures.

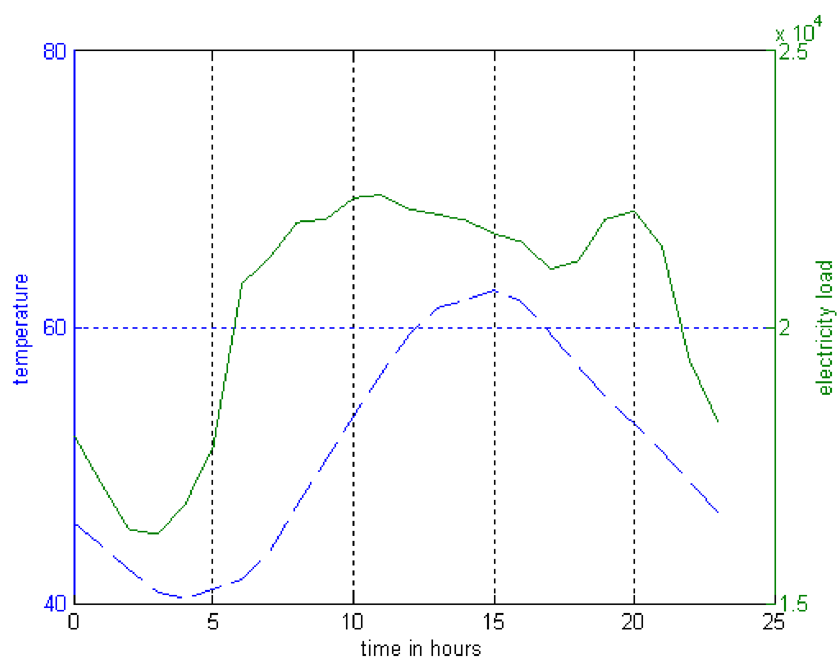
The price generator generates price signals in four steps. First, it simulates electricity loads given outdoor temperatures. I used another simulation tool, Energy-10[1], to generate hourly electricity usage given outside temperature for a typical California house. Energy-10 simulates the whole-building energy consumption for 8760 hours per year, including day lighting, ventilation, air-conditioning/heating and utility loads.

[1]ENERGRY-10 is a building energy simulation program for small commercial and residential buildings.[29]

Figure 3.1: Relations of Temperature and Electricity Loads



(a) Summer Case



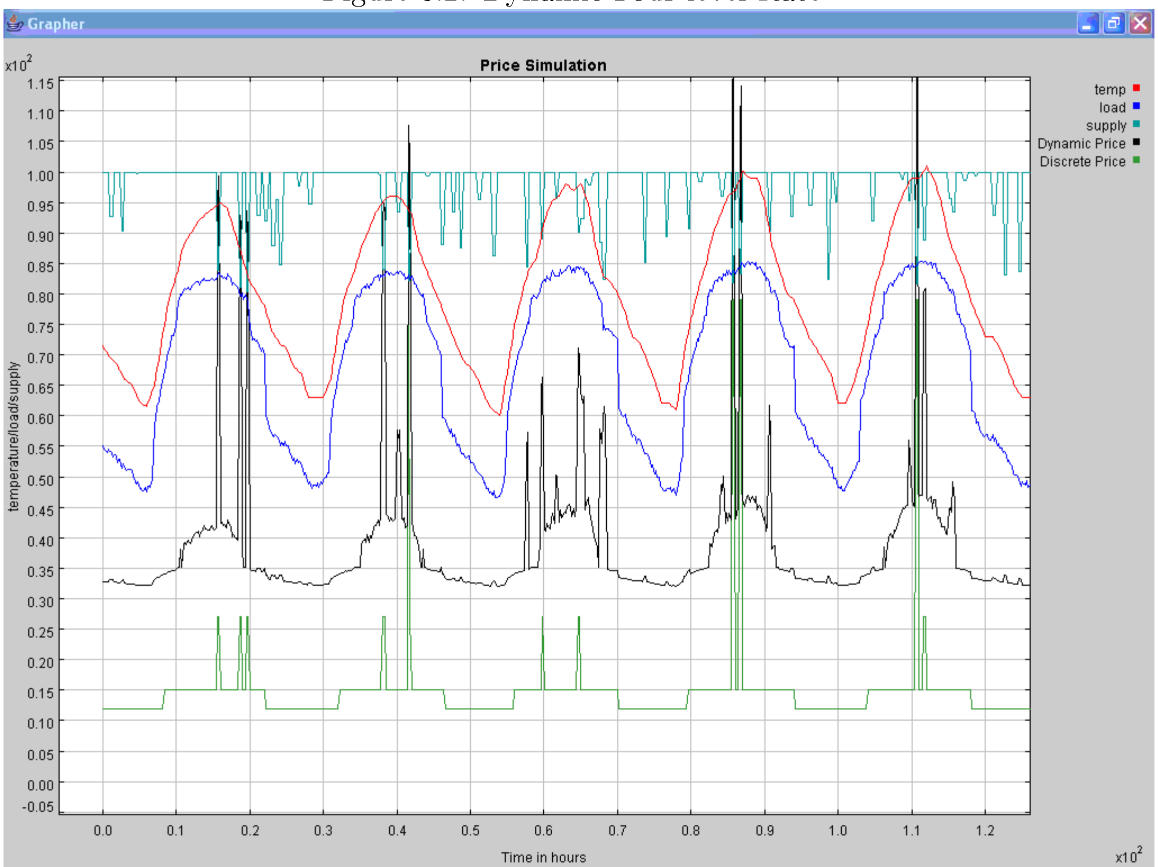
(b) Spring/Autumn/Winter

According to these data, the nonlinear models of electricity loads given temperature are developed. Because electricity load varies across season, models are developed for different seasons. Plots in figure 3.1 are the relationships of outdoor temperature and electricity loads for summer and spring/autumn/winter. Second, it generates electricity supply represented by the percentage of power capacity. Randomly-generated negative impulses simulate the electricity shortage caused by equipment maintenance, malfunctions or other situations that interrupt the supply. These interruptions might happen on schedule or unexpectedly. Third, it generates retail price based on defined pricing policies. The ratio of electricity demand and supply reflects the actual cost of electricity, which is usually represented by the wholesale price. With the ratio, rules were defined to generate retail price. Finally, it set the notice intervals when the dynamic rate is delivered in advance. The range is from one hour ahead to one day ahead. Figure 3.2 and 3.3 present the whole process for both the DR tariff simulations over five summer days. The green curves are the final price signals and the other curves are the intermediate signals generated during the process.

In order to compare different control strategies, identical weather and price sequences should be applied as working conditions. The price generator is able to generate identical time sequences of electricity price given identical weather inputs without losing randomly-generated-events functions. In other words, the price generator could generate the same random sequences with the same weather inputs.

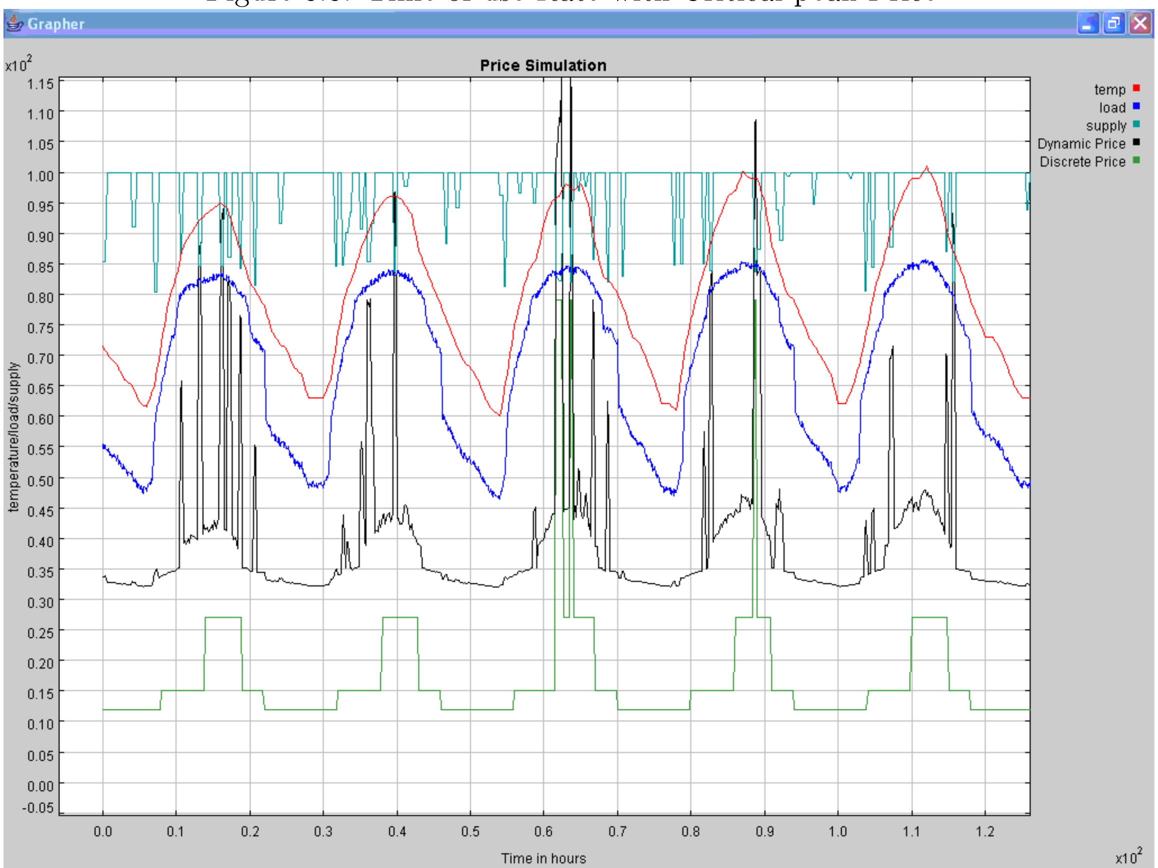
The price generator has been used in both computer simulations and in real house tests. In computer simulations, historical weather data were used as inputs to the price generator. In field tests, we fed hourly weather data forecasted one day ahead by a weather station to generate price sequences. The price generator generated reasonable electricity price signals successfully.

Figure 3.2: Dynamic Four-level Rate



Set different thresholds for low, medium, high and critical price and generate discrete prices (green line).

Figure 3.3: Time-of-use Rate with Critical-peak Price



Based on time of use (TOU) schedule, additional critical peak price is generated from the demand-to-supply ratios. Set fixed rate that changes seasonally for low, medium and high price; when demand-to-supply ratio is over a threshold, critical peak price is triggered.

3.2 House Simulation: MZEST

We use the Multi-Zone Energy Simulation Tool (MZEST) to simulate the energy use of houses. MZEST is a multi-zone extension of the simulation code California Non-Residential Engine (CNE). CNE is used by the CALRES program, which is mandated by the California Energy Commission for showing compliance to California's Title-24 Building Energy Standard in residential buildings. We chose MZEST because it can predict the temperature in several thermal zones and because we had access to the source code.

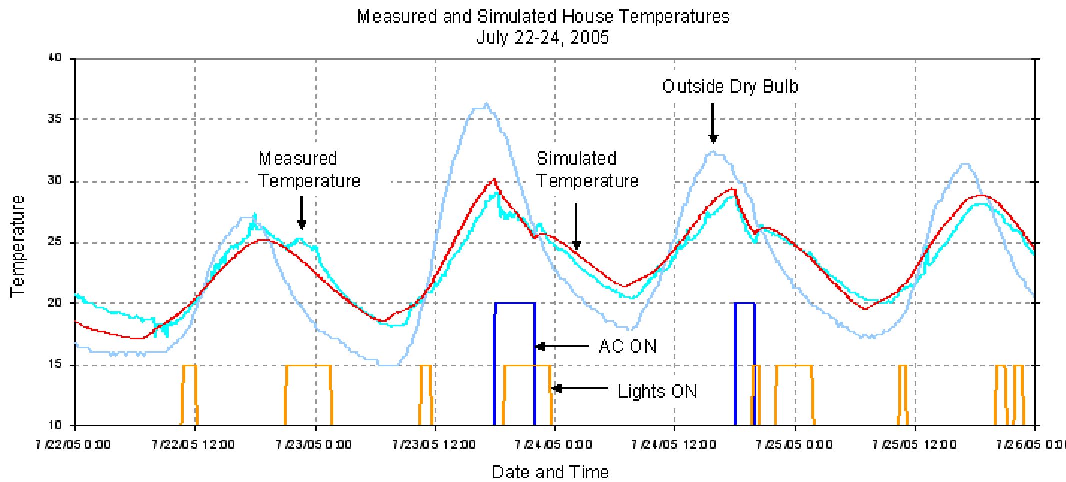
The interior space conditioning system can run MZEST the same way it runs a real house. Based on users' settings, weather conditions and room temperatures, the control system dictates to MZEST whether the HVAC equipments are on or off. MZEST then computes the next-step multi-room temperatures and provides these temperatures to the control system. Hourly climate data necessary for the computation are fed to MZEST. The data are either from TMY2 climate files or real data collected from test houses. Currently, the control system heats or cools the MZEST house to meet the needs of only one zone (the control zone). The other zones are conditioned, but will generally not exactly meet the setpoint, especially if there are large internal gains or some other influence on the temperature of the zones. This is exactly the same case as in central conditioning houses. The control system interfaces with MZEST in an iterative loop by a 5-minute time step. The timing allows us to use an external controller to control it with the same timing as in a real house. The communication between the controller and MZEST is via XML data transfer.

To construct a house model in MZEST, we need to specify house construction parameters in an input file, including insulation values, specific heat capacity of materials, infiltration rates, and adjacencies of rooms or zones. The exact shading coefficient per hour of all windows may be specified. Internal gains, such as equipment and occupant schedules, are also specified as a multiplier. The efficiency of HVAC equipment may be specified as well. The output of MZEST includes several types of report spreadsheets and graphs depicting energy use, cost, and so on. But for the interior space conditioning, only room temperatures are delivered.

We developed a house model using data collected from an occupied residential house in California. It is the basic house model that is used for further expansion. The physical characteristics of the house are described in the next section. The house was inspected and measured with respect to the knowledge needed to build a model in MZEST. By specifying this information and tuning unknown parameters, the house model shows similar thermal behavior as the real house it mimics. Figure 3.4 [30] compares the measured indoor temperature (in light blue) and the simulated indoor temperature (in red) by MZEST given the same HVAC operations. The two sets of temperature curves match closely with each other, including the periods when the AC is on and off. This showed that MZEST is able to simulate the thermal behavior of a real house and its HVAC systems. The detailed work was stated in the thesis "Distributed Sensing and Controlling of Residential HVAC Systems for Thermal Comfort, Demand Response, and Reduced Annual Energy Consumption"[30].

To check the effectiveness of demand responsive control strategies on typical California residential houses, a single MZEST house model is not enough. Based on the analysis of California house characteristics (section 2.2.2), we approximated the spectrum of California houses using four construction types. The house model developed previously is used as the base. First, house parameters were modified to represent typical characteristics of a generic house built before the Title-24 energy efficiency standards were implemented. This modeled house is assumed to be poorly

Figure 3.4: Measured and Simulated Indoor Temperature

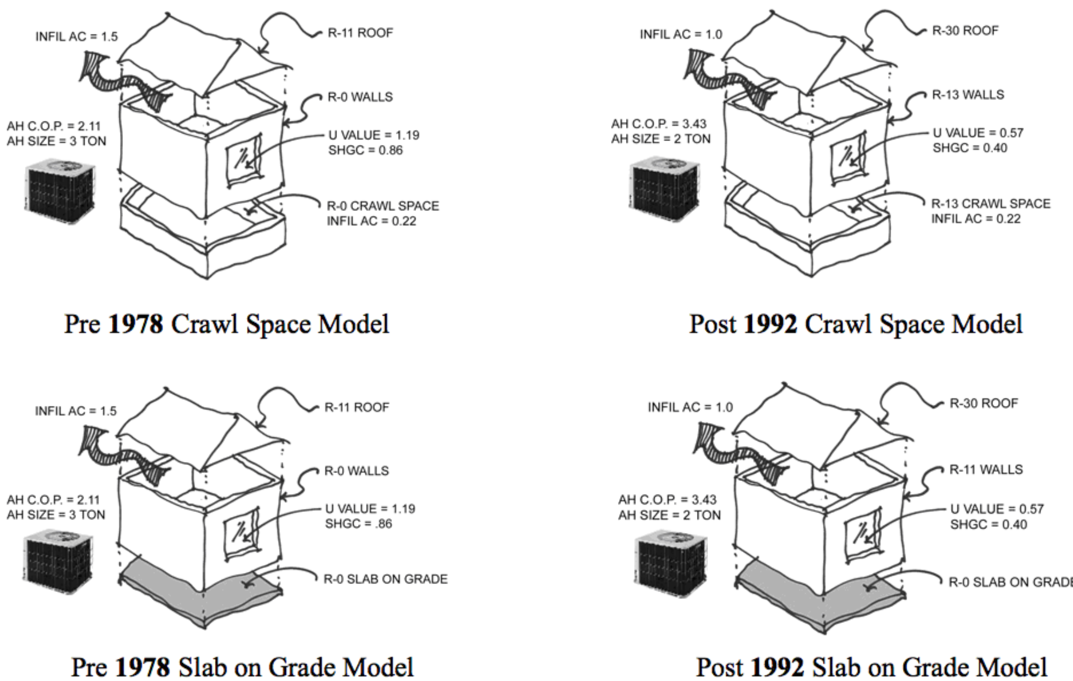


insulated, with single-pane windows and equipment efficiencies typical of the 1970s. To represent the opposite extreme, a post-1992 model was developed representing a generic house with windows, insulation values and equipment efficiency meeting the minimum for Title-24 compliance. Further, because of the important role that thermal mass plays in the attenuation of heating loads, both a crawl-space model and a slab-on-grade version were created for each category (see figure 3.5 [11]). These house models in MZEST enable us to evaluate the effect of the demand responsive autonomous control strategies on a wide variety of houses located in any California climate zone.

3.3 Field Tests

After feeding back the system design by computer simulations, the next step is to deploy the interior space conditioning system in an actual occupied house with multiple residents, and test the system over several weeks. The purposes are to evaluate the

Figure 3.5: Four Typical House Models in California



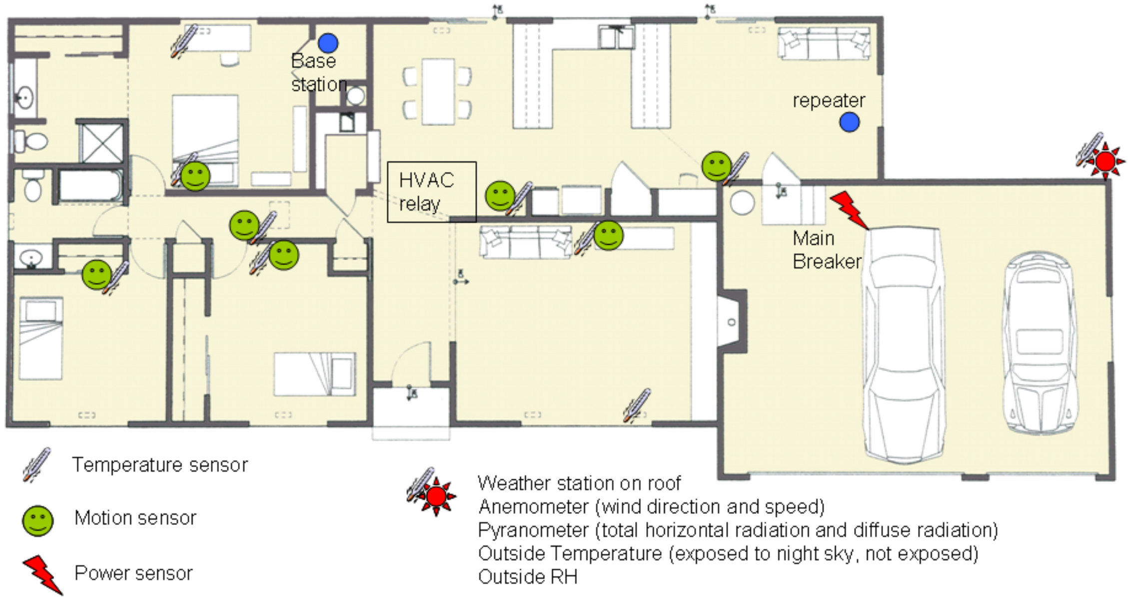
Source: Hand-drawing by Kyle Konis, Architechture Department, University of California, Berkeley system infrastructure, validate the results obtained from simulations, and get feedback from users. We have performed a few field tests over the past four years. Each test had its own focus and provided insightful feedback to evaluate different aspects of the system.

3.3.1 Long-term Field Tests

We ran long-term tests in a single-family house from summer 2004 to spring 2006. The purpose is to validate the infrastructure of the system before complex control strategies are deployed. The house is located southeast of Berkeley, California in a climate that requires both air conditioning in summer and heating in winter. The single-story house has 1825 square feet. It has three bedrooms and two bathrooms; the long axis of the house runs north-south. The east-facing windows are protected from solar exposure by trees and the porch roof; however the west-facing windows catch the full brunt of the sun's rays in the afternoon. The house was built in 1968 with un-insulated floors and walls and single-paned windows; the ceiling has recently been insulated. The packaged HVAC unit sits on the ground outside, and it supplies conditioned air via multiple floor vents distributed throughout the house.

In total, we ran more than twenty tests and each test lasted from days to a few months. The system collected multiple sets of sensing data through a wireless network using 13 motes installed in the house. Figure 3.6 [10] shows the house plan with the final configuration of distributed indoor sensors (motion, air temperature, global temperature, relative humidity, power sensing) and outdoor weather station. Data were stored in local and remote databases. Close loop controls were performed on its air conditioning system. A virtual network connection was set up to monitor the system remotely. The system software was amended after each test and then was tested again. We located and fixed program bugs and modified the methods

Figure 3.6: Plan of Test House Showing Location of Sensors and Actuators



of communication and data transfer. The usability and stability of the system in a real-life environment were improved dramatically.

In addition, we inspected and measured the house construction. Combined with sensed data, a house model was developed in MZEST as the basic model (section 3.2).

3.3.2 2007 Summer Test

The interior space conditioning system was tested in two occupied houses during summer 2007. The purposes of the tests were to test the functionalities of the system, to verify simulation results of control strategies, and to get feedback from participants. Two single-family houses participated in the tests, in which the occupants use their air conditioning during the summer months. Located about 40 miles northwest of Berkeley, the two houses were exposed to similar outdoor conditions, but the house structure, HVAC system and residents' schedules are different. These diversities offered the opportunity to test the system under different conditions.

House 1 is a 1700-square-foot two-story stucco house built in 1991 with two occupants. Three ceiling fans are controlled manually in the living room, kitchen and master bedroom. The HVAC system is a Carrier split system air conditioner/furnace, with supply grilles in the floor throughout the house. The house is occupied most of the time except for irregular hours during the day when the occupants leave for business. The owners reported that they normally keep the setpoint as 74F for both daytime and night, and when they leave and remember to offset the temperature, they set the thermostat to 79F. Participants open the windows (upstairs) at night and close the windows during the day. The main electrical appliances are the clothes washer and dryer.

House 2 is a 1500-square-foot one-story house built in 1984. One ceiling fan continuously runs in the family room. The HVAC system is a General Electric split system air conditioner/furnace, with supply grilles in the ceiling. The house has two skylights in the roof and an attic fan. The two occupants are 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 look at the weather forecast for the day to decide whether or not to use the air conditioning. Usually the setpoint during the day is 70F, and lowered in the evening, and turned off at night. If the weather is hot, the setpoint is 68F and 70F at night to pre-cool the house manually. The participants open up the house at night; two windows are opened during the day as well.

Fourteen and 15 motes were installed in house 1 and house 2 respectively. An additional repeater mote is necessary for house 2 to relay the data from the outside mote to the base mote due to the large size of the house. Table 3.1 lists the details of sensors installed in the two test houses. A plastic sheet was designed to attach a mote to a light switch (figure 3.7), allowing temperature sensors to be read at approximately

Table 3.1: Information of Motes Installed in Test Houses

Information	Location
Temperature	Distributed in all the rooms at the same height approximately
Temperature	In the supply grille in the ceiling of the living room, to sense temperature of HVAC supply air
Relative Humidity	In the control zone (living room for house 1 and bedroom for house 2)
Motion	Near the entrance to the house to detect the occupancy
Temperature	Outside under the southeast eave of the roof
Relative Humidity	Outside under the southeast eave of the roof
Solar Radiation	On top of the roof
Power	At the air conditioner circuit breaker
Power	At the main circuit breaker panel, measuring current from the blower fan, dishwasher, the clothes washer, clothes dryer, the kitchen, and on both main branches of the panel

the same height. Actuation motes are installed to relay HVAC equipments and switch between the original thermostat and our tested interior space conditioning system. A price indicator mote shows price information to users.

We used an ultra mobile PC–the Samsung Q1—to host both the controller and the user interface. The size of the computer is slightly larger than a programmable thermostat, and the touchscreen made it ideal for user input. The computer is shown in figure 3.8.

The total time for the tests was approximately six weeks. The test in house 1 began two weeks earlier than the test in house 2, leaving time to fix problems if any occurred in test 1. Each test was divided into three phases as described in table 3.2,

Figure 3.7: Example of Generic Mote Installation

Figure 3.8: The Controller and Interface

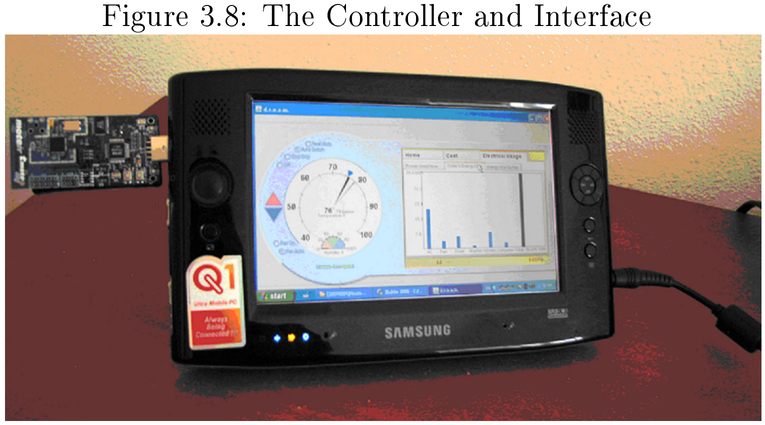


Table 3.2: Field Test Plan

Name	Length	Description
System check out period	1 week	The system monitors temperature, occupancy status, electricity use, and HVAC status under the control of original thermostat. The purpose is to learn participants' temperature preference at different time of a day and evaluate default house model and AC efficiency.
Mimicking period	2 days	The system controls the HVAC system in the same manner as the original thermostat. This period is for testing the actuation functions and training the occupants to interact with the system user interface.
Testing period	5 weeks	The HVAC system is completely under the control of the interior space conditioning system. Test focuses on the optimal control and house model learning: 1) Validate the learned house model by comparing predicted indoor temperature with actual temperature. 2) Validate the strategy transition when price or occupancy status changes. 3) Compare the optimization performance (setpoint) under different values of economics index, using default house model or learned house model.

while the communication reliability was continuously monitored. The participants were interviewed before and after the tests to collect information about their energy use habits and to get feedback.

In the tests, we explored the dynamics of the house and its HVAC systems, tested the optimization control strategies, and looked at the potential for a computer to identify the house dynamic signature. The user interface was used by the participants to control the HVAC system. Interesting feedback was collected about its usability. The detailed analysis was described in paper [15].

3.3.3 Large-scale Field Tests

A start up company, Ecofactor, who provides online services for residential thermal controls, is performing field tests in 22 residential houses, which began winter 2007. The tests adopt traditional sensing and actuating methods: a single temperature sensor and wired HVAC control. The main controller and the user interface are running on a remote server. Communication is through the internet. Users are able to monitor and modify their room temperature through a website, which is supported by a large database. Data obtained from the tests were used to identify house thermal characteristics. Designed control strategies were deployed for the purpose of validation and evaluation.

Tests are being executed in both a summer climate and a winter climate. Minneapolis, Minnesota was selected as the first test market to deploy heating controls. Twelve homes are participating in the study. To allow simultaneous deployment of AC control, Adelaide, South Australia was chosen as another test market, although their HVAC systems are not compatible with U.S. –standard thermostats. Equipment difference was compensated during hardware installation. Table 3.3 lists the important characteristics of the two sets of test houses, including information about home structure, HVAC systems, and thermostat system[28].

Several houses participating in the field tests have similar characteristics. In Adelaide tests, five of the homes all built in 1999 are located on the same street (see figure 3.9). Three of them (B, C and D) have identical house structure – same floor plan, construction methods, etc. In addition, houses C and D have the same orientation. Their exposure to the sun is essentially identical. Similarly, houses A and E have identical house structure and orientation. The similarity among these houses offers possibilities to validate the performance of control strategies: in one house, the treatment, or the control strategy being tested, is applied; in the other, the control,

Table 3.3: Minnesota and Adelaide Test Houses

	Minnesota	Adelaide
Number of houses	12	10
Year built	Ranging from 1937 to 1987 with an average age of 42 years.	Average age is 31 years. One was built in 1980. Five were built in 1999. The other four are unknow.
House structure	House size ranges from 946 to 2204 square feet, with an average of 1300 square feet. All have insulations in both the attic and the walls. Ten homes are primarily wood; 1 is primarily masonry; 1 is unknown.	Five homes located on the same street have similar structure.
HVAC system	Each home uses one single-stage natural gas furnace. Five furnaces are less than five years old, five are 5-10 years old, and one each is 10-20 years and more than 20 years old.	Each home has a single-stage A/C-heat pump unit. Five of the homes have AC units that are less than 10 years old, 3 are less than 5 years old, one is a recently refurbished unit and one homeowner is not sure how old his unit is.
Thermostat	Nine out of 12 homes had programmable thermostat perviously.	All 10 homeowners previously had programmable thermostats

the strategy is not applied.

Large-scale field tests are able to provide convincing results about the performance of the control strategies. Many different kinds of common houses with various occupants were subjected to the tests for several months under normal and extreme weather conditions. Therefore, we were able to evaluate control strategies more extensively and more completely. We noticed that houses responded differently to the same control strategy. Under certain conditions, the diversity is non-trivial. This confirms the necessity and importance of customizing control strategies for each house.

Figure 3.9: Similar houses in field tests, located on the same street

Source: Ecofactor white paper, May, 2008[28]

Further, for the best case and worst case, we explored what worked and what did not work and amended the controller design.

Chapter 4

Optimization Control in Interior Space Conditioning

4.1 Problem Description

Interior space conditioning is a type of temperature regulation by HVAC control. The objective is to minimize electricity cost while creating a comfortable interior thermal environment for a whole billing period. Although thermal comfort and electricity cost are affected by many factors, only indoor temperature is controllable by common residential HVAC systems. In fact, indoor temperature is determined by controller settings, i.e. temperature setpoint.

Of the most interest is the competitive relation between minimizing cost and maximizing thermal comfort. Specifically, it is costly to achieve the most comfort all the time, especially when electricity price is high. Meanwhile, users are able to realize cost savings if they sacrifice a little comfort, by increasing setpoint in summer or decreasing setpoint in winter. Therefore, we consider the problem of interior space conditioning as an optimization problem.

Optimization problems refer to the problems "in which one seeks to minimize or maximize a real function by systematically choosing the values of real or integer variables from within an allowed set"[31]. The real function is called the *utility function*, or the *cost function*. It is a qualitative measure of objectives. And the allowed set is usually represented by a set of constraint functions. To formulate an optimization problem, we need to define both utility function and constraints.

Under the context of interior space conditioning, the optimization problem is formulated as following.

$$U = \sum_{i=1}^{N} h(C(T_s) * p(i), g(T_s))\Delta t = \sum_{i=1}^{N} h(cost, comfort)\Delta t \tag{4.1}$$

s.t. T_s is acceptable and achievale.

where

$$cost = C(T_s) * p(i)$$

and

$$comfort = g(T_s)$$

The variable U is the overall utility in a billing period; Δt is the time interval, typically equal to the smallest time window over which controller settings change, e.g. 0.5 hour; N is the number of the time intervals in a billing period. $C(\cdot)$ is electricity consumption, as a function of setpoints T_s; p is the electricity price within the time interval i; $g(\cdot)$ is the function of thermal comfort index, which is also determined by temperature setpoints. Here I use the adaptive comfort standard proposed in section 2.2.3. Of the most importance is the function $h(\cdot)$, a self-defined function, which indicates the trade-off relationship between electricity cost and users' thermal comfort. There are many ways to define $h(\cdot)$. For example, a straightforward way is to define $h(\cdot)$ as polynomial functions of comfort index and cost, such as the forms defined in equation 4.2 and 4.3.

$$h = (1 - \alpha) * cost + \alpha * (1 - comfort) \tag{4.2}$$

$$h = \beta_1 * cost^2 + \beta_2 * cost + \beta_3 * (1 - comfort)^3 + \beta_4 * (1 - comfort) \tag{4.3}$$

Equation 4.2 defines a linear trade-off between cost and comfort. Different values of α indicate different weights we apply to comfort and cost during optimization. Intuitively its values imply users' sensitivity to price. It has the same effects as the economics index defined in section 2.2.3. A complex form in equation 4.3 implies another trade-off relation between cost and comfort. Parameters β_1, β_2, β_3 and β_4 work as optimization weights for each term as well. $h(\cdot)$ may be defined in any form to express various trade-off profiles between heating/cooling cost and users' thermal comfort.

The values of input variables, a sequence of setpoints, are limited by several constraints. First, they need to be in the endurable temperature range set by users. It may be time variant and price variant. In other words, the acceptable temperature range changes when the electricity rate changes or at different times of day. Choice of optimal setpoints is also constrained by practical implementation. They need to be achievable. If indoor temperature can not reach the optimal setpoint, the optimal setting is not a practical solution.

Optimal temperature setpoints are determined by minimizing the utility function, but this is not the whole story. The system needs to make an effort to realize those settings precisely and efficiently. The typical methods are ON/OFF control or bang-bang control. The controller coordinates the operations of heater/AC and fan to improve energy efficiency. Anticipating function is adopted, in which the heater or the air conditioner is turning off slightly early to prevent the space temperature from greatly overshooting the thermostat setting. Minimum-OFF-time controls for heating/cooling equipment are required to avoid excessive actuations and therefore extend their working lives.

In summary, the optimization problem in interior space conditioning is realized by two levels of control: supervisory control functions and local control functions. The responsibility of top level, supervisory control, is to determine the optimal control settings, specifically a sequence of setpoints that minimize an overall utility function defined in the form of equation 4.1. As low level control, local control functions are the basic temperature controls that allow HVAC systems to operate properly and provide adequate services to realize the temperature setpoints decided by supervisory control. The whole control process is in a hierarchical structure. This thesis focused on the design and the implementation of supervisory control. Local control is described in Jahwi Jang's thesis [32]and the project report [11].

4.2 Theoretical Background

Before describing the design of supervisory control strategies, I will introduce some concepts and methodologies adopted in the supervisory control in the field of interior space conditioning.

4.2.1 Introduction of Supervisory Control

Supervisory control in a controller is usually the top-layer functions that determine the control settings based on overall functionalities or objectives of a control system. The control settings are not the final output of the controller. Instead, they are the goals for the lower-layer controller to achieve.

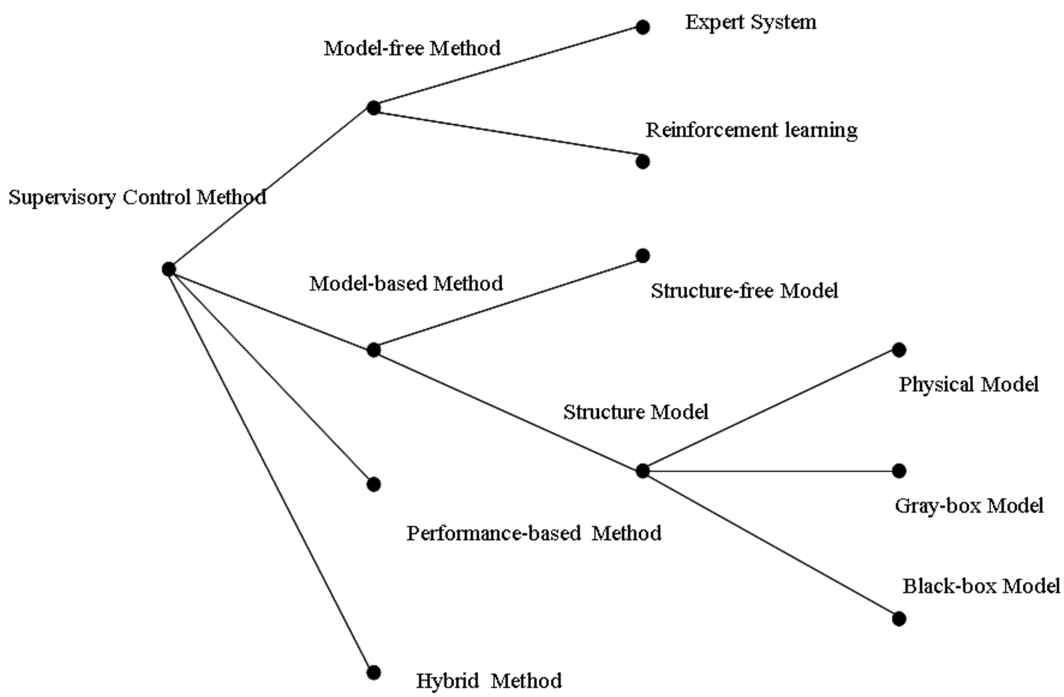
The development of supervisory control in building temperature controls has evolved over time[33]. The earliest supervisory control emphasized the equipment automation to save labor. Later, it stressed the building energy monitoring as well as automatic control. Yet little attention was paid to energy efficiency and cost effectiveness. Nowadays, due to the shortages of energy supply, supervisory control highlights the overall performance improvement of the system involving energy/cost efficiency and users' thermal comfort.

Due to such design concerns, supervisory control is often named optimal control. It seeks optimal solutions of controller settings to minimize operating cost while still providing adequate indoor comfort. A well-defined utility function presents the objective. In the current design, supervisory control also takes into account the ever-changing indoor and outdoor conditions as well as the characteristics of the building and HVAC systems. Remember in Section 2.2 "Other Issues Involved" it is stated that all these components produce a non-trivial impact on the control performance. Supervisory control allows a comprehensive consideration of their characteristics and interactions. Knowledge of these components can be utilized to achieve better predictions about how the building responds to certain control settings, which would improve system autonomy and enlarge energy/cost savings. Global optimization techniques are utilized to locate optimal control settings without violating the operating constraints of each component.

4.2.2 Methodologies

A few research projects addressed the approaches for supervisory optimal control on HVAC operations[34, 35]. According to these previous studies, methodologies of supervisory control could be classified into four categories: model-free supervisory control method, model-based supervisory control method, performance-based super-

Figure 4.1: Supervisory Control Method Classifications



visory control method and hybrid supervisory control method. Each method has further classifications. The details are shown in figure 4.1. Each method has its advantages and disadvantages in relation to the other methods.

Model-free Supervisory Control Method

As the name implies, model-free supervisory control methods do not require a "model" of the target system or component. Here, the model refers to a numerical model specifically. There are several approaches that do not use any model in the optimal control process, including expert system, reinforcement learning[36] and experiment-based control for specific HVAC systems[37].

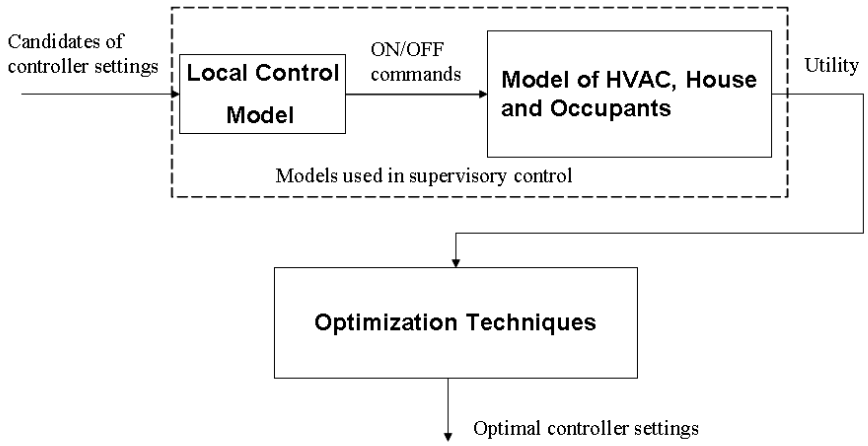
I will introduce the details of expert system as one example of model-free method. An expert system imitates the logic reasoning processes of human experts to make decisions for a certain type of problem[38]. Typically, such a system contains a knowledge base involving facts and a set of reasoning rules. Given a particular situation, the system applies the knowledge base and simulates the decision making of human beings. It is even capable of deducing reasonable solutions with incomplete or partially wrong working conditions, as a real human being can do. In the field of interior space conditioning, an expert system could be adopted to decide controller settings given indoor and outdoor conditions. For example, it could be used to choose the control mode as cooling or heating.

Compared with other supervisory control methods, an expert system is easy to implement, maintain and use. However, its applications are limited by the richness of the knowledge base. If a set of given conditions are outside the knowledge base, the expert system might make significant error. In other words, it does not have the ability to expend the reasoning to unseen situations.

Model-based Supervisory Control Method

In model-based supervisory control methods, the controller needs two tools: models of the controlled system and optimization techniques. Numerical models for the target system and/or its components are required to predict their behavior under certain control settings. With the prediction, optimization algorithms are utilized to seek the optimal control parameters that minimize or maximize the utility function, which is a form of evaluation of control performance. Figure 4.2 illustrates this idea in the context of interior space conditioning. A model of local control simulates the operation of low level control functions given control settings from the supervisory level. It determines a series of ON/OFF commands that actuate the control targets, HVAC systems. Another model predicts the mixed behavior of the house, its HVAC systems and its occupants under such actuations. Then it outputs two important measures, electricity cost and comfort index, to calculate the utility. Finally, the

Figure 4.2: The model-based supervisory control for interior space conditioning



utility as a function of control settings is delivered to the optimization module to seek optimal solutions. To ensure the models perform as the actual systems, measurements collected online from the controller and the target system are used to tune model parameters. We call this the learning processes. The model-based method is relatively complex to realize, but it could provide quick responses to the changes of indoor and outdoor thermal conditions.

According to the form of models, the model-based supervisory control can be divided into the structure model-based method and the structure-free model-based method. Obviously, implied by its name, structure models are the models that can be written as equations with numerical free parameters. These parameters may or may not have physical significance and need to be identified based on experimental data. Nevertheless structure-free models are in the form of a set of numbers, which are also the model parameters. They are certain meaningful measures that are used to identify the signature of target systems or target processes. A typical structure-free model for interior space conditioning consists of the heating/cooling speed corresponding to different indoor and outdoor conditions. In fact, structure models and structure-free models are essentially the same except the significant difference of their parameter numbers. Generally speaking, structure models only have a few parameters, while in structure-free models hundreds of parameters are required to cover all kinds of working conditions.

Comparing these two model-based methods, they both have their own features. Using structure models, the controller has high prediction performance. But it takes some computation to identify parameters in structure models. Structure-free models do not need complex computation to identify their parameters. However, the models do not cover unseen operating conditions. That is, their prediction abilities are restricted by the richness of experimental data. To compensate for this shortcoming, structure-free models can be modified by identifying the trend of parameter values. Then parameters under any input conditions can be determined based on the trend.

The structure models can be further divided into three types based on the amount of system knowledge used to construct the models: physical model, gray-box model and black-box model.

In physical model-based control, physical models are adopted to predict the system responses to the controller settings. Models are built with prior knowledge of the system, the principles on how the system and its components behave. According to fundamental laws of heat transfer, dynamics, fluids, and other fields, mathematical descriptions of the system are derived. MZEST as a validation tool is indeed an example of a physical model for a house and its HVAC system. Usually, due to the complexity of the target system, physical models are simplified by making reasonable assumptions. Physical model-based methods are capable of producing accurate predictions of thermal behavior and therefore the controller has relatively high performance. Since the unknown parameters have physical meanings, it is easy to identify invalid models. However, the model equations are complicated and have high order, even after being simplified. This results in high computational costs and memory demand in both the processes of learning model parameters and seeking optimal solutions. It is hard to realize the physical model-based supervisory control through an online application.

On the contrary, in black-box model-based methods, models are built without utilizing any kind of prior knowledge of the system. They identify the mathematical relations between input variables and output variables directly based on historical data of the system. To define reasonable black-box models that are easy to build, a model space is required. Simple forms of equations such as polynomials are often chosen to reduce computational costs. Artificial neural network (ANN) is also a common choice of black-box models[39, 40]. Whatever forms the models take, the order of the structure needs to be chosen carefully. High order means a relatively large number of parameters, which demand large sets of training data and long time to learn the models. Moreover, redundant parameters may lead to the over-fitting problems. While low order models are easier to fit, they may not be complicated enough to cover the dynamics of the system. In this case, the models may produce totally wrong predictions. In summary, the selection of model order is a type of trade-off between the computational costs and the prediction ability. Additionally, because the parameters in the models have no physical significance, it is difficult to validate the models. The models are reliable only around operating points covered by training data. They cannot guarantee stable and reliable predictions when the operating points are out of that range. Therefore, large sets of training data are necessary to ensure their performance.

Gray-box models are a kind of compromise between physical models and black-box models. A gray-box model can be developed from either side. From black-box models, it can be derived by incorporating prior knowledge of the system as constraints on parameters or variables. From physical models, it can be achieved by simplifying and combining all the equations. Gray-box model-based supervisory control methods inherit the advantages of both methods as well. The model complexity is low so that models are easy to construct. Computational load is acceptable for achieving optimal solutions. Parameters in the models still have some sense of physical significance. Models have good performance when applied to operating points outside the range of training data. Yet, the performance of the gray-box model-based method still strongly depends on the richness of training data.

Performance-based Supervisory Control Method

Performance-based supervisory control means the controller settings are chosen based on a system's historical performance under similar working schemes. In this method, a performance map is created over the range of expected operating conditions. It records performance index with respect to various input values, such as the electricity cost under different working conditions. The map is obtained by testing the system over a significant range of working conditions or extracting useful information from historical data. With the performance map, the controller picks optimal control settings for future working conditions.

In performance-based methods, performance information is saved in the performance map in a tabular form. Values in the map can be considered as parameters. By analyzing data collected from the system, parameters are identified and tables are filled. Although this idea is similar to structure-free model-based control methods, we catalog them differently due to the different meanings of parameters they used. In structure-free models, the parameters are not necessary to the performance index. They are certain measures that can be used to identify the characteristics of the target systems or processes. Similarly to structure-free models, the parameter identification in performance map is limited by the richness of historical data. Sometimes not all of the values can be obtained. Extrapolation is necessary to fulfill the performance map. If relations (trends) between table values can be identified, the map can be converted into equations.

Performance-based control methods fit for small systems but might not be practical for complex systems. A complex system has more subsystems and constraints and therefore needs multi-dimensional performance tables. It requires considerable effort to fill them. The methods lack generality: tables are designed for particular systems or control objectives. However, the methods are easy to implement and do not need any prior knowledge of the system. The computation load is very low for simple target systems. They are feasible and practical for online applications.

Hybrid Supervisory Control Method

It is obvious that hybrid supervisory control adopts different control methods to realize entire control functions, including different types of models when utilizing model-based methods and/or the combination of model-free methods, model-based methods and performance-based methods. Such design takes advantages of proper features of each method.

4.2.3 Control Design Concerns

There are important factors addressing the nature of supervisory control problems. They should be seriously considered before we deal with the design and the real implementation of control strategies.

- First of all, the effective supervisory optimization strategies for systems with and without energy storage are significantly different. For the former system, we deal with a dynamic process and seek an optimal trajectory of control settings. While for the latter, systems without significant energy storage, the associated optimization is a quasi-steady optimization[34]. Single-point settings are the optimal solution. Accordingly, optimization techniques applied to these two types of problems are also different. As a popular optimization algorithm, dynamic programming can be used for dynamic processes, while static optimization such as direct search is sufficient for quasi-steady optimization problems.

- It is important to note that for systems with significant ability to store energy, the impact of previous controller settings will last for quite a long time, and therefore affect the decision making process for the following periods. For example, a house with significantly large mass is difficult to cool down at night if the setpoint during the day is high, say 85F. In order to create a comfortable environment in the evening, we need to keep indoor temperature lower in the day although the house is not occupied. This idea is useful when control strategies are designed for long durations.

- In practice, usually near-optimal solutions are identified due to several reasons. Among other things, simplified models, assumptions made to simplify the models, and uncertainty of the target systems all could lead to prediction errors when applying model-based control methods and performance-based methods. Inaccurate information about the surroundings is another reason. Poorly predicted future outdoor temperature and unexpected changes of occupancy status would also generate certain prediction errors. Therefore, robustness is required when control strategies are designed.

4.3 Hierarchical Control Strategy Design

4.3.1 Problem Formulation

The supervisory control problem in interior space conditioning is actually an optimization problem. Defined in equation 4.1, the optimization utility is a function of electricity cost and comfort index over a billing period, usually one month. However, the problem is not easily solved due to the long duration it covers. Uncertainties from the house, users and outdoor surroundings impact the control decisions dramatically. Prediction errors in supervisory control algorithms would accumulate and lead to huge errors. User's thermal requirements may vary during such a long period. Unexpected events such as a weekend party may happen. Also, one month future data that are indispensable to determine control settings are usually not reliable or even available. For example, the predicted outdoor conditions are relatively reliable for only the next few hours. Supervisory controller can not make accurate predictions and determine reasonable control settings without convincing information. Moreover, it is not necessary in practice to decide the control settings for a whole month at one time. People mostly care about the settings for the next a couple of hours. Due to these reasons, the original optimization problem is split into short-period optimization sub-problems.

In the new formulation of supervisory optimization control, the utility function has the same format. But each short-period problem covers only a few hours. The length depends on the changing rates of electricity price and users' thermal requirements. Here, I assume these short-period optimization problems are independent of each other. Each sub-problem has its own control objectives: improving energy efficiency, trading electricity cost with thermal comfort, or achieving temperature requirements with minimum cost. Based on control objectives, these sub-problems are classified into four catalogs, or "control states." Considering the difference of operation environment, high-level strategy classes are defined, namely "control mode."

4.3.2 Control Modes and Control States

The top-level control modes are cooling mode and heating mode. Intuitively, such classification is necessary because it is not common to use the heater and the air conditioner at the same time or the same day in a residential house. From a user's perspective, people have different thermal requirements at these two modes. In cooling mode, people are comfortable when the surrounding temperature is below a threshold, say 76F. While in heating mode, people are comfortable if the temperature is higher than a certain point, for example 70F. Even when the temperature is above 76F in a winter afternoon, users usually adjust to the temperature by changing their clothes instead of turning on the air conditioner, as they would do in summer. Therefore, to mimic human behavior, supervisory control makes completely different control settings under cooling mode and heating mode.

At the second level, four control states are defined according to users' requirements on thermal comfort and economics: the normal state, the pre-cooling/pre-heating state, the pre-conditioning state, and the overlapping state. In each control state, a certain control strategy is adopted to meet the specific control objectives. The control strategy determines setpoints and setpoint schedules if necessary, which are realized by local control functions. These four states work differently under cooling or heating mode. Their definitions are summarized in table 4.1.

Normal State

The normal state is defined when there are no changes of electricity price and thermal requirements during the optimization period. Although electricity rate is invariable,

Table 4.1: Control State Design

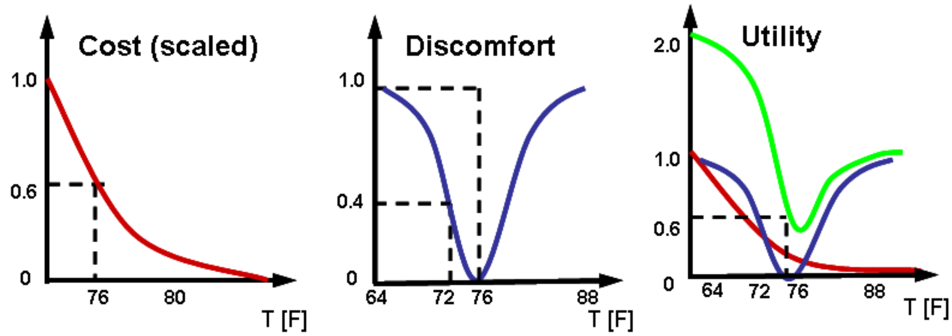
State Name	Definition
Normal	Optimize cost vs. comfort, when there are no changes of electricity price and thermal requirements.
Pre-cooling/Pre-heating	Save cost by shifting load for future price increase period, with a minimum sacrifice of users' comfort.
Pre-conditioning	Achieve an expected temperature just in time, make comfort environment with minimum cost.
Overlapping	Prepare for future comfort or another future price increase when there is a future price increase. The overall cost is minimized under the limitations from both events.

its value could be any TOU or CPP price, i.e. off-peak, partial-peak, peak and critical peak. Supervisory control may make energy/cost savings by sacrificing thermal comfort based on users' willingness. Thus, in the normal state, control strategy is defined to determine a temperature setpoint that optimizes cost and comfort based on the utility function that reflects the trade-off preference of users. Equation 4.4 shows the utility function utilized in the implementation.

$$\begin{aligned} U(T_s) &= (1-e)\cdot cost(T_s) + e\cdot discomfort(T_s) \\ &= (1-e)\cdot power(T_s)\cdot price + e\cdot(1-comfort(T_s)) \end{aligned} \tag{4.4}$$

U is the utility function and T_s is the setpoint candidates that should minimize the utility function. Thermal comfort is determined by the adaptive comfort standard defined in section 2.2.3. It is a percentage number ranging from 0 to 100%. 100% represents the most comfortable temperature, and 0 indicates intolerant environmental conditions. e is the economics index defined in section 2.2.2, ranging from 0 to 1. Electricity cost is calculated by multiplying electricity price by power consumption,

Figure 4.3: Normal State Optimization Strategy



which is a function of temperature setpoint T_s.

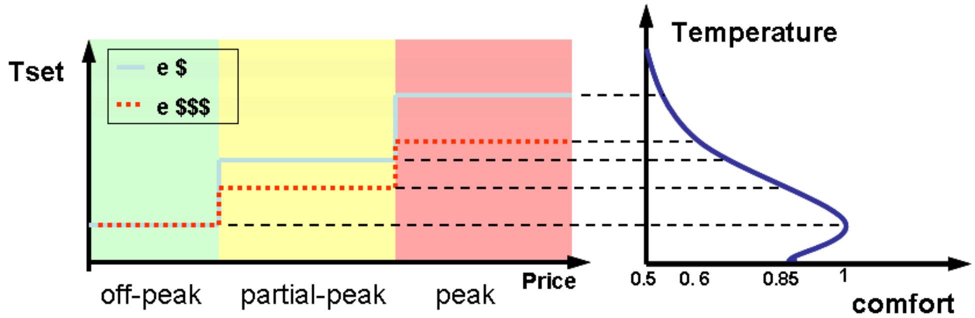
Because cost and comfort do not use the same unit, quantitative optimization requires creating a common currency. One solution is to scale comfort level to dollars, the currency of cost. This method was used in comfort analyses for office buildings: comfort affects employees' productivity, which affects the operation cost of companies. However, it is not applicable in a residential building. We scale both energy consumption and electricity price in percentages, by dividing current values by the full range. Figure 4.3 illustrates the normal strategy using typical curves of cost, comfort and utility in cooling mode.

Since normalized values of electricity cost are used, the absolute value of power consumption is not very important. The power consumption to maintain certain temperature depends on the duty cycle of heating or cooling equipment. Duty cycle provides all the information needed. Supervisory control needs to predict the duty cycle of heater or AC given outdoor temperature and temperature setpoints. Model-based methods or performance-based methods can be used to make such predictions.

After obtaining the utility with respect to temperature setpoint candidates, we can use optimization algorithm to locate the optimal value of T_s. Following are some comments for the formulation of the normal state optimization control.

1. The utility function for normal state clearly presents the competitive relation-

Figure 4.4: Impact of Economics Index in Normal State



ship between cost and comfort (or discomfort). Optimization makes a trade-off between cost and discomfort based on the value of e. A linear relationship is used because it is a simple form to express the idea of competition. Other formulations can be used as well, which will lead to different optimization solutions.

2. The economics index e plays the role of a weighting factor; the temperature setpoint is the optimal under a weighted function. A large value of economics index indicates more concerns on thermal comfort. Users are willing to pay more to get better environment. Thus, optimal temperature setpoint would be less sensitive to price increase. For a small value of economics index, temperature setpoint is set in low comfort range when price is high to make cost savings. The idea is expressed in figure 4.4. For partial-peak and peak price, setpoint changes by larger setbacks for a small value of e. The default value of economics index is 0.5, which means that cost and comfort are evaluated under the same weight. Users are sensitive to price when price changes from partial-peak to peak so that temperature setpoints are adjusted moderately.

3. The algorithm considers only steady-state optimization. We assume the indoor temperature fluctuates around setpoint candidates. Duty cycle to maintain the

temperature setpoints are evaluated. The transition process from the previous indoor conditions is not considered.

4. Notice here energy savings are equivalent to cost savings in the normal state because electricity rate is fixed over this period. But high price would spur the trade-off between energy and comfort. When electricity price is high, users are expected to make more energy savings.

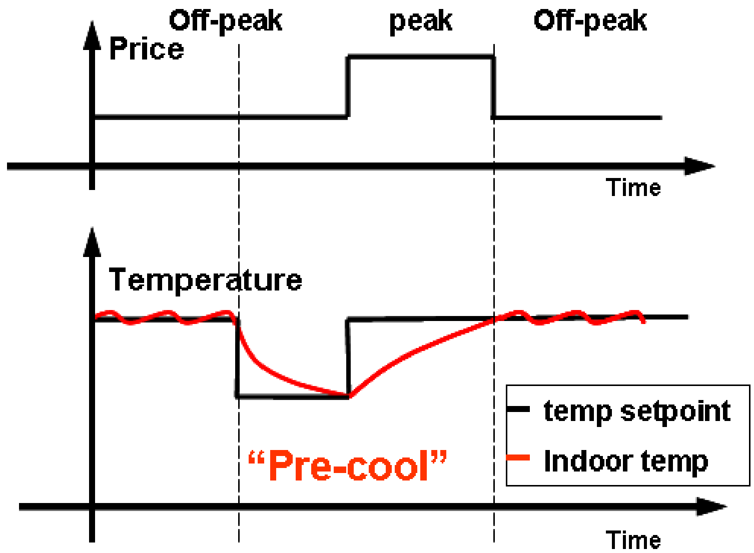
Pre-cooling/Pre-heating State

In the pre-cooling/pre-heating state, the pre-cooling/pre-heating strategy is utilized to reduce electricity usage during a future increased-price period with a minimum sacrifice to users' comfort. The future increased price can be any of the partial-peak, peak or critical peak rates, as long as it is higher than the current value. For the sake of convenience, high price and low price are used to denote the electricity rates before and after the pre-cooling strategy. Its basic idea is to shift the load at high price to low-price period by cooling or heating a house ahead of time. Without losing generality, the pre-cooling state is used in the following as the representative of this strategy. The pre-heating strategy works in a similar way.

Figure 4.5 shows the way the pre-cooling strategy works. Triggered by near-future high electricity rates, supervisory controller selects lower temperature setpoint to "overcool" the house during a low-price period. Ideally, the house stores this negative thermal energy so the temperature stays in the comfort range during the high price period without using air conditioning. Occupants experience minimal discomfort compared with only turning off the AC without "pre-cooling" the house.

Motivated by the electricity price increase, the objectives for the pre-cooling strategy are to minimize electricity cost while maintaining an acceptable comfort environment. The cost refers to the overall cost during the overcooling period and the

Figure 4.5: Concepts of the Pre-cooling Strategy

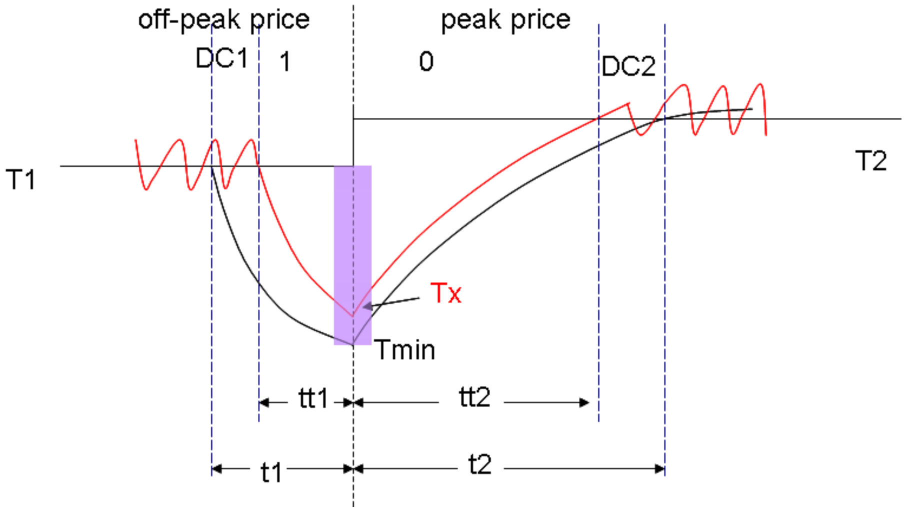


recovery period. The comfort requirement is to maintain indoor temperature in an acceptable range. Thus, thermal comfort need not be evaluated qualitatively. Without the term of comfort index in the utility function, no concept of economics index is needed. Users specify their economics preferences by setting acceptable temperature ranges. Optimal temperature setpoint is constrained by this range. The optimization strategy generates a setpoint profile instead of a single temperature setpoint, including setpoint for overcooling and the time pre-cooling starts. Equation 4.5 is the utility function defined for the pre-cooling strategy. Figure 4.6 shows the detailed explanation intuitively.

$$\begin{aligned} U(T_x) &= [t_1 - tt_1(T_x)] * DC(T_1) * P_1 + tt_1(T_x) * 1 * P_1 + (t_2 - tt_2(T_x)) * DC(T_2) * P_2 \\ &= [t_1 - tt_1(T_x)] * DC_1 * P_1 + tt_1(T_x) * 1 * P_1 + (t_2 - tt_2(T_x)) * DC_2 * P_2 \end{aligned} \tag{4.5}$$

$T_1$and T_2 are temperature setpoints at off-peak price and peak-price, which could be decided by normal state or users. Without losing generality, I assume their values are different. DC_1 and DC_2 are the AC duty cycles needed to maintain indoor

Figure 4.6: Pre-cooling Utility Function Calculation



temperature at T_1 and T_2. P_1 and P_2 are off-peak price and peak price correspondingly. T_x in figure 4.6 represents the candidates of pre-cooling setpoint, which is constrained by T_1 and T_{min}, the upper and lower bound of the setpoint candidates. t_1 is the time needed to reach T_{min} from T_1. It is the longest overcooling interval among all setpoint candidates. Similarly, t_2 is the longest recovery interval, for temperature floating from T_{min} to T_2. tt_1 and tt_2 are overcooling interval and recovery interval for a certain setpoint candidate T_x. With all these definitions, the utility U represents the total cost during t_1 and t_2. The optimal solutions are T_x that minimize the total cost and the corresponding overcooling interval tt_1.

The value of T_{min} is pre-determined by users, which is the lowest acceptable temperature. However, there are other constraints in practice. First of all, it needs to be achievable. In the cases when the AC is not powerful enough and outdoor temperature is extremely high (this is a common scenario when deploying the pre-cooling strategy), it is possible that the lowest acceptable temperature set by users can not be reached. Second, the value of T_{min} should not be so low that temperature is not able to recover to T_2 during a high price period. In that case, the system uses more energy since the indoor temperature is lower after the high price period.

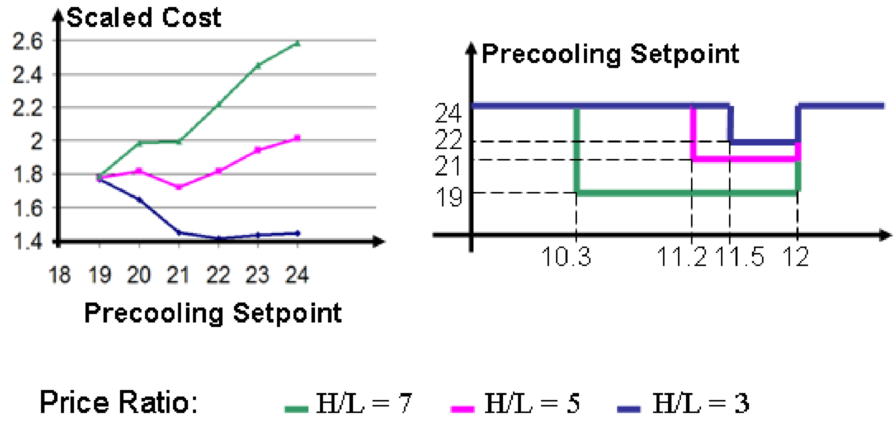
To calculate the utilities for candidates of control settings, the dynamic processes over the whole pre-cooling period need to be estimated. Model-based methods or performance-based methods are used in practice. Details are given in sections 4.5 and 4.6.

Several remarks for the pre-cooling strategy should be made. First, this is a demand response strategy, which reduces peak energy, not an energy savings strategy. In fact, the pre-cool strategy uses more energy because it uses a lower temperature setpoint than normal.

Second, the ratio of high price to low price affects the pre-cooling decision significantly. A high ratio increases the savings by shifting the load to a low price period while a low ratio makes load shifting trivial. Simulation results confirm this hypothesis. Assume the setpoint before and after pre-cooling is 24C. The energy consumptions under different pre-cool settings are generated using MZEST under the same operating conditions. Scaled costs are calculated when the price ratio is 3, 5 and 7. The left graph in figure 4.7 shows the cost curves as a function of temperature setpoint for each price ratio. The corresponding optimal pre-cooling setpoint profiles are shown in the right graph. The plot implies that a high ratio of price changes motivates lower pre-cooling setpoint, which enable more load shifting. The corresponding overcooling intervals vary as well.

Note that the current design of pre-cooling strategy assumes that the indoor temperature should reach the overcooling setpoint just at the moment when electricity price increases. Temperature soaking at overcooling temperature would use more energy and does not increase the cost savings. Here soaking means that the indoor temperature is maintained in the overcooling setpoint over a certain time interval. In fact, this may not be the truth in real life. Temperature soaking is capable of enlarg-

Figure 4.7: Pre-cooling Setpoint Profiles with Different Price Ratio



ing load shifting and therefore improves cost savings under appropriate conditions. During the soaking period, the interior temperature is relatively low. In addition to the interior air, the mass of interior space is cooled down as well. This is reflected by the temperature decreasing of interior walls and other solid objects, such as tables and counters. Under proper conditions, the soaking would delay the temperature recovery speed when the AC is off. Therefore, the electricity load reduction is enlarged for high price periods.

In fact, the effects of temperature soaking depend on the thermal characteristics of the house. Well-insulated houses benefit from the action of soaking while poorly-insulated houses do not. We compared the soaked pre-cooling performance for a 1992 house with a 1978 house using MZEST. The former is well-insulated while the latter is poorly insulated. To simplify the operating conditions, the outdoor temperature is set as a constant 34C. Setpoints before and after pre-cooling are 24C, and the pre-cooling setpoint is 20C. Figure 4.8 shows the simulation results. Table 4.2 lists the recovery intervals with respect to different overcooling durations. We can see that in the case of the 1978 house, soaked pre-cooling does not increase recovery duration. But for the 1992 house, soaked pre-cooling does increase recovery intervals, and the

Table 4.2: Simulation Results for Soaked Pre-cooling

Precooling hours	10-11.16 (1.16h)	10-13 (3h)	10-15 (5h)
Recovery Time	2.0833	1.8333	1.8333

(a) Simulation Results for house built in 1978

Precooling hours	10-10.75 (0.75h)	10-13 (3h)	10-15 (5h)
Recovery Time	4	4.9167	5.4167

(b) Simulation Results for house built in 1992

increased intervals are proportional to the soaking time. In other words, the longer the soaking, the more slowly the indoor temperature recovers. Under an appropriate price ratio, cost savings can be enlarged by the soaking strategy.

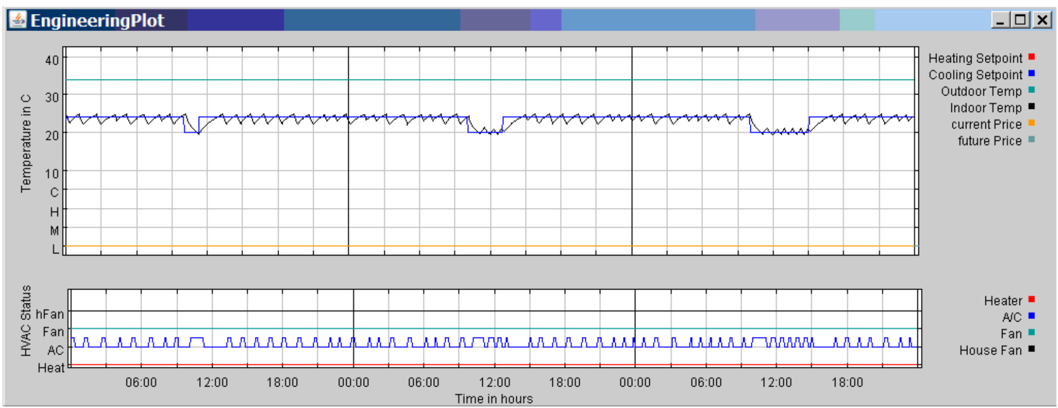
The soaking strategy adds complexity to the original pre-cooling strategy. Besides overcooling setpoint and its schedule, the supervisory control function needs to decide the soaking intervals. It also raises a critical question for the controller design: how to identify the house characteristics in respect to insulation? Only houses with good insulation properties can benefit from the soaking. This question is not answered in this thesis. Further investigation is necessary.

Pre-conditioning State

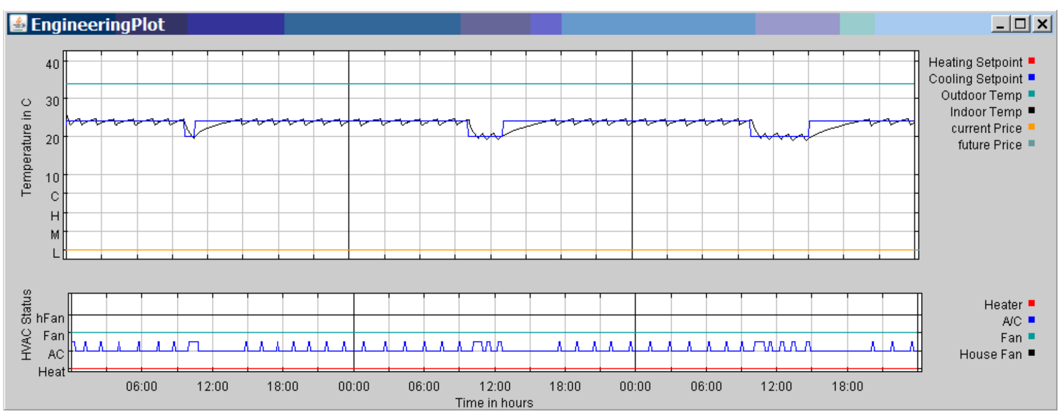
The pre-conditioning state represents the conditions to achieve an expected temperature at a particular time. Consider the following scenarios. On a winter morning, users expect warmer surroundings than during the night when they get up. On a summer afternoon, a cool environment is demanded at the moment users enter the house, although during the daytime when the house is unoccupied the setpoint is set higher to save energy and cost. In both situations, changes of indoor temperature are expected to occur automatically to make a comfortable environment for users.

Conventionally, such functions can be realized by setting setpoint changes through a programmable thermostat. However, a fixed setpoint schedule does not accommo-

Figure 4.8: Simulation for Soaked Pre-cooling



(a) Three day pre-cooling simulation for house built in 1978

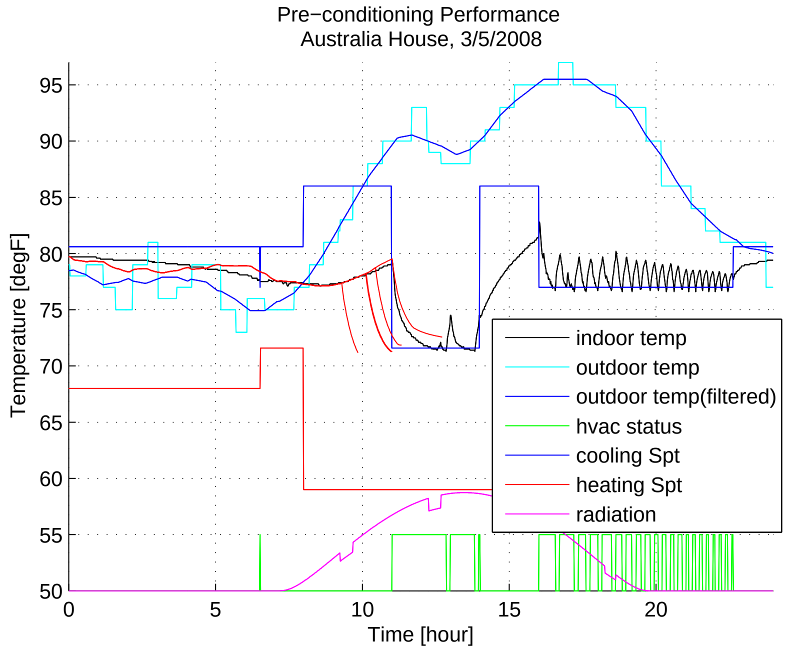


(b) Three day pre-cooling simulation for house built in 1992 date weather conditions. For users who set the thermostat based on the worst-case scenario, they waste energy when the outside temperature is relatively mild because the target temperature is achieved earlier than required. For other settings, they either waste energy when the target temperature is reached ahead of schedule, or fail to achieve the demanded comfort under extreme weather conditions. Field test results[28] imply that the outdoor temperature affects the heating/cooling intervals significantly. In the above example of heating during winter mornings, the heating interval for a particular house under the same temperature settings ranges from 30 minutes to 90 minutes. Further, the heating/cooling intervals differ among various houses. Therefore, precise control for an individual house is necessary to avoid energy wasting and to make satisfactory temperature control.

Toward this end, the pre-conditioning control strategy was designed. It considers the future weather conditions and is able to achieve the target temperature just in time. Thus, this strategy is also called "just-in-time conditioning." In the pre-conditioning state, the expected values of future temperature are pre-determined by users. It is not necessary to evaluate users' thermal comfort. The control objective is to make accurate control to achieve the target temperature considering the ever-changing outdoor conditions. Pre-conditioning is not an optimization problem. The strategy determines when the heating/cooling actuation should start.

There are two ways to realize the accurate control. One is using model-based methods to predict the future temperature profiles. The solution is the profile achieving the target temperature just in time. Performance-based methods are also promising. The heating/cooling interval can be used as performance index. Its values corresponding to different operation conditions can be saved in the performance map. In real implementation, usually the operation conditions (with the exception of outdoor temperature) are almost the same. This decreases the dimension of the performance

Figure 4.9: Pre-conditioning Simulation using Search Algorithm



map dramatically. For both methods, the key is to identify the dynamic signature of each individual house.

To locate the accurate actuation time for "Just-In-Time" (JIT) conditioning, a search algorithm is developed. First, set target temperature schedules and initialize JIT start time using arbitrary values. A good candidate of the initial value is the start time of the previous day. Second, given this setting and the predicted outdoor temperature, predict the interval needed to achieve the goal temperature. Based on the predicted temperature profile, adjust the JIT start time. If the difference between the current and the previous prediction intervals is less than 5 minutes, return the current setting of start time. Otherwise, go back to step 2. In real implementation, the search algorithm locates the solution quickly. Figure 4.9 shows an example using three iterations.

Overlapping State

The overlapping state represents the overlapping of multiple states including the pre-cooling/pre-heating state and the pre-conditioning state. Theoretically, any number of states can overlap over a certain period. But constrained by actual situations, we only need to consider the overlapping of two states. The overlapping of two pre-condition states seldom occurs in real life. I do not discuss it here.

This state is adopted when two control objectives need to be handled together. There are two situations. The first one is the overlapping of the pre-cooling/pre-heating state and the pre-conditioning state, preparing for load shifting for future high price and certain temperature demanded by users. The second occurs when the controller is in pre-cooling/pre-heating state, another future-price-increase event occurs. That is, the controller aims to shift loads for two future-price-increase events occurring closely together. Although the scenarios are different, the optimization problems are essentially the same: minimizing the overall cost under the constraints of maintaining thermal comfort. For the first case, the thermal constraint is the expected temperature pre-determined by users while the temperature is maintained in the comfort range all the time. For the second case, the constraint is to maintain temperature in a comfort range.

In some cases, the two control objectives modify the temperature setpoint in the same direction. For instance, on a summer evening both the pre-cooling state and the pre-conditioning state require a lower temperature setpoint. Thus a setpoint meeting both criteria is chosen. In other cases, the two control objectives conflict because each state pushes the temperature setpoint in different directions. A typical example is the overlapping of the recovery period for the pre-cooling state and the pre-conditioning for future arrival in summer climate. The decision made in such a case depends on the optimization calculation.

Similar to the pre-cooling/pre-heating state, the overlapping state determines a series of setpoints and the corresponding schedules. Usually the overcooling setpoint or recovery setpoint is pre-determined as the expected values users specified. The overall cost is minimized under such constrains. Model-based methods and performance-based methods are both good choices to make estimations.

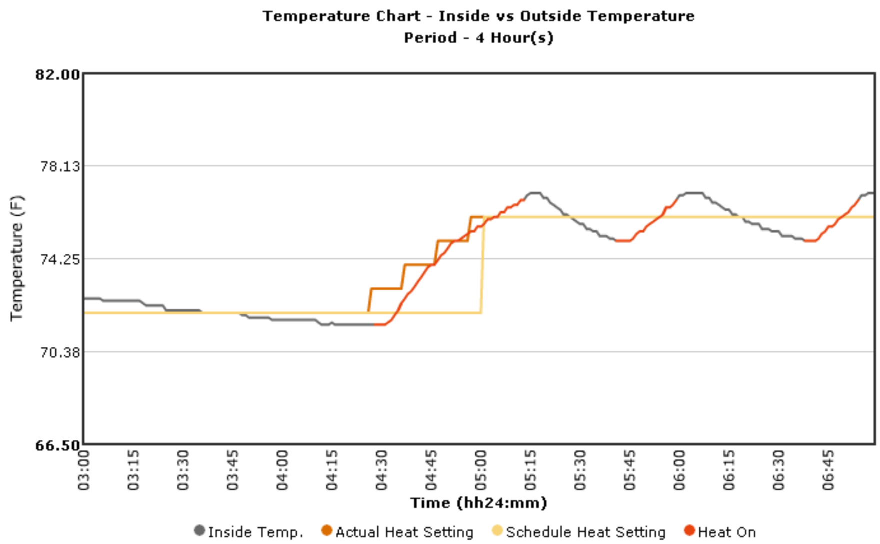
4.3.3 Robust Control Design

Robustness is an important consideration when designing supervisory controllers because prediction errors are inevitable. In the case of interior space conditioning, prediction errors always exist for any operating condition, because the models in model-based methods and the table values in performance-based methods are actually averages among many different uncertainties. Input disturbances are another source of uncertainty. For instance, predicted future outdoor temperatures differ with actual values. Since prediction errors exist universally and constantly, the controller should consider them and be able to perform satisfactorily under such disturbances.

However, it is difficult to evaluate and compensate for the prediction errors for optimization controls. Because the prediction errors exist for all the candidates of control settings, the optimal solutions may or may not actually be optimal. We do not know the answer because the operating conditions can not be duplicated. Among the above four control states, the only strategy that can be evaluated directly is the pre-conditioning strategy. When the actual temperature changing curve is away from the prediction profile, we can take some actions to compensate for the prediction errors.

There are two types of prediction errors for the pre-conditioning strategy: the aggressive temperature profiles in which indoor temperature changes more quickly than predicted; and the slowly responsive profiles when temperature changes more

Figure 4.10: Robust Design for Setpoint Profiles



slowly than expected. A robust control strategy is developed to compensate for the former type. Instead of being a fixed value, setpoints are designed as a smooth curve that the indoor temperature should follow. If the real temperature changes aggressively, HVAC equipment is turned off to slow down the changing speed and force the temperature to follow the designed curve. In other words, the aggressive profiles are corrected by turning off the AC or heater until the temperature floats back to the setpoint profile. In practice, because a thermostat only accepts setpoint settings with resolution of 1F or 0.5F, the continuous temperature setpoint are discretized. Figure 4.7 shows the degree-by-degree setpoint profile in real implementation. But for the other type of prediction errors, this method does not work because the heater or AC is already in full operation.

Combining the robust control strategy with the pre-conditioning strategy, it is guaranteed that the target temperature is not achieved earlier than required but may instead be late. In both cases, minimum energy/cost is used.

4.3.4 Optimization Algorithm

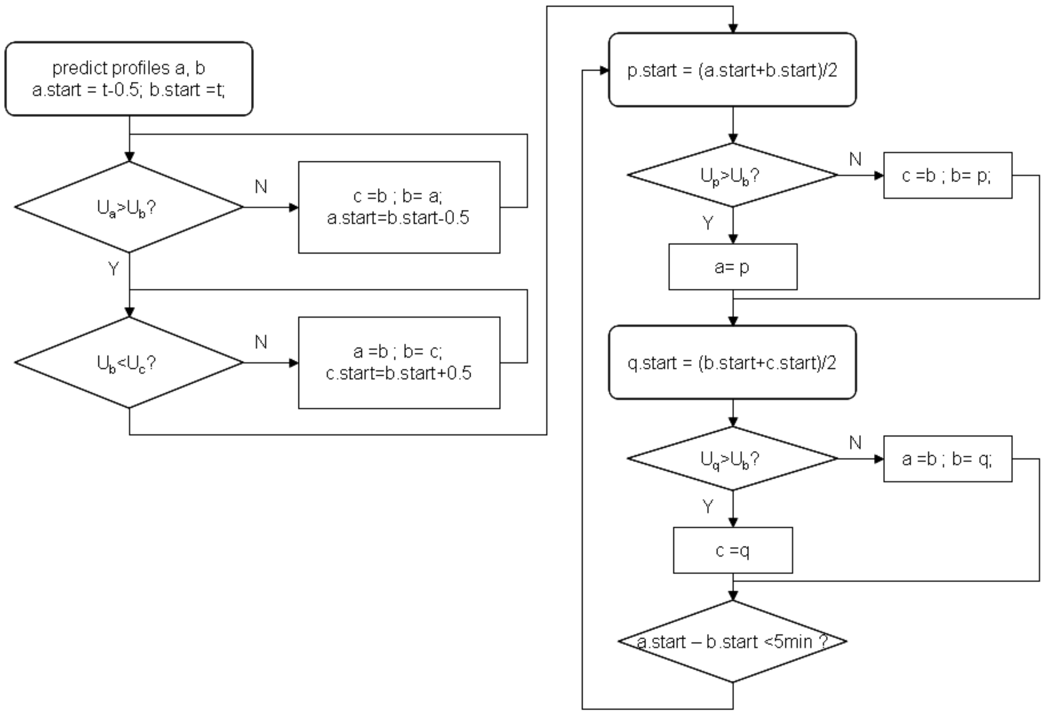
In all the control strategies except pre-conditioning, an optimization technique is used to seek global optimal solutions. An efficient algorithm would reduce computational loads and improve the speed to locate the solutions. An optimization algorithm is proposed here.

The basic idea is as follows: 1) choose arbitrary control settings a, b, c so that $a.utility > b.utility$ and $c.utility > b.utility$. That is, setting b has the lowest utility; 2) locate utility-minimum settings in the searching space from a to c. The distance between settings a, b and c should be selected carefully. Small values of the distance would increase the searching time in step 1. Large values lead to extensive computation in step 2. Figure 4.8 shows the flow diagram of the detailed algorithm. The pre-cooling strategy is used as the example. In real implementation, this algorithm converges quickly.

4.3.5 Discussion

The definitions of control modes and control states classify the objectives of supervisory control functions. In each control state, a certain control strategy is adopted to meet the specific control objectives. The control strategy determines setpoints and setpoint schedules if necessary, which are realized by local control functions. In summary, the supervisory control for interior space conditioning makes decisions on control settings in a hierarchical structure by three steps: 1) choosing cooling/heating mode; 2) choosing control state, i.e. control strategies; and 3) choosing the temperature setpoints and their schedules using the strategy decided in step 2. Supervisory control methods introduced in section 4.2.2 can be utilized in each step to realize their functions.

Figure 4.11: Optimizaiton Algorithm Flow Diagram



Comparing the four control states, there are some interesting facts indicating their nature of optimization.

1. Only the normal state evaluates users' thermal comfort quantitatively. Optimization is performed to balance cost and comfort. In the other three control states, indoor temperature is either maintained in an acceptable comfort range or fixed at a value that is user specified. The controller minimizes the overall electricity cost only.

2. Only the normal state considers the steady state of the interior space thermal dynamics. The other three states consider the dynamics during a time period. Temperature transition processes are involved in the optimization. Accordingly, the optimization algorithm for the normal state is relatively simple, while complex computations are needed for the other states.

3. Optimal solutions of the normal state can not be evaluated. Because the same operating conditions can not be duplicated, we do not know what the real costs would be for other control settings. It is similar for the case of the pre-cooling/pre-heating strategies. But the pre-conditioning strategies can be easily evaluated. Whether or not the control objectives are achieved is obvious.

4. Since the goal of optimization in the pre-cooling/pre-heating state is to reduce peak electricity consumption, the optimization calculation is driven by price but not energy savings. Electricity cost depends on electricity consumption and electricity price. Therefore, price plays an important role in optimization. The system's goal is to use less money (not less energy) and improve or at least maintain users' thermal comfort. In the normal state and the pre-conditioning state, since the price signal does not change, the objective of minimizing cost is equivalent to improving energy efficiency.

Based on the formulation of interior space conditioning and the knowledge of supervisory control methodologies, hybrid supervisory control methods are applied for this problem in a hierarchical structure. In the design, both model-free methods and model-based methods are adopted. Performance-based methods could be used to substitute model-based methods. The following sections explain the details.

4.4 Expert system: choosing control mode and control state

With respect to the choices of control mode and control state, the supervisory controller imitates the logic reasoning of human beings. In other words, expert systems are designed to make such decisions.

Let's consider the first step, choosing cooling or heating mode. Logically, people choose control mode based on the season and the weather conditions. The 2005 California Energy Commission Residential ACM Manual[41] recommends that the choice refers to the average outdoor temperature of the previous 30 days. Based on this criterion, a simple expert system is designed. The flow diagram is shown in figure 4.12. In practice, the value of threshold temperature is set as 60F. According to this criterion, control mode is updated every day based on historical outdoor temperature, and it can not change during the day. In fact, this is not the only standard to decide control mode as cooling or heating. But the reasoning logic used here is very common. The key is the application of an expert system-based control method in this particular topic – interior space conditioning.

At the second step, the system continues to choose a control state or a control strategy. With the definitions of control states, we developed another expert system that decides how the system transitions from one state to another. Figure 4.13 below shows an event-based state transition diagram. The transition is triggered by current and future events of price and comfort expectation. Every arrow indicates an event enabling state change.

The normal state is the default state when the controller starts running. A future-price-increase event triggers the transition from normal state to the pre-cooling/pre-heating state. When price increases, the controller transitions back to the normal

Figure 4.12: Expert system to choose control mode

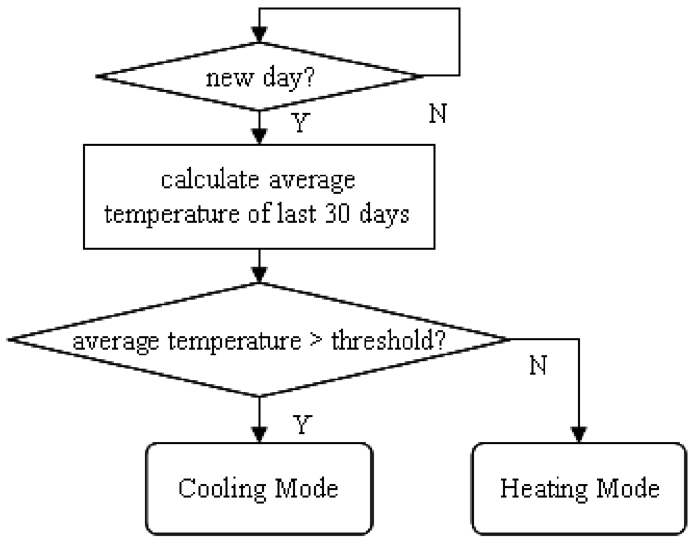
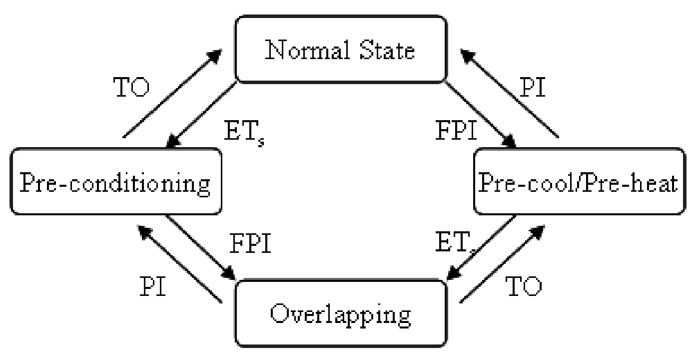


Figure 4.13: Event-based control state transition



Note: TO – Time out; ETs – Expecting Future Temperature T_s;
PI – Price increase; FPI – Future price increase.

state. Settings of expected future temperature would trigger the pre-conditioning state. The state is set back when the target time for the settings arrives. The indoor temperature either achieves the expected value or fails to reach it. In complex cases, when the controller is in the pre-cooling/pre-heating state, the future requirement of temperature change or future-price-increase event would enable the overlapping state; when in the pre-conditioning state, future-price-increase event would trigger the overlapping state. Here the future events are defined as those occuring in the next couple of hours. In the real implementation, considering the prediction ability of supervisory control methods and the information available, events that will occur in the next four hours are defined as future events.

The third and final step in the decision making process for the optimization is deriving the temperature setpoint and its schedules if necessary. The following sections describe the methods for each state and thus control strategy utilized.

4.5 Model-based Supervisory Control

To realize the supervisory control strategies for interior space conditioning, future indoor temperature profiles can be predicted by model-based methods. Three types of models were built, representing the target system – interior space thermal dynamics. The prediction performances and final control performances for each strategy are evaluated and compared.

4.5.1 1^{st} Order Physical Model

As a simplified physical model, a first order time-invariant model is proposed to predict temperature trend and estimate electricity consumption. Considering the mixed processes of heat transfer for the interior air of a house, five heat transfer approaches involved are considered: conduction, infiltration, heat from internal gains, solar radiation, and air conditioning in summer or heating in winter. Based on fundamental laws of thermal dynamics, their effects on indoor temperature are simplified. Conduction and infiltration are proportional to the temperature difference between outside and inside. So the corresponding heat flow is expressed as a linear function of temperature difference. Although internal gains due to people, lights, and equipment fluctuate daily, these influences are usually much less than the other sources of heat transfer and thus it is reasonable to assume this is constant. The temperature changes due to solar radiation depend on the size and the orientation of windows as well as the structures around a house that block or reflect radiation; both are fixed. It is reasonable to linearly correlate temperature changes and radiation. Although such correlation depends on time of day and day of year, the impact is ignored to simplify the model. Finally, we assume that the capacity of the AC and heater remains constant. With all these assumptions, a first order equation (equation 4.6) describes the indoor temperature change rate with respect to previous indoor temperature, outdoor temperature, sun radiation and HVAC status.

$$VHC \cdot \frac{T_{in}(t+\Delta t) - T_{in}(t)}{\Delta t} = \alpha \cdot (Tout(t) - Tin(t)) + \beta + \gamma \cdot Rad(t) + \delta \cdot HVAC \quad (4.6)$$

where VHC represents volumetric heat capacity; α denotes conduction and infiltration rate; β denotes internal gain; γ denotes the dependence coefficient of radiation; and δ denotes the capacity of AC or heater. These parameters are free parameters which need to be identified.

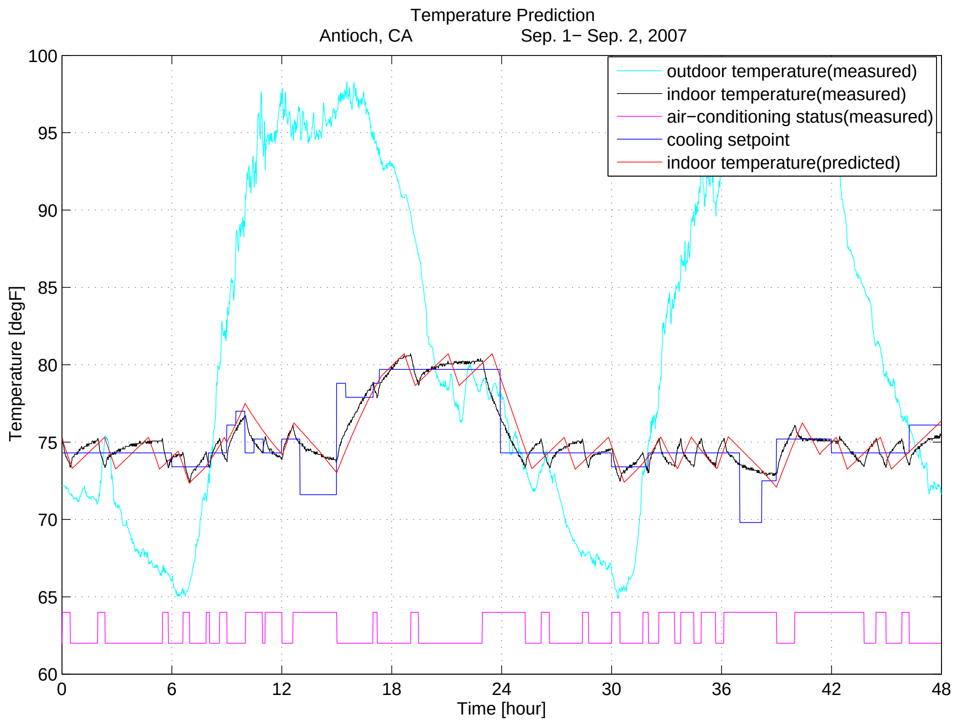
It is important to point out that the free parameters for a "time-invariant" model are not functions of time, but in the above model, parameter values actually change with time. For instance, when a house gets old, its conduction rate would increase and therefore the value of α increases as well. Because the change is so slow, we assume these free parameters are fixed instead of being functions of time. But the model does account for time by updating their values with the latest data.

To identify these parameters, historical data are used, including indoor and outdoor temperature data and AC/heater status. Global radiation is estimated using numerical models based on the weather conditions. The first step to tune these parameters for a specific house is clustering historical data with respect to radiation conditions and air-conditioning status. Data obtained under no radiation and no air-conditioning (usually during night times) are used to tune parameters α and β. After the first two parameters are tuned, the next two parameters γ and δ can be tuned with the data under the effects of radiation and air-conditioning/heating in turn. Least square regression is used. The details are in Chapter 3 of Jaehwi Jang's thesis[32].

Figure 4.14 shows the prediction results for one test house in Antioch, CA. The actual indoor temperature (black curve) and the predicted indoor temperature (red curve) are compared in two consecutive days. The 1^{st} order physical model is identified using part of the data set collected over the previous month. Data with incomplete information or anomalies were not used. Actual indoor temperature was used as the initial condition for the prediction. Actual outdoor conditions were used as inputs and HVAC actuations are generated based on actual setpoints with a model of local control functions. Finally, the indoor temperature profile was predicted given all these inputs.

We observed that the prediction performance is not bad despite the disparities for some long-term HVAC operations. Moreover, the predictions are more linear than the actual temperature curves. The reason is that the model is first order, and the higher order effects are ignored. Therefore, it does not have the ability to catch the

Figure 4.14: Prediction Performance using 1^{st} Order Physical Model

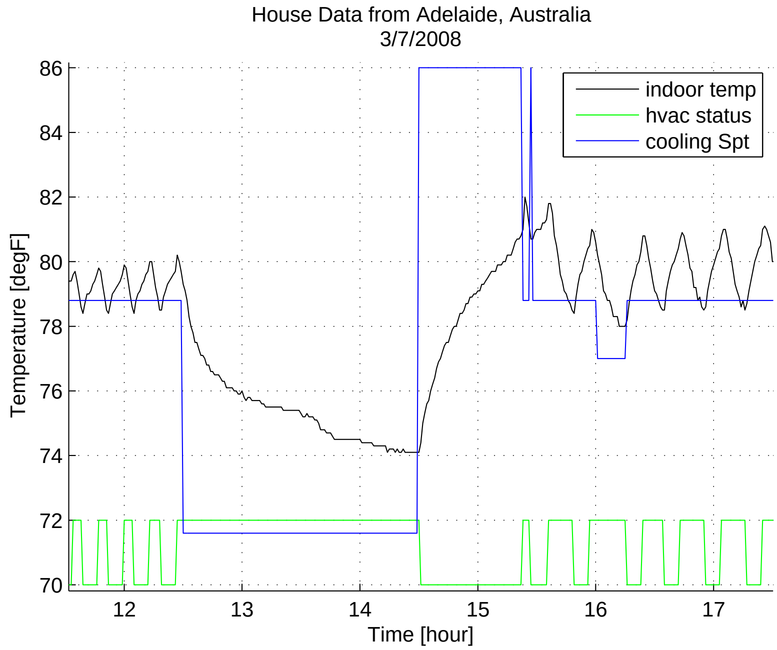


other thermal dynamics besides the dominant heat transfer. But the simplified 1^{st} order physical model is easy to implement and the computational cost is moderate. It is a good choice for real-time application.

4.5.2 Tabular Model

The tabular model is a type of structure-free model. It is expressed using tables instead of equations. To identify the dynamics signature of houses, temperature changing rates (degree/hour), also called the slope, are selected as the model parameters, corresponding to the HVAC status and the temperature difference between indoor and outdoor. Although global radiation has significant impact on the temperature changing rates as well, especially in summer climate, such impact is ignored to decrease the dimension of the model.

Figure 4.15: Temperature Profile for Tabular Method Anaylsis



Therefore, the tabular model uses two dimensional tables. Temperature difference between indoor and outdoor is one dimension, and the HVAC status is the other. Because the slopes are determined by HVAC status, historical temperature profiles are first split into pieces according to the HVAC status. In heating mode, pieces of profiles are grouped as heater-on profiles and heater-off profiles; in cooling mode, AC-on profiles and AC-off profiles are generated. Slopes are identified for each type using least square linear regression. The values are filled into appropriate cells of the model tables. Similar to the 1^{st} order physical model, the parameters in the tabular model are updated frequently with latest sensing and actuating data.

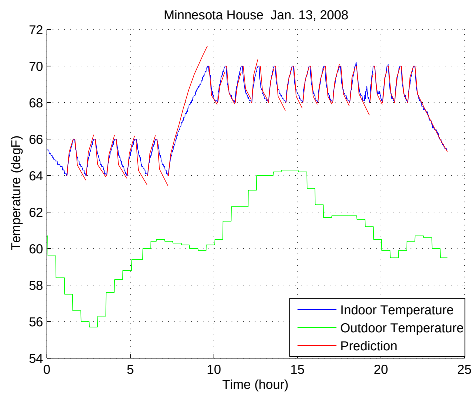
Notice that the temperature profiles are not linear so that the changing slopes vary with the HVAC operating duration. An AC-on profile is used as an example in figure 4.15. The black curve is the indoor temperature, and the blue lines are the AC status (high means on and low means off). At first, the indoor temperature decreases quickly because the interior space thermal dynamics is dominated by AC cooling capacity. Then the temperature changing rate slows down when the dynamics is a mix of AC cooling and outdoor heating through conduction, infiltration, etc. To separate these processes, it is necessary to divide the whole curve into several pieces. Slopes of sub-pieces are identified as model parameters. Based on the number of divisions, the tabular methods are divided into instant slope methods (using one slope), two-slope methods and three-slope methods. Obviously, instant slope methods only work for short-term HVAC operation. Two slope methods and three slope methods are promising for extensive indoor temperature predictions. Fine separation of temperature profiles decreases identification errors, while it increases computational load.

Figure 4.16 shows the prediction performances using both multi-slope tabular models. Real-time data collected from the field tests are used. For the winter cases, data from a Minnesota house are used; and for the summer cases, data are collected from a test house in Antioch, CA. The identification of tabular models is based on the previous 10-day data for all the cases. The predictions are made for each HVAC operation. With the analysis of the prediction performance of the tabular model, there are some findings.

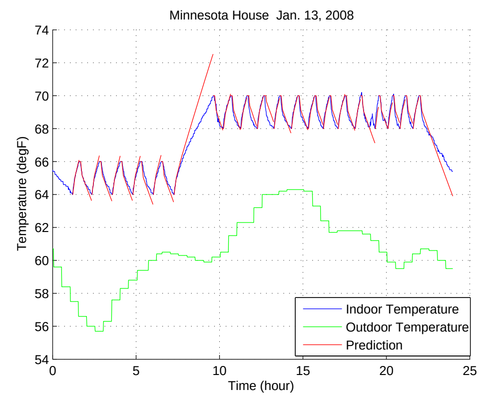
First, two-slope methods and three-slope methods have better performances for both short-term and long-term predictions than using the 1^{st} order physical model. And their performances are similar. Since two-slope methods have fewer parameters and need less computation, they are preferable.

Second, this method shows high prediction ability for heating mode. Its performances are not satisfactory for cooling mode in summer, especially for long-term AC operations. The main reason is that the model ignores the impact of global radiation, which is not a strong factor in winter, but it affects indoor temperature significantly in summer.

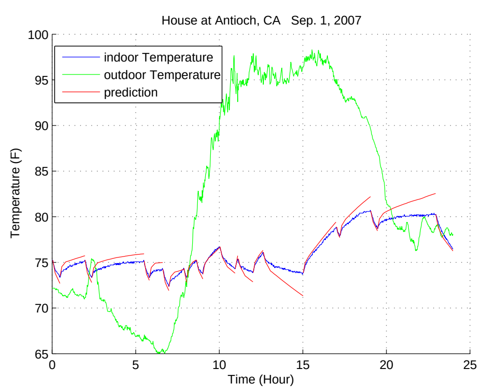
Figure 4.16: Prediction uisng Multi-slope Tabular Models



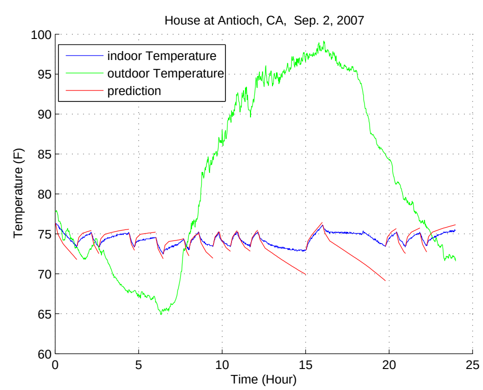
(a) Prediction using 2-slope Tabular Model in Winter Climate



(b) Prediction using 3-slope Tabular Model in Winter Climate



(c) Prediction using 2-slope Tabular Model in Summer Climate



(d) Prediction using 3-slope Tabular Model in Summer Climate

Another drawback of this method is that the predictions for heater-off profiles are also not good. In fact, when the heater is off, the thermal dynamics are dominated by the temperature of interior walls, which depends on the mixed heat transfer process affected by recent indoor and outdoor temperature. Additionally, the impact of indoor and outdoor temperature difference $\triangle T$ is delayed by the house's exterior walls.[42, 43] The tabular model just covers the linear impacts from current $\triangle T$. The temperature of the interior walls and the delayed impact of $\triangle T$ are not expressed in the tabular models. This causes large prediction errors.

Compared with the first order physical model, this method has relatively precise predictions for long-term heater ON events. Therefore, this method is applied for pre-conditioning strategy in heating mode. We got satisfactory results for winter morning heating. The results are in section 4.5.4.

4.5.3 ARX Model

With the analysis of the previous two model-based methods, we realized that it is necessary to develop a model that can cover the higher order thermal dynamics, including the heat transfer from interior walls and exterior walls. Temperature of interior walls dominates the thermal dynamics of interior space when the AC/heater is off or the AC/heater is on for long durations. Exterior walls delay the impacts from outdoor temperature and sun radiation. Considering all these factors, another structure model is developed, namely auto-regressive with exogenous input (ARX) model. Equation 4.6 shows its general form.

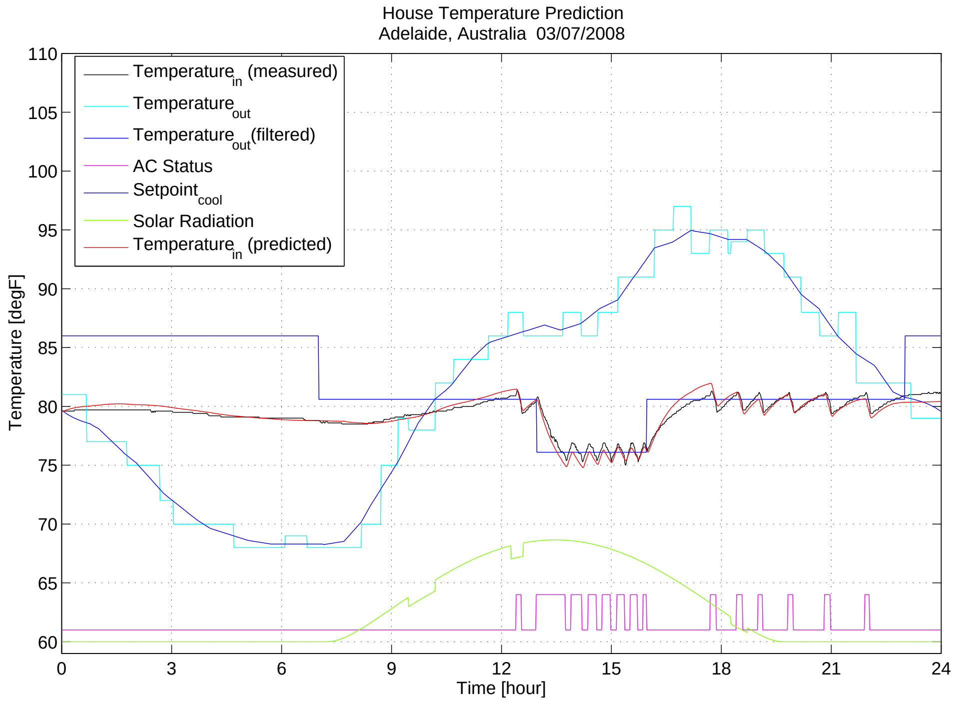
$$T_{in}(t) = \sum_{i=1}^{p} \varphi_i \cdot T_{in}(t-i) + \sum_{j=0}^{q_1} \phi_j \cdot T_{out}(t-j) + \sum_{j=0}^{q_2} \psi_j \cdot HVAC(t-j) + \varepsilon_t \quad (4.7)$$

As a purely statistical model, the ARX model is indeed in the form of a differential polynomial, indicating linear connections of indoor temperature with input variables – outdoor temperature and HVAC status. Equation 4.6 is the form after dicretizing. Theoretical knowledge about building thermal dynamics under HVAC actuations is used to determine the orders of the model[42]. Thus, the ARX model is indeed a gray-box model. The first order terms indicate the linear impacts from the inputs, while the higher order terms represent indirect impacts from outdoor conditions and HVAC heating/cooling through interior and exterior walls. The details are described in Jang, J. thesis[32]. With historical data, model parameters are identified using least square linear regression. The prediction performances are satisfied, with noticeable improvements compared with the other model-based methods using the 1^{st} order physical model and the tabular model.

However, relatively large prediction errors are observed when weather conditions are not normal. To improve the prediction accuracy in such cases, global radiation is added as another input variable. Since its values change slowly, a first order input is enough. The modification improves the prediction when the weather conditions are different. Plots in figure 4.17 show the prediction performance using this version of the ARX model. The outdoor temperature is interpolated from its hourly values (blue line); the sun radiation is modified based on the weather conditions (yellow line). The indoor temperature prediction fits the actual indoor temperature very well.

There are some various versions of this method. The parameter identification for the ARX model is based on data collected over the previous one day or multiple days, or based on the data from a day with similar outdoor conditions. Using any of these variations, the prediction performances are not consistent. That is, the prediction is accurate for some days but still makes large errors sometimes. The main reason is that the thermal dynamics of the house are changed by users' behavior, such as opening the windows. If the ARX model is built based on data when windows are

Figure 4.17: Prediction Performance of AXR models



closed, it must generate large prediction errors for the case when windows are open – the direct impact of outdoor temperature is stronger. To handle such problems, an algorithm to detect dynamics changes is proposed. A combination of multiple models built for different cases is utilized. The weights put on different models are determined by the match of previous 3-hour predictions. The multi model-based method shows promising results. The details are discussed in Chapter 4 in Jaehwi Jang's Ph.D. thesis[32].

The problem with this method is that the parameters do not have physical meanings. It is difficult to evaluate their values. In addition, the problem of over fitting may occur.

4.5.4 Control Performances

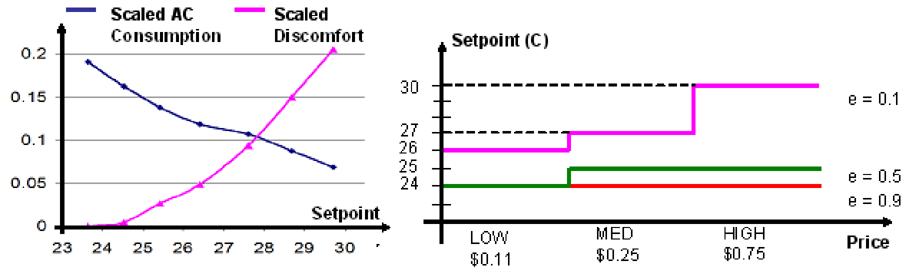
After constructing the above three models, model-based supervisory control methods are applied to realize different control strategies. Their functions are implemented based on the model-based predictions. MZEST simulations and field tests under different weather conditions demonstrate the control performances. The results provide insight about the nature of each control strategy and each model-based control method.

Normal State Optimization

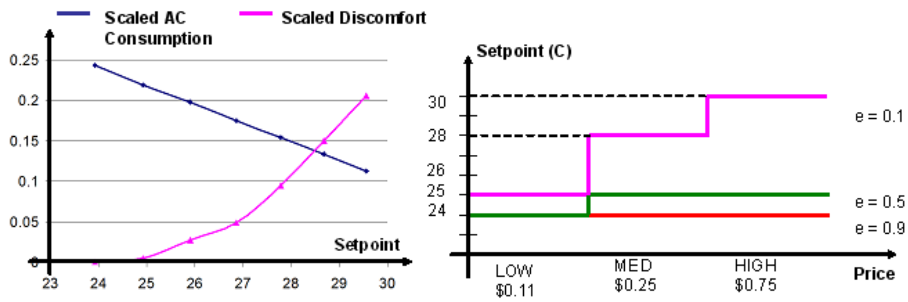
The implementation in normal state acquires energy consumption and the thermal comfort index to decide the optimal setpoints. A first order physical model is created to estimate the HVAC duty cycles under different temperature setpoints. The model parameters are identified using historical data collected over the previous 30 days. Data with incomplete information or anomalies are not used. The comfort index is calculated using adaptive comfort standards.

To validate the optimal solutions located using 1^{st} order physical model-based prediction, we use MZEST to create identical operating conditions and generate comparable results. The test house in Moraga, CA is simulated by MZEST. The house thermal behavior with HVAC operations is simulated under different setpoint settings in the normal state cooling mode. To guarantee the indoor temperature reaches steady state, constant outdoor conditions are set. The "actual" energy consumption index – duty cycle is obtained from the simulation. And the corresponding discomfort indexes are calculated. With full information, the supervisory controller is able to locate the "actual" optimal solutions. Figure 4.18 (a) shows the optimization results in this case. The left figure shows the curves of scaled energy consumption and discomfort. The right one expresses the optimal setpoint settings under different choices

Figure 4.18: Setpoint Profiles Genereted in Normal State Optimization



(a) Normal State Optimization with Full Information on Cost and Comfort



(b) Normal State Optimization with 1st Order Physical Model

of economics index e and electricity prices. To compare with the "actual" solutions, the "house" characteristics are identified using a 1^{st} order physical model. AC duty cycles are predicted under the same setpoint settings. The optimization results are shown in Figure 4.18 (b) in the same forms.

The predicted AC consumption differs from the "actual" values simulated by MZEST. However, since the prediction errors exist for all the setpoint candidates, they do not necessarily impact the choice of the optimal solution. In fact, the optimal solutions for both cases are exactly identical when e is 0.5 and 0.9. Only solutions when e is 0.1 are affected by prediction errors: the setpoints are 1 degree off the "true" optimal. Such difference is acceptable in practice.

The simulation results also prove that the optimal setpoints are different with different choices of economics index. However, the profile shape is slightly different

Table 4.3: Average Setpoint at Different Prices for Two Days

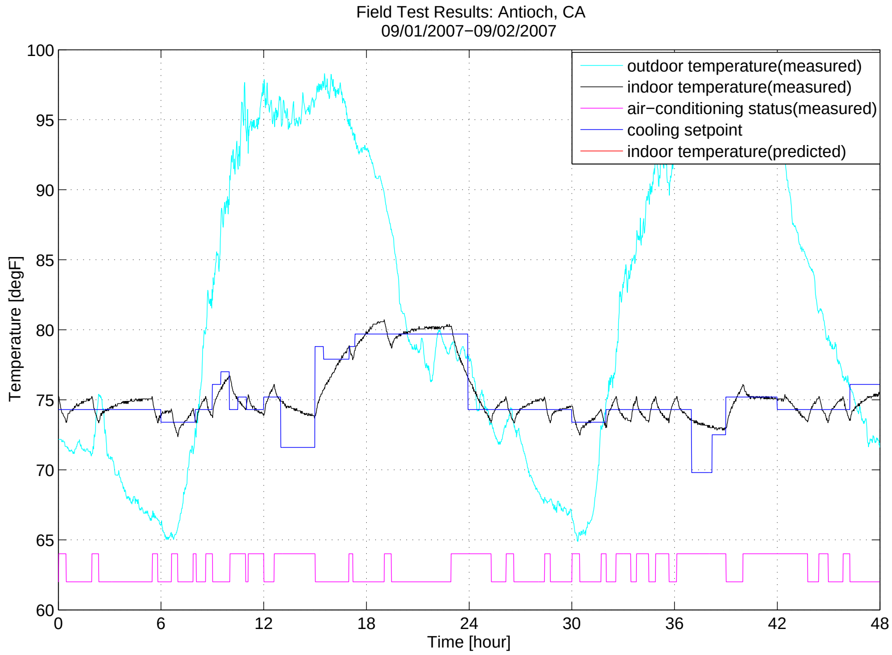
Economics Index	Low Price	Medium Price	High Price
Day 1: 0.3	74F	76F	79F
Day 2: 0.7	74F	74F	75F

from the original design. When the economics index is 0.5, the setpoint is supposed to be different for medium and high price. The simulation results do not show the proper economics sensitivity. This is caused by the design of the utility function. Other forms of utility functions should be able to fix this problem.

Field tests at Antioch, CA validate the normal state performance as well. A two-day field test was executed under typical California hot weather. Figure 4.19 shows the results. The two days experienced similar weather conditions. The controller was running at only the normal state and the pre-cooling state. Economics index for the normal state was set as 0.3 for day 1 and 0.7 for day 2. Users are assumed to be comfortable (100%) at 74F. Considering the ever-changing outdoor temperature, setpoints were recalculated by optimization control strategies every half hour. Table 4.3 shows the average setpoints determined in the normal state for each day. Temperature setpoints are the same at low price, while slightly higher at medium price periods and much higher during high price periods for day 1, due to the smaller value of the economic index.

According to the results from MZEST simulation and field tests, the normal state strategy has satisfactory performances using 1^{st} order physical model-based control. Since the normal state considers the steady-state energy consumption, ignoring high order thermal dynamics in the model does not cause large diversity when deciding optimal temperature setpoints. The controller is able to respond to DR signals by adjusting temperature setpoint autonomously. At the same time, users' economics preferences are considered by introducing the concept of economics index. In the

Figure 4.19: Field Test Results



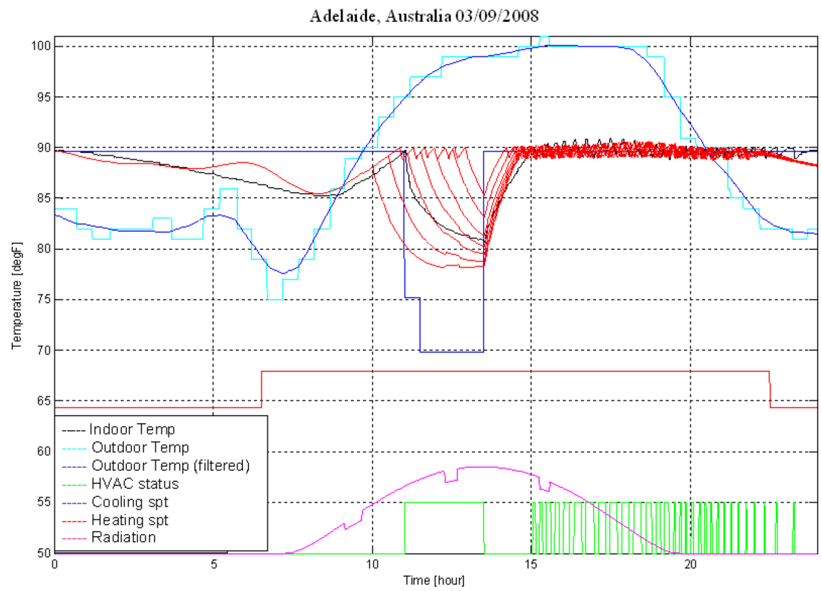
simulation, the effect of economics index is slightly different with the hypothesis. However, it still leads to reasonable trade-off between energy cost and thermal comfort. Improvement can be made with other forms of utility functions.

Pre-cool/pre-heat Strategy

I again use pre-cooling strategy as an example. Unlike the normal state, pre-cooling strategy needs to consider the thermal transient processes of house interior air. Therefore, the 1^{st} order physical model-based control cannot perform satisfactorily, because it ignores high order terms in the dynamics. The plot from field tests shows large errors when using the physical model. Therefore, ARX model-based control method is used.

Figure 4.20 demonstrates the predicted temperature profiles for the candidates of pre-cooling settings using the ARX model. The red curves are predictions, and the

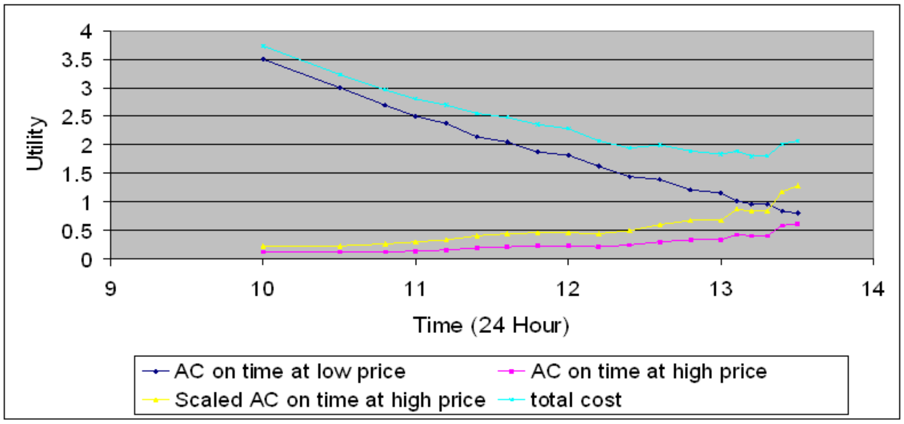
Figure 4.20: Pre-cooling Settings Searching



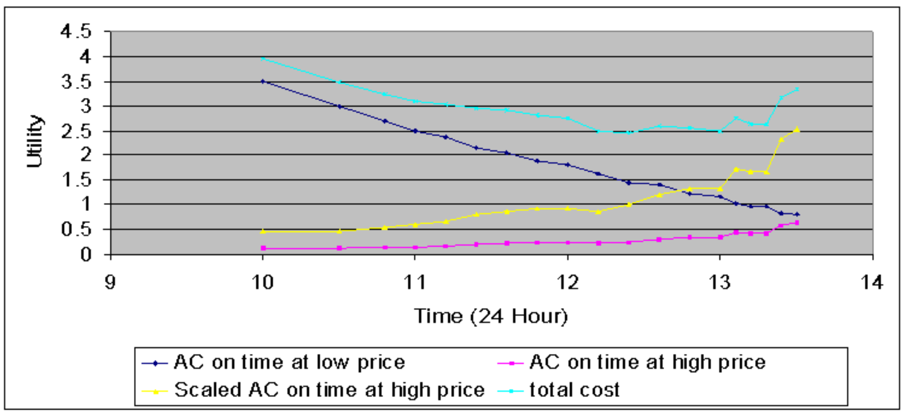
black curve is the real indoor temperature. By calculating the energy consumption and cost for each of them, the optimal setting that uses minimum electricity cost can be located.

Figure 4.21 shows the cost calculation with respect to setpoint candidates. Results are compared for different price ratios of high price to low price (after-pre-cooling price to before-pre-cooling price). AC on time at high price and low price are shown as the index for energy consumption (blue curves and red curves). Considering the price difference, the scaled AC on time at high price is shown in yellow. The total cost is represented by light blue curves. It is easy to locate the optimal settings from the plots. It is important to mention that in practice it is not necessary to calculate energy cost for all candidates of control settings, as shown in the graph. The optimal settings are obtained using a real-time optimization algorithm described in section 4.3.4. The results imply that the price ratio of high price to low price impacts the optimal settings significantly. In the demonstration, the price increases to high price

Figure 4.21: Utility Calculation for Pre-cooling Strategy



(a) Utility Calculation when Price Ratio is 2

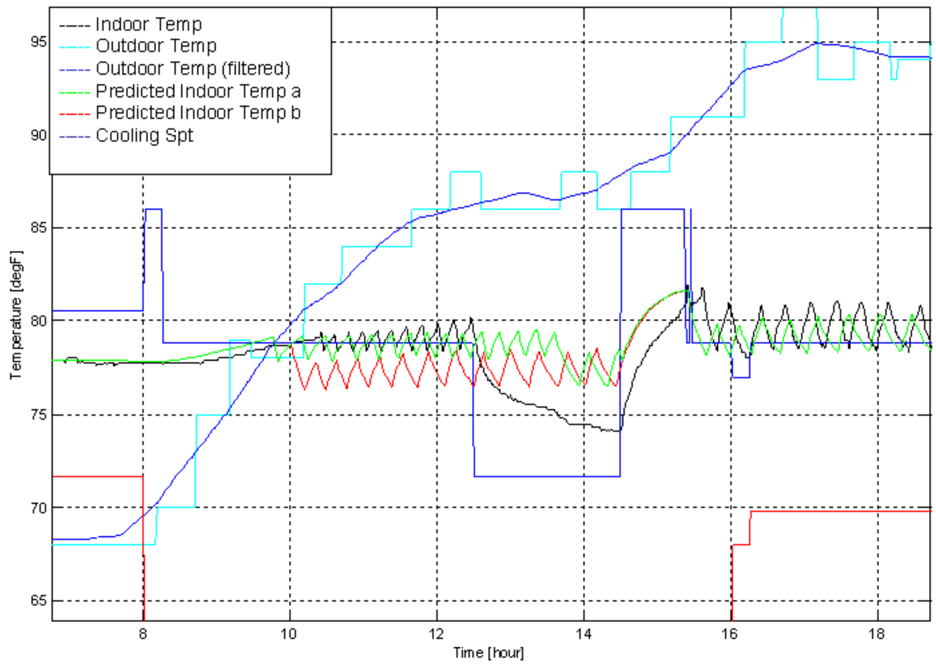


(b) Utility Calculation when Price Ratio is 4

at 13:30. When the price ratio is 2, the optimal settings occur when pre-cooling start at 13:15. Not much over-cooling is needed. While the price ratio is 4, the controller decides to start pre-cooling much earlier, at 12:15pm. This would shift more electricity use from the high price period to the low price period and therefore lead to cost savings. Meanwhile, this simulation is a good example of showing how utility tariff impacts the control settings and control performances. High price is able to spur users to take actions when electricity shortages occur.

In section 4.3.2, I stated the effect of soaking in the pre-cooling strategy. However, the ARX model is not able to produce such an effect. The predictions for future

Figure 4.22: Prediction for Soaking Performance in Pre-cooling



(a) Utility Calculation when Price Ratio is 4

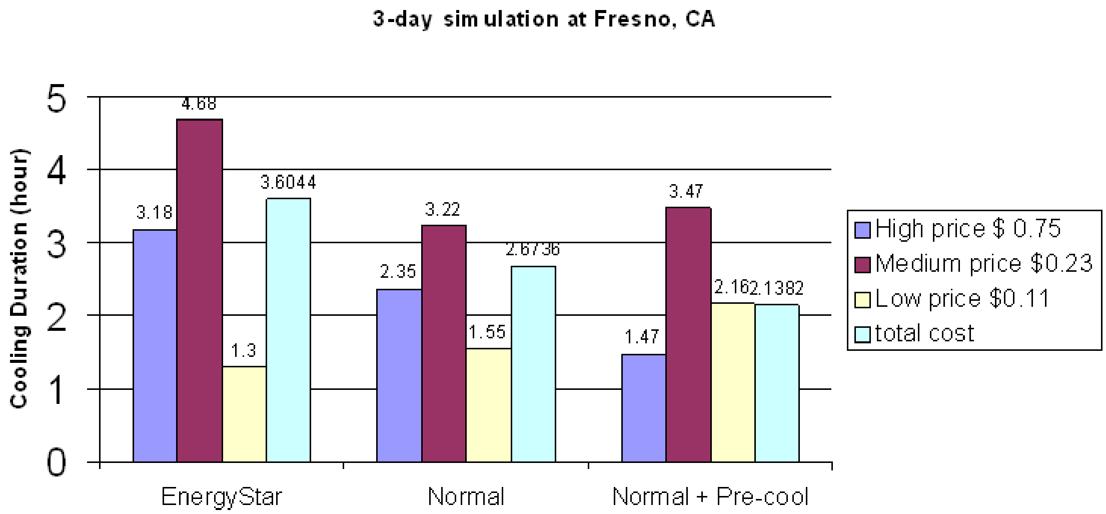
indoor temperature are identical although previous indoor temperature has different profiles. Figure 4.22 demonstrates this point. Red and green temperature profiles are generated by setting the setpoint at 77F and 78.5F from 10 a.m. The temperature stays at those values for 3 hours and 30 minutes. Then the temperature setpoints are synchronized before the recovery period. Finally we observed that the recovery profiles are identical for these two cases. In other words, the recovery interval does not depend on the previous series of indoor temperature, although this is not necessarily true. Based on such predictions, the soaked profiles can not be the optimal solutions because it uses more energy during the overcooling period and uses the same amount of time to recover. Therefore, using the ARX model-based control method, the soaked pre-cooling strategy can not be realized.

Since the pre-cooling strategy is a demand responsive strategy, its performance of load shifting is validated using MZEST. Remember that simulations can provide identical operation conditions for strategy comparison.

To evaluate the performance of the DR strategy, we compared three control settings. One is the default settings of an EnergyStar programmable thermostat: daytime setpoint 25.5C and nighttime set-back setpoint 28C [44]. It does not consider the ever-changing DR rates. The second strategy is the designed interior space conditioning system running at the normal state only. Note that the normal state strategy also has the effect of decreasing high price load. The economics index is set as its default value 0.5. The last one is the designed system running at both the normal state and the pre-cooling state. The normal state adopts 1^{st} order physical model-based control; while the pre-cooling strategy uses the ARX model to determine the optimal settings. Model parameters are identified using appropriate data over the previous month. Using MZEST, we ran 3-day simulations of a pre-1978 house in a Fresno climate. The controller ran under these three strategies. The metrics measured were AC on time at the different electricity rates and the scaled total electricity cost.

The results are presented in figure 4.23. First, the system running in the normal state uses less energy for both high price periods and medium price periods compared with programmable thermostat settings. The reductions of energy consumption are caused by higher temperature setpoints. It uses slightly more energy for low price periods, and when the setpoint is not a constant, the indoor space needs to be cooled down at the beginning of each low price period, from the higher setpoint set for medium price. This process increases the duration the AC is used for the low price period. For the case of deploying both the normal strategy and the pre-cooling strategy, much less electricity is consumed for high price periods. Consequently, it uses more electricity at medium price and low price than only running in the

Figure 4.23: DR Strategies Performance Comparison



normal state. These results indicate that the DR strategies, especially the pre-cooling strategy, successfully shift the loads from high-price periods to medium price periods and low price periods. The total cost under such utility tariff decreases as well. Thus we see that the interior space conditioning system responds automatically to price signals with appropriate energy saving behavior.

Pre-conditioning Strategy

The pre-conditioning strategy is utilized when users demand a certain temperature at a specific time. For example, users would like to have a warm temperature, say 74F, when they get up at 5 a.m. on a winter morning. The supervisory controller needs to determine when to start HVAC operations to achieve the target temperature just in time. In fact, the actuation time is not a constant. Instead, it depends on outdoor weather conditions and an individual house's characteristics. The tabular model-based method is adopted to identify the thermal signature of the target house and predict the temperature transient processes based on forecasted outdoor temperature.

The robust control design introduced in section 4.3.3 is applied.

To see the significance of the learning function in the pre-conditioning scenario, we compare two pre-conditioning settings: the duration of HVAC actuation is predicted by using a general tabular model, or by adopting the individual tabular model identified from each house. Data from seven Minneapolis houses are used to compare the two settings in heating mode. The general tabular model is obtained by averaging the individual tabular models of the seven houses. The results indicate how much the pre-conditioning performances are improved after control parameters are customized for an individual house. The results also imply the importance of house signature identification in supervisory control.

In the seven test houses, we did not actuallyapply the pre-conditioning strategy. In fact, long-term heating events are considered as the pre-conditioning events. Long-term heating event means the temperature drifting due to setpoint increasing. We compare the actual heating durations and the predicted values using the above two tabular models. The tabular model construction is based on data collected over ten days; evaluations are performed in three days for each house. Figure 4.24 gives an example of the results. It shows the actual indoor temperature collected from the house and the predicted indoor temperature curves using the above two models. Table 4.4 compares the prediction errors for seven test houses over three evaluation days. The results indicate that by customizing the pre-conditioning strategy for each house, the prediction on actuation time is more accurate. Such accurate predictions provide users the required comfort without wasting energy. In conclusion, it is necessary to acclimate control settings to both the climate and the individual house in the pre-conditioning state.

Finally, the pre-conditioning strategy was deployed in two test houses in Minneapolis, Minnesota. The tabular model is identified based on data collected over

Figure 4.24: Pre-conditiong Strategy Evaluation: General Tabular Model v.s. Individual Tabular Model

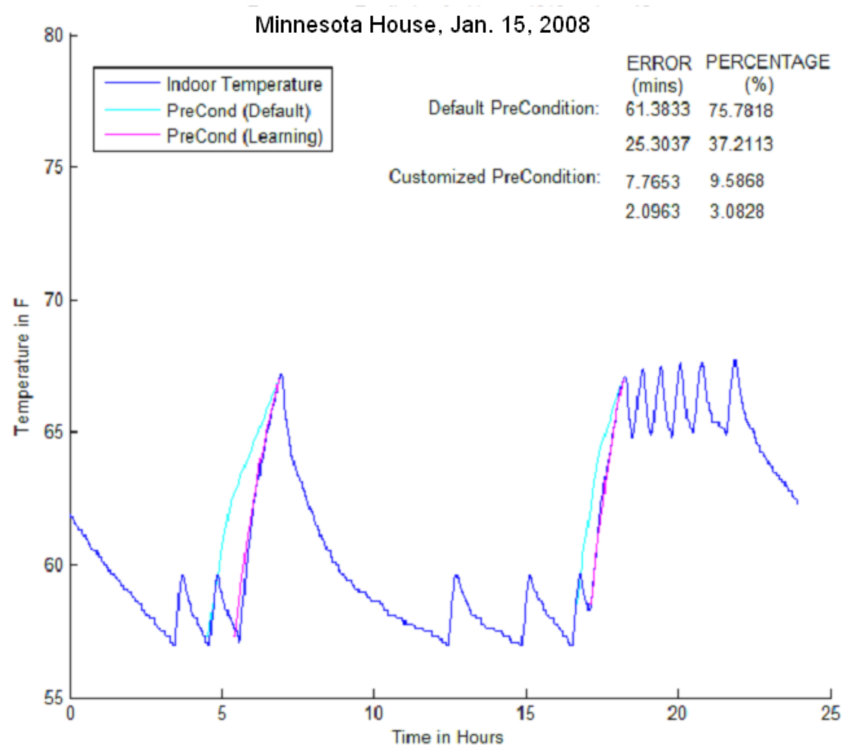


Table 4.4: Pre-conditiong Strategy Evaluation: General Tabular Model v.s. Individual Tabular Model

	Max error Time (minutes)	Max error Percentage (%)	Average error Time (minutes)	Average error Percentage (%)
Average characteristics (average 7 houses)	166.9103	81.42	42.0859	52.16
Customized performance	76.5819	55.47	12.6669	19.1

Table 4.5: Field Test Results on Pre-conditioning Strategy

House ID	A	B
Year Built	1985	1937
Test duration	24 days	25 days
Settings	72°F -> 76°F at 5am	65°F -> 69°F at 6am
Outside Temperature range	16°F to 50°F	15°F to 51°F
Anticipated heating interval	12 to 35 minutes	31 to 89 minutes
Rate of succeed	20/24, 83%	24/25, 96%
Average prediction error	0.64°F	0.61°F

the previous day. Every midnight, the tabular model is updated. Temperature is expected to reach 76F at 5 a.m. for house A and reach 69F at 6 a.m. for house B. In both settings, the temperature setpoint increases 4F. The real-time tests were executed over 24 and 25 days, and the performances were satisfactory. For house A, the algorithm successfully reached the target temperature at the desired time 20 out of 24 days. For house B, the rate of success is even higher. During 25 test days, there was only one day when the controller failed to achieve the target. The average prediction error of 0.6°F is essentially indistinguishable from a perfect result. Table 4.5 lists the detailed results. The wide ranges of outdoor temperature and anticipated heating interval indicate the necessity and significance of applying the customized pre-conditioning strategy.

From the field tests, it is interesting to see that the heating intervals for the two houses are quite different although operating conditions are similar. For house A, the intervals range from 13 minutes to 35 minutes while for house B, the range is from half an hour to an hour and a half. This is caused by the difference of the thermal characteristics of the two test houses: house A is much newer than house B so it is better-insulated. This fact indicates a useful characteristic of the pre-conditioning strategy. It will most benefit the least efficient houses. Such houses include poorly-insulated houses or houses with undersized HVAC units. In those houses, temperature transient intervals have strong correlations with outdoor conditions. Accurate predictions are critical to avoid wasting energy or failing to achieve the desired level of comfort.

4.6 Performance-based Supervisory Control

To seek the optimal control settings in each control state, performance-based supervisory control is another option. Instead of predicting temperature profiles as is done in the model-based method, the controller settings are determined based on the system's historical performances under similar operation conditions. Compared with the model-based control methods, performance-based supervisory control does not need any prior knowledge of the target house and its HVAC system. The computation load is relatively small. However, the usefulness of the method is limited by the richness of historical data. It cannot be applied to the operating conditions that have not been observed. To overcome this issue, an extrapolation technique is utilized to extend the working ranges.

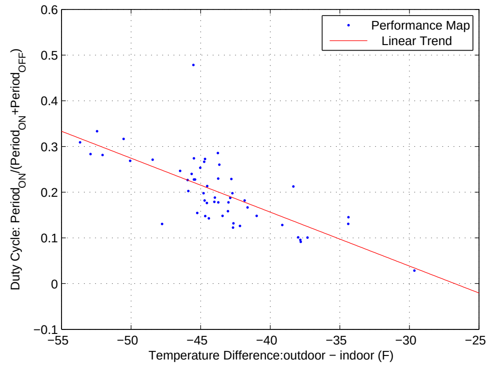
4.6.1 Performance Map Construction

The first step of the performance-based control is to generate a performance map. Choosing a good performance index is critical to implement the strategy. A meaningful measure that can be obtained easily from temperature profiles is a good choice. It simplifies the construction of a performance map. Meanwhile, it should be easy to calculate utility functions by integrating its values. A simple idea is to use the utility or its component as the performance index. Finally, considering the computational complexity, the dimension of the performance map should be small. The performance index should have simple relationships with input variables, such as outdoor temperature.

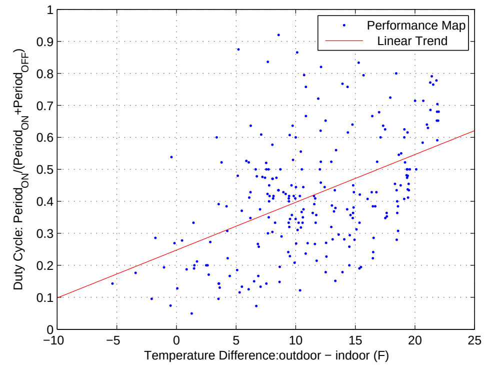
First, consider the normal state. The optimization strategy involves the evaluations of energy consumption and the discomfort index when maintaining a certain temperature setpoint. To represent energy consumption, duty cycle is chosen as performance index, which is not hard to obtain from indoor temperature profiles. The performance map records the duty cycle values with respect to the temperature difference between outdoor and indoor. The values of the duty cycle are calculated based on every on-off cycle of HVAC operation when indoor temperature is maintained at a certain setpoint. Transient processes are filtered out. The corresponding differences of indoor and outdoor temperature over one operation cycle are averaged as the input. Figure 4.25 shows the performance map generated according to 10-day data collected from test houses in Minneapolis, Minnesota and Adelaide, Australia. The x axis is the indoor and outdoor temperature difference, and the y axis is the value of duty cycle. Their linear trends are expressed in red lines. The data show a clear linear relationship when outdoor weather conditions do not fluctuate in large ranges, such as in winter climate. However, in a summer climate, the map is subject to much noise due to the impact from sun radiation and users' activity such as opening or closing windows. The linear trends of the data imply the relationship of HVAC duty cycle and temperature difference between outdoor and indoor environment: the larger the temperature difference, the larger the HVAC duty cycle needs to be. And the linear trends are used as the map extension to unobserved operating conditions.

The performance map generation for the pre-cooling/pre-heating strategy is not straightforward. The pre-cooling strategy implementation is used as an example. The utility function is the total cost over the overcooling period and the recovery period. Without considering the benefit of indoor temperature soaking at low temperature, there are determined relationships among control variables: overcooling interval, pre-

Figure 4.25: Normal State Performance Map Generation



(a) Winter Climate

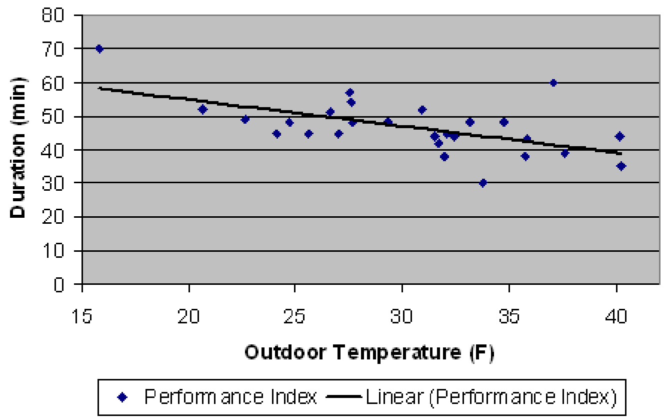


(b) Summer Climate

cooling setpoint and recovery interval. Under certain initial indoor temperature and outdoor conditions, the overcooling duration determines the pre-cooling setpoint. It is the indoor temperature at the end of the overcooling period. It is also the lowest achievable temperature over the overcooling period. Similarly, the pre-cooling setpoint determines the recovery interval given the temperature setpoint after pre-cooling. In other words, although there are three undetermined values, only one is the free parameter. Because of such relationships, the performance index can be chosen as any one of them. The input variables are average outdoor temperature and radiation over the whole pre-cooling period, and temperature setpoints before and after pre-cooling. With the proposed structure, the performance map has five dimensions. Because there are only a few pre-cooling events occurring every day, it takes a long time to fulfill the map in a real-time application. Therefore, we have not applied performance-based supervisory control to realize the pre-cooling strategy.

The pre-conditioning strategy is the most effective strategy that is realized by the performance-based method. As stated earlier, its purpose is to seek the start time of HVAC actuation in order to achieve the target temperature at a specific time. Therefore, we choose the operation duration as the performance index intuitively. In

Figure 4.26: Pre-conditioning State Performance Map Generation



practice, usually the working conditions when applying the pre-conditioning strategy are partially identical everyday: the indoor temperature is expected to reach a fixed target setpoint at a fixed time with a fixed initial setpoint, while outdoor temperature varies. Thus, based on the fundamental laws of heat transfer, the performance map only needs to record the relationship between the heating duration and the averaged outdoor temperature. The map has two dimensions, and it is relatively easy to fill. Although there is only one such pre-conditioning event everyday, the map can be filled after several days. Figure 4.26 shows an example of performance map generation based on data collected from Minneapolis, Minnesota. Each morning, the temperature is expected to change from 72F to 76F at 5 p.m. A 4-degree warm-up is a typical setting for winter morning setbacks. Data over 30 days were collected, and there are 30 pre-conditioning events recorded in the map. Over these 30 days, the outdoor temperature ranges from 16F to 41F, and the heating duration ranges from 31 minutes to 70 minutes. All these values form the performance map. To seek the heating duration under different outdoor temperature, the linear trend is identified.

4.6.2 Control Performances

Normal State

Using the performance-based method, it is easy to obtain the HVAC duty cycle for each setpoint candidate. Combined with the discomfort index calculated using adaptive comfort standards and economics index specified by users, the optimal settings that minimize utilities can be achieved. In figure 4.27, we show the utility calculation when outdoor temperature is 34C. The blue line is the AC duty cycle with respect to setpoint candidates obtained from the performance map, and the red curve is the corresponding discomfort index. Table 4.6 lists the optimal control settings at various price levels when the economics index takes different values. The electricity rates are set as \$0.11, \$0.25, \$0.75 according to PG&E pilot programs[19]. When economics index e equals 0.9 (high comfort and high bill), the setpoints are all 24C for off-peak, shoulder-peak and peak price. When e is 0.1 (low comfort and low bill), the setpoints increase to 25C, 28C and 30C. The table clearly shows how the setpoint settings change when users' economics preferences change from one extreme to another. Thus, using performance-based supervisory control, we obtain reasonable control settings. The normal state control performances are similar as using the 1^{st} order physical model-based control method.

Pre-conditioning Strategy

For the pre-conditioning strategy, the performance map indicates the heating or cooling duration needed given outdoor temperature. In practice, the outdoor temperature is obtained from weather forecasting. Given outdoor temperature, the controller settings can be read directly from the map and no further calculation is needed. To evaluate the performance-based control method, the control settings are compared

Figure 4.27: Normal State Utiltiy Calculation using Performance-based Method

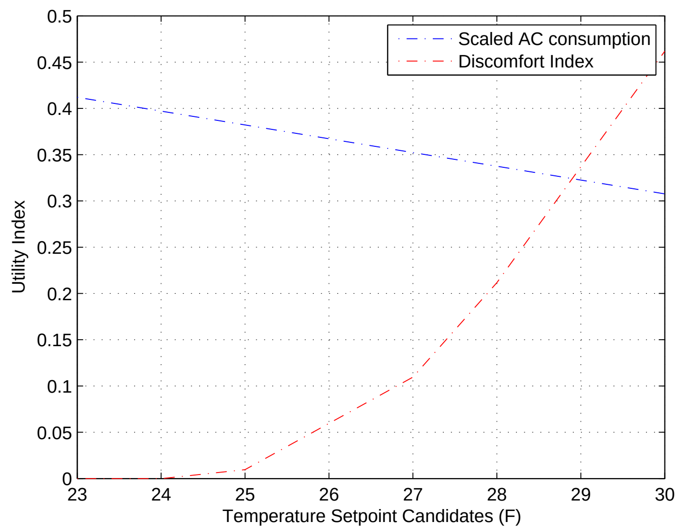
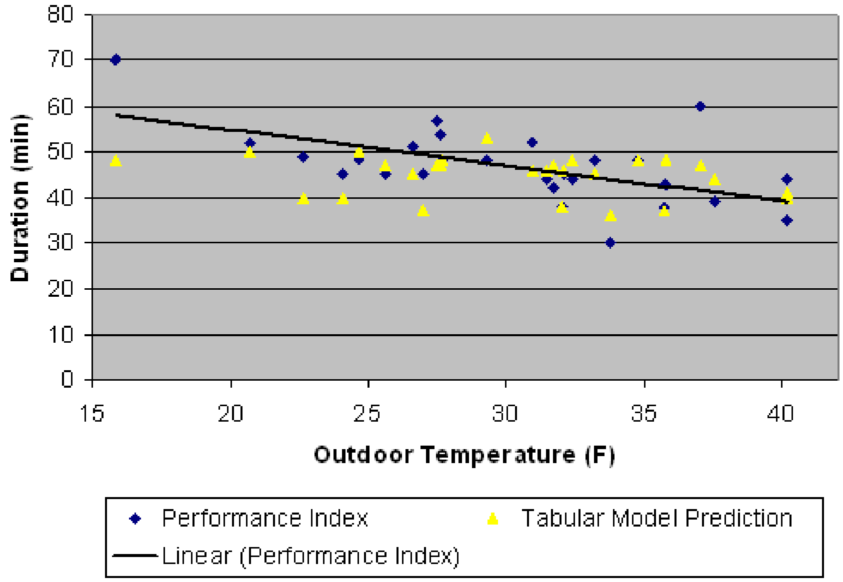


Table 4.6: Setpoint Generated for Different Ecnomics Index and Price

Economics Index	Off-peak Price	Shoulder-peak Price	Peak Price
0.1	25	28	30
0.2	25	25	30
0.3	25	25	27
0.4	24	25	27
0.5	24	25	25
0.6	24	24	25
0.7	24	24	25
0.8	24	24	24
0.9	24	24	24

Figure 4.28: Pre-conditioning Strategy Comparison: Performance-based Method vs. Tabular Model-based Method



with the values obtained using the tabular model-based control. In figure 4.28, blue dots represent the performance map. The heating intervals are determined based on its linear regression (black line). The yellow dots represent the heating intervals decided by the tabular model-based method. Because the tabular models are updated every midnight based on data collected from that day, the final decisions on control settings are a bit noisy. Even under the same outdoor conditions, it is possible for the controller to make different decisions. The plot indicates that the two methods generate similar results.

4.6.3 Discussion

There are some concerns about the performance-based control method. To generate the performance map, data collected over multiple days are needed. For instance, in the above demonstration of the pre-conditioning strategy, 30-day data were used to construct the map. But the model construction for the model-based control methods is much quicker. Usually data collected over one day or two days are sufficient. Therefore, before the performance map is generated, initial values of performance index are required to deploy performance-based control. Model-based methods are a reasonable option to generate the initial values (i.e., using the models to predict the values of performance index under different input conditions and fulfill the map). Another option is the combination of two methods: using model-based supervisory control at the very beginning until the performance map is constructed using real data.

Another drawback is that the performance-based method works well only for fixed scenarios. To decrease the dimensions of the performance map, the method takes particular input variables as constants. In normal state realization, we assume the values of sun radiation are constant. In pre-conditioning implementation, we consider only the case when the comfort requirements are fixed – the previous setpoint, the expected temperauture and its schedule are all fixed. This limits the application of performance-based methods. But the performance-based methods require little computation. They are very useful for real-time programs.

4.7 Further Discussion

Up to now, four supervisory control strategies were developed to realize interior space conditioning. However, they may not work equally for all residential houses, because a house and its HVAC systems have their own characteristics.

The pre-cooling strategy is more beneficial for houses with small leakage and a good ability to store heat. The more heat a house can store, the longer the recovery period, and more peak load can be shifted to the previous off-peak period. The strategy is best suited to newer, better-insulated concrete homes. On the other hand, the pre-conditioning strategy will most benefit the least efficient homes. For poorly-insulated houses, heating/cooling intervals are affected by weather conditions dramatically. Such houses make significant energy savings by deploying the pre-conditioning strategy, considering the large variation of heating/cooling intervals. Similarly, houses with less powerful HVAC systems make larger savings: it takes much longer to achieve comfort under extreme weather.

Some strategies do not work properly under some particular conditions, according to the observations obtained from simulations and the field tests. For example, in one test house in Bay Point, CA, its air conditioner is so undersized that the controller can not run the normal state or the pre-cooling strategy appropriately when the outside temperature is extremely hot. Further, the indoor temperature keeps increasing when the outdoor temperature is hot, and it can not be maintained at a reasonable set-point for the normal state or at a pre-cooling setpoint. In order to create a tolerable environment on a hot summer afternoon, users keep the air conditioner on continuously from the early morning. They check the predicted outdoor temperature every morning before taking such actions. Currently, no specific strategies are designed to mimic such behavior. Except for mimicking what users do, another suggestion is to upgrade the HVAC equipments. Actually, this option is more appropriate from the point of view of economics.

The system should give such suggestions automatically, as an HVAC professional would. Further analysis on house signature is needed. Theoretically, this feature is named automated continuous commissioning. In addition to the HVAC system, the objects of the commissioning include malfunctions of control software, incorrect operations by users, hardware failures and communication failures. When anomalies are detected, they should be diagnosed and evaluated. Finally, a course of action should be suggested by the system. This is one of the directions of future work.

Chapter 5

Conclusion

In this thesis, a demand-responsive autonomous system was developed for interior space conditioning in residential houses. Its functions of multiple sensing and actuating are built on low-cost, low-power wireless technology, providing informative knowledge and independent operations that enable advanced control strategies. Intuitive user interfaces are designed to teach users the concept of DR and inform them how the system works, improving the usability and acceptability of the system. The system interacts with various objectives including public utilities, residential houses, HVAC equipment, and human beings. To handle the complicated working environment, control functionalities are embedded in a layered structure. Such design provides modularization of functions and semi-independent designs for each layer.

To realize demand responsiveness and autonomous optimal control, the control functions are realized by supervisory controls and local controls. This thesis focuses on the development of the former – supervisory controls. Generally speaking, supervisory optimal control aims at seeking the minimum operating cost while providing satisfactory indoor comfort. Adopting a hierarchical structure, supervisory controls are realized by three steps: deciding control modes, choosing control states, and finally choosing control strategy settings – temperature setpoints and their schedule if necessary, which will be delivered to local controls as the control objectives.

Several control strategies for interior space conditioning are designed to meet users' various requirements on utility cost and thermal comfort. The results from computer simulations and field tests prove the effectiveness and efficiency of the control strategies.

- The normal state utilizes indoor temperature control with a constant setpoint. The key is to locate a balance between utility cost and thermal comfort according to users' economics sensitivity. As the innovation of the thesis, economics indexes are proposed to express users' economics choice. Since the normal strategy has the effect of decreasing load for peak-price-period, it is considered a DR strategy.

- The pre-cooling/pre-heating strategy is a typical DR strategy – shifting peak loads to off-peak periods. To minimize the total electricity cost instead of electricity consumption, the temperature profiles under different settings are predicted, and the optimal settings are located using optimization techniques. We found the pre-cooling/pre-heating settings are significantly affected by the price ratio of peak to off-peak. In addition, temperature soaking shows potential to enlarge load shifting.

- The pre-conditioning strategy is not a type of DR strategy. No price issue is considered here. Instead, it is designed to satisfy users' thermal requirements with minimum cost/energy consumption. Toward this end, the controller needs to customize its settings based on the individual house and the local climate. House signature identification is the key enabling technology.

- The overlapping strategy is more complex than the above three strategies. It considers the combination of two objectives: load shifting plus target thermal comfort or load shifting for two future price-increasing events. Due to its complexity, the overlapping strategy had not been implemented so far.

The hierarchical supervisory controls are realized by hybrid control methods. A model-free method – an expert system determines control mode and control state; control strategy in each state is realized by model-based methods or performance-based methods. Three model-based methods are discussed in the thesis. Their characteristics and applications are listed in table 5.1. The performance-based method is deployed to realize normal state control and pre-conditioning control as well. These methods perform acceptably when realizing control strategies, although problems exist. First, in the normal state and the pre-cooling/pre-heating state, near-optimal settings are located due to the prediction errors in model-based methods. Second, the soaking effects of pre-cooling strategy for well-insulated, newly-constructed houses can not be predicted using any of these methods. Finally, users' behavior sometimes leads to large noise to the controller.

In conclusion, the thesis demonstrates the potential of a smart, adapting, demand responsive, disaggregated control system for interior space conditioning. Here are the main contributions: 1) constructed the system and validation tools, 2) developed hierarchical controls that respond to DR price signals autonomously, and 3) deployed supervisory control methods to realize optimization control strategies and validated the performance through computer simulations and field tests.

Table 5.1: Comparison for Model-based Supervisory Control Methods

Method	Parameter Number	Prediction	Application
1^{st}order physical model	4	Linear shape, good for short-term HVAC operations	Normal
Tabular Model	Hundreds	Good for short-term HVAC operations in cooling mode	Normal, Pre-conditioning
ARX Model	10-plus	Good for both short-term and long-term HVAC operations. But short-term predictions are not as accurate as using Tabular Method.	Pre-conditioning, Pre-cooling/Pre-heating

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