Zoning and Occupancy-Moderation for Residential Space-Conditioning under Demand-Driven Electricity Pricing

by

Woei Ling Leow

B.Eng. (Electrical Engineering), National University of Singapore, 2002

M.S.E.C.E., University of Massachusetts Amherst, 2007

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Author ....
Engineering Systems Division
April 24, 2012

Certified by ....
Richard C. Larson
Mitsui Professor of Engineering Systems
Thesis Supervisor

Certified by ....
James L. Kirtley Jr.
Professor of Electrical Engineering

Certified by ....
Roy E. Welsch
Professor of Statistics and Management Science and Engineering Systems

Accepted by ....
Olivier L. de Weck
Associate Professor of Aeronautics & Astronautics and Engineering Systems
Chair, ESD Education Committee

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Abstract

Occupancy-moderated zonal space-conditioning (OZS) refers to the partitioning of a residence into different zones and independently operating the space-conditioning equipment of each zone based on its occupancy. OZS remains largely unexplored in spite of its potential to reduce the cost of space-conditioning. Despite the excitement surrounding cloud-connected devices like mobile phones and tablet computers, the benefit of using them to aid energy management agents (EMAs) in reducing space-conditioning cost under demand-driven pricing of electricity is not well understood.

We develop a novel framework and the algorithms to enable an EMA to implement OZS for multiple inhabitants under a demand-driven pricing scheme for electricity. We further investigate the effects that influencing factors can have on the effectiveness of OZS under different scenarios using Monte Carlo simulations. The simulation results demonstrate that OZS is realizable on a simple home computer and can achieve significant space-conditioning cost reductions in practice. In our studies, both the financial operating cost of space-conditioning and the cost associated with discomfort are included in a single aggregate cost function.

We then expand the simulations to study the cost reduction that is achievable when using cloud-connected devices to provide remote schedule updates to an EMA. This part of the study reveals that reduction in space-conditioning cost is appreciable if a working resident remotely updates an EMA at mid-day of his return time in the evening. In addition, we establish a directly proportional relationship between the level of space-conditioning cost reduction achievable and the variance of return time.

Based on the research findings, we further offer recommendations and ideas for future research on the use of OZS and remote schedule updates to different stakeholders like policy-makers and homeowners.

Thesis Supervisor: Richard C. Larson
Title: Mitsui Professor of Engineering Systems

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"For what purpose should one cultivate wisdom? May you always ask yourself this question."

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Chapter 1

Introduction

1.1 Motivation and Overview

Residential demand response is often predicated on the presence of an energy management agent (EMA) in the house under a demand-driven pricing of electricity, such as those described in [Hammerstrom, 2007b, Livengood and Larson, 2009]. The current state of affairs, however, is such that price per unit of electricity facing the overwhelming majority of residential consumers in the world is fixed at a constant rate independent of the time of the day. Changes in legislation is often hampered by inertia while consumers so used to a pricing system that has been in place for decades are not ready-adopters of new electricity pricing schemes. An incentive of some kind, such as a monetary reward in the form of cost savings for example, is likely needed to motivate the average homeowner to install an EMA to control the home appliances. The status quo is expected to endure. Residential demand response schemes that require demand-driven pricing will remain in the realm of pilot studies, test beds and scale-limited rollouts as long as the status quo is maintained.

Under the current circumstances, it is desirable to have a bridging solution or application that incentivizes the homeowner to adopt the said EMA under the promise of cost savings in the absence of demand-driven pricing. This bridging solution or application should also enhance the cost savings achieved by the EMA under a demand driven pricing scheme for electricity when such an arrangement is in place.

Residential heating and cooling, which is referred to as space-conditioning in this dissertation, accounts for 26% of American residential electricity consumption in 2001 [EIA, 2001], which translates to 25.6 billion dollars. This is approximately equivalent to 30 billion dollars today, which can literally solve the world hunger problem. (According to the Food and Agriculture Organization (FAO) of the United Nations, the "world only needs 30 billion dollars a year to eradicate the scourge of hunger." [FAO, 2008]) In addition, the Commonwealth of Massachusetts is projected to expend thirty billion dollars in government spending for FY2011. These figures suggest that residential space-conditioning deserves a closer look as a candidate for the said bridging application. Within the domain of space-conditioning and demand response applications, prior work [Chen, 2008, Lu et al., 2010] suggested the usefulness of zonal space-conditioning as a strategy to reduce electrical consumption but did not explore the subject further.

According to the American Housing Survey [Szymanoski and Johnson, 2009], there are 130 million housing units in the United States, of which 112 million are occupied year round. In the same survey, 103 million or 92% of occupants responded to having some type of air-conditioning in their residence. In addition, 35 million or 32% of occupants reportedly have some form of electric heating in their homes. Given that 99.7% of housing units have more than two rooms [Szymanoski and Johnson, 2009], zonal space-conditioning appears to be a reasonable strategy towards the objectives of increasing energy efficiency of a residence and reducing the space-conditioning load.

All the above motivated the author to study zonal space conditioning as a strategy and a bridging application to enhance the savings of an EMA, with or without a demand-driven pricing scheme of electricity in place. The astute reader will also note that zonal space-conditioning entails that the occupancy of each zone will influence or moderate the degree of conditioning for that zone. To be exact, the strategy in question can be termed occupancy-moderated zonal space-conditioning. By occupancy-moderated zonal space-conditioning (OZS), we refer to the partitioning of a residence into different zones and independently operating the space-conditioning equipment of each zone based on occupancy and in so doing, achieve some degree of reduction in energy needed to maintain a level of comfort acceptable to the occupant. Under a demand-driven pricing scheme, the potential for cost savings is further enhanced through the use of pre-conditioning to shift loads, as discussed in [Chen, 2008, Constantopoulos et al., 1991, Livengood and Larson, 2009].

Livengood [Livengood, 2011], under the tutelage of Larson [Livengood and Larson, 2009], has laid the groundwork for an Energy Box that controls individual appliances such as clothes washing machine, dryer, etc. and instructs the space-conditioning system in place about the most desirable temperature to maintain the house at. The author aims to lay the groundwork to realize zonal space-conditioning in an EMA at the level of individual space-conditioning in each zone that factors in the the occupancy state of each zone to complement the work by Livengood. In other words, instead of deriving a most desirable temperature, the current work will enable the EMA to provide actual control signals to the individual space-conditioning equipment in each zone.

Occupancy is inherently random. Intuition suggests that the less random and the more predictable one's occupancy patterns are, the greater the potential for savings achieved by OZS. The advent of cloud computing and ubiquity of smart mobile devices offers the EMA an ally in reducing the uncertainty of occupancy patterns. This further motivates the author to investigate the notion of remote schedule updates (RSU), where possibly real-time information from mobile devices is used to advise the EMA of expected occupancy patterns.

1.2 Research Questions and Objectives

It is most logical to question the efficacy of OZS now that we have identified it as a promising bridging solution. In addition, we would also like to know how RSU can aid space-conditioning in general. In view of these queries, we pose the following research questions which this dissertation will address:

1. What level of cost savings can OZS achieve under a demand-driven electricity pricing scheme under realistic settings?

2. How do influencing factors impact the savings achieved by OZS under a demand-driven electricity pricing scheme?

3. What level of space-conditioning cost reduction can remote schedule updates bring about?

The influencing factors referred to in the second research question are the number of occupants and zones, the randomness of the occupancy patterns, the level of similarity between the occupancy patterns of inhabitants and the thermal mass of the residence.

1.3 Research Methodology, Framework Formulation and Algorithm Design

Monte Carlo (MC) simulation is the primary method of investigation for both of the studies on OZS and RSU. Towards this end, virtual residences were set up in the Matlab environment and MC simulations driven by random signals including occupancy, meteorological inputs and price of electricity under different scenarios were ran. The total cost of operating the space-conditioning equipment for the case with and without OZS under the same conditions were collected and compared.

Since the value of any results obtained using MC simulation is highly dependent on the random inputs driving the simulations, we used real-world data observed in practice or highly-realistic proxy data to drive the MC simulations as far as possible.

To the best knowledge of the author, there does not exist a readily available framework or formulation to implement OZS. While there are occupancy learning algorithms, optimal control techniques and inverse-modeling methods to characterize the thermodynamics of buildings, there does not exist a unified framework that consolidates all the necessary elements from the various disciplines to realize a practically feasible EMA or controller to implement OZS. This compels the author develop the framework, formulation and algorithms needed to realize OZS, with Constantopoulos' dissertation [Constantopoulos, 1983] as the starting point.

The effort required to investigate the benefits of RSU, though challenging, was less involved. This is possible only because the author could adopt the newly completed Energy Box simulator [Livengood, 2011] to run MC simulations to investigate the cost of space-conditioning with or without RSU.

1.4 Outline of Dissertation

Following a survey of the literature in the second chapter, the third chapter begins the more technical discussion of the control strategy developed for realizing OZS and paints a clearer picture of the need for learning of thermal characteristics and occupancy patterns described in the fourth and fifth chapters.

Chapter Four provides a survey of common heating systems and discusses in detail a simplified model for describing the thermal characteristics of a zone and the means of learning about the parameters of the model. Chapter Five delves into the different aspects of occupancy, including the source of occupancy data used in this work, the framework to model occupancy patterns and method of learning about them. The results of Monte Carlo simulation runs under the different scenarios and settings using the framework and formulation described in previous chapters can be found in Chapter Six. An account of the random inputs used to drive the simulations is also included in the sixth chapter.

The subject of using mobile devices as an aid for RSU is discussed in Chapter Seven. Chapter Seven will also describe some aspects of the Energy Box simulator developed by Livengood [Livengood, 2011] as the study on RSU is based on the said simulator. The dissertation is brought to a close in the concluding chapter, which summarizes the results obtained, offers the different stakeholders e.g. homeowners a few pointers about OZS and puts forth possible avenues for future research.

1.5 List of Acronyms

AC Air-Conditioner

ADP	Approximate Dynamic Programming
ATUS	American Time Use Survey
DP	Dynamic Programming
DPI	Deterministic Perfect Information
EBA	Event-based Appliance
EBS	Energy Box Simulator
EMA	Energy Management Agent
MCS	Monte Carlo Simulation
OAT	Outdoor Air Temperature
OZS	Occupancy-Moderated Zonal Space-Conditioning
RSU	Remote Schedule Update
RTP	Real Time Pricing

Chapter 2

Literature Review

2.1 Founding and Foundations

We begin our survey of the literature by tracing the beginnings of demand-driven pricing and demand response in the electric industry and zonal space-conditioning.

The impact of the early work by Schweppe [Schweppe et al., 1988] and colleagues at the Massachusetts Institute of Technology (MIT) [Schweppe et al., 1980] on demand response can be likened to that made by Shannon on communications theory and technology with his seminal work [Shannon, 1948]. Schweppe et. al. aimed to provide the framework and foundation for the realization of utility-customer transactions based on contemporary needs with the publication of [Schweppe et al., 1988]. A key element of such a realization is the use of spot pricing of electricity which was discussed from different aspects including those on spot price behavior, energy marketplace transaction, means of implementation, generation and revenue reconciliation. With remarkable prescience, one chapter in [Schweppe et al., 1988] prognosticated a deregulated energy market place. Schweppe's idea and vision remain highly-regarded by his colleagues at MIT and practitioners in the industry, including Dr. Chao of ISO New England.

The idea of homeostatic utility control (HUC) was introduced in [Schweppe et al., 1980]. Although an uncommon word in engineering literature, homeostatic aptly captures the notion of the supply and demand systems in an electric power grid working together to maintain a continuous equilibrium to the benefit of both the utilities and the consumer that is central to the idea of HUC. In essence, HUC utilizes the rational supplier's and consumer's response to price, enabled by communication and computation technologies, to realize an efficient, internally-correcting control scheme. The paper goes on to explore the various elements and structures to bring about this state of homeostasis.

Thus was the subject of demand-driven pricing founded, and the foundations of demand response laid. An excellent account on the history of inducing responsive electricity demand can be found in the doctoral thesis by Livengood [Livengood, 2011].

Working on the ground-breaking ideas of spot pricing and HUC, Constantopoulos explored the idea of load shifting under a spot pricing scheme as a strategy to achieve demand response in his doctoral dissertation [Constantopoulos, 1983]. In addition to developing the framework, formulation and control strategy to shift loads using the pre-conditioning of residences when the spot price is relatively low, his dissertation factored in the occupant's utility function and introduced the means to appropriately account for monetary cost and "service loss". In [Constantopoulos, 1983], the controller of space-conditioning equipment allows the temperature in the house to deviate from the desired temperature but within strict upper and lower bounds. The resident decides and sets these bounds and the desired temperature.

It is worthy to note that Constantopoulos's dissertation appears to be a harbinger to future work that occurs at the intersection of engineering, management and social science. The more readily accessible paper by Constantopoulos, Schweppe and Larson [Constantopoulos et al., 1991] published in an important journal describes the key ideas and results from his dissertation and bears testament to the value and validity of his work.

A discussion on the history of zonal space-conditioning is included here for the sake of completeness. The earliest implementation of zonal space-conditioning dates back to antiquity, in ancient China, Europe, Greece, India and the Near East, where occupants of a space use portable fire stoves called braziers to provide heating when needed. The use of portable stoves for zonal space-conditioning is likely due to the limitations of technology and for the sake of convenience, rather than solely out of a desire to conserve fuel.

The Nimrud brazier [Russell, 2011] which dates back to at least 824 BCE, discovered in the mid-1990s at the Neo-Assyrian capital of Nimrud in Iraq, was made of wood clad with bronze that takes the form of a square box on four spoked wheels. It remains the only known mobile firebox or portable brazier that Assyrian kings used to provide heating in winter. In the mid-19th century, excavators working on archaeological research sites in Iraq reported grooved "tramlines" running down the centre of Assyrian throne rooms. With such "tramlines" in place, the brazier could be wheeled along the lines to where heat is needed. The practice of installing or operating space-conditioning equipment at zones where it is needed continues to this day, with portable electric heaters or window-unit air-conditioners joining the modern brazier in the quest for thermal regulation in zones. Chen [Chen, 2008] provides a concise but informative account of the history of interior space conditioning.

The patent issued to Stacey [Stacey, 1936] in 1936 marks the beginning of modern zonal space-conditioning systems. To the best knowledge of the author, Stacey is the first to have as an objective in an invention to "*provide a system of atmospheric control which includes the division of the enclosure into a number of zones... and the control of atmospheric conditions in individual zones.*" This was followed by others [Capps, 1965, Locke, 1940, Nessell, 1941, 1942] over the years that made incremental improvements on different aspects of zonal space-conditioning systems. These developments, along with other advancements, eventually led to the development of HVAC systems with ducts delivering conditioned air to different zones and multi-split air-conditioning systems that has become indispensable to the modern lifestyle.

2.2 Recent Resurgence

A growing concern for the environment, a desire for greater energy independence, an ever-increasing global demand for energy and other trends have ignited the interest in clean technology. Like a boat on a rising tide, demand response that aims to "shave the peaks and fill in the valleys of demand" is an area that has garnered much attention since the early 2000s. This renewed enthusiasm has brought about a resurgence of research interest in the area founded by Schweppe.

The works by Black [Black, 2005, Black and Larson, 2007] can be seen as a herald of this resurgence. His doctoral dissertation [Black, 2005] provides an in-depth look at the technical, regulatory, and market issues to determine a system structure that incentivizes demand response. The paper by Black and Larson is not limited to electric power systems and investigates congestion pricing in general across critical infrastructures in terms of the expected benefits of forgone investment achieved by reducing peak demand [Black and Larson, 2007].

Frequency Adaptive Power Energy Reschedulers, or FAPERs, were introduced by Schweppe in [Schweppe et al., 1980]. Brokish continued the work on FAPERs in [Brokish, 2009] by investigating their use in the adaptive load control of microgrids. FAPERs aim to use temperature-bounded appliances e.g. air-conditioners, electric space or water heaters for energy storage by using grid frequency as a signal. When grid frequency is too high or too low, FAPER-enabled appliances can power up or down and consequently increase or shed load to aid with frequency regulation (assuming the pre-determined temperature bounds are not exceeded). A novel FAPER control algorithm proposed by Brokish uses probabilistic functions outperformed one that does not by achieving better frequency regulation and having less clustering of appliances operations. In addition, Brokish discovered the limitations in using Markov Chains to model wind power which he detailed in [Brokish and Kirtley, 2009].

Continuing from where Constantopoulos had left off, Livengood and Larson introduced the idea of the Energy Box in [Livengood and Larson, 2009]. The Energy Box is an energy management agent (EMA) that runs round the clock to manage energy usage in a residence or small office/home office (SOHO) with the aim of achieving an objective. The intelligence of the Energy Box lies in its algorithm bank, and can operate either locally on a computer or remotely on a server. Using an implementation of approximate dynamic programming, Livengood reports cost reduction (compared to a baseline) between 5% and 44% in simulations runs involving a residential energy system that includes thermostat control, batteries, wind turbines etc.

The interested reader is referred to Livengood's doctoral dissertation [Livengood, 2011] for a more detailed account of research related to the Energy Box and the development of a software simulator. Using the simulator he developed, Livengood ascertained that coordinating decisions across appliances and devices within a home did not bring about additional benefits for the typical consumer. In the case where the resident is a 'prosumer' i.e. one who produces and consumes electricity, coordinating decisions between appliances may bring about additional benefits as compared to independently controlling the appliances and devices. In addition, it was reported that a joint dynamic programming decision method that includes the thermostat of an air-conditioner, the dishwasher and wind forecasts provides the most improvement over independent control.

The testbed demonstrations projects completed by the Pacific Northwest National Laboratory [Hammerstrom, 2007a,b] serve as good examples of successful real-world experimentation of demand response. The report on the Olympic Peninsula Project [Hammerstrom, 2007b] details the realization and results of a field demonstration involving residential electric water heaters and thermostats, commercial building space conditioning, municipal water pumps etc. The report concludes that the price is an effective control signal for managing transmission or distribution congestion, thus proving the value of Schweppe's vision in practice, albeit on a smaller scale.

The Grid Friendly Appliance Project [Hammerstrom, 2007a] has a greater residential flavor to it, involving 50 residential electric water heaters and 150 clothes dryers in homes for a year. These appliances were modified so that they will shed load when the power grid frequency was below 59.95 Hz. The appliances were found to have responded reliably to each underfrequency event (averaging one per day) while end-users reported little or no noticeable inconvenience to them and that the appliances' load shedding activity went unnoticed.

The trilogy of doctoral dissertations [Chen, 2008, Jang, 2008, Peffer, 2009] captures the essence of a study involving policy analysis, system design, software development, hardware integration, among other tasks, that addresses the topic of residential demand response with some emphasis on space-conditioning to realize a demand-responsive electrical appliance manager (DREAM [Berkeley, 2011]). The DREAM is in essence made up of a wireless network of sensors, actuators and controller that intelligently manages a residential space-conditioning system and informs the residents of their energy usage patterns through a user interface.

In her dissertation [Peffer, 2009], Peffer provided a detailed account of the design and testing of the DREAM and a user-interface, the evaluation of machine-learning algorithms to predict a user's temperature preference and developed an algorithm that generated temperature setpoints based on the outdoor air temperature (OAT). The simulated energy used by the space-conditioning system using the generated setpoints were compared to that used in the case where the default setpoints of the traditional EnergyStar programmable thermostat were used. The former resulted in running 17% fewer hours of heating and 34% fewer hours of cooling when compared to the latter. A strength of the DREAM project lies in the fact that real-time data collected from field tests are used. For instance, data was collected from test houses in locations like Antioch, CA.

Of the trilogy, the dissertation [Chen, 2008] is the most relevant to the current work on OZS, where Chen detailed the demonstration of an intelligent, adaptive and autonomous residential space conditioning system under the context of demand response. The discussion on optimization that focuses on the design and the implementation of supervisory control forms a significant portion of [Chen, 2008]. The DREAM adopts a hierarchical structure for its supervisory controls, which is realized in three steps: first is to decide the control mode, the second of which is to choose the control states, and finally selecting the control strategy settings - temperature setpoints and their schedule if need be, which will in turn be sent to local controls as the control objectives.

In addition to describing local control, Jang's doctoral dissertation [Jang, 2008] was primarily concerned with developing an algorithm to characterize the thermal dynamics of a house. A multi-model approach was adopted, where several candidate models whose parameters were calculated from seven consecutive days were used. The system could either operate in the multiple-model hard switching (MMHS) mode where it picks one of the models or fuses all of them in the multiple-model soft switching (MMSS) mode. The MMSS produced better overall performance when compared to the MMHS.

Like in [Chen, 2008], Lu suggested but did not explore the usefulness of zonal space-conditioning in [Lu et al., 2010]. In his paper, Lu described the use of low-cost sensing technology to learn about occupancy patterns which will in turn moderate the space-conditioning system in the residence, thereby saving energy. The proposed method was evaluated by a deployment of sensors in eight homes, which achieved an average savings of 28%.

2.3 Current Attempts to Kill Bill

With the cost of power on the rise, it is increasingly imperative to understand energy consumption and adjust usage to non-peak times so as to lower power usage and costs. There are already dozens of companies building home energy management systems that typically use a home network to communicate with devices and the utilities. In this section, we survey a non-exhaustive selection of products, tools, platforms and services that attempt to help the average homeowner kill the utility bill. The inclusion of any commercial offering in this survey should not be interpreted as an endorsement.

2.3.1 Products and Tools

Kill A Watt [P3, 2012] can help the user assess how efficient appliances are. Its large LCD display gives measurements of consumption by the kilowatt-hour and shows meter readings in terms of volts, amps, watts, hertz and VA. Users can calculate electrical expenses by the day, week, month, or even year. They can also check the quality of power by monitoring voltage, line frequency and power factor. Its sister product, the Save A Watt timer, will turn on and off based on users preferred settings.

It can be programmed ON/OFF to save money and prolong the life of electronic gadgets. Meanwhile, its cousin Kill A Watt Wireless monitors power consumption remotely and calculates carbon emissions and costs by day, week, month and year. It can also transmit data to the central LCD display where users can see their cumulative electrical expenses and the carbon footprint of their appliances.

The Nest Learning Thermostat [Nest, 2012] is an independent gadget that does away with the fiddling of knobs and programming of temperature. Set it like a traditional thermostat, and it will pick up energy-saving habits and program itself in a week. It ignores one-off changes but is quick to catch on when users make changes at least a couple of times. Easy to install, its activity sensors have a 150° wide-angle view so its Auto-Away feature knows when to kick in and turn down heating and cooling when no one is home. Its three temperature sensors track the space-conditioning of the residence, an important function since a change in set-point can significantly affect energy consumption.

It uses its Wi-Fi connection to monitor weather conditions so it can understand how external temperature can impact internal energy use. The Energy History function shows how much energy is used each day. Its Nest Leaf icon pops up to show users that they are saving energy, thereby encouraging energy-saving habits. Nest is also nested online so a laptop, tablet or smartphone is all users need for real-time control to view multiple thermostats at home or adjust the temperature, wherever they may be. Nest is also secure and boasts public key cryptography. Its money-saving sensibilities are made more attractive by its sleek minimalist design.

The Prestige programmable thermostat [Honeywell, 2012] from Honeywell features a full-color touchscreen that makes it easier to program than other offerings in the market. It asks users questions and then programs itself based on the answers given. The gadget allows separate programming for each day of the week and can save up to 33% on annual energy costs - or up to $200 per year. It can function as a load-shifter by automatically adjusting setpoint temperature when the price of electricity are at their highest to help slash energy costs. Prestige HD also controls temperature and indoor air quality such as humidification, dehumidification and air filtration from a single control. Its Total Connect Comfort Services function offers remote control over the Internet from a PC, smartphone or tablet so users can adjust home temperature settings on the fly. It can communicate in English, Spanish or French and its Wireless Outdoor Air Sensor displays outdoor temperature readings.

The Home Energy Saver [HES, 2012] is a set of on-line resources developed by the U.S. Department of Energy to help consumers and energy analysts evaluate, reduce, and manage home energy use. Created at the Lawrence Berkeley National Laboratory, this energy assessment tool enables consumers to carry out home energy audit and provides recommendations to help reduce household energy consumption and utility costs. Users enter a zip code to receive estimates for typical and efficient homes in their area. The estimates break down energy consumption by "end use", such as cooling, water heating, major appliances, and lighting. The more details a user enters, (e.g., insulation levels, roofing, age of major equipment, how systems are used), the more customized the assessment results and energy efficiency recommendations become. The reports shed light on the estimated cost of improvements, anticipated payback time, projected utility bill savings, and how much energy use and green house gas production will be cut. Consumers can adjust energy efficiency assumptions and upgrade costs, (e.g., replacing the default values with actual estimates from contractors) and recalculate payback times and other details.

The website has a section that provides tips on energy savings, explain the house-as-system energy efficiency approach, and gives other information to help users understand how energy is used in a home. Launched in 1994, Home Energy Saver has been used by 6 million people to analyze their home energy use. The site is visited by nearly a million people each year. In 2009, a second version of the tool, Home Energy Saver Professional, was launched and boasts a low-cost, interactive energy simulation/assessment tool for building professionals, contractors, and weatherization professionals.

2.3.2 Platforms

Tendril Connect [Tendril, 2012] is an energy management platform that offers the different stake-holders unprecedented insight, choice, control and access to the Smart Grid. This scalable, open and standards-based, end-to-end solution empowers utilities and their customers to deploy cutting-edge energy solutions and gives them access to data and analytics about energy consumption, so that they can cut costs, reduce environmental impact and realize operational efficiencies. Consisting of an integrated suite of utility and consumer applications, as well as robust application program interfaces (APIs), Tendril Connect aims to create a two-way dialogue between utilities and their customers. This dialogue promotes customer participation and improves customer satisfaction in tandem with energy efficiency and demand response programs.

The result is improved compliance with Public Utilities Commission (PUC) mandates as well as long-term operational and infrastructure cost savings. Its open APIs enable extensibility and third-party application integration. Its horizontally scalable architecture provides high-availability infrastructure and lowers the total cost of ownership. Infrastructures are kept at a high level of availability through the use of redundancy and replicated service instances.

Its event-driven architecture allows for real-time data capture, improves processing capacity and throughput. Customers can track home energy costs and consumption by appliances, electronics, and household devices. Tendril Connect links a set of applications and devices that form a reliable and secure ZigBee enabled Home Area Network (HAN). These devices interact beyond the meter with existing home appliances to provide access and information about energy usage in the home as well as insight into the applications deployed on the platform, including energy awareness, load control, and demand response applications. The repertoire includes the Tendril Insight in-home display, Tendril SetPoint smart thermostat, Tendril Volt smart outlet, Tendril Relay range extender, Tendril Translate gateway and the Tendril Load Control Switch. The information captured and displayed by Tendril HAN products can be accessed over the Internet or smart mobile devices through the Tendril web portals. Multi-tier security is possible thanks to standards-based authentication, authorization and encryption procedures.

The Qurrent Qbox [Qbox, 2010] is a Local Energy Network Interface, or 'energy modem', that entered the scene with much acclaim, clinching the top prize of the Postcode Lottery Green Challenge in 2007. It collects energy data from a building, communicates with the server and can switch appliances to improve efficiency within the limits set, such as when a task has to be completed and the amount of time allowed. Qbox will decide what will be the best time to work on a task. It takes into account the user's production profiles and energy rates, as well as the neighbors consumption and production. It will independently measure all electricity production and consumption and make it possible to share capacities with the neighborhood or cluster, all within a Local Energy Network. Qbox ensures that self-produced energy is used to the maximum. It comes with four standard switches but can be expanded through serial connection. This allows users to control other energy-equipment, such as heat pumps and combined heat and power systems, and also to switch appliances in the building, further optimizing energy efficiency.

Qbox has multiple means of flexible connection to meters, appliances and energy systems. These multiple interfaces (pulse, serial, digital and analog i/o) allow Qbox to be applied in myriad of situations. Qbox also measures energy usage at a very detailed level. The data is then transferred to the central Qurrent Qserver which holds all records. User can then log on to the Qmunity website and analyse their energy consumption and production. Energy data is stored indefinitely but secured according to the highest privacy standards and laws.

2.3.3 Services

Verizon's fiber-optic communications network forms the backbone to connect a gateway-based smart-home automation system named Home Monitoring and Control (HMC) [Verizon, 2012] to the cloud, thereby allowing users to remotely access the system as long as they have Internet access. This is done by having the gateway in the house connect to Verizon's existing high-speed Fios broadband network. The management system which Verizon markets as a subscription service for $9.95 a month gives real-time access to view and make changes to a home's lighting, security cameras, locks, and thermostats, as well as appliances and consumer electronics devices connected to the home network. The software application can be accessed by smartphone, computer, or Fios TV. Customers who sign up for the home service have the option to either install the home control equipment themselves, including electronic door locks, or hire an installer. Professional installation can be provided by installation company InstallerNet. Verizon will extend InstallerNet's InstallCard program to customers so they can go online and chose a local installer to schedule an installation.

In Verizon's HMC, space-conditioning applications can be realized through the 110V appliance switch, which uses the Z-wave protocol, to turn an appliance on or off at the command of the gateway and can also track energy use. This operates on the simple principle where the appliance to be controlled e.g. air-conditioner, space heater, can be plugged into the appliance switch which is then plug into a wall outlet. In residences where there is a compatible space-conditioning system, the smart thermostat can be set via the Internet, such as through a smartphone.

In addition, users can connect as many as accessories as they deem fit. For instance, the Schlage door latches and deadbolts can be locked and unlocked by key, access code or smartphone. The cameras can be connected by wire or wirelessly and come in three versions: indoor camera, pan and tilt indoor camera, and outdoor camera. Sensors and switches are available for windows and doors and can let users know whether a door or window is open or shut. They can be easily installed with screws or double-sided tape. Light modules can be turned on or off by plugging a light into a module which is in turn plugged into a wall outlet. Remote controls are available to control lights and other tools at the push of a button. The energy reader analyzes the energy use of the entire house.

According to industry representatives in the know, Verizon worked with Motorola to offer the HMC. Motorola muscled its way into the smart home market by buying home automation and energy monitoring startup 4Home Connected Solutions

(4Home) via its communications subsidiary Motorola Mobility. 4Home's strength lies in its user-interface, and provides the software that gives home owners remote and round the clock access to information — from digital media to energy info, home security and health data — across devices. 4Home provides affordable home security (alerts home owners to security breaches, avoids false alarms), energy management and analysis (reduces carbon footprint, manages energy use, cuts costs), life management (ensures elderly or young family members are safe, helps users stay connected with loved ones), and home control (multi-feed video display, remote camera toggling, entry/exit logs, appliance scheduling, go to bed mode). 4Home also boasts a business working with utilities and smart meter installers on home energy management projects.

Microsoft trotted out the Microsoft Hohm [Microsoft, 2012b] in conjunction with PowerCost Monitor for managing home electricity use. Hohm is a free online application that helps save energy and money. Hohm helps users understand their home energy usage and gives them recommendations to conserve energy and enjoy saving. Hohm uses advanced analytics licensed — from Lawrence Berkeley Laboratories and the Department of Energy — to give personalized energy saving recommendations. These recommendations are tailored based on specific household circumstances including home attributes and use of appliances and systems. The recommendations will also be refined as the beta application evolves with feedback from users, their communities and the energy industry. Users can also compare energy usage with that of other users in the area. Actual energy savings vary and depend on a variety of factors, including local weather data, personal habits, and home age, size, and structure. Slow overall market adoption of the service, however, has made Hohm unsustainable as a business proposition and will be discontinued on May 31, 2012 [Microsoft, 2012a].

Google launched its PowerMeter service as a Google.org project to increase awareness about the importance of giving people access to data pertaining to their energy use. It is worthy to note that Google.org is the philanthropic arm of Google. Despite the fact that Google has retired the service on September 16 2011, the PowerMeter has nevertheless demonstrated the usefulness of access to energy information and provided a model for other developers or service providers [Google, 2011]. The project did get off the ground in that Google rolled out the PowerMeter to U.K. residents, and used the "white space" spectrum of the broadcast system left open by TV's switch to digital for smart-grid communications in Plumas-Sierra County, California in a partnership with Spectrum Bridge and the Plumas-Sierra Rural Electric Cooperative and Telecommunications utility. Although no longer in active service, the Google PowerMeter deserves a mention for having shown the way.

PowerMeter is realized through a free opt-in software tool that allows users to see detailed home energy information right on their computer. The online application takes information from a smart meter or electrical monitoring device in the home and provides real-time information about power usage. The advantage is that users can see which appliances are using the most power, when the peak power usage is, and how to adjust usage to benefit from lower off peak electricity prices. With PowerMeter, users can view details, such as weekly trends, from a Web browser or a smart phone running iGoogle. Users can use PowerMeter without having to have a smart meter installed.

PowerMeter works with TED 5000, a small-screen monitor that provides a real-time read-out of home electricity use. TED, which stands for The Energy Detective, is one of many monitors aimed at giving consumers more detailed information so they can find ways to reduce energy use. Though straightforward, installation of the TED 5000 requires technical savvy. Google was looking to expand the number of devices that work with PowerMeter and had wanted to expand beyond simple energy monitoring. While the project was still active, there were plans to implement features like ways to control home appliances to take advantage of off-peak electricity rates and demand-response programs.

General Electric (GE) offers a smart-grid home-monitoring system that can also be tied to using a home electric vehicle (EV) charger in anticipation of what is to come. The Nucleus [GE, 2012] home energy monitor and energy management system can monitor electricity use and control appliances using a home wireless network. About the same size and shape as a mobile phone charger, Nucleus can monitor and control connected appliances. It will only work with a smart meter that uses the Zigbee wireless protocol, which means it will only be available to consumers who are customers of utilities that have installed and activated smart meters. With Nucleus, users can see their energy usage in real time through a PC or a smartphone application. The device, which connects to an Internet broadband router with an Ethernet cable, can store up to three years' worth of energy data. Future models will have a removable data storage option.

By communicating with a smart meter, Nucleus allows users to program appliances to participate in demand response and take advantage of off-peak pricing plans offered by utilities that have time-of-use electricity plans. GE is making a line of networked appliances that can go into energy-saving mode when a utility sends a load shed request. While these appliances will operate automatically, the peak-time modes can be manually overridden so as not to frustrate and alienate the user. It is also worthy to note that the WattStation EV charging pedestal or wall-mount is made for charging electric vehicles for use in cities, residences, university campuses, offices or parks. GE is expected to play a big role in the future as its biggest advantage may be its relationship with utilities, which could recommend the device as part of smart-meter programs.

2.4 Behavioral Aspects of the Problem

There are literally hundreds of studies on the behavioral aspect of user response, interaction and engagement with devices and systems related to energy use. Stern [Stern, 1999] reports that the most useful information is the one that captures the user's attention, wins his involvement and is useful and reliable in the user's situation. In other words, what matters most is how the information motivates the user into action and not the content or means of presentation. This section aims to highlight studies and their results that can inform the design and implementation of an energy management agent (EMA) in the mold of an Energy Box to achieve the best possible results for engaging the user.

Wood and Newborough published a series of papers [Wood and Newborough, 2003, 2005, 2007a,b] addressing the subject of user behavior and its relationship with the presentation of energy information. This series collectively presents the results from one of the more comprehensive investigations so far. They report that electrical feedback methods are more effective in engendering behavior change while antecedent information is found to be of limited effectiveness in [Wood and Newborough, 2003]. In [Wood and Newborough, 2007a], they presented a useful summary of factors influencing the effectiveness of energy information display in an intelligent home.

Consistent with the belief that money makes the world go around, Wood and Newborough further reported in [Wood and Newborough, 2007a] that given a financial incentive for reducing their energy consumption, people tend to perform better than if there were no monetary reward. In a Canadian study [Dobson and Griffin, 1992] involving 25 homes over 50 days where a "residential electricity cost speedometer" to provide feedback to users was implemented, Dobson and Griffin observed that the average daily electricity consumption fell by 12.9%.

Apart from financial incentives, emotional rewards, perhaps in the form of social commendation, may be helpful as a motivating factor but the jury is still out on its effectiveness. According to Katzev et. al. [Katzev et al., 19801981], social reinforcement, in the form of a card that says "we are saving electricity", have no effect on users' energy-consumption behavior. The use of social reinforcement may have greater effect on those who are environmentally conscious. According to Osbaldiston and Sheldon in [Osbaldiston and Sheldon, 2003], people who are environmentally conscious significantly outperform than those who feel that the goals were imposed on them or whose compliance were engendered by a guilty conscience.

Related to the notion of a guilty conscience, some studies [Humphries and Hyldon, 2004, Wood and Newborough, 2005] investigated the usefulness of self-other comparison. Humphries and Hyldon [Humphries and Hyldon, 2004] suggested that self-other comparison is typically unpopular among as a means of motivating behavioral change among end-users. In particular, participants remains doubtful of the service provider's ability to accurately ascertain self-other comparisons. This view is also echoed in [Wood and Newborough, 2005].

Self-comparison and goal setting, on the other hand, display much promise in terms of effectiveness in engendering behavior change. Wood and Newborough [Wood and Newborough, 2007a] note that self-comparison of historical data by consumers have been positively received, a position supported by Humphries and Hyldon in their study that enlisted the help of focus groups to identify preferences [Humphries and Hyldon, 2004]. Goal setting, as reported by Harkins and Lowe [Harkins and Lowe, 2000], is effective in improving performance of tasks in general. Wood and Newborough [Wood and Newborough, 2003] reports an average reduction of 15% in energy use in a study that investigates goal setting by consumers.

The astute reader will observe that apart from motivating factors, the type of energy information displayed and the manner in they are presented will play a key role in engaging the user. Numerical data used in field studies to provide information on appliances revealed significant energy savings [Wood and Newborough, 2003]. While it is tempting for a interface designer with a technical background to include technical units like kWh, tons of carbon dioxide emitted, etc., it will be foolhardy to assume that such units are readily understood by the average user. Research in the United Kingdom [Mansouri et al., 1996, Newborough and Probert, 1994] shows that the majority of the population do not understand energy units and face difficulty estimating how much energy is required for different tasks.

Since financial incentive is known to be a good motivating factor, an obvious piece of information to display for the purpose of seeking consumer engagement will be energy expenditure (or savings) per unit time. Wolinsk [Wolsink, 1997] reports that such an approach can be effective if the potential savings is considerable or if time-of-use tariffs are in place. This suggests that any savings to be presented to the user ought to be projected or averaged out over weeks, months or the year, rather than hours or days.

A Finnish study further reports that graphical representation like pie and bar charts actually receive more attention than numerical values of kWh readings, prices, etc. [Arvola et al., 1993]. According to [Preece and Keller, 1990], pie charts may be useful for pattern detection but do not measure up as well for determining values or making comparisons. In addition, a pie chart should not have more than five segments and that each segment should be clearly labeled with numerical values on the segments. With these in mind, the practitioner should try to use a bar chart as much as possible as it allows for more accurate comparisons. The venerable handbook [Harris, 1999] advises that bar and column charts are effective in showing values for separate quantities while line graphs are suited for displaying trends and changes over time. The bar chart was put to good use in the "residential electricity cost speedometer" [Dobson and Griffin, 1992].

An important caveat to take note of is that cultural differences may cause the mileage to vary for a certain means of presentation in different cultures. For instance, Wilite et al. [Wilite et al., 1999] reports that the univariate graph was more easily comprehensible to the 2000 Norwegian households tested. On the other hand, Egan in an American study [Egan, 1999] found the opposite result, where the univariate graph did not do as well as the distribution graph when it comes to consumer understanding of what the graphs wanted to present. Given that both studies were well-conducted, cultural differences appear to be a reasonable explanation for the contradiction in outcomes.

With a more avant garde approach, Rodgers and Bartram [Rodgers and Bartram, 2011] investigated the use of artistic visualization for energy use feedback. One of the novel, artistic representation they developed used spinning pinwheels, where power used is represented by the rate of spinning and the number of pinwheels.

Chapter 3

Optimization in the Energy Box

The performance of the Energy Box is highly dependent on the optimization and optimal control technique(s) used to decide on the operations of the space-conditioning equipment. Inheriting the rigorous approach adopted in [Constantopoulos, 1983, Constantopoulos et al., 1991], we attempt to reformulate the multi-zone space-conditioning problem in the dynamic programming (DP) framework while including occupancy as a random disturbance. The problem involves several state and random variables such as the temperature of a zone and that of neighboring zones, the outdoor air temperature (OAT) and the price of electricity. The OAT and price of electricity pose an additional challenge as the range of values they can take are wider than that of indoor zone temperatures. This is especially so in the case of price of electricity which can take on values that differ by at least one order of magnitude. The "curse of dimensionality" seems to have reared its ugly head.

Against this backdrop, just like in [Constantopoulos, 1983], exact backward dynamic programming (DP) is ineffective given the need for speed in a real-time application like space-conditioning as the nature of the task and variables involved make the "curse of dimensionality" unavoidable. The presence of other stochastic disturbances in addition to price makes the determination of expected values relating to all these random quantities intractable in practice. These factors motivate the use of approximate dynamic programming (ADP) and Monte Carlo (MC) simulations.

Thankfully, decades of advancement have produced many new techniques such as

ADP and neuro-dynamic programming described in [Bertsekas and Tsitsiklis, 1996, Bertsekas, 2007, Powell, 2007] to address the issue of dimensionality, which we will explore in this chapter. We begin by first presenting the framing and formulation of the problem, which introduces the elements of DP involved. At the heart of the said framework is an ADP algorithm that makes use of value function approximation and seeks to minimize the cost of space-conditioning. Dimension is reduced through the aggregation of variables and estimation of parameters for use with models.

3.1 Framing and Formulation

The DP framing is carried out at the zone level i.e. each zone is seen as an agent with its own state variable, control action, disturbance etc. We proceed to discuss each of the key elements of our DP framework in greater detail. All quantities and variables are standardized i.e. normalized by their maximum or mean value to give a dimensionless quantity often with absolute value less than or equal to unity. The control horizon consists of one-hour blocks ($\tau = 1$) over the course of a normal work day, which sets the stage for a finite horizon DP problem with $N = 24/\tau = 24$.

3.1.1 State Variable (x_i), Control Action (u_i) and Stochastic Disturbances

All variables pertaining to temperature are standardized by subtracting the desired temperature from it and dividing the difference by the maximum allowable temperature deviation for each zone, as described in [Constantopoulos, 1983]. For example, with a desired temperature of 75°F and a maximum swing of 15°F, a 90°F temperature corresponds to 1 after standardization. The temperature of the zone of interest (e.g. the master bedroom) at time period i, denoted by x_i, is the main state variable, where $x_i \in [-5, 3]$, which corresponds to the limits of [0°F, 120°F]. This extended limit is motivated by the need for consistency with the outdoor or solar air temperature in the external environment. Other operational constraints limit the value of x_i

such that $x_i \in [-1, 1]$.

The use of value function approximation [Bertsekas and Tsitsiklis, 1996, Powell, 2007] motivates the formulation of an augmented state variable, which will include the difference between temperature of the zone of interest and the outdoor (sol-air) temperature denoted by d_i and the occupancy probability of neighboring zones denoted by $\widehat{\Omega}_{k,i}$ in addition to the temperature of the zone of interest denoted by x_i. As will be discussed in section 3.2, the augmented state variable can be seen as an information vector that enables value function approximation by providing the relevant information as inputs to the approximating function. It may appear to the astute reader that an augmented state space exacerbates the curse of dimensionality. The problem is worsened only when exact DP is used. As will be made clear in later expositions, the ADP technique adopted does not make any evaluation at every possible combination of the augmented state variable, and hence the issue of dimensionality does not matter.

The control action for the zone at time period i, denoted by u_i, is simply the actuated power of the heater or air-conditioner, expressed as a fraction of maximum power. In this application, we set $u_i \in \{0, u^1, \dots, u^{10}\}$, where $u^p = \frac{p}{10}$.

We represent the set of stochastic disturbances, which consists of the price of electricity, temperatures in adjacent zones and occupancy, with a vector quantity $\underline{w}_i$. The price of electricity at time i is denoted using p_i, with $p_i \in [0, 1]$ and the maximum possible price of electricity is used as the normalization factor. Occupancy Ω_i is used to represent the presence of an occupant in the zone of our interest. The random variable of occupancy, which takes a binary value where $\Omega_i \in \{0, 1\}$, corresponds to the notion of an occupant being "absent" or "present" In the augmented state variable, the occupancy probability is denoted by $\widehat{\Omega}_{k,i}$, where $\widehat{\Omega}_{k,i} \in [0, 1]$, gives the probability of zone k being occupied.

For a zone with m adjacent zones in the house, it has $m + 1$ temperature-related stochastic disturbances at time period i, denoted by w_i^j, where $j = \{0, 1, \dots, m\}$. The outdoor or solar air temperature of the external environment is denoted by w_i^0.

In some instances, we suppress the subscript $k = l$ when referring to any quantity pertaining to zone $l-$ the zone of interest, while quantities with subscripts e.g. $x_{k,i}$ refers to the quantity related to zone k with $k = 0$ referring to the outdoor environment and $k = j\ \forall j \neq 0, l$ relating to the neighboring zones e.g. $\Omega_{2,i}$ denotes the occupancy of the neighboring zone 2. Control (u) and occupancy (Ω) are meaningless for the outdoor environment, while control for the neighboring zones in the house is not part of the optimization.

3.1.2 Transition, Cost and Objective Functions

The transition function pertaining to x_i, which is derived from the laws of thermodynamics, captures the relationship between the temperatures in the different zones, the control action and the current temperature in the zone. The quantity d_i is simply the difference between the new zone temperature and the current outdoor temperature. Predicted occupancy probabilities are given by occupancy probabilities for each zone given the current occupancy, based on a conditional probability mass function.

The augmented state variable and the associated transition functions are given by

$$\tilde{x}_{i+1} = \begin{pmatrix} x_{i+1} \\ d_{i+1} \\ \underline{\widehat{\Omega}}_{j,i+1} \end{pmatrix} = \begin{pmatrix} \epsilon_k x_i + \gamma_k u_i + \sum_{j=0}^{m} \varepsilon_{k,j} w_i^j \\ x_{i+1} - w_i^0 \\ \underline{P}(\Omega_{j,i+1} = 1 | \Omega_{1,i}, \dots, \ \Omega_{m,i}) \end{pmatrix} \tag{3.1}$$

where ϵ_k, γ_k and $\varepsilon_{k,j}$ are known constants and the underlined quantities (Ω and $P(.)$) are column vectors with m entries and the j^{th} entry corresponding to zone j in the residence. One may question how the transition functions for the state variable and the conditional probability in (3.1) can be obtained. In short, the state variable transition function is to be learned i.e. the parameters estimated during the process of zone thermal characteristics learning. The conditional probability is provided by an occupancy learning algorithm. Chapters 4 and 5 detail the zone thermal characteristic and occupancy learning respectively.

The cost function aims to capture the trade-off between the cost of operating the space-conditioning equipment and the cost of service loss due to discomfort when the zone temperature deviates from the preferred temperature. It is given by

$$g_k(\tilde{x}_{k,i}, u_{k,i}, \underline{w}_{k,i}) = \alpha_i p_i u_{k,i} + \beta_i b(\ f_k(\tilde{x}_{k,i}, u_{k,i}, \underline{w}_{k,i})\ )\Omega_{k,i} \tag{3.2}$$

where

$x_{k,i}, u_{k,i}, \underline{w}_{k,i}$	state variable, control action, disturbance for zone k at period i
p_i	normalized price of electricity at period i
w_i^j	temperature of adjacent zone j at period i
α_i, β_i	constants related to inhabitant preference at period i.
$\Omega_{k,i}$	occupancy status of zone k at period i
$b(.)$	service loss function.

The service loss function is assumed to be a quadratic function that takes in the zone temperature as the input and returns the squared value as the output, as described in [Constantopoulos, 1983]. The service loss function does not exceed one since its argument is standardized and is limited to a value between -1 and 1.

With the aim of jointly minimizing the cost of operating the space-conditioning equipment and of service loss, the objective function is formulated as

$$J_{k,i}(\tilde{x}_{k,i}) = \min_{u_{k,i}} E\{\ g_k(\tilde{x}_{k,i}, u_{k,i}, \underline{w}_i) + J_{k,i+1}(\ f_k(\tilde{x}_{k,i}, u_{k,i}, \underline{w}_{k,i})\ )\ \} \tag{3.3}$$

where $g_k(.)$ and $f_k(.)$ denote the cost and transition functions, as described by equations (3.1) and (3.2) respectively. The expectation is taken with respect to the random quantities in vector $\underline{w}_{k,i}$. We suppress the tilde's ($\tilde{}$) commonly associated with cost, transition and objective functions that involve augmented state variables to reduce clutter in the nomenclature.

3.2 ADP for Finite Horizon Problem

3.2.1 Backward Value Function Approximation

The framing and formulation of the problem as described in section 3.1 readily lends itself to a solution based on sequential backward approximation for finite horizon problems discussed in [Bertsekas and Tsitsiklis, 1996, pp. 330].

For the problem at hand, the DP algorithm for a zone l takes the form

$$J_N^*(\tilde{x}_N) = \min_{u \in U(\tilde{x}_N)} \sum_{\tilde{y}} p_{\tilde{x_N}\tilde{y}}(u)(g(\tilde{x_N},\ u,\ \tilde{y}) + G(\tilde{y})) \tag{3.4}$$

and

$$J_i^*(\tilde{x}_i) = \min_{u \in U(\tilde{x}_i)} \sum_{\tilde{y}} p_{\tilde{x}_i\tilde{y}}(u)(g(\tilde{x}_i,\ u,\ \tilde{y}) + J_{i+1}^*(\tilde{y})),\ i = 1, ..., N-1 \tag{3.5}$$

where

$p_{\tilde{x}\tilde{y}}$	transition probability from state $\tilde{x}$ to state $\tilde{y}$
$G(\tilde{x})$	terminal cost of being in state $\tilde{y}$
$J_i^*(\tilde{x}_i)$	optimal cost to go of an i-stage problem starting from state $\tilde{x}_i$.

and we suppress the subscript l to improve readability. (With the subscript, the variables will appear as $J_{l,i}^*, \tilde{x_{l,i}}$ and so on.)

Equation (3.4) relates to the terminal stage, while (3.5) is for all other stages. The difference arises because the terminal stage does not have to account for the cost to go of the next stage in this formulation, but has to include the terminal cost. In this case, the terminal cost function is given by the product of a scalar and the service loss function.

A solution is offered through recursively approximating the cost to go ($J_i^*(.)$) function. We begin by making an approximation of the optimal cost to go using a function $\tilde{J}_N(\tilde{x}_N, r_N) \approx J_N^*(\tilde{x}_N)$, where r_N is a parameter vector given by the solution to

$$\min_{r_N} \sum_{\tilde{x_N} \in S_N} (J_N^*(\tilde{x}_N) - \tilde{J}_N(\tilde{x}_N, r_N))^2 \tag{3.6}$$

where S_N is a representative set of states. This formulation omits the weight factors that are present in [Bertsekas and Tsitsiklis, 1996, (6.58)] as all time periods are considered to be equally important. In this case, (3.6) was solved by fitting a minimum mean-squared error linear regression model, which will be discussed later.

The approximating function to the cost to go function in subsequent (preceding) time periods can be obtained by first finding the approximate cost to go function values $\widehat{J}_i(\tilde{x}_i)$ for a representative subset of states S_i through an approximate DP formula:

$$\widehat{J}_i(\tilde{x}_i) = \min_{u \in U(\tilde{x}_i)} \sum_{\tilde{y}} p_{\tilde{x}_i \tilde{y}}(u)(g(\tilde{x}_i,\ u,\ \tilde{y}) + \tilde{J}_{i+1}(\tilde{y}, r_{i+1})),\ \tilde{x}_i \in S_i \tag{3.7}$$

The values obtained from this representative set S_i are then used to derive an approximation of the cost to go function $J^*(\tilde{x}_i)$ by a function $\tilde{J}_i(\tilde{x}_i, r_i)$, which can be obtained by solving

$$\min_{r_i} \sum_{\tilde{x}_i \in S_i} (\widehat{J}_i(\tilde{x}_i) - \tilde{J}_i(\tilde{x}_i, r_i))^2. \tag{3.8}$$

In this way, we recursively derive $\widehat{J}_i(.)$ and $\tilde{J}_i(.)$ for all time periods.

3.2.2 Linear Regression for Approximation

We first use minimum mean-squared error linear regression to address the family of problems defined by (3.6) and (3.8). This implies

$$\tilde{J}_i(\tilde{x}_i, r_i) = r(0) + r(1)x_i + +r(2)d_i + \sum_{j=1}^{m} +r(j+2)\widehat{\Omega}_{j,i}. \tag{3.9}$$

where

$r(l)$ parameters and components of the vector r, $(l = 0, 1, ..., m+2)$

x_i state variable for zone temperature at time i

d_i difference between the zone temperature and the outdoor temperature

$\widehat{\Omega}_{j,i}$ probability of zone j being occupied at time i.

The variables x_1, d_i and $\widehat{\Omega}_{j,i}$ are embedded in the state variable $\tilde{x}_i$. In addition, there are m neighboring zones that is indexed by j.

The parameters $r(l)$ was obtained through the use of standard minimum mean-squared error linear regression, which affords a simple and possibly speedy solution. In addition, the R^2 statistic associated with linear regression turns out to be a convenient indicator of getting a sense of the "closeness of fit" provided by the parameters obtained for each time period.

The R^2 statistic from the linear regression conducted for each time period suggests that linear regression will do well. Most time periods have $R^2 \approx 0.9$ with those corresponding to the graveyard shift closing in on unity. Time periods corresponding to time of day where there is greater uncertainty in occupancy e.g. just before and right after working hours tend to score lower on R^2. The high R^2 statistic hints that a simple linear model may suffice for the problem at hand, and that additional complexity in the model may only marginally improve performance but render the algorithm less robust to noise. While the statistics suggest great promise, the proof of the pudding remains in the eating.

3.2.3 Monte Carlo Simulation and Resulting Policy

The reader will observe from the discussion in section 3.2.1 that knowledge of the transition probabilities $p_{\tilde{x}_i\tilde{y}}$ is needed for determining the expected values necessary for sequential backward value function approximation to be possible. Given the multi-dimensional nature of the augmented variable and the large state-space that results, coupled with the complexity of random disturbances, the use of transition probabilities is impractical. In the same vein as approximate policy iteration based on Monte Carlo (MC) simulations in [Bertsekas and Tsitsiklis, 1996, pp. 271], MC simulations, instead of transition probabilities, were used to find the expected values.

To determine the expected value, we simply run a sufficiently large number of simulations using $\tilde{x}_i$ as the beginning state, then apply a candidate control u and take the average of the sum of all the resulting costs. The resulting cost from each simulation includes both the one-step cost ($g(.)$) and the value function approximate ($\tilde{J}(.)$) of being in the resulting state.

The resulting policy is also based on Monte Carlo simulations. Using the approach described in section 3.2.1, we obtain a set of approximate cost to go functions $\tilde{J}_i(., r_i)$, where $i = 1, 2, ..., N$. Based on these approximate functions, the resulting policy is then given by

$$\overline{\mu}_i(\tilde{x}_i) = \arg \min_{u \in U(\tilde{x}_i)} \sum_{\tilde{y}} p_{\tilde{x}_i \tilde{y}}(u)(g(\tilde{x}_i,\ u,\ \tilde{y}) + \tilde{J}_{i+1}(\tilde{y}, r_{i+1})) \tag{3.10}$$

where the expected value corresponding to each control $u \in \{0, u^1 ... u^{10}\}$ on the RHS is obtained by taking the average of the outcomes of a large number of MC simulations. One will observe that this may not be suitable for a controller operating in real-time, especially if each time period is short. In this case, a possible improvement lies in the use of an action network [Bertsekas and Tsitsiklis, 1996, pp. 261].

Chapter 4

Zonal Space Conditioning and Thermodynamics

An objective of studying zonal space-conditioning and building thermodynamics is simply to develop a sufficiently-sophisticated model that will provide a transition function (3.1) of appropriate fidelity for use with the ADP algorithm discussed in section 3.2. While not at the same level of fidelity as that used in commercial building simulators, the derived transition function should be computationally efficient such that it can work in a real-time controller and yet be accurate enough for ADP to work well. In addition, the parameters of the transition function should be easily estimated with as little user input or intervention as is possible. A deeper look at space-conditioning systems will also provide insights on the types of space-conditioning system that can work with an energy management agent (EMA) like the Energy Box and hence outline the scope of the work.

The first section of this chapter aims to provide an overview of space-conditioning systems and the scope of the work. This is followed by a section that surveys the different well-established models of building thermodynamics and provides the theoretical basis for the model that is developed for use with the ADP framework. Section three presents the derivation of the model and the transition function for use in the ADP framework. It also describes the virtual residential set-up for simulations.

4.1 Overview of Space-Conditioning Systems

4.1.1 Heating Systems

We begin by surveying the landscape of heating systems and determine the types that are suitable for use with the Energy Box. Heating systems can be broadly categorized along two dimensions, namely the energy used to generate heat and the response time of the heating system. For simplicity, we divide heating systems into those that are powered by electricity and those that use combustible fuels or other sources of energy. With regard to response time, we categorize heating systems into those that have short response times and those that have long ones. Response time refers to the time elapsed between the moment of actuation and the instant the heater begins to emit heat at the maximum power or the desired power level. A short response time has an order of magnitude in seconds or less while a long response time could mean minutes or even hours are needed to attain maximum power from the moment of actuation.

Publications from the venerable American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) such as [ASHRAE, 2004] were used as the primary reference and were complemented by technical data sheets, commercial catalogues and product literature in the public domain. Table 4.1 presents the various commonly-available heating systems according to their response time and energy source. The information presented here is not intended to be exhaustive but is the result of a "best effort" attempt to capture the essential and relevant characteristics of common heating systems in North America which are used for automatic residential zonal space conditioning.

Observe that the hydronic and steam heating systems require the bulk heating of water in a boiler before the heated fluid is circulated to different zones. This means that without making changes to such systems, it is not possible to calculate the amount of energy that was transferred to each zone with a sufficient degree of accuracy for dynamic programming (DP) to be useful. Infra-red heaters can be differentiated from conventional resistance-based heaters by their operating temperature where the former typically operates at temperatures between 300 - 5000 °F while the latter

	Short Response Time	Long Response Time
Powered by Electricity	resistance-based heaters forced hot air systems heat pumps infra-red heaters	hydronic heating systems steam heating systems
Powered by Combustible Fuels and Others	fireplaces/stoves forced hot air systems geothermal infra-red heaters	hydronic heating systems steam heating systems infra-red heaters

Table 4.1: Heating systems categorized according to response time and energy source.

usually operates at temperatures below 300 °F [ASHRAE, 2004, p.15.1]. Another peculiar feature of infra-red heaters is that they directly heat the object or person using infra-red radiation and very little energy is used to heat up the air. As such, the indoor air temperature of the zone may not give a good indication of thermal comfort, unlike other heaters. The infra-red heaters will most likely work best under manual control due to this peculiarity.

Forced air systems are usually used in a central space conditioning system. A typical electric forced hot air furnace works by blowing filtered, cool air directly through electric heating elements [ASHRAE, 2004, p.28.4] and transferring the heated air to different zones through ducts. We assume there exists a means of accurately measuring the amount of electricity used for space-conditioning for each zone at any time. The energy used to move the conditioned air as well as heat gain or loss en route to the zones can be accounted for by an efficiency or coefficient of performance (COP) factor, denoted by η.

Panel heating, as described in [ASHRAE, 2004], refers to a class of heating system that can be categorized in all the four categories in Table 4.1. When they run on electricity using heating elements to generate heat, they fall under the categorization of resistance-based heaters. A possible disadvantage of electric panel heating is that "response time can be slow if controls and/or heating elements are not selected or installed correctly" [ASHRAE, 2004, p. 6.1]. In other words, the long response time is the consequence of incorrect deployment rather than a design consideration, and suggests that it is more the exception than the rule.

4.1.2 Heating Time Constants

The heating time constant, denoted by T_H, is a measure of how quickly a heater can "ramp up" to warm a given space. This is different from the power rating of the heater, and is largely dependent on the technology used for heating. For a given power rating, a radiating electric heater that works by running a high current through a heating element will have a much shorter heating time constant compared with one that is based on forcing hot water through a system of pipes.

One way to capture the effects of the heating time constant is through the use of a time-dependent factor that scales the power output from the heater, to give the effective power output. We can express the effective power output at time t in the n^{th} control interval as

$$E_{\text{eff}} = (1 - e^{-\frac{t-n\tau}{T_H}})E, \quad t \in [n\tau,\ (n+1)\tau]$$

where E is the power rating of the heater and τ is the length of each control interval. It is assumed that the heater is actuated at the beginning of each control period i.e. at multiples of τ. Observe that for small T_H, $E_{\text{eff}} \approx E$. For larger values of T_H, say T_H =24 and assuming $\tau = 1$, $E_{\text{eff}} \leq 0.04E$ regardless of the value of t, n.

An alternative formulation is to assume a linear relationship between the time elapsed, the maximum power and the effective power output. We express this as

$$E_{\text{eff}} = \min(\ 1, R_H(t - n\tau)\ )E, \quad t \in [n\tau,\ (n+1)\tau],\ R_H \in (0, \infty)$$

where R_H is a parameter that captures the rate at which the heater "ramps up" to full power. Regardless of the values of R_H, t and τ, the effective power output cannot exceed the rated, maximum power rating of the heater.

4.1.3 Scope of Discussion for Space-Conditioning Systems

In this dissertation, the discussion is limited to properly installed, residential air-conditioning and heating systems powered by electricity, which allows for an accurate, quantitative account of how much energy is used to cool or heat a zone. Resistance-based heaters, forced hot air systems and heat pumps with heating time constants equal to or approximately zero ($T_H = 0$ or $T_H \approx 0$) are heaters of interest that are considered in this work.

The typical air-conditioner can be considered to have a short or even negligible response time. One constraint air-conditioners have, however, is that a mandatory time delay is required between the time it is powered down and the next actuation. Personal communication by the author with those familiar with the operations of air-conditioners revealed that a 20 minute delay between power down and re-actuation is usually sufficient. Consequently, we do not consider any control interval that is less than 20 minutes for air-conditioners in this study.

4.2 Modes and Models of Heat Transfer

The fact that universities dedicate entire departments to the study of building thermodynamics underscores the vastness of the field. In this work, we consider the general, first-order effects of heat transfer between a zone in the house and the outside environment as well as to other zones. The objective is to develop a model that captures the dominant heat transfer processes accurately for the ADP algorithm to perform well and can be used in a software running on a simple home computer.

The author surveyed the different modes of heat transfer using [Givoni, 1998, ASHRAE, 1997, 2005] as the primary references with the aim of identifying the dominant heat transfer processes. Once the dominant processes were identified, a deeper look at the physics underlying the processes was made with the hope of finding a suitable model on which the transition function described in Chapter Three can be based upon. The heat transfer processes of conduction, air infiltration and radiation were considered, and were looked into with greater detail. Other possible modes of heat transfer were considered to be less dominant and can either be assumed to be negligible or dominated by the three modes listed above.

4.2.1 Conduction

Thermal conduction in buildings is simply the transfer of heat through solid materials such as a building element e.g. a wall, a roof, from the side of the element at a higher temperature to the other side at a lower temperature. The rate of heat transfer depends on many factors, key among them are the conductivity of the material and the thickness of the element in question.

Each type of material has a measure, called thermal conductivity, to indicate its ability to conduct heat. Conductivity values of common building materials can be obtained from many public domain resources such as online databases maintained by the National Institute of Standards and Technology [NIST, 2010] and published references such as [Givoni, 1998]. Conductivity has energy per unit time per unit temperature difference per unit length for its dimension.

As thermal conductivity relates to building materials, we need other measures of heat conductivity or resistance for building elements, such as walls. In a building element made up of more than one layer of material, the thermal resistance of any given layer i is the ratio of the thickness of that layer l_i to the conductivity of the material k_i used in that layer i.e.

$$r_i = \frac{l_i}{k_i} \tag{4.1}$$

For building element m with n layers, its total resistance R_m is given by the sum of the resistance from each of the n layers i.e.

$$R_m = \sum_{i=1}^{n} r_i = \sum_{i=1}^{n} \frac{l_i}{k_i} \tag{4.2}$$

where r_i, l_i and k_i are the thermal resistance, thickness and thermal conductivity for layer i respectively, as used in (4.1).

The concept of thermal resistance, though useful and intuitive, is not often used in heat calculations in the literature. Thermal transmittance, which is often known as the "U value", is commonly used instead. The thermal transmittance of an element with one side indoors and the other outdoors refers to the thermal transmission of heat through a unit area of the element per unit time per unit temperature difference between the indoor and outdoor temperatures. Its dimension is given by energy per unit time per unit temperature difference per unit area. Mathematically, it is given by the reciprocal of thermal resistance:

$$U_m = \frac{1}{R_m} = \frac{1}{\sum_{i=1}^{n} \frac{l_i}{k_i}} \tag{4.3}$$

where R_i, r_i, l_i and k_i are as defined in (4.1) and (4.2). The astute reader will observe that it is in general easier to calculate the thermal resistance of a building element as it involves summing several quantities while the thermal transmittance simplifies any heat transfer calculation as it is a multiplicative factor to any temperature difference.

In the calculation of the thermal resistance for any building element, it is important to account for the resistance due to the air attached to its surface. The thermal resistance of any such air film depends on the air speed. The indoor surface is usually exposed to still, indoor air which means its resistance, commonly denoted by R_{in}, is typically higher and assumed to take on 0.12 in the metric system or 0.68 in the British system [Givoni, 1998, pp. 116]. The outdoor surface, being exposed to wind, has a smaller air film thermal resistance R_{out} associated with it, which is commonly assumed to be 0.03 (metric) or 0.17 (British).

The rate of heat flow Q_m through a building element m with area A_m is given by

$$Q_m = U_m A_m (T_h - T_c) \tag{4.4}$$

where

- U_m thermal transmittance or U value of building element m
- A_m area of exposed surface on building element m
- T_h air temperature on the hotter side of building element m

T_c air temperature on the cooler side of building element m.

Equation (4.4) can be modified for use in the case of windows. For a glazed window w of area A_w with U value of glazing U_{gl}, the rate of heat flow through the window is given by [Givoni, 1998, pp. 131]

$$Q_w = U_{gl} A_w (T_h - T_c) \tag{4.5}$$

with T_c and T_h denoting the same quantities defined in (4.4).

The astute reader will observe that another possible avenue of heat transfer, via conduction through the ground, exists. It is noted, however, that "the state-of-the-art in ground modeling is not very good even in detailed building energy simulation programs," according to [ASHRAE, 2007, p.70]. Consequently, it is assumed that heat transfer through the ground occurs at a constant rate.

4.2.2 Air Infiltration

Given that residential buildings cannot be assumed to be air tight in general, air infiltration as a potential cause of heat loss (or gain) cannot be neglected. Air infiltration is usually accounted for in the literature [ASHRAE, 2007, Givoni, 1998] through a rate of air change statistic. The air change rate or air changes per hour, denoted by "ach", essentially specifies how many times the whole air volume of the space changes in an hour.

Obviously, the airflow and air change rate depend on the air tightness of the building. A very tight building may have an ach rate of 0.5 or even lower. A value of 1 ach is typically assumed in standard calculation of heat transfer [Givoni, 1998, pp. 128].

Infiltration heat loss (or gain) of air is proportional to the difference between the indoor and outdoor air temperatures, and is directly related to the ach and the heat capacity of air. For an enclosure or zone k, the rate of heat transfer due to air infiltration $Q_{V,k}$ can be written as

$$Q_{V,k} = V_k ach_k (\emptyset c)_a (T_h - T_l) \tag{4.6}$$

where

V_k	volume of air in enclosure/zone k
ach_k	air changes per hour statistic of enclosure/zone k
$(\emptyset c)_a$	heat capacity of air
T_h	temperature of the volume of hotter air
T_l	temperature of the volume of colder air.

The value of $(\emptyset c)_a$ is typically taken as 0.33 Wh/m^{3}C (metric), 1200 J/m^{3}C (SI) and 0.018 Btu/ft^{3}F (British) according to [Givoni, 1998].

4.2.3 Radiation

Radiation is another process through which a building gains or loses heat. Radiant energy emitted by an object is known to be proportional to the fourth power of its surface absolute temperature. As energy is conserved, radiating energy also means losing energy, which entails a drop in temperature of the object emitting the radiant energy.

The energy radiated by the object travels through space in the form of electromagnetic waves until it strikes an opaque surface, where it is partially reflected and partly absorbed. (There exist extreme cases where almost all the energy is absorbed or reflected but these are not commonly encountered in buildings.) The absorbed radiation raises the temperature of the object that the radiation is incident upon.

Emissivity, absorptivity and reflectivity are three properties of a surface which relate to its behavior with regard to incident radiation. In the context of building elements, the emissivity of a surface has to do with the emission and absorption of long-wave radiation while absorptivity and reflectivity relate to its response to solar radiation.

Radiant Energy Loss

The emissivity of a surface, typically denoted by E_o, is a dimensionless ratio between zero and unity that captures its capacity to emit long-wave radiation relative to a "perfect" black body. In physics, a black body is a body or surface that absorbs all incident radiation.

Long-wave radiation denoted by Rad_{LW} emitted by a surface with dimensions in energy per unit time per unit length per unit temperature squared is given by

$$Rad_{LW} = \sigma E_o (\frac{T}{100})^4 \tag{4.7}$$

where

σ	Stefan-Boltzmann constant (5.67 in metric or 0.1713 in British)
E_o	emissivity of surface
T	absolute temperature of surface.

For a surface on buildings, emissivity can be assumed as 0.9, which is the typical value for masonry material in general [Givoni, 1998].

Solar Heat Gain

While emissivity decides the rate at which a surface emits energy, (short-wave solar) absorptivity dictates how much energy is absorbed by a surface. While emissivity is largely dependent on material, absorptivity can be altered relatively easily by changing the color of the surface. While the proportion of absorbed radiation is proportional to absorptivity, the reflected radiation is proportional to the reflectivity of the surface. Absorptivity (a) and reflectivity (r) are related by

$$r = 1 - a$$

In this work, we assume absorptivity to be 0.4 which corresponds to a surface with a lighter grey, green, brown or another light color [Givoni, 1998].

4.2.4 Sol-Air Temperature

At first glance, it seems that a complicated model is required to capture all of the effects of conduction, solar heat gain and radiant energy loss. An ingenious abstraction in the form of a theoretical temperature called the "sol-air" temperature enables us to capture the effects of conduction, solar heat gain and radiant energy loss in one fell swoop. In addition, the effects of wind are also captured. The concept of using the "sol-air" temperature was mentioned in [Constantopoulos, 1983, 1987]. In this work, the author attempts to justify the appropriateness of its use for home space-conditioning applications.

According to [Givoni, 1998], the "sol-air" temperature T_{SA} is given by

$$T_{SA} = T_{OA} + \frac{aI}{h_o} - T_{LWR} \tag{4.8}$$

where

T_{OA}	outdoor air temperature
a	absorptivity of the surface, assumed to be 0.4
I	intensity of incident solar radiation
h_o	overall external surface coefficient
T_{LWR}	temperature drop due to long-wave radiation to the atmosphere.

Observe that the T_{SA} is a function of a few other parameters and random variables, which are a, T_{OA}, I, T_{LWR} and h_0. We proceed to account for and specify each of these parameters or random variables.

T_{OA} is simply the outdoor air temperature, which can be obtained from outdoor thermometer readings, or from one of the many online weather resources. We assume an accurate value of T_{OA} is available, and any forecast of it is the best available.

The intensity of incident solar radiation is a less familiar quantity to the average homeowner but nevertheless needs to be accounted for. In residences where an instrument capable of accurately measuring solar radiation intensity is present, the value of I can be obtained easily and accurately. In the absence of such an instrument, we assume $I = 600$ W/m^2 (or 190 Btu/hr sq. ft.) when the sun is shining, as per standard calculations presented in [Givoni, 1998]. A higher level of sophistication can be incorporated into the model by formulating I as a function of another meteorological phenomenon, namely cloud cover. We assume that I and cloud cover as well as time of day are related in the following way:

$$I \text{ in W/m}^2 \text{ (Btu/hr sq. ft.)} = \begin{cases} 600\ (190), & \text{Clear sky in the day} \\ 300\ (95), & \text{Partly cloudy sky in the day} \\ 0, & \text{Cloudy sky or at night.} \end{cases}$$

Information on cloud cover and times at which the sun will rise or set can be obtained from online services providing weather information.

Cloud cover also plays an important role in determining the value of the temperature drop due to long-wave radiation to the atmosphere, T_{LWR}. According to [Givoni, 1979, 1998], T_{LWR} is equal to 6°C (11°F) for a roof in an arid climate and equal to 4°C (7°F) in a humid climate, under a clear sky. As for a wall facing an open field, T_{LWR} is 2°C (5°F). Under a cloudy sky, and for walls facing other walls in a built-up urban area, T_{LWR} can be assumed to be zero. For simplicity, we assume T_{LWR} to be related to cloud cover in the following way:

$$T_{LWR} = \begin{cases} 3^oC\ (6^oF), & \text{Clear sky} \\ 0^oC/F, & \text{Cloudy or partly cloudy sky.} \end{cases}$$

The overall external surface coefficient h_0 depends on the wind speed and serves as the mechanism through which the effects of wind is captured. A h_0 value of 20 W/m^{2}C (or 6 Btu/hr sq. ft. F), under the assumption that wind speed is 3.5 m/s (or 700 fpm), is suggested for design purposes [Givoni, 1998]. We assume h_0 to take the suggested value for simplicity. This simplification is reasonable as "wind speed effect in case of light-colored walls is much smaller[Givoni, 1998]," which is consistent with the assumption that the residence has a light-colored envelope, as discussed earlier.

The "sol-air" temperature is useful in the quest for a suitable transition function in that it captures the most important environmental factors that play a key role in heat transfer to a building. Consequently, it becomes the key proxy variable in the model.

4.3 Thermodynamic Characterization of Zones

4.3.1 Assumptions and Formulation

The model derived and described in this section is not intended to be a high-fidelity thermodynamic model suitable for use in a building simulator. Instead, it is a sufficiently-sophisticated prediction model that enables the ADP control strategy described in Chapter Three to work by providing a reliable state transition function.

The formulation and methods developed in earlier doctoral dissertations related to the current work are for a single-zone space-conditioning scenario [Jang, 2008, Constantopoulos, 1983], and can be used directly in the multi-zone case under the (relatively strong) assumption that the heat transfer between zones is negligible and that the temperature in each zone is influenced only by the "sol-air" temperature. While this assumption may be true for houses with very good insulation between zones, it cannot be assumed to be true for all houses. This motivated the author to develop a model that accounts for inter-zone heat transfer and an accompanying set of procedures to learn the parameters of such a model for occupancy-moderated zonal space-conditioning to be possible.

In order to develop a tractable model that captures the thermal effects of interest and relevance to occupancy-moderated zonal space-conditioning, we make the following modeling assumptions:

1. A house with K zones, where each zone can be independently conditioned by

space-conditioning equipment e.g. air-conditioner or heater is considered. Without any loss of generality, it is assumed that the rated (maximum) power of the equipment is the same for all zones for simplicity.

2. The thermodynamic characteristics of zone k are captured by its total thermal mass mc_k and a set of effective thermal conductivities A_{ki}'s describing the heat transfer characteristics between it and the adjacent zones. The total thermal mass of a zone is due to the envelope, the air mass and other contents in the zone.

3. The partitions between zones are not perfect insulators and heat exchange between zones though not negligible, does not dominate. Solar heating and heat exchange with the outdoors through building envelope remain the primary drivers of changes in zone temperature while heat exchange between zones, though accounted for, are higher-order effects.

4. We capture the effects of weather elements using the effective outside temperature, denoted by T^0. This is the "sol-air" temperature T_{SA} described in section 4.2.3. The effects of incident solar radiation or radiative heat loss can raise or lower the effective outside temperature respectively and it is modeled in the manner described in section 4.2.3. An estimation of T^0 or T_{SA} under various weather conditions is given by (4.8).

5. Ventilation and airflow between zones is assumed to be zero, as is the case presented in [Khoury et al., 2005].

6. The space-conditioning equipment in each zone is able to ensure uniform temperature in the zone and the parameter η on efficiency or coefficient of performance captures any loss, or additional heat load e.g. sensible heat load. This allows the model to account for humidity for air-conditioning by increasing the sensible heat load by 30% [ASHRAE, 1997].

7. The cycling effects of the thermostat are neglected, as in [Constantopoulos, 1983].

An introduction to the nomenclature prior to the discussion on a model that captures the dynamics of inter-zone heat transfer is in order. The notation used in thermodynamic modeling can be found in Table 4.2. The overall or effective thermal conductivity between two zones k and i denoted by A_{ki} aims to capture the characteristics of the heat transfer between the two zones and we assume a symmetric relationship i.e. $A_{ki} = A_{ik}$. The set of zones adjacent to zone k denoted by $\kappa(k)$ refers to all the zones that are located in such a way that there is a potential for heat transfer between that zone and zone k. The outdoor environment, assumed to be adjacent to all zones, is indexed by zero i.e. zone zero refers to the zone that is outside of the house.

Variable	Symbol	Unit
No. of zones, occupants	K, M	-
Zone k Temperature at time t or n^{th} time interval	$T^k(t), T_n^k$	C/F
Thermal time constant for zone k	TC_k	h
Thermal mass for zone k	mc_k	kWh/F
Thermal Conductivity between zones k and i	A_{ki}	kW/F
Occupancy of zone j at time period i (binary r.v.)	$\Omega_{j,i}$	-
Set of zones adjacent to zone k	$\kappa(k)$	-

Table 4.2: Notation adopted in models

The overall external surface coefficient h_0 depends on the wind speed. A h_0 value of 20 W/m^{2}C (or 6 Btu/hr sq. ft. F), under the assumption that wind speed is 3.5 m/s (or 700 fpm), is suggested for design purposes [Givoni, 1998]. We assume h_0 to take the suggested value for simplicity. This simplification is reasonable as "wind speed effect in case of light-colored walls is much smaller [Givoni, 1998]," which is consistent with our assumption that the residence has a light-colored envelope. In scenarios where the residence does not have a light-colored envelope, it is possible to adopt another model and include other additional terms, say one that relates to wind speed or any other meteorological quantity, to the equation describing the model (4.8). Intensity of incident solar radiation I is a function of time while T_{LWR} is assumed to be 6°C when the sun is up with a clear sky and is set to zero otherwise. An equation with a different set of parameter values can be used for different regimes or different times of the day.

In general, if a more sophisticated model is desired or required, the model and equation for T_{OA} can be similarly made more complex. The resulting model and equation(s) can still be used with other parts of the framework as long as the thermodynamic model provides an accurate approximation of the temperature trajectory of each zone.

In continuous time, the energy balance equation for the said simplified system consisting of zone k and a set of adjacent zones $\kappa(k)$ is given by

$$\frac{dT^k(t)}{dt} = -\sum_{i\in\kappa(k)} \frac{A_{ki}}{mc_k}[T^k(t) - T^i(t)] \pm \frac{\eta}{mc_k} e_k(t) \tag{4.9}$$

Solving (4.9) over an arbitrary time interval $[0, t]$ and assuming $e_k(t)$ and $T^i(t)\ \forall\, i \neq k$ remain constant over the said interval, we obtain

$$T^k(t) = T^k(0)e^{-\frac{t}{TC_k}} + \frac{1}{\sum_{i\in\kappa(k)} A_{ki}}[\sum_{i\in\kappa(k)} A_{ki}T^i(t) \pm \eta e_k(t)](1 - e^{-\frac{t}{TC_k}}) \tag{4.10}$$

where the thermal time constant is given by $TC_k = \frac{mc_k}{\sum_{i\in\kappa(k)} A_{ki}}$. The temperature of adjacent zone i denoted by $T^i(t)$ can take the value of the average temperature in zone i if the temperature is not held constant over the said interval. The same approximation can also be used for $e_k(t)$.

Since our interest lies in the value of $T^k(t)$ at the beginning of each control interval $T^k(n\tau)$, we can express T^k_{n+1} in terms of T^k_n and other parameters by substituting the appropriate values into (4.10) to give

$$T^k_{n+1} = T^k_n e^{-\frac{\tau}{TC_k}} + \frac{1}{\sum_{i\in\kappa(k)} A_{ki}}[\sum_{i\in\kappa(k)} A_{ki}T^i_n \pm \eta e_k(t)](1 - e^{-\frac{\tau}{TC_k}}), \tag{4.11}$$

where T^i_n can take the estimated value of the average of $T^i(n\tau)$ and $T^i((n+1)\tau)$ instead of $T^i(n\tau)$ for better accuracy. For brevity, we let $\epsilon'_k = e^{-\frac{\tau}{TC_k}}$, $A_k = \sum_{i\in\kappa(k)} A_{ki}$ and

$\zeta_k = \pm\frac{\eta}{\sum_{i\in\kappa(k)} A_{ki}} = \pm\frac{\eta}{A_k}$ and rewrite (4.11) to give

$$T^k_{n+1} = \epsilon'_k T^k_n + [\frac{1}{A_k}\sum_{i\in\kappa(k)} A_{ki}T^i_n \pm \zeta e_k(t)](1-\epsilon'_k) \tag{4.12}$$

The "sol-air" temperature is denoted by T^0 or T^0_n which correspond to T^i or T^i_n respectively when $i=0$. Since the outdoor environment indexed by $k=0$ is adjacent to all zones, $\{0\} \in \kappa(k)\ \forall\ k \neq 0$. The astute reader will observe from (4.12) that a linear regression model can fully relate T^k_{n+1} with other quantities (albeit some will be proxy values or estimates). Statistical learning can provide us with the regression coefficients. The derivation for the single zone case can be found in [Constantopoulos, 1983]. By setting $A_{ki} = 0\ \forall\ i \neq 0, k$, we obtain an expression for T_{n+1} from (4.12) that is the same as that in [Constantopoulos, 1983, 1987, Constantopoulos et al., 1991]. This verifies that the present model is consistent with the single-zone case developed by Constantopoulos.

4.3.2 Set-up of Building Structures for Simulation

To the best knowledge of the author, there is currently no standardized test for evaluating the performance of building energy analysis computer programs for the multi-zone case. The standardized tests described in [ASHRAE, 2007] come closest to what is needed, but do not provide test cases for multi-zone scenarios.

This section describes the set-up of building structures for the simulation of different zone configurations based on standardized tests in ASHARE Standard 140-2007 [ASHRAE, 2007].

Using Case 900 for structures with heavy thermal mass described in [ASHRAE, 2007], the author developed a set-up with three configurations which has two to four zones for the purpose of evaluating the performance of any method to learn the thermal characteristics of the zones. The set-up will also be used when simulating the different scenarios for other parts of the research.

Case 900 has the same dimensions, structure and orientation as Case 600, which is depicted in Figure 4-1. Case 900, however, is the heavyweight case which has a

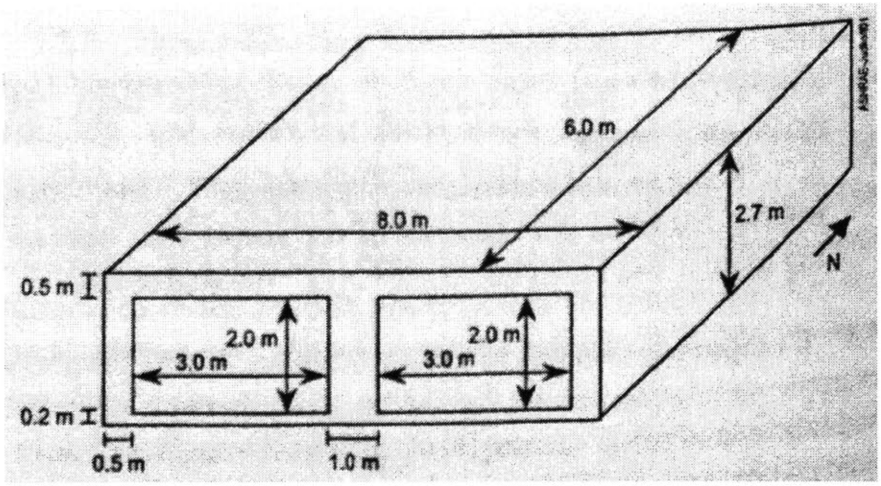

Figure 4-1: Isometric view of Case 600. Extracted from [ASHRAE, 2007].

different material specification from that of Case 600. The material specification of Case 900, which is excerpted from [ASHRAE, 2007], can be found in Appendix A. A south-facing configuration was chosen to limit the effects of fenestration. Having windows that face the east or the west will aid heating in winter but add to the cooling load during summer. Windows that face south (or north) will capture the effects of fenestration without potentially adding bias to the heating or cooling processes.

By cascading more than one Case 900 structure and adding partitions to each structure, we obtain the set-up with the desired number of zones. It is assumed that the indoor partitions separating the zones are 0.2 m thick and made of the same type of plasterboard used in Case 960, which is the same design adopted in [Khoury et al., 2005]. The thermodynamic properties of the said plasterboard can be found in Appendix A. This is to enhance the realism of the set-up as houses in temperate places tend to have, from a thermal perspective, lighter indoor partitions and heavier walls for the envelope. Figures 4-2, 4-3 and 4-4 depict the floor plans for the structures with two, three and four zones respectively.

It is worthy to note that "the state-of-the-art in ground modeling is not very good even in detailed building energy simulation programs," according to [ASHRAE, 2007, p.70]. This may pose a problem as it introduces uncertainty into the testing and evaluating, which can be circumvented by making the floor insulation very thick to

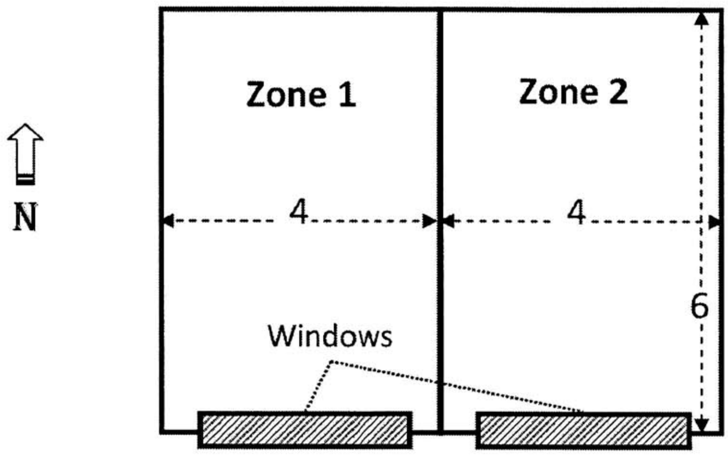

Figure 4-2: Floor plan for configuration with two zones. All dimensions in metres.

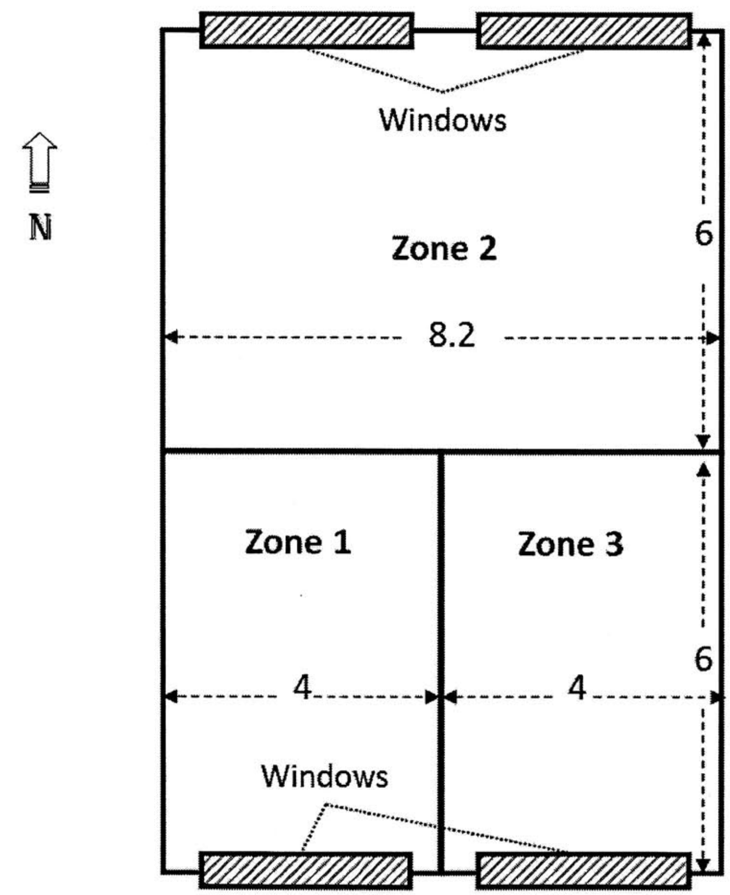

Figure 4-3: Floor plan for configuration with three zones. All dimensions in metres.

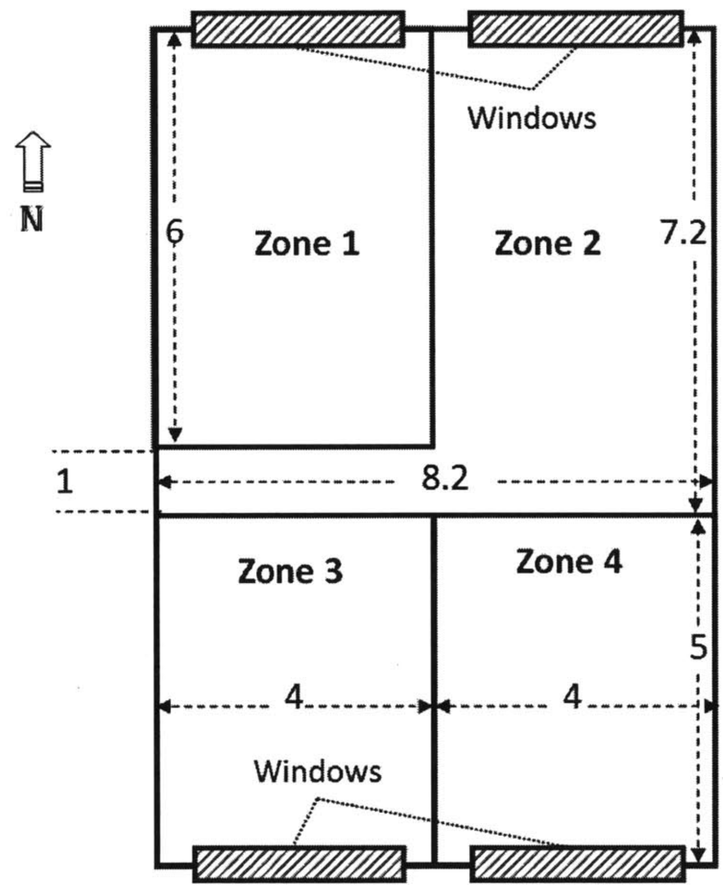

Figure 4-4: Floor plan for configuration with four zones. All dimensions in metres.

thermally decouple the floor from the ground. Taking a leaf out of the ASHRAE playbook [ASHRAE, 2007], the set-up is assumed to have thick floors that are thermally decoupled from the ground and that the rate of heat loss through per unit area of the floor is a constant. It is further assumed that the doors leading to the outside, with the help of insulation, have the same thermodynamic property as the walls, and any heat loss or gain through air exchange is captured by the air changes per hour (ach) statistic. Interior doors leading from one zone to another are assumed to be made of similar material to the plasterboards and hence, share the same thermodynamic properties. Heat exchange due to door openings is assumed to be negligible or fully accounted for by air infiltration. These assumptions make it possible for us to do away with the doors in the set-up.

4.3.3 Characterizing Zone Thermodynamic Properties

The characterizing or learning of zone thermodynamic properties must be completed before any dynamic programming can be possible. During the characterizing and learning phase, for each regime, the zone thermodynamic properties are characterized by estimating the coefficients to each term on the RHS of (4.12). These coefficients are simply given by the regression coefficients obtained from running a large number of simulations on the building simulator adapted from [van Schijndel, 2007] based on the set-up, such as those depicted in Figures 4-2, 4-3 and 4-4. Random realizations of the terms on the RHS of (4.12) are fed into the simulator and the outcome, which corresponds to the zone temperature of the next stage, is observed. Standard linear regression using the random realizations as independent variables and the outcome as the dependent variable yields the regression coefficients.

In the actual operation of the EMA or controller in the field, observations of the independent and dependent variables can be made and recorded. If a less noisy version is desired, the EMA or controller can actuate the space-conditioning equipment when the house is vacant and record the outcomes. The same linear regression technique can be used to obtain the coefficients.

The transition function described in Chapter Three that is needed for dynamic programming to be possible can indeed be accounted for.

4.3.4 Summary

Fig. 4-5 provides an overview of zone thermal characteristic learning, laying out the key topics discussed in this chapter are presented. Zone thermal characteristic learning aims to estimate a transfer function that can be used by the dynamic programming algorithm discussed in Chapter Three. The transfer function actually takes the form of a set of linear regression models, with a model corresponding to a different regime in the day. The transfer function estimates the temperature for a given zone at the next time period based on the current zone temperature, the net energy gain from the external environment, the net energy gain from neighboring zones and the net energy gain from the space-conditioning equipment.

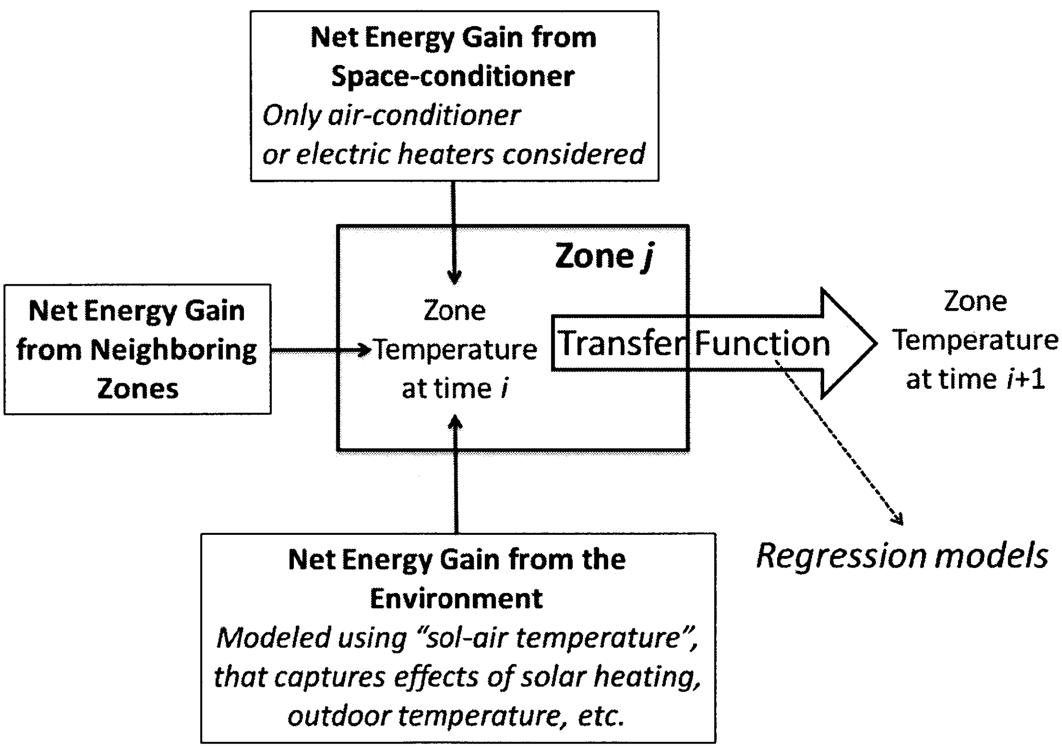

Figure 4-5: Overview of zone thermal characteristics learning.

Net energy gain from the external environment is modeled using a proxy measure called "sol-air temperature" that captures the effects of outdoor air temperature, solar radiation and other phenomena. Net energy from neighboring zones is estimated using the temperature of the neighboring zones. Net energy gain from the space-conditioning equipment is easily obtainable as only air-conditioners and heaters that run on electricity are considered.

Chapter 5

Modeling and Learning of Occupancy

An occupancy pattern is a daily record of the location of residents within the house made on an individual basis. This chapter discusses the source and nature of the occupancy patterns used in this study and describes how they were sourced, processed and obtained. In addition, it also details the way in which the occupancy patterns were used in simulations after being processed and how the probability of each zone being occupied at each time period was obtained.

Fig. 5-1 provides an overview of the phases and tasks described in this chapter. The work on occupancy begins with the phase of processing the occupancy patterns. This phase, which is described in section 5.1, produces three sets of occupancy vectors, each corresponding to a different type of resident. This is followed by a study to develop quantifiable measures to characterize occupancy patterns in a meaningful way, which is discussed in section 5.2. The task of occupancy modeling aims to develop and train a model that will provide the dynamic programming algorithm discussed in Chapter Three with the probability of a zone being occupied at every time period. Section 5.3 details the occupancy modeling task and the use of occupancy vectors in Monte Carlo (MC) simulations.

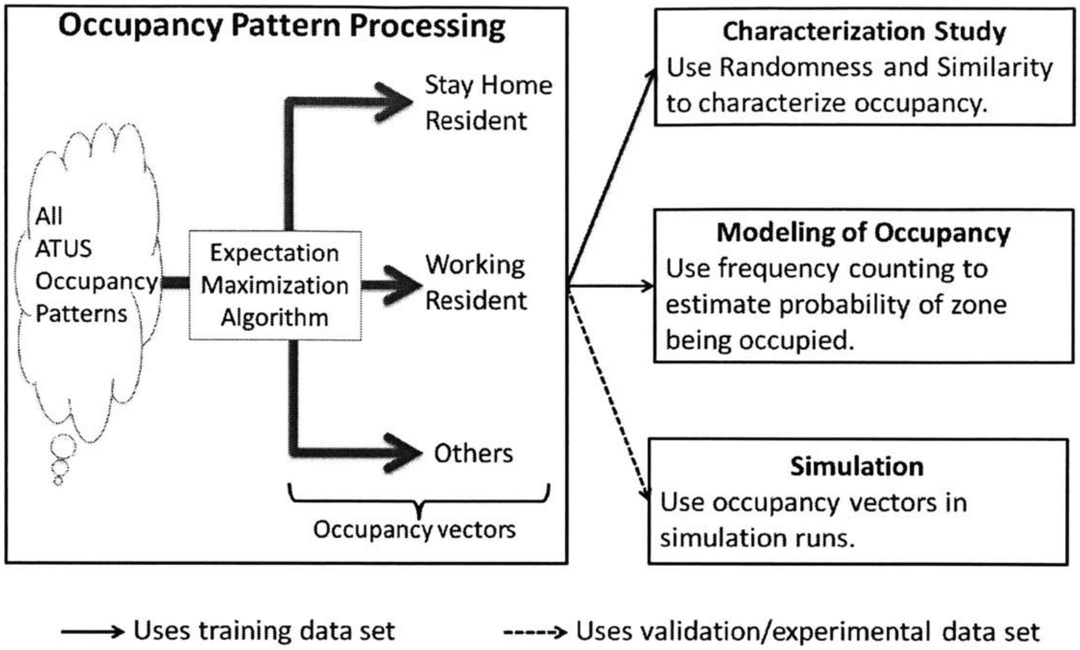

Figure 5-1: Overview of phases and tasks relating to occupancy modeling.

5.1 Occupancy Pattern Processing

5.1.1 Source and Nature of Occupancy Data

While there exist studies like [Tapia, 2003, van Kasteren et al., 2008, Youngblood and Cook, 2007] that provide quality data sets of occupancy patterns, they are specific cases of individuals and are limited in size. In order to get a sizable data set that is suitable for training models and to use occupancy patterns that are more reflective of the population at large, the author chose to derive proxy data from the American Time Use Survey (ATUS) [ATUS, 2007], where each participant has a record of activities detailing the nature, start time, end time, etc. of the activities undertaken on a particular day.

Each participant is randomly drawn from a subset of the population that represents a range of demographic characteristics. This subset of the population is characterized by their participation in the Current Population Survey (CPS). Some degree of selection bias may be present in that the survey only considers those who do not mind participating in surveys of this nature and have actually participated in the

CPS conducted by the Department of Labor in 2007 and 2008. The author regrettably notes that there is no easy means to make up for this imperfection. It is worthy to note, however, that the use of time use survey results for the purpose of modeling occupancy in domestic buildings for energy demand studies has a precedence in [Richardson et al., 2008].

Although not a perfect representation of the U.S. population, the ATUS data provide a rich source of information with over 100,000 activity journal entries from more than 12,000 respondents from all over the United States. This translates to more than 100,000 occupancy schedules in total.

As the survey does not capture the location where an activity takes place, we infer the whereabouts of residents at each time period from, and derive occupancy patterns based on, the participants' responses to the ATUS. For example, if a participant reports that he is sleeping, we assume he is in the bedroom, while if he is participating in an out of house activity like "shopping for groceries," he is assumed to be out of the house and in zone zero. In this way, we obtain a rich, sizable proxy data set that captures the multitude of occupancy patterns in the U.S. population. Though not exactly the actual occupancy schedule collected by an observational study, the derived data set serves as a good, convenient proxy.

The data set obtained from [ATUS, 2007], after some post-processing, yields a large number of occupancy vectors of length N and denoted by ν that represents an occupancy pattern. Each of the N entries or components in a vector corresponds to one of N defined time periods of the day and takes an integer value between 0 and K i.e. $\nu \in \{0, 1, ..., K\}^N$. Each of the N entries describes the location of the inhabitant during the corresponding time period, where the first entry corresponds to the hour between midnight and 1 a.m. and so on such that $N = 24$. An entry with zero value, corresponding to zone zero, indicates that the inhabitant is outside of the house or not in any of the zones during that time period. Each occupancy vector corresponds to an occupancy pattern of a particular day as recorded by any one of the respondents to the ATUS study.

The vector ν listed below depicts an occupancy vector of length $N = 24$ that corresponds to the occupancy pattern of a random respondent who participated in the ATUS and is assumed to live in a residence with two zones:

$$\nu = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 2 & 2 & 1 & 1 \end{bmatrix}$$

The j^{th} entry of an occupancy vector ν is denoted by $\nu(j)$. In the example above, $\nu(1) = 1$ while $\nu(8) = 2$ and $\nu(17) = 0$. To further illustrate, we assume that zone one corresponds to the bedroom while zone two corresponds to other parts of the residence and includes the dining area and living room. The resident was asleep between midnight and 7 a.m. Between 7 and 8 a.m. which corresponds to the eighth time period, he was in the dining area and/or living room getting ready for work. He was commuting or at work between 8 a.m. and 7 p.m., and hence was out of the house from the ninth time period to the nineteenth time period. He returned home at 7 p.m. and stayed in zone two until he retires at 10 p.m. which corresponds to the twenty-third time period. Note that we round time to integers representing hours. The general argument could be extended to more fine-grained time intervals.

In this study, each occupancy vector is an actual realization of a random process and is made up of 24 multinomial random variables. Each entry of the occupancy vector corresponds to an hour of the day and can be seen as a multinomial random variable with a properly-defined probability mass function. The location of residents in a house is greatly influenced by the time of day. For instance, it is most likely that the residents are asleep and hence in the bedroom (zone one) between 12 midnight and 6 am. This relatively heavy time-dependence suggests that modeling each entry as a multinomial random variable will capture the dominant occupancy characteristics of residents in general. Some loss of fidelity is expected if the dependence between entries in an occupancy vector is not captured. Results presented in Chapter Six go on to reveal that the multinomial model is indeed sufficient to address the problem, and the said loss of fidelity does not critically impair the model to render it useless for the purpose of realizing OZS.

A formulation based on a Markov process is expected to be an improvement as it addresses the said loss of fidelity suffered by the model that uses multinomial random variables. A Markov-based formulation will capture both the time-dependence of each entry as well as the dependence between entries. In such a formulation, the probability mass function of the random variable for the next time period is dependent on the value of the current time period. The reader is referred to section 5.3 for a discussion on how the two models can be used in practice for the purpose of realizing OZS.

5.1.2 Classifying the Occupancy Patterns

Faced with thousands of occupancy vectors, the author tried to find patterns within the collection of vectors and come up with a meaningful way of organizing them. A visual inspection of a subset of the occupancy vectors revealed that there are at least two types of occupants or residents, namely those who are out in the day during working hours and those who are not. A closer look at the occupancy vectors further revealed that there are possibly three types of residents, with the third as those who are out of zone one (which corresponds to the bedroom) later in the day and exhibit a more random schedule for the rest of the day. This implies that the set of occupancy vectors is essentially a mixture of occupancy vectors corresponding to different types of residents.

With this insight, the author framed the problem as a clustering problem and developed a model for clustering or classifying different types of occupancy vectors using an implementation of the Expectation-Maximization (EM) algorithm [Dempster et al., 1977, Hastie et al., 2008]. In this way, it is possible to assign each occupancy vector to a particular type, differentiated from the others based on their differences in occupancy characteristics. These occupancy vectors, once classified correctly in their respective types, can be used to drive the MC simulations central to addressing the research questions listed in the introductory chapter.

Types of Residents and Simulation Scenarios

It is most reasonable to ask why do we not just use the occupancy vectors as they are to run the simulations. Put another way, it is logical to question the necessity of classifying the occupancy vectors into the different constituent types. As discussed earlier, the entire set of occupancy vectors is made up of occupancy vectors from different types of residents. To facilitate the discussion, let us further assume there are D different types of residents and use an analogy to explain a possible problem associated with using the entire collection of occupancy vectors as it is without regard for the constituent types of residents.

Using the set of occupancy vectors in totality as a single set can be likened to conducting a coin tossing experiment with D coins where each is biased differently. With each coin toss, one randomly picks one of the D coins and uses it for a single toss. Any conclusion drawn from a large number of coin tosses conducted in this manner is representative of the collection of the D coins, and does not tell us anything specific about each of the individual coins.

By using the entire collection of occupancy vectors as it is, it is as if the MC simulations are run based on a schizophrenic resident, whose occupancy characteristic randomly takes on the features of a working resident on some days and another type of resident on other days. It is likely that simulations conducted in this manner with our schizophrenic resident will give poor results through no fault of the underlying framework or algorithms used. In addition, people in general do not exhibit such schizophrenic behavior in life. Results obtained from simulations based on our schizophrenic resident may not be of great relevance or interest to the industry and the academic community.

The presence of more than one type of resident requires that the simulations be run as a series of different scenarios based on a logical, realistic combination of different types of resident e.g. a stay home resident and a working resident. In this way, the results obtained will be closer to what one can expect when occupancy-moderated zonal space-conditioning is deployed in real settings.

Consequently, appropriately compartmentalizing or classifying the entire collection of occupancy vectors into the D constituent sets is necessary.

Additional Characterization of Occupancy Pattern

A person's daily activities can be highly dynamic and this implies that the nature of one's occupancy patterns may vary greatly due to many different factors e.g. day of week. It is clear that simply characterizing the occupancy patterns by the type of resident as described in the preceding section may not address the problem at hand to satisfaction. Additional dimensions of characterization are needed in order for the framework developed by the author to include more realistic scenarios.

In this study, occupancy vectors are further characterized along the additional dimensions of randomness and similarity. This is in addition to the type of resident characterization discussed earlier. For example, the simulations can be based on scenarios which involve a stay home resident, who is further characterized along the dimension of randomness. A set of simulation runs can be based on the case where the stay home resident has less random occupancy patterns and another set of simulations can be based on highly random occupancy patterns.

An advantage of using randomness as an additional characterization is that it allows for a more convenient means of generalization as compared with a characterization based on day of the week or the date. Instead of running additional simulations for New Year's Day, Sunday, Saturday and "Lots of Errands to Run Day", we can consider all these cases as a single case characterized by high randomness in occupancy patterns. The reader is referred to section 5.2 for a detailed treatment of using randomness and similarity in characterizing occupancy patterns.

Using the EM Algorithm

Classification is a broad topic in machine learning and a discussion on using the EM algorithm for classification (in the presence of hidden or unavailable data) requires a lengthy exposition. The author will make a modest attempt to outline the approach adopted to classify the occupancy patterns using the EM algorithm in this section.

In Maximum Likelihood (ML) estimation, the objective is to estimate the model parameter(s) for which the observed data are the most likely. The EM algorithm is an iterative procedure to compute the ML estimate in the presence of missing or hidden data. In this case, the latent or missing data is a label that describes which type of occupancy vector (1, 2, ... or D) a particular occupancy vector ν belongs to. In other words, in an ideal situation, every occupancy vector would have a label that stipulates which type e.g. working resident or stay-home resident the vector belongs to. In practice, however, the vectors do not come with such labels and some means of accurately assigning a label to each vector must be in place in order for the vectors to be useful for MC simulations. (Recall from the earlier sections that the MC simulations will be based on logical combinations of different types of residents. This makes it important that every occupancy vector is correctly labeled.) Given the large number of occupancy vectors available, a manual assignment of labels to each vector is too onerous to be feasible. Consequently, the author decided to use the EM algorithm to help with the task.

For any occupancy vector ν_l drawn from a mixture consisting of D different types, we denote the mixture type it belongs to using Υ_l, and Ω_i^l to represent the i^{th} entry of ν_l i.e. $\Upsilon_l \in \{1, 2, \ldots D\}$ and $\Omega_i^l = \nu_l(i)$. The objective of the labeling task can be seen as determining $P(\Upsilon_l = j \mid \Omega_1^l = v_1, \ldots, \Omega_N^l = v_N)$ for each vector ν_l and ν_l is assigned label j_l corresponding to the j_l^{th} type where $j_l = \arg\max_j P(\Upsilon_l = j \mid \Omega_1^l = v_1, \ldots, \Omega_N^l = v_N)$.

Using the Naive Bayes Model, where each entry of an occupancy vector is independent of other entries given the mixture type, the joint distribution for an occupancy vector ν_l can be formulated as

$$\begin{aligned} P(\Upsilon_l = j, \Omega_1^l = v_1, \ldots, \Omega_N^l = v_N) &= \prod_{i=1}^{N} P(\Omega_i^l = v_i | \Upsilon_l = j) P(\Upsilon_l = j) \\ &= \prod_{i=1}^{N} p(v_i|j)p(j). \end{aligned} \tag{5.1}$$

With the formulation of the joint distribution in place, the EM algorithm is used to determine $j_l = \arg\max_j P(\Upsilon_l = j \mid \Omega_1^l = v_1, \ \ldots \ , \ \Omega_N^l = v_N)$. In essence, the EM algorithm has two key steps that are iteratively carried out. In this implementation, the "E" step computes, using the current values of the parameters, the posterior probability $P(\Upsilon_l = j|\Omega_1^l = v_1, \ \ldots \ , \ \Omega_N^l = v_N)$ that is sought. This is followed by an "M" step that updates the parameters $P(\Upsilon = j)^t$ and $p_{j,i}(k)^t$. The two steps are iteratively executed until the log-likelihood values, which are obtained by taking the logarithm of $\prod_{i=1}^{N} p_{j,i}(v_i; \theta^t)$, of two consecutive iterations are sufficiently close as defined by a threshold ϵ. The EM algorithm is presented in the following pseudocode:

EM Algorithm for Discrete Mixture of Occupancy Vectors:

Initialization:

Set parameters θ^0 i.e. $p(j)$ and $p_{j,i}(k)^0$ to initial values based on "guesstimates" of proportion of each type of occupancy vector and typical schedule for a type of occupancy vector.

Algorithm:

while | previous log-likelihood - log-likelihood | $> \epsilon$ **do**

at the t^{th} iteration,

E-Step: Compute posterior probability

$$P(\Upsilon_l = j|\Omega_1^l = v_1, \ \ldots \ , \ \Omega_N^l = v_N) = \frac{P(\Upsilon_l=j) \prod_{i=1}^{N} p_{j,i}(v_i;\theta^{t-1})}{\sum_{j'} P(\Upsilon=j') p_{j',i}(x_i;\theta^{t-1})}$$

M-Step: Compute updates for

1) $P(\Upsilon = j)^t = \frac{\sum_{l=1}^{N_T} P(\Upsilon=j|\Omega_1^l=v_1^l, \ \ldots, \ \Omega_N^l=v_N^l)+\alpha}{N_T+\alpha'}$, and

2) $p_{j,i}(k)^t = \frac{\sum_{l=1}^{N_T} \delta(v_i^l=k) P(\Upsilon_l=j|\Omega_1^l=v_1^l, \ \ldots, \ \Omega_N^l=v_N^l)+\beta}{\sum_{l=1}^{N_T} P(\Upsilon_l=j|\Omega_1^l=v_1^l, \ \ldots, \ \Omega_N^l=v_N^l)+\beta'}$.

where

N_T is the number of occupancy vectors,

$\delta(A) = 1$ if expression A is true and $\delta(A) = 0$ otherwise, and

$\alpha, \alpha', \beta, \beta'$ are smoothing constants

end while

5.2 Quantitative Characterization of Occupancy

5.2.1 Randomness in Occupancy Patterns

The author adopted the information-theoretic concept of entropy developed by Shannon [Shannon, 1948] as a measure of randomness in occupancy patterns. For the purpose of this discussion, it suffices to say that a discrete random variable with a probability mass function that gives a lower entropy is less random and more predictable than one with a higher entropy and vice versa. The reader is referred to [Shannon, 1948, Cover and Thomas, 2006] for a detailed discussion on information-theoretic entropy.

For a given set of occupancy vectors denoted by Ψ, the average occupancy entropy $H_\Omega(\Psi)$ of the set of occupancy vectors is defined by

$$H_\Omega(\Psi) = \frac{1}{N}\sum_{i=1}^{N} H_i, \tag{5.2}$$

where H_i is the information-theoretic entropy of the probability mass function (PMF) of the location of the occupant at time period i, a random variable denoted by Ω_i with $i = 1, ..., N$. The PMF of Ω_i can be obtained from the histogram of the occupant's location at each time period. Given the PMF of Ω_i, which describes the probability of the occupant being at zone j at time i denoted by $P(\Omega_i = j)$, where $\sum_{j=0}^{K} P(\Omega_i = j) = 1$, H_i is calculated using

$$H_i = -\sum_{j=0}^{K} P(\Omega_i = j)\log_2 P(\Omega_i = j) \tag{5.3}$$

In general, an occupant who has an occupancy pattern with a lower entropy and lower randomness can look forward to greater savings if OZS was in place, as compared with another occupant displaying an occupancy pattern with higher average entropy.

The use of Shannon's information-theoretic entropy is motivated by necessity, as the underlying random variable that relates to the occupant's location is a categorical random variable. Standard measures of central tendency e.g. mean, variance are meaningless in the context of a categorical random variable. The use of Shannon's entropy, however, means that it is harder to develop an intuition for how entropy relates to randomness. The reader may find a numerical example useful in developing such an intuition.

In a high entropy, high randomness time period h where the occupant is equally likely to be in any one of the $K = 2$ zones and the outside zone, the entropy is given by

$$H_h = -\sum_{j=0}^{2} P(\Omega_i = j) \log_2 P(\Omega_i = j) = -\log_2 \frac{1}{3} = 1.58$$

which we calculate using (5.3).

In another case, where the occupant is more predictable and the entropy associated with him is lower, let us assume he stays in zone one with probability 0.95 and is equally likely to be in zone two or outside the house for a particular time period l. In this case, the entropy is given by

$$H_l = -(0.025 \log_2 0.025 + 0.95 \log_2 0.95 + 0.025 \log_2 0.025) = 0.34$$

which is significantly smaller than H_h. Taking the average entropy over all the time periods, we obtain a quantitative measure that gives an indication of the level of randomness associated with the set of occupancy vectors. This is given by (5.2).

5.2.2 Dice's Coefficient and Similarity

The concept of similarity of occupancy patterns between or among the occupants becomes relevant in cases where there is more than one occupant. We adopt the Dice's coefficient [Dice, 1945] as the measure of similarity. For any two sets A and B, the Dice's coefficient is given by

$$r_D = \frac{2|A \cap B|}{|A| + |B|} \tag{5.4}$$

where $|A|$ gives the cardinality of set A.

In this case, for any two occupancy vectors ν_j and ν_k, the Dice's coefficient $r_D(\nu_j, \nu_k)$ is given by the fraction of entries the two vectors have in common e.g. $r_D(\nu_j, \nu_k) = 0.75$ if the first 18 entries of the two vectors ν_j and ν_k, both of length 24, take on the same value.

5.2.3 A Note on Frequency of Change in Location

While randomness and similarity are two relevant dimensions to look at with regard to occupancy, they do not paint the complete picture. The (very) astute reader will observe that there is also the notion of frequency of change in the location of the residents that may also impact the performance of OZS.

To illustrate the concept of frequency of change in location, let us suppose there are two occupancy vectors, v_l and v_h, given by

$$v_l = [\ 1\ 1\ 1\ 2\ 0\ 0\ 0\ 0\ 0\ 2\ 2\ 1]$$

and

$$v_h = [\ 0\ 1\ 0\ 2\ 1\ 2\ 0\ 1\ 2\ 1\ 0\ 2].$$

Clearly, v_l displays a lower frequency of change in the location of the resident. On the other hand, v_h represents the occupancy schedule of a resident who is always moving from one zone to another. Intuition suggests that a higher frequency of change will mean a poorer showing by OZS.

This is a perspective that is not explored to the full in this dissertation. It is the hope of the author that other researchers will explore the notion of frequency of change in the resident's location in a future study.

5.3 Using the Occupancy Model and Vectors

5.3.1 Estimating Probabilities of A Zone Being Occupied

A naive occupancy learning method, which is essentially a frequency counter, that predicts occupancy based on the number of times a zone has (historically) been occupied for a time period or stage was used in this study. This means that we approximate the conditional probability $P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i})$ using the probability of occupancy $P(\Omega_{j,i+1} = 1)$ as if $\Omega_{j,i+1}$ is independent of the occupancy state of the zones in the previous time period i to give $P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i}) \approx P(\Omega_{j,i+1} = 1)$ $\forall$ j in this study. The probability of occupancy $P(\Omega_{j,i+1} = 1)$ can be simply derived from the frequency of occupancy of zone j at time period i.

We can then approximate $P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i})$ using

$$P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i}) \approx P(\Omega_{j,i+1} = 1) = \frac{\sum_{k=1}^{N_T} \delta(\nu(i+1) = j)}{N_T} \tag{5.5}$$

where

$\delta(A)$ returns 1 if expression A is true and returns 0 otherwise, and

N_T total number of occupancy vectors considered.

Improvements may be achieved by using a more sophisticated probabilistic model, such as one that actually models the conditional probability $P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i})$. A Markov model was not used in this study but is included in this discussion as an example of a more sophisticated model. In a Markov model, the probability of a zone being occupied is dependent only on its occupancy state in the previous time period. In such a Markov model, the conditional probability $P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i})$ will be approximated as

$$P(\Omega_{j,i+1} = 1|\Omega_{1,i}, ..., \Omega_{K,i}) \approx P(\Omega_{j,i+1} = 1|\Omega_{j,i}) \tag{5.6}$$

In a Markov model that uses the approximation in (5.6), the occupancy information is captured by the transition probability from one stage to another. The computation of $P(\Omega_{j,i+1} = 1|\Omega_{j,i})$ in (5.6) requires the stochastic matrix $T(i)$, which describes the transition probability from one zone to another at time period i, to be specified for all i based on the training data. This can be done by setting the entries $a_{l,j}(i)$ of $T(i)$ according to

$$a_{l,j}(i) = \frac{n_{l,j}(i)}{\sum_{j=0}^{K} n_{l,j}(i)} \tag{5.7}$$

where $n_{l,j}$ denotes the number of transitions from zone l to zone j at time i, considering all the N_T occupancy vectors.

In practice, the energy management agent (EMA) or controller will have amassed a (possibly sizable) collection of occupancy patterns of the occupant(s), and can derive the conditional probability using (5.5) when a frequency counter is used or (5.7) if a Markov model is used instead.

5.3.2 Occupancy Characteristics and Models of Working and Stay-Home Residents

The probability vector and stochastic matrices for the naive and Markov models can be obtained by using equations (5.5) and (5.7) with the labeled occupancy vectors produced by the EM algorithm. (Recall that the EM algorithm produces different sets of occupancy vectors, corresponding to those of a working resident, a stay-home resident and a resident on a non-working day.) This section presents samples of probability vectors $\mathbf{p}(t)$ and stochastic matrices $T(t)$ corresponding to the naive and Markov models respectively. For ease of understanding, the time t in parentheses gives the starting time of the control period the vector or matrix corresponds to.

Naive Model: Stay Home and Working Residents

$$\mathbf{p}_S(9\ a.m.) = \begin{pmatrix} 0.2909 \\ 0.4996 \\ 0.2095 \end{pmatrix} \qquad \mathbf{p}_W(9\ a.m.) = \begin{pmatrix} 0.0367 \\ 0.0464 \\ 0.9169 \end{pmatrix}$$

$$\mathbf{p}_S(1\,p.m.) = \begin{pmatrix} 0.1166 \\ 0.5810 \\ 0.3024 \end{pmatrix} \qquad \mathbf{p}_W(1\,p.m.) = \begin{pmatrix} 0.0142 \\ 0.0466 \\ 0.9392 \end{pmatrix}$$

Markov Model: Stay Home and Working Residents

$$T_S(9\,a.m.) = \begin{pmatrix} 0.2003 & 0.0590 & 0.7407 \\ 0.0305 & 0.4180 & 0.5515 \\ 0.0078 & 0.0328 & 0.9594 \end{pmatrix} \quad T_W(9\,a.m.) = \begin{pmatrix} 0.0074 & 0.0033 & 0.9893 \\ 0.0035 & 0.0179 & 0.9786 \\ 0.0035 & 0.0055 & 0.9910 \end{pmatrix}$$

$$T_S(1\,p.m.) = \begin{pmatrix} 0.0847 & 0.0209 & 0.8944 \\ 0.0248 & 0.5209 & 0.4543 \\ 0.0100 & 0.0568 & 0.9332 \end{pmatrix} \quad T_W(1\,p.m.) = \begin{pmatrix} 0.0070 & 0.0011 & 0.9919 \\ 0.0024 & 0.0241 & 0.9735 \\ 0.0063 & 0.0192 & 0.9744 \end{pmatrix}$$

For the vectors and matrices above, it is assumed that a two-zone, two-occupant scenario is in place, where zone one is the (single) bedroom and zone 2 is the rest of the residence that has space conditioning e.g. living room. Zone 3 refers to the case where the resident is actually outside of the residence. The subscripts "S" and "W" represent the "stay home" and "working" residents respectively.

The i^{th} row of $\mathbf{p}(t)$ gives the probability of the resident being in zone i at time t. Similarly, the element in the i^{th} row and j^{th} column of $T(t)$ i.e. entry $a_{i,j}(t)$ corresponds to the transition probability from zone i at time t to zone j at time $t+1$.

The above probabilities can be considered as "inhabitant-centric" as it captures the characteristics of inhabitant occupancy in a probabilistic fashion. A "zone-centric" probabilistic model, however, is needed for controlling the space-conditioning equipment in the zones. In scenarios with multiple occupants, some organized means of combining occupancy vectors of different types is needed. In order to do that, some metrics, e.g. information-theoretic entropy to help quantitatively characterize the occupancy vectors as discussed in section 5.2, is required.

5.3.3 Occupancy Patterns in Simulation

From the occupancy pattern processing phase (described in section 5.1), we discover that there are three different sets of occupancy vectors, each corresponding to a different type of resident. This motivates the use of scenarios generated by combining the different types of residents at different degrees of randomness and similarity. (Similarity is applicable in the scenarios with more than one resident.) Using the occupancy vectors is a matter of randomly choosing an occupancy vector from the collection that corresponds to the type of resident to be included in the study and using it to drive an instance of the MC simulation. For instance, as depicted in Fig. 5-2, simulating a scenario that involves a couple (M=2) will entail drawing an occupancy vector from the collection corresponding to stay home residents and one from the pool for working residents.

To obtain a set of occupancy vectors with low randomness, one simply has to randomly pick a set of occupancy vectors, with the help of the Dice coefficient, such that they collectively give a set that has the appropriate degree of randomness. The appropriate degree of randomness is determined by the average entropy (5.2). If the average entropy of the collection of occupancy vectors is below a threshold value, it is considered to have low randomness. The criterion for having high randomness is similarly defined.

In the case of two inhabitants, the occupancy vector of the working resident is randomly drawn from the collection of all vectors for working residents, and compared to a randomly chosen vector from the stay-home resident pool of vectors based on the Dice coefficient. As long as their Dice coefficient satisfies the criterion set out, the random pair can be used for simulation. Another draw is made if the pair fails to meet the criterion.

The work on occupancy modeling and learning completes the jigsaw. With the dynamic programming algorithm, thermal characteristics learning and occupancy models in place, the next step is simply to combine all the elements developed thus far and put them to the test in a simulation environment. Chapter Six provides the details behind the simulation runs and the results obtained.

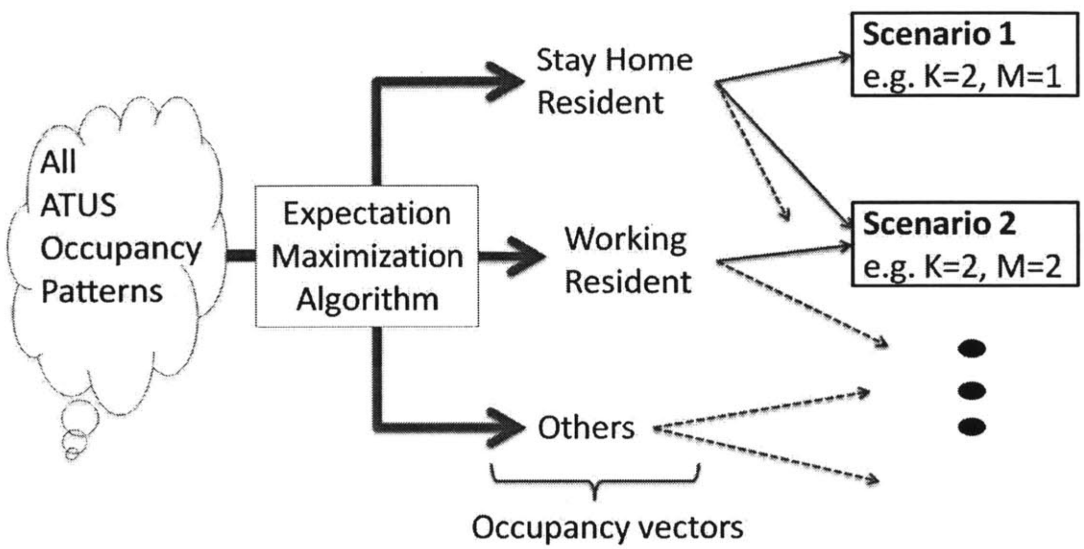

Figure 5-2: Use of occupancy vectors in Monte Carlo simulation runs.

Chapter 6

Simulation and Results

The proof of the pudding is in the eating. This chapter describes the activity that puts all the elements for achieving occupancy-moderated zonal space-conditioning (OZS) to the test. The first section of the chapter describes the Monte Carlo (MC) simulations that were run to study the effectiveness of OZS and the effects of influencing factors. Section 6.2 presents and discusses the results obtained from the MC simulation. Recommendations on the realization of OZS in practice are included in the discussion of results as well.

6.1 Scenarios and Simulations

Since an analytic solution eludes the problem, we use Monte Carlo (MC) simulation as the primary means of investigation. We implemented the proposed framework and algorithms in the MATLAB simulation environment to investigate the potential improvement that can be achieved with OZS in place. Simulation results have an error margin of two percent at 90% confidence.

Prior to running the simulations, there was a learning and training phase where all the models were trained and parameters were estimated and fine-tuned using appropriate data sets. The data sets were divided into mutually exclusive training and experimental partitions, where the former is used during the learning phase to train the models while the latter is used during simulation runs when carrying out the experimentation.

6.1.1 Choice of Building Simulator

In both the learning phase and during experimentation, the HAMBase building simulator described in van Schijndel's doctoral dissertation [van Schijndel, 2007] was used to simulate the evolution of zone temperature under the influence of random inputs over time. In practice, the temperature of a zone will vary under the influence of many variables e.g. outdoor air temperature (OAT) according to the laws of physics. In the simulation environment, the HAMBase simulator takes the role of Mother Nature. The HAMBase takes into account the underlying physical processes and all the relevant inputs to simulate the temperature in each zone at all time periods. The building simulator receives and uses all the meteorological inputs that were available at the time of this study and not just the OAT.

While there are a number of software simulators of building envelope and indoor environment, few are capable of simulating multi-zone residential space. The simulators described in [DREAM, 2011, Mendes et al., 2003] appear to be good candidates but are not publicly available or easily obtainable. There exists other high-performance building simulation applications e.g. TrnSys, ESP-r, EnergyPlus but these offer a less direct integration path with popular mathematical computing and simulation environments e.g. MATLAB. Two MATLAB-based simulators, described in [van Schijndel, 2007, Khoury et al., 2005], are publicly available but [Khoury et al., 2005] may be priced beyond the reach of some researchers. To the best knowledge of the author, the software developed in [van Schijndel, 2007] remains the only freely available simulator that can be easily adapted to simulate multi-zone residences in the MATLAB computing environment, and hence was adopted in this study.

6.1.2 Influencing Factors

In this study, the author exhaustively considered the cases where there were one or two inhabitants ($M = 1, 2$) and two or three zones ($K = 2, 3$). In the cases where there were two inhabitants ($M = 2$), it was further assumed that they were a married couple, where one worked in the day while the other was a stay-home spouse (SHS). The single inhabitant in the case where $M = 1$ is assumed to have a daily schedule similar to that of a SHS. The reader may question the relevance and usefulness of occupancy-moderated zonal space-conditioning (OZS) for a single working resident. While this is a pertinent question, the problem poses by the single working resident is less interesting as he/she is typically highly predictable e.g. sleeping in the bedroom or being out of the house for more than 18 hours of the day. This limits the opportunity for OZS to come into play. Instead of studying the problem related to the single working resident, the author chose to invest his time and effort in another research direction that will directly benefit the single working resident - using remote schedule updates to inform the energy management agent (EMA) of a more accurate return time. This is discussed in Chapter Seven.

Unless stated otherwise, the baseline scenario refers to the single zone case ($K = 1$) where the EMA space-conditions the house as a single-unit at the same desired temperature under demand-driven electricity pricing that enables pre-conditioning. In other words, the baseline result produces what achievable with pre-conditioning but without zoning.

Intuition suggests that the more predictable the occupancy patterns, the greater the potential for savings when OZS is in place. We adopt a probabilistic approach to quantify the predictability of occupancy by modeling the location of an inhabitant at each time period as a discrete random variable with a well-defined probability mass function.

Similarity, a measure related to predictability, is relevant in any case where $M > 1$ and it measures the degree of similarity with respect to occupancy among a group of inhabitants. The reader is referred to section 5.1 for a discussion on the different types of occupants included in this study while section 5.2 elaborates on the concept of similarity.

The effectiveness of OZS under demand-driven pricing in reducing cost is dependent on the extent to which each zone can be pre-conditioned. The extent of pre-conditioning is in turn dependent on the thermal mass of the residence, thus motivating the inclusion of thermal mass as an influencing factor in this study.

In addition to the approximate dynamic programming (ADP) technique described in Chapter Three, an exact, deterministic dynamic programming (DP) technique that operated with perfect information was used as well. In the deterministic perfect information (DPI) case, it was assumed that the EMA or controller has the power of clairvoyance and knows the values of all random inputs prior to the time period. This assumption reduces the DP problem into a deterministic one and can be solved using backward induction or reducing it into a shortest path problem as described in [Bertsekas, 2007]. Even though it is impossible to implement in practice, the DPI is a useful indicator of the theoretical upper bound of performance. Although not exactly an influencing factor, the type of DP algorithm used was varied so as to provide the reader with a sense of what is achievable in practice (as illustrated by the ADP case) and how far it is from the ideal, as achieved by the DPI case.

6.1.3 Parameters and Random Inputs

The value or usefulness of any results obtained using MC simulation is highly dependent on the random inputs driving the simulations. As such, we elected to use real-world data observed in practice as far as possible. Atmospheric data were downloaded from the National Oceanic and Atmospheric Administration [NOAA, 2011] while the price of electricity was obtained from organizations overseeing power generation in the various regions. For instance, for simulations involving Dallas in Texas, the price of electricity related to Dallas was obtained from the Electric Reliability Council of Texas [ERCOT, 2011]. In cases where a time-series of values for a given random input is available over an entire time period, the average value of the series is calculated and used as the value for that time period.

Table 6.1 summarizes all the parameter values used in the simulation. As zone temperatures were allowed to fluctuate between the given bounds and never exceed the limits that were acceptable to the inhabitant, it was assumed that the inhabitant did not have to manually override and interfere with the EMA or controller. As

Parameter	Symbol	Value/Unit
Desired Indoor Temperature (Cooling)	-	23.9°C (75°F)
Desired Indoor Temperature (Heating)	-	21.1°C (70°F)
Maximum Allowable Indoor Temperature Deviation	-	±8.3°C (15°F)
Overall external surface coefficient	h_0	20 W/m^{2}C
Temperature drop due to long-wave radiation	T_{LWR}	6 °C
Absorptivity of surface	a	0.4
Equipment rating (Air-conditioner or Heater)	E	4.2 kW
Air-conditioner Coefficient of Performance	η	2.5
Heater Efficiency	η	1
Control Interval	τ	1 h
No. of stages or time periods in DP	N	24

Table 6.1: Parameter values used in simulations

presented in the third chapter on optimization, the cost consists of both monetary charges due to the operations of the space-conditioner and the "service loss" arising from the zone temperature deviating from the desired temperature. (The astute reader familiar with the concept of utility functions [Keeney and Raïffa, 1993] may notice that "disutility" is a more precise term to capture the notion of penalty in this study. The author decided to use "cost" instead of disutility to maintain consistency with the vocabulary used to discuss dynamic programming in Chapter Three and to reduce clutter in the nomenclature.)

It was further assumed that the user was equally conscious of the financial operating cost as he was mindful of comfort. This implies that the financial operating cost and the cost associated with discomfort have equal weights in the aggregate cost function described in Chapter Three.

6.1.4 Overview of Scenarios

Except in the investigation of heating scenarios, a summer cooling in Dallas, TX scenario, similar to that presented in [Constantopoulos, 1983], was adopted. Unless stated otherwise, the baseline is the case where space-conditioning of the residence is carried out using a single set point, the same desired temperature, for all the zones in the residence, similar to that described in [Constantopoulos et al., 1991, Livengood and Larson, 2009]. This implies that the results of interest presented in this dissertation are improvements expressed as a percentage over the baseline which is the case with pre-conditioning but without zoning that was introduced in section 6.1.2, unless stated otherwise.

The author first investigated the effects that the number of zones and the number of inhabitants have on improvement, in a residence with heavy thermal mass using the different types of control algorithms. In the case where there is more than one inhabitant, their occupancy showed a high degree of similarity. This is followed by a study on similarity and randomness in a two-inhabitant, two-zone setting in a residence with high thermal mass. A set of occupancy vectors is considered to have low randomness if the average entropy as defined by (5.2) is less than or approximately 0.5 while an average entropy greater than 0.7 means that the randomness is high. A couple is considered to have highly-similar occupancy patterns if the Dice's coefficient of their occupancy vectors is greater than 0.55 and is said to have low similarity if the Dice's coefficient is less than 0.45. A Dice's coefficient of 0.45 means that the pair of occupancy vectors had the same value for 45% of their entries. This also means that the corresponding pair of occupants spent 45% of that day in the same place. The reader is referred to section 5.2 for a more detailed treatment on the measures of randomness and similarity.

The author next studied the effects that different thermal masses have on the improvements in a single inhabitant residing in a three-zone house. The low thermal mass setting is identical to the heavy thermal mass one except for the thermodynamic property of the material used in construction, which is based on the "lightweight" case in [ASHRAE, 2007]. The heavy thermal mass setting is also known as the "heavyweight" case.

To compare the improvement that can be achieved in heating and cooling scenarios, we looked at cooling in Dallas, TX and heating in Los Angeles, CA. The author further introduced an imaginary city Sallad in the state of Saxet as the climatic and meteorological analog to Dallas, conjured for the purpose of exploring a heating scenario. The OAT trajectory of Sallad is given by the mirror reflection of the OAT

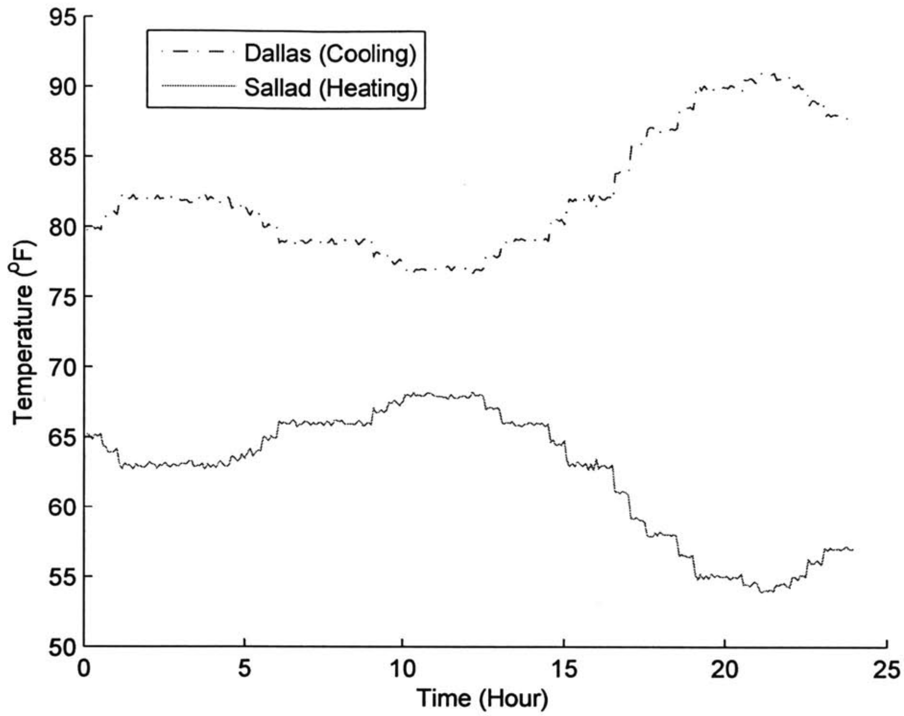

Figure 6-1: Relationship between outdoor air temperatures in Dallas and Sallad.

in Dallas reflected about the desired indoor air temperature. For instance, for the cooling scenario in Dallas where the desired temperature is 75 °F (23.9 °C), if the OAT is 79 °F (26.1 °C), the corresponding temperature in Sallad will be $70 - 4 = 66$ °F (18.9 °C), when the desired indoor temperature is 70 °F or 21.1 °C (which is the desired temperature used in all heating scenarios). Fig. 6-1 graphically depicts the relationship between the OAT of Dallas and Sallad.

To study the individual contributions of zoning and pre-conditioning to the overall savings achieved, the author ran a series of simulations with zoning only while controlling the temperature of the residence at the desired temperature, with pre-conditioning only and with both strategies simultaneously. The baseline used is the case of maintaining the temperature of the entire residence at the desired temperature. Just like in the case where we compared heating and cooling, the setting in this case is a single-inhabitant in a three-zone residence with high thermal mass. In all simulations, except for the investigations on randomness and similarity, all single inhabitants were assumed to have low-randomness occupancy patterns.

The last scenario has to do with a family of four, consisting of a working spouse, a stay home spouse and two school-going children, staying in a "heavyweight" residence with four zones as depicted in Fig. 4-4 in the fourth chapter of this dissertation. In the absence of actual occupancy patterns of families fitting the description, the author had to generate occupancy vectors for the imaginary family of four. Similarity in the occupancy patterns of the four family members was qualitatively described, rather than quantified using a metric.

6.2 Results and Discussions

6.2.1 Inhabitants and Zones

As shown in Fig. 6-2, where the height of the bar corresponds to the improvements achieved (in percentage), we observe the trend of improving performance when there are more zones with fewer inhabitants. The improvement is the reduction in cost achieved over the $K = 1$ case where all the space in the residence is conditioned as a single unit. Both the financial operating cost of space-conditioning and the cost associated with discomfort are included in the aggregate cost function.

In the DPI case, which is where all the stochastic inputs are made known a priori to the EMA or controller and the optimization is deterministic, an improvement over the baseline from approximately 30% to 41% can be expected. Intuition suggests that improvements of 50% and around 67% should be achievable with DPI in the case of a single-inhabitant in two or three zones respectively. This is not achieved even with DPI simply because all zones, even unoccupied ones, are kept within the user-defined limits, and some overheads have to be incurred to keep all the zones within the acceptable bounds.

We borrow the concept of hits and misses in marksmanship to help explain the results obtained. Observe that the EMA operates the space-conditioner of a zone

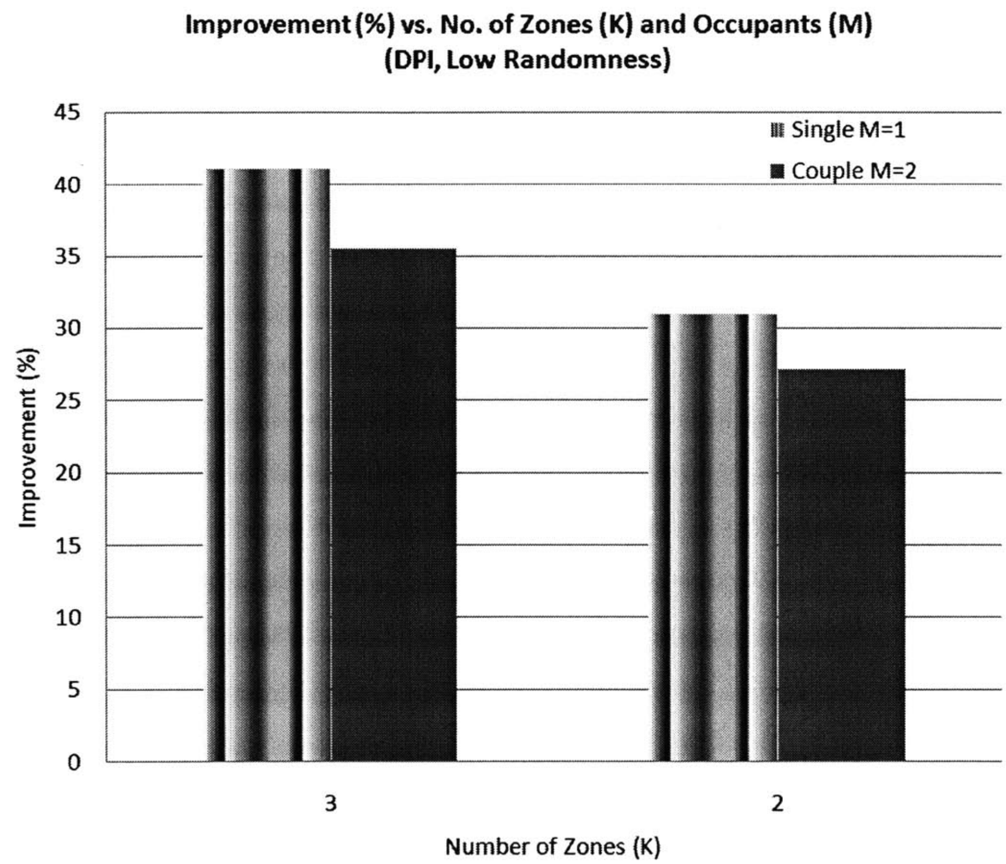

Figure 6-2: Variation of improvements over the baseline with different numbers of zones and inhabitants.

partly based on the anticipated occupancy of the zone. A "miss" is said to have occurred if the EMA conditions a zone in anticipation of it being occupied for a particular time period but it is unoccupied when the time comes. A "hit" happens when the EMA conditions a zone such that it expects the zone to be occupied at a time period and it turns out that the zone is occupied when the time comes.

In practice, the improvements achieved were typically at least 10% lower than the theoretical upper bound achieved, as depicted in Fig. 6-3 which presents the ADP result. The same relationship between improvement and the number of zones or inhabitants was observed as well. These results do not come as a surprise as having an inhabitant whose occupancy is predictable with more zones simply means that a comfortable temperature can be maintained for the inhabitant using a smaller cooling load as compared to the case with fewer zones.

From the floor plans of the residences with two or three zones depicted in Figures 4-2 and 4-3, it is clear that with OZS, an EMA can theoretically save up to half the cooling load for a single inhabitant. In the case of a single inhabitant in a scenario with three zones, the EMA can theoretically save anything between half and three-quarters of the cooling load. These theoretical limits were not achieved even in the DPI case because the unoccupied zones were still maintained within the maximum tolerable temperature limits and possibly further away from the desired temperature.

In practice, the drop in performance was even bigger as there were times when the "misses" occurred, where the inhabitant occupies the zone that the EMA thought would be unoccupied and was hence maintained at a temperature away from the desired temperature. The "misses" are not expected to happen too often and more "hits" can be expected if the inhabitant's occupancy pattern is predictable.

It is this interplay of overheads due to maintaining unoccupied zones within tolerable limits, "hits and misses", among other factors that rendered an analytic solution to be untenable and motivated the use of MC simulation.

Looking at these results, one can infer that single inhabitants in residences with more zones should try to have OZS in place if possible. This also suggests that policy makers should target their incentive schemes that encourage the use of OZS at the

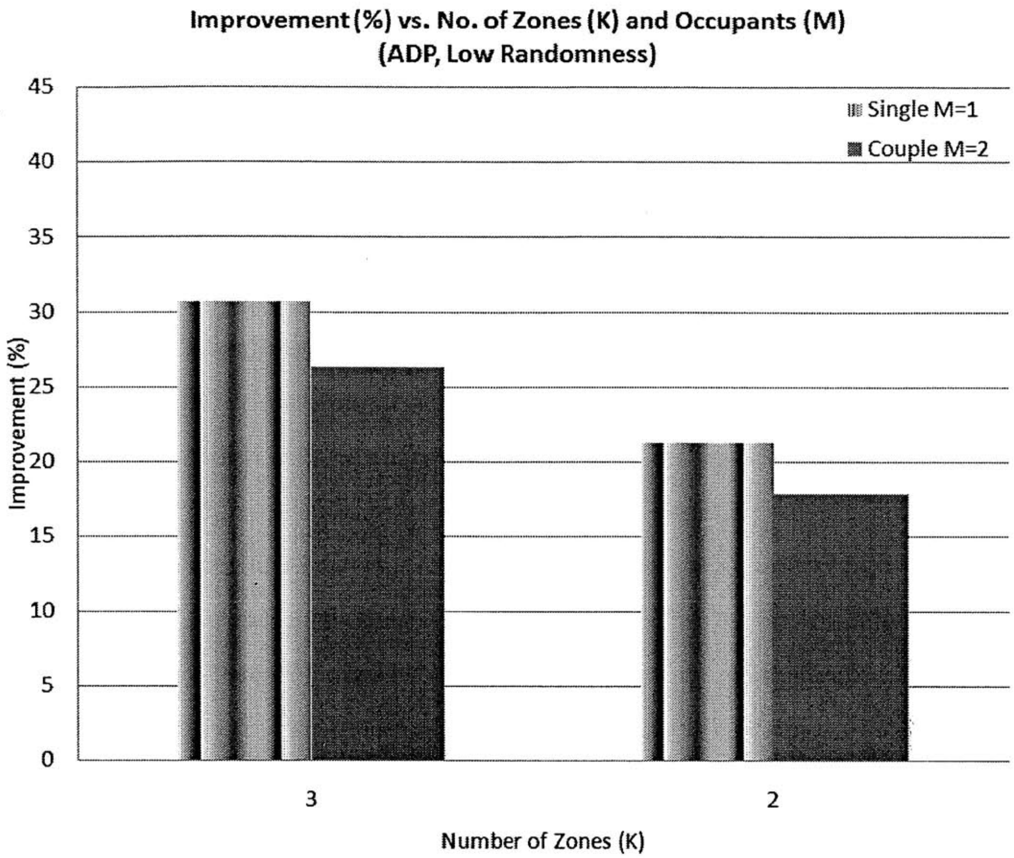

Figure 6-3: Scenarios with fewer inhabitants and more zones do better than those with more inhabitants in fewer zones.

demographic segment of single inhabitants in houses with more zones in order to get the most out of their expenditures on incentive schemes. Ideally, the inhabitant should be someone with a more regular and predictable occupancy pattern than one who is not.

In the case where $M = 2$ as depicted in Figures 6-2 and 6-3, the inhabitants exhibit a high degree of similarity, which means that the inhabitants are in the same zone most of the time. This implies that the results will not drastically differ from the case where there is only one inhabitant. This begs the questions, what happens when the couple in question has low similarity with regard to occupancy patterns and how do predictability and similarity affect improvement over the baseline?

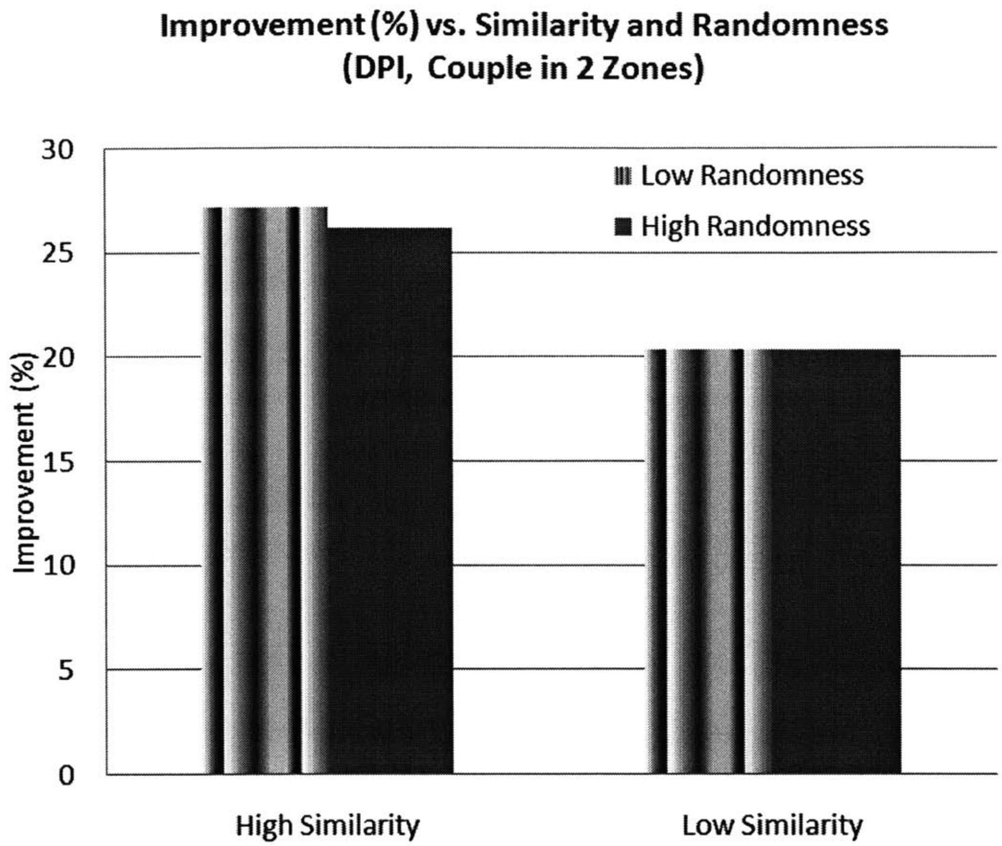

Figure 6-4: Low similarity impacts improvement in DPI case.

6.2.2 Randomness and Similarity

In the DPI case where the stochastic inputs have no effect with $K = 2$ and $M = 2$, we observe that lower similarity leads to smaller improvements, as depicted in Fig. 6-4. The picture is not as rosy in practice, especially when similarity is low as depicted in Fig. 6-5 for the ADP case.

The performance drop from the low randomness case to the high randomness case can be due to the higher number of "misses" where the inhabitant(s) are in the zone that the EMA did not expect them to be in. (With greater randomness or lower predictability, we can expect more "misses".)

Low similarity implies that the two inhabitants are in different zones more often than in the case where similarity is high. In the case where there are only two zones,

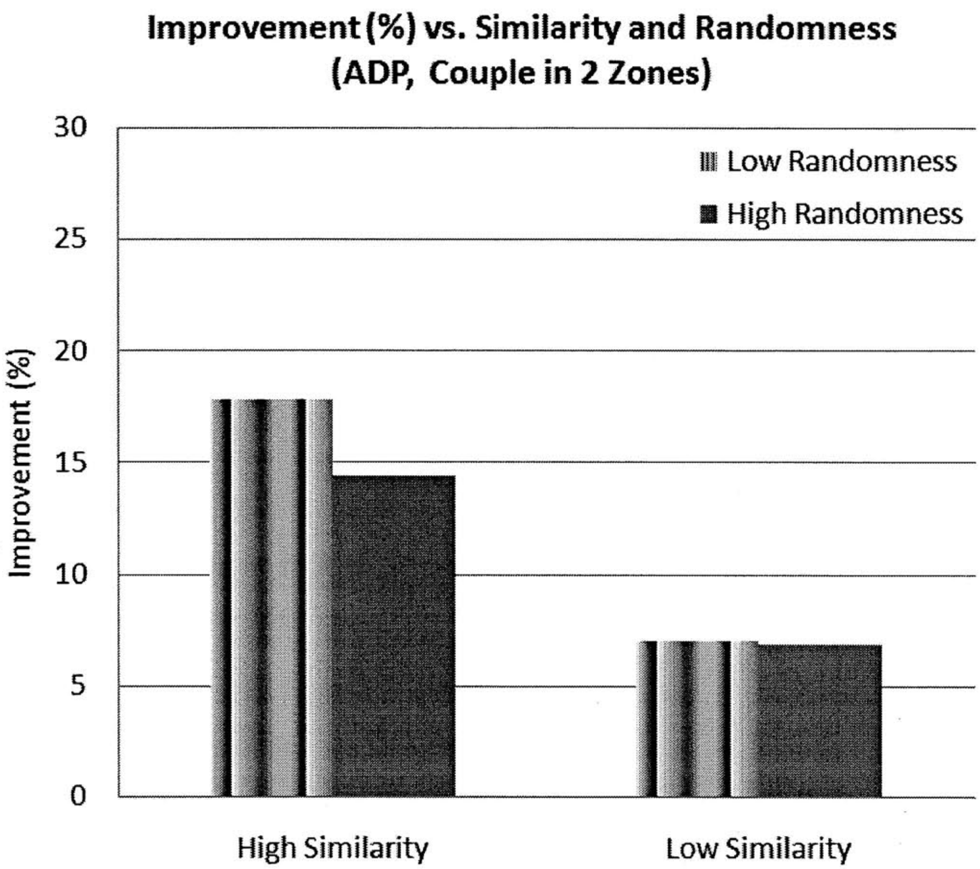

Figure 6-5: Low similarity among multi-inhabitants significantly impacts improvements.

the savings are marginal as the EMA is operating as if it was space-conditioning the residence with two zones as a single-unit. This explains the almost precipitous drop in performance, to improvements of around 7%. In summary, the effects of low similarity dominate the potential gains from high randomness.

As expected, a combination of low randomness with high similarity, which corresponds to a SHS with high predictability and a WS who is usually in the same zone when (s)he is home, yields the best performance. Observe that with high similarity, even poor predictability yields relatively better improvement.

This set of results suggests that a couple whose residence has OZS will benefit from having a routine of their activities at home to reduce the randomness of their occupancy patterns and try to organize their activities such that they are in the same zone more often than not.

6.2.3 Thermal Mass

From Fig. 6-6, it is evident that a house with greater thermal mass achieves a greater improvement over one with a lighter thermal mass. This discrepancy can be due to the heavyweight house having both the effects of zoning and pre-conditioning at work, while the thermally lighter residence, which is less thermally inert, is largely unaided by pre-conditioning that gives rise to load shifting. This was further investigated by running another set of simulations at constant price, which nullifies the effects of pre-conditioning and load shifting.

We observe that in both cases of constant and spot price in a light thermal mass setting, the performances achieved are similar, especially in a practical implementation using ADP, thus verifying the explanation. In theory, one can still expect a slightly higher savings ($< 5\%$) achieved by the perfect information case under spot pricing as compared to a constant price, as some albeit limited degree of pre-conditioning and load shifting is still possible.

Our study on thermal mass allows us to infer that a thermally light house is not well-suited for pre-conditioning. Consequently, OZS remains the more viable strategy to achieve savings, since load shifting arising from pre-conditioning is severely limited

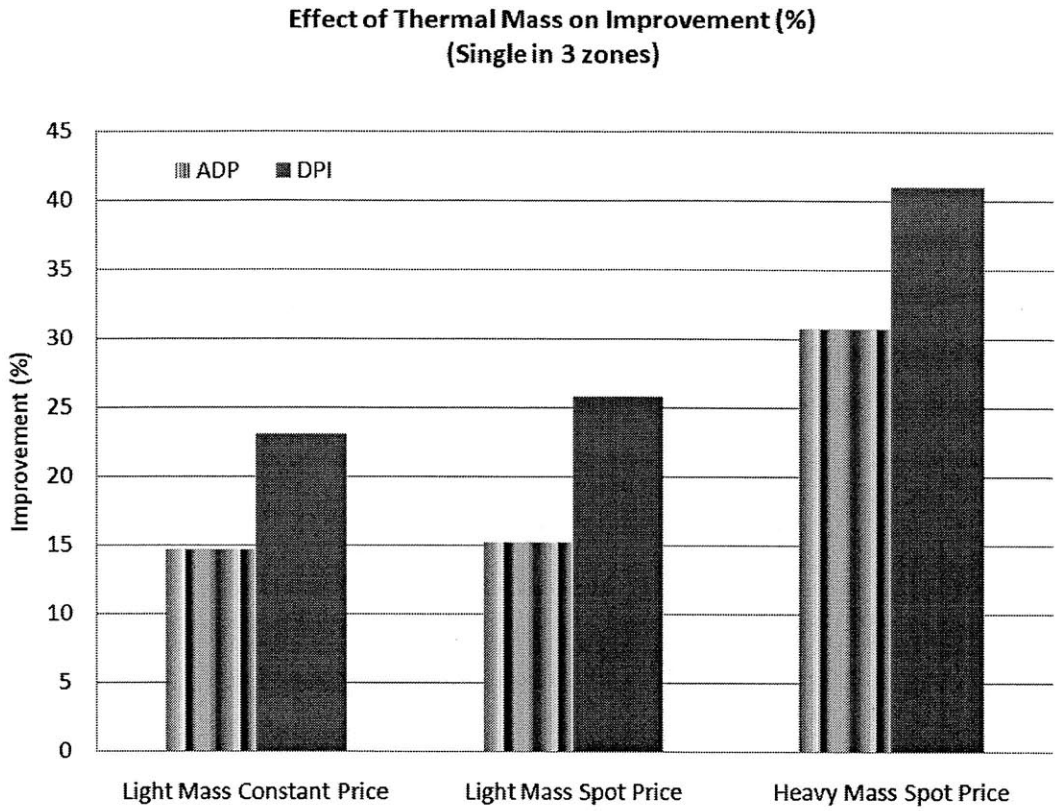

Figure 6-6: Lightweight residences achieves smaller improvements as potential savings from pre-conditioning are absent.

or perhaps even inadmissible. This result underscores the importance of OZS to an EMA, as OZS enables an EMA to bring value to a lightweight residence by allowing the resident to reduce space-conditioning cost through OZS. In other words, OZS provides the owner of a house of light thermal mass with a reason to install an EMA because an EMA with OZS can potentially reduce the space-conditioning cost in a lightweight house.

6.2.4 Heating

Looking at Fig. 6-7, it is evident that cooling seems to benefit the most from OZS when compared to heating. While climatic differences may explain the disparity in improvement between Los Angeles and Dallas, the disparity between Dallas and its heating analog Sallad is counter-intuitive. One would expect cooling in Dallas and

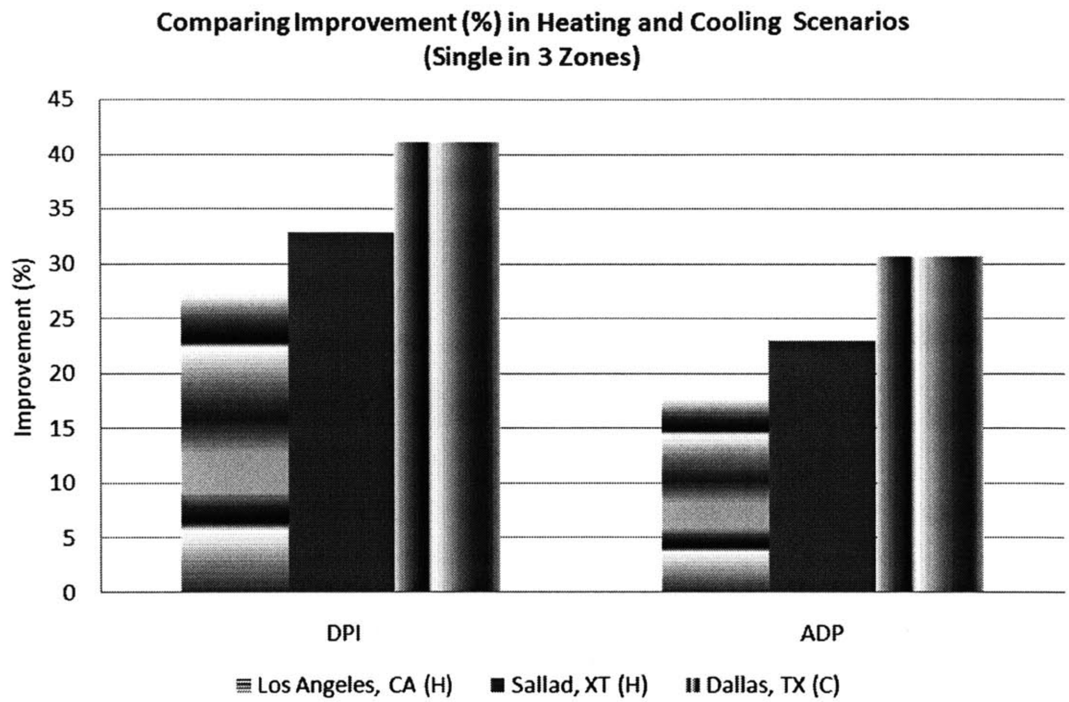

Figure 6-7: Heating does not benefit as much as cooling.

heating in Sallad to benefit to a similar if not the same extent, given that one is the analog of the other.

The disparity can be explained by the fact that solar heating in the day, which is when Sallad is the coldest, actually aids the heating process thereby reducing the need for heating or pre-heating. This reduces the opportunity for pre-conditioning or OZS to come into play. This result also implies that performance or savings achieved by OZS cannot be assumed to be symmetrical for both heating and cooling in general.

A policy maker, presumably operating with limited funding for his programs, should first target locations where cooling takes place to achieve the greatest benefit. This all the more so given that the cost of electricity is higher in the day during office hours, which is when there is solar heating (barring cloudy or inclement weather) which will lower the heating load.

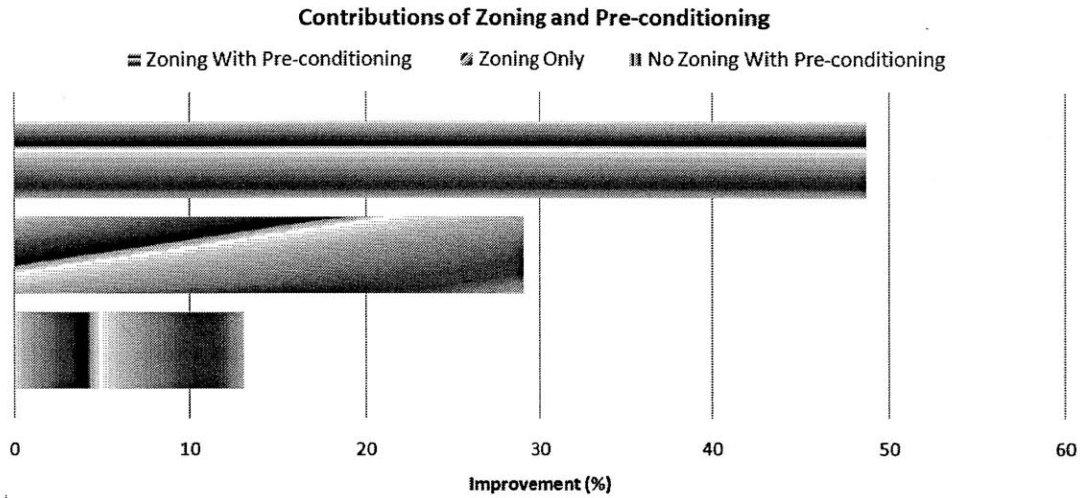

Figure 6-8: Individual contributions from zoning, pre-conditioning and combined effect of both.

6.2.5 Individual Contribution

Fig. 6-8 shows the extent to which zoning and pre-conditioning contributes to the total improvement, expressed as a percentage over the baseline and represented on the horizontal axis. The baseline is the case where the entire residence is maintained at the desired temperature. In other words, the baseline is the case where there was neither zoning nor pre-conditioning in place. Observe that without zoning, the use of pre-conditioning to shift the load as described in [Constantopoulos et al., 1991, Chen, 2008, Livengood and Larson, 2009], achieves savings of around 12%.

With zoning only, the savings achieved is close to 30%. In the case where only zoning is deployed, the effects of pre-conditioning were nullified by having the space-conditioning equipment maintain the zone temperature at the preferred temperature, just like the baseline case. With both strategies in place, the overall savings rises to around 48%.

This set of results would suggest to the policy maker that in some cases, zoning may turn out to be more cost effective than pre-conditioning/load-shifting. For instance, in locations where houses are "lightweight", it may be more cost effective to implement OZS than to embark on a program to increase the thermal mass of houses to enable pre-conditioning/load-shifting.

Similarity	Description
Normal	Dine together, other activities conducted separately
High	Most activities conducted together, including dining, entertainment, doing homework (for children)
Ultra	Same as High, and family retires in the same bedroom at night

Table 6.2: Description of degrees of similarity in occupancy patterns.

6.2.6 Results on A Family of Four

We now turn our attention to the aforementioned imaginary family of four. Similarity in this scenario takes a more qualitative tone, as described in Table 6.2. The "ultra" case was inspired by a celebrity, despite enjoying fame and fortune, but having experienced poverty in the past, continues her family's habit of retiring in the same room so as to run one fan or air-conditioner every night. It should also be noted that in places where space comes at a steep premium, it is not uncommon for a family to roll out the beddings every night and sleep in the living room.

The results depicted in Fig. 6-9 shows that OZS can potentially help a family achieve savings. A typical family can look forward to improvements that are close to the 20% level, with the "ultra" case achieving an improvement of around 40%. This is possible because every night, there is only one room, which may potentially have a footprint that is about one-quarter that of the entire residence, that is occupied and maintained at a temperature close to the desired temperature while other zones can have temperatures at the maximum tolerable limit.

6.2.7 Summary

The first research question asks about the level of cost savings OZS can achieve under a demand-driven electricity pricing scheme under realistic settings. The simulations reveal that a single occupant of a house with three zones can reduce up to 30% of total cooling cost in practice. Under less favorable circumstances, such as in the case

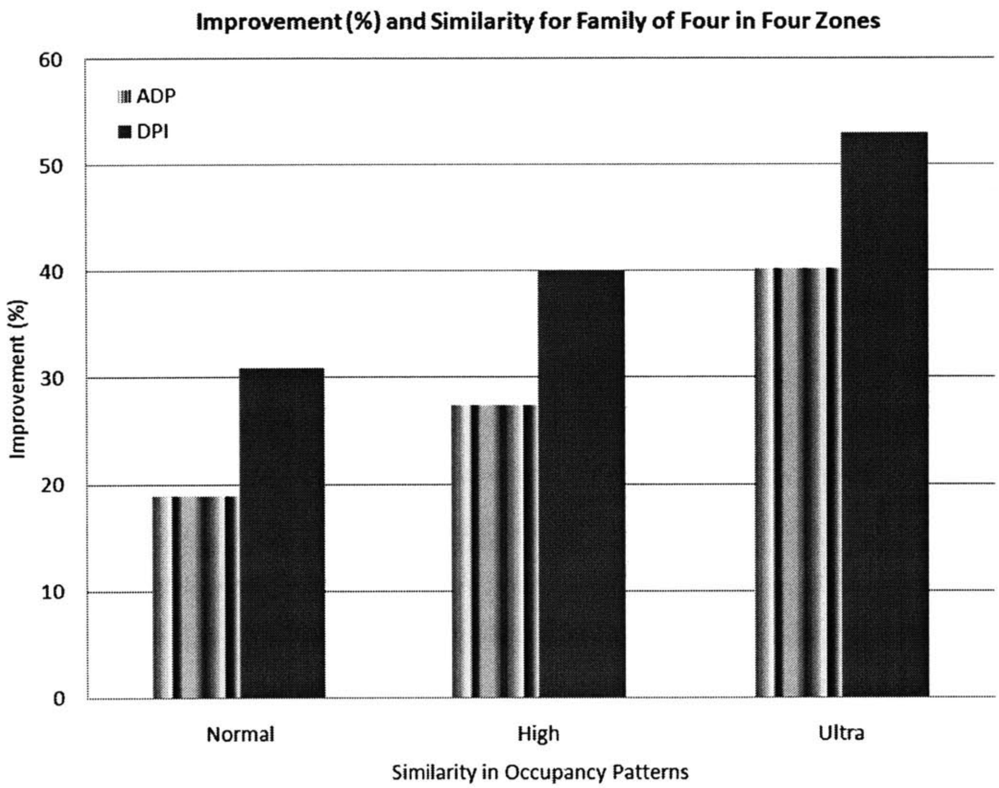

Figure 6-9: Results on a family of four at different degrees of similarity in occupancy patterns.

of a couple with dissimilar occupancy patterns in a two-zone house, a marginal 7% reduction in cooling cost was observed.

The second research question queries how influencing factors impact the savings achieved by OZS under a demand-driven electricity pricing scheme. The number of zones and the similarity of residents' occupancy patterns are found to have a positive relationship with the level of savings. (A positive relationship means that the larger the magnitude of the influencing factor, the greater the level of savings, when everything else remains the same.) The number of residents and the randomness in their occupancy patterns have a negative relationship with the level of savings.

In addition, given the same temperature difference between outdoor air temperature and desired zone temperature, the cost associated with cooling is expected to be lowered to a greater extent than that for heating.

The results presented in this chapter relates to families, couples and singles who stay home. It appears that the single working adult who leaves for work in the day has been left out. As explained in section 6.1.2, zoning is less useful to working singles as their typical occupancy pattern leaves the OZS with a limited role. The author chose to investigate another variation of occupancy moderation that will directly help working singles. The said variation of occupancy moderation, which is discussed in Chapter Seven, involves the use of cloud-connected devices to provide schedule updates to the EMA.

Chapter 7

Remote Schedule Updates

7.1 Motivation and Objective

The advent of cloud computing, the ubiquity of mobile devices and the convergence of computing and communications has enabled a "hyperconnected world" [Friedman, 2012]. According to an industry group CTIA The Wireless Association, there are 323 million wireless subscriber connections in the United States as of June 2011 [CTIA, 2012]. This translates to having a Wireless Penetration Equals of 102.4%, which is a statistic given by the number of active units divided by the total U.S. and territorial population, including those of Puerto Rico, Guam and the Virgin Islands.

Mobile phones and their ecology of apps are revolutionizing almost every aspect of our lives. Enterprising service providers have identified this ubiquity as an opportunity for greater profits by offering more services to their subscribers. For instance, residents can now monitor and control appliances in their homes through their mobile devices [Verizon, 2012]. While this can bring about greater convenience, it is not clear from the literature to what extent the end user benefits from the use of mobile devices to monitor and control home appliances, especially under a demand-driven pricing scheme. This motivates a study to investigate and possibly quantify the benefit of using mobile devices as an aid to home control and monitoring for the application of space-conditioning.

One way in which a mobile device can help is to provide additional information in the form of schedule updates to inform an appliance or its controller so that it can operate at a time that best achieves an objective, such as to minimize cost. In this regard the mobile device enhances the knowledge base of the appliance or the controller by allowing the resident to remotely provide schedule updates. Such "remote schedule updates" (RSU) may bring about better performance by improving the predictability of the return time of a resident

The author studied how RSU provided by a mobile device can improve the cost performance of a residential air-conditioning system controlled by an energy management agent (EMA) in the case of a resident who works or leaves the house in the day. This is a variation on the theme of occupancy-moderation and an attempt to address the third and final research question listed in the introductory chapter of this dissertation, "What level of space-conditioning cost reduction can remote schedule updates bring about?

Towards that end, the author adapted the Energy Box simulator (EBS) developed by Livengood and described in [Livengood, 2011] to simulate the effect RSU have on the cost of air-conditioning for a working adult who lives alone. The objective is to compare the total cost, which includes both monetary cost and level of discomfort, in the case where there is RSU to the case without, under different settings. In simulation runs with RSU, the Energy Box received an accurate return time of the resident at mid-day and carried out optimization based on the return time to arrive at a control sequence for the air-conditioner that achieves the best balance between monetary cost and discomfort. Fig. 7-1 aims to illustrate the difference between the baseline case that does not have RSU in place and the case with RSU.

In the baseline case, the EBS operates using the default setting that the resident arrives at home some time between 17:00 (5 pm) and 18:00 (6 pm). The EBS may, depending on factors like price of electricity and other parameters, cool the room with the aim of lowering the discomfort of the resident. This effort, however, is wasted as the resident is not home until after 19:00 (7 pm). In the case with RSU, the resident updates the EBS between 12:00 (noon) and 13:00 (1 pm), that he expects to be home some time between 19:00 (7 pm) and 20:00 (8 pm). With this additional information,

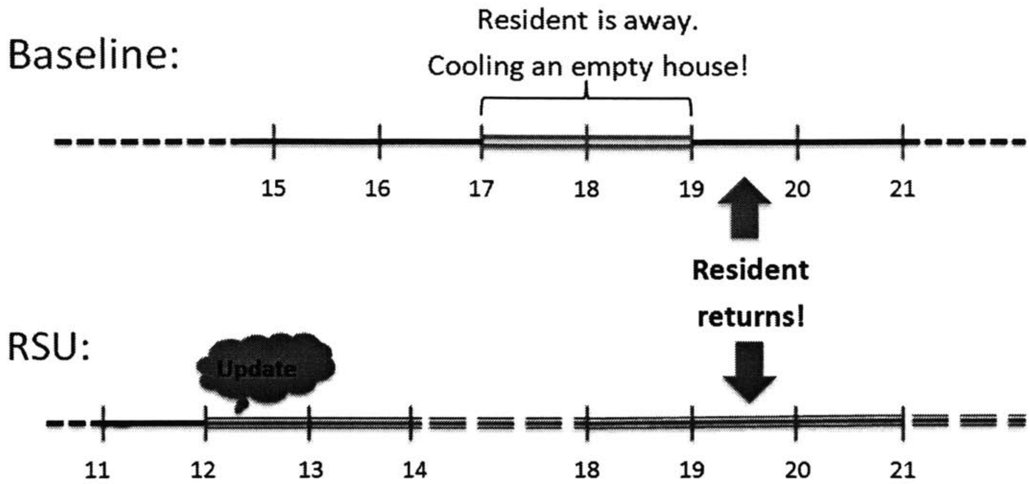

Figure 7-1: Illustration of case with RSU and baseline case. Numbers on horizontal scale correspond to time of the day.

the EBS is able to reduce the cooling load without adversely affecting the comfort of the resident and in so doing, achieve some degree of cost reduction.

7.2 Introduction to the Energy Box Simulator

The EBS is a highly-flexible, easily-configurable simulator of the Energy Box developed in the Matlab computing environment. It simulates the response and behavior of an Energy Box controlling event-based appliances (EBA) e.g. clothes washing machines and thermostatically-controlled appliances (TCA) e.g. air-conditioners, electric space heaters under different pricing schemes e.g. real-time pricing, flat rate. The simulations are driven by historical or highly-realistic meteorological inputs e.g. outdoor air temperature, wind speed that are typical of a Bostonian summer. For space-conditioning applications, the entire residence is considered as a single-unit that is maintained at a single temperature. Furthermore, it can operate in a "prosumer" mode and simulate the effects of having residential distributed generation in place e.g. rooftop wind turbine in addition to simultaneously simulating the control of EBAs and TCAs. The EBS produces a number of output variables, including actual control sequence for an appliance, temperature trajectory, total operating cost and

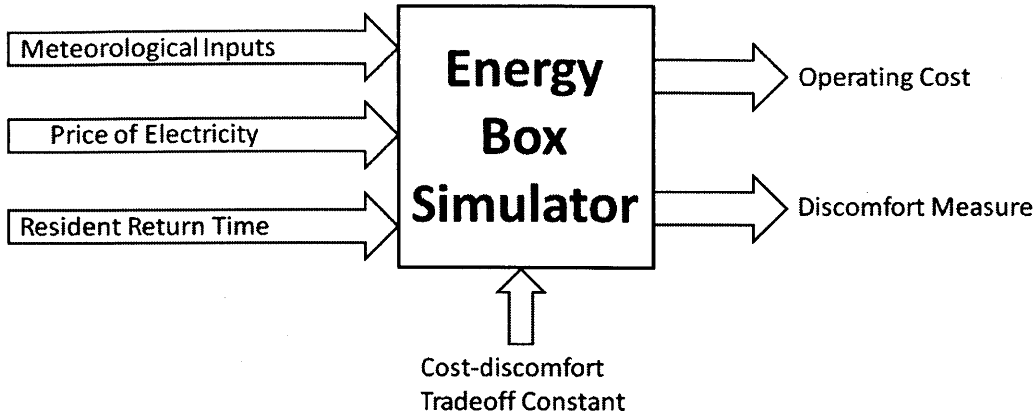

Figure 7-2: Key input and output variables and parameters used in the study of RSU.

discomfort measure.

7.2.1 Key Variables and Parameters

Given the large number of parameters, input and output variables that the EBS has, the author had decided to focus the discussion on several key variables used in the study on RSU. Figure 7-2 depicts the key input and output variables and parameters of the EBS used in investigating the benefits of RSU.

The EBS has the capacity to incorporate different meteorological inputs, such as temperature, sunshine and wind. The outdoor air temperature (OAT) is the primary meteorological input of concern in space-conditioning applications. Using 25 years of historical weather data from the National Oceanic and Atmospheric Administration, Livengood developed an hourly Markov chain to model and simulate the OAT. The OAT was bounded and discretized to a set ranging from 50°F to 110°F, which captured all except for a few hours out of the entire 25 years of data.

With regards to the price of electricity, the EBS can run simulations with any of the following retail tariffs:

1. flat rate,

2. time-of-use, and

3. hourly real-time pricing (RTP).

The flat rate and time-of-use tariffs were implemented relatively easily as they are deterministic. The RTP, however, was more involved and required the development of a model. An RTP model was developed based on the dynamics of an hourly real-time wholesale electricity market in New England using hourly grid-level electricity demand information from 1993 to 2002 obtained from the Independent System Operator of New England (ISO-NE). (The ISO-NE oversees the operation of electricity markets in the New England region.)

Another important random input is the return time of the said resident, who leaves his residence earlier in the day and returns home in the evening each day. The return time is simply the nearest hour at which the resident arrives home. This random input variable is a new addition to the EBS and enables the study of RSU. In this implementation, the author went back to the American Time-Use Survey (ATUS) dataset and obtained instances of the actual return times (ART) from the records of activities from the survey respondents. The mode of this distribution of return times is 17:00, which is the same as the default return time used by the EBS. Since the scenario under study entails having an RSU during the noon to 13:00 time slot, the return times considered in this study range from 14:00 to 24:00. Section 7.3.1 has a more detailed discussion on the value of using the ART derived from the ATUS data.

The astute reader will probably notice that despite the more accurate return time that the RSU provides, it is possible that the resident may still reach home early or late due to a variety of reasons, such as uncertainty in commute time. To illustrate, let us suppose a resident remotely updates the EMA that he will arrive home at 19:00 (7 pm). Due to heavy traffic, he may actually reach home at 20:00 (8 pm). Consequently, the improvement achieved may suffer as a result. This is all the more important if the duration of each control period is short e.g. 20 minutes. In this study, it is assumed that any deviation from the reported return time is small relative to the duration of each time period, which is an hour.

The cost-discomfort tradeoff constant is a key user-defined parameter. It allows the user to decide the extent to which discomfort plays a role vis a viz the operating cost in the dynamic programming (DP) process. An individual who is more concerned about the finances and the operating cost than he is about comfort will set the cost-discomfort tradeoff constant to a low level. Another individual, such as one more affluent, may value comfort over cost and hence set the cost-discomfort tradeoff constant to a larger number.

The operating cost in one time period is simply given by the number of units of electricity used by the air-conditioner multiplied by the price per unit of electricity for that time period. The discomfort measure at time period i, which we denote using d_i, is given by the square of the difference between the desired temperature and the actual temperature in the residence at time period i, with a lower bound of zero i.e. $d_i = \max(0, (T^d - T_i)^2)$ where T^d and T_i are the desired temperature and the actual temperature respectively.

7.2.2 Using Total Cost as A Performance Measure

The EBS aims to minimize the Total Cost J_{Total} of a simulation run, and J_{Total} is given by:

$$J_{Total} = \sum_{i=1}^{N_{Total}} c_i + d_i \tag{7.1}$$

where

c_i	operating cost of running air-conditioner at time period i
d_i	discomfort measure at time period i
k	cost-discomfort tradeoff constant, and
N_{Total}	total number of time periods in a simulation run.

The astute reader will observe that (7.1) essentially describes a cost function that is a weighted average of two types of cost, that of the financial, operating cost and a discomfort measure. Operating cost c_i has dollars for its dimension while d_i is dimensionally given by temperature squared and k has dollars per unit temperature squared as its dimension.

Clearly, (7.1) assumes a linear, additive model in modeling the personal cost accrued or "disutility" suffered and adds the two types of costs together. It allows for a comparison that accounts for both the financial cost and discomfort over a wide range of user preferences. An alternative means of modeling is based on the concepts of utility function, decisions with multiple objectives, preferences and value tradeoffs introduced in [Keeney and Raïffa, 1993]. The alternative is more formal and requires a more grounded approach that necessitates the derivation of utility functions to relate financial cost to discomfort. Given that all that is needed is a fair means to compare the total costs of the scenario with RSU to the case without, the author decided on the model described in (7.1) since the values of c_i and d_i are readily available from the EBS.

The reader is referred to [Livengood, 2011] for an in-depth treatment of the DP formulation and solution, as well as other details on the EBS.

7.3 Simulation and Results

7.3.1 Simulation

In this study, the dependent variable is simply improvement, which is the reduction (expressed as a percentage) in total cost as defined in (7.1) in the case with RSU over the baseline case without RSU. The author adopted the cost-discomfort tradeoff constant as an independent variable to be varied across an interval of values, ranging from 0.6 to 10. In this way, it will be possible to tell how the performance of RSU varies with the value of the cost-discomfort tradeoff constant. Although a uniformly-distributed return time may sound far-fetched, it is possible that the return time of some sales representative is best modeled by a uniform distribution.

The performance of RSU under different electricity tariffs and types of return time was investigated as well. The author modeled the return time of the resident using the uniform distribution to simulate the case of a resident whose return time is less predictable as compared with someone whose return time is normally distributed. In this case, the residents return time is assumed to be uniformly distributed between 2 p.m. and 12 midnight, giving a total of 10 control periods, each an hour long. In this way, it is now possible to study the performance of RSU under both the ART of working residents obtained from ATUS and the uniformly-distributed return time (URT).

The use of the word "actual" in ART connotes the quality of representativeness i.e. the ART is representative of the U.S. population at large. This, however, may not be the case and the author makes no claim of representativeness. A deeper discussion of the ART is in order so as to better understand the value of using it to drive simulations.

A histogram, such as the one depicted in Fig. 7-3, is an informative way to represent the entire set of ART as it graphically represents the distribution of the return time. Each respondent to the ATUS can be characterized by a probability density function (PDF) of return time that describes the distribution of return time for the respondent. Each recorded return time is a realization of a random draw out of all the possible return time according to the PDF characterizing the respondent. The collective accumulation of all the realizations from all the respondents yields the set of ART.

We turn to Alice and Bob and the PDFs of their return time depicted in Fig. 7-3 for an illustrative example. Suppose that Bob reaches home at 14:00 (2.00 pm) on a particular day and at 18:01 (6.01 pm) on another, which corresponds to realizations one and two in Fig. 7-3 respectively. The first realization will add one to the count of the 14:00 bin. Similarly, the second realization adds one to the 18:00 bin. For Alice, her first and second realizations give 21:15 (9.15 pm) and 17:10 (5.10 pm), thus her return times add one to the 21:00 and 17:00 bins. Accumulating the random realizations from all the respondents, in the form of their recorded return time, gives us the ART.

The astute reader will conclude that the ART cannot be treated as representative of a "typical American", and cannot be used as such. This begs the question, what then is the value of using ART in the simulations investigating RSU? The results from

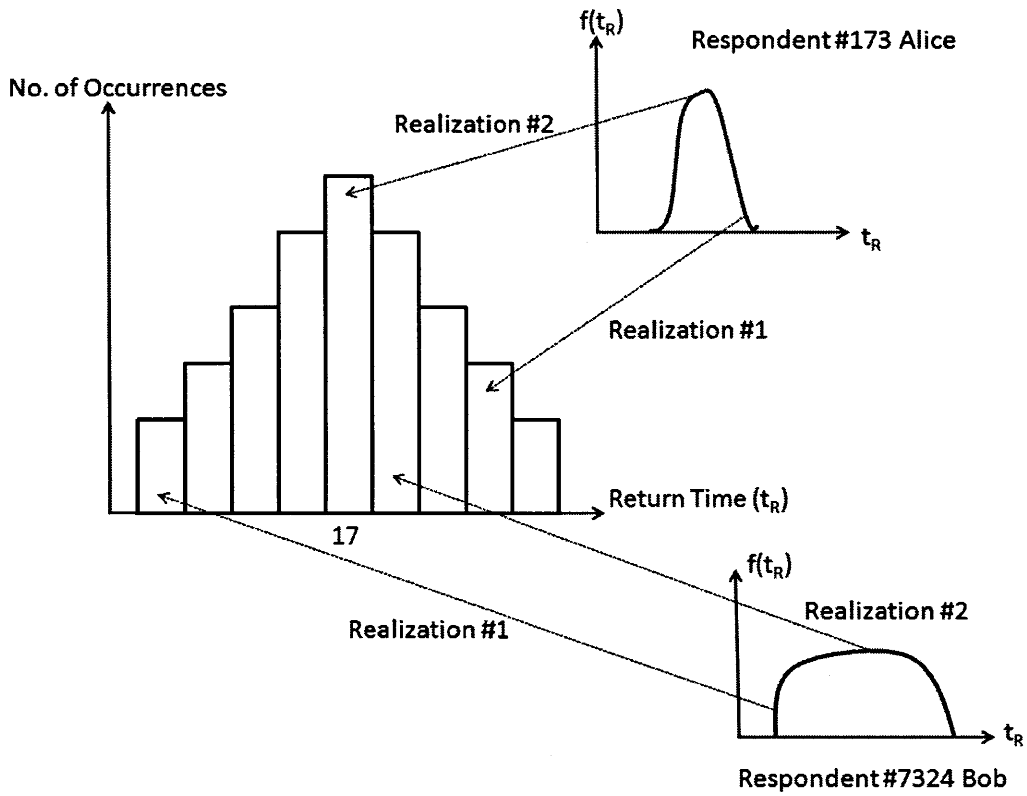

Figure 7-3: Illustration for example on random realizations of return time by respondents to the American Time Use Survey form the set of actual return times used in simulations.

using the ART in simulations are valuable in that they tell us the collective level of cost reduction we can expect if RSU were adopted by a large number of people from the population of which the set of ATUS respondents represents, under conditions similar to those being assumed in the simulations.

Intuition suggests that a positive relationship exists between the variance of the return time and improvement i.e. greater variance entails a greater potential for improvement. To test this hypothesis and explore the relationship between return time variance and improvement, another set of simulations was run with URT at different values of variance under both types of pricing tariffs.

The desired temperature was 71°F (21.67°C) while the maximum tolerable temperature was set at 79°F (26.11°C) and the performance of RSU under both the flat rate and the real-time pricing tariffs was investigated. All runs were made using the "Full Historical Variation" mode of the EBS i.e. using the models derived using archived data of weather and electricity prices. All results presented have a margin of error of 2% at 90% confidence.

7.3.2 Results

Fig. 7-4 depicts the results of the simulation runs using ART over a range of values of the cost-discomfort tradeoff constant, k. The level of improvement brought about by RSU with ART ranges from zero to more than 14%. Each marker represents a data point obtained from simulation while the lines joining the markers in a series are trendlines of best fit obtained by fitting a polynomial to the data.

At low values of k, which corresponds to region A in Fig. 7-4 where $k \leq 3$, the (financial) operating cost is highly-valued by the resident. In region A, where A can stand for "Austere", there is little or almost no difference in the improvement gained for both types of pricing schemes as the temperature of the residence is largely maintained at the maximum tolerable temperature.

This means that in order to minimize financial cost, the EMA operates at the maximum tolerable temperature so as to minimize the frequency and duration of actuating the air-conditioner. Pre-conditioning, which is the trump card real-time

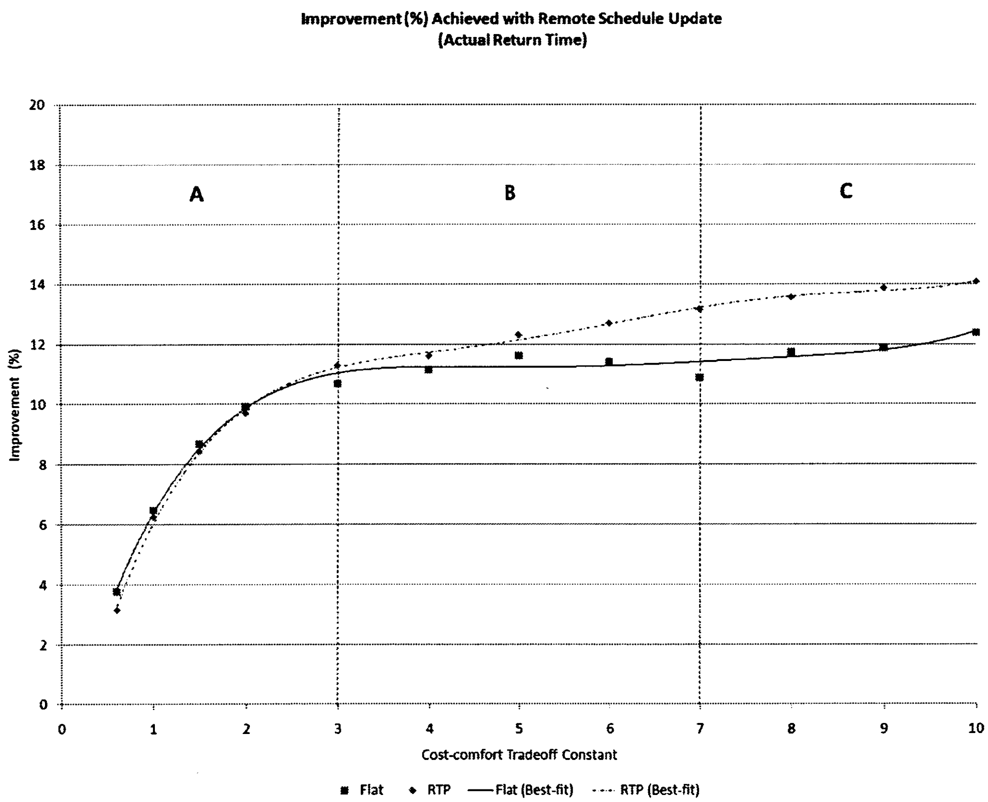

Figure 7-4: Improvement achieved at different values of cost-discomfort tradeoff constant with actual return time.

pricing has over flat rate tariff, has limited opportunity to come into play under such operating conditions.

Region B, which is where the value of k lies between three and seven, can be seen as a transitional phase. During this transitional phase, the improvement achieved by RTP begins to pull away from that gained by the flat rate tariff. From Fig. 7-5, which depicts the improvement in the discomfort measure over different values of k, we observe that in region B where $3 \leq k \leq 7$, the improvement in discomfort measure for the RTP increasingly outperforms the flat rate tariff case. This trend comes about as pre-conditioning is able to play an increasingly significant role as the weight given to discomfort is increased with increasing values of k. This improvement drives the trend observed in the overall improvement achieved depicted in Fig. 7-4. Region B also corresponds to the phase where some degree of balance between operating cost and discomfort is achieved. In this regard, the "B" in region B can mean "balanced".

Beyond $k \geq 7$, which corresponds to region C in figures 7-4 and 7-5, we observe that the difference in improvement between the two pricing schemes has stabilized. This stabilization comes about because the EMA has reaped all the benefits that pre-conditioning can offer. Region C corresponds to the region of "comfort", where the temperature is closer to the desired temperature as compared to the other regions.

These results bode well for RSU as a cost reduction strategy. Although no guarantees about the level of cost reduction can be made to individual residents who may decide to adopt RSU, we can surmise that a large population of users who can be represented by the ATUS respondents with the characteristics described earlier, can collectively expect to reduce their air-conditioning cost by 12% under flat rate or 14% with RTP, under the same conditions e.g. setting the cost-discomfort tradeoff constant at 10.

7.3.3 Effects of Greater Return Time Variance

Intuition suggests that a resident with a return time distribution of higher variance e.g. URT can expect greater savings compared with one whose return time has a smaller variance e.g. ART. A very logical question to ask at this juncture is, how

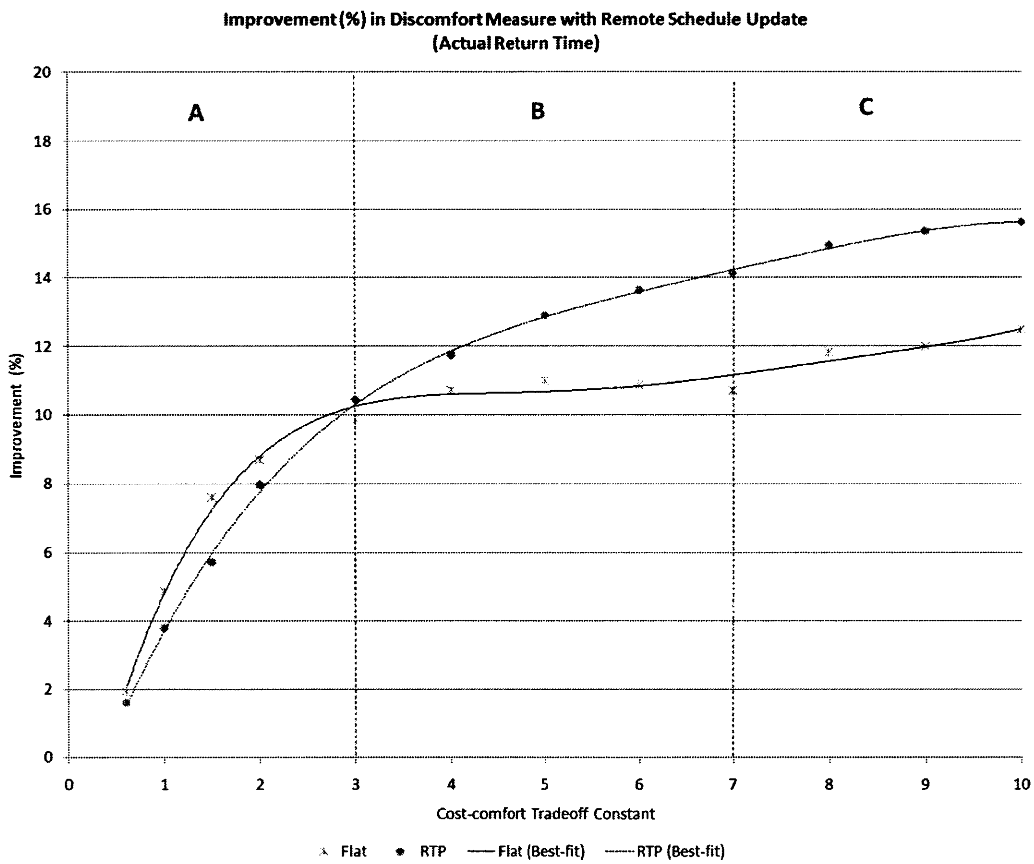

Figure 7-5: Discomfort measure observed at different values of cost-discomfort trade-off constant with actual return time.

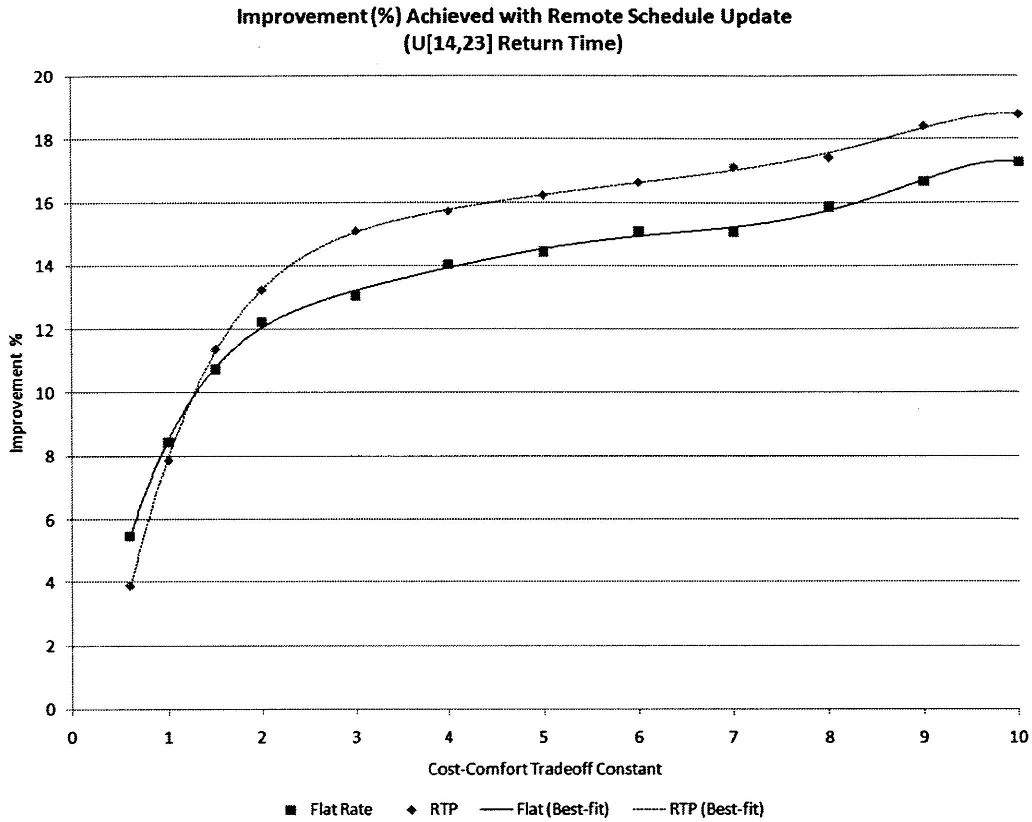

Figure 7-6: Improvement achieved at different values of cost-discomfort tradeoff constant with uniformly-distributed return time.

does the variance of the return time influence improvement? To address this question, simulations were run to investigate improvement achieved at different values of k under RTP and flat rate tariff with return time assumed to be uniformly-distributed between 14:00 (2 pm) and midnight.

The results of these simulation runs are presented in Fig. 7-6, where we observe that the level of improvement achieved at every value of k is higher. The highest level achieved exceeds 18%, compared with 14% in the ART case. Based on this result, we can hypothesize that a larger variance for the return time leads to greater improvement, with all else remaining equal.

Additional simulations were run to test this hypothesis and to investigate the relationship between return time variance and improvement achieved. From Figures 7-4 and 7-6, it is clear that the highest improvement is achieved when the cost-

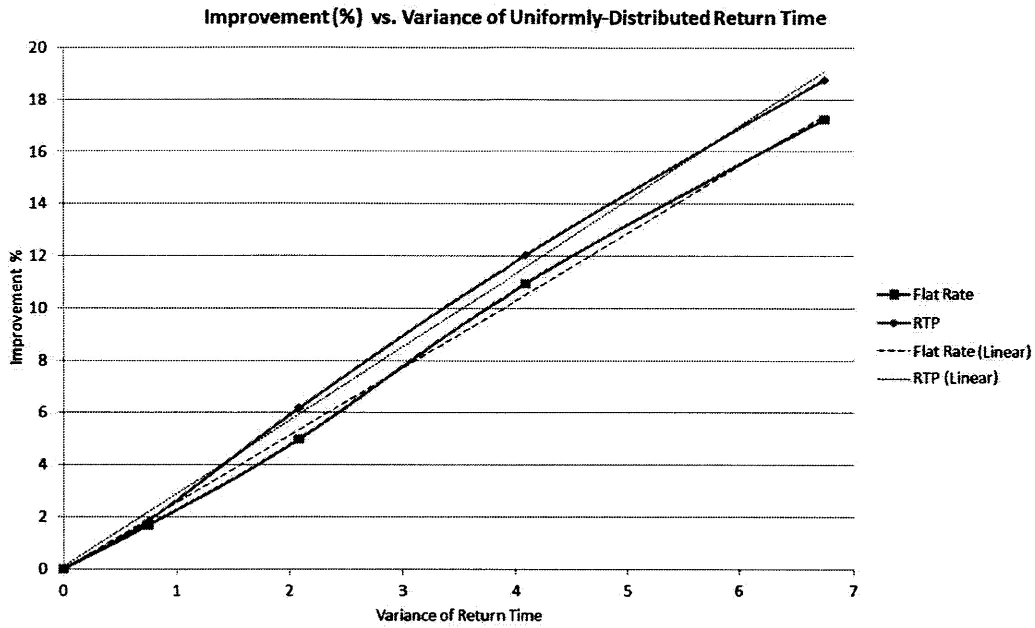

Figure 7-7: Improvement varies positively with variance of return time for both types of electricity tariffs over all values of comfort-discomfort tradeoff constant..

discomfort tradeoff (k) is set at 10, and that improvements at other settings are lower. The author ran simulations at k=10 with uniformly-distributed return times with variance that ranged from 0.75 to 6.75. Each value of the variance was obtained by narrowing the window of the return time by two hours to give uniformly-distributed return times over the intervals [14,23], [15,22], [16,21], [17,20] and [18,19].

The results are shown in Fig. 7-7, where every point corresponds to the improvement obtained when the cost-discomfort tradeoff constant is set at 10 for a uniformly distributed return time with variance on the horizontal axis. In other words, when the variance of the return time is approximately two, the improvement obtained under the flat rate and the RTP tariffs are approximately given by five and six percent respectively.

The plots in Fig. 7-7 were obtained by plotting the experimentally obtained results and the origin as an additional point. The origin corresponds to the theoretical case where the return time is a degenerate random variable with zero variance. Consequently, if the return time is a known constant, it is assumed that RSU has no effect and thus yield no improvement. This qualifies the origin as a valid point to be used in modeling the relationship between return time variance and improvement. Fitting a minimum mean-squared error line of best fit using standard linear regression yielded a linear regression model with a very high R-squared value of 0.998.

This positive relationship between improvement and variance is simply due to the fact that a resident with a larger variance in return time will have a greater likelihood of deviating from the expected return time that is used as the default return time in the EBS. This greater likelihood leads to a greater potential to have RSU save the day by providing a more accurate update, thereby leading to larger improvements.

Chapter 8

Summary, Conclusions and Future Research

8.1 Summary of Results

In 2010, the residential sector of the United States of America spent approximately 52 billion dollars on electricity for space-conditioning [DOE, 2010]. This is very close to the projected total government spending by the Commonwealth of Massachusetts for the financial year of 2011 [NASBO, 2010]. Clearly, space-conditioning is the elephant in the room. Occupancy-moderated zonal space-conditioning (OZS), which is the partitioning of a residence into different zones and independently operating the space-conditioning equipment of each zone based on occupancy, is a promising strategy to reduce the cost of space-conditioning. It should be noted that the cost of space-conditioning in this dissertation includes both the financial operating cost of running air-conditioners or electric space heaters as well as the cost associated with "service loss" or discomfort.

Although the use of zones in space-conditioning is simple and well-known, OZS under a demand-driven electricity pricing scheme electricity is not well understood. This dissertation presents the results of a modest effort to realize OZS and investigate its effectiveness.

The author developed the framework and algorithms to enable a local energy

Influencing Factor	Relationship with Level of Savings
Number of Zones	Positive
Number of Occupants	Negative
Randomness of Occupancy Pattern	Negative
Similarity of Occupants' Occupancy Patterns	Positive

Table 8.1: Summary of relationship between influencing factor and level of savings.

management agent (EMA) to accomplish occupancy-moderated multi-zone, multiple inhabitant space-conditioning under a demand-driven pricing scheme for electricity. The framework enables the EMA, once equipped with the right sensors and furnished with the needed information, to learn about the thermodynamic characteristics and occupancy patterns of the zones. This knowledge is then incorporated into a model to be used by an approximate dynamic programming algorithm to produce a series of control actions to the space-conditioning equipment.

In order to address the research questions listed in the introductory chapter, the author further investigated the effectiveness of the proposed framework and algorithm using Monte Carlo simulations. These simulations were run under realistic settings, made possible by using actual historical data or highly-realistic proxy data as the random inputs in virtual residential set-ups put together based on test cases presented in international standards.

The first research question asks about the level of cost savings OZS can achieve under a demand-driven electricity pricing scheme under realistic settings. The simulations reveal that a single occupant of a house with three zones can reduce up to 30% of total cooling cost in practice. Under less favorable circumstances, such as in the case of a couple with dissimilar occupancy patterns in a two-zone house, a marginal 7% reduction in cooling cost was observed.

The second research question queries how influencing factors impact the savings achieved by OZS under a demand-driven electricity pricing scheme. Table 8.1 summarizes the relationship between the influencing factors and the level of savings achieved. A positive relationship means that the larger the magnitude of the influencing factor, the greater the level of savings, when everything else remains the same.

In addition, given the same temperature difference between outdoor air temperature and desired zone temperature, the cost associated with cooling is expected to be lowered to a greater extent than that for heating.

The usefulness of remote schedule updates (RSU) as an ally to the EMA to reduce cost was investigated to address the third research question of "what level of space-conditioning cost reduction can remote schedule updates bring about?" RSU refers to the use of a cloud-connected device, such as a mobile phone, to provide additional information in the form of schedule updates to inform the appliances, their controller or the EMA so that they can operate at a time that best achieves an objective, such as to minimize cost. In this regard, the mobile device enhances the knowledge base of the appliance or the controller by allowing the resident to remotely provide schedule updates to the EMA.

The highest level of cost reduction brought about by RSU stands at 18%. The level of cost reduction, however, is highly dependent on the variance of the return time of the resident. A directly proportional relationship between the level of cost reduction and the variance of the return time was established as well, with cases where the variance is low reporting no cost reduction.

8.2 Conclusions

The research results described in the sixth and seventh chapters enable us to arrive at many conclusions. This section aims to present these conclusions as recommendations or pointers that may be useful to different stakeholders like homeowners, policy makers and developers of EMAs and related service providers. Cost in this section refers to a total cost that includes both the financial operating cost of running the space-conditioning equipment and the cost associated with service loss or discomfort.

8.2.1 Policy Makers

Policy makers may find themselves in a position where there are many different programs and initiatives in different candidate locations competing for a limited pool of funding. The author hopes that the following recommendations will help policy makers in formulating policy that pertains to energy efficiency in residential buildings.

1) Policy makers should consider promoting OZS and RSU for houses with light thermal masses as an alternative to weatherizing them and/or enabling them to participate in real-time pricing.

From Chapter Six, we see that houses with light thermal mass or "lightweight" houses do not benefit from pre-conditioning as they are unable to maintain the indoor zone temperature well on their own. The concept of pre-conditioning can be explained with the help of an example. In summer, the price of electricity typically peaks in the afternoon when the outdoor air temperature is high. Under a demand-driven pricing scheme, a house owner may save money by over-cooling or pre-conditioning the house in the early afternoon to a temperature below the desired temperature. Once the peak price sets in, he can switch off the air-conditioner, thereby refraining from using expensive electricity. The homeowner will not be too uncomfortable with the air-conditioner off as the house has been pre-cooled and is heating up slowly, assuming the house maintains indoor temperature well on its own.

In order for "lightweight" houses to benefit from pre-conditioning, some degree of weatherization or effort to increase their thermal mass must happen. The cost involved in doing so may be prohibitive, especially if it entails enhancing certain building elements.

OZS and RSU can make use of existing infrastructure and a ready-installed base of home computers to achieve the objective of reducing the cost of space-conditioning. For houses with broadband access, OZS is viable and may be more cost-effective as additional hardware to control space-conditioning devices are relatively inexpensive, compared with the cost of weatherizing a house that entails upgrading the insulation of the walls. This makes OZS and RSU a viable alternative to weatherization. The author is aware, however, that some houses can be weatherized at little cost. In such cases, weatherizing may turn out to be more cost-effective than implementing OZS and/or RSU.

2) Policy makers should consider implementing OZS in locations with large demand for cooling first.

The simulation results reveal that given the same temperature difference between the outdoor air temperature and the desired zone temperature, the cost associated with cooling is expected to be lowered to a greater extent than that for heating. Consequently, we can expect to achieve a greater degree of cost reduction in an air-conditioning situation vis-a-viz an electric heating one, with other things being the same.

In addition, the cooling load typically peaks at the same time as electricity demand does e.g. on a hot summer afternoon. OZS will also reduce peak demand and bring about the benefits of shaving the peaks of electricity, as described in [Black, 2005, Black and Larson, 2007]. Heating, on the other hand, is aided by solar heating and peak heating load typically does not coincide with peak electricity demand.

Since a cooling scenario is expected to give more bang for the buck, it should have priority over a heating scenario, assuming other conditions are similar, if not the same. This will help make the most out of the financial outlay.

3) Policy makers should consider adopting a cloud-based approach towards improving energy efficiency in residences by using strategies like OZS and RSU as this offers a relatively low-cost but potentially high impact option.

Being one of the most developed countries in the world, the U.S. has relatively high broadband and wireless penetration rates. The U.S. had a Wireless Penetration Equals of 102.4% as of June 2011 [CTIA, 2012] while 63.5% of American homes had broadband Internet connections [OECD, 2011] as of 2009. These statistics suggest a ready-installed base that is connected to the cloud in the U.S. which makes for a fertile ground for OZS and RSU to thrive on. In houses with broadband Internet connections, OZS can be realized by installing low-cost hardware that enables a home computer to control space-conditioning equipment.

With regard to OZS, the hardware needed for each zone is as simple as an occupancy sensor and a plugin device that goes between the wall socket and the space-conditioner. The plugin device serves as a switch that can be remotely controlled to manage the power supplied to the space-conditioner. To communicate with all the plugin devices, a wireless transmitter that is attached to the computer (that functions as an EMA) through the universal serial bus connection is needed as well [Leow, 2008] . This is the same set-up adopted by Verizon to control air-conditioners in the house [Verizon, 2012]. The combined cost of such a set-up (excluding the cost of the computer) is not expected to exceed hundreds of dollars for a house with many zones. For houses with broadband Internet, this comes as good news as it makes OZS viable since the additional hardware needed is relatively inexpensive.

8.2.2 Consumer/Homeowner

The residential sector currently does not have ready access to demand-driven pricing in most retail electricity markets. Consequently, opportunities for cost reduction through load shifting for homeowners are limited. Homeowners who have OZS or are considering OZS as an alternative cost-reduction strategy may find the following recommendations useful:

4) Home buyers or owners who can easily and economically realize OZS should consider doing so.

With OZS in place, they may see cost reduction exceed 40% if pre-conditioning that makes use of demand-driven pricing is in place as well. Without pre-conditioning, employing zoning only can bring the cost reduction close to 30%.

OZS is especially useful in residences where there are fewer residents and more zones. In general, if there are fewer residents and more zones, a greater degree of cost reduction can be expected.

5) In the absence of demand-driven pricing or in the case of a "lightweight" house, homeowners should consider installing OZS in their residences.

Pre-conditioning is not realizable without demand-driven pricing or if the house does not maintain the indoor temperature well on its own. This leaves OZS as the alternative to pre-conditioning in reducing space-conditioning cost. Simulations show that a single resident in a three-zone "lightweight" house can look forward to a 14% reduction in cooling cost with only OZS in place.

6) Homeowners should consider having a regular schedule and similarity in routines (for multiple inhabitants) as this will enable OZS to operate more efficiently.

Occupants having a regular schedule of activities and adhering to it will establish a pattern that the EMA can learn. (This is assuming that the occupants do not change the location where they conduct each activity i.e. always watching the television in the living room.) Consequently, this will reduce the randomness in his/her/their occupancy pattern(s) and enhance the predictability of their occupancy. The effect of this is that the EMA will be able to make more accurate predictions about the occupancy of a zone and make better decisions about when to actuate the space-conditioning equipment of a zone.

In the case with multiple occupants, having the occupants use the same zone at the same time will reduce the cooling load. For instance, based on the simulation results, a family of four that makes an effort to conduct most activities together could stand to gain an extra 8% of cost reduction than one that does not.

8.2.3 Developers of EMAs and Related Service Providers

Although home automation is several decades old, the development of EMAs that can operate appliances based on demand-driven electricity pricing for the mass market is relatively nascent. The following recommendations may be of use to future developers of EMAs and related service providers:

7) Developers should consider incorporating a simple override control for residents to inform the EMA that the current day is expected to be a day where occupancy will be highly random or that a large number of guests are expected, and it is better to go without OZS for the day.

While the EMA should operate with as little human intervention as possible, giving the user an option to change some aspect of its operation will be helpful. After all, people like to be in control.

From the simulation results, the gains from OZS tend to be low (at 7%) when the randomness is high and/or when occupants have dissimilar occupancy patterns. At such times, it may be better to do without OZS. This motivates the inclusion of an override control for the user to switch off OZS at will.

8a) Developers should consider incorporating a preset function for days when the occupancy schedule is known and will be followed very closely.

8b) Developers should consider realizing a function that will suggest changes to the residents' routine based on the learned occupancy model to reduce cost.

Pointers 8a and 8b aim at improving the predictability of occupancy patterns. The preset function will enable the EMA to operate as if it has perfect information on occupancy. For instance, during the baseball season, an avid baseball fan will be catching games on game days and can most likely be found in the entertainment room when the game is being played. Having a "Home Game Day" preset will inform the EMA that the resident will most likely be home by 7 pm that day and that the entertainment room will almost surely be occupied between say 8 pm and 11 pm. It is interesting to note that from the simulation runs, there is often a difference of at least 10% in the cost reduction achieved between the "perfect information" scenario and the realistic one, with all else being equal.

To realize OZS, the EMA would have learned an occupancy model of the occupant(s). Based on this model, it can actually look for times when it is advantageous for the occupant(s) to be at a zone at a particular time. For instance, it can recommend occupants to conduct their activities in the same zone on a hot summer afternoon when the price of electricity is at its peak.

A more sophisticated suggestion function can incorporate the thermodynamic model of the house as well. For instance, the EMA can recommend the occupant(s) to 'seek refuge' in the room that is least affected by the afternoon sun on a hot summer day. In this way, cost reduction is achieved by reducing the number of zones that need to be cooled, as well as the amount of electricity needed to pre-cool a zone or maintain the zone at a comfortable level.

9) Developers should consider incorporating OZS and RSU that make use of cloud-connected devices, like smartphones, and information from the cloud, like online calendars and television program listings, as much as possible.

A strength of OZS and RSU lies in the fact that they can make use of infrastructure that is already in place and can have allies that come for free. For instance, a mobile app on a Global Positioning System(GPS)-enabled smartphone can provide real-time updates to the EMA about the predicted arrival time of a resident as he commutes home from work. Having the EMA check the online calendar of the resident and even television listings of the resident's favorite program is another means of improving the predictability of occupancy patterns.

8.3 Future Work

This section discusses several directions for future research. These suggested directions for research aim to advance our understanding of OZS and RSU in the context of residential EMAs, or to address certain limitations of the study presented in this dissertation.

8.3.1 Remote Schedule Updates

From the discussion in the preceding chapter, we know that even with RSU, the resident may still reach home early or late due to a variety of reasons, such as uncertainty in commute time. Further studies to understand the degree of degradation due to deviations from the time reported by RSU will enhance our understanding of the true value of using RSU in practice. Towards this end, future researchers can run simulations with RSU while incorporating a random deviation on the actual return time to observe the drop in cost reduction due to such deviations.

As smartphones typically come with the capability to locate themselves using the GPS, there are mobile apps on the market that enables a smartphone to function as an in-vehicle GPS unit that provides navigational assistance and projected arrival times. The projected arrival times can potentially be used to advise the EMA in real-time of the resident's expected return time. If such an arrangement can be put in place, it can complement the RSU described in Chapter Seven. Residents with lengthy commutes will stand to benefit the most from such GPS-enabled updates. Further research to investigate the actual benefit arising from the use of GPS-enabled updates will be of great interest to consumers and policy makers alike. Gupta, Intille and Larson [Gupta et al., 2009] and Kleiminger, Santini and Weiss [Kleiminger et al., 2011] have investigated the use of mobile phones as an aid to residential space-conditioning.

8.3.2 Prototype Implementation and Evaluation

Future researchers may want to implement the proposed framework and algorithms in a prototype for a field study to investigate how OZS and RSU will perform in practice. This will tell us about the effectiveness of OZS and RSU and can serve as a litmus test of their usefulness. Furthermore, a field study will enable engineers and builders to understand the issues and subtleties that may arise in practice, and come up with modifications or enhancements should any be needed. This will bring us one step closer to an EMA with OZS and RSU capabilities which is ready for deployment in houses.

In addition, such field studies can advise decision makers on public policy on the effectiveness of policy schemes involving OZS, RSU and residential responsive demand for electricity. By informing the decision makers in cost-benefit analysis, they can determine socially-equitable levels of subsidies to encourage modifications to houses to implement OZS and/or RSU.

Future researchers can also consider extending this work to other disciplines. For instance, researchers working on the behavioral aspects of energy consumption can consider implementing the proposed framework and algorithm in a house to observe user response.

In this study, it is assumed that the space-conditioning equipment can be actuated at evenly-spaced levels of power, from zero to maximum. In practice, especially with the option of using a plugin device described in [Leow, 2008] and adopted in [Verizon, 2012], the actuation may only occur at two levels i.e. On-Off in a binary control scheme.

The performance of OZS and RSU under binary control should be investigated as well. And if the degradation in performance is large, a solution may be to operate the space-conditioning device using a duty cycle to simulate the effects of having graduated power levels. For instance, for an electric space heater on binary control, operating it at a duty cycle of 50% over the duration of the control period effectively produces a heater operating at 50% of maximum power. (Air-conditioners in general should not be turned on and off in quick succession.)

8.3.3 Further Study on Number of Zones and Occupants

The results presented in Chapter Six validate our intuitive notion that having fewer occupants and more zones leads to better OZS performance. This leads naturally to the question of how the performance of OZS varies with different number of zones and occupants, where asymptotic results are of particular interest.

Future researchers can consider investigating how the performance of OZS improves given a fixed number of occupants and occupancy characteristics. A possible way to frame the problem is:

$$p = f(M, K|\underline{O}_M) \tag{8.1}$$

where

p	a metric measuring the performance of OZS,
f	a function to be estimated or determined,
M	number of occupants,
K	number of zones, and
$\underline{O}_M$	vector describing occupancy characteristics of M occupant(s).

We can approximate the limiting case where K is very large as each occupant being in a zone consisting of a space of infinitesimally small width away from the occupant that is maintained at the preferred temperature. The physical realization of this is is a "comfort suit", which operates like a space suit except that the "comfort suit" aims to keep the person wearing it comfortable. Observe that in such a case, occupancy pattern does not matter as the space surrounding the occupant is always with the occupant. We can express this as:

$$\begin{aligned}\lim_{K\to\infty} p &= \lim_{K\to\infty} f(M, K|\underline{O}_M) \\ &= \lim_{K\to\infty} f(M, K).\end{aligned}$$

With the above formulation, determining p is a matter of finding the cost of powering the "comfort suit" by a battery (which can presumably be charged during the hours when electricity is the cheapest) and the cost of conditioning the residence as a single unit. Monte Carlo simulation can be used to investigate the cases where the residence has an intermediate value for the number of zones i.e. $K \in [5, \infty)$.

Another interesting direction of research is to investigate the number of occupants at which the performance of OZS is virtually zero, given a fixed number of zones. We expect this to be highly dependent on the occupancy patterns of the occupants. Intuition suggests that if the occupants have dissimilar occupancy patterns, one can expect performance to degrade significantly as the number of occupants comes close to the number of zones. On the other hand, if the occupants have very similar occupancy patterns, it may turn out that performance will suffer significantly when the number of occupants exceeds that of the number of zones by a large extent.

8.3.4 Learning and Characterization

An important thrust for future research ought to be studies that improve the performance of OZS, as this will directly and positively impact the level of cost reduction attainable by an EMA. The performance of OZS may be improved through the use of more sophisticated thermodynamic modeling to arrive at a state transition function. For example, a neural network can be used in place of the linear regression model in learning about the thermodynamic characteristics of each zone. The author would like to urge future researchers to adopt the same virtual set-up of residences presented in Chapter Four in their investigations so as to share a common basis for comparison.

One of the key lessons from Chapter Six is that a residence with light thermal mass may not benefit from pre-conditioning. This begs the question if there is a threshold below which pre-conditioning is not worth pursuing. A possible line of inquiry is to investigate if the said threshold can be determined from the thermal mass of a zone, the price difference between the peak price of electricity and the off-peak price and the duration of time between the peak and the off-peak prices of electricity.

While randomness and similarity in occupancy patterns discussed in Chapter Five are two key influencing factors, there is also the notion of frequency of change in the location of the resident that may also impact the performance of OZS. It will be of great interest to determine, possibly with the help of Monte Carlo simulations, the relationship between frequency of location change and improvements achieved by OZS.

Recall from Chapter Five that the current implementation uses a frequency counting approach to learn occupancy patterns. In this approach, the probability of a zone being occupied at a certain time period is given by the historical record of it being occupied. An approach that uses a Markov model can be developed in conjunction with the investigations on the relationship between frequency of location change and improvements achieved by OZS.

A Final Note

It is a tall order to ask of homeowners to overhaul their houses at great financial costs just to lower the cost of space-conditioning. While we await the renewal of the housing stock in the United States over the coming decades such that they are more energy efficient through weatherization or having a built-in OZS system, an EMA in the mold of an Energy Box realizing OZS and perhaps aided by RSU remains a viable bridging solution for the near future and the medium term. It is the wish of the author that the findings presented in this dissertation will contribute in some modest ways towards the overarching objective of addressing the energy needs of our civilization.

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Appendix A

Material Specifications

TABLE 11 Material Specification Heavyweight Case

Element	k, W/(m·K)	Thickness, m	U, W/(m²·K)	R, m²·K/W	Density, kg/m³	C_p, J/(kg·K)
Heavyweight Case: Exterior Wall (inside to outside)						
Int Surf Coef			8.290	0.121		
Concrete Block	0.510	0.100	5.100	0.196	1400	1000
Foam Insulation	0.040	0.0615	0.651	1.537	10	1400
Wood Siding	0.140	0.009	15.556	0.064	530	900
Ext Surf Coef			29.300	0.034		
Total air—air			**0.512**	**1.952**		
Total air—surf			**0.556**	**1.797**		
Heavyweight Case: Floor (inside to outside)						
Int Surf Coef[a]			8.290	0.121		
Concrete Slab	1.130	0.080	14.125	0.071	1400	1000
Insulation	0.040	1.007	0.040	25.175	(see Note b)	(see Note b)
Total air—air			**0.039**	**25.366**		
Total air—surf			**0.040**	**25.246**		
Heavyweight Case: Roof (inside to outside)[c]						
Int Surf Coef[a]			8.290	0.121		
Plasterboard	0.160	0.010	16.000	0.063	950	840
Fiberglass quilt	0.040	0.1118	0.358	2.794	12	840
Roofdeck	0.140	0.019	7.368	0.136	530	900
Ext Surf Coef			29.300	0.034		
Total air—air			**0.318**	**3.147**		
Total air—surf			**0.334**	**2.992**		

Summary: Heavyweight case

Component	Area, m²	UA, W/K
Wall	63.600	32.580
Floor	48.000	1.892
Roof	48.000	15.253
S. Window	12.000	36.000
Infiltration		18.440[d]
Total *UA* (with S. Glass)		**104.165**
Total *UA* (without S. Glass)		**68.165**

ach	**Volume, m³**	**Altitude, m**
0.500	129.6	1609.0

[a]The interior film coefficient for floors and ceilings is a compromise between upward and downward heat flow for summer and winter.
[b]Underfloor insulation shall have the minimum density and specific heat the program being tested will allow, but not < 0.
[c]The heavyweight case roof is the same as the lightweight case roof.
[d]UA corresponding to infiltration based on: ach × volume × (specific heat of air) × (density of air at specified altitude).

Figure A-1: Material specification for heavy thermal mass Case 900 (Extracted from [ASHRAE, 2007].)

TABLE 1 Material Specifications Lightweight Case

Element	k, W/(m·K)	Thickness, m	U, W/(m²·K)	R, (m²·K)/W	Density, kg/m³	C_p, J/(kg·K)
Lightweight Case: Exterior Wall (inside to outside)						
Int Surf Coef			8.290	0.121		
Plasterboard	0.160	0.012	13.333	0.075	950.000	840.000
Fiberglass quilt	0.040	0.066	0.606	1.650	12.000	840.000
Wood Siding	0.140	0.009	15.556	0.064	530.000	900.000
Ext Surf Coef			29.300	0.034		
Total air—air			**0.514**	**1.944**		
Total air—surf			**0.559**	**1.789**		
Lightweight Case: Floor (inside to outside)						
Int Surf Coef[a]			8.290	0.121		
Timber flooring	0.140	0.025	5.600	0.179	650.000	1200.000
Insulation	0.040	1.003	0.040	25.075	(see Note b)	(see Note b)
Total air—air			**0.039**	**25.374**		
Total air—surf			**0.040**	**25.254**		
Lightweight Case: Roof (inside to outside)						
Int Surf Coef[a]			8.290	0.121		
Plasterboard	0.160	0.010	16.000	0.063	950.000	840.000
Fiberglass quilt	0.040	0.1118	0.358	2.794	12.000	840.000
Roofdeck	0.140	0.019	7.368	0.136	530.000	900.000
Ext. Surf Coef			29.300	0.034		
Total air—air			**0.318**	**3.147**		
Total air—surf			**0.334**	**2.992**		

Summary: Lightweight Case

Component	Area, m²	UA, W/K
Wall	63.600	32.715
Floor	48.000	1.892
Roof	48.000	15.253
S Window	12.000	36.000
Infiltration		18.440[c]
Total *UA* (with S Glass)		**104.300**
Total *UA* (without S Glass)		**68.300**

ach	Volume, m³	Altitude, m
0.500	129.600	1609.000

[a]The interior film coefficient for floors and ceilings is a compromise between upward and downward heat flow for summer and winter.
[b]Underfloor insulation shall have the minimum density and specific heat the program being tested will allow, but not < 0.
[c]UA corresponding to infiltration based on: ach × volume × (specific heat of air) × (density of air at specified altitude).

Figure A-2: Material specification for light thermal mass Case 600 (Extracted from [ASHRAE, 2007].)

TABLE 12 Thermal and Physical Properties of the Sun-Zone/Back-Zone Common Wall (Case 960)

k, W/(m²·K)	Thickness, m	U, W/(m²·K)	R, (m²·K)/W	Density, kg/m³	Specific Heat, J/(kg·K)	Shortwave Absorptance	Infrared Emittance
0.510	0.20	2.55	0.392	1400	1000	0.6	0.9

Figure A-3: Material specification for common wall in Case 960 (Extracted from [ASHRAE, 2007].)